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USING SIMULATION TO DETERMINE THE REORDER POINT UNDER UNCERTAINTY OF A RETAIL STORE

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Abstract
This study uses the discrete-event simulation approach to determine the reorder point of a retail store based on an acceptable service level under uncertainty in demand, lead time, and product damage. The proposed model is applied to A1–A12 products in a retail store under study where the owner requires a service level of at least 90 %. The model variables are both deterministic (i.e., order quantities, daily inventory cost per unit, purchase cost, and unit selling price) and probabilistic (i.e., client demand, lead time, and product damage). A simulation technique is used to describe the distribution of the probabilistic parameters and to produce them randomly. The profit and customer service simulation results determine the retail store's inventory policy. Since the retailer decided on the *ROP* based on the simulation results, it has an impact on 1) reducing the total daily inventory of A1–A10 by 23.0 %, which would increase storage space for the additional products A11 and A12 to their sales, 2) increasing total daily profit of A1–A10 by 2.9 %, and 3) reducing total annual product damage numbers of A1–A10 by 22.2 %.
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Key Words: Discrete-Event Simulation, Inventory Management, Reorder Point Determination, Uncertain Demand, Uncertain Leadtime

1. INTRODUCTION

Every business, whether manufacturing or trading, must have stock (i.e., raw materials and completed items) to ensure prompt customer product delivery. Stock preservation is used to ensure smooth operation and the provision of good services to customers. Customer satisfaction, as expressed in terms of customer service level, is critical to the retail sector's success since it is a customer-facing industry with fast-moving products. However, there may be challenges with ordering or storing adequate products due to pricing rises.

This study is motivated by a retail store where the owner needs to sell new products within the storage space limits while some original products have more than demand. To maintain an appropriate balance between cost management and customer service level and to enhance the opportunity of profiting from new items, it is crucial to store a reasonable amount of inventory [1]. Many studies focus on service-level management, the reorder point (*ROP*) and acceptable service levels must be considered [2, 3]. The *ROP* indicates a reasonable point of replenishment indicated by the remaining inventory to achieve an acceptable service level. The principle of fixed order quantity systems is used for controlling inventories to minimise the annual inventory cost and to specify appropriate safe levels of stocks to maintain customer service levels. The time to derive stock items after order is known as the lead time, and the quantities ordered to respond to customer demand are defined to calculate the *ROP* [4].

Demand and lead time are assumed as known variables in the basic model to determine the *ROP*, having no uncertainty [5, 6]. However, demand and lead time are commonly represented in probabilistic terms [7-11]. Since the simulation model can explain uncertain events arising in the system using a probability distribution [12-16], this approach is suitable for determining the *ROP*. It can reduce the risk of variation in inventory policy by performing what-if simulation.

To analyse the inventory policy of a retail store using a simulation approach, Sridhar et al. [17] applied a simulation approach to improve the inventory management system of a retail store under their study. The optimised values of service level, inventory level, and total inventory cost were determined while taking into account inventory behaviour factors (i.e., customer arrival, customer demand, and purchase patterns). Heng and Chiadamrong [18] explored a retail store's different replenishment inventory policies affecting net profits. The simulation-based optimisation model was based on varying cost structures resulting from uncertain operations and product shelf life. The replenishment policy was decided based on a reorder point that maximises net profit. Jackson [19] used discrete-event simulation to determine the replenishment inventory policy of a retail store under limited inventory capacity. Maximising profit was an indicator to decide the policy affected by uncertain demand size, demand inter-arrival time, and lead time. Kim et al. [20] determined the inventory policy of a supply chain consisting of one supplier and multiple retailers in the system. Kim et al. [20] defined the inventory policy of a supply chain consisting of one supplier and multiple retailers in the system. The parameters used to determine the policy (i.e., lead time and safety stocks) were adaptive changes from demand uncertainty. The satisfied service level of each retailer was their model objective. These studies apply the simulation method to identify the inventory policy based on the optimisation model; however, we use the simulation method as a search algorithm in our work.

The main contribution of our study is the decision model that we suggest utilising the discrete-event simulation approach to decide the inventory policy of the retail store in this study. The *ROP* of a single-item inventory is determined under an acceptable service level since demand, lead time and product damage used in this study are uncertain and not presumed to be a normal distribution (triangular for demand, Poisson for lead time, and binomial for product damage). Additionally, the pseudo-code presented in our study can be used to calculate the *ROP* for other case studies.

