Journal of Artificial Intelligence and Data Mining (JAIDM), Vol. 13, No. 2, 2025, 207-226.

Shahrood University of Technology

Journal of Artificial Intelligence and Data Mining (JAIDM)
Journal homepage: http://jad.shahroodut.ac.ir

Research paper

ISUD (Individuals with Substance Use Disorder): A Novel Metaheuristic Algorithm for Solving Optimization Problems

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Article Info

Article History:
Received 05 October 2024
Revised 19 January 2025
Accepted 04 March 2025

DOI:10.22044/jadm.2025.15175.2621

Keywords:
Optimization, Meta-heuristic Algorithms, Swarm Intelligence.

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Abstract

In the field of optimization, metaheuristic algorithms have garnered significant interest. These algorithms, which draw inspiration from natural selection, evolution, and problem-solving strategies, offer an alternative approach to solving complex optimization problems. Unlike conventional software engineering methods, metaheuristics do not rely on derivative calculations in the search space. Instead, they explore solutions by iteratively refining and adapting their search process. The No-Free-Lunch (NFL) theorem proves that an optimization scheme cannot perform well in dealing with all optimization challenges. Over the last two decades, a plethora of metaheuristic algorithms has emerged, each with its unique characteristics and limitations. In this paper, we propose a novel meta-heuristic algorithm called ISUD (Individuals with Substance Use Disorder) to solving optimization problems by examining the clinical behaviors of individuals compelled to use drugs. We evaluate the effectiveness of ISUD by comparing it with several well-known heuristic algorithms across 44 benchmark functions of varying dimensions. Our results demonstrate that ISUD outperforms these existing methods, providing superior solutions for optimization problems.

1. Introduction

Metaheuristic algorithms are powerful optimization techniques designed to tackle complex problems that cannot be effectively solved using standard approaches. These algorithms draw inspiration from natural processes such as genetics, swarm behavior, and evolution. Their goal is to explore a broad search space and identify the global optimum of a problem. A metaheuristic scheme is a search strategy that mimics the behavior of biological, natural, or social systems. It aims to find optimal solutions by exploring various alternatives. Metaheuristics address optimization problems where conventional techniques fall short. These problems often involve intricate constraints, non-convex functions, or large solution spaces. Metaheuristics offer a versatile toolbox for solving challenging optimization problems. They harness the power of nature-inspired processes to navigate complex landscapes and find optimal solutions [1]. Metaheuristic algorithms inspired by various principles and phenomena, exhibit diverse characteristics that classify into distinct categories based on their underlying features.

- Nature-inspired metaheuristics draw inspiration from natural phenomena beyond simple crowding and evolution. Examples include Firefly Algorithm [2], Bat Algorithm [3] and Flower Pollination Algorithms [4].
- Population-Based Metaheuristics algorithms maintain a population of candidate solutions and collectively explore the solution space. They facilitate global exploration. Notable

examples include Genetic Algorithm [5], Particle Swarm Optimization [6] and Ant Colony Optimization [7].
- Physics-based metaheuristics mimic physical processes or principles. For instance, Simulated Annealing [8] emulates the annealing process in metallurgy. Quantum-Inspired Algorithm [9] leverage quantum principles.
- Evolutionary Algorithms are inspired by biological and genetic evolution. These algorithms include Evolutionary Strategies [10] and Differential Evolution [11].
- Local Search Metaheuristics iteratively explore the solution space by making small adjustments to a solution. They focus on finding local optima but may struggle to escape suboptimal solutions. Examples are Hill Climbing [12] and Tabu Search [13].
- Trajectory-based approaches follow a path in the solution space, aiming for improvement. Genetic Programming [14] and Iterative Local Search [15] are such examples.
- Constructive algorithms build solutions incrementally by assembling components. They start with an empty or partial solution and iteratively add elements. Examples included Greedy Algorithm [16].
- Hybrid approaches combine elements from different categories to create powerful algorithms. For instance, Genetic Programming [14] integrates evolutionary principles with tree-based representations.

In recent years, the field of optimization has witnessed a surge in novel metaheuristic algorithms. While classic approaches like genetic algorithms, particle swarm optimization, and simulated annealing remain widely used, researchers have introduced a plethora of innovative methods. Some of these include the Blue Monkey Optimization [17], Green Anaconda Optimization [18], Crow Search Algorithm [19], Quantum Multiverse Optimization [20], Black Widow Optimization [21], Moth Flame Optimization [22], Teaching-Learning Optimization [23], Sine Cosine Algorithm [24], Human Mental Search [25], Ions Motion Algorithm [26], Adaptive Greedy Algorithm [27] and Lion Optimization [28]. The landscape of optimization techniques continues to evolve, with new methods being introduced regularly.

In summary, understanding the diverse categories of metaheuristics allows researchers and practitioners to choose appropriate algorithms for specific optimization tasks. These versatile techniques continue to evolve and contribute significantly to solving real-world problems.

In this paper, we propose a novel meta-heuristic algorithm, ISUD, for solving optimization problems by drawing inspiration from the behavior of individuals who are compelled to use drugs. we leverage behaviors from substance users to improve optimization outcomes. Our approach demonstrates superior performance compared to existing methods and effectively addresses optimization challenges.

The subsequent sections of the paper are outlined as follows: in section 2, we review studies conducted on the behaviors of individuals who are forced to use drugs. By analyzing their decision-making processes, we gain valuable insights that inspired our proposed method. Section 3 defines the mathematical model of our meta-heuristic approach. We formulate the optimization theories, considering the unique characteristics observed in substance users' behavior. Section 4 provides a concise description of the validation functions used to assess the effectiveness of our proposed method. These functions serve as benchmarks for evaluating its performance. Finally, in Section 5, we present the results of our research. We compare our meta-heuristic approach with existing methods, highlighting its advantages and demonstrating its efficacy.

2. Understanding the Clinical Behavior of Individuals with Substance Use Disorder

Substance Use Disorders (SUDs) affect a significant portion of the populations. While it is essential to recognize that those who are forced into drug use often face health challenges and engage in risky behaviors, it is equally important to acknowledge their intelligence, creativity, and strong will.

With investigating the clinical behavior of individuals with SUD within a population (a neighborhood) and leveraging the experiences of those who have successfully recovered, we gained valuable insights into the patterns and motivations driving drug consumption. Our findings revealed that individuals with a compulsion to use drugs often find themselves trapped in a repetitive cycle: acquiring drugs and seeking a suitable location for consumption. Their primary goal is to achieve successful consumption (consumption that sustains their functioning over more duration). Additionally, they constantly contemplate about the promise of the next consumption and make plans for it.

In a given SUDs population, a diverse group of drug consumers exists, including a smaller subset of new recent consumers who find themselves compelled to participate in the cycle of consumption. Novice consumers, lacking experience in using drug, seek guidance from their more seasoned counterparts. They have less compulsion to consume drug, which lead to their overlook to their commitment. Consequently, they share their drugs with more experienced consumers.

Experienced users, who form a larger segment of the population with SUDs, exhibit different patterns of behavior. They have more compulsion to consume and they prioritize securing drugs for future. Their awareness of the importance of sustained consumption drives them to save their drugs. In pursuit of this goal, older consumers actively seek out novice counterparts to exploit. They recognize that exploiting new consumers can enhance their own chances of survival. Curiously, older consumers rarely interact with one another. Perhaps their self-interest leads them to avoid sharing drugs with those who are equally adept at consumption.

Consumer behavior analysis reveals that individuals operate within specific consumption deadlines. These deadlines dictate the extent of their search efforts within the population. Notably, these deadlines vary among consumers. The more time a consumer has, the broader their search options become. They can explore greater distances, seek better consumption partners, and identify optimal consumption locations. Some consumers have more deadline after current consumption, while others have felt the urge to consume sooner. New consumers typically enjoy more extended deadlines compared to their older counterparts. This difference arises from the absence of consumption compulsion in new consumers. In contrast, older consumers face shorter deadlines. When unable to meet their consumption needs within the allotted time, they seek drugs for consumption any means. This failure to consume disrupts their normal activities.

Importantly, if a consumer (regardless of their experience) fails to achieve successful consumption during the current cycle, the deadline loses significance. Their focus shifts solely to consumption, irrespective of form or location.

The consumption deadline (defined as the interval between successive consumption events) undergoes a consistent reduction over multiple cycles. Remarkably, this phenomenon remains independent of user tenure (whether they are new or old consumers) or the success of their consumption attempts. Intriguingly, the frequency of usage directly correlates with shorter deadlines.

Consumers tend to retain memories of individuals and locations associated with successful consumption experiences, including contact numbers, addresses, and favorite hangouts. Conversely, they tend to forget those connected to negative consumption encounters. Consequently, when seeking a consumption partner or place, consumers instinctively gravitate toward the most favorable option.

In a SUDs population, over time, new consumers transit into the category of old consumers. During this transition, they acquire all the characteristics associated with the existing older consumers.

In summary, the intricate interplay between consumption behaviors (guided by compulsion, experience, and drug allocation) shapes the survival strategies within this population.

It is important to consider whether complex human behaviors can effectively serve as models for solving optimization problems. Relying solely on human behavior for optimization may lead to algorithms that fail to accurately replicate the nuanced nature of these behaviors, potentially undermining their effectiveness in addressing optimization tasks. To confront this challenge, we derived numerous insights from clinical studies of individuals with SUD, including various drug-related behaviors, drug effects, potential alternatives, patterns of use, interactions with vendors, and instances of unsuccessful attempts to quit. From this comprehensive understanding, only the specific behaviors described above were selected to introduce the proposed method.

3. Mathematical model and formulation of the proposed method

In line with established metaheuristic algorithms, our proposed ISUD (Individuals with Substance Use Disorder) method commences by creating an initial population. This initial population represents a diverse set of candidate solutions. Within the context of a given neighborhood, each consumer possesses a distinct location. These locations may correspond to residences, workplaces, social gathering spots, or any other relevant places. Consequently, we define the primary population as the collection of these positions:

$$ISUDs = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_m \end{bmatrix}_{m\times 1} = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,n} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m,1} & x_{m,2} & \cdots & x_{m,n} \end{bmatrix}_{m\times n} \quad (1)$$

$$lb \le x_{i,j} \le ub$$

Where m is number of agents, n is number of features (variables in search space), lb is lower bound and ub is upper bound of variables.

