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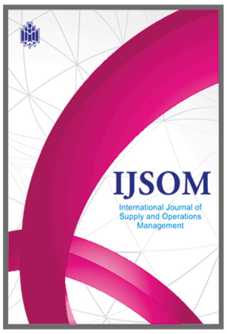

Supplier Selection in Three Echelon Supply Chain & Vendor Managed Inventory Model under Price Dependent Demand Condition

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Abstract
This study examines the supplier selection in three echelon supply chain and Vendor Managed Inventory (VMI) strategy underprice dependent demand condition. It seems that the study of supplier selection has been underexplored following the literature on, this paper presents a VMI model in supply chain including multi-supplier, one distributer and multi-retailer that distributer selects suppliers. Two class models (traditional vs. VMI) are presented and compared to study the impact of VMI on supply chain and supplier selection. As the proposed model is an NP-hard problem, a meta-heuristic, namely Harmony Search, is employed to optimize the proposed models. We show that how the VMI system affects supplier selection and can change the set of selected suppliers. The implications and suggestions for further research are given.

Keywords: Supplier Selection; Vendor Managed Inventory; Price Dependent Demand; Harmony search.

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1. Introduction

In recent years, companies and organizations are required to employ an efficient supply chain management (SCM) to afford competition in the markets where decision and integration play an important role. In supplier-retailer partnership, many issues are discussed; Continuous Replenishment (CR), Advanced Continuous Replenishment (ACR) and Vendor Managed Inventory (VMI) are the most popular cases in SCM David Simchi-levi (2007).

VMI – the main subject of this paper- has become an important case in supply chain management. In a VMI program, the vendor manages the inventory held at the retailer side. He/she is also responsible for the replenishment of goods according to a specified inventory control policy. This partnership increases the benefit of supply chain and cost saving for retailer(s), while the vendor may benefit by integrating his/her operational decisions of production and supply in order to attain the economies of scale and flexible deliveries in the distribution process . VMI strategy has been successfully implemented in many companies like Wal-Mart, Kmart and Procter & Gamble (P&G); and they take the advantages of VMI strategy with increasing the costs and improving the customer service level (David Simchi-levi, 2007).

Supplier selection is a fundamental decision process in VMI; the retailer or distributer has to decide whether to select supplier(s) or not. This is especially real for competitive suppliers. Supplier selection in VMI faces complicated and interesting functional models and algorithms in attempting to maximize the profit of the supply chain and satisfy some conditions. This paper extends the model presented by Sadeghi et.al (2014) to consider three-echelon VMI supply chain. It is expected that the proposed model profits, and the capacity of suppliers and satisfying the demands of costumers are constraints. The proposed VMI model and traditional model are formulated as an integer nonlinear programming (INLP) problem. Following the literature on (Altiparmak, Gen, Lin, & Paksoy, 2006; Bandyopadhyay & Bhattacharya, 2014) our model is NP-hard so it is impossible It seems that it is difficult to solve it simply. Therefore, the "Harmony Search" is suggested to solve the model. Tagouchi method is utilized to tune the parameters of the proposed algorithms to provide a reliable solution.

In the following sections organized as follows:

2. Literature review

Previous research on of this study on supplier selection in VMI problem can be classified into two classes: pricing in VMI, and supplier selection in supply chain.

2.1. Pricing in VMI

Game theory is one of the main methods used in this part of problems. Yugang et.al (2009) studied the pricing and optimal policy of order quantity with considering commercial costs. They showed that the function of investment in commercial problem is concave, and the retailer price function is convex. They used Stackelberg game to find the best price.

Yu and Huang (2010) applied Nash game model to determine the best price in two-echelon multi-supplier one-retailer supply chain. Xiayang (2011) discussed the relation between inventory level, demand and price. He found that because of VMI implementation, the supply chain's profit will improve. Yu et al.(2009) investigated a VMI system with two-echelon supply chain and suggested the Game Theory To optimize the proposed model. Their observations showed that nonlinear function in multi-supplier or multi-retailer VMI supply chain will transform the problem into an NP-hard one. Nachiappan and Jawahar (2007) worked on two-echelon one-supplier multi-retailer supply chain with VMI strategy and found that conjoint pricing and optimal ordering in VMI is NP-hard problem; therefore, they used Genetic Algorithm to solve it. Yu et al. (2012). They examined raw materials in VMI, assumed that the price of retailers is related to each other, and the retailers in fact are in competition. Because of nonlinear deteriorating function, the model is considered as NP-hard and solved with Genetic Algorithm.

2.2. Supplier selection in supply chain

Following the literature on supply chain offers a range of methods and techniques for supplier selection problems. Multi-criteria decision making (MCDM) is a typical example of such models including Analytic Hierarchy Process (AHP) (Mani, Agrawal & Sharma, 2014), Analytic Network Process (ANP) (Dargi, Anjomshoae, Galankashi, Memari & Tap, 2014), and Data Envelopment Analysis (DEA) (Veni, Rajesh & Pugazhendhi, 2012).

Mathematical programming is another rapprochement to supplier selection problems. Goal programming (Jadidi, Cavalieri & Zolfaghari, 2015), linear and non-linear programming (Amin, Razmi & Zhang, 2011); (Ware, Singh & Banwet, 2014) and dynamic programming (Mafakheri, Breton & Ghoniem, 2011) are proposed methods to solve this kind of problems.

Regarding the serious problems, researchers attempted to develop heuristic and meta-heuristic approach. (Esmaeili Aliabadi, Kaazemi & Pourghannad, 2013; Kuo, Pai, Lin & Chu, 2015; P. C. Yang, Wee, Pai & Tseng, 2011) are some researchers who applied the model to this method in supplier selection. Previous research have suggested that, the basic criteria typically utilized for supplier selection are price, delivery and product quality. (Deshmukh & Chaudhari, 2011)

Therefore, Earlier studies were most concerned with VMI consider the optimal pricing or the optimal order quantity. However, it seems that few studies (Yu, Hong, Zhang, Liang, & Chu, 2013) examined on retailer selection in VMI. Our research is different with them as we investigated supplier selection in VMI system. A three-echelon supply chain is defined with supplier selection and pricing in VMI as this study is then an attempt to explore. The problem is modeled as a mixed integer programming. Considering (Altiparmak et al., 2006; Bandyopadhyay & Bhattacharya, 2014) the problem is Np-hard and solved with Harmony Search method.

