Simulation based optimisation Model for a joint inventory pricing problem for perishables

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***Abstract* — We consider the problem of jointly determining the optimal pricing and inventory replenishment strategy for a perishable inventory system in which demand is stochastic and price dependent. The perishable item is assumed to have a fixed life time. The retailer has the opportunity to change prices every period of the planning horizon in order to boost customer's demand. We investigate the impact of this practice on improving revenues and reducing the waste. We develop a simulation based optimization model to find the best dynamic pricing strategy and the optimal order quantity. We analyze the effectiveness of discrete pricing policy by comparing the profit obtained and the amount of items wasted with another pricing strategy. We also analyze the effect of different parameters on the optimal solution through numerical experiments.**

Keywords— perishables, inventory, dynamic pricing, waste, stochastic demand

I. Introduction

Perishable items exist on many industries such as food, newspapers, medications, blood products and organs. Besides, with the fast advancement of technology and customer predictions, various nonperishable products have now a short sellable life, for example automobiles, software and electronics. These goods are important to grocery retailers, as they have a significant impact on the sales revenue. For instance, according a survey by [1] "perishable products represent 30% of total supermarket sales all over the world". According to another survey from the Food Market Institute, perishables make up more than half of the sales in US supermarkets, contributing to over than $260 billion of the sales revenue in 2014 [2]. Furthermore, perishables have become a significant reason why consumers select one supermarket over another [3].

However, perishable products differ from the durable products since they have to be rejected from inventory at the end of their lifetime due a drop in their utility to consumers. Subsequently, they impose considerable losses to supermarkets. For example, it is observed that billions of dollars are lost each month due to food wastage [4]. "A survey by the National Supermarket Research Group found that a 300-store grocery chain loses about $34 million a year due to spoilage. On an industry-wide level, losses due to spoilage and shrinkage translate into $32 billion for chilled meats, seafood, and cheese; $34 billion for produce; and $504 billion for pharmaceutical and biomedical products (EPCGlobal)."[5]

Hence, a suitable inventory management of perishables is a problem of major concern. Sellers can compensate the negative impact of perishability by applying different marketing policies. In this regard, the selling price plays a crucial role on determining demand, since most consumers have predetermined standards of price versus quality. In fact, freshness' item decline decreases the sales as the product could not be sold at the same price of the freshest one. Therefore, putting on an appropriate pricing policy improves the ability of industries in managing demand for perishables [6]. In this context, a latest firm's study supported by IBM [7] highlights that dynamic pricing may help vendors to efficiently decrease food wastage by allowing the seller to be more reactive to customer expectations. In addition, thanks to the fast changing of technology and the progress of the e-commerce, dynamic pricing has become much easier to implement.

Thus, the coordination between pricing and replenishment decisions has become an important issue and has been recognized in practice and by the academic community. The basic idea is that the demand and the potential profits will be influenced by the pricing decisions.

Nevertheless, some sellers permit consumers to choose items of different ages on the same time. In such case, if all the items are sold at the same price, one can assume that customers will select the freshest product, leading to a last-in-first-out (LIFO) issuing policy. In practice, sellers such as Bruegger's Bagels offer markdowns for old items. Several other retailers such as Chesapeake Bagel choose to dispose of old inventory when fresh products are available for sales for marketing and operational purposes [8] [9].

In order to reflect the above mentioned real life aspects, we study a stochastic joint inventory and pricing control problem where a seller has to manage an inventory of perishable products in a periodic-review system. For each period, the retailer decides how much to order and sets a single price for inventories of different ages. At the end of each period, the retailer chooses how much ending inventory to dispose of, including the old inventory in this period and possibly some of old items yet to expire. The objective is to maximize the total expected profit above the planning horizon with regards to the ordering cost, inventory holding and lost-sales penalty cost and disposal cost. We assume that the demand faced each period is stochastic and price dependent.

