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Performance Analysis of the Supply Chain Management System Applying Monte Carlo Simulation Integrated with Linear Regression

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Abstract

Supply Chain Management (SCM) has attracted a substantial amount of attention from academics as well as engineers working in industry. The intricacy of current supply chain models is frequently beyond the capabilities of traditional analytical approaches, which is why simulation is such an important tool. Among the several design and evolutionary approaches to Supply Chain Management (SCM), inventory simulation is the most successful and widely used one. This study suggests the use of computer simulation and linear regression analysis in the process of modeling and assessing the effectiveness of supply chain operations, as well as analyzing the risks associated with making decisions in the face of uncertainty. This study indicates that a computer-based inventory simulation can support achieving the supply chain objectives for the beverage industry by evaluating service level performance, which in this case reached 83.02%. The projection of sales losses is derived from a linear regression analysis that meets all necessary statistical assumptions. Simulation applications are feasible alternatives to analytical approaches for displaying the fundamental behavior of systems at a much lower costs and significantly assist in improving the performance of the supply chain.

Keywords
Supply Chain Management, Monte Carlo Simulation, Simulation, Linear Regression, Performance Measure.

1. Introduction

The role of supply chain management (SCM) is evolving daily in modern industrialized economies, in which a firm seeks to enhance its compatibility and proficiency to meet customers' anticipated demands. Contemporary businesses are suffering from several unexpected and random causes nowadays (Eggert & Hartmann, 2023). Sustainable supply chain management can perform a significant impact on eliminating this hindrance (Zavala-Alcívar et al., 2020). Simulation in the supply chain is inevitable today due to its complex and subtle nature. Using simulation will help analyze and optimize the supply chain's overall performance and expenditure. Simulation is crucial to abate the complexity and forge a simple model. Therefore, precise utilization of simulation will be cost-effective and can deliver a sustainable sample to avoid any obstacles. This study also includes linear regression to make it more viable and straightforward. Linear regression is considered essential for understanding future predictions reliably. By incorporating linear regression and simulation in supply chain management, industries can gain fruitful insight from their data-driven analysis. Here, simulation and linear regression will predominantly address the pertinent critical phenomena related to this topic.

A durable system is built in this study by implementing a robust simulation method in the supply chain. To minimize risk, Monte Carlo simulation for risk analysis shows the range of risk, its impact and overall system performance. Here, a reputed beverage industry is considered, and relevant data has been collected from this company. This industry's monthly production is analyzed considering risk, profit, seasonal sales rate and several related factors. To access a supply chain system according to its performance, simulation can be used to visualize the entire system and develop a linear regression to portray a graph to optimize profit while reducing possible risk. This study aims to analyze risk in supply chain by using Monte Carlo simulation, and to visualize the entire system and develop a linear regression model to portray a graph to optimize profit while reducing possible risk.

The structure of this paper unfolds as follows: Section 2 explores literature review; research design and methods are explained in Section 3 and 4 respectively. In Section 5, the result is presented. Finally, in Section 6, the conclusion and a summary of the study are presented.

2. Literature Review

In recent years, it has become tough to eliminate supply chain obstacles due to various disruptions. In the context of Bangladesh, traffic jams, natural disasters, and political instability are the main reasons for supply chain disruptions. Hence, it is inevitable to make approximate risk analyses using simulation methods to give additional importance to the entire supply chain network. Lavastre et al. (2012) showed how companies managed supply chain risk, a topic that was becoming increasingly important. Risks came from many sources, including processes, demand, supply, and the environment. Based on a survey of French managers, the study showed that effective risk management needed to be collaborative across organizations. Sharing information and creating joint processes with partners greatly improved supply chain risk management. Ritchie & Brindley (2007) examined how changing types of supply chain risk created new challenges for risk management. The authors proposed a supply chain risk management framework with five components and focused on risk management influencers, including rewards, risks, timescale, and portfolio effects. A manufacturing case demonstrated how these factors shaped decisions. The study concluded that more diverse quantitative and qualitative tools were needed for effective risk management. Bandaly et al. (2016) examined how variable lead times affect supply chain risk management. Using simulation based optimization the authors showed that lead time variability did not always harm performance but high variability increased the need for coordination. They also found that different strategies are required when lead times are uncertain.

