Dynamic Cat Swarm Optimization algorithm for backboard wiring problem

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Abstract
This paper presents a powerful swarm intelligence metaheuristic optimization algorithm called Dynamic Cat Swarm Optimization. The formulation is through modifying the existing Cat Swarm Optimization Algorithm. The original Cat Swarm Optimization suffers from the shortcoming of “premature convergence,” which is the possibility of entrapment in local optima which usually happens due to the off balance between exploration and exploitation phases. Therefore, the proposed algorithm suggests a new method to provide a proper balance between these phases by modifying the selection scheme and the seeking mode of the algorithm. To evaluate the performance of the proposed algorithm, 23 classical test functions, 10 modern test functions (CEC 2019) and a real-world scenario are used. In addition, the dimension-wise diversity metric is used to measure the percentage of the exploration and exploitation phases. The optimization results show the effectiveness of the proposed algorithm, which ranks first compared to several well-known algorithms available in the literature. Furthermore, statistical methods and graphs are also used to further confirm the outperformance of the algorithm. Finally, the conclusion and future directions to further improve the algorithm are discussed.

Keywords Dynamic Cat Swarm Optimization · Cat Swarm Optimization · Exploration and exploitation phases · Metaheuristics · Optimization

1 Introduction
The aim of optimization is to identify the best solution for a specific problem among many alternative solutions. The objective can be minimization, such as minimizing cost or time, or it can be maximization, such as maximizing profit or production. There are two main families of optimization algorithms, namely exact and approximate algorithms [1]. In the first one, some specific rules are used in which the same inputs will give the same outputs all the time. However, in the second type, because it always has some randomness and depends on some probabilistic rules, the same inputs would not necessarily give the same outputs [2]. Metaheuristic algorithms are of approximate types. They are referred as a high-level scheme that directs and changes other heuristics in order to generate solutions further than those solutions which are typically achieved in the pursuit of local optima [3]. It is proven that when the number of possible solutions is large enough that makes it infeasible for the exact algorithms to be used, metaheuristic algorithms come to play their important role by providing fairly decent solutions during an acceptable time [4].

Swarm intelligence algorithms are of metaheuristic types, in which multiple agents move in the search space. These agents are decentralized and self-organized, which somehow communicate and work together to find the optimal solution [4]. In general, these agents perform the search in two phases, namely exploration and exploitation. Exploration means jumping out to search for new regions on a global scale, while exploitation means focusing on those regions that have already been searched to find better solutions. Over-exploitation of an algorithm will lead to diversification of agents, and it is unlikely to reach the
near-optimum solutions. On the other hand, over-exploitation of an algorithm will increase the chance of falling into local optima and not being able to find the global optimum. Therefore, having a proper balance between these two phases is very critical in any metaheuristic algorithm [5].

Cat Swarm Optimization (CSO) is a metaheuristic algorithm, which is inspired by the resting and hunting behavior of cats. The algorithm has the limitation of being trapped into local optima. Therefore, many modified versions have been developed to overcome this issue. For example, Pappula et al. used a normal mutation technique [6]; Nie et al. [7] adopted quantum mechanics and tent map techniques, Orouskhani et al. used an inertia value to the velocity equation [8], etc. A relevant detailed survey can be found in [9]. This paper proposes a Dynamic Cat Swarm Optimization (DCSO) algorithm, in which the main contribution is to provide a proper balance between the global and local searches and hence avoid the local optima trap. In order to achieve this, the selection scheme and the seeking mode of the algorithm are modified. Regarding the selection scheme, MR parameter was replaced with two new adaptive parameters and the selection process was changed to be fitness dependent instead of random selection. As for the seeking-mode modification, greedy method was used instead of roulette wheel method and SRD parameter was removed as well. This idea was first introduced in Simulated Annealing algorithm by Kirkpatrick et al. [10]. Therefore, DCSO algorithm exploits the idea to propose a novel adaptive method and improve the original CSO algorithm.

The rest of the paper is organized as follows: Sect. 2 presents the motivation and novelty of this study. Section 3 describes the backboard wiring problem. Section 4 discusses the methodology used to formulate the original CSO algorithm as well as the proposed DCSO algorithm. Section 5 presents the results and discussions, where the proposed algorithm is evaluated against Chimp Optimization Algorithm (ChOA) [11], the original CSO algorithm (CSO) [12] and Differential Evolution (DE) [13]. Finally, Sect. 6 concludes this study and provides future directions.

2 Motivation and novelty

The tracing and seeking modes of CSO algorithm are playing the role of exploitation and exploration phases of the algorithm, respectively. These two modes are controlled by a parameter called mixture ratio (MR). This parameter has two weaknesses that critically affect the performance of the algorithm, with the following details:

1. It is a static parameter and its value is unchangeable throughout the iterations. This prevents the algorithm from assigning the right number of cats to the exploration or exploitation phases at different stages of optimization process.

2. The cats assigned to each mode are selected randomly. This also causes confusion to the agents and misleads them to defect areas. Supposing there is a cat in a promising area, this cat should be assigned to the seeking mode for the next iterations. However, CSO algorithm might randomly assign the cat to the tracing mode, which takes the cat away from the promising area and transfers it toward a local optimum.

