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Original Research

Simulation model of perishable item picking policies in the buffer stock of a push-pull supply chain

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Abstract: This paper studies the influence of different picking policies in a stock of perishable items on the quantity of waste, the degree of freshness of the stored products and the profit. We consider a push-pull supply chain with three echelons (an agricultural producer, a manufacturer and a retailer), in which the quantity ordered from the upstream supplier is determined using a forecast based on a simple exponential smoothing of historical sales data of perishable products. To meet a stochastic demand that is symmetrically distributed around a given average, the stock of this perishable product must be sufficient without exceeding the expiration dates to avoid any waste. If the demand exceeds the available stocks, the manufacturer can resort to external suppliers on a spot market to deliver the products very quickly. We developed a simulation model to compare three picking policies (FIFO: first-in-first-out, LIFO: last-in-first-out and RDM: random picking policy) and their performance in terms of the average age of stored goods, the quantity of waste and the profit. A counterintuitive result showed that under certain conditions, the LIFO policy led to better performance than the FIFO policy, a result we proved mathematically. We then simulated different scenarios by varying product depreciation and margin rates. When margins decrease linearly with product age, the FIFO policy is the least competitive. In the case of normally distributed demand, LIFO is the most efficient picking policy, whereas in the case of uniform demand, the RDM policy performs better. We also studied the sensitivity of the model to the parameters of the demand function and the smoothing coefficients used to forecast the quantities of perishable products to be supplied. Finally, we applied our model to some specific features of the poultry and meat industry and simulated a policy of preventive production reduction.

Keywords: Simulation, Perishable inventory, FIFO, LIFO, Push-pool supply chain, Food waste

Introduction

In Europe, around 11 million tons of waste are generated every year by the manufacture of food and drink products (Eurostat 2024 [1]). EU members have set a target of reducing food waste by 10% by the end of 2030, both at the processing and manufacturing level [2]. Garonne et al. [3] explained how food manufacturers can prevent the degradation of surplus food and propose a structured system to control surplus food. For example, La Scalia et al. [4], Bertonlini et al. [5] and Salinas Segura et al. [6] have noted a rise in new technologies for monitoring inventory operations, aimed at reducing this waste. When it comes to product picking strategies such as

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FIFO (First-In First-Out) or LIFO (Last-In First-Out), the FIFO method is most often used for perishable products. Derman and Klein [7] and Lieberman [8] were the first to model LIFO and FIFO picking policies for perishable inventory. They considered that the FIFO policy is used to avoid waste, while the LIFO policy is used to maximize the total life of the inventory [9].

The main causes of waste in the food industry can be explained by non-optimized inventory management, although numerous models have been proposed in the literature [7-9], or by inefficient product picking methods. Although our research aims to investigate the influence of different picking policies on loss reduction, product freshness and profits, we considered it worth citing work on optimizing the replenishment of perishable products, taking picking policies into account. Cohen and Prastacos [10] optimized the replenishment policies for perishable products in a retail store, comparing FIFO and LIFO methods, as did Keilson and Seidman [11], who relied on Markov processes. They considered Poisson distributions of delivery rates and demand as well as a deterministic delivery time and found that a LIFO policy reduced the average age of delivered products. They also compared inventory holding costs and shortage costs. More recently, Parlar et al [12] considered an inventory system for perishable products with arrival times λ of products to be stocked and arrival times μ of demands that follow independent Poisson processes. Their objective was to maximize the long-term average net profit as a function of the system parameters λ and μ over their permissible ranges in FIFO and LIFO, taking into account the revenue generated by a satisfied demand, the cost of shelf space per item per unit of time, the penalty for an unsatisfied demand, and the obligation to pay for each incoming item stored on the shelf. Haijema and Minner [13] found that current technologies enable many supermarkets and retailers to determine replenishment quantities based on stock age. They cited research based on this principle ([14-16]) and proposed a simulation-based method for optimizing order quantity according to two new policies that depend on inventory age, one of which gives a lower weight to products that are likely to expire soon and the other increases the order quantity by adding an estimate of product wastage. Hendrix et al. [17] studied an inventory control problem for a perishable product with a short-fixed shelf life in Dutch retail practice. They considered a non-stationary demand during the week, but stationary over the weeks, with mixed LIFO and FIFO picking on products whose age distribution is not always known. In this context, they proposed a new heuristic that provides a low level of cost and waste and does not require information on product age. Broekmeulen and Van Donselaar [18] proposed a discrete-event simulation model to compare different age-based replenishment policies for perishable products. Ding and Peng [19] analyzed the impact of issue policies on the age distribution of available stock. They proposed two heuristics to obtain the order quantity under the LIFO issue policy based on a LIFO and a combination of FIFO and LIFO, which corresponds to observed consumer behavior in retail stores. For a given issue policy and a given stock level, their objective was to minimize the expected total cost over a given time horizon using dynamic programming.

Of these different works, which essentially sought to optimize inventory management, only a few have focused on the impact of different inventory selection policies on the average age of products sold, on waste generation and on economic performance. A number of studies have focused more specifically on picking policies as a function of product age and degree of deterioration. Akkas et al. [20] proposed that manufacturers establish shipping policies linked to product age, taking into account variable product characteristics. Boxma et al. [21] considered a process known as virtual obsolescence, with a time that would elapse from an instant t until the next outdating if no new demands arrived after t. Yang et al. [22] assumed that the rate of deterioration decreases with the effort required to maintain freshness, which is an additional cost. Tromp et al. [23] developed a simulation model for a Dutch pork supply chain, in which the expiry date was adjusted according to the increase in microbial numbers as a function of time and temperature.

Our research is based on field observations of different picking policies for perishable products in the buffer stock of an integrated push-pull supply chain with three echelons. We found no research dealing with this configuration specific to certain food industries, such as the poultry industry, where all chickens must be slaughtered after a fixed, contractually agreed number of days (Figure 1).

The specific characteristics of this type of hybrid supply chain are as follows. At the upstream stage, the farmer produces in batches on the basis of prior contracts with his manufacturer, and delivery times are often long and fixed, as in the case of breeding. The food manufacturer produces on a pull-flow basis according to a demand from the retailer at the start of each day, and delivers the products to the retailer after a fixed lead time of one day. Demand is highly uncertain, so the manufacturer must manage a buffer stock as efficiently as possible, to (1) ensure that there are enough goods to produce and meet demand, (2) not have too many goods in stock and run the risk of exceeding expiry dates, which will cause waste, and (3) not be out of stock when an order arrives and have to buy finished products on external spot markets at higher costs to meet demand. In each period, the manufacturer must decide on the quantity of perishable goods to order based on consumption forecasts. After each customer order, we evaluate the amount of waste, the average age of the remaining stock and the profit for three picking policies LIFO, FIFO and RANDOM.

