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Demand Prediction and Inventory Management of Surgical Supplies

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Demand Prediction and Inventory Management of Surgical Supplies

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ABSTRACT

Effective supply chain management is critical to operations in various industries, including healthcare. Demand prediction and inventory management are essential parts of healthcare supply chain management for ensuring optimal patient outcomes, controlling costs, and minimizing waste. The advances in data analytics and technology have enabled many sophisticated approaches to demand forecasting and inventory control. This study aims to leverage these advancements to accurately predict demand and manage the inventory of surgical supplies to reduce costs and provide better services to patients. In order to achieve this objective, a Long Short-Term Memory (LSTM) model is developed to predict the demand for commonly used surgical supplies. Moreover, the volume of scheduled surgeries influences the demand for certain surgical supplies. Hence, another LSTM model is adopted from the literature to forecast surgical case volumes and predict the procedure-specific surgical supplies. A few new features are incorporated into the adopted model to account for the variations in the surgical case volumes caused by COVID-19 in 2020. This study then develops a multi-item capacitated dynamic lot-sizing replenishment model using Mixed Integer Programming (MIP). However, forecasting is always considered inaccurate, and demand is hardly deterministic in the real world. Therefore, a Two-Stage Stochastic Programming (TSSP) model is developed to address these issues. Experimental results demonstrate that the TSSP model provides an additional benefit of $2,328.304 over the MIP model.

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1 Introduction

The US national healthcare expenditure as a share of the gross domestic product (GDP) is anticipated to be just above 18.0% in 2023, with a projected growth rate of 5.1% from 2021 to 2030, reaching approximately $6.8 trillion by 2030 [1, 2]. A substantial share of this expenditure includes the cost associated with performing the surgical procedures and supplies required for it. Day by day, these costs are getting increasingly high [3]. A study by [4] in 2016 found that a single neurosurgery department wasted nearly $2.9 million in obsolete surgical supplies. This large amount of obsolete inventory creates additional problems by pushing the costs back on the patients and insurance providers. This results in healthcare being more expensive and less accessible.

Managing the inventory of surgical supplies is a very challenging task as it involves dealing with the demand uncertainty and perishability of certain surgical supplies. Demand uncertainty is one of the most significant challenges faced by hospitals or healthcare facilities. Hospitals must ensure they have the essential items available to provide services to the patients. However, demand uncertainty makes it very hard for them to determine a profitable and accurate level of inventories while ensuring a high service level. As a result, the healthcare supply chain frequently runs into the risk of overstocking and understocking.

On the other hand, certain emergency medical and surgical supplies, such as emergency vaccines, flu shots, syringes, solutions, gowns, gloves, etc., are often perishable and have a limited lifespan [5]. In general, the supplies are expected to remain stable or retain their identity, strength, quality, and purity until the expiration date written on them. Hence, these items need to be used before the expiration date to avoid health risks and ensure quality service. Often time, the manufacturers offer a discounted price on the items to increase sales and reduce the risk of items becoming obsolete in their inventory [6]. Although overstocking and understocking both impose loss and harm the supply chain performance, understocking is much more harmful in healthcare settings and could be life-threatening to the patient. As a result, hospitals often make frequent purchases of supplies to benefit from the discounted price, reduce the risk of product shortage, and increase the average product shelf life [7].

In this study, surgical supplies are broadly divided into two categories, procedure-specific supplies like certain types of equipment and drugs necessary to perform a specific surgery, etc., and commonly used surgical supplies like surgical blades, forceps, preoperative skin antiseptics, skin preparation solutions, etc. The expected demand for unique surgical supplies is forecasted by mapping the supplies with the forecasted demand of respective procedures. On the other hand, the expected demand for commonly used surgical supplies can be derived by either forecasting the total number of expected surgical cases or by developing a demand forecasting model using historical consumption data. It could be very complicated to predict the overall surgical case volume for a certain period. Moreover, the accuracy of the prediction is not also guaranteed, which makes the indirect prediction of surgical supply demand unreliable. Therefore, it is preferable to predict the demand for commonly used surgical supplies using a direct demand forecasting model.

The objective of this study is to contribute to the existing literature on the healthcare supply chain with a focus on demand prediction and inventory replenishment. The advancement of machine learning and the availability of data has opened many doors to solving intricate problems, including the possibility of accurately predicting the demand in healthcare industries [8]. In this study, a Long Short-Term Memory (LSTM) forecasting model is developed to predict the commonly used surgical supplies using historical material consumption data. This study also uses the LSTM forecasting model developed by Bui et al. [9] to predict the volume of surgical cases and derive the demand for procedure-specific surgical supplies from the forecasting results. A multi-item capacitated dynamic lot-sizing replenishment model is developed using Mixed Integer Programming (MIP) to manage the inventory and reduce the cost. However, demand is never deterministic in real-world settings, and forecasting results are always considered inaccurate. Therefore, a two-stage stochastic programming replenishment model is also developed and solved to account for the stochasticity involved with the demand.

The report of this study is structured as follows: Section 1 provides the background, research objective, and overview of the study. Section 2 discusses the hospital supply chain and available literature on surgical case volume prediction, surgical supply demand prediction, and surgical supply inventory management. Section 3 describes the data, data collection, analysis, and feature engineering. Section 4 presents the different models used in this study, including the LSTM model for demand prediction and economic order quantity, dynamic lot sizing, and a two-stage stochastic programming model for inventory management. Section 5 presents the results and the sensitivity analysis. The final section summarizes the findings and concludes the report with insights for future research opportunities.

2 Literature Review

2.1 Hospital Supply Chain

A hospital supply chain is a network of organizations, systems, and processes for obtaining and managing resources to ensure the timely delivery of supplies to providers and patients. Although 25% to 30% of the hospital's total expenses consist of the supply chain management costs [10], unlike the manufacturing and retail sectors, the healthcare supply chain has not become matured yet [11]. Hence, there is room for improvement. Due to the increasing pressure for waste reduction and competitive market opportunities, hospital supply chains are getting more attention now than ever [12].

Unlike typical industrial supply chains, hospital supply chains are unique and more complex. In healthcare settings, physicians have the most influence on purchasing decisions. They often prioritize certain equipment over others because of their training and experience with certain products [13]. Moreover, the hospitals require a huge variety of products and equipment depending on the service request, most of which are not listed in a universal product classification system which helps find available alternative economic options [14]. Most of the time, these supplies are job-specific and require good domain knowledge to deal with, making the healthcare supply chain knowledge-intensive and more complex.

All these complexities make the construction and establishment of a hospital supply chain time-consuming. A hospital supply chain needs careful and frequent investment in the design and maintenance of the system to ensure timely delivery and avoid significant disruptions [15]. Various organizations play important roles in building and operating a hospital supply chain. Such major organizations are:

1. Hospital Administration: In general, the hospital administration department initiates a purchase order [16]. The department prepares a purchase order and sends it to the distributor (in most cases) or manufacturer. Some hospitals which have acquired automation typically have a tracking system to track the consumption of supplies and automatically place the orders when the stocks hit the reordering point. However, most hospitals still operate traditionally. Either way, it's the responsibility of the hospital administration department to initiate and complete the purchase [17].

2. Manufacturer: Manufacturers are one of the key players in the hospital supply chain [15]. They acquire raw materials, conduct research, development, and process medicines and products. They manage the distribution of their products from the point of production to the distributors and sometimes to the hospitals [15].

3. Distributor: Distributors are another key player in the system. Most of the hospital purchases are done via distributors. They purchase medical supplies in bulk from the manufacturers and stock them in key strategic points. After receiving a purchase order from the hospital, it verifies the information and requirements and confirms the order based on the availability of the requirements. Distributors are often product-focused; for example, some distributors deal with nursing supplies, some deal with electronics and equipment supplies, etc.

4. Third-Party Logistics Providers: Third-party logistics providers carry out the transportation and delivery of medical supplies between the manufacturer, distributor, and hospital. They enable more frequent and economic shipments from regional suppliers.

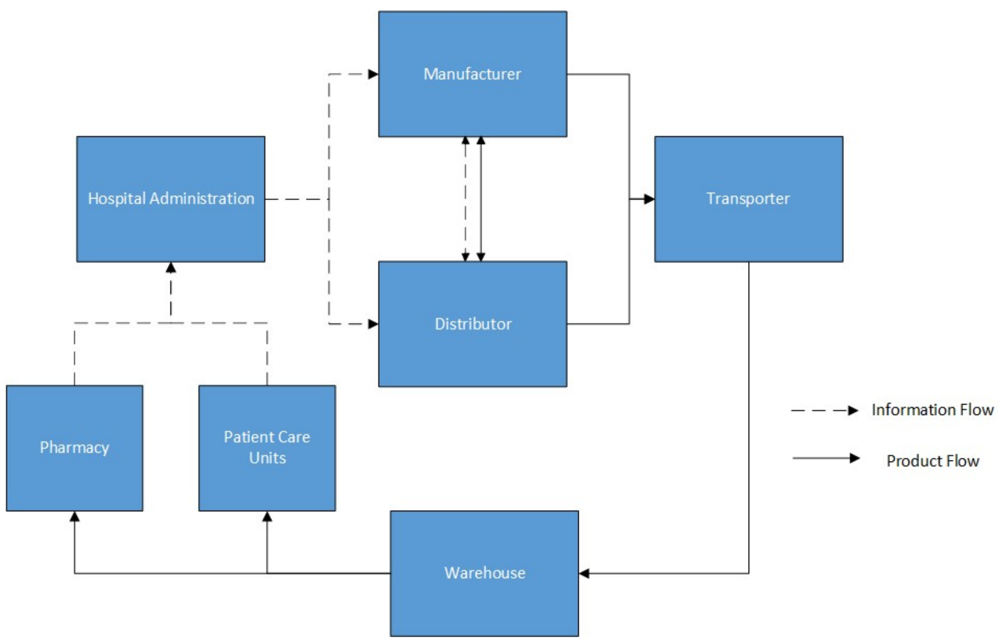

Figure 2.1: Hospital Supply Chain (Inspired from the figure used in [16])

Supplies are delivered to a single delivery point where the hospitals receive the shipments and store them in the warehouse. Then the hospital distributes the supplies based on the needs of different departments and providers. Sometimes deliveries are directly made to the individual departments by the logistics providers. The providers and the patients use the supplies and generate orders for the future.

The rest of the sections in this chapter focus on the literature related to surgical supply demand prediction and inventory management. In the next section, past works related to the prediction of surgical supply and demand will be explored, while in the subsequent section, literature related to the inventory management of surgical supplies will be studied.

2.2 Demand Prediction

This study calculates the demand for surgical supplies in two steps. First, surgical supplies are matched with the surgical procedure, and the demand is predicted using a surgical case volume forecasting model. Second, an LSTM forecasting model is developed to predict the demand for surgical supplies based on historical material usage data. So, both streams of literature are studied.

2.2.1 Surgical Case Volume Prediction

Hospitals use forecasting models to predict the number of surgical cases, which helps the administration schedule the operating room and staff and replenish surgical supplies [18, 19]. Both underestimation and overestimation of surgical resources increase costs. Hence, mapping surgical supplies with the demand (surgical procedures) and managing the resource accordingly helps minimize inventory and operating costs [20]. So, accurate predictions of the anticipated number of surgical cases are essential to planning the resources.

Despite its significant importance, the literature on surgical case volume prediction is very limited. Among the existing literature, time series forecasting models like ARIMA and Seasonal ARIMA (SARIMA) are prevalent [21]. Trivedi et al. [22] used an ARIMA model to forecast surgical volume at a hospital. The study found that an average of the forecasting values generated by each independent ARIMA model performs better than selecting an optimal ARIMA model and forecasting from it. However, while considering independently, the ARIMA models with lower autoregressive and moving average terms perform better. Although this study gives an overall prediction of surgical case volumes, it does not account for the seasonal elements of time series data which has a major impact on patient behavior in scheduling surgeries. Zinouri et al. [6] worked with a historical per-day surgical volume dataset to forecast the surgical case volume at a hospital. The authors accounted for the seasonality presented in the data and developed a three-stage identification, estimation, and diagnosis SARIMA model. The authors also considered the holidays in their forecasting but excluded the weekends as the weekend demands differ from the regular weekdays. The study suggests that the SARIMA model performs better than the hospital's existing prediction method and achieves a MAPE score of less than 10%.

Linear regression models are also studied to predict surgical case volumes. Tiwari et al. [23] performed a linear regression analysis to predict surgical case volumes. Eggman et al. [8] studied the surgical case volume prediction problem using the multiple linear regression (MLR) model. The authors predicted the number of surgeries seven, fourteen, and twenty-one days before the day of the surgery using four different MLR models. Their study includes four independent variables, i.e., the volume of the surgeries scheduled, the number of surgeons scheduled, the total minutes scheduled, and the released group block. The evaluation finds that the seven-day-out model accounts for the highest variance and provides the most accurate prediction. Nevertheless, the model performance, as expected, drops with time.