DCSO algorithm proposes the following modifications to tackle these issues and balance between exploration and exploitation phases:

1. The MR parameter is replaced with TCN and SCN parameters, which are adaptive and their values change according to the number of iterations. These two parameters form a dynamic selection scheme, where at the beginning of iterations two cats are assigned to the tracing mode and the remaining cats are assigned to the seeking mode. Then progressively and according to the number of iterations, the number of tracing cats increases and the number of seeking cats decreases, i.e., TCN and SCN parameters are inversely proportional. Thus, at the last iteration all cats are in the tracing mode and are moving toward the global optimum. This means that at the early iterations, the algorithm performs global search to find the promising areas. Then, the algorithm makes a smooth and gradual transition toward local search.

2. The proposed algorithm, in each iteration, sorts the cats according to their fitness costs. This sorting is used to distinguish between the cats with higher fitness cost and those with lower fitness costs. Therefore, cats with lower fitness costs are always assigned into the seeking mode so as not to leave the promising area prematurely. Meanwhile, cats with higher fitness costs are assigned to tracing mode because it is preferable for these cats to leave their defective areas and move toward the global best.

3. The proposed algorithm also has two modifications in the seeking mode. First, greedy method is used instead of roulette wheel method. Second, SRD parameter is removed and only a random ratio is used to mutate the positions. As the name implies, greedy method always selects the best candidates as its next position. On the other hand, the roulette wheel method gives the chance to the other solutions to be selected as well. Therefore,
the greedy method is in favor of seeking phase as it allows the agents to move to better areas only.

3 DCSO algorithm for quadratic assignment problem: backboard wiring problem

This section is dedicated to discuss the concept and mathematical details of the backboard wiring problem. Moreover, it explains how the DCSO algorithm is applied on the problem.

3.1 Problem description

Backboard wiring problem is an optimization problem, which considers the placement of electronic elements on a computer backboard so as to minimize the total length of wires required to connect them. Solving such problem plays an important role in enhancing the speed and efficiency of the system. In the example of Steinberg, 34 components with a total of 2625 interconnections are involved to be located on 36 positions in a backboard. Two dummy components are also added to equalize the number of components and locations [14]. Figure 1 is the geometry of the backboard wiring problem where a possible permutation for a dataset instance is presented [15].

3.2 Problem formulation

Mathematically, this problem can be formulated as the quadratic assignment problem (QAP). Practically, QAP is considered as one of the most complicated combinatorial optimization problems. It was first introduced by Koopmans and Beckmann, and it has many other real-world applications, such as hospital layout facility, airport gate assignment and dartboard design [16]. Given \( n \) elements, \( n \) locations and two \( n \times n \) matrices, the flow matrix \( A = (a_{ik}) \) and the distance matrix \( D = (d_{jl}) \). Here, \( a_{ik} \) denotes the number of wires, which connect elements \( i \) and \( k \) and \( d_{jl} \) denotes the distance between locations \( j \) and \( l \) on the backboard. Therefore, the formulation of Steinberg wiring problem (SWP) can be written as:

\[
\text{min} \sum_{j=1}^{n} \sum_{k=1}^{n} a_{ik}d_{jl}x_{ij}x_{kl}
\]

Subject to

\[
\sum_{j=1}^{n} x_{ij} = 1,
\]

\[
\sum_{i=1}^{n} x_{ij} = 1,
\]

Where

\[
x_{ij} = \begin{cases} 
1, & \text{if facility } i \text{ is assigned to location } j \\
0, & \text{otherwise.}
\end{cases}
\]

3.3 Problem constraints

As stated in the previous subsection, \( x_{ij} \) matrix would be 1 if element \( i \) is assigned to location \( j \) on the backboard and it will be 0 otherwise. The constraints guarantee that each element \( i \) is allocated to exactly one location \( j \) and each location \( j \) contains one element \( i \) merely.

3.4 Problem objectives

The problem involves assigning \( n \) elements on \( n \) locations on a backboard while minimizing the assignment cost value. This assignment is denoted by a permutation, which specifies the location of each element [17]. Therefore, the following steps are followed in order to apply the DCSO algorithm on the problem:

1. The algorithm generates a population of cats (solutions) in each iteration.
2. The position values of each cat are sorted in ascending/descending order.
3. The indices of these sorted values are obtained in order to create a permutation.
4. The achieved permutation will be used in Eq. (1) to calculate the cost value.
5. After calculating the cost values for all the permutations, the one with the least cost value is selected as the best permutation.

For example, let us assume that lower and upper bounds are equal to 0 and 1, respectively. Let us also assume that the position of a four-dimensional agent is like: (0.12, 0.74, 0.01 and 0.46). Therefore, by taking the indices of their sorted values, a permutation like (2, 4, 1 and 3) is obtained. The sets of permutations of all agents are then used in Eq. (1) to calculate their fitness values. Next, the best permutation is chosen which has the least cost value.
4 Cat Swarm Optimization

This section consists of two main parts, where both of the original Cat Swarm Optimization (CSO) algorithm and the proposed Dynamic Cat Swarm Optimization (DCSO) algorithm are presented, respectively.

4.1 The original Cat Swarm Optimization

Cat Swarm Optimization (CSO) was originally developed by Chu et al. [18]. It is inspired by two main behaviors of cats, which are resting and hunting. Accordingly, the algorithm consists of two modes, namely seeking and tracing modes. Each cat denotes a solution set, which has its own position, a cost value and a flag. The position is comprised of $M$ dimensions, where each dimension has its own velocity. The cost value reveals how well a solution set (cat) is. Finally, the flag is to specify whether the cat is in seeking mode or tracing mode. In each iteration, the best cat is identified, which represents the best solution found so far.

