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Determination of the optimal sales level of perishable goods in a two-echelon supply chain network

Seyyed Amir Hossein Salehi Amiri[a,*], Ali Zahedi[a], Morteza Kazemi[a], Javad Soroor[a], Mostafa Hajiaghaei-Keshteli[b]

[a] Department of Industrial Engineering, Shiraz University of Technology, Shiraz, Iran
[b] Department of Industrial Engineering, University of Science and Technology of Mazandaran, Behshahr, Iran

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ABSTRACT

In recent years, Supply Chain Management (SCM) has been the main focus in many industries in order to decrease costs and improve efficiencies. In today's supply chains, sale determination for a product in a specific time period and for a specific customer is highly considered. The importance of this efficiency is increased when dealing with perishable products, such as blood, vaccine, foods, etc. These products not only have various customers, but they also must be used before perishing. This paper represents a model to determine the optimal sales level of perishable products in a two-echelon supply chain, using a Vendor Managed Inventory (VMI) policy. Based on the literature most studies have considered two-echelon supply chain for perishable products with one buyer. The proposed model is formulated based on one vendor and multiple buyers. Considering buyers' requests in various periods, this model aims to optimize the sales profit by exact and meta-heuristics methods. Three efficient meta-heuristics including GA, PSO and CPSO are utilized to solve the problem and the results showed the good consistency with the results obtained from exact method. The obtained results show that applying VMI policy on two-echelon supply chain for perishable products is an effective approach to optimize the profitability of the proposed network.

1. Introduction

Perishable products have made companies consider different factors for chain management and network logistics because of their soon expiry date. Moreover, the costs of perishable products and the subsequent failure to deliver them to customers are very high. In addition, many expenditures before the product reaches to the final consumer are done, including costs relating to the manufacture, warehousing, inventory, and transportation. However, these perishable products will no longer be usable after their expiry date. To illustrate, in 2010, one state in Canada suffered a two-million-dollar financial loss over a six-month period of time because of the perished influenza vaccine H1N1.[1]

The deterioration of perishable products makes these products to be consumed within their shelf time period. This characteristic result not only in direct loss of these products, but also reduces the potential customers and the acceptability of these items. In addition, the results of studies have shown that there is a significant demand for these products in recent years and its growth (see Fig. 1). Fig. 1 shows value of U.S. product shipments of perishable prepared food to customers. According to the report, the value of U.S. product shipments of perishable prepared food amounted to approximately 14 billion U.S. dollars in 2016.

To address this issue, in recent years, the focus has shifted to methods that not only increase the profitability of perishable products, but also prevents losses on different goods like dairies. One highly considered method found in various papers is using the two-echelon supply chain with a Vendor Managed Inventory policy. Vendor Managed Inventory (VMI) has been employed in many papers, because of its impact on cost efficiency of supply chain networks. In VMI based supply chain networks, unlike traditional supply chains, each participant of the chain is aware of customer information and needs. This awareness helps the vendors and retailers contribute in a way that causes better collaboration within the components of the chain, and therefore optimal profit.

The contribution of entities and also successful application of VMI affect both upstream and downstream in supply chain network. In one hand, the downstream entities that previously used to track and manage inventory level are released from this burden and this provide

* Corresponding author.
E-mail addresses: a.salehi@sutech.ac.ir (S.A.H. Salehi Amiri), kaazemi@sutech.ac.ir (M. Kazemi), mostafahaji@mazust.ac.ir (M. Hajiaghaei-Keshteli).
[1] www.worldbank.org/pandemic_risk.

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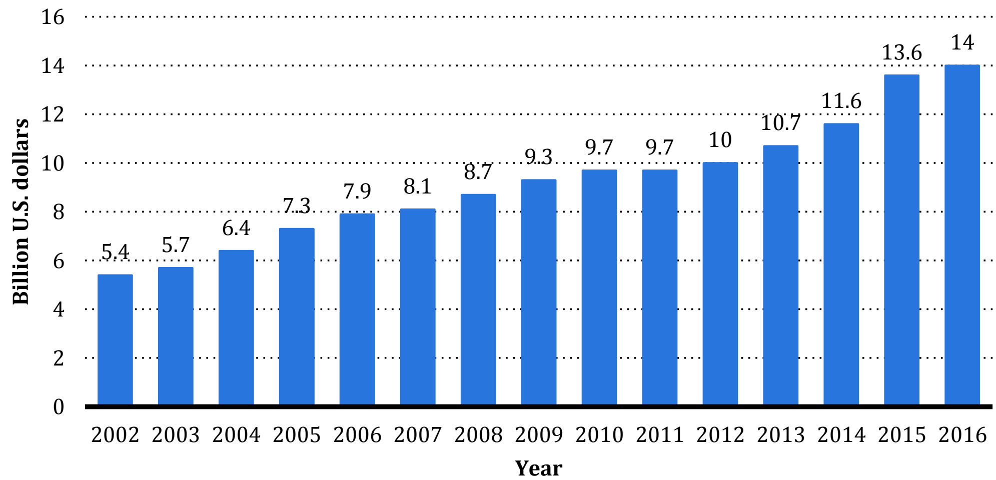

Fig. 1. U.S. product shipments of perishable prepared food to the customers [US Census Bureau; Available at census.gov].

them with environment to focus on enhancing their service quality. On the other hand, the upstream entity has the ability to view the customer orders properly and to better organize manufacturing decisions. In this regard several companies have reported significant cost saving by using VMI system, including Procter & Gamble, Walmart, General Electric, and Johnson & Johnson and other companies declared the successful implementation of VMI including Kmart and Dillard Department Store, Fruit of the Loom, JCPenney, Dell and HP and Lucent Technologies (Akhbari, Zare Mehrjerdi, Khademi Zare, & Makui, 2014; Fry, 2010).

In order to establish the optimal parameters of the proposed VMI system, we can use exact or meta-heuristic methods. Finding the optimal solutions for small-sized problems, exact methods can be used to obtain final answers. However, the optimal solution to such problems can be infeasible using traditional algorithms, particularly for larger problems. Therefore, three meta-heuristic methods have been proposed in this paper, including Particle Swarm Optimization (PSO), co-evolutionary particle swarm optimization (CPSO) and Genetic Algorithm (GA).

