Research Article

Solving the Manufacturing Cell Design Problem through Binary Cat Swarm Optimization with Dynamic Mixture Ratios

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In this research, we present a Binary Cat Swarm Optimization for solving the Manufacturing Cell Design Problem (MCDP). This problem divides an industrial production plant into a certain number of cells. Each cell contains machines with similar types of processes or part families. The goal is to identify a cell organization in such a way that the transportation of the different parts between cells is minimized. The organization of these cells is performed through Cat Swarm Optimization, which is a recent swarm metaheuristic technique based on the behavior of cats. In that technique, cats have two modes of behavior: seeking mode and tracing mode, selected from a mixture ratio. For experimental purposes, a version of the Autonomous Search algorithm was developed with dynamic mixture ratios. The experimental results for both normal Binary Cat Swarm Optimization (BCSO) and Autonomous Search BCSO reach all global optimums, both for a set of 90 instances with known optima, and for a set of 35 new instances with 13 known optima.

1. Introduction

Group technology is a manufacturing philosophy in which similar parts are identified and grouped together to take advantage of their similarities in design and production [1] by organizing similar parts into part families, where each part of the family has similar design and manufacturing characteristics. The basic concept of group technology has been practiced for many years around the world, as part of good engineering and scientific management practices [2, 3], which states that similar things should be manufactured in a similar way [4].

The Manufacturing Cell Design Problem (MCDP) is an application of group technology to organize cells containing a set of machines to process a family of parts [5]. In this context, MCDP involves the creation of an optimal design of production plants, in which the main objective is to minimize the movement and exchange of material between these cells, thus generating greater productivity and reducing production costs.

The Manufacturing Cell Design Problem belongs to the complex NP-hard class of problems, and then exploring good search algorithms is always a challenging task from the optimization and now also from the artificial intelligence world [5]. In particular, in this paper, an efficient metaheuristic implementation is proposed to tackle this problem, demonstrating through several benchmark instances its performance (various global optima are reached), which is also valuable from an artificial intelligence and optimization standpoint. Additionally, this algorithm includes an Autonomous Search Component (dynamic mixture ratio), which is currently an important research trend in the...
optimization and metaheuristic sphere. Metaheuristics are intrinsically complex to be configured in order to reach good results, and Autonomous Search comes to facilitate this task by letting the metaheuristic itself to self-tune its internal configuration without the need of a user expert for reaching good results. To the best of our knowledge, the work done on Autonomous Search in metaheuristics is very recent, and no Autonomous Search work for cat swarm exists.

The research work that has been done to solve the problem of cell formation has followed two complementary lines, which can be organized into two groups: approximate methods and exact methods. Approximate methods are mostly focused on finding an optimal solution in a limited time; however, they do not guarantee a global optimum. Exact methods, on the contrary, aim to fully analyze the search space to ensure a global optimum [6]; however, these algorithms are quite time-consuming and can only solve cases of very limited size. For this reason, many research efforts have focused on the development of heuristics, which find near-optimal solutions within a reasonable period of time.

This research focuses on solving the MCDP through a recent metaheuristic in the vein of Swarm Intelligence (SI) [7] called Binary Cat Swarm Optimization (BCSO) [8]. This algorithm was generated from observations of cat behavior in nature, in which cats either hunt or remain alert. BCSO is based on the CSO algorithm, recently proposed by Chu and Tsai [9]. The difference is that in BCSO, the vector position consists of ones and zeros, instead of real numbers (CSO), and the proposed alternate version makes use of a dynamic mixture ratio.

As aforementioned, reaching good results for problems belonging from the NP class is always a challenging and appealing task from the optimization and artificial intelligence world. In this research, our goal was to provide an intelligent algorithm for solving this problem by additionally integrating self-tuning features, which is a very recent research trend in the optimization and metaheuristic sphere.

2. Theoretical Framework

The formation of manufacturing cells has been researched for many years. One of the first investigations focused on resolving this set of problems was Burbidge’s work in 1963 [4], which proposed the use of an incidence matrix reorganized into a Block Diagonal Form (BDF) [4]. In recent years, many exact and heuristic algorithms have been proposed in the literature to solve MCDP. Such metaheuristic techniques include genetic Algorithm (GA) [10], inspired by biological evolution and its genetic-molecular basis; the Neural Network (NN) [11] that takes the behavior of neurons and the connections of the human brain; and Constraint Programming (CP) [12] where the relationships between the variables are expressed as constraints. For extensive reviews of previous research and other methods of cell formation, see Selim et al. [1].

Among the metaheuristics used for cell formation, there is also the branch of Swarm Intelligence, which was initially introduced by Beni and Wang in 1989 [13]. Inspired by nature, Swarm Intelligence systems are typically formed by a population of simple agents who interact locally with each other and with their environment and who are able to optimize an overall objective through the search for collaboration in a space [14]. Within this branch, the main techniques are Particle Swarm Optimization (PSO) designed and presented by Eberhart et al. [7, 9] in 1995; Ant Colony Optimization (ACO), which is a family of algorithms derived from Dorigo’s 1991 work based on the social behavior of ants [15, 16]; Migrating Birds Optimization (MBO) [17] algorithm based on the alignment of migratory birds during flight; Artificial Fish Swarm Algorithm (AFSA) [18], based on the behavior of fish to find food by themselves or by following other fish; and the discrete Cat Swarm Optimization (CSO) Technique presented in 2007 by Chu and Tsai [9], which is based on the behavior of cats. Interestingly, the CSO cat corresponds to a particle in PSO, with a small difference in its algorithms [19, 20]. CSO and PSO were originally developed for continuous value spaces, but there are a number of optimization problems where the values are discrete [21].

3. The Manufacturing Cell Design Problem

The Manufacturing Cell Design Problem (MCDP) divides an industrial production plant into a number of cells. Each cell contains machines with similar process types or part families, determined according to the similarity between parts [4]. A manufacturing cell can be defined as an independent group of functionally different machines, located together, dedicated to the manufacture of a family of similar parts. In addition, a family of parts can be defined as a collection of parts that are similar, either because of their geometric shape and size or because similar processing steps are required to manufacture them [22].

