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**College of Professional Studies**

**Northeastern University San Jose**

**MPS Analytics**

**Course: ALY6050: Introduction to Enterprise Analytics**

**Assignment:**

Module 4 Project-  A Prescriptive Model for Strategic Decision-making: An Inventory Model

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**Submitted to:**  **Submitted by:**

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# **ABSTRACT**

A decision model is a systematic approach to making decisions. It is a formalized representation of a decision-making process that defines the factors and criteria involved in making a decision, as well as the possible outcomes and their probabilities.

Decision models can be used in a wide range of applications, from business and finance to healthcare and government. They can be used to support decision-making at various levels, from individual decision-making to strategic planning at the organizational level.

Components of a decision model:

* Model parameters are the fixed values or assumptions that are used in the decision model. These are the inputs that do not change during the analysis.
* Variables are the inputs that can vary in the decision model. These are the factors that can change based on the decision maker's choices or external factors.
* Objectives are the goals or outcomes that the decision-maker wants to achieve through the decision-making process. These are the criteria that the decision model uses to evaluate the different alternatives.

A prescriptive decision model is a structured approach to decision making that helps decision makers identify and evaluate alternative courses of action to select the best option based on a set of criteria or objectives. It involves a step-by-step process that includes defining the problem, generating alternatives, evaluating them against the criteria, selecting the best alternative, and monitoring and evaluating its outcomes. Prescriptive models are proactive in nature and provide specific recommendations or actions to be taken. They can be categorized into different types based on the nature of the decision and the context in which it is made.

**INTRODUCTION**

Effective inventory management is critical for businesses as it ensures that the right amount of inventory is available at the right time to meet customer demand. However, poor inventory management can lead to significant costs, including the cost of holding inventory and the cost of ordering inventory from suppliers.

The purpose of this project is to develop and implement a prescriptive decision model for a client to make strategic decisions related to their inventory. The client has provided us with data related to their inventory, such as the cost of holding inventory and the cost of ordering from suppliers. Our objective is to assist the client in minimizing the total inventory cost by determining the optimal amount of inventory to order and when to order it.

To achieve this goal, the prescriptive decision model will take into account various factors such as demand variability, lead time, and order quantity to determine the optimal inventory level that minimizes the total cost of inventory. By using a prescriptive decision model, we intend to provide the client with a structured and systematic approach to inventory management that can enhance their operational and financial performance.

This project will involve several steps, including defining the problem, identifying the variables and parameters, formulating the mathematical model, implementing the model, and performing sensitivity analysis. The sensitivity analysis will assess the impact of changes in variables and parameters on the optimal solution. Based on the results of the analysis, we will provide recommendations to the client to help them make informed and optimal decisions that align with their strategic goals and objectives.

**ANALYSIS & INTERPRETATION**

**Part 1:**

1. Uncontrollable inputs, model parameters, and the decision variables

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**Figure 1- Table with Variables, Model Parameters, Objective**

Based on the information, we can define the following variables and parameters for our inventory model:

**Uncontrollable Variable:**

Annual Demand: 15,000 units

**Model Parameters:**

Unit Cost: $80 per unit

Unit Holding Cost (Opportunity Cost): 17% of the unit cost price of inventory product, which is 0.18 x $80 = $14.40 per unit per year

Ordering Cost: $220 per order

**Decision Variables:**

Predetermined Reorder Point: The inventory level at which the company will place an order to replenish the inventory.

Order Quantity: The number of units to be ordered each time an order is placed. We will denote this as "EOQ" in our model.

**EOQ (Economic Order Quantity) = square root of [(2 x annual demand x ordering cost per order) / (holding cost rate x unit cost)]**

**Objective:**

Total Costs: The goal is to minimize the total cost of inventory, which includes the cost of holding inventory and the cost of ordering inventory.

1. Mathematical Model

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**Figure 2 – Mathematical model**

**Annual Ordering Cost:** Annual ordering cost is the cost associated with placing an order for inventory, such as the cost of paperwork, communication, and transportation. This cost also includes the cost of setting up the equipment, labor, and other administrative costs associated with placing an order.

