A Critical-Level Dynamic Pricing Mechanism for Improving Supply Chain Inventory Policies With Multiple Types of Customers: An Integration of Rationing Policy and Dynamic Pricing

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In today's highly dynamic and competitive environment, an effective and practical inventory policy is critical for every supply chain and can dramatically affect its performance. When a supply chain faces multiple types of customers with different characteristics, management encounters even more challenges in making decisions about inventory policies. By integrating inventory rationing policies and dynamic pricing strategies, this study proposes a critical-level dynamic pricing (CLDP) mechanism associated with inventory ordering policies to address these challenges. Furthermore, to demonstrate the implementation and evaluate the effectiveness of the proposed policy, we develop a simulation model with the CLDP mechanism and apply it to a specific numerical case. The results show that the proposed inventory policy improves the total net profit by 12.58%. Finally, the conclusions and future research topics are discussed.

Keywords: inventory management, dynamic pricing, simulation optimization, supply chain management

INTRODUCTION

In a highly competitive market, more organizations differentiate their customers according to demand patterns and profit margins (Biller, Chan, Simchi-Levi, & Swann, 2005). Differentiation allows organizations to customize their operations and fully utilize their resources to better serve the needs of different customer types and achieve improved performance. For example, at Amazon.com, customers who are willing to wait longer for their orders can receive free shipping services. This allows Amazon.com to utilize this flexibility to increase its processing speed for customers who require products as soon as possible and are willing to pay for this service (Duran, Liu, Simchi-Levi, & Swann, 2007). Similar practices have been observed in various industries, such as manufacturing (ElHafsi, Fang, & Hamouda, 2021), retail (Gumasta, Chan, & Tiwari, 2012), health care (Papastavrou, Andreou, & Efstathiou, 2014), and electronic business (Imroz, 2021).

Due to the potential for achieving improved efficiency, profitability, and customer satisfaction, managing supply chain inventories with multiple types of customers has attracted the attention of academics and practitioners. Veinott (1965) and Topkis (1968) first studied inventory ordering policies for multiple types of customers with different priorities. They established a set of critical inventory levels that triggered a decision to stop deliveries to certain customers. Sobel and Zhang (2001) considered a periodic review-based inventory system with deterministic (scheduled) demand and stochastic (unscheduled) demand. Deterministic demand must be satisfied immediately, and stochastic demand may be backordered. Isotupa Isotupa (2011) studied a lost-sale (r, Q) inventory model with two types of customers by comparing two policies. Both customers were treated alike in one policy, while in the other, the critical-level inventory policy was applied. The results showed that the critical-level inventory policy yielded lower costs and better customer service levels. More recently, ElHafsi et al. (2021) studied an inventory system with two types of customers: one class had long-term commitment and accepted backorders, while the other class had no long-term commitment and would cancel their order if no inventory was available. They proposed three heuristic policies for minimizing the total costs.

In addition to relying only on inventory rationing methods to minimize costs, several studies have investigated the impacts of price incentives on total revenue or net profit. For example, Ding, Kouvelis, and Milner (2006) proposed a dynamic pricing mechanism that provides optimal discounts to multiple types of customers during the backorder stage to improve net profit and customer satisfaction. Gumasta et al. (2012) studied two types of customers in perishable product supply chains: one customer buys only the newest and freshest goods, and the other buys both fresh and old goods while considering price incentives. They proposed a transportation model to maximize revenue and minimize inventory and transportation costs.

However, most of the literature has focused either on inventory rationing methods without pricing adjustments or on dynamic pricing strategies for fixed amounts of inventory without considering reordering policies. Therefore, research that integrates inventory ordering policies with dynamic pricing is highly desirable for both marketing and operations scholars (Eliashberg & Steinberg, 1993; Elmaghraby & Keskinocak, 2003; Simchi-Levi, Kaminsky, & Simchi-Levi, 2003; Transchel & Minner, 2009). Academic scholars and business practitioners have noted the value of price-inventory decision-making. For example, Nicholls (2018) identified customer differentiation and corresponding pricing strategies as the top approaches for making better business decisions. A global survey of 1,700 business leaders revealed that 85% of the respondents believed they needed to improve their pricing decision mechanisms (Kermisch & Burns, 2018). As a pricing leader, Amazon.com dynamically updates the prices of millions of its products multiple times a day based on inventory levels and other factors to increase its conversion rates and revenue (Naceva, 2024).

