International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 05 | May - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

Forecasting Demand and Managing Surgical Supply Inventory

Beer Chandra Prajapati[1], Praveen Nigam[2], Hari Mohan Soni[3]

[1]Mechanical Engineering Department, Bansal Institute of Science and Technology, Bhopal (M.P.), India.
[2]Mechanical Engineering Department, Bansal Institute of Science and Technology, Bhopal (M.P.), India.
[3]Mechanical Engineering Department, Bansal Institute of Science and Technology, Bhopal (M.P.), India.

---***---

Abstract - A successful supply chain is essential to the functioning of many different industries, including the healthcare sector. Healthcare management of supply chains require demand forecasting and inventory control to guarantee the best possible patient outcomes, keep costs under control, and reduce waste. Numerous advanced methods for inventory control and demand forecasting have been made possible by technological and data analytics advancements. To lower costs and improve patient care, this study intends to take advantage of these developments to precisely forecast demand as well as control the surgical supply inventory. A long-short-term memory (LSTM) model is created to forecast the demand for frequently used surgical supplies to accomplish this goal. Furthermore, the number of scheduled surgeries impacts the demand for specific surgical supplies. A literature-based LSTM model is used to predict medical case volumes and supplies for specific procedures. The adopted model now includes new features to account for COVID-19-related variations in surgical case volumes in 2020. The study uses Mixed Integer Programming (MIP) to create a dynamic replenishment model for multiple items. Forecasting can frequently be inaccurate, and demand is rarely predetermined in the real world. To address these issues, we developed a Two-Stage Stochastic Programming (TSSP) model.

Key Words: forecasting demand, healthcare supply chain, inventory management, LSTM model.

1.INTRODUCTION

With a predicted growth rate of 5.1% from 2021 to 2030, the US national healthcare expenditure as a percentage of GDP is expected to be slightly above 18.0% in 2023 and reach roughly $6.8 trillion by that time [1, 2]. A significant portion of this expense is attributed to the cost of carrying out the surgical procedures and the supplies needed for them. These expenses are growing more and more expensive daily [3]. According to a 2016 study by [4], a single neurosurgery department squandered almost $2.9 million on out-of-date surgical supplies. Due to the significant amount of outdated inventory, patients and insurance companies bear the brunt of the increased costs. As a result, access to and cost of healthcare are increased. Since some surgical supplies are perishable and demand is unpredictable, inventory management for surgical supplies is an extremely difficult task. One of the biggest issues facing hospitals and other healthcare facilities is demand uncertainty. Hospitals need to make sure they have everything they need to give patients the care they need. They find it extremely difficult to determine the right level of inventories while maintaining a high level of service, though, due accurately and profitably to demand uncertainty. The risk of both overstocking and understocking arises frequently in the healthcare supply chain as a result.

However, some emergency medical and surgical supplies, like gloves, gowns, syringes, and emergency vaccinations, are consumable and have a short shelf life [5]. The supplies should hold steady or hold onto their identity, strength, quality, and purity through the indicated expiration date. Therefore, to prevent health hazards and guarantee high-quality service, these items must be used before the expiration date. To boost sales and lower the chance of items in their inventory going out of manner, manufacturers frequently offer a discounted price on their products [6]. Because of this, hospitals frequently buy supplies in bulk to take advantage of the lower prices, lower the chance of a product shortage, and lengthen the typical product shelf life [7]. A healthcare supply chain presented in figure 1.1.