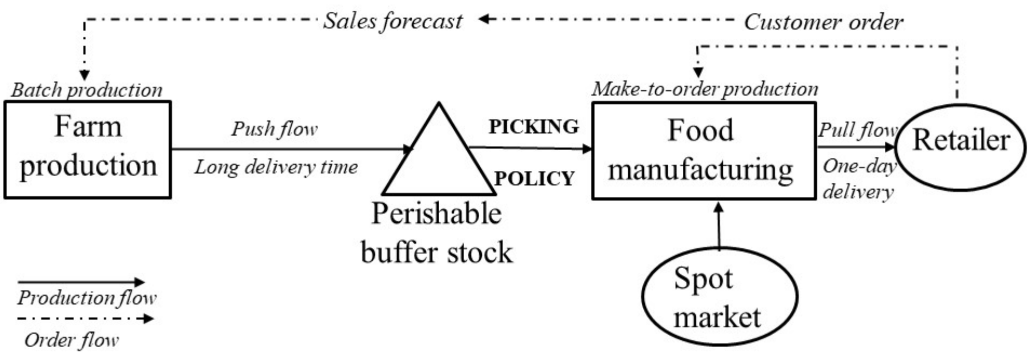


Figure 1. Management of a perishable buffer stock in a three-echelon supply chain

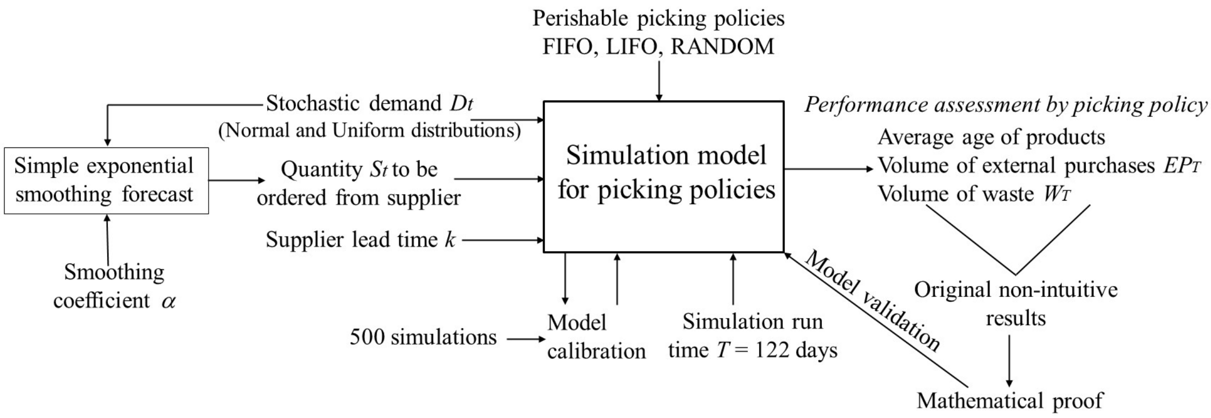


Figure 2. Modeling approach

2. Simulated-based research methodology

We chose to model the supply chain presented in Figure 1 and analyzed the performance as a function of picking policies, using a simulation-based research methodology [24]. After the introduction, in which we set our research objective in relation to the existing literature, we formalize the research question using a simulation model (Figure 2), which we test on a simple data set (Section 3). After calibration and robustness tests, the results obtained on this basis are then demonstrated mathematically. Based on this model, we simulated different scenarios for the depreciation of perishable goods and the margins on products sold (Section 4).

Then, based on the scenario closest to reality, we investigated the sensitivity of this model to different demand smoothing coefficients that predict the quantities to be supplied and to different stochastic demand parameters (Section 5). Finally, we showed the applicability of our model to specific problems of certain push-pull food chains, such as the meat production and processing industry (Section 6).

3. Model description

We considered a manufacturer who faces a stochastic demand D_t for a single perishable item in each time period $t = 1,\ldots,T$. We assumed that Dt fluctuates according to a symmetric probability distribution. This allows the company to replenish its product at $\bar{t} = t + k$, considering a fixed supply lead time k and a quantity S_t varying according to forecasts F_t derived from a simple exponential smoothing model. We assumed that the quantity ordered from the supplier and the delivery time are deterministic. The age of the quantity delivered is dated to day $j = 0,..., J$, where J is the product's expiration date, and evolves according to a process of deterioration or perishability of the product. To meet demand D_t, a certain quantity of product of age j is withdrawn from the stock, depending on the choice of picking policy. If the total stock falls short of demand, the manufacturer calls in a subcontractor to supply the missing products. We did not focus on the commitment between the manufacturer and the subcontractor and therefore we assumed that the availability of these external purchases EP is deterministic and unlimited. At the end of each discrete time period, each remaining stock will age by one day if its age j was less than J. Remaining stocks W_t at the end of period J are scrapped (waste).

Let $Inv_j^b(t)$ (respectively $Inv_j^e(t)$) be the level of stock of age j at the beginning and b (respectively e) of each period t. Sales at each period t are then equal to D_t and can be expressed by the following equation

$$D_t = Min\left\{D_t;\ \sum_{j=0}^{J} Inv_j^b(t)\right\} + Max\left\{0;\ D_t - \sum_{j=0}^{J} Inv_j^b(t)\right\}$$

(1)

The aim is to compare three different picking policies. Two of them, FIFO and LIFO, are well known and commonly used in food production and distribution. The third one was mentioned by Nahmias [25] in cases where there is no information on the actual age of products in stock, or where inventory management is disorganized. Han et al. [26] defined such a policy as a mixed issue policy, and Haijema [27] modeled it as a random order service issue policy. For this case of "random" sampling (RDM), a table is created for each period t that randomly selects the sampling sequence in each inventory with age $j = 0,..., J$. The method consists of picking the first item drawn at random and, if the demand is not met, picking the second, and so on. Table 1 shows an example of the principle of picking the same item using three different policies for a demand $D_t = 15$ and quantities available in the buffer stock of 7, 3, 1, 2, 1, 4 corresponding to the age between 0 and $J = 5$ days, i.e. a total quantity of 18. The principle of FIFO method starts with picking from the stock available $Inv_5^b(t)$ to $Inv_0^b(t)$, while for LIFO, it starts from $Inv_0^b(t)$ to $Inv_5^b(t)$. In the case of RDM, picking is conducted in the order of product age, products of age i =1 will first be picked, i.e. 3 products, then of age i =4, 1 product etc., until demand is met with only 2 products of age i = 5.

Table 1. Example of three picking policies

	$Inv_0^b(t)$	$Inv_1^b(t)$	$Inv_2^b(t)$	$Inv_3^b(t)$	$Inv_4^b(t)$	$Inv_5^b(t)$
Actual level	7	3	1	2	1	4
FIFO	4	3	1	2	1	4
LIFO	7	3	1	2	1	1
Random order	3	1	6	4	2	5
RDM picking	7	3	0	2	1	2

These policies are then converted into a discrete-time simulation model using a structural algorithm. Let the set $K(t) = \{k_0(t),\dots, k_J(t)\}$, where $k_i(t)$ is the age of the inventory from which we will pick in period t, and $Stockout_{ki(t)}(t)$is the part of the demand that is not satisfied before we pick the inventory with age $ki(t)$. We denote by $Stockout_{kJ+1(t)}(t)$ the demand that is not satisfied after all stocks have been withdrawn. For $t = 1,\dots,T$ and $i = 0,\dots, J$, the set $K(t)$ is defined as $ki(t) = (J - i)$ for FIFO and $ki(t) = i$ for LIFO. In the example shown in Table 1, the set $K(t)$ is defined by $K(t) = \{1, 4, 0, 3, 5, 2\}$ for a random RDM picking policy.