4.1.1 General steps for CSO algorithm

The algorithm takes the following steps while looking for the optimal solution:

1. Identify the upper and lower bounds for the solution sets.
2. Randomly create $N$ cats and scatter them into the $M$ dimensional space. Each cat should have a random velocity value within the predefined velocity limits.
3. According to MR value, the cats are randomly assigned to seeking mode or tracing mode. MR parameter is a mixture ratio, which is selected in the range of $[0, 1]$; for instance, if $N$ was equal to 10 and MR was equal to 0.2, then two cats will be randomly selected to go through the tracing mode and the remaining eight cats will go through the seeking mode.
4. Evaluate the cost value for all cats and then the best cat of the current generation will be identified.
5. Move the cats according to their flags. If a cat was assigned to the seeking mode, apply the cat to the seeking mode process, if not apply it to the tracing mode process.
6. For the next iteration, re-pick the cats according to MR and set them to go through either seeking or tracing modes.
7. Check the termination condition, if satisfied; terminate the program; otherwise, repeat Step 4 to Step 6.

4.1.2 Seeking mode

This mode mimics the resting behavior of cats and has four vital parameters, which are seeking memory pool (SMP), seeking range of the selected dimension (SRD), counts of dimension to change (CDC) and self-position consideration (SPC).

SMP identifies the number of copies of a cat (candidate positions) to be produced in the seeking mode. For instance, if SMP was set to 5, then for each cat in the seeking mode, five random copies will be generated in which the cat chooses one of them as its next position. The way these random copies are generated depends on CDC and SPC. CDC parameter is in the range of $[0, 1]$ and specifies how many dimensions to be modified. For instance, if CDC was set to 0.8 and the number of dimensions in the search space was 10, then for each cat eight dimensions will be modified and the rest will stay constant. SRD is a mutative ratio for those dimensions, which are selected by CDC. Lastly, SPC is a Boolean-valued parameter, which specifies whether the current position of the cat will be selected as one of the copies of SMP or not. For instance, if SPC was set to true and SMP was set to 5, then only four random copies will be generated and the current position will be the fifth candidate position. The steps of this mode are as follows:

1. Make $J$ copies of the current position of a cat, where $J = SMP$. If SPC is true, then $J = (SMP - 1)$ and keep the current position as one of the candidates.
2. For each copy, according to CDC choose some random dimensions to be changed. Then, randomly add or subtract SRD values from the existing positions as shown in Eq. (2):

   \[
   X_{j,d} = (1 \pm \text{rand} \times \text{SRD}) \times X_{j,d} \\
   \]

   where $X_{j,d}$ is the cat’s position and $j$ and $d$ represent the number of copies and dimensions for the cat, respectively.
3. Calculate the cost value for the candidate positions.
4. Using the roulette wheel method, calculate the selecting probability of each candidate point according to Eq. (3). Therefore, candidate points with better fitness costs have more chances to be selected. However, if all fitness costs were the same, then the selecting probability of each candidate point would be 1.

   \[
   P_l = \frac{|FS_l - FS_b|}{FS_{\max} - FS_{\min}}, \quad 0 < i < j. \\
   \]

   If the objective is minimization, then $FS_b = FS_{\max}$; otherwise, $FS_b = FS_{\min}$.
4.1.3 Tracing mode

This mode mimics the hunting behavior of cats, and the steps are as follows:

1. Update the velocities for all dimensions according to Eq. (4):

\[ V_{k,d} = V_{k,d} + c_1 \times \text{rand} \times (X_{\text{best},d} - X_{k,d}) \]  

where \( V_{k,d} \) is the velocity for the \( k \)th cat in the \( d \)th dimension; \( X_{\text{best},d} \) is the position of the cat with the best fitness cost; and \( X_{k,d} \) is the current position of the \( k \)th cat in the \( d \)th dimension. \( c_1 \) is a constant and \( \text{rand} \) is a single uniformly distributed random number in the range of [0, 1].

2. Set the new velocity value to the limits if it out-ranged the bounds of velocity.

3. Update the position of \( k \)th cat according to Eq. (5):

\[ X_{k,d} = X_{k,d} + V_{k,d} \]  

where \( X_{k,d} \) is the position of \( k \)th cat in the \( d \)th dimension.

4.2 The proposed Dynamic Cat Swarm Optimization

The MR parameter in the original CSO specifies what percentage of the population to go through the seeking or tracing modes. It is a static parameter, which has a fixed value throughout the entire iterations of the algorithm. DCSO reformulates this selection scheme by Eqs. (6) and (7):

1. Tracing Cat Number (TCN): specify the number of cats, in \( i \)th iteration, that are entering the tracing mode and it is defined according to Eq. (6):

\[ \text{TCN} = \frac{\text{Total Number of Cats}}{\text{Iteration Number}} \times \text{MR} \]

Fig. 2 Number of seeking and tracing cats in different iterations. As number of iterations increases, number of tracing cats (exploitation phase) increases and number of seeking cats (exploration phase) decreases.
$$TCN = \begin{cases} i \times N \quad & \text{if } TCN \leq 2 \\ \text{MaxIter} & \text{if } TCN > 2 \end{cases}$$  \hspace{1cm} (6)

where \( i \) is the current number of iteration; \( \text{MaxIter} \) is maximum iteration; and \( N \) is the population size.