Therefore, the problem is very complex even when selling prices are static [8] [10]. We begin with developing a mathematical model for the joint pricing and inventory problem. Then, in order to model the real stochasticity of demand while dealing with complexity of the problem, we developed a simulation based optimization model (SBO-model). Incidentally, we coupled a simulation model, based on the Arena language with optimizer, Optquest, for solving the problem. We first validated this SBO-model on deterministic instances studied in [8]. We show that we can reach the optimal solution found through the mathematical formulation implemented in CPLEX. Then, we investigate the capability of our SBO-model to solve the stochastic problem.

This paper is organized as follows: Literature review is discussed in Section II. In Section III. the problem and the mathematical formulation of the problem is described. Section IV. details the implementation of the SBO model for the joint pricing inventory problem. Section V. presents computational results and analysis. Finally, conclusions are discussed in Section VI.

II. STAT OF ART

There is a significant progress made in the past decade on perishable inventory management. The initial work in this filed focuses on designing effective replenishment policies that consider the perishability of the product. References [10], [11], [12], [13] and [14] give a comprehensive survey of the work done in this area.

Coordinating pricing and inventory control for perishables is also a rich area of research which has been widely studied in operations research. This literature exposes abundant benefits from pricing and inventory coordination and suggests important structures of optimal policies.

Knowing the significance of pricing decisions, [10] notes that defining pricing policies for perishable items under stochastic demand was an open problem. [12] provides a comprehensive review of dynamic pricing in diverse situations including inventory subjects (e.g. replenishment vs. non-replenishment of inventory, strategic vs. myopic consumers, etc.). Some recent research works in this area include [15], [16], [17], [18], [19] and [20]. Those studies do not model the pricing and replenishment decisions in the manner in which we do in this paper. In particular, they consider a small change in price by considering a discounting policy for old items.

Among the first works considering the joint pricing inventory management for perishables we present [21] who considers a continuous price function $p(t)$ over the planning horizon. Then, [22], [23] and [24] study the same problem while considering a deterministic demand and proposing a single optimal price in the system. Then, [25] extends the results of [22] by proposing an all unit quantity discount.

[26] establishes a joint pricing and ordering policy for deteriorating items, where items have a random lifetime following a weibull distribution. They study a quantity discount policy, while considering a single price over the planning horizon. In the same way, [27] also studies perishable goods without allowing price variation over the whole cycle.

[28] introduces the multiple pricing in the perishable inventory models with price and freshness dependent demand. They aim to determine the optimal number of prices changes over the planning horizon, price values and order quantities. [6] extends this study by introducing a discrete pricing policy for perishable products that decides on the optimal times to change the prices in addition to the optimal price values. They conclude that discrete pricing can lead to important savings depending on the system factors. Furthermore, they observe that varying the prices at the same time intervals is very beneficial and gives very close results to the optimal solution.

[29] considers a dynamic coordinated pricing and replenishment problem for a perishable product over an infinite horizon, with backlogging orders, a price dependent demand, and zero lead time. They determine the structure of the optimal policy for a lifetime of two periods and then develop a base stock list-price (BSLP) heuristic policy for stationary systems with multi period lifetime. Under this policy, when the inventory is under an order level, the retailer brought up the inventory to this level and he charges the price, otherwise, there is no replenishment decisions to be made and the old items are sold at a discount depending on the amount of inventory level.

[9] analyzes the infinite-horizon lost-sales case in which the seller does not sell simultaneously new and old inventory. In fact, at the end of a period the seller can decide whether to dispose of or carry all ending inventory until it perishes. So, a replenishment decision will be made at the beginning of a period if there is no inventory carried over to the current period. They propose a static policy deciding on the inventory order-up-to level, age-dependent price and inventory disposing decisions. However, it is not clear whether the proposed policy is optimal.

A different version of the problem is modeled by [30] where he models the consumer choice behavior between old and new units in a realistic way. In fact, he considers a vertical differentiation model for customers having different observations of quality of products. [31] extends this work by focusing on discounting decisions and how they affect the consumer behavior. Then, they develop a model to determine the optimal inventory and the optimal prices for perishables of different age with a two period lifetime.

