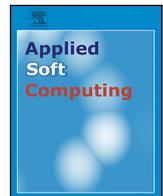




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A hybrid genetic and imperialist competitive algorithm for green vendor managed inventory of multi-item multi-constraint EOQ model under shortage

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ABSTRACT

The purpose of this paper is to develop a multi-item economic order quantity (EOQ) model with shortage for a single-buyer single-supplier supply chain under green vendor managed inventory (VMI) policy. This model explicitly includes the VMI contractual agreement between the vendor and the buyer such as warehouse capacity and delivery constraints, bounds for each order, and limits on the number of pallets. To create a kind of green supply chain, tax cost of green house gas (GHG) emissions and limitation on total emissions of all items are considered in the model. A hybrid genetic and imperialist competitive algorithm (HGA) is employed to find a near-optimum solution of a nonlinear integer-programming (NIP) with the objective of minimizing the total cost of the supply chain. Since no benchmark is available in the literature, a genetic algorithm (GA) is developed as well to validate the result obtained. For further validation, the outcomes are also compared to lower bounds that are found using a relaxed model in which all variables are treated continuous. At the end, numerical examples are presented to demonstrate the application of the proposed methodology. Our results proved that the proposed hybrid procedure was able to find better and nearer optimal solutions.

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1. Introduction

One of the most important problems in companies that utilize vendors to provide raw materials, components, and finished products is to determine the order quantity and the points to place orders. Various models in production and inventory control field have been proposed and devoted to solve this problem in different scenarios. Two of the models that have been employed extensively are the economic order quantity (EOQ) and economic production quantity (EPQ) models (see for example [1,2]). However, these models are developed based on some assumptions and conditions that bound their applicability in real-world situations. The EOQ formula gives an optimal solution when the vendor and buyer inventory problems are treated in isolation under the deterministic conditions [3].

In real business world, sometimes a manufacturer, supplier and markets/retailer would like to make a long-term cooperative relationship as an integrated system to get a tensionless stable source of supply and demand of items as well as reliability to gain optimum profit from each other. Globally, the industrial environment gradually becomes more and more competitive and much effort has been made toward the efficiency and effectiveness. So in this connection, the supply chain (SC) management plays an important role in the present situation [4]. Several programs of collaboration and coordination between SC partners have been successfully implemented in practice. Vendor managed inventory (VMI) is collaborative initiatives that have been theoretically and empirically shown to improve SC efficiency and responsiveness [5]. Under VMI partnership, the vendor (supplier) is responsible for managing inventory levels at the retail store by determining the right timing and size of the orders. In return, the vendor gets a better visibility about the final customer demand. Historically, VMI originated in the retail industry to overcome some of the problems regarding the amount of required retail shelf space, the amount of inventory to be kept on hand, inventory obsolescence, and the logistics of returned products [6,7]. The benefits of VMI are well recognized

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by successful retail businesses such as Wal-Mart, JC Penney, and Dillard Department Stores [8]. Successful VMI implementations in retailing are more observed in the apparel industry. For example, VF Corporation was able to increase the sales of its men's jeans by 20% through the adoption of a replenishment system based on point-of-sales data and VMI principles [9].

With the developing global consciousness of environmental protection and the corresponding growth in legislation and regulations, green purchasing has become an essential issue for enterprises to improvement environmental sustainability. Now, numerous businesses have begun to perform green SC management and take into account environmental subjects and the measurement of their vendors' environmental performance. In recent literature [10–12], incorporating environmental performance into inventory and logistics systems has been strongly accentuated, and has been achievement momentum in the past few years. Numerous models that investigated the classical economic order quantity (EOQ) for some environmental problems have been suggested. A common outcome among these models is that the performance of an inventory policy becomes sensitive when greenhouse gases (GHG) emissions (e.g. CO₂) are accounted for.

While a substantial amount of research works are available in the literature, a brief review of the works on the vendor-managed inventory of supply chains is presented in the next section.

2. Literature review

A number of authors extended some of the classical inventory models by assuming that the demand is a function of the inventory level. Baker and Urban [13] were the first to extend the EOQ model by considering a demand rate that is a function of the instantaneous inventory level of an item. They developed an extended EOQ model for a power-form inventory level dependent demand. Baker and Urban's [13] model was further extended to cover other inventory situations such as deteriorating items, different classes of customers, presence of defective items, effects of inflation and time value of money, and stochastic demand.

Several research works in the SC literature have been devoted to the study of the economic benefits resulting from the implementation of VMI partnerships. Magee [14] discussed who should have authority over the control of inventories. However, interest in the concept has only really developed during the 1990s. Waller et al. [15] indicated that the VMI method could improve inventory turnover and customer service levels at every stage of a supply chain. Moreover, Dong and Xu [8] evaluated the impacts of VMI on the profits of the different supply channel's members within the EOQ framework. Cetinkaya and Lee [16] presented an analytical model for coordinating inventory and transportation decisions in VMI systems. Woo et al. [17] and Yu and Liang [18] extended their two-echelon inventory supply chains to three-echelon ones where the supplier was a manufacturer and his raw materials' inventory was involved. Furthermore, the studies by Lee et al. [19] and Vergin and Barr [20] conclude that VMI is becoming an effective approach for implementing the channel coordination initiative, which is critical and imperative to improve the entire chain's financial performance.

Bertazzi et al. [21] compared the order-up-to level policy and the fill-fill-dump policy of VMI. They showed that the fill-fill-dump policy leads to a lower average cost than the order-up-to level policy. Yao et al. [22] proposed an EOQ based analytical model to study the effect of the supply chain parameters on VMI benefits. They showed that inventory cost reduction depends on the vendor-buyer ordering and holding costs ratios. Moreover, Haisheng et al. [23] analyzed VMI partnership using evolutionary game theories and showed that VMI partnership is not beneficial to the supplier at early stage of

the VMI implementation. However, the entire chain will benefit by increasing the transaction quantity in the long run. It is also necessary for the buyer to share profit with the supplier to cover the later initial loss and to exploit and sustain the benefit of VMI.

Bookbinder et al. [24] analyzed the tradeoff between independent and coordinated decision making for a manufacturing-retailer system adopting VMI agreement. They investigated the inventory control policies under independent, VMI agreement, and centralized decision-making scenarios to assess the benefits of VMI arrangements. Pasandideh et al. [25] developed an analytical model to explore the effect of important supply chain parameters on the cost savings realized from collaborative initiatives by an investigation of vendor managed inventory application based on EOQ with shortage and examines the inventory management practices before and after implementation of VMI. Razmi et al. [26] compared the performance of a VMI supply chain system with the one of a traditional "serially linked" one in terms of the total inventory cost. The supply chain was considered in two levels, i.e., buyer and supplier, with the assumption that the supplier faces only one buyer as the contract party. Pasandideh et al. [27] presented a genetic algorithm (GA) for vendor management inventory system with multiproduct, multi-constraint based on EOQ with backorders considering two classical backorders costs: linear and fixed. Lately, Roozbeh Nia et al. [28] proposed a fuzzy multi-item multi-constraint EOQ model with shortage for a single-vendor single-buyer supply chain under vendor managed inventory. They employed three meta-heuristic algorithms (genetic algorithm, ant colony optimization and differential evolution), to find a near-optimum solution of the fuzzy nonlinear integer-programming problem with the objective of minimizing the total cost of the supply chain.

For environmental topics containing GHG emissions, when making inventory decisions, has been stressed in Bonney and Jaber [11], who outlined their paper as a research agenda. For demonstrative purposes, they proposed an improved type of the EOQ model (i.e. Enviro-EOQ), which accounts for transportation cost and taxes due to GHG emissions produced. Under such situations, it was recommended that it is not economical to work under the EOQ strategy. The model of Bonney and Jaber [11] generated some works beside the same line with changing assumptions (e.g. [29–31]). Jaber et al. [32] study the effects of GHG emissions on the joint lot size strategy of a two-level supply chain similar to that of Hill [33,34]. The model proposed by Zanoni et al. [12] has been motivated by the work of Jaber et al. [32] who accounted for GHG emissions produced from the vendor's production process by taking into consideration both emissions costs and penalties paid for exceeding the annual emissions' quota under vendor managed inventory with only a single product.

This research has been inspired by the works of Pasandideh et al. [27] and Roozbeh Nia et al. [28], a multi-item multi-constraint EOQ model with shortage is developed for a green SC with single supplier and single buyer under the VMI policy. However, to bring their model to be applicable to closer to reality problems, additional contractual agreement between the vendor and the buyer including constraints on the number of pallets required to deliver the items, the number of deliveries, and the quantity of an order are considered. To create a kind of green SC, tax cost of green house gas (GHG) emissions and limitation on total Emissions of all items are considered in the model. In addition, a hybrid genetic and imperialist competitive algorithm (HGA) is employed to find a near-optimum solution of the developed nonlinear integer-programming (NIP) with the objective of minimizing the total cost of the green SC. Since no benchmark is available in the literature, a genetic algorithm (GA) is developed as well to validate the result obtained. For further validation, the results are also compared to lower bounds that are found using a relaxed model in which all variables are treated continuous.

