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Robotic Optimal Assembly Sequence Using Improved Cuckoo Search Algorithm

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Abstract

The demand for manufacturing newer products are increasing day-by-day, keeping this demand in mind many modern manufacturing processes have been evolved to meet the demand and supply the product in time. Even though many modern methods have been evolved, still there is lack in time to meet the consumer's requirements. This is due to assembly, which takes 20% of cost in manufacturing. To do effective assembly, optimal sequence is required; achieving the optimal assembly sequence is a difficulty process because it is one of them Non Probabilistic (NP) hard combinatorial problems. Achieving an effective optimal assembly sequence involves more than one objective function to develop the fitness equation (number of directional changes, gripper changes, time of assembly etc.), which converts the problem into discrete optimization problem. At the starting stages of assembly planning, researchers implemented mathematical models to achieve the feasible solution. These methods performs very poorly when comes to large part assemblies. Meanwhile, Artificial Intelligence (AI) techniques are evolved to solve the Assembly Sequence Planning (ASP) Problems. Performances of these methods are quite impressive in solving ASP problems, but most of these algorithms fall in local optimal during execution. More over these methods consumes more time for getting optimal solution especially for the more part assemblies. Keeping the above difficulties in mind, in this paper an Improved Cuckoo Search (ICS) algorithm is implemented to obtain the optimal solution. The proposed algorithm is compared by considering two assemblies (wall rack assembly and eccentric milling machine) with the algorithms like Genetic Algorithm (GA), Ant Colony Optimization (ACO), Grey Wolf Optimization (GWO), Particle Swarm Optimization (PSO) algorithm and Hybrid Ant Wolf Algorithm (HAWA). The results of the different algorithms are compared in terms of number of iterations and fitness values with the proposed algorithm. The results show that the proposed algorithm performs better than the compared algorithms.

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Keywords: Assembly Seqeunce Planning, Improved Cuckoo Search Algorithm, Assembly predicates.

1. Introduction

In today's market, efficiency of manufacturing and cost are facing great challenge because of severe competition in global market. Day-by-day more and effective design are coming into market to satisfy the needs of the customer. Even though a variety of designs are coming, still there is a gap which has to be fill-up by the manufacturer. In manufacturing, assembly is one of the major processes, which occupies around 20% of manufacturing cost [1]. To reduce the assembly cost, effective assembly sequence is required. To achieve the optimal assembly sequence, initially researchers applied mathematical models [2], these are helpful to achieve only feasible sequence not the optimal sequence.

Later researchers turned towards knowledge based methods to achieve the optimal assembly sequence. These methods are very good enough to achieve all possible optimal assembly sequences. But these methods consumes lot of search space and require high configuration processors when comes larger assemblies [3-5]. Meanwhile Design for Assembly (DFA) concept has been introduced to obtain the modified topology of the industrial products with reduced number of parts [6, 7]. Even though by application of DFA concept still there exists problem to obtain the optimal assembly sequence.

Meanwhile researchers attracted towards soft computing techniques, in which different algorithms are used to obtain the optimal assembly sequence [8, 9]. Even for the complex parts, these methods achieve optimal assembly sequences successful up to certain extent but most of the times the solution fall under local optimal. To avoid the local optimal solution hybrid algorithms have been introduced by combing the two more algorithms characteristics to obtain the optimal assembly sequence [10-12]. These algorithm performs good for the larger part assemblies but when comes to lesser part assemblies the algorithms takes more execution time, which increases the cost of assembly.

Keeping the above difficulties in view an improved cuckoo search algorithm has been proposed in this paper. This ICS algorithm takes the help of random search algorithm to assign the local optimal solution as input cuckoo instead of random cuckoo assignment to the algorithm. This improves the solution quality and chances of obtaining the more optimal assembly sequences with less fitness value can be achieved. The proposed algorithm is implemented on different assemblies and compared the same with the existing literature; it is observed that the results obtained from the proposed algorithm are quite impressive.