[8] characterizes the structure of the optimal policy of a dynamic joint pricing and inventory systems for perishables. They present a significant generalization of previous papers since it studies the positive lead time, arbitrary lifetime and both backlogging and lost-sales cases, while deciding about ordering, disposing and pricing decisions. In order to solve this problem, [8] develops an effective heuristic policy. They conclude that dynamic pricing has significant impact on reducing waste and improving profit in the finite-horizon setting and that the BSLP heuristic performs very well on both stationery and non-stationery demand.

As stated above, the majority of the researchers in the literature, considering the pricing and inventory decisions for perishables, allow a single price over the planning horizon or consider discounts for old items. Only a few researchers study multiple pricing, as they either consider a continuous price function without taking into account costs related to price changes or the price changes are made at predefined times [6]. Nevertheless, from a realistic vision, it is not conceivable to vary prices continuously at no cost. Furthermore the timing of price changes is an important factor that can expressively affect the revenues.

In this study, we extend the work of [8] by considering another dynamic pricing policy called discrete pricing which is adopted in [6] where the seller has the ability to change the prices many times at any period he wants over the planning horizon in order to maximize the total profit.

So, our target is to find the best times to change the prices as well as the optimal values of these prices. This assumption make the problem more difficult [10]. In order to deal with this complexity and the stochasticity of demand we begin with developing a mathematical model for the generalized deterministic version of the problem. Then, we develop a simulation based optimization model in order to tackle the stochastic joint pricing inventory management problem using the discrete pricing policy.

In summary, the key aspects, which have not been considered together before to the best of our knowledge, make this paper unique: (i) considering the generalized stochastic joint dynamic pricing and inventory problem, and (ii) analyzing the effect of using a discrete pricing policy on the profit and the wasted quantity.

III. MATHEMATICAL MODEL FORMULATION

A. Problem description

We consider a retailer, who follows periodic inventory replenishment, selling a perishable product with a shelf life of l periods over a finite horizon of $T>>l$ periods. Therefore, in any period, the retailer sells l versions of the product with ages $0...l$-1, where age 0 refers to the new units, while the others refer to older units of various ages.

The retailer faces a stochastic demand depending on the price of items. Unsold units of age i, if they are not discarded, at the end of a period, get transferred to the next period as units of age i +1, for i = 1...l-2 with a unit holding cost h.

Unsold units of age l-1 are discarded at the end of a period at zero salvage value and disposing cost c_d. Moreover, the demand that is not satisfied from on-hand inventory incurs a penalty cost c_l per unit. This penalty incurs a lost sale.

The retailer can procure new units with a procurement cost c_p per unit in order to complete the inventory up to level S. The order up to level S is chosen for the entire planning horizon. The procurement lead time is deterministic and equals to k periods with $k<l$. The age of the new units received after k periods is 0.

The sequence of events are as follows:

For all period t = 1...T:

1. At the beginning of the period, the order placed k periods ago (if any) is received. The age of on hand inventory, designated by I_t^b with b=0...l-1 is updated.
2. The selling price p_t is chosen within an interval $[p_{min}, p_{max}]$. This price applies to all products sold in period t.
3. During period t, demand $d_t(p_t)$ arrives, which is stochastic and depends on the selling price p_t, and is satisfied by on-hand inventory. Unsatisfied demand is lost.
4. At the end of the period, remaining inventory with age l-1 has to be discarded.
5. Meanwhile, unused inventory with positive useful lifetimes ($b=0...l$-2) can be either intentionally discarded. The retailer reviews the inventory levels of old items, denoted by I_t^1 ... I_t^{l-2}.
6. Subsequently, he decides the quantity O_t of items to be disposed of from old inventory sequentially with increasing useful lifetimes using a FIFO depletion policy. At the same time the retailer determines the order Q_t .

We assume that the issuing policy is first in first out (FIFO). The retailer makes these decisions in order to maximize her expected profit, i.e. the total expected profit from period t until the end of the horizon.

B. Parameters

T = Maximum number of periods of the finite time horizon

t = Index denoting the period

c_p = The constant purchasing cost per unit

c_d= The disposing cost per unit of waste

c_l = The penalty cost per unit of lost sales

h = the holding cost per unit for items that are carried over from one period to the next

l = the life time per period

b = index for product age b=0...l

k = the lead time

C. Decision Variables

p_t = The dynamic price of product per unit. The selling price p_t is restricted to an interval $[p_{min}, p_{max}]$.