Responding to calls from industry and academia, we approach the supply chain inventory management problem with multiple customer types by linking inventory rationing policies and dynamic pricing strategies, proposing a critical-level dynamic pricing (CLDP) mechanism. The proposed mechanism modifies the critical-level inventory rationing policy with dynamic and continuous price functions of on-hand stock for each type of customer, and it is expected to increase the total net profit.

This study contributes to the literature in at least three ways. First, although many existing studies have been conducted on supply chain inventory management, few studies have considered the case of multiple customer types. This study fills these research gaps by addressing cases with multiple types of customers in terms of their order sizes, order frequencies, shortage costs, and profit margins. These customer classifications are more practical and comprehensive. Second, the critical-level rationing policy dominates the inventory management literature with multiple types of customers, and extensions of these models are expected and necessary. By integrating the policies and strategies derived from the operations and marketing fields, we propose a new supply chain inventory ordering policy to increase the total net profit obtained with multiple customer types. Decision-makers can practically implement the newly proposed ordering policy without much computational complexity. Third, we treat all customer types equally without priority differences. Unlike the traditional rationing policy, which prevents low-end customers from accessing the existing inventory, we use dynamic pricing strategies to provide all types of customers with access to the existing inventory. This setting can be valuable for low-end customers who need products in an emergency.

The remainder of this paper is organized as follows. Section 2 first defines the problem and variables used in the model development stage. This is followed by Section 3, where we develop the CLDP mechanism based on the research concerning inventory management policies and dynamic pricing strategies. A simulation model is developed in Section 4 for the investigated problem, and then the CLDP mechanism is applied to a numerical example in Section 5 to illustrate its implementation and effectiveness. Finally, conclusions and suggestions for future studies are discussed in Section 6.

PROBLEM DEFINITION

The investigated inventory system contains multiple customer types i (i = 1,2, …, n) with demands following a compound Poisson distribution. The numbers of orders per day follow Poisson distributions with arrival rates of λ_i, and the order sizes follow exponential distributions with means of μ_i. No partial shipments are allowed, and unmet demand is lost. The shortage cost G_i is fixed per unfilled customer order, and its value varies for different customer types. The selling price p_i for each type of customer has two stages: when the inventory is abundant, it remains at a constant regular price P_i, and when the inventory is lower than the critical level K, the dynamic pricing system is triggered, and p_i is adjusted based on a function of the on-hand inventory. Simultaneously, the demand of this customer type D_i will be modified according to the newly adjusted price p_i. The variables used in the model development process are listed in Table 1, and they are followed by the objective function, which is expected net profit E[NP].

TABLE 1
VARIABLES USED IN THE MODEL

Variables	Meaning
λ_i	Means of the arrival rates
μ_i	Means of the customer order sizes
L	Lead time for replenishment from the external suppliers
P_i	Regular prices for high-end and low-end customers, respectively
p_i	Adjusted prices when the CLDP is triggered
D_i	Demand per unit time
F_i	Fulfilled demand in units
I	Current inventory on hand
TI	Total inventory (on-hand inventory + in-transit inventory)
B	Product buying cost per unit
C_i	Coefficients of price-demand functions
A	Ordering cost of placing an order
N_r	Number of replenishment orders placed from external suppliers
H	Holding cost per unit per unit time
I_a	Average on-hand inventory
G_i	Shortage cost per unfulfilled order
S_i	Number of customer orders lost due to shortage
K	Critical level
Q	Order quantity
r	Reorder point
E[NP]	Expected net profit

The objective function is the expected net profit per unit time, which relates to the revenue, cost of goods sold (COGS), ordering cost, holding cost, and shortage cost. Using the variables defined in Table 1, we present this relationship as follows:

$$E[NP] = Revenue - COGS - ordering\ cost - holding\ cost - shortage\ cost$$

where the $Revenue = \sum p_i F_i$, $COGS\ =\ BF_i$, the ordering cost = AN_r, the holding cost = HI_a, and the $shortage\ cost\ = \sum G_i S_i$.