The simulation algorithm is defined as follows:

Init

$Inv_j^b(0)$ and $Inv_j^e(0)$ $= 0$ j=0,...,J

Forecast (F) and supply (S)

$F_t = \alpha D_{t-1} + (1 - \alpha) F_{t-1}$ with $F_1 = D_1$

$S_t = F_{t-k}$ with $S_t = D_1$ for $t = 1,\dots,k$

Main procedure

For t = 1 to T

$Inv_0^b(t) = S_t$ and $Inv_j^b(t) = Inv_{j-1}^e(t-1)$ j =1, ...J

$Stockout_{k0(t)}(t) = D_t$

For i = 1 to J

$Sales_{ki(t)} = \min\{Stockout_{ki(t)}(t);\ Inv_{ki(t)}^b(t)\}$

$Stockout_{ki+1(t)}(t) = \max\{0; Stockout_{ki(t)}(t) - Inv_{ki(t)}^b(t)\}$

EndFor i

$Inv_{ki(t)}^e(t) = \max\{0:\ Inv_{ki(t)}^b(t) - Stockout_{ki(t)}(t)\}$

$i = 0, \dots, J$

$EP(t) = Stockout_{J+1(t)}(t)$ and $W(t) = Inv_J^e(t)$

EndFor t

4. Case study of perishable buffer stock picking in a three-echelon supply chain

4.1 Initial model calibration

First, we simulated two stochastic demands that are normally and uniformly distributed with an equal mean $\mu = 2000$: $N(\mu, \sigma) = N(2000, 500)$ and $U([1000, 3000])$. The lead time of an item is assumed to be deterministic and equal to 2 days, and the forecasting model is based on a smoothing coefficient $\alpha = 0.3$ (values between 0.2 and 0.3 are generally used [28]). The items can be withdrawn from the buffer stock at 6 different ages $j = 0,..., J = 5$ days. The simulation model was run 500 times with different types of demand over a long period of time (T = 122 days) and for each stock picking policy. To simulate RDM random picking, we generated six different samples based on 122 different picking sequences.

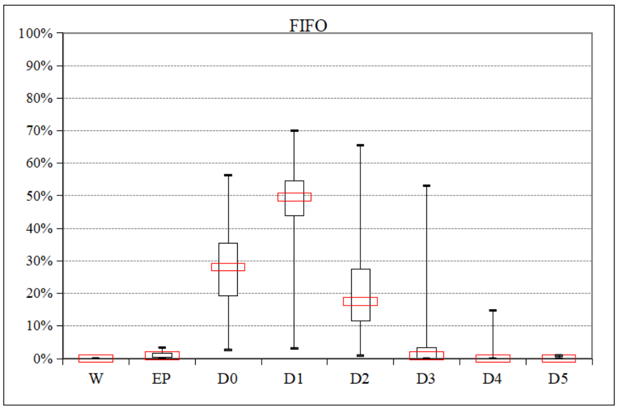
4.2 Simulation results

Table 2 and Figures 3 and 4 show the simulation results after a period T. The D_i sales with $i = 1,...,5$ are made from perishable products of different ages i and their percentage of total sales is shown. Also presented are the volume of external purchases (EP) made in the event of stock-outs, and the quantity of waste at the end of the period.

Table 2. Comparison of three picking policies with normal and uniform distributions of retailer demand

Normal	**Sales D0**	**Sales D1**	**Sales D2**	**Sales D3**	**Sales D4**	**Sales D5**	**EP**	**Waste**
FIFO	20,646	112,842	89,824	23,744	161	0	0	0
	8%	46%	36%	10%	0%	0%	0%	0%
LIFO	224,152	8,581	1,467	2,707	996	1,433	7,881	12,195
	91%	3%	1%	1%	0%	1%	3%	5%
RDM	154,347	47,791	26,776	9,789	2,884	4,585	1,044	4,769
	62%	19%	11%	4%	1%	2%	0%	2%
Uniform	**Sales D0**	**Sales D1**	**Sales D2**	**Sales D3**	**Sales D4**	**Sales D5**	**EP**	**Waste**
FIFO	56,077	103,539	63,619	15,996	1,924	87	2,812	0
	23%	42%	26%	7%	1%	0%	1%	0%
LIFO	212,130	8,949	3,472	2,930	2,257	1,678	12,638	11,860
	87%	4%	1%	1%	1%	1%	5%	5%
RDM	154,869	39583	25,735	9,517	5,483	3,392	5,482	4,040
	63%	16%	11%	4%	2%	1%	2%	2%

Note: The accuracy of the forecast model is expressed as the mean absolute percentage error MAPE = $\frac{1}{n}\sum_{t=1}^{n} |D_t - F_t|$. In the simulations presented, for n = 122 and α = 0.3, MAPE= 23%.



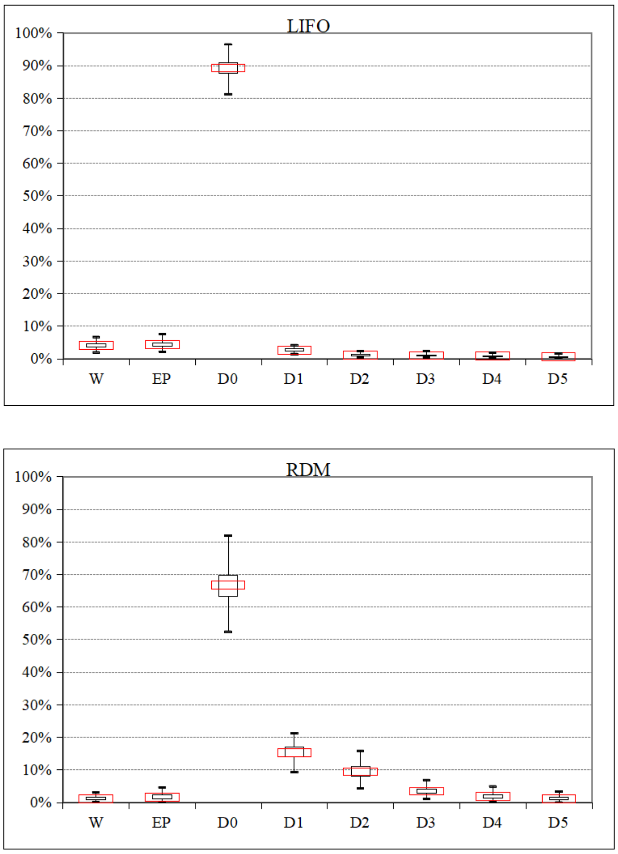
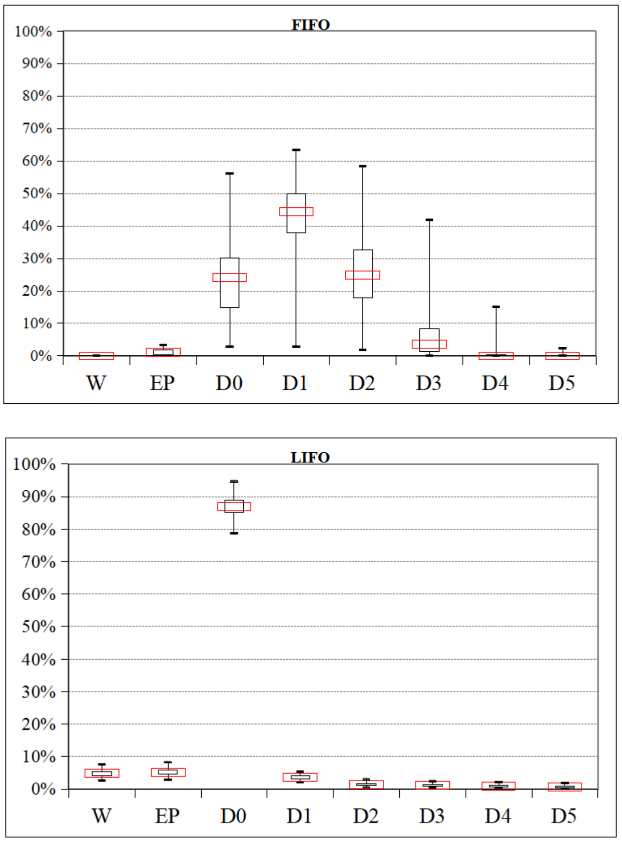