3. Problem description

The following notations and assumptions are used throughout this paper:

3.1 Assumptions

- Shortages are not allowed.
- There is not any quantity discount.
- Replenishment is instantaneous for retailers.

- Shipping cost is zero.
- The sale price is the same for all retailers.

3.2 Notations

i	an index used for suppliers; $i=1, 2,\dots, m$
k	an index used for retailers; $k=1, 2,\dots, n$
z_i	number of batches that sends to distributer from the i^{th} supplier
HS_i	holding cost for the i^{th} supplier
H_d	holding cost for the distributer
HR_k	holding cost for the k^{th} retailer
AS_i	ordering cost for the i^{th} supplier
A_i	ordering cost for the distributer from i^{th} supplier
AR_i	ordering cost for the k^{th} retailer from distributer
PS_i	sale price of the i^{th} supplier
P_d	sale price of the distributer
PR_k	sale price of the k^{th} retailer
DS_s	demand rate of the i^{th} supplier
DR_k	demand rate of the k^{th} retailer
D_i	demand rate of the distributer for supplier i
Q_i	order quantity of supplier i
q_i	order quantity for supplier i from the distributer
qR_k	order quantity for the distributer from the k^{th} retailer
CS_i	purchasing price for supplier i
SS_i	capacity of supplier i
F_i	failure rate of the i^{th} supplier
T_k	replenishment cycle time for the k^{th} retailer
T	common replenishment cycle time
φS_i	income function of supplier i
φD	income function of the distributer
φR_k	income function of retailer k
π	profit function of supply chain
π_s	profit function of the supplier
π_d	profit function of the distributer
π_r	profit function of the retailer

y_i the supplier selection variable $y_i = \begin{cases} 1 & if\ i^{th}\ supplier\ selected \\ 0 & o/w \end{cases}$

3.3. Modeling

In this section, the mathematical model is presented to maximize the profit of supply chain, considering the above assumptions and notations. The supply chain includes multi-supplier one-distributer and multi-retailer. According to the mentioned assumptions, total profit of supply chain is calculated as follows: $\pi = \pi_s + \pi_d + \pi_r$ (1)

Profit calculation includes income and cost functions. The income of each player in the supply chain can be calculated as the whole demand quantity multiplied by the sale price; then:

$$\varphi S_i = DS_i PS_i \tag{2}$$

$$\varphi D = D_d P_d \tag{3}$$

$$\varphi R_k = DR_k PR_k \tag{4}$$

The total cost function (TC) includes purchase and inventory costs. For calculating the purchase cost, we can multiply the annual demand of each player to his/her purchase price; then:

$$\lambda S_i = DS_i CS_i \tag{5}$$

$$\lambda D = \sum_{i=1}^{m} DS_i PS_i \tag{6}$$

$$\lambda R_j = DR_k P_d \tag{7}$$

The total inventory cost of supply chain (TIC), involves the total ordering cost of the retailers (TOCR), the total holding cost of the retailers (TCHR), the total ordering cost of the distributer (TOCD), the total holding cost of the distributer (TCHD), the total ordering cost of the suppliers (TOCS) and the total holding cost of the suppliers (TCHS). Then we can obtain TIC as below:

$$TIC = TOCR + TCHR + TOCD + TCHD + TOCS + TCHS \tag{8}$$

After obtaining some parts of the model, we investigate the model in two classes:

a. The *traditional model* in which each part controls his/her costs and inventories.
b. The *VMI model* in which the suppliers decide to control the holding and ordering costs and the inventory volume of distributer.

The basic model is shown in Figure (1).

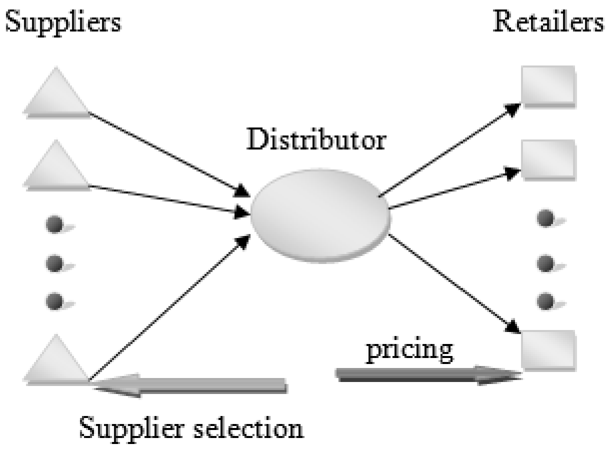

Figure 1. The basic model

3.3. a. Traditional model

In this model, the distributer requests the order quantity (q_i) from the ith supplier. Then he/she controls his/her inventories to maximize the profit. For supplier i, the total ordering cost can be written as:

$$TOCS_i = \frac{DS_i}{Q_i} AS_i \tag{9}$$

For obtaining the holding cost, the average inventories of suppliers must be calculated. Considering the quantity batches shipped from supplier i to the distributer (q_i), the inventory reduces at discrete times of order. In other words, the ith supplier's average inventory is obtained by:

$$\bar{IS}_i = \frac{(Q_i - q_i) + (Q_i - 2q_i) + \cdots + (Q_i - (z_i - 1)q_i)}{z_i} = Q_i - \frac{z_i + 1}{2} q_i \tag{10}$$

Also notes that supplier i sends all of the Q_i inventories by z_i batches; then the average inventory of supplier i is calculated as follows:

$$\bar{I}_{s_i} = Q_i - \frac{z_i + 1}{2} q_i \xRightarrow{Q_i = z_i q_i} \bar{I}_{s_i} = \frac{z_i - 1}{2} q_i \tag{11}$$

Consequently, the total annual holding cost of supplier i is

$$THCS_i = \frac{z_i - 1}{2} q_i HS_i \xRightarrow{z_i = \frac{Q_i}{q_i} \ \& \ q_i = TDS_i} THCS_i = \frac{\left(\frac{Q_i}{TDS_i} - 1\right)}{2} TDS_i HS_i \tag{12}$$