The time series is assumed to be a linear function of the past values and random errors by these models. Therefore, these models fail to account for the nonlinear patterns of the data and, hence, cannot provide high accuracy. These disadvantages and limitations have prompted researchers to explore probabilistic models as well as machine learning (ML) and deep learning (DL) models for time series forecasting [21]. Although ML and DL models like Support Vector Regression (SVR), Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory Network (LSTM), Multilayer Perceptron (MLP), etc. are very popular among researchers for time series forecasting [24, 25, 26, 27, 28, 29, 30], their application for surgical case volume prediction is scant in the literature.

The authors of this study [31] developed four probabilistic prediction models to predict the daily surgical case volumes weeks in advance. In their first model, Limited Info (LI), they considered the probability of a surgeon performing surgeries on a given day and the number of cases on that day. Their second model, Partial Info (PI), incorporates additional information, the effect of the day of the week, in the LI model. The third model, Imperfect Info (IMI), incorporates the Provider Time Away (PTA) information in the previous model. However, the PTA information is often noisy and needs to be corrected. The author treated this information and incorporated it in their final model, Full Info (FI), and evaluated the models with real data collected from a hospital. Their evaluation reveals that the LI model performs poorly, while the FI model performs best (with the lowest MAPE). However, the difference between the performance of the PI and the IMI models is not statistically significant. These probability-based surgical case volume prediction models are not the best-performing models in the literature, but they incorporate important information which significantly improves the model performance than the univariate time series forecasting models like ARIMA, SARIMA, etc., found in the literature. While incorporating additional information, sometimes even these models outperform the generalized regression neural networks models [31].

Aravazhi [21] developed four forecasting models, including SARIMA, SVR, MLP, and LSTM, for a comparative analysis of forecasting models for predicting surgical case volumes in four surgical units. The author also developed twelve hybrid models by the combination of the four models mentioned earlier. The author accounted for the trend and seasonality of the time series data and forecasted the surgical case volume for each unit ten weeks in advance. The results show that none of the models perform best in all four units. LSTM-SARIMA had the best prediction results for two units, and the MLP-SARIMA and the LSTM model had the best prediction in two different units.

The quality of the prediction of surgical case volume depends on various variables like the provider's availability, weather conditions, holidays, even sometimes the facility's location, traffic conditions, etc. Therefore, multivariate time series forecasting models provide higher accuracy than univariate models.

Bui et al. [9] developed a multivariate seq2seq LSTM model to predict the expected volume of surgical case procedures. The author performed feature engineering and incorporated variables like the number of available providers, federal holidays, weather conditions, etc., in the forecasting model. The authors developed and verified the model with historical data from an academic hospital. The results show that the proposed model can forecast surgical case volume six weeks in advance with high accuracy.

This study works with the same dataset used in [9], and both studies are part of the same project. In this study, the forecasting model developed by Bui et al. [9] is used to predict the expected volume of surgical case procedures, and the surgical supplies are then matched with the procedures to derive the demand for the supplies.

The COVID-19 pandemic has had a significant impact on daily surgical case volumes. In many parts of the world, elective surgeries were postponed or canceled in order to reduce the spread of the virus and to free up hospital resources for COVID-19 patients. This resulted in a decrease in daily surgical case volumes and a backlog of surgeries [32]. In the first part of this study, the forecasting model developed by Bui et al. [9] was investigated in detail, and the number of per day new COVID cases were incorporated to explain the variability of surgical case volume during the COVID-19 pandemic.

2.2.2 Surgical Supplies Demand Prediction

Over the years, professionals and academic researchers studied various methods and models to forecast the demand for hospital supplies, including statistical learning, machine learning, deep learning, queueing theory [33], and fuzzy grey forecasting [34]. Statistical methods like ARIMA, SARIMA, Exponential Smoothing, and Holt-Winters Model have been extensively studied in the literature for time series forecasting in the healthcare industries [35, 36, 37, 38, 39]. These models consider time series forecasting as linear and ignore the nonlinear patterns of the series. This inherent disadvantage motivated researchers to develop machine learning and deep learning models like RF, KNN, ANN, CNN, SVR, RNN, LSTM, etc., for time series forecasting. Over time, these models have become very popular among researchers for time series forecasting in the healthcare industry.

Researchers of this study [40] developed Recurrent Neural Networks (RNN), Support Vector Machines (SVM), and Random Forest (RF) models to forecast the demand for various hospital supplies and compared their performance with traditional methods like Holt-Winters Exponential Smoothing and ARIMA. They divided the products into four categories, erratic, lumpy, intermittent, and smooth, based on their demand patterns and consumption variability and forecasted the demand for various products of each category. The result shows that demand patterns and variability have a significant effect on the performance of forecasting models. The ML algorithms outperformed the statistical methods for items under the smooth demand pattern. Overall, the smooth category exhibits the best results in terms of all the algorithms, and the lumpy and intermittent demands show relatively bad results. Although the items under the erratic category perform better than the lumpy and intermittent categories, the results remain unsatisfactory.

Mbonyinshuti et al. [41] forecasted the demand for various medicines based on their historical consumption using three ML algorithms, random forest, linear regression, and ANN, and compared their performance. The results show that the RF algorithm outperformed the other two models. It is not surprising that the. The tree-based models often perform better than the neural network models based on the data structure and features. Rathipriya et al. [42] predicted demand for pharmaceutical products using different types of shallow neural network (SNN) and deep learning neural network (DNN) models and compared their performance based on the RMSE value. They divided the products into eight categories, and instead of predicting the demand for individual products, they predicted the demand for each category. The results show that SNN-based models perform better than DNN-based models. The reason is that SNN has a solid ability to handle highly noisy datasets, and the algorithms can learn patterns from small datasets with minimal parameters. The authors of this study [43] use a two-layer feed-forward back propagation neural network to predict the short-term demand of highly volatile medical supply in a hospital. The time series data used in this study was very small. Hence, the author focuses on the BP neural network model over the traditional statistical methods to make the prediction. Although this approach cannot predict demand changes with high accuracy, it gives adequate forecasting information for a shorter length of time.

The author of this study [44] developed an LSTM model to predict the demand for medicines in a hospital using historical consumption data. The data analysis shows that the demand for various drugs and medicines varies with the number of patient visits and the types of diseases the patients have. The results show that the model can effectively predict demand. Permanasari et al. [45] and Galkin et al. [46] also used the LSTM model to forecast medicine and pharmaceutical sales demand based on historical consumption.

The author of this study [47] developed a multilayer LSTM model for predicting respiratory equipment demand during the outbreak of the COVID-19 pandemic in Turkey. A dataset comprising data relating to the number of ICU and intubated patients, along with confirmed daily COVID-19 cases in Turkey, was utilized to test the proposed approach. Finally, the authors compared the model's performance with traditional statistical and ML models like ARIMA, SVM, decision tree, linear regression, etc. The proposed multilayer LSTM model outperformed all the other algorithms and predicted the equipment demand with very high accuracy.

In this study, a seq2seq encoder-decoder LSTM model is developed to forecast the demand for surgical supplies. The proposed method can handle both the temporal dependencies and the nonlinear pattern of the historical consumption time series data.

2.3 Surgical Supply Inventory Management

Medical and surgical supplies contribute a big part of healthcare inventory items [48]. Surgical supplies can be divided into two classes—disposable and reusable supplies. Inventory management of reusable surgical supplies is different from other inventory items. Typically, the reusable items are grouped into trays, and once the tray is opened in the OR, each piece of equipment needs to go through a standard sterilization process even if the items are not used [8].

Effective material and inventory management of surgical supplies, especially the location and sourcing of sterilization facilities of reusable supplies, helps reduce the overall inventory cost [49, 50, 51]. Diamant et al. [52] have studied a hospital's inventory management that uses reusable surgical instruments and sterilizes the instruments in outsourced facilities. They modeled the hospital's inventory management process as a discrete-time Markov chain model and calculated the optimal base-stock level for reusable instruments, service level, and implied stockout cost. Their study recommended an onsite sterilization facility and reduced the inventory of reusable instruments. The findings suggest that the service level provided by the hospitals and operating rooms is significantly impacted by decisions regarding the use of reusable surgical instruments and material handling.

Bhosekar et al. [53] has developed three discrete event simulation models to investigate the impact of the inventory level of surgical equipment and material handling activities on the service level. They also studied the impact of joint decisions on inventory level and material handling activities on the service level. Their study found that a JIT instrument delivery reduces inventory without compromising service level. Little et al. [54] developed a model considering multiple products and multiple time periods using a constraint programming approach and determined the frequency of orders, sizes of orders, and optimum service level of sterile items considering space constraints. They tested their model against sterile products used in an Irish hospital. For a comprehensive analysis of the literature on reusable surgical instruments, interested readers can check this literature review study of inventory management of surgical supplies and sterile instruments in hospitals by Ahmadi et al. [55].

Compared to reusable surgical instruments, inventory management of disposable surgical supplies has gained little attention. The author of this study [56] conducted a detailed case study on disposable surgical supplies inventory management. In this data-driven study, the author assumed the demand from purchase history and calculated the base stock level for multiple items. The author defined four key metrics, total PAR level, cost, space, and access, and calculated and compared the optimum inventory level in different scenarios for multiple items. The implementation of the recommended changes saved 30-40% in inventory levels and space.

Demand for certain surgical supplies directly depends on the number of surgical procedures performed. Chan [57] used the Advance Booking Information (ABI) of elective surgery schedules to make replenishment decisions for surgical supplies. The author also assessed the value of ABI in the inventory control performance by incorporating it in a periodic-review stochastic inventory control problem. The empirical study resulted in a reduction of 29% in costs over the current inventory setup without compromising the desired service level constraint. In this study [58], the author calculated the disposable surgical supply demand as an indirect demand estimated from surgical procedures. The author modeled the expected demand distribution for several surgical procedures of the same type from the historical demand data and used recursion to estimate the demand for a certain surgical supply. Next, a reorder point algorithm was developed and implemented using the demand. They also developed a Markov Decision Process and compared the result with the results from the reordering point algorithm. In both cases, they introduced a minimum service level and assessed the long-term costs of both models. Although the idea of assessing the demand of this paper matches our study, the assessment process is different in our case. For some supply, we estimate the demand directly from the predicted number of surgical procedures using a forecasting model. For others, we derived the demand from another forecasting model developed using historical demand data.

Epstein et al. [59] also attempted to link the surgery schedule and materials management to improve just-in-time inventory control. In their study, an order for expensive items utilized for elective surgeries is ordered only after the surgery is scheduled. This way, the inventory cost reduces because fewer items are held in inventory, but the ordering frequency increases, and so do the costs because of rush delivery. They analyzed the system performance using a computer simulation and found the policy cost-effective for expensive and frequently used materials. The authors of this study [60] developed inventory policies using a search algorithm and discrete event simulation of disposable surgical supplies. They analyzed the cost benefits of inventory control parameters under empirical scenarios like replenishment orders being placed, received, and reviewed only on weekdays, and stochastic demand varied upon daily usage and empirically represented lead time. In their empirical study, they performed an ABC analysis to select items that represented the entire inventory of disposable surgical supplies and implemented the developed policies. The new inventory control policies outperformed classical (s, S) and optimistic experts' intuition-based control policies.

The author of this study [61] developed a new simulation optimization model for managing the inventory of a specialized hospital considering its system dynamics. They aimed to find a replenishment policy for all the items used during critical cardiac surgery while meeting the target budget and desired service level. Their model also incorporated storage space limitation, supplier constraint, product expiry constraint, and maximum deliver lot size constraint. Another aspect of this research was to compare the simulation optimization results with the results from a MILP model. The simulation model results are slightly lower than the MILP results, while the execution time was significantly shorter.

A dynamic drum-buffer-rope (DDBR) model-based demand-pull replenishment approach was proposed by Wang et al. [62] for overcoming the limitations of an existing reorder point model and minimizing the inventory cost and stockout incidents. This DDBR mathematical model comprises three parts: demand, dynamic buffer management, and replenishment constraints. As the demand changes, the buffer inventory level needs to be adjusted in a DDBR model. The authors used a Powell search algorithm to find the optimal buffer adjustment rate. Finally, the proposed model was tested with real data collected from the hospital and found to be well-performed and robust under high demand variation and was able to effectively reduce the overall inventory level and achieve zero stockout cases.

Bijvank et al. [63] developed two Markov chain models to explore inventory control in point-of-use locations at a hospital for disposable supply items. The objective function of the first model maximizes the service level with a given capacity limit, while the second model minimizes the capacity with a given service level limit. They tested both models and compared the performances for the continuous and periodic review policies. The findings suggest that both models perform equally well in a high-service-level environment. The authors further developed an inventory rule to find the reorder point and order quantity in a lost sale and short lead time environment and found near-optimal results.

