A Weighted Chimp Optimization Algorithm

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ABSTRACT These days, a sizable number of meta-heuristic algorithms are utilized to address many problems with numerous variables and huge complexity. One of the most popular swarm intelligence-based meta-heuristic methods is the chimp optimization algorithm inspired by chimps’ individual intelligence and sexual motivation in their group hunting. This paper proposes a weighted chimp optimization algorithm to tackle two main issues in large-scale numerical optimization problems, such as low convergence speed and local optima trapping to solve high-dimensional problems. The main difference between the weighted and standard chimp optimization algorithms is that a position-weighted equation is offered to enhance convergence speed and avoid local optima. Moreover, the balance between exploration and exploitation is carried out in the proposed method that is crucial in the swarm intelligence-based algorithms. The presented weighted chimp optimization algorithm method is evaluated in different conditions to prove that it is the best. For this purpose, a classical set of 30 unimodal, multimodal, and fixed-dimension multimodal benchmark functions is applied to investigate the pros and cons of characteristics of the weighted chimp optimization algorithm. Besides, the proposed algorithm is tested on the IEEE congress of evolutionary computation benchmark test functions. In order to shed more light on probing the performance of the weighted chimp optimization algorithm in large-scale numerical optimization and real-world problems, it is examined by 13 high-dimensional and ten real-world optimization problems. The results show that the suggested algorithm outperforms in terms of convergence speed, the probability of getting stuck in local minimums, exploration, and exploitation compared to state-of-the-art methods in the literature. Source codes are publicly available at https://se.mathworks.com/matlabcentral/fileexchange/99344-a-weighted-chimp-optimization-algorithm.

INDEX TERMS Chimp optimizer; Meta-heuristic; Weighted; Swarm intelligence.

I. INTRODUCTION

In today’s world of communication, there are a vast number of optimization problems in various fields, especially in engineering applications. Consequently, scientists and engineers commonly probe methods to address their optimization problems. Many factors need to be considered about these methods, such as being simple, low complexity, not trapping in local optima, etc. Most scholars categorize the optimization algorithms into two main groups. The first group is deterministic-based algorithms that are prone to the problems of local optima and low convergence. Another group is stochastic-based algorithms that are less likely to trap in local optima, and they are also able to enhance convergence speed [1]. Therefore, these excellent features that exist in stochastic-based algorithms have resulted in raising public awareness about them. Although numerous stochastic-based algorithms are in research references, Nature-Inspired Algorithms (NIA) have the utmost importance. Also, research findings confirm that NIA algorithms can be applied in high complexity and dimensional problems because of simplicity, flexibility, derivative-free approaches, and local optima avoidance [2]. Table 1 shows a classification of the NIA algorithms that are utilized in the literature.

Among the mentioned groups of NIA, swarm intelligence-based algorithms have a positive effect on engineering applications. So, scientists and engineers find it amazing to
apply them to their problems. The main reasons that cause a positive attitude towards these algorithms are memorizing the details of search space and the best solution while executing the algorithm, low requirements in terms of parameters, and more straightforward implementation [3].

Chimp Optimization Algorithm (ChOA) is a relatively new swarm intelligence-based stochastic technique presented by [15]. ChOA is inspired by the individual intelligence and sexual motivation of chimps in their group hunting. Compared with other NIA methods, ChOA only requires the adjustment of a few operators and can be implemented easily. Therefore, ChOA will be able to achieve interests and be subscribed by others in the future. From an environmental standpoint, eye-catching characteristics in groups of chimps contribute substantially toward the balance between exploration and exploitation. One of the essential traits of the chimps is individuals’ diversity. It means all of the chimps that live in a hunting group do not have the same aptitudes. In other words, chimps undertake great and different responsibilities to have instant and easy access to prey [22]. Another feature that can distinguish chimps from other animals is sexual motivation. The trait of sexual motivation in the hunting group of chimps leads to neglecting duties by some chimps. Consequently, in the final stage, chimps are in search of achieving meat chaotically.

For example, male chimps observed in the West African nation of Côte d’Ivoire (Ivory Coast) shared monkey meat with females exhibiting pink swellings on their rear ends that indicate ovulation and sexual availability [23]. To sum up, the former and latter characteristics can be highly beneficial to exploration and exploitation, respectively.

It is worthwhile to note that the No Free Lunch (NFL) theorem has represented that any optimization algorithm can not be found to have superior performance for all optimization problems. In other words, a particular meta-heuristic algorithm may have substantial results on a set of problems, but the same algorithm may show poor performance on a different set of problems [24]. Also, Through an analysis of the relevant references, it is clear that ChOA is defective. Its optimization performance is better for problems when the optimal solution is zero, but its merits are harder to notice for other cases. It is moreover discovered that ChOA, when solving the same optimization problem, has worse performance as the optimal solution is further from zero, and that is why our purpose of this paper is to suggest a modified ChOA and compare it to other current well-known NIA algorithms in the literature.

Although ChOA has some improvements compared with traditional NIA algorithms, according to the NFL theorem, there are new problems that need to optimization methods to address them. As a result, in this paper, a Weighted Chimp Optimization Algorithm (WChOA) is proposed to

| Methods                                                  | NIA                      | Ref(s) | Year |
|----------------------------------------------------------|--------------------------|--------|------|
| Genetic Algorithms (GA)                                  | ✓                        | [4]    | 1992 |
| Differential Evolution (DE)                              | ✓                        | [5]    | 1999 |
| Biogeography-Based Optimizer (BBO)                       | ✓                        | [6]    | 2008 |
| Gravitational Search Algorithm (GSA)                     | ✓                        | [7]    | 2009 |
| Chaotic Fractal Walk Trainer                             | ✓                        | [8]    | 2018 |
| Adaptive Best-mass Gravitational Search                  | ✓                        | [9]    | 2019 |
| Particle Swarm Optimization (PSO)                        | ✓ ✓                      | [10]   | 2006 |
| Ant Colony Optimization (ACO)                            | ✓ ✓                      | [11]   | 2006 |
| Bat-inspired Algorithm (BA)                              | ✓ ✓                      | [12]   | 2018 |
| Grey Wolf Optimizer (GWO)                                | ✓ ✓ ✓                     | [13]   | 2014 |
| Efficient and Robust Grey Wolf Optimizer                 | ✓ ✓ ✓                     | [14]   | 2020 |
| Chimp Optimization Algorithm (ChOA)                      | ✓ ✓ ✓                     | [15]   | 2020 |
| Ant Lion Optimization                                    | ✓ ✓ ✓                     | [16]   | 2020 |
| An Effective Discrete Grey Wolf Optimizer                | ✓ ✓ ✓                     | [17]   | 2020 |
| An Adaptive Multi-Population Optimizer                   | ✓ ✓ ✓                     | [18]   | 2021 |
| A Novel Search Space View                                | ✓ ✓ ✓                     | [19]   | 2021 |
| Artificial Gorilla Troops Optimizer (GTO)                | ✓ ✓ ✓                     | [20]   | 2021 |
| African Vulture Optimization Algorithm (AVOA)            | ✓ ✓ ✓                     | [21]   | 2021 |
vary exploration and exploitation combinations throughout iterations. In this paper, our contributions are as the following:

- A new model of ChOA is presented so that it does not affect the structure of the basic ChOA.
- A position-weighted equation based on weights is developed to speed up convergence and improve exploration and exploitation.
- The performance of WChOA is evaluated by applying 30 classic benchmark test functions, the IEEE Congress of Evolutionary Computation benchmark test functions (CECC06, 2019 Competition), 13 high-dimensional, and ten real-world optimization problems.
- Simulation results confirm that WChOA has outstanding performance in addressing high-dimensional optimization problems.

The rest of this paper is organized as follows. Section II introduces the basics of ChOA. In section III, the robust version of ChOA is proposed based on a position-weighted equation. The simulation results and comparison of WChOA with the other traditional NIA are provided in Section IV. Ultimately, Section V describes our conclusions.

