An Integrated Pricing and Deteriorating Model and a Hybrid Algorithm for a VMI (Vendor-Managed-Inventory) Supply Chain

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***Abstract*—This paper studies a vendor-managed-inventory (VMI) supply chain where a manufacturer, as a vendor, procures a type of nondeteriorating raw material to produce a deteriorating product, and distribute it to multiple retailers. The price of the product offered by one retailer is also influenced by the prices offered by other retailers because consumers can choose the product from any of the retailers. This paper is one of the first papers that propose an integrated model to study the influence of pricing and deterioration on the profit of such a VMI system. A hybrid approach combining genetic algorithms and an analytical method is developed for efficiently determining the optimal price of the product of each retailer, the inventory policies of the product and the raw material. Our results of a detailed numerical study show that parameters related to the market and deterioration have significant influences on the profit of the VMI system. However, different from common intuition, we find that an increase in the substitution elasticity of the product among different retailers can bring an increase in the retail prices of the product, while the increase of the market scale can reduce the retail prices.**

***Index Terms*—Deteriorating rate, inventory, pricing, supply chain, vendor managed inventory.**

I. Introduction

VENDOR MANAGED INVENTORY (VMI) is an inventory cooperation scheme where a vendor is responsible for system-wide inventory control. There are many successful VMI cases in the real world. For example, the implementation of VMI between Wal-Mart and Procter & Gamble (P&G) had dramatically improved P&G's on-time deliveries and Wal-Mart's sales by 20%–25% and the inventory turnover by 30% [1]; Barilla, a pasta manufacturer, adopted VMI in 1988, which made an inventory reduction by near 50% at its retailers [2]. In practice, many VMI vendors are manufacturers, like Barilla, Dell, and HP [3]. They buy raw materials from their suppliers to produce products. With VMI, the products are delivered to VMI retail partners (e.g., retailers) whose inventories are managed by the manufacturers to meet the product demands of end customers. The demands are a function of retail prices and are coordinated by the manufacturer as an integrated supply chain system.

In the case of a VMI system where the vendor is a food manufacturer such as Barilla, it purchases raw materials (like wheat and rice) to produce the deteriorating products (like pasta, pizza, or bread). The products are fast deteriorating while the deteriorating rate of the raw material can be comparably neglected. Therefore, with VMI, the manufacturer has to manage inventories of both nondeteriorating raw materials and deteriorating products. Meanwhile, different firms share information under VMI, and they attach much importance to integrate their decisions, not only on inventory integration [4], but also on pricing integration [5], [6].

We focus on the Barilla-like VMI system in which the vendor buys a type of nondeteriorating raw material to produce a deteriorating product, and delivers the product to its retailers with a VMI-based common replenishment cycle. In the retail markets, the products sold by different retailers are substitutable by each other and then make their markets depend on each other. Our research aims to propose an integrated model for the entire VMI system and a solution algorithm to determine the price of the product at each retailer's market, the common replenishment cycle of the product, and the replenishment cycle of the raw material, so that the total profit of the whole VMI system is maximized.

Many studies have focused on VMI related research, including those on integrated VMI models, those on marketing policies in VMI systems, and those on pricing and deteriorating inventory. However, the commonly found Barilla-like VMI system with pricing and deteriorating products is widely omitted in the previous work.

For the integrated VMI models, Banerjee and Banerjee [7] consider an EDI-based VMI system in which a vendor makes all replenishment decisions for its buyers to reduce the joint inventory cost. Woo *et al.* [8] extend the work to consider raw material procurement decisions. They propose a model considering a three-level supply chain in which the replenishment cycle of the raw material is assumed to be an integer multiple of the VMI

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common replenishment cycle. After this, Zhang *et al.* [5] study a similar VMI system and Arora *et al.* [6] study a VMI system where an order-up-to policy is applied.

Considering marketing policies in VMI systems, Yu *et al.* [4] study a pricing problem in a VMI system where the inventory control of raw materials is considered in a Stackelberg game structure. Yu *et al.* [9] consider a VMI-type supply chain in which both advertising and pricing are considered. They assume retailers' markets are independent of each other. Yu and Huang [10] investigate a VMI system under a Nash game where bill of materials (BOM) structures of products in manufacturing are considered and retailers compete each other.

Some study exists on combinations of pricing and deteriorating product inventory. Kotler [11] first incorporates marketing policies into inventory decisions and discusses the relationship between economic ordering quantity (EOQ) and price decisions. Ladany and Sternleib [12] study the effect of price variations on demand and consequently on EOQ. Goyal and Gunasekaran [13] extend the previous work, considering deteriorating goods in a multistage inventory model. Although the product price is considered in their paper, it is only treated as an input parameter. Dye [14] considers product price as a decision variable in a deterministic inventory model for deteriorating items. Teng and Chang [15] consider the economic production quantities (EPQ) for a deteriorating item with stock level and selling-price dependent demand. They provide the necessary conditions to solve their problem. Chung and Wee (e.g., [5] and [8]) investigate a supply chain with single-retailer and single-manufacturer cooperation for deteriorating items. They propose an integrated production inventory model considering the pricing policy, the imperfect production, the inspection planning, the warranty-period, and the stock-level-dependant demand with the Weibull deterioration, partial backorder and inflation. The classical optimization technique and the heuristic method are used to derive the optimal solutions.

To the best of our knowledge, the literature on the combination of pricing and deteriorating for a VMI-type supply chain with a manufacturing vendor is very limited. Compared with the above papers discussing integrated VMI models [4], [9], [16], our research considers a deteriorating product and pricing in a Barilla-like VMI system. Moreover, our paper aims to maximize profit, instead of minimizing total cost. Compared with the above papers discussing marketing policies in a VMI system [17], our research studies a deteriorating product in a cooperative supply chain with an integrated model, instead of a nondeteriorating product by using a noncooperative model such as a Nash or Stackelberg game. Different from the above deteriorating and pricing related papers, we consider the problem in the unique Barilla-like VMI system with nondeteriorating raw materials and deteriorating products. Moreover, the demand of a retailer is not only a function of its retail price, but also those of other retail prices.

