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Section: 1: Introduction

This report has been for a comprehensive analysis of Winter Rock, a UK-based winter sports venture specialising in a diverse range of skiing, snowboarding, and climbing gear. The market demand is affected by domestic winter sports enthusiasts and international tourists, with an increasing interest in winter tourism and artificial dry ski slopes in the UK. This study aims to give a data-driven analysis of the company's existing market position, study historical sales patterns, forecast future product demand, optimise distribution logistics, and examine the potential of bringing a new product.

This report includes the following analyses:

Sales Trend Analysis: Using historical sales data from **January'19** to **June'22**, this task provides a detailed time series analysis, showing underlying trends and seasonal patterns that may be used for strategic decision-making and marketing initiatives.

Forecasting Sales for Year-round Products: Based on sales data for items that typically perform well throughout the year, forecasting the sales for these products for the duration of **July'22** to **December'22** with Single Exponential Smoothing, for inventory management.

Optimisation of Distribution Plans: With an emphasis on growing into new local markets, this section uses linear programming (Solver) to develop a cost-effective distribution strategy utilising the company's two distribution centres.

Market Analysis for a New Product Launch: This section involves a decision analysis for a new low-cost ski product, assessing supplier choices and demand scenarios to maximise profitability.

Impact Analysis of New Product Demand: This section uses simulation techniques to predict potential profit in various demand scenarios for the new ski product, to support decision-making under uncertainty.

These analyses will provide strategic suggestions focused on enhancing operational efficiency, capitalising on market opportunities, and ensuring Winter Rock's long-term success.

Section: 2: Investigating Sales Trends

This study analyses Winter Rock's historical aggregate sales data from **January'19** to **December'22** to identify trends and seasonality for strategic decision-making, with an emphasis on capacity planning and promotional efforts. The dataset comprises monthly sales numbers, which were extensively studied using a range of time series analyses and visualisations to ensure a comprehensive understanding of sales dynamics.

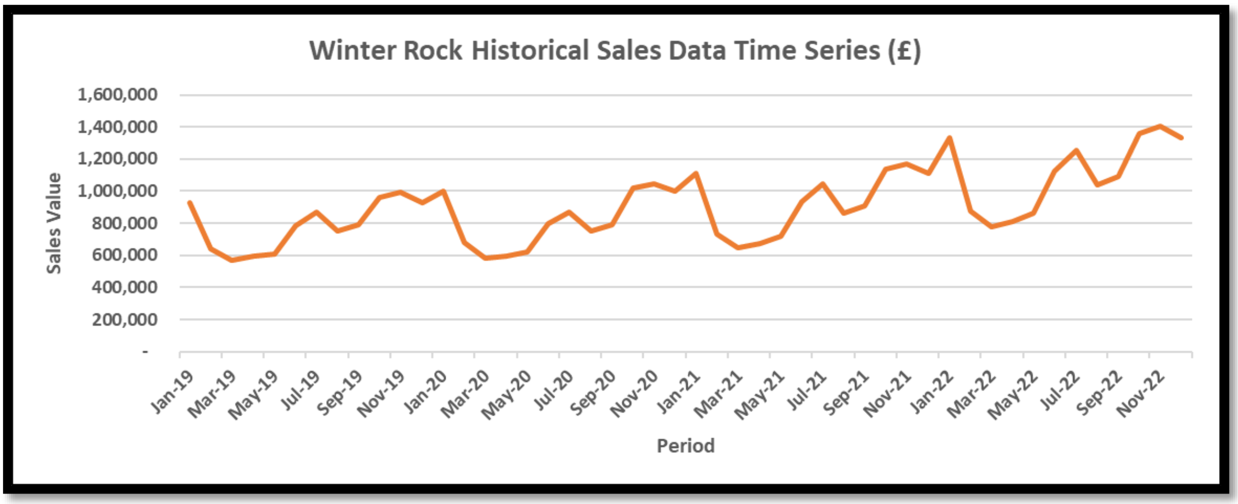


Figure: 1.1: Winter Rock Historical Sales Data Time Series Plot (Created by Author)

Time Series and Moving Averages Analysis: The historical sales data was plotted as a time series to demonstrate monthly variations over a four-year period. Additionally, to smooth out the fluctuations and to examine the underlying trend moving average for 12 months was calculated, followed by a Centred Moving Average (CMA) was computed using the formula:

$$\mathbf{CMA}\boldsymbol{t} = \mathbf{MA}\boldsymbol{t} - \mathbf{1} + \mathbf{Ma}\boldsymbol{t}\ /\ \mathbf{2}$$

Formula: 1.1: Centred Moving Average (CMA)

Where MAt is the 12-month moving average at time t. The CMA effectively demonstrates a general upward trend in sales, with the CMA growing from around **£800,000** in early 2019 to over **£1,000,000** by the end of 2022. This increasing trend indicates a growing market demand and an effective marketing strategy.

Table: 1.1: Historic Sales Data and Year-Round Sales Data Descriptive Statistics (Created by Author)

Historic Sales Descriptive Statistics		*Year-Round Sales Descriptive Statistics*	
Mean	905,981	Mean	386,761
Standard Error	32,256	Standard Error	3,361
Median	872,836	Median	380,159
Mode	927,616	Mode	428,280
Standard Deviation	223,477	Standard Deviation	23,286
Sample Variance	49942179847	Sample Variance	542241218.9
Kurtosis	-51%	Kurtosis	181%
Skewness	43%	Skewness	129%
Range	833,388	Range	113,775
Minimum	569,679	Minimum	352,746
Maximum	1,403,067	Maximum	466,521
Sum	43,487,096	Sum	18,564,512
Count	48	Count	48
Confidence Level(95.0%)	64891.09319	Confidence Level(95.0%)	6761.570916

