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Article

Inventory Policy Improvement with Periodic Review for Perishable Goods: A Case Study of a Retail Coffee Shop in Thailand

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Abstract. Inventory management is a fundamental component of successful retail operations. Effective techniques in retail inventory management are important in fulfilling customer demands, minimizing costs, and enhancing profitability for business in the competitive environment. This study aims to improve the inventory management strategy for perishable goods in a Thai coffee shop case study. The primary goals include minimizing occurrences of inventory surplus or shortage and indicating the most suitable inventory management approach for each stock-keeping unit (SKU). The most efficient inventory strategy is determined by evaluating the total inventory costs, composing of waste costs, potential loss costs, and holding costs. To this end, computational experiments are employed, deploying three varied periodic inventory policies per SKU. These policies differ in term of utilizing mean weekly demand, average daily demand, and modifying delivery schedules and frequencies. In addition to exploring various policies, the service level for each SKU is adjusted according to profit-cost ratio of each SKU to determine the most suitable service level corresponding to the most effective inventory management strategy. Following the experiments, an effective inventory policy for each SKU is determined. Results show that the new proposed policies can reduce costs by 60.74%, or about 256,922 Baht yearly, compared to the current policy. The new policy, based on daily demand and delivery adjustments, leads to smaller order, more frequent deliveries, allowing the perishable goods to be more refreshed.

Keywords: Inventory policy, perishable products, retail inventory management, retail supply chain.

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1. Introduction

Swiftly evolving global landscape, coffee transcends its traditional role as a mere morning stimulant; it has morphed into a cultural symbol that mirrors the diverse values and preferences across generations. From the emblematic Baby Boomers to the digitally adept Generation Z, each demographic contributes distinct perspectives to the coffee culture [1]. The coffee shop market in Thailand is expected to grow at more than 10% per year for the next 3 years. However, in the past, 10% of new coffee shop failed within two years due to factors like intense competition, location, product quality, and poor management [1]. Effective strategies and strong operations, particularly in inventory management, are crucial for business competitiveness. Good inventory management, by reducing waste and opportunity loss, can increase profits [2].

The case study company is a compact, $10m^3$ coffee kiosk located in a leading public hospital in Bangkok, Thailand, established in 2014. Despite its small size and competition, it earns significant profit from high foot traffic, quality products, and reasonable pricing. Its revenue derives mainly from two categories: 'Coffee' (59%) and 'Bakery & Others' (41%). The Coffee category consists of custom-made beverages, requiring distinct raw materials like coffee beans, milk, and syrups, separate from the 'Bakery & Others' category.

Bakery & Others items, including sandwiches, buns, cakes, and juices, are purchased wholesale and sold at retail prices. Most products are delivered directly to the store, except cakes, which are initially stored in a central office freezer due to lack of on-site storage, and then transported weekly to the store.

In the case study company, all items in the 'Bakery and Others' category are purchased from suppliers. Given their lower margins compared to coffee and the fact they are not made-to-order, optimizing inventory to minimize waste and avoid out-of-stock situations is vital for maximizing profit. This necessitates the implementation of effective inventory policies for each SKU. The study focuses on the 'Bakeries and Others' category, which comprises nineteen SKUs. To ensure impactful results, this research will concentrate on the eight SKUs that contributed most significantly to the category's revenue. Figure 1 presents a Pareto chart illustrating annual revenue by SKU from the 'Bakery and Other' Category, with the study concentrating on the top 8 SKUs, highlighted in green.

The case study company manually reviews 'Bakery & Others' category products daily for stock recording, but there's been no data analysis or initiative taken regarding stock levels. Employees, aware of stock levels, refrain from adjusting them due to the need for supplier negotiations and fear of disrupting current inventory policies. Consequently, the inventory policy for each SKU remains unchanged, leading to overlooked issues such as opportunity loss from understocking and waste from overstocking.

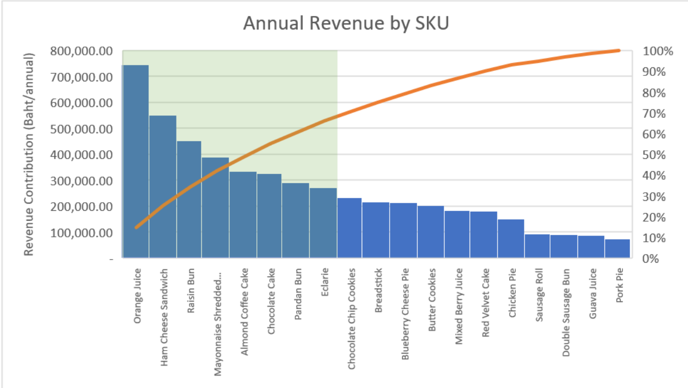

Fig. 1. Revenue contribution by SKU from 'Bakery and Others' category.

From an inventory standpoint, there is room for inventory management improvement. Data analysis reveals overstocking issues in some SKUs, evident from high waste levels in products with a shelf life of five days or less. Conversely, some SKUs show understocking, indicated by days with out-of-stock situations.

Equation (1) outlines the waste percentage formula, derived by dividing the annual expired SKU units by the annual delivered units. Higher percentages indicate more waste, while lower percentages suggest less waste per SKU. The 'Out of Shelf' percentage, an understocking indicator, is calculated as shown in Eq. (2) by dividing the number of days of having zero inventory by the total operational days. A high 'Out of Shelf' percentage indicates greater opportunity loss, as products are unavailable for sale, leading to potential profit loss. Conversely, a low 'Out of Shelf' percentage implies fewer days with stock shortages, resulting in reduced opportunity loss and a higher service level to meet customer demands.

$$\%\text{ Waste} = \frac{(\text{SKU products units watsed per year}) \times 100\%}{(\text{Total SKU products units delivered per year})} \tag{1}$$

$$\%\text{ Out of Shelf} = \frac{(\text{Number of days with zero inventory}) \times 100\%}{(\text{Total operation days in a year})} \tag{2}$$

For example, Orange Juice (the top revenue contributor) is procured from Supplier A in quantities of 150 bottles per delivery, scheduled for Mondays, Wednesdays, and Fridays. This product necessitates storage at temperatures below 20°C and has a shelf life of up to three days. Figure 2 illustrates the end-of-day inventory and waste for Orange Juice. In 2021, this product experienced an out-of-stock rate of 26.85% and a waste rate of 4.13%, highlighting challenges in both understocking and overstocking, attributable to significant opportunity loss and waste. To understand the current situation of all 8 products, Table 1 summarizes

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percent of waste and understock for each item recorded in 2021.

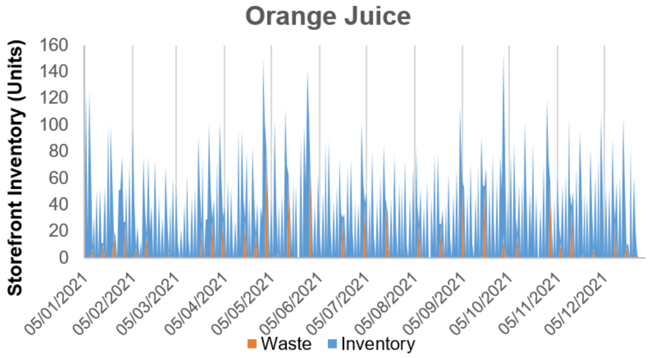

Fig. 2. Orange juice's end of day inventory and wastes generated in 2021.

Table 1. The current situation of the focused products.

SKU	Product	Sup.	Shelf Life (day)	% Waste	%Out of shelf
1	Orange Juice	A	3	4.13	26.85
2	Ham and Cheese Sandwich	B	5	0.97	24.11
3	Raisin Bun	C	7	2.63	23.01
4	Mayonnaise Shredded Pork Bun	C	5	3.26	24.66
5	Almond Coffee Cake	D	7	10.59	22.47
6	Chocolate Cake	D	5	10.10	36.44
7	Pandan Bun	C	4	4.49	36.44
8	Eclair	E	5	0.10	67.95

The objective of this research is to improve inventory management policy for perishable products in a case study coffee shop. Since periodic ordering policy where the ordering and delivery day are fixed is suitable for the practical perspective, three different periodic inventory policies for each SKU are considered, varying between mean weekly demand, daily demand, and adjustments in delivery schedules and frequencies. The policy's result is determined by analyzing total inventory costs, including waste, potential loss, and holding expenses.

