Implementation of a Supply Chain Analytics for Stochastic Demand of Inventory Control using Python

Dr. Ahmad M. A. Zamil
Professor,
Department of Marketing,
College of Business Administration,
Prince Sattam bin Abdulaziz University,
Saudi Arabia
ORCID 0000-0002-3700-8458

Dr. T. G. Vasista
Associate Professor,
Pallavi Engineering College,
Hyderabad, India
ORCID: 0000-0002-6496-6547

Mohamed Abdel Kader Adel Hamid
Assistant Professor,
Arab Academy for Science and Technology and Maritime Transport,
Egypt

Ahmad Yousef Areiqat
Professor,
Department of Business Administration,
Business School, Al-Ahliyya Amman University
Amman, Jordan
ORCID ID: 0000-0003-0379-7409

Abstract

In a supply chain scenario, companies have a stock of goods on hand. Companies face many challenges in making decisions under customer demand uncertainty. So, firms have to decide upon their inventory policy as part of the supply chain to compute average inventory levels, backorder levels, optimal order quantity, reduced loss of orders, and inventory cost, thus improving the profit. When traditional techniques such as Economic Order Quantity arenot providing the right solution concerning gaining optimal supply chain management application solutions, such as optimal inventory control under demand uncertainty, supply chain analytics employ inventory control policies that regulate the order to replenish stocks. For effective inventory control, two policies are used in the paper: periodic review policy and continuous review policy. With these policies, companies can get feasible inventory management solutions using mathematical, statistical modeling, and Simulation techniques. So, in this research,the Monte Carlo simulation technique has been applied and computed with visualizing charts using Python programming. The results show that managing inventory control with optimal values is possible using the simulation technique with negligible loss of orders. Profit distribution, safety stock, and order quantity values are determined and tabulated.

Keywords: Continuous Review Policy, Inventory Control, Monte Carlo Simulation, Periodic Review Policy, Stochastic demand, Supply Chain Analytics.

Introduction

An organization that applies make-to-stock production systems depends on maintaining inventories to respond to the fluctuating demand effectively. Incorrect inventory stock policies cause either overstock or stock-out problems. So, the accuracy of determining consumer demand becomes very important (Rizkyaet al., 2018). The inventory system is a set of policies applied to maintain and control inventory levels (Kulkarni &Rajhan, 2013). An effective and efficient inventory management system can significantly affect supply chain management (SCM) to improve cyclic service levels and reduce costs (Tee & Rosette, 2001;

Setyaningsih&Basri, 2013). In a realistic scenario, inventory management faces a barrier in having a tradeoff between minimizing total cost and maximizing service levels. Therefore, choosing the right inventory policy becomes essential to manage the customer's ever-changing needs, which has become the biggest threat to competitive business (Aisyatiet., 2014). The unique needs of customers are also becoming another threat. Under the increasing environmental uncertainty and diversified needs of the customers, SCM is becoming a strategic tool to gain a competitive advantage (Hadrawi, 2019).A supply chain is a set of organizations directly linked where supply flows from upstream to downstream relating to products, services, information, and finance (Kleab, 2017). In the supply chain, the uncertainty of market demandis usually driven by some macro-level factors related to industry, economy, and environment, which lead to cause bullwhip effect. These are individually managed demand forecasts (AlSudairi et al., 2012; Nesheim, 2021). To cope-up with the bullwhip effect, Simchi-levi et al. (2003) suggested the following methods:

(i) reducing uncertainty by centralizing the information,

(ii) reducing variability,

(iii) lead-time reduction, and

(iv) building strategic partnerships.

Uncertainties in the supply chain may cause the company's profitability (or costs) to fluctuate more. It also increases the chances of the profit being reduced. Safety stock levels are commonly used in supply chain design operations to avoid demand uncertainty (Jung et al., 2004).The goal of SCM is to improve trust and collaboration among supply chain partners and provide visibility to inventory and its management (growingscience.com, 2010-2020). The purpose of SCM could include managing uncertain, complex, and dynamic demand and supply networks (Nesheim, 2021; Wieland &Wallenburg, 2018) and reducing the risk of uncertainty of occurrence of an event that could affect one or more partners within the supply chain (Pakdeenarong&Hengsadeekul, 2020).

According to Singh et al. (2018), collaboration in the supply chain contributes to overall performance by minimizing demand uncertainty. According to Flynn et al. (2016), uncertainty in the supply chain can be three types viz.:

(i) Micro-level Uncertainty: It is based on input variability to the core of the supply chain.

(ii) Meso-level Uncertainty: It is the lack of information needed by supply chain members.

(iii) Macro-level Uncertainty: It is based on the equivocal construct related to ambiguous situations in a rapidly changing external environment facing supply chain members.

Inventory is held at many points in a supply chain and plays a crucial role in moderating the demand and supply imbalance (Roekchamnog et al., 2014).The inventory management technique helps manage the supply chain cost (Oluwaseyiet al., 2017).Cost-effective supply chain management can be obtained by efficiently managing the inventory and controlling it (Usher, 2021). Inventories are treated as buffers against managing demand variations to overcome supply uncertainty (Basu&Writght, 2008:96). In the scenarioswith high uncertainty and unpredictability in demand and high stock-out cost comparison to the value, traditional inventory control such as economic order quantity (EOQ) methods cannot become efficient, further involving the risk of having large holding stock or making the stock obsolete. Therefore, it is essential to deal with this problem differently (Fernando &Wulansari, 2021; Razaei et al., 2018).

During earlier efforts, supply chain strata, warehouses, distributors, retailers, etc.,were managed inventory independently by keeping large buffers of inventory quantity. However,an increase in competitive pressures in the globalized market forces the firms to develop efficient supply chains torespond to customer needs quickly. Hence, firms must use multi-echelon inventory management to reduce operating costs and improve customer service so that demand, safety stock, and lead-time uncertainty get focused to provide a better solution (Gumus&Guneri, 2007; Wang et al., 2021).Shadur& Bamber (1994) defined supply chain management as a function of customer delivery, inventory management, lean strategy, and strategic integration.The electronic business offers the application of web and other channel-basedtechnologies to enable full integration of end-to-end processes (AlSudairi & Vasista, 2012; Prater et al., 2021).For enterprises, cost-effective supply management amid a variety of market, logistics, and production challenges is critical (Wang et al., 2021). Uncertainties in the supply chain enhance the company's profit or cost variance, as well as the possibility of a profit decline. As a result, safety stock levels based on old theories are ineffective in dealing with demand uncertainty. A simulation-based approach is used to solve the problem of maintaining a sufficient level of safety stock to meet customer demand and satisfaction, as it is flexible in accommodating various types of uncertain parameters and can be applied to a wide range of large-scale stochastic optimization problems (Jung et al., 2004).

This paper aims to tackle the issues and challenges of inventory management under uncertain demand by adopting a stochastic process of computations through a case study. In this case, the sale of four different products is considered by adopting both continuous review policy and periodic review policy to understand inventory control better. Furthermore, the aim is to maximize its expected profit and be aware of any loss of orders by adopting Monte Carlo simulation-basedSupply Chain Analytic solution as it improves the accuracy of inventory solutions under demand uncertainty situations.