Thus, the expected net profit can be written as Eq. (1).

$$E[NP] = \sum_{i=1}^{k} (p_i - B)\, F_i - AN_r - HI_a - \sum_{i=1}^{l} G_i\, S_i \tag{1}$$

where k is the total number of fulfilled customers and l is the total number of unfulfilled customers.

CRITICAL-LEVEL DYNAMIC PRICING MECHANISM

To maximize the total net revenue in Eq. 1, in this section, we first review the supporting research and then present the proposed four-step CLDP mechanism in detail.

Integrating Critical-Level Policies With Dynamic Pricing Strategies

The term "critical level" (also called "reserve level," "stock level," or "threshold level") used in inventory rationing policies generally refers to the amount of inventory such that "at a given time one satisfies the demand of a given class only if no demand of a more important class remains unsatisfied and as long as the stock level does not fall below the critical rationing level for that class at that time" (Kaplan, 1969, p. 160). In other words, when the stock level is lower than a predetermined point (critical level), the inventory will be reserved for future demand from high-priority customers, while the demand from low-priority customers is denied.

Dynamic pricing mechanisms have been developed and used in many industries and studied by researchers from different perspectives (Faruqui, 2010; Marbán, van der Zwaan, Grigoriev, Hiller, & Vredeveld, 2012). *Revenue management* and *price-inventory decision-making* are two closely related but not identical business practices (Ding et al., 2006; Zhang & Bell, 2007). Revenue management is intended to increase profits by charging different prices corresponding to customer characteristics and other market conditions, given that *the amount of total available products is fixed* (Ding et al., 2006; Gallego & Ryzin, 1994; Şen, 2013; Smith, Leimkuhler, & Darrow, 1992).

On the other hand, *price-inventory decision-making* (dynamic pricing in the presence of inventory considerations) involves adjusting the product supply and allows for the use of price adjustments to manage sales and shortages (Elmaghraby & Keskinocak, 2003; Simchi-Levi et al., 2003). Price-inventory decision-making is the interface between marketing and operations (Eliashberg & Steinberg, 1993; Transchel & Minner, 2009).

According to the above analysis, we propose a CLDP mechanism by integrating a critical-level inventory policy and dynamic pricing strategies, and it is expected to increase net profit. We present the details of the proposed mechanism in four steps.

The Four Steps of the CLDP Mechanism

Step 1: Determining Whether the CLDP Mechanism Is Triggered

If the current inventory on hand (I) is greater than the critical level (K), then the price remains the same, and the CLDP mechanism is skipped. Otherwise, we continue to Step 2.

Step 2: Adjusting the Price If the Mechanism Is Triggered

Since the CLDP mechanism is triggered, the selling price p_i must be adjusted according to the current on-hand inventory and other settings. This relationship is represented in Eq. (2).

$$p_i = \begin{cases} P_i & I > K \\ P_i + (K - I) \times C_i & I \leq K \end{cases} \tag{2}$$

Here, C_i is the coefficient linking the price and inventory status, and it represents the slope of the price function. In this study, we set $C_i = \frac{P_i}{K}$, which represents the scenario where the maximum price at which a company can charge its customers is twice the regular price. Following this setting, when the on-hand inventory I is greater than or equal to the critical level K, p_i remains the original price P_i. When the on-hand inventory I is reduced to half of K, the price increases by half of P_i. If the value of I is zero, then p_i is twice the original price P_i, which matches our assumption. Notably, for other practical scenarios, the value of C_i

can be set differently by management, depending on the specific observed market conditions and customer preferences.

Step 3: Updating the Demand Corresponding to the Adjusted Price

After the price is adjusted, the demand must be updated according to the new price. In the literature, at least three classic methods are available for modeling the relationship between price and demand.

1) Linear price-demand relationship: Additive model (Petruzzi & Dada, 1999; Transchel & Minner, 2009)

$$D(p) = \begin{cases} a - b \times p & when\ 0 < p \leq \dfrac{a}{b} \\ 0 & when\ p > \dfrac{a}{b} \end{cases}$$

where $a, b > 0$.

2) Exponential price-demand relationship: (Transchel & Minner, 2009)

$$D(p) = a \times e^{-b \times p}$$

where $a, b > 0$.