The contribution of this paper includes the following.

1) This paper is one of the original efforts to study on pricing and inventory management for a Barilla-like VMI system where the vendor, as a manufacturer, uses a type of nondeteriorating raw material to produce a deteriorating product.
2) We propose an integrated model to investigate the impact of the pricing and deteriorating related factors on the VMI profit in a comprehensive manner.
3) We propose a hybrid approach combining genetic algorithm (GA), enhanced by analytical methods like Newton–Raphson method [8], [16] to solve the problem. The proposed algorithm takes advantage of GA in solving a nonlinear programming model, but avoids its disadvantages in expensively obtaining exact local optima.

This paper is organized as follows. Section II describes the research problem and defines notations. In Section III, we develop the integrated pricing and deteriorating model. Section IV presents a hybrid approach to finding the optimal pricing and inventory policies. Section V gives a detailed numerical study to analyze the influence of parameters such as market-related parameters and the deteriorating rate on the profit of the supply chain. Section VI concludes this paper.

II. Problem Description and Notations

A. Problem Description

Overall, we aim to determine retail prices, the replenishment cycles of the product and the raw material for a VMI system in order to maximize the system-wide profit. The VMI system consists of one vendor and multiple retailers. The vendor is a manufacturer who procures a nondeteriorating raw material to produce a deteriorating product. The product is distributed to multiple retailers by using a VMI policy. With the VMI policy, the manufacturer uses a common replenishment cycle for all retailers (e.g., one week) [18] to multiple inventories of the retailers. Each retailer is replenished once on a fixed date in a common replenishment cycle (e.g., every Tuesday for retailer 1, and every Wednesday for retailer 2, etc.), which makes sure the product to be delivered instantly to avoid deterioration. The common replenishment cycle is a decision variable to manage inventory of the product in the whole VMI system.

The demand rate of a retailer is not only a function of its own retail price, but also the prices of the product in the other retailers' markets. That is, the products sold in different retail markets are substitutable as consumers are free to choose.

The raw material is nondeteriorating and it is replenished to the manufacturer less frequently than the product. We adopt the integer-ratio policy (see also Banerjee [5], Zhang *et al.* [8], Woo *et al.* [19], and Wang [4], [16], [20]), where the replenishment cycle (nC) of raw materials is the integer multiple (n) of the common replenishment cycle (C).

The deteriorating rate for the product is assumed to be deterministic. For the deteriorating cost of a retailer, the deteriorating cost per unit product is its retail price, but for the manufacturer, it is the wholesale price. The retail price of each retailer is a decision variable.

B. Notations

The notations are given below.

Indices:

m	The total number of retailers.
$i = 1, \ldots, m$	Index of retailers.

Input parameters:

A Ordering cost of the manufacturer for a raw material order (\$/order).

H_{bi} Holding cost of the product of retailer i (\$/unit/time).

H_{vm} Holding cost per unit raw material of the manufacturer (\$/unit/time).

H_{vp} Holding cost per unit product per unit time for the manufacturer, (\$/unit/time).

M Usage rate of the raw material for producing one unit of the product.

p_0 Production and raw material cost for producing one unit of the product direct cost including production and raw material cost (it is also used as deteriorating cost per unit of product for the manufacturer) (\$/unit).

P Production rate (capacity per unit time) of the manufacturer.

S Fixed production cost for the manufacturer per common replenishment cycle (\$/order).

T_i Fixed ordering cost for retailer i's order (\$/order).

a_i Market scale factor of retailer i's market (a larger positive value corresponds a bigger market scale of retailer i).

β_{ij} Substitution elasticity for retailer i's demand with respect to retailer j's price, $i \neq j$.

α_i Price elasticity of retailer i's demand with respect to retailer i's price, which equals $(\partial D_i(p)/\partial p_i) * (p_i/D_i(p))$.

ζ_i Transportation cost per unit of product from the manufacturer to retailer i (\$/unit).

θ Deteriorating rate of the product (percentage/unit/time).

Functions:

$D_i(p)$ Demand rate of retailer i (\$/unit/time) which is a function of the retail prices $p = (p_1, \ldots, p_m)$.

$\mathrm{TC}_{\mathrm{VMI}}$ Total cost for the VMI system per unit time, (\$/time).

H_{pi} Holding cost of the product for the manufacturer in a common replenishment cycle (\$).

HC_{vm} Holding cost of the raw material for the manufacturer in a common replenishment cycle C (\$).

Q_i Replenishment quantity of retailer i.

t_{vi} Production time for the manufacturer to satisfy the demand of retailer i in a common replenishment cycle.

TC_{bi} Total inventory cost for retailer i per unit time (\$/time).

TC_{vp} Total inventory cost of the product per unit time for the manufacturer (\$/time).

TC_{vm} Total inventory cost of the raw material for the manufacturer per unit time (\$/time).

π Total profit of the VMI system per unit time (\$/time).

Decision variables:

p_i Retail price of the product at retailer i (\$/unit). $p = (p_1 \ldots . p_m)$. or deteriorating cost per unit of product of retailer i.

C Common replenishment cycle of the product from the manufacturer to every retailer.

n Integral multiple between the replenishment cycle of the raw material and C. $n > 1$ and nC is the replenishment cycle of the raw material.

III. Model

The profit of the VMI system equals the total revenue minus the total costs. The total revenue of the system is collected by all heterogeneous retailers and is addressed in Section III-A. The total cost of the entire system is addressed in Section III-B, which includes the inventory cost and deteriorating cost of every retailer $(TC_{bi}, i = 1, \ldots, m)$, the inventory cost and deteriorating cost of the product (TC_{vp}) of the manufacturer, and the inventory cost of the raw material (TC_{vm}). In Section III-C, we propose an integrated model for maximizing the total profit.