In this paper, we consider the two-echelon supply chain network that includes multiple buyers and one vendor. We try to find the sales quantity, and inventory level between the vendor and the buyers for the proposed model. The PSO, CPSO and GA methods are developed alongside other exact methods to determine the optimal parameters for VMI model.

The remainder of this paper is organized as follows. In Section 2, literature on different studies is reviewed. The main subject of these studies is application of various inventory models using VMI policy for perishable products. At the end of this section, the innovation aspects of this study are explained. In Section 3, problem definition of this study and different aspects of using VMI policy are presented. In Section 4, some assumptions for modeling the considered problem are presented. In Section 5, the mathematical modeling of the two-echelon supply chain system and also problem constraints are presented using VMI policy. The application of the model and appropriateness of the developed solution approach is illustrated in the form of a numerical example in Section 6. Finally, the conclusion of this paper is presented in Section 7.

2. Literature review

Globalization, economic and technology development, have caused organizations to preserve their survival by realizing the importance of satisfying customers' requirements (Beamon, 1998). These needs are constantly changing over time. Identifying correct and immediate needs of the target market geography, considering culture, customs, and social considerations are the most important goals of many companies (Fathollahi-Fard, Hajiaghaei-Keshteli, & Mirjalili, 2018). However, inventory is highly considered in supply chains because of the pressure of government regulations for obtaining environmental standards, growing customers' demands for green product's distribution, protection of resources, product recycling and waste management (Srivastava, 2007). To be successful in a supple chain, a variety of factors and criteria needs to be considered. Investing on environmental performance of a supply chain strategy will have many benefits, such as saving energy, reducing pollution, eliminating or reducing waste, creating value for customers and ultimately enhancing productivity for organizations (Boks & Stevels, 2007).

The two-echelon supply chain tries to reduce the prices for customers, and create added value for dealers (Sadeghi, Saidi-Mehrabad, & Sâdeqi, 2011; Zhao, Wang, & Lai, 2007). Diabat (2014) introduces the two-echelon supply chain under the VMI's inventory system. He has used two-echelon supply chain for designing a model to find the optimal value for sales. Then, by definition of a hybrid method, he has compared his solution with traditional methods. Other studies have been conducted on the two-echelon supply chain including the (Nachiappan & Jawahar, 2007) paper. Pramudyo and Luong (2017) developed a model for one vendor and one retailer in the VMI system. They used stochastic demand rate in their VMI supply chain network to minimize the total system cost. Finally, they solved the model using genetic algorithm. An economic order quantity model was developed by Pasandideh, Niaki, and Nia (2011) using VMI policy. They proposed a non-linear integer-programming model to find the order quantities and the maximum backorder levels with the application of genetic algorithm to find the optimal solutions.

The first inventory model for perishable products was presented by Ghare and Schrader (1963). In recent years, many researchers have analyzed the inventory models of perishable goods in their studies. Chaudhary, Kulshrestha, and Routroy (2018) reviewed various inventory models including VMI for perishable items. They stated that different studies pursued different goals on this topic and most studies have tried to add different constraints to their proposed model to change it into a more realistic one. A new inventory model for perishable products was developed by Janssen, Sauer, Claus, and Nehls (2018). They analyzed the application of new "closing day" constraint and showed a comparative simulation study under specified planning. Inventory control of deteriorating items under VMI policy was proposed by Rabbani, Rezaei, Lashgari, and Farrokhi-Asl (2018). In this study, the authors used Economic Order Quantity (EOQ) inventory system with a shortage in form of backorders using VMI policy and a metaheuristic algorithm to solve their nonlinear integer-programing model.

Table 1
New solution methodology development on VMI.

Paper	Model	Solution methods	Developments
Nachiappan and Jawahar (2007)	Using two-echelon & Single vendor & multiple-buyers	Genetic Algorithm	Changing the presented solutions with the better near optimal solutions
Pasandideh et al. (2011)	Using two-echelon & one supplier & one retailer & multi-product	Genetic Algorithm	Combining VMI with some constraint and using several products in VMI system
Diabat (2014)	Using two-echelon & Single vendor & multiple-buyers	Hybrid methodology of genetic & simulated annealing	Demonstrating the better solutions that overcomes the previous methodologies
Mateen et al. (2015)	Using VMI model for one vendor & multiple retailers	Stochastic programming & simulation	Expressing the optimal methodology for minimizing the total cost of VMI system and prove the validity using simulation
Diabat et al. (2016)	Using VMI model for inventory distribution of perishable goods	Hybrid Tabu search based Algorithm	Using column generation method in comparison with hybrid Tabu search algorithm
Pramudyo and Luong (2017)	Using VMI model for one vendor & one retailers	Genetic Algorithm	Using stochastic demand and applying sensitivity analysis to show the effects the parameters
Rabbani et al. (2018)	Using VMI policy with multi-item EOQ model	Simulated Annealing and Tabu Search	Applying the fuzzy concept to the problem
This paper	Using VMI policy to determine the optimal sales level	Genetic Algorithm, Particle Swarm Optimization Algorithm, Co-evolutionary Particle Swarm Optimization Algorithm	Using exact CPLEX method to find optimal solution and compare the answers with proposed meta-heuristics

All the aforementioned papers are concentrating on developing a new VMI system for the supply chain network. They used VMI policy to optimize the cost, profit or total benefit of the supply chain network by focusing on diverse items, goods and especially perishable products. They also applied different approaches to find the optimal solution of their proposed network. In Table 1 we summarize the various heuristic and meta-heuristic and other methods that have been applied to solve VMI models:

Like any system in a supply chain, the purpose of the VMI based supply chain network is to decrease the costs of the entire chain among different levels of the chain and to increase profits by using the mentioned policy (Mateen, Chatterjee, & Mitra, 2015). Traditional chain distribution can be identified in a way in which each member programs its products, based on its conditions like customer demand, inventory levels and the amount of work in the process of production. At the time of issuing orders, the members of the chain concern themselves with management, and they are only aware of their direct and immediate customer (Ghiani, Laporte, & Musmanno, 2004). This condition prevents suppliers from knowing and fulfilling the customers' expectations. Lack of clarity for actual demands leads to many issues in the supply chain. Disadvantages of traditional systems can be categorized as follows:

- Long delivery times
- Multiple decision points
- Unclarified information and the least coordination in issuing orders
- Low ability to detect final customer's demand

These above issues lead to the least collaboration among the participants of the chain. In this chain, the retailer imposes more fluctuations to demand model because of unpredictable customer's demand. The distributer, whose forecast is mainly based on retailer demands, intensifies such deviation, and its signs continues to the top of the supply chain which can leads to a significant deviation from customer demand once the factory receives the orders (Disney & Towill, 2003).

