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An analysis utilizing the TSSP model to forecast consumption and surgical supply stocks

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Abstract - The healthcare industry is one of the many diverse businesses that depend on a functional supply chain. Demand forecasting and inventory control are essential components of supply chain management in the healthcare industry to ensure optimal patient outcomes, minimise costs, and minimise waste. The development of data analytics and technology has made it feasible to use several sophisticated techniques for demand forecasting and inventory control. This project aims to use these improvements to accurately estimate demand and regulate the surgical supply inventory, therefore reducing costs and improving patient care. To forecast medical caseloads and supplies for certain operations, an LSTM model grounded in literature is employed. In order to account for COVID-19-related variability in surgical case volumes in 2020, new characteristics have been added to the accepted model. The paper builds a dynamic replenishment model for various goods using Mixed Integer Programming (MIP). In the actual world, demand is rarely predetermined, and forecasting is usually erroneous. We created a Two-Stage Stochastic Programming (TSSP) paradigm in order to deal with these problems.

Key Words: mixed integer programming, forecast consumption, inventory management, TSSP model.

1.INTRODUCTION

The network of institutions, procedures, and systems that work together to acquire and manage resources in order to guarantee the prompt delivery of supplies to patients and providers is known as the hospital supply chain. Although supply chain management costs account for 25% to 30% of a hospital's overall expenses [10], the healthcare supply chain is still in its infancy compared to the manufacturing and retail sectors [11]. Therefore, there is potential for enhancement. Hospital supply chains are receiving more attention than ever before because of the growing demand for waste reduction and competitive market opportunities [12]. Hospital supply chains are distinct from ordinary industrial supply chains and require additional complexity. Physicians have the most sway over purchasing decisions in healthcare settings. Because of their familiarity and training with particular products, they frequently give priority to particular equipment over others [13]. Furthermore, based on the services requested, hospitals need a vast array of goods and equipment, the majority of which are not included in a common system for classifying products that makes it easier to identify more affordable alternatives [14]. The majority of the time, handling these supplies calls for specialized knowledge specific to the job, which adds to the complexity and knowledge-intensive nature of the healthcare supply chain. A hospital supply chain takes a lot of time to build and establish because of all these complications. To guarantee timely delivery and prevent major disruptions, a hospital supply chain requires careful and regular investment in the system's design and upkeep [15]. Many organizations are crucial to the development and management of a hospital supply chain. These significant organizations are:

1. **Hospital Administration:** Typically, a purchase order is started by the hospital administration department [16]. The department draughts a purchase order, which it then typically sends to the manufacturer or distributor. When supplies reach the point of reordering, a tracking system in some automated hospitals keeps track of how much is being used and automatically places orders. The majority of hospitals still run conventionally, though. In any case, the hospital administration department is in charge of starting and finishing the purchase [17].
2. **Manufacturer:** One of the important participants in the hospital supply chain is the manufacturer [15]. They procure raw materials, carry out research and development, and manufacture pharmaceuticals and other goods. From the point of production to the distributors and occasionally to the hospitals, they oversee the distribution of their goods [15].
3. **Distributor:** Another important component of the system is the distributor. Hospital purchases are made primarily through distributors. They buy medical supplies in bulk from the producers and store them in strategically important locations. Following receipt of a purchase order from the hospital, it checks the details and specifications, confirms the order if the requirements are available, and places the order. Distributors frequently concentrate on specific products; for instance, some may handle medical supplies, while others may handle equipment and electronics supplies.
4. **Third Party Logistic Providers:** Medical supplies are transported and delivered between the producer, distributor, and hospital by third-party logistics companies. They make it possible to ship from local suppliers more frequently and affordably. Hospitals receive shipments of supplies at a single delivery point, where they are stored in a warehouse. The hospital then allocates the supplies according to the requirements of various departments and healthcare professionals. Occasionally, logistics providers make direct deliveries to the designated departments. The patients and the providers make use of the supplies and create future orders.