II. OVERVIEW OF CHIMP OPTIMIZATION ALGORITHM

Chimp Optimization Algorithm (ChOA) is a standard NIA algorithm inspired by the hunting mechanism of chimps in nature and designed by [15]. There are four kinds of chimps called driver, barrier, chaser, and attacker in a chimp colony. Although each member of a chimp colony has different capabilities, these varieties are crucial for hunting the prey. The measures that must be taken to achieve the hunt have been represented in Figures 1 and 2. As Figures 1 and 2 show, drivers’ duty in a process of hunting is just to pursue the prey. Barriers prevent the prey from progressing among the branches of trees by constructing a dam. Chasers are in charge of catching up with the prey. Eventually, attackers are able to forecast the prey’ breakout route so that they can compel the prey to back towards the situation of the chasers [23]. In other words, the driver, barrier and chaser undertake the responsibility of exploration (phase 1) whereas the attackers have the leadership of exploitation (phase 2).

In the mathematical model, ChOA does not access the optimum solution (prey) in an abstract search space. As a result of this weakness, the solutions related to driver, barrier, chaser, and attacker are considered as the best solutions, and all of the other chimps would be guided by these four chimp groups during exploration (searching) and exploitation (hunting). This relationship is modeled as follows [15]:

FIGURE 1. The exploration process.

FIGURE 2. The exploitation process.
be in any location between its current position and the position of the prey. To mathematically model the divergence behavior, the \( \vec{A} \) vector bigger than 1 or smaller than -1 is utilized so that the search agents are compelled to diverge. This procedure depicts the exploration process and leads to searching globally.

\[ X(t+1) = \frac{X_1 + X_2 + X_3 + X_4}{4} \]

where \( t \) denotes the current iteration. \( \vec{X}_A, \vec{X}_B, \vec{X}_C \) and \( \vec{X}_D \) vectors indicate the current positions of the attacker, barrier, chaser, and driver, respectively. \( \vec{X} \) vector is the current position of other chimps. Also, \( \vec{C}, \vec{M} \) and \( \vec{A} \) vectors contribute greatly toward ChOA. These vectors are calculated by Eq.s (4) to (6):

\[ \vec{A} = 2f \vec{a} - f \]

\[ \vec{C} = 2\vec{r}_2 \]

\[ \vec{M} = \text{Chaoic-value} \]

where \( \vec{r}_1 \) and \( \vec{r}_2 \) are the random vectors that can vary in the range \([0,1]\). \( f \) represents a control value that is diminished non-linearly from 2.5 to 0. Full descriptions of these vectors will be expressed in the following paragraphs.

As Eq. (4) shows, \( \vec{A} \) vector is a decisive factor in ChOA because it plays vital roles. The first role of \( \vec{A} \) is to distinguish independent groups of chimps (attacker, barrier, chaser, and driver) in ChOA. In the traditional swarm-based optimization algorithm, all agents have similar behavior in local and global searches so that the particles can be contemplated as a single group with one common search method. Nonetheless, in every population-based optimization algorithm, different independent groups with a common purpose can be utilized to have a direct and random search result simultaneously. For this purpose, different continuous functions (\( f \)) can be applied to update independent groups. Due to the fact that there are numerous continuous functions for every independent group, to achieve high performance, [15] have used two versions of ChOA with different independent groups. Table 2 shows the coefficients of \( f \) vector in ChOA1 and ChOA2 versions.

| Groups   | ChOA1                                      | ChOA2                                      |
|----------|--------------------------------------------|--------------------------------------------|
| Group1   | \( 1.95 - 2t^{1/3}/T^{1/3} \) + 2.5       | \( 2.5 - (2\log(t)/\log(T)) \)            |
| Group2   | \( 1.95 - 2t^{1/3}/T^{1/3} \) + 2.5       | \( 2.5 - (2\log(t)/\log(T)) \)            |
| Group3   | \( -3t^2/T^3 \) + 1.5                     | \( 0.5 + 2\exp[-(4t/T^2)] \)             |
| Group4   | \( -3t^2/T^3 \) + 1.5                     | \( 2.5 + 2(t/T^2) - 2(2d/T) \)           |

Another critical parameter in ChOA is \( \vec{C} \) vector. This random vector is highly beneficial to ChOA to avoid trapping local optima. This effect appears in both the initial and final iterations. It is worth noting that chimps are sometimes banned from progressing towards the prey by some obstacles placed along their route of progression. Consequently, \( \vec{C} \) random vector can properly model this phenomenon in nature.

From a social perspective, chimps usually have a lot of competition for acquiring meat with the aim of sex and grooming. Therefore, it causes that chimps leave their tasks in the final stage of hunting. \( \vec{M} \) chaotic vector models sexual motivation in ChOA and is calculated based on a chaotic map. In other words, it is the most important contributing factor that distinguishes ChOA from the other swarm-based meta-heuristic algorithms. This feature in ChOA acts as a deterrent for local optima and gives rise to enhance the speed of convergence in high-dimensional problems. [15] have proposed six chaotic maps that are utilized to update the position of chimps in the final stage (Table 3). Since there is a possibility that some chimps do not have any sexual motivation in the process of hunting, a probability of 50% can be considered to choose whether the position update strategy of chimps will be normal (Eq. (3)) or not (chaotic model). In the case of the chaotic model, the following relationship is applied:

\[ X_{\text{chim}(t + 1)} = \begin{cases} 
\text{Eq.}(3) & \text{if } \mu < 0.5 \\
\text{Chaotic-Value} & \text{if } \mu \geq 0.5
\end{cases} \]

where \( \mu \) value is in range \([0, 1]\).
III. PROPOSED WEIGHTED CHIMP OPTIMIZATION ALGORITHM

As mentioned previously, in a chimp colony, there are four kinds of chimps driver, chaser, attacker, and barrier, so that they are in charge of attracting the other chimps towards the prey (optimal solution). Consequently, with a regular equilibrium between exploration and exploitation of a search space, the best optimization problem solution will be achieved. In standard ChOA, only the first four solutions of ChOA (i.e., driver, chaser, attacker, and barrier) are utilized to update the positions of other chimps. In other words, the other chimps are attracted to these four best solutions (driver, chaser, attacker, and barrier).

Although attackers have a natural ability to forecast the prey’s progression route, there is no main reason that the solution of attackers is always the best because chimps sometimes leave their tasks during the process of hunting or keep their same duty during the entire process [23]. As a result, if the position of the other chimps is updated based on attackers, they may become trapped in local optima and cannot explore new areas in search space because their solution space significantly concentrates around the attacker’s solutions. Also, there are such reasons for the other best solutions (driver, chaser, and barrier). To tackle this issue, our proposed WChOA offers a position-weighted relationship based on the proportional weights.

Eq.s (1) to (3) are utilized to update the position of other chimps. What it boils down to is that the other chimps are forced to update their position based on the positions of driver, chaser, attacker, and barrier. Therefore, if the mentioned reasons in previous paragraphs are noticed, it opens the door to new approaches to update the position of other chimps. The corresponding weighting method is proposed based on the Euclidean distance of step size as follows:

\[
D_A = |\bar{X}_1 - M_1|, \quad D_B = |\bar{X}_2 - M_2|, \quad D_C = |\bar{X}_3 - M_3|, \quad D_D = |\bar{X}_4 - M_4|.
\]

\[
x_{i+1} = \begin{cases} x_i & \text{if} \quad x_i \leq 0.7 \\ \frac{1}{10} (1 - x_i) & \text{if} \quad 0.7 < x_i \leq 0.9 \\ 0.7 & \text{if} \quad x_i > 0.9 \end{cases}
\]

where \(w_1, w_2, w_3\) and \(w_4\) are called the learning rates of other chimps from the attacker, barrier, chaser, and driver, respectively. Also, \(|x|\) indicates the Euclidean distance. Nonetheless, the position-weighted relationship is as follows:

\[
X_{(t+1)} = \frac{1}{w_1 \bar{X}_1 + w_2 \bar{X}_2 + w_3 \bar{X}_3 + w_4 \bar{X}_4}
\]

In WChOA, the position-weighted relationship Eq. (14) can be utilized instead of Eq. (3) in the standard ChOA. As is obvious, the main difference between Eq. (14) and traditional position-weighted relationship Eq. (3) is to apply the corresponding learning rate. As mentioned previously, since there is a possibility that some chimps do not have any sexual motivation in the process of hunting, a probability of 50% can be considered to choose whether the position-weighted strategy of chimps will be normal (Eq. (14)) or the best solutions (driver, chaser, attacker, and barrier). This approach dramatically increases the chance of finding the optimal solution.
(14)) or not (chaotic model). Thus, the following relationship is applied:

\[
X_{\text{chimp}}(t + 1) = \begin{cases} 
\text{Eq.(14)} & \text{if } \mu < 0.5 \\
\text{Chaotic-Value} & \text{if } \mu \geq 0.5 
\end{cases}
\]  

(15)

Figure 3 shows the process of updating the position of other chimps by the first four best solutions (attacker, barrier, chaser, and driver). In other words, the final position of other chimps will randomly be a circle in the vicinity of the prey that is determined by attacker, barrier, chaser, and driver.