**Annual Ordering Cost = Ordering Cost per Order x Number of Orders per Year**

**Annual Holding Cost:** Annual holding cost is the cost of storing and holding inventory in a warehouse or storage facility over a given period of time. It includes costs such as rent, utilities, insurance, and labor.

**Annual Holding Cost = (Unit Cost x Holding Cost Percentage) x (EOQ/2)**

**Annual Number of Orders:** The number of orders placed in a year is 22.12 orders, which is calculated by dividing the total annual demand by the economic order quantity

**Total Inventory Cost** refers to the overall cost incurred by a company to maintain its inventory levels. By understanding and managing total inventory costs, businesses can improve their overall profitability and operational efficiency.

**Total Inventory Cost = Purchase Cost + Holding Cost + Ordering Cost**

**Where:**

**Purchase Cost = unit cost x annual demand**

1. The values have been calculated in Excel
2. One-way data table

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**Figure 3 – Data Table**

The table represents a one-way data table that shows the total inventory cost for different order quantities ranging from 638 to 728. This shows that the total inventory cost is lowest when the order quantity is equal to the EOQ, which in this case is 678 units.

1. Total Cost vs Order Quantity

**Chart, line chart

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**Figure 4 – Plot**

In the above scatterplot, the x-axis represents the order quantity, and the y-axis represents the total inventory cost. Excel has generated a trendline based on the data points provided, and it appears to be a part of a parabolic curve.

The equation of the parabolic curve, as provided by Excel, is y = 0.0104x^2 – 14.107x + 1e^6. The R² value is a measure of how well the data fits the curve, with 1.0 being a perfect fit. The R² value of 0.9988 indicates a strong correlation between the order quantity and total inventory cost, explaining 99.88% of the variability in the total inventory cost.

1. Excel Solver

Excel Solver is a tool in Microsoft Excel that allows users to find the optimal solution for a problem by changing certain input values. It uses mathematical optimization techniques to find the optimal solution by minimizing or maximizing a certain target cell based on constraints defined in the worksheet. The Solver can be used for a variety of problems such as linear and nonlinear programming, engineering design, financial planning, and scheduling. Users can define the constraints and input values, set the target cell, and use Solver to find the optimal solution.

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**Figure 5 – Optimal value using Solver**

We will be using Excel Solver to confirm the minimum total cost that we calculated earlier. This will help us verify the accuracy of our results. I used the set variable as Total Costs value and by changing variable as EOQ. The values are the same for both methods

1. Two- way Data table

Sensitivity analysis using a two-way data table involves creating a table that shows how changing two input variables affects a particular output. The two input variables are varied systematically to observe how changes in them affect the output. This technique helps to identify the impact of changing the inputs on the output and can be used to make better decisions.

**Graphical user interface, table

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**Figure 6 – Sensitivity Analysis**

This two-way data table shows the sensitivity analysis of unit cost and ordering cost on the total inventory cost.

By looking at the table, we can see that as the unit cost and ordering cost increase, the total cost also increases. It can be useful in identifying the combination of unit cost and ordering cost that results in the lowest total cost.

1. While presenting the results to Vice president of Operations, I would say that whenever the inventory level reaches 339, the company should order 678 units in order to meet demand until the supplier’s order can be shipped and received. By ordering twice as many units, the company can ensure that it has enough stock to meet customer demand while also keeping costs associated with inventory low.

**Part 2:**

For Part 2, I tried to do the analysis in Excel as well as R

**Excel:**

1. **1000 Simulations**A picture containing text

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**Figure 7- Formula for triangular distribution**

I used the built-in function **RAND()** in Excel to generate random values that were then used as inputs. Then I used the formula in Figure 7, for calculating Annual demand (for each simulation).

We have been given the values a, b, and c in the question for Annual demand. The values of K, M and N were also calculated.

* The ratio of the distance from the minimum to the mode and the distance from the minimum to the maximum is denoted as K and can be calculated using the formula **K = (c - a) / (b - a)**
* The product of the distances from the minimum to the mode and from the mode to the maximum is denoted as M and can be calculated using the formula **M = (b - a) \* (c - a)**
* Similarly, the product of the distances from the mode to the maximum and from the minimum to the mode is denoted as N and can be calculated using the formula **N = (b - a) \* (b - c)**

**Table

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**Figure 8- Annual demand, EOQ, Total cost and Annual orders**

This table shows 1000 occurrences with its respective annual demand, EOQ , total cost and annual orders.