To work towards providing a solution of achieving the research objective, this paper is organized into the following sections in addition to the Introduction and Research objective sections: literature review; notations and assumptions; underlying theories; methodology; research process; research variables & hypothesis; inventory management modeling and simulation for hypothesis testing; inventory management modeling and simulation for hypothesis testing; results & discussion for the case described and future research.

Literature Review

Underlying theories

The underlying theory includes Contingency theory (Downey & Slocum, 1975; Flynn et al., 2016), classical organization theory, information processing theory (Flynn, Koufterous& Lu, 2016), game theory (Li, 2014), classical management control theory, model prediction control theory (Ortega & Lin, 2004).

Uncertainty is a central concept of contingency theory. It specifies that organizational performance is contingent on the organizational structure, process, and environment (Downey & Slocum, 1975; Lawrence & Lorsch, 1967; as cited in Flynn et al., 2016). To implement proactive Supply chain risk management, a holistic approach of considering both internal and external contingencies has to be considered (Grotsch et al., 2013).

As cited in Flynn et al. (2016), when supply chain complexity increases, the need for information also increases. Based on the information processing theory, uncertainty in the supply chain is the difference between the amounts of information needed by a supply chain member and the amount being processed. Availability of timely and accurate information helps prevent the loss of sales, prevent over-production, reduce inventory, and speed up the payment cycle. However, decision-makers rarely get complete information on demand while wanting to decide on inventory management. Making optimal local decisions does not help to eliminate the bullwhip effect. Only Supply chain integration level distortion of demand cause helps users better manage inventory in supply chain management.

Grotschet al. (2013) elucidated that supply chain risk management is a complex phenomenon fostered by rationality in the buyer-seller relationship. Dealing with this kind of complex phenomenon's decision-making processes, depends on varying forms of information utilization (Sankaran et al., 2020). The decision-making context also uses financial information. Measuring management control system involves institutionalization of organization, promoting specialization, formalizing procedures and through mechanization and using information technologies (Prater et al., 2021).

Game theory also benefits supply chain management and inventory management applications. Game theory is applied to determine the optimal inventory policy. It can improve the clarity of interactions between different supplier groups competing with each other, thus helping in resolving conflicts. When game theory applications are used with Monte Carlo simulation, it improves the accuracy of inventory models under demand uncertainty (Vaziri& Sodhi, 2014). Cachon&Netessine (2004) explained how game theory is related to supply chains. According to them, game theory has become an essential tool in analyzing supply chains with multiple agents involved with conflicting objectives. Game theory deals with interactive optimization problems. Whenever demand uncertainty is observed in supply chain management, game theory application of cooperative games, dynamic or differential games with incomplete information, or asymmetric information are usually adopted along with the use of simulation techniques in providing solutions of demand uncertainty in inventory control of supply chain management.

According to the demand uncertainty in the supply chain network, model predictive control was applied to solve dynamic inventory optimization towards achieving cost optimization and mitigating the bullwhip effect. Therefore, control and system theories have been becoming the most popular tools to handle the problems with demand uncertainty, time delay, and lack of information in inventory and supply chain applications (Hai et al., 2011; Prater et al., 2021).

2.2 Inventory Policy Studies

Continuous and periodic review inventory policies have been analyzed by many researchers and applied can be found in the research literature, and some are given in this literature review. Research efforts have categorized the input data into three models: deterministic models (Karteek& Jyoti, 2014), stochastic models, and fuzzy models (Sadeghi &Niaki, 2015). However, Kochel &Niclander (2005), Diaz et al. (2016), Betts (2014), Do et al. (2015),Ekren&Ornek (2015) & Murir, Gris and Whipple (2019) have used simulation techniques to handle the complexity of stochastic inventory problems.

Jung et al. (2004) conducted similar research, where a significant challenge for businesses is cost-effective supply chain management in the face of market, logistics, and production risks. Uncertainties in the supply chain typically increase the variance of earnings (or costs) to the company, raising the chances of a profit loss. In supply chain operations and supply chain design, safety stock level estimations are frequently used. A simulation-based optimization strategy is utilized to solve the challenge of establishing the safety stock level required to reach the desired degree of customer satisfaction. The stochastic inventory process is used by Porteus to solve quantitative research solutions connected to inventory management (1990).

To handle demand uncertainties, Jung et al. (2004) recommended employing deterministic planning and scheduling models that incorporate safety stock levels, as well as a simulation-based optimization approach to compute safety stock levels to satisfy the required level of customer satisfaction (Ben Mohamedet al., 2017; Muir et al., 2019; Widyadana et al., 2017).Inventory coordination is challenging due to the customers' demand uncertainty. Similarly, Tang et al. (2004) studied multi-stage decisions using the Bayesian process to update demand information in the successive stage using the newsvendor model to find the optimal inventory quantity. Choi et al.'s (2006) inventory model were studied to determine the order quantity for a lead time and the seasonal demand inventory cost.

Ivanov (2016) developed the knowledge base on decision-oriented operations and supply chain simulation with AnyLogic 7.2, in which the logic is developed in Java Programming under a service-oriented development approach.Cao &Zuo (2017) research provided solutions to supply chain inventory coordination under uncertain demand by combining Monte Carlo simulation and fitness Inheritance.The research by Cunha et al. (2017) proposed a novel methodology for replenishment and control systems for inventories of two-echelon logistics networks using two-stage stochastic programming, considering the periodic review and uncertain demands.

Holden (2017) presented aSimPy simulation model for a simple two-stage supply chain to determine the safety stock formula. In addition, research conducted by Basciftciet al. (2020) proposed distributional facility location under demand uncertainty by considering the dependency between customer demand and facility location decision robustly. These optimization models are implemented in Python using Gurobi 7.5.2 as the solver on an Intel i5, 2.90 GHz machine with 8 GB RAM.

However,this paper adopts a case study-based Inventory modeling and Monte Carlo simulation approach to investigate demand uncertainty within the supply chain management broad-spectrum (Ambra et al., 2020).

Notations and Assumptions

Existing research typically assumes that demand is a deterministic constant or a stochastic variable following a known distribution function. However the former cannot reflect the practical scenario of customers' demand and can reflect an accurate model especially when the demand distribution is ambiguious or with high variance (Cao & Zuo, 2017; Svensson de Jong, 2021). Therefore, the periodic review model assumes a normal distribution of demand and total lead time with a preferable low coefficient of variation (Hossain, 2014).

Base stock level = Estimated Demand during lead time + safety stock.

The present paper proposed a Monte Carlo simulation-based computation using Python programming to mimic a supply chain's inventory changing procedure with uncertain demand. For this study, an assumption was made that the order size would follow a log-normal distribution whose distribution parameters are unknown. So, it is vital to capture the historical sales data of the product. Thus, this case looks at the sale of four different products and adopts either a periodic review policy or a continuous review policy to manage the inventory to meet the objective of maximizing the expected profit (Nagpurkar, 2020).

$$\text{Annual Profit}_i = SPi \sum_{t=1}^{365} S_{i,t} - [(\frac{20Vi}{365})\sum_{t=1}^{365} I_{i,t} + \sum_{t=1}^{365} c_i P_{i,t}]$$

The following are the notations followed for continuous review policy and periodic review policy based computations:

Co = Order Cost; Ch = Holding Cost; q = order quantity; r = reorder point; t = order time; p = probability or customer service level (95%); P = Production rate per year for vendor; I = inventory; S = stock; V = Volume of Sales; N = number of data; Q = order quantity; A = setup cost; D = demand rate; h = holding cost per unit per period; s = safety stock.z = service level; σ = standard deviation; T = periodic review period base.