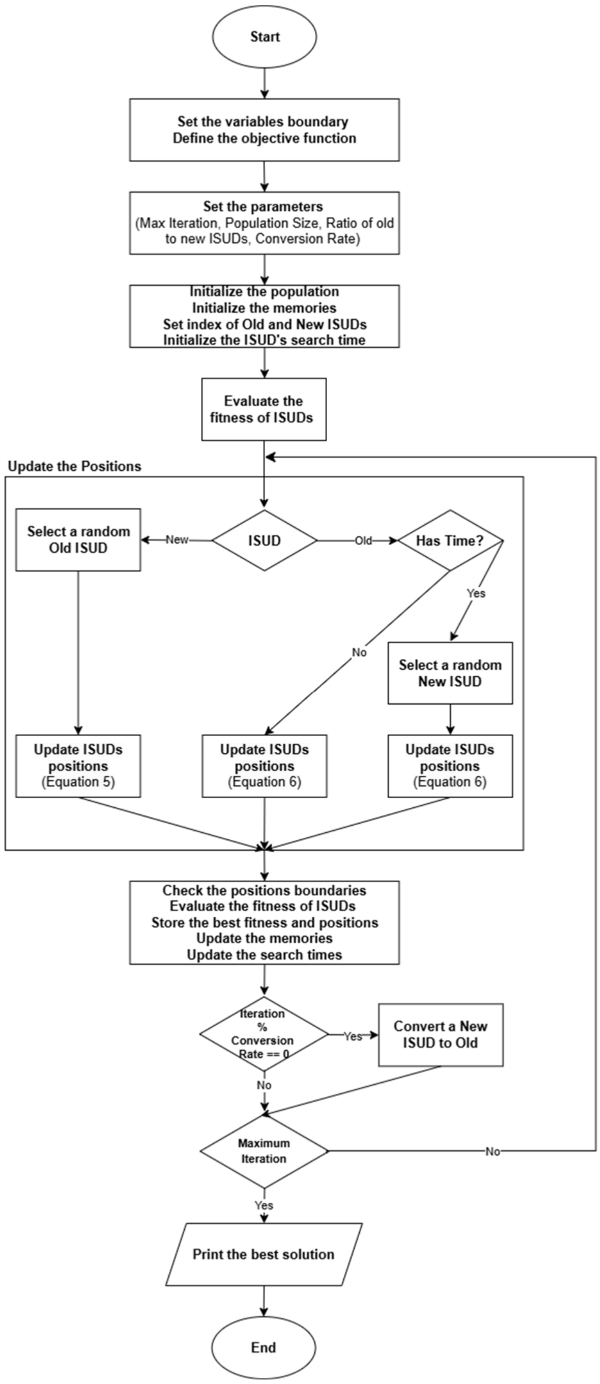

Figure 1. Flowchart of our proposed ISUD algorithm.

Each instance of the ISUD represents a potential solution. Consequently, it becomes essential to assess its merit. To achieve this, the ISUD's position is input into the objective function, and its fitness is computed:

$$F = \begin{bmatrix} F_1 \\ F_2 \\ \vdots \\ F_m \end{bmatrix}_{m\times 1} = \begin{bmatrix} F(X_1) \\ F(X_2) \\ \vdots \\ F(X_m) \end{bmatrix}_{m\times 1} \quad (2)$$

In Section 2, we discussed the composition of SUD communities, which consist of two distinct user types: the majority, represented by older consumers, and the minority, comprising recently joined individuals. Before initiating algorithm, it is crucial to differentiate between these user groups due to varying updating positions. The process of type determination is as follows:

$$ISUD = \begin{cases} NewISUD = m \times r \\ OldISUD = m - (m \times r) \end{cases} \quad (3)$$

Where m is the number of agents, and r is the old to new ISUD ratio and set 0.7 by us.

Each Individual of SUD maintains awareness of the positions of other ISUD. Specifically, they retain knowledge of the best positions achieved in previous iterations. To visualize this information, we represent these positions as follows:

$$Memory = \begin{bmatrix} M_1 \\ M_2 \\ \vdots \\ M_m \end{bmatrix}_{m\times 1} = \begin{bmatrix} m_{1,1} & m_{1,2} & \cdots & m_{1,n} \\ m_{2,1} & m_{2,2} & \cdots & m_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ m_{m,1} & m_{m,2} & \cdots & m_{m,n} \end{bmatrix} \quad (4)$$

The memory positions are regarded as equivalent to the initial positions of the agents at the start of the algorithm, M = X.

In accordance with the ISUD deadline described in Section 2, we examined two distinct initial value ranges for both old and new ISUD. Given the absence of a consumption compulsion in the new ISUD, we opted for a wider search time interval. Conversely, for older consumers, a shorter interval was chosen. Considering the problem's inherent mix of positive and negative values within the search space, we initialized random values from the interval [-2, 2] for the newer ISUD and [-1, 1] for the older ones.

In each iteration of the proposed algorithm, the positions of Individual with SUD are updated based on their type.

- When an agent is new, it seeks interaction with an old existing agent. To achieve this, the new ISUD randomly selects an existing agent and adjusts its position by moving toward the selected one. This movement is guided by the existing deadline:

$$Xnew_i^{t+1} = Xnew_i^t + r_i \times sT_i^t \times \left(M_j^t - Xnew_i^t\right) \quad j = index\ of\ an\ old\ ISUD \tag{5}$$

Where, r_i is a random number in range [0, 1], sT_i^t is search time for i-th agent in t-th iteration and j is index of a random old ISUD.

- There are two scenarios for older agents. First, if an older agent faces enough time, we update their position similarly to new consumers. Second, if an older ISUD has shorter deadlines or did not achieve satisfied consumption in the previous cycle, they also relocate to a random position.

$$Xold_i^{t+1} = \begin{cases} caseA) & Xold_i^t + (r_i \times ST_i^t \times Xold_i^t) \\ caseB) & Xold_i^t + r_i \times sT_i^t \times \left(M_j^t - Xold_i^t\right) \end{cases}$$
$$if\ \ (sT_i^t < dealine) \,\|\, (F(X_i) > threshold)\ \ A,\ else\ B \quad j = index\ of\ a\ new\ ISUD \tag{6}$$

The existence of two types of consumers (old and new) makes it possible to deal with the problem of exploitation and exploration. In this way, the agents move to the best positions in the search space. An older type that has not successfully consumed in the previous cycle or whose deadline has expired will move without thinking to a random position according to the available search time. That is, if it has less time, less displacement and vice versa. This case makes it possible to escape and exit if the algorithm is stuck in the local optimum.

In each iteration, following the fitness evaluation of the updated positions for each agent, the memory (consisting of the best positions) is updated as described below:

$$M_i^{t+1} = \begin{cases} M_i^t, & if\ F(X_i^t)\ is\ better\ than\ F(M_i^t) \\ X_i^t, & else \end{cases} \tag{7}$$

The deadline (search time) is updated as follows:

$$sT_i^{t+1} = \alpha \times sT_i^t \tag{8}$$

Where α is search time reduction rate and kept 0.95 due to reducing the search time in each iteration.

Finally, after a specific iteration, a new consumer becomes an old. As the iteration continues, the number of old consumers increases while the number of new consumers decreases. This dynamic increases the freedom of stochastic search in addition to moving towards optimal positions

The algorithm terminates upon satisfying the predefined termination condition, which is typically based on the number of iterations. Algorithm 1 outlines the pseudo-code for executing the meta-heuristic method proposed by ISUD.

Algorithm 1.

ISUD, a novel metaheuristic algorithm for solving optimization problems.

```
Set the variables boundaries (lower bound, upper bound)
Define the objective function
Set the parameters (maxIter: maximum iteration, NISUD: number of ISUD, ratio: ratio of old to new ISUD number, convRate: conversion rate of new to old ISUD, α: search time reduction coefficient)
Initialize the population (X)
idxOld = {idx | 1 ≤ idx ≤ ratio×NISUD} (indexes of old ISUD)
idxNew = {idx | ratio×NISUD ≤ idx ≤ NISUD, idx ≠ idxOld} (indexes of new ISUD)
M = X (memory of ISUD)
Fit = fitness(X)
globalFit = min(Fit)
x̂ = X[index of min(Fit)]
For 1 ≤ i ≤ NISUD:
    If (i ∈ idxNew):
        sT[i] = rand() ∈ [-2,2]   // Bigger range
    Else:
        sT[i] = rand() ∈ [-1,1]   // Smaller range
For 1 ≤ t ≤ maxIter:
    For 1 ≤ i ≤ NISUD:
        If (i ∈ idxNew):
            j = rand() ∈ idxOld
            X[i] = X[i] + rand×sT[i]×(M[j] – X[i])
        If (i ∈ idxOld):
            If (mean(Fit) < Fit[i]) or (sT[i] < threshold):
                X[i] = X[i] + rand()×sT[i]×X[i]
            Else:
                j = rand() ∈ idxNew
                X[i] = X[i] + rand()×sT[i]×(M[j] – X[i])
    Check the new positions boundaries
    newFit = fitness(X)
    If (newFit < Fit):
        M = X
    Fit = newFit
    If (min(Fit) < globalFit):
        globalFit = min(Fit)
        x̂ = X[index of min(Fit)]
    If (t mod convRate == 0):
        j = rand() ∈ idxNew
        remove j from idxNew and
        add j to idxOld
    sT = sT×α
Print(globalFit, x̂)
```

4. Benchmark functions

In this study, we carefully curated a set of 44 benchmark functions to assess the efficacy of the proposed model. These functions, widely recognized in the research community, have been extensively studied by various researchers. We employ this comprehensive suite of functions to evaluate the ISUD algorithm and compare its performance against other algorithms proposed in the literature. Table 2 provides details such as function names, formulas, variable ranges, and global optima, while Figure 2 visually represents these functions. This benchmark functions are categorized into several distinct types: Multimodal, Unimodal, Composition, Separable, and Non-separable. F1, F2, F3, F4, F11, F23, F26, F27, F29, and F37 fall into the unimodal category. F6, F10, F12, F24, F25, F28, F31, F35, F36, F38, and F39 exhibit multimodal behavior. F32 is a separable function. F9, F13, and F14 are considered composition functions. Additionally, F5, F7, F17, F18, and F43 are multimodal and non-separable. F8, F15, F41, and F42 are multimodal and separable. F16, F19, and F30 are unimodal and separable. F20, F21, F22, F33, F40, and F44 belong to the unimodal and non-separable category.

Table 1. Parameters of the proposed (ISUD) and the compared algorithms.

Algorithm	Parameter	Value
ISUD	r = Old to New ratio	0.7
	α = Time reduction coefficient	0.95
	convRate = Conversion rate	maxIter / 10
	sT = Search time limitation	New = [-2, 2] Old = [-1, 1]
PSO	Inertia weight	2
	Best global experiment	2.2
	Best personal experiment	2.4
	w-damp	0.98
BBO	Rate of keeping habitat	0.6
	Mutation rate	0.4
	Absorption coefficient	0.9
ABC	The number of food source	popSize / 2
	Limit	15
GA	Cross over rate	0.67
	Mutation rate	0.33

5. Results and discussion

In this research paper, we presented a novel meta-heuristic algorithm called ISUD, designed for solving optimization problems. This algorithm, akin to other meta-heuristics, draws inspiration from the swarm behavior of a population striving for survival. Our approach involved studying clinical behavior of drug consumer. By analyzing them particularly those individuals who desired to quit and the experiences of successful quitters, we identified patterns that led to purposeful behavior formation. These insights were then translated into mathematical model, culminating in the introduction of our ISUD optimization algorithm. To evaluate the effectiveness of the ISUD algorithm, we employed 44 diverse benchmark functions. Comparative analyses were conducted against well-known methods such as PSO (Particle Swarm Optimization), BBO (Binary Bat Optimization), ABC (Artificial Bee Colony), and GA (Genetic Algorithm) adopted from Hayyolalam et. al [21].