A. Total Revenue

The product demand $D_i(p)$ for retailer i is a decreasing function of p_i with

$$\frac{\partial D_i(p)}{\partial p_i} < 0. \tag{1}$$

Since the products on different retailers' markets are substitutable, $D_i(p)$ of retailer i is an increasing function of the other retailer's retail prices, $p_j, j = 1, \ldots, m$ with

$$\frac{\partial D_i(p)}{\partial p_j} > 0, \quad j = 1, \ldots, m \text{ and } j \neq i. \tag{2}$$

In other words, each retailer can expect an increase in its sales volume whenever one of the other retailers increases its price. The demand with the above properties can be commonly found in the literature [21], which traces back to Samuelson [8] as a Cobb–Douglas function.

Assuming product demand function, as the function of the retail prices $p = (p_1, \ldots, p_m)$, is a Cobb–Douglas function, we have

$$D_i(p) = a_i p_i^{-\alpha_i} \prod_{j \neq i} p_j^{\beta_{ij}}, \quad i = 1, \ldots, m \tag{3}$$

where $\alpha_i > 0, a_i > 0, \beta_{ij} \geq 0$ for all i and $i \neq j$.

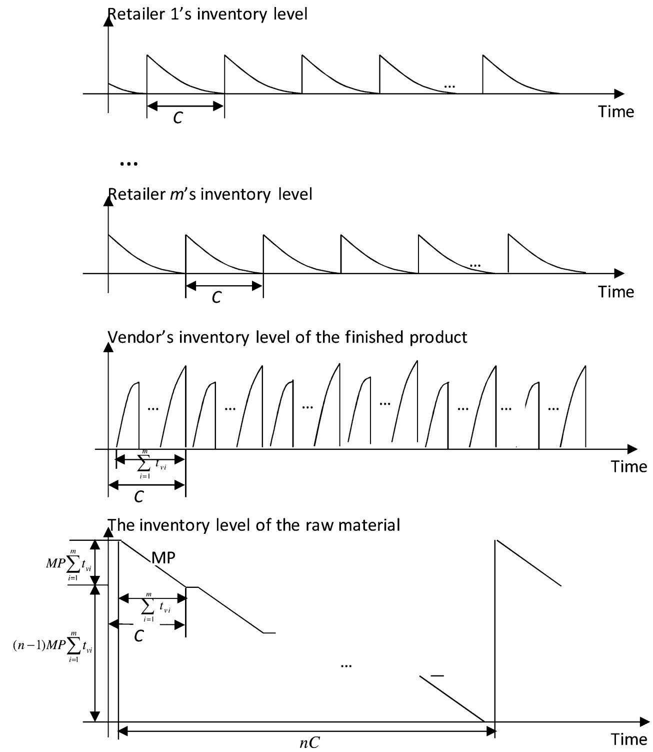


Fig. 1. The inventory levels for all the retailers and the vendor.

With the product sold at the retail price p_i in retailer i's market, the system yields the total revenue

$$\sum_{i=1}^{m} D_i(p)p_i. \tag{4}$$

B. Total Costs

In this section, we calculate the total cost of the manufacturer and all the retailers. The inventory levels of all the retailers and the manufacturer are shown in Fig. 1.

In a common order cycle C, the inventory level of retailer i, denoted by $I_i(t)$ can be formulated by

$$I_i'(t) = -\theta I_i(t) - D_i(p) \quad 0 \le t \le C \tag{5}$$

with a boundary condition

$$I_i(C) = 0. \tag{6}$$

The solution of the differential Equations (5) and (6) is

$$I_i(t) = \frac{D_i(p)}{\theta}\left(e^{\theta(C-t)} - 1\right) \quad 0 \le t \le C. \tag{7}$$

Substituting $t = 0$ into (7), we get the maximum inventory level of retailer i (i.e., the replenishment quantity of retailer i)

$$Q_i = I_i(0) = \frac{D_i(p)}{\theta}(e^{\theta C} - 1). \tag{8}$$

In a common replenishment cycle C, retailer i's total inventory holding cost becomes

$$\int_0^C H_{bi} I_i(t)\,dt = \int_0^C H_{bi}\frac{D_i(p)}{\theta}\left(e^{\theta(C-t)} - 1\right)dt$$

$$= \frac{D_i(p)H_{bi}}{\theta^2}(e^{\theta C} - 1) - \frac{D_i(p)H_{bi}C}{\theta} \tag{9}$$

and total deteriorating cost is

$$p_i(Q_i - D_i(p)C). \tag{10}$$

Retailer i's total inventory and deteriorating cost is given as

$$\mathrm{TC}_{bi} = \frac{1}{C}\left[T_i + \frac{D_i(p)H_{\mathrm{bi}}}{\theta^2}(e^{\theta C} - 1) - \frac{D_i(p)H_{\mathrm{bi}}C}{\theta} + p_i(Q_i - D_i(p)C)\right]. \tag{11}$$

From Fig. 1, it can be seen that the manufacturer replenishes retailers one by one. For collecting replenishment quality Q_i for retailer i, the inventory level of the product, denoted by $I_{vi}(t)$, follows the differential equation:

$$I_{vi}'(t) = P - \theta I_{vi}(t) \quad 0 \le t \le t_{vi} \tag{12}$$

with a boundary condition:

$$I_{vi}(0) = 0. \tag{13}$$

From (12) and (13), we have

$$I_{vi}(t) = \frac{P}{\theta}(1 - e^{-\theta t}) \quad 0 \le t \le t_{vi} \tag{14}$$

where t_{vi} is determined by $I_{vi}(t_{vi}) = Q_i$. The solution is

$$t_{vi} = -\frac{1}{\theta}\ln\left[1 - \frac{D_i(p)}{P}(e^{\theta C} - 1)\right]. \tag{15}$$

