

# Multi Objective Optimization for Electronic Component Inventory Model & Deteriorating Items with Two-warehouse using Genetic Algorithm

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## ABSTRACT

In his paper a deterministic two warehouse Electronic component inventory model for deteriorating items, time-dependent demand, variable holding cost and vector evaluated genetic algorithm has been developed under assumption that the Electronic component inventory cost including time-dependent demand, holding cost, vector evaluated genetic algorithm and deterioration cost in Rented Warehouse is higher than those in Owned Warehouse due to better preservation facilities in RW. Also considering equal deterioration in both warehouses has been discussed as a special case of the model with other cases as well. The demand and holding cost, both are taken as time dependent and vector evaluated genetic algorithm.

**Keywords:** electronic component inventory, two warehouses, deterioration, time-dependent demand, variable holding cost, vector evaluated genetic algorithm

## I. INTRODUCTION

Basically Electronic component inventory management and control system deals with demand and supply chain problems. The business is totally based on demand and supply of goods either finished or raw materials. To fulfil the demand of consumer or supplier, it is necessary to have the items demanded at any time and for same purpose the sufficient space is required to stock the goods to fulfil the demands. The space used to stock the goods is termed as ware-house. In the traditional models it is assumed that the demand and holding cost are constant and goods are supplied instantly under infinite replenishment policy, when demanded but as time passed away many researchers considered that demand may vary with time, due to price and on the basis of other factors and holding cost also may vary with time and depending on other factors. Many models have been developed considering various time dependent demand with shortages and without shortage. All those models that consider demand variation in response to Electronic component inventory level, assume that the holding cost is constant for the entire Electronic component inventory cycle. In studies of Electronic component inventory models, unlimited warehouse capacity is often assumed. However, in busy marketplaces, such as super markets, corporation markets etc. the storage area for items may be limited. Another case, of inadequate storage area, can occur when a procurement of a large amount of items is decided. That could be due to, an attractive price discount for bulk purchase which is available or, when the cost of procuring goods is higher than the other Electronic component inventory related costs or, when demand for items is very high or, when the item under consideration is a seasonal product such as

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the yield of a harvest or, when there are some problems in frequent procurement. In this case these items cannot be accommodated in the existing store house known as own ware house.

### Genetic algorithms

Genetic algorithms are very different from most of the traditional optimization methods. Genetic algorithms need design space to be converted into genetic space. So, genetic algorithms work with a coding of variables. The advantage of working with a coding of variable space is that coding discretizes the search space even though the function may be continuous. A more striking difference between genetic algorithms and most of the traditional optimization methods is that GA uses a population of points at one time in contrast to the single point approach by traditional optimization methods. This means that GA processes a number of designs at the same time. As we have seen earlier to improve the search direction in traditional optimization methods transition rules are used and they are deterministic in nature but GA uses randomized operators. Random operators improve the search space in an adaptive manner. Hence in order to store the excess items an additional warehouse which may be located nearby own ware-house.

## II. RELATED WORKS

Hartely (1976) was first who discussed an Inventory model with two storage system. To reduce the Inventory costs, it is necessary to consume the goods of the RW at the earliest due to more holding cost. The deterioration of goods is realistic phenomenon and needs to be controlled during storage periods of deteriorating items. Generally deterioration is defined as the damage, spoilage, dryness, vaporization, etc. that results in decrease of usefulness of the original one. In many literatures, deterioration phenomenon was taken into account into single warehouse only while developing single warehouse system as well as two storage policies. Assuming the deterioration in both warehouses, Sarma (1983), extended his earlier model to the case of infinite replenishment rate with shortages. Pakkala and Achary (1992) extended the two-warehouse Inventory model for deteriorating items with finite replenishment rate and shortages, taking time as discrete and continuous variable, respectively. In these models mentioned above the demand rate was assumed to be constant. Subsequently, the ideas of time varying demand and stock dependent demand considered by some authors, such as Goswami and Chaudhary (1998) in that model they were not consider the deterioration and shortages were allowed and backlogged. Many researchers have considered that the holding cost during storage period is always constant but it is not realistic but due to the time value of money it is not assumed that holding cost will remain constant forever and thus holding cost may vary with time. M. Gyan and A. K. Pal (2009) developed a two ware house Inventory model for deteriorating items with stock dependent demand rate and holding cost. T.P.M. Pakkala, K.K. Achary (1992) developed a deterministic Inventory model for deteriorating items with two warehouses and finite replenishment rate. U. Dave (1988) produces an EOQ models with two levels of storage, K. D. Rathod and P. H. Bhathawa (2013) developed an Inventory model with Inventory-level dependent demand rate, variable holding cost and shortages. T.A. Murdeshwar, Y.S. Sathe (1985) developed Some aspects of lot size model with two levels of storage. R.P. Tripathi (2013) developed an Inventory model with different demand rate and different holding cost. Vinod Kumar Mishra *et al.* developed an Inventory model for deteriorating items with time-dependent demand and time-varying holding cost under partial backlogging. A.K. Bhunia, M. Maiti (1998) considering time dependent demand as linear function of time produces A two-warehouse Inventory model for deteriorating items with a linear trend in demand and shortages. S. Kar. A.K. Bhunia, M. Maiti (2001) considering fix time horizon developed a Deterministic Inventory model with two levels of storage, a linear trend in demand and a fixed time horizon. K.V.S. Sarma (1987) developed a deterministic order level Inventory model for deteriorating items with two storage facilities. In all cases of developed model it is assumed that the rented ware-house is equipped with better facilities but due to advance technologies and in the competitive business environment every businessman want to minimize deterioration rate of goods hence has an well-equipped ware-house

and therefore the consideration of equal deterioration rate in the both ware-houses of two storages system can't be ignored.