The remainder of the paper is structured as follows. In Section 2, literature review is discussed. The methodology is explained in Section 3. The results and insights are reported in Section 4. The research conclusion, limitation and suggest issues for the future work are in the last section.

2. Literature Review

Effective inventory management, ensuring product availability, significantly influences customer purchasing decisions in perishable retail, with shelf availability and assortment being key factors [3]. The presence of goods not only boosts awareness but also revenue potential, whereas unavailable products lead to revenue loss [4]. Gruen et al. [5] reported a global average out-of-stock rate of 8.3% at retailers. Ferguson and Ketzenberg [6] indicated that perishable loss in grocery stores can reach 15% due to spoilage, representing significant opportunity loss for retailers.

Setyaningsih and Basri [7] explored improving inventory policies in a hospital, focusing on perishable food supplies. Facing financial challenges due to poor inventory management, the study compared continuous and periodic review policies. They recommended mathematical calculations for inventory variables like safety stock and economic order quantity to enhance management. The findings favored a periodic review policy, which offered up to 92% savings on the hospital's main products and adapted to different review periods (10-30 days). Efficient inventory management thus enables firms to adapt to uncertainties and remain competitive [8].

Suttipongkaset & Chaovalitwongse [9] discussed the benefits of periodic review in various industries. In a case study of a self-managed inventory company, the implementation of periodic review led to optimized inventory control, sufficient supply, lower holding costs, and a 99% service level. It also reduced inventory and ordering costs by 35% and 33%, respectively. According to Rizkya et al. [10], selecting an appropriate inventory management policy is critical for smooth business operations. Minner and Transchel [11] proposed a method to determine dynamic order quantities for perishable products with limited shelf-life, positive lead time, FIFO or LIFO issuing policy, and multiple service level constraints. It is suggested that periodic review is practical for managing perishables in both large and small firms, as it helps minimize inventory units and reduce costs associated with high holding expenses.

Lee and Schwarz [12] examined a single-item, periodic-review inventory system with stochastic leadtime, in which a replenishment order is delivered either immediately or one period later, depending on management's own effort or the effort of management's agent. Aisyati et al. [13] determined ordering quantity and reorder point for aircraft consumable spare parts in the aircraft industry. The results showed that using continuous review can reduce total inventory costs by 35.38% compared to manual policies. The research article by Lin and Lin [14] examined an integrated inventory challenge involving a single supplier and a single retailer. In this context, the supplier and retailer have developed a long-term strategic partnership and established a contractual agreement to collaboratively identify the most effective strategy.

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Rizkya et al. [15] examined Continuous and Periodic Review Policies in the automotive industry to find the optimal inventory system. The Continuous Review Policy used varying lead times to determine order quantities, while the Periodic Review focused on optimal ordering intervals. Zhang et al. [16] considered a periodic-review, single-product inventory system with lost sales and positive lead times under censored demand. Tao et al. [17] studied a single stage, periodic review inventory system where two modes, namely regular mode and expediting mode are available for a firm to obtain its replenishment. Murmu et al. [18] examined first-in-first-out (FIFO) and last-in-first-out (LIFO) dispatching policies for their effects of quality on fresh products' sales mind the sustainability concern. Feinberg and Kraemer [19] established the continuity of value functions in discounted, periodic-review, single-commodity, total-cost inventory control problems. These problems featured continuous inventory levels, fixed ordering costs, and potentially limited inventory storage capacity and order sizes, applicable to both finite and infinite planning horizons. For a comprehensive review of periodic review policy, refer to Christou et al. [20].

Sakulsom and Tharmmaphornphilas [21] investigated a two-level inventory system comprising one warehouse and nn retailers under seasonal demand. They determined the inventory policy that minimizes inventory cost while maintaining the required service level. Gutierrez and Rivera [22] studied order quantity probability distributions in periodic review, reorder point, order-up-to-level inventory systems with continuous demand. They concentrate on scenarios characterized by continuous demand, complete backlogging, and variable lead-time. Feinberg and Liang [23] investigated structure of optimal policies for discounted periodic-review, single-commodity, total-cost inventory control problems, incorporating fixed ordering costs across both finite and infinite horizons. Additionally, their study established the continuity of optimal value functions and detailed alternative optimal actions. Poormoaied [24] examined a periodic review base-stock policy in scenarios involving two complementary products with interdependent demands and joint replenishment. Karakatsoulis and Skouri [25] studied a periodic review inventory system with alternating periods of supply availability and unavailability, controlled by a periodic review base stock policy. Xu et al. [26] considered an infinite-horizon periodic-review base-stock inventory system that enforces an endogenously determined fulfillment-time limit for accepted orders.

Numerous studies have underscored the efficacy of periodic review in optimizing inventory management. However, the majority of these studies have concentrated on minimizing inventory holding costs, primarily for non-perishable goods. Research dedicated to improving inventory management for perishable goods remains sparse. Consequently, this research endeavors to investigate the most suitable service level (z) and review periods for perishable items, taking into account factors such as product out-of-stock incidents and waste generation, which have not been extensively examined in existing literature.

3. Methodology

This section presents a comprehensive end-to-end analysis, comprising eight major steps as delineated in Fig. 3.

Fig 3. Overview of the research's methodology.

3.1. Proposed Inventory Policy

Considering the company's practical circumstances, this paper adopts periodic review as the inventory policy model for all SKUs, as shown in Fig. 4. The objective is to identify the most effective inventory policy for each SKU, evaluated in terms of total inventory cost. This involves determining the Base Stock Level (B), or target inventory level, by calculating the average total demand during the review period (r) plus the lead time (L) interval, and incorporating the safety stock (SS), as delineated in Eq. (3)-(4):

$$\mathrm{B} = \mathrm{AVG} \times (\mathrm{r} + \mathrm{L}) + \mathrm{SS} \tag{3}$$

$$\mathrm{SS} = \text{Service Level (z)} \times \mathrm{STD} \times \sqrt{\mathrm{r} + \mathrm{L}} \tag{4}$$

where B is the Base Stock Level, r is the review period (days), L is the lead time (days), SS is the Safety Stock, STD is the standard deviation of daily demand.

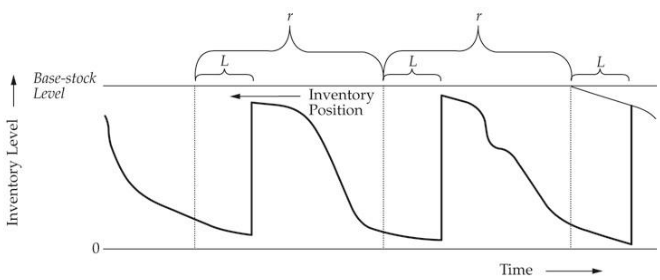

Fig. 4. Periodic review policy.

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3.2. Computational Experiment Setting

From Eq. (3)-(4), several parameters must be identified prior to implementation. For instance, a higher service level (z) necessitates increased safety stock, while a longer review period (r) requires larger order lots to cover the interval. Accordingly, this research explores 3 policies, with variation of service level (z), to assess the effectiveness of periodic inventory review against the current inventory policy. Key metrics for comparison includes waste, days out of shelf, inventory holding cost, and total inventory cost for each policy, benchmarked against the Current policy. The specifics of each policy are detailed as follows:

3.2.1. Current policy:

The existing policy utilizes actual inventory data from 2021, initially employed to categorize each SKU's problem type via calculated waste and out-of-shelf percentages. This current policy serves as a baseline for assessing the effectiveness of the inventory policy in this computational experiment.

3.2.2. Policy 1:

The most appropriate inventory level with respect to optimal service level is determined by using the average weekly demand in 2021, divided by 7, for the average daily demand. This policy will focus on using the same daily demand throughout each delivery order and fixing the same delivery day as the current policy.

