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Impact of backroom operations on replenishment of perishable goods

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Abstract
Because of their short shelf life and quick depreciation in value, traditional approaches to inventory management do not work well with perishable goods. To prevent excessive spoiling, missed sales, and expensive expenses, more advanced planning and monitoring are needed for perishables. We examine replenishment strategies for systems with perishable inventory, taking product age into account as a critical decision element, in this paper. To find out how operational parameters affect policy performance, we test out several replenishment scenarios with and without backroom storage. The comparison findings show that replenishment choices that take product age into account are far more cost efficient, especially in scenarios that are similar to real-world retail operations. In addition, the results show that there are certain scenarios in which policies with backroom storage do better than ones without. The research demonstrates that, in comparison to conventional methods, age-based replenishment techniques provide significant benefits, such as lower overall costs and better service levels for supply chains with perishable goods.

Keywords: Perishable inventory, freshness decay, dynamic pricing, customer behaviour, stock replenishment

Introduction

One of the most important parts of running a contemporary retail or supply chain is handling items with a near-term expiration date. Because of their short shelf life, perishable goods' inventory management is very vulnerable to changes in time, storage conditions, and demand unpredictability, in contrast to those of durable items. Minimizing losses due to spoilage, ensuring product availability, and maintaining customer happiness all depend on efficient replenishment procedures. The impact of backroom activities on perishable inventory is significant, yet often disregarded. Things like receiving, storing, sorting, and getting things ready for sale are all part of backroom operations. Products' freshness, shelf life, and replenishment efficiency are all directly impacted by how fast these activities can transport them from the storage area or warehouse to the retail display. Inventory management becomes more complex when items are perishable. To begin, degradation or decay is an ongoing process that may change with time, temperature, and care taken with the product. Second, variables like pricing, promotions, seasonal patterns, and customer preferences greatly impact the demand for items with a near-term expiration date, which may be somewhat unpredictable. The dynamic complexity of systems with perishable goods cannot be captured by traditional inventory models, which often presume continuous demand and little degradation.

Because inefficiencies or delays in these processes might cause increased waste, stockouts, or overstocking, it is critical to include their function into these models. A link between inbound shipments and shelf availability is maintained by backroom operations. They are kept fresh for longer and have a longer effective shelf life on the retail floor because of efficient backroom operations that decrease the amount of time they spend in storage. Improper rotation, delayed stocking, or insufficient temperature control are examples of poor backroom procedures that may speed up product degradation and increase operating expenses. Another factor that affects the timeliness and amount of replenishment orders is the efficiency of the backroom. Lower holding costs and less spoiling might be possible with smaller, more frequent orders if the backroom can process and redistribute quickly. The flip side is that slower back-end processes call for bigger purchases to cover for delays, which might lead to higher inventory costs and the possibility of becoming obsolete. The integration of real-time data from point-of-sale systems, warehouse operations, and backroom procedures is becoming more and more important in modern retail settings' inventory management systems.

If managers use advanced analytics like demand forecasting, shelf-life prediction, and dynamic replenishment algorithms, they may optimize the timing and quantity of orders while taking operational realities of backroom processing into consideration. Barcoding, RFID tagging, and automated storage and retrieval systems (ASRS) are a few examples of tech-enabled solutions that may improve the transparency and efficiency of back-room operations, which in turn can speed up product flow, decrease human error, and more. Retailers can now better balance consumer demand and the limitations of perishable stock thanks to these developments. The effect of operational delays on the performance of perishable inventory has been highlighted in several studies. For example, in categories with a high concentration of perishable goods, the total spoiling rate may be decreased by 10-20% by including backroom efficiency measures into inventory models. By making sure that fresh items are always accessible on the sales floor, improvements made in the backroom, including quicker unloading, cross-docking, and real-time inventory management, immediately transfer into improved customer happiness. Optimization of backroom operations is even more crucial to sustaining service standards and avoiding losses in the setting of post-pandemic retail, as supply chains experience extra interruptions.