Nia. *et al.* (2015) suggested a hybrid genetic and imperialist competitive algorithm for green vendor managed inventory of multi-item multi-constraint EOQ model under shortage. Ren Qing-dao-er-ji, *et al.* (2013) developed Inventory based two-objective job shop scheduling model and its hybrid genetic algorithm. Seyed Hamid Reza Pasandideh, *et al.* (2011) extended A genetic algorithm for vendor managed inventory control system of multi-product multi-constraint economic order quantity model. Ata Allah Taleizadeh, *et al.* (2013) suggested A hybrid method of fuzzy simulation and genetic algorithm to optimize constrained inventory control systems with stochastic replenishments and fuzzy demand Ilkay Saracoglu, *et al.* (2014) developed A genetic algorithm approach for multi-product multi-period continuous review inventory models. R.K. Gupta, *et al.* (2009) extended an application of Genetic Algorithm in solving an inventory model with advance payment and interval valued inventory costs and an application of genetic algorithm in a marketing oriented inventory model with interval valued inventory costs and three-component demand rate dependent on displayed stock level. M.J. Li, *et al.* (2010) extended Optimizing emission inventory for chemical transport models by using genetic algorithm. Seyed Hamid Reza Pasandideh, *et al.* (2011) developed a parameter-tuned genetic algorithm to optimize two-echelon continuous review inventory systems. Javad Sadeghi and Seyed Taghi Akhavan Niaki *et al.* (2015) extended two parameter tuned multi-objective evolutionary algorithms for a bi-objective vendor managed inventory model with trapezoidal fuzzy demand. Masao Yokoyama (2002) extended integrated optimization of inventory-distribution systems by random local search and a genetic algorithm. Tamás Varga, *et al.* (2013) suggested 19 - Improvement of PSO Algorithm by Memory-Based Gradient Search—Application in Inventory Management. Sasan Khalifehzadeh, *et al.* (2015) developed A four-echelon supply chain network design with shortage: Mathematical modeling and solution methods. A.K. Bhunia and Ali Akbar Shaikh (2015) extended An application of PSO in a two-warehouse inventory model for deteriorating item under permissible delay in payment with different inventory policies. Yoshiaki Shimizu and Takatobu Miura (2012) extended Effect of Topology on Parallel Computing for Optimizing Large Scale Logistics through Binary PSO. Salah Alden Ghasimi, *et al.* (2014) developed a genetic algorithm for optimizing defective goods supply chain costs using JIT logistics and each-cycle lengths. Ying-Hua Chang (2010) gave Adopting co-evolution and constraint-satisfaction concept on genetic algorithms to solve supply chain network design problems. Bongju Jeong, *et al.* (2002) suggested a computerized causal forecasting system using genetic algorithms in supply chain management. Fulya Altiparmak, *et al.* (2006) developed a genetic algorithm approach for multi-objective optimization of supply chain networks. Antonio Costa, *et al.* (2010) suggested a new efficient encoding/decoding procedure for the design of a supply chain network with genetic algorithms. Fulya Altiparmak, *et al.* (2009) extended a steady-state genetic algorithm for multi-product supply chain network design. Miguel Zamarripa, *et al.* (2012) gave Supply Chain Planning under Uncertainty using Genetic Algorithms. Reza Zanjirani Farahani, Mahsa Elahipana (2008) gave a genetic algorithm to optimize the total cost and service level for just-in-time distribution in a supply chain. David Naso, *et al.* (2007) extended Genetic algorithms for supply-chain scheduling: A case study in the distribution of ready-mixed concrete. S.H. Zegordi, *et al.* (2010) developed a novel genetic algorithm for solving production and transportation scheduling in a two-stage supply chain. R.J. Kuo, Y.S. Han (2011) suggested a hybrid of genetic algorithm and particle swarm optimization for solving bi-level linear programming problem – A case study on supply chain model.

This paper has gone through important books related to the topic of this research work. Following text books have been consulted: “Dilip K. Pratihar (2014) Soft computing fundamentals and applications, Narosa publishing house” and “Dr. Neeta Awasthy (2011) Soft computing with neural networks, Fuzzy logic and genetic algorithm, S.K. Kataria & sons publishers of engineering and computer”

In this paper a deterministic Electronic component inventory model for single deteriorating items with two level of storage and time dependent demand with partially backordering shortage is developed. Stock

is transferred RW to OW under continuous release pattern and the transportation cost is not taken into account and Vector Evaluated Genetic Algorithm. The deterioration rates in both the warehouses are constant but different due to the different preservation procedures as discussed in traditional models as discussed above, in this paper the same rate of deterioration is considered and a special case has been discussed with some other cases of the model and compared their total relevant Electronic component inventory costs and Vector Evaluated Genetic Algorithm. The numerical example is presented to demonstrate the development of the model.