3.2.3. Policy 2:

Under this policy, delivery days remain fixed, mirroring the current policy. The most optimized inventory level, corresponding to the chosen service level, will be determined using the average demand for each delivery interval. For instance, if a product is delivered twice a week, say on Monday and Thursday, the inventory level for Monday will be calculated based on the average demand from Monday to Wednesday. Similarly, for Thursday's delivery, the calculation will use the average demand from Thursday to Sunday. This policy is motivated by the evidence that the product’s average daily demand for each day is not identical. Figure 5 presents the average daily demand of an example product (Orange Juice), with observable fluctuations in demand throughout the week; the peak demand occurs on Monday, while Sunday sees the lowest.

Since data collected suggest fluctuation in the daily demand throughout the week, Policy 2 utilize different daily demand rather than overall weekly demand divided by seven as used in Policy 1.

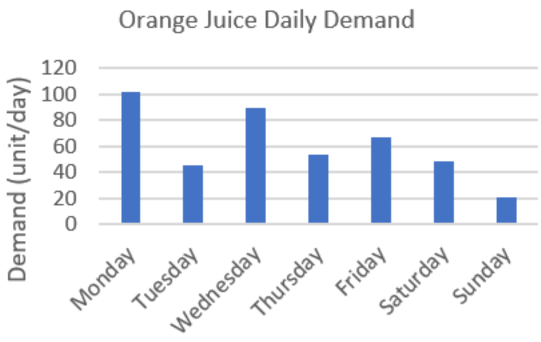

Fig 5. Orange juice average daily demand.

3.2.4. Policy 3:

In this proposed policy, the delivery days for each SKU are varied to align optimally with each product's specific requirements. Implementation of this policy is depending upon supplier agreement to the newly proposed delivery schedule. Therefore, prior to initiating the computational experiment, the case study company must engage in discussions with suppliers to confirm feasibility. This step is critical to ascertain the practical applicability of the policy, should it prove to be the most effective inventory strategy for a given SKU. Table 2 describes the current delivery day of each SKU.

Table 2. The current delivery day of each supplier.

Supplier	Product	Delivery Days	Lead Time + Review Period
A	Orange Juice	Monday, Wednesday, Friday	2 days
B	Ham Cheese Sandwich	Monday, Wednesday, Friday	2 days
C	Raisin Bun, Mayonnaise Shredded Pork Bun, Pandan Bun	Monday	7 days
D	Almond Coffee Cake, Chocolate Cake	Monday	7 days
E	Eclair	Wednesday, Friday	3 days

Various policies will be applied to each SKU to determine the most suitable inventory policy, with service levels varying within a range that aligns with the SKU's categorized problem type, as summarized in Table 3.

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Table 3. Different inventory policy for the experiment.

Policy	Delivery Days		Average Demands	
	Same delivery day with current policy	Change delivery day	Identical average daily demand	Different average daily demand for each day of week
1	✓		✓	
2	✓			✓
3		✓		✓

The service level (z) for each policy will be adjusted to attain the optimal level for each SKU. This variation will be depending on the ration of profit (representing understock cost) and wholesale cost (indicating overstock cost). A higher ratio between these two parameters signifies a greater justification for an elevated service level, as shown in Table 4.

Table 4. Service level range for each product group for the computational experiment.

Product Group	Profit/ Cost	Products	Service Level Computational Experiment Range
Low	<0.9	Almond Coffee Cake, Chocolate Cake	70% – 80%
Medium	0.9-1.1	Orange Juice, Raisin Bun, Mayonnaise Shredded Pork Bun, Pandan Bun	80% – 90%
High	> 1.1	Ham Cheese Sandwich, Eclair	90% – 99%

The computational experiment is designed to address the following key questions:

1. Which products should adjust ordering policy, and what would be the most suitable policy for each?
2. What should be the most appropriate service level(z) and delivery frequency for each SKU so that the total inventory cost can be minimized?

3.3. Policy Evaluation Criteria

The selection of the most effective and optimized inventory policy model for each SKU at a particular service level will be based on the policy with the lowest total inventory cost. This decision hinges on the calculated wastes and opportunity loss, determined from the waste percentage (Eq. (1)) and Out of Stock percentage (Eq. (2)), respectively.

The total annual inventory cost is composed of three components: waste cost, opportunity loss cost, and the inventory holding cost itself, as outlined in Eq. (5).

$$\text{Total Inventory Cost} = \text{Waste Cost} + \text{Opportunity Loss Cost} + \text{Inventory Holding Cost} \quad (5)$$

The annual waste cost is determined by the total waste units multiplied by the wholesale cost as shown in Eq. (6):

$$\text{Waste Cost} = W \times \text{c} \quad (6)$$

where W is the annual number of wasted products (units) and c is the wholesale cost per unit (Baht).

Opportunity Loss Cost represents the profit loss when a product is out of stock. It is calculated based on the total number of days in a year that the product is unavailable, combined with the average daily demand and the profit margin per unit. This calculation is detailed in Eq. (7):

$$\text{Opportunity Loss Cost} = \text{D}_{\text{out}} \times \text{AVG} \times \text{m} \quad (7)$$

where D_{out} is the number of days the product is out of stock, AVG is the average daily demand, and m is the product margin per unit (Baht).

For perishable goods, the inventory holding cost is specifically calculated based on the product's limited shelf life. A carrying cost of 20% is applied, as this is a common average for perishable goods [27], shown in Eq. (8):

$$\text{Inventory Holding Cost} = \text{I} \times \text{c} \times 20\% \quad (8)$$

where I is the average inventory level (units) and c is the product cost per unit (Baht).

Upon completion of the computational experiment, an analysis will be conducted to determine the most effective inventory policy for each SKU, focusing primarily on the total inventory cost.

4. Results

4.1. Supplier Negotiation Results

The outcomes of the negotiation about delivery adjustment with the suppliers are concisely summarized in Table 5.

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Table 5. Potential supplier's delivery day.

Supplier	Current	After Negotiation
A	Monday, Wednesday, Friday	Any day
B	Monday, Wednesday, Friday	Cannot change
C	Monday	Any weekday
D	Monday	Any day
E	Wednesday, Friday	Cannot change

4.2. Computational Experiment Results

The computational experiment is performed using actual daily demand of the focused 8 SKUs in 2022. The most suitable periodic inventory policy for each SKU, with the most effective service level will be identified. The goal is to minimize inventory costs by balancing trade-offs between waste and opportunity loss. An in-depth analysis of each SKU and the overall results of each profit-cost ratio group is presented in the following discussion.

4.2.1. High profit-cost ratio group

There are two products in this group: Ham Cheese Sandwich and Eclair. The Ham Cheese Sandwich, delivered in batches of 60 units thrice weekly on Mondays, Wednesdays, and Fridays, is currently facing understocking issues, evidenced by 88 days of stock unavailability, despite a low waste generation of 0.66%. Demand for this product varies throughout the week, often peaking on delivery days, as shown in Fig. 6. It also implies that the current ordering policy, maintaining consistent SKU quantities for both weekdays and weekends, is not effectively meeting demand fluctuations. The outcomes of the computational experiment, testing three periodic inventory policies, are concisely summarized in Table 6.

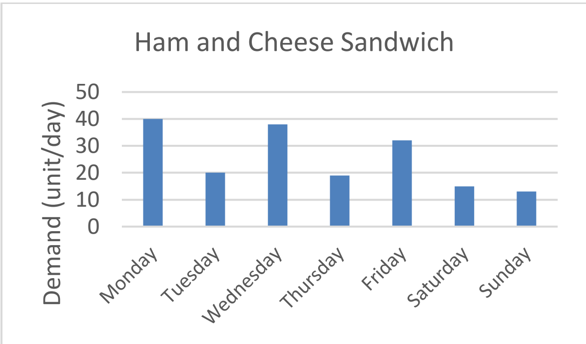

Fig. 6. Ham cheese sandwich average daily demand.

Table 6. Ham cheese sandwich computational experiment results.

