*Article*

# Analysis of electronic component inventory optimization in six stages supply chain management for warehouse with ABC using genetic algorithm and PSO

**Ajay Singh Yadav**[1], **Anupam Swami**[2], **C. B. Gupta**[3], **Ankur Garg**[4]
[1]Department of Mathematics, SRM University, Delhi-NCR Campus, Modinagar, Ghaziabad, U.P., India
[2]Department of Mathematics, Govt. P.G. College, Sambhal, U.P., India
[3]Department of Mathematics, Department of Mathematics, Birla institute of Technology and Science, Pilani, Rajasthan, India
[4]Department of Computer Science, MIET College, Meerut, U.P., India
E-mail: ajay29011984@gmail.com, swami.anupam@gmail.com, cbbits@gmail.com, ankur.g.garg@gmail.com

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**Abstract**
The purpose of the proposed study is to give a new dimension on warehouse with artificial bee colony algorithm using genetic algorithm and particle swarm optimization algorithm processes in six stages - 11 member supply chain in electronic component inventory optimization to describe the certain and uncertain market demand which is based on supply reliability and to develop more realistic and more flexible models. We hope that the proposed study has a great potential to solve various practical tribulations related to the warehouse using genetic algorithm processes in six stages - 11 member supply chain in electronic component inventory optimization and also provide a general review for the application of soft computing techniques like genetic algorithms to use for improve the effectiveness and efficiency for various aspect of warehouse with artificial bee colony algorithm using genetic algorithm and particle swarm optimization algorithm.

**Keywords** supply chain; inventory optimization; warehouse; artificial bee colony algorithm; genetic algorithm; particle swarm optimization algorithm.

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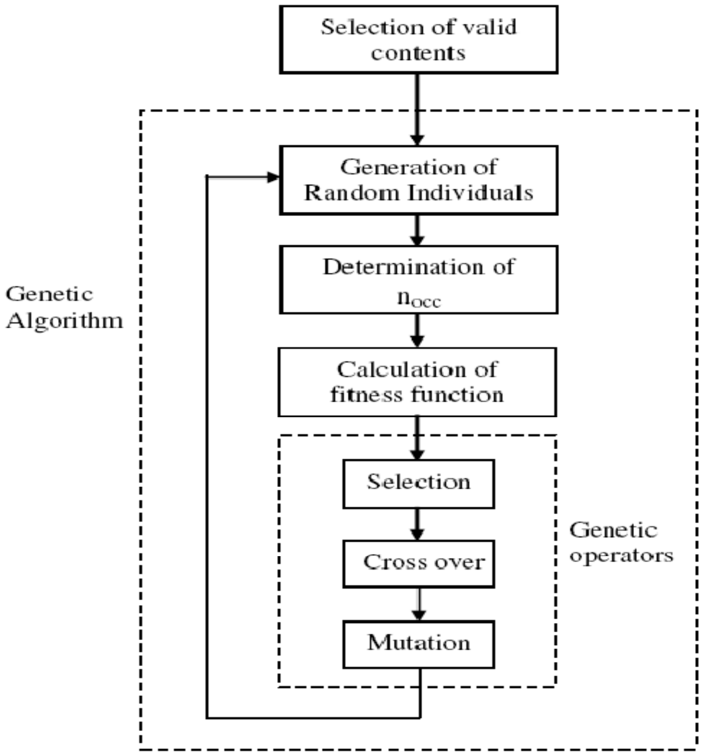
## 1 Introduction

Electronic component inventory is held throughout the supply chain in the form of raw materials, work in process and finished goods. Electronic component inventory exists in the supply chain because of a mismatch between supply and demand. This mismatch is intentional at a manufacturer, where it is economical to manufacture in large lots that are then stored for future sales. The mismatch is also intentional at a retail store where electronic component inventory is held in anticipation of future demand. Electronic component inventory is a major source of cost in a supply chain and has a huge impact on responsiveness. The important role that electronic component inventory plays in the supply chain are: (1) to increase the amount of demand that can be satisfied by having the product ready and available when the customer wants it. (2) To reduce cost by exploiting economics of scale that may exist during production and distribution. (3) To support a firm's competitive strategy. If a firm's competitive strategy requires very high level of responsiveness, a company can achieve this responsiveness by locating large amounts of electronic component inventory close to a customer. Conversely, a company can also use Electronic component inventory to become more efficient by reducing Electronic component inventory through centralized stocking.