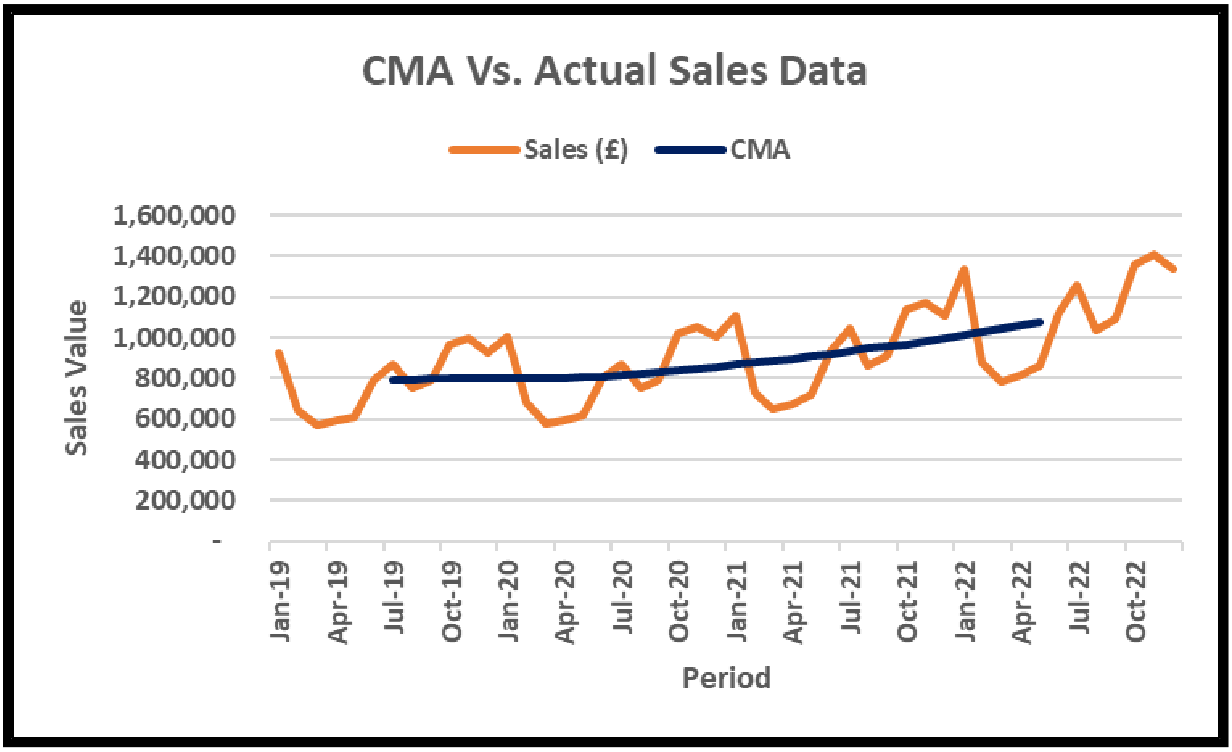


Figure: 1.2: Winter Rock Historical Sales Data Vs. CMA Plot (Created by Author)

Seasonality Analysis and Decomposition Matrix:

To analyse seasonality, the time series was detrended by subtracting the CMA from the original sales. The findings were transformed into a seasonal matrix. Each observation in the matrix indicates a month's deviation from the trend, thus identifying the seasonal influence. This matrix demonstrated dramatic sales increases from October to December each year, with detrend values increasing considerably, indicating a strong seasonal demand associated with winter sports activities.

Table: 1.2: Seasonality Decomposition Matrix Annual Data and Seasonal Profile (Created by Author)

Seasonal Matrix					
Month	**2019**	**2020**	**2021**	**2022**	**Seasonal profile**
Jan		205352	244503	322513	244503
Feb		-119279	-147862	-149955	-147862
Mar		-218493	-237284	-260738	-237284
Apr		-206013	-220781	-246271	-220781
May		-184963	-189799	-216308	-189799
Jun		-9696	18344		4324
Jul	79068	52402	115638		79068
Aug	-39658	-70851	-81880		-70851
Sep	-1918	-36267	-47934		-36267
Oct	167026	180538	166328		167026
Nov	196220	204499	189797		196220
Dec	130596	150261	116980		130596

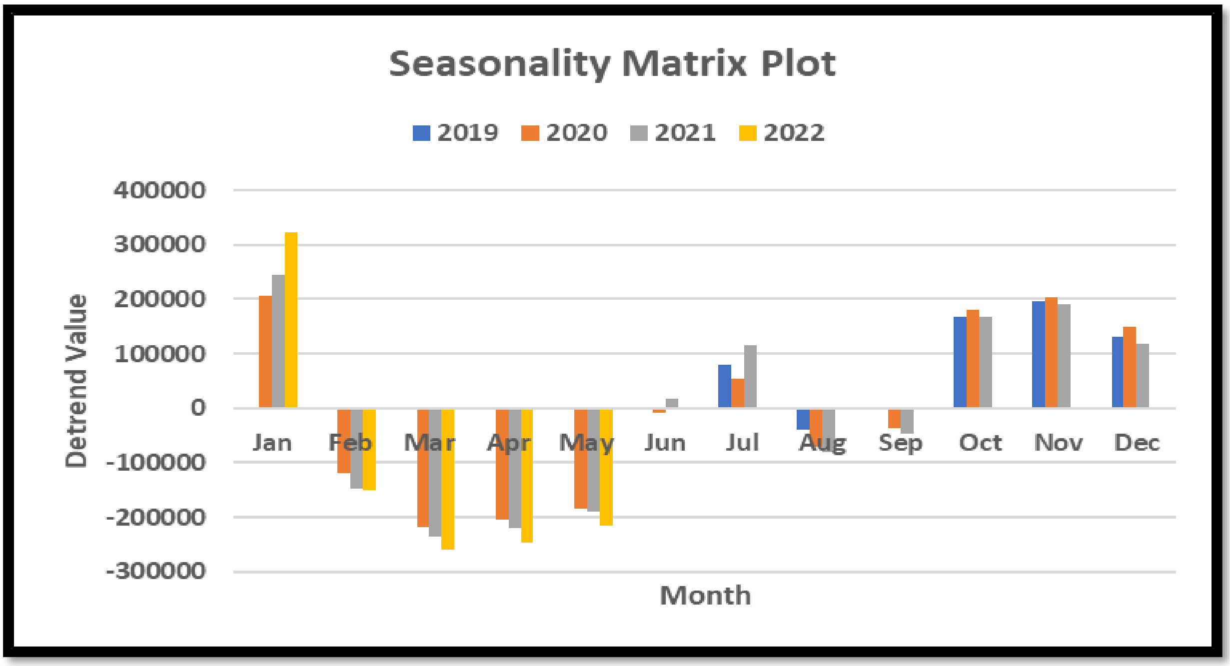


Figure: 1.3: Yearly Seasonal Matrix Plot (Created by Author)

Key Observations:

Peak Seasonal Demand: Sales often increase from October to December every year, with detrend values of **+£167,026** in October and **+£196,220** in November.

Low Seasonal Demand: The months of February and March have negative detrend values every year, such as **-£147,862** in February and **-£237,284** in March, suggesting the lowest sales seasons due to the off-season period.