1. **Expected minimum total cost – Probability distribution**

Then I moved on with the frequency distribution.

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**Figure 9- Calculations for Frequency distribution (Total Min Cost)**

This dataset contains 1000 observations with values ranging from 1060626 to 1366581, giving a range of 305955. The data has been grouped into 32 classes or bins with a class width of 9561.

**Table

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**Figure 10- Frequency distribution (Total Min cost)**

To calculate the theoretical probability for a triangular distribution, the following formulas are used:

**If x ≤ c, then P(X ≤ x) = (1/A) \* (x - a)^2**

**If x > c, then P(X ≤ x) = 1 - (1/B) \* (b - x)^2**

* **Null hypothesis:** The data that has been observed is distributed in a triangular shape, and the minimum value, maximum value, and mode of the distribution are known parameters.
* **Alternative hypothesis:** The observed data is not distributed in a triangular shape with the known minimum value, maximum value, and mode parameters.

Chart, histogram

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**Figure 11-Plots for Min total Cost**

**Table

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**Figure 12- Chi square test, p value for Triangular distribution (Minimum total cost)**

* In this case, there are 32 bins and 3 parameters so, the degree of freedom is calculated to be 28.
* To determine whether the observed frequencies fit the expected theoretical frequencies, we can use the CHISQ.DIST() function and assume a 95% confidence level, which corresponds to an alpha value of 0.05.
* After conducting the chi-squared test, the resulting p-value is found to be 0.741. Since this p-value is greater than the significance level of 0.05, we cannot reject the null hypothesis at the 95% confidence level.
* It is important to note that the P-value may vary with different random values or iterations.

1. **Expected order quantity– Probability distribution**

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**Figure 13- Calculations for Frequency distribution (Expected order quantity)**

We can construct a frequency table with 32 classes/bins, each with a width of 3. The minimum value is 632, and the maximum value is 720, giving a range of 88. The total count of observations is 1000.

**Table

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**Figure 14- Frequency distribution (Expected Order Quantity)**

* **Null hypothesis:** The observed order quantity data follows a triangular distribution with parameters a,b and c.
* **Alternative hypothesis:** The observed order quantity data does not follow a triangular distribution with parameters a,b and c.

**Chart, histogram

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**Figure 15-Plots for Expected Order Quantity**

**Table

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**Figure 16- Chi-square test, p value for Triangular distribution (Expected Order quantity)**

* For triangular distribution, again the number of bins is 32 and the number of parameters is **3** (a,b,c) so the degree of freedom is **28**.
* **Alpha value is 0.05**
* The P-value is **0.313,** which is greater than the significance level of 0.05. Therefore, we fail to reject the null hypothesis at the 95% confidence level. In other words, **the data follows a triangular distribution**.

1. **Expected annual number of orders– Probability distribution**

**Table

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**Table

Description automatically generated with medium confidenceFigure 17- Calculations for Frequency distribution (Expected annual number of orders)**

**Figure 18- Frequency distribution (Expected Annual orders)**

We can see the observed frequency, theoretical probability, expected frequency, and the chi-squared test statistic for each class interval for annual number of orders in Figure 18.

Chart, histogram

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**Figure 19-Plots for Expected annual number of orders**

**Table

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**Figure 20- Chi-square test, p-value for Triangular distribution (Expected Annual number of orders)**

* The degree of freedom (df) is 28
* The chi-squared p-value is 0.313, which is the probability of obtaining a test statistic as extreme as the observed one, assuming that the null hypothesis is true.
* Based on the p-value of 0.313, we can conclude that there is insufficient evidence to reject the null hypothesis at the 5% significance level.

**R:**

1. **1000 Simulations**

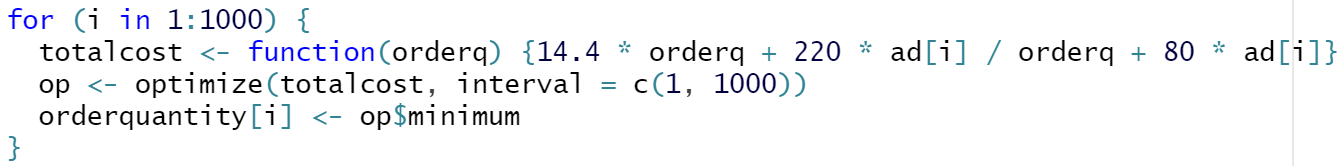
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**Figure 21- R code for 1000 simulations**

The triangle library is being loaded which provides the function rtriangle() to generate random numbers from a triangular distribution.