In short, the highlights of the differences of this research with the above-mentioned studies are as follow:

- Considering green house gas (GHG) emissions tax cost and limitation on total emissions of all items to make a kind of green supply chain
- Adding a VMI contractual agreement between the vendor and the buyer to make the model more applicable
- Proposing a new modeling to the VMI supply chain problem
- Proposing a hybrid GA and imperialist competitive algorithm (ICA) to solve better the new model
- Comparing the results with the ones obtained using a GA and lower bounds for validation

The structure of the rest of the paper is organized as follows. In Section 3, the problem is defined and the assumptions are made. In Section 4, the problem is mathematically formulated into a non-linear integer-programming model. A hybrid ICA and GA (HGA) are proposed to solve the problem in Section 5. In order to demonstrate the application of the proposed approach, numerical examples are solved in Section 6. Finally, conclusions and future research topics are provided in Section 7.

3. The problem and the assumptions

In a single-vendor (as a supplier) single-buyer SC that utilizes the VMI policy, the vendor's information system directly receives consumer demand data. As a result, the vendor has now the combined inventory with order setup and holding cost [8]. Unlike the traditional system, the vendor and the buyer in a VMI system act as a single unit. They work based on an agreement which is admitted by both parties. This agreement is the main idea of VMI and states that the vendor establishes and manages the inventory control policies. Here, it is assumed that the vendor pays the ordering and holding costs on behalf of the buyer as a part of the mentioned agreement; the buyer paying no cost. This assumption has also been taken into considerations in prior studies such as [22,26,27,35] where supply chain integration in VMI has been discussed.

This research is concerned with a green SC with multi-items using the EOQ model in which not only the storage capacity and the volume of all deliveries are restricted, but also the order quantities are limited and depend on the pallet capacity. Moreover, there are bounds on the number of orders and the number of pallets. Tax cost of green house gas (GHG) emissions and limitation on total emissions of all items are considered in the model to make a type of green SC. In order the model to be more applicable to real-world green SC problems, shortages are allowed in the form of backorders. The objective is to find the items' order quantities, their required number of pallets, and their maximum backorder levels per cycle such that the total VMI inventory cost is minimized while the constraints are satisfied.

3.1. Assumptions

The following assumptions are used for the mathematical formulation:

- (a) There is a single supplier, single buyer SC with n items.
- (b) Shortage is allowed in the form of backorder for all of items.
- (c) The time-independent fixed backorder cost per unit is assumed zero for all items.
- (d) The linear backorder cost per unit per time unit is known and applied to all items.
- (e) Orders are delivered by pallets and are assumed instantaneous (lead time is assumed zero).

- (f) Quantity discount is not allowed.
- (g) The price for all items is fixed in the planning period.
- (h) The production rate for all items is infinite (EOQ model).
- (i) Customer's demand for all items is deterministic.
- (j) The storage capacity is limited.
- (k) The buyer's total order quantity of all items is limited.
- (l) The buyer's order quantity of an item has an upper bound.
- (m) The order quantity of each item is constrained (depends on the pallet's capacity).
- (n) The number of pallets for an item is limited.

4. Mathematical model

Before giving the mathematical formulation of the problem at hand, the notations are first introduced.

4.1. Notations

For $j = 1, 2, \dots, n$, let define the parameters and the variables of the model as:

- n : number of items
- Q_j : order quantity of item j (a decision variable)
- L_j : lower limit on the order quantity of item j
- U_j : upper limit on the order quantity of item j
- U_Q : upper bound on total order quantity of all items
- D_j : buyer's demand rate of item j
- E_j : vendor's GHG emissions level of item j
- C_f : vendor's fixed emissions tax cost
- α : emissions function's factor (ton/unit)
- U_e : upper bound on total GHG Emissions of all items
- A_{jS} : vendor's fixed ordering cost per unit of item j
- A_{jB} : buyer's fixed ordering cost per unit of item j
- h_{jB} : holding cost per unit of item j held in buyer's store in a period
- b_j : maximum backorder level of item j in a cycle of the VMI chain (a decision variable)
- π_1 : fixed backorder cost per unit (time independent)
- π_2 : linear backorder cost per unit per time unit
- f_j : space occupied by each unit of item j
- F : available storage space for all items
- K_j : capacity of the pallet for item j
- N_j : number of pallets for an order of item j (a decision variable)
- M_j : upper limit on the number of pallets for each order of item j
- TO_j : total cost of ordering
- TH_j : total cost of holding
- Tb_j : total cost of shortage
- TE_j : total cost of emissions
- TB_{VMI} : total cost of buyer's inventory in the VMI chain
- TS_{VMI} : total cost of vendor's inventory in the VMI chain
- TC_{VMI} : total costs of the VMI chain

Based on the above definitions, the mathematical model of the problem is derived in the next subsections.

4.2. The buyer's total cost

In the SC under the VMI policy, the vendor based on his own inventory cost (which equals to the total cost of the SC) determines the timing and the quantity of production in every cycle. The major difference between not using and using VMI is that the vendor determines the buyer's order quantity in a VMI policy, where it is assumed that the vendor on behalf of the buyer pays the ordering and the holding cost [26]. Thus, the buyer pays no cost and we have:

$$TB_{VMI} = 0 \tag{1}$$

4.3. The vendor's total cost

In EOQ model with shortage under the VMI policy, the vendor total cost per unit time of the j th item is determined by adding the cost of ordering, holding, shortage and emission as:

$$TS_{VMI} = TO_j + TH_j + Tb_j + TE_j \tag{2}$$

where

$$TO_j = \frac{D_j}{Q_j} A_{jS} + \frac{D_j}{Q_j} A_{jB} \tag{3}$$

$$TH_j = \frac{h_{jB}}{2Q_j} (Q_j - b_j)^2 \tag{4}$$

$$Tb_j = \frac{\pi_2 b_j^2}{2Q_j} + \frac{\pi_1 b_j D_j}{Q_j} \tag{5}$$

$$TE_j = E_j D_j C_t \tag{6}$$

where $E_j = Q_j \cdot \alpha$. As a result, the vendor's total cost becomes

$$TS_{VMI} = \sum_{j=1}^n \left(\frac{A_{jS} D_j}{Q_j} + \frac{A_{jB} D_j}{Q_j} + \frac{h_{jB}}{2Q_j} (Q_j - b_j)^2 + \frac{\pi_2 b_j^2}{2Q_j} + \frac{\pi_1 b_j D_j}{Q_j} + E_j D_j C_t \right) \tag{7}$$

4.4. The chain total cost

Based on Eqs. (1) and (7), the total cost of the SC under the VMI policy is determined by

$$TC_{VMI} = TB_{VMI} + TS_{VMI} \\ = \sum_{j=1}^n \left(\frac{D_j}{Q_j} (A_{jS} + A_{jB}) + \frac{h_j}{2Q_j} (Q_j - b_j)^2 + \frac{\pi_2 b_j^2}{2Q_j} + \frac{\pi_1 b_j D_j}{Q_j} + E_j D_j C_t \right) \tag{8}$$

4.5. The constraints

As mentioned previously, there is a contractual agreement between the vendor and the buyer that makes the constraints of the model. The vendor storage capacity is limited and since the average inventory of the j th item is $(Q_j - b_j)$, the space constraint will be [36]:

$$\sum_{j=1}^n f_j(Q_j - b_j) \leq F \tag{9}$$

Moreover, the bounds on the buyer's order quantity of the j th item are

$$L_j \leq Q_j \leq U_j \tag{10}$$

In addition, the buyer's total order quantity of all items is limited to V , that is

$$\sum_{j=1}^n Q_j \leq U_Q \tag{11}$$

Since an order of the j th item is required to be placed in a pallet with capacity K_j , we have

$$Q_j = K_j N_j \tag{12}$$

where N_j is the number of pallets that is limited to [28]

$$N_j \leq M_j \tag{13}$$

The maximum backorder level of item j in a cycle must be equal or less than its order quantity. That is

$$b_j \leq Q_j \tag{14}$$

Finally, the vendor's total emission level of all items is limited to U_e , that is

$$\sum_{j=1}^n E_j \leq U_e \tag{15}$$

4.6. The final model

Based on Eqs. (8)–(15), the multi-item multi-constraint EOQ model under green VMI policy can be easily obtained as:

$$\begin{aligned} \text{Min } TC_{VMI} &= \sum_{j=1}^n \left(\frac{D_j}{Q_j} (A_{jS} + A_{jB}) + \frac{h_j}{2Q_j} (Q_j - b_j)^2 + \frac{\pi_2 b_j^2}{2Q_j} + \frac{\pi_1 b_j D_j}{Q_j} + E_j D_j C_t \right) \\ \text{s.t. } &\sum_{j=1}^n f_j(Q_j - b_j) \leq F \\ &L_j \leq Q_j \leq U_j \\ &\sum_{j=1}^n Q_j \leq U_Q \\ &Q_j = K_j N_j \\ &N_j \leq M_j \\ &\sum_{j=1}^n E_j \leq U_e \\ &b_j \leq Q_j \\ &Q_j, N_j > 0, \quad \text{integer } j = 1, 2, 3, \dots, n \\ &b_j \geq 0, \quad \text{integer } j = 1, 2, 3, \dots, n \end{aligned} \tag{16}$$

The goal is to determine the order quantities (Q_j), the maximum backorder level (b_j), and the number of pallets for each order (N_j) in a cycle so that the total cost of the supply chain under the green VMI policy given in (16) is minimized and all the constraints are fulfilled. In the next section, a hybrid meta-heuristic solution algorithm is proposed to efficiently solve the problem.