2. Proposed improved cuckoo search algorithm for optimum assembly sequence generation

In this paper an improved cuckoo search algorithm has been proposed to obtain the optimal assembly sequence for the eccentric milling assembly and wall rack assembly. The obtained results are compared with the algorithms like Genetic Algorithm (GA), Ant Colony Optimization (ACO), Grey Wolf Optimization (GWO), Particle Swarm Optimization (PSO) algorithm and Hybrid Ant Wolf Algorithm (HAWA).

In this algorithm instead of assigning random cuckoo (assembly sequence), by using random search algorithm a local optimal solution is assigned as the input to the algorithm. So, that the chances of achieving the global optimal solution will increases compared to the general cuckoo search algorithm. The detailed flow chart of the proposed algorithm is shown in the Figure 1.

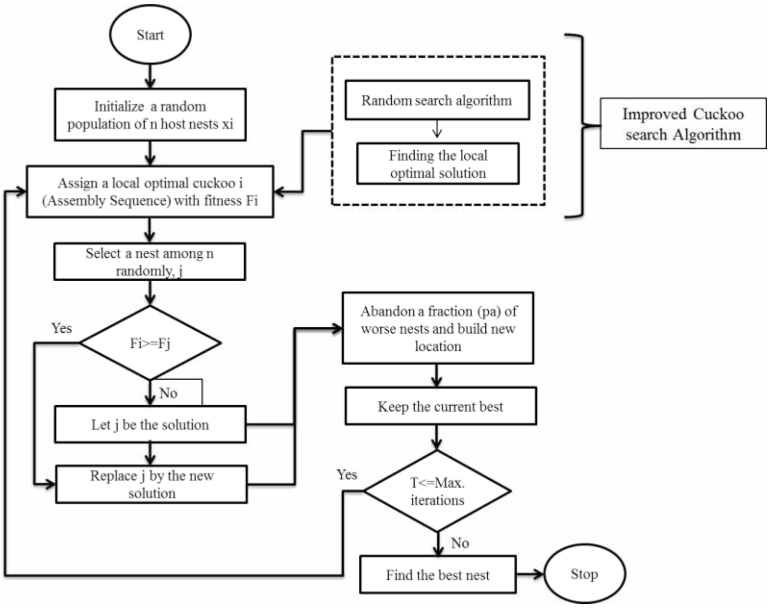

Fig. 1. Detailed flow chart of the Improved Cuckoo Search (ICS) algorithm.

To compare the proposed ICS algorithm with different algorithms, two assemblies (wall rack assembly & Eccentric milling assembly) have been considered. For the wall rack, Directional Changes (DC) and Gripper Changes (GC) are considered as objective constraints to evaluate the fitness of the assembly. The formulation of the equation is as follows:

$$f = \sum_{i=1}^{n-1} w * (DC_i) + (1 - w) * (GC_i) \quad (1)$$

For the comparison, objective constraints are considered with equal priority, and then the equation is as follows:

$$w = 0.5 => \ f = \sum_{i=1}^{n-1} 0.5 * (DC_i) + 0.5 * (GC_i) \quad (2)$$

The second assembly considered for the comparison with the proposed algorithm is eccentric milling. In this only directional changes have been considered as fitness function to evaluate the quality of the sequences. The formulation of fitness equation is as follows:

$$f = \sum_{i=1}^{n-1} w * (DC_i) \quad (3)$$

3. Comparison of results

The proposed algorithm is applied on two different industrial products (wall rack assembly & eccentric milling) shown in the Figure 2 and Figure 4 for the comparison with the other algorithms. The results of the proposed algorithm (for two assemblies) are compared with the Genetic Algorithm (GA), Ant Colony Optimization (ACO), Grey Wolf Optimization (GWO), Particle Swarm Optimization (PSO) algorithm and Hybrid Ant Wolf Algorithm (HAWA), which are considered from the past literature.