This research aims to examine the impact of administrative processes on replenishment strategies for items with a near-term expiration date. Our goal is to help managers create more robust and efficient inventory systems by analyzing the correlation between backroom processing times, order amounts, cycle times, and overall cost. The analysis takes into account both predictable and unpredictable demand, the impact of product degradation rates, and the possibility of partial backlogs, all of which are reflective of actual operating circumstances. In order to maximize product availability, minimize costs, and reduce waste, merchants must grasp the relationship between backroom efficiency and replenishment choices. An essential link in the supply chain for perishable items is the work that goes on behind the scenes. The time of replenishment, inventory levels, product freshness, and overall operating expenses are all affected by them. Better forecasting, decision-making, and customer satisfaction are all possible outcomes of integrating backroom efficiency into models for inventory management. To better understand how to restock current retail settings with perishable commodities, this research delves deeply into these processes, offering theoretical and practical insights.

Literature Review

Li, Lin *et al*., (2021) we provide a novel idea for perishable goods: the backroom effect, which occurs when the rate of degradation is lower in a backroom than on store shelves. This issue greatly affects combined shelf-space and inventory choices using real-time information on perishable items produced by the Internet of Things. We characterize the demand distribution that depends on freshness, with constant replenishment from the backroom to the shelves, and we construct the perceived on-shelf product freshness. Additionally, we define the degradation rate gap. We create a decision-making model that figures out how to replace inventory and where to put different goods on shelves all at once, assuming that demand is dependent on how fresh something is and how high up the shelf it is. In order to make things easier, we provide a hybrid solution strategy that combines genetic algorithm (GA) and variable neighborhood search (VNS). Using the findings, one may create a prioritized inventory strategy that takes the degradation improvement into account when choosing items. The performance study reveals that when the backroom/shelf degradation gap widens, a strategy that takes the backroom impact into account enhances profit. Traditional model results are at odds with the ideal solutions for issues with big backroom/shelf gaps, which also indicate that the practitioner should raise the ordering amount.

Kiil, Kasper *et al*., (2018) [10] the goal of this research is to examine the effects of age-based replenishment strategies for perishable goods on the dissemination and use of grocery store residual shelf life (RSL) data. The performance is assessed using a discrete event simulation model that mimics a portion of the biggest Norwegian grocery store chain, using their point-of-sale data to represent a realistic demand pattern across 232 locations over a year. The results show that for perishables with a shelf life of 4–11 days, the current age-based replenishment policy (EWA policy) significantly improves availability by 17.7 percent, but it has high inventory levels and only reduces waste by 3.4 percent when compared to a base stock policy. By maintaining the same average inventory level, a suggested change to the EWA policy, EWASS, results in a more balanced performance in the study, with a decrease of 10.7 percent in waste and an increase of 10.3 percent in availability. Restocking perishable goods with a set shelf life of 6–11 days may be facilitated by sharing and using RSL information, which might lead to the automation of replenishment procedures. Nevertheless, the advantages gradually fade for items that have a longer shelf life. In comparison to earlier replenishment plans, the proposed age-based approach demonstrated a more balanced increase in performance across waste and availability.

Hübner, Alexander & Schaal, Kai. (2017) [11] optimal shelf-space choices may be made with the help of shelf-space optimization models. Each item in an assortment has its number of facings decided by them. All of these models have the defining feature of ignoring replenishment procedures that take place inside the shop. There is a close relationship between in-store replenishment and shelf-space planning. Having more of a product on hand raises its visibility, which in turn increases demand, allows for less frequent replenishment, and ultimately raises the cost of storing that product. Unfortunately, other things have to go on the shelf because of this, which means they run out quicker and need to be restocked more often due to space constraints. In addition, there is the prospect of storing certain things in the backroom rather than the showroom. This frees up shelf space in the showroom for other items, but it also means there will be extra expenditures to refill the items maintained in the backroom. The current research does not go far enough in discussing how to optimize replenishment operations in conjunction with shelf-space considerations. For a German grocery business, we ran a time and motion analysis to put a price on the key in-store replenishment procedures. These findings inform our proposal for an optimization model that takes into account the interdependence of replenishment procedures and judgments about shelf space. Accounting for space-elasticity effects and limited shelf and backroom space, the model maximizes retail profitability by estimating the optimal number of facings, the optimal display orientation of goods, and the optimal order frequency. We calculated a possible profit of around 29% by applying our methodology to the canned goods area of the grocery store. Additionally, we test our model on data created at random and demonstrate that, even for large-scale problems, it can be optimally addressed in very short run times. Lastly, we illustrate the effect of replenishment cost and available backroom space on retail earnings and solution structures using the model. Our model's results have convinced the grocery shop to rethink its present strategy for deciding where to put shelves and how to prepare for stock outs.

