ISSN 1846-6168 (Print), ISSN 1848-5588 (Online)
https://doi.org/10.31803/tg-20241216050348

Original scientific paper
Received: 2024-12-16, Accepted: 2025-01-13

Enhancing Inventory Simulation Models for Retail: Addressing Design Flaws Using Arena Software

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Abstract: This study aims to propose an improvement to the simulation model of inventory management system in retail stores developed in the reference paper. This paper analyses the process flow of the original simulation model and also conducted an interview with a retail store owner. This study uses the customer arrival and customer demand distribution patterns and most of other parameter data from the reference paper. Both the original and the enhanced models are optimized for the lowest demand lost. Arena simulation software was used to perform the simulations for both models. The results of both models were then compared. When analysing the original model a design flaw was found. In the event where a customer come and demand a quantity that is more than the current inventory level, the original model will only report a stockout without reordering the product. If this event happened while there is no undelivered order to refill the stock, then all the following demand would go to the same route. Hence, from there on, no order will be fulfilled. In the interview, the store owner also shares about a part of the original model which is not a common practice, such as not offering the remaining stock to the customer who needs more than the current inventory level. The new simulation model was then developed. This study addresses critical design flaws in an inventory simulation model for retail stores. By leveraging insights from field interviews and utilizing Arena software, an enhanced model was developed, achieving a 26 % reduction in lost customers and a 35 % improvement in demand fulfilment. The findings provide actionable insights for optimizing inventory management systems in retail environments.

Keywords: arena simulation; improvement; inventory management; retail; simulation model

1 INTRODUCTION

Inventory management systems (IMS) are central to organizational success because they control flow and costs of inventory and customer reactions. When well implemented IMS should ensure minimum levels of stock out and over stocking while it timely delivers the products. Research shows that strong IMS practices result into improved financial performance and supply chain competitive advantage through reducing inventory related costs and decisions based on customer needs [1, 2]. In fact, it is established that organizations that incorporate these advanced inventory tools receive great benefits in terms of resource and profitability [3].

The retail industry defines a huge number of companies and is considered one of the most promising and highly committed to the world market. The nature of the retail business varies because there are different product categories and distribution types, thus facing problems in the store when demand characteristics change and when the market constantly evolves [4]. Intense focus on retailing has been evident in the past few years and any organisation involved in the retail business requires effective IMS to manage the massive volumes of products and customer expectations. The emergence of this industry underscores the necessity to develop new methods for dealing with this industry's inventory issues, with the aim of achieving performance stability in a constantly changing environment [5].

Another theme common to both IMS research and practice is the application of simulation methods to describe and predict the behaviours of systems and objects. By doing so, it is possible to bench test the changes with a number of realistic scenarios in inventory policies while avoiding the impact of the changes on actual business environment; thus providing ideas on the possible benefits – and drawbacks – of certain changes [6]. Simulation henceforth leads an important role as a decision support tool in inventory management. Simulation technologies are continually used to mitigate the unpredictability and variability in the demand of inventory management systems in retail stores, to perfectly optimize its stock levels and, in particular, to overcome threats of supply chain interruptions. Discrete event simulation (DES) has been frequently applied in analysing inventory processes with a focus on such issues as ordering policies and safety stock, which can be convenient for retailers if different demand patterns are considered [7]. In this way, all dynamic aspects of the system are reflected in DES, and knowing how it is possible to optimise inventory policies in order to decrease the frequency of stockouts and, at the same time, eliminate overstock conditions, the efficiency of the system is increased [8]. Moussavi et al. [9] show that discrete-event simulation can be used in managing uncertainty especially in demand and supply chain systems.

A model cannot represent the real thing perfectly [10]. Inventory models should be expanded incrementally by including the concepts of sustainable and efficient and is typical of the tendency towards more intricate, data-based approaches [11]. When researchers develop simulation models to address these complexities, design flaws may arise due to oversimplifications or inadequate representation of real-world dynamics. For instance, many models fail to capture the interplay between multiple variables, such as pricing strategies, demand elasticity, and lead time variability, resulting in limited applicability to practical scenarios [12]. Furthermore, the lack of accurate or comprehensive data can lead to flawed assumptions, reducing the reliability of simulation outcomes [13]. In some cases, the models are not updated to reflect evolving market conditions or emerging technologies, which can render their recommendations obsolete [14].

