A Multi-Item Inventory Control Model using Multi Objective Particle Swarm Optimization (MOPSO)

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Abstract

This study is about a multi item inventory control model which is developed to optimize the total inventory cost and inventory layout management. Prioritizing environmental pollution as an integral part of inventory management, equivalent carbon emission cost is also considered in the proposed inventory control model. Assuming limited number of orders where no shortage is allowed, the raw material inventory control model is designed. The objective of this study is to minimize the inventory cost by determining economic order quantity (EOQ) and to minimize the use of storage space for the inventory. In order to solve the nonlinear programming model, a metaheuristic algorithm named multi-objective particle swarm optimization (MOPSO) algorithm is proposed.

Keywords
Particle Swarm Optimization, Inventory Control, Metaheuristic Algorithm and Multi Objective Optimization.

1. Introduction

Effectiveness of inventory management is generally measured under the basis of responsiveness and cost. Both of these key concepts have different meanings in different stages of operation in an organization. In broader sense, inventory means finished goods or goods kept in different stages of production until goods are sold or converted into finished products. It can be located inside the organization's premise or at a different place supervised by a third party. According to Stevenson (2014) inventory can be classified into raw material, work in process and finished goods inventory. In this paper an inventory control model for raw material inventory is proposed. Most of the classical inventory control models are developed assuming that a single buyer purchase or store a single item. But nowadays this assumption does not hold as most of the companies are interested in purchasing multiple item at a time and attracting a wide range of customers. According to Lenard and Roy (1995) a multi-item model is often necessary, especially when the number of items is very large. This work showed that a large gap exists between theory and practice in inventory control and to solve this a multi-criteria approach was needed.

In day-to-day business operation selecting an economic order quantity (EOQ) and minimizing total space requirement is not easy. EOQ comes with many strategic decisions to be made in every phase of supply chain network like determination of ordering items and order quantities. Again, with the increasing awareness about environmental pollution, more rules and regulation are imposed on business organizations. Green purchasing and suppliers' environmental performance have become important issues to improve environmental sustainability. So, at present a multi-objective inventory optimization can make a significant contribution to an organization's profit as well as increase its return on total assets.

2. Literature Review

A substantial amount of work has already been done on multi-item inventory control model in different researches. A dynamic single stage multi-item inventory control model was proposed by Ould-Louly and Dolgui (2001) where the aim was to determine the average holding cost and stockout probabilities for the components considering a given service level for customer demands and lead time uncertainties. Using Lagrangian method a multi-item single source ordering problem was solved by Ertogral (2008) including transportation cost. But this work is limited by considering finite amount of demand. Lee and Kang (2008) developed a model for managing inventory of a product in multiple periods. Their model was first derived for one item and then was extended for several products.

For any manufacturing organization determination of economic order quantity (EOQ) and optimum stock levels is important in raw material management. Extensive amount of researches have been done on EOQ since the first introduction of this concept by Harris (1990) . Based on constant demand the square root formula of EOQ was developed in 1915. For a long time, inventory control model used this formula for effective planning. Silver and Meal (1969) modified the classical square root formula considering time varying demand instead of constant demand. Later an approximate heuristic solution also proposed by Silver (1973) considering discrete opportunity for replenishment. Donaldson (1977)examined the classical no shortage inventory policy for the case of linear trend in demand. Hayek and Salameh (2001) determined the optimal production quantity that minimizes the total inventory cost and maximize the profit for the finite production model under the effect of imperfect quality with shortage and backorder under the stochastic random variable. Chiu and Chiu (2006) studied optimal replenishment model for imperfect quality using EOQ determined by conventional approach of differential method. Taleizadeh et al. (2008) extended the EOQ model in a joint replenishment policy including holding cost, fixed order cost, insurance cost, transportation cost and capital cost.