Assembly -1 (Wall Rack Assembly):

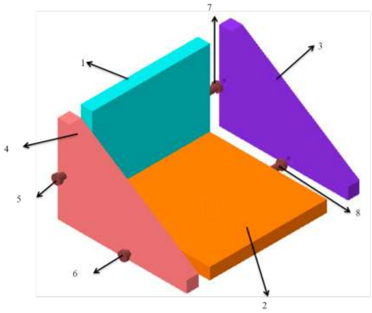

Fig. 2. Wall Rack Assembly

- Connection data/matrix: This matrix provides the information about the connection between the parts in the assembly. In this matrix,'1' represents connection between the parts and '0' represents the no connection between the parts. The required connection matrix for wall rack assembly is extracted from the CATIA V5 R17 using macros.

$$\text{Connection data} = \begin{array}{c|c} & \begin{array}{cccccccc} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 \end{array} \\ \begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7 \\ 8 \end{array} & \begin{bmatrix} 0 & 1 & 1 & 1 & 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 1 & 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 & 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array}$$

- Stability Matrix: Provides the information about the stability between the contact parts is provided by this matrix. This information is drawn on the basis of connection data. In this matrix '1' provides the information about no ability, '2' provides the information about partial stability and '3' provides the information about permanent stability. The required stability matrix for wall rack assembly is extracted from the CATIA V5 R17 using macros.
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$$\text{Stability matrix} = \begin{array}{c|c} & \begin{array}{cccccccc} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 \end{array} \\ \begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7 \\ 8 \end{array} & \begin{bmatrix} 0 & 2 & 1 & 1 & 0 & 2 & 0 & 2 \\ 2 & 0 & 1 & 1 & 2 & 0 & 2 & 0 \\ 1 & 1 & 0 & 0 & 2 & 2 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 2 & 2 \\ 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array}$$

- Assembly direction matrices: These matrices provide the information about the feasibility of part to assembly in any possible six directions during assembly. These matrices help in reducing the number of directional changes of the robot arm during assembly. These matrices are also helpful to build the fitness function in terms of number of directional changes. In these matrices '1' provides the information about not feasible in that direction and '0' provides the information about feasible in that direction to assemble the parts. The required feasibility matrices for wall rack assembly are extracted from the CATIA V5 R17 using macros.

$$X+ \quad \begin{array}{cc} & \begin{matrix}1&2&3&4&5&6&7&8\end{matrix} \\ \begin{matrix}1\\2\\3\\4\\5\\6\\7\\8\end{matrix} & \begin{bmatrix}0&0&0&1&1&0&1&1\\1&0&0&1&0&1&1&1\\1&1&0&1&0&0&1&1\\0&0&1&0&1&1&1&1\\1&1&1&1&0&1&1&1\\1&1&1&1&1&0&1&1\\1&0&1&0&1&1&0&1\\0&1&1&0&1&1&1&0\end{bmatrix}\end{array}$$

$$X- \quad \begin{array}{cc} & \begin{matrix}1&2&3&4&5&6&7&8\end{matrix} \\ \begin{matrix}1\\2\\3\\4\\5\\6\\7\\8\end{matrix} & \begin{bmatrix}0&0&0&1&1&0&1&1\\1&0&0&1&0&1&1&1\\1&1&0&1&0&0&1&1\\0&0&1&0&1&1&1&1\\1&1&1&1&0&1&1&1\\1&1&1&1&1&0&1&1\\1&0&1&0&1&1&0&1\\0&1&1&0&1&1&1&0\end{bmatrix}\end{array}$$

$$Y+ \quad \begin{array}{cc} & \begin{matrix}1&2&3&4&5&6&7&8\end{matrix} \\ \begin{matrix}1\\2\\3\\4\\5\\6\\7\\8\end{matrix} & \begin{bmatrix}0&0&1&1&1&0&1&0\\0&0&1&1&0&0&0&1\\1&1&0&1&0&0&1&1\\1&1&1&0&1&1&0&0\\1&0&0&1&0&1&1&1\\0&1&0&1&1&0&1&1\\1&0&1&0&1&1&0&1\\0&1&1&0&1&1&1&0\end{bmatrix}\end{array}$$

$$Y- \quad \begin{array}{cc} & \begin{matrix}1&2&3&4&5&6&7&8\end{matrix} \\ \begin{matrix}1\\2\\3\\4\\5\\6\\7\\8\end{matrix} & \begin{bmatrix}0&0&1&1&1&0&1&0\\0&0&1&1&0&1&0&1\\1&1&0&1&0&0&1&1\\1&1&1&0&1&1&0&0\\1&0&0&1&0&1&1&1\\0&0&0&1&1&0&1&1\\1&0&1&0&1&1&0&1\\0&1&1&0&1&1&1&0\end{bmatrix}\end{array}$$