The manufacturer's holding cost for the product in C for retailer i is

$$\begin{aligned} H_{pi} &= \int_0^{t_{vi}} H_{vp} I_{vi}(t)\,dt \\ &= \int_0^{t_{vi}} H_{vp}\frac{P}{\theta}(1 - e^{-\theta t})\,dt \\ &= \frac{H_{vp}P}{\theta^2}(\theta t_{vi} + e^{-\theta t_{vi}} - 1). \end{aligned} \tag{16}$$

The manufacturer's deteriorating cost for the product in C is

$$p_0\left(P\sum_{i=1}^{m} t_{vi} - \sum_{i=1}^{m} Q_i\right). \tag{17}$$

Therefore, we obtain the total inventory cost per unit time of the manufacturer

$$TC_{vp} = \frac{1}{C}\left[S + \sum_{i=1}^{m}\frac{H_{vp}P}{\theta^2}(\theta t_{vi} + e^{-\theta t_{vi}} - 1) + p_0\left(P\sum_{i=1}^{m} t_{vi} - \sum_{i=1}^{m} Q_i\right)\right]. \tag{18}$$

As shown in Fig. 1, the raw material level of the manufacturer includes n triangles and $(n-1)$ rectangles in a replenishment cycle nC. The area of a triangle is

$(1)/(2)(MP\sum_{i=1}^{m} t_{vi})\sum_{i=1}^{m} t_{vi}$, and the areas of $n-1$ rectangles are

$$(n-1)\left(MP\sum_{i=1}^{m} t_{vi}\right)C,$$
$$(n-2)\left(MP\sum_{i=1}^{m} t_{vi}\right)C,\ldots,\left(MP\sum_{i=1}^{m} t_{vi}\right)C.$$

Thus, according to Woo *et al.* [12], the holding cost of the raw material in a replenishment cycle nC equals

$$\begin{aligned}\mathrm{HC}_{vm} &= H_{vm}\left[\frac{n}{2}\sum_{i=1}^{m} t_{vi}\left(MP\sum_{i=1}^{m} t_{vi}\right) + \sum_{j=1}^{n-1}(jC\left(MP\sum_{i=1}^{m} t_{vi}\right))\right]\\ &= \frac{nMPH_{vm}}{2}\left(\sum_{i=1}^{m} t_{vi}\right)^2 + \frac{n(n-1)CMPH_{vm}}{2}\sum_{i=1}^{m} t_{vi}.\end{aligned} \tag{19}$$

The total inventory cost of the raw material per unit time is

$$\mathrm{TC}_{vm} = \frac{1}{nC}(A + HC_{vm}). \tag{20}$$

Therefore, the total cost of the VMI system is

$$\begin{aligned}\mathrm{TC}_{\mathrm{VMI}} = \mathrm{TC}_{vm} + \mathrm{TC}_{vp} + \sum_{i=1}^{m}\mathrm{TC}_{bi} + \sum_{i=1}^{m} D_i(p)p_0 + \sum_{i=1}^{m} D_i(p)\zeta_i\end{aligned} \tag{21}$$

where $\sum_{i=1}^{m} D_i(p)p_0$ is the total production cost and raw material cost, and $\sum_{i=1}^{m} D_i(p)\zeta_i$ is the transportation cost from the vendor to its retailers.

C. Integrated Model

From the above analysis, by using the total revenue in (4) and the total cost described in (21), we can obtain the following model for the VMI system, denoted by IM.

Model IM

$$\begin{aligned}\max \pi &= \sum_{i=1}^{m} p_i D_i(p) - \mathrm{TC}_{\mathrm{VMI}}\\ &= \sum_{i=1}^{m} D_i(p)p_i - \sum_{i=1}^{m} D_i(p)(p_0 + \zeta_i)\\ &\quad - \frac{1}{C}\left\{\frac{A}{n} + S + \sum_{i=1}^{m} T_i + \frac{(n-1)CMPH_{vm}}{2}\sum_{i=1}^{m} t_{vi} + \frac{MPH_{vm}}{2}\left(\sum_{i=1}^{m} t_{vi}\right)^2\right.\\ &\quad + \sum_{i=1}^{m}\frac{H_{vp}P}{\theta^2}(\theta t_{vi} + e^{-\theta t_{vi}} - 1)\\ &\quad + \sum_{i=1}^{m}\left[\frac{D_i(p)H_{bi}}{\theta^2}(e^{\theta C} - 1) - \frac{D_i(p)H_{bi}C}{\theta}\right]\\ &\quad + p_0\left(P\sum_{i=1}^{m} t_{vi} - \sum_{i=1}^{m} Q_i\right)\\ &\quad \left. + \sum_{i=1}^{m} p_i(Q_i - D_i(p)C)\right\}.\end{aligned} \tag{22}$$

Constraints: (3), (8), (15), and

$$\sum_{i=1}^{m} t_{vi} \leq C. \tag{23}$$

Decision variables: $p_i \geq 0, i = 1,\ldots,m, C \geq 0$, and n is a positive integer.

Equation (22) represents the profit of the whole VMI system. Equation (23) is the production capacity constraint.

Solving Model IM is difficult. The objective function is a nonlinear and mixed integer function of $n, p_i, i = 1,\ldots,m$, and C. Moreover, the objective function is a composite function of $n, p_i i = 1,\ldots,m$, and C, where the intermediate functions (3), (8), (15) are also very complex. In fact, even when we do not consider (or fix) $n, p_i, i = 1,\ldots,m$, the model is still too complex to find a closed-form analytical solution for computing the optimal C. Only for coping with C, Goyal and Gunasekaran [22] have to use exhaustive search to find their optimal solution where finding each solution may consume a large amount of computer resources. Therefore, for our model, the exhaustive search becomes less applicable since the combinations of $n, p_i, i = 1,\ldots,m$, and C are huge. Finally, Constraint (23) is nonlinear which also creates the difficulty to solve Model IM.

