Risk Minimization of Warehousing System by showing Probable Total Costs towards any Certain Company with the help of Monte Carlo Simulation

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Abstract

Warehousing System is a mandatory part of any existing distribution network which is specially designed to accommodate long-term storage of goods which may include raw materials, work in process materials, packing materials or finished goods associated with manufacturing. Since warehousing has a huge percentage of total supply chain cost, it costs not only a huge amount of money but also requires a large space, which highlights the importance of warehousing efficiency. However due to lack of proper approach towards the forecasting of warehousing system many companies face the loss of significant profits. This article highlights a new way for uplifting the performance of warehousing system by numerical example with the help of Monte Carlo Simulation through total probable cost calculation by controlling order quantity, reordering point, lead time to reduce the effects of holding costs and ordering costs for any certain companies. Eventually, it will contribute to the improvement of customer service level and will influence the performances of entire supply chain more effectively. Nonetheless, many companies will also be able to customize their warehouse according to their necessity to reduce the risk of over inventory.

Keywords
Warehousing System, Monte Carlo Simulation, Reordering Point, Lead Time, Decision Support System.

Introduction

Warehousing System in any supply chain consolidates to reduce transportations costs and achieving economies of scale in manufacturing or purchasing or to provide value-added service to customers. It has also been recognized as one of the main operations where companies can provide tailored services to their customers and gain competitive advantage. Moreover, effective use of warehouse minimizes the losses and helps to increase the profit more prominently. Typically warehouses are large buildings that are often filled with shelving, equipment and other items that pertain to the business of the warehouse owner. A warehouse can serve several functions beyond acting as a storage facility, however. The use of a warehouse largely depends upon the needs of its owner. In order to evaluate the use of warehousing in business, it is essential to understand ways in which warehousing functions to add value to products. Essentially, warehousing provides time and place utility for any product. However, most of them share some general pattern of material flow, and typical warehouse operations include: receiving, put away, internal replenishment, order picking, accumulating and sorting, packing, cross-docking, and shipping which is prescribed in Figure 1.

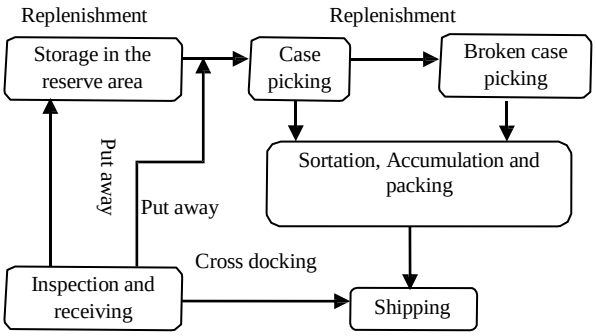


Figure 1. Typical Functions of Warehousing System

In recent times warehouses have been going through various challenges such as – supply chains are becoming more integrated and shorter, globalized operation, customers are more demanding and technology changes are occurring rapidly. In order to cope up with these challenges, organizations are seeking constantly for adopting innovative approaches. In order to consume less time and resources more effectively, it is mandatory to conduct a simulation. Hence this paper is dealing with the Monte Carlo Simulation for better decision support system.

Simulation and Decision Support System

To understand the Monte Carlo Simulation properly it is mandatory to have basics of simulation and Decision Support System. Simulation is the imitation of the operation of a real-world process or system over time in order to understand the behaviour of a system as it evolves over time is studied by developing a simulation model. Whereas Decision Support System (DSS) is a computerized information system used to support decision-making in an organization or a business.

The simulation model is solved by mathematical methods such as differential calculus, probability theory, algebraic methods has the solution usually consists of one or more numerical parameters which are called measures of performance. Design of Experiments is also frequently done with simulations. On the contrary, DSS lets users sift through and analyze massive reams of data and compile information that can be used to solve problems and make better decisions.

According to Banks et al. (2005) simulation process consists of below phases

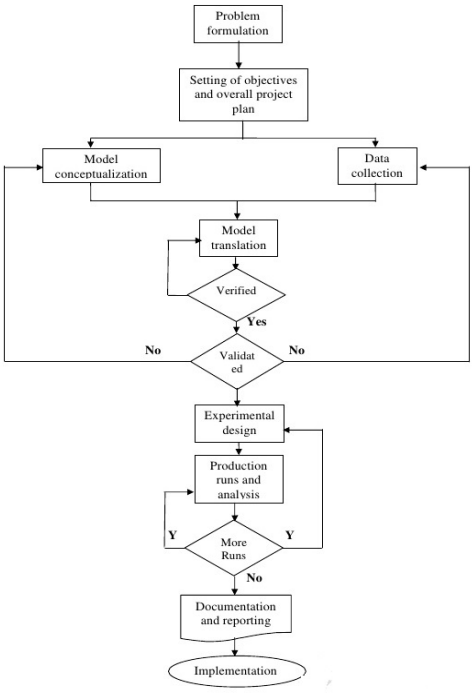


Figure 2. Simulation Process (Banks et. Al 2005)