2. LITERATURE REVIEW

Simulation is one of the most popular techniques used to select the inventory strategy under uncertainty, identifying a suitable reorder point, order quantity, or order-up-to-level obtained to reduce costs or maintain a satisfactory service level. Both Babaï et al. [21] and Bean et al. [22] used a simulation technique to decide the inventory level identification differing by inventory policies in extreme examples of service sectors. Babaï et al. [21] suggested defining the reorder point of pharmaceutical single-item inventory in the presence of demand and lead time uncertainty. The forecasting approach was used to calculate the number of unpredictable demands. On the other hand, the uncertain lead time was a randomised number with a normal distribution. By varying the aim of customer service level and lead time, the simulation technique developed scenarios in both dynamic and static reorder point controls. They tried to convey the simple process for calculating the dynamic reorder point used in inventory management. Bean et al. [22] considered the inventory management outcomes of alternative inventory policy setup (i.e., reorder-point/order-quantity (r, Q), single-item/single-location (s, S), and hybrid policies on both (r, Q), as well as (s, S) concepts). Based on the ideal value of such indicators, the simulation technique was utilised to pick the policy. A study by Conceição et al. [23] was similar to Babaï et al. [21] in that customer demands were forecast. On the other hand, the reorder point and the number of order quantities were determined as static values. Conceição et al. [23] used a simulation approach to examine the effects of inventory control under specific needs generated from different forecasting methodologies.

Postacchini et al. [24] utilised a simulation technique to choose the healthcare logistic management solutions under uncertain demand based on several criteria in the healthcare industry (reorder point, service level, and available transhipment vans). According to Khoukhi et al. [25], inventory policy in the healthcare industry was based on analysing how the reorder point and order-up-to level affect holding and shortfall costs while considering storage space limitations and customer service standards. The effectiveness of the inventory policy was evaluated using a simulation method while taking unpredictable demand and order frequency into account.

Sezen and Kitapci [26] simulated three levels of demand fluctuation (high, medium, and low) in supply chain management to explore how it affects supply chain inventory outputs (average inventory levels, shortage risk, total inventory costs). Silver et al. [27] established the inventory control parameters of reorder point, order-up-to-level, and review interval to obtain the required value of the customer fill rate and the average time between orders. The simulation was used to create a random sample of demands and to evaluate the outcomes of updating each inventory control factor. Grittner and Valverde [28] presented a model for determining the appropriate reorder point and order quantity using simulation to maintain a high service level in a supply chain with uncertain demand. Pamulety et al. [29] used a simulation approach with a specific supply chain structure, information-sharing strategy, and customer demand factors to study the effects of factors (i.e., reorder level, order-up-to level, fixed order size) resulting from the different determining of inventory policies. The optimal policy was chosen after measuring policy performance using Grey Relational Analysis (GRA). The inventory practices of manufacturers and distributors in the supply chain were investigated by Cuc et al. [30]. The effects on inventory cost and lost demand under unpredictable demands and lead times were analysed using a simulation approach based on varying order quantity and reorder point.

Ghafour [31] used simulation techniques to identify the appropriate safety stock and reorder point in the cement industry's production and maintenance sectors with uncertain demand and lead time. Aljanabi and Ghafour [32] extended Ghafour's analysis [31] by accounting for unpredictable demand during the study's lead period. To provide an advanced service level, Chu and You [33] and Arani et al. [34] estimated the reorder point and order quantity for managing seaport spare parts' stocks under uncertainty in demand and lead time. The inventory management performance is assessed based on inventory costs, including holding, ordering, and shortfall. The simulation results determined the appropriate reorder point and order quantity.

These investigations compare situations from replacing certain and uncertain inventory management characteristics using simulation (demand and lead time). Before using simulations to take into account the inventory strategy, they are also used to determine the distribution pattern for parameters with uncertain values. For example, the supply chain management, manufacturing, maintenance, and service sectors all have access to simulation approaches for inventory management. Depending on the study's goals, several aspects are considered while determining inventory policy. When utilising simulation to analyse inventory policy results from defined significant indicators, such as reorder point or service level, these indicators are frequently obtained from inventory management calculations. In practice, all parameters in our study are based on uncertainty, and the distribution is determined using simulation. Our study aims to establish the inventory strategy of a beverage item in a retail store specified by the *ROP* while maintaining acceptable customer service levels in the face of unpredictability in demand, lead time, and product damage.

3. SIMULATION MODEL

A simulation is useful for dynamically analysing changing variables [12]. The proposed model is based on a discrete-event simulation methodology and is used for finding the solution using Rstudio Cloud software. The 95 % confidence interval of purchasing cost and daily income is computed to validate the model. The default settings shown in the first phase of Fig. 1 determine the reorder point based on the acceptable service level. The value of the first service level obtained by completing the steps in Fig. 1 is used to calculate the acceptable service level boundary described in Fig. 2. As seen in Fig. 3, the customer service level boundary will be compressed until it converges to an acceptable level. Due to the customer service level boundary being so near to the required value, the allowed service level values range will be enlarged to offer additional possibilities, as illustrated in Fig. 4. The proposed model is validated based on a 95 % confidence interval.