Hypothesis declaration

H0= Complexity involved in forecasting the Expected (maximized) Profit computation under demand uncertainty with negligible loss of order quantity can be better handled in Python language programming

Methodology

This research uses a case study approach. A case study approach is adopted for the investigation, especially when the realization through theoretical aspects become limited with operational activities and synergies (Zamil & Vasista, 2021b). A case study approach is an empirical investigation that examines a current trend based phenomenon within its real-life context (Dul & Hak, 2008). Essentially a case study tries to illuminate decision or set of decisions explaining why they were taken, how they were implemented and with what results (Schramm, 1971) as cited in Zamil et al., (2020a,b,2021a). Case studies can be well adapted for exploratory purposes or to determine the feasibility towards obtaining the desired solution. Case study can be descriptive describing the contextual phenomenon or an explanatory case study explaining the cause and effect relationship with how events have happened while accessing some data (Seuring, 2008)

The present paper follows a mix of the descriptive and explanatory approaches where in secondary data sources are used for the study. Secondary data files used and accessed are – summary_stats.csv and xyz-1.xlsx and 'py' modules,which are used from the Github website.

Table 1: Additional Product Data
(Source: towardsdatascience.com)

Product	Lead Time (days)	Volume (m3)	Cost ($)	Selling Price ($)	Initial Inventory
1	9	0.57	12	16.1	2750
2	6	0.052	7	8.6	22500
3	16	0.53	6	10.2	5200
4	22	1.05	37	68	1400

Research Process

The research processa consists of the following steps as proposed by Seuring (2005):

(i) Research objective

(ii) Computerized Inventory modeling and simulation as a research instrument

(iii) Historical data file as a Secondary data specific to the case

(iv) Data Analysis coding with Python

(v) Disseminating the results and graphs

Hypothesis testing is the pillar of research findings. Since human reasoning is complex, statistical modeling enables drawing inferences from the research finding through hypothesis testing. Further, software tools help in conducting practical data analysis (Kolawole &Sekumade, 2017).

Research Variables and their relationship

As per the research objective, the target research (independent) variable is Profit Maximization (PM); dependent variables are Expected Average Demand (EAD); Selling Price (SP); Lead Time (LT); Probability (p); indication variable: Loss of Orders (LO).Surti et al. (2013) elucidated the relationship between profit maximization and selling price. According to them, when retailers have exposed various risks due to uncertainty in consumer demand, it might get amplified when the supply is uncertain. This uncertainty can be due to long lead times, loss of orders, damage, or theft of product orders in transit. To neutralize this risk to the retailer, it is required to determine the order quantity and price that maximize the revenue and minimize the loss of orders. The basic assumption here is that retailer considers only the demand uncertainty, and the supply side uncertainty has not been assumed to exist,i.e., adoption of newsvendor model is assumed. The literature corresponds to the applicability of postponed pricing in retailing by Tang & Yin (2007).

In the present study, the simulation modeling is done to access existing libraries of Python in such a way that the relationship between optimal price and order quantity can yield better results of profit. Further, according to Surti et al. (2013), pricing can be called simultaneous pricing, especially when the pricing is set before the supply is received. The retailer may also delay the pricing decision until the supply is received well before the realization of demand. This kind of price setting is called the postponed pricing model. At this setting of price, the retailer prices and sells the product so that the revenue is maximized. They are analytically showed that the optimal expected postponed pricing based expected profit dominates the optimal expected simultaneous pricing based expected profit.

The present study uses a simulation approach to support the demand uncertainty of inventory within supply chain management.There are two types of Inventory models:

1. Demand-based inventory models: These are two types:(i) deterministic and (ii) random. Currently, this paper deals with the case of the random demand model. For this purpose, forecasting techniques are used with secondary historical data available fromGithubto estimate the average and standard deviation of the expected demand.
2. Cost-based inventory models:It could deal with (a) order cost(b) inventory holding cost where order cost involves the (i) product cost and (ii) transportation cost; inventory holding cost (i) involves taxes, (ii) insurance cost, (iii) maintenance cost, etc.Two important decision variables in inventory management are: (i) order quantity and (ii) ordering time

Monte Carlo Simulation

The simulation model is a computerized model that refers to the class of mathematical models and is intended for conducting research of inventory control systems functioning under dynamic and uncertain conditions (Lawe& Kelton, 2004; Muravjovs, 2015).Monte Carlo simulation builds a model with possible outcomes by considering random value inputs from a specified distribution of all possible value range for each input variable defined by the researcher. Usually, random numbers are generated in the uniform distribution interval between 0 and 1. It calculates numerous scenarios by repeatedly picking values from a predefined probability distribution for the uncertain variable (i.e., demand). The generated numbers are genuinely not random, so they are called pseudo-random numbers (Tuzunturk et al., 2015). It follows five steps:

(i) Establishing probability distribution,

(ii) Building a cumulative probability distribution for each variable,

(iii) Setting random number intervals,

(iv) Generating random numbers, and

(v) Simulating the experiment.

When Monte Carlo simulation is used, it produces a probability for an outcome that would occur. In this case, multiple sets of trails are required to be performed. As the frequency of possible outcomes can be controlled, thus frequency becomes always known. Random numbers are generated for ascertaining the stochastic demand. A uniform distribution is used to draw these random numbers (Karim&Nakade, 2019).

Belvardi et al. (20212) reviewed the literature on optimizing inventory control in passing. The determination of safety stock in an inventory model is becoming one of the important actions of inventory management. The simulation-based approach was earlier adopted by Jung et al. (2004) with Monte Carlo-based sampling from historical data and worked on modifications of sagety stock under service level constraints.

The present work proposes modeling the simulationto cope with supply chain management applications such as inventory management under high uncertainty demand scenarios,i.e., scenarios with stochastic behavior, and presents a test case to evaluate the method (Rojas, 2017; Zijm, 2019). Furthermore, this paper simulates continuous and periodic review policies to solve the inventory problem with stochastic demand (Karim&Nakade, 2019; Pires et al., 2018). Many researchers have analyzed replenishment using Continuous review and periodic review policies. In addition, they employed simulation methods to handle the complexity of stochastic inventory problems earlier, as cited in Widyadana et al. (2017) and Zijm (2019). Simulation models are adopted when analytical models have difficulty in handling restrictive assumptions (Kochel & Nielander, 2005) .