Simulation models presented in academic literature have a vast implication in theoretical and management practice. Thus, they need to be verified and validated against the current customer behaviour. However, research on evaluating and improving a simulation model, especially in retail store's inventory management system, is still scarce.

Therefore, the current study aims to build upon the simulation model of IMS outlined by [15] by pointing to its design flaw as well as areas of improvement. Consequently, this paper seeks to increase the understanding and improvement of the simulation model through enabling practical solutions that correspond to the research question: In what way can the simulation model be enhanced? It is believed that this endeavour will be of successful interest to the academia as well as the retail practitioners by offering fresh insights to existing gaps in literature.

2 LITERATURE REVIEW

2.1 Inventory Management System

Inventory systems are a must to have in any business as they ensure appropriative stocking and storage, minimizing on over stocking, or running out of stock. With the help of digital technology, the visibility of supply chain is extended. It will also certainly help the company to track better and improve the time of delivery which of course leads to improved levels of customer satisfaction [16]. Concerning the realisation of the contemporary inventory systems, perhaps due to the boost in the methods of data processing in decision-making processes, inventory performance has improved in terms of precision and reaction time in supply chain networks [17]. In particular, a strategic management of inventory impacts cost control and subsequent customer satisfaction, which are elements critical to diverse industries.

The ever-changing nature of markets has resulted to updates in the use of more appropriate technology of real-time inventory and metrics. Examples include IoT connected inventories through which a business can easily gather fresh knowledge and modify its stock turnover frequency to meet the changing needs while at the same time reducing holding costs [18]. This innovation is most useful in organizations that have inconsistent demand characteristics including the retail and e-commerce businesses.

Research indicates that the deployment of big data, coupled with predictive analytics and machine learning models, complements the traditional inventory management procedures that are actually a part of inventory management and increase the efficiency of demand forecasting of new inventory [19]. These models are useful where the ecosystem structure is larger, and the consumer wants could differ greatly.

Fig. 1 was generated using VOSviewer based on a bibliometric data analysis on the keywords "inventory management system" within Scopus database. The search results in 368 documents. The colour yellow shows the more recent topics. Besides those related with new technology, the new emerging topics of interest within the scope of inventory management system include sustainability, reinforcement learning, and supply chain resilience.

2.2 Inventory Management in Retail Stores

There is always the emphasis to keep high variety of SKUs, fast turnover of inventory and store inventory location with the customer in mind. It is important to understand that retail is not like manufacturing or even the healthcare sectors, where promotions are rare, seasonality is not a key factor, and the use of physical stores along with online platforms is not a requirement [20]. These factors make the inventory systems require special solutions different from the ones used in other industries.