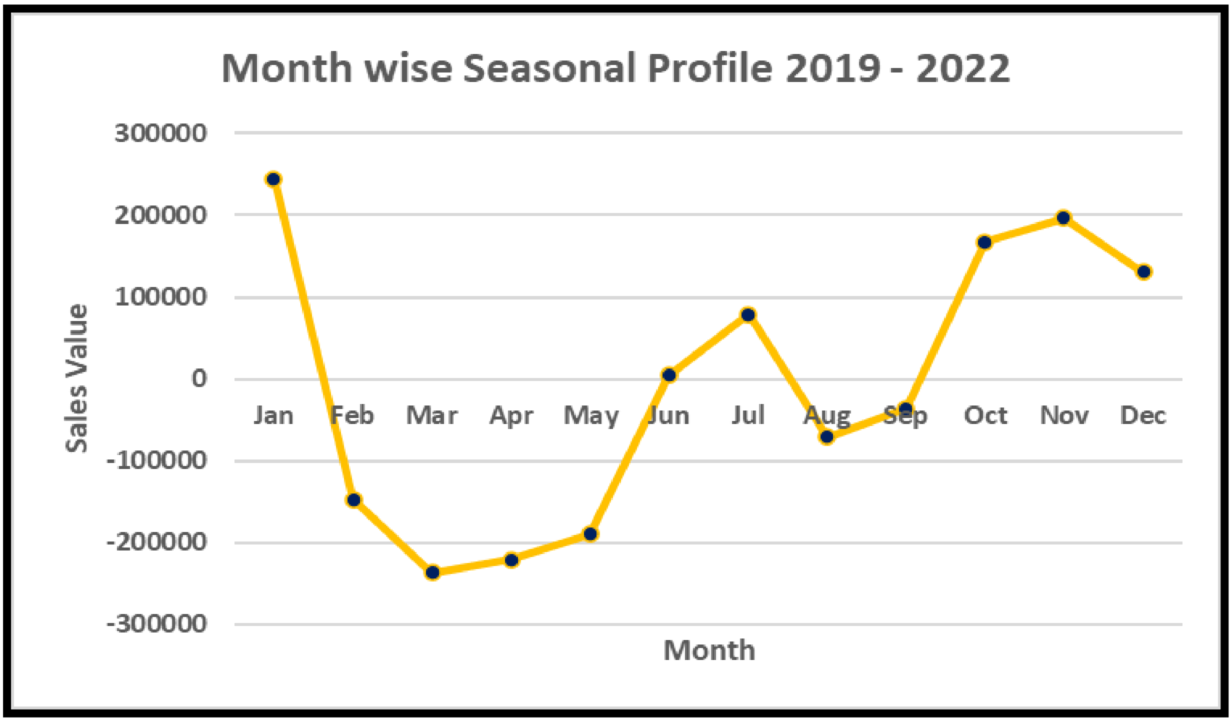


Figure: 1.4: Month-Wise Annual Seasonal Profile 2019 - 2022 (Created by Author)

The yearly seasonal profile has been made by aggregating detrended monthly sales values over four years. The above graph shows that the largest sales occur in January **£244,503** and December **£130,596** due to the peak winter season, while sales are lowest during the off-season period, which runs from February to May.

Implications for Capacity Planning and Marketing

The detailed seasonality analysis of sales provided valuable insights, which may have a significant impact on strategic decision-making at Winter Rock.

Inventory and Supply Chain Management: To fulfil the peak season's demand, adequate stock levels must be maintained. This may require scaling up production or acquiring more suppliers in advance for the peak season.

Targeted Marketing Campaigns: Enhanced tailored marketing campaigns for peak and off-seasons could help to increase sales. Peak season promotions might focus on increasing sales volume and profitability, whilst off-peak months could focus on keeping customers engaged, potentially through off-season sales discounts and events.

The trend and seasonality analysis of Winter Rock's sales data provides a robust basis for optimising operational and marketing strategies. Improved forecasting models may enable to predict seasonality and anticipate future demand more accurately. Leveraging the seasonal matrix findings to tailor marketing and promotional campaigns to align closely with customer spending patterns. By aligning inventory management and marketing campaigns with these data-driven insights Winter Rock can significantly improve its market position and ensure optimal resource allocation and utilisation throughout the year.

Section: 3: Forecasting Sales for Year-Round Products

Winter Rock's strategic emphasis on maintaining the availability of year-round items like all-purpose hiking shoes and t-shirts requires accurate sales forecasting. Analysing Year-round aggregate sales data from January’19 to June’22, the Single Exponential Smoothing (SES) **(Overload, 2024)** approach was employed to forecast sales for the next six months till December’22.

Table: 1.3: Forecasting of In-Sample and Out-of-Sample Sales with SES (Created by Author)

Year-Round Products Aggregate Sales									
Period	In-sample Sales (£)	Out-of-Sample Sales (£)	Month	Alpha (α)	SES (FIT)	e	|e|	|pae|	e^2
Jan-19	378,052	-	1	**0.4**					
Feb-19	395,196	-	2		394,143	1,053	1053	0.27%	1,108,809
Mar-19	364,619	-	3		394,564	- 29,945	29945	8.21%	896,715,003
Apr-19	383,309	-	4		382,586	723	723	0.19%	522,555
May-19	380,548	-	5		382,875	- 2,327	2327	0.61%	5,416,195
Jun-19	375,811	-	6		381,944	- 6,133	6133	1.63%	37,618,144
Jul-22		366,794	7		378,655	- 11,861	11861	3.23%	140,684,255
Aug-22		368,392	8		378,655	- 10,263	10263	2.79%	105,329,977
Sep-22		396,193	9		378,655	17,538	17538	4.43%	307,580,063
Oct-22		374,006	10		378,655	- 4,649	4649	1.24%	21,613,567
Nov-22		419,541	11		378,655	40,886	40886	9.75%	1,671,661,777
Dec-22		428,280	12		378,655	49,625	49625	11.59%	2,462,636,718

Forecasting Analysis: The SES model was employed with an **alpha (α) = 0.4**, chosen after evaluating other values to balance responsiveness and stability. This alpha value struck the optimal balance, yielding an in-sample mean absolute percentage error (MAPE) of **4.37%** and an out-of-sample MAPE of **5.50%**. These numbers demonstrate how the model effectively adapts to the sales trend while avoiding overfitting to slight deviations. The RMSE values are also modestly placed, indicating that this amount of smoothing is effective without being too sensitive to minor fluctuations in sales data.

Table: 1.4: Forecasting Accuracy with Different Alpha Values (Created by Author)

Alpha values	Summary Error Measures (In-sample)					Summary Error Measures (Out-of-sample)				
	ME	MAE	MAPE	MSE	RMSE	ME	MAE	MAPE	MSE	RMSE
0.1	-3521.39	17768.84	4.55%	539,997,184	23237.84	12495.71	22470.33	5.52%	757,567,356	27523.94
0.2	-1961.02	17490.80	4.46%	556,307,088	23586.16	14138.33	22470.33	5.50%	801,317,076	28307.54
0.3	-1272.49	17259.92	4.39%	579,507,097	24072.95	13709.64	22470.33	5.50%	789,378,933	28095.89
0.4	-944.39	17169.74	4.37%	605,685,993	24610.69	13545.96	22470.33	5.50%	784,917,726	28016.38
0.5	-777.45	17332.77	4.41%	636,182,993	25222.67	13995.67	22470.33	5.50%	797,303,542	28236.56

Performance Metrics

Table: 1.5: Forecasting Accuracy of In-Sample and Out-of-Sample Sales (Created by Author)

Summary Error Measures (In-sample)		Summary Error Measures (Out-of-sample)	
ME	-944.39	ME	13545.96
MAE	17169.74	MAE	22470.33
MAPE	4.37%	MAPE	5.50%
MSE	605,685,993	MSE	784,917,726
RMSE	24611	RMSE	28016.38

In-sample forecast accuracy was measured with an MSE of **605,685,993** and RMSE of **24,611**. For the out-of-sample period, the MSE increased to **784,917,726** with an RMSE of **28,016.38**. The minor rise in error metrics out of the sample indicates that, while the model covers overall trends effectively, it may fail to capture sudden changes in the sales pattern.