In addition, according to Power (2002), five different dominant DSS components are as bellows :

- **Communications-driven DSS:** It is a type of DSS that enhances decision-making by enabling communication and sharing of information between groups of people. At its most basic level, a C-D DSS could be a simple threaded e-mail. At its most complex, it could be a web-conferencing application or interactive video.

- **Data-driven DSS:** Data-driven DSS emphasizes the use of large amounts of structured data. They are especially used to present time-series of both internal and external data. Most often this will come in the form of a data warehouse – a database designed to store data in such a way as to allow for its querying and analysis by users. Another example of a data-driven DSS would be a Geographic Information System (GIS), which can be used to visually represent geographically dependent data using maps.

- **Document-driven DSS:** The purpose is to provide document retrieval and analysis techniques with the help of storage and processing technologies. Document-driven DSS are support systems designed to convert documents into valuable business data. While data-driven DSS rely on data that is already in a standardized format that lends itself to database storage and analysis, document-driven DSS makes use of data that cannot easily be standardized and stored. The three primary forms of data used in document-driven DSS are oral (i.e. transcribed conversations) , written (i.e. reports, memos, e-mail and other correspondence) and video (i.e. TV commercials and news reports).None of these formats lends themselves easily to standardized database storage and analysis, so managers require DSS tools to convert them into data that can be valuable in the decision-making process. Examples of document-driven tools can be found in Internet search engines, designed to sift through vast volumes of unsorted data using keyword searches.

- **Knowledge-driven DSS:** Knowledge-driven DSS are systems designed to recommend actions to users. Typically, knowledge-driven systems are designed to sift through large volumes of data, identify hidden patterns in that data and present recommendations based on those patterns. Knowledge-driven DSS contain some kind of artificial intelligence which recommends actions to the users. It can use various rules or data mining techniques to achieve this.

- **Model-driven DSS:** It emphasizes the access to a model and its manipulation. Model-driven support systems incorporate the ability to manipulate data to generate statistical and financial reports, as well as simulation models, to aid decision-makers. Model-based decision support systems can be extremely useful in forecasting the effects of changes in business processes, as they can use past data to answer complex 'what-if' questions for decision makers.

Besides, according to Shim et al. (2002), model-driven DSS consists of three phases: formulation, solution, and analysis. During the formulation phase, the actual problem is translated to an algebraic form. In the solution phase the model is optimized, and in the final phase results of the model are presented to the user. The formulation phase will also impact on how the solution is obtained. Most of the methods use a mathematical programming approach, e.g. a collection of mathematical functions is created and the minimum or maximum value is then obtained by using various algorithms.

After the proper understanding of Simulation System and Decision Support System, risk minimization warehousing system can be conducted by Monte Carlo Simulation.

Monte Carlo Simulation

In the meantime studying the simulation and Decision Support system above it is clearly untestable that Monte Carlo simulation is definitely a part of Simulation Technique which follows a computerized mathematical technique. Monte Carlo Simulation uses repeated random sampling to simulate data for a given mathematical model and evaluate the outcome. This method was initially applied back in the 1940s when scientists working on the atomic bomb used it to calculate the probabilities of one fissioning uranium atom causing a fission reaction in another.

During a Monte Carlo simulation, values are sampled at random from the input probability distributions. Each set of samples is called an iteration, and the resulting outcome from that sample is recorded. Monte Carlo simulation does these hundreds or thousands of times, and the result is a probability distribution of possible outcomes. In this way, Monte Carlo simulation provides a much more comprehensive view of what may happen. It tells you not only what could happen, but how likely it is to happen. This simulation performs risk analysis by building models of possible results by substituting a range of values, a probability distribution, for any factor that has inherent uncertainty.