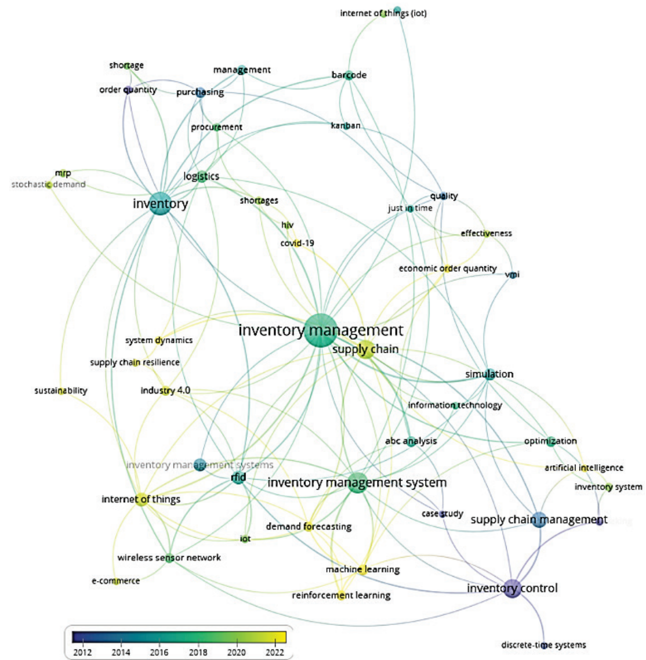

Figure 1 Overlay visualization of keywords co-occurrence

Another difference entails the aspect of quantity and quality of data they manage with regards to the velocities processed. Most retail inventory management depends on POS data and real-time consumer behaviour analysis so that correct restocking techniques are developed. For instance, some retailers such as the grocery stores may work hard to ensure that their perishable stocks are frequently replaced whereas other retail businesses such as the apparel retail stores have to focus on issues to do with high return rates and fashion trends [21]. Another example is different brand loyalty level depends on the product category of the brand being advertised. Where previously brand equity is very strong, current customer can easily seek substitute products for some brands. They would not want to spend time going to another shop in order to purchase what they regard as their own brand [22]. Such behaviour might lead to rising of the number of factors influencing the complexity of the inventory control policy.

The emergence of omnichannel only serves to complicate retail inventory management even more at this stage. Physical and inventory management needs to be in harmony with the digital platform, that requires a strong infrastructure that supports same day updates and cross-channel supply chain execution [23]. Such a high level of integration is not particularly essential in industries like manufacturing as inventory movements are comparatively more efficient and thus more easily predictable.

2.3 Research on Simulation in Retail Inventory Management

Inventory management simulation models are used substantially in retail to forecast the consequences of the corresponding decisions. DES can model and predict different and unstable characteristics of retail operations such as demand and supply changes, and therefore DES especially discrete event simulation is capable of modelling retail operations accurately. These models come in handy because they help retailers to conduct experiments with actual and virtual operations, while not necessarily affecting actual retail stores business.

In the recent past, the use of simulation in the handling of uncertainties has been a focus in many papers. For instance, stochastic models with DES can improve understanding of how to mitigate such risks as the demand shocks, or supply chain disruptions [24]. It is crucial to increase knowledge regarding technologies that facilitate overall business strategy [25]. This capability is especially useful for the retailers dealing with high variability in consumers' behaviour.

The literature also supports the importance of simulation for sustainable retail inventory management. Simulation-based models can evaluate how different approaches toward reducing waste and optimizing energy consumption match company inventory policies with environmentally friendly objectives [26].

2.4 Simulation Software for Inventory Management

Simulation software such as Arena, AnyLogic, and Simio are commonly used in inventory management research and practice. Arena, a leading software for DES, is lauded for its user-friendly interface and extensive library of functions, making it ideal for modelling complex retail environments [15]. However, it requires expertise for customization, which can be a limitation for small businesses.

AnyLogic offers flexibility with its ability to combine DES, system dynamics, and agent-based modelling. This hybrid approach is beneficial for analysing interconnected systems, such as inventory and customer service [27]. However, its advanced features may lead to steeper learning curves and higher costs.

Simio is noted for its graphical modelling interface, which simplifies the creation of simulations. While it is accessible for beginners, its limited scalability for large-scale models can be a drawback [28]. Each software has unique strengths, and the choice often depends on the complexity and specific requirements of the inventory system. Simulation software such as Arena, AnyLogic, and Simio are commonly used in inventory management research and practice. Arena, a leading software for DES, is lauded for its user-friendly interface and extensive library of functions, making it ideal for modelling complex retail environments [15]. However, it requires expertise for customization, which can be a limitation for small businesses.

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Much recent research on inventory management discusses about simulating and modelling the use of technology in inventory management. Simulation models was developed to compare the use of RFID and barcode in manufactures [29]. Positioning technology in the packaging of agricultural products also uses passive ultra-high frequency RFID [30]. Neuroevolution Reinforcement Learning (NERL) framework is created to minimize total system cost in the context of Multi-Echelon Inventory Optimization with Delivery Options and Uncertain Discount (MEIO-DO-UD) [31]. A simulation model was developed for the use of Unmanned Aerial Vehicle (UAV). It simulates the energy consumption difference of UAV under different the flight conditions [32]. Model-based deep reinforcement learning is developed simulating the offline and online environment conditions to optimize inventory control of a new retail product where there the historical data is insufficient [33].