Most papers that address perishable products, have assumed the supply chain network to be one level. This is evident in the studies of different authors like (Duan, Li, Tien, & Huo, 2012; Rabbani, Zia, & Rafiei, 2015; Sana, 2011; Shah, Soni, & Patel, 2013; Singh & Sharma, 2014; Soni & Patel, 2013). Furthermore, there are limited number of studies which considers the two-echelon supply chain network for perishable products, such as studies of Diabat (2014), Diabat, Abdallah, and Le (2016), Shaikh and Mishra (2018), Tayal, Singh, Sharma, and Chauhan (2014). In addition, a few of these studies have considered VMI policy to optimize the total profit of the sales model (Diabat, 2014). Most of the mentioned studies have used metaheuristic methods, such as GA and PSO to present their solutions, but none of them has used co-evolutionary methods to demonstrate their final answers.

To address this research gap, this study has developed two-echelon supply chain network for perishable products with the aim of maximizing the total profit of the proposed supply chain network. Besides, employment of multiple customers alongside with different demand rate has allowed vendor to identify the real need of the market and utilizing VMI system in the whole network helped supply chain management to attain the proper information of the customer and adjust the sale so as to achieve the optimum profit. In addition, applying three efficient meta-heuristics alongside with exact method helps us to obtain better solution when dealing with multiple customers.

Accordingly, this paper considers these issues and develops a model for perishable products to reduce or eliminate the effects of deviations in traditional networks, and tries to maximize the sales profits by using VMI policy in a two-echelon supply chain network.

3. Problem definition

A two-echelon supply chain includes two main components; a vendor and a buyer. In this system, named as Vendor Managed Inventory (VMI), the vendor is responsible for supply, services and support of the product, and he delivers his goods immediately to the buyer. The importance of this issue for perishable goods like dairy products is more evident, because these items have short and determined lives.

In other word, the vendor controls inventory, and does ordering action instead of buyers (Holmström, 1998). The advantage of this model is to meet the demands of final customers in the shortest time possible. The problem of determining the optimal sales level of perishable product in a two-echelon multi-period supply chain, can be converted to a mathematical programming model with non-linear objective function (Diabat, Abdallah, & Le, 2014). In this model, information, such as the capacity of each vendor, the cost of inventory maintenance, ordering costs, upper and lower limit for sale and cost of production and distribution of goods are required. It should be noted that due to vendor capacity constraints and maintenance cost, the inventory cannot be equal to demands (Diabat et al., 2014; Diabat, 2014).

Fig. 2 illustrates the schematic of the proposed network. In this network, which consist of two levels (one vendor and multiple buyers), the vendor is responsible to deliver perishable goods to the buyers. In VMI system, the vendor must be aware of the buyer's need in order to meet their demands. Therefore, information flow is shown from buyers to the vendor alongside with products flow from vendor to the buyers.

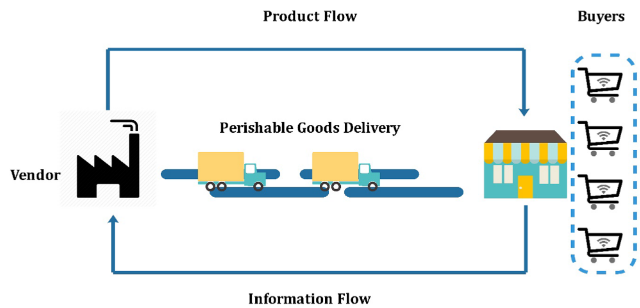

Fig. 2. Schematic of the proposed network.

Table 2
Problem parameters.

Parameters	Definition
I_{jt}	Inventory levels for the buyer j at the end of the period t
d_{jt}	Buyer jth demand in period t
a_{jt}	Price-demand curve intercept for buyer j
b_{jt}	Price-demand curve slope for the buyer j
C	Vendor capacity
H_{bjt}	Maintenance costs for the jth buyer in period t independently
H_{st}	Maintenance costs for the vendor in period t independently
Q_{jt}	Economic order quantity in period t
τ_{max}	The maximum time for expiring a unit of perishable good
S_{bjt}	Setup cost for jth buyer in any order in period t independently
S_{st}	Setup cost for the vendor for any order in period t independently
W_{jt}	The contract cost between the vendor and the buyer j in period t
y_{jtmin}	The minimum amount of sales expected for the jth buyer in period t
y_{jtmax}	The maximum amount of sales expected for the jth buyer in period t
θ_{jt}	The flow cost per unit from vendor to jth buyer in the period t
v_{jt}	Transportation resource cost per unit from the vendor to jth buyer in period t
δ	Production cost per unit

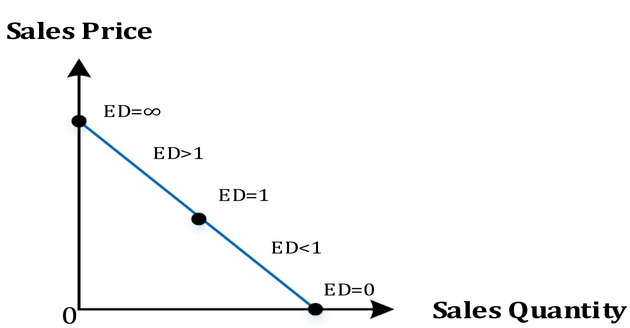

Fig. 3. Elasticity of demand diagram.