S = Order up to level or target starting inventory level at the beginning of periods.

O_t = Total amount of items to dispose of at the end of the period t.

D. Variables

$d_t(p_t)$ = Demand depending on the price of period t.

$$d_t(p_t) = D(p) + \varepsilon_t \tag{1}$$

ε_t follows a truncated distribution from a normal distribution with zero mean.

I_t^b = Inventory level at the beginning of the period t with age b=0…l-1 after receiving the order placed k periods ago.

O_t^b = Amount of items to dispose of at the end of the period t with age b.

X_t^b = Auxiliary variable denotes the residual demand for items of age b with b=0…l-1 in period t.

E. Model

$$\text{Maximise} \sum_{t=1}^{T} \left(\begin{array}{c} p_t \sum_{b=0}^{l-1} X_t^b - c_p I_t^0 \\ - h \sum_{b=1}^{l-1} I_t^b - c_l \left(d_t(p_t) - \sum_{b=0}^{l-1} X_t^b \right) - c_d O_t \end{array} \right) \tag{2}$$

Subject to

$$X_t^{l-1} = min\left(d_t(p_t), I_t^{l-1}\right), \ t=1..T \tag{3}$$

$$Q_t = S - \left(\sum_{b=0}^{l-1} I_t^b - X_t^b - O_t^b \right), \ t=1..T \tag{4}$$

$$I_t^b = I_{t-1}^{b-1} - X_{t-1}^{b-1} - O_{t-1}^{b-1}, \ t=k+1..T, \ b=1..l-1 \tag{5}$$

$$I_t^0 = Q_{t-k-1}, \ t=k+1..T \tag{6}$$

$$X_t^b = max\left(0, min\left(d_t - \sum_{j=b+1}^{l-1} I_t^j, I_t^b \right) \right), \ t=1..T, \ b=0..l-2 \tag{7}$$

$$O_t^b = min\left(I_t^b - X_t^b, \ O_t - \sum_{j=b+1}^{l-1} O_t^j \right), \ b=l-2..0, \ t=k+1..T \tag{8}$$

$$O_t^{l-1} \leq O_t \leq \sum_{j=0}^{l-1} I_t^b - X_t^b, \ t=k+1..T \tag{9}$$

$$O_t^{l-1} = I_t^{l-1} - X_t^{l-1}, \ t=k+1..T \tag{10}$$

$$p_{min} \leq p_t \leq p_{max}, \ t=1..T \tag{11}$$

$$I_t^b = 0, \ O_t = 0, \ X_t^b = 0, \ O_t^b = 0, \ t=0..k, \ b=0..l-1 \tag{12}$$

$$I_t^b, \ Q_t, \ X_t^b, O_t, \ S \geq 0, \ t=1..T, \ b=0..l \tag{13}$$

Equation (2) refers to the objective function which aims at maximizing the total profit.

Constraint (3) guarantees that the inventory levels of all ages are balanced. The inventory at the end of period t equals the starting inventory decreased by an amount of sales in period t and the amount disposed of. Hence, the order-up-to position can be interpreted as the order up to level quantity decreased by the total amount of stock on hand.

Constraint (4) makes sure that the amount of old inventory get transferred to the next period.

Constraint (5) imposes that the new items ordered k periods ago are placed on the on hand inventory.

Constraints (6) and (7) are the FIFO constraints. They make sure that the fulfilment of demand by products of intermediate ages first until the demand is fulfilled by the freshest products.

Constraint (8) guarantees that the disposing policy is FIFO. In fact, the disposing quantity of the older age is fulfilled first.

Constraint (9) imposes that we cannot dispose of more than the on hand inventory at the end of period t.

Constraint (10) states that items of age l-1 cannot be used in the next period.

Constraint (11) imposes that the price p_t should be in $[p_{min}, p_{max}]$

Constraint (12) states that the starting inventory level in the k first periods of all ages is 0.

Constraint (13) imposes that the inventory levels of all ages in all periods are nonnegative.