We use a variety of food in our daily life to eat. Some of us may take rice, while others may take wheat in the form of different dishes as our main food vegetables are sometime available easily when we demand and sometime not, but can be obtained with the payment of more cost than during normal availability. But have we ever thought that from where vegetables, the rice paddy or wheat from which these food items are prepared comes. We all know that these food grains are not produced throughout the year but we need to eat them every day throughout the year. So, how are the farmers able to supply these continuously to us? We might be thinking that they store the food grains in a proper place and supply them at the time of need. Yes, we are right. Since the production takes place during a particular season and in specific areas, there is a need to store these food grains systematically. In our home we may keep limited stock for our own consumption e.g. 4-5 kg of pulses, 20-50 kg of wheat/rice and we need to buy it again form somewhere(shops) after an interval of time. For this purpose i.e. to provide us the desired items when we needed, there are certain places or stores, where these items are stored in huge quantities in a proper and systematic way. We need different types of goods in our day-to-day life. We may buy some of these items in bulk and store them in our house. Similarly, businessmen also need a variety of goods for the business but some of them may not be available all the time. But, they need those items throughout the year without any break. For example, in electricity power plant (thermal plant) needed coal through the year for the production of electricity, coal is used as raw material, coal is not available at every place and is to be transported from a particular place which takes time so the power plant needed to store it for the year to use when it required. Since the demand for coal in the Producer is continuous process for the production of electricity. Thus, the need for storage arises both for raw material as well as finished products (i.e. electricity). Since storage involves proper arrangement for preserving goods from the time of their production or purchase till the actual use therefore it require proper space for storage. When this storage is done on a large scale and in a specified manner it is called **'Warehousing'**.

Discussions so far were limited to GA that handled the optimization of a single parameter. The optimization criteria are represented by fitness functions and are used to lead towards an acceptable solution (Zhang, 2016). A typical single objective optimization problem is the TSP. There the sole optimization criterion is the cost of the tour undertaken by the salesperson and this cost is to be minimized. However, in real life we often face problem which require simultaneous optimization of several criteria. For example, in VLSI circuit design the critical parameters are chip area power consumption delay fault tolerance etc. While designing a VLSI circuit the designer may like to minimize area power consumption and delay while at the same time would like to maximize fault tolerance. The problem gets more complicated when the optimizing criteria are conflicting. For instance an attempt to design low-power VLSI circuit may affect its fault tolerance capacity adversely. Such problems are known as multi-objective optimization (MOO). Multi-objective optimization is the process of systematically and simultaneously optimizing a number of objective functions. Multiple objective problems usually have conflicting objectives which prevents simultaneous optimization of each objective. As GAs are population based optimization processes they are inherently suited to solve MOO problem. However traditional GAs are to be customized to accommodate such problem. This is achieved by using specialized fitness functions as well as incorporating methods promoting solution diversity. Rest of this section presents the features of multi-objective GAs.




Particle swarm optimization is initialized by a population of random solution and each potential solution is assigned a randomized velocity. The potential solutions called particles are then flown through the problem space. Each particle keeps track of its coordinates in the problem space which are associated with the best solution or fitness achieved so far the fitness value is also stored this value is called pbest. Another best value that is tracked by the global version of the PSO is the overall best value and its location obtained so far by any particle in the population. This value is termed gbest.

Thus at each time step the particle change its velocity and moves towards its pbest and gbest this is the global version of PSO when in addition to pbest each particle keeps track of the best solution called nbest or lbest attained within a local topological neighbourhood of the particles the process is known as the local version of PSO

**2 Related Works**

Narmadha at al. (2010) propose inventory management is considered to be an important field in supply chain management because the cost of inventories in a supply chain accounts for about 30% of the value of the product. The service provided to the customer eventually gets enhanced once the efficient and effective management of inventory is carried out all through the supply chain. the precise estimation of optimal inventory is essential since shortage of inventory yields to lost sales, while excess of inventory may result in pointless storage costs. Thus the determination of the inventory to be held at various levels in a supply chain becomes inevitable so as to ensure minimal cost for the supply chain. The minimization of the total supply chain cost can only be achieved when optimization of the base stock level is carried out at each member of the supply chain. This paper deals with the problem of determination of base-stock levels in a ten member serial supply chain with multiple products produced by factories using uniform crossover genetic algorithms. The complexity of the problem increases when more distribution centers and agents and multiple products were involved. These considerations leading to very complex inventory management process has been resolved in this work.