Figure 3. Average age of products in the buffer with normal demand distribution



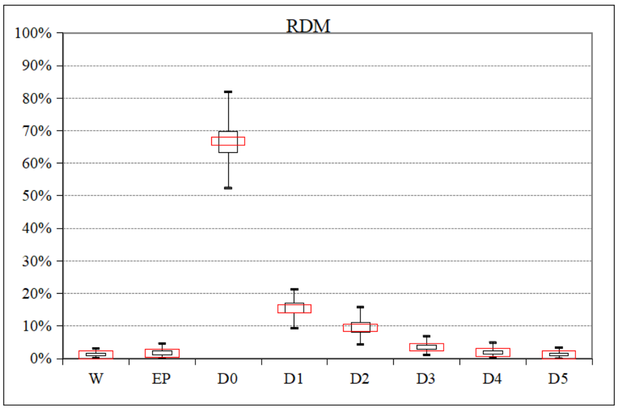


Figure 4. Average age of products in the buffer with uniform demand distribution

Remark: In Figures 3 and Figure 4, sample values between the 1st and 3rd quartiles are symbolized by a rectangle (the median is indicated by a bar). The lower value is the minimum and the upper value is the maximum.

The RDM picking policy is an intermediate situation between LIFO and FIFO for all indicators. LIFO gives priority to the freshest products. As a result, the sales rates according to the age of the products used are less dispersed with LIFO than with RDM and FIFO. Moreover, the lowest average age of products used for sales is obtained by following the LIFO policy. Customers will consume fresher and possibly less risky products assuming that health risks increase with age. Nevertheless, LIFO generates more external purchases and waste than RDM and FIFO. These initial observations underline the importance of a compromise between waste and freshness.

4.3 Mathematical demonstration of the difference between LIFO and FIFO performance

Simulations have shown that both FIFO and LIFO policies have their advantages. For example, the FIFO policy reduces waste and cuts external purchasing costs. On the other hand, LIFO is preferable when the main objective is product freshness.

We will prove these results analytically by considering a uniformly distributed demand $D_t \sim U(0, 2\mu)$ with $\mu \in \mathbb{N}_*^+$, two stocks of perishable products with ages 0 and 1, and a quantity to be ordered from the farmer $S_t = \mu$. Although we simplified for the sake of clarity, the proofs can easily be extended to more general cases.

With this model, we can see that $E(D_t) = \mu$ and $P(D_t = i) = \frac{1}{2\mu+1}$ for $i = 0,\ldots,2\mu$. We denote by $InvL_i^e(t)$ and $InvF_i^e(t)$ $i = 0, 1$ the inventory levels at time t for the LIFO and the FIFO policies respectively. The inventory levels can be described as follows:

$InvL_0^e(t) = (\mu - D_t)^+$ and

$$InvL_1^e(t) = InvL_0^e(t-1) - (D_t - \mu)^+ \quad (2)$$

$InvF_0^e(t) = (\mu - (D_t - InvF_0^e(t-1))^+$ and

$$InvF_1^e(t) = (InvF_0^e(t-1) - D_t)^+ \quad (3)$$

where $a^+ = \max(a,0)$.

- **Amount of waste**

LIFO and FIFO waste quantities $W^L(t)$ and $W^F(t)$ are defined as follows:

$$W^L(t) = \sum_{i=0}^{t-1} InvL_1^e(i) \quad \text{and}$$

$$W^F(t) = \sum_{i=0}^{t-1} InvF_1^e(i)$$

To show that the average amount of waste is greater in LIFO than that in FIFO, we first calculated the expectations of $InvL_1^e$ and $InvF_1^e$:

$$E(InvL_1^e(t)) = \sum_{k=1}^{\mu} kP(InvL_1^e(t) = k) = \frac{\mu(\mu+1)}{3(2\mu+1)}$$

$$E(InvF_1^e(t)) = \sum_{k=0}^{\mu} kP(InvF_1^e(t) = k) = \frac{\mu(5\mu^2+9\mu+4)}{12(2\mu+1)^2}$$

Then $E(InvF_1^e(t)) = \frac{5\mu+4}{8\mu+4} E(InvL_1^e(t)) < E(InvL_1^e(t))$

(4)

The relationship between $E(InvF_1(t))$ and $E(InvL_1(t))$ leads directly to the conclusion:

$$E(W^L(t)) = \sum_{i=0}^{t-1} E(InvL_1^e\ (i)) > \sum_{i=0}^{t-1} E(InvF_1^e\ (i)) = E(W^F(t))$$

The average wastage is greater when products are taken from buffer stock using a LIFO picking policy than a FIFO policy.