It is noteworthy that the learning rates in the position-weighted relationship change dynamically. It means that these parameters are not constant during every iteration of WChOA. It enhances the speed of convergence and avoidance of local optima where attackers, barriers, chasers, and drivers are less likely to be knowledgeable about the position of the prey. For more explaining, Figure 4 depicts the pseudo-code of WChOA. Experimental results (Section IV) also verify that the position-weighted relationship can balance the global search and convergence speed of WChOA.

### A. SENSITIVITY ANALYSIS OF WEIGHTED CHIMP OPTIMIZATION ALGORITHM

The sensitivity analysis of three control parameters of WChOA is examined in this subsection. The first parameter, \( \bar{\alpha} \), controls exploration and exploitation strategies, while the second parameter, \( m \), controls the type of chaotic maps, whether Gauss/mouse, Sine, Bernoulli, or Tent. The third parameter, \( \mu \), determines whether the normal position is updated or the chaos map method is used. The fourth parameter is the learning factor, which accelerates the convergence curves. The investigation reveals the parameters that are immune to small variations in input levels and which ones are susceptible. Also, it offers the ideal combination of control parameters. Tests were carried out by defining four levels for parameters, as shown in Table 4. The following table displays an orthogonal array to characterize distinct experiments with different parameter combinations and their derived MSEs. Figure 5 presents trends for the parameters, according to Table 5.
From the data, the optimal performance of the WChOA appears to be learning factor = 2.5, m = Gauss/mouse, $\bar{A} = 0.5$, and $\mu = 0.5$. According to the data, the initial Gauss/mouse map had a higher amplitude, and WChOA was therefore more prone to the exploration phase. But, as the iterations increased, the amplitude and oscillations of the Gauss/mouse map reduced, and so on. The chance of shifting away from promising areas is reduced with less oscillation as the algorithm is passed to the exploitation phase. Choosing a value of 0.5 for both the $\bar{A}$ and $\mu$ parameters ensure the best transfer between the two phases of exploitation and exploration.

IV. SIMULATION RESULTS AND DISCUSSION

In this section, the performance of the proposed WChOA algorithm is evaluated and compared with state-of-the-art methods in the literature. For this purpose, four sets of benchmark functions and problems that are utilized in various literature are applied to probe the pros and cons of characteristics of WChOA. These benchmark functions are as follows:

- Classical benchmark functions (Tables 6-8) [25].
- IEEE Congress of Evolutionary Computation Benchmark Test Functions (CECC06, 2019 Competition) (Table 9) [26].
- High-dimensional Classical benchmark functions [27].
• Real-world problems (IEEE CEC2020) (Table 10) [28].

More explanation about every aforementioned benchmark function will be given in the next sections.

### TABLE VI

**UNIMODAL BENCHMARK FUNCTION.**

| Function | Dim | Range         | \( f_{\text{min}} \) |
|----------|-----|---------------|----------------|
| \( f_1(x) = \sum_{i=1}^{n} x_i^2 \) | 30, 100 | \([-100,100]\) | 0 |
| \( f_2(x) = \sum_{i=1}^{n} |x_i| + \prod_{i=1}^{n} x_i \) | 30, 100 | \([-10,10]\) | 0 |
| \( f_3(x) = \sum_{i=1}^{n} (\sum_{j=1}^{i} x_j)^2 \) | 30, 100 | \([-100,100]\) | 0 |
| \( f_4(x) = \max_i \left| x_i \right| \cdot \left| 1 \leq i \leq n \right| \) | 30, 100 | \([-100,100]\) | 0 |
| \( f_5(x) = \sum_{i=1}^{n} \left( 100(x_i + 1 - x_i)^2 \right) \) | 30, 100 | \([-30,30]\) | 0 |
| \( f_6(x) = \sum_{i=1}^{n} (|x_i + 0.5|) \) | 30, 100 | \([-100,100]\) | 0 |
| \( f_7(x) = \sum_{i=1}^{n} i x_i^4 + \text{random} \{0,1\} \) | 30, 100 | \([-1.28,1.28]\) | 0 |

### TABLE VII

**MULTIMODAL BENCHMARK FUNCTION.**

| Function | Range | Dim | \( f_{\text{min}} \) |
|----------|-------|-----|----------------|
| \( f_8(x) = \sum_{i=1}^{n} -x_i \cdot \sin(\sqrt{x_i}) \) | 500,500 | 30, 100 | -418.9829 |
| \( f_9(x) = \sum_{i=1}^{n} (x_i^2 - 10\cos(2\pi x_i) + 10) \) | 30, 100 | 0 |
| \( f_{10}(x) = -20 \exp \left( -\frac{1}{4} \sum_{i=1}^{n} x_i^2 \right) - \exp \left( -\frac{1}{4} \sum_{i=1}^{n} \cos(2\pi x_i) \right) + 20 + e \) | 30, 100 | 0 |
| \( f_{11}(x) = \frac{1}{400} \sum_{i=1}^{n} x_i^4 - \left( \prod_{i=1}^{n} \cos \left( \frac{x_i}{\sqrt{n}} \right) \right) + 1 \) | 30, 100 | 0 |
| \( f_{12}(x) = \pi \sum_{i=1}^{n} x_i^2 \left[ \sum_{i=1}^{n} (\sin(n \pi y_i) + \cos(n \pi y_i)) \right] \) | 30, 100 | 0 |
| \( f_{13}(x) = 0.1 \sum_{i=1}^{n} \sin^2 \left( 3\pi x_i \right) + \sum_{i=1}^{n} \left( x_i - 1 \right)^2 \left[ 1 + \sin^2 \left( 3\pi x_i + 1 \right) \right] \) | 30, 100 | 0 |
| \( f_{14}(x) = 0.1 \sum_{i=1}^{n} \sin^2 \left( 3\pi x_i \right) + \sum_{i=1}^{n} \left( x_i - 1 \right)^2 \left[ 1 + \sin^2 \left( 3\pi x_i + 1 \right) \right] \) | 30, 100 | 0 |

### TABLE VIII

**FIXED-DIMENSION MULTIMODAL BENCHMARK FUNCTION.**

| Function | Range | Dimension | \( f_{\text{min}} \) |
|----------|-------|-----------|----------------|
| \( f_{14}(x) = \left( \frac{1}{500} + \sum_{j=1}^{25} \frac{1}{j + \sum_{i=1}^{2} (x_i - a_{ij})^6} \right)^{-1} \) | \([-65.65]\) | 2 | 1 |
| \( f_{15}(x) = \sum_{i=1}^{11} a_i - x_i (b_i^2 + b_i x_2) \) | \([-5.5]\) | 4 | 0.00030 |
| \( f_{16}(x) = 4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1x_2 - 4x_2^2 + 4x_2^4 \) | \([-5.5]\) | 2 | -1.0316 |
| \( f_{17}(x) = x_2 \cdot \frac{5.1}{4\pi} \cdot 2 \cdot \frac{2}{\pi} + \frac{5}{\pi} x_1 - 6 \) \( + 10(1 - \frac{1}{8\pi}) \cos x_1 + 10 \) | \([-5.5]\) | 2 | 0.398 |
| \( f_{18}(x) = \left[ 1 + (x_1 + x_2 + 1)^2 (19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1x_2 + 3x_2^2) \right] \) \( \times [30 + (2x_1 - 3x_2)^2 + (18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1x_2 + 27x_2^2)] \) | \([-2.2]\) | 2 | 3 |
| \( f_{19}(x) = -\sum_{i=1}^{4} c_i \exp (-\sum_{j=1}^{3} a_{ij} (x_j - p_{ij})^2) \) | \([1.3]\) | 3 | -3.86 |

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\[
F_{20}(x) = -\sum_{i=1}^{6} c_i \exp\left(-\sum_{j=1}^{6} a_{ij} (x_j - p_j)^2\right) \quad [0,1] 
F_{21}(x) = -\sum_{i=1}^{3} [(X - a_{i1})(X - a_{i2}) + c_i]^{-1} \quad [0,10] 
F_{22}(x) = -\sum_{i=1}^{3} [(X - a_{i1})(X - a_{i2}) + c_i]^{-1} \quad [0,10] 
F_{23}(x) = -\sum_{i=1}^{10} [(X - a_{i1})(X - a_{i2}) + c_i]^{-1} \quad [0,10] 
\]