2. Seeking Cat Number (SCN): specify the number of cats, in \( i \)th iteration, that are entering the Seeking modes and it is defined according to Eq. (7):

$$SCN = N - TCN.$$  \hspace{1cm} (7)

TCN and SCN are inversely proportional. Together, they form a selection scheme, in which at the beginning of iterations, only two cats are entering the tracing mode and the rest of them are entering the seeking mode. Then, gradually and according to the number of iterations, cats are removed from the seeking mode and sent to the tracing mode. Hence, by the end of iterations, all cats are in the tracing mode to move toward the best solutions found so far. Accordingly, Fig. 2 shows how the agents are chasing the global best and how the number of seeking cats (squares) decreases in an inverse proportional manner to the number of tracing cats (triangles) throughout iterations.

4.2.1 General steps for DCSO algorithm

The algorithm takes the following steps while looking for optimal solutions:

1. Initialize the cat population.
2. Calculate the fitness function for all cats.
3. According to their fitness costs, sort the cats from best to worst and identify the best solution of the current generation.
4. Calculate TCN and SCN (Eqs. 6 and 7).
5. Select as many cats as SCN value from the best cats of the population and Send them to the seeking mode.
6. Send the remaining cats into the tracing mode.
7. Combine and mix all tracing and seeking cats together.
8. If any cat dimension is out of the boundary, it is equal to the limits, as in Eq. (8):

$$X_k; d = \begin{cases} L_d & \text{if } X_{k,d} < L_d \\ U_d & \text{if } X_{k,d} > U_d \end{cases}$$  \hspace{1cm} (8)

where \( X_{k,d} \) is the position of \( k \)th cat in the \( d \)th dimension and \( L_d \) and \( U_d \) are lower and upper bounds for \( d \)th dimension of the search space, respectively.
9. Calculate the fitness cost for all cats and update the global best.
10. Check if the termination condition is satisfied, then terminate the program. Otherwise, repeat Step 4 to Step 9.

4.2.2 Tracing mode

This mode is similar to the original CSO algorithm. However, in DCSO algorithm inertia weight, which is a linear time-varying parameter, is added to the velocity equation. This parameter is used repeatedly in many metaheuristic algorithms to linearly decrease the velocity value and hence balance between the exploration and exploitation phases [8]. So, the algorithm takes the following steps in this mode:

1. The velocities for each dimension are updated according to Eq. (9):

$$V_{k,d} = \omega \times V_{k,d} + c_1 \times \text{rand} \times (X_{\text{best},d} - X_{k,d}).$$  \hspace{1cm} (9)

2. The positions of cats are updated according to Eq. (10):

$$X_{k,d} = X_{k,d} + V_{k,d}.$$  \hspace{1cm} (10)

4.2.3 Seeking mode

In this mode, DCSO algorithm has two main modifications: Firstly, greedy method is used instead of the roulette wheel method. Thus, instead of selecting the candidate positions based on probability, best candidate position is always selected. Secondly, the SRD parameter is removed and...
only a random value in the range of (0, 1) is used. So, the steps of this mode are as follows:

1. For each cat that comes into this mode, make $J$ copies of its current position, where $J = \text{SMP}$.
2. For each copy, in a random permutation manner, select as many dimensions as CDC value.
3. Calculate the copies according to Eq. (11):
   \[ X_{j,d} = (1 \pm \text{rand}) \times X_{j,d}. \]  
(11)

4. Fitness cost for all copies is calculated, and using the greedy method, the best copy is selected to be the next position for the cat.

Figure 3 is for illustrative purposes; it shows how a cat moves in seeking or tracing modes. Additionally, Fig. 4 is the flowchart of DCSO algorithm, which presents the sequence steps of the algorithm.

5 Results and discussion

In this section, the performance of the proposed algorithm is evaluated. Therefore, the algorithm was benchmarked on 33 test functions and a real-world scenario. Besides, the dimension-wise diversity measurement is also presented.
Figure 5 presents the general performance evaluation framework for the proposed algorithm.

The test functions are classified into two groups, which are classical and modern test functions.

### 5.1 Classical test functions

This group contains the unimodal and multimodal test functions (see Table 6 in Appendix for the detailed description of these functions). F1 to F7 are of the unimodal type, and they are used to test the exploitation ability of an algorithm since they have one single optimum. However, F8 to F23 are multimodal test functions, which have multiple local optima, and one of them is the global optimum. Therefore, these types of functions are used to test the exploration ability of an algorithm.

### 5.2 Modern test functions (CEC 2019)

These test functions are also known as composed test functions. They are shifted, rotated, hybridized or expanded versions of other test functions. They are considered to be the most challenging benchmark functions, and they are used to test how well an algorithm can balance between the exploration and exploitation phases. For this work, CEC 2019 special session, also known as “The 100-Digit Challenge,” is used as composed functions [19] (see Table 7 in Appendix).

The comparison results of DCSO algorithm for unimodal, multimodal and CEC 2019 benchmark functions are presented in Tables 1 and 2 in the form of mean and standard deviations. For each benchmark function, the algorithm is executed for 30 independent runs. For each run, the number of search agents and iterations is equal to 30 and 500, respectively. Furthermore, the results are compared with three well-known algorithms, namely Chimp Optimization Algorithm (ChOA) [11], Cat Swarm Optimization (CSO) algorithm [12] and Differential Evolution (DE) [13]. Parameter settings for these algorithms are presented in Table 8 in Appendix. Furthermore, by looking at Tables 1 and 2, it is clear that DCSO algorithm yields competitive results.