5. The hybrid solution algorithm

Since the model in (16) is integer nonlinear in nature, reaching an analytical solution (if any) to the problem is difficult [37]. Furthermore, efficient treatment of integer nonlinear optimization is one of the most difficult problems in practical optimization. In such complicated combinatorial optimizations, exact algorithms and optimization solvers such as CPLEX and LINGO are inefficient, especially on practical-size problems [38]. Hence, a meta-heuristic search algorithm is needed for solution. Many researchers have successfully used meta-heuristic methods to solve complicated optimization problems in different fields of scientific and engineering disciplines. Some of these meta-heuristic algorithms are: simulating annealing [39,40], threshold accepting [41], Tabu search [42], genetic algorithm [35,43,44], particle swarm optimization [45–50], neural networks [51], ant colony optimization [28,52], evolutionary algorithm [53,54], harmony search [55,56] and gravitational search algorithm [57]. Among these algorithms, the population-based ones are usually preferred to others and in some cases show better performances.

Latest studies [38,58–60] have revealed that hybrid meta-heuristics work better than individual meta-heuristics for solving nonlinear models. Generally, hybridization refers to the combination of two search algorithms to solve a given problem [59]. The hybridization does provide some advantages over the individual meta-heuristics to reach better objective functions in less computational times. There are some methods to employ hybrid meta-heuristics, one of which is combining the traditional GA with

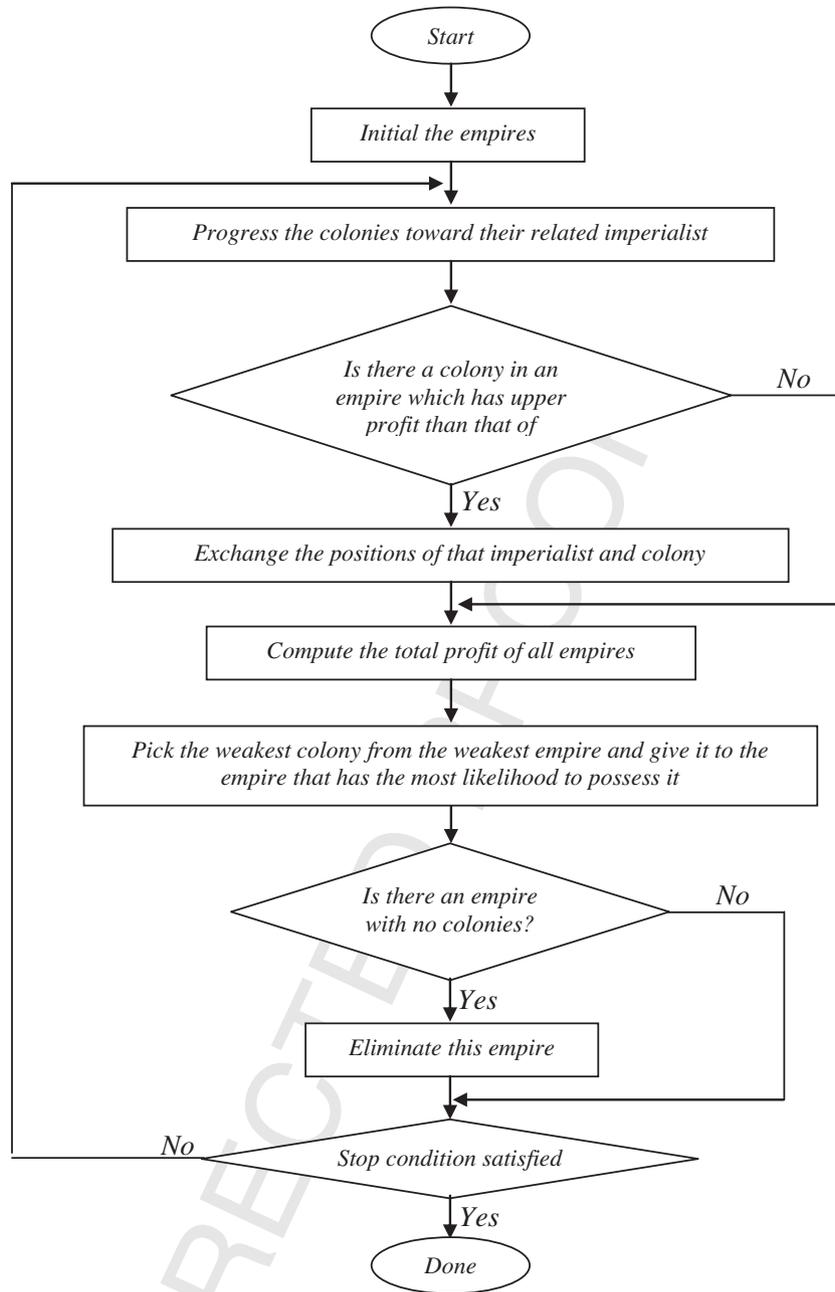


Fig. 1. Flowchart of ICA.

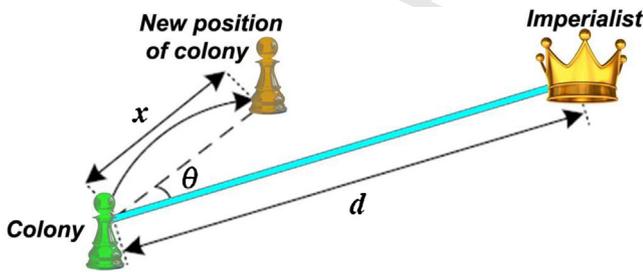


Fig. 2. Movement of colonies toward their relevant imperialist.

thereafter, in order to solve the nonlinear integer-programming (NIP) problem in (16). In the proposed method, to make a hybrid algorithm (HGA), ICA is used to produce the best initial solutions. Accordingly, the initial inputs for the hybrid GA come from the best outputs (Q_j , b_j and N_j) of the ICA. Then, The HGA runs until a termination condition (i.e. on the maximum number of iterations) is met.

In the next tow subsections, brief descriptions are first given for ICA and GA. Then, in the subsequent subsection, the steps involved in HGA are described.

5.1. The imperialist competitive algorithm (ICA)

ICA, proposed by Atashpaz-Gargari and Lucas [61], is a new global heuristic search that applies imperialism and imperialistic competition process as a source of inspiration. The flowchart of

any of the meta-heuristic algorithms. As a result, this research proposes a hybrid algorithm based on a GA and a new global heuristic search of imperialist competitive algorithm (ICA) that applies imperialistic competition process as a source of inspiration, named HGA

