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Profit Maximization in Reverse Logistic based on Disassembly Scheduling using Hybrid Bee Colony Bat Optimization

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Abstract: This work is planned to develop a strategy to enhance the profit in reverse logistic of end of life product. In this paper a novel strategy based on the hybrid bee colony and bat (HBCB) optimization techniques is presented to perform reverse logistic. The aim of the present paper is to maximize the profit in reverse logistic based manufacturing. The proposed optimization technique used to perform the scheduling of disassembly of end of life product. So that the time spent in reverse logistic get reduced. On the other hand the proposed technique accrue the appropriate required amount of product in disassembly, so that the component loss get reduced. Thus the proposed technique can enhance the profit of manufacturer by reducing the required time and cost for disassembly. Ultimately the proposed technique can provide the suitable technique for the multi period disassembly in manufacturing industries.

Keyword: End of Life (EOL); Artificial Bee Colony (ABC); Bat Optimization Algorithm; Adaptive Genetic Algorithm (AGA); Hybrid Bee Colony

1. Introduction

In the recent age the technology development is the most competitive thing in the world. The technology is developed by day to day (Mollenkopf, D., et al 2007; Carter, C. R., and Ellram, L. M. 1998; Karthick, S. 2017). The organisations are developing technology which they compete with the existing developed stuffs in the market. There is no aware of recycling of end of life products by the organisation 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). On the following these days the various analysis is carried out for the utilisation of end of life products in manufacturing. The attitude of modern society is now totally focused on revenue consumption. To maintain a stability in profit, performance and production is developed, so end of life reverse logistic is introduced (Petersen, J. A., and Kumar, V. 2010).

The reverse logistics is defined as the end life of products which is dismantled for the establishment of new product not by affecting the product value and the organisation market strategy (Pishvaee, M. S., et al. 2010). These method is employed for the remanufacture of product by using the same components by small upgrade in the product. Thus the product is compete with similar product in market value. Thus reverse logistics is developed and the product is manufactured by not affecting the environment (Cappelli, F., et al. 2007). The solution is end up with collection, recycling and re-usage of products by the government and the industrialist. The process starts by when a product is manufactured the product life span is also be mentioned by the manufacturer. Thus the product is well functioned after the life span the manufacturer recalls the product or the company need an upgrade in the product, it is collected by the organisation (Ekvall, T., and Tillman, A. M. 1997). These products were recycled and forms in to new product and said to marketing. The collection process is nothing leasing the product in the industry by investing less by the customer. The manufacturer expands the network for the collection of the end of life products (Vogtländer, J. G., et al. 2001).

Thus the collected products give structure to the new products by taking useful components from the old one. After the collection of EOL products which is said to update process, thus the resale components is sold out in used markets (Carter, C. R., and Ellram, L. M. 1998). The re-constructible components are sent to the production unit in the organisation and the harmful polluting components are recycled by the recyclers such as (crushing, melting, and powdering etc.) (Rose, C. M., and Ishii, K. 1999; Boguski, T. K., et al. 1994). As in the side of organisation it is one of the profitable process by more in selling supplies and in serviceability of product which is slightly greater than direct selling in market. Thus the company does not meet with financial needs while selling reverse logistics products. Thus reverse logistics briefly shows the products does not cause any effect in supply chain (Stock, J. R., and Mulki, J. P. 2009). The supply chain is process flow in the organisation where the process include raw material collection, production and selling to customer. The main objective of supply chain is increasing profit by minimize production cost (Subramaniam, U., et al. 2004). In industries all products which is 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 together in a system to make a new product and implemented to the market. To attain a milestone in development of modern technology, the organisation need to upgrade its technology and techniques in product manufacture (Fleischmann, M., et al. 1997; Melissen, F. W., and De Ron, A. J. 1999).

The reverse logistics is classified in to two type open loop and closed loop system. In open loop system the manufacturer took responsibility for collecting and marketing their products. That is if there is any issues in the collected product and in drawback in marketed products. In closed loop system the manufacturer take back their product and updated. The closed loop system shows if there is any defect in launched product, the manufacturer recalls all product, analysed and updated. Thus reverse logistics can improve customer service satisfaction and increase of production material and longer spares available (Kroon, L., and Vrijens, G. 1995).