In this study, surgical supplies are divided into two categories: procedure-specific supplies, such as specific types of equipment and drugs required to perform a specific surgery, and commonly used surgical supplies, such as surgical blades, forceps, preoperative skin antiseptics, skin preparation solutions, and so on. Through combining the supplies with the anticipated demand of the corresponding procedures, the expected demand for special surgical supplies is predicted. Conversely, one can forecast the total number of anticipated surgical cases or create a demand forecasting model using historical consumption data to determine the expected demand for commonly used surgical supplies. Conversely, one can forecast the total number of anticipated surgical cases or create a demand forecasting model using historical consumption data to determine the expected demand for commonly used surgical supplies. Estimating the total number of surgical cases over a given time frame may be exceedingly difficult. Furthermore, there is no guarantee on the prediction's accuracy, making the indirect estimate of surgical supply demand unreliable. Thus, it is better to use a direct demand forecasting model to estimate the demand for frequently used surgical supplies. The surgical supply chain and logistical model are presented in figure 1.2. In order to help the administration schedule the operating room, staff, and restock surgical supplies, hospitals use forecasting models to estimate the number of surgical cases [18, 19]. Costs are increased by both overestimating and underestimating surgical resources. Thus, coordinating surgical supplies with the demand (surgical procedures) and allocating resources accordingly reduces operating expenses and inventory [20]. Thus, precise estimates of the expected number of surgical cases are necessary in order to allocate resources.

The literature on surgical case volume prediction is extremely thin, despite its great importance. Time series forecasting models such as ARIMA and Seasonal ARIMA (SARIMA) are widely used in the literature [21]. To predict the volume of surgeries performed at a hospital, Trivedi et al. [22] used an

ARIMA model. According to the study, averaging the forecasting values produced by each separate ARIMA model outperforms choosing the best ARIMA model and making forecasts using it. Nonetheless, when examined separately, the ARIMA models that have smaller moving average and autoregressive terms function better. While this study predicts surgical case volumes overall, it ignores seasonal variations in time series data, which significantly affects how patients schedule surgeries. To predict the surgical case volume at a hospital, Zinouri et al. [6] used a historical per-day surgical volume dataset. The authors created a three-stage SARIMA model that includes identification, estimation, and diagnosis after taking the seasonality of the data into consideration. The forecasting authors took into account holidays as well, but they did not account for weekends because their demands are different from those of regular weekdays. According to the study, the SARIMA model achieves a MAPE score of less than 10% and outperforms the hospital's current prediction method.

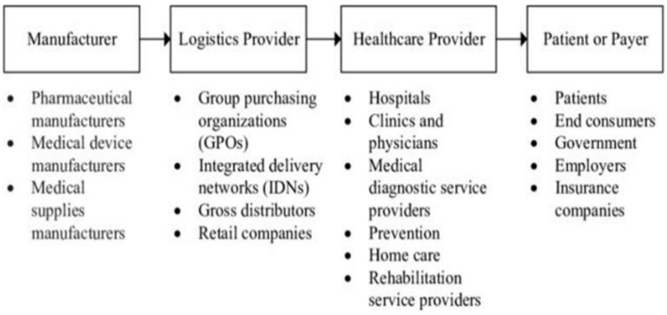

Fig -1.1: Healthcare Supply Chain

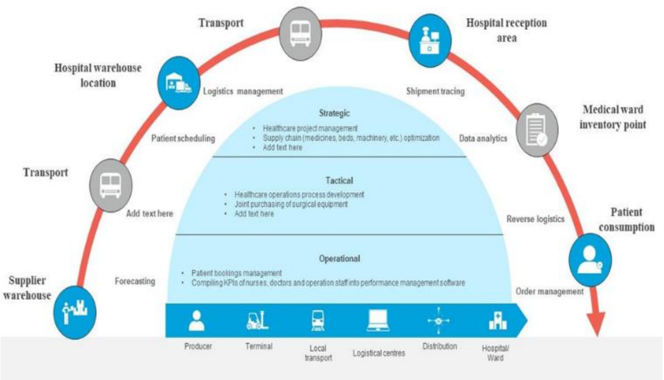

Fig -1.2: Surgical Supply Chain and Logistic Model

The prediction of surgical case volumes is also studied using linear regression models. A linear regression study was conducted by Tiwari et al. [23] in order to forecast surgical case volumes. Eggman et al. [8] used the multiple linear regression (MLR) model to study the medical case volume forecasting problem. Using four distinct MLR models, the authors estimated the number of surgeries seven, fourteen, and twenty-one days prior to the actual surgery day. Four independent variables are included in their study: the volume of scheduled surgeries, the number of scheduled surgeons, the total number of scheduled minutes, and the released group block. The analysis concludes that the seven-day-out model yields the most accurate prediction and accounts for the largest variance. However, as predicted, the model's performance decreases over time. These models assume that the time series is a linear function of historical values and random errors. As a result, these models are unable to provide high accuracy because they are unable to consider the nonlinear patterns of the data. For time series forecasting, these drawbacks and restrictions have led researchers to investigate probabilistic models in addition to machine learning (ML) and deep learning (DL) models [21]. While many researchers use ML and DL models for time series forecasting, such as 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., there is little evidence in the literature that these models are used for surgical case volume prediction [24,25,26,27,28,29,30].

