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Research Article

A STUDY ON STOCHASTIC INVENTORY MODELLING AND RESOURCES OPTIMIZATION STRATEGIES

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Abstract

The research is conducted on the topic "A study on Stochastic Inventory Modelling and Resources Optimization Strategies" To construct a predictive model for the actual quantity consumption, the study focused on the daily/monthly requirements of A-type classified inventory over a 5-year period. Data for the research, spanning from April 1, 2018, to March 31, 2023, was gathered from Toyota Kirloskar Auto Parts. Stochastic inventory modelling tools offer a more realistic depiction of uncertainty, providing valuable insights for decision-making. Utilizing the Holt-Winters approach, a well-established time series forecasting technique, a prediction model was created. This technique incorporates the seasonality, trend, and level components of the data, allowing precise forecasting of future inventory use. To assess the model's accuracy and resilience, the Ljung-Box test was performed. This test analyses if the model effectively depicts underlying patterns in the data by assessing autocorrelation in the residuals. The research's results underlined the usefulness of the created prediction model in foreseeing real amount consumption. Implementing this predictive model helps firms to strengthen their inventory management procedures, optimize resource allocation, and realize cost savings.

Keywords: Inventory Management, Stochastic Inventory Modelling, Shapiro-Wilk Test, Levene's Test, ANOVA, Holt- Winters Methodology, L-Jung Box Test.

Introduction

The primary aim of this research is to provide a comprehensive analysis of the effects that uncertainty and unpredictability in demand, lead times, and supply have on the management of inventory. Furthermore, the objective is to design inventory rules that are optimized to reduce overall costs while simultaneously satisfying client demand. Conventional inventory models, such as deterministic models, may fail to consider the impact of variability and uncertainty in input parameters, which may result in poor conclusions in circumstances characterized by ambiguity. On the other hand, stochastic inventory models provide more dependable and efficient solutions by taking into account the probabilistic characteristics of demand, lead times, and supply.

The study explores the many aspects that impact inventory management, including the unpredictability of lead time, uncertainty in demand, and limits related to capacity.

Employing Holt Winter's Methodology, a technique for forecasting time series data, the study adapts the forecasting equation to incorporate a seasonal element. This adaptation makes the methodology suitable for time series exhibiting seasonal trends. The approach utilizes three smoothing equations for forecasting: one for the series average, one for the trend, and one for the seasonal component.

The trend equation predicts the series' rate of change, the seasonal equation forecasts the seasonal pattern, and the level equation updates the expected level based on the latest observation.

The Holt-Winters method, a potent and flexible forecasting approach, proves effective in predicting time series data. The Ljung-Box test is employed to validate the model's accuracy and robustness by examining autocorrelation in the residuals. The research's conclusions showcase the prediction model's success in forecasting actual consumption levels, incorporating the stochastic nature of inventory consumption, seasonality, trends, and other critical variables.

Businesses can leverage the insights from ANOVA analysis to make informed decisions on inventory control, optimizing resource allocation, and reducing costs. Effective inventory management offers several benefits, including cost savings through reduced inventory, lower storage expenses, and minimized costs associated with stockouts and overstocking.

By ensuring the availability of the right items when needed, inventory management streamlines operations, reduces lead time, and enhances productivity. Monitoring inventory levels allows businesses to improve customer satisfaction and service, mitigating the risk of stockouts and overstocking by predicting future demand and adjusting inventory accordingly.

The study emphasizes practical implications in its conclusion, highlighting how businesses can enhance inventory management practices, allocate resources efficiently, and achieve cost savings by implementing the predictive model.

Effective inventory management not only aids in strengthening relationships with suppliers by accurately estimating demand but also supports the Just-In-Time (JIT) concept. Kanban, a Japanese technique for maintaining a steady inventory flow, aligns with JIT principles. In this system, a kanban serves as a signal to restock and place an order. For example, a yellow line inside a storage bin becomes visible as the number of bolts decreases, notifying the supervisor to request more bolts. This triggers the buying division to manage the order, ensuring the supply of bolts remains above a certain level, thereby sustaining uninterrupted production.