As a result the reverse logistics in end of life products can improve profit by not losing its market value and not harmful treat to environment. The rest of the paper includes related work at section 2, proposed methodology in section 3, Experimentation and performance analysis is explained in section 4, discussion and conclusion is explained in section 5.

2. Related work

The reverse logistics is the technique used by the organisation for equalising the financial needs in marketing the new product. The organisation utilise reverse logistics by collecting, recycling, and re-usage of end of life product from the consumer. The reverse logistics is followed by many organisation to maintain a position in the market (Pishvaee, M. S., et al. 2010). Products are upgrading day to day to obtain a stability in the market without affecting the product value. The organisation carried out reverse logistics in end of life products for the production of new product. The reverse logistics is mainly used in engineering fields like electrical, mechanical, mechatronics and robotics, etc. In electrical field 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. And in mechanical/ mechatronic system, for an example in a vehicle the components such as ECU, chassis, and remaining metal compounds is taken for the remanufacturing after the end of life span of product (Ferrer, G. 2003; Robotis, A., et al 2005). Thus the reverse logistics can increase the profitability by utilising maximum number of components from end of life products. These components can give structure to the new product not by losing any extra allowance in the organisation for the new product manufacture.

On the early days there is no awareness on end of life products, which they believes EOL can cause environmental issues and forms severe treat to the society and in the side of manufacturer. Since now the modern society is completely focussed on revenue consumption (Zikopoulos, C., and Tagaras, G. 2007). So the manufacturer also trying to reduce the manufacturing cost by utilising 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 technique is eco-friendly and is practiced by all over the countries. The products are upgrade by day to day and new technology are displayed every day. So in the market the products should differ from one other. The organisation need to upgrade their product so only it can compete with the market (Stock, J. R., and Mulki, J. P. 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 improve profit by decreasing production cost on new product. In recent researches results reverse logistics can improve overall profit when comparing with the production of a new product. Thus it shows the reverse logistics can achieve a mile stone on improving the economic stability in the society and in the organisation (Rogers, D. S., and Tibben-Lembke, R. 2001; Junshui, M., et al. 1998).

3. Proposed Methodology

In end of life reverse logistics disassembly to order (DTO) and recycling is the major processes, which is more complicated to perform. In recent days many theoretical methods are introduced for the disassembly of reverse logistics EOL processes. Thus an adaptive genetic algorithm (AGA) technique (Karaboga, D., and Basturk, B. 2008; Sathish, T., and Jayaprakash, J. 2015) is applied for the optimum take back of EOL products for the dismantling. Thus the overall cost for the dismantling can be reduced. On the next step the paper focussed on the cost and time duration for the dismantling and recycling of the EOL products based on artificial bee colony (ABC) algorithm is developed (Sathish, T., and Jayaprakash, J. 2017; Sathish, T., and Periyasamy, P. 2019). For the further performance comparison a hybridisation method is carried out. The hybridisation include artificial bee colony and bat optimization for the evaluation of performance in terms of cost and time in the disassembly process. Thus the hybridised technique can improve the overall performance and can achieve a milestone in production. In proposed methodology the production in mechanical products are taken for the reference. The end of life products is said to collection and the collected product is dismantled by DTO process. This process extract components from EOL products not by losing its product quality. Thus it satisfies the requirement of components in production and gain maximum profit by minimizing the overall cost and time duration in dismantling of EOL products. The process involved in proposed system are explained below.

Step 1: Candidate representation

The initial solution is initialized based on the proposed objective which deals with take back products. The main objective is to find combination of take back products during dismantling so it can reduce the overall cost and time for reverse logistics EOL process. In this paper three parameters are taken as the parameters such as [procurement cost (pc), cost of take back products (bc), and cost of disposing (dc)]. The initial populations is shown in fig 1.