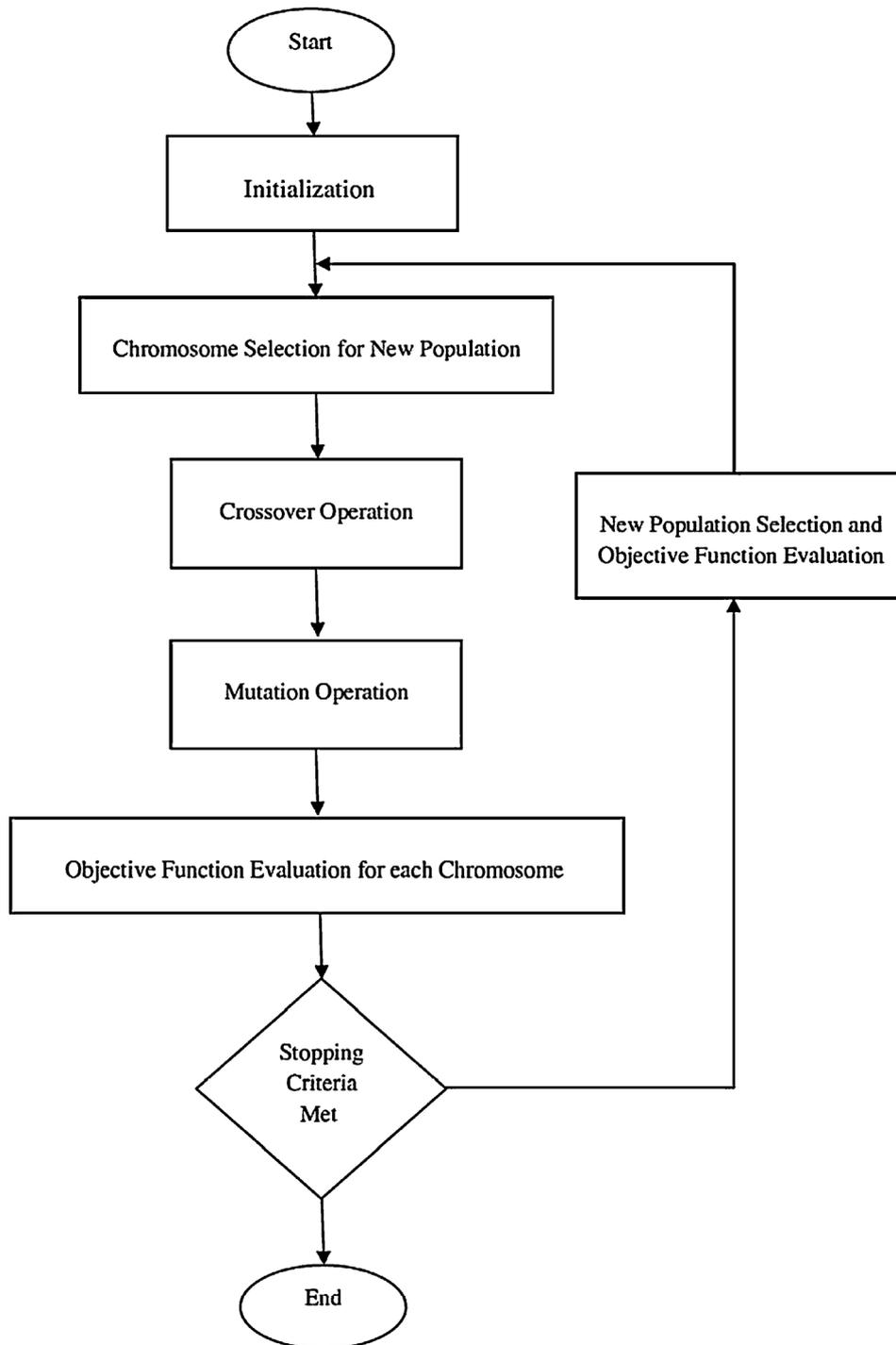


Fig. 3. The flowchart of GA [62].

401 this algorithm is demonstrated in Fig. 1. ICA starts with an initial
 402 population. Several of the best individual of this population,
 403 called countries, are picked up as the imperialist states and all the
 404 rests make the colonies of these imperialists. Due to imperialists'
 405 powers that are reversely proportional to their cost, the colonies
 406 of initial population are divided among them. Having distributed
 407 colonies between imperialists and establishing the initial empires,
 408 these colonies commence proceeding toward their relevant imperi-
 409 alist country. Fig. 2 shows the movement of a colony toward the
 410 imperialist. In this movement, θ and x are arbitrary numbers that
 411 are generated uniformly ($x \approx U(0, \beta \times d)$, $\theta \approx U(-\gamma, \gamma)$). Here, d is
 412 the distance between a colony and the imperialist and β must be

greater than one. This constraint causes the colonies to get closer
 to the imperialist state from both sides. Moreover, γ is a parameter
 that adopts the deviation from the main direction. Although β and
 γ are random numbers, most of the times their best fitted value are
 approximately 2 and $\pi/4$ (rad), respectively [61].

The power of the imperialist country in addition to the power of
 its colonies, determine the total power of an empire. More explic-
 itly, a percentage of the mean power of each imperialist's colonies is
 added to power of imperialist to form the total power of an empire.
 Any empire that does not improve in imperialist competition will be
 diminished. As a result, the imperialistic competition increases the
 power of great empires and weakens the frail ones. Hence, weak

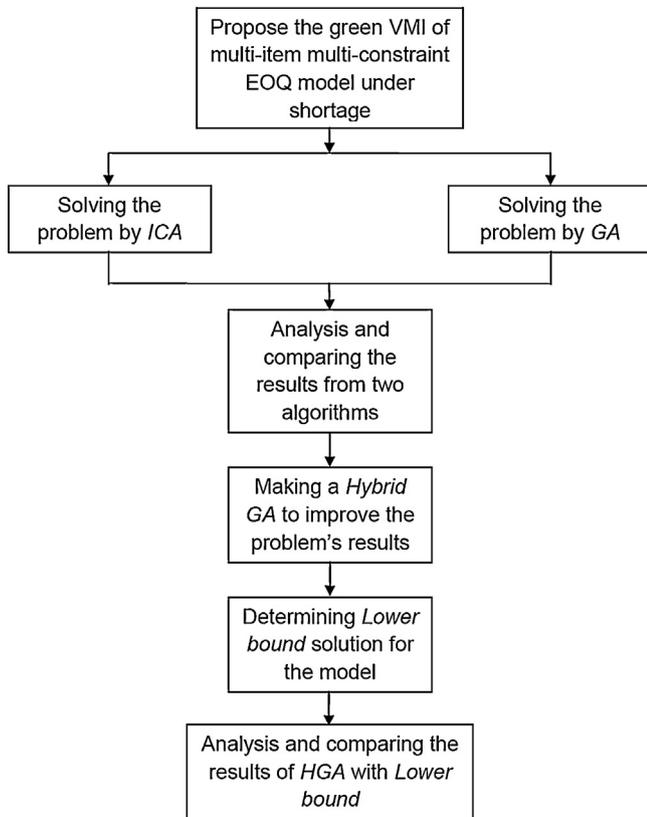


Fig. 4. Box-chart of the solving methodology.

empires will collapse finally. The movement of colonies toward their related imperialists along with competition among empires and also collapse mechanism will bring out the countries to converge to a state in which there exist just one empire in the world and all the rests are its colonies. In this final stage, colonies have the same position and power as the imperialist [61]. Moreover, since determining the optimum values of the initial parameter is the most important task in any meta-heuristic approach, clustering methods can be utilized to do it. As ICA usually works better than other population-based meta-heuristics in terms of both the objective function values of nonlinear optimization problems as well as in terms of computational times required solving the problem, in this research we employ it.

5.2. The genetic algorithm (GA)

The main parameters of a GA are the population size N_{GA} , the crossover probability P_c , and the mutation probability P_m . In this research, setting of GA parameters is based on pilot study. Moreover, the steps involved in the proposed real coded GA algorithm are:

1. Set the parameters P_c , P_m , and N_{GA} .

Table 1
Data for the numerical experimentation.

Item	D_j	A_{jS}	A_{jB}	h_j	K_j	f_j	L_j	U_j	M_j
1	800	400	50	12	1	1	100	240	270
2	1300	400	50	12	2	1	120	260	150
3	1800	400	50	12	5	1	100	240	50
4	2300	400	50	12	6	1	120	264	44
5	2800	400	50	12	10	1	100	240	30
6	3300	400	50	12	1	0.5	120	240	270
7	3800	400	50	12	2	0.5	100	260	150
8	4300	400	50	12	5	0.5	120	240	50
9	4800	400	50	12	6	0.5	100	264	44
10	5300	400	50	12	10	0.5	120	240	30
11	5800	600	70	6	1	1	100	240	270
12	6300	600	70	6	2	1	120	260	150
13	6800	600	70	6	5	1	100	240	50
14	7300	600	70	6	6	1	120	264	44
15	7800	600	70	6	10	1	100	240	30
16	8300	600	70	6	1	0.5	120	240	270
17	8800	600	70	6	2	0.5	100	260	150
18	9300	600	70	6	5	0.5	120	240	50
19	9800	600	70	6	6	0.5	100	264	44
20	10,300	600	70	6	10	0.5	120	240	30
21	10,800	600	70	6	1	1	100	240	270
22	11,300	600	70	6	2	1	120	260	150
23	11,800	400	50	12	5	1	100	240	50
24	12,300	400	50	12	6	1	120	264	44

2. Initialize the population randomly.
3. Evaluate the objective function (total cost) of all chromosomes.
4. Select individuals for mating pool.
5. Apply the crossover operation for each pair of chromosomes with probability P_c .
6. Apply the mutation operation for each chromosome with probability P_m .
7. Replace the current population by the resulting mating pool.
8. Evaluate the objective function.
9. If stopping criterion is met stop. Otherwise, go to Step 5 [28].