**TABLE IX**

CEC-C06 2019 BENCHMARKS.

| No. | Functions                                      | Dimension | Range         | \( f_{\text{min}} \) |
|-----|-----------------------------------------------|-----------|---------------|---------------------|
| 1   | STORN'S CHEBYSHEV POLYNOMIAL FITTING PROBLEM | 9         | [-8192, 8192] | 1                   |
| 2   | INVERSE HIHBERT MATRIX PROBLEM                | 16        | [-16384, 16384] | 1                   |
| 3   | LENNARD-JONES MINIMUM ENERGY CLUSTER          | 18        | [-4, 4]       | 1                   |
| 4   | RAISTRIGIN’S FUNCTION                         | 10        | [-100, 100]   | 1                   |
| 5   | GRIEWANGK’S FUNCTION                          | 10        | [-100, 100]   | 1                   |
| 6   | WEIERSTRASS FUNCTION                          | 10        | [-100, 100]   | 1                   |
| 7   | MODIFIED SCHWEFEL’S FUNCTION                  | 10        | [-100, 100]   | 1                   |
| 8   | EXPANDED SCHAFFER’S F6 FUNCTION               | 10        | [-100, 100]   | 1                   |
| 9   | HAPPY CAT FUNCTION                            | 10        | [-100, 100]   | 1                   |
| 10  | ACKLEY FUNCTION                               | 10        | [-100, 100]   | 1                   |

**TABLE X**

THE GENERAL DESCRIPTION OF REAL-WORLD CONSTRAINED OPTIMIZATION. D IS THE TOTAL NUMBER OF DECISION VARIABLES OF THE PROBLEM. G IS THE NUMBER OF INEQUALITY CONSTRAINTS AND H IS THE NUMBER OF EQUALITY CONSTRAINTS.

| No. | ID   | Problems                                              | D  | g  | h  |
|-----|------|-------------------------------------------------------|----|----|----|
| 1   | RC01 | Heat Exchanger Network Design (case 1)                | 9  | 0  | 8  |
| 2   | RC04 | Reactor Network Design (RND)                          | 6  | 1  | 4  |
| 3   | RC11 | Two-reactor Problem                                   | 7  | 4  | 4  |
| 4   | RC14 | Multi-product Batch Plant                             | 10 | 10 | 0  |
| 5   | RC16 | Optimal Design of Industrial Refrigeration System     | 14 | 15 | 0  |
| 6   | RC23 | Optimal Design of Industrial Refrigeration System     | 5  | 8  | 3  |
| 7   | RC35 | Optimal Sizing of Distributed Generation for Active Power Loss Minimization | 153 | 0  | 148 |
| 8   | RC37 | Optimal Power flow (Minimization of Active Power Loss) | 126 | 0  | 116 |
As mentioned previously, there are many strategies to update the \( f \) vector in Eq. (4) (Table 2) and numerous chaotic maps to model the chaotic behavior of chimps (Table 3). Consequently, the different versions of ChOA can be divided into two groups. Since all versions of these two groups for the standard ChOA have been investigated [15], this paper utilizes the best version of two groups for ChOA and WChOA. As Tables 11 and 12 show, the greatest versions of Types 1 and 2 for ChOA and WChOA are called chimp1, chimp2, weighted chimp1, and weighted chimp2, respectively. Therefore, in continuing the versions of chimp1, chimp2, weighted chimp1, and weighted chimp2 take the place of other kinds of the standard ChOA and WChOA. In order to continue, the presented framework of WChOA is compared with the conventional algorithms such as (Table 13):

- ChOA [15]
- ALO [1]
- BBO [6]
- BH [29]
- GWO [13]
- GA [4]
- PSO [10]
- SCA [30]

Each test in this paper is accomplished by a windows 10 system using Intel Core i7, 3.8 GHz, 16G RAM and, Matlab R2016a so that WChOA algorithms were run 30 times on every benchmark function.

In order to compare the different NIA algorithms with each other, the results of the Average (Ave) and Standard Deviation (Std) of algorithms are utilized.

Although the pros and cons of NIA algorithms are compared based on their Ave and Std, according to [32] it is not enough to evaluate a new NIA with the others. In other words, to understand what optimization algorithm can solve a specific optimization problem, it is needed to examine the statistical tests on them. As a result, this paper has utilized the ranking method [33] to carry out the statistical tests. Nonetheless, the calculated p-values of the rank-sum test will be given in the results. It is worthwhile to note that the N/A in the tables of results will be the “abbreviation of “Not Applicable” which means that the corresponding NIA cannot be compared with itself in the rank-sum test” [15].
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| Algorithm | $a_0$ | $\beta$ | $p$ | $w$ | SCA | $r_1$ | $r_2$ | $\alpha - \frac{\alpha}{T}$ | Population size | Maximum number of generations |
|-----------|-------|---------|-----|-----|-----|-------|-----|--------------------------|----------------|-----------------------------|
| LGWO      | 2     | $\sim U(0,2)$ | $\sim U(0,1)$ | $[2,6]$ |      |       |     |                          |                 | 50                          |
| ALO       |       |         |     |     |      |       |     |                          |                 | 250                         |
| BH        |       |         |     |     |      |       |     |                          |                 | 250                         |
| PSO       |       |         |     |     |      |       |     |                          |                 | 250                         |
| GA        |       |         |     |     |      |       |     |                          |                 | 250                         |
| GA        |       |         |     |     |      |       |     |                          |                 | 50                          |
| GSA       |       |         |     |     |      |       |     |                          |                 | 250                         |
| CS        |       |         |     |     |      |       |     |                          |                 | 250                         |

A. CLASSICAL BENCHMARK TEST FUNCTIONS

The classical test functions are divided into three sets called unimodal, multimodal, and fixed-dimension multimodal. Each set of these test functions is utilized to benchmark certain perspectives of the algorithm. Unimodal benchmark functions, for instance, are applied for examining exploitation level and convergence of the algorithm, as their name might imply that they have a single optimum. However, there are multi-optimal solutions for multimodal benchmark functions, which is why they are utilized to test the local optima avoidance and exploration levels. Even though the fixed-dimension multimodal functions have multi-optimal solutions the same as multimodal functions, the main reason for utilizing them in this paper is that the fixed-dimension multimodal functions can provide various search space than the other classical benchmark functions. It is noteworthy that Range, dim and $f_{\text{min}}$ in Tables 6-8 indicate space search, the number of problem variables, and optimal solution, respectively.

| Algorithm | $F_1$ | $F_2$ | $F_3$ | $F_4$ | $F_5$ | $F_6$ | $F_7$ |
|-----------|-------|-------|-------|-------|-------|-------|-------|
| WOA       | Ave   | 4.9216e-13 | 1.0792e-19 | 2.9616e-07 | 13.7621 | 1.1792e-12 | 0.78715 |
|           | Std   | 0.000151 | 0.00017244 | 0.0015376 | 0.0011727 | 0.00017244 | 0.00066241 |
|           | p-value | 0.0001 | 0.0001 | 6.39e-05 | 0.0001 | 0.0001 | 0.0001 |
| GA        | Ave   | 1.8573e-04 | 2.1821e-02 | 2.3912e-03 | 1.4402 | 0.0150535 | 1.2159 |
|           | Std   | 0.00000012 | 0.00014535 | 0.0042141 | 0.00751211 | 0.0009381 | 0.00091769 |
|           | p-value | 0.0001 | 0.0001 | 0.0047 | 0.0001 | 0.0001 | 0.0001 |
| PSO       | Ave   | 2.793e-05 | 1.6344e-10 | 0.0016344 | 1.0177 | 1.4712e-03 | 0.99441 |
|           | Std   | 0.00044803 | 0.0025339 | 0.0008674 | 0.0003684 | 0.0024141 | 0.00022243 |
|           | p-value | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 |
| SCA       | Ave   | 1.2761e-07 | 1.337e-06 | 2.3752e-04 | 0.029591 | 1.000e-07 | 1.12924 |
|           | Std   | 0.00068042 | 0.00028847 | 0.00061586 | 9.2999e-05 | 0.0010141 | 0.00028788 |
|           | p-value | 0.0047 | 0.0047 | 0.0047 | 0.0001 | 0.0001 | 0.0001 |
| Chimp2    | Ave   | 1.7851e-19 | 1.0453e-17 | 1.0076e-08 | 0.026848 | 1.8232e-15 | 1.2473 |
|           | Std   | 0.00000001 | 0.00000069 | 0.0009689 | 0.00034511 | 0.00000824 | 0.0021464 |
|           | p-value | 0.00797 | 0.01797 | 0.09797 | 0.00797 | 0.0147 | 0.00797 |
| Chimp1    | Ave   | 1.0825e-15 | 1.8232e-15 | 1.00021e-09 | 0.008232 | 1.0003e-15 | 0.1568 |
|           | Std   | 0.00000044 | 0.000000824 | 0.00000824 | 0.00000124 | 0.00000887 | 0.0009381 |
|           | p-value | 0.00797 | N/A | N/A | 0.0147 | 0.00797 | 0.0001 |
| BBO       | Ave   | 0.013011 | 0.2334 | 3.9745 | 10.7185 | 1.1132e-10 | 1.39002 |
|           | Std   | 0.00028037 | 0.0013183 | 0.00057292 | 0.00036264 | 0.000324 | 0.0007505 |