Policy	Delivery Day	Service Level (z)	Base Stock Level (units)	Total Inventory Cost (Baht)
Current	Mon, Wed, Fri	N/A	60	60,999.22
1	Mon, Wed, Fri	90%	86	42,936.95
2	Mon, Wed	90%	92	43,771.58
	Fri	90%	58	
3	Mon	91%	98	22,805.61
	Wed	91%	91	
	Fri	91%	66	

The computational experiment indicates that Policy 3 emerges as the most appropriate inventory policy for Ham and Cheese Sandwich, featuring a marginally higher optimized service level of 91% compared to the other two policies. This policy results in a notably lower total inventory cost than Policy 1 and 2, despite a similar maximum weekly inventory order. Figure 7 illustrates the trade-off between total inventory cost and waste percentage, showing optimal results at a 91% service level, with inventory costs rising more sharply beyond a 92% service level.

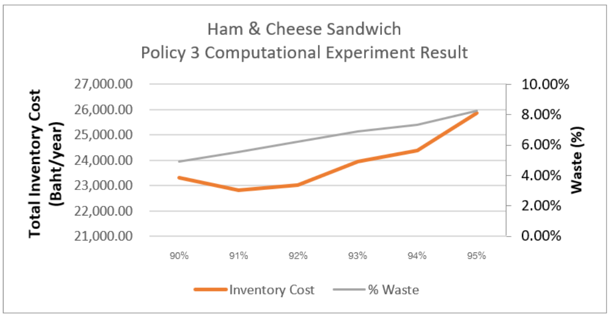

Fig. 7. Ham cheese sandwich Policy 3 computational experiment results from varying service level.

Implementing Policy 3 can yield an annual total inventory cost saving of 38,193.60 Baht, compared to the current one. Especially, the frequency of understocking days is anticipated to decrease by 82.9%, from 88 days to 15 days annually, as detailed in Table 7. This outcome affirms that Policy 3 is the most promising policy, even with a similar maximum weekly order volume as other policies. Its superior performance in adapting to demand fluctuations, by utilizing specific demand data for each delivery day, supports its effectiveness.

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Table 7. %Waste and understocking days from Ham cheese sandwich's optimized service level.

Policy	Service Level(z)	% Waste	Understocking Days
Current	N/A	0.66%	88
1	90.00%	5.62%	44
2	90.00%	4.20%	52
3	91.00%	5.56%	15

Table 9 reveals that the maximum weekly inventory orders across different policy are relatively consistent, yet Policy 3 appears as the most effective due to its adjusted delivery days and enhanced adaptability to demand fluctuations. Despite a higher waste percentage compared to the current scenario and Policy 2, Policy 3's overall effectiveness is emphasized by its reduced total inventory cost and decreased understocking days.

Another product in this group is Eclair, a frequently requested product, facing considerable understocking issues. This is because consistently high demand cannot be met by the supplier's limiting delivery of 40 units per week. Figure 8 shows a peak in daily demand for Eclairs on Wednesdays, Fridays, and Saturdays, with Wednesday and Friday being delivery days and Saturday's demand driven by the residual stock from Friday. Given these demand fluctuations, it is important to utilize different demand for each day in the inventory policy.

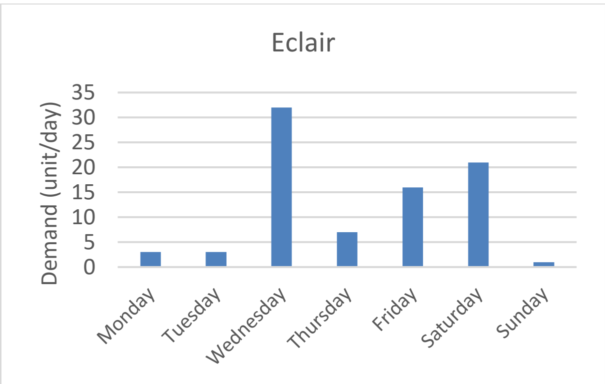

Fig. 8. Eclair average daily demand.

Similar analysis is done for Eclair, shown in Table 8-9 and Fig 9. Due to the inability to change the delivery day from supplier discussion, the computational experiment for Eclair will only explore Policy 1 and 2 as shown in Table 8.

Table 8. Eclair computational experiment results.

Policy	Delivery Day	Service Level (z)	Base Stock Level (units)	Total Inventory Cost (Baht)
Current	Wed, Fri	N/A	40	99,045.88
1	Wed, Fri	98%	93	9,441.37
2	Wed	99.8%	122	6,650.00
	Fri	99.8%	131	

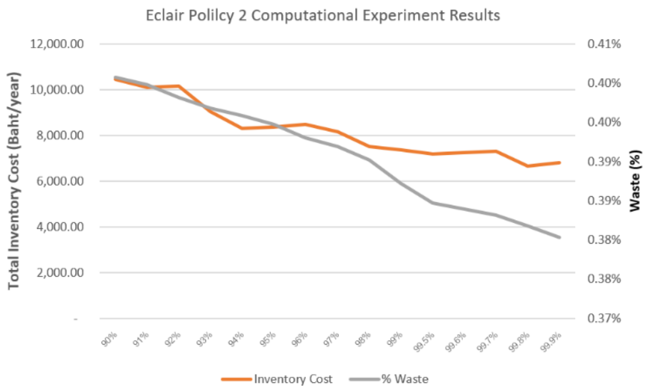

Fig. 9. Eclair Policy 2 computational experiment results from varying service level.

The computational experiment indicates that Policy 2 is the most effective in servicing high demand and mitigating opportunity loss for Eclairs. This approach necessitates a substantial increase in the maximum inventory order in response to the high demand anticipated from the collected data. Consequently, this strategy is expected to yield an annual saving of 92,395.88 Baht, compared to the current policy.

Despite the higher service level, the percentage of waste remains comparatively low, rising only slightly from 0.10% to 0.38%. Simultaneously, there is a significant reduction in the number of opportunity loss days, dropping from 248 to just 7 days, as shown in Table 9.

Table 9. %Waste and understocking days from Eclair's optimized service level.

Policy	Service Level (z)	% Waste	Understocking Days
Current	N/A	0.10%	248
1	98.00%	0.39%	17
2	99.80%	0.38%	7

Two SKUs within the high profit-cost ratio group are Ham and Cheese and Eclair. Figure 10 compares these products' waste cost, opportunity cost, and inventory holding cost under the current policy versus the proposed new policy. The findings suggest the new policy substantially lowers opportunity costs while slightly increasing waste and inventory holding costs. This implies that the current policy understocks, whereas the new policy, by increasing inventory levels, can effectively reduce total inventory costs.

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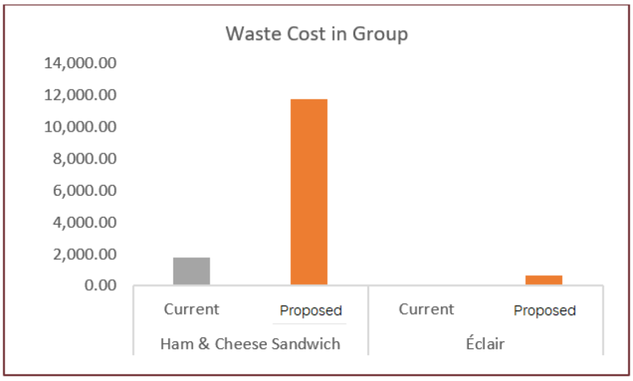

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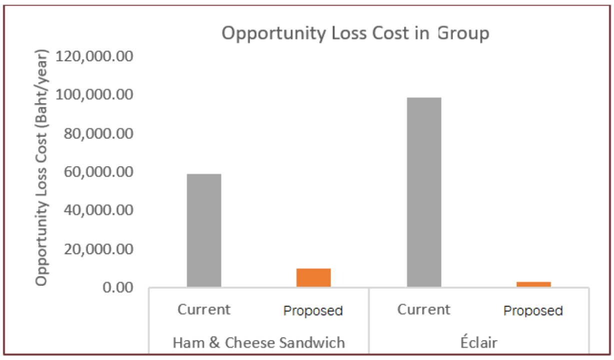

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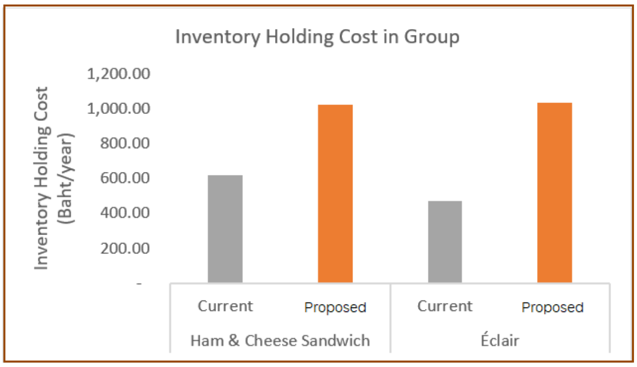

(c)

Fig. 10. Breakdown of inventory cost in high profit-cost ratio group (a). Waste cost (b). Opportunity loss cost (c). Inventory holding cost.