Fig. 3 shows the flowchart of the GA algorithm [62].

5.3. The steps involved in the solution procedure

The main steps in the proposed procedure are as follow:

- Step 1: Determine the total cost of all items using Eq. (16) by ICA and GA separately.
- Step 2: Find the better algorithm for each test problem.
- Step 3: Make a hybrid algorithm (HGA) to determine the better and the near optimum solutions of Q_j , b_j , and N_j for each item again.
- Step 4: Determine the lower bound solution of the model (16) using GA.
- Step 5: Compare the results of the HGA with the lower bound in Step 4.

The box-chart of the solving methodology and a representation of the chromosome for a test problem with 12-item are shown in Figs. 4 and 5, respectively.

Q_j :	188	200	200	210	220	170	235	240	222	228	231	246
b_j :	25	96	71	183	112	18	33	114	118	152	160	154
N_j :	188	100	40	35	22	170	117	48	37	22	231	123

Fig. 5. The representation of the chromosome for the test problem with 12-item.

Table 2
Data of test problem resources.

Problem no.	Number of items	F	V	U_e
1	4	12,000	1000	0.3
2	8	20,000	2000	0.6
3	12	28,000	3000	0.9
4	16	36,000	4000	1.2
5	20	44,000	5000	1.5
6	24	52,000	6000	1.8

Table 3
The initial parameter values for ICA and GA.

ICA	GA
Country = 400	Probability of crossover (P_c) = 0.8
Percent of empire = 0.4	Probability of mutation (P_M) = 0.05
	Probability of reproduction (P_E) = 0.15
	Population (N_{GA}) = 200
Stopping criterion = 200 iterations	Stopping criterion = 200 iterations

6. Numerical examples

In order to demonstrate the application of the proposed hybrid procedure and to study its performances, numerical examples are given in this section. The initial data of the examples is given in Tables 1 and 2 and the initial parameter values for implementation of ICA and GA are shown in Table 3. It is obvious from the literature that the parameters used in ICA and GA has a strong effect on both result time and result quality [63,64]. The ICA and GA parameters used were based on a pilot study. In these examples, it is assumed that is ($\pi_1 = 0, \pi_2 = 3$) and the same for all items. Also, for green VMI, we consider vendor's fixed emissions tax cost (C_f) is 20 (\$/ton) and Emissions function's factor (α) is 3×10^{-4} (ton/unit). In addition, six test problems with different number of items (small: 4- and 8-item; medium: 12- and 16-item; and large: 20- and 24-item size) are used. All the test problems are solved on a personal computer with Intel corei3-2100 processor having 3.10 GHz CPU and 4 Gig RAM. Furthermore, all algorithms are coded using the MATLAB 7.6.0.324 software.

The steps involved in the proposed hybrid procedure to solve the test problems follow.

Table 4
The total VMI cost obtained by the algorithms (Steps 1 and 3).

Item (j)	Total cost			The better algorithm	Difference with GA	Improvement (%)
	ICA	GA	HGA			
4	21898.20	21708.13	21705.06	HGA	3.07	0.01
8	74559.08	72563.80	72303.75	HGA	260.05	0.36
12	159523.26	155623.87	155220.99	HGA	402.88	0.26
16	290706.65	284418.31	283450.04	HGA	968.27	0.34
20	458151.83	448413.99	445509.14	HGA	2904.85	0.65
24	641766.19	623319.78	618587.63	HGA	4732.15	0.76

Improvement (%): Min. = 0.01, Max. = 0.76, Ave. = 0.40.

Table 5
The required CPU time of the algorithms (Steps 1 and 3).

Item (j)	CPU time (s)			The better algorithm	Difference with GA	Improvement (%)
	ICA	GA	HGA			
4	9.59	10.74	13.37	ICA	1.15	10.71
8	9.75	11.49	20.02	ICA	1.74	15.14
12	9.87	11.72	24.81	ICA	1.85	15.78
16	10.34	12.11	27.57	ICA	1.77	14.62
20	10.94	12.53	31.06	ICA	1.59	12.69
24	12.61	13.49	34.75	ICA	0.88	6.52

Improvement (%): Min. = 6.52, Max. = 15.78, Ave. = 12.58.

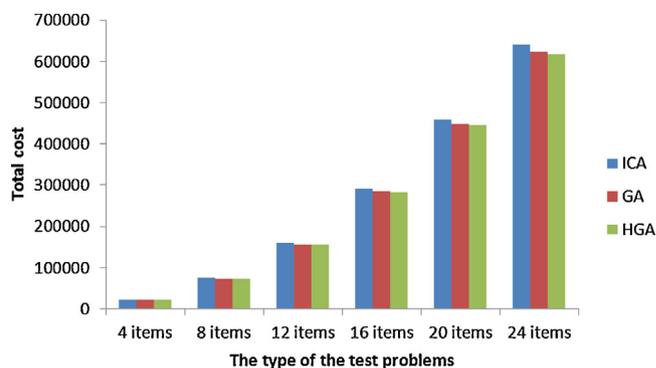


Fig. 6. The total cost comparison of meta-heuristic algorithms (Steps 2 and 3).

Step 1: In a given test problem, determine the total cost of all items using Eq. (16) by ICA and GA.

In this step, each algorithm is executed 15 times for each test problem, where their minimum total costs, the least CPU times (s) and total produced emission are recorded in Tables 4–6, respectively.

Step 2: Find the better algorithm for each item.

The better algorithm is found by determining the percentage difference between their results. Based on the results given in Table 4, GA is absolutely the better than ICA for the total cost of the green SC VMI. However, based on the results in Tables 5 and 6, ICA is the better algorithm in terms of the least CPU time(s) and total produced emissions in the model. Figs. 6–8 show this superiority better. In addition, in term of green SC VMI total cost, GA improvement percentages over ICA are 0.87, 2.68, 2.44, 2.16, 2.13 and 2.87 (average: 2.19) for 4-, 8-, 12-, 16-, 20- and 24-item problems, respectively. Moreover, in term of the CPU time, the ICA improvement percentages with respect to GA are 10.71, 15.14, 15.78, 14.62, 12.69 and 6.52 s (average: 12.58) for 4-, 8-, 12-, 16-, 20- and 24-item problems, respectively. Furthermore, in term of total produced emission, ICA improvement percentages over GA are 3.45, 6.38, 11.63, 11.30, 9.72 and 12.07 (average: 9.09) for 4-, 8-, 12-, 16-, 20- and 24-item problems, respectively. All improvement trends are shown in Fig. 9.

Table 6
The total produced emissions of the algorithms (Steps 1 and 3).

Item (j)	Total emissions (ton/period)			The better algorithm	Difference with GA	Improvement (%)
	ICA	GA	HGA			
4	0.28	0.29	0.29	ICA	0.01	3.45
8	0.44	0.47	0.48	ICA	0.03	6.38
12	0.76	0.86	0.88	ICA	0.10	11.63
16	1.02	1.15	1.17	ICA	0.13	11.30
20	1.30	1.44	1.47	ICA	0.14	9.72
24	1.53	1.74	1.78	ICA	0.21	12.07

Improvement (%): Min. = 3.45, Max. = 12.07, Ave. = 9.09.

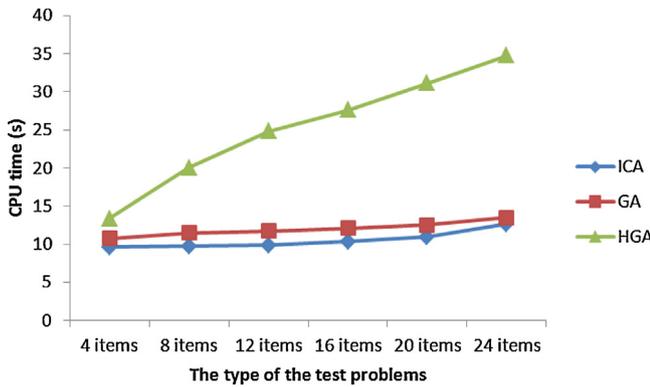


Fig. 7. The CPU time comparison of meta-heuristic algorithms (Steps 2 and 3).

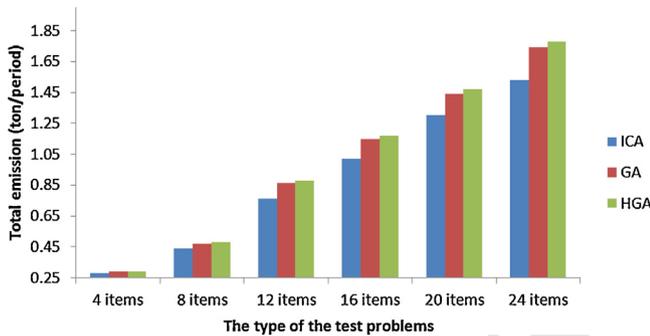


Fig. 8. The total produced emission comparison of meta-heuristic algorithms (Steps 2 and 3).