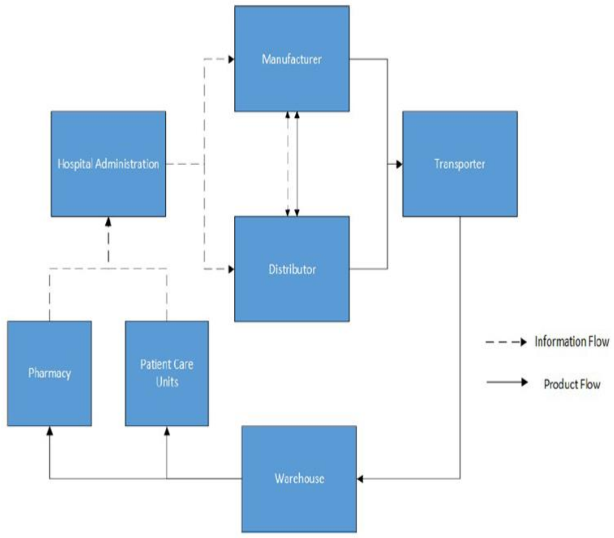

Fig -1: Hospital Supply Chain

1.1 Surgical Case Volume Prediction

Four probabilistic prediction models were created by the study's authors [31] to forecast the number of surgical cases per day weeks in advance. They considered the likelihood that a surgeon will operate on a patient on a particular day as well as the total number of cases in their initial model, Limited Info (LI). The effect of the day of the week is one of the additional details that their second model, Partial Info (PI), incorporates into the LI model. The Provider Time Away (PTA) data from the prior model is incorporated into the third model, Imperfect Info (IMI). Nevertheless, the PTA data has to be updated because it is frequently noisy. After processing and incorporating this data into their final model, Full Info (FI), the authors assessed the models using actual data that was gathered from a hospital. For an evaluation of forecasting methods to predict surgical case volumes in four surgical units, Aravazhi [21] established four forecasting models: SARIMA, SVR, MLP, and LSTM. The four models that were previously mentioned were combined by the author to create twelve hybrid models. The surgical case volume for each unit was predicted by the author ten weeks ahead of time, taking into account the trend and seasonality of the time series data. The findings indicate that no model exhibits optimal performance across all four units.

1.2 Surgical Supplies Demand Prediction

Professionals and academic researchers have investigated a range of techniques and models, such as statistical learning, machine learning, deep learning, queueing theory, and fuzzy grey forecasting, over the years to predict the demand for hospital supplies [33, 34]. Using three machine learning (ML) algorithms—random forest, linear regression, and artificial neural network (ANN)—Mbonyinshuti et al. [41] estimated the demand for different medications based on their historical consumption and compared their effectiveness. The RF algorithm outperformed the other two models, according to the results. That they should come as no surprise. Depending on the features and data structure, tree-based models frequently outperform neural network models in terms of performance. Using various types of superficial neural network (SNN) and deep learning neural network (DNN) models, Rathipriya et al. [42] predicted the demand for pharmaceutical products and compared their performance based on the root mean square error (RMSE). They predicted the demand for each of the eight categories they created by dividing the products into rather than just the demand for the individual products. Using past consumption data, the study's author [44] created an LSTM model to forecast the demand for medications in a hospital. The data analysis reveals that the number of patient visits and the types of diseases the patients have an impact on the demand for different drugs and medicines. The model's ability to forecast demand is demonstrated by the results. Based on past consumption, Permanasari et al. [45] and Galkin et al. [46] also projected medicine and pharmaceutical sales demand using the LSTM model. To predict the demand for surgical supplies, a seq2seq encoder-decoder LSTM model is developed in this study. The temporal dependencies and nonlinear pattern of the historical consumption time series data can both be handled by the suggested method.

1.3 Surgical Supply Inventory Management

A significant portion of the items in the healthcare inventory are medical and surgical supplies [48]. There are two categories of surgical supplies: disposable and reusable. Reusable surgical supplies require different inventory management than other inventory items. The reusable items are usually placed into trays, and even if the items are not used, every piece of equipment in the tray needs to undergo a routine sterilization procedure once it is opened in the operating room [8]. Reducing the overall cost of inventory can be achieved through effective materials and inventory control of surgical supplies, particularly with regard to the location and sourcing of sterilization facilities for reusable supplies [49, 50, 51]. The inventory management of a hospital that employs recyclable surgical instruments and sanitizes them in external facilities has been examined by Diamant et al. [52]. They determined the ideal base-stock levels for reusable instruments, the level of service, and implied stockout cost by modelling the hospital's inventory management procedure as a discrete-time Markov chain model. Their analysis suggested reducing the number of reusable instruments in stock and adding an on-site sterilization facility. The results indicate that choices about the handling of materials and the utilization of recyclable surgical instruments have a major influence on the quality of service that healthcare facilities and operating rooms provide.