Statement of Problem

Inventory and resource management are key components of supply chain management. Traditional inventory models and resource optimization tactics presume that all input factors, such as demand, lead times, and supply, are certain and stable throughout time. In reality, demand and resource availability are often susceptible to random changes and uncertainty, making precise forecasting and perfecting inventory levels difficult.

A Probabilistic inventory mechanism that can effectively determine demand and perfect inventory levels while accounting for uncertain and random variables is needed. Furthermore, various resource optimization techniques must be researched to reduce costs, boost efficiency, and improve overall performance in a stochastic environment. Stochastic models can expect demand correctly by accounting for the random changes and uncertainty that occur in real-world circumstances. This can help organizations in perfecting inventory levels and decreasing stockouts. This research attempts to address these issues and give organizations with practical solutions and insights to enhance their inventory management and resource allocation practices.

Objectives

- To build a stochastic inventory model capable of accurately forecasting demand and perfecting inventory levels while accounting for uncertain and unpredictable inputs.
- To investigate various resource optimization solutions that might help minimize expenses, boost efficiency, and improve overall performance.
- To supply suggestions a n d guidelines for the company to implement thedeveloped inventory model and resources optimization strategies effectively.

The study aims to supply practical solutions and insights for organizations to improve their inventory management and resources allocation practices.

Review of Literature

Becerra, Mula, and Sanchis (2021) For green supply chains, have presented sustainable inventory management approaches. Mixed integer linear programming has been shown to be the most common modeling technique, and it is supplemented with heuristic and metaheuristic algorithms. These methods mainly concentrate on cutting costs and greenhouse gas emissions, paying little regard to social factors. Holding costs, order quantity, safety stock, and backorders are essential inventory management parameters. The most often exchanged data is demand. Notably, operational and strategic choices are subordinated to tactical ones.

Amani & Okdinawati (2023). A concept for inventory management that incorporates the EOQ Model for Telecommunication Tower Accessories was presented by Amani & Okdinawati (2023). A significant amount of forecasting error, assessed at 4.7 using the MAD parameter and 78.37% using the MAPE parameter, has resulted from inconsistent demand spikes across time. When compared to the company's present inventory system, the implementation of the EOQ model in the inventory management system might result in significant cost savings of up to 68%.

Song, Houtum, and Mieghem (2023). Comprehensive Analysis, Trends, and Projections on Capacity and Inventory Management have been carried out by Song, Houtum, and Mieghem (2023). They found that around half of all articles published in M&SOM are related to the capacity–inventory area by using text mining to identify relevant studies. Based on the development of research trends, these forecasts seek to identify possible directions for further investigation. The report makes recommendations for more research in the field of capacity and inventory management but does not provide a firm conclusion.

Siddiqui et al. (2022) For improved accuracy, Siddiqui et al. (2022) provide a hybrid demand forecasting model, especially for the pharmaceutical sector. Their findings, which center on a particular therapeutic class, indicate that the created model is appropriate for all brands and benefits pharmaceutical businesses in the same way. The better forecasting performance of the ARHOW model is shown by a comparative comparison with the ETS, Naïve, and Theta models. Additionally, it helps producers schedule and restock inventory in accordance with demand, shielding them against stock-out or bullwhip scenarios.

Thakre (2021) The effect of Just-in-Time (JIT) inventory management on the Indian automobile sector is investigated in this research. The study's conclusions show how suppliers, customers, and organizational planning may all be linked together via the efficient use of the Just-in-Time (JIT) approach, which is backed by the usage of enterprise resource planning (ERP) or database management systems (DMS). Several systems integrated result in lower expenses, better inventory control, and more productivity in workflow and production cycles.

The McMaster Group (2020) In light of the COVID-19 pandemic, the purpose of this article is to reevaluate risk management for multinational corporations in the context of fashion supply chain management. The continuing worldwide epidemic has highlighted the inherent problems with supply networks that depend on manufacturing concentration. This has led to a noticeable shift in favor of flexible and networked supply chain strategies. This study looks at the current state of fashion supply chains, as well as historical and modern hazards and the strategies that are now in use to reduce them. The COVID-19 pandemic has had a major influence on supply chain management and operations, underscoring the need of flexibility in order to handle risks associated with demand variations and epidemics.