The goal of MCDP is to identify a cell organization in a way that minimizes the transport of different parts between cells, in order to reduce production costs and increase productivity. The idea is to represent the processing requirements of machine parts through an incidence matrix called machine part. This reorganization involves the formulation of two new matrices called machine-cell and part-cell.

A detailed mathematical definition of the formulation of the machine-part clustering problem is defined by the optimization model explained below [6]:

(i) \( M \): number of machines
(ii) \( P \): number of parts
(iii) \( C \): number of cells
(iv) \( i \): machine index \((i = 1, 2, \ldots, M)\)
(v) \( j \): part index \((j = 1, 2, \ldots, P)\)
(vi) \( k \): cell index \((k = 1, 2, \ldots, C)\)
(vii) \( M_{\text{max}} \): maximum number of machines per cell
(viii) \( A = [a_{ij}] \): machine-to-part binary incidence matrix, where
Algorithm 1 describes the general BCSO pseudocode where the mixture ratio (MR) is a percentage that determines the number of cats in the seeking mode.

4.1. Seeking Mode. This submodels the state of the cat, which is resting, looking around, and seeking the next position to move towards. The seeking mode has the following essential factors:

(i) PMO: probability of mutation operation, a percentage that defines the mutation probability for the selected dimension.

(ii) CDC: counts of dimensions to change, a percentage that indicates how many dimensions are candidates to change.

(iii) SMP: seeking memory pool, a positive integer used to define the memory size for each cat. SMP indicates the points to be scanned by the cat and can be different for different cats.

The following pseudocode describes the behavior of the cat in the seeking mode. Here, FS_{i} is the fitness of the i-th cat, and FS_{b} = FS_{\text{max}} finds the minimum solution and FS_{b} = FS_{\text{min}} the maximum solution. To solve the MCDP, we use FS_{b} = FS_{\text{max}}.

Step 1: create SMP copies of current cat_{i}.
Step 2: for each copy:
for dimensions that are candidates for change (based on CDC percentage):
get a random number (rand) between 0 and 1
if rand < PMO, then the position changes.
Step 3: evaluate Fitness of all copies.
Step 4: calculate the selection probability by applying a roulette wheel or, by default, choose the best copy according to Fitness.

\[ P_{i} = \frac{FS_{i} - FS_{b}}{FS_{\text{max}} - FS_{\text{min}}} \]  

Step 5: evaluate if the chosen copy is a better solution than the currently selected cat, and replace accordingly.

Figure 1 shows the flow chart of the behavior of the cat in the seeking mode.

4.2. Tracing Mode. This submodel is used to model the state of the cat in hunting or tracing behavior, where the cats are moving towards the best solution obtained so far. Once a cat enters the tracing mode, it moves according to its own velocities for each dimension. Each cat has two velocity vectors, defined as V_{kd} and V_{\text{old}}^{kd}, where V_{\text{old}}^{kd} is the probability that the bits of the cat change to zero and V_{kd} is the probability they change to one. The velocity vector changes its meaning with the probability of mutation for each dimension d. The tracing mode action is described in the following pseudocode.
Step 1: calculate $d_{1d}^k$ and $d_{0d}^k$ according to the following expression, where $X_{\text{best},d}$ is the dimension $d$ of the best cat, $r_1$ has random values in the range of $[0,1]$, and $c_1$ is a user-defined constant.

If $X_{\text{best},d} = 1$, then $d_{1d}^k = -r_1 c_1$, and $d_{0d}^k = r_1 c_1$.
If $X_{\text{best},d} = 0$, then $d_{1d}^k = r_1 c_1$, and $d_{0d}^k = -r_1 c_1$.

Step 2: update values for $V_{1d}^k$ and $V_{0d}^k$ according to the expression, where $w$ is the inertia weight and $M$ is the number of columns.

$$V_{1d}^k = \omega V_{1d}^k + d_{1d}^k, \quad V_{0d}^k = \omega V_{0d}^k + d_{0d}^k, \quad d = 1, \ldots, M.$$  \hspace{1cm} (6)

Step 3: calculate the velocity of cat $k$, $V_{k}^{d'}$, according to

$$V_{k}^{d'} = \begin{cases} V_{1d}^k & \text{if } X_{kd} = 0, \\ V_{0d}^k & \text{if } X_{kd} = 1. \end{cases}$$  \hspace{1cm} (7)

Step 4: calculate the probability of mutation in each dimension, defined by parameter $T_{kd}$ which takes a value in the interval of $[0,1]$

$$T_{kd} = \frac{1}{1 + e^{-V_{k}^{d'}/\Delta V}}.$$  \hspace{1cm} (8)

Step 5: based on the value of $T_{kd}$, the new value of each dimension of the cat is updated as follows:

$$X_{kd} = \begin{cases} X_{\text{best},d} & \text{if } \text{rand} < t_{kd}, \\ X_{kd} & \text{if } t_{kd} < \text{rand}. \end{cases} \quad d = 1, \ldots, M.$$  \hspace{1cm} (9)

The maximum velocity vector of $V_{kd}$ must be limited to value $V_{\text{max}}$.

If the value of $V_{kd}$ surpasses that of $V_{\text{max}}$, $V_{kd}$ must be selected for the corresponding velocity dimension.

The following is a flow chart for a cat in the tracing mode (Figure 2).

5. Solving the Manufacturing Cell Design Problem (MCNP)

To solve the MCNP, it is essential to use a repair method for solutions that were not feasible. Algorithm 2 describes the pseudocode used to solve the MCNP.
6. Repair Method

A solution may not satisfy the constraints, resulting in an unworkable solution. For this reason, the value that violates the constraint is repaired instead of the matrix being removed. In this section, a function is described to transform nonfeasible solutions into feasible solutions.

