Optimizing a bi-objective inventory model for a two-echelon supply chain management using a tuned meta-heuristic algorithm

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Since vendor-managed inventory strategy plays an important role to reduce total inventory costs, the focus of this paper is to develop an economic order quantity model presented for a two-echelon supply chain management including one vendor and one retailer. In this bi-objective model, the vendor delivers several products to the retailer while shortages are allowed. The aim of this paper is to determine order sizes and maximum backorder levels for each product to simultaneously minimize total inventory costs and a storage space. Moreover, two main constraints, namely budget and the number of orders, are considered to simulate real-world operating conditions for the proposed model. Since the presented model belongs to integer non-linear programming problems, a meta-heuristic algorithm, particle swarm optimization (PSO), is employed to optimize it. In addition, because the quality of solutions depends on the values of parameters of meta-heuristics, the parameters of PSO are tuned using the Taguchi method. Then, the proposed algorithm is compared to branch and bound method.

Keywords: vendor managed inventory (VMI); shortages; particle swarm optimization (PSO); storage space; design of experiments (DOE)

1. Introduction

While great uncertainty in stock markets occurs by the global financial crisis, there is some evidence to suggest that those companies and organizations that have a flexible supply chain are able to cope with this crisis. The supply chain management (SCM) is an integrated approach to schedule and control materials and data. The supply chain consists of production and distribution operations, transportation, stores, and customers (Chopra & Meindl, 2007). In order to overcome fluctuant customer demands, SCM has to integrate their chains to make better decision in the inventory management, which leads to many studies. As the inventory plays an important role in the total cost, several approaches such as vendor-managed inventory (VMI) as a well-known strategy were provided to manage inventory levels for echelons in SCM. In VMI, a vendor satisfies retailer’s orders so that the vendor controls the retailer’s inventory levels while determining the retailer’s order quantity and time (Disney & Towill, 2002). JCPenney and Wal-Mart, as successful retailers, took advantage of VMI policy (Dong & Xu, 2002) so

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VMI is an obvious example of reduction in inventory costs (Achabal, McIntyre, Smith, & Kalyanam, 2000).

There are several approaches to model VMI problems, and two policies are often used in inventory systems: economic order quantity (EOQ) and economic production quantity (EPQ). EOQ is one of the most popular strategies in SCM because of its simplicity (Axsäter, 2010). Regarding deterministic demands, the retailer’s inventory system can be modeled using EOQ policy (Dong & Xu, 2002).

Elvander, Sarpola, and Mattsson (2007) presented a framework to implement VMI policy. Next, Yao, Evers, and Dresner (2007) considered an analytical model for a single-vendor and single-retailer supply chain, which results showed inventory costs. Then, Zammori, Braglia, and Frosolini (2009) presented a flexible framework to implement VMI in several industrial fields. Afterwards, Darwish and Odah (2010) extended a VMI model for several retailers such that the vendor faced the penalty if items exceeded definite bounds, and then they presented an algorithm that reduced the computational efforts significantly. Additionally, Borade and Bansod (2010) provided a case study to employ VMI in Indian industry. Finally, Pasandideh, Niaki, and Nia (2011) presented a framework to implement VMI in several industrial fields. Afterwards, Borade and Bansod (2010) extended a VMI model for several retailers such that the vendor faced the penalty if items exceeded definite bounds, and then they presented an algorithm that reduced the computational efforts significantly. Additionally, Borade and Bansod (2010) provided a case study to employ VMI in Indian industry. Finally, Pasandideh, Niaki, and Nia (2011) proposed a one-vendor one-retailer VMI model with two constraints, namely the number of orders and the warehouse space; then, they used a genetic algorithm (GA) for solving their proposed model.

Moreover, Yang, Chan, and Kumar (2012) developed a VMI problem considering single-warehouse, and then they proposed a GA to solve it. In other environments, to model VMI problems, cases involving no shortages are allowed; Sadeghi, Mousavi, Niaki, & Sadeghi (2013) investigated the multi-vendor multi-retailer single-warehouse case; in addition, Sadeghi, Sadeghi, & Niaki (2014) hybridized an inventory problem with a redundancy allocation optimization problem near real-world problems.