Three separate event simulation models have been created by Bhosekar et al. [53] to examine the effects of material handling operations and surgical equipment levels of inventory at the level of services. Additionally, they looked into how cooperative decisions affected inventory levels and activities related to material handling at the service level. According to their research, a JIT instrument Delivery lowers inventory levels without sacrificing the quality of service. Little and colleagues [54] created a model employing constraint programming to take into account several products and time periods approach and ascertain the best service, order sizes, and frequency number of sterile products given the limited space. Their model was tested using sterile goods found in a hospital in Ireland. The multi-item equipped dynamic lot-sizing restocking problem is first solved in this study using a Mixed Integer Programming (MIP) model. Subsequently, a two-stage stochastic programming model is formulated and solved in order to accommodate potential demand uncertainty.

2. DATA ANALYSIS & MODEL DEVELOPMENT

The Arkansas Clinical Data Repository provided the data for this investigation [66]. There are two main kinds of records in the dataset. The first type contains details about the surgery, like the day of the procedure, the kind of service provided, a description of the surgery, the operating room's location, and the names of the staff and surgeon. Additionally, it includes patient data such as county, height, weight, gender, and age. The period covered by these records is May 2014–September 2021.

The second category of data relates to medical and surgical supplies and includes information about past purchases, such as purchase histories, material IDs, brief summaries, purchase quantities, item prices, and vendor information. Purchase tradition from July 2019 to April 2022 is included in this dataset. Furthermore, a dataset covering the inward and outward movements of items from storage is accessible from January 2019 to April 2022. Additional datasets contain supply-related data, such as order posting date, movement type (in/out), preservation location, material description, manufacturer name, and vendor, as well as location-related information, such as replenishment location, delivery address, and unloading point. It should be mentioned that the data set used in this study to forecast the surgical situation volumes is the same one that Bui et al. [9] used. Data from 2014 to 2019 was used to train the model, and in 2021, its performance was evaluated.

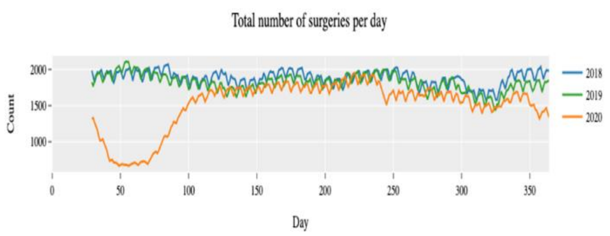

Fig -2: Number of regular surgeries in three years

To obtain a general sense of the effect of COVID-19 on the overall number of operations in 2020, the total amount of surgeries performed every day in 2020 was first compared with the surgeries performed in the preceding two years. Figure 2 shows that, compared to 2018 and 2019, there will be fewer surgeries performed daily in 2020, particularly in the early months when all procedures were put on hold. The figure shows that, after approximately three and a half months, there were more surgeries performed overall each day. But not every kind of procedure was affected by the pandemic in the same way. While emergency surgeries cannot be postponed or cancelled, non-emergency surgeries may not be scheduled during the pandemic. Consequently, to predict surgical case volumes with any degree of accuracy, it is imperative to determine which surgical procedures were actually affected by the pandemic. But there isn't sufficient information about this in this plot. Based on the level of urgency, the total number of surgical procedures was split into three categories: mixed-type, non-emergency, and emergency or time-sensitive surgeries. This allowed us to determine which procedures were actually affected by the pandemic. Procedures classified as emergencies are extremely critical and cannot be postponed. The COVID-19 pandemic had no effect on these surgeries, as shown by the graphs in figure 3. Rather, the number of these interventions in 2020 is nearly the same as it was in the preceding two years. This graphic analysis supports the notion that an emergency Pandemic had no effect on surgeries.