- **Average age of inventory**

We started by calculating the average age for each policy. Let us denote by $A^L(t)$ the average age of the products for the LIFO policy and by $A^F(t)$ the average age of the products for the FIFO policy. We get:

$$A^L(t) = \frac{E(InvL_0^e\ (t)) + 2E(InvL_1^e\ (t))}{3} \quad \text{and}$$

$$A^F(t) = \frac{E(InvF_0^e\ (t)) + 2E(InvF_1^e\ (t))}{3}$$

Using equations (2), (3) and (4), we can show that:

$$A^L(t) = \frac{7\mu\left(\mu+1\right)}{18\left(2\mu+1\right)} \quad \text{and}$$

$$A^F(t) = \frac{1}{3}\left(\frac{\mu}{2} + \frac{2\mu(5\mu^2+9\mu+4)}{\left(2\mu+1\right)^2}\right)$$

To compare these quantities, we introduce the function $f: \mathbb{R}^+ \rightarrow \mathbb{R}$ given by:

$$f(\mu) = \frac{1}{3}\left(\frac{\mu}{2} + \frac{2\mu(5\mu^2+9\mu+4)}{\left(2\mu+1\right)^2}\right) - \left(\frac{7\mu(\mu+1)}{18(2\mu+1)}\right)$$

We first remark that $f(0) = 0$ and

$$f'(\mu) = \left(\frac{(58\mu^3+87\mu^2+55\mu+22)}{9\left(2\mu+1\right)^3}\right) > 0$$

That is, f is increasing and starts from 0, so

$$f(\mu) = \frac{1}{3}\left(\frac{\mu}{2} + \frac{2\mu(5\mu^2+9\mu+4)}{\left(2\mu+1\right)^2}\right) - \left(\frac{7\mu(\mu+1)}{18(2\mu+1)}\right) > 0$$

and $A^F(t) > A^L(t)$

From this we concluded that the average age is lower for the LIFO picking policy than for the FIFO policy.

- **External purchases**

External purchases are made when stock is insufficient to meet demand. We have:

$$E\left(EP^L(t)\right) = E(((D_t - \mu)^+ - InvL_0^e\ (t-1))^+) = \frac{\mu(\mu+1)}{3(2\mu+1)} \quad (5)$$

$$E\left(EP^F(t)\right) = E(((D_t - InvF_0^e\ (t-1))^+ - \mu)^+) = \left(\frac{\mu(5\mu^2+9\mu+4)}{12\left(2\mu+1\right)^2}\right) = \frac{5\mu+4}{8\mu+4}E\left(EP^L(t)\right) < E\left(EP^L(t)\right)$$

This shows that external purchases are lower when the FIFO picking policy is applied. This analytical model proves and corroborates the simulation results we obtained for waste, average age and external purchases.

4.4 Simulation of different scenarios

To evaluate the three inventory policies, our research focused on waste production, the average age of products sold associated with food safety and the external purchases needed to satisfy demand in the event of a stock shortage. In order to assess economic performance, we associate the following exogenous parameters for each product sold from the stock of age j (j=1,..., J):

- a margin m_j for each product sold from perishable goods of age j ;
- a margin m_{EP} for each product sold from products purchased from an external supplier;
- a negative waste margin m_w;
- a quality rate $r_j(r_{EP})$ which indicates the freshness of the products.

We define the margin as the percentage gain between the selling price of an item, regardless of its age or remaining stock, and the cost price. Producers or retailers often offer discounts on perishable products with a short shelf life to encourage consumers to buy them (Solari et al. 2024 Hou et al. 2024, Hansel et al. 2024). We assumed that the margin does not increase with the age of the product.

We proposed to study three scenarios that differ in terms of product margins according to the age of the perishable items used and their depreciation rate. The corresponding data set is presented in Table 3.

We considered that the product depreciation coefficient is proportional to the age of the product, i.e. there is a linear depreciation of the product as a function of age.

In scenario 1, the margin is independent of age. This is the case for many food products, which are sold at the same price regardless of their expiration date. However, some fresh fruit and vegetable products are sold at a price that is linked to their degree of freshness. This has been taken into account in scenarios 2 and 3, in which the margins on products sold decrease linearly with the age of the components used.

We also assumed that the products purchased from external suppliers are as fresh as the youngest products used by the manufacturer (i.e. $r_{EP} = r_0$). The commitment with an external supplier is then captured by m_{EP}. Three assumptions are proposed in the three scenarios. For example, m_{EP} =0 illustrates a short-term cooperation between the manufacturer and its supplier. In this case, the manufacturer obtains a higher purchase price and then issues no margin. For all scenarios, when products are scrapped, the margin is negative (waste margin = -1).

The objectives of the simulation are to investigate the influence of each inventory policy on profit (the economic objective), the freshness of the products sold (the health objective) and waste (the sustainability objective). In a first step, we compared the simulation results (Table 4) for two demand distributions (normal N (2000, 500) and uniform U (1000, 3000)) and a sales forecasting method based on simple exponential smoothing and a smoothing coefficient $\alpha = 0.3$.

Table 3. Simulation parameters for the three scenarios

		D0	D1	D2	D3	D4	D5	EP	W
	Depreciation rate	1	2	3	4	5	6	1	
	Scenario 1	1	1	1	1	1	1	0.5	-1
Margins	Scenario 2	1	0.9	0.8	0.7	0.6	0.5	1	-1
	Scenario 3	1	0.9	0.8	0.7	0.6	0.5	0	-1

Table 4. Simulation results with normal and uniform distributions

	N(2000, 500)			U(1000, 3000)		
	FIFO	LIFO	RDM	FIFO	LIFO	RDM
Wastes	0	12,195	4,769	0	11,860	4,040
EP	0	7,881	1,044	2,812	12,638	5,482
Average age	2.04	1.14	1.60	2.27	1.19	1.68
Profit scen. 1	242,790	218,525	216,076	239,746	208,848	205,466
Profit scen. 2	218,525	230,304	226,123	208,848	218,904	219,766
Profit scen. 3	216,076	219,484	221,666	205,466	211,096	216,046

Whatever the picking policy, the average product age is lower in the case of normally distributed stochastic demand, which can be explained by the wider dispersion of sales generated by uniform distribution. When forecasts overestimate actual sales, this leads to overstocking with the risk of subsequent depreciation if sales do not increase. On the other hand, LIFO picking always guarantees a lower average age of products sold than FIFO picking.

When products are sold at the same margin regardless of age, the total profit is always better for the FIFO policy, which generates less waste and external purchases (EP). When margins decrease linearly with the product age, the FIFO policy is the least competitive. When demand is normally distributed, LIFO is the most efficient picking policy, whereas in the case of uniform demand, the RDM policy performs better. This difference is due to the higher volume of EP sold at zero margin in scenario 3.

The main conclusion drawn from the simulations based on these three scenarios is that under normal and uniform demand distributions, the LIFO policy is always better than the FIFO and RDM policies in terms of average age. LIFO therefore offers safer products to consumers. The LIFO and RDM policies are always more efficient than the FIFO policy in terms of total profit when margins decrease linearly with product age.

5. Model sensitivity to demand smoothing coefficient and stochastic demand parameters

In this section we focus on previous scenario 1 (see Table 3), the most representative one, in which product prices do not change with age and the manufacturer will have higher costs for products purchased on external spot markets than in the case of its own production. We proposed to study the sensitivity of the model to the demand-smoothing coefficient and to the mean and standard deviation of demand assumed to be normally distributed.