In brief, Yao et al. (2007) presented a simple VMI model, and then they took advantage of VMI policy, and reducing inventory costs were shown by numerical examples. Next, Pasandideh et al. (2011) extended the model presented by Yao et al. (2007) for the multiple-product case. Therefore, this paper extends the model presented by Pasandideh et al. (2011) for the case of multi-objective optimization problem. In this paper, considering backordering shortages, the vendor is responsible to supply products for a retailer with two restrictions, namely the number of orders and the available budget. The aim of this bi-objective mathematical programming model is to find a near-optimal solution, including the order quantities and maximum backorder levels for each product at a cycle time, to simultaneously minimize the storage space and total inventory costs. Since the proposed model belongs to the integer non-linear programming (INLP) problems, a meta-heuristic, particle swarm optimization (PSO), is employed to optimize it. Moreover, a Taguchi method, as a design of experiments analysis, calibrates parameters of PSO to achieve a higher performance of PSO. To validate model and evaluate PSO, a branch and bound (BB) method via Lingo software is utilized.

This paper is organized as follows. The assumptions and the proposed model are presented in the next section. Section 3 describes PSO. Tuning parameters and the numerical examples are provided in Sections 4 and 5, respectively. Finally, the conclusion and the future research are presented in Section 6.

2. The proposed VMI model

This paper uses the following notations to formulate the proposed model.

\(j\) An index for products, \(j = 1, \ldots, n\)

\(D_j\) Retailer’s demand rate of \(j\)th product
The single-vendor single-retailer supply chain is studied for $n$ products in which the proposed model is confronted with two constraints: the budget and the number of the orders. In VMI system, the integrated supply chain, including one retailer and one vendor, determines order quantity, not the vendor and the retailer individually. Shortages are allowed and backordered. It seems reasonable to assume that the retailer sells all the vendor’s products; thus, the annual demand of retailer and vendor is equal. It is also assumed that the payment of the backorders is received when they occur in a period. Finally, the assumptions used in this paper are as follows: (i) the vendor determines the amount of orders; (ii) the delivery time is zero; (iii) discounts are not allowed, and costs are fixed; and (iv) the vendor’s order and the available capital are restricted.

Considering the above-mentioned assumptions, the total inventory cost consists of ordering, holding, and shortage costs. In other words, in the proposed VMI model, a vendor, as a supplier to replenish a retailer, includes the ordering cost while the retailer’s costs consist of the holding and shortage costs. The vendor, as a supplier, is responsible for providing goods for the retailer; thus, the vendor’s cost includes the retailer and the vendor costs that are as follows.

The total ordering cost is

$$\text{TOC} = \sum_{j=1}^{n} \left( \frac{D_j}{Q_j} (A_{js} + A_{jr}) \right)$$

Then, total holding cost can be given as follows.

$$\text{THC} = \sum_{j=1}^{n} \left( \frac{h_{jr}}{2Q_j} (Q_j - b_j)^2 \right)$$

Since, the shortages are backordered, total shortage cost is,

$$\text{TSC} = \sum_{j=1}^{n} \left( \frac{\pi b_j^2}{2Q_j} + \frac{\pi b_j D_j}{Q_j} \right)$$

So, total system cost can be written as follows.

$$\text{Min } TC_{VMI} = \text{TOC} + \text{THC} + \text{TSC}$$

The second objective is to optimize storage space, we have,

$$\text{Min } F = \sum_{j=1}^{n} f_j (Q_j - b_j)$$
In addition, there are two constraints on the proposed model. First, the available budget is limited to \( C \), so,

\[
\sum_{j=1}^{n} c_j(Q_j - b_j) \leq C
\]  

Note that the maximum inventory must be used for available capital constraint in EPQ environment or when shortages as backordered (Axsäter, 2010; Tersine, 1993).