Figure 6 presents the ranking of algorithms in the experiment, in which DCSO algorithm ranks first in the
Table 1 Comparison results between DCSO and the selected algorithms for classical test functions in terms of average and standard deviation

|  | DCSO  |  |  |  |  |
|---|---|---|---|---|---|
|  | Ave | SD | Ave | SD | Ave | SD | Ave | SD |
| F1 | 0 | 0 | 2.20E–18 | 7.24E–18 | 7.72E–09 | 1.37E–08 | 2.35E–19 | 1.97E–19 |
| F2 | 9.64E–261 | 0 | 1.56E–12 | 3.35E–12 | 1.14E–05 | 8.58E–06 | 5.61E–12 | 3.08E–12 |
| F3 | 0 | 0 | 8.17E–07 | 3.72E–06 | 0.000283 | 0.000619 | 3.52E+01 | 2.53E+01 |
| F4 | 5.93E–233 | 0 | 4.93E–06 | 1.11E–05 | 0.165671 | 0.080876 | 3.35E–03 | 1.30E–03 |
| F5 | 5.873546 | 0.634312 | 8.930067 | 0.171717 | 28.25196 | 62.01179 | 8.033931 | 5.981155 |
| F6 | 5.42E–06 | 2.89E–06 | 0.218349 | 0.203071 | 1.335225 | 0.404781 | 2.05E–19 | 1.88E–19 |
| F7 | 9.04E–05 | 9.71E–05 | 0.000813 | 0.000807 | 0.032696 | 0.024015 | 0.006223 | 0.001798 |
| F8 | 3.21E+03 | 341.5937 | 2212.45 | 77.8367 | 2730.32 | 265.2633 | 4.19E+03 | 2.16E+01 |
| F9 | 0 | 0 | 3.657066 | 4.512448 | 31.09397 | 11.43579 | 2.13E–10 | 7.15E–10 |
| F10 | 8.88E–16 | 0 | 1.93E+01 | 2.64E+00 | 3.711059 | 1.902422 | 1.87E–10 | 9.32E–11 |
| F11 | 0 | 0 | 0.070081 | 0.078762 | 0.498361 | 0.236176 | 0.001331 | 0.003798 |
| F12 | 2.60E–03 | 0.006745 | 0.037791 | 0.015315 | 2.579259 | 2.335587 | 1.40E–20 | 1.51E–20 |
| F13 | 0.082788 | 0.090575 | 0.935028 | 0.093016 | 1.513306 | 0.699265 | 4.30E–20 | 6.80E–20 |
| F14 | 1.852603 | 1.902283 | 1.324236 | 1.782733 | 1.031145 | 0.181483 | 1.392995 | 1.258379 |
| F15 | 3.08E–04 | 3.68E–08 | 0.001316 | 0.054665 | 0.002151 | 0.050056 | 0.001538 | 0.000369 |
| F16 | 1.03163 | 1.09E–09 | 1.03162 | 1.32E–05 | 1.03161 | 3.31E–05 | 1.03163 | 6.78E–16 |
| F17 | 0.304251 | 8.07E–10 | 0.304253 | 2.33E–06 | 0.30435 | 0.000331 | 0.305665 | 0.000774 |
| F18 | 3.000027 | 3.30E–05 | 3.000177 | 2.11E–07 | 3.013953 | 0.01674 | 3 | 2.22E–15 |
| F19 | 3.86173 | 2.72E–03 | 3.8546 | 0.001786 | 3.86104 | 0.001995 | 3.86278 | 2.71E–15 |
| F20 | 3.28481 | 7.03E–02 | 2.56611 | 0.568237 | 3.24127 | 0.086369 | 3.32199 | 5.73E–06 |
| F21 | 5.0552 | 1.23E–06 | 3.47675 | 2.009677 | 7.98884 | 2.388095 | 9.71627 | 1.61675 |
| F22 | 5.61919 | 1.621814 | 3.84991 | 2.042037 | 9.84256 | 1.324076 | 10.3887 | 0.071691 |
| F23 | 5.489 | 1.372025 | 4.24164 | 2.034003 | 9.11802 | 2.201779 | 10.3576 | 0.978724 |

Bold values are the lowest cost value achieved in the experiment

Table 2 Comparison results between DCSO and the selected algorithms for modern test functions (IEEE CEC 2019) in terms of average and standard deviation

|  | DCSO  |  |  |  |  |
|---|---|---|---|---|---|
|  | Ave | SD | Ave | SD | Ave | SD | Ave | SD |
| Cec01 | 4.09E+04 | 1.83E+03 | 4.24E+09 | 9.67E+09 | 3.57E+09 | 3.6E+09 | 1.91E+10 | 9.33E+09 |
| Cec02 | 18.34314 | 1.98E–04 | 18.40831 | 0.018587 | 19.6833 | 0.607681 | 18.34286 | 6.43E–15 |
| Cec03 | 13.7024 | 3.32E–07 | 13.70242 | 7.11E–06 | 13.70249 | 0.000454 | 13.70241 | 4.55E–06 |
| Cec04 | 55.97322 | 24.34732 | 5932.62 | 2855.207 | 244.6425 | 88.65511 | 21.26087 | 3.156334 |
| Cec05 | 2.308367 | 0.13647 | 4.209471 | 0.887398 | 2.683806 | 0.146979 | 2.175169 | 0.05137 |
| Cec06 | 6.611216 | 1.22108 | 12.14444 | 0.682671 | 11.66816 | 0.434781 | 9.244935 | 0.581621 |
| Cec07 | 207.6113 | 85.5053 | 1007.134 | 179.0166 | 462.3794 | 196.4319 | 249.976 | 104.1378 |
| Cec08 | 4.591039 | 0.713487 | 6.784621 | 0.156237 | 5.967812 | 0.414544 | 5.307605 | 0.456854 |
| Cec09 | 5.089876 | 0.990137 | 449.2725 | 245.4902 | 11.81882 | 7.975786 | 3.490228 | 0.046099 |
| Cec10 | 20.48603 | 3.006093 | 21.49854 | 0.071956 | 21.43583 | 0.086047 | 21.09283 | 0.51391 |