3.1 Simulation model for finding service level

Fig. 1 shows the steps for finding the service level using the simulation model, starting with the randomisation of the order quantity at the replenishment point, given the distribution from the Input Analyser of daily demand (*RDe*) and lead time (*RLe*). The number of days (*Nday* = 365 days) and the number of replications (*Nrep* = 1000) are defined for the running simulation model. The initial value of *ROP* is based on the number of order quantities with free delivery, following the retail store's supplier policy in 2019–2021, which is half of the minimum required order quantities (*Nor*) with free delivery. The number of daily inventories on day 1 (In_1) is used to calculate the daily holding cost (*In_U*: USD per unit per day). The product sale price (*Pri_U*: USD per unit), the purchased cost of a unit product (*Pur_U*: USD per unit) and the probability of product damage (*Prob_Da*) are used to calculate income ($Income_j$; $j = 1, 2, \dots, 1000$) and profit ($Profit_j$; $j = 1, 2, \dots, 1000$).

The daily demand (De_i; $i = 1, 2, \dots, 365$) is an integer that is randomised based on the parameters resulting from the fitted distribution, i.e., Round*(RDe)*. The number of products damaged in each replication (N_Da_i; $i = 1, 2, \dots, 365$) is simulated based on a binomial distribution with the parameters of daily inventories (In_i; $i = 1, 2, \dots, 365$) and the *Prob_Da*. The De_i is compared with In_i, which does not include the N_Da_i ($In_i - N\_Da_i$). The lowest value between De_i and $In_i - N\_Da_i$ is chosen to define the number of products that can be sold (Sup_i; $i = 1, 2, \dots, 365$). The daily inventories will be updated after sales (In_{i+1}; $i = 1, 2, \dots, 365$) with the balancing value between In_i, Sup_i, and N_Da_i ($In_i - Sup_i - N\_Da_i$).

Suppose the number of In_i is less than the number of the reorder point (*ROP*). In that case, the items will be ordered as the number of order quantities defined in the starting procedure in Fig. 1. There will be no order during delivery in the lead time (Le_i as the number of order's lead time on day i; $i = 1, 2, \dots, 365$). The value of lead time is randomised based on a defined distribution. It continuously counts down until the delivery date (*Count*). The delivered inventory is filled as the last step of the day (*Fill*) and updated. The values of service level ($SerLv_j$ as the service level of round j; $j = 1, 2, \dots, 1000$) are calculated by the summation of Sup_i (ΣSup_i) divided by the summation of De_i (ΣDe_i). ΣIn_i is the total number of daily inventories in 365 days of round j (In_d_j). The holding cost in 365 days is calculated from ΣIn_i multiplied by inventory cost (*In_C*) of round j ($Inven\_C_j$). The number of products damaged in round j (To_Da_j) is obtained from the total number of products damaged in 365 days (ΣN_Da_i). The purchasing cost in round j (Pur_C_j) is obtained from the total of currently purchased orders (*N_Pur*) multiplied by the *Pur_U*. The total cost in round j (To_C_j) is represented as the total number of $Inven\_C_j$ and Pur_C_j. The ΣSup_i multiplied by *Pri_U* calculates the number of income in round j ($Income_j$). The amount of profit in round j ($Profit_j$) as the difference between $Income_j$ and To_C_j are derived after being completely simulated following the specified number of days and recorded. The model is iterated until the set number of 1000 replications has been completed. The average values are calculated of service level (*Avg_SerLv*). *Avg_Inven_d* is the value of daily inventories. *Avg_Inven_C* is the value of daily inventory cost. *Avg_To_Da* is the value of daily products damaged. *Avg_Pur_C* is the value of daily purchasing cost. *Avg_To_C* is the value of daily total cost. *Avg_Income* and *Avg_Profit* are the value of daily income and daily profit, respectively.