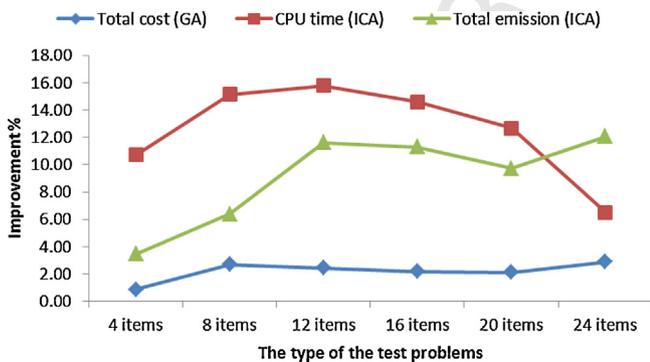


Fig. 9. GA and ICA improvement trends for total cost, CPU time, and total emission (Step 2).

As a result, GA in terms of total cost shows a sharply upward trend to hit the second highest point 2.68% in 8-item test problem and then a slightly drop for medium size test problem and finally a significantly rise to reach a peak 2.87% in 24-item. Similarly, CPU time improvement trend by ICA has a surge to reach a

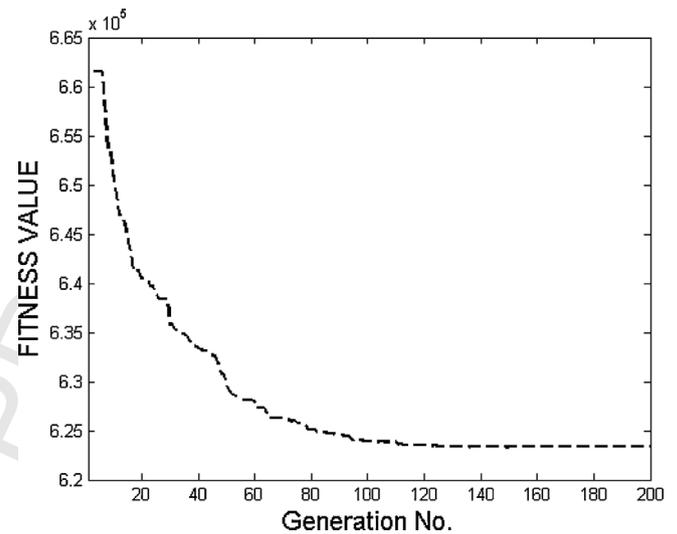


Fig. 10. The graph of the minimum total cost using GA for the 24-item problem (Step 2).

peak 15.78% in 12-item and then a gradually decline trend in large size test problems. Correspondingly, total emission improvement trend by ICA has a dramatically increase in small size test problem to reach the second highest point 11.63% in 12-item and then a gentle fall in medium size test problems and lastly a rise in 24-item. Furthermore, the graph of the minimum total cost using GA for 24-item problem is displayed in Fig. 10.

Step 3: Make a hybrid algorithm (HGA) to determine the better near optimum solutions of Q_j , b_j , and N_j for each item again.

Regarding the results in Step 1, in this step, a hybrid GA (HGA) is proposed to find a better near optimum solution. We take the best outcomes of Q_j , b_j , and N_j obtained by ICA for each test problem as an initial solution and input them to GA to make a HGA. Running HGA 15 times for each test problems and minimum total costs, the least CPU times (s) and total produced emissions are noted in Tables 4–6. In addition, the detailed results of HGA for all test problems include the near optimum value for Q_j , b_j , and N_j are shown in Table 7. With regard the results given in Table 4, HGA performance is completely the better than both ICA and GA for the total cost of the green SC VMI. However, based on the results in Tables 5 and 6, HGA outcomes in both terms of the least CPU time (s) and total produced emissions in the model are not good enough because ICA is the better algorithm. Figs. 6–8 show these conditions well.

In addition, in term of green SC VMI total cost, HGA improvement percentages over GA are 0.01, 0.36, 0.26, 0.34, 0.65 and 0.76 (average: 0.4) for 4-, 8-, 12-, 16-, 20- and 24-item problems, respectively. This improvement trends is shown in Fig. 11. As a result, HGA in terms of total cost shows at first a sharply upward trend (in small size test) until 0.36% in 4-item test problem and then a slightly drop for medium size test problem and finally a

Table 7
The detailed results of HGA for all test problems (Step 3).

Item (j)	Q _j	b _j	N _j	Total cost	CPU time (s)	Total emissions
4	240, 240, 240, 240	193, 192, 193, 192	240, 120, 48, 40	21705.06	13.37	0.29
8	200, 200, 200, 200, 200, 200, 200, 200	162, 154, 163, 161, 162, 154, 163, 161	200, 100, 40, 33, 20, 200, 100, 40	72303.75	20.02	0.48
12	242, 240, 240, 246, 240, 254, 242, 244, 240, 246, 240, 254	194, 167, 205, 169, 184, 215, 194, 167, 205, 169, 164, 145	242, 120, 48, 41, 24, 254, 121, 48, 40, 24, 240, 127	155220.99	24.81	0.88
16	198, 252, 230, 252, 240, 264, 248, 240, 246, 252, 230, 252, 240, 264, 248, 240	133, 233, 170, 203, 191, 215, 201, 190, 133, 233, 170, 203, 191, 141, 177, 190	198, 126, 46, 42, 24, 264, 124, 48, 41, 25, 230, 126, 48, 44, 24, 240	283450.04	27.57	1.17
20	240, 248, 240, 264, 240, 239, 252, 240, 264, 230, 240, 248, 240, 264, 240, 239, 252, 240, 264, 230	156, 139, 161, 195, 182, 224, 153, 199, 178, 216, 156, 139, 161, 195, 182, 156, 153, 199, 178, 216	240, 124, 48, 44, 24, 239, 126, 48, 44, 23, 240, 124, 48, 44, 24, 239, 126, 48, 44, 23	445509.14	31.06	1.47
24	240, 264, 240, 252, 244, 230, 258, 240, 235, 258, 240, 264, 240, 264, 240, 252, 244, 230, 258, 240, 235, 258, 240, 264	138, 158, 151, 198, 126, 190, 174, 204, 167, 179, 166, 167, 138, 158, 151, 168, 126, 190, 174, 157, 159, 179, 166, 219	240, 132, 48, 42, 24, 230, 129, 48, 39, 25, 240, 132, 48, 44, 24, 252, 122, 46, 43, 24, 235, 129, 48, 44	618587.63	34.75	1.78

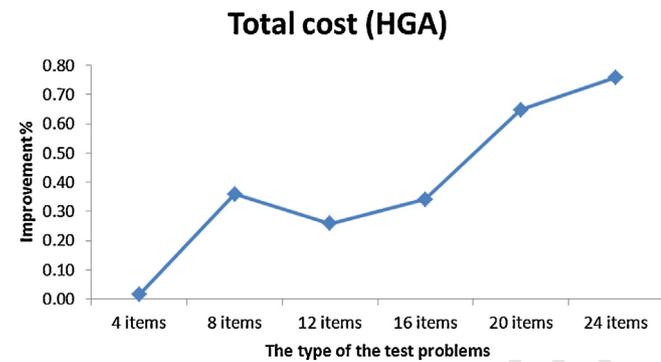


Fig. 11. HGA improvement trends over GA for total cost of all test problems (Step 3).

sharply surge (in large size test problem) to reach the highest point 0.76% in 24-item test problem. In terms of total cost, this is clear that HGA performance with increasing in size of test problem get improved.

Step 4: Determine the lower bound solutions using GA

In order to get a feel of the solution given by the proposed heuristic algorithm, a solution must be compared with a lower bound. The lower bound is determined by solving the relaxed problem (Eq. (16)) considering all variables as continuous [36]. The lower bounds for the relaxed model of all the test problems solved by a GA are given in Table 8.

Step 5: Compare the results of the HGA with the lower bound in Step 4.

Now, one can determine the difference between the total costs of the heuristic solution with the lower bound. The difference can be determined by

$$\text{Difference} = \text{total cost of heuristic solution} - \text{lower bound} \quad (17)$$

If the difference between the total costs obtained by HGA and the lower bound is small, then the difference between the proposed

Table 8
Comparison of HGA results with the lower bounds (Step 5).