Authors of this study [64] developed a two-stage stochastic programming model to determine the optimal parameters for a single-item inventory control system considering periodic review policy and demand uncertainty. The proposed model considers the demand uncertainty more comprehensively and provides flexibility to account for backlogs or lost sales.

This paper [65] used a two-stage stochastic programming approach to solve the multi-item replenishment problem under demand uncertainty. In the first stage, the model minimizes the replenishment costs with an expectation operator. In the second stage, the model uses the replenishment decisions made in the first stage for a realization of the random variable to minimize the expected total cost. The study also introduces a risk-averse approach called Conditional Value at Risk (CVaR) which performs better than the risk-neutral model under increased uncertainty.

In this study, at first, a Mixed Integer Programming (MIP) model is developed for solving the multi-item capacitated dynamic lot-sizing replenishment problem. Then, a two-stage stochastic programming model is also developed and solved to account for the possible demand uncertainty.

3 Data Collection, Analysis, and Feature Engineering

3.1 Collection and Description of Data

The data used for this study was sourced from the Arkansas Clinical Data Repository [66]. The dataset consists of two primary types of records. The first type includes information related to the surgical procedure, such as the day of the surgery, service type, surgical description, location of the operating room, and surgeon and staff names. It also contains patient information, including age, gender, height, weight, and county. These records span from May 2014 to September 2021.

The second type of data pertains to hospital and surgical supplies, such as purchase history details, including purchase documents, material IDs, short descriptions, purchase quantities, item price, and vendor. This dataset covers purchase history from July 2019 to April 2022. Additionally, there is a dataset that contains information about the in and out movements of materials from storage, which is available from January 2019 to April 2022. Other datasets include location-related details, such as replenishment location, delivery address, unloading point, and supply-related information, such as order posting date, movement type (in/out), storage location, material description, manufacturer name, and vendor.

Here should be noted that Bui et al. [9] worked with the same data set this study uses for predicting the surgical case volumes. They trained the model using data from 2014 to 2019 and then tested its performance in 2021. However, they did not include the data from the year 2020 in their model to avoid the variability in surgical case volumes because of the pandemic. In this study, data from the year 2020 is included. At first, the impact of COVID-19 on the surgical case volumes was analyzed. A few COVID-19-related features were included in the forecasting model to account for the variability in the year 2020. These analyses will be discussed in detail in the data analysis and feature engineering sections. To incorporate the new features, COVID-19 open data were obtained from Github, including information on the number of new cases, newly deceased, newly recovered, newly tested, etc., for each day and specific geographic regions identified by the FIPS code. This data ranges from January 2020 to May 2022.

Meteorological data, such as temperature, snowfall, rainfall, etc., can significantly impact the behavior of people who visit service industries like hospitals. Sometimes extreme weather leads to appointment cancellation or rescheduling. These relationships will be discussed in detail in the feature engineering section later. Therefore, to study the impact of weather conditions on forecasting, meteorological data were collected from the National Centers for Environmental Information (NCEI) API for a specific meteorological station located near the partnering hospital. These data range from January 2014 to December 2021 and include precipitation, snow, and maximum and minimum temperature for each day.

3.2 Data Analysis

The objective of the data analysis section is (*i*) to investigate if the volume of surgeries was affected by the pandemic and (*ii*) to identify a suitable surgical supply to develop the LSTM forecasting model for predicting the commonly used surgical supplies. All the analyses performed to achieve both of these objectives will be discussed in the following two subsections.

3.2.1 Objective One

At first, the total number of daily surgeries in 2020 was compared with the previous two years to get an overall idea of the impact of COVID-19 on the number of surgeries in 2020. Figure 3.1 illustrates that the total number of surgeries per day in 2020 is lower than in 2018 and 2019, especially at the beginning of 2020 when all kinds of surgeries were on hold. It can be observed from the figure that after about three and a half months, the total number of per day surgeries has increased. However, not all types of procedures were equally impacted by the pandemic. People might not want to schedule a non-emergency surgery during the pandemic, whereas emergency procedures cannot be canceled or rescheduled. Therefore, it is vital to identify which types of surgeries were genuinely impacted by the pandemic to accurately forecast the number of surgical case volumes. However, this plot does not provide enough information about this.

To identify the procedures that were truly impacted by the pandemic, the overall surgical procedures were divided into three categories based on the urgency of the surgery: emergency or time-sensitive surgeries, non-emergency surgeries, and mixed-type surgeries. Surgeries that fall under the emergency category are highly time-sensitive and cannot be delayed. As seen in the graphs of figure 3.2, these surgeries were unaffected by the COVID-

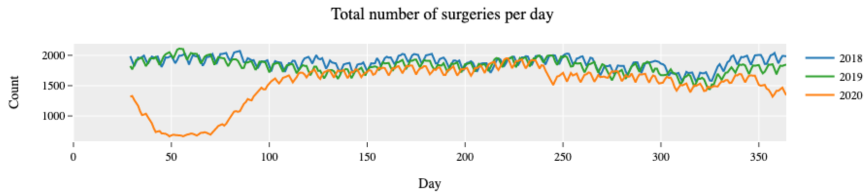

Figure 3.1: No of daily surgeries in three years

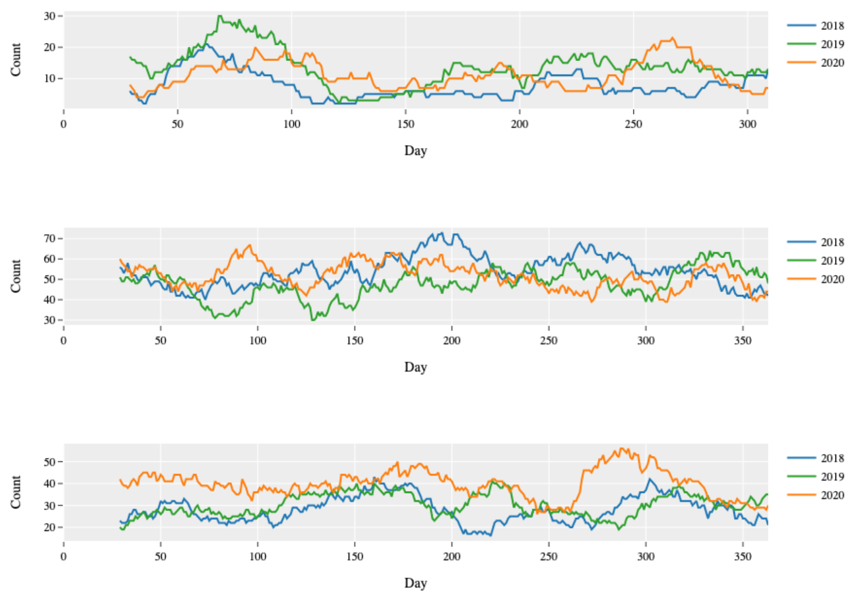

Figure 3.2: Emergency procedures

19 pandemic. Instead, the frequency of these types of surgeries in 2020 is almost similar to the previous two years. This visual analysis helps to make an assumption that emergency surgeries were not impacted by the pandemic.

The number of surgeries for non-emergency procedures, figure 3.3, was either zero or almost zero at the beginning of 2020. This could be because all non-emergency surgeries were canceled or rescheduled during the first wave of COVID-19. However, as the situation improved, the backlog of surgeries was performed, leading to a rise in the number of surgeries. This analysis helps make another assumption that COVID-19 has impacted non-emergency surgeries.

Mixed-type procedures, figure 3.4, include both emergency and non-emergency cases and show variations depending on the urgency of the surgery. For example, the first plot in

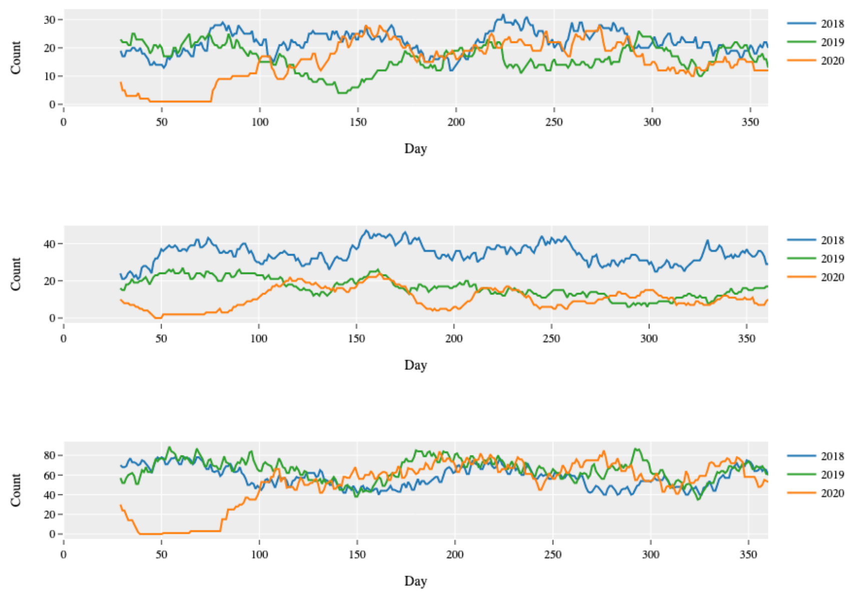

Figure 3.3: Non-emergency procedures

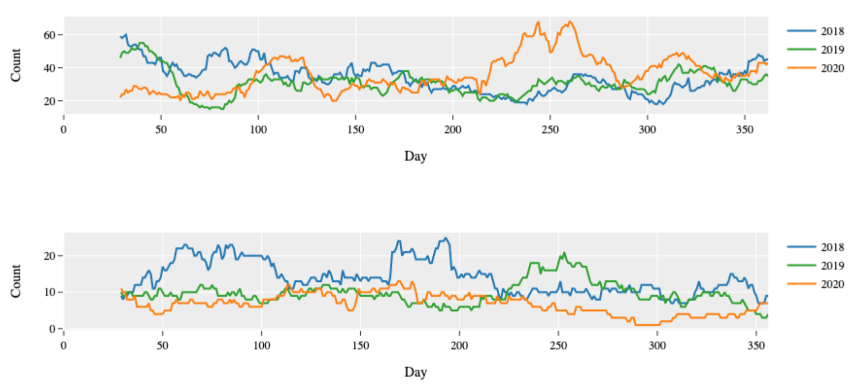

Figure 3.4: Mixed type procedures

figure 3.4 displays that the number of surgeries was lower at the beginning of 2020 than in the previous years. However, the numbers varied throughout the year, with occasional spikes after a certain period of low surgeries. This could be due to the cancellation or rescheduling of less urgent cases. As the COVID situation improved, the backlog surgeries were performed, which is evident in the plot. The second plot in figure 3.4 displays that the overall number of surgeries was lower than in the previous years, with a negative trend. Therefore, it can be assumed that the pandemic also impacted the mixed type of procedures.

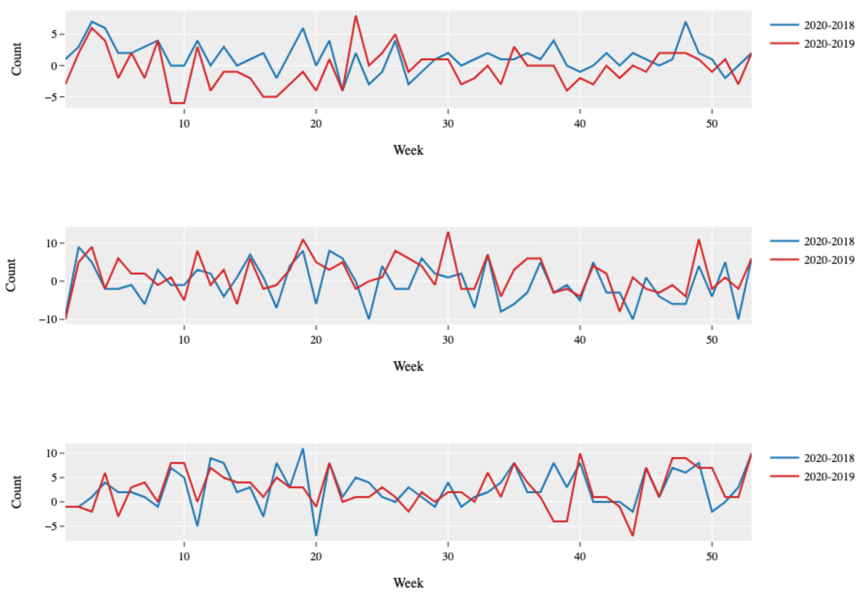

Figure 3.5: Difference in the weekly number of emergency procedures

The time series data inherently exhibit trend and seasonality, and not all procedures are performed daily. To address these issues, the weekly number of surgeries in 2019 and 2018 were subtracted from the weekly number of surgeries in 2020 for different procedures. Thus, if the number of surgeries per week was lower in 2020 than in 2019 or 2018, the difference would be negative and vice versa.