Algorithm 3 presents a repair method in which all rows not covered are identified and assigned accordingly. This will cover all restrictions.

7. Autonomous Search

Autonomous Search (AS) is a modern approach that allows the solver to automatically reconfigure its resolution parameters to provide better performance when bad results are detected [40].

In this context, performance is assessed through indicators that collect relevant information during the search. Search parameters are then updated advantageously according to the results obtained by the fitness evaluation.

8. Results

The BCSO implementation process of MCDP has led to results that will be presented in the following section. The metaheuristic was programmed in the JAVA programming language. For the execution of the algorithm, the parameters considered were the following:

(i) Iterations = 5000
(ii) Number of cats = 30
(iii) MR = 0.75 (75% seeking; 25% tracing)
(iv) SMP = 15
(v) CDC = 0.2
(vi) PMO = 0.76
(vii) \( w = 1 \)
(viii) \( c_1 = 1 \)
(ix) \( r_1 \in [0, 1] \)

9. Boctor Instances

Tests with the implemented solution were carried out based on 90 instances of 16 \( \times \) 30 matrices, obtained from 10 problems found in the paper of Boctor [48], hereafter called Boctor Instances. These problems included the use of 2 or 3 cells. In the case of 2 cells, the maximum number of machines \( (M_{max}) \) in each task varied between 8 and 12. In the case of 3, \( M_{max} \) varied between 6 and 9 machines per cell. In both cases, the value of \( M_{max} \) remained constant throughout the execution of the algorithm.

The values obtained by submitting each problem to the Classic BCSO and BCSO with Autonomous Search are summarized in Tables 1–9, where “O” denotes the global optimum given in [48]; “BCSO,” the best value obtained by the BCSO here proposed; “A,” the average number of optima obtained; “I,” the average number of iterations in which the optimum is reached; “Ms,” the time (in milliseconds) used to reach the optimum; and “RPD,” the Relative Percent Difference, calculated as follows:

\[
\text{RPD} = \frac{Z - Z_{opt}}{Z_{opt}} \times 100, \tag{10}
\]

where \( Z_{opt} \) is the best known optimal value and \( Z \) is the best optimal value achieved by BCSO.

Figure 2: Tracing mode.
The above results were run 40 times for each of the 90 Boctor Instances. It is important to point out that 100% of these were optimized, proving that BCSO can work with any MCDP instance. The performance of the BCSO metaheuristic in its Autonomous Search version was slightly better, demonstrated by some of the optima averages reached in the experimental results.

10. Other Author Instances

To analyze the effectiveness of the implemented algorithm in a wider range of problems, new instances from different authors were investigated. Matrix sizes ranged from 5 to 40 machines and from 7 to 100 parts. Table 10 shows the instances used:

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**Algorithm 2: Solving MCDP.**

1. Create \( C \) cats, each cat is a machine-cell matrix
2. Initialize the machine-cell matrices with random values (1 or 0)
3. Initialize all other parameters for each cat
4. while \( (i < \text{NumberIterations}) \) do
5. Evaluate MCDP fitness of the cats
6. Store position of Best Matrix cat, with highest fitness value
7. for \( (x = 1 \text{ to } C) \) do
8. if (randomNumber < MixtureRatio) then
9. Apply seeking mode process to cat \( x \)
10. Repair each modified matrix
11. else
12. Apply tracing mode process to cat \( x \)
13. Repair each modified matrix
14. end if
15. Evaluate new solution and update values
16. end for
17. end while
18. Postprocess results and visualization

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**Algorithm 3: Repairing solutions.**

1. for \( (i \text{ to Machines}) \) do
2. for \( (j \text{ to Cells}) \) do
3. Count the number of cells the same machine is assigned to
4. end for
5. if (Assignments! = 1) then
6. Calculate least cost column
7. Assign the machine to the calculated least cost cell
8. end if
9. end for
10. for \( (i \text{ to Machines}) \) do
11. for \( (j \text{ to Cells}) \) do
12. Count the number of machines in the same cell
13. end for
14. if (Number of grouped machines is greater than \( M_{\text{max}} \)) then
15. Find cell with fewer machines assigned
16. Reassign the machine to found cell
17. end if
18. end for

---

In order to improve the quality of the exhibited behavior by the autonomous version of the Binary Cat Swarm Optimization, we performed a detailed comparison by using these new instances, because they are hardest. This comparison includes two well-known metaheuristics: the first one is inspired by the behavior of the Egyptian vulture (EVOA) [71], and the second one mimics the flashing behavior of fireflies [72]. Table 11 reports the result comparison between our proposal and the methods published in [73].

If it observes the showed results for instances CF01 to CF11, we can conclude that BCSO presents a similar performance to EVOA. In both cases, the optimal values are reached. Moreover, we note the worst and mean values are equal. This behavior can be attributed to the similarity of the
operations between both algorithms. Now, if it evaluates MFAO with respect to BCSO, we again can report a similar conclusion. Nevertheless, in CF05 and CF07, BCSO achieves two optimal values that they are not reached with MFAO.

From CF12 onwards, BCSO begins to exhibit an outstanding performance. For instance, in CF12, BCSO is the only one that finds the best solution (optimum value) reaching RPD 0%. Its closer competitor (MBFA) obtains RPD 28.57%. However, the biggest significant difference can be seen from CF15. In this instance, BCSO exhibits higher efficiency than EVOA and it overcomes the reached value by MBFA. Now, if taken any instances between CF16 and CF 35 (more than 57% of instances), the good yield of the BCSO exceeds the two compared approaches term of the best-found values, average-found values, and worst-found values also. Therefore, we can state that BCSO is more than a competitive technique. It is a real alternative for solving the Manufacturing Cell Design Problem.

Now, the values obtained by submitting each problem to Classic BCSO and BCSO with Autonomous Search are summarized in Table 1, where the global optimum is given in [74].