Item (j)	HGA total cost	Lower bound	Difference	Percentage penalty%
4	21705.06	21667.52	37.54	0.17
8	72303.75	71975.79	327.96	0.46
12	155220.99	154894.48	326.51	0.21
16	282220.37	281844.34	376.03	0.13
20	445509.14	444994.49	514.65	0.12
24	618587.63	617469.78	1117.85	0.18

Percentage penalty (%): Min. = 0.12, Max. = 0.46, Ave. = 0.21.

solution procedure and the unknown optimal solution should be small and the solution given by the proposed hybrid algorithm turns out to be the near-optimal solution because it is very close to the lower bound. However, if there is a large difference between the two solutions, then this gives us uncertainty about the effectiveness of the hybrid algorithm. Therefore, it is better to define another comparison measure. The percentage penalty is a well known measure of performance that is generally used. The percentage penalty is defined as

$$\text{percentage penalty} = \frac{\text{difference}}{\text{lower bound}} \times 100\% \quad (18)$$

Based on Eq. (18), if the percentage penalty measure is low, then the actual percentage difference between the solution obtained by HGA and the unknown optimal solution should be low [36]. Table 8 contains the comparison results of the proposed HGA with the lower bound. Moreover, Fig. 12 shows HGA percentage penalty of all test problems. As a result, Fig. 12 shows percentage penalties of HGA in large size test problem are below 0.2%. According to the solutions reported in Table 8, the minimum, the maximum and the average percentage penalties are very small; one can conclude that the solution given by the proposed hybrid algorithm turns out to be the near-optimal solution because it is very close to the lower bound.

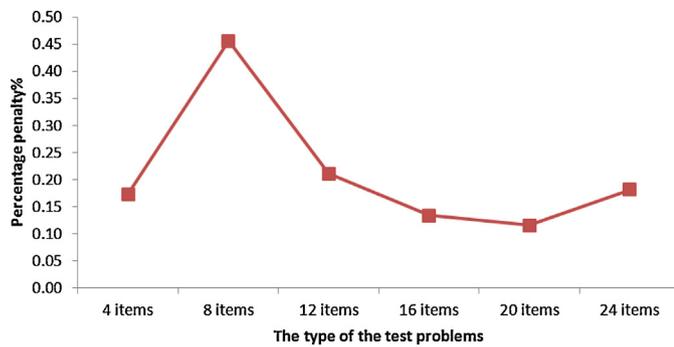


Fig. 12. The HGA percentage penalty of all test problems (Step 5).

7. Conclusions and recommendation for future research

In this paper, a multi-item multi-constraint EOQ model with shortage for a single-vendor single-buyer green supply chain under vendor managed inventory policy was developed. In comparison to the models proposed by Pasandideh et al. [27] and Roozbeh Nia et al. [28], the our model contains extra constraints based on the VMI contractual agreement between the vendor and the buyer and green SC conditions such as tax cost of green house gas (GHG) emissions and limitation on total emissions of all items. We proposed a 5-step hybrid meta-heuristic procedure consisting of a genetic and an imperialist competitive algorithm (HGA) to find a near-optimum solution of a nonlinear integer programming problem with the objective of minimizing the total cost of the supply chain. Since there were no benchmarks available in the literature, a genetic algorithm was also developed for the solution. In addition, to assure the proposed hybrid algorithm works well, its results were compared to lower bounds that were obtained by solving a relaxed model when all variables are treated continuous using a GA. At the end, six numerical examples in three categories (small, medium and large size) were presented to demonstrate the application of the proposed methodology. The results showed that the proposed hybrid procedure was able to find better and nearer optimal solutions because they were very close to their lower bounds.

For future researches in this area, we recommend the followings:

- Quantity discounts can be allowed.
- In addition to backorders, lost sales can also be assumed for shortages.
- Some parameters can be considered fuzzy or random. In this case, the model has either fuzzy or stochastic nature.
- Other meta-heuristic algorithms such as simulated annealing (SA), ant colony optimization (ACO), and particle swarm optimization (PSO) may also be employed to solve the problem.
- Multi-echelon supply chain such as one-buyer multi-supplier, multi-buyer one-supplier, and multi-buyer multi-supplier supply chains can be investigated.
- The economic production quantity (EPQ) model can also be utilized.
- For parameters setting up of meta-heuristic algorithms, developing an automatic tuning procedure can be considered.

References

[1] E.A. Silver, D.F. Pyke, R. Peterson, *Inventory Management and Production Planning and Scheduling*, third ed., John Wiley and Sons, New York, 1998.
 [2] R.J. Tersine, *Principles of Inventory and Materials Management*, fourth ed., Prentice Hall PTR, 1993.
 [3] L. Lu, A one-vendor multi-buyer integrated inventory model, *Eur. J. Oper. Res.* 81 (1995) 312–323.

[4] B.C. Das, B. Das, S.K. Mondal, An integrated production inventory model under interactive fuzzy credit period for deteriorating item with several markets, *Appl. Soft Comput.* 28 (2015) 453–465.
 [5] M.A. Hariga, A. Al-Ahmari, An integrated retail space allocation and lot sizing models under vendor managed inventory and consignment stock arrangements, *Comput. Ind. Eng.* 64 (2013) 45–55.
 [6] A. Blatherwick, Vendor-managed inventory: fashion, fad or important supply chain strategy? *Supply Chain Manag.* 3 (1998) 10–11.
 [7] G. Cachon, M. Fisher, Campbell soup's continuous replenishment program: evaluation and enhanced inventory decision rules, *Prod. Oper. Manag.* 6 (1997) 266–276.
 [8] Y. Dong, K. Xu, A supply chain model of vendor managed inventory, *Transp. Res. Part E* 38 (2002) 75–95.
 [9] R. Kaipia, K. Tanskanen, Vendor managed category management – an outsourcing solution in retailing, *J. Purch. Supply Manag.* 9 (2013) 165–175.
 [10] G. Büyükközkcan, G. Cifci, An integrated QFD framework with multiple formatted and incomplete preferences: a sustainable supply chain application, *Appl. Soft Comput.* 13 (2013) 3931–3941.
 [11] M. Bonney, M.Y. Jaber, Environmentally responsible inventory models: non-classical models for a non-classical era, *Int. J. Prod. Econ.* 133 (1) (2011) 43–53.
 [12] S. Zaroni, L. Mazzoldi, M.Y. Jaber, Vendor-managed inventory with consignment stock agreement for single vendor–single buyer under the emission-trading scheme, *Int. J. Prod. Res.* 52 (1) (2014) 20–31.
 [13] R.C. Baker, T.L. Urban, A deterministic inventory system with and inventory-level-dependent demand rate, *J. Oper. Res. Soc.* 39 (1988) 823–831.
 [14] J.F. Magee, *Production Planning and Inventory Control*, McGraw-Hill Book Company, New York, 1958.
 [15] M. Waller, M.E. Johnson, T. Davis, Vendor-managed inventory in the retail supply chain, *J. Bus. Logist.* 20 (1999) 183–203.
 [16] S. Cetinkaya, C.Y. Lee, Stock replenishment and shipment scheduling for vendor-managed inventory systems, *Manag. Sci.* 46 (2000) 217–232.
 [17] Y.Y. Woo, S.L. Hsu, S.S. Wu, An integrated inventory model for a single vendor and multiple buyers with ordering cost reduction, *Int. J. Prod. Econ.* 73 (2001) 203–215.
 [18] Y.G. Yu, L. Liang, An integrated vendor-managed-inventory model for end product being deteriorating item, *Chin. J. Manag. Sci.* 12 (2004) 32–37.
 [19] C.C. Lee, W. Chu, J. Hung, Who should control inventory in a supply chain? *Eur. J. Oper. Res.* 164 (2005) 158–172.
 [20] R.C. Vergin, K. Barr, Building competitiveness in grocery supply through continuous replenishment planning: insights from the field, *Ind. Mark. Manag.* 28 (1999) 145–153.
 [21] L. Bertazzi, G. Paletta, M.G. Speranza, Minimizing the total cost in an integrated vendor-managed inventory system, *J. Heuristics* 11 (2005) 393–419.
 [22] Y. Yao, P.T. Evers, M.E. Dresner, Supply chain integration in vendor managed inventory, *Decis. Support Syst.* 43 (2007) 663–674.
 [23] Y. Haisheng, A.Z. Zeng, L. Zhao, Analyzing the evolutionary stability of the vendor-managed inventory supply chains, *Comput. Ind. Eng.* 56 (2009) 274–282.
 [24] J.H. Bookbinder, M. Gumus, E.M. Jewkes, Calculating the benefits of vendor managed inventory in a manufacturer–retailer system, *Int. J. Prod. Res.* 48 (2010) 5549–5571.
 [25] S.H.R. Pasandideh, S.T.A. Niaki, A. Roozbeh Nia, An investigation of vendor-managed inventory application in supply chain: the EOQ model with shortage, *Int. J. Adv. Manuf. Technol.* 49 (2010) 329–339.
 [26] J. Razmi, R.H. Rad, M.S. Sangari, Developing a two-echelon mathematical model for a vendor-managed inventory (VMI) system, *Int. J. Adv. Manuf. Technol.* 48 (2010) 773–783.
 [27] S.H.R. Pasandideh, S.T.A. Niaki, A. Roozbeh Nia, A genetic algorithm for vendor managed inventory control system of multi-product multi-constraint economic order quantity model, *Expert Syst. Appl.* 38 (2011) 2708–2716.
 [28] A. Roozbeh Nia, et al., A fuzzy vendor managed inventory of multi-item economic order quantity model under shortage: an ant colony optimization algorithm, *Int. J. Prod. Econ.* (2013), <http://dx.doi.org/10.1016/j.ijpe.2013.07.017>.
 [29] G. Hua, T.C.E. Cheng, S. Wang, Managing carbon footprints in inventory management, *Int. J. Prod. Econ.* 132 (2) (2011) 178–185.
 [30] M.I.M. Wahab, S.M.H. Mamun, P. Ongkunaruk, EOQ models for a coordinated two-level international supply chain considering imperfect items and environmental impact, *Int. J. Prod. Econ.* 134 (1) (2011) 151–158.
 [31] Y. Bouchery, A. Ghaffari, Z. Jemai, Y. Dallery, Including sustainability criteria into inventory models, *Eur. J. Oper. Res.* 222 (2) (2012) 229–240.
 [32] M.Y. Jaber, C.H. Glock, A.M.A. El Saadany, Supply chain coordination with emission reduction incentives, *Int. J. Prod. Res.* 51 (1) (2013) 69–82.
 [33] R.M. Hill, The single-vendor single-buyer integrated production-inventory model with a generalized policy, *Eur. J. Oper. Res.* 97 (3) (1997) 493–499.
 [34] R.M. Hill, The optimal production and shipment policy for the single-vendor single-buyer integrated production-inventory problem, *Int. J. Prod. Res.* 37 (11) (1999) 2463–2475.
 [35] S.H.R. Pasandideh, S.T.A. Niaki, J. Aryan Yeganeh, A parameter-tuned genetic algorithm for multi-product economic production quantity model with space constraint, discrete delivery orders and shortages, *Adv. Eng. Softw.* 41 (2010) 306–314.
 [36] L.E. Cárdenas-Barrón, G. Treviño-Garza, H.M. Wee, A simple and better algorithm to solve the vendor managed inventory control system of multi-product multi-constraint economic order quantity model, *Expert Syst. Appl.* 39 (2012) 3888–3895.

