CHAPTER 7

BCBO ALGORITHM AND PERFORMANCE COMPARISON

The previous chapter (chapter 6) proposed a strategy using hybrid bee colony cuckoo for the optimal scheduling and product selection. The previous strategy provided better convergence rate than the ABC based strategy. But, due to the update rule of cuckoo the convergence rate can fluctuate. Hence in this chapter the update rule of bat optimization is used in bee colony to obtain the stable and better convergence rate. The better convergence can provide better outcome in terms of cost and time spend for the E-O-L reverse logistics.

The technology in the world is changing day by day, so the manufacturer needs to upgrade the products in short time to compete with similar products in the market. The production of the new product is hard to the manufacturer for a short period. So the manufacturer followed reverse logistics for dismantling the end of life products and obtain components for the manufacturing of new products. So the organization can gain more profit by implementing product with EOL product components rather by producing the newer product.

In this chapter, the major objective is to develop a steady state in reverse logistics disassembly process for the end of life products. In the initial stage, an adaptive genetic algorithm was used for the dismantling process. In the second stage, an artificial bee colony (ABC) algorithm is used for the time minimization in reverse logistic process. Then in the third stage, a hybrid bee colony and cuckoo search strategy is proposed for the scheduling of disassembly in EOL reverse logistic.

Ultimately in this approach a new hybridization of algorithms which include a bee colony and bat optimization for the disassembly of EOL product. Moreover, this chapter comprises a performance comparison of reverse logistics process which is compared with our previous and conventional methods. Thus proposed strategy can improve performance in terms of both production time and the cost of manufacture in real time reverse logistics process.

In the recent age the technology development is the most competitive thing in the world. The technology is developed day to day (Mollenkopf D et al. 2007), (Carter CR and Ellram LM 1998). The organizations are developing technology with which they compete with the existing developed stuffs in the market. There is no aware of recycling of end of life products by the organization in early days. Since in early day's end of life products cause a severe treat to the environmental and in the side of manufacturers. It is due to the production in end of life products with hazardous content (Scharnhorst W et al. 2005).

Various analysis is carried out for the utilization of end of life products in manufacturing new products. The attitude of modern society is now totally focused on revenue consumption. Achieve stability in the profit, performance and production are developed, so the end of life reverse logistic is introduced (Petersen JA and Kumar V 2010).

The reverse logistics is defined as the end life of products which is dismantled for the establishment of a new product not by affecting the product value and the organization market strategy (Pishvaee MS et al. 2010). The product is competing with a similar product in market value. A reverse logistics process is developed, and the product is manufactured by not affecting the environment (Cappelli F et al. 2007). The solution ends up with collection, recycling and re-usage of goods by the government and the industrialist.

In an organization when a product is manufactured the product life span is also being mentioned by the manufacturer. If the product is well functioned after the lifespan the manufacturer recalls the product or the company needs an upgrade in the product, it is collected by the organization (Ekvall T and Tillman AM 1997). These products were recycled and form into new product and sent to market. The manufacturer expands the network for the collection of the end of life products (Vogtländer et al. 2001).

The collected products give structure to the new products by taking valuable components from the old one. After the collection of EOL products which is said to update process, hence the resale components are sold out in used markets (Carter CR and Ellram LM 1998). The re-constructible components are sent to the production unit in the organization, and the harmful polluting components are recycled by the recyclers such as (crushing, melting, and powdering, etc.) (Rose CM and Ishii K 1999; Allacker, K, et al. 2016). As in the side of the organization, it is one of the profitable processes by more in selling supplies and in serviceability of product which is slightly greater than direct selling in the market. The company does not meet with financial needs while selling reverse logistics products.

The reverse logistics briefly shows the products does not cause any effect in the supply chain (Stock JR and Mulki JP (2009). The supply chain is process flow in the organization where the process includes raw material collection, production and selling to the customer. The main objective of the supply chain is increasing profit by minimizing production cost (Allacker, K, et al. 2016). In industries, all products which are either electrical or mechanical which is recycled by collecting old products from the consumers and upgraded the product by picking up functional components. These components are joined in a system to make a new product and implemented to the market. The organization need to upgrade its technology and strategies in product manufacture to show their market value (Subramaniam et al. 2004; Kroon L and Vrijens G 1995).

The reverse logistics is classified into two types, they are open loop and closed loop system. In open loop system, the manufacturer took responsibility for collecting and marketing their products. That is if there are any issues in the collected product and in a drawback in marketed products. In closed loop system, the manufacturer takes back their product and updated. The closed loop system shows if there is any defect in launched product, the manufacturer recalls all products, analyzed and updated. Thus reverse logistics can improve customer service satisfaction and an increase of production material and longer spares available (Fleischmann M et al. 2001).

Reverse logistics is applied by acquiring components like (IC's, transistors) from the end of life products. These components are used for reconstruction of new circuits or new electric equipment. Moreover, in the mechanical/mechatronic system, for example in a vehicle, the components such as ECU, chassis, and remaining metal compounds is taken for the remanufacturing after the end of the lifespan of product (Fleischmann et al. 1997; Ferrer G 2003). Thus the reverse logistics can increase the profitability by utilizing a maximum number of components from the end of life products. These components can give structure to the new product not by losing any extra allowance in the organization for the new product manufacture.

On the early days, there is no awareness on end of life products, which they believe EOL can cause environmental issues and forms a severe threat to the society and on the side of the manufacturer. Since now the modern society is entirely focused on revenue consumption (Robotis A et al. 2005). So the manufacturer is also trying to reduce the manufacturing cost by utilizing maximum amount of EOL products in the industries. Thus reverse logistics can decrease the EOL electronic waste by consuming more useful components from the EOL products. The reverse logistics strategy is eco-friendly and is practiced by all over the countries. The products are upgraded by day to day, and new technology is displayed every day. So in the market, the products should differ from one other.