Stability and repeatability of results are crucial for optimization algorithms. A robust algorithm should produce the same or very similar results under identical or similar conditions. Without such consistency, the optimization process may behave unpredictably, rendering the results unreliable. It is acknowledged that no single optimization scheme can perform optimally across all optimization challenges. Therefore, the ISUD algorithm was evaluated for the repeatability and stability of its results across different experiments to assess its strengths and weaknesses under varying conditions.

Evaluations were conducted with iterations of 500, 1000, 1500, and 2000; population sizes of 100, 150, 200, 300, 500, 600, and 800; and dimensions of 10, 20, 50, 100, 500, and 1000 to analysis on scalability and the algorithm's performance with larger and more complex problems. These parameters were selected to match those utilized in the PSO, BBO, ABC, and GA algorithms, ensuring an equitable evaluation and comparison. Specifically, we repeated all calculations ten times and retained both average and best results. The detailed outcomes are presented in Tables 3 to 6.

In the context of metaheuristic algorithms, parameter tuning plays a crucial role in enhancing the efficiency of problem-solving processes. Table 1 presents the parameters of our proposed novel algorithm, ISUD, alongside the four mentioned methods. Adjusting the ratio between old and new ISUD can lead to significant solutions improvements. An increased proportion of old ISUD results in smaller steps within the search space, attributed to the influence of the search time parameter. Conversely, a higher proportion of new ISUD induces greater movement within the search space. It is noteworthy that old ISUD exhibit a higher likelihood of random movements due to their shorter search times, which enables to escape local optima. Another critical parameter is the conversion rate, which stands out as a key strength of this algorithm. This parameter facilitates the inheritance of behaviors from old ISUD by converting a new ISUD into an old one. Additionally, the time reduction coefficient is a significant parameter that diminishes the search time in agents, reflected from their clinical behavior. Setting higher values for this factor accelerates the reduction of search time across iterations.

Table 2. Benchmark functions (Part 1).

No	Function	Equation	Range	Optimal
F1	Powell Sum (Some of different powers)	$f_1(x)=\sum_{i=1}^{n}\lvert x_i\rvert^{i+1}$	$-5.12 \le x_i \le 5.12$	0.0
F2	Cigar	$f_2(x)=x_1^2+10^6\sum_{i=2}^{n}x_i^2$	$-5.12 \le x_i \le 5.12$	0.0
F3	Discus	$f_3(x)=10^6x_1^2+\sum_{i=2}^{n}x_i^2$	$-5.12 \le x_i \le 5.12$	0.0
F4	Rosenbrock	$f_4(x)=\sum_{i=1}^{n-1}\left(100\left(x_{i+1}-x_i^2\right)^2+\left(x_i-1\right)^2\right)$	$-30 \le x_i \le 30$	0.0
F5	Ackley	$f_5(x)=-20exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2}\right)-exp\left(\frac{1}{n}\sum_{i=1}^{n}cos\left(2\pi x_i\right)\right)+20+exp(1)$	$-35 \le x_i \le 35$	0.0
F6	Weierstrass	$f_6(x)=\sum_{i=1}^{n}\left(\sum_{k=0}^{kmax}a^k cos\left(2\pi b^k\left(x_i+0.5\right)\right)\right)-n\sum_{k=0}^{kmax}a^k cos\left(2\pi b^k\cdot 0.5\right)$ $a = 0.5,\ b = 3,\ kmax = 20$	$-10 \le x_i \le 10$	0.0
F7	Griewank	$f_7(x)=\sum_{i=1}^{n}\frac{x_i^2}{4000}-\prod_{i=1}^{n}cos\left(\frac{x_i}{\sqrt{i}}\right)+1$	$-100 \le x_i \le 100$	0.0
F8	Rastrigin	$f_8(x)=10n+\sum_{i=1}^{n}(x_i^2-10cos(2\pi x_i))$	$-5.12 \le x_i \le 5.12$	0.0
F9	Modified Schwefel	$f_9(x)=418.9829n-\sum_{i=1}^{n}h(x_i),\ h(x)=g\left(x+420.9687462275036\right)$ $g(x)=\begin{cases} zsin(\lvert z\rvert^{\frac{1}{2}}) & \lvert z\rvert\le 500 \\ (500-mod(z,500))sin(\sqrt{\lvert 500-mod(z,500)\rvert})-\frac{(z-500)^2}{10000n} & z>500 \\ (mod(\lvert z\rvert,500)-500)sin(\sqrt{\lvert mod(\lvert z\rvert,500)-500\rvert})-\frac{(z-500)^2}{10000n} & z<-500 \end{cases}$	$-100 \le x_i \le 100$	0.0
F10	Katsuura	$f_{10}(x)=\frac{10}{n^2}\prod_{i=1}^{n}\left(1+i\sum_{j=1}^{32}\left(\frac{\left\lvert 2^j x_i-\text{round}\left(2^j x_i\right)\right\rvert}{2^j}\right)^{\frac{10}{n^{1.2}}}\right)-\frac{10}{n^2}$	$0 \le x_i \le 10$	0.0
F11	HappyCat	$f_{11}(x)=\left\lvert\sum_{i=1}^{n}x_i^2-n\right\rvert^{\frac{1}{4}}+\frac{0.5\sum_{i=1}^{n}x_i^2+\sum_{i=1}^{n}x_i}{n}+0.5$	$-5.12 \le x_i \le 5.12$	0.0
F12	HGBat	$f_{12}(x)=\left\lvert\left(\sum_{i=1}^{n}x_i^2\right)^2-\left(\sum_{i=1}^{n}x_i\right)^2\right\rvert^{\frac{1}{2}}+\frac{0.5\sum_{i=1}^{n}x_i^2+\sum_{i=1}^{n}x_i}{n}+0.5$	$-5.12 \le x_i \le 5.12$	0.0
F13	Expanded Griewank's plus Rosenbrock	$f_{13}(x)=f_7(f_4(x_1,x_2))+f_7(f_4(x_2,x_3))+...+f_7(f_4(x_{n-1},x_n))+f_7(f_4(x_n,x_1))$	$-5.12 \le x_i \le 5.12$	0.0
F14	Expanded Schaffer's F6	$f_{14}(x)=g(x_1,x_2)+g(x_2,x_3)+...+g(x_{n-1},x_n)+g(x_n,x_1)$ $g(x,y)=0.5+\frac{sin^2\left(\sqrt{x^2+y^2}\right)-0.5}{\left(1+0.001\left(x^2+y^2\right)\right)^2}$	$-5.12 \le x_i \le 5.12$	0.0
F15	Some of different powers	$f_{15}(x)=1-\frac{1}{n}\sum_{i=1}^{n}cos(kx_i)exp^{\frac{-x_i^2}{2}}$	$-\pi \le x_i \le \pi$	0.0
F16	Sphere	$f_{16}(x)=\sum_{i=1}^{n}x_i^2$	$-5.12 \le x_i \le 5.12$	0.0
F17	Penalized	$f_{17}(x)=\frac{\pi}{n}\left\{10sin^2\left(\pi y_1\right)+\sum_{i=1}^{n-1}\left(y_i-1\right)^2\left[1+10sin^2\left(\pi y_{i+1}\right)\right]+\left(y_n-1\right)^2\right\}+\sum_{i=1}^{n}u\left(x_i,10,100,4\right)$ $y_i=1+\frac{x_i+1}{4},\qquad u\left(x_i,a,k,m\right)=\begin{cases}k\left(x_i-a\right)^m & x_i>a \\ 0 & -a<x_i<a \\ k\left(-x_i-a\right)^m & x_i<-a\end{cases}$	$-50 \le x_i \le 50$	0.0
F18	Penalized2	$f_{18}(x)=0.1\left\{sin^2\left(3\pi x_1\right)+\sum_{i=1}^{n-1}\left(x_i-1\right)^2\left[1+sin^2\left(3\pi x_{i+1}\right)\right]+\left(x_n-1\right)^2[1+sin^2(2\pi x_n)]\right\}$ $+\sum_{i=1}^{n}u\left(x_i,5,100,4\right)$	$-50 \le x_i \le 50$	0.0

Table 2. Benchmark functions (Part 2).