Figure 3.5 shows that for the emergency procedures, the differences were around zero with occasional ups and downs, indicating that the weekly number of surgeries was not significantly different in 2020, which supports the initial assumption. Figure 3.6 indicates that for some non-emergency procedures, such as the first and third plots, the difference in the weekly number of surgeries per week was below zero at the beginning of the year and around zero for most weeks. The second plot in figure 3.6 shows that the differences were

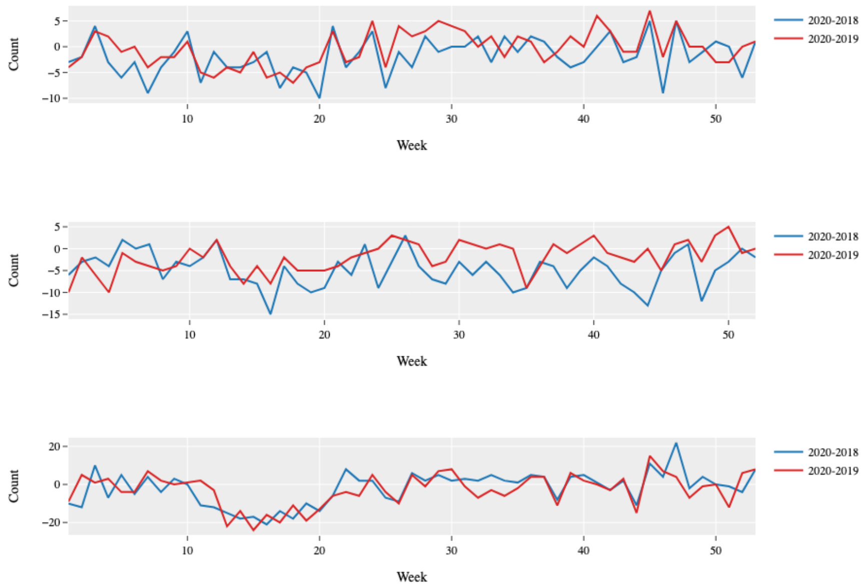

Figure 3.6: Difference in the weekly number of non-emergency procedures

mostly below zero throughout the year. The first plot of the mixed-type procedures, figure 3.7, shows that the differences were mostly below zero in the first half of the year and then went up at the end of the year. However, in the second plot, the differences were around zero throughout the year. These analyses also affirm the previously made assumption that some of the non-emergency and mixed types of procedures were impacted by the pandemic.

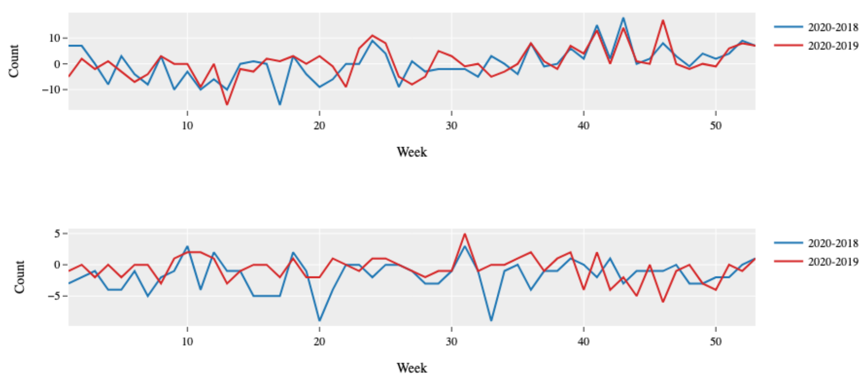

Figure 3.7: Difference in the weekly number of mixed type procedures

Although the visual analyses suggest that for some non-emergency and mixed-type procedures, the number of surgeries in 2020 was somewhat smaller than in past years for some procedures, these are not conclusive. Hence, two two-sample t-tests were performed to determine if the number of surgeries was significantly smaller in 2020 than in 2019 and 2018.

Let us assume some alias for the procedures explored so far to effectively discuss the results of the hypothesis test. The three emergency procedures are represented by XX1, XX2, and XX3. The three non-emergency procedures are represented by YY1, YY2, and YY3. And the two mixed types of procedures are represented by ZZ1 and ZZ2. The findings of the first hypothesis test indicate that the difference between the population means of the weekly number of surgeries in 2020 and 2019 for the second and third non-emergency procedures (YY2 and YY3) and second mixed type procedure (ZZ2) are significant at p-values of 0.000012, 0.012865, and 0.014322. The second hypothesis test finds that the first and second non-emergency procedures (YY1 and YY2) and second mixed type procedure (ZZ2) are significant at p-values of 0.000409, $6.297254e^{-15}$, and $3.828128e^{-06}$. The above analysis indicates that some of the non-emergency and mixed-type procedures were impacted by the pandemic in 2020. Therefore, it is worth exploring whether the newly confirmed COVID-19 cases have any impact on the forecasting model's performance.

3.2.2 Objective Two

The hospital and surgical supplies datasets did not have direct material consumption data. However, the inventory dataset offered a record of the quantity stored and moved out of inventory. It was assumed that all supplies moved out of the inventory were utilized by the hospital. This assumption enabled the quantities moved out of the inventory to be treated as the indirect historical demand for supplies. Figure 3.8 presents a summary of the total quantity moved out of inventory and the frequency of moving out of the inventory between January 2019 to April 2022 for all hospital supplies. This figure helped select a proper item for developing the forecasting model for commonly used surgical supplies.

A large volume of historical data is required for a good forecasting model. Therefore, an item XYZ is selected from the figure 3.8 with enough historical data. It is a surgical solution commonly used for preoperative skin preparation in various surgeries. It has been moved out of the inventory 1057 times over time, making it a very frequently used product.

Figure 3.9 shows the quantity vs frequency of inventory out for item XYZ. Some occasional very large spikes are present in the plot. To better understand these spikes, a cumulative inventory plot is developed.

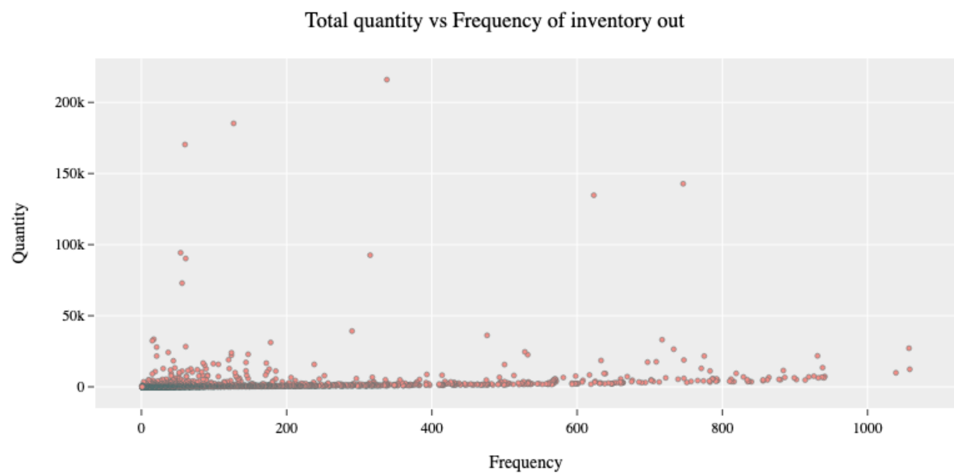

Figure 3.8: Quantity moved out of inventory vs Frequency of moving out

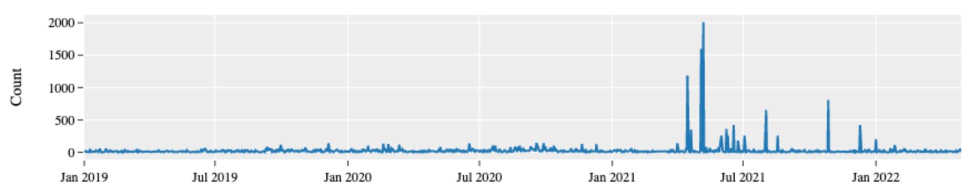

Figure 3.9: Quantity moved out of inventory over time - item XYZ

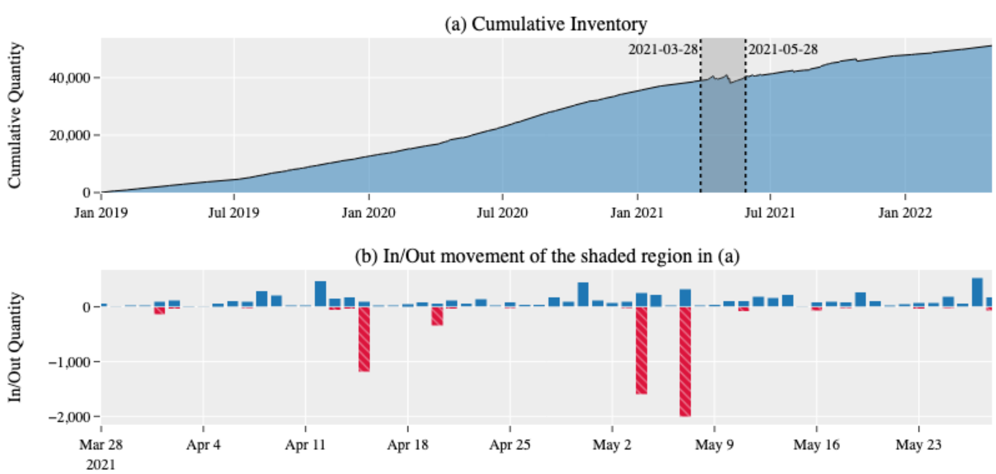

Figure 3.10: Accumulation of inventory over time - item XYZ

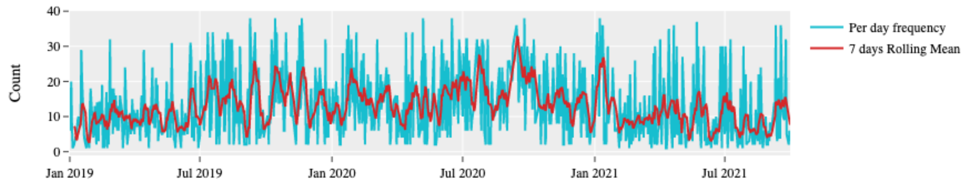

Figure 3.11: Demand over time - item XYZ

Figure 3.10 reveals that the inventory is progressively increasing over time, indicating that the hospital purchases more products than it uses. Occasional spikes are also visible in the plot, and it is reasonable to assume that they occur due to the hospital disposing of expired, unused supplies, as medical supplies have a limited shelf life. These high spikes should be treated as outliers and removed from the dataset. Additionally, there are also missing data that need to be accounted for. The maximum threshold is set to be the 90^{th} percentile to remove the outliers, and the missing data points are imputed using linear interpolation. Figure 3.11 displays the demand over time after cleaning the data and ready to be used in the forecasting model.

3.3 Feature Engineering

Feature engineering is the process of selecting, transforming, and creating new features (i.e., input variables) to improve the performance of machine learning models. As discussed previously, in the study conducted by Bui et al. [9], the forecasting model did not include data from 2020 in training to avoid the fluctuations in the number of surgeries caused by the COVID-19 pandemic. This study tried to improve the model performance by including the 2020 data in the model. Hence, new features were introduced that considered the per day new confirmed COVID cases. As mentioned earlier, the patient data included the county from which each patient came, and each county has a unique FIPS code. The new confirmed COVID cases were mapped to the FIPS code. Instead of using the number of new confirmed cases as a single feature, four binary features were created, namely no COVID, low COVID, medium COVID, and high COVID, by specifying a range for each one. If the number of new cases is zero, the no COVID feature will have a value of 1, and the rest of the three features will have a value of 0. If the number is between 1 to 10, then the low COVID feature will have a value of 1; if between 11 to 20, then the medium COVID feature will have a value of 1, and if the number of new cases is greater than 20, the high COVID feature will have a value of 1.

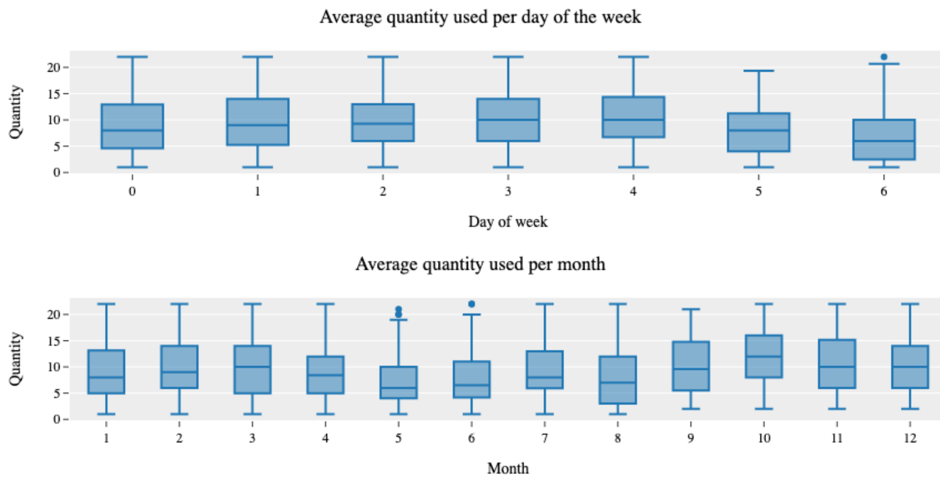

Figure 3.12: Average material usage vs day of week and months

Some new features were created by analyzing the data for the surgical supply forecasting model. Figure 3.12 displays that the average quantity of materials used on weekends is typically lower than on weekdays. It is also visible from the figure 3.12 that the average material usage is lower during May, June, July, and August than in the other months. To capture these temporal characteristics of the data, temporal features (integer features) were introduced that represents the week of the year, day of the week, month of the year, quarter of the year, and year. The figures show that seasonality is present in the data, and some of these temporal features are cyclical. A common approach to encoding cyclical features is to transform them using sine and cosine transformation [67]. The month of the year and quarter of the year features were transformed using the sine and cosine transformation.