2.5 Arena Simulation Software for Inventory Management

DES employing the Arena has been widely used in inventory management research because of its accuracy and flexibility. The software allows order replenishment cycles and stock out to be effectively modelled, decision makers being able to assess situations in order to come up with better strategies [34].

The key strength of Arena is the capacity to model variation nature of demand and lead time usually encountered in retail environment. Therefore, Arena models can capture real-life random characteristics by integrating stochastic features [35]. This feature makes it a good tool for use by researchers who have an interest in inventory management with an intention of improving the strategies to be used.

The last-mentioned focus on improving the usability of Arena through integration with machine learning algorithms with the possibility of a dynamic adjustment and the continuing improvement of simulation models [36]. These advancements take the application beyond merely an inventory tracking tool.

3 METHODOLOGY

The main objective of this study is to develop a better simulation model for inventory management in retail store. This study uses an existing simulation model reported in a literature as the base model [15]. The authors of the literature used as the reference studied on how the retail store responds to customers' demand with regard to the level of inventory. It includes the procedures of fulfilling customers' demand and the reorder or restock procedures.

The product studied in the reference paper is sugar. Fig. 2 represents the simulation model of inventory management system in the reference paper. It is drawn slightly differently from the one presented in the reference paper to avoid copyright issues. However, Fig. 2 shows the process flow of the simulation model exactly as it is in the reference paper.

- The process starts with customer arrival to place an order (demand). In the arena simulation model, the distribution patterns form the reference paper were used. The distribution pattern for customer arrival is –0.001 + Gamma(0.697, 0.529) while the distribution pattern for customer demand is –0.001 + Expo(51.4). These distribution data are collected from the retail store being studied.

- After the customer place an order, the sugar inventory was checked. If the stock is smaller than the demand, then the shopkeeper will report a stockout and end the process.
- If the sugar stock is larger than the amount requested by the customer, then the transaction is completed.
- After the transaction, the shopkeeper will check whether the remaining stock is lower than the reorder point.
- If the remaining stock is higher than the reorder point, then the process ends.
- However, if the remaining stock is lower than the reorder point, the shopkeeper will place an order to the wholesaler. After a certain lead time, the order arrives at the store and the shopkeeper updates the inventory level.

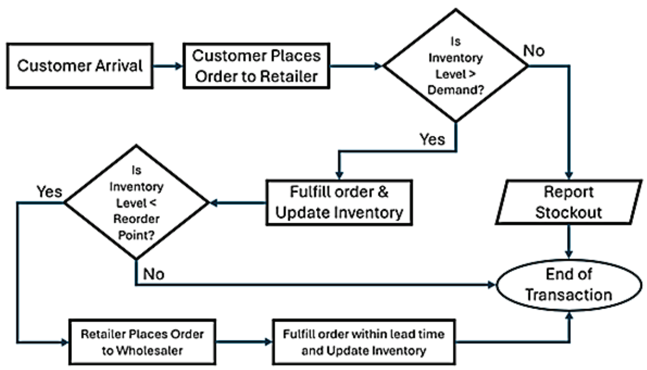

Figure 2 The simulation model of the reference paper [15]

The customer arrival pattern and demand pattern from the reference study are also used in this study. However, there are still some unknown data from the reference paper that make it impossible to re-create the exact results of the simulation model. For example, the initial value of inventory level and the delay time before reordering. This study is more concerned with simulation model improvement rather than the results. Therefore, showing an improvement in the inventory management system using the new proposed simulation model when compared to the reference model previously developed.