Probability Distributions for Monte Carlo Simulation

Without probabilistic simulation, it is nearly impossible to perform Monte Carlo Simulation. For this reason by using probability distributions, variables can have different probabilities of different outcomes occurring. Probability distributions are a much more realistic way of describing uncertainty in variables of a risk analysis. Common probability distributions include:

- **Normal – Or "bell curve."** The user simply defines the mean or expected value and a standard deviation to describe the variation in the mean. Values in the middle near the mean are most likely to occur. It is symmetric and describes many natural phenomena such as people's heights. Examples of variables described by normal distributions include inflation rates and energy prices.

- **Lognormal –** Values are positively skewed, not symmetric like a normal distribution. It is used to represent values that don't go below zero but have unlimited positive potential. Examples of variables described by lognormal distributions include real estate property values, stock prices, and oil reserves.

- **Uniform –** All values have an equal chance of occurring, and the user simply defines the minimum and maximum. Examples of variables that could be uniformly distributed include manufacturing costs or future sales revenues for a new product.

- **Triangular –** The user defines the minimum, most likely, and maximum values. Values around the most likely are more likely to occur. Variables that could be described by a triangular distribution include past sales history per unit of time and inventory levels.

- **PERT-** The user defines the minimum, most likely, and maximum values, just like the triangular distribution. Values around the most likely are more likely to occur. However values between the most likely and extremes are more likely to occur than the triangular; that is, the extremes are not as emphasized. An example of the use of a PERT distribution is to describe the duration of a task in a project management model.

- **Discrete –** The user defines specific values that may occur and the likelihood of each. An example might be the results of a lawsuit: 20% chance of positive verdict, 30% change of negative verdict, 40% chance of settlement, and 10% chance of a mistrial.

Typical Steps in Monte Carlo Approach

Depending on the number of factors involved, simulations can be very complex. But at a basic level, all Monte Carlo simulations have four simple steps:

- **Identifying the mathematical model (Transfer Equation):** To do a Monte Carlo simulation, a quantitative model of the business activity, plan, or process is necessary which a firm/company/person wish to explore. The mathematical expression of the process is called the "transfer equation." This may be a known engineering or business formula, or it may be based on a model created from a designed experiment (DOE) or regression analysis.

- **Defining the Input Parameters:** For each factor in consideration to transfer equation, a determination is required to know about how its data are distributed. Some inputs may follow the normal distribution, while others follow a triangular or uniform distribution. Then a determination of distribution parameters for each input is needed. For instance, someone would need to specify the mean and standard deviation for inputs that follow a normal distribution.

- **Creating Random Data:** To do valid simulation, one must create a very large, random data set for each input—something on the order of 100,000 instances. These random data points simulate the values that would be seen over a long period for each input. For instance: Minitab can easily create random data that follow almost any distribution you are likely to encounter.

- **Simulating and Analyzing Process Output:** With the simulated data in place, one can use transfer equation to calculate simulated outcomes. Running a large enough quantity of simulated input data through model will give a reliable indication of what the process will output over time, given the anticipated variation in the inputs.

Advantages of using Monte Carlo Simulation Approach

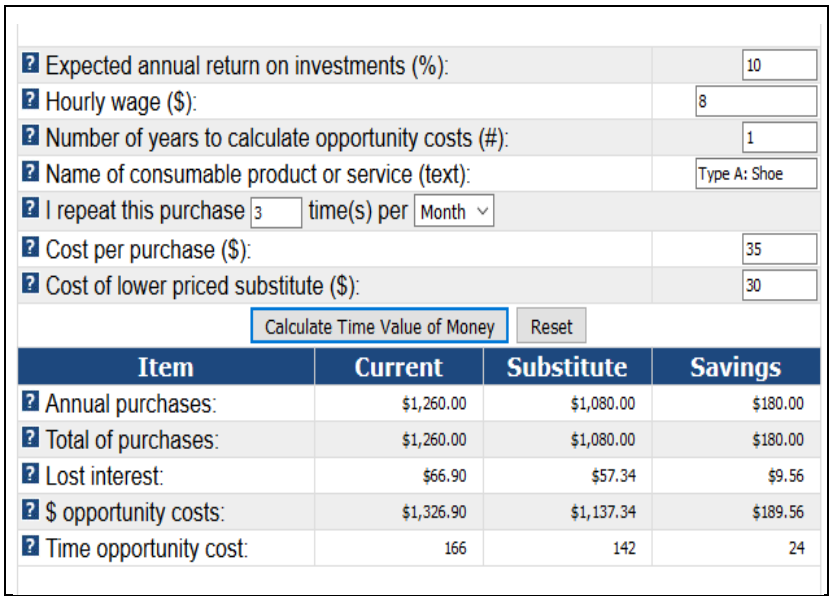
Monte Carlo simulation provides several advantages over deterministic, or "single-point estimate" analysis:

- **Probabilistic Results:** Results show not only what could happen, but how likely each outcome is.
- **Graphical Results**: Because of the data a Monte Carlo simulation generates, it's easy to create graphs of different outcomes and their chances of occurrence. This is important for communicating findings to other stakeholders.
- **Sensitivity Analysis:** With just a few cases, the deterministic analysis makes it difficult to see which variables impact the outcome the most. In Monte Carlo simulation, it's easy to see which inputs had the biggest effect on bottom-line results.
- **Scenario Analysis:** In deterministic models, it's very difficult to model different combinations of values for different inputs to see the effects of truly different scenarios. Using Monte Carlo simulation, analysts can see exactly which inputs had which values together when certain outcomes occurred. This is invaluable for pursuing further analysis.
- **Correlation of Inputs:** In Monte Carlo simulation, it's possible to model interdependent relationships between input variables. It's important for accuracy to represent how, in reality, when some factors go up, others go up or down accordingly.

Data Analysis for Numerical Examples of Monte Carlo Simulation

To minimize the risk of warehousing system with the help of Monte Carlo Simulation, Excel Data Analysis is formulated with the help of Risk Analysis Pro to show several numerical examples under different conditions. The main intention was to show probable total cost by controlling order quantity, reordering point, lead time to reduce the effects of holding costs and ordering costs for any certain companies so that customer service level and performances of entire supply chain more could be increased effectively. Since Lost Opportunity Cost is required for the formulated Excel Analysis of Monte Carlo Simulation, it can be either collected from certain organization according to their respective policy.

Maximum capacity for any certain company was assumed to be about 2000 units whereas Lost Opportunity cost was assumed to be around US$ 190 for the numerical example. Calculation of lost opportunity cost was done accordingly to below via online "Time Value of Money Calculator" from http://www.free-online-calculator-use.com/time-value-of-money-calculator.html#calculator. (Figure 3.)



Item	Current	Substitute	Savings
Annual purchases:	$1,260.00	$1,080.00	$180.00
Total of purchases:	$1,260.00	$1,080.00	$180.00
Lost interest:	$66.90	$57.34	$9.56
$ opportunity costs:	$1,326.90	$1,137.34	$189.56
Time opportunity cost:	166	142	24

Figure 3. Lost Opportunity Cost Calculation by Online Calculator

Assuming that "Type A Shoe" will be ordered 3 times per month where per unit cost is US $ 35 while the less costly product is near to US $30 with the same hourly age of US$ 8 per employee Lost Opportunity Cost of US$ 189.56 ≈190 is found with the help of this calculator. However, Lost Opportunity Cost also can be directly gathered from the authority of the certain company. It depends on certain company's policy.

After getting the lost opportunity cost several simulations (Monte Carlo Simulation) are carried away with the help of Risk Analysis Pro to find out probable total cost for each run under various conditions(condition-1,condition-2 and condition-3) followed by Table 1. , Table 2. and Table 3 where assumption for ordering cost is US $35/unit, holding cost is US $ 0.45/unit and lost opportunity cost is US $ 190/year.

Table 1. Condition-1 for Monte Carlo Simulation for warehousing

Order Quantity (units)	**Lead Time (weeks)**	**Reordering Point (units)**	**Ordering Cost/ Item (US $)**	**Holding Cost/Item (US $)**	**Lost Opportunity Cost (US $)**
1500	3	350	35	0.45	190
	2				
	1				

Finding Total Cost by Simulation Run 1 for 3 weeks lead time under condition 1 (Table 1):-

Total Holding Cost	$20,394
Total Order Cost	$70
Total Opportunity Cost	$0
Total Costs	$20,464

Finding Total Cost by Simulation Run 2 for 2 weeks lead time under condition 1 (Table 1):-

Total Holding Cost	$20,736
Total Order Cost	$70
Total Opportunity Cost	$0
Total Costs	$20,806

Finding Total Cost by Simulation Run 3 for 1 week lead time under condition 1 (Table 1):-

Total Holding Cost	$22,137
Total Order Cost	$70
Total Opportunity Cost	$0
Total Costs	$22,207