Chiadamrong, Navee & Lhamo, Rigzin. (2017) [14] the term "perishable goods" refers to commonplace items whose quality or worth declines as time passes. Conventional approaches to inventory management do not work well with perishable goods since their freshness level fades with time and stock is lost due to degradation. Then, additional systems are needed to control the stock of such items. In order to analyze the influence on the management of perishable product inventory, the research considers the age of stocks and investigates these processes in various scenarios with varied cost combinations. To further understand how and when the policy with backroom storage performs better than the others, leading to cost reduction and higher profit, we compare the results of the replenishment policies under different purchasing batch sizes with and without a backroom. These results are useful for businesses in determining how to handle items with a near-term expiration date in a certain industry.

Eroglu, Cuneyt *et al*., (2013) [18] when it comes to retail, the dynamics between the sales floor and the backroom—where excess storage is often kept—are overlooked by traditional inventory models. It is common for retail stores to need to use backroom storage when a replenishment order for a certain item comes, since it may not fit on the designated shelf space. Here we present the backroom effect (BRE), which occurs when the dimensions of case packs, available shelf space, and the point of reorder are not properly aligned. This discord impacts fundamental trade-offs in inventory models and is a consequence of the disjointed process by which retail organizations decide on inventory policies. We define the BRE's existence circumstances, estimate the quantity of stock that will accumulate in the back room, determine the best course of action for the near future, and evaluate how the BRE affects both the optimum policy and overall expenses. Neglecting the BRE causes reorder points and overall prices to be inflated, according to our research. Implications for theory and management are addressed in the latter section of the article.

Broekmeulen, Rob & Bakx, C. (2010) [20, 21] Customers at grocery stores would rather take the most recent goods off the shelf than the older, more perishable ones. This withdrawal behavior causes a large amount of out-of-date costs; hence we propose a process that restricts shelf life to one batch per product. We presume the backroom has sufficient storage space for the remaining product. When compared to in-store replenishment procedures that ignore customer withdrawal behavior and shelf storage capacity, we demonstrate that this procedure significantly reduces costs for products with large available shelf space, short product lifetimes, expensive outdating, and low handling cost.

Simulation experiments

Objective Function

Making as much money as possible is the primary goal of our approach. The notations used are summarized in Figure 1.

Symbol	Quantity
SP	Unit Selling Price of the product
R	Revenue
C_t	Total costs incurred
C_Q	Unit Purchasing cost
C_Z	Unit Outdating (Disposal) cost
C_K	Unit Lost sales cost
C_{GW}	Unit Loss of good will cost
C_H	Holding cost
Q_t	Number of units ordered
Q_g	Number of good parts sold to customer
Q_b	Number of bad parts sold to customer
Z_t	Number of units outdated in 1 year
K_t	Lost Sales per year
H_t	Average inventory

Fig 1: Notations used

The following represents the expense for time period t:

Total Costs = Purchasing Cost + Outdating Cost + Lost Sales Cost + Loss of goodwill cost + Holding Cost

$$Ct = CQ.\ Qt + Cz.\ Zt + CK.\ Kt + CH.\ Ht + CGW.\ Qb \quad (1)$$

Revenue = Units Sold * Selling Price of the product

$$R = ((Qg + Qb).\ SP) \quad (2)$$

Profit = Revenue – Total Costs

$$\text{Pro it} = ((Qg + Qb).\ SP) - Ct \quad (3)$$

Figure 2 shows the results of a complete factorial experiment in which we examined many values for the input parameters.

Input parameter	Levels	Measurement
Product lifetime	14	Days
Re-order cycle period	1	Week
Mean period demand μ	70	Units
Coefficient of variation σ/μ	0.25	
Lead-time L	1	Days
Review Period R	1	Week
Outdating cost ratio C_z/C_Q	-0.5,0, 0.5	

Fig 2: Input parameters

Although the holding cost is determined by the product's selling price, loss sales cost and loss of good will costs are derived from the predicted profit that was gained from the preliminary results of running the model. The outdating cost parameters in the model are standardized on the purchase cost. You may find relative outdating prices ranging from -0.5 to 0.5. If the old goods can still make a profit (their "salvage value"), then the negative parameter represents that. The keeping cost was estimated to be around 40% of the selling price. The experiment involves varying the predicted profit from 140 ฿ (based on preliminary findings) to 200 ฿ (the top limit) and 80 ฿ (the lower bound) by using lost sales charges and loss of goodwill cost. The relative handling expenses for each trip are fixed at 5% of the purchase cost.