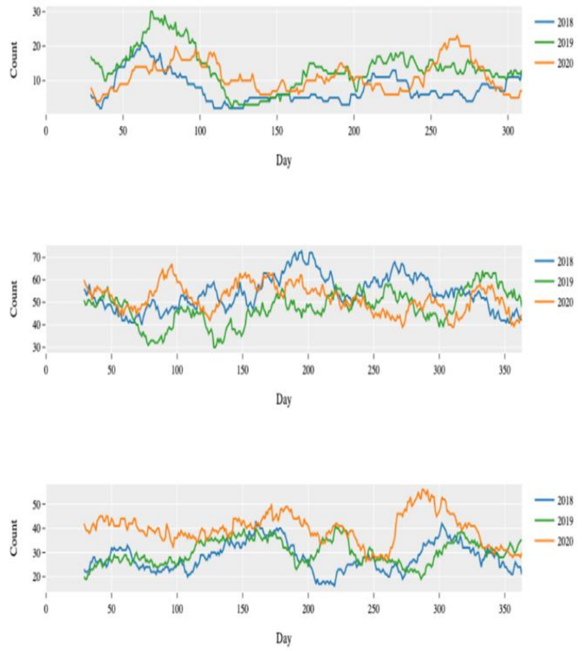

Fig -3: Emergency procedures

At the start of 2020, figure 4. shows that there were either zero or almost zero surgeries performed for non-emergency procedures. This might be the result of the non-emergency surgeries being postponed or cancelled during the initial COVID-19 wave. But as things got better, the accumulation of surgeries got cleared, which increased the total number of surgeries. The presumption that COVID-19 has affected non-emergency surgeries is supported by this analysis.

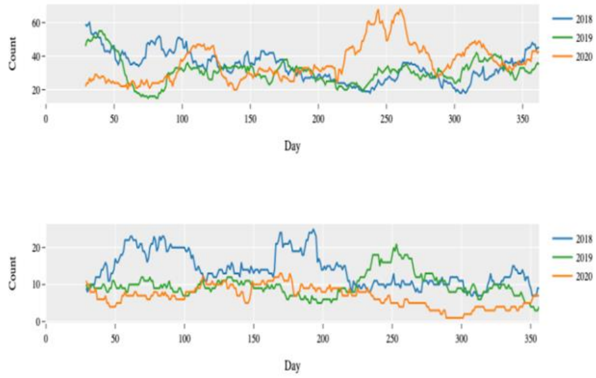

Fig -4: Mixed type procedures

The first hypothesis is supported by Figure 5, which demonstrates that for medical emergencies, the differences were roughly zero with sporadic ups and downs. This suggests that the average weekly frequency of surgeries was not substantially different in 2020. Figure 6 shows that the difference in the average weekly number of surgeries performed was less than zero at the start of the year and remained close to zero for the majority of weeks for certain procedures that weren't emergencies, including the initial and final plots. Figure 3.6's second plot demonstrates that most of the year's variations were less than zero. Figure 7, a preliminary chart of the mixed-type methods, demonstrates that the differences increased towards the end of the year after primarily remaining below zero during the initial half of the year. In contrast, there were very little variations in the subsequent plot over the course of the year. Additionally, these analyses support the earlier hypothesis that the pandemic affected some non-emergency and mixed procedures. While the visual analyses indicate a slight decrease in the number of surgeries performed in 2020 compared to previous years for certain non-emergency and mixed-type procedures, these findings are not definitive.

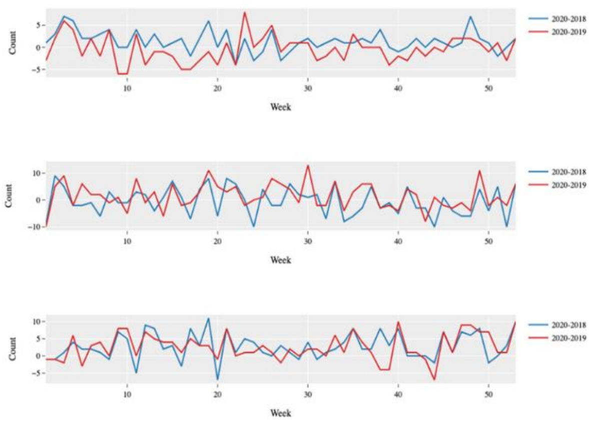

Fig -5: Variation in the amount of emergency procedures performed each week.