IV. Solution Methodology

Model IM is a continuous and differential function of p and C, which gives the chance to find local optimal solutions analytically if n is given. This is addressed in Section IV-A. However, due to the existence of multiple local optimal solutions and that n is an integer, it is still difficult to be solved by an analytical method. Fortunately, a genetic algorithm (GA) can overcome these difficulties. GA can jump out local optima by feeding new inputs for using the analytical method in Section IV-A. The introduction of GA is addressed in Section IV-B, Section IV-C then discusses how to combine the analytical method and GA to find a global optimum.

A. Analytical Method for Local Optima

For any given n, we can find local optimal values of $p_i \geq 0$, $i = 1,\ldots,m$, and $C \geq 0$. We first introduce Lagrange multiplier vectors $\mu_1 \geq 0, \lambda = (\lambda_1,\ldots,\lambda_m) \geq 0$, and $u_2 \geq 0$ for constraints (23), $p_i \geq 0, i = 1,\ldots,m$, and $C \geq 0$, respectively. Considering that $D_i(p), Q_i$ and t_{vi} can be removed by substituting (3), (8), (15) into Model IM, we can get the Lagrangian function of Model IM

$$L = \pi - \mu_1\left(\sum_{i=1}^{m} t_{vi} - C\right) + \sum_{i=1}^{m}\lambda_i p_i + \mu_2 C. \tag{24}$$

The objective function (22) and the left-hand side of constraints (23) are continuous and differential functions of p and C. According to Bertsekas [17], the local maximal solutions of Model IM must satisfy the Karush–Kuhn–Tucker necessary conditions that can be described as follows:

$$\partial L/\partial p_i = 0, \quad i = 1, \ldots, m \tag{25}$$
$$\partial L/\partial C = 0 \tag{26}$$
$$\mu_1 \left(\sum_{i=1}^{m} t_{vi} - C \right) = 0 \tag{27}$$
$$\lambda_i p_i = 0, \quad i = 1, \ldots, m \tag{28}$$
$$\mu_2 C = 0. \tag{29}$$

A local maximal solution of Model IM is then corresponding to a solution of the simultaneous equations (25)–(29). The equations are nonlinear. Press *et al.* [17] provide a C++ code library in their book where the Newton–Raphson method can be just recalled to solve the equations, which converges in $O(n^2)$, where n is the number of equations. Therefore, a local minimum can be obtained.

Moreover, the solution of (25)–(29) can make sure that the found local optima are feasible solutions.

The value of n is a small integral number in practice, which can be enumerated within a range, such as $1, \ldots, 10$.

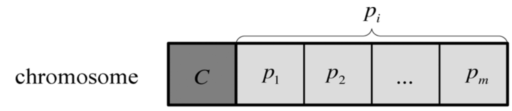
The difficulty for solving the model is now how to find a global optimal solution with a given n.

B. Basic Steps of Genetic Algorithms for Approximate Global Optimization

The disadvantages of the above analytical method lies in no way to find multiple local optimal solutions of $(C, p_1, \ldots, p_m)$ with a given n. Fortunately, GA can overcomes the difficulty of multiple local optima, and has been widely used by many researchers (see [23]–[25]). We here use GA to generate inputs of $(C, p_1, \ldots, p_m)$ in a wide range for the Newton–Raphson method. Thus, the all local optimal solutions can be found and the best ones can be kept.

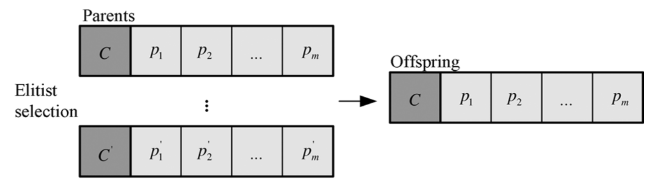
In GA, a population of chromosomes is generated and evolves toward optimal solutions. A chromosome corresponds to a solution of Model IM. The first generation of the population is commonly generated randomly. To avoid a local solution, we first set large enough ranges for C and $p_1, \ldots, p_m$, and then adjust them into relatively small ones to save computation time. In practice, small ranges can commonly be set at the very beginning based on empirical judgments.

The chromosomes in generations afterwards are produced by using selections, mutations, and crossovers. The quality of a chromosome is evaluated by a fitness function. The fitness function is often defined by the objective function plus some costs for panelizing the constraint violations. By using the fitness function, the chromosomes can be ranked from good to bad ones. In our model, the objective function is defined as the fitness function. The random generation of the chromosomes for the first generation population is the first step to avoid local optima.



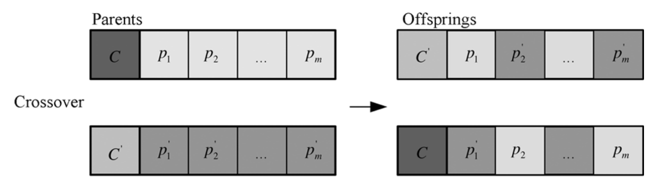
Note. A chromosome consists of one gene for *C* and *m* genes for the retail prices.

Fig. 2. Chromosome generation.



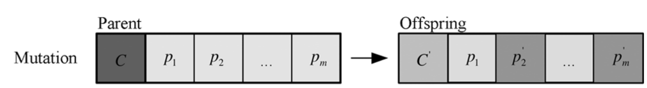
Note. The offspring is the best parent that gives the highest profit.

Fig. 3. Elitist selection operation.



Note. C, p_2 and p_m are crossed with C', p_2' and p_m', respectively.

Fig. 4. Crossover operation.



Note. C, p_2 and p_m are mutated to C', p_2' and p_m'.