An organization needs to upgrade its product then only it can compete with the market (Stock JR and Mulki JP (2009). Thus reverse logistics does not cause any effect in product supply chain thus marketing invest is low and thereby increase in profit. The objective of reverse logistics is improved profit by decreasing production cost on the new product. In recent researches results reverse logistics can improve overall profit when compared with the manufacture of a new product. Thus it shows the reverse logistics can achieve a milestone on improving the economic stability of the society and in the organization (Zikopoulos C and Tagaras G 2007; D.S.Rogers and R.S. Tibben-Lembke, 2011).

7.1 Bat Algorithm

The bat-inspired algorithm is a unique meta-heuristic optimization algorithm flagged off by (X.S. Yang, 2010). The big-bang bat algorithm takes its cues from the echolocation phenomenon of micro bats with fluctuating pulse rates of emission and loudness (J.D. Altringham, 1996; P. Richardson, 2008). It effectively employs the unique nature of bats otherwise known as echolocation of bats. Bats employ sonar echoes to identify and thereby prevent roadblocks. It is a fact that sound pulses are converted to a frequency which rebounds from the obstacle. Bats can resort to time gap from emission to reflection and exploit it for navigation.

They characteristically give out small, loud, sound impulses. The pulse rate is demarcated as 10 to 20 times per second. After hitting and reflecting, bats convert their pulse to fruitful data to ascertain the possible distance of the prey. Bats, as a rule, employ wavelengths in the range of (0.7, 17) mm or inbound frequencies (20,500) kHz. Using execution, pulse frequency and rate are demarcated. It is easy to decide pulse rate from range 0 to 1, where 0 indicates the death of emission and 1 represents the maximum emission (A.H. Gandomi et al. 2013; X.S. Yang, 2011).

This trend may be employed to give shape to a novel bat algorithm. Yang (X.S. Yang, 2010) efficiently evolved three normalized regulations for bat algorithms:

1) All bats invariably employ echolocation to ascertain distance, in addition to reducing the divergence between food or prey and backdrop hassles in a certain amazing manner.
2) Bats fly discretely with velocity ‘v_i’ at position ‘x_i’ with a set frequency ‘$f_{\min}$’, fluctuating wavelength ‘λ’ and loudness ‘A_0' to look out for the prey. They can freely adapt the wavelength (or frequency) of their emitted pulses and the rate of pulse emission $r \in [0,1]$, by the nearness of their goal.
3) Even though the loudness may fluctuate in several ways, our presumption is that the loudness changes from a large (positive) ‘A_0’ to a minimum constant value ‘$A_{\min}$’.

1. Objective function $f(x)$, $x = (x_1, \ldots\ldots x_d)^T$.
2. Initialize the bat population x_i and v_i for $i = 1 \ldots\ldots n$.
3. Define pulse frequency $Q_i \in [Q_{\min}, Q_{\max}]$.
4. Initialize pulse rates r_i and the loudness A_i.
5. While $(t < T_{\max})$ // number of iterations.
6. Generate new solutions by adjusting frequency and
7. updating velocities and locations/solutions [Eq.(2) to (4)]
8. If($rand\ (0,10) > r_i$)
9. Select a solution among the best solutions
10. Generate a local solution around the best solution
11. end if
12. Generate a new solution by flying randomly
13. If($rand\ (0,1) < A_i\ and\ f(x_i) < f(x)$)
14. Accept the new solutions
15. Increase r_i and reduce A_i.
16. end if
17. Rank the bats and find the current best
18. end while
19. Post process results and visualization

Algorithm 7.1. Pseudo code for Bat Optimization

The unique bat algorithm is pictured in Algorithm 7.1. Here, bat's behavior is ensnared into fitness function of the dilemma to be tackled. It comprises the following segments:

- Activation (lines 2-4),
- Production of fresh parts (lines 6-7)
- Restricted probe (lines 8-11),
- Production of a fresh solution by flying discretely (lines 12-16),
- Location of the present best solution

Activation of the bat population is carried out discretely. Creating the new solutions is done by moving virtual bats as per the equations are shown below:

$$X_i^{(t+1)} = X_i^{(t)} + V_i^t, \tag{7.1}$$

$$V_i^{(t+1)} = V_i^t + \left(X_i^t - best\right)Q_i^t, \tag{7.2}$$

$$X_i^{(t+1)} = X_i^{(t)} + V_i^t, \tag{7.3}$$

Where, U (0, 1) represents a uniform distribution.