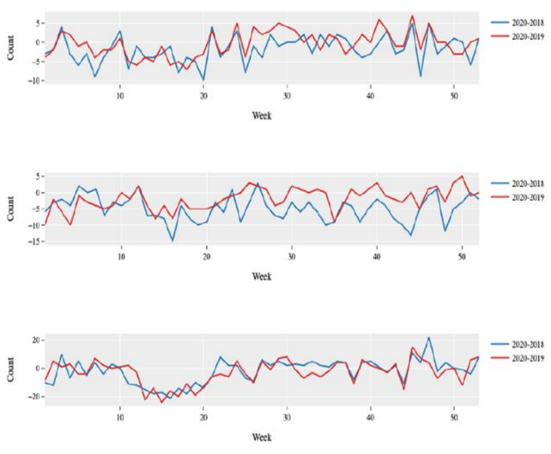

Fig -6: Variation in the number of non-emergency procedures performed each week.

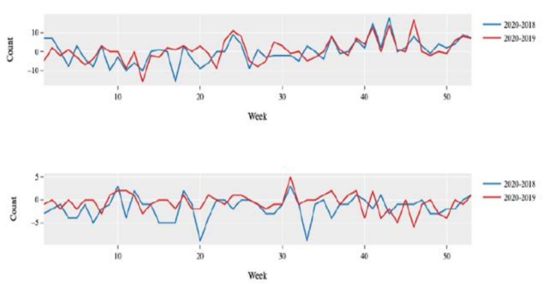

Fig -7: Variation in the quantity of mixed-type procedures per week.

To properly discuss the outcomes of the hypothesis test, let's assume a few things about the procedures that have been investigated thus far. The three emergency protocols are symbolized by the numbers XX1, XX2, and XX3. Representing the three non-emergency protocols are YY1, YY2, and YY3. ZZ1 and ZZ2 represent two distinct but mixed types of procedures. The results of the first hypothesis test show that there is a significant difference (p-values of 0.000013, 0.0131, and 0.0142) between the population means of the weekly total of treatments in the years 2020 and 2019 for both subsequent non-emergency procedures (YY2 and YY3) and the second mixed type procedure (ZZ2). The results of the second hypothesis's test indicate that the second hybrid procedure (ZZ2), as well as both initial non-emergency processes (YY1 and YY2), have significance at p-values of 3.9128e-06, 6.312e-15, and 0.000519. According to the analysis above, the pandemic in 2020 influenced a few non-emergencies and mixed-type procedures. Consequently, it is worthwhile investigating if the performance of the forecasting model is impacted in any way by the recently confirmed COVID-19 cases.

3. RESULTS AND DISCUSSION

The inventory replenishment models took into account nine items across five periods. Demand for the items was assumed at random and it is used to develop and solve an equivalent MIP model for the TSSP. In addition, the model was coded and solved using AMPL. Table 3.1 shows the model's optimal ordering decisions. The total cost is $352,191.26.

Item	Period 1	Period 2	Period 3	Period 4	Period 5	Total Quantity Ordered
1	0	35	0	0	0	35
2	189	0	0	0	0	189
3	330	0	0	0	0	330
4	74	0	0	0	0	74
5	46	82	0	47	0	175
6	66	170	0	83	0	319
7	39	0	0	23	0	62
8	60	104	0	45	0	209
9	62	177	0	90	0	329

Table 3.1: Optimum ordering decisions by the TSSP model

To evaluate the benefits of gathering additional information, consider the expected value of perfect information (EVPI) and the value of stochastic solutions (VSS). The expected value of perfect information (EVPI) assesses how much a decision maker would be willing to pay for complete and precise information about uncertain variables in a problem. Stochastic programming can be utilised to assess the possible advantages of lowering uncertainty in demand scenarios through the use of EVPI. The expected value of the optimal decision without perfect information (EVwoPI), or using the TSSP model with uncertain demand scenarios, and the expected value of the optimal decision with perfect information (EVwwPI), or using the simple MIP model with known demand scenarios, are what define the EVPI [80].

