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Raw Material Inventory Control Model for RMG with Shortage Prediction using Nature Inspired Algorithm

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Abstract

Inventory control management is one of the most important tasks in RMG industry for optimizing lead time, production time, total inventory cost and storage space and buyer-supplier relationship. This research is about optimizing the total inventory cost and inventory layout management by controlling the inventory model and determining the economic order quantity (EOQ). Assuming deterministic demand, the raw material inventory control model is designed. In order to solve the nonlinear inventory control model, a metaheuristic nature inspired algorithm named multi-objective particle swarm optimization (MOPSO) algorithm is proposed. Raw material shortage is predicted using support vector regression (SVR), in order to meet the production demand before deadline.

Keywords

Ready Made Garment Industry, Particle Swarm Optimization, Inventory Control, Metaheuristic Nature Inspired Algorithm, Multi-objective Optimization. *Mushaer Ahmed.

1. Introduction

The readymade garments (RMG) industry of Bangladesh contributes almost 84% of total export of $36.66 billion to date. Feature wise the export oriented RMG industry of Bangladesh is quite different from other industries (Hasan, 2017). Wage, Supply chain, Time-frame, Procurement and Compliances are among the most important features of this business. All these five features are correlated to each other in many aspects. To meet the short delivery time and to minimize stock level and wastage, to reduce an extra load on finance and to gain customer satisfaction there is no alternative than an effective supply chain management (SCM) system in place. Inventory management plays a big role in apparel manufacturing organization in order to meet deadline and reduce extra inventory cost that comes with excessive tardiness.

Effectiveness of inventory management is generally evaluated by trading off two conflicting objectives – maximizing responsiveness and minimizing cost. Controlling both comes handy with respect to RMG factory especially for a fast growing market comprising large number of competitors like Bangladesh. Most of these RMG factories handle multiple orders at a time. For each style various items have to be procured simultaneously from different buyers. So classical single buyer- single supplier inventory control doesn't hold much importance here. Inventory control management in real practice is quite different from its theoretical aspect. In this regard a multi-criteria approach makes more sense especially when the number of items is very large.

Economic order quantity (EOQ) is an important element of pre costing before starting bulk production. Procurement of each raw material and accessories require perfect estimation in order to achieve the desired profit margin. It comes with the possibility of unwanted shortage and delay in production. So to incorporate proper costing allowance not only respective manager's experience but also a quantitative model is much needed. In this paper an inventory control model for raw material inventory is proposed considering multiple conflicting objective with shortage prediction.

2. Literature Review

Cost reduction and profit maximization of raw material inventory can be ensured with the help of effective planning and efficient management. Modeling of this inventory control management had been a research interest among industrial engineers for a long time. Agrell (1995) proposed a multi-criteria framework for inventory control problem, in which the solution procedure was IDEM to determine batch size and security stock. To determine the average holding cost and stock out probabilities with lead time uncertainties, a dynamic single stage multi-item inventory control model was proposed by Ould-Louly and Dolgui (2001). A multi item single source ordering problem was solved by Ertogral (2008) including transportation cost based on Lagrangian method. Lee & 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. Similar to the evaluation of multiple item model, multi-objective models got the interest of researchers. Roy & Maiti (1998) presented multi-item inventory models of deteriorating items with the objectives of maximizing the profit and minimizing the wastage cost in a fuzzy environment. But they didn't consider any shortage, (Pasandideh et al. (2013)investigated a bi-objective economic production quantity problem for defective items 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. With the same objectives, Mousavi et al. (2014) developed a multi-item multi-period inventory control model for known-deterministic demand under budget limitation

For any apparel manufacturer determination of economic order quantity (EOQ) and optimum stock levels is important in raw material management. The basic model of EOQ was first conceptualized by Harris (1990) which paved the way for further researches .The popular square root formula of EOQ was developed in 1915 and a lot of inventory models were developed applying this. Considering time varying demand instead of constant demand, Silver & Meal (1969) modified the classical square root formula. Goyal (1988) introduced the inventory replenishment policy for an item having a deterministic demand pattern with a linear (positive) trend and shortages. After that lots of researches had been done economic ordering policy for perishable goods. Like, Xu and Wang (1990) developed a deterministic inventory model for deteriorating items with time proportional demand along with a numerical example. Hayek and Salameh (2001) measured EOQ taking imperfect items in consideration with backorder and shortage. Taleizadeh et al. (2008) extended the EOQ model in a joint replenishment policy considering holding cost, fixed order cost, insurance cost, transportation cost and capital cost. In this research a deterministic total inventory cost model has been formulated considering holding, ordering and shortage costs and from that model EOQ had been determined using differential approach.