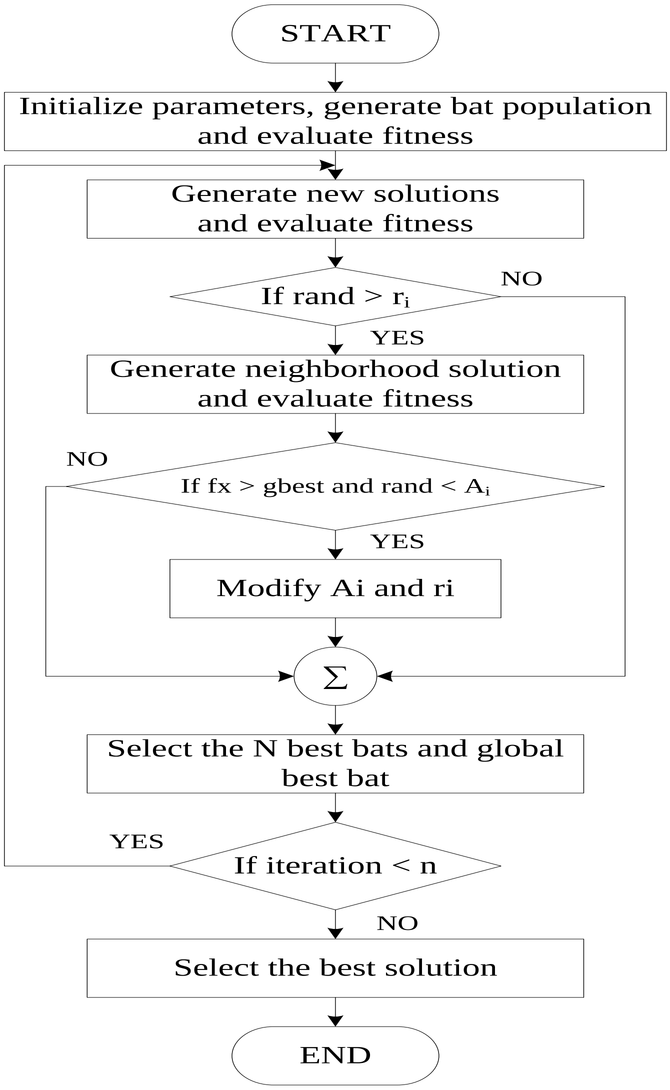

Figure 7.1. Flowchart of Bat Optimization

A discrete walk with direct exploitation is employed for restricted probe which adapts the existing best solution by Eqn. 7.4:

$$X^{(t)} = best + \varepsilon A_i^{(t)}(2U(0,1) - 1), \tag{7.4}$$

Where 'ε' represents the scaling factor, and '$A_i^{(t)}$' the loudness. The restricted probed is kick-started with the nearness based on the pulse rate 'r_i'. The term in line 13 is analogous to the replicated annealing trend, where the new solution is received with certain nearness by the constraint ‘ A_i ’. In tandem with this, the rate of pulse emission ‘ r_i ’ perks up and the loudness ‘ A_i ' falls. In fact, both the traits toe the line of innate bats, where the rate of pulse emission goes up, and the loudness comes down immediately when a bat meets with prey. Scientifically, these traits are ensnared with the ensuing equations:

$$A_i^{(t+q)} = \alpha A_i^{(t)} \ , \quad r_i^{(t)} = r_i^{(0)}\left[1-\exp(-\gamma\varepsilon)\right], \tag{7.5}$$

Where ‘ α ’ and ‘ γ ’ signify the constants. In reality, the ‘ α ' constraints cast an analogue part to the cooling factor in replicated annealing algorithm which checks the convergence pace of the related algorithm. The flowchart for the bat algorithm is furnished below, in Fig 7.1 (Ma J et al. 1998).

7.2 Proposed Methodology

The objective of this thesis discusses the manufacturing of new product by utilizing end of life product components by reverse logistics and disassembly to order process. These process can increase the organization profitability and by reducing the time and cost for the production of new product. In end of life reverse logistics disassembly to order (DTO), and recycling is the major processes, which is more complicated to perform. The reverse logistics method used in this thesis focused on the disassembly and manufacture of vehicle equipment.

Disassembly and Recycling of electronic components from the vehicles by improving the profitability in the organization not by losing the time in a production of new products. The cost for the dismantling is high due to the inclusion of product take back cost from the consumers. Thus adaptive genetic algorithm is introduced for the optimizing the cost of goods takes back for the dismantling. The chapter describes a hybrid algorithm which is a combination of the artificial bee colony and bat optimization for the performance analysis of dismantling and recycling in reverse logistics process.

In recent days many analytical methods are introduced for the disassembly of reverse logistics EOL processes. An adaptive genetic algorithm (AGA) strategy is applied for the optimum take back of EOL products for the dismantling. Hence the overall cost for the dismantling can be reduced. Next step in the chapter focused on the cost and time duration for the dismantling and recycling of the EOL products in reverse logistics. For the optimal prediction, artificial bee colony (ABC) algorithm is developed. For the further performance comparison, a hybridization algorithm is carried out. The hybridization algorithm includes hybrid artificial bee colony and bat optimization for the evaluation of return regarding cost and time in the disassembly process (Karaboga D and Basturk B 2008).