2. METHODOLOGY & MODEL DEVELOPMENT

2.1 The Long Short Term Memory Model (LSTM)

Recurrent neural networks (RNNs) of the type known as Long Short-Term Memory (LSTM) were first presented by Hochreiter, along with Schmidhuber, in 1997 [31] to address the issue of gradients that diminish, which standard RNNs frequently encounter during training. The network cannot develop long-term dependencies if mistake gradients, all of which transmit back via the network throughout instruction, get substantially inadequate as they shift back in time. This phenomenon is known as the "vanishing gradient problem." With the help of multiple gates that control the flow of information into and out of the memory cell, LSTMs created a cell with memory that can store information for a long time. The input, output, and forget gates are among the gates; their respective activation functions regulate how much data is permitted to flow through them. For data records, the LSTM model incorporates the encoder-decoder phenomenon. However, due to various limitations, it is a conditional model with many complexities.

2.2 Inventory Management

2.2.1 Economic Order Quantity (EOQ)

The most well-known inventory control model is the conventional economic ordered quantity or EOQ. Ford Whitman Harris, an American production engineer, created this model in 1913 [32]. While there's a single product and demand is consistent, EOQ is used. The classical EOQ model's formulation is given below [33].

Assumptions

Ordering and holding costs are fixed over time.

Lead time (L) is either zero or fixed.

Shortages are not permitted.

Demand is either deterministic or fixed per unit of time.

Notation

D = demand for the product

d = demand per unit of time

S = Fixed cost

C = purchasing price of per unit product

Q = Ordering quantity

H = Holding cost

EOQ establishes the ideal order quantity to reduce the costs associated with ordering and keeping inventory. The total cost (TC) is, therefore.

TC = Purchasing cost + Order cost + Holding cost

EOQ = Q* = √2DS/hC

Despite being a well-known and widely used inventory control model over time, EOQ has a few discernible shortcomings. Assuming a steady demand can result in stockouts or overstocking of inventory should the demand fluctuate. Additionally, it makes the assumption of a fixed order quantity, which may not be flexible when production costs or demand fluctuate.

Furthermore, the EOQ model may not be appropriate for controlling inventory systems with numerous products or items since it was created for a single-item system of inventory.

2.3 A simple MIP Model

For the aim of this study, a multi-item equipped lot sizing problem was given a basic MIP model. The goal is to reduce all expenses, which include those related to ordering, holding inventory, purchasing, and shipping. Among the presumptions are that the time frame for planning remains constant and finite, the demands are known and deterministic, and each period has the same length. Requests are submitted at the start of each period, and every item is delivered at the start of the subsequent one.

Below are definitions for every notation used in the model.

Indices

i = Item (i = 1,2,……..,I)

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

Parameters

Dij = Demand of item i in period j

Ci = Purchasing price of item i

hi = Inventory holding cost

F = Fixed ordering cost

T = Transportation cost

U = Maximum capacity

Vi = Volume of item

M = A Big number

Decision Variables

Iij = Inventory of item i at the end of period j

Xij = Binary variable (it is set as equal to 1 if item i is purchased in period j, 0)

Qij = Quantity ordered

Zij = Number of pellets dispatched

Model Formulation

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

Subject to

$$I_{ij-1} + Q_{ij-1} - D_{ij} = I_{ij} \quad \forall i, \forall j$$
$$MX_{ij} \geq Q_{ij} \quad \forall i, \forall j$$
$$\sum_{i=1}^{I} V_iQ_{ij} \leq UZ_j \quad \forall j$$
$$I_{ij} \geq 0 \quad \forall i, \forall j$$
$$Q_{ij} \geq 0 \quad \forall i, \forall j$$
$$Z_j \geq 0 \quad \forall j$$
$$X_{ij} \in 0,1 \quad \forall i, \forall j$$

This model's goal is to reduce the total cost, which includes the costs associated with ordering, transportation, inventory holding, and total purchases. The inventory balance restriction is the first one. Every period's inventory level is determined by adding up all of the previous period's inventory and deducting the demand for the current period from any fresh orders set at the start of the previous period. If an order is submitted for any specific item, the second constraint guarantees that the binary value is set to 1. The capacity constraint is the last restriction.