5.1 Influence of the demand smoothing coefficient

We considered a normal demand distribution N (2000, 500) and different smoothing coefficients ranging from $\alpha = 0.01$ (high smoothing of sales histories) to $\alpha = 0.99$ (low sales smoothing). Once α exceeds a certain threshold, waste production remains stable. We observed that the volume of losses decreases when the sales smoothing coefficient is increased, regardless of the picking policy (Figure 5). On the other hand, it is advisable to avoid too much smoothing of past sales when making forecasts and calculating the quantities to be supplied. However, if the alpha values are too low, there will be a higher level of waste.

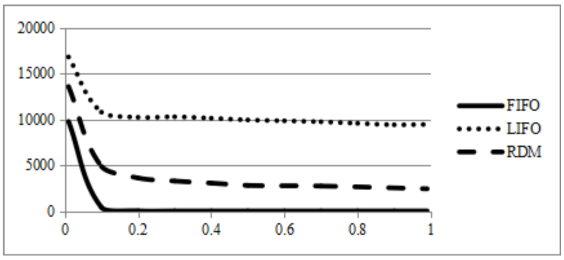


Figure 5. Evolution of the number of losses as a function of the demand smoothing coefficient α

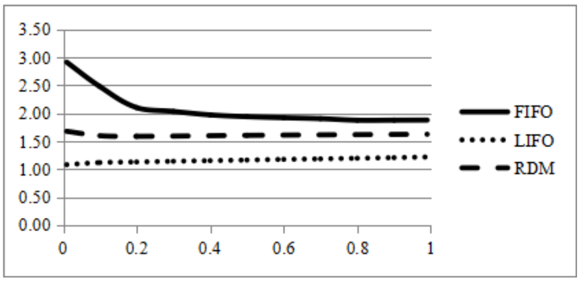


Figure 6. Evolution of average age as a function of demand smoothing coefficient α

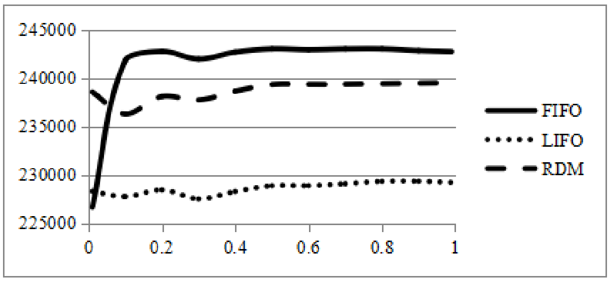


Figure 7. Evolution of total profit as a function of the demand smoothing coefficient α

Figure 6 shows that a low value of α increases the average age with FIFO inventory policy. Nevertheless, the average ages with LIFO and RDM policies are less sensitive to α due to the use of fresher products.

By adopting the LIFO and RDM policies, the total profit remains stable as the smoothing coefficient varies (see Figure 7). As for the profit obtained by following a FIFO policy, it falls sharply when α is very low. This is because when α is low, the manufacturer reacts quickly to a drop in demand by ordering fewer perishable items than necessary and, in this case, calling on an external supplier more often.

In conclusion, whatever the demand smoothing coefficient (high, low or optimal) is, the LIFO policy remains preferable in terms of achieving the objectives of health risk minimization. With a very high smoothing coefficient, the RDM policy leads to the highest profit, while the FIFO policy achieves its highest profit when α is greater than 0.15.

5.2 Influence of average demand

Keilson and Seidman [11] proposed to study the influence of the demand mean on the average age of items when using FIFO or LIFO policies. We simulated different demand averages with a standard deviation σ equal to a quarter of the demand average: N (1000, 250); N (2000, 500); N (4000, 1000) and a smoothing coefficient α of 0.3. The results of the simulation based on scenario 1 are shown in Table 5.

Figure 8 shows that waste generation increases as average demand rises with LIFO and RDM picking policies, in contrast to FIFO, which generates very little waste regardless of the average demand. This shows that LIFO is highly sensitive to average demand with a stable average age.

Figure 9 shows that the average age of items picked under the LIFO policy is always lower than under FIFO and RDM. In addition, LIFO and RDM picking policies are more stable in terms of product freshness than FIFO.

As for total profit, it showed that the simulations increased proportionally to the average of demand. The main result of these simulations is that an increase in average demand, with a proportionally increasing standard deviation considerably increases waste in the case of a LIFO picking policy.

5.3 Influence of standard deviation of demand

We assumed a two-day delivery time for perishable products, an average demand of 2,000 units with three standard deviations σ = 100; 500; 750 and with an exponential smoothing coefficient α = 0.3. The results are shown in Table 6.

We first observed that the average age increased in all cases with a large standard deviation. Consequently, a higher value of σ generates a larger quantity to be supplied than necessary and therefore a larger buffer stock. Next, we noticed that the average age under the FIFO policy varied most strongly with σ. It is also more robust to the amplitude of these fluctuations in demand. On the other hand, the LIFO policy always leads to a lower average age regardless of the value of σ, and is therefore the best policy from a health point of view, but waste increases proportionally to σ. However, the benefit decreases mainly under this policy when σ increases.

Table 5. Influence of average demand on the performance of each policy (waste/average age/ profit)

Lead time = 2 days	N (1000, 250)			N (2000, 500)			N (4000,1000)		
	FIFO	LIFO	RDM	FIFO	LIFO	RDM	FIFO	LIFO	RDM
Wastes	0	4,968	1,513	0	10,199	3,250	7	20,277	6,405
Average age	1.9	1.15	1.59	2.05	1.14	1.60	2.01	1.14	1.59
Total profit	121,749	114,735	119,772	242,929	228,578	238,699	484,763	456,144	476,344

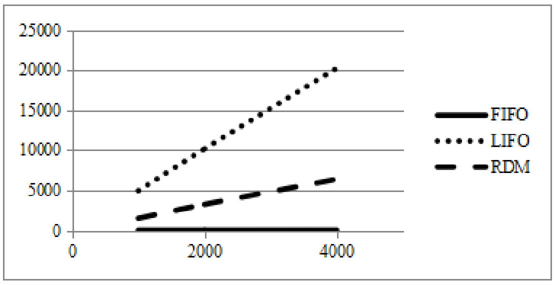


Figure 8. Evolution of waste volume as a function of average demand

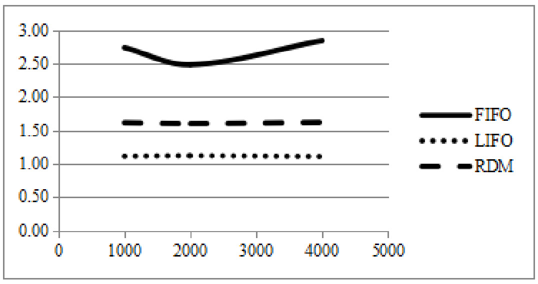


Figure 9. Evolution of average age as a function of average demand

Table 6. Influence of the standard deviation of demand on the performance of each policy (waste/average age/benefit

	N (2000,100)			N (2000,500)			N (2000,750)		
	FIFO	LIFO	RDM	FIFO	LIFO	RDM	FIFO	LIFO	RDM
Wastes	0	2,026	509	3	9,943	3,145	169	15,154	6,421
Average age	1.21	1.03	1.16	2.01	1.14	1.59	2.53	1.21	1.74
Total Profit	243,747	240,886	243,107	242,673	228,627	238,549	241,723	220,528	233,274

6. Model applications in the food industry

In this final section, we simulated our model by studying three realistic cases that can be observed in the food industry. In the first case, we investigated the impact of lead times for perishable products on the performance of a push-pull supply chain.