In this paper, the problem of determining the optimal level of sales in a two-echelon multi-period supply chain for perishable items is introduced, modeled and solved with the purpose of maximizing the total profit of the chain. In this regard, beside the general information in each levels of the supply chain, it is necessary to maintain the product's maximum storage capability (the inventory level in each period).

4. Model assumptions

In this section, VMI model is discussed at two-echelon supply chain including one vendor and multiple buyers with perishable goods. It is assumed that the goods are sold to different buyers with different demand rate and the vendor can only sale its products within predefined values. In addition, to avoid deterioration of these products, all inventory should be sold at the end of the periods. According to the aforementioned condition of problem, assumptions can be defined as follows:

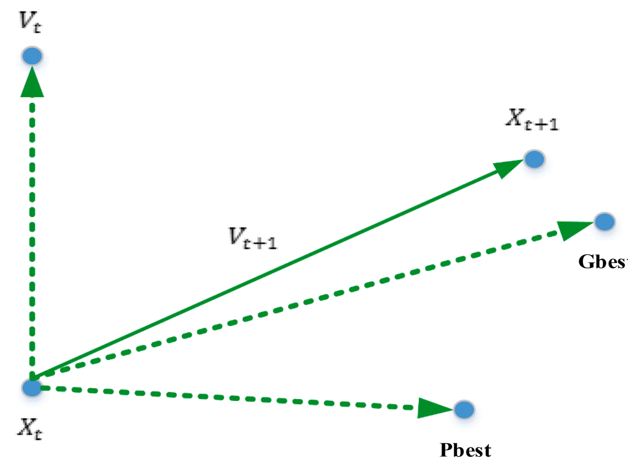

Fig. 4. Particle behavior in PSO algorithm.

- Buyers have different and definite demands in different periods.
- Vendor can only sell products in predefined values. In this case, upper and lower bonds are considered for each vendor's sale in each period.
- Due to the nature of perishable items, each unit of inventory remains intact up to the certain period.

In addition, it is assumed that these model parameters have been considered; including vendor's demand, the capacity of each vendor, maintenance and ordering costs, the cost of setting up production in each period and the cost of sending goods from supplier to vendor.

5. Modeling

Given the above assumptions, the parameters are shown in Table 2:

After solving the model, the amount of product sent from the supplier to every vendor in each period should be determined showed by y_{jt} which represents the amount of sending products from suppliers to the buyer j in period t.

5.1. The objective function

As previously mentioned in the literature review, the objective function is the maximization of the profits by selling products to the buyers. Vendor costs are related to the manufacturing, distribution, demands and inventory maintenance. The objective function is calculated as the difference between net profit and associated costs with the vendor, which its components are as follows:

- Gross profit

In the real world, prices on various items change over time. These changes can be used for modeling the elasticity of the demand curve. Fig. 3 shows the elasticity of a demand diagram with which ED (Elasticity-Demand) values in different areas are presented in the figure. Indicated values of ED show the degree of responsiveness of the demands in relation to changes in price. For example, if a curve is more elastic, then small changes in price will cause large changes in quantity consumed. If a curve is less elastic, then it will take large changes in price to effect a change in quantity consumed. Graphically, elasticity can be represented by the appearance of the supply or demand curve.

By using this curve, prices in each period will be a function of the demand in that period. If we assume j^{th} buyer demand in period t is equal to y_{jt}, the price of a good can be obtained using the following

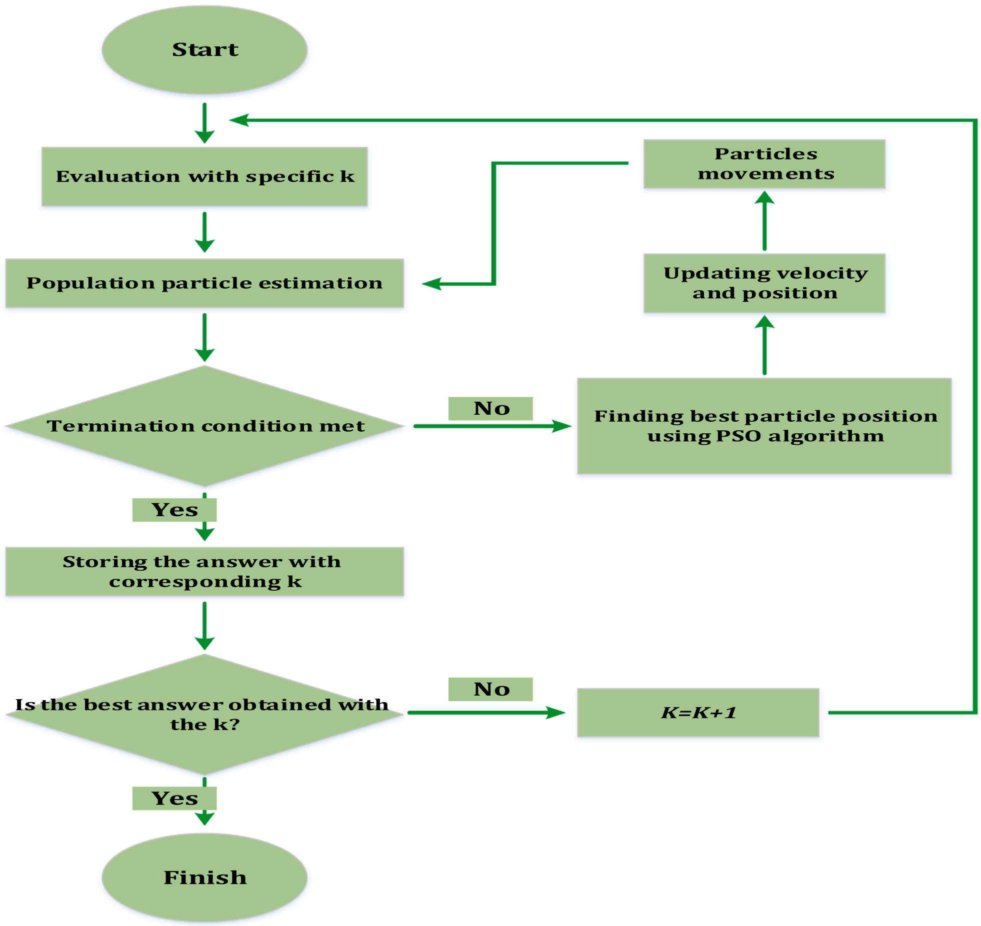

Fig. 5. CPSO flowchart.