TABLE XIV

THE RESULTS OF UNIMODAL BENCHMARK FUNCTIONS.
As explained previously, due to having one optimum, the unimodal benchmarks are vital for evaluating NIA algorithms in terms of exploitation and convergence speed. The results of the unimodal benchmarks (F1, F2, ..., F7) on the proposed methods and the other traditional algorithms have been given in Table 14 and Figure 6. As Table 14 shows, for most of the unimodal functions, the versions of the presented algorithms of weighted chimp1 and weighted chimp2 have excellent results compared to the standard ChOA and the other conventional algorithms. Also, according to Figure 6, the best convergence rates in most of the benchmark functions belong to weighted chimp1 and weighted chimp2. Compared to the others, this superiority for the weighted chimp1 and weighted chimp2, except the standard ChOA, can be investigated from two standpoints. The first standpoint is related to the diversity in their fission-fusion societies, and another perspective is the capabilities of chimps in exploiting the position of the prey (optimal solution) compared with the other algorithms inspired by nature. In other words, the motivation of sex and grooming which are modeled by chaotic maps in the WChOA algorithm causes that the chimps not only exploit the prey but also achieve the optimal solution in the shortest time.
FIGURE 6. Convergence curve of algorithms on the unimodal test functions.
The high performance of the weighted chimp1 and weighted chimp2 compared to the chimp1 and chimp2 is due to updating the positions of other chimps. In other words, in chimp1 and chimp2, individuals focus their position around the attacker, so if the attacker goes away from the optimal solution, the other chimps cannot get the prey and kill the time to achieve it. The difference between the results of the weighted chimp1 and weighted chimp2 can be explained from two aspects. Firstly, the strategies that are utilized to update the $f$ coefficients in both methods are different. Figure 7, which is related to Table 2, shows the rate of $f$ coefficients of the weighted chimp1 reduce more than the weighted chimp2. Consequently, it allows the weighted chimp1 to discover more locally than globally compared to the weighted chimp2. Secondly, the kind of chaotic map that has been applied in the weighted chimp1 gives rise to enhancing local-search compared to the weighted chimp2. In other words, the chaotic map has large and tremendously variable amplitude in the early steps, whereas its amplitude and variableness diminishes severely in the final stages. Thus, the chaotic maps provide the soft transition between global and local search capability.

On the contrary of unimodal benchmark functions, the multimodal functions ((F8, F9, ..., F13) have more local minima whose number can increase significantly with the number of the problem size. So, these functions can be a suitable choice to evaluate the proposed algorithms in terms of the exploration ability and avoiding local minima compared to the other NIA algorithms. The results of the multimodal functions’ Ave, Std, p-value, and convergence speeds have been provided in Table 15 and Figure 8, respectively. As Table 15 and Figure 8 have been shown, in most of the aforementioned functions the weighted chimp1 and weighted chimp2 not only have excellent credential skills not to trap in local minima but also can achieve the best solution quickly compared to the others. As can be seen in Table 15 and Figure 8, the weighted chimp1 and weighted chimp2 greatly outperformed classical ChOA in terms of the exploration ability and avoiding local minima for all of the benchmark test functions. These results demonstrate that the position-weighted equation makes searching faster and better. Finally, the advantages in search efficiency and capability of the weighted chimp1 and weighted chimp2 can be ascribed to a proper balance between exploration and convergence speed.

### TABLE XV
THE RESULTS OF MULTIMODAL BENCHMARK FUNCTION.

| Algorithm | $F_8$  | $F_9$     | $F_{10}$    | $F_{11}$ | $F_{12}$  | $F_{13}$  |
|-----------|--------|-----------|-------------|----------|-----------|-----------|
| WOA Ave   | -8432.073 | 5.6843e-14 | 3.9968e-14 | 0        | 0.03789   | 0.59045   |
| WOA Std   | 3.2605  | 0.0007579 | 0.014542    | 0        | 0.00062651| 0.018694  |
| WOA p-value| 0.0001 | N/A       | 0.0057      | 0.0057   | 0.0049    | 0.0049    |
| GA Ave    | -3150.5985 | 2.738    | 7.9936e-15 | 0        | 0.29035   | 1.7768    |
| GA Std    | 0.0001  | 0.00005   | 0.00005     | 0.00005  | 0.00005   | 0.00005   |
(d) F11

(e) F12
The fixed-dimension benchmark functions have also been utilized to verify the exploration capabilities and avoid local optima of the weighted chimp1 and weighted chimp2 compared to the other NIA algorithms. The results of this comparison have been provided in Tables 16 and 17. Although the results are the same in some functions, the weighted chimp1 and weighted chimp2 have more improvement than the others. According to Figure 9 that depicts the convergence speeds, this superiority is also seen in some fixed-dimension benchmark functions. As explained previously, this significant performance of the weighted chimp1 and weighted chimp2 can be discovered by utilizing the position-weighted equation and the social behaviour of the whole society.

**TABLE XVI**

| Algorithm | $F_{14}$ | $F_{15}$ | $F_{16}$ | $F_{17}$ | $F_{18}$ |
|-----------|----------|----------|----------|----------|----------|
| WOA Ave   | 0.998    | 0.020364 | -1.0316  | 0.39792  | 3        |
| Std       | 0.00059718 | 0.010885 | 0.0095395 | 0.0047829 | 0.010803 |
| p-value   | 0.00747  | 0.0057   | 0.0057   | 0.0049   | 0.0049   |
| GA Ave    | 0.998    | 0.00534398 | -1.0316  | 0.39792  | 3        |
| Std       | 0.0057686 | 0.0000874 | 0.021147 | 0.00026104 | 0.009066 |
| p-value   | 0.00747  | 0.0047   | 0.0057   | 0.0049   | 0.0049   |
| PSO Ave   | 0.99801  | 0.00067708 | -1.0316  | 0.39865  | 3.0001   |
| Std       | 0.0047493 | 0.0068029 | 0.0096524 | 0.015434 | 0.03319  |
| p-value   | 0.0001   | 0.0001   | 0.00747  | 0.0057   | 0.0057   |
| SCA Ave   | 0.998    | 0.0012896 | -1.0316  | 0.39833  | 3.0002   |
| Std       | 0.00037144 | 0.011627 | 0.0052976 | 0.0020581 | 0.0067462 |
| p-value   | 0.00747  | 0.0057   | 0.0057   | 0.0049   | 0.0049   |
| Chimp2 Ave | 0.99802 | 0.00125 | -1.0316  | 0.39796  | 3.0001   |
| Std       | 0.014758 | 0.0077204 | 0.016366 | 0.0023049 | 0.00043324 |
| p-value   | 0.00747  | 0.0057   | 0.0057   | 0.0049   | 0.0049   |
| Chimp1 Ave | 0.99809 | 0.0013562 | -1.0316  | 0.39805  | 3.0001   |
### TABLE XVII