3) Log-linear price-demand relationship: Multiplicative model (Petruzzi & Dada, 1999; Ray, Gerchak, & Jewkes, 2005)

$$D(p) = a \times p^{-b}$$

where $a > 0, b > 1$

In this study, we use the linear price-demand relationship (additive model) for demonstration purposes, as shown in Eq. (3). The proposed mechanism can also be applied to other price-demand relationships.

$$D_i(p_i) = \begin{cases} a_i - b_i \times p_i & when\ 0 < p_i \leq \frac{a_i}{b_i} \\ 0 & when\ p_i > \frac{a_i}{b_i} \end{cases} \tag{3}$$

where the constants $a_i, b_i > 0$.

Step 4: Updating the Customer Arrival Rate to Reflect the New Demand Level

Because the units of demand are updated according to the new price, the arrival rate of this type of customer needs to be reduced corresponding to the updated demand. Since $D = \lambda\mu$, the relationship between the arrival rate and price can be stated as follows:

$$\lambda_i(p_i) = \frac{D(p_i)}{\mu_i} = \begin{cases} \frac{a_i - b_i \times p_i}{\mu_i} & when\ 0 < p_i \leq \frac{a_i}{b_i} \\ 0 & when\ p_i > \frac{a_i}{b_i} \end{cases} \tag{4}$$

The above is the design of the four-step CLDP mechanism, which is also summarized in the comprehensive flowchart (Fig. 1) presented in Section 4.

DEVELOPMENT OF THE SIMULATION MODEL

Simulation modeling is a valuable and powerful tool for making business decisions and analyzing dynamic and complex systems (Bazargan, Lange, Tran, & Zhou, 2013; Heidary, 2023; Moosavi & Hosseini, 2021). In this section, we develop a simulation to model the investigated inventory system for random situations in practical scenarios. The simulation model is described in detail, and an overall logic flowchart is presented in Fig. 1.

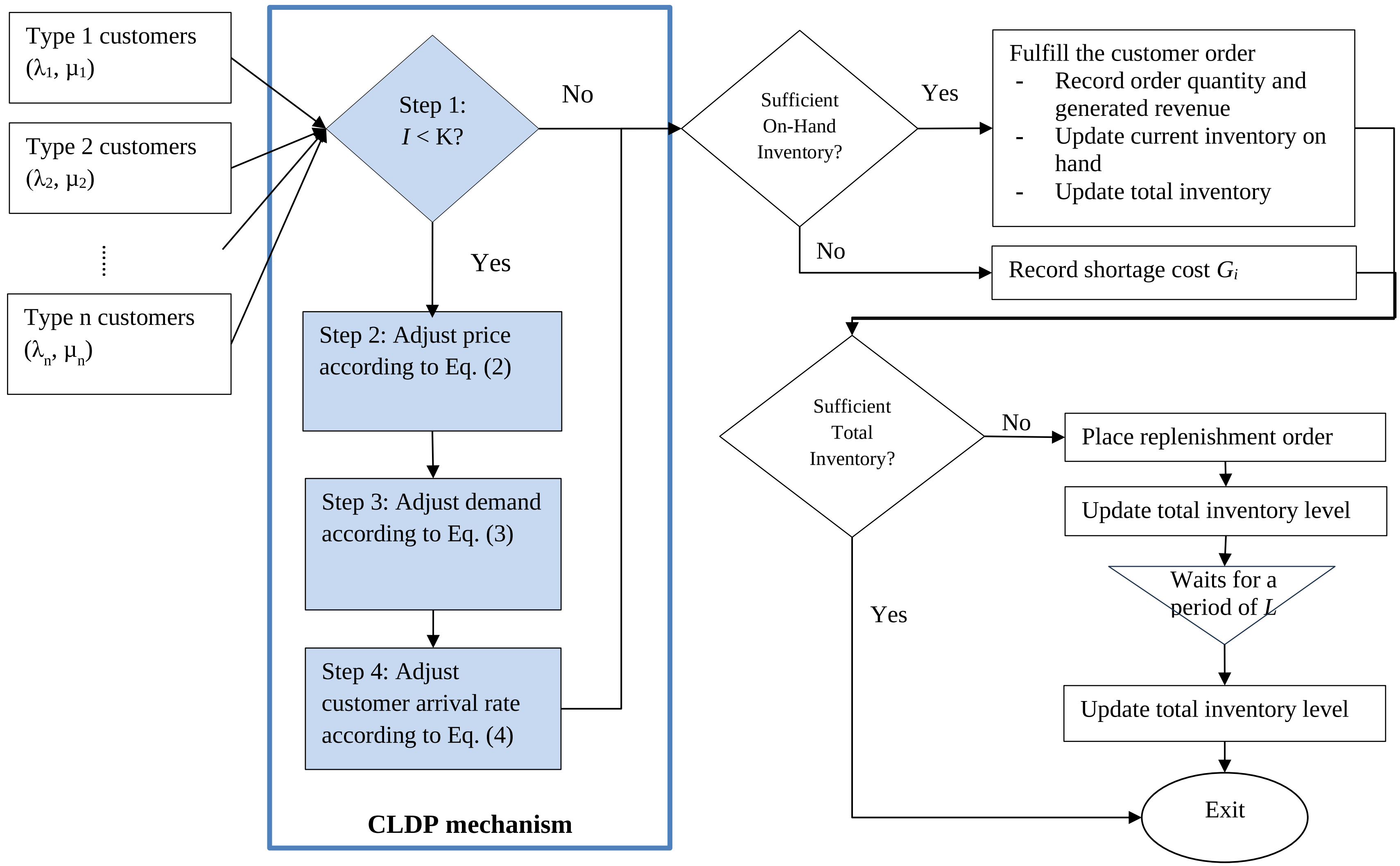
The simulation model generates different types of entities to represent the multiple types of customers in this investigated inventory problem. Customer entities enter the simulation system following Poisson distributions with average arrival rates of λ_i, and their order quantities are assigned following exponential distributions with average order quantities of μ_i. After a specific customer entity enters, the simulation model compares the currently available on-hand inventory (I) with the critical level (K). If I is less than K, then the CLDP mechanism is triggered, and the four steps developed in Section 3 are implemented. If the value of I is not less than K, then the CLDP mechanism is skipped, and the regular price P_i remains the same.