No	Function	Equation	Range	Optimal
F19	Quartic	$f_{19}(x)=\sum_{i=1}^{n} ix_i^4 + random[0,1)$	$-1.28 \le x_i \le 1.28$	0.0
F20	Schwefel 1.2	$f_{20}(x)=\sum_{i=1}^{n}\left(\sum_{j=1}^{i} x_j\right)^2$	$-100 \le x_i \le 100$	0.0
F21	Schwefel 2.21	$f_{21}(x)=\max_{i=1..n} \lvert x_i \rvert$	$-100 \le x_i \le 100$	0.0
F22	Schwefel 2.22	$f_{22}(x)=\sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	$-10 \le x_i \le 10$	0.0
F23	Step2	$f_{23}(x)=\sum_{i=1}^{n} (\lfloor x_i + 0.5 \rfloor)^2$	$-200 \le x_i \le 200$	0.0
F24	Alpine1	$f_{24}(x)=\sum_{i=1}^{n} \lvert x_i sin(x_i) + 0.1x_i \rvert$	$-10 \le x_i \le 10$	0.0
F25	Csendes	$f_{25}(x)=\sum_{i=1}^{n} x_i^6 \left(2 + sin\frac{1}{x_i}\right)$	$-1 \le x_i \le 1$	0.0
F26	Rotated Ellipse	$f_{26}(x)=7x_1^2 - 6\sqrt{3}x_1x_2 + 13x_2^2$	$-500 \le x_i \le 500$	0.0
F27	Rotated Ellipse2	$f_{27}(x)=x_1^2 - x_1x_2 + x_2^2$	$-500 \le x_i \le 500$	0.0
F28	Schwefel 2.4	$f_{28}(x)=\sum_{i=1}^{n} (x_i - 1)^2 + (x_1 - x_i^2)^2$	$0 \le x_i \le 10$	0.0
F29	Sum Squares	$f_{29}(x)=\sum_{i=1}^{n} ix_i^2$	$-10 \le x_i \le 10$	0.0
F30	Step	$f_{30}(x)=\sum_{i=1}^{n} (\lfloor \lvert x_i \rvert \rfloor)$	$-100 \le x_i \le 100$	0.0
F31	Schwefel	$f_{31}(x)=\sum_{i=1}^{n} 418.9829 - x_i sin\left(\sqrt{\lvert x_i \rvert}\right)$	$-500 \le x_i \le 500$	0.0
F32	Xin-She Yang1	$f_{32}(x)=\sum_{i=1}^{n} \varepsilon_i \lvert x_i \rvert^i, \quad \varepsilon = random[0,1]$	$-5 \le x_i \le 5$	0.0
F33	Schaffer	$f_{33}(x)=0.5+\frac{sin^2(x_1^2 - x_2^2)^2 - 0.5}{1+0.001(x_1^2 + x_2^2)^2}$	$-100 \le x_i \le 100$	0.0
F34	Sign	$f_{34}(x)=x.\mathrm{sgn}(x)$	$-1 \le x_i \le 2$	0.0
F35	Adjiman	$f_{35}(x)=cos(x_1)sin(x_2) - \frac{x_1}{(x_2^2 + 1)}$	$-1 \le x_1 \le 2$ $-1 \le x_2 \le 1$	−2.02181
F36	Bartels Conn	$f_{36}(x)= \lvert x_1^2 + x_2^2 + x_1x_2 \rvert + \lvert sin(x_1) \rvert + \lvert cos(x_2) \rvert$	$-500 \le x_i \le 500$	1.0
F37	Ackley2	$f_{37}(x)=-200exp(-0.02\sqrt{x_1^2 + x_2^2})$	$-500 \le x_i \le 500$	−200.0
F38	Eggcrate	$f_{38}(x)=x^2 + y^2 + 25\left(sin^2x + cos^2y\right)$	$(x, y) \in$ $[-2\pi, 2\pi]\times[-2\pi, 2\pi]$	0.0
F39	Chichinadze	$f_{39}(x,y)=x\sin(4x)+1.1y\sin(2y)$	$0 \le (x, y) \le 10$	−18.5547
F40	Powel Singular 2	$f_{40}(x)=\sum_{i=1}^{n-2} (x_{i-1} + 10x_i)^2 + 5(x_{i+1} - x_{i+2})^2 + (x_i - 2x_{i+1})^4 + 10(x_{i-1} - x_{i+2})^4$	$-4 \le x_i \le 5$	0.0
F41	Quintic	$f_{41}(x)=\sum_{i=1}^{n} \lvert x_i^5 - 3x_i^4 + 4x_i^3 + 2x_i^2 - 10x_i - 4 \rvert$	$-10 \le x_i \le 10$	0.0
F42	Qing	$f_{42}(x)=\sum_{i=1}^{n} (x_i^2 - i)^2$	$-500 \le x_i \le 500$	0.0
F43	Salomon	$f_{43}(x)=1-cos\left(2\pi\sqrt{\sum_{i=1}^{n} x_i^2}\right)+0.1\sqrt{\sum_{i=1}^{n} x_i^2}$	$-100 \le x_i \le 100$	0.0
F44	Dixon & Price	$f_{44}(x)=(x_1 - 1)^2 + \sum_{i=1}^{n} i(2x_i^2 - x_{i-1})^2$	$-10 \le x_i \le 10$	0.0

To initiate our optimization process, we establish the termination criterion at 500 iterations, configure the population size to 100, and fix the number of variables for all functions at 10. In Table 3, we observe that our proposed ISUD algorithm demonstrates enhanced efficiency for a subset of functions (F2, F3, F5, F6, F7, F8, F9, F10, F14, F16, F20, F21, F22, F23, F24, F25, F29, F30, F35, F36, F37, F39, F40, and F43) compared to other methods. Specifically, the ISUD method outperforms PSO, BBO, ABC and GA methods in 25 out of the 44 total functions. These results highlight the superiority of our approach in terms of function optimization.

Upon further examination and analysis of the results presented in Figure 3 and Table 3 (500 iterations, population size of 100, and 10 dimensions), it is evident that the majority of the 44 benchmark functions have consistently progressed towards the optimal point. This trend underscores the robustness of the algorithm and its capability to avoid entrapment in local optima. Notably, functions F6, F10, and F35 (Weierstrass, Katsuura, and Adjiman, respectively) exhibit non-decreasing curves, which can be attributed to their expedited convergence to the global optimum.

In the second simulation, we extended the number of iterations to 1000 as the termination condition. Additionally, we augmented the population size to 150 and expanded the number of variables (search space dimensions) to 20. As indicated in Table 4, our proposed method outperformed other approaches across multiple functions, including F2, F3, F4, F5, F6, F7, F8, F9, F10, F14, F15, F20, F21, F22, F23, F24, F25, F28, F29, F30, F33, F35, F36, F37, F39, F40, and F43. Specifically, our method achieved superior results in 28 out of the 44 functions compared to other methods.

Figure 4 illustrates that as the dimensions transform from 10 to 20 and the complexity of the problem increases, our proposed ISUD method not only avoids stagnation in local optima but also progresses towards the global optimum. The results clearly indicate that increasing the population size and the number of iterations—two critical parameters in metaheuristic algorithms—significantly enhances the convergence of the ISUD algorithm.

In our further evaluation, we extended the termination condition to 1500 iterations. The population size was set to 200, and the search space dimensions were defined as 50. The results are summarized in Table 5. Notably, the newly introduced ISUD algorithm outperformed PSO, BBO, ABC and GA methods across a significant portion of the benchmark functions. Specifically, in 30 out of 44 functions, the ISUD algorithm demonstrated superior performance.

A further significant observation can be derived from Figure 5. Despite the increase in the search space dimension to 50, our proposed algorithm demonstrates robust convergence towards the global optimum.

Obtaining these convergence criteria validates that the proposed algorithm is capable of escaping local optima, a common challenge faced by meta-heuristic algorithms. To emphasis this, we explored the impact of iteration, population size, and dimensionality. Specifically, we evaluated the algorithm's performance with five sets of varying parameters on the following functions: F1, F4, F5, F7, F8, F16, F20, and F29. Case (a); 2000 max iterations for termination condition, the populations size 200 and dimensions 10. Case (b); 2000 max iterations for termination condition, the populations size 300 and dimensions 50. Case (c); 1000 max iterations for termination condition, the populations size 500 and dimensions 100. Case (d); 1500 max iterations for termination condition, the populations size 600 and dimensions 500. Case (e); 2000 max iterations for termination condition, the populations size 800 and dimensions 1000. The results of these evaluations are presented in Table 6 and Figure 6. The results obtained from our proposed ISUD algorithm are remarkable. In comparison to other existing methods, the efficiency of ISUD significantly outperforms them across all functions listed in Table 6. Even when dealing with high-dimensional problems (e.g., dimensions of 1000, as indicated in the last part of Table 6), the ISUD model achieves impressive outcomes.

In Figure 6, the convergence curves of five sets of functions, each subjected to varying iterations, population sizes, and dimensions, are presented. The specific numbers of iterations, population sizes, and dimensions are indicated above each corresponding column. It is evident from the figure that the proposed method maintains robust performance at higher dimensions, including 100, 500, and 1000, consistently progressing towards the optimal solution.

Specifically, ISUD has yield an output of 2.22E−57, surpassing the performance of the best similar method (BBO), which achieves only 3.67E−19 for function F1. For function F4, ISUD obtains a value of 9.99E+02, demonstrating superiority over the GA with a value of 3.39E+04. The optimal solution using the ABC algorithm is 2.04E+00, while ISUD achieves an even better result of 4.44E−16 for function F5. ISUD converges to the optimal value of 0.00E+00 for both F7 and F8 functions. ISUD significantly outperforms GA, with a value of 7.31E−54 compared to GA's 5.83E+00 for function F16. Similarly, against GA's value of 8.60E+03, ISUD achieves 2.66E−50 for function F29.

Upon analyzing the results obtained, it can be concluded that our proposed algorithm demonstrates significant potential for solving various optimization problems. As evidenced in Tables 3, the ISUD algorithm outperforms other methods in 4 out of 10 unimodal functions. For the 11 multimodal functions assessed, our method yielded superior results in 7 instances. Among the 3 composition functions, our approach was superior in 2 cases. Furthermore, of the 5 multimodal and non-separable functions, our method showed better performance in 3 cases, and of the 5 unimodal and non-separable functions, 4 were outperformed by the ISUD method in comparison to others. Notably, all three unimodal and separable functions exhibited improved results with our proposed method. Similar patterns of performance are observed in Tables 4 and 5.

These results emphasize the robustness and effectiveness of the proposed ISUD algorithm in solving complex optimization problems and overcome the fundamental challenge of metaheuristic methods, getting stuck in local optima, by using three parameters: New-to-Old ISUD rate, New-to-Old conversion rate, and search time deadline.

The time complexity and resource consumption are crucial factors for assessing the efficiency and feasibility of an algorithm. In metaheuristic methods, the termination condition is often specified by the number of iterations. In population-based methods such as PSO, BBO, ABC, and etc. number of populations also influences the time complexity. As demonstrated in Algorithm 1, the proposed ISUD method comprises two primary nested loops: the number of iterations and the number of populations. Consequently, its time complexity is of the order $O(maxIter \times N_{ISUD})$. Regarding to resource consumption, two variables, specifically position and search time, are maintained and continually updated in memory for each ISUD. Considering the population size, the memory requirements for storing these variables are negligible.

The experiment has been carried out on a computer with 2.40 GHz, 16.0 GB of RAM and Windows 10 operating system.

Code Availability

The Python codes implemented during the current study are available to the editors, reviewers and readers in our GitHub page. https://github.com/Farzad-Zandi/ISUD.

Acknowledgments

The authors would like to express their gratitude to Mahdi Nabawi and Rahil Hoshyar, Master of Science in Psychology (Salamat addiction treatment clinic), for valuable contributions in providing clinical behavioral research and experiences related to the Individuals with Substance Use Disorder.

References

[1] E. G. Talbi, "Metaheuristics: from design to implementation". *John Wiley & Sons*, vol. 205, no. 2, pp. 486-487, 2009.

[2] I. Fister, Jr. Fister, X. S. Yang, & J. Brest, "A comprehensive review of firefly algorithms". *Swarm and Evolutionary Computation*, vol. 13, pp. 34-46, 2013.

[3] X. S. Yang, and X. He, "Bat algorithm: literature review and applications". *International Journal of Bio-Inspired Computation*, vol. 5, no. 3, pp. 141-149, 2013.

[4] M. Abdel-Basset, and L. A. Shawky, "Flower pollination algorithm: a comprehensive review". *Artificial Intelligence Review*, vol. 52, pp. 2533-2557, 2019.

[5] A. Lambora, K. Gupta, and K. Chopra, "Genetic algorithm-A literature review". In *2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon)*, pp. 380-384. IEEE. 2019, February. https://doi.org/10.1109/COMITCon.2019.8862255

[6] J. Kennedy, and R. Eberhart, "Particle swarm optimization". In *Proceedings of ICNN'95-International Conference on Neural Networks*, vol. 4, pp. 1942-1948), IEEE, 1995, November.

[7] M. Dorigo, M. Birattari, and T. Stutzle, "Ant colony optimization". *IEEE Computational Intelligence Magazine*, vol. 1, no. 4, pp. 28-39, 2006.