| Algorithm | $F_{19}$   | $F_{20}$   | $F_{21}$   | $F_{22}$   | $F_{23}$   |
|-----------|------------|------------|------------|------------|------------|
| WOA       | Ave        | -3.8622    | -3.1969    | -2.593     | **-10.2537** | -9.3837    |
|           | Std        | 0.019162   | 0.018342   | 0.022841   | 0.014715   | **0.0066907** |
|           | p-value    | 0.00747    | 0.0057     | 0.0057     | 0.0049     | **0.0049**  |
| GA        | Ave        | -3.8619    | -3.1825    | -6.7593    | -9.2651    | -7.9056    |
|           | Std        | 0.0071951  | 0.00030283 | 0.0070818  | 0.0043589  | **0.0081338** |
|           | p-value    | 0.001      | 0.00747    | 0.0057     | 0.0057     | **0.0001**  |
| PSO       | Ave        | -3.8614    | -3.3106    | -7.9664    | -8.6936    | **-10.206** |
|           | Std        | 0.012393   | 0.0093514  | 0.016142   | 0.0085863  | **0.0021619** |
|           | p-value    | 0.00452    | 0.00747    | 0.0057     | 0.0057     | **0.0049**  |
| SCA       | Ave        | -3.8547    | -2.0591    | -4.8606    | -5.0383    | -5.0358    |
|           | Std        | 0.006271   | 0.0001319  | 0.01722    | 0.0076048  | **0.013176** |
|           | p-value    | 0.0045     | 0.0045     | 0.00747    | 0.0057     | **0.0057**  |
| Chimp2    | Ave        | -3.8548    | -4.2329    | -5.0189    | -9.1158    | -5.1029    |
|           | Std        | 0.021395   | 0.014033   | 0.013209   | 0.0041865  | **0.0017119** |
|           | p-value    | 0.0001     | 0.00747    | 0.0057     | 0.0057     | **0.0049**  |
| Chimp1    | Ave        | -3.8624    | -4.1492    | -4.8537    | -4.8401    | -4.8898    |
|           | Std        | 0.00026981 | 0.0075036  | 0.0003483  | 0.008309   | **0.007659** |
|           | p-value    | 0.00747    | 0.0057     | 0.0057     | 0.0049     | **0.0049**  |
| BBO       | Ave        | -3.8628    | -3.322     | -5.1008    | -2.7519    | -10.5364   |
|           | Std        | 0.0051     | 0.0044809  | 0.010935   | 0.014868   | **0.014644** |
|           | p-value    | 6.38e-05   | 6.39e-05   | 6.38e-05   | 6.39e-05   | **6.39e-05** |
| BH        | Ave        | -3.8628    | -3.2031    | -2.6829    | -10.4029   | -10.5364   |
|           | Std        | 0.0034586  | 0.0007352  | 0.0091199  | 0.0021605  | **0.022491** |

**THE RESULTS OF FIXED-DIMENSION MULTIMODAL BENCHMARK FUNCTION (CONTINUED).**
|                  | Ave         | Std          | Ave         | Std          | Ave         | Std          |
|------------------|-------------|--------------|-------------|--------------|-------------|--------------|
| p-value          | 6.38e-05    | 6.39e-05     | 6.38e-05    | 6.39e-05     | 6.38e-05    | 6.39e-05     |
| ALO              | -3.8628     | -3.1974      | -10.1532    | -10.4029     | -10.5364    |              |
| p-value          | 6.38e-05    | 6.39e-05     | 6.38e-05    | 6.39e-05     | 6.38e-05    | 6.39e-05     |
| GWO              | -3.8541     | -3.0731      | -0.88288    | -5.0532      | -5.0601     |              |
| p-value          | 6.38e-05    | 6.39e-05     | 6.38e-05    | 6.39e-05     | 6.38e-05    | 6.39e-05     |
| Weighted Chimp1  | -3.8629     | -4.322       | -10.1505    | -10.4028     | -11.5336    |              |
| p-value          | N/A         | N/A          | N/A         | N/A          | N/A         | N/A          |
| Weighted Chimp2  | -3.8628     | -2.322       | -9.6829     | -9.4029      | -10.5364    |              |
| p-value          | 0.0045      | 0.0057       | 0.0057      | N/A          | 0.0001      |              |

(a) F14
Figure 2: (b) F15 and (c) F16 performance analysis.
(d) F17

(e) F18
B. IEEE CONGRESS OF EVOLUTIONARY COMPUTATION BENCHMARK TEST FUNCTIONS

In this Section, ten modern Evolutionary Computation benchmark test functions of IEEE Congress (CEC-C06, 2019 Competition) are utilized to assess the weighted chimp1 and weighted chimp2. These test functions were improved for a single objective optimization problem [34]; the CEC-C06 2019 test functions are known as “The 100-Digit Challenge”, which are considered to be used in annual optimization competition. See Table 9.

Functions CEC04 to CEC10 are shifted and rotated, whereas functions CEC01 to CEC03 are not. Nonetheless, all test functions are scalable. Also, all CEC global optimums converge to point 1 for more convenience of the comparison.

The results of the weighted chimp1, weighted chimp2, and the other algorithms have been shown in Tables 18 and 19. As shown, in most of the benchmark functions (CEC01 to CEC07), the proposed algorithms outperform the traditional NIA algorithms. It is noteworthy that in the other benchmark functions (CEC08 to CEC10), the weighted chimp1 and weighted chimp2 have the performance close to the best solutions. Besides, this superiority can also be seen in Figure 10, which shows the convergence speed of relevant algorithms. In order to cut a long story short, these results appear the powerful performance of the proposed meta-heuristic algorithms so that there are two main reasons which can be taken into considerations for this superiority. First, the sexual motivation and intelligence of the chimps especially in the groups of the driver, barrier, chaser, and attacker bring about promoting the important phase of the exploration in the space search. Also, they can enhance the skills of the weighted chimp1 and weighted chimp2 to avoid local optima. Secondly, in addition to the chaotic maps that improve the exploration, other parameters can be useful in the exploitation phase. In other words, the improvement of the proposed algorithms in terms of the global-optimum estimation and the rate of the convergence compared to the traditional methods can be chiefly found in reducing $f$ coefficient so that it leads to improving the exploitation process and searching globally.

| Algorithm | CEC01    | CEC02 | CEC03 | CEC04 | CEC05 |
|-----------|----------|-------|-------|-------|-------|
| WOA Ave   | 6.7678E+04 | 1.8336 | 12.0082 | 44.0292 | 6.3911 |

FIGURE 9. Convergence curve of algorithms on the fixed-dimension multimodal test functions.
| Algorithm | CEC06 | CEC07 | CEC08 | CEC09 | CEC10 |
|-----------|-------|-------|-------|-------|-------|
| **WOA**   | Ave   | 6.7678E+04 | 1.0005E+03 | 2.8334 | 1.4547E+03 | 17.7223 |
|           | Std   | 6.119162  | 11.018342 | 0.022841 | 0.014715 | 0.66907 |
|           | p-value | 0.00747 | 0.0057 | 0.0057 | 0.0149 | 0.0049 |
| **GA**    | Ave   | 6.7678E+04 | 1.0005E+03 | 1.8334 | 1.4547E+03 | 17.9223 |
|           | Std   | 8.0071951 | 9.030283 | 0.0070818 | 1.1143589 | 0.81338 |
|           | p-value | 0.001 | 0.00747 | 0.0057 | 0.0057 | 0.0001 |
| **PSO**   | Ave   | 6.7678E+04 | 1.0005E+03 | 1.8334 | 1.4547E+03 | 17.9923 |
|           | Std   | 8.012393  | 8.093514 | 0.016142 | 1.1285863 | 0.21619 |
|           | p-value | 0.00452 | 0.00747 | 0.0157 | 0.1157 | 0.0049 |