### Algorithm 4: Autonomous search.

```plaintext
(1) while (i < NumberIterations) do
(2) if (FitnessIteration == FitnessIterationPrevious) then
(3)   RepetitionsFitness++
(4) else
(5)   RepetitionsFitness = 0
(6) end if
(7) if (RepetitionsFitness > 30) then
(8)   Change MixtureRatio to 1/(MixtureRatio * 50)
(9)   if (MixtureRatio < 10%) then
(10)  Change MixtureRatio to MixtureRatio * 15
(11)  if (MixtureRatio < 50%) then
(12)   Reinitialize 5 cat (machine-cell matrices) with random values (1 or 0)
(13)   for (x = 1 to C) do
(14)    Change PMO to 0.9
(15)    Change CDC to 0.3
(16)   end for
(17)   else
(18)    for (x = 1 to C) do
(19)     Restore PMO value to 0.76
(20)    Restore CDC value to 0.2
(21)   end for
(22)   RepetitionsFitness = 0
(23) end if
(24) end if
(25) Order cat arrangements
(26) end if
(27) end while
```

### Table 1: Experimental results with cell = 2 and $M_{max} = 8.$

| $P$ | $O$ | Classic BCSO | Autonomous Search BCSO |
|-----|-----|--------------|------------------------|
|     |     | BCSO | A | RPD  | $I$ | Ms | BCSO | A | RPD  | $I$ | Ms |
| 1   | 11  | 11   | 11 | 0.00 | 5  | 30697.5 | 11 | 11 | 0.00 | 5  | 15977.6 |
| 2   | 7   | 7    | 7  | 0.00 | 7  | 27797.7 | 7  | 7  | 0.00 | 7  | 14487.6 |
| 3   | 4   | 4    | 4.05 | 0.00 | 79 | 27927.8 | 4  | 4  | 0.00 | 133 | 14175.7 |
| 4   | 14  | 14   | 14 | 0.00 | 5  | 29998.9 | 14 | 14 | 0.00 | 6  | 15149.6 |
| 5   | 9   | 9    | 9  | 0.00 | 93 | 28348.8 | 9  | 9  | 0.00 | 102 | 14358.0 |
| 6   | 5   | 5    | 5.05 | 0.00 | 5  | 28233.3 | 5  | 5  | 0.00 | 8  | 14165.0 |
| 7   | 7   | 7    | 7  | 0.00 | 5  | 28338.9 | 7  | 7  | 0.00 | 7  | 14562.7 |
| 8   | 13  | 13   | 13 | 0.00 | 6  | 28860.8 | 13 | 13 | 0.00 | 7  | 14895.6 |
| 9   | 8   | 8    | 8  | 0.00 | 6  | 28206.7 | 8  | 8  | 0.00 | 8  | 14583.8 |
| 10  | 8   | 8    | 8  | 0.00 | 19 | 28547.1 | 8  | 8  | 0.00 | 20 | 14750.2 |
| $\bar{X}$ | 8.6 | 8.6 | 8.605 | 0.00 | 23 | 28695.7 | 8.6 | 8.6 | 0.00 | 30.3 | 14710.6 |
The above results were obtained after 40 executions for each of the 35 new instances. It should be noted that it was possible to reach optima in 100% of instances for both algorithms, proving that BCSO can work with almost any instance. The performance of the BSCO metaheuristic in its Autonomous Search version was slightly better, demonstrated in some of the optima achieved, improving by 3% with respect to the original.

### Table 2: Experimental results with cell = 2 and $M_{\text{max}} = 9$. 

| $P$ | $O$ | Classic BCSO | | Autonomous Search BCSO | |
|---|---|---|---|---|---|
| | | BCSO | $A$ | RPD | $I$ | Ms | BCSO | $A$ | RPD | $I$ | Ms |
| 1 | 11 | 11 | 11 | 0 | 5 | 19412 | 11 | 11 | 0 | 5 | 15109.4 |
| 2 | 6 | 6 | 6 | 0 | 5 | 17860.6 | 6 | 6 | 0 | 12 | 14284.1 |
| 3 | 4 | 4 | 4 | 0 | 5 | 16817 | 4 | 4 | 0 | 6 | 14140.3 |
| 4 | 13 | 13 | 13 | 0 | 5 | 18236.3 | 13 | 13 | 0 | 5 | 15027.4 |
| 5 | 6 | 6 | 6 | 0 | 81 | 16863.1 | 6 | 6 | 0 | 57 | 14228.9 |
| 6 | 3 | 3 | 3 | 0 | 10 | 16552.5 | 3 | 3 | 0 | 24 | 13997.8 |
| 7 | 4 | 4 | 4 | 0 | 5 | 17681.6 | 4 | 4 | 0 | 5 | 14432.9 |
| 8 | 10 | 10 | 10 | 0 | 7 | 18277.8 | 10 | 10 | 0 | 9 | 14734.4 |
| 9 | 8 | 8 | 8 | 0 | 5 | 17690.7 | 8 | 8 | 0 | 5 | 14473.7 |
| 10 | 5 | 5 | 5 | 0 | 7 | 18035.8 | 5 | 5 | 0 | 7 | 14645.4 |
| $\bar{X}$ | 7 | 7 | 7 | 0 | 13.5 | 17737 | 7 | 7 | 0 | 13.5 | 14507.4 |