For the distributer side, similar to the supplier's calculations, the total holding cost is:

$$THCD = \sum_{k=1}^{n} \frac{g_k - 1}{2} q R_k H_d \tag{13}$$

According to Fig.2, we can rewrite Eq.13 as below:

$$THCD = \sum_{k=1}^{n} \frac{g_k - 1}{2} qR_k H_d = \sum_{k=1}^{n} \frac{\left(\frac{DR_k T}{qR_k} - 1\right)}{2} qR_k H_d \tag{14}$$

The total ordering cost for distributer is:

$$TOCD = \sum_{i=1}^{m} \frac{D_i}{q_i} A_i = \sum_{i=1}^{m} \frac{A_i}{T} \tag{15}$$

Therefore the profit function of distributer would be::

$$\pi_d = \sum_{k=1}^{n} DR_k P_d - \sum_{i=1}^{m} DS_i PS_i - \sum_{i=1}^{m} \frac{A_i}{T} - \sum_{k=1}^{n} \frac{\left(\frac{DR_k T}{qR_k} - 1\right)}{2} qR_k H_d \tag{16}$$

For the k[th] retailer, the average inventory is $\frac{qR_k}{2}$; as a result, the annual holding cost of retailer k is obtained by:

$$THCR_k = \frac{qR_k}{2} HR_k \tag{17}$$

And the annual ordering cost of retailer k is:

$$TOCR_k = \frac{DR_k}{qR_k} AR_k \tag{18}$$

The Wilson ordering quantity is proposed and the optimal order quantity of the k[th] retailer is:

$$qR_k = \sqrt{\frac{2AR_k DR_k}{HR_k}} \tag{19}$$

Also the optimal total ordering and holding cost is:

$$THC_k + TOC_k = \sqrt{2AR_k DR_k HR_k} \tag{20}$$

Because of failure rate for each supplier and note that the distributer sends the entire inventory to the retailers, we can conclude that:

$$\sum_{k=1}^{n} DR_k = \sum_{i=1}^{m} DS_i (1 - F_i) \tag{21}$$

After the problem modeling, the distributer can solve it and choose the best supplier that maximizes the profit function. Accordingly we can obtain the model as below:

$$\text{Maxz} = \sum_{i=1}^{m} y_i DS_i ((1 - F_i) P_d - PS_i) - \sum_{i=1}^{m} \frac{A_i}{T} y_i - \sum_{k=1}^{n} \frac{\left(\frac{DR_k T}{qR_k} - 1\right)}{2} qR_k H_d \tag{22}$$

st:

$$DS_i \leq SS_i \tag{23}$$

$$\sum_{i=1}^{m} y_i DS_i(1 - F_i) = \sum_{k=1}^{n} DR_k \quad (24)$$

The objective function is the profit of distributer; hence, it must be maximized. This model confronts with two constraints; the first constraint guarantees that each supplier can afford his/her demands. The second constraint is defined to satisfy the whole demands of retailers by suppliers. After solving the process, the suppliers are selected and the price is specified.
For the selected suppliers, the profit function is calculated as:

$$\pi s_i = DS_i PS_i - DS_i CS_i - \frac{\left(\frac{Q_i}{TDS_i} - 1\right)}{2} TDS_i HS_i - \frac{DS_i}{Q_i} AS_i \quad (25)$$

And we can obtain the best order quantity for the i^{th} supplier as bellow:

$$\frac{\partial \pi s_i}{\partial Q_i} = 0 \Rightarrow Q_i^* = \sqrt{\frac{2AS_i DS_i}{HS_i}} \quad (26)$$

3.3. b. VMI model

In this class of model, after the supplier selection process, the supplier adopts VMI's commitments; therefore he is responsible for the order and the holding costs of distributer.
The retailers' costs formulas are the same with the traditional model with differences for the suppliers and distributer. Regarding to the VMI assumption, the formulas change as below:

$$TOCS_i = \frac{DS_i}{Q_i} AS_i + \frac{A_i}{T_i} \quad (27)$$

This formula is the result of VMI adoption. Each supplier must undertake the inventory costs (the holding cost and the ordering cost) of the distributer.
Similar to the traditional model's calculations, the holding cost of i^{th} supplier is obtained as below:

$$THCS_i = \frac{\left(\frac{Q_i}{TDS_i} - 1\right)}{2} TDS_i (HS_i + H_d) \quad (28)$$