Radhakrishnan et al. (2009) gives an inventory management plays a vital role in supply chain management. The service provided to the customer eventually gets enhanced once the efficient and effective management of inventory is carried out all through the supply chain. Thus the determination of the inventory to be held at various levels in a supply chain becomes inevitable so as to ensure minimal cost for the supply chain. Minimizing the total supply chain cost is meant for minimizing holding and shortage cost in the entire supply chain. The minimization of the total supply chain cost can only be achieved when optimization of the base stock level is carried out at each member of the supply chain. A serious issue in the implementation of the same is that the excess stock level and shortage level is not static for every period. In this paper, we have developed a new and efficient approach that works on Genetic Algorithms in order to distinctively determine the most probable excess stock level and shortage level required for inventory optimization in the supply chain such that the total supply chain cost is minimized.

Singh and Kumar (2011) gives an optimal inventory control is one of the significant tasks in supply chain management. The optimal inventory control methodologies intend to reduce the supply chain cost by controlling the inventory in an effective manner, such that, the SC members will not be affected by surplus as well as shortage of inventory. In this paper, we propose an efficient approach that effectively utilizes the Genetic Algorithm for optimal inventory control. This paper reports a method based on genetic algorithm to optimize inventory in supply chain management. We focus specifically on determining the most probable excess stock level and shortage level required for inventory optimization in the supply chain so that the total supply chain cost is minimized. We apply our methods on three stage supply chain model studied for optimization

Priya and Iyakutti (2011) present an approach to optimize the reorder level (ROL) in the manufacturing unit taking consideration of the stock levels at the factory and the distribution centers of the supply chain, which in turn helps the production unit to optimize the production level and minimizing the inventory holding cost. Genetic algorithm is used for the optimization in a multi product, multi level supply chain in a web enabled environment. This prediction of optimal ROL enables the manufacturing unit to overcome the excess/ shortage of stock levels in the upcoming period

Thakur and Desai (2013) suggest the dramatic increase in the use of the internet for supply chain-related activities. There is a growing need for services that can analyze current and future purchases possibilities as well as current and future demand levels and determine efficient and economical strategies for the procurement of direct goods. Such solutions must take into account the current quotes offered by suppliers, likely future prices, projected demand, and storage costs in order to make effective decisions on when and from whom to make purchases. Based on demand trends and projections, there is typically a target inventory level that a business hopes to maintain. This level is high enough to be able to meet fluctuations in demand, yet low enough that unnecessary storage costs are minimized. Hence there is a necessity of determining the inventory to be held at different stages in a supply chain so that the total supply chain cost is minimized. Minimizing the total supply chain cost is meant for minimizing holding and shortage cost in the entire supply chain. This inspiration of minimizing Total Supply Chain Cost could be done only by optimizing the base stock level at each member of the supply chain which is very dynamic. A novel and efficient approach using genetic algorithm has been developed which clearly determines the most possible excess stock level and shortage level that is needed for inventory optimization in the supply chain so as to minimize the total supply chain cost.