### Table 3: Experimental results with cell = 2 and $M_{\text{max}} = 10$. 

| $P$ | $O$ | Classic BCSO | | Autonomous Search BCSO | |
|---|---|---|---|---|---|
| | | BCSO | $A$ | RPD | $I$ | Ms | BCSO | $A$ | RPD | $I$ | Ms |
| 1 | 11 | 11 | 11 | 0 | 5 | 18084.4 | 11 | 11 | 0 | 5 | 15047 |
| 2 | 4 | 4 | 4 | 0 | 9 | 16894.2 | 4 | 4 | 0 | 11 | 14336.8 |
| 3 | 4 | 4 | 4 | 0 | 5 | 16221.7 | 4 | 4 | 0 | 5 | 13991 |
| 4 | 13 | 13 | 13 | 0 | 6 | 17602.6 | 13 | 13 | 0 | 6 | 15051.8 |
| 5 | 6 | 6 | 6 | 0 | 7 | 16459.6 | 6 | 6 | 0 | 36 | 14620.4 |
| 6 | 3 | 3 | 3 | 0 | 8 | 16217.7 | 3 | 3 | 0 | 38 | 14853.1 |
| 7 | 4 | 4 | 4 | 0 | 5 | 16828.9 | 4 | 4 | 0 | 6 | 15199.7 |
| 8 | 8 | 8 | 8 | 0 | 8 | 17648.1 | 8 | 8 | 0 | 8 | 15858.6 |
| 9 | 8 | 8 | 8 | 0 | 6 | 16669.3 | 8 | 8 | 0 | 5 | 15226.4 |
| 10 | 5 | 5 | 5 | 0 | 6 | 16713.1 | 5 | 5 | 0 | 7 | 15591.5 |
| $\bar{X}$ | 6.6 | 6.6 | 6.6 | 0 | 6.5 | 16933.96 | 6.6 | 6.6 | 0 | 12.7 | 14977.63 |

### Table 4: Experimental results with cell = 2 and $M_{\text{max}} = 11$. 

| $P$ | $O$ | Classic BCSO | | Autonomous Search BCSO | |
|---|---|---|---|---|---|
| | | BCSO | $A$ | RPD | $I$ | Ms | BCSO | $A$ | RPD | $I$ | Ms |
| 1 | 11 | 11 | 11 | 0 | 5 | 17173.2 | 11 | 11 | 0 | 5 | 16818.2 |
| 2 | 3 | 3 | 3 | 0 | 7 | 16000.2 | 3 | 3 | 0 | 9 | 15159.5 |
| 3 | 3 | 3 | 3 | 0 | 8 | 15755.9 | 3 | 3 | 0 | 29 | 14537.3 |
| 4 | 13 | 13 | 13 | 0 | 6 | 17011.4 | 13 | 13 | 0 | 6 | 15634.2 |
| 5 | 5 | 5 | 5 | 0 | 9 | 16680.3 | 5 | 5 | 0 | 18 | 14958.3 |
| 6 | 3 | 3 | 3 | 0 | 6 | 16433.2 | 3 | 3 | 0 | 7 | 28722.4 |
| 7 | 4 | 4 | 4 | 0 | 5 | 16714.5 | 4 | 4 | 0 | 6 | 15837.8 |
| 8 | 5 | 5 | 5 | 0 | 6 | 17223.9 | 5 | 5 | 0 | 6 | 17155.2 |
| 9 | 5 | 5 | 5 | 0 | 10 | 16733.8 | 5 | 5 | 0 | 22 | 16827.5 |
| 10 | 5 | 5 | 5 | 0 | 6 | 16698.9 | 5 | 5 | 0 | 7 | 17077.1 |
| $\bar{X}$ | 5.7 | 5.7 | 5.7 | 0 | 6.8 | 16642.53 | 5.7 | 5.7 | 0 | 12 | 17272.75 |

### 11. Results for Boctor Instances Using BCSO and BCSO with Autonomous Search

Figure 3 shows the results of the experiments conducted for the Boctor Instances presented above. Thanks to the operation mode of the BCSO, a fast optimum convergence is obtained at $C = 2$; however, when $C = 3$, the BCSO does not converge as quickly that said, the optimum is reached.
in most cases before 100 executions, which demonstrates the effectiveness of the proposed approach.

Figure 4 shows the results of problem 3, \( C = 2 \) and \( M_{\text{max}} = 8 \), over iterations. Both versions converge quickly: while the Autonomous Search BCSO reaches the optimum early (iteration 10), the normal BCSO is stuck at optimum of fitness 5 at iteration 4.

The following graph (Figure 3) shows the results of problem 7, with \( C = 3 \), \( M_{\text{max}} = 8 \), reaching the overall optimum in both cases at similar iterations: normal
Table 8: Experimental results with cell $3$ and $M_{\text{max}} = 8$.

| $P$ | $O$ | Classic BCSO | Autonomous Search |
|-----|-----|--------------|-------------------|
|     |     | BCSO | A   | RPD | $I$ | Ms | BCSO | A   | RPD | $I$ | Ms |
| 1   | 11  | 11   | 11  | 0   | 16  | 21580 | 11  | 11 | 0   | 15 | 18090.8 |
| 2   | 6   | 6    | 6   | 0   | 20  | 20246.3 | 6   | 6  | 0   | 20 | 17017.4 |
| 3   | 4   | 4    | 4   | 0   | 17  | 19927.2 | 4   | 4  | 0   | 42 | 16878.1 |
| 4   | 14  | 14   | 14  | 0   | 19  | 21022.2 | 14  | 14 | 0   | 24 | 18642.2 |
| 5   | 8   | 8    | 8   | 0   | 36  | 19499.3 | 8   | 8  | 8   | 215 | 17156.4 |
| 6   | 4   | 4    | 4   | 0   | 31  | 19735.9 | 4   | 4  | 4   | 144 | 16542.7 |
| 7   | 5   | 5    | 5   | 0   | 30  | 20064.9 | 5   | 5  | 5   | 39 | 17352 |
| 8   | 11  | 11   | 11  | 0   | 19  | 21113.4 | 11  | 11 | 0   | 76 | 18459.6 |
| 9   | 8   | 8    | 8   | 0   | 36  | 20879.4 | 8   | 8  | 8   | 56 | 17950 |
| 10  | 8   | 8    | 8   | 0   | 17  | 19959.3 | 8   | 8  | 8   | 17 | 18353.6 |
| $\bar{x}$ | 8  | 7.9  | 8   | 0   | 24  | 20402.8 | 7.9 | 7.9| 0   | 65 | 17644.3 |