Next, the number of ordering is restricted to \( M \), thus,

\[
\sum_{j=1}^{n} \frac{D_j}{Q_j} \leq M
\]  

Finally, the bi-objective VMI model can be written as follows.

\[
\text{Min } TC_{VMI} = \sum_{j=1}^{n} \left( \frac{D_j}{Q_j} (A_{jS} + A_{jR}) + \frac{h_{jR}}{2Q_j} (Q_j - b_j)^2 + \frac{\pi b_j^2}{2Q_j} + \frac{\pi b_j D_j}{Q_j} \right)
\]  

\[
\text{Min } F = \sum_{j=1}^{n} f_j(Q_j - b_j)
\]  

\[s.t.,\]

\[
\sum_{j=1}^{n} c_j(Q_j - b_j) \leq C
\]  

\[
\sum_{j=1}^{n} \frac{D_j}{Q_j} \leq M
\]  

\[
b_j \leq Q_j
\]  

\[b_j, Q_j : \text{integer, } j = 1, \ldots, n.\]

Considering Equation (12), backorder levels cannot be bigger than order quantity.

This paper has several innovations as follows. First, VMI model is extended to consider the second objective minimizing storage space. In addition, there is a considerable improvement on modeling (Equation 12). Moreover, the variables \( Q_j \) and \( b_j \) are considered as integer variables. The next section presents a meta-heuristic algorithm to optimize the obtained model and compares it to a BB method.

3. Solution algorithm: PSO

Since the obtained model is an INLP, we use a PSO in meta-heuristic optimization methods to solve it similar to these studies Nachiappan and Jawahar (2007), Pasandideh et al. (2011), and Yu and Huang (2010) that presented an INLP model, and then they utilized a meta-heuristic to solve it. At first, Kennedy and Eberhart (1995) presented PSO in 1995, which simulated social behavior process of fish school or bird flock. PSO is a population-based search algorithm like GAs. PSO has been used as a powerful tool to solve problems (Shi et al., 2007).
To start PSO, the particles are randomly generated with respect to the number of population \((N_{\text{pop}})\) similar to chromosome in GA (see Figure 1). Since all particles have a velocity \((v_{\text{gen}}^i)\) and a position \((x_{\text{gen}}^i)\) in the generation of particles \((\text{gen})\), the velocities of all particles are calculated regarding acceleration coefficients that have been set by \(\phi_1\) and \(\phi_2\) coefficients. Next, the new positions of particles are determined considering their velocities and previous locations. Afterwards, particles are evaluated by the fitness function (Equations 8 and 9) to determine the best particle. This process is iterated until the stop condition is satisfied. It is hoped that the swarm, a large number of particles, moves near-optimal solution (for more details of PSO please refer to (Shi & Eberhart, 1998)).

This paper uses the fixed iteration number \((It)\) to stop PSO. Note that the parameters of PSO (i.e. \(It, \phi_1, \phi_2, \text{and } N_{\text{pop}}\)) are tuned by the Taguchi method in the next section. In addition, since there are several constraints on the bi-objective VMI model in this paper, the candidate solution in PSO algorithm may never satisfy the constraints. Thus, in PSO, the death penalty method is employed to make feasible solutions. This penalty is added to the objective function evaluation. In brief, the flowchart of PSO to solve the proposed problem of this research is given in Figure 2.

4. Tuning parameters: Taguchi method

Considering various factors and levels, Fisher presented the experiments called the factorial design of experiments (Roy, 1990). Since the complete experiments confront financial and time restrictions, Taguchi developed the fractional factorial experiments.

In the Taguchi method, factors are divided into two groups: controllable (called signal) and uncontrollable (called noise). The aim of the Taguchi method is to maximize the rate of signal to noise \((S/N)\). There are two approaches for analyzing results of experiments, analysis of variance, and \(S/N\) according to Taguchi’s emphasis (Roy, 1990). Since PSO runs several times to obtain better solution, we employ \(S/N\) method for analysis. The quality design should be used at the beginning of production and not during it (Roy, 1990); thus, the amount of the parameters, presented in Table 1, is initialized via trial and error procedure.