[8] D. Bertsimas, and J. Tsitsiklis, "Simulated annealing". *Statistical Science*, vol. 8, no. 1, pp. 10-15, 1993.

[9] F. S. Gharehchopogh, "Quantum-inspired metaheuristic algorithms: comprehensive survey and classification". *Artificial Intelligence Review*, vol. 56, no. 6, pp. 5479-5543, 2023.

[10] T. Bartz-Beielstein, J. Branke, J. Mehnen, and O. Mersmann, "Evolutionary algorithms". *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 4, no. 3, pp. 178-195, 2014.

[11] K. V. Price, "Differential evolution". In *Handbook of Optimization: From Classical to Modern Approach*, pp. 187-214. Springer Berlin Heidelberg, 2013.

[12] S. Chinnasamy, M. Ramachandran, M. Amudha, and K. Ramu, "A review on hill climbing optimization methodology". *Recent Trends in Management and Commerce*, vol. 3, no. 1, pp. 1-7, 2022.

[13] F. Glover, and M. Laguna, "*Tabu search*". In: *Du, DZ., Pardalos, P.M. (eds) Handbook of Combinatorial Optimization*. Springer Boston MA, 1998.

[14] M. J. Willis, H. G. Hiden, P. Marenbach, B. McKay, and G. A. Montague, "Genetic programming: An introduction and survey of applications". In *Second International Conference on Genetic Algorithms in Engineering Systems: Innovations and Applications*, pp. 314-319. IET, 1997, September.

[15] H. R. Lourenço, O. C. Martin, and T. Stützle, "Iterated local search". In *Handbook of Metaheuristics*, pp. 320-353. Boston, MA: Springer US, 2003.

[16] D. Jungnickel, and D. Jungnickel, "The greedy algorithm". *Graphs, Networks and Algorithms*, vol. 3, pp. 129-153, 1999.

[17] M. Mahmood, and B. Al-Khateeb, "The blue monkey: A new nature inspired metaheuristic optimization algorithm". *Periodicals of Engineering and Natural Sciences*, vol. 7, no. 3, pp. 1054-1066, 2019.

[18] M. Dehghani, P. Trojovský, and O. P. Malik, "Green anaconda optimization: a new bio-inspired metaheuristic algorithm for solving optimization problems". *Biomimetics*, vol. 8, no. 1, pp. 121, 2023.

[19] A. Askarzadeh, "A novel metaheuristic method for solving constrained engineering optimization problems: crow search algorithm". *Computers & Structures*, vol. 169, pp. 1-12, 2016.

[20] G. I. Sayed, A. Darwish, and A. E. Hassanien, "Quantum multiverse optimization algorithm for optimization problems". *Neural Computing and Applications*, vol. 31, pp. 2763-2780, 2019.

[21] V. Hayyolalam, and A. A. P. Kazem, "Black widow optimization algorithm: a novel meta-heuristic approach for solving engineering optimization problems". *Engineering Applications of Artificial Intelligence*, vol. 87, pp. 103249, 2020.

[22] S. Mirjalili, "Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm". *Knowledge-Based Systems*, vol. 89, pp. 228-249, 2015.

[23] R. V. Rao, V. J. Savsani, and D. P. Vakharia, "Teaching–learning-based optimization: a novel method for constrained mechanical design optimization problems". *Computer-Aided Design*, vol. 43, no. 3, pp. 303-315, 2011.

[24] S. Mirjalili, "SCA: a sine cosine algorithm for solving optimization problems". *Knowledge-Based Systems*, vol. 96, pp. 120-133, 2016.

[25] S. J. Mousavirad, and H. Ebrahimpour-Komleh, "Human mental search: a new population-based metaheuristic optimization algorithm". *Applied Intelligence*, vol. 47, pp. 850-887, 2017.

[26] B. Javidy, A. Hatamlou, and S. Mirjalili, "Ions motion algorithm for solving optimization problems". *Applied Soft Computing*, vol. 32, pp. 72-79, 2015.

[27] A. Hadian, M. Bagherian, and B. Fathi Vajargah. "A Heuristic Algorithm for Multi-layer Network Optimization in Cloud Computing". *Journal of AI and Data Mining*, vol. 9, no. 3, pp. 361-367, 2021.

[28] M. Yazdani, and F. Jolai, "Lion optimization algorithm (LOA): a nature-inspired metaheuristic algorithm". *Journal of Computational Design and Engineering*, vol. 3, no. 1, pp. 24-36, 2016. https://doi.org/10.1016/j.jcde.2015.06.003

Table 3. The obtained results from our proposed ISUD algorithm with 500 iterations using 100 agents in a 10-dimensional space and comparison with several well-known methods.

F	ISUD		PSO		BBO		ABC		GA	
	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean
1	2.61E-14	7.37E-11	1.12E-18	1.21E-12	3.12E-22	**1.81E-16**	3.35E-12	4.55E-09	**4.09E-24**	1.68E-09
2	**9.24E-07**	**2.66E-03**	9.07E-04	16.6E+0	1.84E-04	2.98E-01	2.29E-02	6.67E-01	1.11E-01	8.24E-01
3	**8.83E-09**	6.25E-06	1.10E-04	1.79E-02	1.26E-07	**1.31E-06**	3.63E-06	1.08E-03	1.50E-08	4.36E-03
4	8.95E+00	8.98E+00	9.12E-01	2.38E+02	6.52E-01	**5.39E+00**	4.52E+00	1.38E+01	**4.45E-01**	1.02E+01
5	**3.25E-06**	**5.71E-05**	8.44E-05	4.43E-03	1.45E-03	1.89E-01	1.17E-01	3.23E-01	4.82E-05	4.97E-02
6	**0.00E+00**	**0.00E+00**	5.72E-02	1.98E-01	2.46E-02	3.37E-02	3.01E-01	5.86E-01	1.20E-05	7.62E-02
7	**1.26E-11**	**1.54E-04**	1.22E-01	5.48E-01	7.40E-03	7.12E-02	5.15E-02	1.51E-01	7.33E-08	4.28E-02
8	**3.15E-10**	**1.46E-08**	2.03E-01	7.90E+00	1.99E+00	5.87E+00	1.30E+01	2.90E+01	4.81E-10	5.73E-01
9	**1.27E-04**	2.30E-04	1.27E-04	1.40E-04	1.29E-04	**1.30E-04**	1.22E+00	2.92E+01	1.30E-04	1.78E-04
10	**0.00E+00**	**0.00E+00**	1.67E-08	2.89E-01	1.49E-03	7.82E-03	1.07E-02	4.37E-02	3.90E-04	2.97E-03
11	3.09E+00	3.23E+00	3.65E-01	5.90E-01	**1.10E-01**	**1.90E-01**	9.84E-01	1.79E+00	1.28E-01	2.17E-01
12	4.02E-01	4.79E-01	1.64E-01	**3.00E-01**	1.70E-01	4.41E-01	2.34E-01	6.53E-01	**1.51E-01**	3.74E-01
13	1.59E+00	3.28E+00	**9.10E-02**	4.16E-01	1.60E-01	2.87E-01	7.33E-01	1.05E+00	1.16E-01	**2.48E-01**
14	**4.27E-13**	**2.47E-10**	9.65E-02	3.71E-01	7.78E-02	1.31E-01	2.40E-01	5.06E-01	7.79E-02	1.93E-01
15	**1.13E-14**	**3.98E-12**	1.19E-01	2.32E-01	5.33E-02	1.22E-01	5.94E-02	1.04E-01	5.62E-13	6.45E-03
16	**3.35E-13**	**2.27E-08**	8.33E-05	8.60E-03	5.70E-08	1.69E-07	4.82E-05	6.54E-04	1.30E-11	6.15E-04
17	2.17E-01	9.00E-01	1.06E-07	1.33E-02	1.13E-07	**2.12E-07**	1.96E-04	2.14E-03	**1.14E-14**	3.02E-03
18	3.42E-01	8.47E-01	2.00E-06	3.29E-03	**2.25E-07**	7.34E-04	3.83E-04	1.91E-03	6.38E-07	**1.72E-05**
19	**1.11E-04**	**5.37E-04**	1.38E+00	2.28E+00	1.11E+00	1.47E+00	2.02E+00	2.77E+00	1.24E+00	1.54E+00
20	**3.31E-10**	**7.45E-07**	3.10E-05	7.61E-03	3.50E-05	1.04E-04	5.34E-03	2.23E-01	3.04E-09	6.43E+00
21	**1.35E-05**	**4.35E-04**	7.04E-02	6.39E-01	1.69E-03	2.91E-03	1.41E+01	2.44E+01	5.65E-02	1.38E-01
22	**4.01E-06**	**3.00E-05**	4.72E-05	2.18E-03	7.37E-04	9.50E-04	2.31E-02	8.13E-02	7.11E-04	2.22E-03
23	**0.00E+00**	**0.00E+00**	0.00E+00	2.33E-01	0.00E+00	0.00E+00	0.00E+00	1.93E+00	0.00E+00	0.00E+00
24	**8.18E-07**	**1.12E-05**	1.00E-04	4.77E-02	6.76E-05	1.17E-04	9.88E-03	7.99E-02	4.68E-05	3.91E-04
25	**1.69E-41**	**4.77E-28**	2.13E-20	3.23E-14	1.11E-27	7.32E-27	1.77E-19	8.66E-17	8.93E-23	1.03E-20
26	1.26E-08	3.19E-06	6.36E-05	4.58E-04	1.06E-22	2.13E-11	8.64E-04	2.19E-02	**7.26E-196**	**1.14E-23**
27	2.42E-10	2.75E-07	4.99E-45	1.49E-43	3.29E-84	1.49E-10	7.18E-06	1.42E-03	**4.38E-201**	**5.55E-25**
28	3.29E-02	2.60E-01	7.45E+01	2.43E+03	**1.12E-06**	**6.70E-03**	5.58E-02	2.34E-01	5.17E-03	2.42E-02
29	**8.92E-12**	**2.50E-07**	1.51E-07	1.76E-04	3.50E-07	1.04E-06	1.03E-03	3.33E-03	9.05E-10	1.10E-01
30	**0.00E+00**	**0.00E+00**	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	6.67E-01	0.00E+00	0.00E+00
31	8.42E+02	1.37E+03	1.18E+02	9.92E+02	5.13E+02	1.17E+03	1.56E+02	5.13E+02	**6.64E+00**	**4.01E+02**
32	5.36E-05	1.57E-03	2.41E-04	2.48E-02	2.57E-09	7.45E-06	3.09E-02	5.05E-01	**1.09E-14**	**2.99E-08**
33	4.22E-15	**8.54E-12**	**0.00E+00**	8.47E-07	0.00E+00	4.88E-03	1.35E-10	1.91E-06	0.00E+00	5.91E-03
34	8.10E-08	1.57E-06	1.16E-145	1.57E-136	1.75E-156	1.54E-24	1.06E-21	1.46E-15	**3.19E-146**	**7.98E-142**
35	**-2.02E+00**	**-2.02E+00**	-2.02E+00	-2.02E+00	-2.88E+00	-2.81E+00	-2.02E+00	-2.02E+00	-2.01E+00	-1.96E+00
36	**1.00E+00**	**1.00E+00**	1.00E+00	1.00E+00	1.00E+00	1.00E+00	1.00E+00	1.01E+00	1.00E+00	1.00E+00
37	**-2.00E+02**	**-2.00E+02**	-2.00E+02	-2.00E+02	-1.99E+2	-1.99E+2	-2.00E+02	-2.00E+02	-	-
38	3.68E-14	3.95E-08	**4.87E-178**	3.00E-02	3.34E-174	4.69E-15	4.37E-15	4.04E-09	1.04E-160	**1.42E-33**
39	**-1.85E+01**	-1.83E+01	-1.85E+01	-1.51E+01	-1.85E+01	1.71E+01	-1.85E+01	**-1.85E+01**	-1.85E+01	-1.77E+01
40	**4.03E-11**	**8.97E-09**	3.07E+00	1.74E+01	1.35E-06	2.09E-02	8.95E-03	6.48E-02	1.41E-05	4.71E-02
41	1.19E+01	2.11E+01	1.93E+01	7.67E+01	7.01E-03	**1.26E-02**	6.38E-01	1.02E+00	**2.19E-07**	1.17E+00
42	4.31E+01	8.57E+01	1.04E+01	1.38E+02	**2.44E-02**	**4.85E-02**	5.44E-01	5.85E+00	1.18E+00	2.00E+02
43	**7.58E-07**	**1.55E-05**	2.11E+00	3.66E+00	9.99E-02	2.53E-01	1.41E+00	2.30E+00	9.99E-02	1.53E-01
44	8.94E-01	9.64E-01	4.97E-03	9.46E+00	**6.23E-06**	5.78E-01	2.39E-01	**5.72E-01**	4.40E-01	7.23E-01