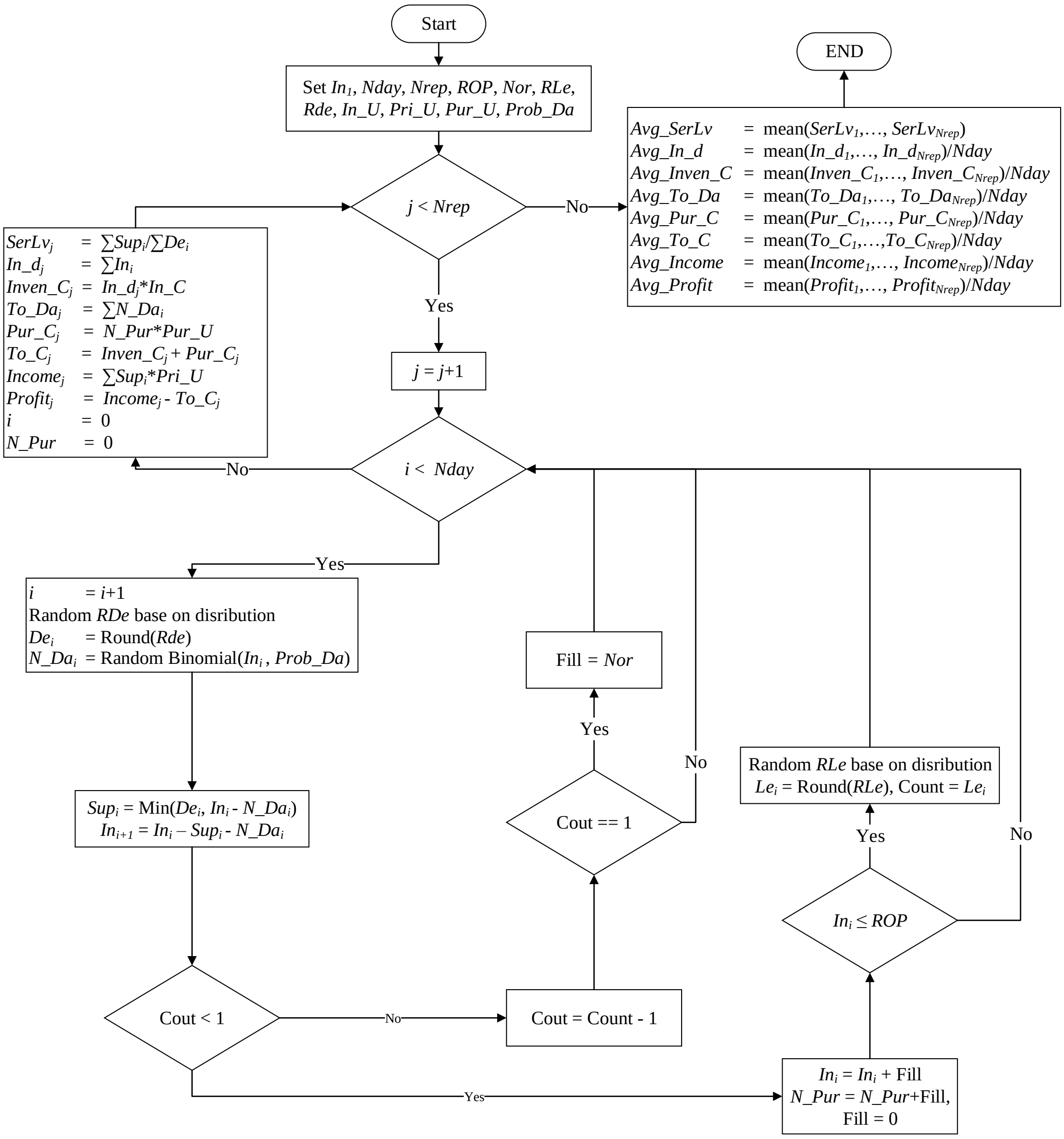

Figure 1: Flow diagram of the simulation model for finding service level.

3.2 Simulation model for finding *ROP*

Fig. 2 shows the steps in finding the reorder point based on the value of service level derived from the following steps in Fig. 1. The result of reorder point (*New_ROP*) is represented in terms of interval values. The service level represents the desired probability of not getting a stock-out that also returns the value in terms of interval value based on the result of the reorder point. The starting step in finding the reorder point is to define a value of the reorder point (*F_ROP*) based on a value of service level (*F_SerLv*) for finding the lower bound (*Min_ROP*) and upper bound (*Max_ROP*) of ROP. The values of lower and upper *ROP* are used to find the new *ROP* based on an acceptable service level (*Ex_SerLv*), following the steps in Fig. 6. The new *ROP* (*New_ROP*) is used to define an *ROP* under interval values of the new *ROP*. It is used to find the average value of service level (*Avg_SerLv*). Both results are recorded and used to decide the final value of *ROP*.

The value of the final *ROP* based on the acceptable service level (*Ex_SerLv*) is used to decide the interval value of *ROP* as *Max_ROP* and *Min_ROP* represent the upper and lower bounds closely covered by the final *ROP* (*Final_ROP*). The average service level is used to determine the confidence interval for decision-making to define the value of *ROP* in practice. The steps for finding the average service level (*Avg_SerLv*) based on the interval value of *ROP* are shown in Fig. 3.

From the following steps in Fig. 3, the *Final_ROP* is used to create the *ROP* boundaries. The *Max_ROP* is defined as a 10 % increase in the *Final_ROP* (1.1×*Final_ROP*), while the *Min_ROP* is defined as a 10 % decrease in the *Final_ROP* (0.9×*Final_ROP*). The first step in Fig. 4 depicts the creation of the *ROP* boundary, and they are recorded ($\mathit{Rec\_ROP}_k$) where k is the number of *ROP*s created in such an interval ($k = 1, 2, \ldots, m$). The average service level, daily inventory, inventory cost, the number of daily products damaged, purchasing cost, total cost, income, and profit based on the values of *ROP* resulting in such an interval are represented as $\mathit{Rec\_SerLv}_k$, $\mathit{Rec\_In\_d}_k$, $\mathit{Rec\_Inven\_C}_k$, $\mathit{Rec\_To\_Da}_k$, $\mathit{Rec\_Pur\_C}_k$, $\mathit{Rec\_To\_C}_k$, $\mathit{Rec\_Income}_k$, and $\mathit{Rec\_Profit}_k$, respectively.