Fig. 5. Mutation operation.

Each solution is represented by a chromosome consisting of $(m+1)$ genes where the first gene is for C and the other m genes are for the retail prices, as shown in Fig. 2.

Three genetic operators are used to create chromosomes for next generations. First, a GA elitist selection is considered. Our GA selection introduces the elitist strategy [26] to ensure that the best chromosomes can survive in the evolution. Some elite solutions that give good fitness function values in the current generation are selected and directly included in the next generation. An example is shown in Fig. 3.

Next, GA crossovers are used to produce some chromosomes for the next generation. In a GA crossover, current chromosomes are paired as parents. In every pair, some chromosome genes of one parent are randomly selected as crossover points and are used to swap genes with the corresponding ones of the other parent. This generates two offspring and they will be included as two chromosomes of the next generation if a mutation in the next step does not happen. The examples of crossover and mutation operations are shown in Figs. 4 and 5, respectively. To choose pairs of parents, the roulette wheel selection approach [27] is used which gives a better chromosome a higher probability to be chosen.

When the next generation population of chromosomes is produced, they will be evaluated by the fitness function. The selection, crossovers, and mutations can then be repeated as the result of the solution evaluation. The population of chromosomes can therefore evolve until a termination criterion is satisfied. In the last generation, the chromosome giving the maximum value of objective function (22) is selected as the final solution of Model IM. We stop the process if the population does not improve within a certain number of generations, or a predetermined maximum number of steps have been reached.

C. A Hybrid Approach for a Global Optimum

Our hybrid approach combines the advantages of the analytical method and GA to find a global optimal solution for every given n. The optimal n is solved by enumerating all possible n since n is a small integer number, like commonly between 1 to 10. The hybrid approach is deployed as follows.

Step 0 (Input parameters): set $n = 1$, and preassign the population size, the percentage of elitist selection p_s, crossover probability p_c, and mutation probability p_m

Step 1 (Initialize chromosomes by combining GA and the Newton–Raphson method): We first use GA to randomly generate a chromosome for a solution of $(C, p_1, \ldots, p_m)$, which is used as an input by the Newton–Raphson method in Section IV-A to iteratively find the corresponding local optimal solution of $(C, p_1, \ldots, p_m)$. This local optimal solution instead of the randomly generated solution is included as a chromosome in the population. Similarly, we then produce all the other chromosomes in the population. Compared to the traditional GA, the introduction of the Newton–Raphson method makes sure all solutions represent local optima. Therefore, GA evolution for searching the local optima of $(C, p_1, \ldots, p_m)$ can be saved. Moreover, the feasibility of the chromosomes can be guaranteed because Constraints (23) has been satisfied in the analytical method. Note that n is not coded in a chromosome since it is optimized by enumeration.

Step 2 (Evaluate the pop-size chromosomes by the fitness function): The chromosomes are ranked in a decreasing sequence of their fitness values. We select the objective functions as the fitness function. The penalty of the constraint violation is not necessary to be included in the fitness function because the analytical method only produces feasible solutions and the violation of the constraints has already been removed.

Step 3 (elitist selection): We adopt the selection procedure in Section IV-B such that good chromosomes can survive during the GA evolution.

Step 4 (generate a next generation by combining crossover, mutation, and the Newton–Raphson method): We adopt the mutation and crossover procedure in Section IV-B to produce offspring chromosomes to keep the diversity of the population, which can avoid local optima. We then take the chromosomes as inputs for the Newton–Raphson method in Section IV-A for finding locally optimized chromosomes. These optimized chromosomes, instead of the ones generated by mutation and crossover will be included as the chromosomes of the next generation to save the computation time. As we explain in Step 1, these chromosomes remain feasible.

TABLE I
INPUT PARAMETERS

Parameters	Values	Parameters	Values
P	6×10^4	H_{b1}, H_{b2}, H_{b3}	80,160,220
p_0	40	$\zeta_1, \zeta_2, \zeta_3$	3, 6, 2
A	5000	$T_1, T_2, T_3(10^3)$	1.0,1.6,1.2
S	2000	$\alpha_1, \alpha_2, \alpha_3$	1.25, 1.45, 1.6
H_{vp}	40	$a_1, a_2, a_3\ (10^7)$	2.5, 1.5, 0.95
M	0.95	$\beta_{1,1}, \beta_{1,2}, \beta_{1,3}$	-, 0.025,0.012
θ	0.02	$\beta_{2,1}, \beta_{2,2}, \beta_{2,3}$	0.015, -, 0.016
H_{vm}	15	$\beta_{3,1}, \beta_{3,2}, \beta_{3,3}$	0.018, 0.02, -

TABLE II
OPTIMAL DECISIONS OF THE BASE EXAMPLE

(p_1^*, p_2^*, p_3^*)	$\sum_{i=1}^{3} D_i$ (10^4)	n^*	C^*	TC^*_{VMI} (10^6)	π^* (10^6)
(238.15, 213.35, 186.44)	4.27	3	0.046	2.18	7.66

TABLE III
SENSITIVITY ANALYSIS BY VARYING THE MARKET SCALE FACTOR a_1

a_1 (10^7)	(p_1^*, p_2^*, p_3^*)	$\sum_{i=1}^{3} D_i$ (10^4)	n^*	C^*	TC^*_{VMI} (10^6)	π^* (10^6)
0.5	(252.30,179.04,149.34)	1.94	3	0.064	1.09	2.71
1.5	(240.34,192.88,162.82)	3.12	3	0.054	1.64	5.18
2.0	(239.02,202.15,172.91)	3.69	3	0.050	1.91	6.42
2.5	(238.15,213.35,186.44)	4.27	3	0.046	2.18	7.66
3.0	(237.64,227.37,207.15)	4.85	3	0.043	1.38	8.91
4.0	(254.58,280.71, Infinity*)	6.00	4	0.034	3.00	12.42

* When the optimal p_i calculated by GA is larger than 10^9. We then give Infinity to p_i.
Note: other data sets of a_i are analyzed and shows the similar result.