Simulation approach is utilized in many studies to solve supply chain problems. Utomo et al. (2018) reviewed how agent based simulation could be used in agri food supply chain research. Most studies focused on single level supply chains in higher income countries and used real data on unprocessed products. Many models addressed production decisions but ignored key actors like processors and retailers. The review highlighted researched areas such as collaboration competition and buyer seller relationships. González-Reséndiz et al. (2018) showed how combining simulation and optimization can improve lean logistics in a real company. The authors used simulation to understand the current process and identify waste, then optimization was done to find better solutions. The results demonstrated that this integrated approach reduces delays, lowers operating costs, and increases efficiency, making it a useful tool for improving logistics. Kalasky (1996) showed how discrete event simulation could be used to model a consumer product supply chain. By adding optimization to the simulation the authors generated useful operating recommendations. The study utilized ProModel for building the model and SimRunner for optimization demonstrating how this software combination colud support better supply chain planning and daily operations.. Gunasekaran & Ngai (2004) reviewed how information technology supports supply chain management. As companies seek more flexibility and competitiveness they rely on SCM strategies and new technologies. The authors analyzed existing studies to identify key factors and insights. From the review they proposed a framework and suggested directions for future research.

Lee et al. (2002) focused on production-distribution planning, a key part of supply chain management. Both analytical methods and simulation had been used to solve this planning problem, but each had limitations. To improve results, the authors proposed a hybrid approach that combined the strengths of both methods. Experiments showed that this hybrid method produces more realistic solutions, especially when considering the uncertainty found in real systems. These results differ noticeably from the original solutions produced by the analytic model alone. Miranzadeh et al. (2015) showed how simulation helps companies to improve supply chain performance. A three level supply chain with a supplier, manufacturer and customers was modeled using ARENA software. Results found that the contract queue had the most waiting requests and the longest delays. This indicated that the first stage of the supply chain needs the most improvement to enhance overall performance. Sajedinejad et al. (2020). used simulation to analyze and improve a lean, multi-product supply chain. Their model incorporated withdrawal and production Kanbans as well as delivery batch sizes to manage inventory and to test different production scenarios. A genetic algorithm was applied to optimize these variables and to reduce costs, delays, and inventory levels. A case study showed that the proposed approach improved the balance between cost, inventory, and delivery time. Zheng et al. (2008) provided an overview of how simulation was used to study supply chains. They explained fundamental concepts related to systems, models, and simulation, and described various types of simulation methods. The paper also reviewed simulation-based optimization techniques and recent advances in supply chain simulation. Finally, it highlighted future trends and directions for applying simulation in supply chain research. Oliveira et al. (2016). presented a meta-analysis on how modeling and simulation were used in supply chains and what future opportunities existed. The authors conducted a systematic literature review and statistical analysis of published papers to understand prevailing practices. Their results showed that modeling and simulation needed closer integration and that more advanced models were needed to capture real supply chain behavior. They also identified a growing trend of combining optimization methods with agent-based simulation. Hybrid approaches that blended theoretical models with real-world data were shown to improve decision-making. Overall, the article contributed to building a clearer framework for advancing modeling, simulation, and decision processes in supply chains.