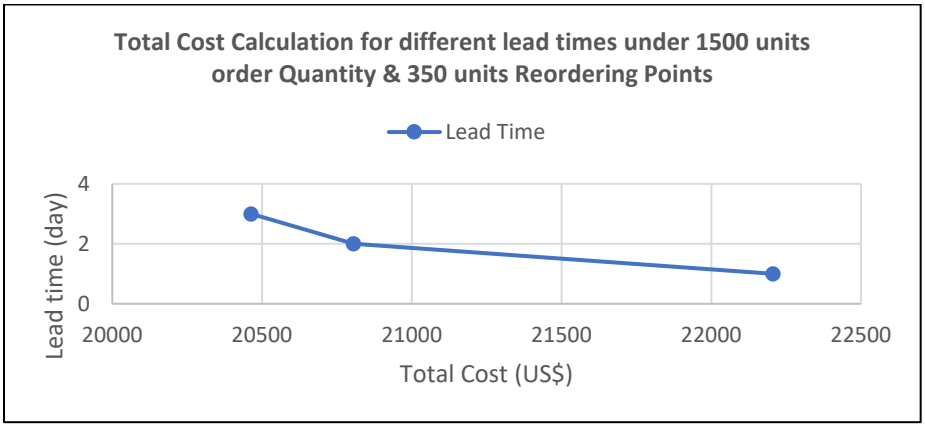


Figure 4. Total Cost Calculation for different lead times under constant Order Quantity & Reordering Points

Figure 4. elaborates that for an order quantity of 1500 units and reordering points of 350 units total probable costs were found to be US $20,464, US $20,806 and US $22,207 respectively for the lead time of 3 weeks, 2 weeks and 1 week.

Table 2. Condition-2 for Monte Carlo Simulation for warehousing

Order Quantity (units)	**Lead Time (weeks)**	**Reordering Point (units)**	**Ordering Cost/ Item (US $)**	**Holding Cost/Item (US $)**	**Lost Opportunity Cost (US $)**
1500	3	350	35	0.45	190
		300			
		250			

Finding Total Cost by Simulation Run 4 for 350 units reordering point under condition 2 (Table 2):-

Total Holding Cost	$21,166
Total Order Cost	$70
Total Opportunity Cost	$0
Total Costs	$21,236

Finding Total Cost by Simulation Run 5 for 300 units reordering point under condition 2 (Table 2):-

Total Holding Cost	$20,655
Total Order Cost	$70
Total Opportunity Cost	$0
Total Costs	$20,725

Finding Total Cost by Simulation Run 6 for 250 units reordering point under condition 2 (Table 2):-

Total Holding Cost	$19,519
Total Order Cost	$70
Total Opportunity Cost	$0
Total Costs	$19,589

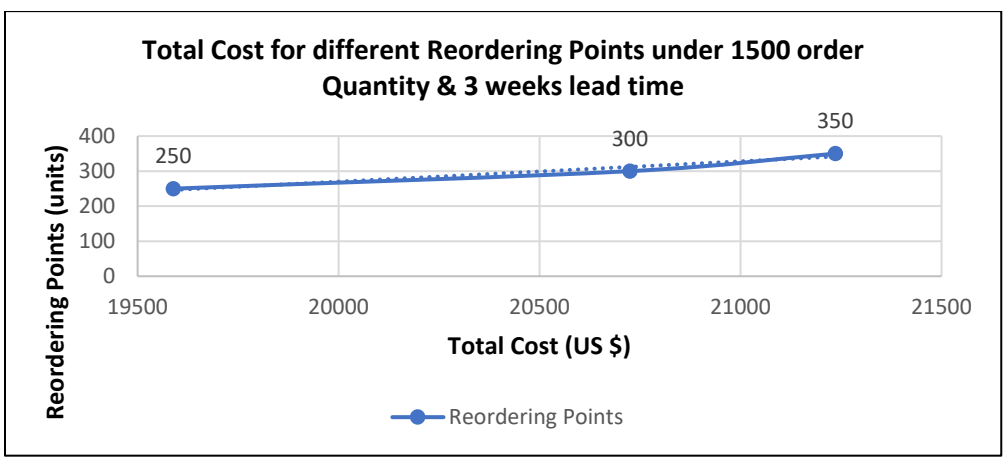


Figure 5. Total Cost Calculation for different Reordering Points under constant order Quantity & lead time

For order quantity of 1500 units and lead time of 3 weeks' total probable costs were found to be US $21,236, US $20,725 and US $19,589 respectively for the reordering points of 350 units, 300 units and 250 units which are shown in Figure 5.