This study was conducted following a few steps. First, the authors studied the simulation model in the reference paper. Second, the authors interviewed a retail store owner or shopkeeper regarding the inventory management system there. Third, the new simulation model was developed. Fourth, confirm the new model to the interviewee. Fifth, develop both simulation models using Arena 16.20.03. Sixth, adjusted the parameter values to optimize each model. Seventh, compared the results.

4 RESULTS AND DISCUSSIONS

The Arena Simulation model was then developed. Fig. 3 shows the Arena Simulation model for the original model from the reference paper. It represents the same workflow as the original model in Fig. 2. There are some data needed to be placed into the variables within the model. Aside from the previously mentioned Customer arrival and demand patterns in the methodology section, the reorder point (288) and the reorder amount (667) also follow the reference paper. Both numbers come from the calculation of re-order point and economic order quantity (EOQ) performed by the authors that developed the original model in the reference paper. However, there are some data and information that are not mentioned in the reference article. For example, data such as the delay period from detecting the inventory level to reorder the stock and the initial values of the inventory level are unknown. Therefore, the simulation in this study cannot replicate the original model perfectly.

The simulation is run for 30 replications. Each replication uses 365 days without warm up period. In the reference paper, it is mentioned that the store is open from 08:00 to 20:00. Therefore, the number of hours per day in the simulation is set to 12. The delay for starting the reorder process was unknown from the reference article. In this study, it is set at a constant of 1 hour. The initial inventory level value was also previously unknown. The original model was developed to minimize the demand lost. Therefore, in this study, the authors tested the number manually until the demand lost is minimal. It is found that 50 is the initial value that creates the optimum result.

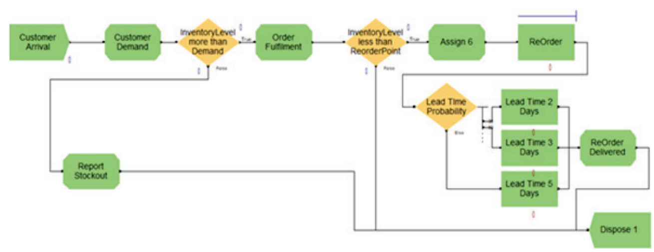

Figure 3 Arena Simulation model for the original model

The reference paper mentioned that the lead time (probability) for reorder delivery is 2 days (0.3), 3 days (0.5), and 5 days (0.2). Since it is not exactly a triangular distribution, in the Arena Simulation model, it is modelled as shown in Fig. 4. The entity passes through a probability choice first and then the lead time delay processes are placed according to the probability outcome.

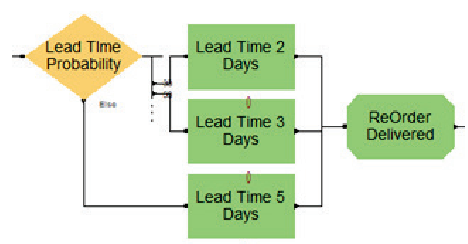

Figure 4 Reorder delivery lead time model in Arena Simulation

The authors simulated the original model of the reference paper and found a design flaw. It is when the shopkeeper checks whether the shop has enough stock to fulfil customer's demand and found out that the stock is not enough, the shopkeeper only report a stockout before ending the process. In the simulation model, the shopkeeper does not place an order to the wholesaler in the event of a stock out. It does not seem like a usual practice in a retail shop. In the event of a stockout is reported and there is no previous order that is undelivered, the stock in the store will remain lacking. As the consequence, when the simulation software is run, the rest of customer demands will always go straight to stockout report, because the inventory is never replenished.

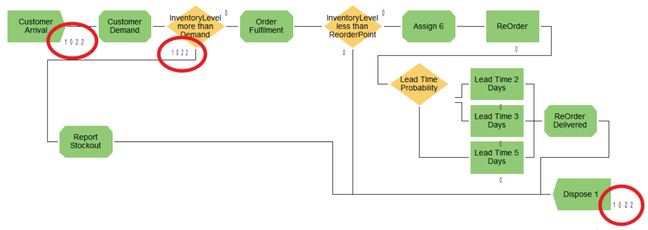

Figure 5 Example when model is run with inventory level initial value = 0

This design flaw will be directly observable when the initial value of the inventory level is set to zero. Fig. 5 shows the results when the simulation of the original model is run with the inventory level initial value is set to 0. It shows that from 1022 customers that come to the store (the left red circle), not one customer's demand is fulfilled. All 1022 is reported as stockout (the middle red circle). However, the flaw might go unnoticed if there is always undelivered order when the stock put was reported within the time limit of the simulation.