Step 2: Employee Bee Phase

Generally this phase is used for the comparison of solutions, thus fitness function is introduced for the valuation of each solution is solved. Thus it is solved by the formation of string breaking and objective function evaluation (4) for attain solution. To attain the fitness function for the valuation, the following steps are completed for each candidate solution is explained in equation (4).

$$Fit = \min\{T_{DTO} \times T_{COST}\} \tag{4}$$

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 equation (5) and (6) respectively.

$$T_{DTO} = \sum_i \left(EP_I \left(T_{Di} + T_{Ni}\right)\right) \tag{5}$$

$$T_{COST} = \sum_i \left(EP_i \cdot bc_i\right) + \sum_j \left(pc_j \cdot PC_j\right) + \sum_j \left(dc_j \cdot DC_j\right) \tag{6}$$

Where, PC_j is the sum of procured components in unit, DC_j is the sum of 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 per unit 'j' (price/unit), EP_i i^{th} 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 taken by the disassembling of 'i^{th}' non-destructive components in seconds. These corresponding expression are given in equation below.

$$T_{Di} = \sum_i \left(\left(EP_i - NDY_i\right) \times t_{DM\_j}\right) \tag{7}$$

$$T_{Ni} = \sum_i \left(\left(NDY_i \right) \times t_{NM\_i} \right) \tag{8}$$

$$PC_j = RUD_j - \sum_i \left(EP_i \cdot NDY_j \right) \tag{9}$$

$$DC_j = \sum_i \left(EP_i \cdot NDY_j \right) - RUD_j \tag{10}$$

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 percentage 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 select food source by the forced optimal DG location and upgrade the food sources. Thus it reach the solution of the location with low power loss and high voltage profile which can upgrade the population velocity which is defined in equation (11).

$$V_{ij} = x_{ij} + \phi_{ij} \left(x_{ij} - x_{kj} \right) \tag{11}$$

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 equation (12) defines the probability function as below.

$$Probability,\ y = \frac{\phi}{\sum_{i=1}^{n} \phi} \tag{12}$$

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 behaviour of micro bats, basically bat randomly flies with velocity v_i, position x_i and with varying frequency/loudness A_i. The bat uses sonar waves to detect the prey and avoid obstacles. Thus the bat search its prey by changing its frequency, loudness and pulse rate r and for local search random values of -1 to 1 is generally used. Thus the bat algorithm for the optimization is deduced in the following equations below.

Distance at location function,

$$x_i^t = x_i^{t-1} + v_i^t \tag{13}$$

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

Velocity function,

$$v_i^t = v_i^{t-1} + \left(x_i^{t-1} - x_* \right) f_i \tag{14}$$

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

Frequency function,

$$f_i = f_{\min} + (f_{\max} - f_{\min})\beta \tag{15}$$

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

Objective function for bat algorithm

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

Initialisation for the bat

$$x_i = x_1, x_2, \cdots\cdots\cdots x_n \tag{16}$$

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 initialisation.

Fitness function for the algorithm

The fitness function for the bat characters is shown in equation (17)

$$fit_i = \begin{cases} \dfrac{1}{1+f_i} & if \quad f_i \geq 0 \\ 1 + bat(f_i) & if \quad f_i < 0 \end{cases} \tag{17}$$

Bat velocity function

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 (18).

$$v_i^t = [v_i^{t-1} + (X_i^{t-1} - X_\Psi) f_i] \tag{18}$$

Where, X_i^{t-1} is the iteration of 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.

Bat position function

The bat generally flies with position x_i with varying loudness A_i by varying these parameters the bat can find its prey and avoid obstacles. Thus the bat adjust its position with the varying time interval t and t-1 which is explained in the equation (19) as below.

$$X_i^t = X_i^{t-1} + \in_{i,j} l^{At} \tag{19}$$

Where, X_i^{t-1} is the Position of 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 ends with finding of current best solution if not possible the process is continued and maximum number of iteration will be carried out for obtain a best solution. The process shows that the optimal DTO process in reverse logistics EOL products using hybridised HBCB optimization algorithm is generated in process flow diagram. Thus the data is initialised in the HBCB and the random solution of reclaim product is generated. The fitness function for this random solution is generated in employee bee phase and the onlooker bee select some solution for further altering. The bat algorithm based optimization technique is to find out optimal best solution in number of products for low cost of operation. The implementation and performance calculation is explained in next section. The pseudo code for the hybridised HBCB optimization is explained in fig 2.