4.2.2. Medium profit-cost ratio group

The service level range for this computational experiment is 80-90%, where the target is to identify the most suitable level (z) for the periodic policy described in section 3.

The first product in this group is the orange juice, with current understocking problems, evident from a high out-of-stock rate of 26.85%. Figure 3 in section 1 shows demand peaking on delivery days, while remaining substantial on other days. This pattern reflects a trend of both high demand and notable demand variation, as revealed in a waste percentage of 4.14% and 98 days of stock unavailability. The computational experiment result suggests the most optimized service level for each policy as shown in Table 10.

Table 10. Orange juice computational experiment results.

Policy	Delivery Day	Service Level (z)	Base Stock Level (units)	Total Inventory Cost (Baht)
Current	Mon, Wed, Fri	N/A	150	142,148.48
1	Mon, Wed, Fri	80%	167	96,299.57
2	Mon, Wed	87%	195	77,788.57
	Fri	87%	126	
3	Mon	85%	303	125,153.66
	Thurs	85%	159	
	Sat	85%	100	

Policy 2 appears as the most advantageous inventory policy, balancing service level with waste generation. Despite Policy 3 often being beneficial for other SKUs due to more precise demand adjustments, Policy 2 is preferable here due to high demand fluctuations leading to greater waste and understocking in Policy 3.

Policy 2's optimal service level is 87%, trading off at a 7.07% waste percentage, a 2.94% increase from the current policy, as shown in Table 11 and Fig. 11. The average inventory level with this policy rises from 34.36 to 52.04 units, compared to the current situation. However, this increase has a minimal impact on inventory holding costs, considering the perishable nature of the products and their short shelf life and cycle.

Table 11. %Waste and understocking days from Orange juice's optimized service level.

Policy	Service Level (z)	% Waste	Understocking Days
Current	N/A	4.13%	98
1	80%	10.19%	45
2	87%	7.07%	40
3	85%	12.45%	57

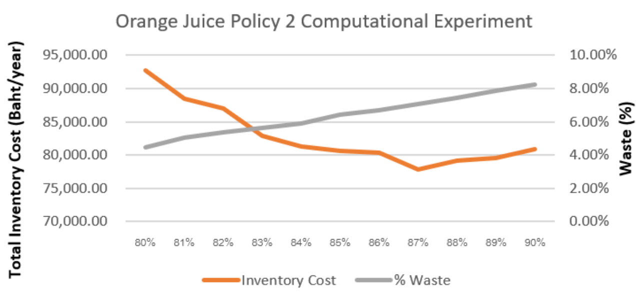

Fig. 11. Orange juice Policy 2 computational experiment results from varying service level.

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Raisin Bun's supplier, working with the company for over three years, delivers raisin buns every Monday. As indicated in Fig. 12, demand for raisin buns peaks early in the week and declines towards the weekend, likely due to reduced shelf availability and nearing expiration dates. Therefore, Policy 2 and 3, which consider each day of week's demand rather than average weekly demand, are explored to better address these demand fluctuations.

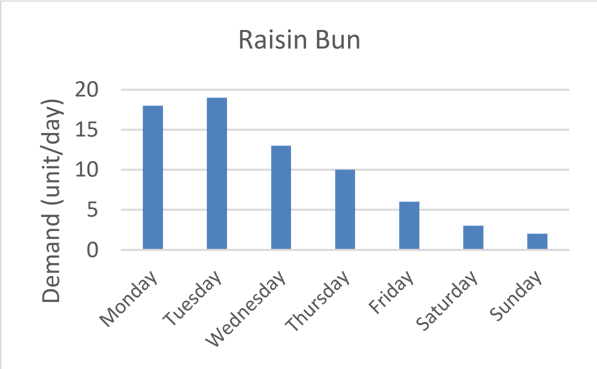

Fig. 12. Raisin bun average daily demand.

Table 12. Raisin bun computational experiment results.

Policy	Delivery Day	Service Level (z)	Base Stock Level (units)	Total Inventory Cost (Baht)
Current	Mon	N/A	70	21,130.77
1	Mon	85%	108	24,685.59
2	Mon	85%	100	27,814.95
3	Mon	86%	71	14,324.67
	Thurs	86%	55	

Table 12-13 show the computational experiment, identifying Policy 3 as the most suitable inventory policy for this SKU. Other policy incurs higher costs due to increased waste from product expiration. Policy 3, with bi-weekly deliveries, effectively minimizes expiration risks. The optimal service level, as demonstrated in Fig. 13, is determined to be 86%, marking it as the most effective service level (z) for the periodic policy's Base stock level formula.

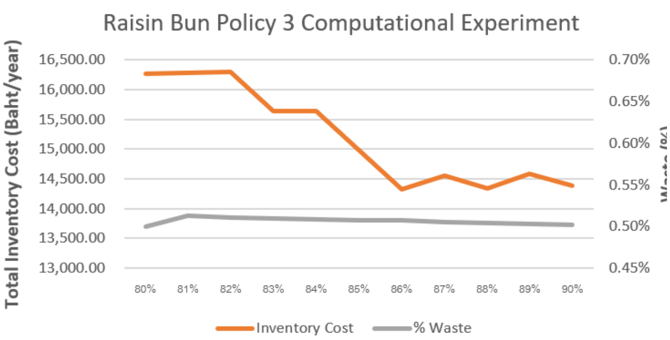

Fig. 13. Raisin bun Policy 3 computational experiment results from varying service level.

Table 13. %Waste and understocking days from Raisin bun's optimized service level.

Policy	Service Level (z)	% Waste	Understocking Days
Current	N/A	2.63%	84
1	85%	4.90%	88
2	85%	1.96%	114
3	86%	0.50%	59

Policy 3 increases product delivery frequency, enabling the company to adjust maximum inventory levels based on weekday and weekend demands. This approach enables improved management of inventory holding costs and shelf space, while also reducing the risk of product expiration. The effectiveness of Policy 3 is evident in Table 13, which shows a reduction in both waste percentage and understocking days. The cost saving from implementing Policy 3 as the inventory policy is 6,806.10 Baht lower than the current situation. This strategy reduces understocking frequency by aligning orders with demand trends and also decreases waste, despite a higher maximum inventory level, due to improved control over the expiration dates of goods.
Similar analysis is done for Mayonnaise Shredded Pork Bun and Pandan Bun. Table 14-15 and Fig. 14-15 display computational experiment results for each product, respectively.

Table 14. Mayonnaise shredded pork bun computational experiment results.

Policy	Delivery Day	Service Level (z)	Base Stock Level (units)	Total Inventory Cost (Baht)
Current	Mon	N/A	70	21,194.68
1	Mon	80%	95	14,725.99
2	Mon	80%	88	14,226.99
3	Mon	87%	64	8,554.91
	Thurs	87%	49	

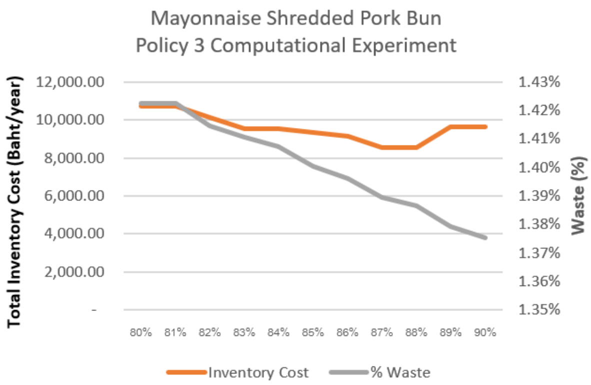

Fig. 14. Mayonnaise shredded pork bun Policy 3 computational experiment results from varying service level.