equation:

$$P(y_{jt}) = a_{jt} - b_{jt}y_{jt} \tag{1}$$

In this equation, a_{jt} and b_{jt} represent the price-demand curve intercept and slope of price-demand curve for j^{th} buyer. As in Eq. (1) determine, the selling price of goods to the buyers can vary in different time intervals. By this definition, net profit from sales of the product is equal to multiplying the amount of sales $P(y_{jt})$ in the sale price y_{jt}:

$$a_{jt}y_{jt} - b_{jt}y_{jt}^2 \tag{2}$$

- Production costs

Production cost is calculated by multiplying the cost of each product in the amount of sales (demand for the product) and this value can be displayed by δy_{jt}in the problem based on defined parameters.

- Distribution costs

Distribution cost is calculated by multiplying the current cost$\theta_{jt}y_{jt}$ by the cost of transportation resources$v_{jt}y_{jt}$.

$$v_{jt}\theta_{jt}y_{jt}^2 \tag{3}$$

- Ordering and inventory maintenance costs

In this paper, Economic Order Quantity inventory ordering system or EOQ is used to calculate the total cost of ordering and inventory maintenance costs:

$$\frac{DA}{Q} \tag{4}$$

By substituting them with values in Eq. (4) for ordering costs, it will be:

$$\frac{y_{jt}(S_{st} + S_{bjt})}{Q_{jt}} \tag{5}$$

Similarly, we can calculate the cost of maintenance:

$$\frac{HQ}{2} = \frac{(H_{st} + H_{bjt})Q_{jt}}{2} \tag{6}$$

Finally, based on the Diabat (2014) model, by substituting Q_{jt} with the optimum value of economic order model $EOQ = \left[\frac{2(S_{st} + S_{bjt})y_{jt}}{(H_{st} + H_{bjt})}\right]^{1/2}$ the ordering and inventory maintenances total cost can be calculated as following:

$$[2(H_{st} + H_{bjt})(S_{st} + S_{bjt})y_{jt}]^{\frac{1}{2}} \tag{7}$$

Based on mentioned points, the objective function of Eq. (8) is to maximize the total profits of selling perishable products in different periods. Besides, due to utilizing factors related to the flow cost and economic order quantity inventory system, the optimization problem will be non-linear. It is essential to consider that the index v_{jt} include costs, such as costs of transportation methods, human router cost and costs of administration per unit which is assigned 0.5 by reviewing various papers (Dong & Xu, 2002).

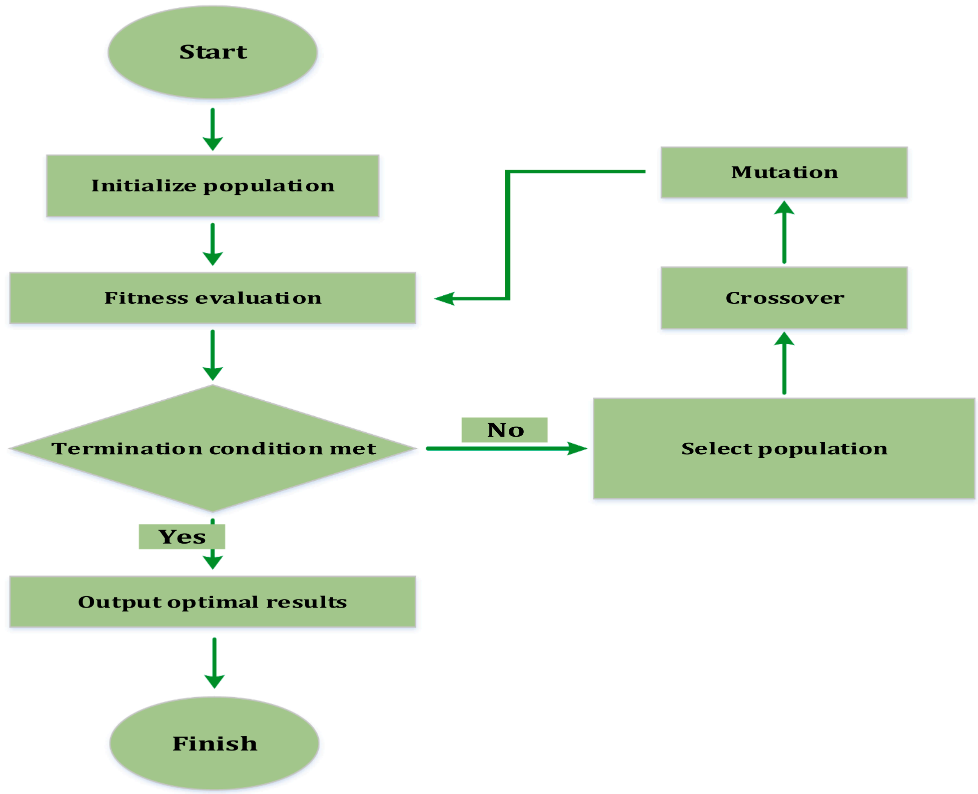

Fig. 6. Basic structure of genetic algorithm.

Table 3
Parametric input data for the first buyer.