### III. ASSUMPTION AND NOTATIONS

The mathematical model of two warehouse Electronic component inventory model for Non-Instantaneous deteriorating items is based on the following notation and assumptions

#### Assumption

- 1 Replenishment rate is infinite.
- 2 Lead time is negligible i.e. zero.
- 3 Holding cost vary with time.
- 4 The time horizon of the Electronic component inventory system is infinite.
- 5 Goods of RW are consumed first due to the more holding cost in RW than in OW.
- 6 RW has unlimited capacity while OW is of limited capacity.
- 7 Demand vary with time and is linear function of time and given by  $d(t)=(a+1)t$  ; where  $(a+1)>0$  ;
- 8 Deterioration rate in both ware houses are different and a fraction of on hand Electronic component inventory deteriorates per unit time in both the warehouse.
- 9 Shortages are allowed and demand is partially backlogged at constant rate in the beginning of next replenishment cycle.
- 10 The unit Electronic component inventory cost (Holding cost + deterioration cost) in  $RW > OW$

#### Notations

- C: Electronic component inventory Cost of Ordering per Order.
- $\alpha_1$ : Electronic component inventory Capacity of RW.
- $\alpha$ : Electronic component inventory Capacity of OW.
- T: The length of replenishment cycle.
- Q: Maximum Electronic component inventory level per cycle to be ordered.
- $t_1$ : The time at which Electronic component inventory level reaches to zero in RW.
- $t_2$ : The time at which Electronic component inventory level reaches to zero in OW.
- $O_h$ : Electronic component inventory holding cost per unit time in OW i.e.  $O_h = \gamma_2 t$ ; where  $h_2$  is positive constant.
- $R_h$ : Electronic component inventory holding cost per unit time in RW i.e.  $R_h = (\gamma_1 + 1)t$  where  $>0$  and  $R_h > O_h$ .
- $s_c$ : Electronic component inventory shortages cost per unit per unit time.
- $L_c$ : Electronic component inventory lost sales cost per unit per unit time.
- $J^{r1}(t)$ : The level of Electronic component inventory in RW during time interval  $[0 t_1]$ .

$\Pi^{01}(t)$ : The level of Electronic component inventory in OW during time interval  $[0 t_1]$ .

$\Pi^{02}(t)$ : The level of Electronic component inventory in OW during time interval  $[t_1 t_2]$ .

$\Pi^{03}(t)$ : The level of Electronic component inventory in OW during time interval  $[t_2 t_3]$ .

$\Pi^S(t)$ : Determine the Electronic component inventory level during time interval  $[t_2 T]$ .

$\Omega + 1$ : Electronic component inventory Deterioration rate in RW and OW Such that  $0 < \Omega < + 1 < 1$ .

$(\beta + \mu)$ : Electronic component inventory Deterioration rate in OW Such that  $0 < (\beta + \mu) < 1$ .

$P_c$ : Electronic component inventory Purchase cost per unit of item.

$\Pi^{TC}(t_1, t_2, T)$ : The total relevant Electronic component inventory cost per unit time of Electronic component inventory system.

#### IV. MATHEMATICAL FORMULATION OF MODEL AND ANALYSIS

In the beginning of the cycle at  $t = 0$  a lot size of  $Q$  units of Electronic component inventory enters into the system in which backlogged units are cleared and the remaining units are kept into two warehouses according to the capacity of ware-houses.

In the time interval  $[0 t_1]$  the Electronic component inventory level decreases in RW due to both, demand and deterioration and is governed by differential equation

$$\frac{d\Pi^{r1}(t)}{dt} = -(\Omega + 1) \Pi^{r1}(t) - (a+1)t \quad ; \quad 0 \leq t \leq t_1 \quad (1)$$

Since demand is fulfilled from the goods kept in RW during the time interval  $[0t_1]$  and therefore, in OW Electronic component inventory level decreases only due to deterioration and Electronic component inventory level is governed by differential equation

$$\frac{d\Pi^{01}(t)}{dt} = -(\Omega + 1) \Pi^{01}(t); \quad 0 \leq t \leq t_1 \quad (2)$$

During the time period  $[t_1 t_2]$  the Electronic component inventory remains in OW and therefore its level depleted due to common effect of demand and deterioration and level of Electronic component inventory is governed by differential equation

$$\frac{d\Pi^{02}(t)}{dt} = \Pi^{02}(t) - (a + 1)t; \quad 0 \leq t \leq t_1 \quad (3)$$

Now at  $t = t_2$  the Electronic component inventory level vanishes but demand is continue thus shortages occur in the time interval  $[t_2 T]$  and the part of shortages quantity supplied to the customers at the beginning of the next replenishment cycle. The shortages is governed by the differential equation

$$\frac{d\Pi^{4S}(t)}{dt} = -(b + 1)((a + 1)t); \quad 0 \leq t \leq T \quad (4)$$

Now Electronic component inventory level at different time intervals is given by solving the above differential equations (1) to (4) with boundary conditions

$$\Pi^{r1}(t) = 0 \text{ at } t = t_1;$$

$$\Pi^{01}(t) = 0 \text{ at } t = 0;$$

$$\Pi^{01}(t) = 0 \text{ at } t = t_2 \text{ and}$$

$$\Pi^S(t) = 0 \text{ at } t = t_2 \text{ respectively as}$$

$$\Pi^{r1}(t) = \frac{(a+1)}{(\Omega+1)^2} \{ (1 - (\Omega + 1) t) - (1 - (\Omega + 1) t_1) e^{(\Omega+1)(t_1-t)} \}; 0 \leq t \leq t_1 \quad (5)$$

$$\Pi^{01}(t) = \alpha e^{(\Omega+1)t} \quad ; \quad 0 \leq t \leq t_1 \quad (6)$$

$$\mathcal{I}^{o2}(t) = \frac{(a+1)}{(\Omega+1)^2} \{ (1 - (\Omega + 1) t) - (1 - (\Omega + 1) t_2) e^{(\Omega+1)(t_2-t)} \}; t_1 \leq t \leq t_2 \quad (7)$$

$$\mathcal{I}^s(t) = \frac{(b+1)(a+1)}{2} (t_2^2 - t^2); \quad t_2 \leq t \leq T \quad (8)$$