Besides a single objective, multiple item inventory control problems often consist of multiple conflicting objectives. Roy and Maiti (1998) presented a multi-objective inventory model of deteriorating items with stock-dependent demand under limited imprecise storage area and total cost budget. Taleizadeh et al. (2009) developed a hybrid method of Pareto, TOPSIS and genetic algorithm to optimize multi-product multi-constraint inventory control systems considering both continuous review and periodic review with fuzzy replenishments and fuzzy demand. Again, quantity of different materials that can be stored in the plant is limited by storage capacity and size of the material. Pasandideh et al. (2013) investigated a bi-objective economic production quantity problem for defective items using non dominated sorting genetic algorithm and multi objective particle swarm optimization. The problem was formulated as a multi-objective nonlinear programming model, where the goal was to find the order quantities of the product so that both the total inventory cost and the required warehouse space are minimized. Mousavi et al. (2014) developed a multi-item multi-period inventory control model for known-deterministic variable demands under limited available budget. A weighted combination was shown as objective function and the target was to minimize both the total inventory cost and required warehouse space. In recent literatures incorporating environmental performance into inventory control has been recommended and several models have been suggested. The present research prioritizes environmental pollution as an integral part of inventory management and carbon emission cost is considered equivalently in total cost function.

Many metaheuristic nature inspired algorithms have been developed over the years to solve various inventory related multi-objective optimization problem like- genetic algorithm (Taleizadeh et al. 2010; Pasandideh et al. 2014), ant colony optimization (Dorigo et al., 2008), bat algorithm (X. S. Yang 2012), cuckoo search (Yildiz, 2013), firefly algorithm (X. S. Yang, 2013) and etc. Particle swarm optimization (PSO) is another metaheuristic algorithm for solving global optimization problem. It's a nature inspired algorithm which is developed by Kennedy and Eberhart (1997) analyzing social behavior of flock of birds. Park and Kyung (2014) employed PSO to suggest a method for optimizing the total inventory cost and the order fill rate by determining the initial inventory condition, and reflecting information quality level. As the complexity of controlling inventory is increasing day by day, need for multi-objective optimization arises. PSO is enough for solving single objective optimization problem but to solve a problem consisting multiple conflicting objective a modification is required. In 2002, a successful conversion of PSO to multi-objective PSO (MOPSO) was proposed by Coello Coello and Lechuga (2002). They extend the general PSO approach to deal with constrained multi-objective optimization problems. Tsou (2008) was the first to apply PSO to the multi-objective inventory planning problems to generate the non-dominated solutions of order size and safety stock in a multi-objective inventory controlling model. Mousavi et.al (2014) used MOPSO to solve a bi-objective multi-item multi-period inventory planning problem with total available budget under all unit discount and incremental quantity discount. To perfectly model inventory related optimization inventory cost, space and shortage are also important considerations. Tavana (2016) evaluated a bi-objective inventory optimization problem under inflation and discount. The goal of this work to and Pareto optimal solution in different periods and minimize total inventory cost as well as total storage space, simultaneously. NSGA-II along with non-dominated ranked genetic algorithm (NRGA), and multi-objective particle swarm optimization (MOPSO) were proposed to solve the problem.

Metaheuristic algorithms are sensitive to the value of parameters. In this regard, Taguchi method can be applied to tune the level of parameter to get near optimal solution. Both the work of Mousavi (2014) and Tavana (2016) used Taguchi L_9 approach to improve the quality of solution.

Inspired from previous researches a weekly periodic multi-item inventory control model is proposed considering single supplier single buyer relation with shortage and constant demand for different items. In order to apply the model in close to reality problem a limited budget, order capacity, truck space and warehouse space constraint is also included. To create a kind of green model equivalent cost of greenhouse gas (GHG) emissions and limitation on total emissions of all items are considered in the model. However, a Pareto-based multi-objective metaheuristic algorithms MOPSO is employed to find near optimum solution for different items so that total inventory cost and warehouse space is minimized. The proposed multi-objective inventory model can be used in situations in which purchasing managers desire to purchase multiple product that requires an extended storage space to locate their purchased items with limited budget. For efficient control on inventory, they must consider shortage, truck capacity and other realistic limitations.