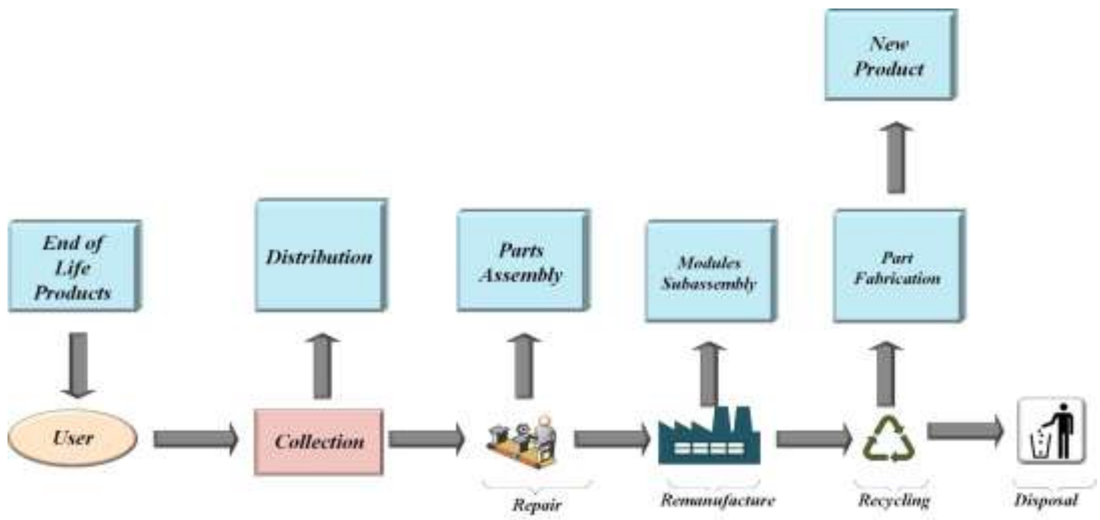

Figure 7.2. Reverse Logistics Data Flow

Hence the hybrid strategy can improve the overall performance and can achieve a milestone in production. In the proposed methodology, the production in mechanical products is taken for the reference. The end of life products is send to the collection, and the collected product is dismantled by DTO process. This process extract component from EOL products not by losing its product quality. Thus it satisfies the requirement of elements in production and gains maximum profit by minimizing the overall cost and time duration in the dismantling of EOL products. The process involved in proposed system is explained below.

7.2.1 Components of Proposed System

7.2.1.1 *End of Life Products*

The end of life products is defined as the end of product life after its working life and manufacturer stops its production and selling in the company. In most cases, the manufacturer supplies its product by using the end of the sale on the market. Each product is manufactured with expected product lifespan.

7.2.1.2 *User/Customer*

Customer satisfaction occurs if manufactured product and service might not meet customer expectations. The products are upgrading day by day so the need of customer to upgrade their product by comparing with the competitors. Customers prefer products by service and support from the manufacturer and they need the response from the vendors to do something for their queries.

7.2.1.3 *Collection*

Collection is the next process in reverse logistics. It is a fact of recovering materials which is a part of the recyclable product. The Collection phase collect end of life products for the disassembly and remanufacture of the new product. The collection starts from the customer's end of life products, and the vendors collect the goods and extract the working components from the product. These collected products are distributed to the manufacturer for the production of new product.

7.2.1.4 *Repair*

In this section, if the collected end of life products has any issues with the working is found out by the repair unit. If the product is still working the product will be the prelaunch with some up gradation and utilizes most of its working components. In case if the collected product has any issue with working parts it is repaired, and the parts are assembled for the remanufacturing.

7.2.1.5 *Modules Subassembly*

The small components of the product are assembled in the modules subassembly phase. After the subassembly, the product is sent to the manufacturing unit where the needed components are taken, and the excess is sent to the recycling unit.

7.2.1.6 *Recycling*

In recycling the components required for the fabrication is forwarded to the fabrication unit and the excess is recycled for the reuse. The recycled wastage is disposed of either by dumping on earth or burned. Thus the product is fabricated by the utilizing maximum components from the end of life products.

Step 1: *Candidate representation*

The initial solution is initialized based on the proposed objective which deals with taking back products. The main purpose is to find the combination of taking back products during dismantling so it can reduce the overall cost and time for reverse logistics EOL process. In this chapter, three parameters are taken such as [procurement cost (pc), the cost of taking back products (bc), and cost of disposing of (dc)].

Step 2: *Employee Bee Phase*

This phase is used for the comparison of solutions. Thus fitness function is introduced for the evaluation of each solution is solved. It is solved by the formation of string breaking and objective function evaluation for attaining a solution. Attain the fitness function; the following steps are completed for each candidate solution is explained in eqn. (7.6).

$$Fit = \min\{T_{DTO} \times T_{COST}\} \tag{7.6}$$

Where, T_{DTO} is the time taken for the DTO process, T_{COST} is the overall cost needed for the DTO process. The steps to formulate T_{DTO} and T_{COST} are defined in eqn. (7.7) moreover, (7.8) respectively.

$$T_{DTO} = \sum_{i=1}^{n} \left(EP_i \left(TD_i + TN_i \right) \right) \tag{7.7}$$

$$TCOST = \sum_{i=1}^{n} \left(EP_i \cdot bc_i \right) + \sum_{j=1}^{m} \left(PC_j \cdot pc_j \right) + \sum_{j=1}^{m} \left(DC_j \cdot dc_j \right) \tag{7.8}$$

Where PC_j is the sum of procured components in unit, DC_j is the sum of the disposed component in unit, bc_i is the product unit take back cost ‘i’ (price/unit), pc_j is the cost for procured components ‘j’ (price/unit). dc_j Is the cost of disposing of per unit ‘j' (price/unit), EP_i the number of EOL products per unit, T_{Di} is the time taken by the disassembling of i^{th} destructive products in seconds, T_{Ni} is the time adopted by the disassembling of ‘ i^{th} ' non-destructive components in seconds. These similar expressions are given in equation below.

$$T_{Di} = \sum_{i}^{m} \left(\left(EP_i - NDY_i \right) \times t_{DM\_j} \right) \tag{7.9}$$

$$T_{Ni} = \sum_{i}^{m} \left(\left(NDY_i \right) \times t_{NM\_i} \right) \tag{7.10}$$

$$PC_i = RUD_i - \sum_{i}^{m} \left(EP_i \cdot NDY_i \right) \tag{7.11}$$

$$DC_i = \sum_{i}^{m} \left(EP_i \cdot NDY_i \right) - RUD_i \tag{7.12}$$

Where t_{DM_j} is time taken for disassembling the j^{th} destructive components in seconds, t_{NM_j} is time taken for disassembling j^{th} non-destructive components in seconds, EP_i is the sum of EOL products is determined by units, NDY_i is the percentage of yield destructive disassembly. NDY_j, is the proportion of yield non-destructive disassembly. RUD_j, is the j^{th} number of reusable components defined in units.