IV. THE SIMULATION BASED OPTIMIZATION MODEL

In this work the simulation model for the joint pricing inventory problem for perishables is built with Arena Software. This choice is motivated by the fact that, according to the recent review [32], Arena is the first used software in logistics and supply chain simulation. For more insight, interested reader can consult the reference [33].

The objective of the developed simulation model is to reproduce the processing of perishable items and customers above the planning horizon. Here, we developed a sequence diagram, Fig. 1, to formally model the behavior and the interaction between entities of the simulation model [34].

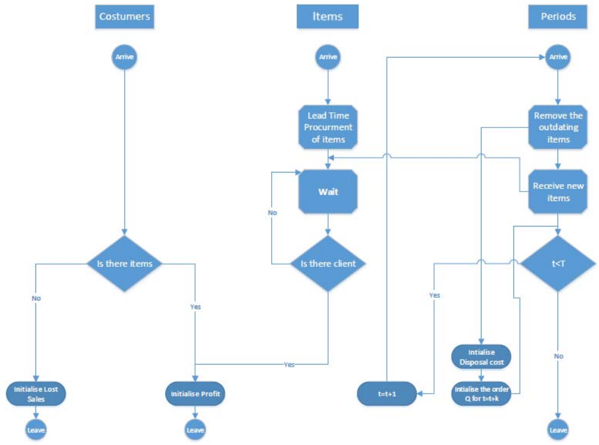

Fig. 1. Behavioral view of joint pricing inventory problem

Once the simulation model is developed, the next step consists of coupling this model with an optimization technique to find an optimal price and order up to level. The technique of combining simulation and optimization methods, also called simulation-based optimization has been successfully applied to solve complex decision making problems [35]. The basic concept of this method (Fig. 2) is to use an optimization module to find a set of values for the input parameters (i.e., decision variables), and uses the responses generated by the simulation model output (i.e., performance indicators) to search for the next trial solution. This iterative search aims at finding a set of input values with the highest contribution to the performance indicators (i.e., best optimal/suboptimal Solution).

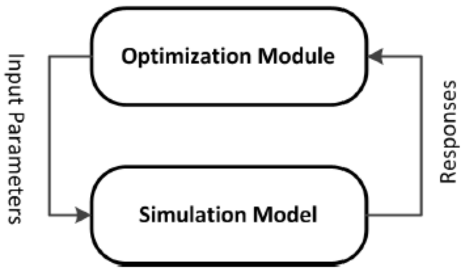

Fig. 2. Simulation-based Optimization approach [35]

In the last two decades, research papers have reported benefits of this simulation based optimization process to solve problems with stochastic components [36] [37] [38]. Many extents were proposed to the original approach. [36] presents the simulation-based multi-objective optimization. [37] introduces real-time control architecture based on the simulation optimization process. Also, commercial software propose powerful optimizer modules, such as Optquest (provide by OptTek System Inc.) and implemented in Arena, to deal with complex stochastic optimization. The Search Algorithm used in Optquest is based on a combination of the metaheuristics of tabu search, neural networks, and scatter search.

V. Computational Results and Analysis

For the computational analysis, we first apply our proposed SBO-Model to the deterministic version of the instances obtained from [8]. Once the model is validated, we use it on a stochastic version of the problem.

The following numerical study considers a finite horizon setting and a lost sales cases with zero lead time. We study three different performance criterion in order to compare our results with those presented in [8]. The problem's parameters are specified as follows [8]:

- A five-period horizon T=5.
- The demand function is specified as an additive linear model :

$$d_t(p_t) = \alpha - \beta p_t + \varepsilon_t \tag{14}$$

- Three lifetimes l are considered: 2, 3 and 4.
- For any l, we first fixe the base case as in table I:

TABLE I. Systeme Parameters

A	B	$c.v.$	c_d	c_l	c_p	h	p_{min}	p_{max}
174	3	0.6	10	10.78	22.15	0.22	25	44

We then vary the parameters $c.v.$, c_d, and c_l, respectively, such that $c.v.$ in {0.6, 0.8, 1, 1.2, 1.6}, c_l in {1.98, 4.18, 10.78 21.78} and c_d in {5, 10, 20}. Entirely, 36 instances are reported in the stochastic case.