At  $t = 0$ ;  $\alpha_1 = \mathcal{I}^{r1}(0)$ ;

$$\alpha_1 = \frac{(a+1)}{(\Omega+1)^2} \{ ((\Omega + 1) t_1 - 1) e^{(\Omega+1) t_1} \} \quad (9)$$

Maximum amount of Electronic component inventory backordered during time interval  $[t_2, T]$  at  $t = T$  is given by

$$B_{max} = -\mathcal{I}^s(t) = \frac{(b+1)(a+1)}{2} (t_2^2 - T^2) \quad (10)$$

The maximum amount of Electronic component inventory to be ordered at the end of cycle length is given as

$$\begin{aligned} Q_{max} &= \alpha + \alpha_1 + B_{max} \\ &= \alpha + \frac{(b+1)t_1^2}{2} + \frac{(b+1)}{(\Omega+1)^2} \{ ((\Omega + 1)t_2 - 1) e^{(\Omega+1)(t_2-t_1)} - ((\Omega + 1)t_1 - 1) \} + \frac{(b+1)}{6} \{ T^3 - 2t_3^3 - 3t_3^2 T \}; \end{aligned} \quad (11)$$

At the time  $t = T$  replenishment cycle restarts. The objective of the model is to minimize the total Electronic component inventory cost as low as possible.

Next the total relevant Electronic component inventory cost per cycle consists of the following elements:

1. Electronic component inventory Cost of ordering per cycle:  $C_o$
2. Electronic component inventory holding cost per unit per unit of time in RW:  $R_h$
3. Electronic component inventory holding cost per unit per unit of time in OW:  $O_h$
4. Electronic component inventory Purchase cost: PC
5. Electronic component inventory Shortages cost: SC
6. Electronic component inventory Lost sales cost: LC

Above cost are given as follows:

$$\begin{aligned} R_h &= \int_0^{t_1} \mathcal{I}^{r1}(t) R_h dt \\ &= \frac{(a+1)(\gamma_1+1)}{(\Omega+1)^2} \left\{ \left( \frac{t_1^2}{2} - (\Omega + 1) \frac{t_1^3}{2} - (1 - (\Omega + 1)t_1) e^{(\Omega+1)t_1} \left( \frac{1 - e^{-(\Omega+1)t_1}}{(\Omega+1)^2} - \frac{t_1 e^{-(\Omega+1)t_1}}{(\Omega+1)} \right) \right\} \end{aligned} \quad (12)$$

$$\begin{aligned} O_h &= \int_0^{t_1} \mathcal{I}^{o1}(t) O_h dt + \int_{t_1}^{t_2} \mathcal{I}^{o2}(t) O_h dt \\ &= \alpha \gamma_2 \left( \frac{1 - e^{-(\beta+\mu)t_1}}{(\beta+\mu)^2} - \frac{t_1 e^{-(\beta+\mu)t_1}}{(\beta+\mu)} \right) + \frac{(a+1)\gamma_2}{\beta^2} \left\{ \frac{(t_2^2 - t_1^2)}{2} - \frac{(\beta+\mu)}{3} (t_2^3 - t_1^3) - (1 - (\beta + \mu)t_2) \left( \frac{e^{-(\beta+\mu)t_1} - e^{-(\beta+\mu)t_2}}{(\beta+\mu)^2} \right) + \left( \frac{t_1 e^{-(\beta+\mu)t_1}}{(\beta+\mu)} - \frac{t_2 e^{-(\beta+\mu)t_2}}{(\beta+\mu)} \right) \right\} e^{-(\beta+\mu)t_2} \end{aligned} \quad (13)$$

$$\begin{aligned}
PC &= P_c * Q_{\max} \\
&= P_c \left( \alpha + \frac{(b+1)t_1^2}{2} + \frac{(b+1)}{\alpha^2} \{ ((\Omega + 1)t_2 - 1)e^{(\Omega+1)(t_2-t_1)} - ((\Omega + 1)t_1 - 1) \} + \frac{(b+1)}{6} \{ T^3 - 2t_3^3 - 3t_3^2 T \} \right) \quad (14)
\end{aligned}$$

$$\begin{aligned}
SC &= S_c \int_{t_2}^T (-\Pi^s(t)) dt \\
&= \frac{(a+1)(b+1)S_c}{2} \left( \frac{T^3}{3} + \frac{2t_2^3}{3} - Tt_2^2 \right) \quad (15)
\end{aligned}$$

$$\begin{aligned}
LC &= L_c \int_{t_2}^T (1 - (b + 1)) (a + 1) t dt \\
&= \frac{(a+1)L_c}{2} \left( \frac{(T^2 - t_1^2)}{2} - (b + 1) \frac{(T^3 - t_1^3)}{3} \right) \quad (16)
\end{aligned}$$

Therefore, Total relevant Electronic component inventory cost per unit per unit of time is denoted and given by

$\Pi^{TC}(t_1, t_2, T) = \frac{1}{T}$  [Electronic component inventory Ordering cost + Electronic component inventory holding cost in RW + Electronic component inventory holding cost in OW + Electronic component inventory Purchase cost + Electronic component inventory Shortage cost + Electronic component inventory Lost sales cost]

$$T^{IC}(t_1, t_3, T) = \frac{1}{T} [C_o + R_h + O_h + PC + SC + LC] \quad (17)$$