To optimize solution by searching in large search space a number of nature inspired metaheuristic algorithms have been proposed. Particle swarm optimization (PSO) is one of the metaheuristic algorithms for solving global optimization problem. Kennedy and Eberhart (1997) developed this algorithm by analyzing social behavior of flock of birds or fishes. Since then many researchers worked with this algorithm to solve inventory related optimization problems. Like Taleizadeh et al. (2009) solved a single buyer- single vendor problem using a PSO approach in which the demand is stochastic and the lead time is assumed to vary linearly with respect to the lot size. PSO is enough for solving single objective optimization problem but to solve a problem consisting multiple conflicting objective a modification is required. In early 2000, Coello Coello & Lechuga (2002) proposed a new approach named multi-objective particle swarm optimization (MOPSO) which was a constrained multi-objective formulation of PSO.

To meet the desirable demand of customer with minimum cost or budget most of the real life inventory problem could be recast in to a multi-objective optimization problem. Tsou (2008) developed such a model and applied MOPSO to build the Pareto front of non-dominated solutions and sorted them using technique for order preference by similarity to ideal solution (TOPSIS) by the preference of decision makers. Mousavi et al. (2014) used MOPSO to solve a multi-item multi-period inventory planning model with known deterministic demand under limited budget. Storage space is another important decision comes with inventory management as the decision to keep more inventory and storage space requirement have contradictory objective with respect to cost. Tavana (2016) evaluated an inventory optimization problem with the objective to find Pareto optimal solution in different periods and minimize total inventory cost as well as total storage space, simultaneously. As all these proposed algorithms are very much parameter sensitive, Taguchi method was used in this model to tune the level of parameter and model response variable. This method also has the advantage of giving near optimum solution.

Shortage forecasting in RMG has been a challenging issue for decades. With continuously changing order, style, fashion and limitation of historical data make it more difficult to predict; mostly for small size apparel manufacturers. Traditional forecasting methods have many limitations and also reduces competitive advantages. An unconventional approach like support vector machine theory based on structural risk minimization (SRM) can be a better solution to this problem. The theory has originally been developed by Vapnik and his co-workers on a basis of a separable bipartition problem at the AT and T Bell Laboratories (Vapnik 1963). A version of a SVM for regression has been proposed in 1997 by Vapnik et al. (1997). This method is called support vector regression (SVR). An overview of the basic ideas underlying support vector (SV) machines for regression and function estimation has been given by Smola & Schölkopf (2004) saying that the model produced by support vector classification only depends on a subset of the training data. SVM can be used in circumstance with few observations in a forecasting process, and construct nonlinear mapping relationship between the factors and demand series. Thus, it is convenient to overcome the limitations of traditional methods. The proposed multi-objective inventory model can be useful in situation when procurement department in any garments manufacturer decides to purchase raw materials which require extra storage space but the budget is fixed. To perfectly model this type of inventory controlling scenario shortage cost, truck capacity and other realistic limitations must be considered.

The rest of this paper is structured as follows: In Section 3, the problem is explained along with the necessary notations and assumptions. In Section 4, the problem is formulated. The solution algorithm is demonstrated in Section 5. Section 6 provides results and analysis with shortage prediction method. At last, conclusion and recommendations for future works are given in Section 7.