Before developing the new and enhanced model, the authors managed to interview a retail store owner. This person is a co-founder of "Toko 27" a retail shop in Semarang City. During the interview, when the authors explained the model used in the reference paper, the store owner gave important feedback. It is highly unusual for a store to not sell anything at all if the store does not have the requested amount. For example, if a customer came and wanted to buy 5 kg of sugar while there were only 3 kg in stock, it was not likely that the customer would walk away emptyhandedly. The shopkeeper usually asks if the customer wants to purchase the remaining 3 kg or not. About 80 % of the time, the customer will purchase the remaining stock, instead of leaving the store with nothing.

The new simulation model was developed taking the design flaw and offering the remaining stock into consideration. Fig. 6 shows the new simulation model. The changes made from the original model are as the following:

- It addresses the need to reorder when stockout is reported (the second decision point → report stockout → places order).
- It also addresses the process of offering the customer the remaining stock when the inventory level is not enough to fulfil the original demand (the third decision point).
- In the case of the customer accepts the offer, the sales will be processed, and the inventory will be updated. In the case of the customer declines the offer, the shopkeeper will report a stockout and then make an order to the wholesaler.
- Based on the interview, the simulation will have 80 % of the customers accept the offer.

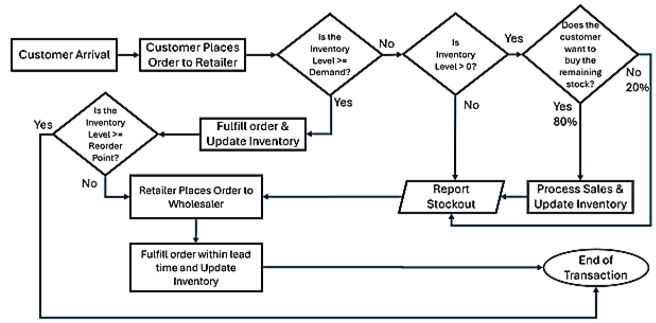

Figure 6 The new and improved simulation model

Fig. 7 shows the Arena simulation model or the new and improved model in this study. It tells the same flow as the new model in Fig. 6. All of the parameter values used in the simulation variables of the new model are the same as the ones used in the original model, including the distribution patterns, initial value of inventory level, re-order point, re-order amount, and time delays. The simulation was also run as much as 30 replications, each uses 365 days limit.

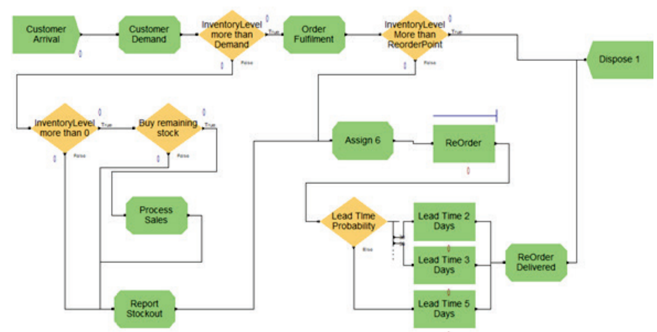

Figure 7 Arena Simulation model of the new and improved model

The next step is performing a comparison analysis. Tab, 1 shows several results of the two models as 30 replications were run in the arena simulation. The complete statistical data are shown in Tab. 2. The study shows an improvement in the service level by 1.25 % from a 26 % lower number of lost customers. It means that the new model really can reduce the number of customers that go empty-handed. The potential loss of sales is also lower with the new model by 35 %. It is caused by the additional activities of offering the customer the remaining stock instead of just sending them away and look for the good in another store. The new inventory management model maximizes the revenue of the store and arguably reduce the level of customer dissatisfaction.