Minimize TC =

$$\sum_{j=1}^{j}[\sum_{i=1}^{i}(C_iQ_{ij} + FX_{ij} + \frac{1}{W}\sum_{w=1}^{W}(PC_iS_{ij}^{w} + h_iI_{ij}^{w})) + TZ_j]$$

Subject to

$$Q_{ij-1} + S_{ij-1}^{w} - D_{ij}^{w} = I_{ij}^{w} - I_{ij-1}^{w} \quad \forall i,j,w$$

$$MX_{ij} \geq Q_{ij} \quad \forall i,j$$

$$Q_{ij} \geq 0 \quad \forall i,j$$

$$(I_{ij}^{w}) \geq 0$$

3. RESULTS AND DISCUSSION

3.1 Demand Forecasting

Section 3.1 stated that data pertaining to the surgical procedure is included in the first category of data. But not every procedure is carried out on a regular basis. Only 22 procedures have more than 800 records apiece, according to the data analysis. For every one of them, LSTM models were created by Bui et al. [9]. Based on some similarities, they clustered the remaining procedures into 26 groups and created LSTM models for each group. To see if the forecasting has improved, new features are added to a single, frequently used non-emergency procedure in this study. Between May 2014 and September 2021, there were 1684 days with 5988 schedulings for this procedure.

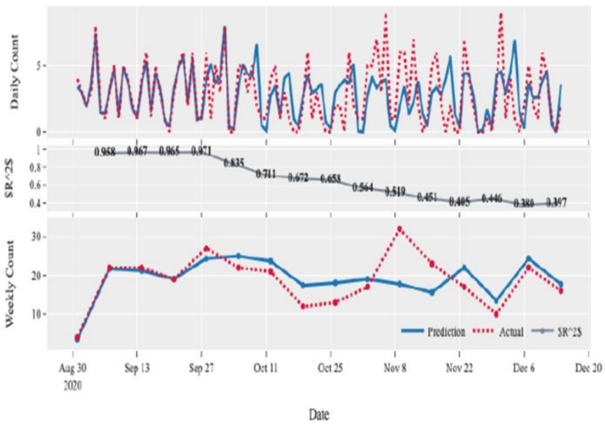

Fig -3.1: Prediction with original model

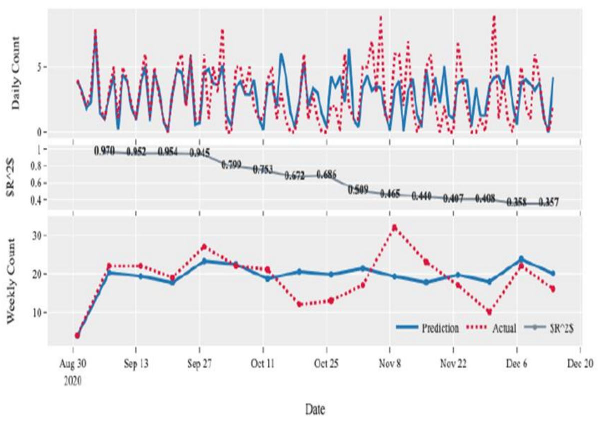

Fig -3.2: Prediction with original model

Figures 3.1 and 3.2 show the predictions made by the original forecasting model (which lacked COVID features) and its modified version (which included COVID features) for surgical case volumes. The findings show that both models' performances drastically decline after the first four weeks, when predictions are still quite high.

It is noteworthy that the adjusted model initially exhibits a marginally higher prediction accuracy, with corresponding R2 values of 0.970 and 0.958. However, for later periods, the model without COVID features performs better. The model's long-term performance does not seem to have been appreciably improved by the addition of new features. 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.