The Deslisland Group (2020) In order to improve the Supply Carset in BMW Logistics at the Jakarta Plant, this study will examine the Kanban System and how it applies the Just in Time (JIT) methodology. The deployment of the Carset process seeks to address issues with frequent shortages and damages brought on by disorganization in the handling and ordering of components. The improvements included into the Carset process are intended to tackle problems including component shortage, part damage, and a high percentage of damaged parts in the carset supply.

Jackson, Kegenbekov, and Tolujevs (2020) I propose doing a thorough literature review on inventory control models, concentrating on grouping them based on the techniques used to determine the best control parameters. Inventory control theory addresses the complex and analytical challenges related to business-driven concerns by using a broad variety of approaches from numerous scientific domains. Methodologies based on management theory have shown their effectiveness in modeling inventory control systems that handle a single product. However, for inventory management problems with stochastic components, dynamic programming approaches have shown remarkable success in identifying control parameters that are almost optimal. However, in the case of inventory management systems with a large number of goods and tiers, the computational burden necessitates the incorporation of simulation and approximation techniques into the algorithmic framework.

According to Inegbedion, Eze, and Asaleye (2019), I suggest doing a thorough literature research on inventory control models with a focus on categorizing them according to the methods used to identify the best control parameters. The theory of inventory control utilizes several methods from various scientific fields to address the intricate and analytical difficulties associated with business-related issues. The modeling of inventory management systems that particularly handle a single product has shown the efficacy of management theory-based methodologies. On the other hand, dynamic programming techniques have shown exceptional effectiveness in determining control parameters that near optimality for stochastic inventory management issues. However, the computational load of inventory management systems with a large number of commodities and levels requires the employment of simulation and approximation methods within the algorithmic framework.

Makokha, Namusonge, and Musau (2017) I advise doing a thorough review of the literature on inventory control models, paying close attention to how these models are categorized based on the approaches used to determine the best control parameters. Inventory control theory addresses the complex and analytical challenges connected to business-related problems by using a range of approaches drawn from several scientific domains. The modeling of inventory management systems that are intended to handle a single product solely has shown the effectiveness of techniques developed from management theory. However, dynamic programming techniques have shown a great deal of success in identifying control parameters that are almost optimum for stochastic inventory management problems. However, the computational burden of inventory management systems with a large number of commodities and tiers necessitates the employment of approximation techniques and simulation inside the algorithmic framework.

Willems & Graves (2014) It was suggested that supply networks optimize the placement of key safety stocks. In order to strategically distribute safety stock throughout supply networks that are represented as spanning trees, the study provides a unique optimization approach. A network model of the supply chain, periodic-review base-stock rules at each stage, restricted demand, and a stochastic nature are used to define the problem as a deterministic optimization.

Julka & Lamba (2014). Supply Chain and Logistics Management Innovations at Maruti Suzuki India Limited were examined by Julka & Lamba (2014). Maruti Suzuki India Limited benefited from the study's analysis of several advances in supply chain and logistics management, which increased operational effectiveness, cut expenses, and guaranteed customer happiness. The results point to continuing advancements at Maruti Suzuki and provide opportunities for further research with other Indian automobile makers.

Bretthauer, Sheet, and Syam (2006). Proposing production and inventory management under numerous resource restrictions was Bretthauer, Sheet, and Syam (2006). According to the study's conclusions, the model's formulation is flexible and enables businesses to handle a variety of multi-item choices, including those involving order amounts, manufacturing runs, batch sizes, and cycle periods. It is possible to modify the generic model for multiple resource limitations to fit different sectors and decision-making situations.

Research Methodology

Type of Research: This study is Causal in nature. The research includes creating and contrasting mathematical models for inventory control, and optimization, which involves collecting and analyzing numerical data related to inventory levels, demand, lead time, and other factors of Toyota Kirloskar Auto Parts. The study uses statistical methods and simulations to evaluate the performance of the models under many situations and to test hypotheses about the effectivenessof different strategies.