Becerra et al. (2022). reviewed existing models used for sustainable inventory management in supply chains and provided suggestions for future research. Their goal was to understand how sustainability had been incorporated into quantitative inventory models. The authors analyzed and classified 36 studies based on supply chain structure, environmental focus, problem type, and modeling methods. The results showed that very few studies considered social sustainability, while environmental sustainability received more attention. The review also highlighted the need to include uncertainty in future models. The authors proposed a research roadmap that encouraged future studies to combine economic, environmental, and social goals, employ more integrated decision models, and apply advanced algorithms. Researchers have long studied how to manage inventory for perishable products, which spoil or expire over time. Earlier studies focused on basic ordering rules, but newer research looks at closed-loop supply chains where products can also return for reuse. Hasani et al. (2018). used simulation and multi-objective methods to find effective solutions. Studies showed that response surface methods and desirability functions helped balance costs, risks, and performance. These approaches also provided more robust decisions when dealing with multiple goals and uncertainty. Vieira (2004) described a project that aimed to create a computer simulation to help managers study how well a supply chain operated. The simulation was able to show problems such as the bullwhip effect, where small changes in customer demand caused larger fluctuations for suppliers. The project examined two main measures. The amount of inventory each stage held and how well customer demand was met. The supply chain included suppliers, manufacturers, distributors, retailers, and customers. The first version of the simulation model, developed using Arena software, had been completed and was presented in the study. Belil et al. (2019). examined how to plan a supply chain network, a difficult task because it involved many interconnected components. The authors proposed a hybrid method that combined simulation with mixed-integer linear programming. The supply chain they studied included both discrete and continuous processes, and both needed to be modeled together. First, they developed a discrete-event simulation model to show how the supply chain operated over time. This model was then used to validate whether the planning solution from the optimization model was realistic. The approach was tested on a complex real-world supply chain in a chemical fertilizer plant.

3. Research Design

3.1 Software Components

Various materials and equipment are needed for carrying out any research to make it viable and impactful. We considered a reputed beverage industry in Bangladesh to do our research here. So, the material and equipment, which is extensively related to the supply chain in the beverage industry, will be taken into account. SPSS and Microsoft Excel are used in this study.

3.2 Design Flow Diagram

The monthly production rate must first be analyzed as we would like to build up linear regression. Therefore, we consider four years in a row to develop our simulation-based supply chain model integrating linear regression. We aim to minimize the potential risk and build a sustainable model. Figure 1 is given to show the whole approach.

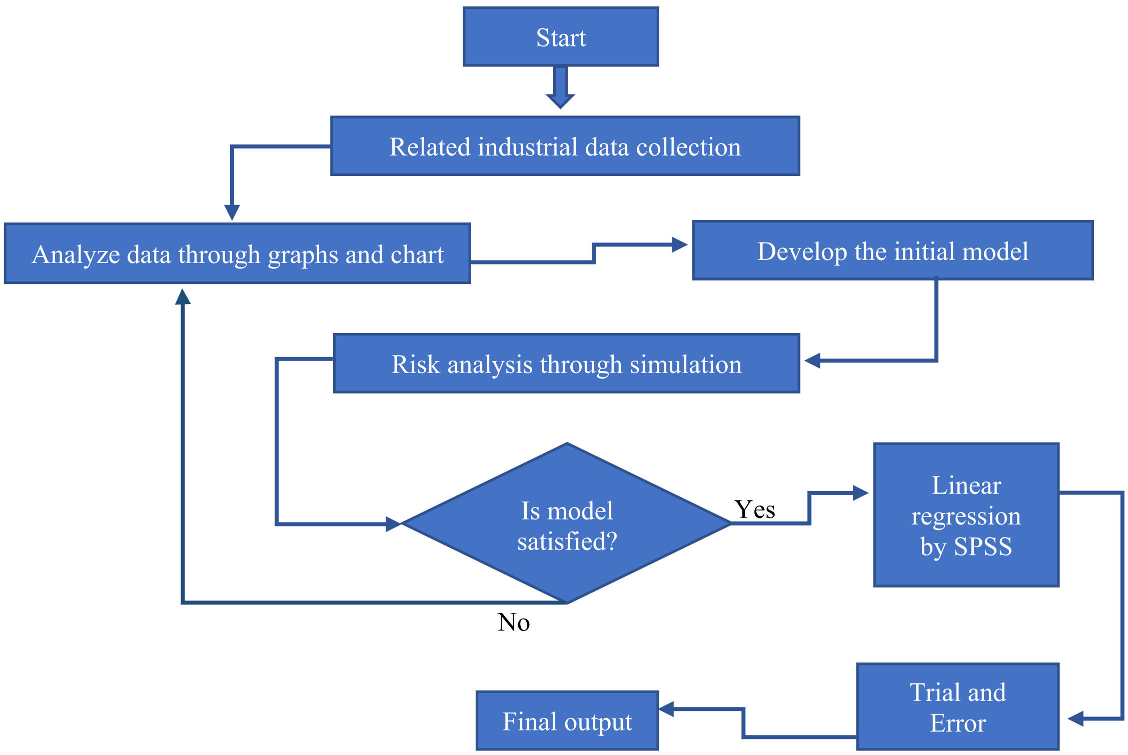

Figure 1. Step by step approach for the study.