Parametric data	Period 1	Period 2	Period 3	Period 4	Period 5
a_{jt}	20	19	18	21	18
b_{jt}	0.003	0.005	0.008	0.003	0.006
θ_{jt}	0.004	0.006	0.008	0.005	0.007
H_{st}	9	9	9	9	9
H_{bjt}	7	8	9	7	9
S_{st}	12	10	11	11	12
S_{bjt}	15	15	15	15	15
I_{jt}	1000	1200	1580	2200	3400
δ	7	7	7	7	7
D.S.K.1	3742	3190	3571	1775	2198

$$\sum_{j=1}^{n}\sum_{t=1}^{\tau_{max}}\left\{a_{jt}y_{jt} - b_{jt}y_{jt}^2 - \delta y_{jt} - 0.5\theta_{jt}y_{jt}^2 - [2(H_{st}+H_{bjt})(S_{st}+S_{bjt})y_{jt}]^{\frac{1}{2}}\right\} \tag{8}$$

5.2. Model constraints

The problem of determining the optimal level of selling perishable items in the two-echelon supply chain network has various constraints. These constraints are as follows:

$$\sum_{j=1}^{n} y_{jt} \le C \tag{9}$$

$$y_{jtmin} \le y_{jt} \le y_{jtmax} \tag{10}$$

$$I_{j,t-1} + \sum_{j=1}^{n} y_{jt} = d_{jt} + I_{j,t} \tag{11}$$

$$I_{j,t} \le \sum_{t<\tau<t+\tau_{max}} d_{jt} \tag{12}$$

$$y_{jt},\ d_{jt},\ I_{j,t} \ge 0 \tag{13}$$

In Constraint (9), the amount of sales products in different time periods is considered less than or equal to the capacity of the vendor. Due to the variety of items and several buyers' demands in different time periods, the upper and lower limits are considered for the sale of different items (Constraint (10)). Constraint (11) suggests that the total inventory of the previous period and sales of the current period should be equal to the amount of demand and inventory of the present time. In Constraint (12), the inventory level should always be lower than or equal to the total demands in different time periods. Finally, Constraint (13) shows that the sale amount, inventory and demand should be positive in each time period.

6. Solution approach

Considering the objective function and constraints of the proposed model, the problem is a type of bounded optimization in which two methods can be used to solve it; (A) Classic methods, and (B) Using intelligent methods or evolutionary. In this paper, meta-heuristic methods PSO, CPSO and GA have been used to obtain the optimal solution of the problem. Finally, solutions solved by these methods have been compared through GAMS software.

- **PSO particle swarm optimization algorithm**

PSO method is a global method for minimizing. By using this method, we can address the problems that their answers are a point or a surface in n-dimensional space. Communication channels between the particles are considered by allocating an initial speed. Then, the particles move in the space. And the results are based on an "eligibility criteria" which is calculated after each period. Over time, the particles

Table 4
Problem results.

Problem	Upper limit	Lower limit	Capacity	Demand	GAMS	PSO	CPSO	GA
1	4000	250	9850	D.S.K.1	41,194	31,890	32,178	40,927
2	3548	233	5060	D.S.K.2	33,200	32,528	32,869	33,050
3	3700	215	5173	D.S.K.3	34,159	32,662	32,074	34,027
4	3711	215	5952	D.S.K.4	38,730	35,783	36,001	38,612
5	3684	232	5033	D.S.K.5	33,009	31,971	32,122	32,827
6	3991	245	5252	D.S.K.6	34,246	33,978	33,826	34,104
7	3909	226	5682	D.S.K.7	37,246	34,952	35,812	37,142
8	3763	222	5391	D.S.K.8	35,182	31,622	33,176	34,875
9	3774	235	5920	D.S.K.9	38,361	37,675	37,812	38,197
10	3730	219	5561	D.S.K.10	36,613	35,687	34,590	36,485
11	3865	244	8704	D.S.K.11	43,483	35,430	38,966	43,298
12	3909	249	7156	D.S.K.12	42,451	35,673	38,703	42,220
13	3708	201	8687	D.S.K.13	48,747	40,244	45,443	48,671
14	3971	233	8781	D.S.K.14	48,092	43,379	45,957	47,973
15	3991	210	7019	D.S.K.15	41,663	37,280	37,888	41,411
16	3672	241	6896	D.S.K.16	43,483	34,703	38,003	43,403
17	3861	232	8671	D.S.K.17	37,474	32,748	33,606	37,215
18	3828	249	9378	D.S.K.18	44,125	40,851	41,123	43,958
19	3709	227	7378	D.S.K.19	42,802	39,254	39,904	42,632
20	3578	221	9122	D.S.K.20	41,435	37,693	36,826	40,962

Table 5
Results for the second problem.

GAMS	Period1	Period2	Period3	Period4	Period5
Buyer1	465	233	233	524	233
Buyer2	461	233	233	524	233
Buyer3	465	233	233	521	233
PSO	Period1	Period2	Period3	Period4	Period5
Buyer1	233	233	233	636	233
Buyer2	590	233	233	233	233
Buyer3	233	233	233	634	233
CPSO	Period1	Period2	Period3	Period4	Period5
Buyer1	793	404	233	233	270
Buyer2	233	233	250	524	233
Buyer3	233	233	233	233	322
GA	Period1	Period2	Period3	Period4	Period5
Buyer1	497	249	238	554	241
Buyer2	392	238	236	542	236
Buyer3	443	251	236	480	236

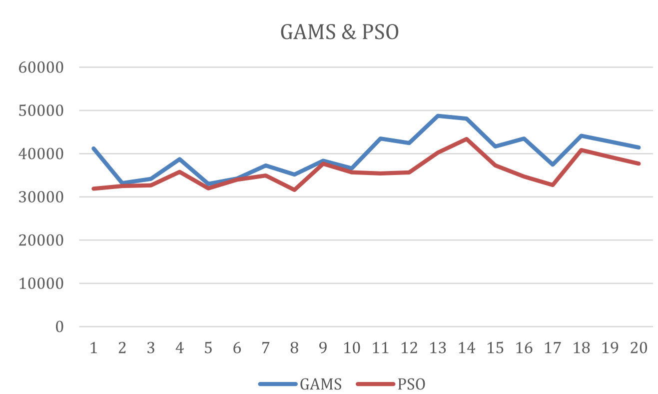

Fig. 7. Comparing the results between GAMS and PSO.