Next, the simulation model checks whether the currently available on-hand inventory is sufficient for the order quantity of this customer. If the answer is “Yes”, the model immediately fulfills the customer order using the available on-hand inventory and records the revenue generated from this customer. At the same time, the simulation model updates not only the currently available on-hand inventory level but also the total inventory level, which includes both the on-hand inventory and in-transit inventory. If the answer is “No”, then a shortage occurs, and the shortage cost (G_i) is recorded according to the customer type.

Before the customer entity exits, the simulation model checks the most recently updated total inventory level to determine whether it is time to place a replenishment order with the external suppliers. On the one hand, if the current total inventory level (TI) is equal to or lower than the designed reordering point (r), then a new replenishment order (Q) is placed. In this case, the total inventory level must be updated immediately, but the on-hand inventory level needs to wait for a lead time period. On the other hand, if TI is greater than r, then the entity exits the system without making any replenishment orders.

Following this design logic, we implement the simulation model by using the ARENA@ software, which is the most widely used simulation software for discrete event modeling (Bazargan et al., 2013; Tsai, Wang, & Hung, 2023; Yousefi, Yousefi, & Fogliatto, 2020). We use this simulation model to implement and evaluate the CLDP mechanism through a numerical example in Section 5.

FIGURE 1
FLOWCHART OF THE SIMULATION MODEL WITH THE CLDP MECHANISM



AN ILLUSTRATIVE EXAMPLE

In this section, we apply the proposed policy to a specific numerical example to illustrate its implementation and evaluate its effectiveness. We first define the sample dataset and then use it to apply the CLDP mechanism step-by-step. Next, the developed simulation model is implemented with and without the CLDP mechanism, and finally, the results are compared to evaluate the effectiveness of the developed approach.