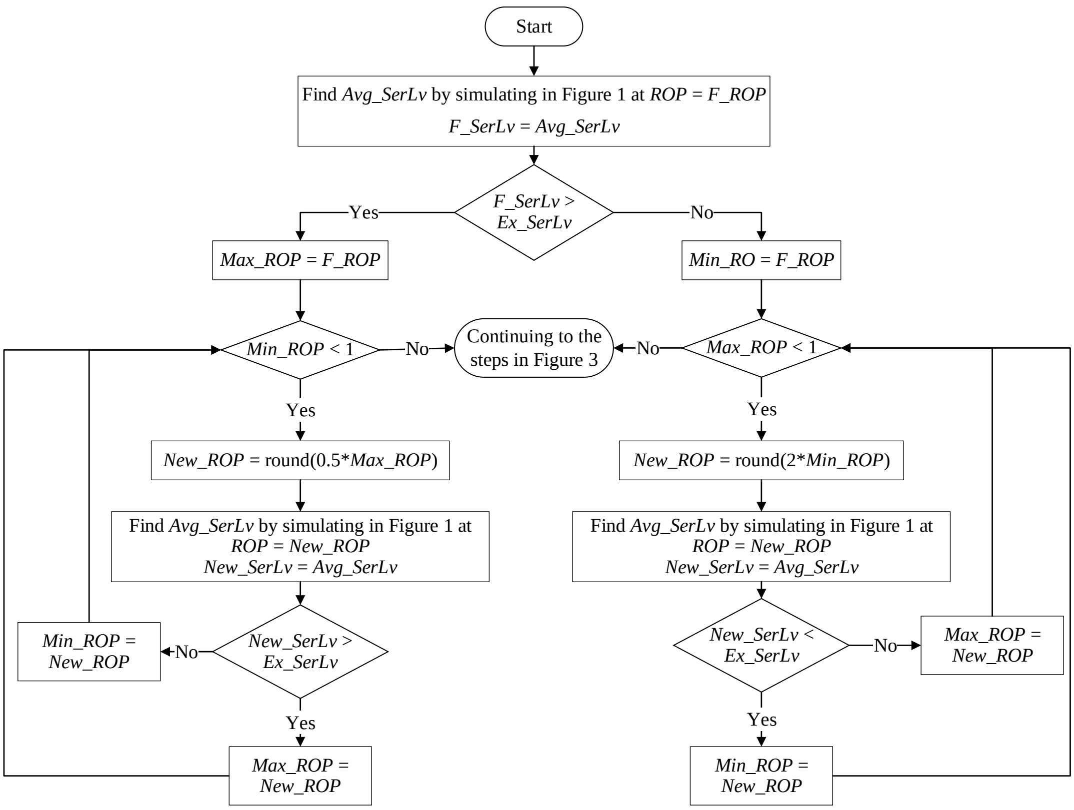

Figure 2: Flow diagram for finding lower and upper bounds of *ROP*.

4. NUMERICAL EXPERIMENTS

The computer hardware (Intel® core (TM) i7-7700 CPU @ 3.60 GHz, RAM 32.0 GB) has been used for the experiments. The data used in the model is sourced from the retail store under study. It is separated into two categories: deterministic (minimum order quantities with free delivery, traditional *ROP*, daily inventory cost per unit, purchasing cost, unit selling price) and probabilistic (consumer demand, lead time, and product damage). The *ROP* for the ten beverage product categories in group A (A1–A10) is determined based on an acceptable service level as low as 90 %, daily inventory, and the possibility of adding new products and increasing profit.

Because customer demands are never recorded, product sales data is utilised as a surrogate. Sales and product damage data in 365 days from 2019 to 2020 and 50 lead time values from 2018 to 2020 are used in the model. Input Analyser shows both consumer demand and lead time in terms of distribution. The *ROP* is simulated using RStudio Cloud depending on acceptable service levels [35].

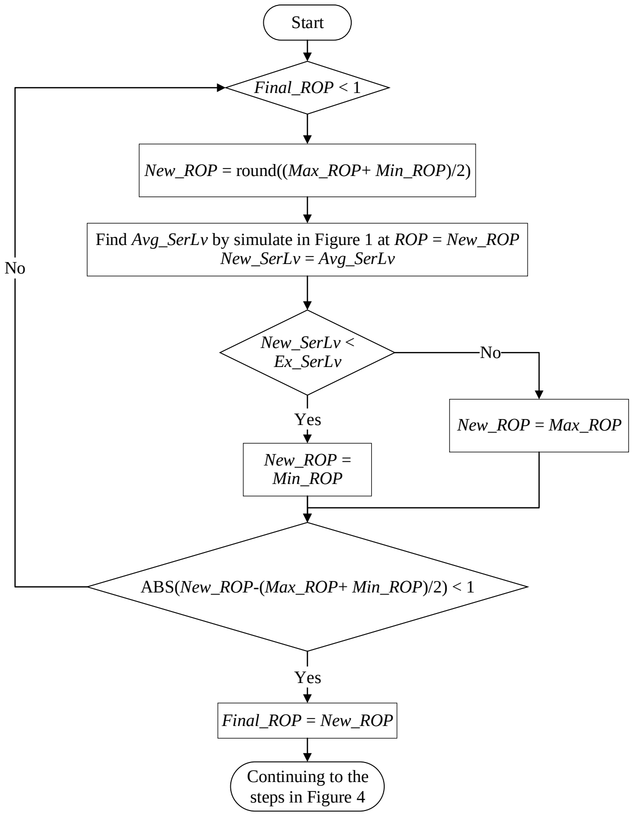

Figure 3: Flow diagram for finding final *ROP*.