Step 3: *Onlooker bee phase*

This onlooker bee phase selects food source by the forced optimal DG location and upgrades the food sources. Thus it reaches the solution of the place with low power loss and high voltage profile which can update the population velocity which is defined in eqn. (7.13).

$$V_{ij} = x_{ij} + \phi(x_{ij} - x_{kj}) \tag{7.13}$$

Where k is the solution near to 'i', ϕ is the random vector from limit (-1 to 1), V_{ij} is the nearest solution of M_{ij}.

Step 4: *Selection*

The selection process is used to visualize maximum fitness of the solution which is updated to decide the chance. The following eqn. (7.14) defines the probability function as below.

$$\text{Probability, } y = \frac{\phi}{\sum_{i=1}^{n} \phi} \tag{7.14}$$

Step 5: *Bat*

The bat algorithm is a metaheuristic algorithm inspired by the bat motion developed by Xin-She Yang in 2010. In recent years various metaheuristic algorithms are developed. The bat algorithm deals with the behavior of micro bats, basically bat randomly flies with velocity v_i, position x_i and varying frequency/loudness A_i.

The bat uses sonar waves to detect the prey and avoid obstacles. Thus the bat searches its prey by changing its frequency, loudness and pulse rate termed as r and for local search, random values of -1 to 1 is used. Thus the bat algorithm for the optimization is deduced in the following equations below.

Distance at location function,

$$x_i^t = x_i^{t-1} + v_i^t \tag{7.15}$$

Where x_i^t is the location distance with time t, x_i^{t-1} is the input distance at a location with different time t-1, v_i^t is the velocity function at time t.

$$v_i^t = v_i^{t-1} + \left(x_i^{t-1} - x_*\right) f_i \tag{7.16}$$

Where v_i^t is the input velocity at time interval t, v_i^{t-1} is the input velocity with different time t-1, x_* is the current best solution, f_i is the input frequency function.

$$f_i = f_{\min}(f_{\max} = f_{\min})\beta \tag{7.17}$$

Where $f_{\min}$ and $f_{\max}$ is the minimum and maximum frequency β is the random vector [0, 1] at uniform distribution.

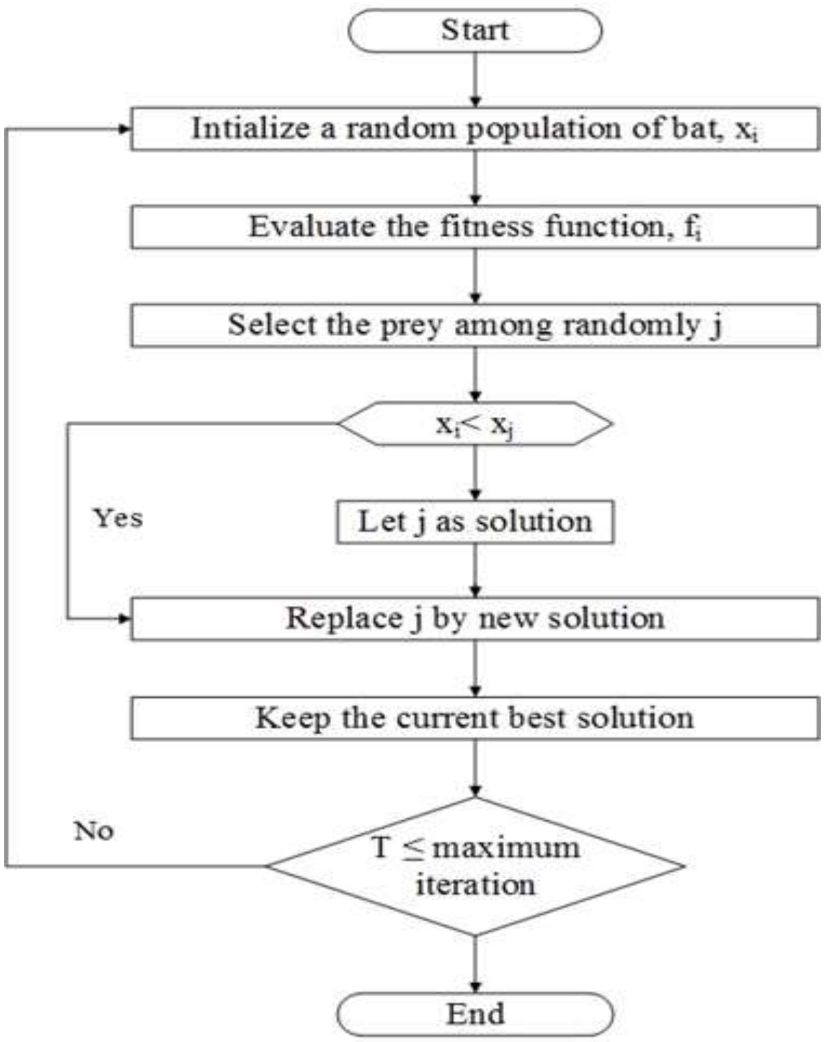

Figure 7.3. Flow chart for the Proposed Bat Process

The bat algorithm is used for the reducing the fitness of the solution by estimating direct proportional objective function value. Thus the initialization of the algorithm is carried out in following steps.

$$x_i = x_1, x_2, \ldots\ldots\ldots x_n \tag{7.18}$$

Where x_i is the initial input for the function, x_1, x_2 is the input function value at first order and second order, x_n is the n^{th} number of input for the initialization. The fitness function for the bat characters is shown in equation (7.19)

$$fit_i = \begin{cases} \dfrac{1}{1+f_i} & if \quad f_i \geq 0 \\ 1+bat(f_i) & if \quad f_i < 0 \end{cases} \tag{7.19}$$

The bat randomly flies with velocity to find its nearby prey. Thus the velocity function is deducing the new solution to iterating each character for the solution. The velocity function is explained in equation (7.20).

$$v_i^t = [v_i^{t-1} + (X_i^{t-1} - X_\Psi)\, f_i] \tag{7.20}$$

Where X_i^{t-1} is the iteration of the bat at time interval t-1, V_i^{t-1} is the input velocity at time interval t-1, X_ψ is the current best solution exists and f_i is the fitness function for the bat algorithm.