4. Methods

4.1 Monthly Production Dynamics

From 2021 we can observe that the model plan accurately for the beverage industry. Here, we can see that their high production rate month is June and September, like as 6.60 and 11.20. Their lowest production month is January which is 0.40 million units in an average. So, we considered that the company target the summer month because this month's customer demand is very high. January is the lowest production rate because this is the winter season. Usually, these months' demand is low. This variation occurs due to several factors, such as customer demand, marketing strategies, the weather of the region etc. Table 1 shows the month wise production rate in million bottles for four-year range.

Table 1. Month wise production rate in million bottles for four-year range.

	Rate of Production (Million)						
Month	**Year 2021**	**Year 2022**	**Year 2023**	**Year 2024**	**Max**	**Min**	**Avg**
January	0.40	0.80	2.50	0.16	2.50	0.16	0.97
February	1.20	4.10	3.50	0.30	4.10	0.30	2.28
March	2.20	6.50	4.50	0.38	6.50	0.38	3.40
April	4.20	4.80	8.50	0.46	8.50	0.46	4.49
May	5.80	5.80	11.00	2.50	11.00	2.50	6.28
June	6.60	7.00	2.50	1.16	7.00	1.16	4.32
July	3.00	6.90	3.60	2.10	6.90	2.10	3.90
August	6.10	7.90	4.80	1.22	7.90	1.22	5.01
September	11.20	12.50	6.00	2.40	12.50	2.40	8.03
October	3.20	9.50	3.50	0.64	9.50	0.64	4.21
November	1.00	2.50	4.00	0.50	4.00	0.50	2.00
December	2.80	2.00	4.50	0.34	4.50	0.34	2.41

The Figure 2 depicts the monthly trend in data values from 2021 to 2024. Each month has four bars reflecting the different years, allowing for easy comparison throughout time. Overall, the graph shows a constant seasonal trend over the four-year period. The values begin very low in January, averaging 3 million to 4 million units, and steadily rise over the first months of the year. By March and April, the values had increased dramatically, reaching roughly 8 to 9 million units. The highest values are observed in September, when all four years peak at roughly 12 million to 13 million, showing that this month regularly has the most activity or production.

Across all four years, the general pattern is quite consistent, indicating a steady and predictable cycle. Minor deviations occur, such as slightly higher mid-year values in 2023 and marginally lower year-end values in 2024, but they are not significant. Because of war, the production of beverage dramatically drops in many countries like as Bangladesh, Saudi Arab, Arab emirates etc. This suggests that whatever drives these numbers has a stable yearly pattern, rising in the middle of the year and decreasing down towards the end.

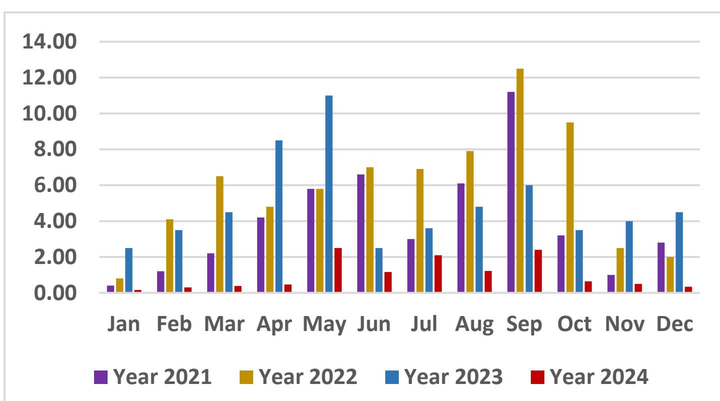

Figure 2. Integrated Production Rate for each year.