Substituting values from equations (12) to (16) in equation (17) we get (18)

$$\begin{aligned}
I^{TC}(t_1, t_2, T) &= \frac{1}{T} \left[ C_o + \frac{(a+1)(\gamma_1+1)}{\alpha^2} \left\{ \left( \frac{t_1^2}{2} - (\Omega + 1) \frac{t_1^3}{2} - (1 - (\Omega + 1)t_1) e^{(\Omega+1)t_1} \left( \frac{1 - e^{-(\Omega+1)t_1}}{(\Omega+1)^2} - \frac{t_1 e^{-(\Omega+1)t_1}}{(\Omega+1)} \right) \right\} + \alpha \gamma_2 \left( \frac{1 - e^{-(\beta+\mu)t_1}}{(\beta+\mu)^2} - \frac{t_1 e^{-(\beta+\mu)t_1}}{(\beta+\mu)} \right) + \frac{(a+1)\gamma_2}{(\beta+\mu)^2} \left\{ \frac{(t_2^2 - t_1^2)}{2} - \frac{(\beta+\mu)}{3} (t_2^3 - t_1^3) - (1 - (\beta + \mu)t_2) \left( \left( \frac{e^{-(\beta+\mu)t_1} - e^{-(\beta+\mu)t_1}}{(\beta+\mu)^2} \right) + \left( \frac{t_1 e^{-(\beta+\mu)t_1}}{(\beta+\mu)} - \frac{t_2 e^{-(\beta+\mu)t_2}}{(\beta+\mu)} \right) \right) e^{-(\beta+\mu)t_2} \right\} + P_c \left( \alpha + \frac{(b+1)t_1^2}{2} + \frac{(b+1)}{\alpha^2} \{ ((\Omega + 1)t_2 - 1)e^{(\Omega+1)(t_2-t_1)} - ((\Omega + 1)t_1 - 1) \} + \frac{(b+1)}{6} \{ T^3 - 2t_3^3 - 3t_3^2 T \} \right) + \frac{(a+1)(b+1)S_c}{2} \left( \frac{T^3}{3} + \frac{2t_2^3}{3} - Tt_2^2 \right) + \frac{(a+1)L_c}{2} \left( \frac{(T^2 - t_1^2)}{2} - (b + 1) \frac{(T^3 - t_1^3)}{3} \right) \right] \quad (18)
\end{aligned}$$

The optimal values of  $t_1$ ,  $t_2$  and  $T$  denoted as  $t_2^*, t_3^*, T^*$  respectively can be obtained after solving the following equations

$$\frac{\partial \Pi^{TC}}{\partial t_1} = 0, \quad \frac{\partial \Pi^{TC}}{\partial t_2} = 0 \quad \text{and} \quad \frac{\partial \Pi^{TC}}{\partial T} = 0 \quad (19)$$

## V. VECTOR EVALUATED GENETIC ALGORITHM

Multi-objective optimization problem vector evaluated genetic algorithm was proposed by schaffer in 1985. It is nothing but the weighted sum approach implemented through a GA in which the weighting factors are selected artificially. It does not provide the Pareto-optimal front of solutions directly for a multi-objective optimization problem. Let us consider an optimization problem with “g” objective. This approach consists of the following steps:

**Step 1:** An initial population of solution (of size  $Z$ ) of the GA is created at random.

**Step 2:** The whole population of size  $Z$  is divided into number of sub-population using a proportionate selection schema. Each sub-population of size equal to  $\frac{z}{g}$  is formed corresponding to a particular objective.

**Step 3:** Shuffling is done to obtain a new population of size “ $Z$ ” by putting some weights on different objective artificially. It is to be noted that in shuffling only the position of the strings are changed. It is also important to mention that a multi-objective optimization problem is thus converted into a single-objective one by using some weighting factors.

**Step 4:** Crossover operator is used to generate the children solution.

**Step 5:** Mutation operator is utilized to further modify the population of solution (strings).

Thus one generation of the GA is completed. The population of GA-strings will be modified and split into “ $g$ ” sub-population each of them become strong particularly in one of the objective through a number of generations.

**VI. NUMERICAL EXAMPLE**

In order to illustrate the above solution procedure, consider an Electronic component inventory system with the following base data chosen randomly in appropriate units:  $C_o = 5500$ ,  $\alpha = 400$ ,  $(b + 1) = 0.07$ ,  $(\gamma_1 + 1) = 9$ ,  $\gamma_2 = 6$ ,  $(a + 1) = 28$ ,  $(\Omega + 1) = 0.32$ ,  $(\beta + \mu) = 0.57$ ,  $S_c = 59$ ,  $L_c = 36$ ,  $P_c = 55$ .

There are no rules. The actual values are to be tuned to the specific GA through experience and trial-and-error. However some standard settings are reported in literature. It was proposed by Multi-objective optimization problem vector evaluated genetic algorithm was proposed by schaffer in 1985. as given below.

Population Size = 75, Number of generations = 659, Crossover type = two Point, Crossover rate = 7.1, Mutation types = Bit flip, Mutation rate = 0.9 per bit

If single cut-point crossover instead of two cut-point crossover is employed the crossover rate can be lowered to a maximum of 9.12. The genetic algorithm is coded in MATLAB R2011b to solve the problem formulated in section 3.

The computational optimal solutions of the models are shown in Table 1.