The experiment is demonstrated using only product A1 datasets. According to the retailer's supplier policy for 2019–2021, the number of orders with free delivery is the conventional basis for calculating the *ROP* of the retail store. With free delivery of 144 units, the traditional *ROP* is 72 units, which is half of the minimum order quantity (*Nor*). The ongoing simulation model has two parameters: *Nday* (365 days) and *Nrep* (1000 replications). The daily holding cost (*In_U*), which equates to 0.04 USD per unit per day, is calculated using the 144 daily inventories on day 1 (In_1). A product's sale price per unit (*Pri_U*) and the unit's purchasing cost (*Pur_U*) are 1.73 and 0.86 USD, respectively.

Figs. 5 and 6 demonstrate the distributions of customer demand (*RDe*) and lead time (*RLe*). The product damage probability (*Prob_Da*) is considered a binomial distribution with the number of initial daily inventories and the chance of a product loss. The likelihood of a product loss is computed by dividing the average number of daily product losses by the average number of beginning daily inventories. The average number of daily product losses and initial daily inventories of product A1 are 0.1 and 95 units, respectively, with a 0.1 % likelihood of product damage.

According to the *p*-value of 0.47, the parameters of the triangular customer demand distribution (Fig. 5) are the minimum value of 2.50 units per day, the most likely value of 9.01 units per day, and the highest value of 17.5 units per day. The lead time distribution is represented in Fig. 6 as a Poisson distribution, with average values of 4.92 based on a *p*-value of 0.24.

We use the procedures outlined in Figs. 1 to 4 to calculate the *ROP* of product A1, with the interval value findings based on 95 % confidence intervals displayed in Table I.

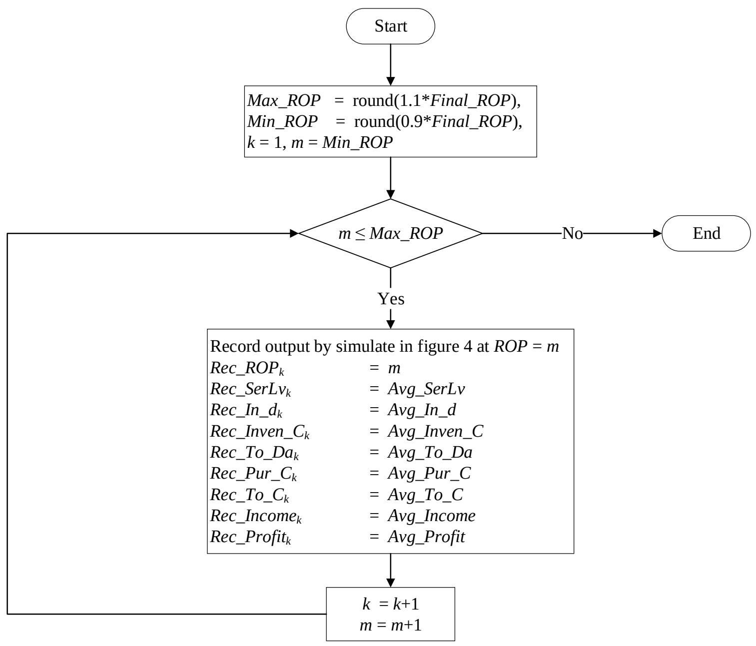

Figure 4: Flow diagram for finding average service level based on interval value of *ROP*.

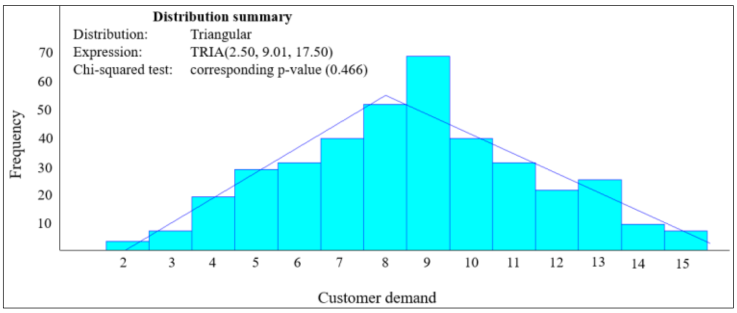

Figure 5: Distribution of customer demand values of product A1.