Khalifehzadeh et al. (2015) present a four-echelon supply chain network design with shortage: mathematical modelling and solution methods. Kannan et al. (2010) discuss a genetic algorithm approach for solving a closed loop supply chain model: A case of battery recycling. Jawahar and Balaji (2009) propose a genetic algorithm for the two-stage supply chain distribution problem associated with a fixed charge. Zhang et al. (2013) present a modified multi-criterion optimization genetic algorithm for order distribution in collaborative supply chain. Che and Chiang (2010) propose a modified Pareto genetic algorithm for multi-objective build-to-order supply chain planning with product assembly. Sarrafha et al. (2015) discuss a bi-objective integrated procurement, production, and distribution problem of a multi-echelon supply chain network design. Taleizadeh et al. (2011) give a harmony search algorithm for multiple-buyer multiple-vendor multi-product multi-constraint supply chain problem with stochastic demand and variable lead-time. Yeh and Chuang (2011) use multi-objective genetic algorithm for partner selection in green supply chain problems. Yimer and Demirli (2010) present a genetic approach to two-phase optimization of dynamic supply chain scheduling. Wang et al. (2011) propose location and allocation decisions in a two-echelon supply chain with stochastic demand – A genetic-algorithm based solution. Humphreys et al. (2009) reduce the negative effects of sales promotions in supply chains using genetic algorithms. Sherman et al. (2010) give a production modelling with genetic algorithms for a stationary pre-cast supply chain. Ramkumar et al. (2011) propose erratum to "A genetic algorithm approach for solving a closed loop supply chain model: A case of battery recycling". Ye et al. (2010) propose some improvements on adaptive genetic algorithms for reliability-related applications. Guchhait et al. (2010) present multi-item inventory model of breakable items with stock-dependent demand under stock and time dependent breakability rate. Changdar et al. (2015) give an improved genetic algorithm based approach to solve constrained knapsack problem in fuzzy environment. Sourirajan et al. (2009) present a genetic algorithm for a single product network design model with lead time and safety stock considerations. Jiang et al. (2015) gives joint optimization of preventive maintenance and inventory policies for multi-unit systems subject to deteriorating spare part inventory. Dey et al. (2008) propose two storage inventory problem with dynamic demand and interval valued lead-time over finite time horizon under inflation and time-value of money. Jawahar and Balaji (2012) propose a genetic algorithm based heuristic to the multi-period fixed charge distribution problem. Pasandideh et al. (2010) give a parameter-tuned genetic algorithm for multi-product economic production quantity model with space constraint, discrete delivery orders and shortages.

## 3 Electronic Component Inventory Analysis Using Genetic Algorithm

The proposed method uses the genetic algorithm to study the stock level that needs essential electronic component inventory control. This is the pre-requisite idea that will make any kind of Electronic component inventory control effective. For this purpose, we are using artificial bee colony algorithm method as assistance. In practice, the supply chain is of length m, means having m number of members in supply chain such as Storage, Producer, Transporter-1 (in-bound), warehouse, Transporter-2 (out-bound), Distribution centers, Distribution Center 1, Distribution Center 2 and Distribution Center 3. Each distribution center further comprises of several agents but as stated in the example case, each Distribution center is having one agent. So, in aggregate there are three agents, Agent 1 for Distribution Center 1, Agent 2 for Distribution Center 2 and Agent 3 for Distribution Center 3 so on. Here, for instance we are going to use a six stages - 11 member supply chain that is illustrated in the Fig. 1. Our exemplary six stages - 11 member supply chain consists of a Storage, Producer, Transporter-1 (in-bound), warehouse, Transporter-2 (out-bound), distribution centers-1, distribution centers-2, distribution centers-3, Agents-1, Agents-2, Agents-3.