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Table 15. Pandan bun computational experiment results.

Policy	Delivery Day	Service Level (z)	Base Stock Level (units)	Total Inventory Cost (Baht)
Current	Mon	N/A	90	36,786.11
1	Mon	80%	97	26,786.97
2	Mon	80%	93	27,510.02
3	Mon	88%	52	13,380.98
	Thurs	88%	53	

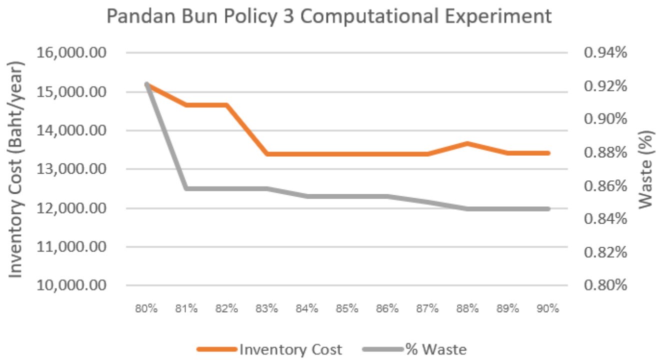

Fig. 15. Pandan bun Policy 3 computational experiment results from varying service level.

SKUs in this medium benefit-cost ration group include Orange Juice, Raisin Bun, Shredded Mayonnaise Pork Bun, and Pandan Bun. Orange Juice is sourced from Supplier A, while the other three are supplied by Supplier C. Following discussions, Supplier C agreed to flexible delivery dates.

From the computational experiment, Fig. 16 presents a breakdown of total inventory costs, encompassing waste cost, opportunity loss cost, and inventory holding cost. Notably, SKUs under Policy 3 policy exhibit lower waste, primarily due to altered delivery dates, which reduces inventory per delivery and extends product expiration dates. Additionally, opportunity loss is reduced by better meeting demand, particularly towards week's end when products are likely to expire under the current policy.

4.2.3. Low profit-cost ratio group

For this group, the risk of shorting is less significant than the risk of wasting. Thus, the computational experiment is set at the range of 70-80% service level. The first product in this group is almond coffee cake. Fig. 17 depicts the average daily, illustrating demand fluctuations. Therefore, it is interesting to explore how policy 2 and 3, using average daily demand specific to each date for simulation, perform as compared to the current policy.

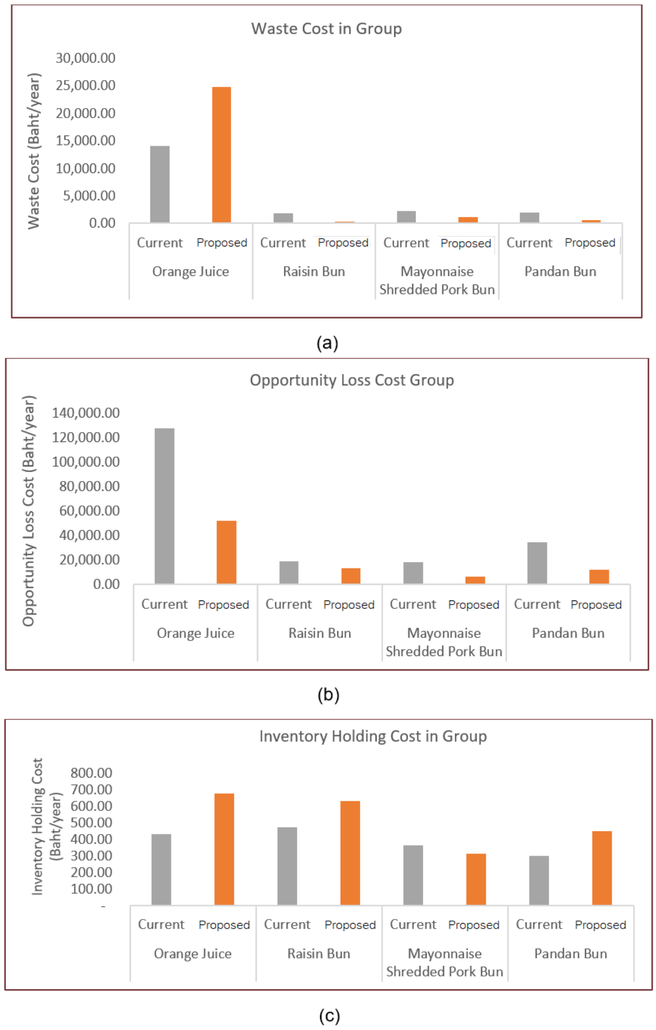

Fig. 16. Breakdown of inventory cost in medium profit-cost ratio group (a). Waste cost (b). Opportunity loss cost (c). Inventory holding cost.

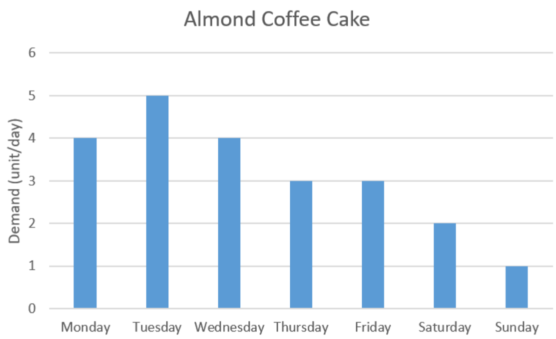

Fig. 17. Almond coffee cake average daily demand.

A key limitation of this SKU lies in its low demand and the necessity for refrigerated storage. Currently, this SKU is subject to overstocking issues, as evidenced by a high waste percentage of 10.80%. From Table 16, policy 3 emerges as the most suitable for this SKU, with annual cost saving of 4,503.55 Baht. This advantage arises from adding a delivery date and base inventory levels on separate weekday and weekend demands. While Policy 3 effectively reduces waste, it does not cause significant understocking issues, which is from demand fluctuations.

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Additionally, Policy 3 also optimizes fridge space by distributing total unit deliveries across different days.

Table 16. Almond coffee cake computational experiment results.

Policy	Delivery Day	Service Level (z)	Base Stock Level (units)	Total Inventory Cost (Baht)
Current	Mon	N/A	20	16,521.61
1	Mon	80%	23	17,405.38
2	Mon	80%	23	17,969.84
3	Mon	80%	18	12,018.06
	Thurs	80%	6	

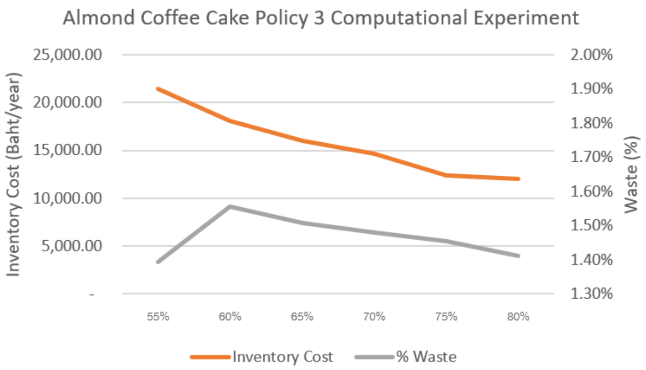

Fig. 18. Almond coffee cake Policy 3 computational experiment results from varying service level.

Table 17. %Waste and understocking days from Almond coffee cake's optimized service level.

Policy	Service Level (z)	% Waste	Understocking Days
Current	N/A	10.59%	82
1	80%	13.40%	85
2	80%	11.61%	95
3	80%	1.39%	80

The computational experiment indicates that an 80% service level is most effective for Policy 3, as shown in Fig. 18 and Table 16. However, despite its advantages over the current inventory policy, the number of understocking days remains notably high. This is possibly due to fluctuating demands and the availability of alternative products (e.g., other cakes) on the shelf.

The Chocolate Cake, another product in this group, faces overstocking issues due to its low and fluctuating demand. Figure 19 shows the daily varying demand for Chocolate Cake, which is consistently low. Notably, demand on Saturdays and Sundays is zero, as the product's shelf life is limited to 5 days. Therefore, employing the average daily demand for each day, as done in Policy 2 and 3, seems to be advantageous.