Decision Variable

Our simulation model uses the maximum amount of goods in the business, known as the Target goods Level (TSL), as its decision variable. To ensure that the range encompasses the ideal value, we set the variable's lower limit to 0 and its upper bound to 1,000 units. Optimal TSLs that maximize profit were determined for all cases using the OptQuest program.

Experimental Condition

We ran 15 sets of simulations. The breadth of the 95% confidence interval of the flow time is less than 5% of the mean, according to the 15 replications. Stable estimations of the steady-state outcomes might be generated throughout the warm-up phase.

Results

Experiment I

The data collected from Arena was subjected to a statistical test in Minitab using the ANOVA to identify the important variables. Data analysis using ANOVA revealed that, with the exception of lost sales cost, all components were statistically significant at the 95% confidence level. Figure 1 displays the analysis of variance (ANOVA) findings for the important variables.

Table 1: ANOVA Results for Factors Affecting Inventory Management of Perishable Goods (P-values for Main Effects and Interactions)

Factors	P-value
Demand type	0.000
Replenishment policies	0.000
FIFO/LIFO	0.001
Loss of goodwill cost	0.000
Disposal/Outdating cost	0.000
Demand Type * Replenishment policies	0.000
Demand Type * Loss of goodwill cost	0.000
Demand Type * Loss of goodwill cost	0.000
Replenishment policies * FIFO/LIFO	0.000
Replenishment policies * Loss of goodwill cost	0.000
Replenishment policies * Disposal/Outdating cost	0.000

Here is the calculation that compares the average profit of the Base policy to that of the EWA policy to see how well it performs:

The EWA policy's average profit is denoted as P (EWA). Base policy's average profit is denoted as P (Base). We also used the Pair-t test to determine if there was a statistically significant profit disparity between the Base policy and EWA. Table 2 shows that the EWA policy's advantages under the FIFO withdrawal are much higher than those under the LIFO withdrawal. While there were instances when the Base policy outperformed LIFO withdrawal (as shown by negative percentage values), the difference was determined to be insignificant (P-value < 0.05).

Furthermore, it was discovered that when demand remains constant throughout the week, as opposed to having probabilistic demand, both the EWA policy and the Base Policy would function better. On the other hand, the disparity widens with probabilistic demand, indicating that EWA policy is best implemented with more variable demand, which is often the case in practice.

Table 2: Comparative Profit Improvement of EWA Policy over Base Policy under FIFO and LIFO Inventory Withdrawal

Parameter	Level	FIFO	P-value	LIFO	P-value
Demand	Probabilistic	5.6%	0.000	-0.2%	0.700
	Constant	1.9%	0.000	1.5%	0.000
Outdating cost	-25	4.6%	0.000	1.9%	0.000
	0	3.6%	0.000	0.6%	0.214
	25	2.7%	0.000	-0.4%	0.376
Lost Sales cost	80	3.4%	0.000	0.9%	0.076
	140	3.7%	0.000	0.7%	0.169
	200	3.8%	0.000	0.5%	0.377
Loss of goodwill cost	80	1.6%	0.000	-1.0%	0.021
	140	3.7%	0.000	0.7%	0.057
	200	5.7%	0.000	2.4%	0.000

There is a significant difference between the Base policy and EWA when the store uses LIFO since consumers tend to choose products with later expiration dates. Implementing EWA outperforms the Base policy, nevertheless, if the store can manage and allow customers to choose products according to FIFO. More units will be out of date on the shelf after LIFO removal, driving up the out-of-date cost. With EWA, the employee will remove the old units from the shelf every day after the shop closes, which will raise the cost of losing sales. If we compare FIFO withdrawal to LIFO withdrawal, we see that there are fewer out-of-date products on the shelf since customers purchase the older ones first. This means that we lose less sales and goodwill cost.