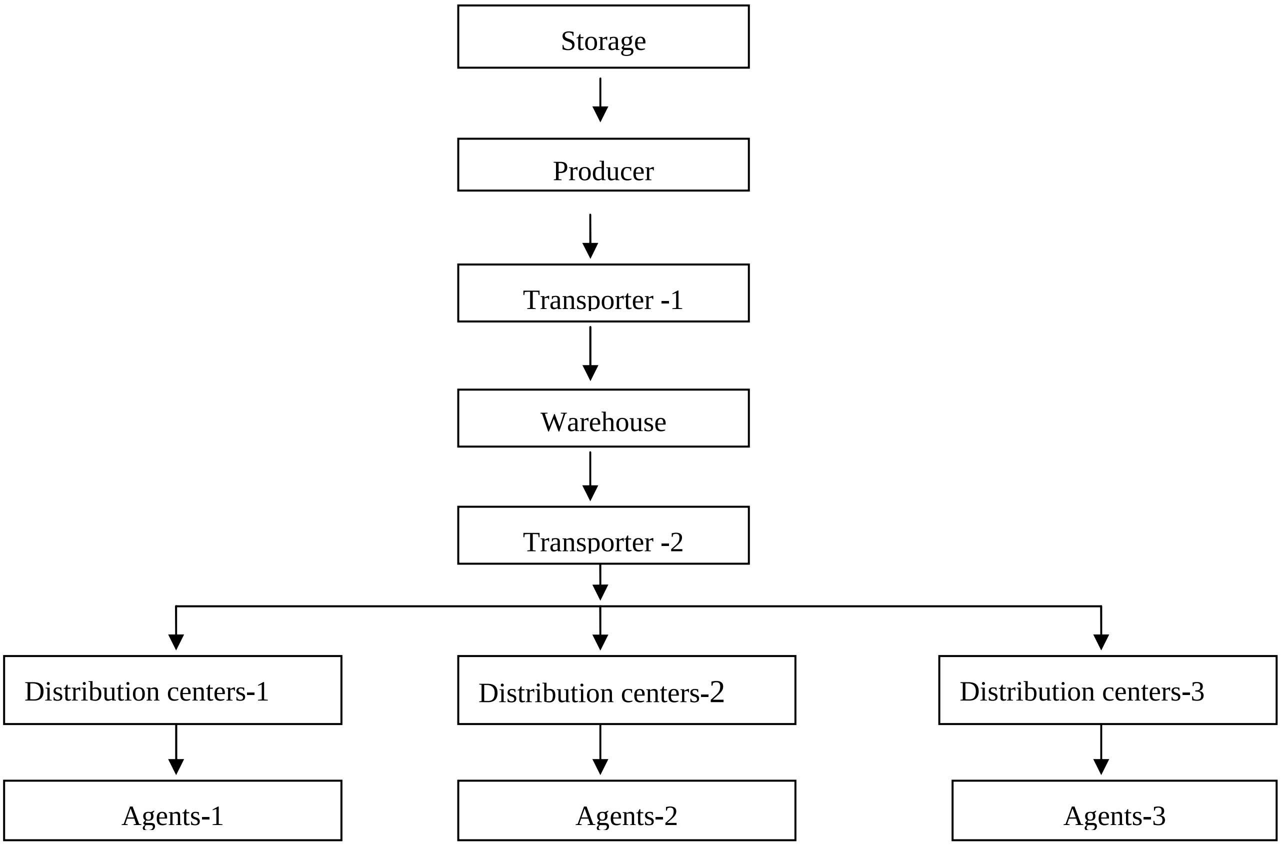



**Fig. 1** Six stages - 11 member supply chain.

In the six stages - 11 member supply chain we are illustrated, the raw material is the massive stock holding area where the stocks are Storage. The Producer is the massive stock holding area where the stocks are manufactured as per the requirement of the warehouse using Transporter-1 (in-bound). Then the warehouse using Transporter-2 (out-bound) will take care of the stock to be supplied for the distribution center. From the distribution center, the stocks will be moved to the corresponding agents. As earlier discussed, the responsibility of our approach is to predict an optimum stock level by using the past records and so that by using the predicted stock level there will be no excess amount of stocks and also there is less means for any shortage. Hence it can be asserted that our approach eventually gives the amount of stock levels that needs to be held in the six stages - 11 member supply chain, Storage, Producer, Transporter-1 (in-bound ), warehouse, Transporter-2 (out-bound ), Distribution centers, Distribution Center 1, Distribution Center 2, Distribution Center 3 Agents-1, Agents-2, and Agents-3. Each distribution center further comprises of several agents but as stated in the example case, each Distribution center is having one agent. So, in aggregate there are three agents, Agent 1 for Distribution Center 1, Agent 2 for Distribution Center 2 and Agent 3 for Distribution Center 3. In our proposed methodology, the artificial bee colony algorithm using genetic algorithm and particle swarm optimization algorithm is used for finding the optimal value.

It depicts the steps applied for the optimization analysis. Initially, the amount of stock levels that are in excess and the amount of stocks in shortage in the different supply chain contributors are represented by zero or non-zero values. Zero refers that the contributor needs no Electronic component inventory control while the non-zero data requires the Electronic component inventory control. The non-zero data states both the excess amount of stocks as well as shortage amount. The excess amount is given as positive value and the shortage amount is mentioned as negative value.

The first process needs to do is the clustering that clusters the stock levels that are either in excess or in shortage and the stock levels that are neither in excess nor in shortage separately. This is done simply by clustering the zero and non-zero values. For this purpose we are using, the efficient artificial bee colony algorithm algorithm.

After the process of artificial bee colony algorithm method using genetic algorithm is performed, the work starts its proceedings on Genetic algorithm, the heart of our work. For the Artificial bee colony algorithm using genetic algorithm and particle swarm optimization algorithm, instead of generating an initial population having chromosomes of random value, a random chromosome is generated in each time of the iteration for further operation.