6.1 Case 1. Influence of the procurement lead time

Donselaar et al. [29] have shown that shortening the lead time for perishable items can reduce waste (see also [18]). In Table 7 below, we tested this proposition by applying the three picking policies and different lead times (2, 5 and 10 days, respectively). We also considered that, since order lead time is known, aging is only applied to available units and not to ordered units [30]. We studied only scenario 1 (see Table 3), in which all items have the same margin, whatever their ages are. The performance of each policy as a function of lead time is shown in Table 7.

Figure 10 shows that the amount of waste is highest under the LIFO and RDM policies. This result contradicts previous analyses and highlights some ambiguous management practices in terms of sustainability. For example, a shorter supply lead time may improve the sanitary quality of food products (lower average age) but worsen the loss indicator. A compromise may therefore be reached between these two opposing indicators.

As the lead time increases, the average age also increases progressively with a FIFO picking policy, while it decreases slightly with a LIFO policy and remains almost stable with an RDM policy. This result was observed for all scenarios. Figure 11 shows how the average age varies with the different lead times for each policy. Moreover, the average age is always lower with the LIFO method.

The profit is always higher for scenario 1 (Table 3) when a FIFO policy is chosen (see Figure 12). The evolution of profit as a function of lead time is convex in the case of a FIFO policy, while it decreases for LIFO and RDM policies. An increase in lead time leads to a decrease in profit in the latter two cases.

Table 7. Influence of lead time on the performance of each policy (waste/average age/benefit)

$\alpha = 0.3$	N (2000,500) lead time = 2 days			N (2000,500) lead time = 5 days			N (2000,500) lead time = 10 days		
	FIFO	LIFO	RDM	FIFO	LIFO	RDM	FIFO	LIFO	RDM
Wastes	3	10,108	3,157	28	12,123	4,676	0	7,370	1,879
Average age	2.01	1.14	1.59	2.15	1.11	1.60	2.27	1.10	1.59
Total profit	242,860	228,575	238,741	244,323	226,304	237,146	241,534	225,832	234,804

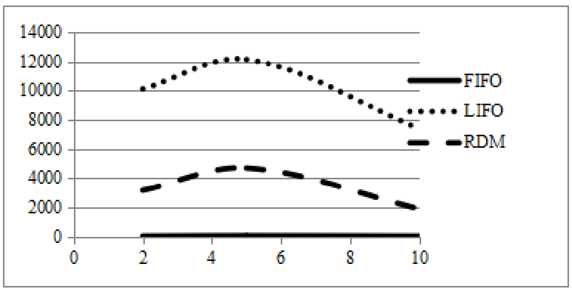


Figure 10. Evolution of waste as a function of lead time

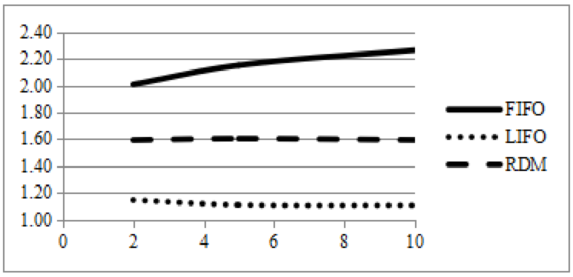


Figure 11. Evolution of average age as a function of lead time

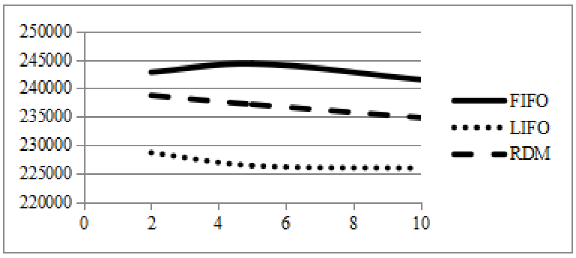


Figure 12. Evolution of total profit as a function of lead time

6.2 Case 2. Influence of a preventive production reduction policy

Some food manufacturers decide to produce less than their forecasting model suggests in order to avoid excessive stocks in case demand is lower than expected. In the event of insufficient stock to meet demand, the manufacturer supplements it with external purchases on a spot market. The simulations of this particular choice were based on a normally distributed demand N (2000, 500), a lead time of two-day delivery and the parameters of scenario 1 (Table 3).

Figure 13 shows that with a very low reduction rate, the average age of stock is high when adopting a FIFO or RDM picking policy. However, by reducing production more sharply, the average age can be considerably reduced under these policies. On the other hand, under the LIFO policy, the average age remains low. The increase in external purchases (EP) due to the reduction in production explains these trends.

We could observe that the volume of waste under the LIFO and RDM policies decreases significantly with the drop in production. The impact is not significant for the FIFO policy (Figure 14). However, this reduction leads to a significant increase in external EP for all three policies.

Figure 15 shows that the total profit obtained by choosing the FIFO or RDM policy is higher than that of the LIFO policy when production reduction rates are low. On the other hand, profit decreases significantly when the reduction rate increases, whatever the policy adopted.

In conclusion, by reducing production, the manufacturer reduces the volume of waste and the average age of products sold, but also reduces profits and remains more dependent on the spot market.

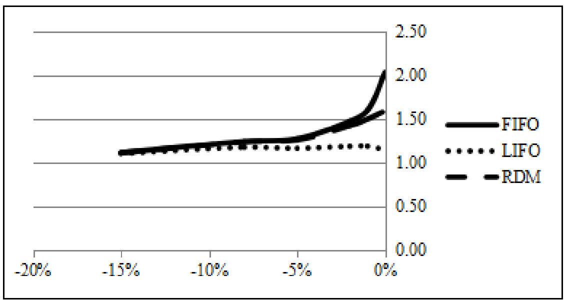


Figure 13. Evolution of average age as a function of production reduction rate

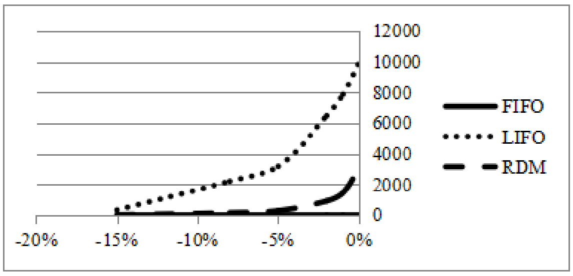


Figure 14. Evolution of waste as a function of average demand

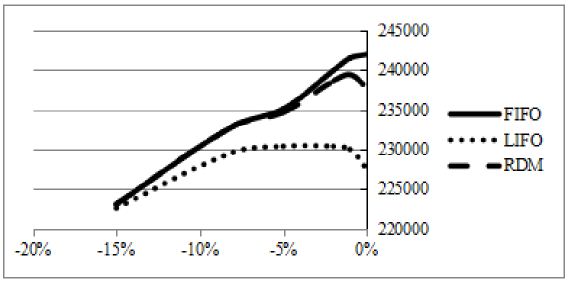


Figure 15. Evolution of total profit as a function of production reduction rate

6.3 Case 3. Simulation of fresh meat product depreciation

We considered time to be a critical factor for microbial growth in determining the shelf life of a product. The post-mortem storage time of meat also affects the product's color stability and during aging, compounds influence flavor and odor. Some studies show the effect of aging period on consumer acceptability of meat based on visual inspection and tenderness [31].

