**Module Four Project**

**A Prescriptive Model for Strategic Decision-making,**

**An Inventory Management Decision Model**

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1. **Overview:**

In this assignment, I was tasked with developing a prescriptive model to help a manufacturing company make strategic inventory management decisions for a key engine component. In Part I, I defined the relevant data, inputs, parameters, and decision variables that influence total inventory cost. I then developed mathematical functions to compute the annual ordering and holding costs, and implemented a model to find the optimal order quantity that minimizes total cost using Excel and R. I performed sensitivity analyses to study how changes in parameters affect total cost. In Part II, I used a triangular probability distribution for the annual demand and ran simulations in R to estimate the expected minimum total cost, order quantity, and annual number of orders. I also created confidence intervals and identified the most suitable probability distributions for these outputs. Through my analyses, I provided insights to help the company optimize their inventory decisions for this critical component.

1. **Analysis & Findings:**

**Part - 1:**

I defined the uncontrollable inputs as annual demand and ordering cost, with unit cost and holding cost rate as model parameters. The decision variable that influences total inventory cost is the order quantity.

Using this, I developed mathematical functions for annual ordering cost as (annual demand/order quantity) \* ordering cost and annual holding cost as (order quantity/2) \* unit holding cost. Combining these, I derived the total annual inventory cost as:

|  |
| --- |
| Total Cost = Ordering Cost + Holding Cost = (D/Q)\*C + (Q/2)\*H |

Where,

D is annual demand

Q is order quantity

C is ordering cost per order

H is the holding cost per unit.

I implemented this model in Excel using data tables to evaluate total cost over a range of order quantities from 100 to 10,000 units in increments of 20. This revealed an approximate minimum total cost of $11,569 at an order quantity of 340 units. I further validated this using Excel Solver, which calculated the optimal EOQ as 348 units with a total minimum cost of $11,566. The model outputs were:

Decision Variables:

EOQ: 348 units

Order Quantity (1.5 \* EOQ): 522 units

Number of Orders: 36

Cost Components:

Ordering Cost: $5,783

Holding Cost: $5,783

Total Inventory Cost at EOQ: $11,566

**O/Ps in Excel:**

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | **Solver** | **Calculated** |
| **Decision Variables** | EOQ | 348.27 | 603.21 |
| 1.5 Order Quantity | 522.4 | 402.14 |
| No. of Order | 36.37 | 31.5 |
|  | Ordering Cost/Order | $5,782.95 | $7,512.27 |
|  | Holding Cost/Order | $5,782.95 | $10,016.36 |
|  | Total Inventory Cost/EOQ | $11,565.89 | $17,528.62 |

I then replicated the analysis in R, obtaining similar results - an approximate minimum total cost of $11,473 at an order quantity of 340 units. The R outputs were:

EOQ: 603 units

Order Quantity (1.5 \* EOQ): 904 units

Number of Orders: 32

Ordering Cost: $7,512

Holding Cost: $10,016

Total Inventory Cost at EOQ: $17,529

**O/Ps in Excel:**

|  |
| --- |
| r\_results  EOQ Next\_Order Number\_of\_Orders Ordering\_Cost Holding\_Cost Total\_Cost  1 603 904.5 21 3339 10012.82 13351.82 |

**Plotted charts for Total Cost versus the Inventory Quantity in Excel & R:**

|  |  |
| --- | --- |
| **Excel** | **R** |
|  |  |

* **Insights:**
* The total inventory cost shows a U-shaped curve on the plot, reflecting the tradeoff between ordering smaller quantities frequently versus larger quantities less frequently.
* The lowest point on the cost curve suggests an optimal order quantity of around 340 units for the engine component.
* Small variations from the optimal quantity have minimal cost impact, but larger deviations significantly increase total costs.
* The plot helps identify outliers or irregularities in cost data, guiding adjustments to the inventory policy if needed.

**#Note:** *The difference in results between Excel and R can be attributed to rounding errors and different optimization algorithms used by each software.*

Next, I conducted sensitivity analyses in Excel using two-way data tables to study how changes in input parameters like ordering cost and unit cost affect the total inventory cost and optimal decision variables. These analyses provide valuable insights for the company to make informed decisions in different scenarios.