Data, Variable Definition and Time Period

The study is designed to supply resource optimization policies and build a suitable stochastic inventory modelling. The daily/monthly inventory requirement, categorized under A-type Classification for 5 years, was adopted for the study. The data set consists of the actual quantity consumed for R transmission parts from 2018-19 to 2022-23. The data for the study was collected from the Amrut Toyota Kirloskar Auto Parts.

Model Framework

HOLT-Winter's Methodology

This method of time series forecasting uses historical data to create predictions. The technique makes time series with seasonal patterns useful for forecasting by including a seasonal part. The Holt-Winters method requires the specification of three parameters which are alpha, beta, and gamma, which control the smoothing of the level, trend, and seasonal components, respectively.

Predicted Inventory of prescribed part = f {Averaged daily/ Monthly Requirement, Trend over time, cyclicalseasonality}

$$\widehat{P_i} = \alpha_i + \beta_i T + \gamma_i S + \epsilon_i \qquad ...3.3.1.1$$

Where $\widehat{P_i}$ is the predicted inventory of prescribed part.

α_i is the Level part standing for the average value.

T is the Trend part standing for the direction and size.

S is the Cyclical Seasonality part being the periodic fluctuations.

β_i is the exposure to trend over time

γ_i is the exposure to cyclical seasonality

ϵ_i is the error part

L-JUNG BOX (LB) TEST

It is a statistical test used to decide the existence of autocorrelation in a time series dataset. The correlation between observations at various time points in the same dataset is referred to as autocorrelation. The Ljung-Box test is widely used in time series analysis and is particularly effective in detecting whether a series is a random white noise process or has considerable autocorrelation. The test aids in figuring out if the autocorrelation coefficients of a time series at various Lags are identical from zero, the diagnosis of model appropriateness, the comparison of models, and the evaluation of prediction performance. It aids in the development of dependable and exact time series models by offering insights into the existence and relevance of autocorrelation.

$$LB = n(n+1)\sum_{k=1}^{m}\left(\frac{\widehat{P_k}}{n-k}\right) \sim X^2 m \qquad \ldots 3.3.2.1$$

Where LB is the overall significance of autocorrelation in the time series.

n is the sample size

m is the lag length

k is the lag index ranging from 1 to m

$\widehat{P_k}$ is the estimated autocorrelation at a specific lag

X^2 is the chi square distribution with degrees of freedom equal to number of lags being Tested

Hypothesis

Testable Hypothesis for Normality Test (Shapiro-Wilk)

H_0: The actual quantity consumed Pertaining to RTM 1, RTM 2, RTM 3, RTM 4 & RTM 5 for the period between 2018-19 and 2022-23 follows normal distribution.

H_1: The actual quantity consumed Pertaining to RTM 1, RTM 2, RTM 3, RTM 4 & RTM 5 for the period between 2018-19 violates the assumption of normality.

Testable Hypothesis for Homogeneity of Variance (Levene's Statistics)

H_0: The Variance of actual quantity consumed for the period between 2018-19 and 2022-23 are Homogenous.

H_1: The Variance of actual quantity consumed for the period between 2018-19 and 2022-23 are Heterogenous.

Testable Hypothesis for Analysis of Variance (ANOVA)

H_0: There is no significant difference between average consumption for the periods 2018-19 to 2022-23.

H_1: There is a significant difference between average consumption for the periods 2018-19 to 2022-23.

Testable Hypothesis for L-Jung Box Test

H_0: There is no auto correlation between successive occurrence of observation (Residuals generated through the fitted model)

H_1: There is auto correlation between successive occurrence of observation (Residuals generated through the fitted model)

Limitations

1. Time restraint: Due to time restrictions, a thorough examination of all the materials was not workable.
2. Confidentiality: TKAP may not be willing or able to share confidential information or data related to their inventory management practices, which could restrict the scope and depth of the study.
3. constrained scope: Because the study only looked at one part of TKAP inventory management, it may have constrained our understanding of inventory management practices.