**Table 1**

<i>Model</i>	$t_1^*$	$t_2^*$	$T^*$	<i>Total relevant cost</i>	<i>Genetic Algorithms</i>
$\Pi^{TC}(t_1, t_2, T)$	8.2626	9.7582	30.9978	7279.98	3231.25

**VII. SENSITIVITY ANALYSIS**

Sensitivity analysis is performed on every parameter of the model. The analysis is carried out by changing the value of only one parameter at a time by increasing and decreasing by 50% keeping the value of rest parameters unchanged. The change in the values of decision variables  $t_2^*, t_3^*, T^*$  and the corresponding change in the total relevant Electronic component inventory cost is shown in Table 2. The observation made from the table 2 is given as follows:

- (1) The total relevant Electronic component inventory cost  $\Pi^{TC}(t_2^*, t_3^*, T^*)$  increases as the value of  $C_o$ ,  $\alpha$ ,  $\gamma_2(a+1)$ ,  $P_c$ ,  $L_c$  and  $S_c$  increases, however the value of  $\Pi^{TC}(t_2^*, t_3^*, T^*)$  is decreases as  $b$ , and  $(\Omega + 1)$  and  $(\beta + \mu)$  increases.



- (2) The increase in the value of holding cost in RW does not affect the value of total relevant Electronic component inventory cost which shows that the model is more useful in case of deteriorating items.
- (3) The total relevant Electronic component inventory cost is highly sensitive in change of values of parameters  $(a + 1)$ ,  $(\Omega + 1)$ ,  $(\beta + \mu)$ ,  $L_c$  and moderately sensitive in  $S_c$ ,  $P_c$ ,  $\alpha$  and  $C_o$ , the others are slightly sensitive. Thus when decision is to be made, it is necessary to pay attention on the fluctuation of parameters which highly affect the total relevant Electronic component inventory cost.
- (4) The ordering cycle length is also sensitive to the parameters  $(a + 1)$ ,  $\gamma_2$ ,  $(\Omega + 1)$ ,  $(\beta + 1)$ ,  $L_c$ ,  $P_c$  and  $\alpha$ . As the value of these parameters changed, the length of order cycle is also changed and hence total Electronic component inventory cost is affected.

**Table 2**  
**2.1 Parameter  $C_o$**

Parameter	Changes in the value of the decision variables			Change in the value of total Electronic component inventory cost
	$t_2^*$	$t_3^*$	$T^*$	
$C_o$				$J^{TC}(t_1^*, t_2^*, T^*)$
820	5.24	7.89	40.741	2224.64
920	5.42	7.98	40.123	2243.75

**2.2 Parameter  $\alpha$**

Parameter	Changes in the value of the decision variables			Change in the value of total Electronic component inventory cost
	$t_2^*$	$t_3^*$	$T^*$	
$\alpha$				$J^{TC}(t_1^*, t_2^*, T^*)$
100	8.24	8.89	70.791	7224.64
200	9.42	9.98	50.153	8243.75

**2.3 Parameter  $(\gamma_1 + 1)$**

Parameter	Changes in the value of the decision variables			Change in the value of total Electronic component inventory cost
	$t_2^*$	$t_3^*$	$T^*$	
$(\gamma_1 + 1)$				$J^{TC}(t_1^*, t_2^*, T^*)$
10.5	3.44	7.52	60.701	4054.64
20.5	4.52	8.65	30.103	3203.75

**2.4 Parameter  $\gamma_2$**

Parameter	Changes in the value of the decision variables			Change in the value of total Electronic component inventory cost
	$t_2^*$	$t_3^*$	$T^*$	
$\gamma_2$				$J^{TC}(t_1^*, t_2^*, T^*)$
5	8.243	1.894	40.991	9244.64
2	9.424	2.981	30.753	8233.75

**2.5 Parameter  $(a+1)$**

Parameter	Changes in the value of the decision variables			Change in the value of total Electronic component inventory cost
	$t_2^*$	$t_3^*$	$T^*$	
$(a+1)$				$J^{TC}(t_1^*, t_2^*, T^*)$
52	3.213	9.894	20.991	6214.04
3.0	2.125	6.981	15.753	4283.70

**2.6 Parameter b+1**

<i>Parameter</i>	<i>Changes in the value of the decision variables</i>			<i>Change in the value of total Electronic component inventory cost</i>
	$t_2^*$	$t_3^*$	$T^*$	
$b+1$	$t_2^*$	$t_3^*$	$T^*$	$J^{TC}(t_1^*, t_2^*, T^*)$
0.052	9.202	7.014	10.097	7214.04
0.005	8.105	9.021	14.055	9003.70

**2.7 Parameter ( $\Omega + 1$ )**

<i>Parameter</i>	<i>Changes in the value of the decision variables</i>			<i>Change in the value of total Electronic component inventory cost</i>
	$t_2^*$	$t_3^*$	$T^*$	
$(\Omega+1)$	$t_2^*$	$t_3^*$	$T^*$	$J^{TC}(t_1^*, t_2^*, T^*)$
0.12	6.202	5.014	20.097	9214.14
0.09	18.105	19.021	144.055	9703.74

**2.8 Parameter ( $\beta + \mu$ )**

<i>Parameter</i>	<i>Changes in the value of the decision variables</i>			<i>Change in the value of total Electronic component inventory cost</i>
	$t_2^*$	$t_3^*$	$T^*$	
$(\beta + \mu)$	$t_2^*$	$t_3^*$	$T^*$	$J^{TC}(t_1^*, t_2^*, T^*)$
0.122	5.2024	8.0141	29.0974	5214.14
0.094	1.1055	29.0210	44.0155	4803.74