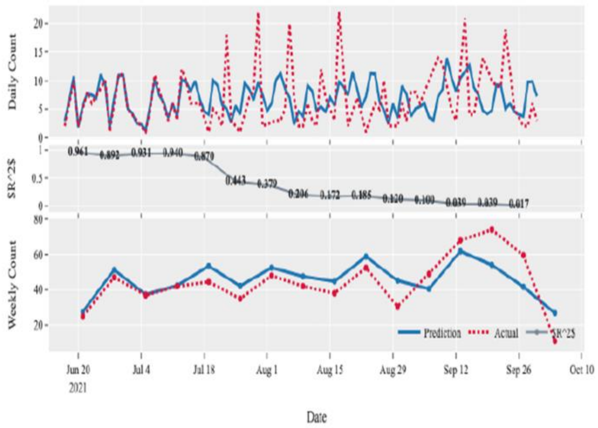

Fig -3.3: Demand prediction for item XYZ

The demand prediction results for item XYZ are shown in Figure 3.3. The plot shows that the first five weeks' forecasting accuracy is noticeably high. But then there is a sharp decline in accuracy, as evidenced by the corresponding R2 value falling from 0.870 to 0.443.

3.2 Inventory Replenishment

3.2.1 Data Generation

The inventory replenishment models took into account nine items across five periods. Demand for the items was assumed at random. We used three demand categories (10-40, 40-70, and 70-100) and three price categories (1-50, 50-200, and 200-500) to estimate the items' demand and price. The items have varying demand and price levels, such as low demand-low price, low demand-medium price, low demand-high price, medium demand-low price, and medium demand-medium price. For each of the nine items, 52 random numbers were generated based on their demand. The first five numbers were assumed to reflect the item's demand over the first five periods. Safety stock was calculated for each item with a 95% service level. The average demand and safety stock values were combined to determine the initial inventory level for each item. Item volume (in cubic inches) was also assumed. Table 5.1 shows the demand, price, and volume of items used in replenishment models.

The cost of keeping inventory was estimated to be 20% of the item's base price. It was estimated that the fixed ordering cost would be $50 and the fixed transportation cost per pallet would be $300. Pallet dimensions of 48 by 40 by 48 inches were regarded as standard.

A new parameter, the shortage penalty, was added to the TSSP model. Its value is assumed to be twice the base price of the corresponding item. There were five different uncertain demand states included. The demands for every state were produced by randomly choosing a number for each product in each period from the range of the actual demand, plus or minus three. The five-week planning horizon and the very high forecasting accuracy of the first five weeks led to the creation of new demands that were within a narrow range of the actual demands.

Item	Period 1	Period 2	Period 3	Period 4	Period 5	Price	Volume
1	15	21	13	13	12	8.88	12
2	51	69	55	40	49	25.00	24
3	93	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 -3.1: Demand, price, and volume of items

3.2.2 Results and Analysis of Optimization Models

3.2.2.1 Simple MIP model

First, the data from 5.2.1 were used to solve the basic MIP model. AMPL was used to code and solve the model. The model's best ordering selections are shown in Table 5.2. It comes to $352936.81 in total.

Item	Period 1	Period 2	Period 3	Period 4	Period 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 -3.2: Optimum ordering decisions by the simple MIP model

To examine their effects on the overall cost and decision variables, the fixed ordering cost, transportation cost, and inventory holding cost coefficients have been changed one at a time, from 0.6 to 1.4 with an increment of 0.1. Variations in fixed ordering costs and transportation costs have nearly identical effects on the overall cost, as Figure 5.4 illustrates.

It is evident from figure 5.4 that changing the fixed ordering and transportation costs has a greater impact on the overall cost than does changing the holding cost.