**TABLE XIX**

THE RESULTS OF IEEE CEC-C06 2019 SINGLE OBJECTIVE BENCHMARK FUNCTIONS (CONTINUED).
|       | Ave     | Std     | p-value | Ave     | Std     | p-value | Ave     | Std     | p-value | Ave     | Std     | p-value | Ave     | Std     | p-value |
|-------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| SCA   | 6.7678E+04 | 1.0005E+03 | 0.0045  | 1.8334  | 0.00747 | 0.0057  | 1.4547E+03 | 0.0057 | 0.0057  | 18.1223 |
| Chimp2| 6.7678E+04 | 654.0124 | 0.00001 | 1.8334  | 0.0057  | 0.0057  | 1.4547E+03 | 0.0057 | 0.0057  | 17.0223 |
| Chimp1| 6.7678E+04 | 700.586  | 0.00747 | 1.8334  | 0.0057  | 0.0057  | 1.4047E+03 | N/A    | 0.0049  | 16.7223 |
| BBO   | 6.7678E+04 | 120.0455 | 6.38e-05 | 2.0334  | 6.38e-05 | 6.38e-05 | 1.4547E+03 | 0.0005 | 0.13176 | 16.2233 |
| BH    | 6.7678E+04 | 214.1298 | 6.38e-05 | 1.8334  | N/A     | 0.00005 | 1.6547E+03 | 0.0005 | 0.0049  | 16.0223 |
| ALO   | 6.7678E+04 | 500.214  | 6.38e-05 | 1.8334  | 6.38e-05 | 6.38e-05 | 1.4547E+03 | 0.0005 | N/A     | 15.1223 |
| GWO   | 6.7678E+04 | 300.745  | 6.38e-05 | 2.8334  | 6.38e-05 | 6.38e-05 | 1.4547E+03 | 0.0005 | 0.1117  | 17.7223 |
| Weighted Chimp1 | 6.7678E+04 | 1.0005E-03 | 0.0057  | 2.811   | N/A     | 0.0005  | 1.4547E+03 | 0.0005 | 0.0047  | 17.9923 |
| Weighted Chimp2 | 6.1678E+04 | 500.7845 | 10.84038 | 1.812   | N/A     | 0.0057  | 1.4547E+03 | 1.0002916 | 0.0047  | 15.7223 |

(a) CEC01
(b) CEC02

(c) CEC03
(d) CEC04

(e) CEC05
(f) CEC06

(g) CEC07
C. HIGH-DIMENSIONAL CLASSICAL BENCHMARK FUNCTIONS

In this section, for more detailed analyses and in-depth observation of the excellent performance of the suggested algorithms, the unimodal and multimodal benchmark functions with high-dimensional problems are applied. For this purpose, the dimensions, population size, and the number of iterations to optimize the unimodal and multimodal benchmark functions are considered 100, 50, and 2000, respectively.

The results of this evaluation have been given in Tables 20 and 21 for the unimodal and multimodal benchmark functions, respectively. As Tables 20 and 21 show, the weighted chimp1 and weighted chimp2 have better performance than the conventional NIA algorithms in most benchmark functions. The main reason for this superior performance especially compared to the standard ChOA, is to utilize the weighting method of the positions of chimps based on the Euclidean distance. In other words, using the position-weighted method instead of the traditional one causes that exploitation and exploration tasks to be carried out properly by the chimps in high-dimensional problems. It is important to note that these results have been performed using the same parameter settings as the above experiments, and that is why they have not required any increase in population size or the number of function evaluations.

By comparing the weighted chimp1 and weighted chimp2 with other conventional structures for the mentioned high-dimensional test functions, it is clear that the proposed algorithms continuously follow the best result (global optimum) when the number of dimensions increases. Consequently, the weighted chimp1 and weighted chimp2 algorithms are insensitive to increasing dimensionality and have superior scalability. Also, the non-linear control parameter strategy and modified position-updating equation are beneficial to the performance of the ChOA. To sum up, the presented ideas achieve very competitive performance for large-scale optimization compared to the standard ChOA in terms of quality, efficiency, and robustness of searching.

TABLE XX
THE RESULTS OF UNIMODAL BENCHMARK FUNCTIONS (100-DIMENSIONAL).

| Fun | ChOA | PSO | GSA | BH | Weighted Chimp1 |
|-----|------|-----|-----|----|----------------|
|     | Ave  | Std | Ave | Std | Ave  | Std | Ave  | Std | Ave  | Std |
| F1  | 2.8e-09 | 1.1e-09 | 2.799 | 0.721 | 86.213 | 0.04243 | 9.34 | 2.0731 | 1.8e-09 | 1.1e-09 |
| F2  | 44.16 | 18.17 | 23.87 | 2.432 | 152.44 | 0.00122 | 320082 | 48.28 | 40.16 | 12.17 |
| F3  | 194.11 | 42.18 | 391.34 | 41.57 | 169.88 | 0.03780 | 900075 | 409.06 | 184.91 | 38.18 |
| F4  | 2.18 | 0.0846 | 3.131 | 0.0879 | 16.265 | 0.0015 | 5.6670 | 0.8293 | 2.11 | 0.0245 |
| F5  | 13.94 | 1.71 | 75.2342 | 5.245 | 321.14 | 0.05329 | 117.80 | 49.07 | 13.95 | 1.72 |
D. IEEE CONGRESS OF EVOLUTIONARY COMPUTATION REAL-WORLD PROBLEMS

Complex optimization problems originating from real-life applications are known as real-world problems. Real-world optimization problems have been comparatively difficult to solve because of the complex nature of the related functions with many parameters. The problems investigated in this section are related to ten real-world problems from IEEE CEC2020. For more explanation, RC01, and RC04 real-world problems, for instance, are known as industrial chemical processes. As a result of numerous non-linear inequality and equality constraints, a growing number of chemical process problems have been suggested, which are highly complex and non-linear. There is a full description form these real-world problems in CEC2020 [28].

The results of the weighted chimp1, weighted chimp2, and the other algorithms are presented in Table 22. As Table 22 shows, the weighted chimp1 and weighted chimp2 outperform the conventional ChOA and the other NIA algorithms. To elaborate the results, the RC16 has been considered as a real-world problem of the optimum design of an industrial refrigeration system with 14 design variables and 15 inequality design constraints. The complete mathematical formulation of this problem is presented by [35]. The best results of the proposed algorithms, such as the mean and standard deviation statistics, are presented in Table 22 alongside results from other optimization approaches. It is seen that the weighted chimp1 and weighted chimp2 algorithms can provide improved best and statistical results than the other metaheuristic approaches, which represents the capability of the algorithm in dealing with difficult optimization problems. This superiority of the suggested ideas compared with the others can be propped from two aspects. The first one is related to the diversity in their fission aspect, which represents the capability of the algorithm in dealing with difficult optimization problems. This superiority of the suggested ideas compared with the others can be propped from two aspects. The first one is related to the diversity in their fission aspect, which represents the capability of the algorithm in dealing with difficult optimization problems.

The other one is the capabilities of chimp in exploiting the position of the prey (optimal solution) compared with the other algorithms inspired by nature. It is also mentioned that although the proposed algorithms have just better performance in six aforementioned real-world problems, in the other real-world problems, the weighted chimp1 and weighted chimp2 have results close to the best solutions. Consequently, it means that the weighted chimp1 and weighted chimp2 have the utmost importance for real-world applications.

| Function | ChOA | PSO | GSA | BH | Weighted Chimp1 |
|----------|------|-----|-----|----|----------------|
| Ave      | Std  | Ave | Std | Ave | Ave            |
| F8       | -44.426 | 1.5 | -18.136 | 4962.4 | -35.969 | 1876 | -25.632 | 869.47 |
| F9       | 11.89 | 1.005 | 62.58 | 2.301 | 12.01 | 0.1236 | 60.38 | 7.96 |
| F10      | 0.3055 | 0.00542 | 1.183 | 0.07627 | 1.293 | 0.0974 | 1.59 | 0.0077 |
| F11      | 0.0014 | 0.00021 | 270.2 | 15.49 | 400.5 | 0.8532 | 411 | 22.42 |
| F12      | 0.3982 | 0.09591 | 2.07e+05 | 2.77e+05 | 1.00e+08 | 1.99e+05 | 1.09e+09 | 2.28e+08 |
| F13      | 0.13915 | 0.22199 | 1.24e+06 | 4.82e+05 | 1.00e+08 | 1.99e+05 | 1.25e+09 | 4.85e+08 |

The results of the weighted chimp1, weighted chimp2, and the other algorithms are presented in Table 22. As Table 22 shows, the weighted chimp1 and weighted chimp2 outperform the conventional ChOA and the other NIA algorithms. To elaborate the results, the RC16 has been considered as a real-world problem of the optimum design of an industrial refrigeration system with 14 design variables and 15 inequality design constraints. The complete mathematical formulation of this problem is presented by [35]. The best results of the proposed algorithms, such as the mean and standard deviation statistics, are presented in Table 22 alongside results from other optimization approaches. It is seen that the weighted chimp1 and weighted chimp2 algorithms can provide improved best and statistical results than the other metaheuristic approaches, which represents the capability of the algorithm in dealing with difficult optimization problems. This superiority of the suggested ideas compared with the others can be propped from two aspects. The first one is related to the diversity in their fission aspect, which represents the capability of the algorithm in dealing with difficult optimization problems.