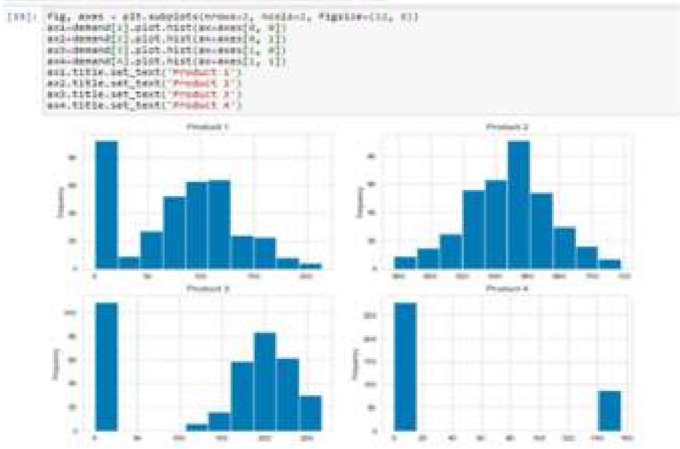
A Monte Carlo simulation was conducted using Python programming language to simulate the behavior of stochastic demand and calculate the profit for one instance realization, iterating through each day and capturing the product's inventory level, thus generating the product demand for that day. The inventory simulation model usesthe Monte Carlo simulation techniqueuses day-by-day calculations in this research. A Monte Carlo simulation is a valuable tool for predicting future results by calculating a formula multiple times with different random inputs (Moffitt, 2019; Rojas, 2017).

5. Results and Discussion

Case Description: Distributor X offers highly customized products, and the demand for this product is unique to every customer. So, it is unlikely that orders are always receivedevery day. Some products are offered seasonally, and some others are trendy. The Sales information is already captured in the form of data files, as mentioned earlier. It is also assumed that the customer who enters the store may not buy a product item. Thus, it is difficult to understand consumer behavior. As such, a rough estimate with probability 'p' of placing the order on any given day is worked out. Order size is also assumed uncertain and would follow a logarithmic-normal distribution; however, its parameters are unknown.The algorithm and solution approach is illustrated in Anderson et al. (2015) &Nagpurkar (2020). Further, the following computations are worked out:

Demand Distribution and Statistical Summary

Inventory control and its distribution are the key processes in the supply chain management application performance.In this research, state of the art information management solution for the supply chain management, details regarding the relationship between inventory policies and the stochastic demand are provided by modeling the simulation-based optimization methods to provide an appropriate solution (Roldan, Basagoiti & Onieva, 2014). In addition, histograms depict the demand distribution of each product based on previous sales.



From Fig. 1, it can be understood that Product 2 is a high-volume product that is bought every day (p=1) and the mean = 649 (rounded); Product 1 is purchased 76% of the time; Product 3 is at 70%, and Product 4 is at 24% with corresponding mean values as 104, 202 and 150 respectively.

```
In [2]: import numpy as np
        import pandas as pd

        import seaborn as sns
        import matplotlib.pyplot as plt

        import warnings
        warnings.filterwarnings('ignore')

        sns.set_style('whitegrid')

In [3]: import operator

In [5]: summary = pd.read_csv('summary_stats.csv')
        df = pd.read_excel('XYZ-1.xlsx', 'Data')
        demand = df[6:]

In [42]: summary
Out[42]:
```

	Purchase Cost	Lead Time	Size	Selling Price	Starting Stock	Mean	Std Dev	Co	Ch	Probability	Demand_lead
0	12	9	0.570	16.1	2750	103.501935	37.317994	1000	20	0.756831	705
1	7	6	0.052	5.8	22500	648.651913	26.446797	1200	25	1.000000	3891
2	6	16	0.500	10.2	5200	201.677043	31.076001	1000	25	0.702198	2266
3	37	22	1.050	68.0	1400	150.058965	3.216598	1200	25	0.237705	785

Fig. 2 Statistical Summary of Each Product

Table 2: Statistics of the demand during lead time (as extracted from Table 1)

Product	Lead Time	Expected Average Orders
1	9	705
2	6	3891
3	16	2266
4	22	785

Table 2 values must be considered while placing the original orders; otherwise, the distributor would fall short of meeting the demand.

Periodic Review: Periodic review indicates that inventory status is tracked at regular periodic intervals and reorder made to raise the inventory level to the predefined point (Setyaningsih&Basri, 2013). With a periodic review system, the inventory is checked and reordered only at specified times like weekly, biweekly, monthly, orperiodically (Chu &Pizano, 2019). Thus, the coordination of shipping and receiving of multiple products orders becomes easy. The Monte Carlo simulation technique is used to simulate the daily demand for each product in the store. If a product is purchased, the demand will follow a logarithmic-normal distribution. The logarithm of the daily values of the previous year's demand distribution is computed. Random number generation between 0 and 1 is done from a uniform distribution to simulate daily customer purchasing behavior.

Logic of Algorithm

1. IF the demand can be fulfilled entirely by the current inventory level, THEN the demand is reduced. The number of units sold is based on increments of that day.

2. IF the demand cannot be entirely fulfilled by the inventory level, THEN the inventory in hand is equal to a number of units sold on that day.

   The algorithm keeps track of the current day in the year.

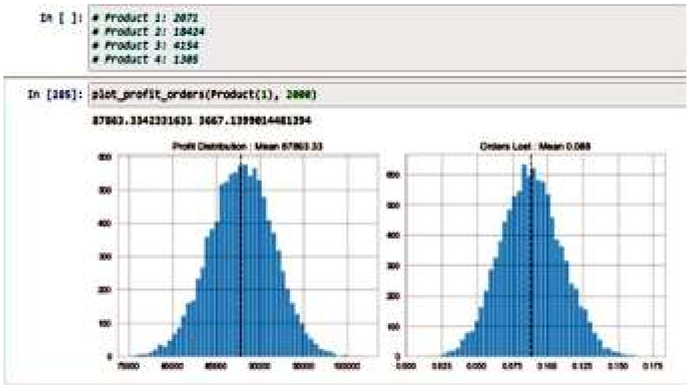
3. IF (the day of the year = the review period) THEN the order is placed to replenish the stock to an order up-to quantity M.

This value is passed as an input to the algorithm as a decision variable. The order quantity updates the inventory after passing the value of lead time for that particular product. This will be looped for a one-year duration (i.e., 365 days).

The inventory levels for one simulation of a year are used to determine the store's profit for that year.Revenue = units sold * products selling price.

Profit Distribution and Loss of Orders

The simulation is carried for Product 1 with an order quantity upto 2071. The simulation is carried out for 10,000 iterations to give multiple realizations of profit and the number of losses of orders.



6.1.3 Periodic Review Simulation Results

```
# Product 1: 2071
# Product 2: 18424
# Product 3: 4154
# Product 4: 1305
# creating a dataframe with all the results
idx = ['Order-point M', 'Expected Profit', 'Profit Standard Deviation', 'Proportion of Lost Orders']

review = p_review_optimum(Product(1), 2701)
prod_review_1 = max(review.items(), key=operator.itemgetter(1))
review = p_review_optimum(Product(2), 18424)
prod_review_2 = max(review.items(), key=operator.itemgetter(1))
review = p_review_optimum(Product(3), 4154)
prod_review_3 = max(review.items(), key=operator.itemgetter(1))
review = p_review_optimum(Product(4), 1305)
prod_review_4 = max(review.items(), key=operator.itemgetter(1))

df_product_review = pd.DataFrame(
    {'1': [prod_review_1[0], prod_review_1[1][0], prod_review_1[1][1], prod_review_1[1][4]],
     '2': [prod_review_2[0], prod_review_2[1][0], prod_review_2[1][1], prod_review_2[1][4]],
     '3': [prod_review_3[0], prod_review_3[1][0], prod_review_3[1][1], prod_review_3[1][4]],
     '4': [prod_review_4[0], prod_review_4[1][0], prod_review_4[1][1], prod_review_4[1][4]]})

df_product_review = df_product_review.set_index(pd.Index(idx))
df_product_review
```