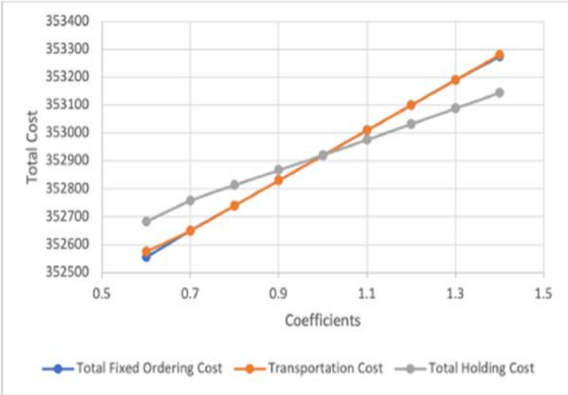

Fig -3.4: Effect of varying each parameter one at a time on the total cost obtained by the simple MIP model.

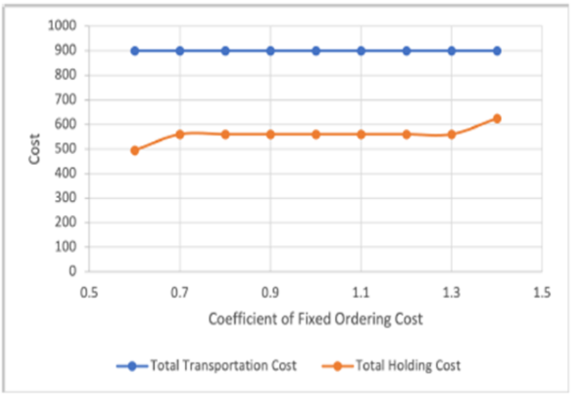

Fig -3.5: Effect of varying fixed ordering cost on total transportation and total inventory holding costs.

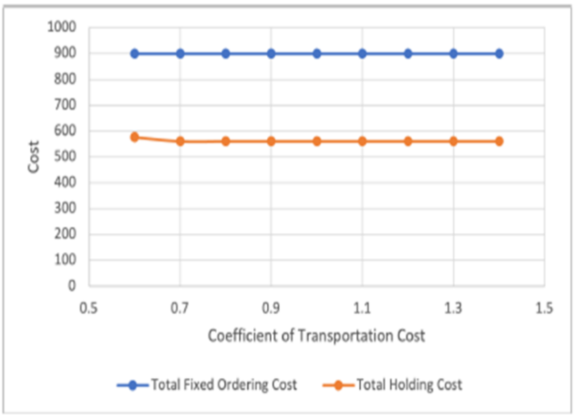

Fig -3.6: Effect of varying transportation costs on total fixed ordering and total inventory holding costs.

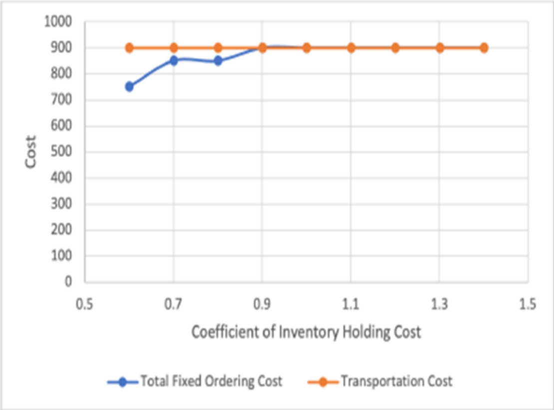

Fig -3.7: Effect of varying inventory holding cost on total fixed ordering and total transportation costs.

The fixed order cost, transportation Figures 3.5, 3.6, and 3.7 show the relationship between the parameters. Figure 3.5 demonstrates that changing the fixed cost has no effect on the overall transportation cost but does have a minor impact on the total holding cost at both extremes. Lower fixed costs lead to lower overall inventory holding costs, and vice versa. However, the inventory holding cost remains constant, while the fixed ordering cost coefficient ranges from 0.7 to 1.3. Figure 3.6 demonstrates that while transportation costs have no effect on fixed ordering costs, they do have a minor impact on holding costs at the lower end. The holding cost is slightly reduced but remains unchanged.

Figure 3.7 shows that when the holding cost changes, the total transportation cost remains constant, while the total fixed ordering cost initially increases and then stabilises. The analyses indicate a positive correlation between inventory holding costs and fixed ordering costs, but no effect on transportation costs. The model's performance is validated by the consistent total number of orders per item across all scenarios.