Extreme weather conditions, such as heavy rainfall and snowfall, along with temperature changes, can potentially cause appointment cancellations and traffic accidents. These incidents also influence material usage. Figure 3.13 displays the average material usage and average weekly temperature. It is noticeable from the plot that the per-day average material usage is typically lower during the high-temperature weeks and vice versa. To capture the meteorological impacts on the material usage, four new features, daily precipitation, minimum temperature of the day, maximum temperature of the day, and daily snow depth, were introduced.

The rate of consumption for a supply is related to the number of scheduled surgeries

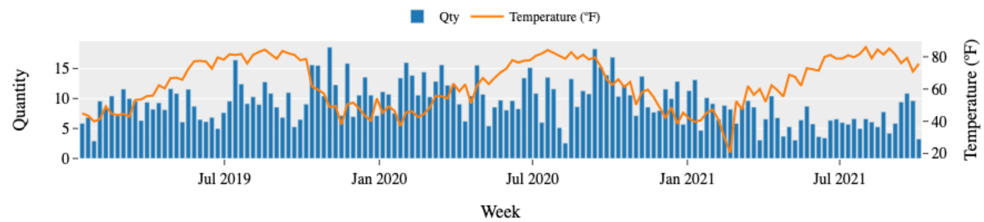

Figure 3.13: Average material usage per week and the average temperature of the week

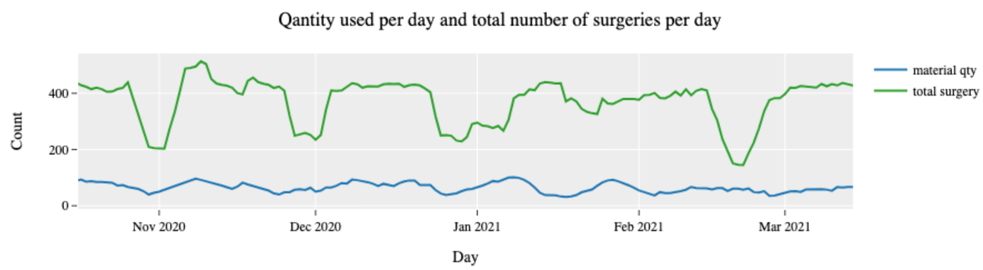

Figure 3.14: Per day material usage vs the number of surgeries scheduled for that day

or procedures that require this supply. However, this domain knowledge was not available during the model formulation. Hence, the total number of per-day surgeries was introduced into the model. As shown in figure 3.14, the material usage varies in relation to the number of surgeries scheduled per day. It should be noted that the relationship between material usage and surgeries would have been more apparent if only the number of relevant surgeries were taken into consideration instead of the total number of surgeries.

It is also observed that the average quantity of material usage is lower in the weeks when there is a federal holiday (6.2 per day) than in the regular weeks (9.5 per day). To capture the impact of holidays, a binary feature was introduced.

4 Model Development

4.1 The Long Short Term Memory Model

Long Short-Term Memory (LSTM) is a kind of recurrent neural network (RNN) that was initially introduced by Hochreiter and Schmidhuber in 1997 [68] to solve the problem of vanishing gradients, which standard RNNs often face during training. The vanishing gradient problem occurs when error gradients, which propagate back through the network during training, become exponentially small as they move back in time, making the network unable to learn long-term dependencies. LSTMs introduced a memory cell that can store information for an extended period, composed of various gates regulating the information flow in and out of the cell. The gates include the input gate, output gate, and forget gate, each controlled by an activation function that determines the amount of information allowed to pass through.

The forget gate determines which information to retain or forget, while the input gate controls the amount of input to be used to update the memory cell. The output gate decides which memory cell element to use to compute the output [69]. LSTM includes a hidden state vector that serves as the network's memory, updated at each time step by a combination of the current input and the previous hidden state, controlled by the gates.

Time series data is a form of sequential data that records observations at fixed time intervals. In such scenarios, an Encoder-Decoder LSTM model, also known as a seq2seq model, can be used to forecast future time series data by analyzing previous time steps.

The encoder is an LSTM network that takes the input sequence and generates a fixed-length context vector [70]. The LSTM network processes the input sequence one token at a time and produces a sequence of hidden states. After the final hidden state is obtained, it undergoes processing through a dense layer, resulting in the generation of the context vector. The context vector is a compact and fixed-length representation of the entire input sequence.

The decoder is another LSTM network that utilizes encoder generated context vector and produces the output sequence [70]. It is programmed to generate the sequence token-by-token by using the context vector and the previously generated token. The decoder component is also an LSTM network, which generates the output sequence based on the context vector and the previously generated token. At each time step, the decoder uses the previous token and the context vector to produce a sequence of hidden states, and the final hidden state is passed through a dense layer and generates the output token.

To train the encoder-decoder LSTM model, the predicted output sequence is compared to the actual output sequence by minimizing the loss between them. During training, the actual output sequence is fed into the decoder with a delay of a one-time step so that the decoder predicts the next token in the sequence at each time step.

Besides the historical material usage $y(t_i) = y_i$, there are some auxiliary features $X(t_i) = X_i$ at each time step that are related to or have an impact on the value of y_i. Some of the features are known for all times, like the temporal features, i.e., day of the week, month of the year, etc. However, not all the features are known at the time of forecasting, i.e., the weather features. These unknown features need to be filtered to forecast the time series values. Figure 4.1 illustrates the concept clearly.

To tackle this problem, Bui et al. [9] used a seq2seq encoder-decoder LSTM model. The goal is to predict the surgical case volume by encoding the past observations in a latent space and then using the encoded past as a context vector. Figure 4.2 illustrates the model architecture. Keras deep learning API is used to build the LSTM model. Huber is used as the loss function, and ADAM optimizer is used to optimize the loss function. They used R^2, $RMSE$, and MAE metrics to assess prediction accuracy. The model used the data from the past twenty-eight days (4 weeks) to predict seven days (1 week) ahead.

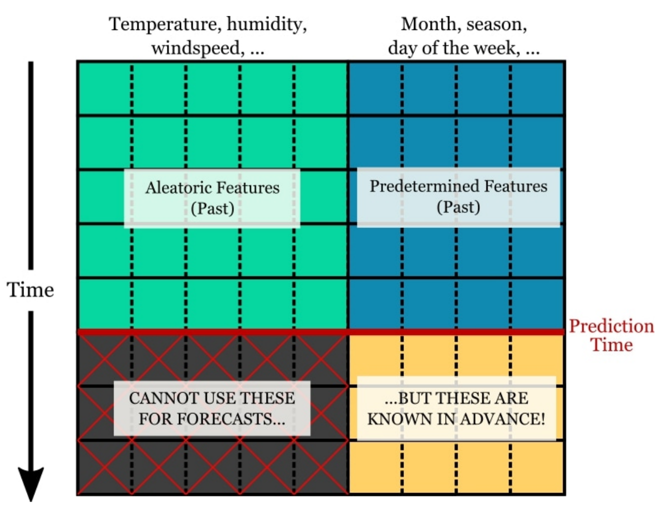

Figure 4.1: Types of features, obtained from https://shorturl.at/anI07

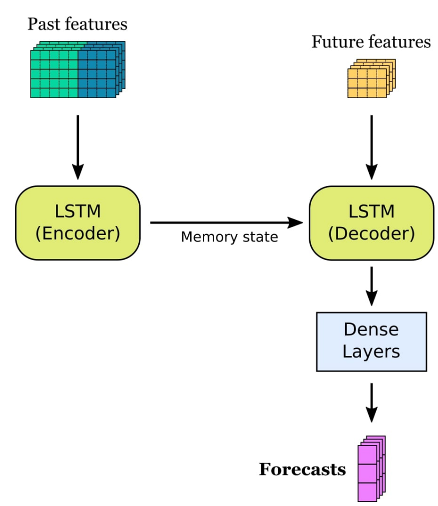

Figure 4.2: LSTM model architecture, obtained from https://shorturl.at/anI07

The features used in the model are the number of surgeries performed per day, meteorological features such as minimum temperature, maximum temperature, snow depth, and precipitation, the temporal features such as day of the week, week of the year, month of the year, quarter of the year, day of the year, year, holiday feature, and anomaly feature. Bui et al. [9] transformed the day of the week, month of the year, and quarter of the year features using sine and cosine transformations. They used integer features to represent the rest of the temporal features. The holiday feature and anomaly feature are binary features. A set of newly developed COVID-related features are added to the model to account for the fluctuations in surgical case volumes because of the pandemic. These are no covid, low covid, medium covid, and high covid.

The time series forecasting model used for predicting the commonly used surgical supplies is also a seq2seq encoder-decoder LSTM model and is developed upon exactly similar architecture used by Bui et al. [9]. The features used in the demand prediction model are the quantity moved out of the inventory per day, the total number of surgeries per day, meteorological features such as minimum temperature, maximum temperature, snow depth, and precipitation, the temporal features such as day of the week, week of the year, month of the year, quarter of the year, day of the year, year, holiday feature. Like the model developed by Bui et al. [9], this study used Keras deep learning API to build the LSTM model. Huber is used as the loss function, and ADAM optimizer is used to optimize the loss function. In this study, only the R^2 metric is used to assess the prediction accuracy for both models.

Hyperparameter tuning is an important step in building machine-learning models. Various techniques are available for tuning hyperparameters, including grid search, random search, Bayesian optimization, etc. However, in this study, the batch size, number of recurrent layers, and number of epochs were adjusted based on trial and error. After several trials and errors, batch size, number of recurrent layers, and number of epochs were set to 16, 55, and 300 in the model for predicting commonly used surgical supplies. In the modified model (model with COVID features), batch size, number of recurrent layers, and number of epochs were set to 32, 60, and 250, respectively. In the model without COVID features (original model developed by [9] et al.), these parameters were set to 32, 64, and 230. Early stopping with a patience of 30 is also used in all models to prevent overfitting.

4.2 Inventory Management

4.2.1 Economic Order Quantity (EOQ)

The classical economic order quantity, or EOQ, is the most well-known model in inventory control. American production engineer Ford Whitman Harris developed this model in 1913 [71]. EOQ is used when there is only one product and the demand is steady. The formulation of the classical EOQ model is stated below [72].

Assumptions

- Demand is deterministic or fixed per unit of time
- Ordering and holding costs are constant over time
- Replenishment lead time (L) is either zero or fixed
- No shortages are allowed

Notation

D	Annual demand of the product
d	demand per unit time
S	Fixed cost incurred per order
C	Purchasing price of per unit product
Q	Ordering quantity
H	Holding cost per unit per year

The demand is fixed for a particular time unit, and therefore, there is no need for safety stock. In case of zero lead time, the order is placed and delivered as soon as the inventory becomes zero. When there is a fixed lead time, the order is placed L time units before the start of the next demand cycle or at the time when there are Ld units left in the inventory. As no shortages are allowed, and there is no safety stock, the inventory level varies over time.

EOQ determines the optimal order quantity that minimizes the inventory holding and ordering costs. So, the total cost (TC) is

$$\text{TC} = \text{Annual purchasing cost} + \text{Annual order cost} + \text{Annual holding cost}$$

Because the unit price doesn't change over time and the demand is fixed, we have

$$\text{Annual Purchasing Cost} = CD$$

The total demand is D, and given the economic order size Q, the number of orders is D/Q. As there is a fixed cost associated with each order. We have,

$$\text{Annual Ordering Cost} = \left(\frac{D}{Q}\right) S$$

As the demand has a constant rate, the average inventory level during each cycle is $Q/2$. Therefore, the annual holding cost is the cost of holding $Q/2$ units in inventory for one year is $(Q/2)H$ We can express the holding cost, H, as a fraction, h, of the unit cost, C, of the product or good. So,

$$\text{Annual Holding Cost} = \left(\frac{Q}{2}\right) hC$$

By combining all the costs, we get

$$\text{Total Cost (TC)} = CD + \left(\frac{D}{Q}\right) S + \left(\frac{Q}{2}\right) hC$$

Now, the optimal lot size or order quantity can be obtained by taking the first derivative of the total cost with respect to Q and setting it equal to 0. We get,

$$\begin{aligned}
\frac{d(TC)}{dQ} &= -\frac{DS}{Q^2} + \frac{hC}{2} \\
0 &= -\frac{DS}{Q^2} + \frac{hC}{2} \\
Q^2 &= \frac{2DS}{hC} \\
EOQ = Q^* &= \sqrt{\frac{2DS}{hC}}
\end{aligned}$$

Although EOQ has been a very popular and well-known inventory control model over time, it has some inferent shortfalls. It assumes a constant demand, which can lead to inventory stockouts or overstocking if the demand changes. It also assumes a fixed order quantity, which can be inflexible in situations where demand or production costs change. Moreover, the EOQ model is designed for a single-item inventory system, which may not be suitable for managing inventory systems with multiple items or products.