### 3.1 Artificial bee colony algorithm algorithms

Artificial bee colony algorithm was first created by Karaboga in 2005. It is an optimization algorithm based on the intelligent foraging behaviour of honey bee swarm. It is also called swarm based meta-heuristic algorithm. It consists of a queen, a few drones and thousands of workers. For food foraging workers plays an important role. Abandonment of a source and recruitment of a nectar source are two main modes of behavior for foraging. ABC consists of three groups of bees, employed artificial bees, onlooker bees, and scouts bees. Employed bees related with specific food sources, within the hive the dance of employed bees is watched by onlooker bees to choose a food source, scout bees randomly searching for food sources. In ABC, solution to the problem is provided by the position of a food source and the quality (fitness) of the associated solution is represented by the nectar amount of a food source. The number of food sources (solutions) is equal to the number of employed bees is equal to since each employed bee is associated with a single food source. ABC model contains three main components

1. Food Sources: A forager bee evaluates several properties related with the food source such as its closeness to the hive, taste of its nectar, richness of the energy to select a food source. For the ease, only one quantity represents the quality of a food source as it depends on various parameters mentioned above.

2. Employed foragers: At a specific food source an employed forager is employed for which she is currently exploiting. About this specific source she carries information and shares it with other bees waiting or presented in the hive with all information about the direction, the distance and the profitability of the food source.

3. Unemployed foragers: A forager bee also called unemployed that looks for a food source to exploit it. It can be either an onlooker who tries to find a food source by the help of employed bee's information or scout who randomly searches the environment.

This section provides proposed pseudo code of hybrid algorithm with the parameters of Electronic component inventory model.

Step 1: Set the parameters of artificial bee colony algorithm.

Step 2: Initialize the population of bees is state for holding cost that is case 1 for acceleration coefficient 1.

Step 3: Initialize the population of bees is state for holding cost that is case 2 for acceleration coefficient 2.

Step 4: Find the Abandonment Counter for onlooker bees.

Step 5: For case 1 check the recruited bees from acceleration coefficient 1.

Step 6: For case 2 check the recruited bees from acceleration coefficient 2.

Step 7: Produce the new solution for employed bees with two cases.

Step 8: If $k \neq i$, then best solution equal to $\infty$.

Step 9: If new bees cost ≤ total population cost the cycle = cycle + 1.
Step 10: Now find the fitness value of all probabilities.
Step 11: Find the best cost solutions so far.

The total production cost and the error has to be minimized which leads to the maximization of fitness function.

**3.2 Chromosome**

The randomly generated initial chromosome is created by having the stock levels within the lower limit and the upper limit for all the contributors of the supply chain, factory and the distribution centers. As known, chromosome is constituted by genes which defines the length of the chromosomes. The stock level of each member of the chromosome is referred as gene of the chromosome. Hence for n length supply chain, the chromosome length is also n. Since a 10 member supply chain is used for illustration, the length of the chromosome n is 10, i.e. 10 genes. And the chromosome representation is pictured in Fig. 2. Each gene of the chromosome is representing the amount of stock that is in excess or in shortage at the respective members of the supply chain.

**Chromosome 1**

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 3165 | 2510 | 1275 | -537 | -357 | 756 | 499 | -320 | 936 | 578 | 640 |

**Chromosome 2**

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 3175 | 2400 | 1535 | -835 | -657 | 856 | 789 | -320 | 546 | 678 | 240 |

**Fig. 2** Random individual generated for the genetic operation.

These kinds of chromosomes are generated for the genetic operation. Initially, only two chromosomes will be generated and from the next generation a single random chromosome value will be generated. The chromosomes thus generated is then applied to find its number of occurrences in the database content by using a Select count () function.

The function will give the number of occurrences/ repetitions of the particular amount of stock level for the ten members $M_P$ that are going to be used further in the fitness function.

**3.3 Selection**

The selection operation is the initial genetic operation which is responsible for the selection of the fittest chromosome for further genetic operations. This is done by offering ranks based on the calculated fitness to each of the prevailing chromosome. On the basis of this ranking, best chromosomes are selected for further proceedings.