A. Results for the deterministic problem

The purpose of this section is to validate the simulation model. Actually, in simulation model-validation is a fundamental step before experimentation. We choose to realize this phase by comparing our results found by the mathematical model in CPLEX and those by the simulation based optimization model. For the deterministic case, we consider the following demand function by omitting the random part (see (15)).

$$d_t(p_t) = \alpha - \beta p_t \tag{15}$$

Obtained results from our SBO-model and CPLEX are reported in Table II. We varied the cost related to both disposal and lost sales for the three existing life time.

The optimal results presented in Table II are the same results obtained by CPLEX when we used the analytical formulation presented in section III.E. That means that our SBO-model can efficiently tackle this NP-hard optimization problem. Even if the computational time seems high compared to the analytical formulation, our approach remains competitive as such planning decision is not taken in real time. Actually, when using Simulation, we have to be aware that it is not a competitive faster method.

We observe in Table II that optimal solution's values are the same for all the instances which could be explained by the short horizon setting (T=5). However, we are facing an NP-hard problem and when dealing with such a complexity, CPLEX could not solve larger instances (T>5). We also note that the same price is chosen for all the periods, it may be explained by the deterministic statue of demand. However, the CPLEX model could not deal with the stochastic demand nature, leading us to use the simulation based optimization approach.

TABLE II. RESUTAS FOR THE DETERMISTIC CASE

Parameters			Decision variables		Profit	CPU_{SBO} (sec)	CPU_{CPLEX} (sec)
Life time	***c_d***	***c_l***	***S***	***P(t)***			
2	10	10.78	42	44	3218.04	302.98	3.02
		1.98	42	44	3587.64	310.69	
		4.18	42	44	3495.24	301.12	
		21.78	42	44	2756.04	302.31	
	5	10.78	42	44	3218.04	302.98	
	20	21.78	42	44	2756.04	302.31	
3	10	10.78	42	44	3218.04	310.69	
		1.98	42	44	3587.64	301.25	
		4.18	42	44	3495.24	304.09	
		21.78	42	44	2756.04	302.15	
	5	10.78	42	44	3218.04	310.69	
	20	21.78	42	44	2756.04	302.15	
4	10	10.78	42	44	3218.04	311.54	
		1.98	42	44	3587.64	308.12	
		4.18	42	44	3495.24	304.52	
		21.78	42	44	2756.04	302.81	
	5	10.78	42	44	3218.04	311.54	
	20	21.78	42	44	2756.04	302.81	

From this section, we can conclude that our SBO-model is valid. Thus, we can use it to solve complex stochastic versions of the problem.

B. Results for the stocastic problem

The first objective herein is to investigate the capability of the proposed SBO to find optimal/sub-optimal solution; while considering realistic non-stationary stochastic demand. We apply our SBO model for the same instances as in [8]. Then, we compare them with the results obtained from the BSLP policy studied in [8]. For the purpose of comparison, we assume that the decision criterion is to maximize the total profit over the planning horizon and we compute the outdated quantity and the number of sales lost.

Specifically, we consider a five-period horizon and the time-varying demand functions are specified in (16):

$$d_t(p_t) = \alpha\, k_t - \beta\, p_t + \varepsilon_t \tag{16}$$

where k_t is a time-varying seasonality factor such that (17):

$$k_t = 1.2 - 0.1\,(t-1) \tag{17}$$

The numerical results obtained from our SBO model are reported in Table III. For the Optimization Loop, we fixed the time up to 30 minutes. Since we are using stochastic simulation model, the indicators output performance is estimated, as the sample average over n independent replications. The corresponding half widths of the 95% confidence intervals are computed.

In order to investigate the effect of dynamic pricing policy in improving the profit, we compute the performance of the discrete pricing policy measured by the percentage profit gain ρ in comparison with the pricing policy used in [8]. The observations are summarized as follows.

As the results in Table III indicate, the SBO finds solutions that lead to better profit and less waste compared to [8], in all tested cases. In our base case, the difference of the profits between the two pricing strategies is about 20% on average, but this difference changes depending on the system parameters. For example, it reaches 62% for higher disposal cost. Furthermore, even though the lost sales seems to be large for the proposed solution, the related satisfied demand remains good (on average 75%).