The design of \(L^9\), which includes 9 designs, and which is selected for the design of experiments in the Taguchi method, consists of four parameters and three levels. Taguchi suggested Equation (14) obtaining \(S/N\) for the experiments that follow minimizing problems.

\[
S/N = -10 \log \left(\frac{1}{n} \sum_{i=1}^{n} Y_i^2\right)
\]  \hspace{1cm} (14)

where \(n\) is the iteration of experiments (here it is 5), and \(Y_i\) is the response of experiments or the fitness function that is gained by the proposed model. Considering the example with five items in Table 2, Table 3 shows \(S/Ns\) that are calculated from \(Y_i\)s.

\[
\begin{bmatrix}
Q \rightarrow [91, 12, 22, 32, 650] \\
\delta_i \rightarrow [25, 43, 33, 234, 63]
\end{bmatrix}
\]

Figure 1. A particle for a problem with five items.
and Figure 3 shows the mean of $S/N$. Note that ‘1’, ‘2’, and ‘3’ in Table 3 refer to the levels of parameters in Table 1.

In the Taguchi method, the design that has higher $S/N$ is the best design; therefore, the optimal values of the parameters are shown in Table 4. There is a marked tendency for those meta-heuristics to be tuned to have a better performance in the optimization of problems. Thus, in the next section PSO is compared to BB method.
5. Numerical example

There are several methods to combine the two objective functions (Equations 8 and 9) into one scalar objective \((T)\). This paper employs the weighted sum method, sometimes called linear scalarization, to solve the proposed model as follows (Yang, 2010).

\[
\begin{align*}
\text{Min } & \quad \text{TC}_\text{VMI} \\
\text{Min } & \quad \text{F} \\
\end{align*}
\rightarrow \quad \text{Min } T = w_1 \text{TC}_\text{VMI} + w_2 F
\tag{15}
\]

where \(w_1\) and \(w_2\) are the weights of the objectives \((w_1 + w_2 = 1)\), so with different parameters for \(w_1\) and \(w_2\), different Pareto optimal solutions are produced. In this study, it is assumed that \(w_1 = 0.8\) and \(w_2 = 0.2\). Note that these values are assumed considering the Pareto principle and they are varied by a decision-maker.

This paper uses a meta-heuristic, PSO, to optimize the proposed model. There are two approaches to validate meta-heuristics used in optimization of INLP problems. First,

| Table 1. The parameters of PSO. |
|-----------------------------|
| Variable | 1 | 2 | 3 |
| \(I_t\) | 200 | 250 | 300 |
| \(N_{\text{pop}}\) | 100 | 150 | 200 |
| \(\Phi_1\) | 2 | 2.25 | 2.5 |
| \(\Phi_2\) | 1.95 | 2 | 2.05 |

| Table 2. The example data (Pasandideh et al., 2011). |
|-----------------|
| Product | \(D_j\) | \(A_{JS}\) | \(A_{JR}\) | \(h_{JR}\) | \(f_j\) |
| 1 | 420 | 1 | 3 | 4 | 3 |
| 2 | 360 | 2 | 2 | 9 | 2 |
| 3 | 540 | 3 | 1 | 7 | 3 |
| 4 | 390 | 5 | 4 | 2 | 1 |
| 5 | 480 | 2 | 2 | 4 | 4 |
| 6 | 510 | 4 | 2 | 6 | 3 |
| 7 | 530 | 1 | 3 | 5 | 2 |
| 8 | 380 | 2 | 1 | 3 | 1 |
| 9 | 430 | 3 | 4 | 2 | 3 |
| 10 | 580 | 4 | 2 | 8 | 4 |