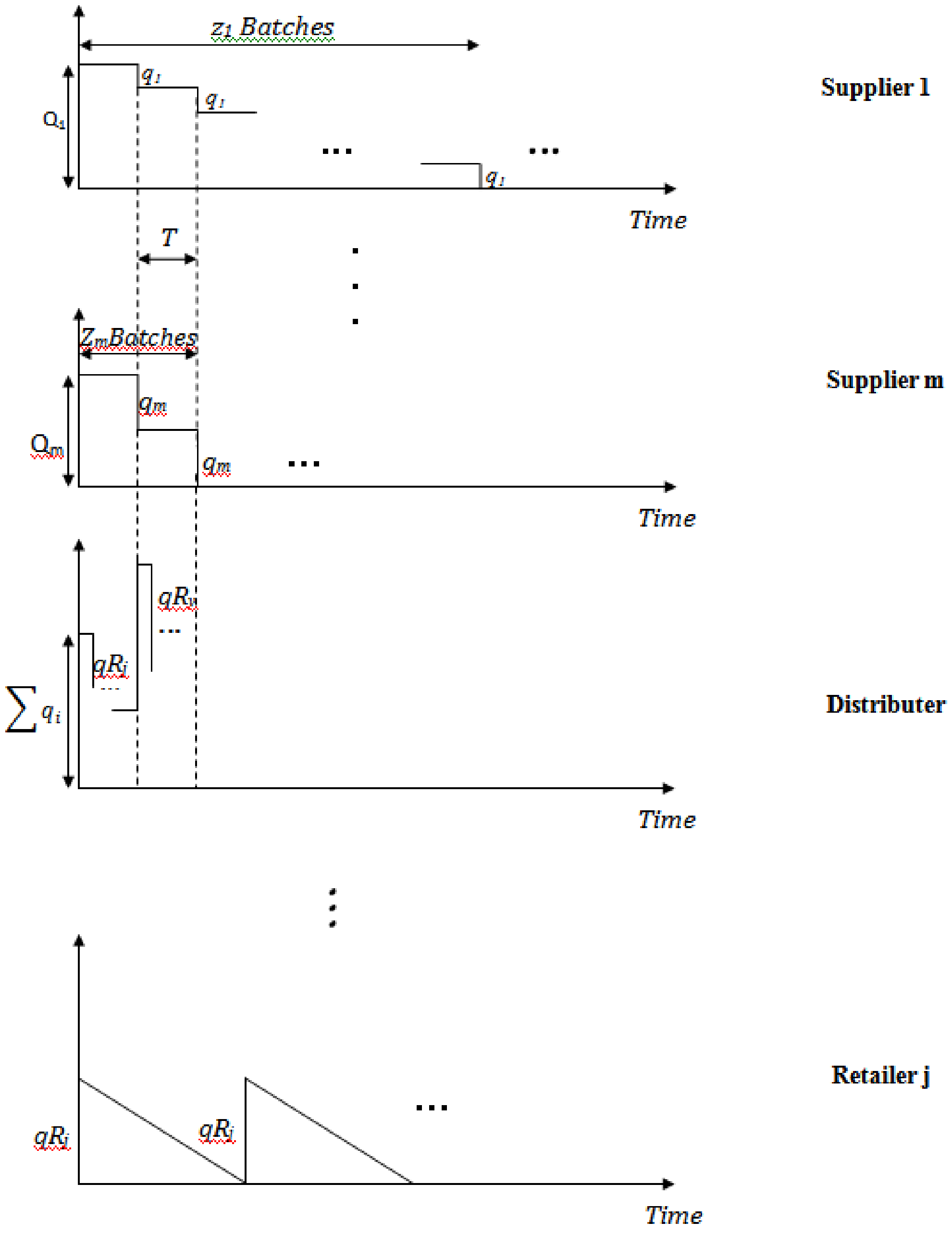

Figure 2. Inventory level in the supply chain players' storeroom: Traditional model

Because of alliance between suppliers and distributer, the profit of them is considered simultaneously. Therefore the supplier selection decision making includes the profit functions of the suppliers and the distributer. Total profit of suppliers and distributer is:

$$\sum_{i=1}^{m} DS_i((1-F_i)P_d - CS_i) - \sum_{i=1}^{m}\left(\frac{A_i}{T_i} + \frac{DS_i}{Q_i} AS_i\right) - \sum_{k=1}^{n} \frac{\left(\frac{Q_i}{T_i DS_i}-1\right)}{2} T_i DS_i (H_d + HS_i) \quad (29)$$

Therefore, the model for supplier selection can be written as:

$$\text{Max}z = \sum_{i=1}^{m} y_i DS_i((1-F_i)P_d - CS_i) - \sum_{i=1}^{m} Y_i(\frac{A_i}{T_i} + \frac{DS_i}{Q_i} AS_i)$$

$$-\sum_{k=1}^{n} Y_i \frac{\left(\frac{Q_i}{T_i DS_i}-1\right)}{2} T_i DS_i (H_d + HS_i) \quad (30)$$

st:

$$DS_i \leq SS_i \quad (31)$$

$$\sum_{i=1}^{m} y_i DS_i(1-F_i) = \sum_{k=1}^{n} DR_k \quad (32)$$

The objective function is the profit of distributer and selected suppliers; therefore it must be maximized. The model has two constraints; the first constraint explains that each supplier can afford his/her demands. The second constraint is defined to satisfy the whole demands of retailers by suppliers.

This model can determine the best suppliers and price of the distributer.

4. Proposed harmony search algorithm

Nature has used various ways of continual improvement for million years. Mimicking the nature, scientists have recently attempted to use some algorithms for solving complex optimization problems. In regarding the complexity of the problem is very complex so that exact algorithms cannot solve it or it is time consuming; these algorithms can help to find a near optimum solution in a reasonable period. In computer science and operations research, these algorithms called "meta-heuristics" (Dorigo & Blum, 2005). The Harmony Search (HS) is one of these meta-heuristic algorithms that have been inspired by the act of the improvisation process of musician groups where the musicians (in an ensemble) adjust their pitches in order to reach a better harmony. This algorithm searches for the optimum solution of a complex optimization problem by generating random vector. Harmony search is emerging as a powerful metaheuristic algorithm, and incorporates the structure of existing heuristic methods (Geem, Kim, Loganathan, & G.V., 2001). Other algorithms like particle swarm optimization (Taleizadeh, Niaki, Shafii, Meibodi, & Jabbarzadeh, 2010), ant colony optimization (Silva, Sousa, Runkler, & Sá da Costa, 2009), Genetic Algorithm (Naso, Surico, Turchiano, & Kaymak, 2007), and simulated annealing (Lim & Zhu, 2006) are also being employed to solve complex supply chain problems. a characteristic increasing the flexibility of HS and distinguishing it from other metaheuristics (especially GA) is that the implementation of HS algorithm is easier than the other metaheuristic algorithms. There is some evidence to suggest that HS is less sensitive to the chosen parameters; meaning that there is no need to fine-tune these parameters to get quality solutions. Furthermore, HS is a population-based metaheuristic; in other words multiple harmonics groups can be used in parallel. Proper parallelism can usually result in better implantation with higher efficiency (X.-S.

Yang, 2009)

In harmony search algorithm the following options are formulized:

1- usage of harmony memory
2- pitch adjusting
3- randomization

Our proposed HS algorithm is shown in Fig.3.