In short, the highlights of this study are developing raw material inventory control model for multiple item under shortage with limited budget, developing a mathematical formulation for obtaining economic ordering quantity (EOQ), considering greenhouse gas (GHG) emissions cost in total inventory cost and limitation on total emissions of all items to make a kind of green supply chain and analyzing the results obtained for optimum level of parameters from Taguchi L_9 design.

The remainder of this paper is organized as follows: In Section 3, the problem is stated along with the notations and assumptions. In Section 4, the problem is formulated in a nonlinear programming model. The solution algorithm MOPSO is introduced in Section 5 to solve the problem. Section 6 provides experimental results along with analysis. Conclusion and recommendations for future works are given in Section 7.

3. Problem Definition, Assumptions and Notations

Considering a periodic inventory control model for single provider having constant and distinct demand of items. Raw materials are supplied from a single supplier using third party logistic (3PL) service to the buyer in a single period. The costs associated with the inventory control system are holding, ordering and transportation costs. Several items are considered here with real life constraints like warehouse space, order capacity and budget constraints. To prioritize environmental pollution as an integral part of proposed inventory model. Tax cost of greenhouse gas (GHG) emissions and limitation on total emissions of all items are included. Furthermore, the lead-time is assumed zero, and the decision variables are integer digits. The assumptions of this study are inspired from previous researches (Mousavi et al. 2014; Roozbeh Nia et al. 2015). The goal is to identify the inventory levels of the items and required warehouse space, such that the total inventory cost is minimized.

3.1 Assumptions

- Independent demand rate of items
- Demand rate is constant in each period.
- Same cartons or pallet boxes are used for different items. Thus order quantities must be a multiple of a fixed-sized batch.
- All truck has same capacity.
- No volume discount.
- Holding, Ordering and Shortage costs are considered.

3.2 Notations

The following parameters are decision variables used for items $i = 1, 2, \ldots\ldots\ldots\ldots, n$.
n: number of items to be purchased
Q_i: order quantity of the ith item (decision variable)
D_i: annual demand of the ith item
S_i: ordering cost per ordering an item
H_i: unit inventory holding cost for item i

I_i: shortage level of the *i*th item
E: Green House Gas (GHG) emission level
C_t: fixed emission tax cost
P_i : Number of carton or pallet boxes for an order of item *i*
C_p: truck capacity
A_i: required storage space per unit of the *i*th item
F: total available warehouse space
T_i: shipping cost per unit of demand
U_e: upper bound on total GHG emission
L_i: annual per-unit cost of shortages of the *i*th item
B_i: purchasing cost per unit of item
M: total budget

Based on the above assumptions and notations, the mathematical model of the problem is derived in the next section.

4. Mathematical Model Formulation

4.1 Objective Functions

The first objective function of the problem, the total inventory cost, is obtained as

$$Z_1 = \text{Total Inventory Cost} \tag{1}$$

$$= \text{Total Ordering Cost} + \text{Total Holding Cost} + \text{Total Shortage Cost}$$

$$+ \text{Total Carbon Emission Cost} + \text{Total Transportation Cost}$$

where each part is derived as follows.

$$\text{Total Ordering Cost, OC} = \sum_{i=1}^{n} \frac{D_i}{Q_i} S_i \tag{2}$$

$$\text{Total Holding Cost, HC} = \sum_{i=1}^{n} \frac{H_i}{2Q_i} (Q_i - I_i)^2 \tag{3}$$

$$\text{Total Shoratge Cost, SC} = \sum_{i=1}^{n} \frac{L_i}{2Q_i} {I_i}^2 \tag{4}$$

$$\text{Total Carbon Emission Cost, TE} = \sum_{i=1}^{n} E D_i C_t \tag{5}$$

$$\text{Total Transportation Cost, TC} = \sum_{i=1}^{n} D_i T_i \tag{6}$$

So the 1st objective of this problem is as follows.