The variable n is defined as 1000, which is the number of simulations to be run. Then, the rtriangle() function is used to generate 1000 values of the annual demand, with a minimum value of 13000, a maximum value of 17000, and a mode of 15000, according to the parameters specified.



**Figure 22- for loop for total cost and order quantity**

The for loop is then used to iterate over each of the 1000 annual demand values generated by the rtriangle() function. For each iteration, a function called totalcost() is defined, which takes the order quantity as an argument and calculates the total cost of ordering that quantity based on the annual demand value for that iteration.

The optimize() function is then used to find the minimum of the total cost function within the interval of 1 to 1000, which represents the range of possible order quantities. The optimal order quantity for that iteration is stored in the orderquantity vector.



**Figure 23- inventory cost**

This code calculates the total inventory cost for each simulation, based on the optimal order quantity and the corresponding annual demand generated earlier.

The holding cost is represented by the term **220 \* ad / orderquantity**, which is the cost of holding one unit of inventory for a year (represented by the annual demand ad) multiplied by the number of times the product is ordered and divided by the order quantity. The stockout cost is depcited by the term 80 \* ad, which is the 80 is the unit cost, multiplied by the annual demand.

1. **Expected minimum total cost – Probability distribution**

**Chart, histogram

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**Figure 24- Histogram (Minimum total cost)**

Null hypothesis - the data follows a normal distribution

Alternative hypothesis - the data follows a normal distribution

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**Figure 25- Chi-square and Shapiro test (Minimum total cost)**

The chisq.test() function is then used to perform a chi-squared goodness-of-fit test between the observed data and the expected probabilities.

The output indicates that the chi-squared test statistic is 1.44e+09, with 999 degrees of freedom, and a very small p-value of less than 2e-16. The output of the shapiro.test() function indicates that the Shapiro-Wilk test statistic is 0.991, with a very small p-value of 5.3e-06. This suggests strong evidence against the null hypothesis that invcost follows a normal distribution, and therefore we reject the null hypothesis in favor of the alternative hypothesis.

1. **Expected order quantity– Probability distribution**

**Chart, histogram

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**Figure 26- Histogram (Order Quantity)**

Null hypothesis - the order quantity data follows a normal distribution

Alternative hypothesis – the order quantity data follows a normal distribution

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**Figure 27- Chi-square and Shapiro test (Order Quantity)**

The Shapiro-Wilk test indicates that the data is not normally distributed, with a p-value of less than 0.05. The chi-squared test indicates that the observed data is significantly different from the expected probability distribution, with a p-value of less than 2e-16.

1. **Expected annual number of orders– Probability distribution**

Chart, histogram

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**Figure 28- Histogram (Annual numbers of orders)**

Null hypothesis - the annual number of orders data follows a normal distribution

Alternative hypothesis – the annual number of orders data follows a normal distribution

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**Figure 29- Chi-square and Shapiro test (Annual number of orders)**

Again the p value is less for both the tests so we can say that annual number of orders also doesn’t follow normal distribution.

**2.** We can present to the Vice president of operations that all three variables are not normal but follow triangular distribution based on the results of tests and analysis done in Excel and R.

**CONCLUSION**

This assignment allowed us to apply our knowledge of decision modeling, simulation, and statistical inference to a real-world problem. The results and analyses we conducted will provide valuable insights to the vice president of operations in making informed decisions about inventory management.

We developed a decision model that provides the company with a tool to minimize its total inventory cost by determining the optimal order quantity. By using what-if analyses and simulations, we were able to assess the sensitivity of the model to changes in the model parameters and provide the company with a range of expected costs and quantities.

The analysis revealed that triangular distributions were the most suitable probability distributions to describe the expected minimum total cost, expected order quantity, and expected annual number of orders, based on the simulation results.

**REFERENCES**

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