4. CONCLUSION

The primary goal of this investigation is to create efficient models and methodologies that can precisely forecast demand and effectively oversee the surgical supply inventory within the supply chain for healthcare. This study made two predictions about the demand for surgical supplies. With an LSTM model, the demand for frequently used supplies is forecasted. Specific surgical procedures have a direct impact on the demand for surgical supplies. Therefore, another LSTM model that was found in the literature is used to forecast the demand for surgical supplies that are specific to a given procedure. In conclusion, this study has significantly advanced the development of efficient models and strategies for precisely forecasting demand and controlling inventory of surgical supplies in the healthcare supply chain, even though there is still room for improvement. This research has important practical ramifications since it can be used to enhance the effectiveness of healthcare supply chains in actual scenarios. Hospitals can cut expenses, minimize waste, and enhance patient care by precisely forecasting demand and managing inventory levels. This makes healthcare more widely available and reasonably priced.

REFERENCES

[1] "Cms office of the actuary releases 2021-2030 projections of national health expenditures," CMS.gov, Mar 2022. [Online]. Available: https://www.cms.gov/newsroom/press-releases/cms-office-actuary-releases-2021- 2030-projections-national-health-expenditures
[2] M. E. Chernew, "National health expenditure projections and a few ways we might avoid our fate," Mar 2022. [Online]. Available: https://www.healthaffairs.org/do/10.1377/forefront.20220324.48476
[3] Definitive Healthcare, "Changes in Supply Costs Year to Year," https://www.definitivehc.com/resources/healthcare-insights/changes-in-supply-costsyear- to-year, accessed 2023.
[4] C. C. Zygourakis, S. Yoon, V. Valencia, C. Boscardin, C. Moriates, R. Gonzales, and M. T. Lawton, "Operating room waste: disposable supply utilization in neurosurgical procedures," Journal of neurosurgery, vol. 126, no. 2, pp. 620–625, 2017.
[5] L. Leaven, K. Ahmmad, and D. Peebles, "Inventory management applications for healthcare supply chains," International Journal of Supply Chain Management, vol. 6, no. 3, pp. 1–7, 2017.
[6] Y.-M. Lee, S. Mu, Z. Shen, and M. Dessouky, "Issuing for perishable inventory management with a minimum inventory volume constraint," Computers & Industrial Engineering, vol. 76, pp. 280–291, 2014.
[7] E. Ahmadi, H. Mosadegh, R. Maihami, I. Ghalehkhondabi, M. Sun, and G. A. S¨uer, "Intelligent inventory management approaches for perishable pharmaceutical products in a healthcare supply chain," Computers & Operations Research, vol. 147, p. 105968, 2022.
[8] S. Xu and H. K. Chan, "Forecasting medical device demand with online search queries: A big data and machine learning approach," Procedia Manufacturing, vol. 39, pp. 32–39, 2019.
[9] B. Hieu, E. Sandra D., V. Adria A., S. Joseph A., and S. Kevin W., "A long short-term memory model for forecasting the surgical case volumes at a hospital," 2022, accepted for publication in the IISE Transactions on Healthcare Systems Engineering.
[10] M. Gebicki, E. Mooney, S.-J. G. Chen, and L. M. Mazur, "Evaluation of hospital medication inventory policies," Health care management science, vol. 17, no. 3, pp. 215–229, 2014.
[11] J. De Vries and R. Huijsman, "Supply chain management in health services: anoverview," Supply chain management: An international journal, 2011.
[12] D. Elmuti, G. Khoury, O. Omran, and A. S. Abou-Zaid, "Challenges and opportunities of health care supply chain management in the United States," Health marketing quarterly, vol. 30, no. 2, pp. 128–143, 2013.
[13] F. Freij, "What makes a physician prefer one supplier over another? a study on physicians' supplier preference criteria." B.S. thesis, University of Twente, 2022.
[14] D. Q. Chen, D. S. Preston, and W. Xia, "Enhancing hospital supply chain performance: A relational view and empirical test," Journal of Operations Management, vol. 31, no. 6, pp. 391–408, 2013.
[15] R. Dadmun, "What is the healthcare supply chain?" https://healthcareready.org/whatis- the-healthcare-supply-chain/, accessed: 2022-07-13.
[16] S. Kitsiou, A. Matopoulos, V. Manthou, and M. Vlachopoulou, "Evaluation of integration technology approaches in the healthcare supply chain," International Journal of Value Chain Management, vol. 1, no. 4, pp. 325–343, 2007.
[17] Intelemark, "Selling to Hospitals: How to Reach Decision Makers in Healthcare," https://www.intelemark.com/blog/selling-hospitals-decision-makers-healthcare/, accessed 2023.
[18] S. A. Jones, M. P. Joy, and J. Pearson, "Forecasting demand of emergency care," Health care management science, vol. 5, no. 4, pp. 297–305, 2002.
[19] F. Dexter, A. Macario, R. D. Traub, M. Hopwood, and D. A. Lubarsky, "An operating room scheduling strategy to maximize the use of operating room block time: computer simulation of patient scheduling and survey of patients' preferences for surgical waiting time," Anesthesia & Analgesia, vol. 89, no. 1, pp. 7–20, 1999.