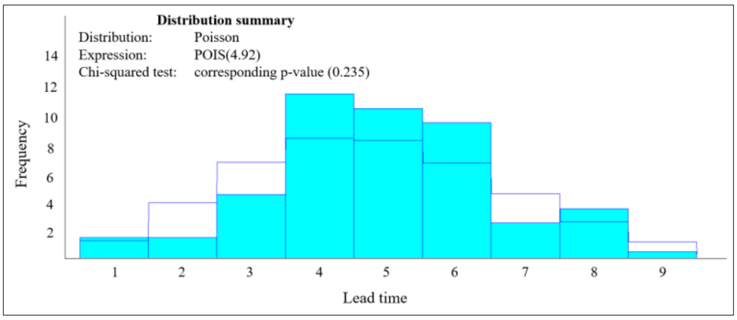

Figure 6: Distribution of lead time values of product A1.

According to Table I, the reorder point should be 40 units per day if the acceptable service level is 90 %. The service level is decreased by 10 % compared to the old value of 72 units per day at the reorder point of 40 units per day. However, there is a 24.5 unit per day reduction in the average daily inventory (25.1 %). There will be additional storage space and a profit increase of 11.4 % if the daily inventory is reduced. To accommodate addition of new items (A11 and A12), the owner of retail store under study decides to change the determination of *ROP* of product A1 from 72 to 40 in 2021. The *ROP* determination based on product A1 is applied to items A2–A10. The data on the initial values of products A2–A10 can be accessed using the link: *https://docs.google.com/spreadsheets/d/1uK5vqybFDkenQLim7CGXL1HOzTF9pRtv/edit?usp=sharing&ouid=104155151998882950218&rtpof=true&sd=true*.

Table I: Indicator values resulting from *ROP* determination.

ROP (units)	***SerLv*** (percent)	***In$_i$*** (units/day)	***Yearly_Da*** (units/year)	***In_U*** (USD/day)	***Pur_U*** (USD/day)	***To_C*** (USD/day)	***Income*** (USD/day)	***Profit*** (USD/day)
39.0	89.6 ± 0.13	72.6 ± 0.15	29.9 ± 0.34	3.14 ± 0.01	7.38 ± 0.01	10.51 ± 0.02	14.96 ± 0.02	4.45 ± 0.01
40.0	90.0 ± 0.13	73.3 ± 0.16	30.2 ± 0.35	3.16 ± 0.01	7.41 ± 0.01	10.58 ± 0.02	15.04 ± 0.02	4.46 ± 0.01
41.0	90.4 ± 0.13	73.9 ± 0.16	30.5 ± 0.35	3.19 ± 0.01	7.45 ± 0.01	10.64 ± 0.02	15.11 ± 0.02	4.47 ± 0.01
42.0	90.7 ± 0.13	74.4 ± 0.17	30.5 ± 0.35	3.21 ± 0.01	7.47 ± 0.01	10.68 ± 0.02	15.15 ± 0.02	4.47 ± 0.01
43.0	91.1 ± 0.13	75.1 ± 0.18	31.0 ± 0.36	3.25 ± 0.01	7.50 ± 0.01	10.75 ± 0.02	15.22 ± 0.02	4.47 ± 0.01
72.0*	98.1 ± 0.06	97.8 ± 0.25	40.2 ± 0.39	4.22 ± 0.01	8.16 ± 0.01	12.38 ± 0.02	16.39 ± 0.01	4.01 ± 0.01

* Traditional value before using the simulation model.

RDe, *RLe*, and *Prob_Da* represent customer demand, lead time, and chance of product damage, respectively, in terms of a probabilistic distribution. In this study, the distributions of *RDe* and *RLe* are Poisson (*Pois*) with real number (λ) parameters, normal (*Norm*) with a mean (μ) and variance (σ^2) parameters, uniform (*Unif*) with minimum (a) and maximum (b) value parameters, and triangular (*Tri*) with lower limit (a), upper limit (b), and mode (c) parameters. *Prob_Da*, *ROP*, *Nor*, *Pur_U*, *In_U*, and *Pri_U* are taken from the same source as the values for product A1 given above.

Based on the findings, the *ROP* is calculated using each product's actual service level and profit advantages from 1st February through 31st December 2021. The choice to establish the *ROP* based on the 90 % service level, which is lower than the traditional method, might be made while taking profit into account. Reduced inventory will follow lower profit as a result of this. Finally, the impacts of a suitable *ROP* continue to raise overall earnings. The results from the actual trials of the choice to establish *ROP*s based on the simulation model's output are shown in the results and discussion section regarding daily inventory and revenue.

5. RESULTS AND DISCUSSION

From using a simulation model to calculate the *ROP* for items A1–A10, based on the acceptable service level as low as 90 % and profit advantages, the retailer utilises the findings to decide at what value to determine the *ROP* in practice in 2021, for example, product A1's results are presented in Table I. By clicking on the link mentioned in section 4, you can see the comparison between the findings of the *ROP*, service level, profit, and daily inventory numbers acquired when utilising conventional and simulation methodologies to calculate the *ROP*. Since the retailer decides to determine the *ROP* based on the simulation results, it influences reducing the total daily inventory of A1–A10 by 23.0 % from 990 units per day to 762 units per day, as shown in Fig. 7, which can increase the storage space by an additional 228 units of new products per day. As the retail owner intends to increase the variety of products sold in the stores, the owner chooses to add new products (A11 and A12) with similar properties (unit sale price and product trend) to products A9 and A4, respectively, where the storage space is available.