In order to analyze the efficiency of the proposed approach we will observe the trend of the pricing decisions. When we look at the prices, we observe that the average price values proposed are lower than those proposed in [8]. Actually, under multiple prices, the higher price is charged at the beginning, after that prices vary over time. We can see that changing prices allows us to increase profit and also to decrease wastage rate comparatively to [8].

At first glance, the trend shown in the pricing column in Table III is perhaps surprising. It may be expected that increasing the prices from a period to another could not be natural and may decrease the demand as well as the benefit. However, it turns out that when the inventory level of old inventory is low in comparison with new one, it is more convenient and profitable to increase the prices. For some other cases we observe that the prices decrease and maintain a single price for more than two periods which could be interpreted by the same distribution of inventory ages in this period. Here raises again the effectiveness of discrete pricing policy as it provides a flexibility on the number and times of price changes. This is in concordance with the conclusion made in [6] that employing a discrete pricing strategy with equal time intervals to change the prices is very efficient and practical.

In addition when we look at the effects of the parameters on the system, we observe that the profit decreases slightly in the coefficient of variation, the unit penalty cost, and the unit disposal cost, respectively, while it increases in the product lifetime.

Thus, we can conclude that the multiple pricing becomes more beneficial and effective when the coefficient of variation, the penalty cost, or the disposal cost increases, or the lifetime becomes shorter. For instance, when the lifetime increases the outdated quantity decreases to reach zero for the fourth lifetime. This is because the probability to dispose of the inventory becomes smaller when the items' lifetime becomes longer. However, even for the smallest lifetime, as we can see