Table 4. The obtained results from our proposed ISUD algorithm with 1000 iterations using 150 agents in a 20-dimensional space and comparison with several well-known methods.

F	ISUD		PSO		BBO		ABC		GA	
	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean
1	3.50E-28	**2.59E-18**	7.47E-15	1.78E-09	5.70E-21	5.98E-18	9.34E-10	2.14E-07	**3.32E-33**	3.05E-13
2	**2.63E-20**	**4.77E-16**	5.88E+00	2.12E+02	4.24E+02	2.71E+03	4.26E+00	1.44E+01	3.81E-01	1.39E+00
3	**4.03E-23**	**4.05E-20**	1.40E-06	2.18E+01	5.57E-02	2.62E-01	7.58E-05	3.09E-03	1.02E-06	4.42E-03
4	**1.89E+01**	**1.89E+01**	2.18E+01	9.70E+03	1.42E+01	8.03E+01	2.68E+01	5.10E+01	4.07E+00	3.87E+01
5	**2.85E-13**	**2.79E-11**	9.86E-01	2.50E+00	3.05E-03	2.89E-01	1.41E+00	2.27E+00	3.40E-07	1.05E-01
6	**0.00E+00**	**0.00E+00**	8.17E-01	2.55E+00	6.67E-02	9.70E-02	1.88E+00	2.73E+00	6.87E-03	2.37E-01
7	**0.00E+00**	**0.00E+00**	3.68E-01	8.43E-01	1.02E-05	2.56E-03	2.31E-01	4.15E-01	2.44E-10	4.96E-02
8	**0.00E+00**	**0.00E+00**	1.75E+01	5.11E+01	9.85E+00	2.26E+01	8.68E+01	1.14E+02	3.29E-08	4.94E-02
9	**1.27E-04**	**2.30E-04**	9.80E-02	7.45E-01	2.70E-02	2.89E-01	1.80E+02	6.35E+02	2.65E-04	3.16E-04
10	**0.00E+00**	**0.00E+00**	1.59E-05	3.57E-02	2.26E-02	9.79E-02	2.97E-02	7.05E-02	3.15E-04	1.11E-03
11	4.64E+00	4.70E+00	3.65E-01	5.90E-01	**1.10E-01**	**1.90E-01**	9.84E-01	1.79E+00	1.28E-01	2.17E-01
12	4.78E-01	4.97E-01	**2.30E-01**	6.04E-01	3.18E-01	**4.32E-01**	2.08E+00	1.28E+01	3.41E-01	4.39E-01
13	7.04E+00	9.19E+00	7.06E-01	1.59E+00	**3.72E-01**	7.40E-01	1.27E+00	3.91E+00	4.19E-01	**5.63E-01**
14	**0.00E+00**	**0.00E+00**	5.78E-01	1.33E+00	2.66E-01	8.41E-01	1.30E+00	2.38E+00	1.58E-01	4.11E-01
15	**0.00E+00**	**0.00E+00**	3.66E-01	4.50E-01	6.21E-02	1.69E-01	1.79E-01	2.14E-01	3.98E-10	1.89E-03
16	**9.71E-27**	**7.41E-22**	2.75E-03	1.33E-02	2.63E-07	4.67E-07	2.85E-03	8.89E-03	5.86E-15	6.82E-04
17	1.56E-01	9.37E-01	9.25E-01	6.72E+00	3.56E-07	5.18E-03	1.06E-03	7.05E-03	**1.22E-11**	**1.32E-03**
18	1.44E+00	1.88E+00	4.07E-01	6.56E+00	**3.79E-06**	**8.80E-03**	7.97E-04	1.70E-02	4.48E-05	5.43E-02
19	**4.56E-06**	**1.09E-04**	5.99E+00	6.99E+00	3.68E+00	4.49E+00	7.48E+00	9.02E+00	4.20E+00	4.59E+00
20	**4.56E-22**	**8.02E-18**	1.44E+00	7.25E+02	4.19E-04	7.56E-04	1.89E+00	5.11E+00	2.91E-03	5.05E-03
21	**8.42E-13**	**2.70E-12**	7.83E+00	1.51E+01	8.03E-01	2.97E+00	3.38E+01	5.05E+01	1.84E-01	2.66E-01
22	**1.75E-12**	**1.10E-11**	5.73E-02	4.01E-01	4.63E-02	2.08E-01	2.78E-01	5.75E-01	1.34E-03	3.78E-03
23	**0.00E+00**	**0.00E+00**	6.00E+00	4.39E+01	0.00E+00	8.23E+00	2.00E+00	1.47E+01	0.00E+00	0.00E+00
24	**2.21E-13**	**7.59E-09**	2.31E-02	8.31E-01	2.42E-03	2.06E-02	3.66E-01	8.28E-01	1.19E-04	4.27E-04
25	**1.67E-83**	**1.44E-68**	3.04E-10	2.05E-07	1.28E-12	1.01E-09	1.14E-12	7.64E-11	2.19E-21	1.73E-20
26	4.44E-22	3.68E-14	5.23E-05	2.83E-03	1.20E-36	2.59E-13	9.25E-09	4.36E-03	**6.29E-312**	**4.29E-143**
27	2.58E-23	3.12E-19	0.00E+00	0.00E+00	3.00E-303	7.39E-17	1.47E-10	4.13E-09	**0.00E+00**	**0.00E+00**
28	**8.26E-05**	**2.02E-01**	4.03E+03	1.03E+04	2.20E+02	3.83E+02	4.24E-01	1.52E+00	9.34E-02	2.05E-01
29	**1.99E-25**	**3.93E-17**	2.64E-02	1.18E+01	1.20E-02	2.01E-01	1.19E-02	5.87E-02	3.84E-06	5.45E-05
30	**0.00E+00**	**0.00E+00**	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	6.67E-01	0.00E+00	0.00E+00
31	2.60E+03	3.95E+03	**9.92E+02**	**2.33E+03**	2.52E+03	3.24E+03	2.10E+03	2.73E+03	2.68E+03	3.40E+03
32	1.84E-05	1.80E-04	1.90E-02	6.91E+00	5.08E-10	1.36E-05	1.00E+01	4.85E+02	**1.13E-14**	**1.58E-08**
33	**0.00E+00**	**0.00E+00**	0.00E+00	2.52E-12	0.00E+00	5.18E-17	2.04E-11	1.80E-07	0.00E+00	9.59E-04
34	1.49E-16	2.53E-13	0.00E+00	0.00E+00	0.00E+00	1.43E-17	1.50E-21	1.75E-16	**0.00E+00**	**0.00E+00**
35	**-2.02E+00**	**-2.02E+00**	-2.02+00	-2.02+00	-4.60E+00	-4.53E+00	-2.02E+00	-2.02E+00	2.02E+00	-2.00E+00
36	**1.00E+00**	**1.00E+00**	1.00E+00	1.00E+00	1.00E+00	1.00E+00	1.00E+00	1.00E+00	1.00E+00	1.00E+00
37	**-2.00E+02**	**-2.00E+02**	-2.00E+02	-1.99E+02	-2.00E+02	-2.00E+02	-2.00E+02	-2.00E+02	-	-
38	1.75E-27	1.21E-15	0.00E+00	0.00E+00	0.00E+00	0.00E+00	2.48E-12	1.43E-09	**0.00E+00**	**0.00E+00**
39	**-1.85E+01**	-1.84E+01	-1.85E+01	-1.68E+01	-1.85E+01	-1.78E+01	-1.85E+01	**-1.85E+01**	-1.85E+01	-1.84E+01
40	**1.96E-24**	**6.58E-18**	9.22E+01	4.28E+02	4.01E-05	5.36E-03	7.65E-02	3.35E-01	5.16E-04	1.15E+00
41	3.67E+01	5.11E+01	9.48E+01	2.56E+03	**2.55E-02**	**7.04E-01**	1.78E+00	3.03E+00	4.28E-01	5.87E+00
42	4.42E+02	6.49E+02	1.35E+05	2.08E+06	**1.32E-01**	**2.16E-01**	2.59E+01	1.17E+02	9.92E+00	7.71E+01
43	**1.84E-13**	**3.92E-10**	4.96E+00	8.79E+00	2.00E-01	4.37E-01	5.37E+00	7.87E+00	9.99E-02	1.97E-01
44	9.86E-01	9.91E-01	1.17E+00	9.11E+01	**3.24E-03**	**6.67E-01**	1.03E+00	2.56E+00	8.68E-01	3.73E+00

Table 5. The obtained results from our proposed ISUD algorithm with 1500 iterations using 200 agents in a 50-dimensional space and comparison with several well-known methods.