Dataset Used in the Example

In this illustrative example, we analyze an inventory system containing two types of customers: commercial customers and retail customers. The two types of customers have different order sizes, order frequencies, profit margins, and shortage costs. Commercial customers typically have larger order sizes and higher profit margins but lower ordering frequencies and higher shortage costs. In comparison, retail customers typically have smaller order sizes and lower profit margins but higher ordering frequencies and lower shortage costs. According to these characteristics, the data and parameters of this numerical example are listed in Table 2.

TABLE 2
PARAMETERS USED IN THE NUMERICAL EXAMPLE

Parameters	Values	Parameters	Values
λ_1	1 customer per day	b_1	14
λ_2	4 customers per day	b_2	9
μ_1	700 units per customer	L	5 days
μ_2	75 units per customer	B	\$10 per unit
P_1	\$30 per unit	A	\$1,000 per order
P_2	\$20 per unit	H	\$0.02/unit/day
G_1	\$1400 per order	Simulation length (hour)	80,000
G_2	\$150 per order	Warm-up period (hour)	8,000
a_1	1,120	Number of replications	50
a_2	480		

Implementation of the CLDP Mechanism

Following the four steps developed in Section 3, we apply the CLDP mechanism to this specific dataset, and the details of each step are presented as follows.

- **Step 1:** We first determine when to trigger the CLDP mechanism by comparing the inventory level (*I*) and the critical level (*K*). For demonstration purposes, this section selects the reordering point (r) as K. A further discussion concerning other cases with different critical level settings is provided in Section 8.
- **Step 2:** By applying Eq. (2) to the dataset described in Table 2, we obtain that for the commercial customers, $P_1 = 30$ and $p_1 = 30 + (r - I) \times \frac{30}{r}$, and for the retail customers, $P_2 = 20$ and $p_2 = 20 + (r - I) \times \frac{20}{r}$.
- **Step 3:** We then apply Eq. (3) to establish the relationships between demand and price for the commercial and retail customers as follows.

$$D_1(p_1) = \begin{cases} 1{,}120 - 14p_1 & when\ 0 < p_1 \leq 80 \\ 0 & when\ p_1 > 80 \end{cases}$$

and

$$D_2(p_2) = \begin{cases} 480 - 9p_2 & when\ 0 < p_2 \le 53 \\ 0 & when\ p_2 > 53 \end{cases}$$

– **Step 4:** Finally, we apply Eq. (4) and obtain the arrival rates of the commercial and retail customers as follows.

$$\lambda_1(p_1) = \frac{D(p_1)}{\mu_1} = \begin{cases} \frac{1{,}120 - 14p_1}{700} & when\ 0 < p_1 \le 80 \\ 0 & when\ p_1 > 80 \end{cases}$$

and

$$\lambda_2(p_2) = \frac{D(p_2)}{\mu_2} = \begin{cases} \frac{480 - 9p_2}{75} & when\ 0 < p_2 \le 53 \\ 0 & when\ p_2 > 53 \end{cases}$$

Simulation Model With and Without the CLDP Mechanism

Utilizing the above parameters and results, we implement the proposed CLDP mechanism in the simulation model and search for the optimal solution (Q, r) that maximizes the total net profit. We use the classic economic order quantity of 10,000 ($\sqrt{\frac{2(700+4\times 75)\times 1000}{0.02}}$) as the initial search point for the optimal order quantity Q and extend the search range to 5000, 10,000, 15,000, and 20,000. For the initial reordering point, we use the expected lead-time demand, which is 5,000 ((4×75+700)×5), and conduct a search among 5,000, 10,000, 15,000, and 20,000 for the optimal reordering point r. We thus need to search for 16 combinations (4×4) of (Q, r). The simulation runs for 80,000 hours (10,000 days) for each combination and is repeated 50 times. To prevent the initial settings of the parameter values, such as the initial on-hand inventory, from impacting the results, the simulation runs for a warm-up period of 8,000 hours (1,000 days) before starting to collect simulation results.

We first implement the simulation model without the CLDP mechanism for comparison purposes. With the above settings, the simulation-based search process finds that the optimal solution includes an order quantity of 10,000 and a reordering point of 15,000, which leads to a net profit of $16,593.33 per day. Then, we implement the simulation model with the CLDP mechanism and find that when the order quantity is 5,000 and the reordering point is 10,000, the net profit is maximized at $18,680.46 per day.