Table 9: Experimental results with cell $3$ and $M_{\text{max}} = 9$.

| $P$ | $O$ | Classic BCSO | Autonomous Search |
|-----|-----|--------------|-------------------|
|     |     | BCSO | A   | RPD | $I$ | Ms | BCSO | A   | RPD | $I$ | Ms |
| 1   | 11  | 11   | 11  | 0   | 13  | 21872.7 | 11  | 11 | 0   | 16 | 18462.7 |
| 2   | 6   | 6    | 6   | 0   | 20  | 20489.4 | 6   | 6  | 0   | 16 | 17624.9 |
| 3   | 4   | 4    | 4   | 0   | 14  | 20044  | 4   | 4  | 4   | 15 | 16748.8 |
| 4   | 13  | 13   | 13  | 0   | 15  | 22408  | 13  | 13 | 0   | 17 | 17698.7 |
| 5   | 6   | 6    | 6   | 0   | 69  | 22768.2 | 6   | 6  | 6   | 168 | 17120.3 |
| 6   | 3   | 3    | 3   | 0   | 69  | 19580.2 | 3   | 3  | 3   | 139 | 17167.1 |
| 7   | 4   | 4    | 4   | 0   | 24  | 20863.5 | 4   | 4  | 4   | 29 | 17602.5 |
| 8   | 10  | 10   | 10  | 0   | 66  | 23977.9 | 10  | 10 | 0   | 184 | 18202.8 |
| 9   | 8   | 8    | 8   | 0   | 15  | 26618.9 | 8   | 8  | 8   | 21 | 17849.1 |
| 10  | 5   | 5    | 5   | 0   | 17  | 20694.3 | 5   | 5  | 5   | 26 | 18483.6 |
| $\bar{x}$ | 7  | 7    | 7   | 0   | 32  | 21931.7 | 7   | 7  | 7   | 63 | 17696.1 |

Table 10: New instances from other authors.

| Problem | Author                  | Machines | Parts | Cells | $M_{\text{max}}$ |
|---------|-------------------------|----------|-------|-------|-------------------|
| CFP01   | King and Nakornchai [49]| 5        | 7     | 2     | 3                 |
| CFP02   | Waghodekar and Sahu [50]| 5        | 7     | 2     | 4                 |
| CFP03   | Seifodinni [51]         | 5        | 18    | 2     | 3                 |
| CFP04   | Kusiak and Cho [52]     | 6        | 8     | 2     | 3                 |
| CFP05   | Kusiak and Chow [53]    | 7        | 11    | 5     | 2                 |
| CFP06   | Boctor [48]             | 7        | 11    | 4     | 2                 |
| CFP07   | Seifodinni and Wolfe [54]| 8       | 11    | 4     | 3                 |
| CFP08   | Chandrasekharan and Rajagopalan [55]| 8 | 20 | 3 | 4 |
| CFP09   | Chandrasekharan and Rajagopalan [56]| 8 | 20 | 2 | 5 |
| CFP10   | Mosier and Taube [57]   | 10       | 10    | 5     | 4                 |
| CFP11   | Chan and Milner [58]    | 10       | 15    | 3     | 4                 |
| CFP12   | Askin and Subramanian [59]| 14     | 24    | 7     | 3                 |
| CFP13   | Stanfel [60]            | 14       | 24    | 7     | 3                 |
| CFP14   | McCormick et al. [61]   | 16       | 24    | 8     | 5                 |
| CFP15   | Srinivasan et al. [62]  | 16       | 30    | 6     | 6                 |
| CFP16   | King [63]               | 16       | 43    | 8     | 4                 |
| CFP17   | Carrie [64]             | 18       | 24    | 9     | 4                 |
| CFP18   | Mosier and Taube [65]   | 20       | 20    | 6     | 7                 |
| CFP19   | Kumar et al. [66]       | 23       | 20    | 7     | 6                 |
| CFP20   | Carrie [64]             | 20       | 35    | 5     | 5                 |
| CFP21   | Boe and Cheng [67]      | 20       | 35    | 5     | 5                 |
| CFP22   | Chandrasekharan and Rajagopalan [68]| 24 | 40 | 12 | 5 |
Table 10: Continued.

| Problem  | Author                                      | Machines | Parts | Cells | $M_{\text{max}}$ |
|----------|---------------------------------------------|----------|-------|-------|-----------------|
| CFP23    | Chandrasekharan and Rajagopalan [68]        | 24       | 40    | 7     | 5               |
| CFP24    | Chandrasekharan and Rajagopalan [68]        | 24       | 40    | 7     | 5               |
| CFP25    | Chandrasekharan and Rajagopalan [68]        | 24       | 40    | 11    | 5               |
| CFP26    | Chandrasekharan and Rajagopalan [68]        | 24       | 40    | 12    | 3               |
| CFP27    | Chandrasekharan and Rajagopalan [68]        | 24       | 40    | 12    | 3               |
| CFP28    | McCormick et al. [61]                      | 27       | 27    | 6     | 11              |
| CFP29    | Carrie [64]                                 | 28       | 46    | 10    | 4               |
| CFP30    | Kumar and Vannelli [69]                     | 30       | 41    | 14    | 4               |
| CFP31    | Stanfel [60]                                | 30       | 50    | 13    | 3               |
| CFP32    | Stanfel [60]                                | 30       | 50    | 14    | 4               |
| CFP33    | King-Nakornchai [49]                       | 36       | 90    | 17    | 6               |
| CFP34    | McCormick et al. [61]                      | 37       | 53    | 3     | 15              |
| CFP35    | Chandrasekharan and Rajagopalan [70]        | 40       | 100   | 10    | 6               |

Table 11: Comparison between classic BCSO.