Product A7 is a good example to illustrate the consequences of considering this value when estimating the *ROP* in terms of profit advantages. The profit of product A7 is 7.83 USD per day, a decrease in profit of 2.8 % from the traditional determination of the *ROP* of 72 units. This profit is determined using the *ROP* values of 54 units, which results from the simulation model is only based on a 90 % service level. The store decides to set the *ROP* equal to 60 units to guarantee that the profit is as near to the old value (8.06 USD per day) as is feasible, which results in a service level of 93 % and a profit of 8.00 USD per day. The overall profit from the simulation-based *ROP* determination is 2.9 % higher than the conventional *ROP* determination. Additionally, the simulation-based *ROP* calculation reduces the proportion of damage for each product by 9.6–32.8 %, based on the amount of product damage for products A1–A10, as shown in Table I. After the damage value has been converted back to income, the yearly revenue is 409.48 USD.

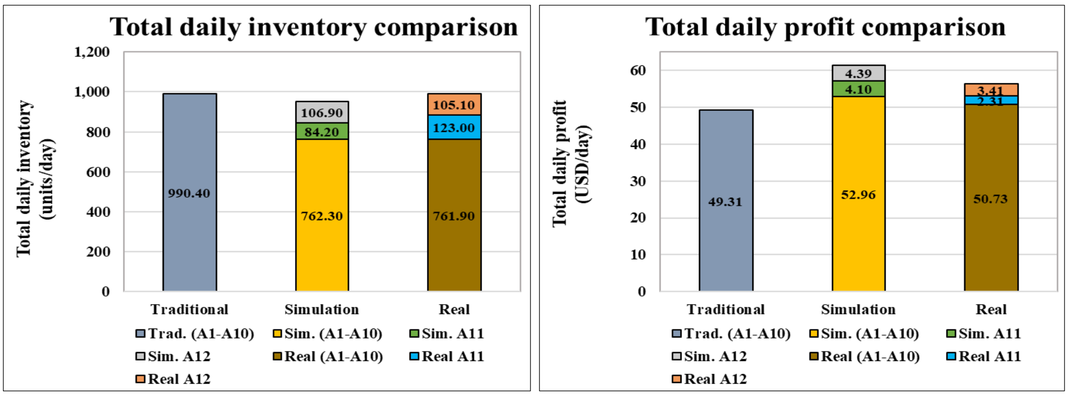

Figure 7: Histogram showing comparative results of total daily inventory and total daily profit using different approaches.

The results (*ROP*, service level, and profit) created by utilising the simulation model and the practical work are validated based on the products A1–A10 since the products A11 and A12 are only shown in practical results. The *ROP* of products A9 and A4 are evaluated using data from products A11 and A12 because they are similar to those items. The differences between the simulation results and the actual results for the daily inventory and profit values of the A1–A10 products are less than 4.5 %, the differences for the daily inventory are 0.05 %, and the differences for the profit are 4.2 %. The model validation is estimated by determining the *ROP* of 72 units. The average purchasing cost and daily income collected from the retail store in 2020, 8.17 USD and 16.40 USD, respectively, are within the calculated 95 % confidence interval of [8.15, 8.17] and [16.38, 16.40], indicating the reliability of the proposed model for determining the *ROP*.

6. CONCLUSIONS

Based on expected future service levels and profitability of a retail store, this study suggests a decision model for determining the *ROP* of a single-item inventory of items A1–A12 with demand, lead time, and product damage uncertainty. The data used in this study can be divided into two categories: deterministic (i.e., minimum required order quantities with free delivery, conventional *ROP*, daily inventory cost per unit, purchasing cost, and unit sale price) and probabilistic (i.e., cost of the unit, cost of the purchase, customer demand, lead time, and product damage). The inventory management indicators, such as service level, daily inventory, product damage, and profit, resulting in interval values that the retail store owner can use to determine how to set a reasonable *ROP* based on acceptable values for each indicator. These results are shown in Table I.

Based on the findings of this study, the retailer's owner decided to determine the *ROP* in 2021 from 72 units to 40 units, which resulted in a 23.03 % decrease in the total daily inventory of goods A1–A10 as shown in Fig. 7. The total daily inventory has decreased, allowing for the addition of new items (A11 and A12). Fig. 7 shows that despite the addition of items A11 and A12, the simulation model's total daily inventory (953 units) is still less than the initial strategy (990 units). In addition, it also results in retailers having an overall profit increase of 7.40 % or up to 24.62 % when adding new products (A11 and A12) to be sold due to increased storage space resulting from a decrease in the total daily inventory of A1–A10 products. The findings of this study are based on a one-year application, however, when the results from the simulation model and the actual (Real) results are compared, it reveals an accuracy of 96.30 % for total daily inventory and 91.86 % for total daily profit. The forecasting technique will be used to evaluate customer demands to design a more accurate *ROP* based on the acceptable service level. However, in some years, significant demand volatility may impact model accuracy.

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