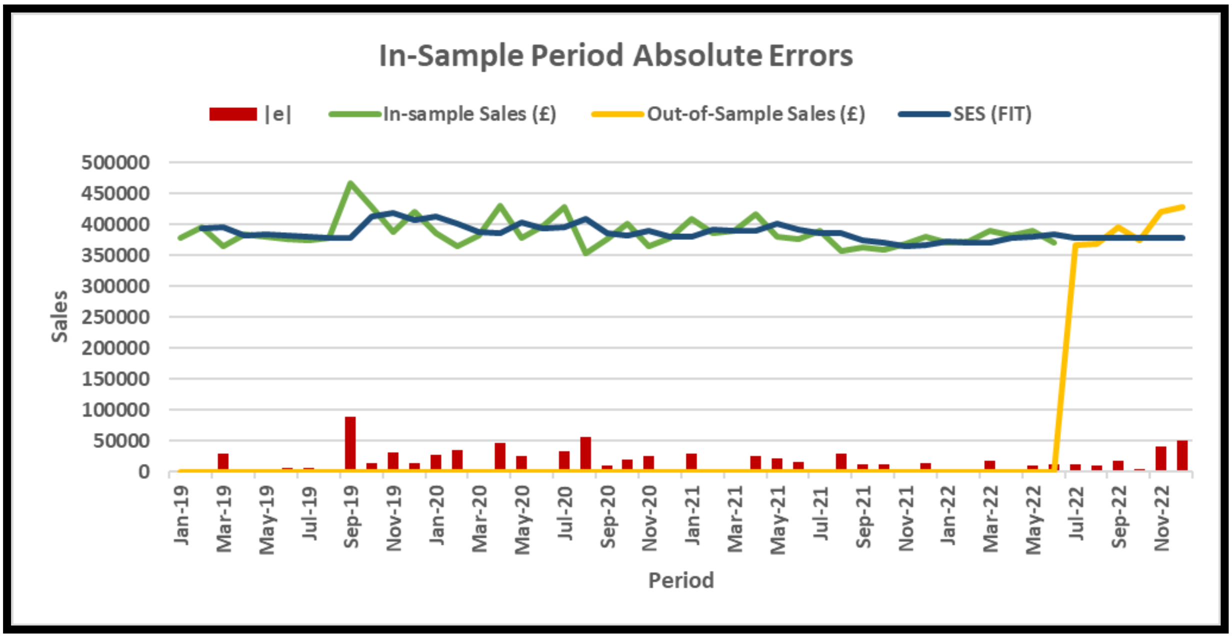


Figure: 1.5: In-sample and Out-of-Sample Absolute Errors SES Plot (Created by Author)

Re-order Point Calculation

Utilising the forecast data, the re-order point was calculated to ensure product availability and minimal stockouts. Based on the lead time and prediction span, the re-order point was calculated using the formula below.

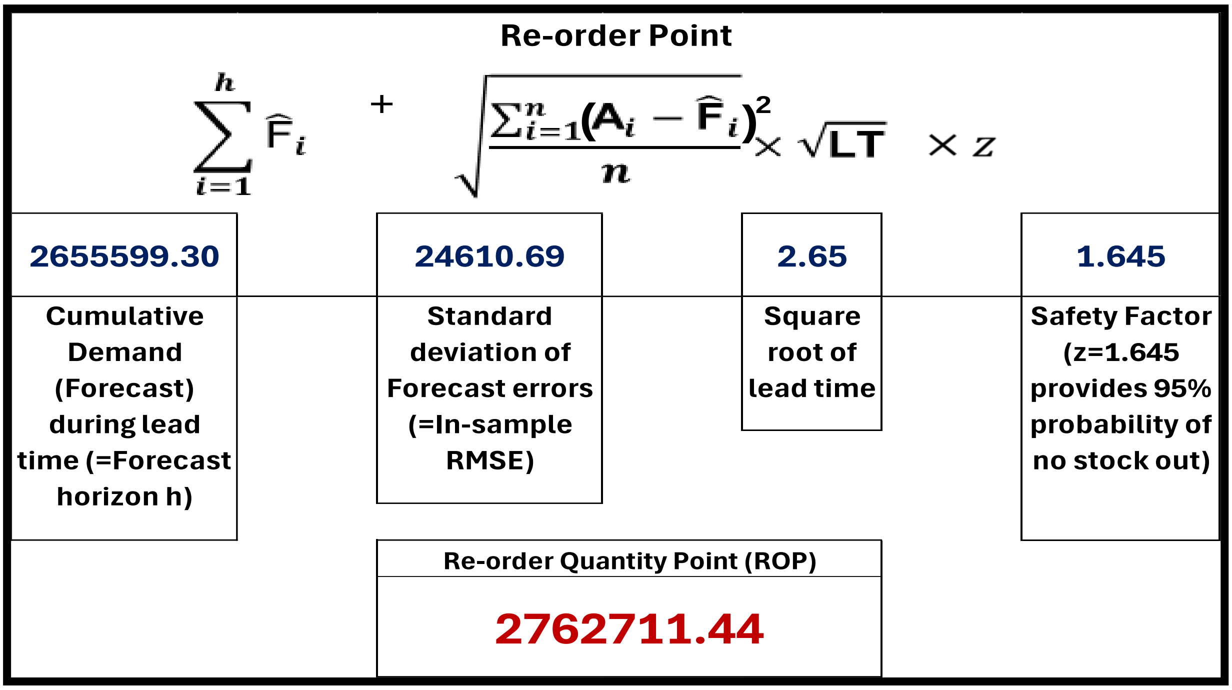


Figure: 1.6: Quantity Re-order Point Formula and Calculation (Created by Author)

ROP=2,655,599.30+ √2.65×24,610.69×1.645=2,762,711.44

Formula: 1.2: Quantity Re-order Point Calculation

In this equation, F is the cumulative predicted demand of **2,655,599 units**, σ is the in-sample RMSE **24,610.69**, LT is the lead time in months **2.65 months**, and Z is the 95% confidence interval for minimal stockouts. This yielded a re-order point of about **2,762,711** units, rounded for ease of understanding.

Advantages of the SES method

Simple and efficient: Easy to implement and requires minimal computational resources.

Adaptability: Correct optimisation of **α** allows the model to react quickly to the changes in sales, making it ideal for items with non-constant mean sales levels.