Therefore, we can compare the two optimal results to demonstrate the effectiveness of the CLDP mechanism. In this illustrative example, the simulation study shows that after implementing the proposed CLDP mechanism, the net revenue increases from $16,593.33 to $18,680.46, which is an increase of 12.58%. The results are affected by the parameters assumed for illustration purposes. Still, this explorative example demonstrates the stepwise application of the CLDP mechanism and shows the potential of the CLDP mechanism for improving profits.

CONCLUSIONS AND DISCUSSION

To improve the existing supply chain inventory ordering policies with multiple types of customers and multiperiod continuous demands, we propose a new supply chain inventory policy by integrating rationing inventory policies with dynamic pricing strategies. This research contributes to the literature by conducting an interdisciplinary inventory policy improvement investigation and extending the price-inventory decision-making paradigm to multiple types of customers.

Due to the explorative nature of this study, future research can extend it in multiple ways. The proposed CLDP mechanism allows flexible settings for the key components, such as the critical level and the inventory-price relationship function. The critical level can be a proportion of the reordering point r or studied as an independent variable for optimization. Each type of customer can have a specific critical level, which could provide even further improvement. Although this setting would lead to greater computational complexity, another future research direction is to develop heuristics that identify the optimal critical level for each customer type. Furthermore, our proposed model uses one of the several available price-demand relationships, and future research can develop models based on the other price-demand relationship functions.

Overall, in this study, we propose an inventory ordering policy with a CLDP mechanism by linking the inventory rationing policy with dynamic pricing strategies to improve the net profits obtained while considering multiple types of customers with different characteristics. The developed simulation model produces encouraging results in an illustrative example, potentially leading to more future research on this topic.

REFERENCES

Bazargan, M., Lange, D., Tran, L., & Zhou, Z. (2013). A simulation approach to airline cost benefit analysis. *Journal of Management Policy and Practice*, *14*(2), 54–61.

Biller, S., Chan, L.M.A., Simchi-Levi, D., & Swann, J. (2005). Dynamic pricing and the direct-to-customer model in the automotive industry. *Electronic Commerce Research*, *5*(2), 309–334.

Ding, Q., Kouvelis, P., & Milner, J.M. (2006). Dynamic pricing through discounts for optimizing multiple-class demand fulfillment. *Operations Research*, *54*(1), 169–183. doi:10.1287/opre.1060.0248

Duran, S., Liu, T., Simchi-Levi, D., & Swann, J.L. (2007). Optimal production and inventory policies of priority and price-differentiated customers. *IIE Transactions*, *39*(9), 845–861. doi:10.1080/07408170600972982

ElHafsi, M., Fang, J., & Hamouda, E. (2021). Optimal production and inventory control of multi-class mixed backorder and lost sales demand class models. *European Journal of Operational Research*, *291*(1), 147–161. doi: 10.1016/j.ejor.2020.09.009

Eliashberg, J., & Steinberg, R. (1993). Chapter 18 Marketing-production joint decision-making. In J. Eliashberg, & G.L. Lilien (Eds.), *Handbooks in Operations Research and Management Science* (Vol. 5, pp. 827–880). Elsevier.

Elmaghraby, W., & Keskinocak, P. (2003). Dynamic pricing in the presence of inventory considerations: Research overview, current practices, and future directions. *Management Science*, *49*(10), 1287–1309.

Faruqui, A. (2010). The ethics of dynamic pricing. *The Electricity Journal*, *23*(6), 13–27. http://dx.doi.org/10.1016/j.tej.2010.05.013

Gallego, G., & Ryzin, G.V. (1994). Optimal dynamic pricing of inventories with stochastic demand over finite horizons. *Management Science*, *40*(8), 999–1020.

Gumasta, K., Chan, F.T.S., & Tiwari, M.K. (2012). An incorporated inventory transport system with two types of customers for multiple perishable goods. *International Journal of Production Economics*, *139*(2), 678–686. doi: 10.1016/j.ijpe.2012.06.020

Heidary, M.H. (2023). Risk assessment in the global supplier selection considering supply disruption: A simulation optimization approach. *International Journal of Supply and Operations Management*, *10*(4), 501–522. https://doi.org/10.22034/IJSOM.2023.108989.2110

Imroz, S.M. (2021). Understanding differentiation of user roles and gamification in a professional online community: A case study. *Journal of Management Policy and Practice*, *22*(4), 33–46.