From 2022 we can observe that the model plan accurately describes the beverage industry. Here, we can see that their high production rate month is September, like as 12.50. Their lowest production month is January which is 0.80 million units in an average. So, we considered that the company target the summer month because this month's customer demand is very high. January is the lowest production rate because this is the winter season. Usually, these months' demand is low. This variation occurs due to several factors, such as customer demand, marketing strategies, the weather of the region etc. Figure 3 and 4 shows normal P-P regression plot of regression standardized residual and regression scatterplot respectively.

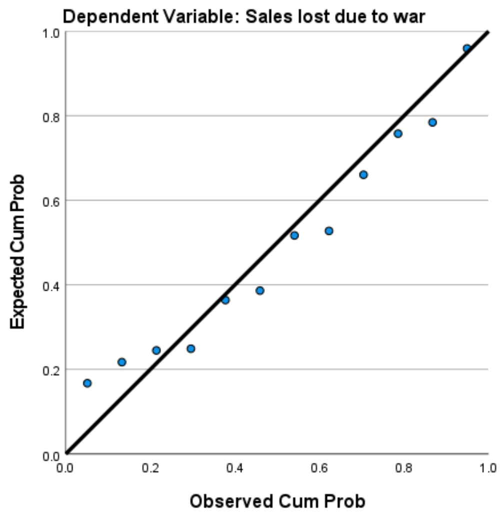

Figure 3. Normal P-P regression plot of regression standardized residual.

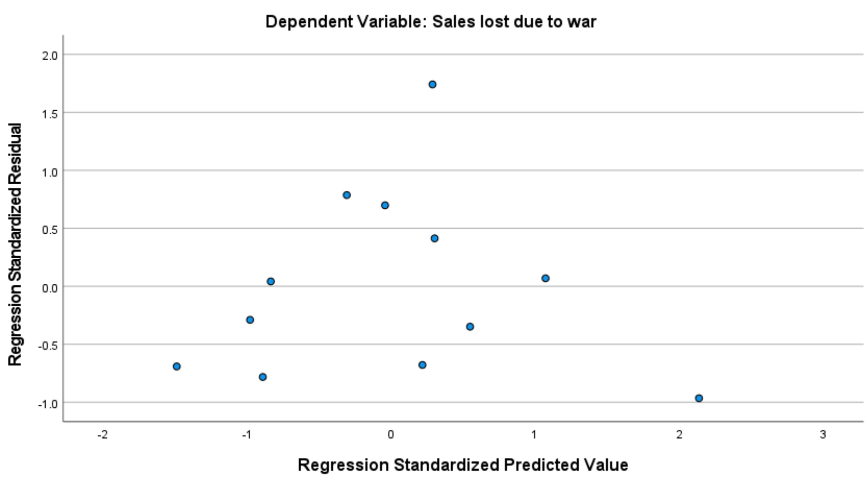

Figure 4. Regression Scatterplot Standardized residuals for wartime sales loss forecasts

Table 2 shows monthly sales losses caused by the war in the current year and provides a projection of expected sales losses for 2026. Each month lists how much revenue (in millions of dollars) the company has already lost and how much it is predicted to lose next year. The projected 2026 losses generally follow similar patterns to the current losses, with some months expected to increase and others expected to decrease slightly. This helps the company anticipate financial impacts and plan accordingly.

Table 2. Sales lost due to war and projection of lost sales for coming year.

Month	Sales lost due to war ($ Million)	Prediction of lost sales ($ Million) 2026
January	0.41	0.58
February	0.78	0.77
March	1.11	0.91
April	1.16	0.99
May	1.32	1.30
June	1.52	1.08
July	1.19	1.08
August	1.06	1.15
September	1.35	1.60
October	0.89	1.06
November	0.65	0.73
December	0.55	0.75

4.2 Service level optimization

Simulation using the Monte Carlo method is an effective way to model and test the uncertainties in an inventory management system. It is based on the idea that random sampling can represent the behavior of complex systems that change over time. In this case, demand and lead time are uncertain and vary from one period to another. Instead of producing a single forecast, the Monte Carlo method draws random numbers from defined probability distributions to create many possible scenarios. The random values in the “RD for Demand” and “RD for Lead Time” columns are mapped to cumulative probability tables to generate actual demand and lead-time values. Each simulated period, or cycle, represents one run of the experiment, meaning that demand, inventory levels, and potential shortages differ from one cycle to the next.