| ID       | $M$ | $P$ | $C$ | $M_{\text{max}}$ | EVOA | MBFA | CSOA |
|----------|-----|-----|-----|------------------|------|------|------|
|          |     |     |     |                  | Best | Worst| Mean |
|          |     |     |     |                  | RPD (%) |     |      |      |
|          |     |     |     |                  | Best | Worst| Mean |
|          |     |     |     |                  | RPD (%) |     |      |      |
|          |     |     |     |                  | Best | Worst| Mean |
|          |     |     |     |                  | RPD (%) |     |      |      |
| CF01     | 5   | 7   | 2   | 3                | 0    | 0    | 0    |
| CF02     | 5   | 7   | 2   | 4                | 3    | 3    | 3    |
| CF03     | 5   | 18  | 2   | 3                | 5    | 5    | 5    |
| CF04     | 6   | 8   | 2   | 3                | 2    | 2    | 2    |
| CF05     | 7   | 11  | 5   | 2                | 8    | 8    | 8    |
| CF06     | 7   | 11  | 4   | 2                | 4    | 4    | 4    |
| CF07     | 8   | 12  | 4   | 3                | 7    | 7    | 7    |
| CF08     | 8   | 20  | 3   | 4                | 7    | 7    | 7    |
| CF09     | 8   | 20  | 2   | 5                | 25   | 25   | 25   |
| CF10     | 10  | 10  | 5   | 4                | 0    | 2    | 1.2  |
| CF11     | 10  | 15  | 3   | 4                | 0    | 4    | 0.8  |
| CF12     | 14  | 24  | 7   | 3                | 7    | 11   | 16   |
| CF13     | 14  | 24  | 7   | 3                | 8    | 12   | 17   |
| CF14     | 16  | 24  | 8   | 5                | Unknown | 35 | 32.9 |
| CF15     | 16  | 30  | 6   | 6                | Unknown | 31 | 35.7 |
| CF16     | 16  | 43  | 8   | 4                | Unknown | 42 | 47   |
| CF17     | 18  | 24  | 9   | 4                | Unknown | 32 | 36   |
| CF18     | 20  | 20  | 7   | 5                | Unknown | 46 | 53   |
| CF19     | 20  | 23  | 7   | 6                | Unknown | 51 | 56   |
| CF20     | 20  | 35  | 5   | 5                | Unknown | 28 | 42   |
| CF21     | 20  | 35  | 5   | 5                | Unknown | 57 | 65   |
| CF22     | 24  | 40  | 7   | 5                | Unknown | 30 | 43   |
| CF23     | 24  | 40  | 7   | 5                | Unknown | 39 | 48   |
| CF24     | 24  | 40  | 7   | 5                | Unknown | 44 | 53   |
| CF25     | 24  | 40  | 11  | 5                | Unknown | 60 | 64   |
| CF26     | 24  | 40  | 13  | 5                | Unknown | 68 | 71   |
| CF27     | 24  | 40  | 12  | 3                | Unknown | 69 | 72   |
| CF28     | 27  | 27  | 6   | 11               | Unknown | 84 | 100  |
| CF29     | 28  | 46  | 10  | 4                | Unknown | 102| 119  |
| CF30     | 30  | 41  | 14  | 4                | Unknown | 57 | 63   |
| CF31     | 30  | 50  | 13  | 3                | Unknown | 70 | 79   |
| CF32     | 30  | 50  | 14  | 4                | Unknown | 86 | 90   |
| CF33     | 36  | 90  | 17  | 6                | Unknown | 136| 153  |
| CF34     | 37  | 53  | 3   | 15               | Unknown | 352| 383  |
| CF35     | 40  | 100 | 10  | 6                | Unknown | 181| 207  |

$M_{\text{max}}$: Maximum value of $M$ for each problem.
Table 12: Experimental results for new instances.