Disadvantages of the SES method:

Lack of trend and seasonality modelling: SES does not account for trend or seasonal variations, which might result in underfitting data with strong seasonal trends.

Sensitivity to α: Choosing the right **α** value is critical for accurate forecasting, requiring careful optimisation of historical data.

The applied SES model and ROP calculation demonstrate the requirement for adaptive inventory strategies in operational planning. The SES model provides a solid foundation for demand forecasting, ensuring that Winter Rock can efficiently satisfy consumer demand throughout the year. Adding additional data points to the forecasting process and adjusting model parameters in response to new sales patterns or market conditions may reduce errors in out-of-sample periods.

Section: 4: Distribution Plan

In response to increasing sales and demand, Winter Rock is strategically expanding its distribution capabilities to efficiently target new local markets in the UK's East Midlands, West Midlands, and Northwest regions. This section provides the optimised distribution strategy for meeting expected demand efficiently and cost-effectively over the next six months, utilising its distribution centres in Manchester and London.

Decision Variables and Objectives

To overcome logistical challenges, this distribution plan involves determining the number of units that each centre should send to each area to reduce overall shipping expenses. The decision variables are described below,

xME = Units shipped from Manchester to the East.

xMW = Units shipped from Manchester to the West.

xMN = Units shipped from Manchester to the North.

xLE = Units shipped from London to the East.

xLW = Units shipped from London to the West.

xLN = Units shipped from London to the North.

The primary objective is to minimise overall transportation costs, which are determined by the distance and quantity shipped between locations. The objective function can be mathematically stated as follows,

Table: 1.6: Region and Centre wise Decision Variables and Objectives (Created by Author)

Region	East (E)	West (W)	North (N)
Manchester (M)	15	21	17
London (L)	23.5	25.5	22

Minimize $Z = 15xME + 21xMW + 17xMN + 23.5xLE + 25.5xLW + 22xLN$

Formula: 1.3: Formula to Expand Distribution with Minimum Shipping Cost

This function ensures that the distribution strategy is cost-effective, considering the different transportation costs from the centre to each region.

Capacity and Demand Constraints

The distribution strategy must consider both the distribution centre's capacity limitation and regional demand.

Capacity Constraints

Table: 1.7: Region and Centre-wise Capacity Constraints (Created by Author)

Region	East (E)	West (W)	North (N)	Limit
Manchester (M)	15	21	17	2500
London (L)	23.5	25.5	22	3000

Manchester Centre has a maximum capacity of **2,500** units. **(xME + xMW + xMN ≤ 2500)** London centre has a maximum capacity of **3,000** units. **(xLQ + xLW + xLN ≤ 3000)**. These constraints ensure that none of the centres are overburdened beyond their operating capacity.

Demand Constraints

Table: 1.8: Region and Centre-wise Capacity Constraints (Created by Author)

Region	East (E)	West (W)	North (N)
Limit	2000	930	2200
Constraint	2000	930	2200

The East has an expected demand of **2,000** units **(xME + xLE = 2000)**. The West has a demand of **930** units **(xMW +x LW = 930)** The Northwest requires **2,200** units **(xMN + xLN = 2200)** By setting these constraints, the distribution strategy ensures that all regional demands are satisfied accurately, with no shortages or surpluses.

Optimal Distribution Plan

Table: 1.9: Region and Centre-wise Optimal Distribution Plan (Created by Author)

Region	East (E)	West (W)	North (N)	Solution	Total Cost
Manchester (M)	**2000**	**0**	**500**	**2500**	**99615**
London (L)	**0**	**930**	**1700**	**2630**	

The optimal distribution strategy as determined by the solver suggests that Manchester should ship **2,000** units to the east and **500** units to the north, fully utilising its capacity of **2,500** units. London, on the other hand, should transport **930** units to the West and **1,700** to the North, utilising **2,630** of its **3,000**-unit capacity. This distribution reduces transportation costs while meeting regional demands accurately, for a total cost of **£99,615**. This distribution makes effective use of each distribution centre's capacity and geographical benefits.

Sensitivity Analysis

Microsoft Excel 16.0 Sensitivity Report
Worksheet: [data.xlsx]Task 4
Report Created: 07/05/2024 06:21:25 AM

Variable Cells

Cell	Name	Final Value	Reduced Cost	Objective Coefficient	Allowable Increase	Allowable Decrease
B8	Manchester East	2000	0	15	3.5	20
C8	Manchester West	0	0.5	21	1E+30	0.5
D8	Manchester North	500	0	17	0.5	3.5
B9	London East	0	3.5	23.5	1E+30	3.5
C9	London West	930	0	25.5	0.5	25.5
D9	London North	1700	0	22	3.5	0.5

Constraints

Cell	Name	Final Value	Shadow Price	Constraint R.H. Side	Allowable Increase	Allowable Decrease
B3	Constraint East	2000	20	2000	370	1700
C3	Constraint West	930	25.5	930	370	930
D3	Constraint North	2200	22	2200	370	1700
F5	Manchester Solution	2500	-5	2500	1700	370
F6	London Solution	2630	0	3000	1E+30	370

Figure: 1.7: Solver Analysis Sensitivity Report (Created by Author)

The Sensitivity report evaluates the solution's resilience to potential alterations. For example, the permissible increase in exports from Manchester to the East is **3.5** units before expenses rise, while the allowable decrease is **20** units. Similarly, the exports from London to the North can be increased by **3.5** units without raising the cost. These findings imply that the existing solution is almost optimum yet allows for modest change without significant cost implications, assuring the solution's durability in small-scale demand variations.

Limits Report

The Limits Report recognises the significant constraints of the distribution strategy. Manchester's overall solution cost is set at **£99,615**, with contributions from each route distinctly identified. Shipping extra units from London to the East, for example, might raise expenses to **£108,310**, suggesting that any increase over the current allocation would not be cost-efficient. This report analyses the effectiveness of the current distribution strategy and calculates the cost impact of deviating from the optimal plan.

Microsoft Excel 16.0 Limits Report
Worksheet: [data.xlsx]Task 4
Report Created: 07/05/2024 06:21:26 AM

Cell	Objective Name	Value
F8	Manchester Solution	99615

Cell	Variable Name	Value	Lower Limit	Objective Result	Upper Limit	Objective Result
B8	Manchester East	2000	2000	99615	2000	99615
C8	Manchester West	0	0	99615	0	99615
D8	Manchester North	500	500	99615	500	99615
B9	London East	0	0	99615	370	108310
C9	London West	930	930	99615	1300	109050
D9	London North	1700	1700	99615	2070	107755

Figure: 1.8: Solver Analysis Limits Report (Created by Author)

Winter Rock's strategic distribution plan efficiently leverages Manchester and London distribution centres to meet growing market demands while minimising operating expenses. This strategy not only corresponds to logistical requirements but also aligns with cost optimisation objectives. This model should be reassessed on a regular basis to respond to any changes in market demand, shipping costs or operational capacity, to ensure that Winter Rock's supply chain strategy is efficient and flexible.