$$Z+ \quad \begin{array}{cc} & \begin{matrix}1&2&3&4&5&6&7&8\end{matrix} \\ \begin{matrix}1\\2\\3\\4\\5\\6\\7\\8\end{matrix} & \begin{bmatrix}0&0&1&1&0&0&0&0\\0&0&1&1&0&1&1&1\\1&1&0&1&0&0&1&1\\1&1&1&0&1&1&1&1\\1&1&1&1&0&1&1&1\\0&1&1&1&1&0&1&1\\1&0&1&0&1&1&0&1\\0&1&1&0&1&1&1&0\end{bmatrix}\end{array}$$

$$Z- \quad \begin{array}{cc} & \begin{matrix}1&2&3&4&5&6&7&8\end{matrix} \\ \begin{matrix}1\\2\\3\\4\\5\\6\\7\\8\end{matrix} & \begin{bmatrix}0&0&1&1&1&0&1&0\\0&0&1&1&1&1&0&1\\1&1&0&1&1&1&1&1\\1&1&1&0&1&1&0&0\\0&0&0&1&0&1&1&1\\0&1&0&1&1&0&1&1\\0&1&1&1&1&1&0&1\\0&1&1&1&1&1&1&0\end{bmatrix}\end{array}$$

- Mechanical feasibility data/matrix: This matrix provides the information about the joining of parts in the presence of other part. The size of the matrix is of NXNXN (3dimensioanl matrix), where ‘N‘ represents the number of parts in the assembly. As there are no such physical connectors in the assembly, the mechanical feasibility matrix is not required.

The results of the proposed ICS algorithm are shown in the table 1, having 8 optimal assembly sequences with minimum fitness value ‘2’ are obtained.

Table 1. Represents the optimal assembly sequences for the wall rack assembly

SI.NO	Assembly sequence								No.of directional Changes	No.of gripper Changes	Fitness value
1	1	2	3	4	7	8	5	6	2	2	2
2	1	2	3	4	7	8	6	5	2	2	2
3	1	2	3	4	8	7	5	6	2	2	2
4	1	2	3	4	8	7	6	5	2	2	2
5	2	1	4	3	5	6	7	8	2	2	2
6	2	1	4	3	5	6	8	7	2	2	2
7	2	1	4	3	6	5	7	8	2	2	2
8	2	1	4	3	6	5	8	7	2	2	2

A graph shown in the Figure 3 is plotted between number of iterations and fitness values. The algorithm is run for 300 iterations in which the fitness value is converged after 152 iterations.

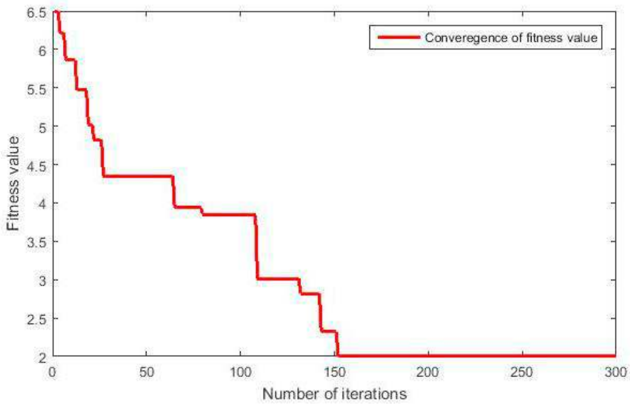

Fig. 3. Convergence graph of wall rack assembly

The results obtained from the developed algorithm (ICS) are compared with the several algorithms from past literature like GA, ACO, GWO and HAWA in terms of fitness value and Central Processing Unit (CPU) time, which is shown in the table 2.