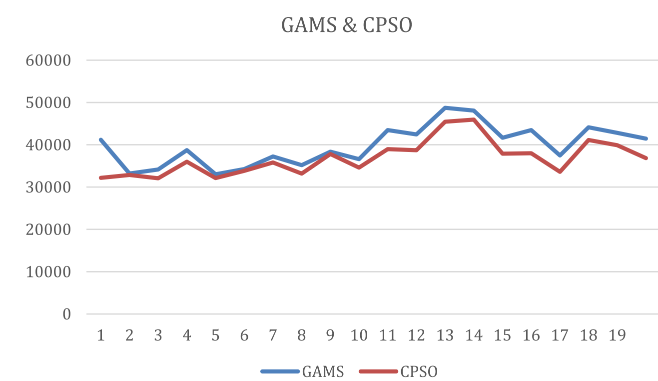

Fig. 8. Comparing the results between GAMS and CPSO.

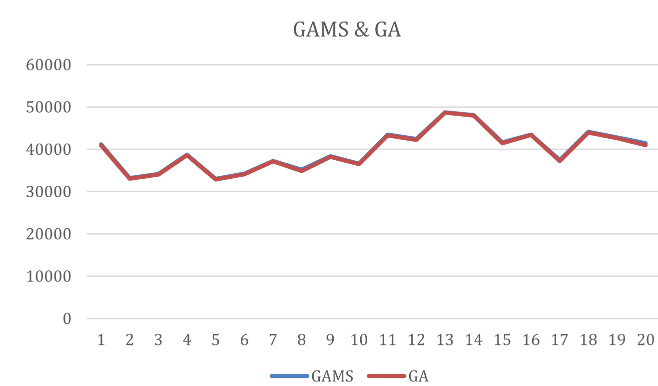

Fig. 9. Comparing the results between GAMS and GA.

accelerate toward other particles with higher eligibility criteria which are in the same communication (Eberhart & Kennedy, 1995; Shi & Eberhart, 1998).

Like other demographic algorithms, the PSO algorithm uses a set of possible responses that continue to move until an optimal response is found or the end condition of the algorithm is realized. In this method, each x solution is represented as a particle. Also, the velocity equation guarantees the movement of particles to the optimal region. This equation is usually based on three main elements which are:

- The*pbest* component: best particle status
- The *gbest* component: The best particle we ever had
- The velocity

In simulating this algorithm, the behavior of each particle can be influenced by the *Personal Best* (in a particular neighborhood, or the best condition it has had) or the *Global Best* particle (best particle

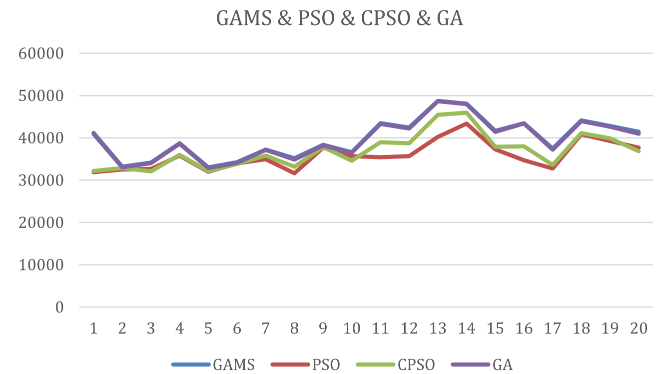

Fig. 10. Comparing the results between GAMS, PSO, CPSO and GA.

Table 6
Mean and standard deviation.

Meta-heuristics	PSO	CPSO	GA
Mean	9.55	7.18	0.47
Standard deviation	0.065	0.048	0.002

between all particles). With this definition, the following Fig. 4 can be represented:

Given the above Fig. 4. X_t is the old (current) state and $X_{t+1}$is the new (future) state of the particle. If we add the current velocity value to the current state, we will arrive at a new (future) state. The V_{t+1} future velocity is obtained from the random velocity of the three components, the current velocity V_t and the values of *Gbest* and *Pbest*. These values are measurable through the following equations:

$$P_{new} = P_{old} + V_{new} \tag{14}$$

$$V_{new} = V_{old} + C_1 * R_1 * (P_{localbest} - P_{old}) + C_2 * R_2 * (P_{globalbest} - P_{old}) \tag{15}$$

According to the above equations, C_1 and C_2 are constant and positive values, and R_1 and R_2 are random numbers that are generated normally in the interval [0, 1]. For a better search, a parameter called the weight of inertia W is shown below and is added as a coefficient in the algorithm's speed parameter:

$$V_{new} = W * V_{old} + C_1 * R_1 * (P_{localbest} - P_{old}) + C_2 * R_2 * (P_{globalbest} - P_{old}) \tag{16}$$

In this paper, we consider the following values by studying several articles for the mentioned parameters (He & Wang, 2007; Venter & Sobieszczanski-Sobieski, 2003):

$C_1 = C_2 = 2,\ R_1 = R_2 = 0.25,\ W = 0.5$

Initially, the particles are randomly assigned throughout the search space, which is also known as the best private particle experience (*Pbest*). In the next step, the best particle is selected among the particles and is recognized as the best answer (*Gbest*). Then, the particle group moves in the search area until the end conditions are met. This move involves applying the velocity equation to the particle group, which changes the position of each particle on the basis of it. The new fitting value obtained from the particle is compared to the particle *Pbest* value. If the new position of the particle has a better fit, this new position replaces the *Gbest* position, and the same procedure follows for *Gbest*.

- **CPSO co-evolutionary algorithm**

This algorithm utilizes two simultaneous processes that are indispensable in achieving the optimum solution. We follow two purposes to achieve an optimal solution in this algorithm; first to get the best answer and the next step if it is feasible. In fact, one process is responsible for finding the best solution and the other evolutionary process is responsible to find the feasible one. Since these two processes are conducted simultaneously, it is called coevolution process (He & Wang, 2007). In fact, this algorithm uses two swarm to adjust its parameters. First, internal swarm which is responsible for optimization and uses the PSO algorithm. Second, external swarm which is responsible for making the constraints feasible.