Table 3. Condition- 3 for Monte Carlo Simulation for warehousing

Order Quantity (units)	**Lead Time (weeks)**	**Reordering Point (units)**	**Ordering Cost/ Item (US $)**	**Holding Cost/Item (US $)**	**Lost Opportunity Cost (US $)**
1500	3	350	35	0.45	190
1300					
1000					

Finding Total Cost by Simulation Run 7 for 1500 units ordering quantity point under condition 3 (Table 3):-

Total Holding Cost	$21,207
Total Order Cost	$70
Total Opportunity Cost	$0
Total Costs	$21,277

Finding Total Cost by Simulation Run 8 for 1300 units ordering quantity point under condition 3 (Table 3):-

Total Holding Cost	$18,399
Total Order Cost	$105
Total Opportunity Cost	$0
Total Costs	$18,504

Finding Total Cost by Simulation Run 9 for 1000 units ordering quantity point under condition 3 (Table 3):-

Total Holding Cost	$14,187
Total Order Cost	$140
Total Opportunity Cost	$0
Total Costs	$14,327

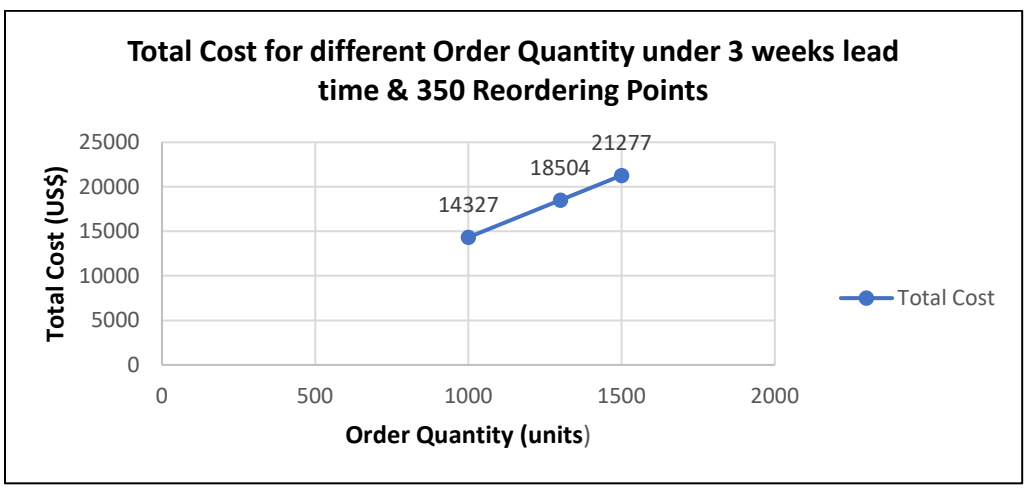


Figure 6. Total Cost of 3 weeks lead time & 350 Reordering Points for different Ordering Quantity

Total probable costs were found to be US $21,277, US $18,504 and US $14,327 respectively for an order quantity of 1500 units,1300 units and 1000 units while lead time was fixed to 3 weeks and reordering points at 350 units showed in Figure 6.

Table 4. Summary of Total Cost Calculation for different scenarios

Simulation Run No	**Total Cost (US$)**	**Average Total Cost (US$)**	**Conditions**		
			Ordering Quantity(unit)	**Reordering Point (unit)**	**Lead Time (weeks)**
Run 1	20464	21159	1500	350	3
Run 2	20806				2
Run 3	22207				1
Run 4	21236	20517	1500	350	3
Run 5	20725			300	
Run 6	19589			250	
Run 7	21277	18036	1500	350	3
Run 8	18504		1300		
Run 9	14327		1000		

From the Summary Table 4. , it is clearly understood that for different conditions different total costs were generated found from 9 simulation runs. Average total Costs are also shown in table 4. Thus for various conditions of ordering quantity, reordering points and lead times various total costs and average total costs can be generated so that certain company could make profits and survive in the market.

Hence Risk minimization for Warehousing System Could be done by Monte Carlo Simulation.Moreover, efficiency can be improved by knowing average total costs which refer various ordering quantity, reordering points and lead times as they have an impact on holding cost and ordering cost per unit items.

Conclusion

This article has proposed a new way for uplifting the performance and risk minimization of warehousing system by showing a numerical example with the help of Monte Carlo Simulation through total probable cost calculation by controlling order quantity, reordering point, lead time to reduce the effects of holding costs and ordering costs for any certain companies. Different Probable total cost is shown in summary in Table 4. so that with the help of this simulation analysis any company can forecast upcoming demand and control inventory without any significant loss.Hence we can conclude that risk minimization through warehousing system could be key the performance factor for competitive Supply Chain Management by Monte Carlo Simulation.

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