3. Problem Definition, Assumptions and Notations

Inventory control management is one of the most important and challenging tasks in RMG industry. Considering a RMG industry, where deterministic demand is followed and raw material is supplied form different buyer demand. The costs associated with the inventory control system are mainly holding and ordering costs. Shortage cost is considered where economic quantity is not maintained during order. Several items are considered here with real life constraints like warehouse space, order capacity and budget constraints. Here zero lead-time is assumed, as raw material is always purchased from a fixed supplier in a continual basis. The assumptions of this study are inspired from the work of Roozbeh Nia (2015) and the decision variables are integer digits. The goal is to identify the optimum level of inventory and required warehouse space, where total inventory cost is minimized as a whole.

3.1 Assumptions

Deterministic demand of the garments.
Multiple production demands are considered.
Production process run by batches or in lot.
No volume discount is considered.
Holding, Ordering and Shortage costs are considered.

3.2 Notations

The following parameters are decision variables used for items *i = 1, 2, ……………, n.*
n: number of items to be purchased annually
Q_i order quantity of the *i*th items (decision variable)
D_i annual demand of the *i*th items
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
C_p order capacity
A_i required storage space per unit of the *i*th item
F: total available warehouse space
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.

& Mathematical Model Formulation

1 Objective Functions

Total inventory cost is the 1st objective function of this model which can be obtained as

Z_1 = Total Inventory Cost (1)

Total Ordering Cost + Total Holding Cost + Total Shortage Cost where each part is derived as follows.

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

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

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

Thus, $Z_1 = \sum_{i=1}^{n} \frac{D_i}{Q_i} S_i + \frac{H_i}{2Q_i}(Q_i - I_i)^2 + \frac{L_i}{2Q_i} {I_i}^2$ (5)

2nd objective function has been derived to minimize warehouse space requirement, which is:

$$Z_2 = \sum_{i=1}^{n} (Q_i - I_i) A_i \quad (6)$$

4.2 The Constraints

There are three non-equality constraints and two non-negativity constraints.
Total budget has some constraint which should be considered. (Mousavi, Niaki, Bahreininejad, & Musa, 2014):

$$\sum_{i=1}^{n} B_i Q_i \leq M \tag{7}$$

There are some limitations in the order capacity:

$$\frac{D_i}{Q_i} \leq C_p \tag{8}$$

Storage space constraint:

$$\sum_{i=1}^{n} A_i Q_i \leq F \tag{9}$$

Non-negativity constraints are:

$$Q_{i,} I_{i,} > 0 \tag{10}$$

Where, *i = 1, 2, ……………, n;* where n is the number of items and decision variables are Q_i and I_i.

4.3 Final Model

Final mathematical model of the total inventory control is to

Minimize, $$TOF = \omega Z_1 + (1-\omega) Z_2 \tag{11}$$

Where,

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

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

Subject to,

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

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

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

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

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)

Two modifications are required to use PSO for solving multi objective optimization problems. The main target is not to find one "global best" solution, but a set of solutions comprising the Pareto Front. After archiving all the solutions, they can be found at each iteration are stored. Inspired by the work of Coello Coello & Lechuga (2002), the detailed formulation is as follows.

Initial position of the particle *i* is $x_i(t)$. In the search space particles interact with each other and after learning their position, particles increase their velocity, $v_i(t)$ to find the best solution for the problem. Local best solution or $p_i(t)$ is the personal best position for each article which is obtained by updating the position by $x_i(t+1)$ and end vector has an velocity of $v_i(t+1)$.

There is a common best experience among the members of the swarm denoted by *g(t)* called the global best solution. So the equation for the position is-

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{12}$$

where,

$$v_i(t+1) = wv_i(t) + C_1\big(p_i(t) - x_i(t)\big) + C_2\big(g(t) - x_i(t)\big) \tag{13}$$

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

$$v_i(t+1) = wv_i(t) + C_1 r_1\left(x_{pbesti} - x_i(t)\right) + C_2 r_2\left(x_{gbest} - x_i(t)\right) \tag{14}$$