In this algorithm, an initial random population is generated using the upper and lower bounds. Then, the external swarm takes a certain value of an interval and the algorithm starts with the initial generated population. After that, the initial value is placed in the value of the objective function and constraints, and generates an initial solution. The value of this initial solution is optimally investigated in the inner swarm, and in the absence of optimality, a new value is generated using the velocity and position updating in the PSO algorithm. This cycle continues until the stoppage condition of the problem is met. Finally, the answer is stored within the initial swarm. In the next step, the external swarm value is increased one unit and the process described continues using new swarm. In this process, the algorithm tries not only to find the optimal solution but also to bind the problem constraints. The algorithm solving process flowchart is described as Fig. 5.

- **Genetic algorithm**

In computer science and operations research, a genetic algorithm (GA) is ~~a~~ meta-heuristically inspired by the process of natural selection that belongs to the larger class of evolutionary algorithms (EA). Genetic algorithms are commonly used to generate high-quality solutions to optimization and search problems by relying on bio-inspired operators such as mutation, crossover and selection (Mitchell, 1998; Sadeghi-Moghaddam, Hajiaghaei-Keshteli, & Mahmoodjanloo, 2019).

A genetic algorithm (GA) is a method for solving both constrained and unconstrained optimization problems based on a natural selection process that mimics biological evolution. The algorithm repeatedly modifies a population of individual solutions. At each step, the genetic algorithm randomly selects individuals from the current population and uses them as parents to produce the children for the next generation. Over successive generations, the population "evolves" toward an optimal solution (Goldberg & Holland, 1988; Hajiaghaei-Keshteli & Fathollahi-Fard, 2018). Fig. 6 shows the basic structure of genetic algorithm.

In this paper three practical metaheuristic methods alongside with the definite programming method GAMS have been proposed to find the optimal solution of the problem. The next section will study the computational results of applying these methods.

6.1. Computational results

In this paper, it is assumed that there are three buyers with five different time periods. The three buyers' requests are specified in five different time periods. To do this, we used the GAMS v24 software and its CPEX solver for exact answers and MATLAB R2013a software for coding the proposed GA, PSO and CPSO meta-heuristic methods.

In this paper, we utilized similar configuration for perishable products as in Diabat (2014). The parametric input data to initiate the proposed algorithms are depicted in Table 3. This table gives the related date considering one vendor and three buyers. To avoid complexity and repetition in five considered periods, the assumed data for the first buyer is displayed as follows:

Given the parameters of the problem, the final answer for 20 different problems is shown in Table 4.

It should be noted that the demand rate for each problem is showed by D.S.K.

The answers for example data collection of problem 2 is shown in Table 5:

In this paper, the Vendor Managed Inventory problem for perishable items in the two-echelon supply chain have been discussed. The problem modeling and the objective function is non-linear. Moreover, considering many constraints (the number of constraints depends on the defined scenario and can be varied in different problems) and model complexity, the problem structure is NP-hard. So, we not only used GAMS optimization software but also three meta-heuristic algorithms including PSO, GA and CPSO. The application results of these meta-heuristic algorithms show the proper answer of these methods. As it is presented in Table 3, the results show the small differences between meta-heuristic algorithms answers and GAMS solutions in multiple problems. In other cases, the difference is connivance due to the spent time for solving. The solution algorithms compared with deterministic methods are shown in the charts below:

The results presented in Figs. 7–10 show the deviations of meta-heuristic algorithms with GAMS definite answers. The GA algorithm could pass the PSO and even CPSO algorithms to find better and close to optimum answers. The reason is within the algorithm steps and right response for choosing good results and also mutation in each iteration of the algorithm. Finally, the GAMS optimization software presented the best answer for the problem.

The mean and standard deviation of meta-heuristic algorithms from GAMS optimization software are as follows (see Table 6):

The Table 5 shows that the results of GA algorithm are very close to definite answers of GAMS and the resolution process of GA is very similar to the definite resolution methods. In this respect, it is more efficient than other two PSO and CPSO algorithms for solving large-sized models.

7. Conclusion and future research

In this paper, Vendor Managed Inventory problem for perishable items in the two-echelon supply chain network was discussed. This supply chain consists of two parts; the vendor and the buyer. The objective function is to optimize the amount of sales in different periods. The problem is in the form of a non-linear programming model, and the two meta-heuristic algorithms, PSO and GA and one co-evolutionary method CPSO which has been used to solve it, as well as GAMS software Algorithm. Various examples were developed by PSO, CPSO, GA algorithms and the results of each approach showed slight deviation from the exact method GAMS, which shows the efficiency of the proposed algorithms. Also, the new co-evolutionary particle swarm optimization (CPSO) method shows proper answers compared with other approaches.

Various examples were generated and the answer obtained from an exact method was compared with the results of meta-heuristic methods. Results of meta-heuristic methods represent an appropriate answer. It has been observed that the exact methods have more optimal solutions. However, by using meta-heuristic algorithms, it can be possible to acquire a near-optimal solution in a very short time even considering multiple buyers in various periods. Another consideration is that the CPSO algorithm provides better solutions than PSO because of further reviews of the answers in each iteration. From the managerial prospective, Vendor Managed Inventory (VMI) policy can sufficiently reduce response time for the buyers and avoid delays when dealing with the perishable supply chain network. Also, VMI as a policy for a perishable supply chain can reduce the response time to multiple buyers' demand through a strong correlation among supply chain members and ensures the profitability of the chain by covering all demands and avoiding deterioration of the products.

Finally, GAMS optimization software presents more accurate and efficient solutions than other utilized algorithms. Therefore, the main objective has been met, which is to maximize the amount of profit from the sale of perishable items in different periods. It is suggested to use new solution approaches in meta-heuristics, such as hybrid algorithms or novel strategies used in the recent developed algorithms. Moreover, developed model can be applied to real case study such as dairy industry. In addition, to extend the mathematical model, other real-life practices such as vehicle routing problem and shortage constraints can be added to the problem.

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