Bold values are the lowest cost value achieved in the experiment

comparison (see Table 9 in Appendix for the ranking details). However, these results only show the overall performance of the proposed algorithm. Therefore, statistical tests are also required to prove the significance of the results. Thus, Wilcoxon sum rank tests were conducted to calculate P-values, and the results are presented in...
Table 3. In all functions, except for F5, where DCSO ranks better, \( P \)-values are less than 0.05, which proves the significance of the results. Hence, the null hypothesis is rejected, as there is no difference between the means.

### 5.3 Results and discussion for the backboard wiring problem

Dataset instances for the backboard wiring problem are taken from QAPLIB [15]. The dimensions of the instances are 36. There are a number of feasible choices for the distance matrix \( D = (d_{ij}) \); in this paper, Steinberg used 1-norm, 2-norm and squared 2-norm distances between the backboard locations which are known as ste36a, ste36b and ste36c, respectively [14]. In the experiment, the DCSO algorithm is compared with Chimp Optimization Algorithm (ChOA) [11], Cat Swarm Optimization (CSO) algorithm [12] and Differential Evolution (DE) [13]. For each dataset instance, the selected algorithms are executed for 30 independent runs. For each time, the number of search agents and iterations is equal to 30 and 500, respectively. The parameter settings for the algorithms are presented in Table 8 in Appendix. The results are presented in Table 4 in terms of mean and standard deviation. Moreover, elapsed time measurement is also added to the table to achieve a fair comparison [20]. Furthermore, Figs. 7, 8 and 9 show the convergence curve of the selected algorithms for these datasets. The convergence curve for an algorithm shows the best-obtained cost values over the course of 500 iterations.

It can be noticed that DCSO algorithm has a better and smoother convergence compared to other algorithms. Furthermore, the results which are presented in Table 4 show that the DCSO algorithm returns the least cost values for all the datasets and outperforms the other competitive algorithms. Regarding the elapsed time measurement, the DE algorithm takes the least amount of time compared to the rest. DCSO takes double amount of time in comparison with the DE algorithm. However, Figs. 7, 8 and 9 show that the DCSO achieves better results in almost one-third of the iterations. As a result, we can conclude that even though the DCSO requires more computation time per an...
iteration, it is more efficient than the DE algorithm on the whole. Finally, it is worth mentioning that the simulation was conducted using MATLAB on an Intel(R) Core(TM) i7-2670 with 6 GB RAM. Therefore, different hardware specifications would surely yield unlike elapsed time results.

5.4 Exploration and exploitation measurements

Swarm individuals generally have two basic search behaviors, which are known as exploration and exploitation. In the first one, the individuals are diverging and the distances between their dimensions are increasing. This phase is used to discover new areas and escape from possible local optima trap. On the other hand, in the exploitation phase, the individuals are intensifying and the distance between their dimensions is decreasing. In this phase, the individuals tend to locally search in the neighborhood and converge toward the global optimum. Finding a proper balance between the exploration and exploitation phases is a key factor to prevent premature convergence in metaheuristic algorithms [21].

In this study, the dimension-wise diversity measurement [21] is adopted to quantitatively measure the exploration and exploitation degree of the selected algorithms. Also, this study substituted mean by median in Eq. (12) because it represents the center of the population more accurately [22, 23].

Table 4 Comparison results of the selected algorithms for backboard wiring problem (QAPLIB) in terms of average, standard deviation and elapsed time

| Algorithms | Ste36a         | Ste36b         | Ste36c         |
|------------|----------------|----------------|----------------|
| DCSO Ave   | 13,431.73      | 29,300.27      | 10,700,541     |
| SD         | 916.932        | 2832.584       | 586,778.3      |
| Elapsed time (s) | 3.963525 | 3.926989      | 3.961443       |
| ChOA Ave   | 15,073.93      | 42,990.93      | 12,707,350     |
| SD         | 454.081        | 4174.001       | 362,543.5      |
| Elapsed time (s) | 11.624100 | 11.493323      | 11.484724      |
| CSO Ave    | 15,230.8       | 41,188.13      | 12,750,790     |
| SD         | 564.1728       | 2511.199       | 457,585.4      |
| Elapsed time (s) | 7.682724 | 7.657057       | 7.634772       |
| DE Ave     | 14,100.53      | 36,701.2       | 11,915,816     |
| SD         | 397.7436       | 1790.165       | 313,946.6      |
| Elapsed time (s) | 2,099774     | 2,063565       | 2,065695       |

Bold values are the lowest cost value achieved in the experiment.

Fig. 7 Convergence curve of DCSO and its competitive algorithms for Ste36a dataset

Fig. 8 Convergence curve of DCSO and its competitive algorithms for Ste36b dataset

Fig. 9 Convergence curve of DCSO and its competitive algorithms for Ste36c dataset
\[
\text{Div}_j = \frac{1}{n} \sum_{i=1}^{n} \text{median}(x^j) - x^j_i;
\]

\[
\text{Div} = \frac{1}{D} \sum_{j=1}^{D} \text{Div}_j
\]

where median\((x^j)\) depicts the median of dimension \(j\) in the entire population. \(x^j_i\) is the dimension \(j\) of search agent \(i\). \(n\) is the population size.