TABLE III. COMPUTATIONAL RESULTS OF SBO

Parameters				Decision variables		Performance Indicators				Results from [8]		The percentage profit gain ρ
Life time	*Disposal Cost cd*	*Penalty Lost sale cl*	*C.V*	*Order up To level S*	*Price/Period*	*Outdated Quantity*	*Lost sales*	*Ratio= Lost sales/Sales*	*Profit*	*Outdated Quantity*	*Profit*	
2	10	10.78	0.60	62	44/35/35/39/26	5.85	56.91	25.78%	5344.75	36.35	4254.17	20%
			0.80	63	44/34/27/28/27	7.21	64.25	27.57%	5289.22	26.84	4120.29	22%
			1.00	61	44/35/45/30/28	6.64	71.21	24.84%	5025.25	34.4	4030.01	20%
			1.20	65	44/28/29/29/25	5.98	73.25	26.85%	4981.58	37.51	3968.62	20%
			1.50	68	44/29/28/27/25	8.21	75.81	29.87%	4798.36	36.74	3908.39	19%
		1.98	1.00	61	44/35/28/26/29	3.64	71.21	24.84%	5841.84	1.13	4580.56	22%
		4.18		62	44/35/26/28/28	4.64	61.21	25.84%	5541.84	8.78	4385.61	21%
		21.78		65	44/35/30/30/30	5.58	52.14	18.69%	4650.25	77.92	3671.74	21%
	5	10.78		67	44/35/28/28/29	1.51	61.21	19.84%	4741.84	22.45	4050.3	15%
	20			58	44/35/28/30/27	4.25	91.21	41.84%	1041.84	51.3	399.49	62%
	20		1.50	62	44/27/26/29/25	5.21	81.25	35.84%	4525.25	10.25	3685.26	19%
	20	21.78	1.50	60	44/35/30/35/25	4.69	62.54	21.54%	4085.47	12.85	3352.22	18%
3	10	10.78	0.60	71	44/40/35/39/30	1.85	45.91	15.77%	5732.87	7.95	4295.98	25%
			0.80	73	44/40/29/32/28	2.21	48.25	16.51%	5358.94	3.71	4419.85	18%
			1.00	74	44/40/32/28/30	3.64	51.25	21.14%	5325.25	6.52	4338.89	19%
			1.20	71	44/35/29/30/28	4.98	63.25	25.15%	5281.21	8.91	4228.68	20%
			1.50	75	44/35/28/27/28	6.21	65.99	18.11%	5198.66	9.52	4178.09	20%
		1.98	1.00	71	44/40/28/26/29	1.64	61.22	24.84%	6041.54	0.13	4591.46	24%
		4.18		72	44/40/26/28/28	0.55	59.44	25.84%	5813.64	1.78	4460.42	23%
		21.78		81	44/35/25/30/30	0.58	42.51	18.69%	4950.25	16.87	4112.85	17%
	5	10.78		79	44/35/28/28/29	0.88	51.21	15.21%	5041.84	5.07	4280.44	15%
	20			67	44/39/28/28/27	1.8	75.26	33.74%	4311.93	10.96	4269.36	8%
	20		1.50	69	44/40/26/29/26	0.84	71.55	25.91%	4725.44	17.58	4236.87	10%
	20	21.78	1.50	65	44/35/25/35/27	0.58	52.19	18.54%	4285.89	29.29	3918.44	9%
4	10	10.78	0.60	71	44/40/30/39/29	0	40.11	13.77%	5832.67	1.22	4340.39	26%
			0.80	72	44/40/28/32/29	0	42.01	14.51%	5558.34	0.25	4445.33	20%
			1.00	74	44/40/32/25/32	0	49.22	20.44%	5225.22	0.77	4387.17	16%
			1.20	71	44/40/29/30/28	0	61.12	22.59%	5311.98	1.58	4303.45	19%
			1.50	75	44/35/28/27/27	0	59.61	17.71%	5288.81	1.9	4262.75	19%
		1.98	1.00	73	44/40/28/29/29	0	61.22	23.84%	6141.64	0	4592.3	25%
		4.18		72	44/40/25/27/27	0	55.14	24.54%	5913.95	0.14	4475.38	24%
		21.78		80	44/40/25/30/30	0	35.25	16.66%	5050.84	3.01	4237.33	16%
	5	10.78		81	44/40/28/31/25	0	49.32	13.29%	5154.87	0.77	4341.07	16%
	20			68	44/40/28/31/29	0	69.96	29.57%	4491.18	1.62	4333.94	11%
	20		1.50	70	44/40/26/30/30	0	61.78	25.91%	4969.25	2.5	4636.89	8%
	20	21.78	1.50	65	44/40/25/35/25	0	45.58	15.66%	4390.54	23.52	3987.25	9%

in Table III, the disposed quantity on average does not exceed 3.7 units over the planning horizon. The results suggest that the dynamic pricing could absorb the variability of the system in order to maintain its performance.

Finally, let's note that despite the complexity and the stochasticity implemented in this model, we can conclude that our SBO model can find a good solution in only 30 minutes.

VI. Conclusion

In this paper, we study a joint pricing and inventory problem for stochastic perishable systems with positive lead time and lost-sales. We employ the simulation optimization approach in order to tackle the stochasticity and the complexity of the problem. Unlike previous work, we consider a discrete pricing policy where the seller chooses when and how the price would change over the planning horizon independently from the inventory level. Numerical study shows that that our SBO model performs very well. In comparison with the pervious study we improved the profit and reduced the wastes arising from the disposals, thanks to the dynamicity of the pricing policy proposed. Thus we can conclude that multiple pricing can lead to significant savings depending on the system parameters. When we look at the effectiveness of the discrete pricing policy, we detect that varying the prices at equal time intervals is very efficient.

We plan to extend our model in the future in several ways. Firstly, different types of demand structure can be analyzed in detail. For example, we could consider a demand that depend on both price and freshness. In fact, our model considers that inventories of any age are sold at the same price and customers are not sensitive to the ages of inventories, which ensures that FIFO inventory issuing rule is convenient. Yet, there are situations in which other inventory issuing policies are more reasonable. For instance, when clients are very sensitive to the ages of inventories and they can select items of different ages on the same period. Then, the LIFO inventory issuing policy becomes more suitable. However, when diverse prices are chosen for inventories of different ages, it becomes crucial to model the consumer choice behavior. Considering these issues in perishable inventory models remains an important challenge.

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