Table 1 Results comparison of the two models

Parameters	Original Model	New Model	Improvement
Service Level	0.9608	0.9728	1.25 %
Lost Customer	39	29	26 %
Lost Demand	2,908.00	1,898.00	35 %
Total Number of Re-orders	79	74	6 %
Total Inventory Cost (INR)	21,11,880.50	19,78,280.50	6.33 %

Using the new model, the number of times which the store needs to re-order is also lowered by 6 %, thus reducing the annual ordering cost by INR 200 and unit cost by INR

1,33,400. Finally, the total inventory cost is also lower by 6.33 % with the new model. The total inventory cost is calculated using the values from the reference paper. The authors of the reference paper use Indian Rupee (INR) to calculate cots and price. Ordering Cost (*Co*) = INR 40/order, Holding Cost (*Cc*) = INR 3/unit and the Unit Cost (*Cu*) = INR 40.

The Total Annual Inventory cost is calculated using the formula $((D/Q)\cdot Co + (Q/2)\cdot Cc + D\cdot Cu)$ where D represent Demand and Q represent Volume per order (667). (D/Q) is the same as the total numbers of reorders that is shown in Tab. 1. The overall results provide evidence that the new simulation model contributes to raising the inventory management performance. The overall saving from lower cost of inventory is INR 1,33,600. Additionally, the customer satisfaction will increase due to the increase in service level and lower number of customers that leave the store empty handedly. An increase of satisfaction might deliver a positive effect to future sales from an increase of customer loyalty and providing word of mouth referral which will attract new customers.

Table 2 Statistical Data from 30 Replications of Model Simulation using ARENA Software

Repli-cation No.	Count Customer Arrival		Count Customer Lost				Count Reorder		Lost Demand	
				Enhanced Model						
	Original Model	Enhanced Model	Original Model	No Stock Lost	Refuse buy Remaining Stock	Total	Original Model	Enhanced Model	Original Model	Enhanced Model
1	919	968	12	19	0	19	77	68	1,136.92	1,483.48
2	960	982	36	39	1	40	79	75	2,562.31	2,734.54
3	1,015	950	32	24	1	25	82	64	2,903.82	1,675.61
4	977	952	36	31	2	33	71	64	2,440.21	1,820.33
5	972	964	19	27	1	28	72	68	1,482.70	1,705.35
6	941	926	30	37	1	38	70	61	1,853.57	1,728.58
7	1,004	1058	52	26	3	29	79	72	4,719.74	1,922.73
8	1,018	953	40	12	3	15	99	75	3,202.61	2,151.68
9	976	970	40	7	2	9	76	68	2,344.18	857.91
10	967	993	41	37	1	38	91	88	3,181.99	3,150.06
11	991	992	39	43	0	43	82	81	2,936.73	2,678.73
12	1,008	959	46	28	1	29	76	65	3,595.02	1,835.42
13	1,034	994	55	19	0	19	77	79	4,196.38	1,345.74
14	1,034	1073	46	46	1	47	90	84	3,715.95	2,857.12
15	1,055	1000	30	42	1	43	76	92	2,086.42	2,377.52
16	1,048	1066	54	29	1	30	84	79	3,637.29	2,176.20
17	993	1014	33	14	3	17	81	74	2,889.05	1,281.14
18	1,011	1025	37	27	1	28	80	79	2,748.64	1,822.82
19	993	1020	45	25	0	25	74	72	3,921.50	2,335.41
20	985	1043	39	28	2	30	77	86	3,174.85	1,799.37
21	967	977	34	28	0	28	88	73	2,733.42	1,699.38
22	1,007	969	47	32	0	32	82	80	3,403.68	1,682.52
23	1,006	976	38	28	0	28	80	77	2,915.09	1,589.50
24	968	1058	50	24	5	29	73	72	3,956.55	2,422.75
25	934	928	32	24	0	24	66	58	2,458.79	1,287.10
26	1,131	1053	55	26	0	26	82	83	3,758.67	1,295.62
27	954	987	58	27	2	29	73	66	3,798.90	2,669.33
28	1,036	983	27	20	0	20	81	83	1,795.27	1,425.24
29	930	960	43	24	2	26	75	65	2,634.04	1,208.69
30	986	967	21	27	2	29	76	68	1,066.61	1,910.58
Rounded Average	994	992	39	27	1	29	79	74	2,908.00	1,898.00