| Table 3. PSO experimental results. |
|-------------------------------|
| \(N_{\text{pop}}\) | \(I_t\) | \(\Phi_1\) | \(\Phi_2\) | \(Y_1\) | \(Y_2\) | \(Y_3\) | \(Y_4\) | \(Y_5\) | Mean | \(S/N\) |
| 1 | 1 | 1 | 1 | 427.881 | 525.544 | 560.313 | 573.013 | 417.231 | 500.796 | −54.0676 |
| 1 | 2 | 2 | 2 | 469.173 | 462.047 | 472.186 | 515.404 | 562.416 | 496.245 | −53.9393 |
| 1 | 3 | 3 | 3 | 370.397 | 416.13 | 516.568 | 217.837 | 261.395 | 356.465 | −51.4175 |
| 2 | 1 | 2 | 3 | 510.491 | 266.19 | 364.644 | 560.698 | 414.495 | 423.304 | −52.7903 |
| 2 | 2 | 3 | 1 | 366.715 | 410.341 | 367.146 | 314.925 | 414.428 | 374.711 | −51.5142 |
| 2 | 3 | 1 | 2 | 419.875 | 514.106 | 465.968 | 317.932 | 260.539 | 395.684 | −52.1837 |
| 3 | 1 | 3 | 2 | 576.622 | 584.141 | 370.131 | 463.14 | 311.704 | 461.148 | −53.5117 |
| 3 | 2 | 1 | 3 | 318.79 | 370.798 | 270.052 | 293.722 | 610.675 | 372.808 | −51.8822 |
| 3 | 3 | 2 | 1 | 476.766 | 408.865 | 566.544 | 464.159 | 367.223 | 456.711 | −53.2868 |
another meta-heuristic in which this approach is utilized for the insolvable models with exact solvers is used to evaluate (see these studies Mousavi, Niaki, Mehdizadeh, & Tavarroth, 2012; Sadeghi et al., 2013). Second, optimizer solvers such as Lingo are used (see these studies (Esmaeili Aliabadi, Kaazemi, & Pourghannad, 2013; Nachiappan & Jawahar, 2007)). Indeed, there are many studies that have failed to perform comparing their proposed algorithms, so they are limited in their innovations such as these studies (Gupta, Bhunia, & Goyal, 2009; Pasandideh et al. 2011; Yang et al., 2012). Lingo, which is a systematic enumeration of all candidate solutions, presents the optimal or near-optimal solution for small-scale problems; therefore, this paper similar to this study (Nachiappan & Jawahar, 2007) employs Lingo optimization solver (ver. 11.0), BB method, to evaluate the performance of the proposed meta-heuristic to optimize the proposed model.

Table 5 shows the results of comparisons between PSO and BB method for three test problems. It can be concluded from Table 5 that PSO algorithm provides better solutions than BB method with respect to the cost functions (TC) and storage space (F) for the proposed model. Note that the third, the fourth, and the fifth rows in Table 5 present the near-optimal solution (Qj and bj) and the objectives values (TC and F) for the test problems with one item, two items, and three items problems, respectively.
In order to describe the sufficiency of the presented strategy regarding the tuned parameter by the Taguchi method, 10 test problems from this study (Pasandideh et al., 2011) are used to be solved by PSO; the solutions obtained for the order quantity ($Q_i$) and the maximum backorder ($b_i$) levels are shown in Tables 6 and 7.

Note that PSO algorithm is coded by MATLAB 2010b, where a PC with 2.2 GHz Intel Core 2 Duo CPU, and 4 GB of RAM memory via Windows 7 is used for all calculations. Moreover, Figure 3 is provided using Minitab 15.1.30.0.

### 6. Conclusion and recommendations for future research

To reduce bullwhip effects in SCM, the VMI is a common policy. According to the literature, the case of multi-item under shortage conditions with respect to minimizing warehouse space has yet to be investigated. Thus, this paper developed a hybrid VMI

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Table 5. The comparison PSO with BB method for three test problems (Pasandideh et al., 2011).

| j | BB method Lingo | PSO |
|---|-----------------|-----|
|   | TC   | F | Q$_{01}$ | Q$_{02}$ | Q$_{03}$ | b$_{01}$ | b$_{02}$ | b$_{03}$ | TC   | F | Q$_{01}$ | Q$_{02}$ | Q$_{03}$ | b$_{01}$ | b$_{02}$ | b$_{03}$ |
| 1 | 78.474 | 36 | 38 | 26 | 16.00 | 21 | 106 | 99 |
| 2 | 159.474 | 50 | 38 | 34 | 26 | 27 | 43.00 | 515 | 36 | 511 | 35 |
| 3 | 256.535 | 77 | 38 | 34 | 41 | 26 | 27 | 32 | 125.86 | 19 | 42 | 42 | 41 | 40 | 40 | 40 |

Table 6. The order quantity for 10 examples.