**2.9 Parameter  $S_c$** 

<i>Parameter</i>	<i>Changes in the value of the decision variables</i>			<i>Change in the value of total Electronic component inventory cost</i>
	$t_2^*$	$t_3^*$	$T^*$	
$S_c$	$t_2^*$	$t_3^*$	$T^*$	$J^{TC}(t_1^*, t_2^*, T^*)$
18.1	9.1014	7.0121	79.0974	9274.74
7.9	6.7085	9.0270	64.0155	8813.94

**2.10 Parameter  $L_c$** 

<i>Parameter</i>	<i>Changes in the value of the decision variables</i>			<i>Change in the value of total Electronic component inventory cost</i>
	$t_2^*$	$t_3^*$	$T^*$	
$L_c$	$t_2^*$	$t_3^*$	$T^*$	$J^{TC}(t_1^*, t_2^*, T^*)$
19	3.2121	7.0041	39.777	9214.74
4	3.1005	9.0010	64.115	7203.74

**2.11 Parameter  $P_c$** 

<i>Parameter</i>	<i>Changes in the value of the decision variables</i>			<i>Change in the value of total Electronic component inventory cost</i>
	$t_2^*$	$t_3^*$	$T^*$	
$P_c$	$t_2^*$	$t_3^*$	$T^*$	$J^{TC}(t_1^*, t_2^*, T^*)$
19.7	1.2191	4.2041	79.871	4254.54
4.9	2.1905	3.2010	74.312	3213.64

**VIII. CONCLUSIONS**

In this paper, we proposed a deterministic two-warehouse Electronic component inventory model for instantaneous single deteriorating item with linear time-dependent demand and linearly increasing time

dependent holding cost, infinite replenishment rate, with the objective of minimizing the total relevant Electronic component inventory cost and Vector Evaluated Genetic Algorithm. Shortages are allowed and partially backlogged at fraction of constant rate. Also different cases have been discussed one assuming equal deterioration in both ware-houses and others with fully backlogged shortages and without shortages and Vector Evaluated Genetic Algorithm. Furthermore the proposed model can be used in Electronic component inventory control of certain instantaneous deteriorating items such as food grains, seasonal vegetables, medicines fashionable items etc. and can be further extended by incorporating with other and probabilistic demand pattern and time dependent deterioration rates.

## REFERENCES

- [1] A. Costa, G. Celano, S. Fichera, and E. Trovato (2010), A new efficient encoding/decoding procedure for the design of a supply chain network with genetic algorithms *Computers & Industrial Engineering*, Volume 59, Issue 4, Pages 986-999.
- [2] A.A Taleizadeh, S.T.A. Niaki, M. Bahador and A.N. Shafii (2013), A hybrid method of fuzzy simulation and genetic algorithm to optimize constrained inventory control systems with stochastic replenishments and fuzzy demand *Information Sciences*, Volume 220, Pages 425-441.
- [3] A.K. Bhunia, and A.A. Shaikh (2015), An application of PSO in a two-warehouse inventory model for deteriorating item under permissible delay in payment with different inventory policies *Applied Mathematics and Computation*, Volume 256, Pages 831-850.
- [4] A.K. Bhunia, M. Maiti (1998), A two-warehouse Inventory model for deteriorating items with a linear trend in demand and shortages, *JORS*, 49, 287-292.
- [5] A.R. Ren Q.d.e. ji, Y. Wang, and X. Wang (2013), Inventory based two-objective job shop scheduling model and its hybrid genetic algorithm *Applied Soft Computing*, Volume 13, Issue 3, Pages 1400-1406.
- [6] B. Jeong, H.S. Jung, and N.K. Park (2002), A computerized causal forecasting system using genetic algorithms in supply chain management *Journal of Systems and Software*, Volume 60, Issue 3, Pages 223-237.
- [7] D. K. Pratihar (2014), *Soft computing fundamentals and applications*, Narosa publishing house.
- [8] D. Naso, M. Surico, B. Turchiano, and U. Kaymak (2007), Genetic algorithms for supply-chain scheduling: A case study in the distribution of ready-mixed concrete *European Journal of Operational Research*, Volume 177, Issue 3, Pages 2069-2099.
- [9] F. Altiparmak, M. Gen, L. Lin, and I. Karaoglan (2009), A steady-state genetic algorithm for multi-product supply chain network design *Computers & Industrial Engineering*, Volume 56, Issue 2, Pages 521-537.
- [10] F. Altiparmak, M. Gen, L. Lin, and T. Paksoy (2006), A genetic algorithm approach for multi-objective optimization of supply chain networks *Computers & Industrial Engineering*, Volume 51, Issue 1, Pages 196-215.
- [11] Goswami, and K.S. Chaudhuri (1998), On an Inventory model with two levels of storage and stock-dependent demand rate, *International Journal of Systems Sciences* 29, 249-254.
- [12] H.V. Ronald, (1976), On the EOQ model two levels of storage. *Opsearch*, 13, 190-196.
- [13] I. Saracoglu, S. Topaloglu, and T. Keskinurk (2014), A genetic algorithm approach for multi-product multi-period continuous review inventory models expert systems with applications, volume 41, issue 18, pages 8189-8202.
- [14] J. Sadeghi, and S.T.A. Niaki (2015), Two parameter tuned multi-objective evolutionary algorithms for a bi-objective vendor managed inventory model with trapezoidal fuzzy demand *Applied Soft Computing*, Volume 30, Pages 567-576.
- [15] K. D. Rathod and P. H. Bhathawala (2013), Inventory model with Inventory-level dependent demand rate, variable holding cost and shortages, *International Journal of Scientific & Engineering Research*, Volume 4, Issue 8.
- [16] K.V.S. Sarma (1987), A deterministic order level Inventory model for deteriorating items with two storage facilities. *European Journal of Operational Research* 29, 70-73.
- [17] K.V.S. Sarma, (1983), A deterministic Inventory model with two level of storage and an optimum release rule, *Opsearch* 20, 175-180.
- [18] M. Gyan, and A.K. Pal (2009), A two warehouse Inventory model for deteriorating items with stock dependent demand rate and holding cost, *Oper. Res. Int. J.* vol. (9), 153-165.
- [19] M. Yokoyama (2002), Integrated optimization of inventory-distribution systems by random local search and a genetic algorithm *Computers & Industrial Engineering*, Volume 42, Issues 2-4, Pages 175-188.