While the results of the new model for retail store inventory management system seem promising, the study is limited to a single dataset. The original research studied a grocery type retail stores and this study uses the data from the original research. The inventory management system model might be different for other types of retail shops. For example, it is quite rare for a customer to purchase more than one microwave in an electronic retail store. In a beauty retail shop, it is also rare that a customer purchase more than one lipstick of the same colour. Besides, in a beauty retail shop, it is easier for the seller to persuade the customer to pick another colour of lipstick the requested colour is not available. Retail stores that sell musical instruments, sport related products, or even pet shops have their own specific activities that might need a different approach in designing their inventory management system.

However, with the critical points are offering the remaining stock and not overlooking the moments to replenish the stock, there are also some types of retail stores that operate similarly with grocery stores. For example, PET food and sand for cat litters in a pet supplies store, raw materials in restaurants or cafes, office furniture retail stores, and many more. These types of stores will benefit from using the new model developed in this study.

The model in this study still has some weaknesses. First, Arena simulation software assumes the customer arrival and demand patterns as a continuous distribution pattern, while in the reality they are not. People do not visit a grocery store and ask for 0.36 kg of sugar like they do not ask for 1.22 Liter of cooking oil. Second, for many types of goods, the distributor set a minimum order or sell the good in a package with a certain quantity. For example, a box of 12 packs of 1 kg of sugar. In this case, the reorder can only be made in multiples of 12 kg. Third, it is also unusual for a retail shop to order instantly whenever the stock is lower than the re-order amount. Unless the supplier can deliver quickly or urgently required, it make more sense if the order to supplier is made daily after closing the store. Due to these weaknesses and maybe many more, although the simulation results can offer a valuable insight for decision making in inventory management, the store manager's intuitions might also have an important role in inventory management, especially in a non-normal condition of the market.

5 CONCLUSIONS

This study enhances an inventory simulation model for retail stores, addressing a significant design flaw that hindered efficient stock replenishment. The improved model reduces lost customers by 26% and lost demand by 35%, demonstrating significant efficiency gains. These findings underscore the importance of iterative model improvements and highlight the value of simulation tools like Arena in addressing real-world challenges. This study also contributes to the literature by showing the need to review the models presented in published articles and to continuously improve the existing model.

The authors of this study acknowledge that the original inventory management model for retail stores developed by the authors of the article referred to has already contributed a lot in improving the existing system in the retail store being studied. Therefore, the improvement of the financial performance of the inventory management system from the new model may seems too little. However, the common goods in retail stores usually have a low profit margin. Having the annual inventory cost cut by 6.33% is quite significant for the retail store profitability. Therefore, the new model is beneficial for the inventory management practitioners.

The inventory management system in one company is most likely different from another. Business and management practitioners can always try to improve the existing model to get more desired results for a certain company. Future research should explore the model's application to diverse retail contexts, integrate additional factors such as customer behaviour and seasonal trends, and leverage advanced simulation technologies to further enhance inventory systems.

Acknowledgement

The authors are grateful to the shop-owner for the interview and for giving many valuable insights. Due to privacy reasons, the name of the store mentioned in this study for the interview is not the real name. Other data and information from the store owner used in this paper are as it is mentioned in the interview.

Data Availability

All the data and information needed to reproduce this study are already mentioned in this work.

Authors' Contribution

Daniel Lukito: Conceptualization, Methodology, Writing - Original Draft, Formal analysis. Andi Kusdiana: Validation, Writing - Review & Editing. Fergyanto E. Gunawan: Supervision, Review. Rida Zuraida: Supervision, Review.

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