Step 5 (check the global optimality of $(C, p_1, \ldots, p_m)$): Repeat the second to fourth steps until a termination condition is satisfied.

Step 6 (output solutions corresponding to an n value): Report the best chromosome in the last generation as the optimal solution for the given n.

Step 7 (enumerate n): Check whether all n has been enumerated (in a given domain of [1] and [10]). If yes, go to next step. Otherwise, let $n = n + 1$ and go to Step 2.

Step 8 (output the global optimal solution): Take the best n and its corresponding optimal $(C, p_1, \ldots, p_m)$ as the final solution and output this solution.

V. NUMERICAL EXAMPLES

This section presents numerical examples to demonstrate the overall impact of the deteriorating and market related parameters on the profit of the VMI system. We exemplify the system including one manufacturer and three retailers. The values of the related input parameters for a base example are given in Table I (all the parameters are generated randomly with their practice ranges). The unit time is one year and the monetary unit is the U.S. dollar.

The optimal decisions for all retailers and the manufacturer are shown in Table II. Moreover, we conduct the sensitivity analysis by changing the market and deteriorating related parameters of retailer 1 including the market scale factor a_1, the price

TABLE IV
SENSITIVITY ANALYSIS BY VARYING THE PRICE ELASTICITY α_1

α_1	(p_1^*, p_2^*, p_3^*)	$\sum_{i=1}^3 D_i$ (10^4)	n^*	C^*	TC^*_{VMI} (10^6)	π^* (10^6)
1.15	(365.20,281.43, Infinity*)	3.81	3	0.045	2.29	13.75
1.20	(286.12,239.60,228.52)	4.28	3	0.046	2.17	9.65
1.25	(238.15,213.35,186.44)	4.27	3	0.046	2.18	7.66
1.30	(206.38,199.14,169.34)	4.11	3	0.047	2.11	6.19
1.50	(143.68,178.57,148.19)	3.09	3	0.050	1.64	3.16
1.80	(110.63,173.64,143.96)	2.02	3	0.063	1.13	1.86

Note: other data sets of α_i are analyzed and shows the similar result.

TABLE V
SENSITIVITY ANALYSIS BY VARYING THE SUBSTITUTION ELASTICITY β_{12}

β_{12}	(p_1^*, p_2^*, p_3^*)	$\sum_{i=1}^3 D_i$ (10^4)	n^*	C^*	TC^*_{VMI} (10^6)	π^* (10^6)
0	(237.89,166.41,176.88)	4.21	3	0.046	2.16	6.90
0.005	(237.96,172.61,178.60)	4.22	3	0.046	2.16	7.04
0.015	(238.02,188.67,182.21)	4.25	3	0.046	2.17	7.34
0.025	(238.15,213.35,186.44)	4.27	3	0.046	2.18	7.66
0.050	(242.33, Infinity*,211.34)	6.00	3	0.038	2.97	11.51
0.080	(290.64, Infinity*,292.58)	6.00	3	0.039	2.97	14.54

Note: other data sets of β_{ij} are analyzed and shows the similar result.

TABLE VI
SENSITIVITY ANALYSIS BY VARYING THE DETERIORATING RATE θ

θ	(p_1^*, p_2^*, p_3^*)	$\sum_{i=1}^3 D_i$ (10^4)	n^*	C^*	TC^*_{VMI} (10^6)	π^* (10^6)
0.005	(238.23,213.52,186.80)	4.23	3	0.047	2.17	7.66
0.02	(238.15,213.35,186.44)	4.27	3	0.046	2.18	7.66
0.1	(237.83,212.49,185.05)	4.28	3	0.044	2.20	7.67
1.0	(237.95,208.95,178.35)	4.31	5	0.027	2.38	7.48
4.0	(242.61,208.85,175.58)	4.24	8	0.015	2.67	7.16
16.0	(257.83,215.42,179.06)	3.97	16	0.008	3.24	6.44
20.0	(261.93,217.46,180.53)	3.90	18	0.007	3.38	6.28

elasticity α_1, the substitution elasticity between different markets β_{ij}, and the deteriorating rate of the product θ. The corresponding results are shown in Tables III–VI. All the examples are solved with the same computational parameters in the GA: the population $\text{size} = 100$, the number of $\text{generations} = 500$, the percentage of elitist $\text{selection} = 2\%$, the crossover $\text{probability} = 0.8$, the mutation $\text{probability} = 0.1$. The ranges of C and $p_i (i = 1, 2, 3)$ is [0.001, 1] and $[0, 10^9]$ initially and is commonly narrowed down to [0.001, 0.1] and [100, 500] after precalculating by GA, respectively.

The algorithm programming is coded in Java 8.0. All the results can be found in a minute with the CPU of 2.4 G and 528 RAM.

From Tables II–VI, we obtain the following observations.

- The market related factors have great impact on the profit of the VMI system. In Table III, it is shown that the change of a_1 from 0.5 to 4 can make a profit increase by more than four times from 2.71×10^6 to 12.42×10^6. Similarly, the change of other market-related parameters of α_i, and β_{ij} can also bring a huge change in the profit (see Tables IV and V).
- When a retailer's market scale increases, its retail price decreases, but the other retailers' prices increase if no retailer quits the system. As shown in Table III, when retailer 1's market scale a_1 increases from 0.5 to 3.0, the retailer decreases its retail price by 14.64, but the prices of retailers 2 and 3 increase by 48.33 and 57.81, respectively. This can be explained as follows: the increase of a market scale makes its retail price decrease for more sells and then worsens other markets via reducing $\prod_{j \neq i} p_j^{\beta_{ij}}$ according to (3). In a worsening market, its pricing is increasing to avoid the decrease of the system profit.
- The price of the product is more influenced by the price elasticity α_i and the substitution elasticity β_{ij} than the market scale factor a_i. For example, in Table III, by increasing a_1 from 0.5 to 4.0, the retail price only increases by less than 10%. However, it is seen from Table IV that a smaller amount change in α_1 from 1.2 to 1.8 can change the retail price by more than 50%. Similarly, a small change in β_{ij} can even get a retailer out of the system.
- The optimal price is an increasing function of the substitution elasticity β_{ij}. This can be explained as follows: because the discussed system is an integrated system where the retailers do not compete with each other. With an increase in β_{ij}, the best solution to the whole system lets all retailers increase their prices simultaneously.