$$Z_1 = \sum_{i=1}^{n} \frac{D_i}{Q_i} S_i \ + \ \frac{H_i}{2Q_i} (Q_i - I_i)^2 + \frac{L_i}{2Q_i} {I_i}^2 + E D_i C_t + \ D_i T_i \tag{7}$$

2nd objective of this problem is to minimize the warehouse space required. That is:

$$Z_2 = \sum_{i=1}^{n} (Q_i - I_i)\, A_i \tag{8}$$

4.2 The Constraints

There are four non-equality constraints and some non-negativity constraints.
Carbon emission has an upper limit above which tax cost becomes higher (Roozbeh Nia et al., 2015):

$$\sum_{i=1}^{n} E \le U_e \tag{9}$$

Since the total available budget is M and purchasing cost per unit is B_i, budget constraint is given below (Mousavi et al., 2014):

$$\sum_{i=1}^{n} B_i Q_i \le M \tag{10}$$

Order capacity have some limitations:

$$\frac{D_i}{Q_i} \le C_p \tag{11}$$

Warehouse have some space constraints:

$$\sum_{i=1}^{n} A_i Q_i \le F \tag{12}$$

Non-negativity constraints are:

$$Q_{i,} P_{i,} I_{i,} > 0 \tag{13}$$

Where, *i = 1, 2, ……………, n;* where n is the number of items.

4.3 Final Model

Final mathematical model of the total inventory control is to

$$\text{Minimize,} \quad TOF = \omega Z_1 + (1-\omega) Z_2 \tag{14}$$

Where,

$$Z_1 = \sum_{i=1}^{n} \frac{D_i}{Q_i} S_i + \frac{H_i}{2Q_i}(Q_i - I_i)^2 + \frac{L_i}{2Q_i} {I_i}^2 + E D_i C_t + D_i T_i$$

$$Z_2 = \sum_{i=1}^{n} (Q_i - I_i)\, A_i$$

Subject to,

$$\sum_{i=1}^{n} E \le U_e$$

$$\sum_{i=1}^{n} B_i Q_i \le M$$

$$\frac{D_i}{Q_i} \leq C_p$$

$$\sum_{i=1}^{n} A_i Q_i \leq F$$

$$Q_{i,} P_{i,} I_{i,} > 0$$

Where, *i = 1, 2, ……………, n;* where n is the number of items.

5. The Proposed Algorithm

In this research a modified version of PSO algorithm named multi-objective particle swarm optimization (MOPSO) is used. The purpose of using this algorithm is its simplicity. It is easy to implement and has the ability to deal with multiple conflicting objectives.

5.1 Multi Objective Particle Swarm Optimization (MOPSO)

In order to solve multi objective optimization problem, PSO needs some modifications. The first one is not to find one "global best" solution, but a set of solutions comprising the Pareto Front. After that an archive of non-dominated solutions is to kept, where all non-dominated solutions found at each iteration are stored. Inspired by the work of Coello Coello and Lechuga (2002), the detailed formulation is as follows.

5.2 Swarm Initialization

For particle *i*, position vector is x_i, which is a member of search space X where, $x_i(t) \in X$. Here, *t* is the time index to distinguish between discrete time steps and it shows the iteration number of the algorithm. Every particles in the swarm have velocity denoted by $v_i(t)$ which is a vector and belongs to the same space.

By interacting and learning from each other, every particle find their personal best denoted by $p_i(t)$ called the local best solution. There is a common best experience among the members of the swarm denoted by *g(t)* called the global best solution.