Isotupa, K.P.S. (2011). An (s, Q) inventory system with two classes of customers. *International Journal of Operational Research*, *12*(1), 1–19.

Kaplan, A. (1969). Stock rationing. *Management Science*, *15*(5), 260–267.

Kermisch, R., & Burns, D. (2018). *A Survey of 1,700 Companies Reveals Common B2B Pricing Mistakes*.

Marbán, S., van der Zwaan, R., Grigoriev, A., Hiller, B., & Vredeveld, T. (2012). Dynamic pricing problems with elastic demand. *Operations Research Letters*, *40*(3), 175–179. http://dx.doi.org/10.1016/j.orl.2012.01.005

Moosavi, J., & Hosseini, S. (2021). Simulation-based assessment of supply chain resilience with consideration of recovery strategies in the COVID-19 pandemic context. *Comput Ind Eng*, *160*, 107593. doi: 10.1016/j.cie.2021.107593

Naceva, N. (2024). *The Ultimate Guide to Amazon Dynamic Pricing Strategy in 2024*. Retrieved from https://influencermarketinghub.com/amazon-dynamic-pricing/

Nicholls, S. (2018). 7 Approaches to make better decisions for your c-store. *Convenience Store News*, *54*(12), 26–30.

Papastavrou, E., Andreou, P., & Efstathiou, G. (2014). Rationing of nursing care and nurse-patient outcomes: A systematic review of quantitative studies. *International Journal of Health Planning & Management*, *29*(1), 3–25. doi: 10.1002/hpm.2160

Petruzzi, N.C., & Dada, M. (1999). Pricing and the newsvendor problem: A review with extensions. *Operations Research*, *47*(2), 183–194.

Ray, S., Gerchak, Y., & Jewkes, E.M. (2005). Joint pricing and inventory policies for make-to-stock products with deterministic price-sensitive demand. *International Journal of Production Economics*, *97*(2), 143–158. doi: 10.1016/j.ijpe.2004.06.054

Şen, A. (2013). A comparison of fixed and dynamic pricing policies in revenue management. *Omega*, *41*(3), 586–597. http://dx.doi.org/10.1016/j.omega.2012.08.001

Simchi-Levi, D., Kaminsky, P., & Simchi-Levi, E. (2003). *Designing and managing the supply chain: Concepts, strategies, and case studies*. Irwin/McGraw-Hill.

Smith, B.C., Leimkuhler, J.F., & Darrow, R.M. (1992). Yield management at American airlines. *Interfaces*, pp. 8–31.

Sobel, M.J., & Zhang, R.Q. (2001). Inventory policies for systems with stochastic and deterministic demand. *Operations Research*, *49*(1), 157.

Topkis, D.M. (1968). Optimal ordering and rationing policies in a nonstationary dynamic inventory model with N demand classes. *Management Science*, *15*(3), 160–176.

Transchel, S., & Minner, S. (2009). The impact of dynamic pricing on the economic order decision. *European Journal of Operational Research*, *198*(3), 773–789. http://dx.doi.org/10.1016/j.ejor.2008.10.011

Tsai, S.C., Wang, H., & Hung, L.H. (2023). Mixed-integer simulation optimization for multi-echelon inventory problems with lost sales. *Journal of the Operational Research Society*, *74*(11), 2312–2326. doi: 10.1080/01605682.2022.2141144

Veinott, A.F. (1965). Optimal policy in a dynamic, single product, nonstationary inventory model with several demand classes. *Operations Research*, *13*(5), 761.

Yousefi, M., Yousefi, M., & Fogliatto, F.S. (2020). Simulation-based optimization methods applied in hospital emergency departments: A systematic review. *SIMULATION: Transactions of The Society for Modeling and Simulation International*, *96*(10), 791–806.

Zhang, M., & Bell, P.C. (2007). The effect of market segmentation with demand leakage between market segments on a firm's price and inventory decisions. *European Journal of Operational Research*, *182*(2), 738–754. doi: 10.1016/j.ejor.2006.09.034