On the other hand, dynamic lot sizing can adjust the order quantity based on the changing demand, reducing the risk of stockouts or overstocking. It also allows for flexibility in adjusting the order quantity based on the changing demand or production costs. Most importantly, dynamic lot sizing is more suitable for managing inventory systems with multiple items or products.

4.2.2 Dynamic Lot Sizing

The dynamic lot sizing inventory model is a widely used approach in inventory management that takes into account changing inventory levels over time. It helps determine the optimal order quantity and the reorder point for a given inventory system while considering the costs associated with inventory holding, ordering, and stockouts, as well as the demand variability and lead time.

4.2.2.1 The Wagner Whitin Algorithm

The dynamic lot-size inventory model is a generalization of the economic order quantity model. This is a finite-horizon, discrete-time model with deterministic but non-stationary demand for a single product at a single stage which was first introduced by Harvey M. Wagner and Thomson M. Whitin in 1958 [73]. Wagner and Whitin developed a dynamic programming forward recursion algorithm to minimize the inventory cost for an uncapacitated, single-item, single-stage, lot-sizing problem [74]. As the demand is deterministic, any future demand for period t can be satisfied by an order placed in period j where $t \geq j$.

There are mainly three types of costs associated with inventory management, ordering cost, inventory holding cost, and purchasing cost. However, purchasing cost is independent of the decision variables [75] (order quantity and order period) since the demand is deterministic over finite periods. There is an ordering cost every time an order is placed, and it can be either fixed or variable. The holding cost is incurred when an item is carried from one period to another. Hence, the goal is to find when to order and how much to order to minimize the total cost. The algorithm is stated below [75].

Let us consider a problem of t periods and assume that the inventory by the end of period t is zero.

Notation

K	Ordering cost
d	demand per period
h	Holding cost per unit per period
$F(t)$	The optimal cost from period 1 through period t
C_t^u	The minimum cost over periods 1 through t when the period t's demand is satisfied by an order placed in period u

C_t^u can be expressed as the sum of the minimum costs over period 1 through periods u–1 and periods s through t. The optimal cost for periods 1 through u–1 is $F(u$–1$)$. The cost incurred between periods u and t includes the fixed cost incurred in period u and the holding costs incurred in periods $u, u+1, \ldots, t$ [75]. So, the cost over periods 1 through t is

$$K + h(d_{u+1} + d_{u+2} + \cdots + d_t) + h(d_{u+2} + d_{u+3} + \cdots + d_t) + \cdots + h(d_t)$$

Therefore,

$$C_t^u = F(u-1) + K + h(d_{u+1} + d_{u+2} + \cdots + d_t) + h(d_{u+2} + d_{u+3} + \cdots + d_t) + \cdots + h(d_t)$$

Let's assume period t–1's demand is optimally satisfied by an order placed in period ν. Then, the period t's demand can be satisfied by placing an order in any period between ν and t. Therefore, the optimal cost over periods 1 through t is

$$F(t) = min\{C_t^{\nu}, C_t^{\nu+1} + \cdots + C_t^{t-1}, C_t^t\}$$

The steps of the WW algorithm are as follows [75]:

Step 1: Set $\nu = 1, t = 2$, and $F(1) = K$ because for the first period, no holding cost is incurred.

Step 2: As an order is always placed in the first period, its time to determine whether it will be optimal to satisfy the demand of period 2 by placing an order in period 1 or period 2.

$$C_2^1 = F(1) = K_1 + hd_2 \text{ and } C_2^2 = F(1) + K_2 = K_1 + K_2$$

The optimal cost for period 2 is the minimum cost between these two periods

$$F(2) = min\{C_2^1, C_2^2\}$$

If $C_2^1 < C_2^2$, ν remains unchanged, that means the demand for period 2 will be satisfied by an order placed in period 1. Otherwise set $\nu = 2$.

Step 3: Consider a t-period problem where the demand for period t is satisfied by an order placed in one of the periods between $\nu, \nu+1, \nu+2+\cdots+t$. So the optimal cost for period t will be

$$F(t) = min\{C_t^{\nu}, C_t^{\nu+1} + \cdots + C_t^{t-1}, C_t^t\}$$

Step 4: Set stopping criteria $t = t + 1$. Repeat the above three steps until the stopping criteria are met.

While the Wagner-Within algorithm is a useful approach to solving inventory problems, it has some limitations that can be overcome by using mixed integer programming (MIP) models. Like, the Wagner-Within algorithm is designed to optimize a specific type of inventory system and is not easily adaptable to handle more complex systems or those with different objectives. In contrast, MIP models are highly flexible and can be adapted to handle a wide range of inventory problems, including those with complex constraints and multiple objectives. This algorithm is also designed for a single product just like the EOQ model, with constant demand over a fixed time horizon. It cannot easily handle multi-product inventory systems or those with variable demand. MIP models, on the other hand, can handle multiple products and can incorporate demand variability into their analysis. The Wagner-Within algorithm assumes that lead times are zero or constant, which is often not true in real-world inventory systems. MIP models can incorporate lead times into their analysis, making them better suited for more complex systems. Moreover, the Wagner-Within algorithm does not consider capacity constraints or other operational constraints, which can limit its effectiveness for more complex inventory systems. MIP models, on the other hand, can handle a wide range of constraints and can incorporate them into their analysis.

Overall, MIP models offer more flexibility, scalability, and versatility compared to the Wagner-Within algorithm, making them a more robust approach for solving inventory problems in a variety of settings.

4.2.2.2 A simple MIP Model

Mixed Integer Programming (MIP) is very popular for modeling and solving dynamic multi-item lot sizing problems. This article [76] presents a general model for a multi-item lot-sizing problem with various realistic constraints, such as multiple suppliers, multiple time periods, quantity discounts, and back ordering of shortages. The problem is formulated as a MIP model. In this study [77], the lot-sizing problem is formulated as a MIP model to minimize total costs, including ordering, holding, purchase, and transportation costs, while ensuring no inventory shortage. However, if the model becomes inherently large and needs to consider many variables and complex constraints, it becomes computationally infeasible to solve optimally. In those cases, a heuristic solution helps get a near-optimal solution. The authors of both studies [76, 77] used Genetic Algorithm (GA) to solve the large-scale version of their problems. The authors of this study [78] developed a MILP multi-item, multi-location, single-supplier lot-sizing problem. They extended this model with quantity discounts, a rolling horizon, multiple inventory locations, transportation between the locations, and the possibility of certain material types to free-ride on the quantity discounts of other materials.

In this study, a simple MIP model was formulated for a multi-item capacitated lot sizing problem. The objective is to minimize the total costs, consisting of purchasing, inventory holding, ordering, and transportation costs. Some of the assumptions are that demands are deterministic and known, the planning horizon is fixed and finite, and the duration of each period is the same. The orders are placed at the beginning of the period, and all items are delivered at the beginning of the next period.

All the notations used in the model are defined below.

Indices

i Item $(i = 1, 2, ..., I)$

j Planning period $(j = 1, 2, ..., J)$

Parameters

D_{ij} Demand of item i in period j

C_i Purchasing price of item i

h_i Inventory holding cost of item i per period

F Fixed ordering cost of each item i for each order

T Fixed transportation cost for each pallet transported

U Maximum capacity of a delivery pallet

V_i Volume of item i

M A very big number

Decision Variables

I_{ij} Inventory of item i at the end of period j

X_{ij} Binary variable, set equal to 1 if item i is purchased in period j, 0 otherwise

Q_{ij} Quantity ordered of item i at the start of period j and delivered at the beginning of period $j+1$

Z_j Number of pallets dispatched at period j

Model Formulation

$$\text{Minimize TC} \quad = \sum_{j=1}^{J} \left[\sum_{i=1}^{I} \left(C_i Q_{ij} + F X_{ij} + h_i I_{ij} \right) + T Z_j \right]$$

$$\begin{aligned}
\text{Subject to} \qquad I_{ij-1} + Q_{ij-1} - D_{ij} &= I_{ij} && \forall i, \forall j \\
M X_{ij} &\geq Q_{ij} && \forall i, \forall j \\
\sum_{i=1}^{I} V_i Q_{ij} &\leq U Z_j && \forall j \\
I_{ij} &\geq 0 && \forall i, \forall j \\
Q_{ij} &\geq 0 && \forall i, \forall j \\
Z_j &\geq 0 && \forall j \\
X_{ij} &\in 0, 1 && \forall i, \forall j
\end{aligned}$$

The objective of this model is to minimize the total cost, which consists of total purchase cost, inventory holding cost, ordering cost, and transportation cost. The first constraint is the inventory balance constraint. The inventory level after every period is equal to the sum of the inventory of the last period, and new orders placed at the beginning of the previous period subtract the demand of the current period. The second constraint ensures that the binary variable is set to 1 if an order is placed for any particular item. The final constraint is the capacity constraint.

In real-life settings, demands are hardly deterministic unless otherwise stated. Most of the time, demands are uncertain or stochastic. Two-stage stochastic programming (TSSP) explicitly considers the uncertainty in demand. TSSP can provide more accurate and robust inventory replenishment decisions, leading to improved customer service levels, reduced stockouts, and better use of available resources. Therefore, a two-stage stochastic programming model is developed and solved.

4.2.3 Two Stage Stochastic Programming Model

Two-stage stochastic programming operates under the premise that optimal decisions must rely on currently available data and cannot be contingent on future observations [79]. In the first stage, decisions are made before the realization of the uncertain data is known. In the second stage, after a realization of stochastic parameters becomes available, adjustments are made by solving an appropriate optimization problem [79].

In the case of multi-product joint replenishment, this involves determining the optimal shipping quantities and inventory levels for each product over a planning horizon. The first stage of the optimization problem involves making decisions based on available information about demand and inventory levels. In this study, demand is considered as the only stochastic parameter. The first stage decision is the ordering decision for each product. In a two-stage stochastic programming model for inventory replenishment, ordering decisions are typically made well before the actual demand realization. This is because demand uncertainty is the primary source of uncertainty in the model, and waiting for actual demand to be observed would lead to suboptimal decisions. By making the ordering decision first, probabilistic information about the demand can be used to optimize the decision. This allows for considering the risk of stockouts and overstocking and making optimal decisions over a range of possible demand scenarios. In other words, by making the ordering decision based on probabilistic information about demand, more informed and optimal decisions can be made that are robust to uncertainty.

In this study, a MIP equivalent of the TSSP model is developed and solved. Decision variable Q_{ij} is the first stage decision. Since demand is an uncertain parameter here, a scenario index w is used to represent different scenarios of demand. This incorporates uncertainty into the second stage of the optimization model. The stochastic nature of the second stage involves using probability distributions to represent the probability of realizing any scenarios of the demands. Here the demand scenarios are considered to follow a uniform probability distribution. Another decision variable S_{ij}^w is introduced into the model to account for any stockouts after realizing the demand in the second stage and thus making adjustments to the decision. If there are any stockouts, a shortage penalty P is imposed for reordering the items, increasing the total cost. On the other hand, if there is overstocking, the additional purchasing and inventory holding costs increase the total cost. Thus, the decisions are adjusted to minimize the total cost. The solution obtained from the two-stage stochastic program provides an optimal joint replenishment plan that minimizes the total cost of inventory replenishment.

All the extra notations are defined below.