5.3 Mathematical model of motion

Initial position of the particle i is $x_i(t)$ and velocity is $v_i(t)$. Particles move toward the personal best and then to the global best and gain an updated position denoted by $x_i(t+1)$ and the addition of these beginning and end vector has an velocity of $v_i(t+1)$. So the equation for the position is-

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{15}$$

where,

$$v_i(t+1) = wv_i(t) + C_1\big(p_i(t) - x_i(t)\big) + C_2\big(g(t) - x_i(t)\big) \tag{16}$$

A simplified approach is used to standardize the PSO equation and that is-

$$v_i(t+1) = wv_i(t) + C_1 r_1 \left(x_{pbesti} - x_i(t)\right) + C_2 r_2 \left(x_{gbest} - x_i(t)\right) \tag{17}$$

where,

$w =$ inertia coefficient
$C_1, C_2 =$ accleration coefficients
$r_1, r_2 \in (0,1)$

Pseudocode of MOPSO (Mousavi et al., 2014) algorithm is as follows.

```
for i = 1 to Pop
    initialize position (i)
    initialize velocity (i)
    if position (i) and velocity (i) be a feasible candidate solution
        penalty = 0
    else penalty = a positive number
    end if
end for
w = [0.4, 0.9]
do while Iter <= Gen
    for j = 1 to Pop
        Calculate new velocity of the particle
        Calculate new position of the particle
        pbest (iter) = min (pbest(i))
    end for
    gbest (iter) = min (gbest)
    w = w_max – ((w_max - w_min)/iter_max) × iter
    modifying the velocity and position of the particle
end while
```

Pseudocode 1: Pseudocode of MOPSO algorithm

6. Results and Analysis

To find near-optimum solution MOPSO algorithm is coded in MATLAB 15a. The obtained Pareto front is presented in Figure 1. The parameter values are presented in Table 1. The outcomes of this solution process are- Pareto front of all local optimum solutions, optimum solution for both objectives and related parameter values, total elapsed time to reach solution and mathematical formulation of EOQ for raw material inventory control.

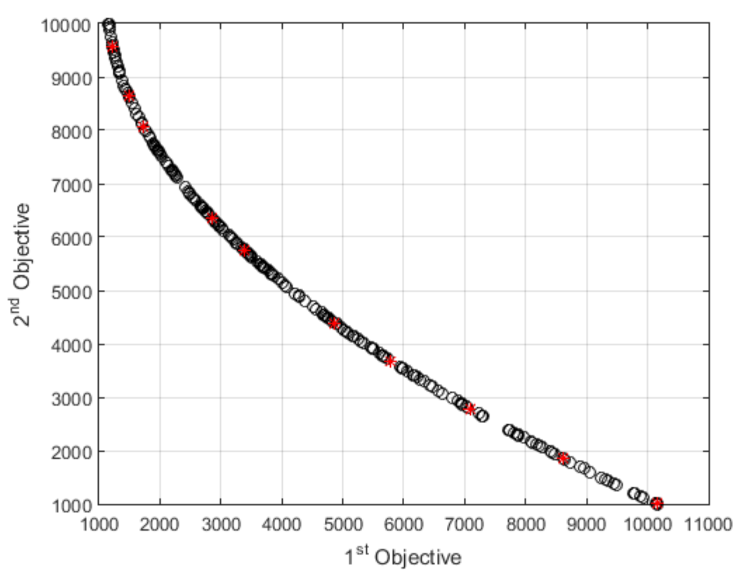

Figure 1: Pareto front of MOPSO

Table 1: Parameter values of MOPSO Pareto front

Iteration No.	C_1	C_2	Pop	Rep	1st Objective	2nd Objective	Elapsed time
200	2.5	1.5	300	10	10160	1000	44.625 s

From equation (7),

$$TC = \frac{D_i}{Q_i}S_i + \frac{H_i}{2Q_i}(Q_i - I_i)^2 + \frac{L_i}{2Q_i}{I_i}^2 + ED_iC_t + D_iT_i$$

Differentiating by Q, we get the equation of economic quantity to order for keeping raw material inventory. Thus,

$$EOQ = \sqrt{\frac{2DS}{H} + \frac{LI^2}{H} + I^2} \tag{18}$$

After choosing four factors for the algorithm, three level of value is selected for each factor based on parameter values of the algorithm from Table 1 in order to implement Taguchi L_9 design. These factors and their levels are shown in Table 2. As a result, nine different combinations of parameter value shown in Table 3 and S/N ratio for parameter levels are obtained using Minitab 18. At the end, from the mean S/N ratio plot shown in Figure 2 the optimal level of parameters' value is chosen along with their optimal values of the algorithm which are shown in Table 4.