The bat flies with a position x_i with varying loudness A_i by varying these parameters the bat can find its prey and avoid obstacles. Thus the bat adjusts its position with the different time interval t and t-1 which is explained in the equation (7.21) as below.

$$X_i^t = X_i^{t-1} + \in_{i,j}\, l^{At} \tag{7.21}$$

Where X_i^{t-1} is the Position of the bat at time interval t and t-1, $\in_{ij}$ is the random value between (-1 to 1), l^{At} is the loudness value at time interval t.

Step 6: *Completion Criteria*

The completion criteria end with the finding of the current best solution if not possible the process is continued, and a maximum number of iteration will be carried out for obtaining the best option. The process shows that the optimal DTO process in reverse logistics EOL products using hybridized HBCB optimization algorithm is generated in process flow diagram. Thus the data is initialized in the HBCB, and the random solution of reclaim product is generated. The fitness function for this random solution is produced in employee bee phase, and the onlooker bee selects some solution for further altering. The bat algorithm based optimization strategy is to find out an optimal best settlement in some products for the low cost of operation. The implementation and performance calculation is explained in next section. The pseudo code for the hybridized HBCB optimization is explained as below.

```
Initialization: Generate the initial population zi=1,2,...,SN
Evaluate the fitness (fi) of the population
cycle=1;
Repeat
        For each employed bee {
                Produce new solution, then calculate the value fi and Apply greedy selection
        process }
        Calculate the probability values pi for the solutions zi
        FOR each onlooker bee {
                Select a solution zi depending on pi, produce new solution, then Calculate fi, and
                Apply greedy selection }
        IF an abandoned solution for the scout exists,
        THEN replace it with a new solution based on bat
        FOR each bat {
                Initialize Population xi=1,2,….N and vi
                Define pulse fi at xi
                Initialise pulse rate ri and loudness Ai
                While (t < maximum number of iterations)
                        Generate N random solutions by adjusting frequency, velocity and location
                       F (rand >ri)
                Select a solution among the best solutions and generate a local solution around the
                selected best solution
                End if
                If ( rand < Ai and f(xi) < f(x*)) and accept new solutions
                Increase ri, reduce Ai
                End if
                Ranks the bats and find current best x*
                End while
                Present results }
        Memorize the best solution so for
```

Algorithm 7.2. Pseudo code for hybridized HBCB optimization algorithm

7.3 Result and Discussion

The proposed system for the best DTO process in EOL reverse logistics based on HBCB optimization algorithm is carried out on the working platform of Matlab with the following system specification.

- Processor : Intel Core 2 Quad @ 2.5 GHz
- RAM : 3GB
- Operating system : Windows 7
- Mat lab version : R 2014a version 8.3

In this analysis, the considered product is 100 and product have a maximum number of 9 components in each. In this thesis, mechanical production of an electric motor is mainly considered, and it is numbered between 1 and 9. The table shows the bill of material for the production which detailed about the components and the type of disassembly. The EOL products do not contain all elements, some of the components will miss, and these missed components is defined by number ‘0'.

The Table 4.2 the details about the product is mentioned, and these data is used for the implementation which is explained in the Appendix section. In this thesis manufacture of 20 products from 100 EOL products is implemented for the experimental implementation section. For the selection of available component proposed HBCB optimization algorithm is used. The reverse logistics for the end of life computer components are plotted for the reference. It shows the single components are taken for the analysis; the details plotted in the table determines the cost and disassembly method for the end of life reverse logistics in manufacturing.

The performance of conventional way is compared with previous algorithms like adaptive genetic algorithm (AGA), artificial bee colony (ABC) algorithm is implemented. This chapter mainly focused on time consumption of DTO process in EOL products for overall profit gain. Hence an artificial bee colony algorithm is proposed. The average time taken for the process is shown in Table 5.1 below.

The Table 5.1 shows disassembling process required more time for operating in complex machining than normal. Disassembly process avoids parts damage and the time needed for disassembly complex product is 40 seconds and a minimum range of 33 seconds for a given product. On the other hand, the time required for disassembling of the natural product is a maximum of 14 seconds and minimum of 9 seconds. To validate the efficiency the algorithms like artificial bee colony and adaptive genetic is used. The time comparison in DTO process is explained in Table 7.1.

Table 7.1: Comparison on Disassembly Time for the Products

No of EOL Products	**Disassembly time (sec)**				
	Proposed HBCB Algorithm	*Hybrid B2CS Algorithm*	*ABC*	*GA*	*EP*
47	164	179	223	247	280

In Table 7.1 the disassembly time for the 47 EOL products is tabulated with previous algorithms such as hybrid B2CS, ABC, GA and EP with the period of 179, 223, 247, and 280. When compared with the proposed HBCB strategy, it has the least value. Thus proves that the proposed method is efficient for the DTO process in short time. In Table 7.2 the cost for disassembly for 47 products is analyzed with various previous algorithmic strategies such as hybrid B2CS, ABC, AGA, GA, and EP. The cost of disassembly is calculated for every strategies and tabulated.