- [37] M. Gen, R. Cheng, Genetic Algorithm and Engineering Design, first ed., John Wiley & Sons, New York, 1997. 760
- [38] A. Diabat, Hybrid algorithm for a vendor managed inventory system in a two-echelon supply chain, Eur. J. Oper. Res. (2014), <http://dx.doi.org/10.1016/j.ejor.2014.02.061>. 761
- [39] E.H.L. Aarts, J.H.M. Korst, Simulated Annealing and Boltzmann Machine: a Stochastic Approach to Computing, first ed., John Wiley and Sons, Chichester, 1989. 762
- [40] A.A. Taleizadeh, M.B. Aryanezhad, S.T.A. Niaki, Optimizing multiproduct multi-constraint inventory control systems with stochastic replenishment, J. Appl. Sci. 8 (2008) 1228-1234. 763
- [41] G. Dueck, T. Scheuer, Threshold accepting: a general purpose algorithm appearing superior to simulated annealing, J. Comput. Phys. 90 (1990) 161-175. 764
- [42] S.J. Joo, J.Y. Bong, Construction of exact D-optimal designs by Tabu search, Comput. Stat. Data Anal. 21 (1996) 181-191. 765
- [43] H. Al-Tabtabai, A.P. Alex, Using genetic algorithms to solve optimization problems in construction, Eng. Constr. Archit. Manag. 6 (1999) 121-132. 766
- [44] M. Shamsavar, S.T.A. Niaki, A.A. Najafi, An efficient genetic algorithm to maximize net present value of project payments under inflation and bonus penalty policy in resource investment problem, Adv. Eng. Softw. 41 (2010) 1023-1030. 767
- [45] A. Alfi, M-M. Fateh, Intelligent identification and control using improved fuzzy particle swarm optimization, Expert Syst. Appl. 38 (2011) 12312-12317. 768
- [46] S.V. Hosseini, H. Moghadasi, A.H. Noori, M.B. Royani, Newsboy problem with two objectives, fuzzy costs and total discount strategy, J. Appl. Sci. 9 (2009) 1880-1888. 769
- [47] A. Kaveh, K. Laknejadi, A novel hybrid charge system search and particle swarm optimization method for multi-objective optimization, Expert Syst. Appl. 38 (2011) 15475-15488. 770
- [48] F. Valdez, P. Melin, O. Castillo, An improved evolutionary method with fuzzy logic for combining particle swarm optimization and genetic algorithms, Appl. Soft Comput. 11 (2) (2011) 2625-2632. 771
- [49] F. Valdez, P. Melin, O. Castillo, Parallel particle swarm optimization with parameters adaptation using fuzzy logic, in: MICAI, vol. 2, 2012, pp. 374-385. 772
- [50] P. Melin, F. Olivas, O. Castillo, F. Valdez, J. Soria, J.M.G. Valdez, Optimal design of fuzzy classification systems using PSO with dynamic parameter adaptation through fuzzy logic, Expert Syst. Appl. 40 (8) (2013) 3196-3206. 773
- [51] B. Abbasi, H. Mahlooji, Improving response surface methodology by using artificial neural network and simulated annealing, Expert Syst. Appl. 39 (2012) 3461-3468. 774
- [52] M. Dorigo, T. Stutzle, Ant Colony Optimization, MIT Press, Cambridge, MA, 2004. 775
- [53] M. Laumanns, L. Thiele, K. Deb, E. Zitzler, Combining convergence and diversity in evolutionary multi-objective optimization, Evol. Comput. 10 (2002) 263-282. 776
- [54] A.A. Taleizadeh, S.T.A. Niaki, M.B. Aryanezhad, A hybrid method of Pareto, TOPSIS and genetic algorithm to optimize multi-product multiconstraint inventory systems with random fuzzy replenishment, Math. Comput. Model. 49 (2009) 1044-1057. 777
- [55] M. Jaberipour, E. Khorram, A new harmony search algorithm for solving mixed-discrete engineering optimization problems, Eng. Optim. 43 (2011) 507-523. 778
- [56] A. Kaveh, M. Ahangaran, Discrete cost optimization of composite floor system using social harmony search model, Appl. Soft Comput. J. 12 (2012) 372-381. 779
- [57] A. Sombra, F. Valdez, P. Melin, O. Castillo, A new gravitational search algorithm using fuzzy logic to parameter adaptation, in: IEEE Congress on Evolutionary Computation, 2013, pp. 1068-1074. 780
- [58] J. Sadeghi, S.M. Mousavi, S.T.A. Niaki, S. Sadeghi, Optimizing a multi-vendor multi-retailer vendor managed inventory problem: two tuned meta-heuristic algorithms, Knowl.-Based Syst. 50 (2013) 159-170. 781
- [59] G. Chen, K. Govindan, Z. Yang, A method to reduce truck queuing at terminal gates: managing truck arrivals with vessel-dependent time windows, Int. J. Prod. Econ. 141 (1) (2013) 179-188. 782
- [60] G. Sue-Ann, S.G. Ponnambalam, N. Jawahar, Evolutionary algorithms for optimal operating parameters of vendor managed inventory systems in a two-echelon supply chain, Adv. Eng. Softw. 52 (2012) 47-54. 783
- [61] E. Atashpaz-Gargari, C. Lucas, Imperialist competitive algorithm: an algorithm for optimization inspired by imperialistic competition, in: CEC IEEE Congress on Evolutionary Computation, 2007. 784
- [62] A.A. Taleizadeh, S.T.A. Niaki, A. Makui, Multiproduct multiple-buyer single-vendor supply chain problem with stochastic demand, variable lead-time, and multi-chance constraint, Expert Syst. Appl. 39 (2012) 5338-5348. 785
- [63] J. Yang, M. Xu, Z. Gao, Sensitivity analysis of simulated annealing for continuous network design problems, J. Transp. Syst. Eng. Info. Technol. 9 (3) (2009) 64-70. 786
- [64] Y.T. Kao, E. Zahara, A hybrid genetic algorithm and particle swarm optimization for multimodal functions, Appl. Soft Comput. J. 8 (2) (2008) 849-857. 787