Data Analysis and Findings

Table No.4.1 describes the outcomes of Normality Test (Shapiro- Wilk) Pertaining to Actual Quantity Consumed for the following Part Numbers.

Part No	Shapiro-wilk P Value	Levene's P Value	ANOVA Test P Value	Kruskal Wallis Test P Value
RTM 01	0.736	0.275	<0.001	-
RTM 02	0.029	0.011	-	<0.001
RTM 03	0.668	0.002	-	<0.001
RTM 04	0.044	0.014	-	<0.001
RTM 05	0.238	0.044	-	<0.001

*Source: Author's own calculation, ***0.01, **0.05, *0.1 Level of Significance*

Table No.4.2 depicts the outcomes of Normality (Shapiro- Wilk) Pertaining to Residuals generated through the Fitted Model.

Part No	W	P Value	Decision
RTM 01	0.991	0.931	Do Not Reject H_0
RTM 02	0.973	0.210	Do Not Reject H_0
RTM 03	0.990	0.904	Do Not Reject H_0
RTM 04	0.981	0.491	Do Not Reject H_0
RTM 05	0.968	0.119	Do Not Reject H_0

*Source: Author's own calculation, ***0.01, **0.05, *0.1 Level of Significance*

In this study, we develop and introduce a new hybrid forecasting model called the Holt-Winters Model, widely practiced for forecasting. In our study we use this model to predict the consumption of Actual quantity in a Monthly Basis by taking the historical data. It is seen from the Normality test analysis that the actual quantity consumed pertaining to Part number RTM 01, RTM 03 and RTM 05 were following normal distribution at 5% Level of Significance ($P_{Cal} > P_{LoS}$: 0.736, 0.668, 0.238 >0.05) and apparently, Part number RTM 02 and RTM 04 were not normally distributed at 5% Level of Significance ($P_{Cal} < P_{LoS:}$ 0.029, 0.044 <0.05). The findings supply insights into the statistical nature of the parts consumption patterns, which can be beneficial for making educated judgements related to inventory management practices and demand forecasting, as it helps in understanding the distribution of quantity consumed for each part. From the Homogeneity test we can see there is a variation in the actual consumption pattern. Hence, there is a requirement for developing a mechanism which can predict actual quantity consumed. From the analysis the variance of actual quantity consumed about Part number RTM 01 are homogenous at 5% Level of Significance ($P_{cal} > P_{LoS:}$ 0.275 >0.05) and Part number RTM 02, RTM 03, RTM 04, and RTM 05 are Heterogenous at 5% Level of Significance ($P_{Cal} < P_{LoS:}$ 0.011, 0.002, 0.014, 0.044 <0.05). The difference in average consumption for Part No. RTM 01 that is Significant statistical evidence, implies that there were fluctuations in the amount consumed over the studied time. This research suggests separate consumption patterns, predicting for this segment becomes more correct. Recognizing these tendencies might be useful with resource allocation, production scheduling, and inventory management for Part No. RTM 01. The results show that, despite violations of the normality and homogeneity of variance assumptions, the Kruskal-Wallis test is still valid. The test reveals substantial changes in average consumption over the time periods studied for Part Nos. RTM 01, RTM 02, RTM 03, and RTM 04. As separate consumption patterns are proven, this knowledge improves forecasting dependability. These suggestions can help with inventory management, production planning, and resource allocation choices for these components.

Table No.4.3 describes the outcomes of L-Jung Box Test (Auto Correlation) Pertaining to Residuals generated through the Fitted Model for RTM 01, RTM 02, RTM 03, RTM 04 & RTM 05.