| P   | O   | BCSO | A   | RPD | I   | Ms   | BCSO | A   | RPD | I   | Ms   |
|-----|-----|------|-----|-----|-----|------|------|-----|-----|-----|------|
| 1   | 0   | 0    | 0   | 0   | 1   | 3583.2| 0    | 0   | 0   | 1   | 3433.4|
| 2   | 3   | 3    | 3   | 0   | 1   | 3619.7| 3    | 3   | 0   | 1   | 3558.5|
| 3   | 5   | 5    | 5   | 0   | 1   | 6273  | 5    | 5   | 0   | 1   | 6155.3|
| 4   | 2   | 2    | 2   | 0   | 1   | 1457.7| 2    | 2   | 0   | 1   | 3807.2|
| 5   | 8   | 8    | 8   | 0   | 1   | 7897.8| 8    | 8   | 0   | 1   | 7575.8|
| 6   | 4   | 4    | 4   | 0   | 2   | 6919  | 4    | 4   | 0   | 2   | 6389.2|
| 7   | 7   | 7    | 7   | 0   | 4   | 8158.6| 7    | 7   | 0   | 4   | 7529.3|
| 8   | 7   | 7    | 7   | 0   | 4   | 10048.4| 7   | 7   | 0   | 4   | 9240.1|
| 9   | 25  | 25   | 25  | 0   | 2   | 9373.3| 25   | 25  | 0   | 2   | 8705.8|
| 10  | 0   | 0    | 0   | 0   | 8   | 8982.7| 0    | 0   | 0   | 10  | 8254.2|
| 11  | 0   | 0    | 0   | 0   | 4   | 8893.5| 0    | 0   | 0   | 4   | 8164.4|
| 12  | 7   | 7    | 7   | 0   | 128 | 21747.6| 7    | 7   | 0   | 194 | 19928.8|
| 13  | 8   | 8    | 8   | 0   | 67  | 21835 | 8    | 8   | 0   | 87  | 20146.5|
| 14  | Unknown | 24  | 24  | 103 | 27558 | 24   | 24  | 147 | 25383.5|
| 15  | Unknown | 17  | 17  | 260 | 27283.5| 17   | 17  | 296 | 25025.1|
| 16  | Unknown | 29  | 29.05| 922 | 40535.1| 29   | 29.08| 1268 | 37265.8|
| 17  | Unknown | 26  | 26.53| 717 | 31776.2| 26   | 26.73| 876  | 30591.1|
| 18  | Unknown | 41  | 41.18| 1241 | 26712.9| 41   | 41.5 | 1174 | 27322.4|
| 19  | Unknown | 38  | 38   | 577 | 31345.7| 38   | 38.3 | 590  | 32086.5|
| 20  | Unknown | 2   | 2    | 300 | 31251.8| 2    | 2   | 358  | 29678.2|
| 21  | Unknown | 35  | 35   | 318 | 34413.4| 35   | 35.08| 443  | 33897.2|
| 22  | Unknown | 0   | 4.9  | 1909 | 42425.3| 0    | 2.48 | 2017 | 103160.1|
| 23  | Unknown | 10  | 13.53| 1649 | 45014.9| 10   | 12.43| 1988 | 42954.3|
| 24  | Unknown | 18  | 20.98| 1958 | 45974.2| 18   | 20.03| 2080 | 43359.1|
| 25  | Unknown | 40  | 43.6 | 2186 | 62062.9| 40   | 44.08| 2096 | 56834.7|
| 26  | Unknown | 59  | 62.15| 815  | 66630.4| 57   | 60.73| 2352 | 61659.3|
| 27  | Unknown | 61  | 64.05| 1204 | 66655.3| 61   | 63.55| 2202 | 62349.9|
| 28  | Unknown | 54  | 54   | 466  | 43228.5| 54   | 54.05| 477  | 41759.4|
| 29  | Unknown | 91  | 96.1 | 1434 | 76860.5| 90   | 95.2 | 2578 | 67203.9|
| 30  | Unknown | 37  | 42.6 | 1270 | 84810.9| 34   | 40.9 | 2520 | 75800.3|
| 31  | Unknown | 52  | 57.9 | 641  | 93391.4| 49   | 54.3 | 2453 | 81183.7|
| 32  | Unknown | 66  | 72.15| 1670 | 99440.7| 67   | 71.8 | 2431 | 87624.9|
| 33  | Unknown | 93  | 94.93| 2423 | 165907.8| 93   | 95.48| 1999 | 143833|
| 34  | Unknown | 256 | 256  | 1345 | 70985.4| 256  | 256  | 1005 | 70893.8|
| 35  | Unknown | 83  | 110.58| 964 | 153404.2| 55   | 82.2 | 3579 | 150723|
| X   | 5.85 | 34.51| 36.63| 0   | 703  | 42547.4| 33.49| 35.51| 0   | 1007 | 41242.1|

Figure 3: Graph showing the results of problem 7 for BCSO and BCSO AS with $C = 3$.

Figure 4: Graph showing the results of problem 3 for BCSO and BCSO AS with $C = 2$. 
12. Results for New Instances Using BCSO and BCSO with Autonomous Search

Figure 5 shows the results of the experiments performed for new instances, in which it can be seen that the Autonomous Search algorithm helps the solution not to get trapped at some local optimum; however, not all results with Autonomous Search present an advantage over the original version.

Figure 5 represents the results of problem 26, with \( M = 24, P = 40, C = 12 \), and \( M_{\text{max}} = 3 \), in which it can be seen that Autonomous Search BCSO does not have a great difference over the normal BCSO; however, Autonomous Search BCSO is able to explore new solutions, which makes it achieve better results.

The graph in Figure 6 represents the results of problem 30, with \( M = 30, P = 41, C = 14 \), and \( M_{\text{max}} = 4 \), in which it can be seen that the Autonomous Search BCSO solutions continue to change without being trapped in a local optimum, whereas normal BCSO is trapped near iteration 4000.

The graph in Figure 7 represents the results of problem 35, with \( M = 40, P = 100, C = 10 \), and \( M_{\text{max}} = 6 \), in which Autonomous Search BCSO solutions are changing, exploring new solutions, expanding their search space early on, before iteration 3000; normal BCSO is trapped in a local optimum near iteration 1000.

13. Conclusions

In the present investigation, a new algorithm inspired by cat behavior, called Cat Swarm Optimization, was presented in solving the Manufacturing Cell Design Problem, used for placement of machinery in a manufacturing plant.

The proposed BCSO was implemented and tested using 90 Boctor Instances plus 35 new instances, for a total of 125 instances: BCSO managed to obtain 100% of known optima in the 90 Boctor Instances, achieving rapid convergence and reduced execution times. In the case of the 35 new instances, it was possible to obtain 100% of the 13 known optima. It should be noted that these results were obtained after a long testing process, where the different parameters of the algorithm were calibrated based on experimentation. For that reason, Autonomous Search was implemented as an optimization method to influence variables in real time, which resulted in dynamic MR that slightly improved results obtained: 3% compared to the original, with 100% of the known optima, both for the 90 Boctor Instances and the 35 new instances.

As can be seen from the results, this metaheuristic behaves well in all observed cases. This research demonstrates that BCSO is a valid alternative for solving the MCDP. The algorithm works well, regardless of the scale of the problem. However, solutions obtained could be improved by using different parameters for each set of instances.
The BCSO performance was significantly increased after selecting a good repair technique. However, relying on a repair method leads us not to recommend the use of this algorithm for other types of problems because it is far less efficient than other techniques for more complex problems.

For future research, a more extensible configuration could be developed to cover a wider set of problems. It would also be interesting to implement this technique in conjunction with other recent metaheuristics where limited work on Autonomous Search exists such as cuckoo search, firefly optimization, or bat algorithms [75]. Finally, hybridization with learning techniques is another interesting research line to pursue, where feedback gathered for the self-tune phase could be processed with machine learning in order to better track the complete solving process.

Data Availability
The authors declare that the data used to support the findings of this study are available from the corresponding author.

Conflicts of Interest
The authors declare that they have no conflicts of interest.

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