We chose to simulate the case of pseudomonas microorganism growth, which corresponds to a deterioration of fresh meat over time. The shelf life of meat is limited by the growth of this specific pseudomonas. Gibson et al. [31] were the first to introduce the Gompertz exponential function to food microbiology. This function can describe the growth of any microorganism over time in a more general way. Another time-sensitive deterioration function with exponential decay was also proposed (Wang et al. [32] used it for the depreciation of electronic products).

Referring to Bruckner's experiments [33], we chose to simulate the development of pseudomonas over time using the function $N(t) = 2\ e\text{-}^{0.0114\ t}$ (microbial count $\log_{10}$ cfu/g at time t). Figure 16 shows this function and a linear depreciation, which was our first assumption (see Table 3). We assumed a shelf life of five days (as for fresh poultry meat) and a lead time of two days.

We simulated two levels of quality for external purchases of EP meat: a microbial count level equal to 2 (cf. medium-risk EP, case 1) and a level of 4.3 (cf. high-risk EP, case 2).

Table 8 compares the results between the exponential growth of micro-organisms EG over time (see Figure 16) and the linear growth LG (see Table 3, where the health risk is proportional to the age of the product).

The results show that exponential product depreciation generates less waste than linear depreciation for both LIFO and RDM policies. This is a non-intuitive result that is difficult to explain. As for the average age of inventory, the linear growth LG of pseudomonas results in a lower average age than the exponential grow EG.

In conclusion, LIFO is also the best policy for picking fresh meat products in the event of micro-organism proliferation, whatever the quality level of external purchases is. This result is somewhat at odds with standard practice.

7. Analysis and discussion

Influence of picking policies on the average product age

Our results show that the LIFO picking policy always achieves the lowest average age (i.e. the lowest health risk) compared with other policies, particularly FIFO.

In addition, a random picking policy (RDM) offers a better average age than the FIFO policy, which is most commonly used for managing stocks of perishable products. We also analyzed the sensitivity of the simulation model to various exogenous parameters and found that the average age under the FIFO policy always increases when the mean and standard deviation of demand or lead time increase. On the other hand, with LIFO and RDM, it remains at the same level or decreases when the supply quantity and demand fluctuate.

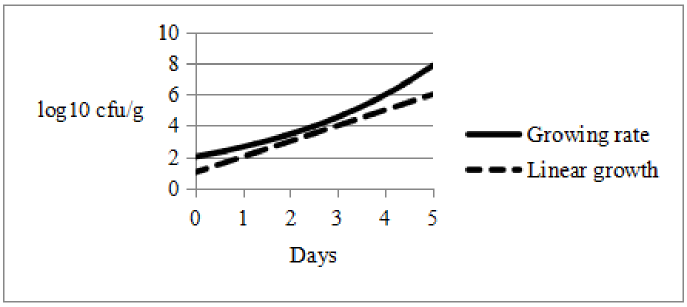


Figure 16. Evolution of the microbial count of pseudomonas in meat products

Table 8. Quantity of waste and average ages in the event of exponential or linear growth in the rate of product depreciation

	Demand N (2000, 500) and α = 0.3		
	FIFO	**LIFO**	**RDM**
Wastes with exponential growth (EG)	3	10,233	3,249
Wastes with linear growth (LG)	0	12,195	4,769
Average age (case 1 with EG)	2.76	2.13	2.49
Average age (case 2 with EG)	2.78	2.23	2.53
Average age with LG	2.04	1.14	1.60

Influence of picking policies on profit

In terms of profit, the FIFO policy offers the highest level of profit when products are sold at the same price regardless of age and when the EP margin is low (0.5). However, LIFO performs better, with a higher and more stable profit when the margin decreases linearly with the product age. In conclusion, LIFO is still the best policy to minimize sanitary risk and stabilize profit in all the perishable product management situations studied.

Influence of picking policies on the quantity of waste

Although we found that the LIFO picking policy produces the most waste, it is well known that it is difficult to determine in advance the exact shelf life of a fresh food product in stock. Consequently, the amount of waste generated by a LIFO policy is actually lower and may encourage companies to choose it.

Other observations

An increase in the exponential smoothing coefficient of past sales, which can be used to deduce a quantity to be supplied, leads to better performance whatever the policy adopt. Furthermore, a strategy of preventive production reduction has no impact on the volume of waste within the framework of a FIFO policy. A company following this strategy has an interest in using the FIFO policy with zero waste and high profits for a low rate of production reduction.

Research limitation and perspectives

We only studied the particular case of picking a single perishable item from a buffer stock and based our results on a realistic data set. However, this simplification reflects the reality in the poultry industry, where standard chickens are raised for a fixed period of 40 days, then slaughtered and processed to order by the manufacturer for rapid delivery of freshly packed products to retail outlets. In terms of research prospects, we proposed to simulate and compare the three picking policies with the FEFO First Expired, First Out method, as La Scalia et al. [4] or Mendes et al. [34] did. We could also draw on the work of Bruckner et al. [35], who proposed a predictive shelf-life model that takes into account a temperature factor and a picking technique based on sensor indications (cf. RFID product tags [5] [6]). In particular, their experiments showed that the LSFO (Least Shelf life, First Out) concept provides better results than the FIFO, which we could also verify using our model. We also plan to include the costs of handling, storage and shortages in the margin calculation, as well as payment strategies and discount facilities depending on the age of the product, referring to the work of Ghosh et al. [36-38].

8. Conclusion

In this paper, we compared three policies for picking products from the buffer stock of a push-pull supply chain based on stochastic demand and deterministic lead time. We chose to investigate the influence of these policies on three performance indicators representing the three pillars (triple bottom line) of sustainable development: the average stock age, which assesses health risk; the waste volume, which represents eco-responsible efficiency; and the total profit, which measures economic performance. A non-intuitive result showed that under certain conditions, the LIFO policy led to better performance than the FIFO policy. This research also responds to the difficulties that some food manufacturers have in meeting the challenges posed by the concept of sustainability.

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Conflict of interest

The authors declare no conflict of interest.

Authors' contributions

Prof. Emer. Daniel Thiel and Prof. Vincent Hovelaque have published several articles on food supply chain management and developed the simulation model presented in this research. Dr. Delphine David is a lecturer and researcher in applied mathematics. She demonstrated an original result observed from the simulations. All three worked on the research problem, methodology, construction and finalization of the article. Together, they discussed results, limitations and research prospects.

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