[20] D. Masursky, F. Dexter, C. E. O'Leary, C. Applegeet, and N. A. Nussmeier, "Long-term forecasting of anesthesia workload in operating rooms from changes in a hospital's local population can be inaccurate," Anesthesia & Analgesia, vol. 106, no. 4, pp. 1223–1231, 2008.
[21] A. Aravazhi, "Hybrid machine learning models for forecasting surgical case volumes at a hospital," AI, vol. 2, no. 4, pp. 512–526, 2021.
[22] S. Trivedi and N. Patel, "Optimizing or efficiency through surgical case forecasting with arima averaging," ACST, vol. 1, no. 1, pp. 7–17, 2021.
[23] V. Tiwari, W. R. Furman, and W. S. Sandberg, "Predicting case volume from the accumulating elective operating room schedule facilitates staffing improvements," Anesthesiology, vol. 121, no. 1, pp. 171–183, 2014.
[24] N. K. Ahmed, A. F. Atiya, N. E. Gayar, and H. El-Shishiny, "An empirical comparison of machine learning models for time series forecasting," Econometric reviews, vol. 29, no. 5-6, pp. 594–621, 2010.
[25] Z. Cui, W. Chen, and Y. Chen, "Multi-scale convolutional neural networks for time series classification," arXiv preprint arXiv:1603.06995, 2016.
[26] S. Kaushik, A. Choudhury, P. K. Sheron, N. Dasgupta, S. Natarajan, L. A. Pickett, and V. Dutt, "Ai in healthcare: time-series forecasting using statistical, neural, and ensemble architectures," Frontiers in big data, vol. 3, p. 4, 2020.
[27] Z. C. Lipton, D. C. Kale, C. Elkan, and R. Wetzel, "Learning to diagnose with lstm recurrent neural networks," arXiv preprint arXiv:1511.03677, 2015.
[28] T. Pham, T. Tran, D. Phung, and S. Venkatesh, "Deepcare: A deep dynamic memory model for predictive medicine," in Pacific-Asia conference on knowledge discovery and data mining. Springer, 2016, pp. 30–41.
[29] I. R. Widiasari, L. E. Nugroho et al., "Deep learning multilayer perceptron (mlp) for flood prediction model using wireless sensor network-based hydrology time series data mining," in 2017 International Conference on Innovative and Creative Information Technology (ICITech). IEEE, 2017, pp. 1–5.
[30] B. Zhao, H. Lu, S. Chen, J. Liu, and D. Wu, "Convolutional neural networks for time series classification," Journal of Systems Engineering and Electronics, vol. 28, no. 1, pp. 162–169, 2017.
[31] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," Neural Computation, vol. 9, no. 8, pp. 1735–1780, 11 1997. [Online]. Available: https://doi.org/10.1162/neco.1997.9.8.1735
[32] F. W. Harris, "How many parts to make at once," 1913.
[33] S. Chopra, Optimal Lot Sizing for a Single Product (Economic Order Quantity), 7th ed. Pearson Education, 2020, p. 269–270.