The TSSP model considered five random demand states. The EVwPI was calculated by solving the five demand states using the simple MIP model as if demand was known, and then calculating the average. Here, EVwPI = 349445.17 and EvwoPI = 352191.26. Therefore,

$$EVPI = 352191.26 - 349445.17 = 2746.09.$$

The potential advantage of employing a stochastic optimisation model as opposed to a deterministic model is gauged by the value of stochastic solution, or VSS. The VSS can assist decision-makers in assessing the possible advantages of utilising a more complex stochastic model by quantifying the value of the additional information the stochastic model provides. By comparing the expected value of the optimal decision made using the stochastic model to the expected value of the optimal decision made using the deterministic model, that is, what the decisions made using the deterministic model would produce in a stochastic environment—the VSS assesses the possible benefits of using a stochastic optimisation model.

A positive variance squared (VSS) suggests that the stochastic model offers noteworthy value, whereas a negative VSS suggests that the deterministic model performs better [80].

In this case, the optimal decision made with the deterministic model is expected to be 354519.564, and the optimal decision made with the stochastic model is expected to be 352191.26. Consequently,

$$VSS = 354519.564 - 352191.26 = 2328.304.$$

These results only apply to one demand case. To assess the model's robustness, ten randomly generated demand datasets were used in a Monte Carlo simulation, given the uncertainty and short range of actual demand.

In modelling and simulation, confidence intervals are frequently used as a quantitative validation technique [81]. To elucidate, a model response variable's confidence interval is calculated. The model is deemed valid for that specific response variable if the observed or known value for that response variable falls within this tolerance limit or within the confidence interval [82]. The 95% and 99% Confidence Intervals (CI) of the TSSP model's ordering choices for each of the nine items are shown in Table 3.2. Tables 3.1 and 3.2 show that the ordering decisions of the simple MIP model for items 2, 4, and 7 marginally deviate from the interval for the 99% CI. The ordering choices made by the simple MIP model for items 1, 2, 4, 5, 7, and 9 are outside of the interval for the 95% CI. The items that didn't fall inside the interval, however, are still inside it by two units.

Then, to examine their effects on the overall cost and decision variables, each of the fixed ordering cost, transportation cost, inventory holding cost, and shortage penalty coefficients have been changed one at a time from 0.6 to 1.4 with an increment of 0.1. Figure 8 illustrates how changing the shortage penalty cost has the biggest impact on overall costs. The figure also demonstrates the nearly similar effects that different fixed ordering, transportation, and inventory holding costs have on the overall cost. In exact terms, the total cost rises by \$706.8, \$715.7, and \$497.4 when the fixed ordering, transportation, and inventory holding costs are changed one at a time from 0.6 to 1.4.

Item	95% C.I.	99% C.I.
1	32,35	31,36
2	187,189	186,189
3	328,331	327,331
4	71,72	70,73
5	174,176	173,177
6	316,319	315,319
7	58,60	58,61
8	209,212	208,213
9	329,331	329,332