Table 2. Represents the assembly sequences for wall rack assembly

Assembly	GA [8]	ACO [8]	GWO [22]	HAWA [8]	ICS
Rack assembly					
Fitness Value	5.2727	5.4545	5.4090	5	2
Avg.CPU time(Sec)	4.7861	4.0984	5.1246	4.4258	3.8253

Assembly -2 (eccentric milling machine):

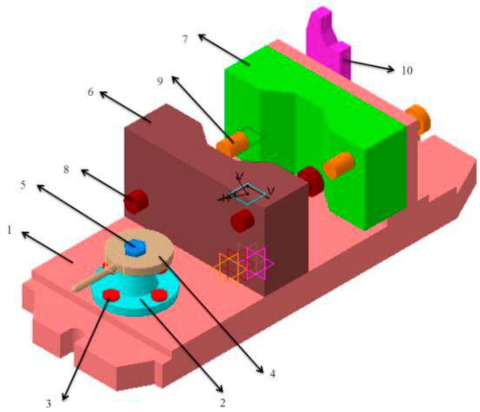

Fig. 4. Eccentric milling machine

$$\text{Connection data} = \begin{array}{cc} & \begin{array}{cccccccccc} 1&2&3&4&5&6&7&8&9&10 \end{array} \\ \begin{array}{c} 1\\2\\3\\4\\5\\6\\7\\8\\9\\10 \end{array} & \begin{bmatrix} 0&1&1&0&0&1&1&1&0&1\\ 1&0&1&1&1&0&0&0&0&0\\ 1&1&0&0&0&0&0&0&0&0\\ 0&1&0&0&1&0&0&0&0&0\\ 0&1&0&1&0&0&0&0&0&0\\ 1&0&0&0&0&0&0&0&0&1\\ 1&0&0&0&0&0&0&0&1&0\\ 1&0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&1&0&0&0\\ 1&0&0&0&0&1&0&0&0&0 \end{bmatrix} \end{array}$$

In this matrix ‘0’ provides the information about no connection between the parts and ‘1’ provides the information about connection between the parts

$$\text{Stability data} = \begin{array}{cc} & \begin{array}{cccccccccc} 1&2&3&4&5&6&7&8&9&10 \end{array} \\ \begin{array}{c} 1\\2\\3\\4\\5\\6\\7\\8\\9\\10 \end{array} & \begin{bmatrix} 0&3&3&0&0&2&2&2&0&2\\ 2&0&2&2&1&0&0&0&0&0\\ 3&3&0&0&0&0&0&0&0&0\\ 0&2&0&0&3&0&0&0&0&0\\ 0&2&0&3&0&0&0&0&0&0\\ 3&0&0&0&0&0&0&0&0&2\\ 2&0&0&0&0&0&0&0&2&0\\ 2&0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&2&0&0&0\\ 2&0&0&0&0&2&0&0&0&0 \end{bmatrix} \end{array}$$

In this matrix ‘1’ provides the information about no stability, ‘2’ provides the information about partial stability and ‘3’ provides the information about permanent stability

Assembly direction matrices:

X+

$$\begin{array}{cc} & \begin{array}{cccccccccc} 1&2&3&4&5&6&7&8&9&10 \end{array} \\ \begin{array}{c} 1\\2\\3\\4\\5\\6\\7\\8\\9\\10 \end{array} & \begin{bmatrix} 0&0&0&0&0&0&0&1&0&1\\ 1&0&0&1&0&1&1&1&1&1\\ 0&0&0&1&1&1&1&1&1&1\\ 1&1&1&0&0&1&1&1&1&1\\ 1&0&1&0&0&1&1&1&1&1\\ 1&0&0&0&0&0&0&1&0&1\\ 1&0&0&0&0&1&0&1&1&1\\ 0&0&0&0&1&0&0&0&1&1\\ 1&1&1&1&1&1&0&1&0&1\\ 0&1&1&1&1&0&0&1&0&0 \end{bmatrix} \end{array}$$