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 = wmax – ((wmax - wmin)/iter_max) × iter
    modifying the velocity and position of the particle
end while
```

Pseudocode 1. Pseudocode of MOPSO algorithm

6. Results and Analysis

MOPSO algorithm is coded in MATLAB 15a in order to fine the near optimal solution. 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.

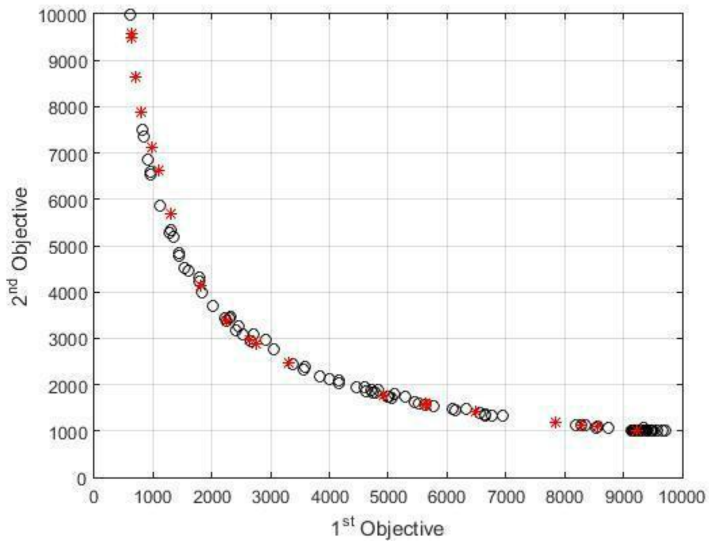

Figure 1. Pareto front of MOPSO

Table 1. Parameter values of MOPSO Pareto front

Iteration No.	C_1	C_2	Pop	Rep	1st Objective	2nd Objective	Elapsed time
100	1.5	2	100	20	9160	999	17.7 s

From equation (7),

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

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

$$EOQ = \sqrt{\frac{2DS}{H} + \frac{LI^2}{H} + I^2} \tag{15}$$

In order to tune the parameters used to solve the problem, Taguchi L_9 design is used. For implementing Taguchi L_9 design, at first four factors for the algorithm is chosen and then three level of value is selected for each factor based on parameter values of the algorithm from Table 1. 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 last, 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] [100 150 200] [10 20 30]

Table 3. Taguchi L_9 design along with their objective values

Run No.	A	B	C	D	MOPSO
1	1	1	1	1	9348
2	1	2	2	2	9625
3	1	3	3	3	9181
4	2	1	2	3	9568
5	2	2	3	1	9217
6	2	3	1	2	9153
7	3	1	3	2	9126
8	3	2	1	3	9521
9	3	3	2	1	9758

Table 4. The optimal levels of the algorithms' parameters

Algorithms	**Factors**	**Optimal Levels**	**Optimal Values**
MOPSO	C_1 C_2 Pop Rep	1.5 2 100 20	9160

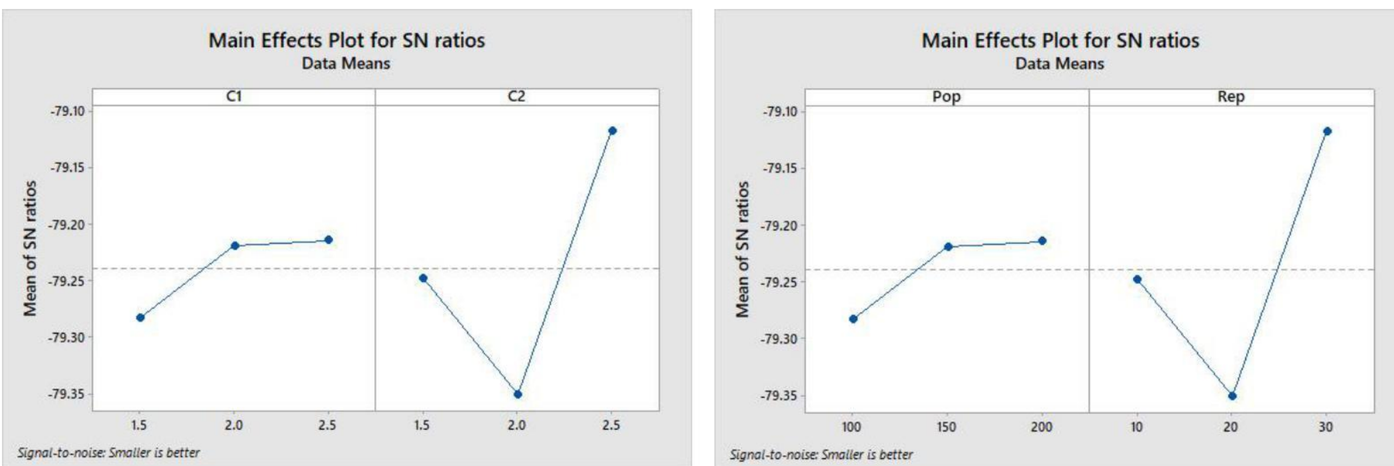

Figure 2. The mean S/N ratio plot for parameter levels of MOPSO

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. In order to predict the shortage in raw material inventory, support vector regression is used. Using Regression learner app in MATLAB 18, shortage is predicted and the graph is shown in figure 3.