Part No	ACF (L_1, L_2, L_3, L_4, L_5, L_6, L_7, L_8, L_9, L_{10})	P Value	Decision
RTM 01	0.14, -0.03, -0.01, -0.21, -0.22, 0.12,0.06,0.04,0.01,0.30	0.26,0.50,0.71,0.35,0.16, 0.18,0.24,0.31,0.40,0.09	Insignificant until L_{10}
RTM 02	0.09, -0.10, -0.15, -0.14, -0.26 0.07,0.15,0.16,0.00,0.10	0.46,0.54,0.41,0.37,0.11 0.15,0.13,0.11,0.16,0.18	Insignificant until L_{10}
RTM 03	0.08, -0.06,0.03, -0.04, -0.22 -0.03,0.17,0.13,0.08,0.02	0.51,0.70,0.85,0.91,0.48 0.60,0.45,0.43,0.48,0.57	Insignificant until L_{10}
RTM 04	0.11, -0.12, -0.07, -0.13, -0.20 0.05,0.11,0.06,0.07,0.13	0.37,0.15,0.24,0.24,0.14 0.20,0.21,0.28,0.33,0.32	Insignificant until L_{10}
RTM 05	-0.008,0.05, -0.03,0.011,0.015 -0.13,0.06,0.05,0.31, -0.02	0.95,0.89,0.95,0.98,0.99 0.59,0.96,0.98,0.40,0.49	Insignificant until L_{10}

*Source: Author's own calculation,***0.01, **0.05, *0.1 Level of Significance*

The residuals generated by the fitted model are normally distributed for all five distinctive parts. This shows that the model stands for the statistical character of the parts' consumption patterns accurately. The result of this research may be used to make educated judgements about inventory management practices and demand predictions for these parts. These results from the outcomes of L-Jung Box Test show that no large autocorrelation exists between next occurrences of data for Part No RTM 01, RTM 02, RTM 03, RTM 04, and RTM 05 at 10 Lags. This implies that the residuals generated by the fitted model have no systematic relationship or dependency. The lack of autocorrelation increases the model's dependability and suggests that the mechanism is reliable. Hence, we can conclude that the business may employ this strategy for predicting the actual quantity required monthly.

Conclusion

For projecting the monthly consumption of real amounts, the Holt-Winters Model, a hybrid forecasting model, was created and introduced in this study. For predicting reasons, this model is widely applicable. Part numbers RTM 01, RTM 03, and RTM 05 showed a normal distribution of actual quantity consumed at a significant level of 5%, according to the normality test analysis. RTM 02 and RTM 04, however, deviated from the regular distribution. Making educated judgements about inventory management procedures and demand forecasts may be made easier with this awareness of the distribution patterns. According to the homogeneity test, there are differences in the actual amounts consumed by the various components. While parts RTM 02, RTM 03, RTM 04, and RTM 05 displayed heterogeneity, part RTM 01 displayed homogeneity. This underlines the necessity of creating systems that can forecast the actual amount consumed with accuracy and implies that various strategies could be needed for certain areas. The difference in average consumption for which it was statistically significant Part No. RTM 01 points to swings in consumption over the research period. This conclusion emphasizes how crucial it is to understand various consumption patterns to increase forecast precision. For Part No. RTM 01, this analysis help with resource allocation, production scheduling, and inventory management. The Kruskal-Walli's test findings revealed substantial variations in average consumption during the time periods analysed for Part Nos. RTM 01, RTM 02, RTM 03, and RTM 04. The test stays valid despite breaches of the normalcy and homogeneity assumptions. Understanding these diverse consumption patterns improves forecasting reliability and can help influence decisions about inventory management, production planning, and resource allocation for various parts.

The residuals obtained by the fitted model were found to have a normal distribution in all five sections, showing that the model properly depicts the statistical character of their consumption patterns. The results generated suggest practical knowledge for decisions making about inventory management and demand predictions for these parts. The autocorrelation study revealed no significant autocorrelation between successive occurrences of data for Part Nos. RTM 01, RTM 02, RTM 03, RTM 04, and RTM 05 at up to 10 Lags. This implies that the residuals generated by the fitted model have no regular link or reliance. The lack of autocorrelation boosts the model's dependability and suggests that it accurately stands for the fluctuation in the data. Based on these findings, it can be said that the built hybrid forecasting model, combined with the insights bought from the statistical analysis, may be efficiently used by the firm to predict the actual quantity necessary monthly. These facts can help with inventory management and resource optimization decision-making.

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