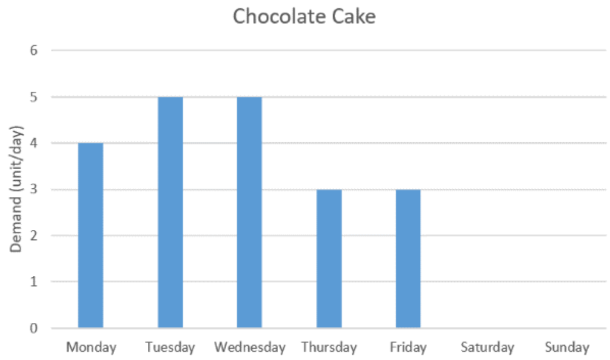

Fig. 19. Chocolate cake average daily demand.

Table 18 presents the results of the computational experiment for Chocolate Cake, identifying Policy 3 as the most suitable inventory policy. According to Fig. 20, an 75% service level under Policy 3 is selected based on maximum yearly cost saving of 14,618.10 Baht. This policy's scheduling of deliveries on different days facilitates efficient fridge space usage, reduces inventory holding costs. Its effectiveness is evident from a marked decrease in waste percentage compared to the current policy.

Table 19 provides a comparative analysis of waste percentage and the number of understocking days across different policies. The results indicate an improvement in understocking days, though they remain high due to demand fluctuations. However, the impact on opportunity loss cost is little, given the low daily demand. Conversely, waste is significantly reduced under the new policy, due to the increased delivery frequency.

From the implementation of the selected inventory policy, the benefits gained from optimizing this SKU are limited due to its small total demand. Consequently, variations in inventory level may not yield significant differences.

Table 18. Chocolate cake computational experiment results.

Policy	Delivery Day	Service Level (z)	Maximum Inventory (units)	Total Inventory Cost (Baht)
Current	Mon	N/A	20	25,144.03
1	Mon	80%	27	11,329.58
2	Mon	78%	25	11,841.77
3	Mon	75%	15	10,525.92
	Thurs	75%	16	

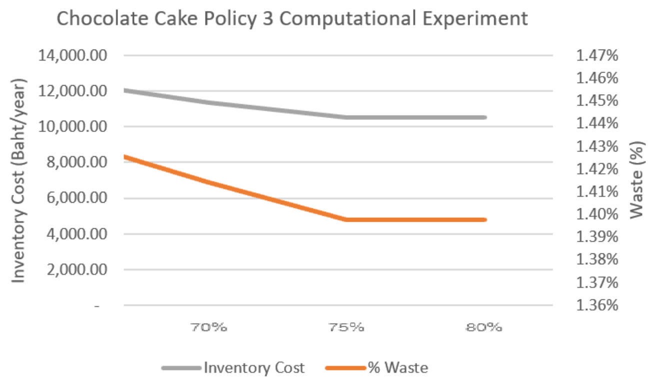

Fig. 20. Chocolate cake Policy 3 computational experiment results from varying service level.

Table 19. %Waste and understocking days from Chocolate cake's optimized service level.

Policy	Service Level (z)	% Waste	Understocking Days
Current	N/A	10.10%	133
1	80%	16.02%	30
2	78%	11.90%	48
3	75%	1.41%	72

Overall, Almond Coffee Cake and Chocolate Cake are the cake category and sourced from the same supplier. Currently, both of them have overstock issues as the current percent waste are above 10%. Fig. 21 provides a detailed breakdown of the total inventory costs, which includes waste cost, opportunity loss cost, and inventory holding cost for these low profit-cost ratio items. With the adoption of Policy 3, there is a significant reduction in waste cost, attributable to increased delivery frequency that leads to smaller delivery quantities and thus fresher product shelf life. The opportunity loss cost shows a marginal decrease, while inventory cost slightly increases. These are not obvious for these products due to their relatively lower daily demand.

4.2.4. Overall results for all products

Computational experiment was conducted to determine the most effective inventory policy for the case study company's top eight SKUs, focusing on finding the most suitable Base Stock Level (B) in relation to service levels. This experiment, based on periodic inventory review policies, is particularly suited for perishable goods and small-scale companies.

The experiment explored three variations of periodic inventory policies, aiming to optimize inventory levels and ordering frequencies in accordance with service levels tailored to each SKU's specific group, as identified by product profit-cost ratio. The experiment successfully achieved its objective of identifying the most effective inventory policy, evaluated by total inventory cost.

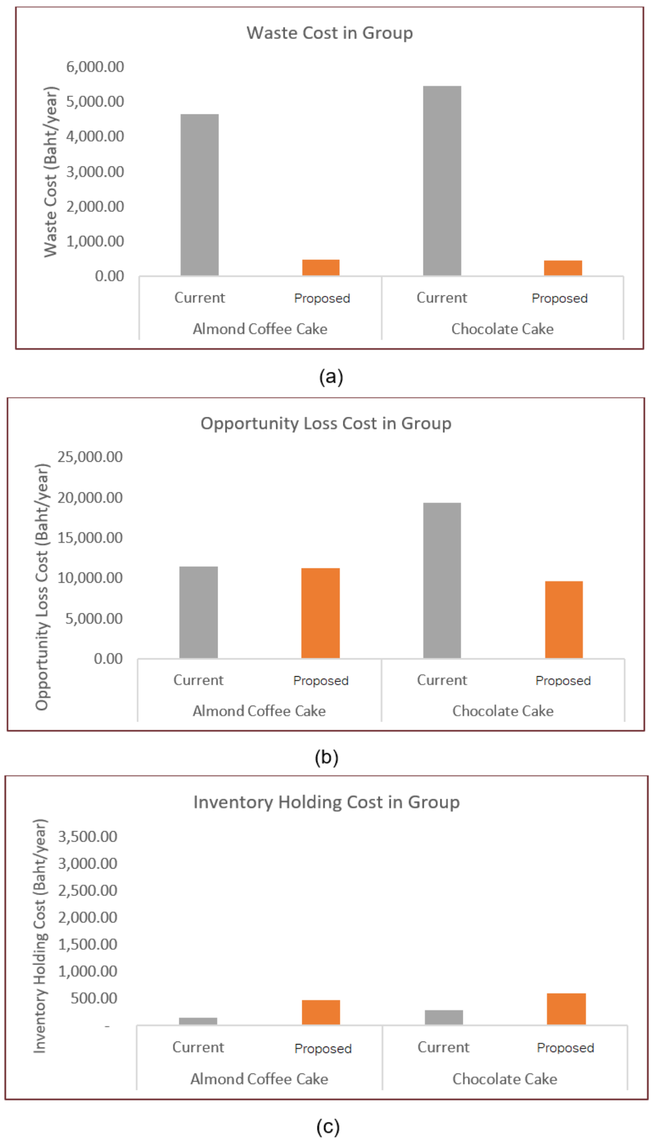

Fig. 21. Breakdown of inventory cost in low benefit-cost ratio group (a). Waste cost (b). Opportunity loss cost (c). Inventory holding cost.

The computational experiment of the selected, most optimized policy for each SKU was found to yield annual total inventory cost saving of 256,922 Baht. This is about 60.74% reduction, as compared to the current policy. The benefit primarily arises from reduced waste costs and opportunity loss costs, attributed to lower waste percentages and decreased out-of-stock days. Inventory holding costs are also included in the total inventory cost calculation, though their impact is less obvious due to the perishable nature of the products, typically held for less than a week. Figure 22 visually presents the breakdown of these total inventory costs.

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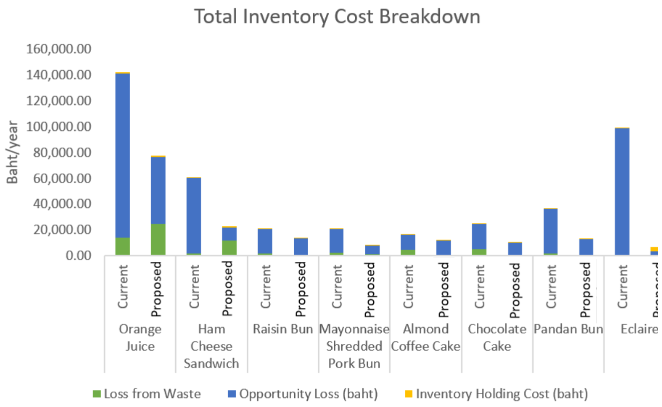

Fig. 22. Total inventory cost breakdown.