4. Result and Discussion

The proposed system for the best DTO process in EOL reverse logistics based on HBCB optimization algorithm is carried out in the working platform of Matlab. In this analysis the considered product is 100 and product has maximum number of 9 components in each. In this paper 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 generally does not contain all components, some of the components will miss and these missed components is defined by number '0'. The table 2 the details about the product is mentioned and these data is used for the implementation which is explained in appendix section. In this paper manufacture of 20 products from 100 EOL products is implemented for the experimental implementation section. For the selection of convenient 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 paper mainly focussed on time consumption of DTO process in EOL products for overall profit gain. Thus artificial bee colony algorithm is proposed. The average time taken for the process is shown in table3 below.

The table 3 shows disassembling process required more time for operating in complex machining than normal. Generally disassembly process avoid parts damage and the time required for disassembly complex product is 40 seconds and a minimum range of 33 seconds for a given product. On other hand the time required for disassembling of normal product is maximum of 14 seconds and minimum of 9 seconds. Thus 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 4.

In table 4 the disassembly time for the 47 EOL products is tabulated with previous algorithms such as hybrid B2CS, ABC, GA and EP with time period of 179, 223, 247, and 280. When comparing with the proposed HBCB optimization algorithm which has least value and proves that the proposed method is efficient for the DTO process in short time.

In table 5 the cost for disassembly for 47 products is analysed with various previous algorithmic techniques such as hybrid B2CS, ABC, AGA, GA, and EP. The cost of disassembly is calculated for each technique and tabulated the values are 465, 498, 525, 591, 614 respectively. When comparing these values with proposed HBCB optimization technique the cost is less for the processes. Thus the tables 4 and 5 shows the proposed HBCB technique is more effective in time as well as in cost for the disassembly of 47 EOL products.

In table 6 the time comparison of (30-100) end of life products is taken for the reference. The disassembly of products is analysed with previous algorithms such as hybrid B2CS, ABC, GA and EP respectively. In these algorithms B2CS has minimum time of 125 seconds to a maximum of 255 seconds. For ABC the time period is between 196-310 seconds, GA is between 215-345 seconds and EP has 249-382 seconds. While comparing with proposed HBCB technique it shows the time period is low from all its comparators. Thus the proposed HBCB technique is more efficient and low time process in disassembly of EOL process.

The table 7 shows the total cost comparison for the (30-100) EOL products with the previous algorithms like hybrid B2CS technique, ABC, AGA, GA, and EP respectively. In previous B2CS technique the cost for the process of (30-100) products is between (421-532), ABC has cost between (448-585), the process in AGA is between (475-591), the cost of GA is between (516-689) and EP cost is between (563-702). Thus comparing all these cost values with the proposed HBCB optimization technique it shows the proposed technique is more cost effective in disassembly in EOL products. The analysis outcome is graphically plotted in figures as below.

The Fig 3 shows the comparison of fitness of previous algorithms such as hybrid B2CS, ABC, AGA, GA, EP with proposed HBCB optimization algorithm shows that the previous algorithm need more fitness. Thus proposed method is converged when comparing with previous algorithms, so the proposed method is more efficient for processing DTO process in end of life products.

In fig 4 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 technique is lower by 100 seconds while the previous algorithmic techniques has higher starts from 130-250 seconds which is higher than proposed technique. Thus proposed technique is more effective in processing disassembly in short time.

In fig 5 the cost comparison of end of life disassembly is plotted with proposed technique and with previous algorithms. Thus cost of disassembly in proposed technique is lower by 400 when comparing with previous algorithms which has starting range of 420- 560. The price range of proposed technique is lower and more profitable in end of life products.

5. Conclusion

The HBCB optimization algorithm is approached for the optimal processing of DTO in EOL products. The hybridisation includes artificial bee colony and bat optimization for the better outcome. In this paper the objective is to find the suitable components for the reduction of disassembly cost and time taken for the completion of DTO process. The test were conducted using suitable data and the performance is analysed, compared with similar data. Thus the performance comparison shows that approached HBCB optimization algorithm is more effective in reverse logistics. Hence from the analysis and comparison can suggest the proposed algorithm is a suitable technique for the implementation in reverse logistics in EOL products.

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Item	*Name of component*	*Material type*	*New product cost*	*Disassembly*	
				Cost ($)	*Method*
1	Outer cover	A	3	2	D
2	Power supply	C	4	3	D
3	System fan	P	3	2	D
4	RAM	P	6	3	N
5	DVD Drive	A	7	4	N
6	Hard Disk slot	P	2	2	D
7	CPU	P	6	2	N
8	Heat sink	A	4	3	D
9	Hard disk	A	6	2	N

Table 1: Single product's components detail
A-Aluminium, C- Copper and P- Plastic; D- Destructive and N- Non Destructive.