X-

$$\begin{array}{cc} & \begin{array}{cccccccccc} 1&2&3&4&5&6&7&8&9&10 \end{array} \\ \begin{array}{c} 1\\2\\3\\4\\5\\6\\7\\8\\9\\10 \end{array} & \begin{bmatrix} 0&1&0&1&1&1&1&0&1&0\\ 0&0&0&1&0&0&0&0&1&1\\ 0&0&0&1&1&0&0&0&1&1\\ 0&1&1&0&0&0&0&0&1&1\\ 0&0&1&0&0&0&0&1&1&1\\ 0&1&1&1&1&0&1&0&1&0\\ 0&1&1&1&1&0&0&0&0&0\\ 1&1&1&1&1&1&1&0&1&1\\ 0&1&1&1&1&0&1&1&0&0\\ 1&1&1&1&1&1&1&1&1&0 \end{bmatrix} \end{array}$$

Y+

$$\begin{array}{cc} & \begin{array}{cccccccccc} 1&2&3&4&5&6&7&8&9&10 \end{array} \\ \begin{array}{c} 1\\2\\3\\4\\5\\6\\7\\8\\9\\10 \end{array} & \begin{bmatrix} 0&1&0&1&1&1&1&1&1&0\\ 1&0&0&1&0&1&1&1&1&1\\ 0&0&0&1&1&1&1&1&1&1\\ 1&1&1&0&0&1&1&1&1&1\\ 1&0&1&0&0&1&1&1&1&1\\ 1&1&1&1&1&0&1&1&1&0\\ 1&1&1&1&1&1&0&1&0&1\\ 1&1&1&1&1&1&1&0&1&0\\ 1&1&1&1&1&1&0&1&0&1\\ 0&1&1&1&1&0&1&0&1&0 \end{bmatrix} \end{array}$$

Y-

$$\begin{array}{cc} & \begin{array}{cccccccccc} 1&2&3&4&5&6&7&8&9&10 \end{array} \\ \begin{array}{c} 1\\2\\3\\4\\5\\6\\7\\8\\9\\10 \end{array} & \begin{bmatrix} 0&1&0&1&1&1&1&1&1&0\\ 1&0&0&1&0&1&1&1&1&1\\ 0&0&0&1&1&1&1&1&1&1\\ 1&1&1&0&0&1&1&1&1&1\\ 1&0&1&0&0&1&1&1&1&1\\ 1&1&1&1&1&0&1&1&1&0\\ 1&1&1&1&1&1&0&1&0&1\\ 1&1&1&1&1&1&1&0&1&0\\ 1&1&1&1&1&1&0&1&0&1\\ 0&1&1&1&1&0&1&0&1&0 \end{bmatrix} \end{array}$$

Z+

$$\begin{array}{cc} & \begin{array}{cccccccccc} 1&2&3&4&5&6&7&8&9&10 \end{array} \\ \begin{array}{c} 1\\2\\3\\4\\5\\6\\7\\8\\9\\10 \end{array} & \begin{bmatrix} 0&0&0&0&0&0&0&0&0&0\\ 1&0&0&0&0&1&1&1&1&1\\ 1&1&0&0&1&1&1&1&1&1\\ 1&1&1&0&0&1&1&1&1&1\\ 1&1&1&1&0&1&1&1&1&1\\ 1&1&1&1&1&0&1&1&1&0\\ 1&1&1&1&1&1&0&1&0&1\\ 1&1&1&1&1&1&1&0&1&1\\ 1&1&1&1&1&1&0&1&0&1\\ 0&1&1&1&1&0&1&1&1&0 \end{bmatrix} \end{array}$$

Z-

$$\begin{array}{cc} & \begin{array}{cccccccccc} 1&2&3&4&5&6&7&8&9&10 \end{array} \\ \begin{array}{c} 1\\2\\3\\4\\5\\6\\7\\8\\9\\10 \end{array} & \begin{bmatrix} 0&1&1&1&1&1&1&1&1&0\\ 0&0&1&1&1&1&1&1&1&1\\ 0&0&0&1&1&1&1&1&1&1\\ 0&0&0&0&1&1&1&1&1&1\\ 0&0&1&0&0&1&1&1&1&1\\ 0&1&1&1&1&0&1&1&1&0\\ 0&1&1&1&1&1&0&1&0&1\\ 0&1&1&1&1&1&1&0&1&1\\ 0&1&1&1&1&1&0&1&0&1\\ 0&1&1&1&1&0&1&1&1&0 \end{bmatrix} \end{array}$$

In these matrices ‘1’ represents the not feasible in that direction and ‘0’ represents the feasible in that direction to assemble the parts.