F	ISUD		PSO		BBO		ABC		GA	
	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean
1	**2.97E-44**	**1.58E-37**	3.79E-09	1.66E-04	1.64E-18	1.86E-13	3.63E-06	2.40E-04	6.82E-17	3.73E-11
2	**4.98E-34**	**7.40E-27**	3.76E+05	1.65E+06	1.12E+05	2.11E+05	7.78E+01	1.17E+03	1.87E+01	2.66E+01
3	**1.44E-36**	**6.82E-32**	9.04E+00	9.15E+01	1.19E+00	2.31E+00	2.31E-03	7.42E-02	2.85E-05	1.10E-02
4	4.89E+01	**4.89E+01**	5.90E+04	2.08E+05	5.32E+02	2.19E+03	1.00E+02	3.18E+02	**3.89E+01**	1.38E+02
5	**4.44E-16**	**4.44E-16**	7.10E+00	1.01E+01	8.20E-03	2.48E-01	9.19E+00	1.15E+01	2.92E-12	4.62E-02
6	**0.00E+00**	**0.00E+00**	2.06E+01	2.79E+01	2.81E-01	4.90E-01	6.55E+00	9.07E+00	7.57E-04	5.82E-01
7	**0.00E+00**	**0.00E+00**	1.17E+00	1.67E+00	6.30E-05	1.32E-03	8.98E-01	1.10E+00	2.59E-12	5.68E-02
8	**0.00E+00**	**0.00E+00**	1.56E+02	3.28E+02	6.70E+01	1.02E+02	1.19E+02	1.51E+02	4.01E-06	1.12E-01
9	**6.36E-04**	**6.36E-04**	1.11E+02	4.29E+02	3.35E+00	9.42E+00	3.62E+03	5.59E+03	1.49E-03	1.97E-03
10	**0.00E+00**	**0.00E+00**	3.86E-04	3.30E-03	6.17E-02	1.77E-01	8.29E-02	1.54E-01	3.86E-04	6.36E-04
11	7.43E+00	7.47E+00	4.96E-01	8.02E-01	**2.82E-01**	5.47E-01	4.31E+00	5.09E+00	3.43E-01	**5.17E-01**
12	4.93E-01	4.99E-01	**3.15E-01**	7.39E-01	3.75E-01	**4.83E-01**	1.09E+02	1.54E+02	4.03E-01	5.30E-01
13	1.40E+01	2.30E+01	2.24E+01	3.76E+02	1.00E+00	1.09E+00	7.05E+02	1.27E+05	**6.91E-01**	**7.59E-01**
14	**0.00E+00**	**0.00E+00**	3.23E+00	6.38E+00	3.67E+00	5.50E+00	3.03E+00	4.77E+00	6.53E-01	1.10E+00
15	**0.00E+00**	**0.00E+00**	5.56E-01	6.79E-01	1.77E-01	2.90E-01	3.45E-01	3.87E-01	5.87E-10	1.20E-03
16	**2.14E-40**	**3.02E-37**	9.66E-01	3.52E+00	3.57E-06	4.94E-06	4.76E-02	2.17E-01	1.39E-15	6.46E-04
17	7.99E-01	1.03E+00	1.50E+01	1.94E+04	**1.86E-06**	2.00E-02	3.67E-02	1.63E-01	1.02E-05	**1.53E-05**
18	4.93E+00	4.99E+00	8.23E+02	1.36E+05	4.48E-05	**2.57E-02**	1.32E-01	4.78E-01	**5.45E-10**	2.21E-01
19	**4.58E-09**	**7.41E-05**	2.50E+01	3.01E+01	1.38E+01	1.58E+01	3.74E+01	5.29E+01	1.37E+01	1.59E+01
20	**3.76E-37**	**7.25E-34**	1.46E+04	8.87E+04	1.88E-02	9.67E-02	6.73E+01	1.14E+03	1.14E-04	2.62E+02
21	**5.00E-20**	**2.49E-17**	4.45E+01	5.31E+01	4.48E+00	7.42E+00	7.16E+01	7.72E+01	6.81E-01	9.25E-01
22	**1.14E-19**	**7.72E-18**	4.50E+00	1.65E+01	2.40E+00	3.47E+00	4.45E+00	7.20E+00	1.90E-02	2.89E-02
23	**0.00E+00**	**0.00E+00**	2.89E+03	6.49E+03	1.72E+02	3.29E+02	1.63E+02	1.05E+03	0.00E+00	0.00E+00
24	**3.34E-20**	**2.45E-17**	2.27E+00	2.09E+01	1.71E+00	3.46E+00	6.00E+00	9.82E+00	1.26E-03	1.95E-03
25	**4.07E-125**	**5.68E-105**	2.73E-04	1.07E-03	3.44E-08	2.01E-07	3.12E-07	1.14E-05	2.85E-17	7.01E-17
26	3.19E-36	3.31E-29	3.26E-08	4.08E-06	**3.25E-316**	1.97E-20	1.27E-05	3.27E-04	4.96E-312	**2.47E-96**
27	5.86E-38	9.06E-30	0.00E+00	4.31E-04	0.00E+00	1.51E-108	7.88E-07	3.71E-05	**0.00E+00**	**0.00E+00**
28	**3.83E-03**	**1.03E-01**	3.19E+04	4.29E+04	3.13E+03	3.83E+03	8.61E+00	2.23E+01	3.13E+01	4.06E+01
29	**3.00E-39**	**4.27E-31**	9.22E+01	7.76E+02	1.46E-04	1.04E-03	1.18E+00	1.60E+01	7.04E-06	1.47E+00
30	**0.00E+00**	**0.00E+00**	6.40E+01	1.62E+02	2.00E+00	9.77E+00	7.70E+01	1.31E+02	0.00E+00	3.36E-02
31	1.17E+04	1.31E+04	6.55E+03	8.33E+03	8.33E+03	1.09E+04	**6.36E+03**	**7.21E+03**	7.88E+03	9.45E+03
32	2.74E-05	1.21E-04	1.30E+07	3.27E+11	1.05E-08	5.99E-04	1.68E+14	7.89E+16	**9.33E-11**	**2.77E-05**
33	**0.00E+00**	**0.00E+00**	0.00E+00	0.00E+00	0.00E+00	0.00E+00	5.57E-13	1.57E-09	0.00E+00	2.90E-04
34	1.39E-22	1.36E-15	0.00E+00	0.00E+00	0.00E+00	1.27E-40	4.58E-20	2.59E-17	**0.00E+00**	**0.00E+00**
35	**-2.02E+00**	**-2.02E+00**	-2.02E+00	-2.02E+00	-5.64E+00	-5.58E+00	-2.02E+00	-2.02E+00	-2.02E+00	-2.00E+00
36	**1.00E+00**	**1.00E+00**	1.00E+00	1.00E+00	1.00E+00	1.00E+00	1.00E+00	1.00E+00	1.00E+00	1.00E+00
37	**-2.00E+02**	**-2.00E+02**	-2.00E+02	-2.00E+02	-2.00E+02	-2.00E+02	-2.00E+02	-2.00E+02	-	-
38	4.38E-40	3.07E-36	0.00E+00	0.00E+00	0.00E+00	0.00E+00	9.49E-12	5.75E-09	**0.00E+00**	**0.00E+00**
39	**-1.85E+01**	**-1.85E+01**	-1.85E+01	-1.77E+01	-1.85E+01	-1.84E+01	-1.85E+01	-1.85E+01	-1.85E+01	-1.85E+01
40	**5.15E-38**	**6.23E-36**	2.62E+03	6.62E+03	7.72E-03	3.93E-02	5.50E+00	1.46E+01	7.13E-02	4.72E+00
41	1.35E+02	1.48E+02	3.28E+04	7.26E+04	6.52E+00	1.95E+01	1.16E+01	**1.83E+01**	**4.80E+00**	2.27E+01
42	9.80E+03	1.07E+04	1.26E+08	7.91E+08	**4.53E+00**	**6.94E+00**	2.30E+03	4.13E+04	4.98E+01	1.77E+02
43	**2.74E-20**	**2.39E-16**	1.47E+01	2.22E+01	1.10E+00	1.56E+00	2.21E+01	2.61E+01	2.00E-01	3.53E-01
44	9.98E-01	**9.98E-01**	1.23E+03	1.84E+04	**6.67E-01**	1.36E+00	1.91E+01	4.50E+01	2.51E+00	1.78E+01

Table 6. The obtained results from our proposed ISUD algorithm with various iterations, population and dimension and comparison with several well-known methods.