Table 7.2: Comparison of Total Cost for the Products

No of EOL Products	**Total Cost ($)**					
	Proposed HBCB Algorithm	*Hybrid B2CS Algorithm*	*ABC*	*AGA*	*GA*	*EP*
47	427	465	498	525	591	614

When comparing these values with proposed HBCB optimization strategy the cost is less for the processes. Thus the Tables 7.1 and 7.2 shows the proposed HBCB strategy is more efficient in time as well as in cost for the disassembly of 47 EOL products.

Table 7.3: Comparison regarding Disassembly Time

EOL Products	Disassembly time (sec)				
	Proposed HBCB Algorithm	*Hybrid B2CS Algorithm*	*ABC*	*GA*	*EP*
30	105	125	196	215	249
40	120	167	202	221	266
50	155	196	237	261	298
70	180	223	256	289	320
100	232	255	310	345	382

In Table 7.3 the time comparison of (30- 100) end of life products is taken for the reference. The disassembly of the goods is analyzed with previous algorithms such as hybrid B2CS, ABC, GA and EP respectively. In these algorithms, B2CS has a minimum time of 125 seconds to a maximum of 255 seconds. For ABC the period is between 196-310 seconds, GA is between 215-345 seconds and EP has 249-382 seconds. While comparing with proposed HBCB strategy it shows the period is low from all its comparators. Thus the proposed HBCB strategy is more efficient and low time process in disassembly of EOL process.

Table 7.4: Comparison regarding Total Cost

EOL Products	Total Cost ($)					
	Proposed HBCB Algorithm	*Hybrid B2CS Algorithm*	*ABC*	*AGA*	*GA*	*EP*
30	400	421	448	475	516	563
40	416	452	487	502	578	597
50	473	485	505	533	602	620
70	490	498	536	558	645	656
100	520	532	585	591	689	702

Table 7.4 shows the total cost comparison for the (30-100) EOL products with the previous algorithms like hybrid B2CS strategy, ABC, AGA, GA, and EP respectively. In previous B2CS strategy, the cost to process (30-100) is between 421

and 532, ABC has cost between 448 and 585, the AGA is between 475 and 591, the cost of GA is between 516 and 689, and EP cost is between 563 and 702. Thus comparing all these cost values with the proposed HBCB optimization strategy, it shows the proposed strategy is more cost effective in disassembly in EOL products.

Fig 7.4 shows the convergence comparison of strategies such hybrid B2CS, ABC, AGA, GA, EP with proposed HBCB strategy. Thus the proposed method is converged when comparing with the previous also shows that the previous algorithm needs more fitness. Items, so the proposed method is more efficient for processing DTO process in end of life products.

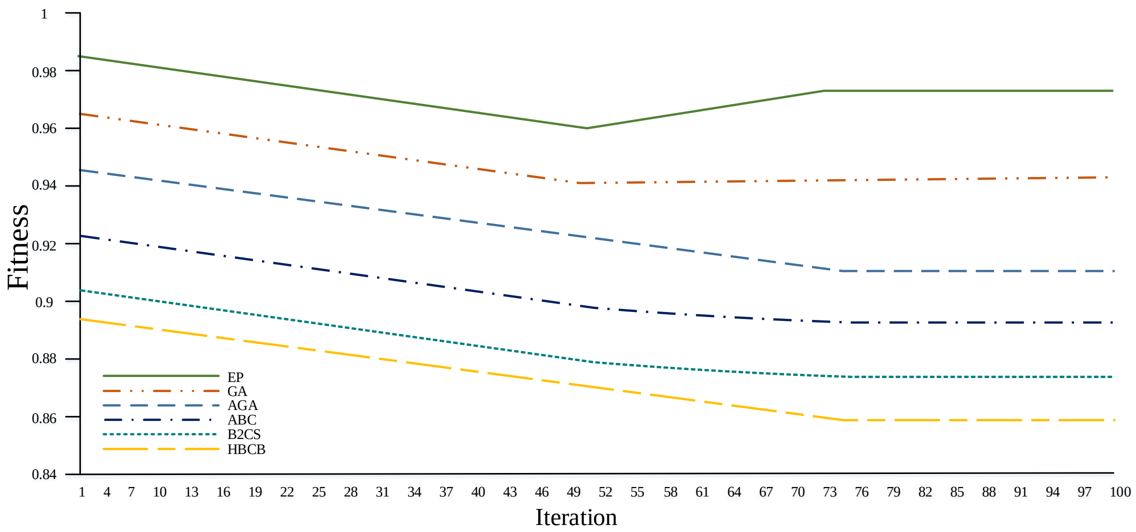

Figure 7.4. Convergence

In Fig 7.5 the time comparison of disassembly of EOL products with previous algorithms such as hybrid B2CS, ABC, AGA, GA and EP respectively. The time taken for the proposed HBCB strategy is lower for 100 seconds while the previous algorithmic strategies have higher starts from 130-250 seconds which is greater than proposed strategy. Thus proposed strategy is more efficient in processing disassembly in short time.