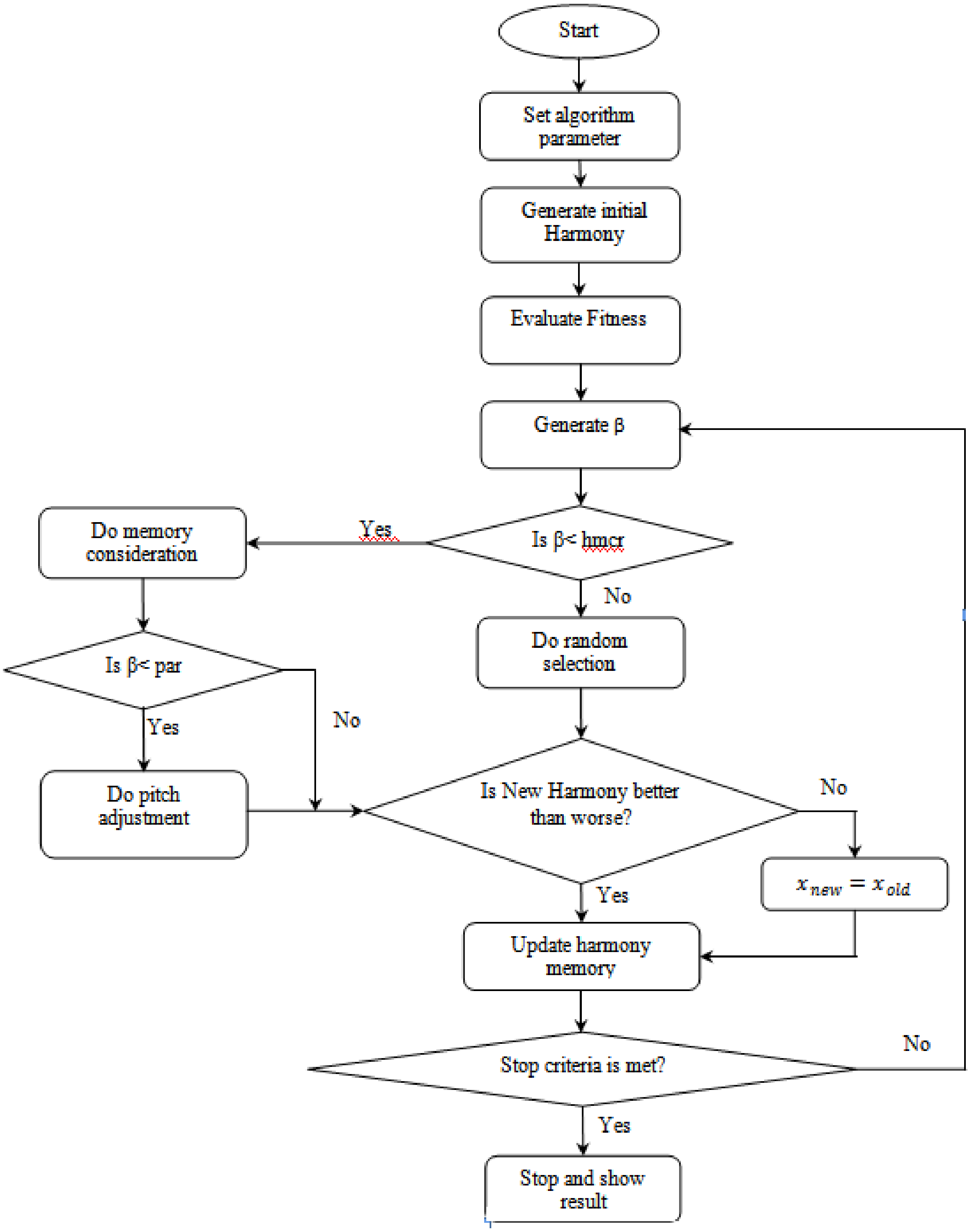

Figure 3. Harmony search algorithm

In the above figure, b is a random variable $\beta \in [0,1]$, HMCR is harmony memory consideration rate and par is pitch adjustment rate.

4.1 Proposed Harmony Search algorithm

For solving the models in section 3 we proposed the following HS algorithm:

4.1.1 Harmony coding

In the HS literature, solution is called harmony, design variable is a harmony and each harmony is a vector. In this study we have a harmony for traditional model and a harmony for VMI model, and each note is a design variable. In this algorithm, we used a matrix for each design variable; for example yi is a ixHMS matrix.

4.1.2 Initializes Solution

To start the algorithm, we need a suitable set of harmonies. The number of solution vector is equal to the size of Harmony Memory Size (HMS). These initialize solutions are generated randomly.

4.1.3 Memory Consideration

The first operator of HS is Memory Consideration; in this part of the algorithm we randomly select a harmony from the HM by probability of HMCR and for each design variable we use the following formula for new harmony:

$$x_{new}(j) = x_a(j)$$

where $x_a(j) \in (1,2,\cdots,HMS)$, and X denote design variables such as yi Pd.

4.1.4 Pitch adjustment

The second operator of HS is pitch adjustment. In this operator we tune a harmony which is selected in the last part of the algorithm by probability of PAR:

$$x_{new} = x_{old} + \alpha \times bw$$

Where α is a random variable and $\alpha \in [0,1]$ and *bw* is pitch bandwidth and x design variable. In the proposed algorithm we used BW1 for the design variables greater than 1 and BW2 for less than 1.

4.1.5 Random selection

The last operator of HS is random selection. This operator generates a new random harmony by probability of 1-HMCR and causes variation in the solutions such that algorithm does not stop in the local optimum solutions:

x_{new}= random generated vector

4.1.6 Feasible solution

One of the problems concerned in modeling of an optimization problem with. HS is how to deal with the constraints. The strategies are rejecting, modifying genetic operators, penalty strategy and repairing. First, in the rejecting strategy, after the New Harmony is made by the HS operators, if the new solution is infeasible, this strategy immediately excludes this harmony in each iteration. Second, in the modifying strategy, the HS operators modify the infeasible solution in each iteration. Third, the penalty strategy uses a suitable penalty function in order to penalize the infeasible individuals to decrease their fitness and thus the chance of selection of this penalized solution decreases, hoping this New Harmony evolves in the next iteration during the algorithm runs. Finally, the repairing strategy, transforms the infeasible solution to a feasible one throughout the mathematical process.
Repairing strategy for equal constraints is defined as follows:

If $\sum_i x_i = S$

$$x_i' = \frac{x_i}{\sum_i x_i}$$

$$x_i^* = x_i' \times S$$

x_i^* is new repaired note in harmony. In the proposed model we first adjust DSi by using the repairing strategy for the both traditional model and VMI model as follows:

$$\mathrm{DS}_i^* = \frac{\mathrm{y_i DS_i (1 - F_i)}}{\sum_{i=1}^{m} \mathrm{y_i DS_i (1 - F_i)}} \sum_{k=1}^{n} \mathrm{DR_k}$$

Then we used penalty function that impels the solutions to satisfy **DSi ≤ SSi** the constraint is formulated as follows:

$$\xi = \begin{cases} DS_i - SS_i & \text{if } DS_i > SS_i \\ 0 & \text{otherwise} \end{cases}$$

4.1.7 Fitness evaluation

Incorporating the objective function and the penalty function, the target function for model can be defined as:

$$\varphi = \sum_{i=1}^{m} y_i DS_i((1 - F_i)P_d - PS_i) - \sum_{i=1}^{m} \frac{A_i}{T} y_i - \sum_{k=1}^{n} \frac{\left(\frac{DR_k T}{qR_k} - 1\right)}{2} qR_k H_d - M \times \xi$$

For traditional model and for VMI model

$$\varphi' = \sum_{i=1}^{m} y_i DS_i((1-F_i)P_d - CS_i) - \sum_{i=1}^{m} Y_i(\frac{A_i}{T_i} + \frac{DS_i}{Q_i} AS_i) - M \times \xi$$

The large positive number *M* forces the solution to meet the constraint before maximizing the fitness function.

4.2 Parameter tuning

In the literature, there are some methods for parameter tuning. Full factorial and taguchi methods are the most applicable for this propose. Full factorial method tests all possible choices and then selects the best or combination of factors. This method is suitable for small problems with low factors and low levels because it must check all possible combinations. In a problem with m factor and n level, full factorial method checks m*n problems. In 50's, Dr. Genuchi Taguchi developed a method for optimization of complex systems that called Taguchi methods. The base of Taguchi method is analyzing the data for simplifying the complex systems. This method calculates the best level of each parameter by peculiarity of orthogonal arrays; this operation reduces the number of experiments to find the best one.

To practice the experimental design for selecting the most suitable level (or scheme) or combination of control factors, we select one problem instance corresponding to different levels of the factors. In this method there are 5 factors and 4 levels for these factors (Table 1). We select orthogonal array L16 (45) design for this problem and we run 9 scenarios 5 times and collect the fitness and computation time (CPU time). Taguchi method reduces dramatically the number of runs from 5120 (in full factorial) to 45. For achieving the best efficiency of algorithm and robust answers, we select the parameters' level with main effect plot for the mean and signal-to-noise ratio (S/N) of objective function and CPU time.

S/N ratio for factors defined as:

$$\eta = -10\log\left(\frac{\sum(1/y_{lk}^2)}{n}\right) \qquad \textit{For larger is better}$$

$$\eta = -10\log\left(\frac{\sum y_{lk}^2}{n}\right) \qquad \textit{For smaller is better}$$

Where y_{lk} is the performance characteristic of observation k at trial l averaged after 5 replications, and n is the number of factors.

Taguchi DOE is solved with Minitab 16. The main effect plot for mean and S/N ratio of objective function and CPU time are shown in Fig.4. Regarding the objective function that is maximization for calculation of S/N ratio we used “the larger is better equation” and for CPU time S/N ratio we used “the smaller is better equation”. The best level of all parameters is marked in Table1. After parameter tuning best level of each parameter is: HMCR=0.6, PAR=0.9, HMS= 300, BW=100, and BW2=0.2.