| j | TC   | F | Time | Q$_1$ | Q$_2$ | Q$_3$ | Q$_4$ | Q$_5$ | Q$_6$ | Q$_7$ | Q$_8$ | Q$_9$ | Q$_{10}$ |
|---|-----|---|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|--------|
| 1 | 16  | 21 | 6   | 106 |
| 2 | 43  | 14 | 7   | 515 | 36 |
| 3 | 125.86 | 19 | 8   | 42  | 42  | 41  |
| 4 | 227 | 1005 | 8   | 564 | 721 | 582 | 618 |
| 5 | 506 | 948 | 9   | 924 | 678 | 737 | 210 | 119 |
| 6 | 509 | 1418 | 9   | 413 | 370 | 676 | 338 | 399 | 269 |
| 7 | 778 | 2376 | 10  | 545 | 859 | 444 | 248 | 653 | 155 |
| 8 | 903 | 2064 | 10  | 473 | 272 | 539 | 727 | 119 | 355 | 576 |
| 9 | 1451.8 | 3665 | 11  | 631 | 830 | 701 | 605 | 330 | 692 | 490 | 888 | 479 |
| 10 | 2051.62 | 3492 | 11  | 155 | 913 | 479 | 276 | 826 | 431 | 42 | 432 | 972 |

Table 7. Maximum backorder level for 10 examples.

| j | TC   | F | Time | b$_1$ | b$_2$ | b$_3$ | b$_4$ | b$_5$ | b$_6$ | b$_7$ | b$_8$ | b$_9$ | b$_{10}$ |
|---|-----|---|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|--------|
| 1 | 16  | 21 | 6   | 99  |
| 2 | 43  | 14 | 7   | 511 | 35 |
| 3 | 125.86 | 19 | 8   | 40  | 40  | 40  |
| 4 | 227 | 1005 | 8   | 380 | 709 | 496 | 447 |
| 5 | 506 | 948 | 9   | 899 | 436 | 692 | 120 | 78 |
| 6 | 509 | 1418 | 9   | 198 | 330 | 674 | 156 | 350 | 166 |
| 7 | 778 | 2376 | 10  | 289 | 712 | 263 | 172 | 530 | 120 | 205 |
| 8 | 903 | 2064 | 10  | 408 | 264 | 366 | 335 | 79  | 247 | 230 | 260 |
| 9 | 1451.8 | 3665 | 11  | 386 | 823 | 544 | 267 | 281 | 392 | 185 | 871 | 351 |
| 10 | 2051.62 | 3492 | 11  | 105 | 871 | 401 | 257 | 764 | 21  | 53  | 185 | 248 | 893 |
model in the SCM in which inventory costs and warehouse space were optimized simultaneously. While a vendor supplied several items to a retailer, shortages were allowed and backordered. The purpose of this paper was to find the order size and backorder levels to synchronously minimize total inventory cost and the warehouse space. Since the proposed model was an integer non-linear programming problem, a PSO was used to optimize it while the Taguchi method calibrated the parameters of PSO. Moreover, PSO was compared to the BB. Finally, this study can be developed as follows.

- Consider variable prices in modeling VMI problem such as discount and inflation.
- Consider the central warehouse in SCM.
- Extend VMI model for production environment such as the EPQ policy.
- Evaluate the Taguchi method with other tuning methods such as response surface methodology in the design of experiments.
- Investigate nondeterministic environments like fuzzy demand.
- Employ a multi-objective particle swarm optimization to present the Pareto solution.