Table 2: Parameters of MOPSO algorithm and their levels

Algorithms	Factors	Levels [1 2 3]
MOPSO	C_1 C_2 Pop Rep	[1.5 2 2.5] [1.5 2 2.5] [100 200 300] [10 30 50]

Table 3: Taguchi L_9 design along with their objective values

Run No.	A	B	C	D	MOPSO
1	1	1	1	1	10273
2	1	2	2	2	10155
3	1	3	3	3	10253
4	2	1	2	3	10156
5	2	2	3	1	10225
6	2	3	1	2	10163
7	3	1	3	2	10356
8	3	2	1	3	10250
9	3	3	2	1	10192

Table 4: The optimal levels of the algorithms' parameters

Algorithms	Factors	Optimal Levels	Optimal Values
MOPSO	C_1 C_2 Pop Rep	2.5 1.5 300 10	10160

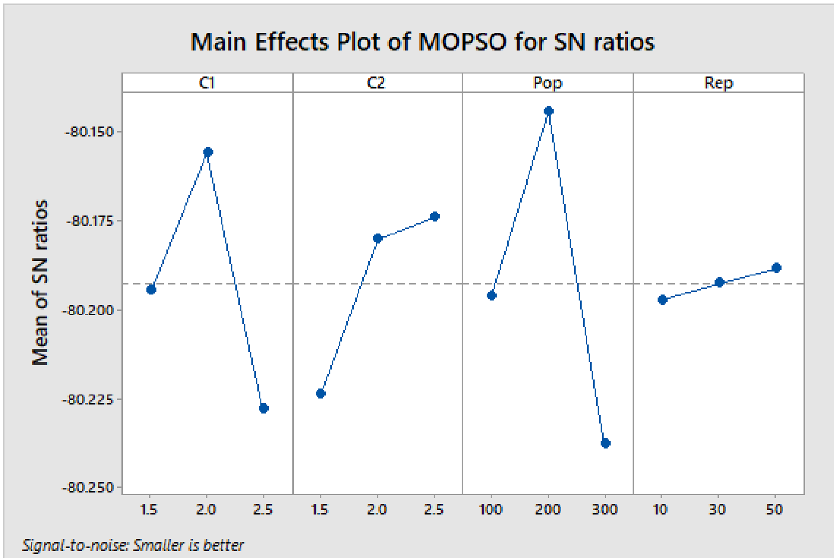

Figure 2: The mean S/N ratio plot for parameter levels of MOPSO

The results obtained with the optimal level of parameters and the one with Pareto front of MATLAB formulation show no difference. It means that MOPSO is capable of finding best result for the proposed inventory control model.

7. Conclusion and recommendation for future work

In this paper a multi-item inventory control problem with limited budget was investigated with the goals of minimizing both the total inventory cost and total required storage space. Independent demand rates of items with shortage considering no volume discount. The aim was to determine optimal order quantity such that objective function is minimized and constraints hold. The developed nonlinear programming model was solved by Pareto based multi-objective particle swarm optimization algorithm. Taguchi L_9 design was applied to calibrate the parameters of the algorithm and the combination that best suited to the objective was chosen.

Some recommendations for future work are to develop a probabilistic model using fuzzy and stochastic demand, to consider volume discount, lead time uncertainty, defective items, inflation and time value of money and other performance metrics and to apply recently developed meta-heuristic nature inspired algorithms to solve the problem.

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