Table 1. Factors and levels

Level	HMCR	PAR	HMS	BW	BW2
I	0.6	0.7	50	10	0.1
II	0.7	0.8	100	30	0.2
III	0.8	0.9	200	70	0.5
IV	0.9	0.95	300	1000	0.6

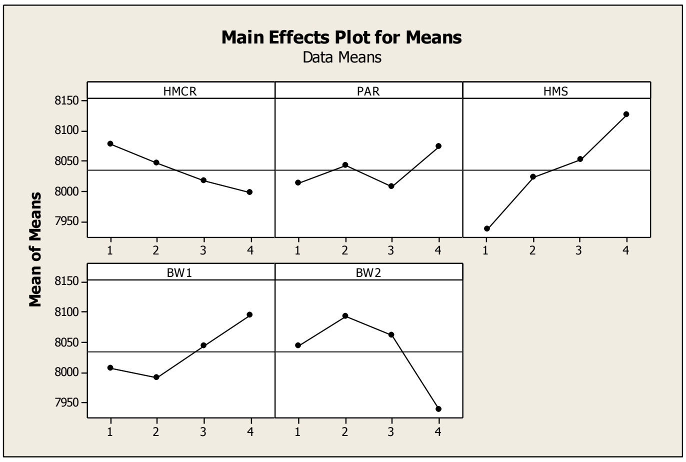

Figure 4. Mean of algorithm solution

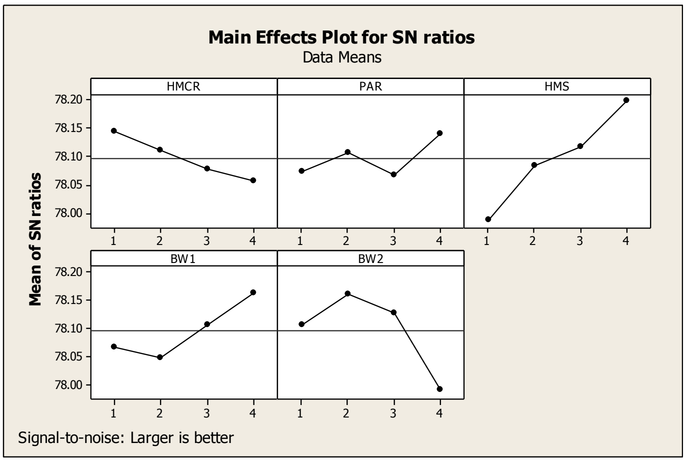

Figure 5. S/N of algorithm solution

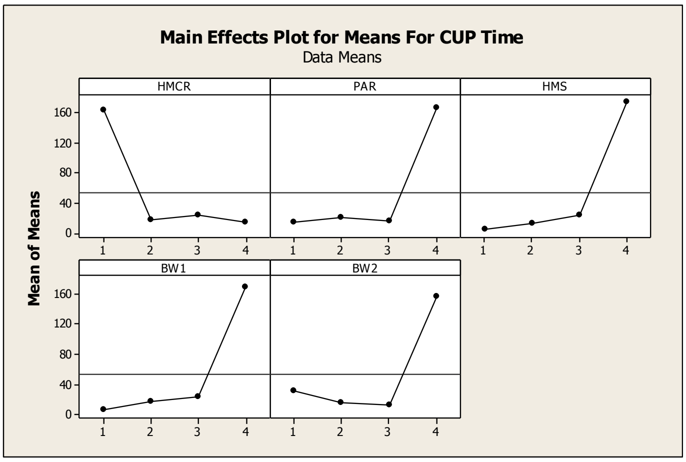

Figure 6. Mean of algorithm time

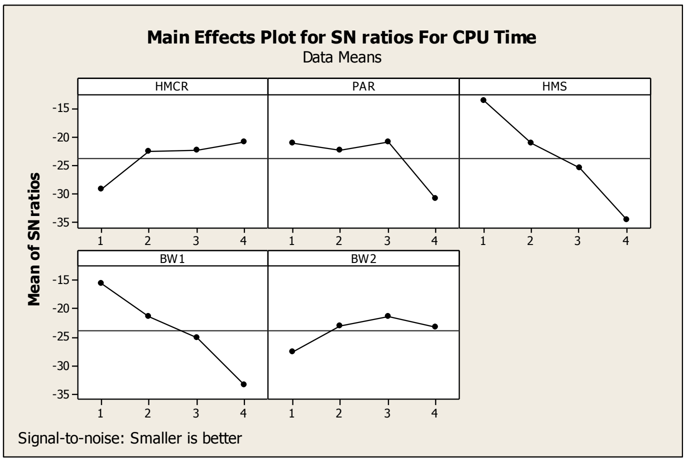

Figure 7. S/N of algorithm time

4.3 Performance evaluation

For evaluating the performance and validation of the proposed algorithm, we compare 3 small problems and one bigger problem solved with LINGO11 and the proposed algorithm. Also, the LINGO11 can solve small size problems; however due to high dimension time of solving rise up dramatically and for some high dimension problems Lingo stops in a local optimum. The result of this comparison is shown in table. For comparison between algorithm and global solution, we used Nearing to Optimum Index (NOI) as fallow:

Table 2 . Comparison between proposed HS and LINGO

Number of retailer	Number of supplier	HS	Lingo
6	4	359957.8	-76694.75*
2	2	135685.8	137237.5
1	3	128948.16	131358.4
3	2	142506.4	144365.0

* Lingo stopped in a local optimum.

5. Empirical study

For empirical study, in this paper, we designed a problem by 7 suppliers 1 distributer and 3 retailers. The general data of the system under consideration is given in Tables 3 and 4. Both models (VMI and traditional) were solved 30 times with the same parameters, and the experiments were conducted on a PC with an Intel ® I7 4510U @ 2.6GH CPU, 8GB of RAM and Windows 8 Ultimate in MATLAB 7.10.0.499 (R2010a). The convergence plot is shown in Fig.8. The figure shows that the proposed algorithm converges to the optimum solution. This model runs 30 times for each type of problem, and the comparison between the VMI and traditional models is shown in Figs. 9 & 10 and Table 5.

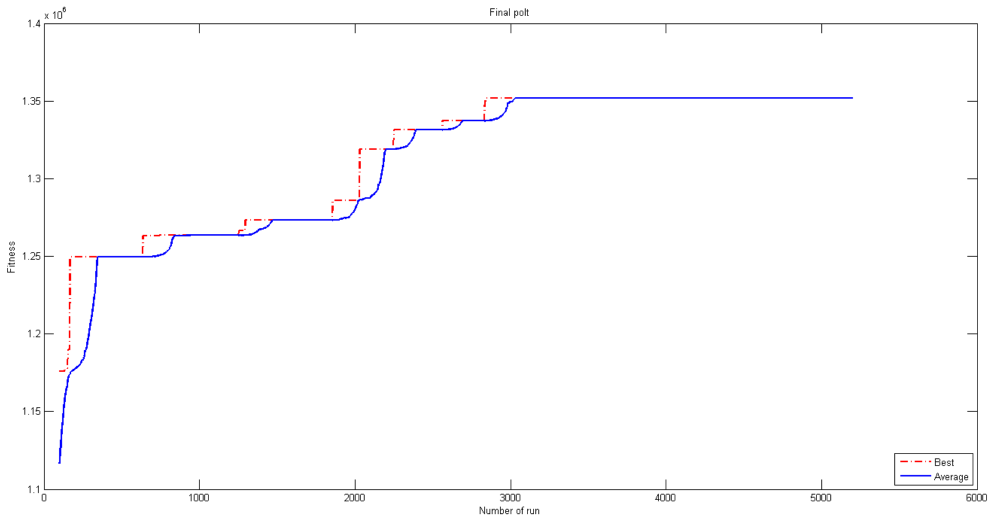

Figure8. Convergence plot of HS algorithm

Table 3. Supplier parameter

Parameter	A	B	C	D	E	F	G
hs_i	10	20	16	10	20	15	13
as_i	200	150	250	200	150	250	190
ps_i	450	469	476	450	469	476	480
cs_i	400	398	409	400	398	409	435
ss_i	1500	1000	5000	2000	2000	5000	3000
f_i	0.05	0.1	0.07	0.05	0.1	0.07	0.03

Table 4. Retailer parameters

Parameter	I	II	III
hr_k	200	150	180
ar_k	250	300	280
a_k	600	620	630
b_k	100	150	200