For most products, Policy 3 is the most suitable inventory strategy, utilizing different mean demand of each day and adjusting delivery dates in agreement with supplier capabilities. Finding the optimal service level for each product allows the case study company to identify the most advantageous balance between waste and out-of-stock days.

5. Conclusion

This study aims to find the most suitable inventory policy for perishable goods sold in a Thai coffee shop case study. The most efficient inventory strategy was determined by evaluating the total inventory costs, composing of waste costs, potential loss costs, and holding costs. The periodic inventory policy was implemented for its top eight revenue-generating products in the 'Bakery and Others' category. This research successfully identified the most appropriate service level, safety stock, and delivery frequency for each SKU.

The computational experiment suggested that average daily demand should be used to accurately capture distinct demand of each day. Increasing delivery frequency could also be helpful in reducing out of stock cost. The results showed that the proposed new policy could reduce the total inventory cost by 256,922 Baht annually by optimizing the periodic inventory policy for each SKU, primarily through reducing waste and minimizing opportunity loss costs. While inventory holding costs were considered, their impact was less obvious given the perishable nature of the products, with a maximum holding period of 7 days.

For future work, regular update of daily demand should be reviewed every year to ensure the effectiveness of the proposed policy. If the future demand fluctuates significantly, revisiting the inventory policy will be necessary to maintain optimized inventory levels. Maintaining strong relationships with suppliers is also crucial for smooth operations and effective supplier management. If the suppliers are more flexible in supply scheduling, more intensive experiment about the optimal scheduling option can further improve the store performance.

References

[1] K. MacDonnell. "15 Thailand Coffee Consumption Statistics & Facts to know in 2023." Accessed Oct. 5, 2023. [Online]. Available: https://coffeeaffection.com/coffee-consumption-statistics-in-thailand/#4_Thailand_consumes_018_kilograms_of_coffee_per_person/

[2] Q. Duan and T. W. Liao, "A new age-based replenishment policy for supply chain inventory optimization of highly perishable products," *International Journal of Production Economics*, vol. 145, no. 2, pp. 658-671, 2013.

[3] G. Mirabelli and V. Solina, "Optimization strategies for the integrated management of perishable supply chains: A literature review," *Journal of Industrial Engineering and Management (JIEM)*, vol. 15, no. 1, pp. 58-91, 2022.

[4] S. Minner and S. Transchel, "Periodic review inventory-control for perishable products under service-level constraints," *OR Spectrum*, vol. 32, pp. 979-996, 2010.

[5] T. Gruen, D. Corsten, and S. Bharadwaj, "Retail out-of-stocks: A worldwide examination of extent, causes and consumer responses," Washington: Grocery Manufacturers of America, The Food Marketing Institute and CIES, 2002.

[6] M. Ketzenberg and M. E. Ferguson, "Managing slow-moving perishables in the grocery industry," *Production and Operations Management*, vol. 17, no. 5, pp. 513-521, 2008.

[7] S. Setyaningsih and M. H. Basri, "Comparison continuous and periodic review policy inventory management system formula and enteral food supply in public hospital Bandung," *International Journal of Innovation, Management and Technology*, vol. 4, no. 2, pp. 253, 2013.

[8] Q. Duan and T. W. Liao, "A new age-based replenishment policy for supply chain inventory optimization of highly perishable products," *International Journal of Production Economics*, vol. 145, no. 2, pp. 658-671, 2013.

[9] P. Suttipongkaset and P. Chaovalitwongse, "Delivery planning of water-treatment chemicals in vendor managed inventory context," *Advanced Materials Research*, vol. 931, pp. 1664-1668, 2014.

[10] I. Rizkya, K. Syahputri, R. Sari, I. Siregar, and E. Ginting, "Comparison of periodic review policy and continuous review policy for the automotive industry inventory system," *IOP Conference Series: Materials Science and Engineering*, vol. 288, no. 1, pp. 012085, 2018.

[11] S. Minner and S. Transchel, "Periodic review inventory-control for perishable products under service-level constraints," *OR Spectrum*, vol. 32, pp. 979-996, 2010.

[12] J. Y. Lee and L. B. Schwarz, "Leadtime management in a periodic-review inventory system: A state-dependent base-stock policy," *European Journal of Operational Research*, vol. 199, no. 1, pp. 122-129, 2009.
[13] A. Aisyati, W. A. Jauhari, and C. N. Rosyidi, "Determination inventory level for aircraft spare parts using continuous review model," *International Journal of Business Research and Management (IJBRM)*, vol. 4, no. 1, pp. 1-12, 2013.
[14] Y. J. Lin and H. J. Lin, "Optimal ordering and recovery policy in a periodic review integrated inventory model," *International Journal of Systems Science: Operations & Logistics*, vol. 3, no. 4, pp. 200-210, 2016.
[15] I. Rizkya, K. Syahputri, R. M. Sari, I. Siregar, and E. Ginting, "Comparison of periodic review policy and continuous review policy for the automotive industry inventory system," in *IOP Conference Series: Materials Science and Engineering*, vol. 288, no. 1, p. 012085, 2018.
[16] H. Zhang, X. Chao, and C. Shi, "Closing the gap: A learning algorithm for lost-sales inventory systems with lead times," *Management Science*, vol. 66, no. 5, pp. 1962-1980, 2020.
[17] Y. Tao, L. H. Lee, E. P. Chew, G. Sun, and V. Charles, "Inventory control policy for a periodic review system with expediting," *Applied Mathematical Modelling*, vol. 49, pp. 375-393, 2017.
[18] V. Murmu, D. Kumar, B. Sarkar, R. S. Mor, and A. K. Jha, "Sustainable inventory management based on environmental policies for the perishable products under first or last in and first out policy," *Journal of Industrial and Management Optimization*, vol. 19, no. 7, pp. 4764-4803, 2023.
[19] E. A. Feinberg and D. N. Kraemer, "Continuity of discounted values and the structure of optimal policies for periodic-review inventory systems with setup costs," *Naval Research Logistics (NRL)*, vol. 70, no. 5, pp. 480-492, 2023.
[20] I. T. Christou, K. Skouri, and A. G. Lagodimos, "Fast evaluation of a periodic review inventory policy," *Computers & Industrial Engineering*, vol. 144, p. 106389, 2020.
[21] N. Sakulsom and W. Tharmmaphornphilas, "Periodic-review policy for a 2-echelon inventory problem with seasonal demand," *Engineering Journal,* vol. 22, no. 6, pp. 117-134, 2018
[22] M. Gutierrezand and F. A. Rivera, "Undershoot and order quantity probability distributions in periodic review, reorder point, order-up-to-level inventory systems with continuous demand," *Applied Mathematical Modelling*, vol. 91, pp. 791-814, 2021.
[23] E. A. Feinberg and Y. Liang, "Structure of optimal policies to periodic-review inventory models with convex costs and backorders for all values of discount factors," *Annals of Operations Research*, vol. 317, pp. 29–45, 2022.
[24] S. Poormoaied, "Inventory decision in a periodic review inventory model with two complementary products," *Annals of Operations Research*, vol. 315, pp. 1937–1970, 2022.
[25] G. Karakatsoulis and K. Skouri, "A periodic review inventory model facing different disruption profiles," *International Journal of Production Economic*s, vol. 265, p.109004, 2023
[26] Y. Xu, D. A. Serel, A. Bisi, and M. Dada, "Setting fulfillment-time guarantees for accepting customer orders in a periodic-review base-stock inventory system," *IISE Transactions*, pp.1-14, 2023
[27] A. Gurtu, "Optimization of inventory holding cost due to price, weight, and volume of items," *Journal of Risk and Financial Management*, vol. 14, no. 2, pp. 65, 2021.

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