By repeating the technique many times, the simulation captures a wide range of possible inventory scenarios, showing how stock levels shift under different demand conditions. This repetition allows the model to estimate expected ending inventory, average shortage amounts, and the probability of stockouts, offering meaningful insight into system performance. According to the law of large numbers, as the number of simulated cycles increases, the results begin to stabilize. The observed values tend to align closely with the expected averages. This convergence highlights a key strength of Monte Carlo simulation: its ability to represent complex probabilistic behavior through repeated random sampling.

The Monte Carlo simulation is a valuable decision-making tool because it reveals not only the most likely outcomes but also the inherent variability and risk within the system. In inventory management, it provides a mathematical structure for determining optimal reorder points, economic production quantities (EPQ), and safety stock levels, aiming to strike a balance between service reliability and cost efficiency. By applying this approach, the simulation produces results that offer a realistic and statistically sound representation of how the inventory system behaves under uncertainty, rather than relying on fixed or overly simplified assumptions. Table 3 presents the random digit assignments used for monthly demand. Table 4 shows random digit assignment for run time in production.

Table 3. Random digit assignment for monthly demand.

Month	Probability	Cumulative Probability	RD	Demand
Jan	2%	2%	1-2	1
Feb	6%	8%	3-8	3
Mar	8%	15%	9-15	4
Apr	9%	25%	16-25	5
May	13%	38%	26-38	7
Jun	9%	47%	39-47	5
Jul	8%	55%	48-55	4
Aug	9%	64%	56-64	5
Sep	17%	81%	65-81	9
Oct	9%	91%	82-91	5
Nov	4%	94%	92-94	2
Dec	6%	100%	95-100	3

Table 4. Random digit assignment for run time in the production

Month	Probability	Cumulative Probability	RD	Lead time
Jan	5%	5%	1-5	1
Feb	5%	10%	6-10	1
Mar	5%	15%	11-15	1
Apr	5%	20%	16-20	1
May	15%	35%	21-35	3
Jun	10%	45%	36-45	2
Jul	15%	60%	46-60	3
Aug	10%	70%	61-70	2
Sep	15%	85%	71-85	3
Oct	5%	90%	86-90	1
Nov	5%	95%	91-95	1
Dec	5%	100%	96-100	1

The dataset shows that final inventory levels fluctuate from zero to positive values, indicating periods of sufficient stock as well as shortages. At times, the shortage amounts rise above zero, demonstrating that demand can shift quickly and available inventory is not always enough to meet it. Delivery times of EPQs and lead times also vary randomly, reflecting real-world replenishment behavior. Monte Carlo methods support decision-making under uncertainty by illustrating a range of possible outcomes. They can be used to estimate economic production quantities or reorder points that help prevent inventory levels from becoming too low or excessively high. These variations make the approach highly persuasive for understanding system behavior.

Table 5. Performance measures in the simulations.

Category	Outcomes
Average ending inventory	1.125
Number of days shortage	31.000
Average beginning inventory	6.646
Service level	83.07%

The Table 5 shows that an inventory simulation started with an average of 6.646 units and ended with an average of 1.125 units, which means that the stock was used well. The system had 31 days of shortfalls because demand was higher than what was in stock. Client demand was met 83 times out of 100, or 83.07% of the time. Shortages happened 17% of the time. Moderate inventory performance strikes a balance between cost and availability, but there is still room for improvement in customer satisfaction at this service level. These numbers are the results of repeated random sampling in a Monte Carlo simulation. They show the likelihood of demand meeting probability in different uncertain situations.