6.1 Shortage prediction using SVR

MATLAB 2018b is used to import a large number of pre-costing data to predict shortage quantity for raw material inventory. All these data are taken from Fiat Fashion Limited located in Gazipur, Bangladesh. The minimization problem is expressed in standard quadratic programming form and solved using quadratic SVM technique (Scholkopf et al. 1997). MATLAB Regression Learner App is used in this regard to select predictor variables, response variables and validation. In this study, response variable is shortage level. 5-fold cross-validation is applied to increase model performance on new data and choose best model. The model is trained into all six SVM regression model type and among them quadratic model gives the lowest root mean square error (RMSE) value. Again, efficiency of prediction is quite good for both model as it is seen from the predicted response vs true response plotting shown in Figure 4.

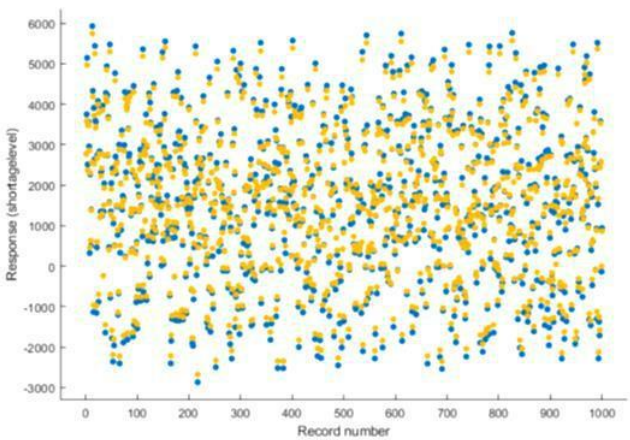

Figure 3. Shortage prediction plot using Quadratic SVR (Yellow dot- record number and blue dot- response)

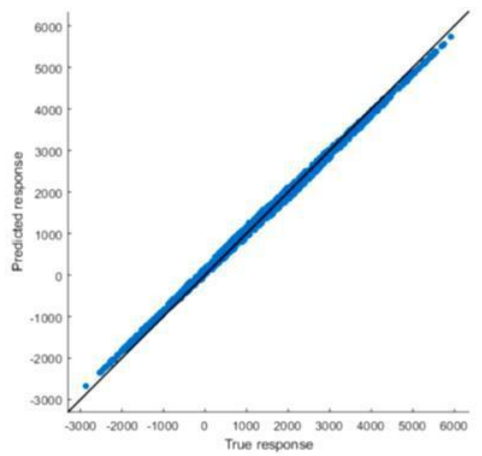

Figure 4. Efficiency of prediction: Predicted response vs true response for raw material inventory

8. Conclusion and recommendation for future work

In this research a multi-item raw material inventory control model was designed 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 where budget was limited. 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. At last shortage in raw material inventory was predicted using support vector regression.

Some recommendations for future work are to develop a probabilistic model using fluctuating demand, to consider green manufacturing, volume discount, lead time uncertainty, multiple supplier selection, 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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9. Biography

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