Fig. 4.1 Periodic Review Simulation in Python

	1	2	3	4
Order-point M	2701.000000	18424.000000	4154.000000	1305.000000
Expected Profit	94457.855305	337896.481345	153261.026346	267364.158945
Profit Standard Deviation	3942.755287	505.492806	879.003244	9540.380174
Proportion of Lost Orders	0.129422	0.188613	0.334743	0.293721

Table 3: Periodic Review Simulation Results

Product	Optimum Expected Profit	Expected Standard Deviation	Order up-to point M	Proportion of Orders Lost
1	$94458	$3943	2071	0.13
2	$337896	$506	18424	0.19
3	$153261	$879	4154	0.34
4	$267364	$9540	1305	0.29

Continuous Review Policy

The continuous review indicates that inventory status is continuously tracked, and ordering is done according to lot size (Q), when the level is reached the assigned inventory reorder point. The advantage of continuous review is to address the situation when demand is high (Setyaningsih&Basri, 2013). In Continuous review, policy inventory is reviewed every day, and a decision is made about how much to order. Whenever the inventory level reaches the reorder point R, place an order quantity of Q to bring the inventory position to the order-up-to level at R+Q (Initially Q value can be chosen using Economic Order Quantity based quantity (Du, undated).

Continuous Review Policy algorithm

1. On each day, the inventory level is checked and compared it with reorder point
2. IF the inventory level is < = reorder point, THEN it places an order. However, the stock is realized only after checking the lead time for that product has passed.

   For example, for Product 1, a lead time of 9 days is given. It means if the order is placed on day 52, the inventory will be replenished on the 52+9= day 61.
3. For updating the inventory level, it follows as per periodic review algorithm logic.
4. The profit and expected lost orders are calculated similarly to that of the periodic review policy

Profit Distribution and Orders Lost

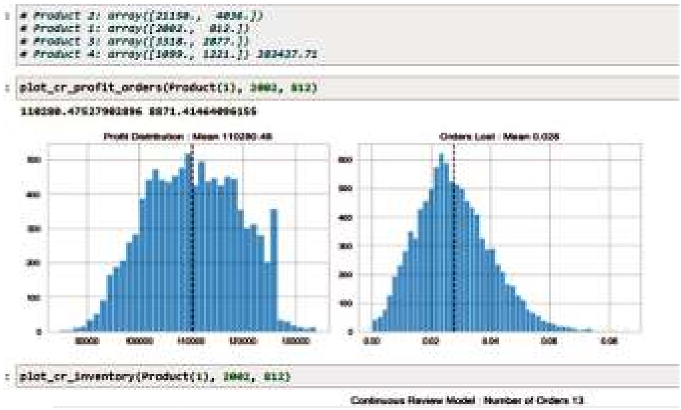
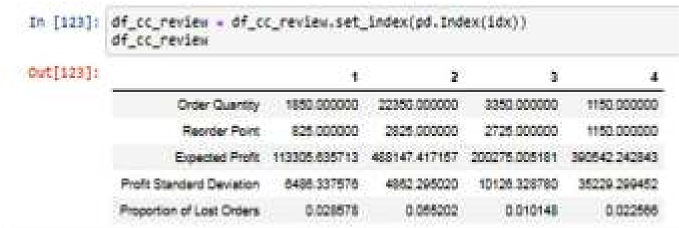


Fig. 5 Profit Distribution and Orders Lost in Continuous Review Policy

Continuous Review Simulation Results



```
In [123]: df_cc_review = df_cc_review.set_index(pd.Index(idx))
          df_cc_review
Out[123]:
```

	1	2	3	4
Order Quantity	1850.000000	22350.000000	3350.000000	1150.000000
Reorder Point	825.000000	2825.000000	2725.000000	1150.000000
Expected Profit	113305.835713	488147.417157	200275.005181	390542.242843
Profit Standard Deviation	6498.337576	4862.295020	10126.328780	35229.299452
Proportion of Lost Orders	0.028578	0.055202	0.010148	0.022566

Fig. 6 Continuous Review Simulation Results in Python

Table 4: Continuous Review Policy Simulation Results

Product	Optimum Expected Profit	Expected Standard Deviation	Order Up-To point M	Proportion of Orders Lost
1	$113306	$6498	825	0.029
2	$488147	$4862	2825	0.055
3	$200275	$10126	2725	0.010
4	$390542	$35229	1150	0.023

Safety Stock

Determination of Safety stock level in the supply chain is a challenging task with stochastic demand; Safety stock is one of the essentialdriving factors of inventory management (Amirjabbari& Bhuiyan, 2014).Safety stock is a term used in logistic management to describe a level of stock. More than that, it is maintained to mitigate the risk of stock-out position caused by uncertainty in demand and supply. In order to permit the business operations to proceed according to the plan maintaining an adequate safety stock level is essential. (Wikipedia, 2020).

Safety stock is calculated in the following way (tradegecko.com):

(i) mul=maximum daily usage * maximum lead time in days

(ii) aul=average daily usage * average lead time in days

(iii) Safety stock = mul-aul

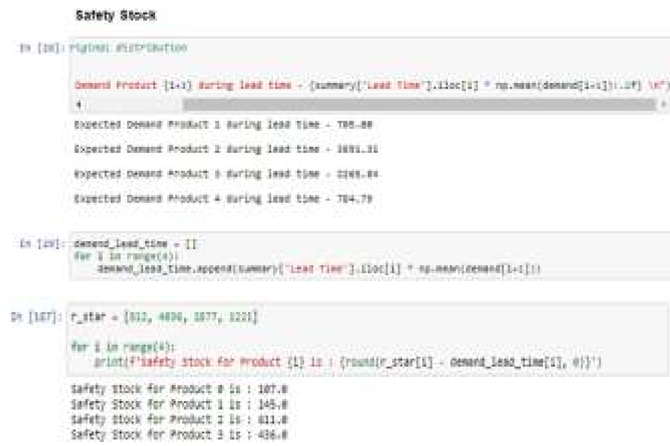


Fig. 7 Expected Demand and Safety stock in Python

Table 5: Expected Demand and Safety Stock for Product 1-4

Product	Expected Demand	Safety Stock
1	705	107
2	3891	145
3	2266	611
4	785	436

Table 6: Comparing Periodic Review Policy and Continuous Review Policy

Aspect	Periodic Review Policy	Continuous Review Policy
Order quantity	Variable order quantity	Fixed Order Quantity
Order time	Fixed order interval	Variable order interval
Safety stock	Larger	Smaller
Item classification	Item C	Item A
Ease of management	Review with low frequency	Review with high frequency
Advantages	Reducing the time of analyzing inventory count;	Easy to know when to reorder; Accurate inventory counting
Disadvantages	Lower investment for counting; Not accurate inventory level counting	Huge investment on counting inventory level

(Source: Ting Lei &Okudan, 2013)

Conclusion

In general, there is a discrepancy between the retailer's actual demand and forecasting demand due to uncertain demand. In this paper, the order quantity decision in the supply chain and the order quantity decisions to meet the random demand of the product in a period cycle and continuous cycle in order the maximize the expected profit is computed using an existing case data in Python language using relevant libraries (Zhou & Li, 2007).