Section: 5: Meeting New Product Demand

Winter Rock is preparing to introduce new low-cost mountain skis with bindings priced at **£150** per unit. Faced with uncertainties in market demand for this upcoming product over the approaching winter season, the company must decide on the optimal supplier, whether from Europe or the USA. The selection of the supplier is critical since it requires understanding potential costs, supplier capacity, and predicted sales demand. To maximise the profit while minimising risk detailed strategic analysis of these factors is required.

Assumptions for Decision Making

1. **Europe Supplier Capacity:** The order quantity in Europe remains fixed at **500** units. So even, if the demand is low, Winter Rock will have to buy **500** units at a cost of **£120** each.
2. **USA Supplier Capacity:** The order quantity for the USA remains fixed at **1000** units. Even if the demand is below this level, **1000** units must be acquired for **£100** per unit, with an additional fixed cost of **£5000**, impacting financial results significantly.

Table: 1.10: Analysis of Potential Costs and Supplier Capacity (Created by Author)

Particular	Europe	USA
Supplier Capacity	500	1000
Minimum Charge	0	5000
Labour Cost per unit	60	30
Material cost per unit	40	40
Shipping cost per unit	20	30
Total Cost per unit	**120**	**100**
Selling Price per unit	150	150
Profit per unit	**30**	**50**

Europe Supplier: With a fixed supplier capacity of **500** units and no minimum charge, the total cost per unit is **£120**. This generates a profit of **£30** per unit. If demand is low (500 units), the profit is **£15,000**; if demand is high (1000 units), a capacity constraint limits the supply to **500** units, again resulting in a profit of **£15,000**.

USA Supplier: This supplier has a capacity of **1000** units and a minimum charge of **£5000**, resulting in a variable cost of **£100** per unit, and a fixed cost of **£5000** for 1000 pieces. The profit per unit is **£50**. For low demand (500 units), the overall outcome is **-£30,000**, which includes unsold stock and the fixed cost. For high demand, the profit is **£45,000**.

Decision Tree Representation and Analysis

The decision tree provides a structured visual representation to support potential decision-making at Winter Rock, illustrating potential outcomes from each supplier under different demand scenarios **(Bryan, 2021)**.

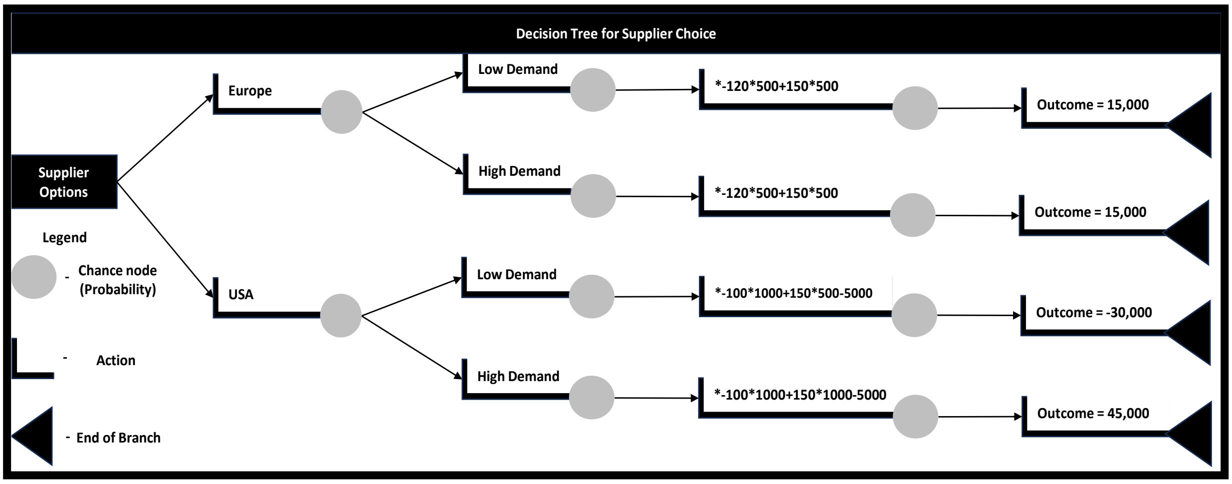


Figure: 1.9: Decision Tree Analysis for Supplier Preference and Profit Outcomes (Created by Author)

The decision tree contains,

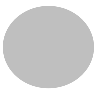
Supplier Options: The decision-making process begins with the selection of either European or USA suppliers.

Demand Scenarios: Each branch is further divided into two paths: low demand (500 skis) and high demand (1000 skis).

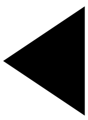
Outcomes: The end of each branch reveals the financial outcome determined using the total costs and total revenue.

Legend for Decision Tree

- Square nodes represent decision points when strategic decisions are taken (for example, selecting a supplier).



- Circular nodes show Probability events that represent different demand situations (high or low).



- Triangles represent the ending outcomes that determine the profit or loss for each decision pathway.

Detailed Interpretation of Decision Tree

Europe Path: Regardless of demand, the outcome shows a constant profit of **£15,000** due to supplier capacity constraints, which limits the maximum number of units sold to **500**. This path does not incur any loss, but it restricts possible gains.

The USA Path: This path presents a striking disparity in potential outcomes. Low demand leads to a significant loss of **-£30,000** owing to unsold inventories and high fixed costs. However, the high demand can yield a substantial profit of **£45,000**, demonstrating the option's high-risk, high-reward characteristics.

Risk-Averse Strategy: The Maximin Rule

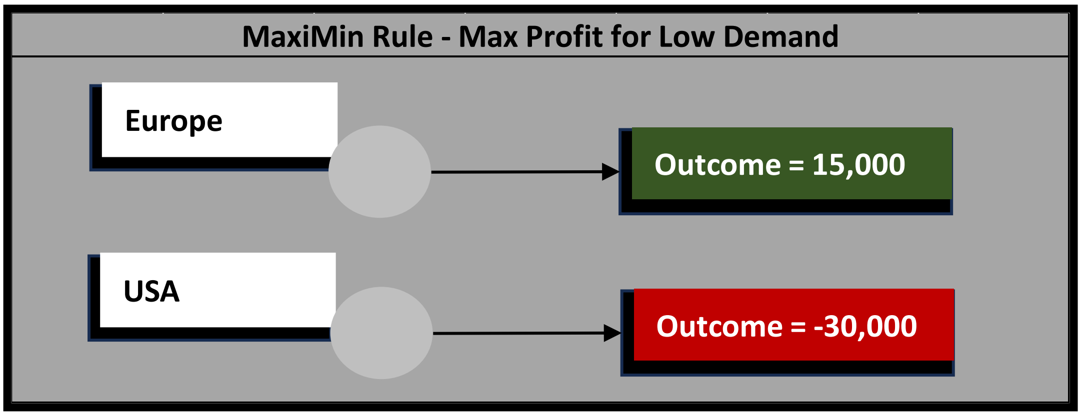


Figure: 1.10: Risk-Averse Strategy: The Maximin Rule (Created by Author)

For a risk-averse business, the Maximin rule is appropriate since it focuses on minimising potential loss by choosing the option with the best worst-case outcome. In the analysis, Europe regardless of demand, the capacity limits the supply to **500** units, resulting in a consistent profit of **£15,000**. The USA indicates a risk, with a potential loss of **-£30,000** if demand is low due to unsold inventory and fixed costs, despite a significant profit potential of **£45,000** if demand is high. Given this rule, Europe is the safer option, since it ensures a profit without the risk of any losses, making it ideal for maintaining consistent financial outcomes.