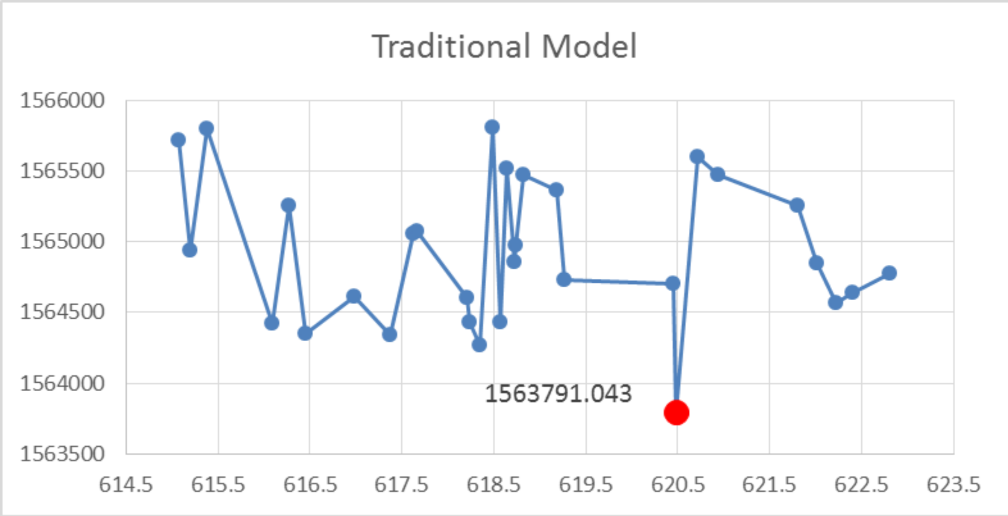

Figure 9. Traditional model result

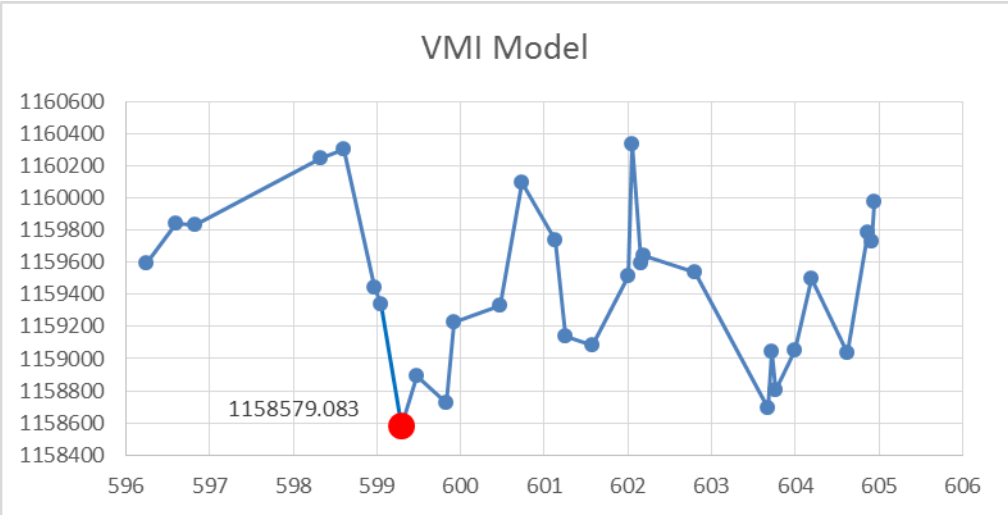

Figure 10. VMI model result

Table.5. Models results

	VMI Model		Traditional Model	
Run	**Price**	**Dis Prof**	**Price**	**Dis Prof**
1	596.246	1159592	615.067	1565715
2	596.5931	1159842	615.1931	1564940
3	596.8346	1159831	615.372	1565801
4	598.3312	1160246	616.0943	1564420
5	598.6062	1160302	616.2697	1565252
6	598.9771	1159441	616.4586	1564349
7	599.0418	1159341	616.9876	1564611
8	599.2974	1158579	617.3686	1564343
9	599.4853	1158893	617.6166	1565053
10	599.8231	1158723	617.6632	1565078
11	599.92	1159225	618.2093	1564600
12	600.4803	1159328	618.2383	1564432
13	600.7356	1160099	618.3466	1564267
14	601.1321	1159733	618.4928	1565809
15	601.2566	1159142	618.567	1564432
16	601.5777	1159083	618.6435	1565518
17	602.0017	1159511	618.728	1564853
18	602.0556	1160334	618.7337	1564976
19	602.1537	1159593	618.8217	1565476
20	602.1925	1159645	619.1851	1565363
21	602.805	1159536	619.2703	1564730
22	603.6733	1158690	620.4583	1564704
23	603.7251	1159047	620.4834	1563791
24	603.7612	1158802	620.7109	1565598
25	603.9987	1159050	620.9407	1565473
26	604.1949	1159498	621.8	1565258
27	604.6212	1159032	622.0118	1564851
28	604.8705	1159787	622.2185	1564570
29	604.9175	1159730	622.3976	1564640
30	604.9473	1159975	622.8132	1564773
Average	601.2752	1159454	618.772	1564923

6. Conclusion

This paper extended a three-echelon supply chain with price-dependent demand consisting of multi-vendor, multi-retailer, and single-distributer. The aim was to select the best set of suppliers and the best distributer's sale price to maximize total supply chain profit. Since the presented problem (NP-hard model) was formulated as an INLP problem, a meta-heuristic algorithm, namely Harmony Search was employed to optimize two class models: traditional model and VMI

model. Moreover, the Taguchi method calibrated the parameters of algorithms for better performance. From the point of view of the whole supply chain, it was shown that the VMI system is more profitable than the traditional system.
Moreover, the study showed that the VMI system can affect on supplier selection process and change the best supplier set. The line of research in this paper can be extended in many directions. For example, the supply chain may contain more than one distributer in the middle echelon. An obvious extension is to consider multi-distributer for three echelon supply chain. Moreover, the transportation cost is not considered so it is assumed zero. However, it would be interesting to include the transportation cost explicitly and investigate its impact on the supplier selection process.

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