System dynamics can have negative influences on supply chain management. Therefore, it's appropriate modeling, and by using simulation techniques, the firm can manage the negative impact of bullwhip (Moosivandet al., 2019). Furthermore, inventory control aims to achieve an economic balance between system costs and customer satisfaction (Rodgers & Stanley, 2017; Atnafu&Balda, 2018). Though simulation does not solve the problem directly, it allows observing the changes in the output according to varied input parameters of the system (Ahmadi, 2012). So,in this study, a dynamic system simulation model has been dealtwith for controlling inventory for well managing the retailing and distribution with the primary goal of evaluating inventory policies and uncertain demand. Two review policies, such as periodic review policy and continuous review policy-based performance of inventory control, are investigated with demand and lead time uncertainty to determine the organizational profit and computing order quantity, reorder point, and safety stock levels.The use of innovative information technology advancements such as Python programming language can ease the efforts of programming in developing solutions with corresponding visualizations. Using this approach, it becomes possible to reduce the variance and do parallel computing by distributing individual simulations to save computation time (Rosenthal, 2000).

Scope for further research

The models presentedin the study may not be suitable for forecasting demand for abnormal circumstances such as sudden change of society's economy, a nation in war conditions, change of interest rates, During Corona and Post Corona pandemic situations (EduPristine, 2018).

Conducting sensitivity analysis for predicting the outcome of a decision and assessing the riskiness of the strategy, especially when replacing the uncertain parameters with expected values and by providing the visualization of sensitivity when applying the solution with normalized Jacobian matrix color codes (Belvardiet al., 2012).

Acknowledgment

This publication was supported by the Deanship of Scientific Research at Prince Sattam bin Abdulaziz University, Alkharj, Saudi Arabia.

References

- Ahmadi, M. (2012). *The application of system dynamics and discrete event simulation in supply chain management of Swedish manufacturing industries*. Master Thesis, submitted to School of Innovation, design and engineering, Malardalen University, Sweden.
- Aisyati, A., Jauhari, W. A. &Rosyidi, C. N. (2014). Periodic Review Model for Determining inventory policy for aircraft consumable spare parts, *International Journal of Business Research & Management*, 5 (3), 41-51.
- AlSudairi, M. A. T. & Vasista, T. G. K. (2012). Design of Strategic business model for electronic enterprise in digital society, *International Journal of Digital Society*, 3(4), 695-702.
- AlSudairi, M., Vasista, T. G., Zamil, A. M. & Algharabat, R. S. (2012). Mitigating Bullwhip Effect with eWord of Mouth: eBusiness Intelligence Perspective, *International Journal of Managing Value and Supply Chain*, 3(4), 27-41
- Ambra, T., Caris, A., &Macharis, C. (2020). Do you see what I see? A simulation analysis of order bundling within a transparent user network in geographic space. *Journal of Business Logistics*, *42*(1), 167-190. https://doi.org/10.1111/jbl.12237

- Amirjabbari, B. & Bhuiyan, N. (2014). Determining supply chain safety stock level and location, *Journal of Industrial Engineering and Management*, 7 (1), 42-71.
- Anderson, Sweeney, Williams, Camm, Cochran, Fry &Ohlmann (2015). *An Introduction to management science: Quantititave approaches to Decision making*. 14th Edition. Cengage Learning. Pp. 457-478.
- Atnafu, D. &Balda, A.; S. Liu (Reviewing. ed.) (2018). The impact of inventory management practice on firms' competitiveness and organizational performance: Empirical evidence from micro and small enterprises in Ethiopia, *Cogent Business & Management*, 5, 1.
- Basciftci, B., Ahmed, S. & Shen, S. (2020). Distributionallyrobus facility location problem under decision-dependent stochastic demand, arXiv: 1912.05577v2.
- Basu, R. & Wright, J. N. (2008). *Total Supply Chain Management*, 1st Edition, Elsevier.
- Belvardi, G., Kiraly, A., Varga, T., Gyozsan, Z. &Abnoyi, J. (2012). Monte Carlo Simulation based Performance analysis of supply chains. *International Journal of Managing value and supply chains*, 3(2), 1-15.
- Ben Mohamed, I., Klibi, W., Labarthe, O., Deschamps, J., &Babai, M. Z. (2017). Modelling and solution approaches for the interconnected city logistics. *International Journal of Production Research*, *55*(9), 2664-2684. https://doi.org/10.1080/ 00207543. 2016.1267412
- Betts, J. M. (2014). Calculating Target Inventory Levels for Constrained Production: A Fast Simulation-based Approximation, *Computers & Operations Research*, 49, 18-27.
- Cachon, G. &Terwiesch, C. (2012). *Matching Supply with demand: An Introduction to operations Management,* Third Edition, McGraw-Hill Publications
- Cachon, G. P. &Netessine, S. (2004). Game theory in Supply chain analysis. In Simchi-Levi, David Wu & Max Shen (eds.) *Handbook of quantitative supply chain analysis: modeling in the e-business era,* Publisher: Kluwer.
- Cao, H. &Zuo, X. (2017). Supply Chain Inventory Coordination under uncertain demand via combining Monte Carlo Simulation and Fitness Inheritance PSO. *International Journal of Swarm Intelligence Research*, 6 (1), 1-22.
- Choi, T. M., Li D., Yan, H. M. (2006). Quick response policy with Bayesian information updates, European *Journal of Operations Research*, 170(3), 788-808.
- Chu, K. K. Y.&Pizano, J. M. M. (2019). *Replenishment policies for retail pharmacies in Emerging Markets,* Master thesis submitted at Massachusetts Institute of Technology, USA.
- Cunha, P. S. A., Oliveira, F. &Raupp, F. M. P. (2017). Replenishment control for a two-echelon logistics network under demand uncertainty: A two-stage stochastic programming approach. *Pesquisa Operational*, 37 (2),
- Diaz, R., Bailey, M. P. & Kumar, S., (2016). Analyzing a Lost-Sale Stochastic, Inventory Model with Markov-Modulated Demands: A Simulation-Based Optimization Study, *Journal of manufacturing systems,* 38, Jan 2016, 1-12.
- Diaz, R., Tulpule, Longo, F. & Cimino, (n. d.), Monte Carlo Simulation: Remanufacturing or not –A Newsvendor perspective. https://pdfs.semanticscholar.org/669f/61a15a1d7b5c4b72e780715925a50a1dc3a9.pdf [Accessed on 24-08-2021].
- Do Rego, J. R. & De Mesquita, M. A. (2015). Demand forecasting and inventory control: A Simulation study on Automotive spare parts*, International Journal of Production Economics*, 161
- Downey, H. K. & Slocum, J. W. (1975), Uncertainty: Measures, research and sources of variation, *Administrative Science Quarterly*, 18, 562-577.
- Du, D. (n. d.) *Supply chain management: Inventory Management*. Lecture Notes http://www2.unb.ca/~ddu/4690/Lecture_notes/Lec2.pdf (Available August 11, 2021).
- Dul, J. & Hak, T. (2008). Case study methodology in business research. Abingdon, England, Routeledge.