Risk-Seeking Strategy: The Maximax Rule

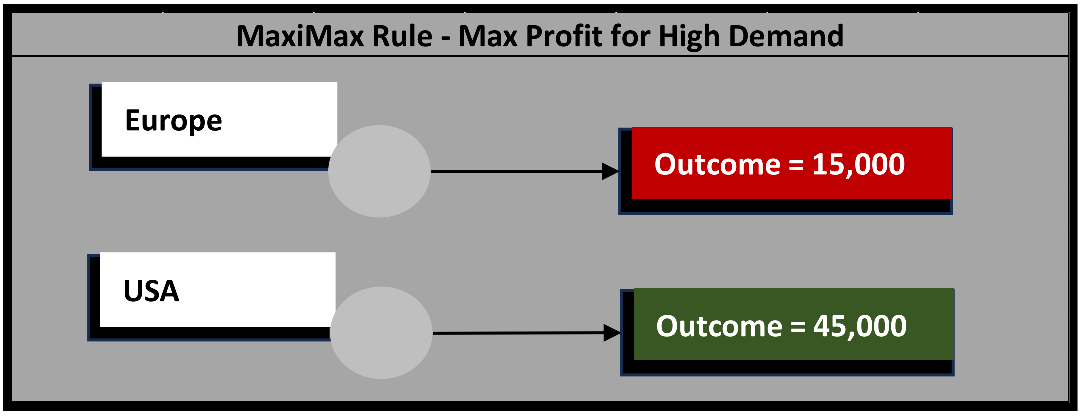


Figure: 1.10: Risk-Seeking Strategy: The Maximax Rule (Created by Author)

On the other hand, the Maximax rule encourages risk-seeking behaviour, with the goal of maximising profits regardless of any potential risks. Under this rule, in Europe, the maximum profit remains at **£15,000**, constrained by the supplier capacity. Whereas the USA Provides a potential profit of **£45,000** in case of high demand for **1000** units, aligning with a more aggressive growth strategy, with increased financial exposure due to fixed costs and the potential risk of unsold inventory. Despite its inherent risks, the USA is the suggested supplier for a company looking to capitalise on potential demand spikes and is prepared to take on greater risks.

Expected Profit Analysis

Table: 1.11: Analysis of Potential Demand and Profitability (Created by Author)

Particular	Demand	Europe	USA
Low Demand	500	15000	-30000
High Demand	1000	15000	45000
Probability	0.2	15000	30000
Probability	0.3	15000	22500
Probability	0.4	15000	15000
Probability	0.5	15000	7500
Probability	0.55	15000	3750
Probability	0.6	15000	0

Europe: £15,000 × 1.0 = **£15,000** (since Europe can only supply up to 500 units)

USA: (0.55 * −30,000) + (0.45 * 45,000) = (−16,500) + 20,250 = **£3,750**

The European supplier provides a consistent profit of **£15,000**, irrespective of demand fluctuations. This is due to the fixed output capacity of **500** units, which aligns with the low-demand scenario, hence eliminating the impact of potential changes in demand. The potential profit estimate for the USA supplier is significantly influenced by demand probability, as each scenario has different results. With a higher probability of low demand **(0.55)**, the adverse impact of the minimum charge and lower unit sales substantially reduces overall profitability, reducing the potential profit to **£3,750**. This is the outcome of balancing a significant loss in low demand against higher profit potential in high demand.

Strategic Implications and Recommendations

In the decision-making process, Winter Rock must balance financial risk against potential profit. The choice of supplier significantly impacts the company's ability to fulfil the market demand, manage inventory costs, and achieve financial objectives. Given the fixed costs and capacity constraints, the decision influences Winter Rock's agility to market demands. Therefore, accurate market trend analysis, combined with adaptive inventory and finance strategies, could be implemented to mitigate the risks associated with demand uncertainty and supply chain disruptions. This strategic decision will significantly impact Winter Rock's market presence and financial stability in the competitive winter sports sector.

Supplier Selection: A Hybrid Model using DEA, Decision Tree, and Neural Network (Wu, 2009)

The study examines the comprehensive strategy for supplier selection that combines Data Envelopment Analysis (DEA), decision trees, and neural networks. This hybrid technique efficiently divides suppliers into efficient and inefficient categories based on their DEA efficiency scores. It also uses decision trees and neural networks to forecast and analyse supplier performance, providing an efficient tool for managing the complexities of supplier evaluation in global supply chains. The model involves both quantitative and qualitative criteria, demonstrating its capacity to handle the frequent issue of missing values and various data types, therefore providing an extensive framework for improving purchase decision-making.

In our study, we employed a decision-analysis framework consistent with the integrated methodology mentioned in the paper **(Wu, 2009)**, emphasising decision trees to navigate through the supplier selection process based on predicted demand and cost considerations. However, our strategy might benefit from integrating similar sophisticated data processing techniques to efficiently manage data unpredictability and ensure more accurate forecasting in supply chain management. A limitation observed in both studies is the obstacle of dataset constraints, which might limit the utilisation and accuracy of the proposed models outside the tested situations.

Section: 6: The Impact of Meeting New Product Demand

As Winter Rock considers the launch of new low-cost skis, a critical concern arises about demand fluctuation, particularly in low-demand circumstances. Given the company's uncertainty about meeting the initial predicted sales demand of **500** units, an updated forecast of **200 to 800** units requires an enhanced profitability analysis with simulation **(Vandeput, 2023)**.

Table: 1.12: Assumption Underpinning the Simulation (Created by Author)

Assumptions:	
1	The Order Quantity for Europe is fixed at **500**, so even if the demand is less than **500** will have to purchase **500** units at the cost price of **120**.
2	The Order Quantity for the USA is fixed at **1000**, so even if the demand is less than **1000** will have to purchase **1000** units at the cost price of **100** with a Fixed cost of **5000**.
3	In the Combined scenario if the demand is higher than **500**, will be purchasing **1000** units from the USA supplier, if the demand is less than **500** will be purchasing **500** units from the Europe supplier.
4	The demand in column B is generated using a Random Number Generator for **1000** samples ranging between **200 to 800**, with the starting seed being **2626**(first 4 digits of student ID).
5	Order Quantity is a Random number generated for ideal understanding, as using a solver did not provide a value to maximise the profit in every scenario.