- Mechanical feasibility data/matrix: This matrix provides the information about the feasibility of joining the parts in the presence of other part. The size of the matrix is of NXNXN (3dimensioanl matrix), where n represents the number of parts in the assembly. As there are no such physical connectors in the assembly, the mechanical feasibility matrix is not required.

The results of the proposed ICS algorithm are shown in the table 3. In this, 6 optimal assembly sequences with minimum fitness value '0' are obtained.

Table 3. Represents the optimal assembly sequences for the eccentric milling assembly

S.No	Assembly Sequence								Directional changes								Fitness value
1	1	2	3	4	5	6	7	8	5	5	5	5	5	5	5	5	0
2	1	2	3	4	5	6	8	7	5	5	5	5	5	5	5	5	0
3	1	2	3	4	5	7	6	8	5	5	5	5	5	5	5	5	0
4	1	2	3	4	5	7	8	6	5	5	5	5	5	5	5	5	0
5	1	2	3	4	5	8	6	7	5	5	5	5	5	5	5	5	0
6	1	2	3	4	5	8	7	6	5	5	5	5	5	5	5	5	0

A graph shown in the Figure 5 is plotted between number of iterations and fitness values. The algorithm is run for 300 iterations in which the fitness value is converged after 56 iterations.

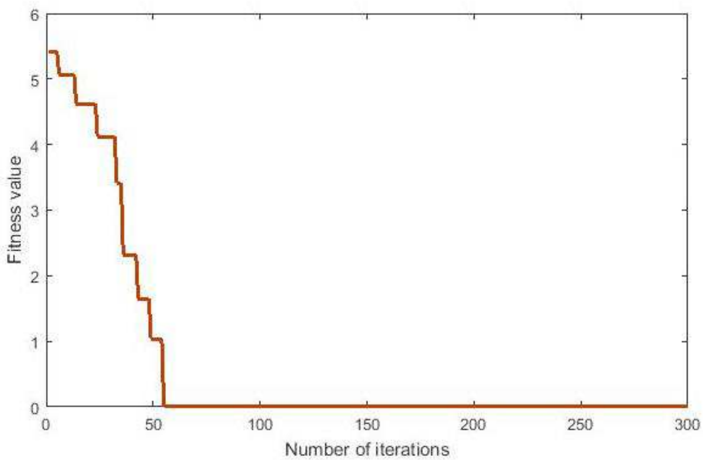

Fig. 5: Eccentric milling machine

The result obtained from the developed algorithm (ICS) is compared with the PSO algorithm from past literature in terms of fitness value, which is shown in the table 4.

Table 4. Represents the assembly sequences for wall rack assembly

Assembly	PSO [10]	ICS
Eccentric milling machine		
Fitness Value	4	0
Number of optimal assembly sequences	1	6

4. Conclusion

In this paper, an improved cuckoo search algorithm is developed by the assigning local best solution obtained from the random search algorithm as cuckoo population. Mainly in this, random consideration of cuckoos has been updated to form improved cuckoo search algorithm. The following conclusions are been observed.

1. The developed algorithm (ICS) is able to obtain the optimal assembly sequences with less Avg. CPU time and generates many optimal sequences with less fitness value compared to the other algorithms, which are shown in in the above section-3.
2. The algorithm is compared with two different assemblies to evaluate the quality of the solution in terms of fitness value and CPU execution time. Initially, the proposed algorithm is compared with the particle swarm optimization algorithm for eccentric milling assembly. In this, the numbers of optimal assembly sequences generated are more compared to the PSO algorithm. Moreover, this algorithm generates optimal assembly sequences with less fitness value compared to the PSO algorithm.
3. The developed algorithm is also compared GA, ACO, GWO and HAWA algorithms for wall rack assembly. In this, the avg. CPU time and fitness value of the proposed algorithm is less compared to the other algorithms

As a future work this algorithm can be implemented for the large part assemblies. Moreover, the algorithm may be extended to the flexible part assemblies and the parts which are to be assemble other than principle axes.

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