- EduPristine (2018). All you want to know about sensitivity analysis. https://www.edupristine.com/blog/all-about-sensitivity-analysis Retrieved 02-09-2021.
- Ekren, B. Y. &Ornek, M. A. (2015). Determining optimum (s, S) levels of floor stock items in a paint production environment, *Simulation Modeling practice and theory*, 57, 133-141.
- Fernando, Y., &Wulansari, P. (2021). Perceived understanding of supply chain integration, communication and teamwork competency in the global manufacturing companies. *European Journal of Management and Business Economics*, *30*(2), 191-210. https://doi.org/10.1108/ejmbe-06-2020-0157
- Flynn, B., Koufteros, X & Lu, G. (2016). On theory in supply chain uncertainty and its implications for supply chain integration. *Journal of Supply Chain Management*, 52(3), 46 pages.
- Grotsch, V. M., Blome, C. & Schleper, M. (2013). Antecedents of proactive supply chain risk management – A contingency theory perspective. *International Journal of Production Research,* 51(10), 2842-2867.
- Gumus, A. T. &Guneri, A. F. (2007). Multi-echelon inventory management in supply chains with uncertain demand and lead times: Literature review from an operational research perspective. *Proceedings of the Institution of Mechanical Engineers & Journal of Engineering Manufacture*, 221(10), 1553-1570.
- Hadrawi, H. K. (2019). The impact of firm supply performance and lean processes on the relationship between supply chain management practices and competitive performance. *Uncertain Supply Chain Management*, 7, 341-350.
- Hai, D., Hao, Z. & Ping, L. Y. (2011). Model Predictive Control for inventory management in supply chain planning. *Procedia Engineering*, 15, 1154-1159.
- Holden, L. (2017). *Inventory Optimization using a SimPy Simulation Model.* Master thesis submitted to School of Graduate Studies, East Tennessee State University, https://dc.etsu.edu/cgi/
- viewcontent.cgi?article=4651&context=etd Retrieved on 02-09-2021.
- Hossain, M. (2014). *Application of Monte Carlo as Support for Inventory Planning Decision*. A Degree project submitted to Industrial Engineering and Management degree at KTH Royal Institute of Technology, Stockholm, Sweden.
- Ivanov D. (2016). Operations and supply chain simulation with AnyLogic 7.2: Decision-oriented introductory notes for master students. E-textbook, Berlin School of Economics and Law (preprint) https://www.anylogic.com/upload/pdf/operations-and-supply-chain-simulation-with-anylogic72.pdf Retrieved 03-09-2021
- Jung, J. Y., Blau, G., Penky, J. F., Reklaitis, G. V., Eversdyk, D. (2004). A simulation based optimization approach to supply chain management under demand uncertainty, *Computers & Chemical engineering,* 28 (10), 2087-2106.
- Karim, R., & Nakade, K. (2019). A stochastic model of a production-inventory system with consideration of production disruption. *International Journal of Advanced Operations Management*, *11*(4), 287. https://doi.org/10.1504/ijaom.2019.103152
- Karteek. P. R & Jyoti, K. (2014). Deterministic and Probabilistic models in Inventory Control, Inventory *Journal of Engineering Development and Research*, 2(3), 3100-3105
- Kleab, K. (2017). Important of Supply chain management. *International Journal of Scientific and Research Publication*, 7(9), 397-400.
- Kochel, P. & Nielander, U., (2005). Simulation-Based Optimization of Multi-Echelon Inventory Systems, *International Journal of Production Economics*, 93-94, 505-513.
- Kolawole, A. O. &Sekumade, A. (2017). *Hypotheses and Hypothesis testing*. Conference of PhD Agricultural Economics seminar, Ekiti State University, Nigeria, DOI:10.13140/RG.2.2.28299.39292
- Kulkarni S &Rajhan N R (2013). Determination of

Optimum Inventory Models for minimizing total inventory cost, chemical, civil and Mechanical Engineering tracks of the 3rd Nirma University International conference on Engineering, Sciverse Science Direct Procedia Engineering 51.

- Lawe A. M. & Kelton, V. D. (2004). *Simulation modeling. Classic CS. 3-ed.*, St. Petersburg: Peter; Kiev: Publishing group.
- Lawrence, P. R., & Lorsch, J. W. (1967). Differentiation and integration in complex organizations. *Administrative Science Quarterly*, 12(1), 1-47.
- Li, X. (2014). Discrete and Dynamic optimization problems in operations management, Discrete dynamics in nature and society, Article ID 70198, 7 pages.
- MIT OpenCourseWare (2014). Newsvendor Inventory Problem. https://ocw.mit.edu/courses/sloan-school-of-management/15-772j-d-lab-supply-chains-fall-2014/calendar/MIT15_772JF14_Newsboy.pdf [Accessed on 16-08-2021]
- Moffitt, C. (2019). Monte Carlo Simulation with Python. https://pbpython.com/monte-carlo.html Retrieved 02-02-2021.
- Moosivand, A., Ghatari, A. R. &Rasekh, H. R. (2019). Supply Chain Challenges in Pharmaceutical manufacturing companies: using qualitative system dynamics methodology. *Iran Journal of Pharmaceutical Research,* 18(2), 1103-1116.
- Muir, W. A., Griffis, S. E., & Whipple, J. M. (2019). A simulation model of Multi Echelon retail inventory with cross channel product returns. *Journal of Business Logistics*, *40*(4), 322-338. https://doi.org/10.1111/jbl.12209
- Muravjovs, A. (2015). *Inventory control system analysis using different simulation modeling paradigms*. Doctoral thesis at Transport and Telecommunication Institute, 167 pages.
- Nagpurkar, M. (2020). Inventory Management – Dealing with unpredictable demand https://towardsdatascience.com/inventory-management-using-python-17cb7ddf9314 [Accessed on 17-08-2021]
- Nesheim, T. (2021). Exploring the resource manager role in a project-based organization. *International Journal of Managing Projects in Business*, *14*(7), 1626-1641. https://doi.org/10.1108/ijmpb-12-2020-0389
- Oluwaseyi, A., Onifade, M. K. &Odeyinka, O. (2017). Evaluation of the role of inventory management in logistic chain of an organization. *Scientific Journal on Transport and Logistics*, 8(2), 1-11.
- Ortega, M. & Lin, L. (2004). Control theory applications to the production-inventory problem: A review, *International Journal of Production Research,* 42 (11), 2303-2322
- Pires, M. C., Frazzon, E. M., Danielli, A. M. C., Kuck, M. & Freitag, M. (2018). Towards a simulation-based optimization approach to integrate supply chain planning and control, *Procedia CIRP*, 72, 520-525.
- Porteus, E. L. (1990). Stochastic inventory theory. In D. Hyman & M. Shobel (Eds.), *Handbooks in Operations Research and Management Science* (vol 2., pp. 605-652). Amsterdam: Elsevier Science Publishers
- Prater, J., Kirytopoulos, K., & Ma, T. (2021). From "Technical newbies" to "Optimistic politicians". *International Journal of Managing Projects in Business*, *14*(2), 329-344. https://doi.org/10.1108/ijmpb-01-2019-0007
- Rezaei, H., Baboli, A., Shahzad, M. K. &Tonadre, R. (2018). A new methodology to optimize target stock level for unpredictable demand of spare parts: A Case study in business aircrafts' industry. *IFAC* PapersOnline 51-11, 538-543.
- Rizkya, I., Syahputri, K., Sari, R., Anizar, A., Siregar, I. &Ginting, E. (2018). Comparison of Periodic Review Policy and Continuous Review Policy for the Automotive Industry Inventory System. IOP Conference Series Materials Science and Engineering, 288(1), 012085.
- Rodgers, N. J. & Stanley, K. (2017). Inventory challenges facing the performance of logistic firms in Kenya: A case of freight forwarders Kenya Limited. *Elixir Finance Management*, 106, 46355-46363.