Simulation Setup and Execution

To handle demand variability, the random number generator function was employed in Microsoft Excel, generating **1,000** samples of demand based on a uniformly distributed scenario ranging from **200 to 800** units. To ensure consistency and uniqueness, I seeded the random number generator with the first four digits of the student ID **(2626)**.

Revenue Calculation and Interpretation

Table: 1.13: Cost, Revenue and Profit Analysis of Random Demand of New Ski Product (Created by Author)

Sample	Demand	Europe				USA				Combined			
		Variable cost	Fixed Cost	Sales Revenue	Profit	Variable cost	Fixed Cost	Sales Revenue	Profit	Variable cost	Fixed Cost	Sales Revenue	Profit
1	358	60,000	-	53,660	- 6,340	100,000	5000	53,660	- 51,340	60,000	0	53,660	- 6,340
2	562	60,000	-	75,000	15,000	100,000	5000	84,346	- 20,654	100,000	5000	84,346	- 20,654
3	361	60,000	-	54,105	- 5,895	100,000	5000	54,105	- 50,895	60,000	0	54,105	- 5,895
4	493	60,000	-	73,930	13,930	100,000	5000	73,930	- 31,070	60,000	0	73,930	13,930
5	723	60,000	-	75,000	15,000	100,000	5000	108,442	3,442	100,000	5000	108,442	3,442

The potential income was determined by multiplying each simulated demand sample by the unit price of **£150**. This approach presented significant unpredictability in revenue, which ranged from **£30,000** to **£120,000** closely aligned with demand fluctuations. Such inconsistency emphasises cautious pricing and promotion to mitigate the risks associated with low demand.

Cost Analysis

Fixed Costs: Winter Rock's fixed costs are an important component of the profitability equation, even though fixed costs are not directly affected by short-term demand fluctuations. Assuming a fixed cost structure (minimum charge value for the USA = **£5000**) is an instance where fixed cost is determined by the supplier's decision, and the buyer doesn't have any authority on it. The impact on profitability is more prominent in low-demand circumstances.

Variable costs: The variable costs, including labour, materials, and shipping costs, were computed per unit, and then scaled to match the predicted demand. For example, in the case of a European supplier where the variable cost for labour, materials, and shipping was **£120**, total variable costs would range from **£24,000** to **£96,000**. This estimate is essential as it demonstrates why cost efficiency must be enhanced to maintain profitability, particularly when demand is unpredictable.

Profit Estimate and Interpretation

For each scenario, the profit was calculated by deducting both fixed and variable costs from sales revenue. This simulation produced a wide variety of possible outcomes, highlighting the financial risks associated with the new product range. Furthermore, scenarios with lower forecasted demand resulted in a break-even or potential losses, indicating a reconsideration of both cost structure and sales methods.

Statistical Summary of Simulated Profits

Table: 1.14: Region-wise Average Profit and Std. Deviation (Created by Author)

Profit	Europe	USA	Combined
Average	3,478	- 30,951	- 7,551
Std. Deviation	14,683	25,772	13,310

Table: 1.15: Region-wise Random Order Quantity with Costs, Revenue and Profit (Created by Author)

Particular	Europe	USA	Combined
Order Quantity	**441**	**770**	**490**
Particular	**Europe**	**USA**	**Combined**
Variable Cost	60,000	100,000	60,000
Fixed Cost	-	5,000	-
Sales Revenue	66,214	115,500	73,500
Profit	**6,214**	**10,500**	**13,500**

The statistical study of simulated profits of Winter Rock's new ski product indicates a range of financial outcomes depending on the supplier approach. Acquiring from a European supplier generates an average profit of **£3,478**, with a large standard deviation of **£14,683**, suggesting small profitability but great risk owing to significant variability in profit results. The USA supplier demonstrates a less favourable scenario, with an average profit of **-£30,951** and a standard deviation of **£25,772**, indicating significant losses and a high level of financial risk, owing mostly to substantial fixed costs. The combined supplier approach marginally improves the situation, resulting in an average profit of **-£7,551** and a standard deviation of **£13,310**, indicating sustained negative profitability and elevated risk. These insights emphasise the necessity for Winter Rock to review supplier agreements and current pricing strategies to mitigate risks and enhance financial outcomes.

Strategic implications and recommendations

Winter Rock's decision to introduce new ski equipment includes choosing between European and American suppliers, each with its own set of financial risks and advantages. The European supplier ensures a constant profit of **£15,000** regardless of demand because of their fixed supply capacity of **500** units. This approach provides stability while limiting potential growth. In comparison, the US supplier presents a high-risk, high-reward scenario: a potential loss of **£30,000** in low demand (**55%** probability) and a profit of **£45,000** in high demand (**45%** probability), with an overall estimated profit of **£3,750**.

To optimise financial outcomes, Winter Rock should employ a hybrid strategy: acquire baseline inventory through the consistent European supplier while capitalising on potential market demands through the USA supplier. This approach would ensure a balance between financial stability and growth potential, which is critical for responding to market fluctuations. Implementing advanced analytical approaches such as Decision Trees and Neural Networks might help to further enhance this strategy by improving accuracy in demand forecasting and supplier selection, hence increasing Winter Rock's market agility and competitive advantage in the winter sports business.

Section 7: Conclusions and Recommendations

This study provides a comprehensive overview of Winter Rock's operations, including sales patterns and the strategic launch of new products. Utilising historical sales data from 2019 to 2022, a time series analysis demonstrated an increasing trend and considerable seasonality, emphasising the importance of specialised inventory and marketing strategy during peak winter months. Year-round product sales were forecasted using Single Exponential Smoothing, which demonstrated efficient management of inventory levels with an optimistic reorder point to ensure minimal stockouts.

The distribution plan leveraged linear programming to optimise logistics between two distribution centres, aiming to minimise transportation costs while adhering to regional demands. The technique efficiently used both centres' capacities, ensuring efficient resource allocation.

The new product launch analysis comprised a thorough decision tree analysis that compared supplier potential under various demand scenarios. The European supplier offered a reduced risk with consistent earnings, but the American supplier presented higher potential returns but with increased risk, as indicated by the possibility of considerable loss in low-demand scenarios.

Recommendations

Distribution Plan: Reevaluate the distribution model regularly to consider changes in demand or operating capacity. This proactive strategy will assist in keeping the logistics network cost-efficient and flexible.

New Product Launch: Employ a hybrid supplier approach to balance risk and potential growth. Purchase baseline inventory from the European supplier for stability and negotiate with the USA supplier to capitalise on high-demand periods, leveraging advanced analytics to improve demand forecasts and supplier selection.

This balanced strategy ensures that Winter Rock not only optimises ongoing operations but is also well-prepared to adapt market fluctuations, enhancing its competitive advantage in the winter sports sector.

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