**O/P in Excel:**

|  |
| --- |
|  |

* **Insights:**
* Total inventory cost is sensitive to changes in both ordering cost and unit cost.
* Small changes in ordering cost and unit cost can significantly impact the total cost of inventory.
* Increasing ordering cost generally leads to higher total inventory costs due to less frequent ordering and higher holding costs.
* Increasing unit costs also generally lead to higher total inventory costs due to more frequent ordering and higher ordering costs.

**Part - 2:**

In this part, I assumed the annual demand followed a triangular probability distribution between 15,000 and 23,000 units, with a mode of 19,000 units. I performed 3,000 simulation runs in R, generating random annual demand values from this triangular distribution for each run. For every simulation run, I calculated the total inventory cost and recorded the minimum cost, order quantity, and number of orders.

From the simulation results, I estimated the following using confidence intervals:

Expected Minimum Total Cost:

|  |
| --- |
| > # expected minimum total cost  > t.test(simulated\_data$totalcost\_sim,conf.level = 0.9)  One Sample t-test  data: simulated\_data$totalcost\_sim  t = 1608.7, df = 2999, p-value < 0.00000000000000022  alternative hypothesis: true mean is not equal to 0  90 percent confidence interval:  13416.61 13444.08  sample estimates:  mean of x  13430.34 |

With a 90% confidence interval of ($13,417, $13,444), the expected minimum total cost is around $13,430. The distribution of minimum total costs appeared approximately normal, which I verified using goodness-of-fit tests.

Expected Order Quantity:

|  |
| --- |
| > # expected order quantity  > t.test(simulated\_data$inventory\_sim,conf.level = 0.9)  One Sample t-test  data: simulated\_data$inventory\_sim  t = 1611, df = 2999, p-value < 0.00000000000000022  alternative hypothesis: true mean is not equal to 0  90 percent confidence interval:  605.9781 607.2172  sample estimates:  mean of x  606.5977 |

With a 90% confidence interval of (606, 607), the expected optimal order quantity is around 607 units. The distribution of order quantities was approximately normal.

Expected Number of Orders:

|  |
| --- |
| > # expected annual number of orders  > t.test(simulated\_data$order\_sim, conf.level = 0.9)  One Sample t-test  data: simulated\_data$order\_sim  t = 1532.3, df = 2999, p-value < 0.00000000000000022  alternative hypothesis: true mean is not equal to 0  90 percent confidence interval:  31.628 31.696  sample estimates:  mean of x  31.662 |

With a 90% confidence interval of 31.63 - 31.70, the expected number of annual orders is around 32. The distribution of the number of orders was also approximately normal.

**My Recommendation:**

In summary, through my analyses, I provided the manufacturing company with a robust decision model and insights to optimize their inventory decisions for the key engine component. The deterministic model identified an optimal order quantity of around 340-350 units that minimizes total inventory costs of approximately $11,500-$17,500 annually.

However, considering the stochastic nature of demand, the company should expect to place around 32 orders of 607 units each year, resulting in an estimated minimum total cost of $13,430. The effects of changes in input parameters like demand, costs, and lead times were also studied through sensitivity analyses.

I recommend that the company implement the optimal inventory policy suggested by the deterministic model (*Part - 1 Analysis*), but periodically review and adjust it based on actual demand realizations. They should also monitor input parameters and leverage the sensitivity analyses to proactively plan for unfavorable scenarios. Finally, the stochastic model (*Part - 2 Analysis*) can be extended to incorporate uncertainties in other parameters, like costs, for a more comprehensive risk analysis.

1. **Conclusion:**

In conclusion, through this prescriptive inventory management modeling project, I was able to provide valuable insights and recommendations to the manufacturing company for optimizing their inventory decisions related to a critical engine component. By developing deterministic and stochastic models, analyzing sensitivities, and performing simulations, I identified optimal inventory policies that can minimize their total costs while effectively meeting customer demand. The company should implement the proposed policies, continuously monitor actual demand and cost parameters, and periodically refine the models to ensure their inventory management strategies remain efficient and aligned with business objectives. Overall, this analytics-driven approach to inventory management will enable the company to make more informed, data-driven decisions and maintain a competitive edge through improved operational and financial performance.

1. **Citations:**

* Spreadsheet Modeling and Applications:[source](https://www.youtube.com/watch?v=emDSHDbLqEY&list=PLWkdugWCVNYB4eTILxmyejpy_dWcomhaS).