Random variables such as demand and lead time determine the outcome of each simulation run for every cycle or month. Over a four-year period, the simulation repeats the same procedure to evaluate how well the system performs under uncertainty. By using repeated random sampling, it becomes possible to see how inventory levels evolve, how often stockouts occur, and how frequently replenishment is required. As the number of simulations increases, the averages for shortages and ending inventory become more stable. In principle, running hundreds or even thousands of simulation cycles can produce probability estimates that closely reflect the behavior of the actual inventory system.

5. Results & Discussions

The ability of four control measures to forecast sales loss as a result of conflict in the brand was evaluated using multiple regression. To make sure that the assumptions of normality, linearity, multicollinearity, and homoscedasticity were not broken, preliminary studies were carried out. It is showed that there were no univariate outliers and that every variable in the regression had a normal distribution. Second, an examination of the scatterplot of standardized residuals versus standardized expected values and the normal probability plot of standardized residuals revealed that the residuals' homoscedasticity, linearity, and normalcy assumptions were satisfied. Third, for just one instance in the data set, Mahalanobis distance did not surpass the necessary $\chi 2$ for df = 4 (at α =.001) of 18.82, suggesting that multivariate outliers were not a cause for worry. Fourth, the regression model's four predictors showed comparatively highest tolerances but remained in the tolerance limit, suggesting that multicollinearity would not affect our capacity to understand the model's results.

Together, 2021, 2022, 2023, and 2024 explained 65.70% of the variation in war-related sales losses ($R2$ =.657, adjusted $R2$ =.461, $F (4, 7) = 3.35$, $p < 0.001$). The beta value in 2021 was.238, $p <.001$, the beta value in 2022 was higher (beta =.374, $p <.001$), the beta value in 2023 was lower (beta =.146, $p <.001$), and the beta value in 2024 was.220, $p <.001$). The revenues lost as a result of war scores would probably fall by.374 standard deviation units if we were to reduce the year 2022 by one standard deviation. Figure 5 shows prediction of sales lost for the future year.

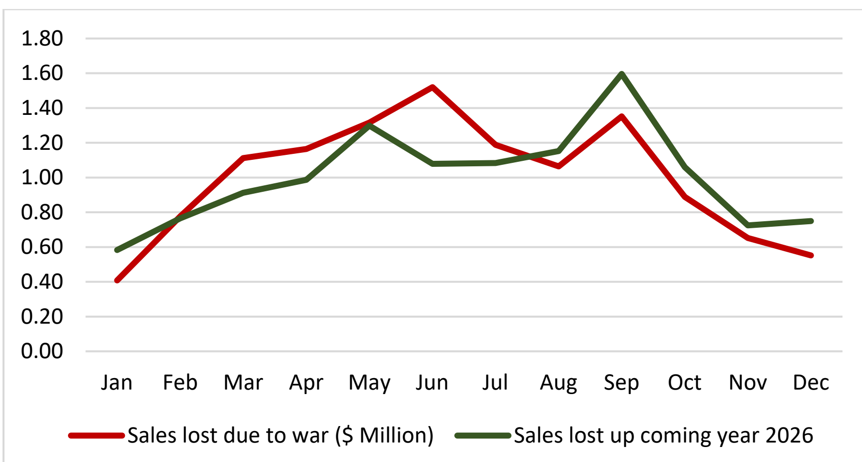

Figure 5. Prediction of sales lost for the future year.

Figure 6 shows the histogram of demand distribution. The chart shows how often different demand levels occurred during the simulation. Most simulated demand values cluster around 5 units, making it the most common outcome, while lower and higher demands appear less frequently. This distribution illustrates the variability in demand and highlights the typical demand level the system is likely to face.

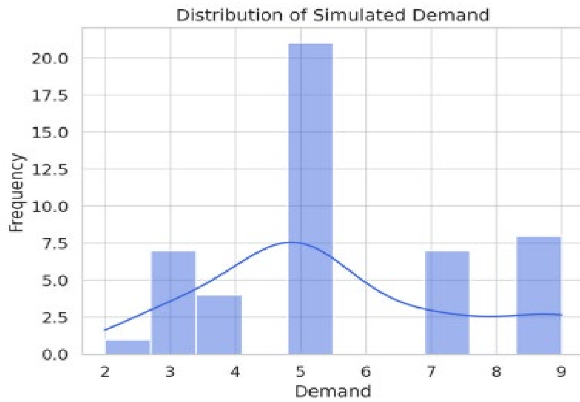

Figure 6. Histogram of demand distribution.