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References
Achabal, D. D., McIntyre, S. H., Smith, S. A., & Kalyanam, K. (2000). A decision support system for vendor managed inventory. Journal of Retailing, 76, 430–454.
Axsäter, S. (2010). Inventory control (2nd ed.). New York, NY: Springer.
Borade, A. B., & Bansod, S. V. (2010). Study of vendor-managed inventory practices in Indian industries. Journal of Manufacturing Technology Management, 21, 1013–1038.
Chopra, S., & Meindl, P. (2007). Supply chain management: Strategy, planning, and operation (3rd ed.). Upper Saddle River, NJ: Pearson Prentice Hall.
Darwish, M. A., & Odah, O. M. (2010). Vendor managed inventory model for single-vendor multi-retailer supply chains. European Journal of Operational Research, 204, 473–484.
Disney, S. M., & Towill, D. R. (2002). A procedure for the optimization of the dynamic response of a vendor managed inventory system. Computers & Industrial Engineering, 43, 27–58.
Dong, Y., & Xu, K. (2002). A supply chain model of vendor managed inventory. Transportation Research Part E: Logistics and Transportation Review, 38, 75–95.
Elvander, M. S., Sarpola, S., & Mattsson, S.-A. (2007). Framework for characterizing the design of VMI systems. International Journal of Physical Distribution & Logistics Management, 37, 782–798.
Esmaeili Aliabadi, D., Kaazemi, A., & Pourghannad, B. (2013). A two-level GA to solve an integrated multi-item supplier selection model. Applied Mathematics and Computation, 219, 7600–7615.
Gupta, R. K., Bhunia, A. K., & Goyal, S. K. (2009). An application of genetic algorithm in solving an inventory model with advance payment and interval valued inventory costs. Mathematical and Computer Modelling, 49, 893–905.
Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. Proceedings of IEEE International Conference on Neural Networks (pp. 1942–1948). Perth, WA, Australia.
Mousavi, S. M., Niaki, S. T. A., Mehdizadeh, E., & Tavarroth, M. R. (2012). The capacitated multi-facility location–allocation problem with probabilistic customer location and demand: Two hybrid meta-heuristic algorithms. International Journal of Systems Science, 44, 1–16.
Nachiappan, S. P., & Jawahar, N. (2007). A genetic algorithm for optimal operating parameters of VMI system in a two-echelon supply chain. *European Journal of Operational Research, 182*, 1433–1452.

Pasandideh, S. H. R., Niaki, S. T. A., & Nia, A. R. (2011). A genetic algorithm for vendor managed inventory control system of multi-product multi-constraint economic order quantity model. *Expert Systems with Applications, 38*, 2708–2716.

Roy, R. (1990). *A primer on the Taguchi method: Society of manufacturing engineers*. New York, NY.

Sadeghi, J., Mousavi, S. M., Niaki, S. T. A., & Sadeghi, S. (2013). Optimizing a multi-vendor multi-retailer vendor managed inventory problem: Two tuned meta-heuristic algorithms. *Knowledge-based Systems, 50*, 159–170.

Sadeghi, J., Sadeghi, S., & Niaki, S. T. A. (2014). A hybrid vendor managed inventory and redundancy allocation optimization problem in supply chain management: An NSGA-II with tuned parameters. *Computers & Operations Research, 41*, 53–64.

Shi, Y., & Eberhart, R. (1998). A modified particle swarm optimizer. *Proceedings of IEEE International Conference on Evolutionary Computation* (pp. 69–73). Anchorage, Alaska.

Shi, X. H., Liang, Y. C., Lee, H. P., Lu, C., & Wang, Q. X. (2007). Particle swarm optimization-based algorithms for TSP and generalized TSP. *Information Processing Letters, 103*, 169–176.

Tersine, R. J. (1993). *Principles of inventory and materials management*. New Jersey: Prentice Hall.

Yang, X.-S. (2010). *Engineering optimization*. New Jersey: Wiley.

Yang, W., Chan, F. T. S., & Kumar, V. (2012). Optimizing replenishment policies using genetic algorithm for single-warehouse multi-retailer system. *Expert Systems with Applications, 39*, 3081–3086.

Yao, Y., Evers, P. T., & Dresner, M. E. (2007). Supply chain integration in vendor-managed inventory. *Decision Support Systems, 43*, 663–674.

Yu, Y., & Huang, G. Q. (2010). Nash game model for optimizing market strategies, configuration of platform products in a vendor managed inventory (VMI) supply chain for a product family. *European Journal of Operational Research, 206*, 361–373.

Zammori, F., Braglia, M., & Frosolini, M. (2009). A standard agreement for vendor managed inventory. *Strategic Outsourcing: An International Journal, 2*, 165–186.