The diversity in each dimension \(\text{Div}_j\) is formulated as the average distance between the dimension \(j\) of every search agent and the median of that dimension. Then, the average of diversity for the whole dimensions is computed.
in Div. The percentage of exploration and exploitation in an algorithm can be calculated by taking the average of the following:

\[
XPL\% = \left( \frac{\text{Div}}{\text{Div}_{\text{max}}} \right) \times 100
\]

\[
XPT\% = \left( \frac{|\text{Div} - \text{Div}_{\text{max}}|}{\text{Div}_{\text{max}}} \right) \times 100
\]

where \(\text{Div}_{\text{max}}\) is the maximum diversity value found in the whole optimization process. XPL\% and XPT\% are the degree of exploration and exploitation, respectively, and they complement each other. Table 5 presents the explorative and exploitative capabilities of DCSO and the selected algorithms for all test functions and datasets used in the experiment. For each test function or dataset, each algorithm is executed for 30 independent runs, and the average values of these 30 runs are presented in Table 5. In each run of the experiment, the number of search agents and iterations is equal to 30 and 500, respectively.

Furthermore, by looking at Table 5, it can be noticed that the algorithms do not have the same percentage of exploration and exploitation for the different test functions or datasets. This means that this measurement, to some degree, is problem dependent. However, on average, the ratio between these two phases in DCSO is close to 50%:50%, while this ratio for CSO is approximately 75%:25%. Therefore, it can be concluded that DCSO algorithm is considerably more balanced as compared to the original CSO algorithm. Regarding ChOA and DE algorithms, they have an explorative nature except for ChOA algorithm in which it becomes exploitative for the QAP datasets.

In the case of DCSO and CSO algorithms, approaching the balance ratio of 50%:50% provided better results. However, this might not be true for every algorithm. The reason is that there are other factors that may play crucial roles in metaheuristic algorithms such as the structure of the algorithm, the relationship and coherence between the search agents and parameter setting.

### 6 Conclusion and future directions

CSO algorithm is hugely limited by the shortcoming of premature convergence, which is the likelihood of falling into local optima. Balancing the exploration and exploitation phases can be used to address this issue. Therefore, in this paper, DCSO algorithm was proposed that modifies the selection scheme and the seeking mode of the existing CSO algorithm. These modifications gave a dynamic nature to the algorithm and more importantly provided a proper balance between the exploration and exploitation phases of the algorithm. Moreover, to confirm this balance and expose the percentage of these phases the dimension-wise diversity measurement was also used. The results show, on average, the proportion between these two phases in DCSO is close to 50%:50%, while this ratio for CSO is roughly 75%:25%. In the experiment, the robustness of the proposed algorithm was validated by testing it on a total of 33 benchmark functions and a real-world scenario called backboard wiring problem. The results are then compared with three other well-known algorithms. We can conclude that the proposed method addresses the premature convergence issue and yields very competitive results. Having said that, there is still room for further enhancements in the algorithm; for example, combining the seeking mode of the algorithm with a suitable local search technique such as Golden Section search might considerably enhance the efficiency of the algorithm.

### Appendix

See Tables 6, 7, 8 and 9.
Table 6 Details of the test functions that are used in the experiments [24]

| Functions | Dimension | Range          | \( f_{\text{min}} \) |
|-----------|-----------|----------------|-----------------------|
| \( F_1(x) = \sum_{i=1}^{n} x_i^2 \) | 30 | \([-100, 100]\) | 0 |
| \( F_2(x) = \sum_{i=1}^{n} |x_i| + \prod_{i=1}^{n} |x_i| \) | 30 | \([-10, 10]\) | 0 |
| \( F_3(x) = \sum_{i=1}^{n} \left( \sum_{i=1}^{n} x_i \right)^2 \) | 30 | \([-100, 100]\) | 0 |
| \( F_4(x) = \max(|x_i|, 1 \leq i \leq n) \) | 30 | \([-100, 100]\) | 0 |
| \( F_5(x) = \sum_{i=1}^{n} \left[ 100(x_{i+1} - x_i)^2 + (x_i - 1)^2 \right] \) | 30 | \([-30, 30]\) | 0 |
| \( F_6(x) = \sum_{i=1}^{n} (|x_i + 0.5|)^2 \) | 30 | \([-100, 100]\) | 0 |
| \( F_7(x) = \sum_{i=1}^{n} ix_i^3 + \text{random}[0, 1] \) | 30 | \([-1.28, 1.28]\) | 0 |
| \( F_8(x) = \sum_{i=1}^{n} -x_i \sin(\sqrt{|x_i|}) \) | 30 | \([-500, 500]\) | \(-418.9829 \times 5\) |
| \( F_9(x) = \sum_{i=1}^{n} [x_i^2 - 10 \cos(2\pi x_i) + 10] \) | 30 | \([-5.12, 5.12]\) | 0 |
| \( F_{10}(x) = -20 \exp \left( -0.2 \sqrt{\frac{\sum_{i=1}^{n} x_i^2}{n}} \right) - \exp \left( \frac{1}{n} \sum_{i=1}^{n} \cos(2\pi x_i) \right) + 20 + e \) | 30 | \([-32, 32]\) | 0 |
| \( F_{11}(x) = \frac{1}{300} \sum_{i=1}^{n} x_i^2 - \frac{n}{\prod_{i=1}^{n} \cos(x_i)} + 1 \) | 30 | \([-600, 600]\) | 0 |
| \( F_{12}(x) = \frac{1}{n} \left( 10 \sin(\pi y_1) + \sum_{i=1}^{n-1} \left[ y_i - 1 \right]^2 \left[ 1 + 10 \sin^2(\pi y_{i+1}) \right] + (y_n - 1)^2 \right) \) | 30 | \([-50, 50]\) | 0 |
| \( y_i = 1 + \frac{5+1}{4} u(x_i, a, k, m) = \left\{ \begin{array}{ll} k(x_i - a)^m x_i > a \\ 0 - a < x_i < a \\ k(-x_i - a)^m x_i < -a \end{array} \right. \) | 30 | \([-50, 50]\) | 0 |
| \( F_{13}(x) = 0.1 \left\{ \sin^2(3\pi x_1) + \sum_{i=1}^{n} (x_i - 1)^2 \left[ 1 + \sin^2(3\pi x_i + 1) \right] + (x_n - 1)^2 \left[ 1 + \sin^2(2\pi x_n) \right] \right\} + \sum_{i=1}^{n} u(x_i, 10, 100, 4) \) | 30 | \([-50, 50]\) | 0 |
| \( F_{14}(x) = \left( \frac{1}{100} + \sum_{i=1}^{25} \frac{1}{x_i + 1} \right)^{-1} \) | 2 | \([-65, 65]\) | 1 |
| \( F_{15}(x) = \sum_{i=1}^{n} \left[ a_i - \frac{n(x_i^2 + b_i^2)}{b_i^2 + b_i x_i + n} \right]^2 \) | 4 | \([-5, 5]\) | \(0.00030\) |
| \( F_{16}(x) = 4x_1^3 - 2.1x_1^2 + \frac{1}{3}x_1^3 + x_1x_2 - 4x_2^2 + 4x_2 \) | 2 | \([-5, 5]\) | \(-1.398\) |
Table 6 (continued)