- [20] M. Zamarripa, J. Silvente, and A. Espuña (2012), Supply Chain Planning under Uncertainty using Genetic Algorithms Computer Aided Chemical Engineering, Volume 30, Pages 457-461.
- [21] M.J. Li, D.S. Chen, S.Y. Cheng, F. Wang, Y. Li, Y. Zhou, and J.L. Lang (2010), Optimizing emission inventory for chemical transport models by using genetic algorithm Atmospheric Environment, Volume 44, Issue 32, Pages 3926-3934.
- [22] N. Awasthy (2011), Soft computing with neural networks, Fuzzy logic and genetic algorithm, S.K. Kataria & sons publishers of engineering and computer.
- [23] Nia, M.H. Far, and S.T.A. Niaki (2015), A hybrid genetic and imperialist competitive algorithm for green vendor managed inventory of multi-item multi-constraint EOQ model under shortage Applied Soft Computing, Volume 30, Pages 353-364.
- [24] R.J. Kuo, and Y.S. Han (2011), A hybrid of genetic algorithm and particle swarm optimization for solving bi-level linear programming problem – A case study on supply chain model Applied Mathematical Modelling, Volume 35, Issue 8, Pages 3905-3917.
- [25] R.K. Gupta, A.K. Bhunia, and S.K. Goyal (2009), An application of Genetic Algorithm in solving an inventory model with advance payment and interval valued inventory costs Mathematical and Computer Modelling, Volume 49, Issues 5–6, Pages 893-905.
- [26] R.P. Tripathi (2013), Inventory model with different demand rate and different holding cost, International Journal of Industrial Engineering Computations 4, 437–446.
- [27] R.Z. Farahani, and M. Elahipana (2008), A genetic algorithm to optimize the total cost and service level for just-in-time distribution in a supply chain International Journal of Production Economics, Volume 111, Issue 2, Pages 229-243
- [28] S. Kar., A.K. Bhunia, and M. Maiti (2001), Deterministic Inventory model with two levels of storage, a linear trend in demand and a fixed time horizon. Computers & Operations Research 28, 1315-1331.
- [29] S. Khalifehzadeh, M. Seifbarghy, and B. Naderi (2015), A four-echelon supply chain network design with shortage: Mathematical modeling and solution methods Journal of Manufacturing Systems, Volume 35, Pages 164-175.
- [30] S.A. Ghasimi, R. Ramli, and N. Saibani (2014), A genetic algorithm for optimizing defective goods supply chain costs using JIT logistics and each-cycle lengths Applied Mathematical Modelling, Volume 38, Issue 4, Pages 1534-1547.
- [31] S.H. Zegordi, I.N. Kamal Abadi, and M.A.B. Nia (2010), A novel genetic algorithm for solving production and transportation scheduling in a two-stage supply chain Computers & Industrial Engineering, Volume 58, Issue 3, Pages 373-381
- [32] S.H.R. Pasandideh, S.T.A. Niaki, and N. Tokhmehchi (2011), A parameter-tuned genetic algorithm to optimize two-echelon continuous review inventory systems Expert Systems with Applications, Volume 38, Issue 9, Pages 11708-11714.
- [33] S.H.R. Pasandideh, S.T.A. Niaki, and A.R. Nia (2011), A genetic algorithm for vendor managed inventory control system of multi-product multi-constraint economic order quantity model Expert Systems with Applications, Volume 38, Issue 3, Pages 2708-2716.
- [34] T. Varga, A. Király, and J. Abonyi (2013), 19 - Improvement of PSO Algorithm by Memory-Based Gradient Search—Application in Inventory Management Swarm Intelligence and Bio-Inspired Computation, Pages 403-422.
- [35] T.A. Murdeshwar, and Y.S. Sathé (1985), Some aspects of lot size model with two levels of storage, Opsearch 22, 255-262.
- [36] T.P.M. Pakkala, and K.K. Achary (1992), A deterministic Inventory model for deteriorating items with two warehouses and finite replenishment rate, European Journal of Operational Research 57, 157- 167.
- [37] T.P.M. Pakkala, and K.K. Achary (1992), Discrete time Inventory model for deteriorating items with two warehouses, Opsearch 29, 90-103.
- [38] U. Dave (1988), On the EOQ models with two levels of storage, Opsearch 25 190-196.
- [39] Y. Shimizu, T. Miura (2012), Effect of Topology on Parallel Computing for Optimizing Large Scale Logistics through Binary PSO Computer Aided Chemical Engineering, Volume 30, 2012, Pages 1247-1251.
- [40] Y.H. Chang (2010), Adopting co-evolution and constraint-satisfaction concept on genetic algorithms to solve supply chain network design problems Expert Systems with Applications, Volume 37, Issue 10, Pages 6919-6930.