Product no	*Components Details*	*Disassembly Method*
1	100000000	D00000000
2	100000002	D0000000D
3	100000009	D0000000N
4	100000089	D000000DN
5	100000089	D000000DN
-	-	-
100	900000000	N00000000

Table 2: Example EOL Product Details

Non-destructive Machine	*Time (Sec)*	*Destructive Machine*	*Time (Sec)*
NM1	33	DM1	11
NM2	36	DM2	9
NM3	35	DM3	13
NM4	40	DM4	14
NM5	32	------	------

Table 3*:* Average Time Taken by the Various Machines

No of EOL Products	***Disassembly time (sec)***				
	Proposed HBCB	*B2CS (Sathish, T., and Jayaprakash , J. 2015.)*	*ABC*	*GA*	*EP*
47	164	179	223	247	280

Table 4*:* Comparison on Disassembly Time for the Products

No of EOL Products	***Total Cost ($)***

	Proposed HBCB	B2CS (Sathish, T., and Jayaprakash, J. 2017)	ABC	AGA (Sathish, T., and Jayaprakash, J. 2015.)	GA	EP
47	427	465	498	525	591	614

Table 5: Comparison on Total Cost for the Products

No of EOL Products	***Disassembly time (sec)***				
	Proposed HBCB	*B2CS (Sathish, T., and Jayaprakash, J. 2017)*	*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

Table 6: Comparison in Terms of Disassembly Time

No of EOL Products	***Total Cost ($)***					
	Proposed HBCB	*B2CS (Sathish, T., and Jayaprakash, J. 2017)*	*ABC*	*AGA (Sathish, T., and Jayaprakash, J. 2015.)*	*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

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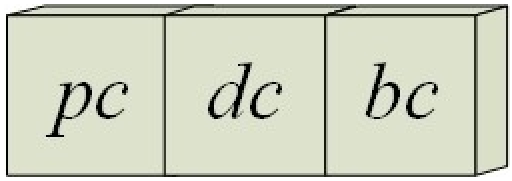


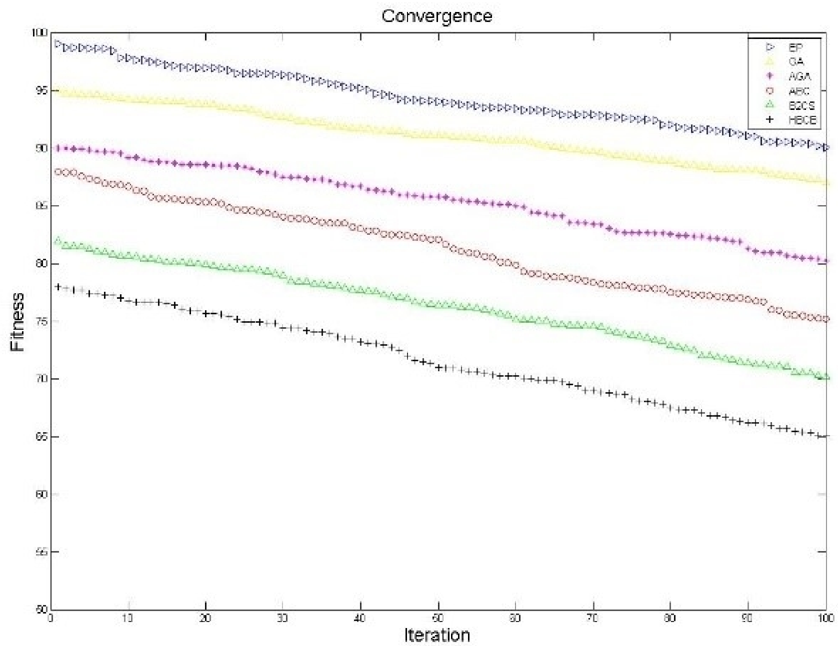
Initial Populations

66x22mm (96 x 96 DPI)

```
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
```