| Functions | Dimension | Range | $f_{\text{min}}$ |
|-----------|-----------|-------|-----------------|
| $f_{17}(x) = \frac{x^2}{C_0}$ | 3 | $[-5, 5]$ | 3.86 |
| $f_{18}(x) = \left[ (1 + a_1 + a_2 + b)^3 (19 - 14a_1 + 12a_2 + 27a_1^2 + 27a_2^2) \right]^{1/3}$ | 3 | $[-2, 2]$ | 3.32 |
| $f_{19}(x) = \left( 1 + \sum_{i=1}^{4} c_i \exp \left( \sum_{j=1}^{3} a_{ij} x_j \right) \right)$ | 6 | $[0, 10]$ | 0.398 |
| $f_{20}(x) = \left( 1 + \sum_{i=1}^{4} c_i \exp \left( \sum_{j=1}^{3} a_{ij} x_j \right) \right)$ | 4 | $[0, 10]$ | 0.4028 |
| $f_{21}(x) = \left( 1 + \sum_{i=1}^{4} c_i \exp \left( \sum_{j=1}^{3} a_{ij} x_j \right) \right)$ | 4 | $[0, 10]$ | 0.583 |

Table 7 CEC 2019 benchmarks “the 100-digit challenge”

| No | Functions | Dimension | Range   | $f_{\text{min}}$ |
|----|-----------|-----------|---------|-----------------|
| CEC01 | Storn’s Chebyshev polynomial fitting problem | 9 | $[-8192, 8192]$ | 1 |
| CEC02 | Inverse Hilbert matrix problem | 16 | $[-16,384, 16384]$ | 1 |
| CEC03 | Lennard–Jones minimum energy cluster | 18 | $[-4, 4]$ | 1 |
| CEC04 | Rastrigin’s function | 10 | $[-100, 100]$ | 1 |
| CEC05 | Griewangk’s function | 10 | $[-100, 100]$ | 1 |
| CEC06 | Weierstrass function | 10 | $[-100, 100]$ | 1 |
| CEC07 | Modified Schwefel’s function | 10 | $[-100, 100]$ | 1 |
| CEC08 | Expanded Schaffer’s F6 function | 10 | $[-100, 100]$ | 1 |
| CEC09 | Happy cat function | 10 | $[-100, 100]$ | 1 |
| CEC10 | Ackley function | 10 | $[-100, 100]$ | 1 |

Refer to [19] for more details.

Table 8 Control parameter values for the selected algorithms

| Algorithms | Parameters | Values |
|------------|------------|--------|
| DCSO | Population size | 30 |
| | Max iteration | 500 |
| | Inertia weight $W(I)$ | [0.4, 0.9] |
| | SMP | 5 |
| | CDC | 0.8% |
| | Constant (C) | 2.05 |
| | Random values | [0, 1] |
| ChOA | Population size | 30 |
| | Max iteration | 500 |
| | Random values: $R_1, R_2$ | [0, 1] |
| | $M$ | Chaotic |
| CSO | Population size | 30 |
| | Max iteration | 500 |
| | Constant (C) | 2.05 |
| | Random values | [0, 1] |
| | SMP | 5 |
| | CDC | 0.8 |
| | MR | 0.2 |
| | SRD | 0.2 |
| | Constant (C) | 2 |
| DE | Population size | 30 |
| | Max iteration | 500 |
| | BETA_MIN | 0.2 |
| | BETA_MAX | 0.8 |
| | Crossover rate | 0.2 |
Data availability The MATLAB code for DCSO algorithm can be found in the below repository link: https://github.com/aramahmed/DCSO-Algorithm/.

Declarations

Conflict of Interest The authors declare that they have no conflict of interest.

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