Indices

w Demand scenario ($w = 1, 2, ..., W$)

Parameters

D_{ij}^w Demand of item i in period j for demand scenario w

P Shortage Penalty

Decision Variables

I_{ij}^w Inventory of item i at the end of period j for demand scenario w

S_{ij}^w Quantity of item i fell short during period j for demand scenario w

Model Formulation

$$\text{Minimize TC} \quad = \sum_{j=1}^{J}\left[\sum_{i=1}^{I}\left(C_iQ_{ij} + FX_{ij} + \frac{1}{W}\sum_{w=1}^{W}\left(PC_iS_{ij}^w + h_iI_{ij}^w\right)\right) + TZ_j\right]$$

$$\begin{aligned}
\text{Subject to} \qquad Q_{ij-1} + S_{ij-1}^w - D_{ij}^w &= I_{ij}^w - I_{ij-1}^w && \forall i,j,w \\
MX_{ij} &\geq Q_{ij} && \forall i,j \\
\sum_{i=1}^{I} V_iQ_{ij} &\leq UZ_j && \forall j \\
I_{ij}^w &\geq 0 && \forall i,j,w \\
S_{ij}^w &\geq 0 && \forall i,j,w \\
Q_{ij} &\geq 0 && \forall i,j \\
X_{ij} &\in 0,1 && \forall i,j
\end{aligned}$$

Like the previous model, the objective of this model is to minimize the total cost, which consists of total purchase cost, inventory holding cost, ordering cost, and transportation cost. Since a new demand scenario index is introduced into the model to account for the demand uncertainty, the expected value of the inventory holding cost is now calculated by multiplying the inventory holding costs for different scenarios by their probability values and summing them over the total number of scenarios. The shortage cost is calculated by multiplying the item price by the quantity shortage variable and the shortage penalty parameter.

The inventory balance constraint has been slightly changed from the previous model. In this model, the inventory level after every period was equal to the sum of the inventory level from the previous period, quantity fell short and reordered in the previous period, and new orders placed at the beginning of the previous period subtract the demand of the current period. The rest of the constraints remained the same as before.

5 Experimental Results and Discussion

5.1 Demand Forecasting

It was mentioned in section 3.1 that the first type of data includes information related to the surgical procedure. However, not all procedures are performed frequently. The data analysis shows that only 22 procedures have more than 800 records per procedure. Bui et al. [9] developed LSTM models for each of them. They grouped the rest of the procedures into 26 clusters based on certain similarities and built LSTM models for those clusters. In this study, one highly frequent non-emergency procedure is chosen, and new features are incorporated to test for any improvement in the forecasting. This procedure was scheduled 5988 times in 1684 days from May 2014 to September 2021.

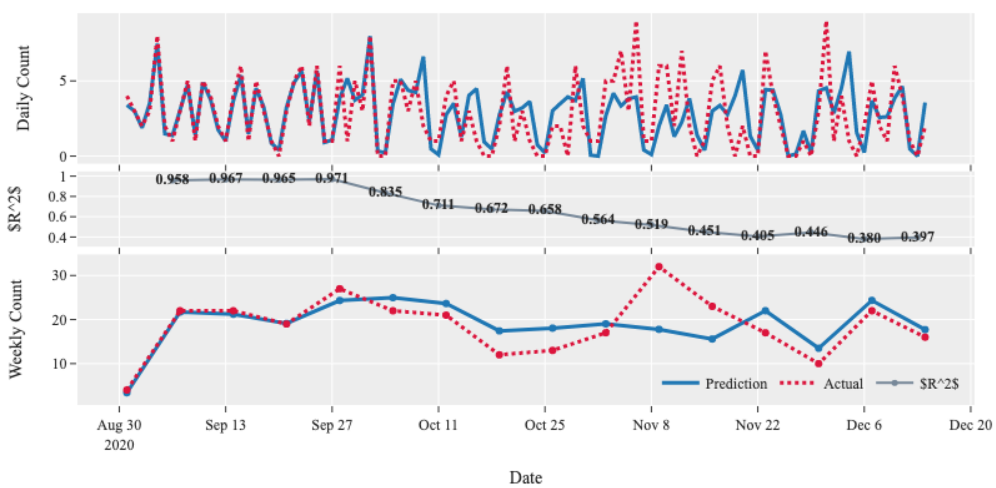

Figure 5.1: Prediction with original model

The outcomes of the original forecasting model (without COVID features) and its modified version (the model with COVID features) for predicting surgical case volumes are presented in Figure 5.1 and 5.2. The results indicate that the initial four weeks' predictions are considerably high, but their performance drops significantly thereafter for both models. It is worth noting that the modified model shows a slightly better prediction accuracy in the beginning, with respective R^2 values of 0.970 and 0.958. Nevertheless, the model without COVID features performs better for later periods. The inclusion of new features does not

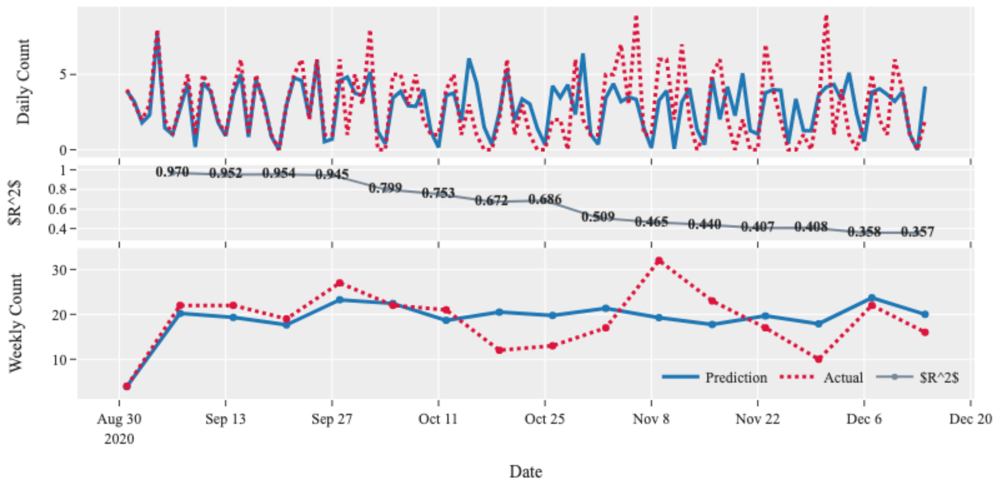

Figure 5.2: Prediction with modified model

appear to have significantly enhanced the model's long-term performance.

The modified model's projected surgical case volumes are assumed to represent procedure-specific surgical supply demand and can be used in the inventory replenishment model.

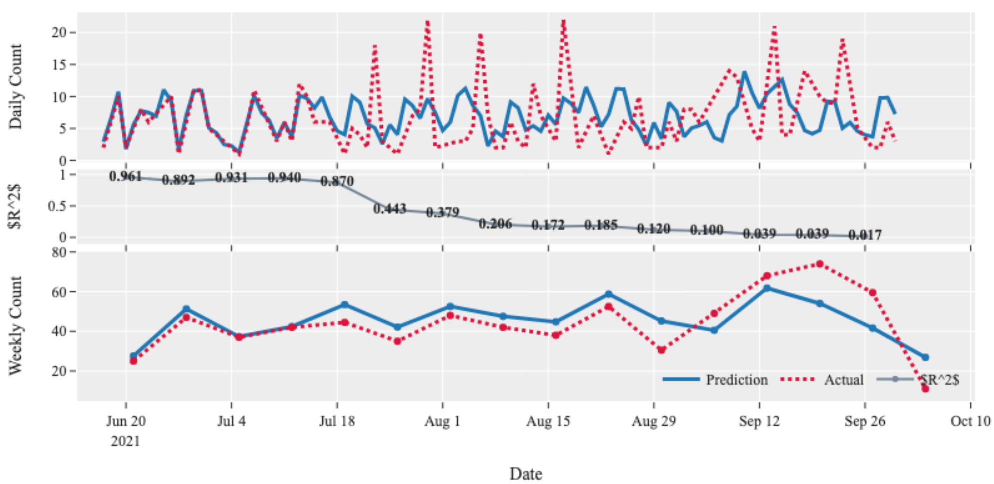

Figure 5.3: Demand prediction for item XYZ

Figure 5.3 displays the demand prediction results for item XYZ. The plot indicates that the forecasting accuracy for the first five weeks is significantly high. However, the accuracy drops steeply afterward, which is supported by a decrease in the corresponding R^2 value from 0.870 to 0.443.

5.2 Inventory Replenishment

5.2.1 Data Generation

A total of nine items and five periods were considered for the inventory replenishment models. Demands for the items were randomly assumed. Three demand categories, low (10 - 40), medium (40 - 70), and high (70 – 100), and three price categories, low (1 – 50), medium (50 – 200), high (200 – 500) were used to assume the demand and price of the items. The items are a combination of different demand and price levels like low demand - low price, low demand - medium price, low demand - high price, medium demand - low price, medium demand medium price, etc. Fifty-two random numbers were generated within the demand range for each of the nine items. Among those, the first five numbers were assumed to represent the demand for that item for the first five periods. Additionally, safety stock was calculated for each item with 95% service level, and the average demand and safety stock values were summed together to set the initial inventory level for each item. Item volumes (in cubic inches) were also assumed. Table 5.1 contains the demand, price, and volume of items used in the replenishment models.

Item	Demand					Price	Volume
	Period 1	Period 2	Period 3	Period 4	Period 5		
1	15	21	13	13	12	8.88	12
2	51	69	55	40	49	25.00	24
3	92	85	93	80	78	33.00	80
4	26	19	11	25	33	71.00	120
5	56	59	42	42	47	200.97	336
6	75	87	94	77	84	157.00	48
7	29	17	21	10	24	289.00	75
8	62	67	58	49	46	346.00	105
9	79	80	89	87	92	459.00	192

Table 5.1: Demand, price, and volume of items

Inventory holding costs were assumed to be 20% of the base price of the items. Fixed ordering cost and fixed transportation cost per pallet were assumed to be \$50 and \$300, respectively. The pallet was considered a standard size of 48 inches by 40 inches by 48 inches.

In the TSSP model, a new parameter, namely shortage penalty, was introduced, with a value assumed to be twice the respective item's base price. A total of five uncertain demand states were incorporated. The demands for each state were generated by randomly selecting a value from the range of actual demand, with a variation of plus or minus three, for each product in each period. As the planning horizon is five weeks and the forecasting accuracy for the initial five weeks was very high, the new demands were generated from a short range of the actual demands.

5.2.2 Results and Analysis of Optimization Models

5.2.2.1 Simple MIP model

First, the simple MIP model was solved using the data described in 5.2.1. The model was coded and solved in AMPL. Table 5.2 contains the optimum ordering decisions obtained by the model. The total cost is $352936.81.

Item	Peiod 1	Peiod 2	Peiod 3	Peiod 4	Peiod 5	Total Quantity Ordered
1	0	36	0	0	0	36
2	190	0	0	0	0	190
3	80	251	0	0	0	331
4	74	0	0	0	0	74
5	88	0	89	0	0	177
6	64	94	161	0	0	319
7	28	0	34	0	0	62
8	59	58	95	0	0	212
9	64	89	179	0	0	332

Table 5.2: Optimum ordering decisions by the simple MIP model

The fixed ordering cost, transportation cost, and inventory holding cost coefficients have been varied one at a time from 0.6 to 1.4 with an increment of 0.1 to check their impacts on the total cost and decision variables. Figure 5.4 shows that varying fixed ordering cost and transportation cost have almost similar effects on the total cost. From the figure 5.4, it is visible that the total cost varies more with varying fixed ordering cost and transportation cost than varying the holding cost.