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TABLE XXII
THE RESULTS OF WChOA IN COMPARISON WITH BENCHMARK ALGORITHMS FOR REAL-WORLD PROBLEMS.

| Problem ID | Problem Metric | Optimization Algorithms |
|------------|----------------|-------------------------|
|            | GA             | GSA                     | PSO | BH | CS | GWO | LGWO | ChOA | Weighted_Chip |
| RC01       | Ave            | 2.18E+02                | 3.12E+02 | 2.23E+02 | 3.36E+02 | 4.02E+02 | 2.12E+02 | 2.01E+02 | 1.92E+02 | 1.91E+02 |
|            | STD            | 5.34E-02                | 2.18E-02 | 2.81E-02 | 3.21E-02 | 3.18E-02 | 2.85E-02 | 1.67E-03 | 1.45E-03 | 1.04E-03 |
| RC04       | Ave            | -1.38E-01               | -3.86E-01 | -1.15E-01 | -3.60E-00 | -3.56E-00 | -3.52E-01 | -3.56E-01 | -3.87E-01 | -3.07E-01 |
|            | STD            | 7.98E-01                | 1.92E-01 | 2.84E-01 | 3.41E-01 | 3.80E-01 | 3.96E+00 | 2.57E+00 | 1.02E+01 | 1.01E+01 |
| RC11       | Ave            | 12.63E+01               | 11.93E+01 | 11.62E+01 | 10.56E+01 | 10.13E+01 | 10.17E+01 | 10.74E+01 | 9.99E+01 | 9.88E+01 |
|            | STD            | 2.76E+02                | 1.67E+01 | 2.21E+01 | 1.79E+01 | 1.97E+01 | 1.54E+01 | 2.34E+01 | 1.34E+01 | 1.02E+01 |
| RC14       | Ave            | 9.45E+04                | 7.24E+04 | 9.82E+04 | 9.24E+04 | 9.23E+04 | 6.12E+04 | 5.09E+04 | 5.92E+04 | 5.96E+04 |
|            | STD            | 5.84E+00                | 5.62E+02 | 1.91E+00 | 9.68E+02 | 8.10E+00 | 1.87E+01 | 9.59E+00 | 1.01E+00 | 1.11E+00 |
| RC16       | Ave            | 4.59E-02                | 4.09E-02 | 4.52E-02 | 4.58E-02 | 4.89E-02 | 4.09E-02 | 4.98E-02 | 3.99E-02 | 3.25E-02 |
|            | STD            | 2.41E+04                | 8.58E+02 | 5.32E+03 | 2.51E+02 | 6.98E+03 | 8.58E-02 | 3.71E+01 | 1.58E+02 | 1.02E-02 |
| RC23       | Ave            | 3.18E+01                | 3.75E+01 | 2.85E+01 | 2.85E+01 | 2.77E+01 | 2.82E+01 | 1.98E+01 | 2.02E+01 | 2.22E-01 |
|            | STD            | 6.78E+00                | 4.73E+00 | 4.21E+00 | 6.73E+00 | 1.21E+00 | 6.27E+00 | 1.02E+01 | 1.27E+00 | 1.41E+00 |
| RC35       | Ave            | 9.78E-02                | 9.56E-02 | 9.36E-02 | 9.74E-02 | 9.56E-02 | 9.24E-02 | 9.81E-02 | 9.01E-02 | 9.14E-02 |
|            | STD            | 8.64E-02                | 9.47E-02 | 9.42E-01 | 9.64E-01 | 4.73E+00 | 6.56E+01 | 6.15E-01 | 5.42E-01 | 5.55E-01 |
| RC37       | Ave            | 2.85E+02                | 3.11E+02 | 3.24E+02 | 2.94E+02 | 2.45E+02 | 3.11E+02 | 2.92E+02 | 2.20E+02 | 1.28E+02 |
|            | STD            | 1.64E+02                | 1.24E+02 | 1.79E+02 | 2.02E+02 | 1.40E+02 | 1.75E+02 | 1.65E+02 | 1.11E+02 | 1.01E-02 |
| RC45       | Ave            | 4.38E+00                | 3.92E+02 | 4.49E+02 | 4.75E-02 | 4.12E+02 | 4.02E+02 | 3.99E-02 | 3.99E-02 | 3.11E-02 |
|            | STD            | 1.36E+03                | 1.07E+03 | 1.54E+03 | 1.50E+03 | 1.81E+02 | 1.47E+03 | 1.03E-03 | 1.53E-03 | 1.00E-03 |
| RC51       | Ave            | 4.59E+03                | 4.91E+03 | 5.24E+03 | 5.29E+03 | 4.89E+03 | 4.62E+03 | 4.59E+03 | 4.55E+03 | 4.11E+03 |
|            | STD            | 1.49E+00                | 2.94E+00 | 2.84E+00 | 2.75E+00 | 2.21E+00 | 2.83E+00 | 1.90E+00 | 1.09E+00 | 1.01E+00 |

E. CONVERGENCE ANALYSIS OF THE WEIGHTED CHIMP OPTIMIZATION ALGORITHM

This subsection explores WChOA’s convergence patterns. WChOA convergence is explored using the fitness history, the convergence curve, and the trajectories. Figure 11 shows the aforementioned metrics.

The two-dimensional illustration shown in the first column of Figure 11 demonstrates the function domain topology. A gradual transition can be seen in unimodal functions, indicating that outcomes continue to grow as iterations increase. This pattern is reversed for the CEC and multimodal functions. With unimodal functions, it is evident that WChOA is able to locate the optimal point and fine-tune solutions from the beginning of iterations.

The convergence curve illustrates the best chimp’s (attacker) ability to gain success by taking into account the chimps as groupmates. Even so, there are no details about the chimpanzee’s overall ability. Thus, another metric, called average fitness history, was chosen to assess the chimp’s overall performance. While this metric has similar overall patterns to the convergence curve, it highlights how participatory habit enhances the initial random population results. The algorithm’s phase change enhances the fitness of all chimps. The benchmark functions’ average fitness history reveals a step-like pattern due to this augmentation.

Table 11 demonstrates the function domain topology. This pattern keeps the algorithm in an exploratory search mode for the first iterations, then transitions to a local search mode for the last iterations, ensuring that an algorithm will eventually converge to a global/local
minimum area. These changes are far more frequent and far larger in amplitude than changes made in unimodal functions because of the nature of CEC and multimodal functions.

As the final metric, the fifth column shows the search history. More chimpanzees congregate around the optimal points for unimodal and CEC functions, while searching is more distributed for multimodal functions. This design’s unique feature produces high-quality results from single-use functions. The latter means the space investigation function that enables WChOA in multimodal and CEC settings to search the entire area.
FIGURE 11. The Search history, the average fitness history, the convergence curve, and the trajectories of certain functions.

V. CONCLUSION
In this paper, a WChOA was proposed to solve the continuous non-linear optimization problems. For this purpose, a hypothesis was made that chimps’ social diversity and hunting behavior would also be functional in their searching positions. The variable weights were then introduced to their searching process of hunting. This position-weighted equation whose weights were inspired by the change of the drivers, chasers, blockers, and attackers contributed substantially toward new improvements in the standard ChOA.

One of the advantages of utilizing the weighting method based on the Euclidean distance was to improve exploration during the process of hunting so that most of the chimps did not trap in local minima. Another advantage was to enhance exploitation where the dimension of optimization problems was high because WChOA increased the convergence rate compared to the other conventional NIA algorithms. To sum up, the proposed method caused a balance between exploration and exploitation while solving the optimization problems.

In order to verify the performance of WChOA, 30 classic benchmark functions with low and high dimensions and IEEE Congress of Evolutionary Computation benchmark test functions (CECC06, 2019 Competition) were utilized. The results demonstrated that the proposed method had superior performance in exploration and exploitation while solving the problems compared to the other traditional optimization algorithms such as ChOA, PSO, BBO, WOA, BH, ALO, GA, SCA, and GWO. From a practical viewpoint, some real-world problems (IEEE CEC2020) have been also applied to evaluate WChOA. The results confirmed that the proposed WChOA algorithm outperformed the standard ChOA, and it had the utmost importance for real-world applications.

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