  The replenishment policy of the deteriorating product is significantly influenced by the total demand and the deteriorating rate of the product. In Tables II–V where the deteriorating rate is the same, a larger $\sum_{i=1}^3 D_i$ often corresponds to a smaller C. This means that any factor such as a_i or β_{ij} that influences the demand can influence the replenishment cycle in the end. In Table VI, by increasing θ from 0.005 to 20, C decreases by more than 85%.
- The optimal n^* is quite stable with the change in a_i, α_1, and β_{ij}. For example, in Tables II–V, n^* is commonly equal to 3. This indicates that, although the replenishment cycle of the product C is significantly influenced by many factors, n can often be kept to be the almost same.
- The optimal n^* is quite sensitive to the deteriorating rate of the product. For example, in Table VI, at $\theta = 20$, n equals 18 that is much larger than $n = 3$ in the most cases. The reason is that if the unit time is one year, $\theta = 20$ represents the product can be completely deteriorated in about $365/20 = 18$ days, while $\theta = 1$ represents a completely deterioration takes a year. Such a large change in n is resulted from that the increase in θ would lead more frequent replenishments of the product to avoid deteriorating.
- The results of our model actually reveal the retailer selection procedure. From Table V, p_2 becomes infinite at $\beta_{12} = 0.05$, which means that retailer 2 has to be excluded from the VMI system to maximize the profit of the VMI system.
- The deteriorating rate can significantly influence the total cost TC^*_{VMI}, and then the profit. From Table VI, with the increasing of θ from 0.005 to 20, TC^*_{VMI} arises from 2.17×10^6 to 3.38×10^6 by 55.76%. Consequently, π decreases by 17.01%.
- With an increase in the deteriorating rate, the retail price only increases slightly if the deteriorating rate is not too high. For example, as shown in Table VI, if $\theta \leq 0.1$

TABLE VII
PERFORMANCE OF THE HYBRID ALGORITHM AND GA

algorithm	time					average time
hybrid algorithm	53.1	44.1	43.1	46.2	35.6	43.2
	38.2	43.3	37.81	37.8	52.4	
GA	860.3	574.3	904.7	477.2	603.3	726.1
	727.2	807.7	1041.4	695.2	569.9	

Note: 10 data sets are tested. Each data set contains 3 retailers. The parameter valuess are generated with P=rand(1,50)×10^4, p_0=rand(10,200), A=rand(1,10) ×10^3, S= rand(1,10) ×10^3, H_{vp}=rand(10,100), M =rand(0,1), θ =rand (0.001, 20), H_{vm}=rand(10,100), H_{bi}=rand(50,300), $\beta_{i,j}$ =rand(0, 0.1) , ζ_i =rand (1,10), α_i =rand(1.1, 2), and a_i =rand(1,10) ×10^7.

the retail price keeps almost no change. This is because the product price is mainly influenced by the demands of customers.

To evaluate the performance of our hybrid algorithm, we randomly generate input parameter values in large ranges and Table VII show the difference of the hybrid algorithm and the pure GA method in computation times for finding the optimal solutions. The large ranges for generating parameter values are given with. The results in Table VII show that the hybrid algorithm proposed in this paper needs less than 1/10 computation time of the pure GA on average.

Except for the examples introduced above, we also examined some other data sets. Similar findings can be obtained and we omit the related discussion here.

VI. CONCLUSION

This paper has studied a Barilla-like VMI system where a vendor, as a manufacturer, buys a type of nondeteriorating raw material to produce and distribute a deteriorating product for multiple retailers. All the retailers sell the product and customers are free to choose and buy the product from any of the retailers. An integrated model is developed to maximize the system-wide profit by determining the optimal common replenishment cycle for the product, the replenishment cycle for raw material and all retailers' prices. A hybrid approach combining GA and an analytical method is proposed to fast obtain the optimal decisions. Our numerical study has revealed that the deteriorating rate θ, the elasticity of its own price α_i, and substitution elasticity β_{ij} have significant impact on the profit of the VMI system.

Based on the numerical examples, we obtain some valuable counter-intuitive managerial insights below.

- When the substitution elasticity of the product among different retailers increases, we can simultaneously increase retail prices in the VMI setting to increase the system profit. Therefore, product substitution among different markets should be considered as an incentive to a system-wide integration instead of an obstacle.
- A retailer should decrease its product price when its market scale increases; while the other retailers should simultaneously increase their markets' prices in order to maximize the system-wide profit (see Table III).
- With the increase in the deteriorating rate, the product should be priced very carefully since the retail prices may not be an increasing function of the deteriorating rate. As shown in Table VI, when the deteriorating rate increases between 1 and 2, the prices should be kept almost no change. Only when the deteriorating rate is too high, the price should increase with an increase in the deteriorating rate to slow down the profit reduction.

For the future research, deteriorating problems can be extended to consider a decentralized VMI system [4], [9], outsourcing [28], [29], and the influence of taxes on optimally pricing [30].

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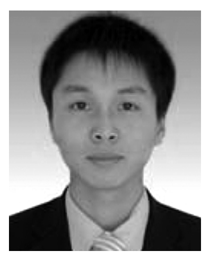

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