Experiment II

Both the in-store replenishment strategies and EWA were evaluated using a Tukey multiple range test. Table 3 displays the results of the Tukey multiple range tests. As far as in-store replenishment procedures go, "Direct to Shelf" is the most effective. It reduces goodwill cost by restocking units straight to the shelf, which means you get items that are fresher. In addition, the space on the shelf is better used when the units are restocked from the backroom anytime the sales associate notices that there are less units on the shelf than what is indicated by the TSL. Because of this, you won't have to worry about the potentially crippling effect of missed sales.

Multiple batches are permitted on the shelf with the 'FS2' policy, which allows for greater use of the shelf space compared to other policies. While 'FS2' and 'Direct to Shelf' policies have a smaller proportion of store inventory kept in the Backroom, 'Single Batch' and 'FS1' policies have a bigger share. Hence, 'FS2' and 'Direct to Shelf' policies have lower out-of-dates in the Backroom than 'Single Batch' and 'FS1' guidelines. As a result, there is a significant out-of-date expense, as well as a loss of goodwill and revenues. Under the 'Single Batch' policy, the impact of stocking the Backroom with the most recent batches on the ability to provide consumers goods that are reasonably fresh is minimal.

Table 3: Performance ranking from the best to worst of in-store replenishment policies in comparison to EWA by Tukey multiple range test

Parameter	Level	1	2	3	4	5
Demand	Probabilistic	DTS	EWA	FS2	FS1	SB
	Constant	FS2	EWA	DTS	SB	FS1
Customer	FIFO	DTS	EWA	FS2	SB	FS1
Withdrawal	LIFO	DTS	FS2	EWA	SB	FS1
Outdating cost	-25	DTS	EWA	FS2	FS1	SB
	0	DTS	EWA	FS2	FS1	SB
	25	DTS	EWA	FS2	FS1	SB
Loss of goodwill cost	80	DTS	EWA	FS2	FS1	SB
	140	DTS	EWA	FS2	SB	FS1
	200	DTS	EWA	FS2	SB	FS1

DS stands for "Direct to Shelf," SB for "Single Batch," FS1 for "Full Shelf," and both FS1 and FS2 mean to replenish when the SOH level is zero or less than the total shelf life (TSL).

Out of the four in-store replenishment strategies we tested, only the "Direct to Shelf" strategy beat the EWA policy in every scenario with the exception of steady demand, as shown in our experiment. While the 'FS2' policy does better than the EWA policy under constant demand conditions, it falls short in all other scenarios. Figure 3 displays the average profit for all experiments' tested policies.

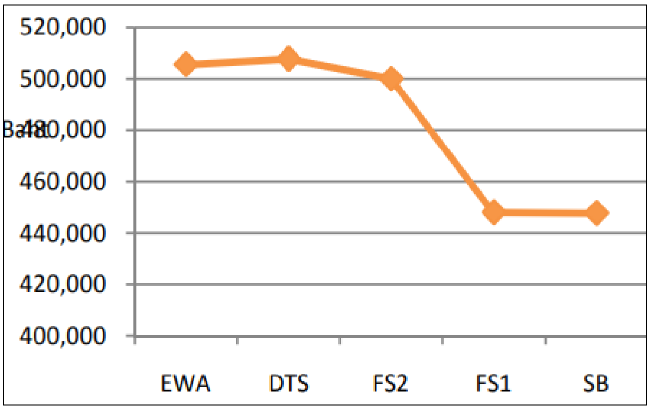

Fig 3: Profit Performance of In-Store Replenishment Policies versus EWA Policy

Conclusion

Restocking perishable items efficiently relies on backroom activities. Product freshness, shelf life, and total inventory costs are impacted by backroom efficiency, which facilitates the timely flow of items from storage to the retail floor. It is necessary to include backroom performance into inventory management techniques to prevent spoiling, stockouts, and increased operating expenditures caused by delays or inefficiencies in these procedures. Retailers may optimize order amounts and replenishment cycles by considering backroom processing times, degradation rates, and demand unpredictability. This will eventually save costs while assuring product availability, as shown by the research. Backroom operations are further improved by modern technology like automated storage systems, real-time inventory management, and demand forecasting tools. This allows shops to react swiftly to changes in demand while maintaining product quality. Not only does it increase customer satisfaction and supply chain resilience by incorporating backroom efficiency into perishable inventory models, but it also saves operating expenses and waste. Prioritizing backroom activities is crucial for sustainable and profitable management of perishable commodities in evolving retail contexts, particularly in post-pandemic circumstances.

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