Figure 7 shows how ending inventory levels change across simulation cycles. Inventory frequently drops to zero, indicating repeated stockouts, but occasionally rises to higher levels when demand is lower or replenishment arrives. The fluctuations illustrate how variability in demand and lead time affects inventory availability over time.

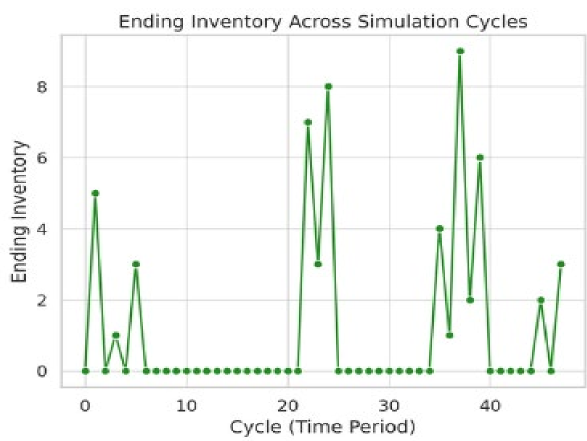

Figure 7. Ending inventory variation across simulation cycles.

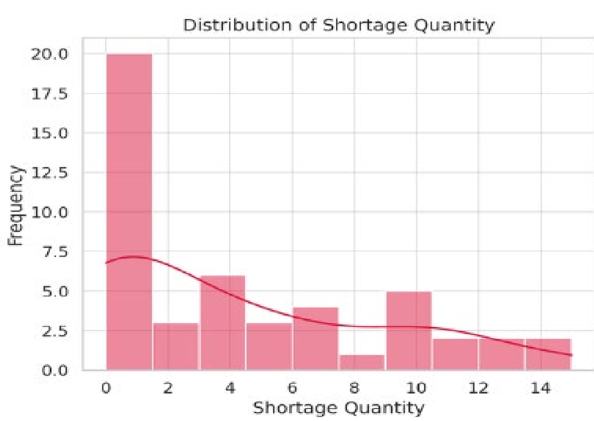

Figure 8. Frequency distribution of shortage quantities.

Figure 8 shows how often different shortage quantities occurred during the simulation. Most shortages are small, clustering near zero, while larger shortages happen less frequently. This pattern indicates that although shortages are common, severe shortages are relatively rare.

6. Conclusion

Simulation is an important tool for testing how well a system works, figuring out risks, and making supply chain operations run more smoothly. This study utilized Monte Carlo simulation and linear regression techniques to model uncertainty, detect potential sales losses, refine inventory-related decision-making, elevate service level performance, and predict forthcoming sales losses. The Economic Production Quantity (EPQ) model was used in addition to this method to find the best amount of production needed to keep inventory levels high while keeping costs low. Furthermore, the sales lost are predicted using linear regression, where the dependent variables are four-year monthly production and the dependent variable is sales lost due to war. This prediction result assisted in designing the inventory simulation model to optimize the inventory system in the Supply Chain Management System. The study demonstrates that adjusting reorder points can significantly mitigate stockouts by emulating fluctuations in demand, lead time, and inventory dynamics. This can help businesses lose fewer sales and make customers happier because products are easier to find, orders are filled faster, and changes in demand are handled faster. These improvements further strengthen industry capability by reinforcing financial stability, supporting innovation, enhancing operational efficiency, and increasing competitiveness. The findings confirm that the combined application of Monte Carlo simulation and the EPQ model provides useful concepts for reducing sales losses and meeting customer demand more effectively.

7. Future Work

The study can be expanded by using data from additional years to better capture long-term patterns. Other simulation methods could also be applied to compare results and improve accuracy. Future work may further refine inventory policies and enhance decision-making under uncertainty.

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