- Roekchamnong, W., Pornchaiwiseskul, P.& Chiarawongse, A. (2014). The effects of Uncertainties on Inventory management of petroleum products: A case study of Thailand. *International Journal of Energy Economics and Policy*, 4(3), 380-390.
- Rojas, F. (2017). A methodology for stochastic inventory modelling with ARMA triangular distribution for new products, *Cogent Business & Management*, 4(1), 1270706, DOI: 10.1080/23311975.2016.1270706
- Roldan, R., Basagoiti, R. &Onieva, E. (2014). Inventory Routing Problem with stochastic demand and lead time: State of the art. International Joint Conference, SOCO'14, CISIS'14, ICEUTE'14, 73-82. Jose Gaviria et al. (Ed.) Advances in Intelligent Systems and Computing, vol. 299. Springer Publishing.
- Rosenthal, J. S. (2000). Parallel computing and Monte Carlo algorithms. *Far East Journal of Theoretical Statistics*, 4, 207-236.
- Sadeghi, J &Niaki, S. T. A. (2015). Two parameter tuned multi-objective Evolutionary algorithms for a Bi-Objective vendor managed inventory model with trapezoidal fuzzy demand, *Applied Soft Computing*, 30, 567-576
- Sankaran, S., Vaagaasar, A.L. and Bekker, M.C. (2020), Assignment of project team members to projects: project managers' influence strategies in practice, *International Journal of Managing Projects in Business*, Vol. 13 No. 6, pp. 1380-1400.
- Schramm, W. (1971). Notes on case studies of instructional media projects. Washington D. C. Academy for Educational Development. Schumann.
- Secondary data files: https://github.com/wiredtoserve/datascience/tree/master/InventoryManagement Retrieved and used during the year 2021.
- Setyaningsih, S. &Basri, M. H. (2013). Comparison Continuous and period review policy inventory management system formula and enteral food supply in Public hospital Bandung, *International Journal of Innovation, management and technology*, 4(2), 253-258.
- Seuring, S. (2005). Case Study Research in Supply chains- An outline and three examples. In H. Kotzab, S. Seuring, M. Muller & G. Reiner (eds.) *Research Methodologies in Supply Chain Management*
- Shadur, M. A. & Bamber, G. J. (1994). Toward lean management? International transferability of Japanese management strategies to Australia. *The International Executive*, 36(3), 43-364.
- Simchi-Levi, D., Kaminsky, P. &Simchi_levi, E. (2003), *Designing and managing the supply chain*, 2nd Edition, London:McGraw-Hill.
- Singh, H., Garg, R. K. & Sachdeva, A. (2018). Supply chain collaboration: A state-of-the-art literature review, 6, 149-180. (GrowingScience Publishing)
- Surti, C., Hassini, E. & Abad, P. (2013). Pricing and inventory decisions with uncertain supply and stochastic demand, *Asia-Pacific Journal of Operational Research*, 30, 25 pages.
- Svensson de Jong, I. (2021). Under construction: Action research in innovation measurement. *International Journal of Managing Projects in Business*, *14*(1), 87-107. https://doi.org/10.1108/ijmpb-01-2020-0036
- Tang, C. S. & Yin, R. (2007). Responsive pricing under supply chain uncertainty. *European Journal of Operational Research,* 182(1), 239-255.
- Tang, C. S., Rajaram, K., Alptekinglu, A. and Ou, J. H. The benefits of advance booking discount programs: Model and analysis, *Management Science*, 50 (4), 465-478.
- Tee, Y. S. & Rosetti, M. D. (2001). Using simulation to evaluate a continuous review (R, Q) Two-Echelon inventory model, In Proceedings of the 6th Annual International Conference on Industrial Engineering, San Francisco, CA, USA
- Ting Lei, J. M. &Okudan, G. E. (2013). In Proceedings of the 2013 Industrial and Systems Engineering Research Conference (eds.) A. Krishnamuthy and W,K,V, Chan, 10 pages.

- Tuzunturk, S., Senaras, A. E., &Sezen, H. K. (2015). Forecasting water demand by using Monte Carlo simulation. *Academic View Magazine*, 49, May-Jun, 25-44.
- Usher, G. S. (2021). Next decision node (NDN) planning: An ambidextrous planning model. *International Journal of Managing Projects in Business*, *14*(2), 390-411. https://doi.org/10.1108/ijmpb-03-2019-0069
- Vaziri, M. & Sodhi, M. (2014). Application of game theory on Inventory level decision making, *International Journal of Business and Economics Research*, 3(6), 211-219.
- Wang, D., Li, H., & Lu, Y. (2021). Factors affecting transaction costs in megaprojects: A qualitative comparative analysis. *International Journal of Managing Projects in Business*, *14*(6), 1245-1269. https://doi.org/10.1108/ijmpb-08-2020-0267
- Widyadana, I G. A, Tanudireja, A. D. & Teng, H-M (2017). Optimal Inventory Policy for Stochastic Demand using Monte Carlo Simulation and Evolutionary Algorithm, *International Journal of Industrial Research and Applied Engineering*, 2(1), 8-11.
- Widyadana, I. G. Tanudireja, A. D., Teng, H-M (2017). Optimal Inventory policy for stochastic demand using Monte Carlo Simulation and Evolutionalry Algorithm, *JIRAE*, 2(1), 8-11.
- Zamil, A. M. A. & Vasista, T. G. (2021a). Customer Segmentation using RFM analysis: Realizing through Python implementation, Pacific Business Review International, 13 (11), 24-36
- Zamil, A.M.A., Nusairat, N.M., Vasista, T.G., Shammot, M.M., Areiqat, A.Y.(2021b). Prediction of Sales based on ana effective advertising media sales data: A Python Implementation approach, Academy of Strategic Management Journal, 20(Special Issue 2), pp. 1–9
- Zamil, A.M.A., Nusairat, N.M., Vasista, T.G., Shammot, M.M., Areiqat, A.Y.(2020 a). Predicting telecom customer churn: An example of implementing in python, Journal of Legal, Ethical and Regulatory Issues, 24(Special Issue 1), pp. 1-11
- Zamil, A. M., & Al Adwan, Ahmad, Vasista, T. G., 2020 b, Enhancing Customer Loyalty with Market Basket Analysis Using Innovative Methods: A Python Implementation Approach., International Journal of Innovation, Creativity and Change, Volume 14, Issue 2, pp. 1351-1368.
- Zhou, Y. & Li, D-H (2007). Coordinating order quantity decisions in the supply chain contract under random demand. *Applied Mathematical Modeling*, 31 (6), 1029-1038.
- Zijm, H. (2019). Stochastic Inventory Models. In H. Zijm, M. Klumpp, A. Regattieri, & S. Heragu (Eds.), *Operations, Logistics and Supply Chain Management* (pp. 441-467). (Lecture notes in logistics). Springer. https://doi.org/10.1007/978-3-319-92447-2_20