**3.4 Fitness**

Fitness functions ensure that the evolution is toward optimization by calculating the fitness value for each individual in the population. The fitness value evaluates the performance of each individual in the population.

$$U(i) = \log\left(1 - \frac{M_P}{M_q}\right) \quad i = 1,2,3,4,5,6,7LL, n$$

where, $M_P$ is the number of counts that occurs throughout the period. $M_q$ is the total number of Electronic component inventory values obtained after clustering. n is the total number of chromosomes for which the fitness function is calculated.

The fitness function is carried out for each chromosome and the chromosomes are sorted on the basis of the result of the fitness function. Then the chromosomes are subjected for the genetic operation crossover and mutation.

### 3.5 Crossover

As far as the crossover operation is concerned, a single point crossover operator is used in this study. The first two chromosomes in the mating pool are selected for crossover operation. The crossover operation that is performed for an exemplary case is shown in the following Fig. 3.

**Before Crossover**

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 3510 | 3050 | 4025 | -654 | 675 | 400 | -655 | 620 | 410 | 650 | -520 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 3477 | 3100 | 4035 | -535 | -657 | 456 | 499 | -620 | 436 | 578 | 340 |

**After Crossover**

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 4550 | 5000 | 2000 | 500 | -330 | 200 | 650 | -400 | 605 | 700 | -100 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 4100 | 4236 | 4250 | -150 | 178 | -156 | 104 | -254 | 327 | 521 | -315 |

**Fig. 3** Chromosome representation.

The genes that are right of the cross over point in the two chromosomes are swapped and hence the cross over operation is done. After the crossover operation two new chromosomes are obtained.

### 3.6 Mutation

The newly obtained chromosomes from crossover operation are then pushed for mutation. By performing mutation, a new chromosome will be generated as illustrated below.

**Before Mutation**

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 6110 | 1110 | 3110 | 550 | 350 | -122 | -278 | 650 | -452 | 132 | -221 |

**After Mutation**

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 7210 | 1750 | 4236 | -440 | 277 | 364 | 325 | 685 | 759 | -164 | 375 |

**Fig. 4** Chromosomes subjected to operation.

This is done by random generation of two points and then performing swaps between both the genes.

## 4 Electronic Component Inventory Analysis Using Particle Swarm Optimization Algorithm

1: P: =0

2: $\{M_x, N_x, U_x, V_x\}_{x=1}^{X}$ := initialize()

3: for a:= 1: U

4: for b:= 1: X

5: for r:= 1: R

6: $n_{xc}^{(a+1)} = yn_{xc}^{a} + c_1 d_1 [V_{xc} - m_{xc}^{a}] + c_2 d_2 [U_{xc} - m_{xc}^{a}]$

7: $M_x^{a+1} = M_x^{a} + mN_x^{a} + \in^{a}$

end

$M_x$:= enforce Constraints($X$ )

$Y_x$ := f($M_x$ )

if $M_x \npreceq$ e $\forall$ e $\in$ P

P:= {e $\in$P/ e$\nprec M_x$ }

P:= P$\cup M_x$

end

end

if $M_x \leq V_x \vee (X M_x \nprec V_x \wedge V_x \nprec M_x)$

$V_x$ := $M_x$

end

$U_x$ := selectGuide($X$ , A)

end

## 5 Experimental Results

The optimization of electronic component inventory control in supply chain management based on artificial bee colony algorithm using genetic algorithm and particle swarm optimization algorithm is analyzed with the help of MATLAB. The stock levels for the six stages - 11 member supply chain, Raw material, Storage, Producer, Transporter-1 (in-bound ), warehouse, Transporter-2 (out-bound), distribution centers-1, distribution centers-2, distribution centers-3, Agents-1, Agents-2, Agents-3 are generated using the MATLAB script and this generated data set is used for evaluating the performance of the genetic algorithm. Some sample set of data used in the implementation is given in Table 1. Some 15 sets of data are given in the table 1 and these are assumed as the records of the past period.