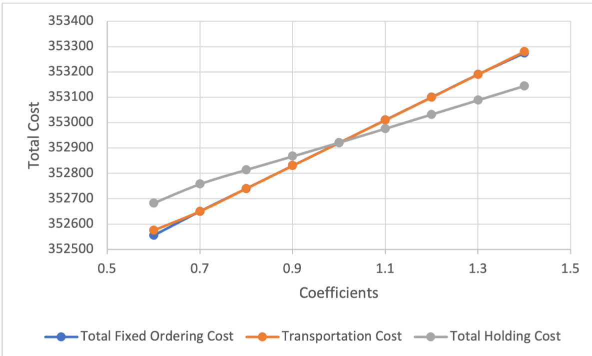

Figure 5.4: Effect of varying each parameter one at a time on the total cost obtained by the simple MIP model

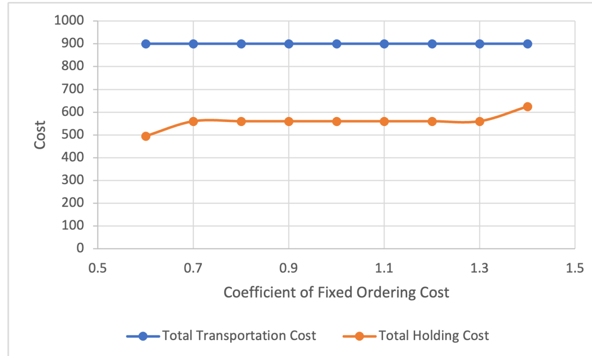

Figure 5.5: Effect of varying fixed ordering cost on total transportation and total inventory holding costs

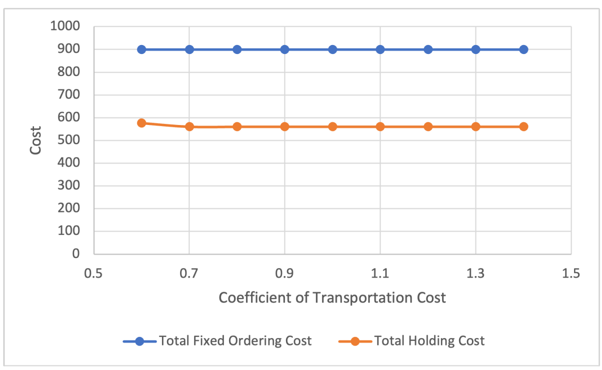

Figure 5.6: Effect of varying transportation cost on total fixed ordering and total inventory holding costs

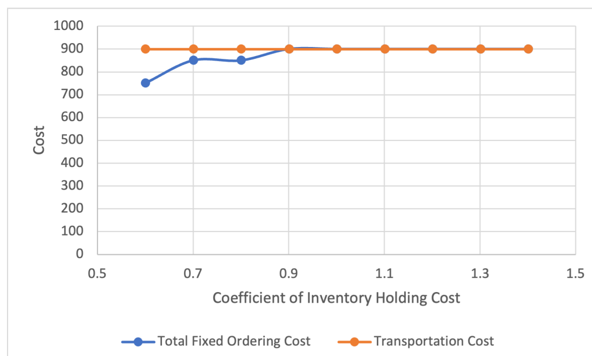

Figure 5.7: Effect of varying inventory holding cost on total fixed ordering and total transportation costs

The figure 5.5, 5.6, and 5.7 displays the relation between the parameters. Figure 5.5 shows that varying the fixed cost does not impact the total transportation cost but has a small effect on the total holding cost at the two extremes. When the fixed cost is lowest, the total inventory holding cost is also lowest, and vice versa. However, the inventory holding cost remains unchanged while the fixed ordering cost coefficient varies from 0.7 to 1.3. Figure 5.6 shows that varying transportation cost does not impact the fixed ordering cost but has a small effect on the holding cost at the lower extreme point. The holding cost is reduced slightly and remains unchanged. Figure 5.7 displays that with the change in the holding cost, the total transportation cost remains unchanged, and the total fixed ordering cost increased gradually at the beginning and then became constant. These analyses show that the inventory holding cost and fixed ordering cost have some positive relation, while transportation cost is unaffected by the inventory holding cost and fixed ordering cost.

In all scenarios, the total number of quantities ordered per item remains unchanged, which validates the model's performance.

5.2.2.2 TSSP model

An equivalent MIP model of the TSSP is developed and solved using the data described in 5.2.1. The model was also coded and solved in AMPL. Table 5.3 contains the optimum ordering decisions obtained by the model. The total cost is $352191.26.

Item	Peiod 1	Peiod 2	Peiod 3	Peiod 4	Peiod 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 5.3: Optimum ordering decisions by the TSSP model

The expected value of perfect information (EVPI) and the value of stochastic solution (VSS) are two important concepts to assess the potential benefits of gathering additional information. The expected value of perfect information (EVPI) measures the maximum value that could be gained by obtaining perfect information about the uncertain variables in a decision problem or The maximum value that a decision maker would be willing to pay to obtain complete and precise information. In the context of stochastic programming, EVPI can be used to evaluate the potential benefits of reducing uncertainty in demand scenarios. The EVPI is defined as the difference between the expected value of the optimal decision with perfect information (EVwPI), i.e., using the simple MIP model with known demand scenarios, and the expected value of the optimal decision without perfect information (EVwoPI), i.e., using the TSSP model with uncertain demand scenarios [80].

In the TSSP model, five random demand states were considered. To calculate the EVwPI, the five demand states were solved using the simple MIP model as if the demand were known, and the average was calculated. Here, EVwPI = 349445.17 and EVwoPI = 352191.26. Therefore,

$$\text{EVPI} = 352191.26 - 349445.17 = 2746.09.$$

The value of stochastic solution (VSS) measures the potential benefit of using a stochastic optimization model instead of a deterministic model. The VSS quantifies the value of the additional information provided by the stochastic model and can help decision-makers evaluate the potential benefits of using a more complex stochastic model. The VSS measures the potential benefit of using a stochastic optimization model by comparing the expected value of the optimal decision obtained using the stochastic model to the expected value of the optimal decision obtained using the deterministic model, meaning what would the decisions resulted from the deterministic model yield in the stochastic environment. A positive VSS indicates that the stochastic model provides significant value, while a negative VSS indicates that the deterministic model is better [80].

Here the expected value of the optimal decision obtained using the deterministic model is 354519.564, and the expected value of the optimal decision obtained using the stochastic model is 352191.26. Therefore,

$$\text{VSS} = 354519.564 - 352191.26 = 2328.304.$$

These results represent one demand case only. Since the demand is uncertain and randomly generated within a short range of the actual demands, a Monte Carlo simulation was performed with ten different randomly generated demand datasets to evaluate the robustness of the model.

Confidence intervals are commonly employed as a quantitative validation technique in modeling and simulation [81]. To explain, a confidence interval is computed for a response variable of the model. If the known or observed value for the same response variable falls within this confidence interval or a tolerance limit, the model is considered valid for that particular response variable [82]. Table 5.4 contains the 95% and 99% Confidence Intervals (CI) of the TSSP model's ordering decisions for each of the nine items. A comparison between Table 5.2 and 5.4 indicates that for the 99% CI, the simple MIP model's ordering decisions for items 2, 4, and 7 slightly fall outside of the interval. For the 95% CI, the simple MIP

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 5.4: 95% and 99% confidence interval of ordering decisions by TSSP model

model's ordering decisions for items 1, 2, 4, 5, 7, and 9 fall outside of the interval. However, the items that fell outside of the interval are within two units of the interval.

Next, the fixed ordering cost, transportation cost, inventory holding cost, and shortage penalty coefficients have been varied one at a time from 0.6 to 1.4 with an increment of 0.1 to check their impacts on the total cost and decision variables. Figure 5.8 shows that the total cost varies most with varying the shortage penalty cost. The figure also shows that varying fixed ordering, transportation, and inventory holding costs have almost similar effects on the total cost. In precise numbers, varying the fixed ordering, transportation, and inventory holding costs one at a time from 0.6 to 1.4 positively increases the total cost by \$706.8, \$715.7, and \$497.4, respectively.

According to the figure 5.8 presented, the shortage penalty has a significant impact on the total cost, making it essential to study how variations in shortage penalty influence ordering decisions. It is plausible that reducing the shortage penalty would result in the model ordering fewer quantities in the initial stage, 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. Conversely, increasing the shortage penalty would prompt the model to minimize the total cost by ordering more quantities initially to avoid stockouts and incurring higher total shortage costs. A one-tailed paired t-test was conducted to test this hypothesis, and the results are reported in Table 5.5. The results of the hypothesis test suggest that when the shortage penalty is lower, the quantities ordered

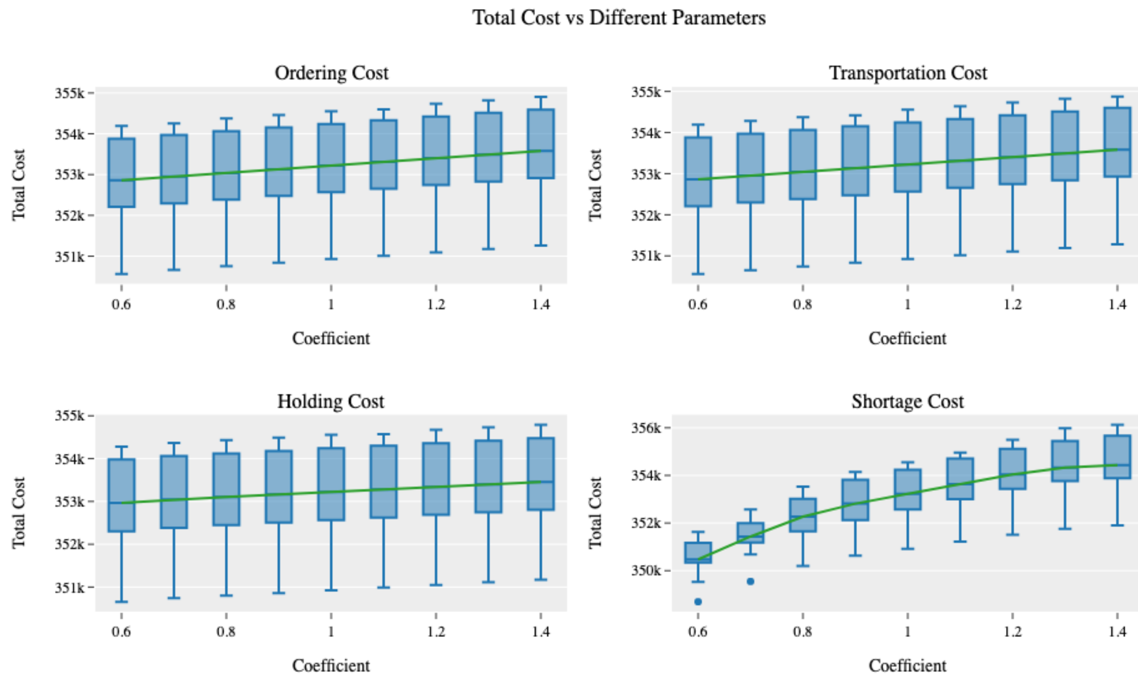

Figure 5.8: Effect of varying each parameter one at a time on the total cost obtained by the TSSP model

are significantly lower compared to when the shortage penalty is higher.

The analysis suggests that the TSSP model performs better than the simple MIP model. The results of EVPI and VSS provide useful information for decision-makers when considering the potential benefits of gathering additional information and using stochastic optimization models. In this specific case, the EVPI of 2746.09 indicates that if perfect information about the demand scenarios was available, the decision-maker could potentially gain an additional value of $2,746.09. This value represents the maximum amount that the decision-maker should be willing to pay for the perfect information. If the cost of obtaining the information is less than this amount, then it is economically beneficial to acquire the information. The VSS of 2328.304 indicates that using the stochastic optimization model provides a benefit of $2,328.304 compared to using the deterministic optimization model. This means that the additional information provided by the stochastic model is valuable and that the decision-maker should use the stochastic model instead of the deterministic model. Overall, these results highlight the importance of considering uncertainty and gathering additional information in decision-making processes. By doing so, decision-makers can

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 5.5: Statistical significance test for varying shortage penalty

potentially gain significant benefits and make more informed decisions.

Furthermore, the sensitivity analysis shows that the shortage penalty significantly impacts the total cost, indicating that it is a crucial factor to consider in optimizing the ordering decisions. The fixed ordering, transportation, and inventory holding costs have minimal and almost similar effects on the total cost.

6 Conclusion

The main objective of this study is to develop effective models and approaches that can accurately predict demand and efficiently manage the inventory of surgical supplies in the healthcare supply chain. This study predicted the demand for surgical supplies in two steps. Demand for commonly used supplies is predicted using an LSTM model. The demand for certain surgical supplies is directly influenced by specific surgical procedures. Hence, the demand for procedure-specific surgical supplies is predicted using another LSTM model obtained from the literature. This study modified this second LSTM model by adding COVID-related features to capture the variation in the surgeries scheduled during the pandemic. However, adding the COVID features did not significantly enhance the model's long-term performance. The possible reason could be that the new features did not provide meaningful information to the model. Additionally, adding new features could increase the model complexity and make it harder to train effectively. Another possible reason could be the absence of proper hyperparameter tuning. However, all the LSTM models showed promising performance in predicting the demand accurately at the beginning of the forecasting horizon.

This study then developed two inventory replenishment models and conducted a comparative performance analysis to manage the inventory better and reduce costs. First, a simple MIP model was developed and solved for this multi-item lot-sizing capacitated joint replenishment problem. Since the forecasts are always considered inaccurate, and the demand is hardly deterministic in the real world, a TSSP model is developed and solved. The experimental results showed that the TSSP model performs better than the deterministic model. The expected value of perfect information was also calculated to assess the value that could be gained by obtaining perfect information about uncertain demands. As part of the analysis, a sensitivity analysis was carried out to determine how changes in various parameters would affect the total cost of the TSSP model. The findings of the analysis highlighted that changing the shortage penalty parameter had the most significant impact on the model's overall cost.

Future research could explore testing other machine learning models to improve forecasting accuracy over longer horizons. In addition, real-world scenarios such as discounts on quantity purchases, storage capacity, and service level could be integrated into the model for better performance. Most of the data used in the inventory replenishment models were assumed, making them somewhat impure. Hence, it would be interesting to see how the models perform with actual data.

In conclusion, although there is still room for improvement, this study has made significant contributions towards developing effective models and approaches for accurately predicting demand and managing inventory of surgical supplies in the healthcare supply chain. The practical implications of this research are significant, as it can be applied to real-world situations to improve the efficiency of healthcare supply chains. By accurately predicting demand and optimizing inventory levels, hospitals can reduce waste, lower costs, and improve patient services, making healthcare more accessible and affordable.

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