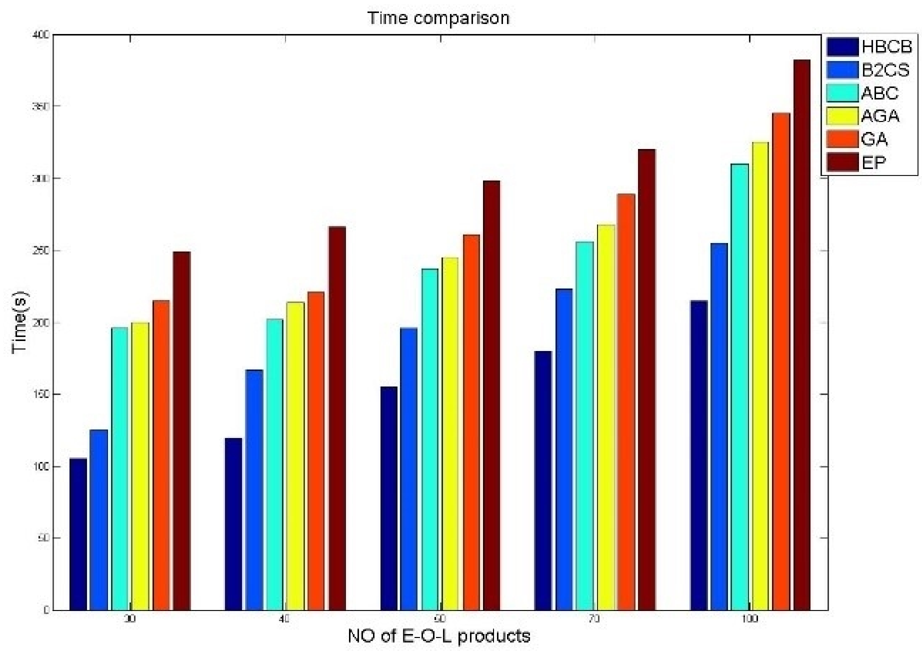
Pseudo code for hybridised HBCB optimization algorithm

80x80mm (220 x 220 DPI)



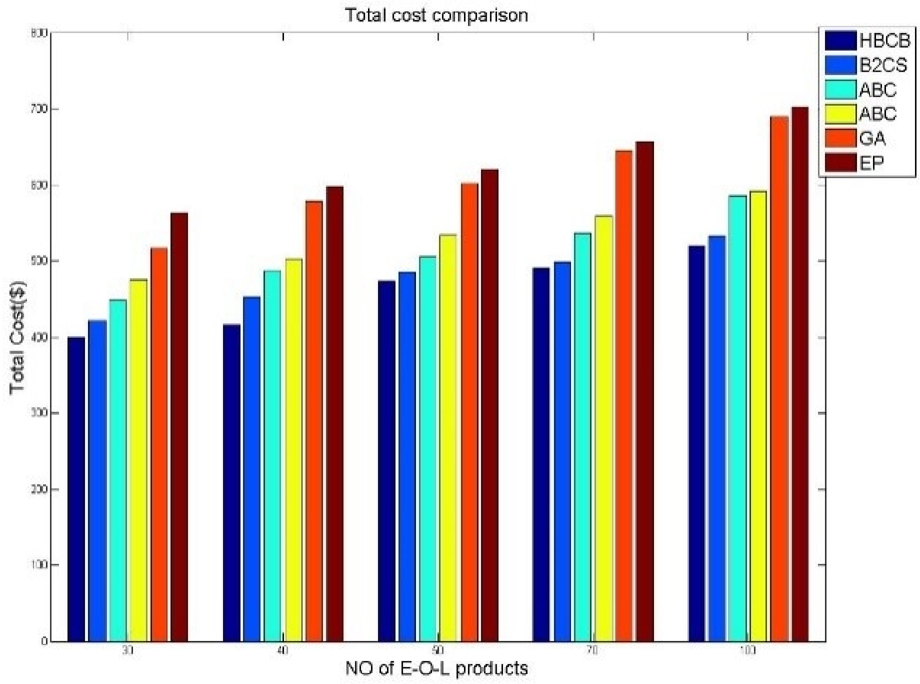
Convergence Comparison

81x57mm (220 x 220 DPI)



Disassembly Time Comparison

81x57mm (220 x 220 DPI)



Total Cost Comparison

79x59mm (220 x 220 DPI)