**Table 1** Some sample set of data used in the implementation.

| S | P | T-1 | W | T-2 | DC-1 | DC-2 | DC-3 | A-1 | A-2 | A-3 |
|---|---|---|---|---|---|---|---|---|---|---|
| -650 | 820 | -550 | -850 | 150 | 750 | 740 | -760 | 250 | 110 | 300 |
| 665 | -845 | 545 | 845 | 145 | 745 | 755 | 775 | -241 | 125 | 205 |
| 654 | 854 | -554 | 854 | -154 | -754 | 764 | -794 | 258 | 134 | -304 |
| 636 | 866 | 36 | -836 | 136 | 736 | 746 | 746 | 239 | 156 | 206 |
| 687 | 887 | 487 | 887 | -187 | 787 | 727 | 727 | -287 | -167 | 317 |
| -652 | -82 | 452 | 852 | 152 | -752 | 732 | -732 | -257 | 112 | -152 |
| 646 | 846 | -446 | 846 | 146 | 746 | -776 | 756 | 145 | 246 | -136 |
| 611 | 851 | 451 | -811 | 111 | 711 | 781 | -715 | 117 | -251 | 171 |
| -610 | -810 | -610 | 810 | 110 | 710 | -720 | 716 | -119 | 220 | 190 |
| 621 | 851 | 651 | 821 | 121 | -721 | 751 | 727 | 151 | -231 | 271 |
| 631 | 891 | -721 | 831 | -131 | 731 | -721 | 738 | 153 | 261 | -391 |
| 665 | 815 | 745 | -865 | 165 | 765 | 735 | 762 | 168 | 215 | 165 |
| 678 | 828 | 678 | 878 | -178 | 778 | 748 | 774 | -172 | 268 | -678 |
| 663 | -833 | 463 | 863 | 163 | 763 | 753 | 761 | 168 | -233 | 561 |
| -678 | 878 | -778 | 878 | -178 | 778 | 728 | 777 | 146 | 218 | -678 |

The two initial chromosomes are generated at the beginning of the artificial bee colony algorithm using genetic algorithm and particle swarm optimization algorithm are ‘100, -735, 674, -421 757, 518, 287, 979 -253, 527, -475.’ and ‘145, 689, 525, -346 457 -568, 259, 451, 126, 356, -567.’ These initial chromosomes are subjected for the genetic operators, crossover and mutation. The resultant chromosome thus obtained after the application of crossover and mutation is ‘212, 474, 785, 641, 557 -769 258, 569, -258, 358, -258.’ As for our iteration value of ‘100’, the resultant chromosome moved towards the best chromosome after the each iterative execution (Table 2). Hence at the end of the execution of $100^{th}$ iteration, best chromosome ‘101, 774, 545, -681 -439, 767, 357, 451, 326, -258, 456.’ is obtained. While comparing the obtained result from the artificial bee colony algorithm using genetic algorithm and particle swarm optimization algorithm with the past records, it can be decided that controlling this resultant chromosome is sufficient to reduce the loss either due to the holding of excess stocks or due to the shortage of stocks. Hence it is proved that the analysis obtains a stock level that is a better prediction for the Electronic component inventory optimization in supply chain management.

**Table 2** PSO results.

| P | WW | PSO | | | |
|---|---|---|---|---|---|
| | OPT | BEST | MAX | AVG | STD |
| 1 | 415.50 | 415.50 | 411.75 | 408.00 | 4.25 |
| 2 | 417.00 | 477.00 | 415.75 | 418.75 | 2.69 |
| 3 | 451.00 | 451.00 | 451.00 | 405.00 | 6.10 |
| 4 | 439.00 | 439.00 | 403.00 | 403.00 | 5.70 |
| 5 | 411.25 | 411.25 | 402.50 | 402.70 | 3.78 |
| 6 | 424.50 | 424.50 | 414.60 | 424.70 | 5.01 |
| 7 | 434.50 | 434.50 | 414.70 | 468.30 | 4.75 |

## 6 Conclusions

Electronic component inventory optimization for warehouse and Artificial bee colony algorithm using genetic algorithm and particle swarm optimization algorithm is a significant component of supply chain management. we have discussed a method based on artificial bee colony algorithm genetic algorithm to optimize electronic component inventory in supply chain management and warehouse we also focus on how to specifically determine the most probable excess stock level and shortage level required for electronic component inventory optimization in the supply chain and warehouse such that the total supply chain cost and warehouse is minimized. We apply our methods on six stages - 11 member supply chain, Raw material, Storage, Producer, Transporter-1 (in-bound), warehouse, Transporter-2 (out-bound), distribution centers-1, distribution centers-2, distribution centers-3, Agents-1, Agents-2, Agents-3 studied model for optimization. The proposed method was implemented and its performance was evaluated using MATLAB.

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