Table 3.2: 95% and 99% confidence interval of ordering decisions by TSSP model

Total Cost vs Different Parameters

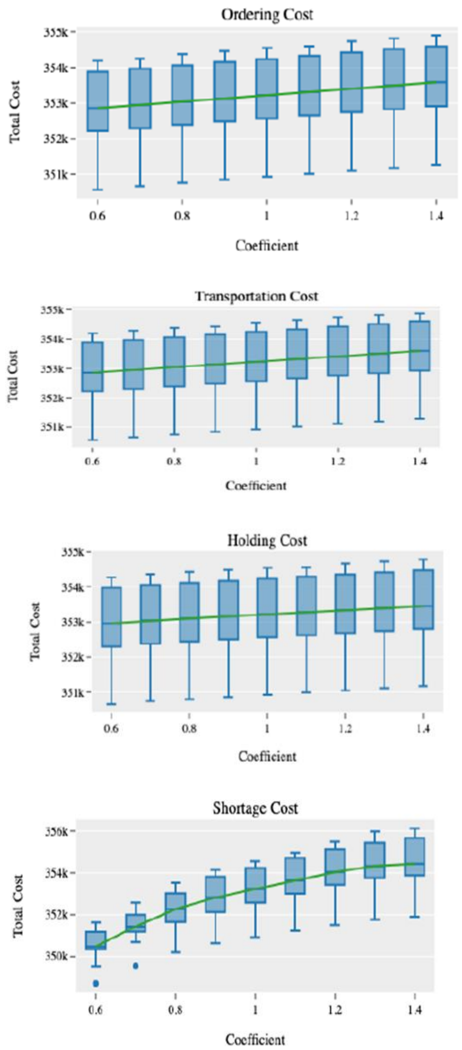

Fig- 8: Effect of varying each parameter one at a time on the total cost obtained by the TSSP model.

The shortage penalty has a major effect on the overall cost, as shown in figure 5.8. For this reason, it is crucial to investigate how variations in the shortage penalty affect ordering decisions. As replenishing the shortfall quantities would be more cost-effective than ordering additional quantities and incurring holding and purchasing costs, thereby reducing the total cost, it is conceivable that lowering the shortage penalty would cause the model to order fewer quantities in the initial stage. On the other hand, if the shortage penalty were increased, the model would be prompted to order larger quantities at first in order to prevent stockouts and pay a higher total cost for shortages. The hypothesis was tested using a one-tailed paired t-test, with results shown in Table 5.5. The hypothesis test found that lower shortage penalties result in significantly lower quantities ordered compared to higher penalties.

According to the analysis, the TSSP model outperforms the basic MIP model. When weighing the possible advantages of obtaining more data and applying stochastic optimization models, decision-makers can find valuable information in the EVPI and VSS results. In this particular instance, the EVPI of 2746.09 suggests that the decision-maker might be able to obtain an extra value of $2,746.09 if perfect knowledge about the demand scenarios was available. This figure indicates the highest price the decision-maker ought to be prepared to pay for flawless information. If the information can be obtained for less than this sum, then doing so is financially advantageous. The VSS of 2328.304 shows that the stochastic optimization model outperforms the deterministic model by $2,328.304. The stochastic model offers valuable information and should be preferred over the deterministic model for decision-making. These findings emphasize the need to consider uncertainty and gather additional information during decision-making processes. Decision-makers may benefit significantly and make better decisions as a result.

Item	t value	p value	Significance
1	-3.091944	3.22E-03	Significant
2	-10.206766	7.54E-07	Significant
3	-6.227762	3.84E-05	Significant
4	-7.719754	7.35E-06	Significant
5	-7.485631	9.37E-06	Significant
6	-10.893779	4.37E-07	Significant
7	-6.754094	2.08E-05	Significant
8	-11.625	2.52E-07	Significant
9	-7.01066	1.56E-05	Significant

Table 3.3: Statistical significance test for varying shortage penalty

Additionally, the sensitivity analysis demonstrates that the shortage penalty has a substantial effect on the overall cost, suggesting that it is an important consideration for ordering decisions that are optimised. The fixed costs associated with inventory holding, transportation, and ordering have negligible and nearly equal effects on the overall cost.

4. CONCLUSION

To improve inventory management and cut costs, this study created two models for inventory replenishment and carried out a comparative performance analysis. Initially, this multi-item lot-sizing capacitated joint replenishment problem was solved using a basic MIP model. A TSSP model is created and solved since the forecasts are always regarded as being erroneous and the demand is rarely deterministic in the real world. The TSSP model outperforms the deterministic model, according to the experiment's findings. To evaluate the value that could be obtained by acquiring flawless information about uncertain demands, the anticipated benefit of perfecting information was also calculated. A sensitivity assessment was performed as part of the analysis to ascertain how adjustments to different parameters would impact on the TSSP model's overall cost. The analysis's conclusions showed that altering the insufficient penalty variable had the biggest effect on the total cost of the model. In order to increase forecasting accuracy over longer time horizons, future research could investigate testing alternative machine learning models. For improved performance, real-world scenarios like storage capacity, service level, and discounts on 48-quantity purchases could be incorporated into the model. The inventory replenishment models' predominant source of data was assumed, which rendered it relatively tainted. Therefore, it would be interesting to observe the models' performance when applied to real data.

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