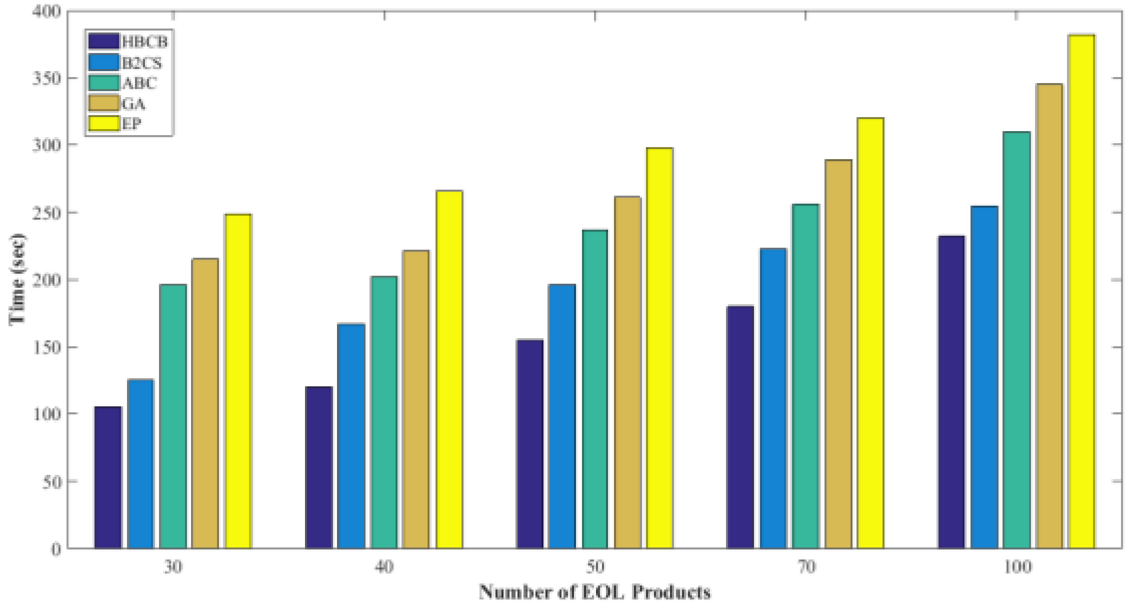

Figure 7.5. Disassembly Time Comparison

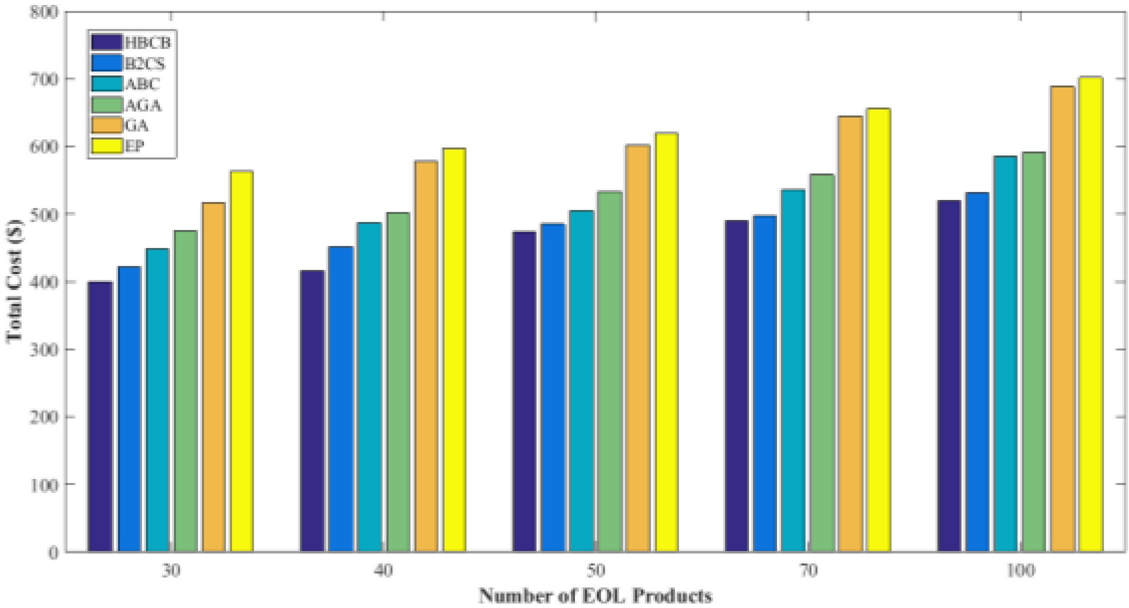

Figure 7.6. Total Cost Comparison

In Fig 7.6 the cost comparison of the end of life disassembly is plotted with proposed strategy and with previous algorithms. Thus the cost of disassembly in proposed strategy is lower by 400 when comparing with previous algorithms which have starting range of 420-560. The price range of proposed strategy is lower and more profitable in end of life products.

Since many companies admit the necessary possibility of effective reverse logistics interest is higher than before. Firms are taking seriously in the investment of their reverse logistics programs in the organization. Mention that the amount of money invested in managing the business statics for processing reverse logistics. Reverse logistics companies reduce production cost on a new product by recovering components for reuse by reducing the raw materials for the manufacture. The reverse logistics is practiced in the industries for the optimal revenue from the end of life products by recovering components for the production of new products.

In this chapter, the HBCB optimization algorithm is approached for the optimal processing of DTO in EOL products. The hybridization includes artificial bee colony and bat optimization for the better outcome. The main objective of this study is to find the suitable components for the reduction of disassembly cost and time taken for the completion of DTO process. The test was conducted using suitable data, and the performance is analyzed, compared with similar data. Thus the performance comparison shows that the approached HBCB optimization algorithm is more efficient in reverse logistics. The comparative analysis suggested that the proposed algorithm is suitable for the implementation in reverse logistics of EOL products.