	F	ISUD		PSO		BBO		ABC		GA	
		Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean
Iter 2000 Pop 200 Dim 10	1	**1.97E-57**	**1.30E-44**	1.16E+04	2.13E+05	7.98E-29	7.47E-16	9.12E-13	1.02E-10	8.37E-11	9.66E-10
	5	**4.44E-16**	**4.44E-16**	8.44E-05	4.43E-03	7.27E-05	1.30E-04	1.17E-01	1.30E-04	1.15E-08	3.95E-02
	7	**0.00E+00**	**0.00E+00**	5.26E-01	7.68E-01	7.46E-09	2.69E-02	4.12E-02	1.09E-01	6.28E-11	4.55E-03
	8	**0.00E+00**	**0.00E+00**	1.47E-02	2.88E+00	9.95E-01	4.74E+00	3.62E-08	1.72E+00	2.96E-11	1.07E-01
	16	**1.50E-55**	**6.56E-52**	7.31E-08	1.82E-05	6.59E-11	2.27E-10	6.18E-05	2.15E-04	3.63E-16	2.58E-05
	20	**1.55E-52**	**2.01E-47**	2.09E-10	9.21E-07	2.28E-07	5.22E-07	4.01E-03	1.48E-02	2.39E-12	1.20E-01
	29	**1.67E-55**	**3.56E-47**	9.59E-13	9.04E-09	4.61E-09	1.28E-08	9.88E-05	7.61E-04	2.60E-12	1.99E-03
Iter 2000 Pop 300 Dim 50	1	**1.65E-57**	**2.28E-52**	9.93E-08	2.48E-04	1.35E-17	8.81E-16	1.50E-05	1.85E-04	1.62E-30	4.25E-15
	5	**4.44E-16**	**4.44E-16**	6.46E+00	8.58E+00	5.53E-03	6.69E-03	8.87E+00	1.09E+01	4.63E-10	3.54E-02
	7	**0.00E+00**	**0.00E+00**	1.09E+00	1.32E+00	3.17E-05	4.22E-05	1.01E+00	1.08E+00	5.14E-14	1.23E-01
	8	**0.00E+00**	**0.00E+00**	1.71E+02	4.00E+02	8.96E+00	2.54E+01	9.39E+01	1.40E+02	1.34E-08	8.35E-02
	16	**2.25E-55**	**3.27E-48**	8.22E-01	3.59E+00	1.84E-06	2.73E-06	5.10E-02	1.28E-01	3.01E-18	1.85E-04
	20	**4.08E-51**	**1.20E-45**	1.58E+04	8.36E+04	2.01E-02	9.63E-02	4.34E+01	4.49E+02	1.48E-03	1.03E+02
	29	**4.53E-53**	**4.69E-49**	1.21E+02	6.53E+02	2.20E-04	3.83E-04	1.57E+00	5.73E+00	3.35E-05	1.29E+00
Iter 1000 Pop 500 Dim 100	1	**8.80E-30**	**1.94E-24**	8.87E-04	-	3.54E-15	-	3.04E-02	-	2.59E-16	-
	4	**9.89E+01**	**9.89E+01**	3.95E+04	-	2.27E+03	-	9.49E+02	-	4.65E+02	-
	5	**1.53E-13**	**1.20E-12**	1.00E+01	-	3.71E+00	-	1.70E+01	-	2.53E-01	-
	7	**0.00E+00**	**0.00E+00**	1.62E+00	-	4.09E-04	-	9.46E-01	-	2.39E-03	-
	8	**0.00E+00**	**0.00E+00**	4.39E+02	-	2.25E+02	-	4.71E+02	-	4.43E+00	-
	16	**2.74E-26**	**3.70E-25**	2.40E+01	-	4.79E-01	-	1.79E-02	-	7.19E-03	-
	29	**2.85E-24**	**1.39E-22**	5.24E+03	-	6.33E+01	-	1.06E+03	-	1.00E+00	-
Iter 1500 Pop 600 Dim 500	1	**3.63E-47**	**1.36E-40**	1.38E+00	-	1.16E-14	-	4.70E-01	-	2.59E-16	-
	4	**4.99E+02**	**4.99E+02**	3.12E+08	-	6.63E+04	-	1.81E+08	-	1.19E+04	-
	5	**4.44E-16**	**4.44E-16**	2.04E+01	-	5.16E+00	-	1.99E+01	-	2.00E-01	-
	7	**0.00E+00**	**0.00E+00**	4.66E+00	-	5.77E-02	-	1.89E+00	-	1.51E-01	-
	8	**0.00E+00**	**0.00E+00**	6.49E+03	-	2.05E+03	-	4.27E+03	-	2.36E+02	-
	16	**6.73E-40**	**6.88E-38**	1.98E+06	-	1.03E+01	-	3.68E+02	-	1.62E+00	-
	29	**1.84E-37**	**1.71E-35**	1.64E+06	-	9.20E+03	-	9.17E+05	-	1.21E+03	-
Iter 2000 Pop 800 Dim 1000	1	**2.22E-57**	**6.40E-54**	1.67E+00	-	3.67E-19	-	7.21E-01	-	9.32E-17	-
	4	**9.99E+02**	**9.99E+02**	6.36E+09	-	1.86E+05	-	2.20E+09	-	3.39E+04	-
	5	**4.44E-16**	**4.44E-16**	2.06E+01	-	5.13E+00	-	2.04E+00	-	5.95E+00	-
	7	**0.00E+00**	**0.00E+00**	8.57E+00	-	6.47E+00	-	4.06E+00	-	5.95E+00	-
	8	**0.00E+00**	**0.00E+00**	1.38E+04	-	3.57E+03	-	1.08E+04	-	8.71E+02	-
	16	**7.31E-54**	**4.77E-52**	4.45E+03	-	1.84E+01	-	2.14E+03	-	5.83E+00	-
	29	**2.66E-50**	**6.71E-49**	8.13E+06	-	3.62E+04	-	5.12E+06	-	8.60E+03	-

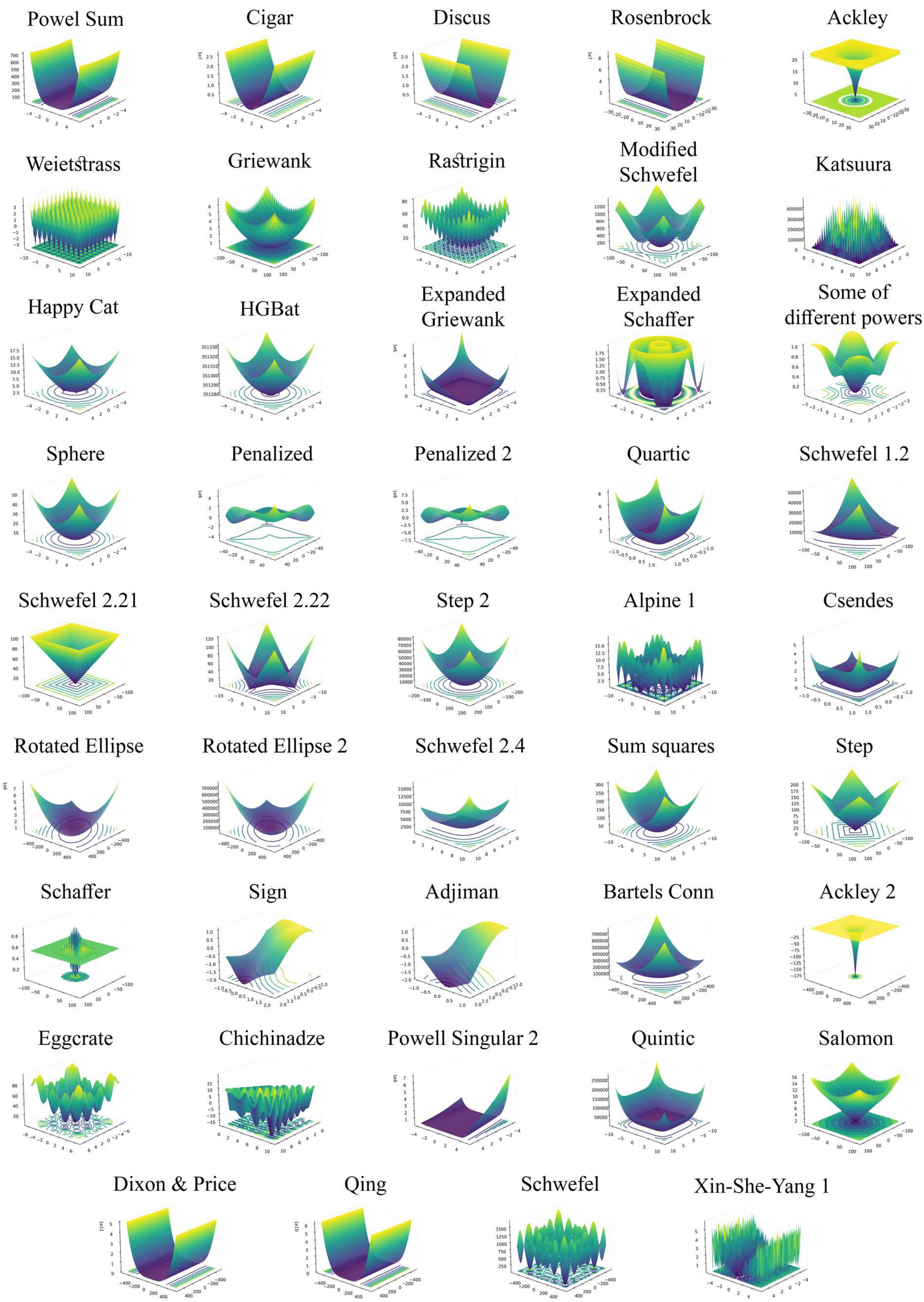

Figure 2. Illustration of 44 benchmark function used for evaluating our proposed ISUD optimization algorithm.

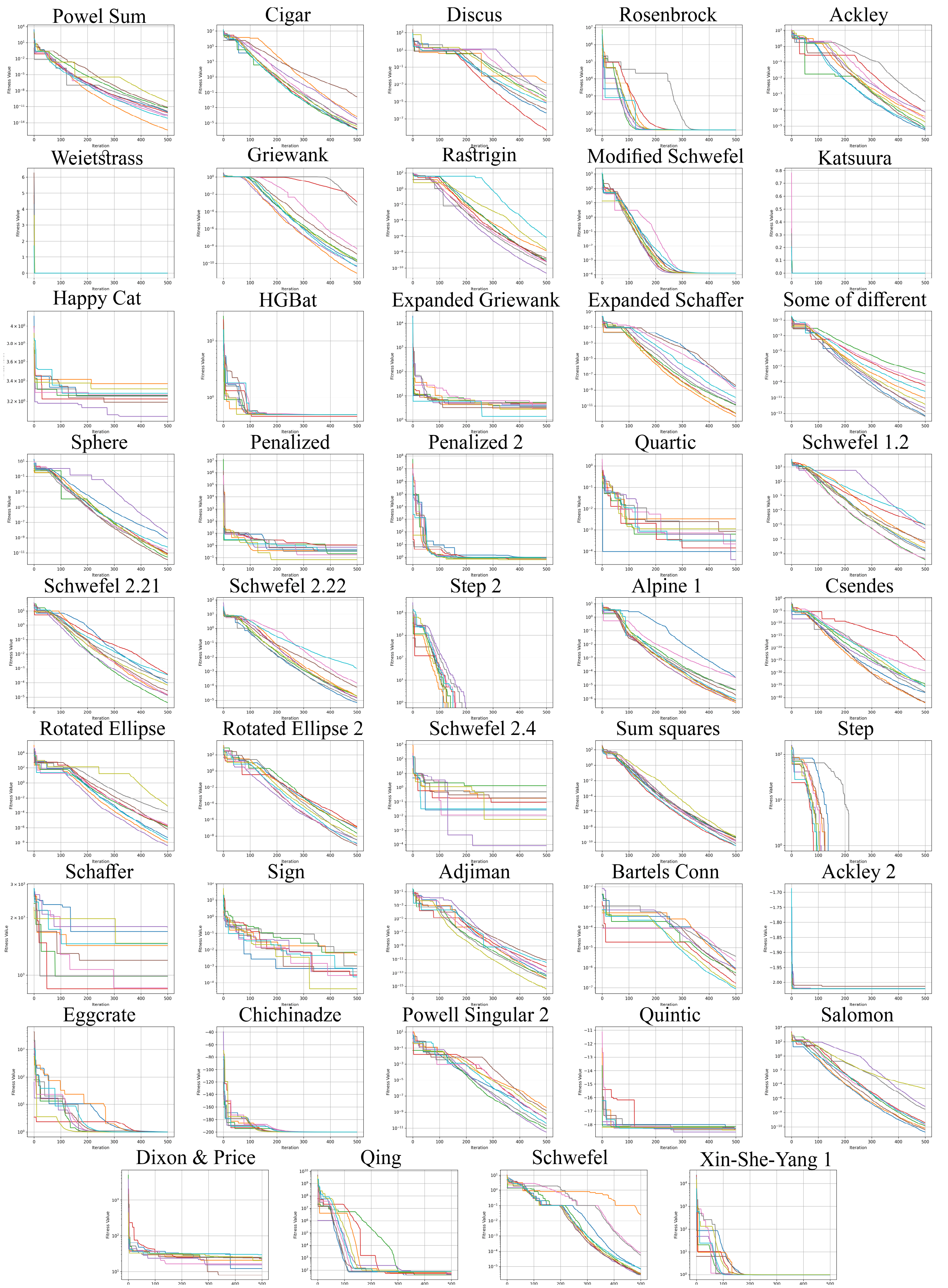

Figure 3. Convergence curves of 10 trials for each of the 44 benchmark functions (dimension: 10, iterations: 500, population: 100) with our proposed ISUD optimization algorithm.

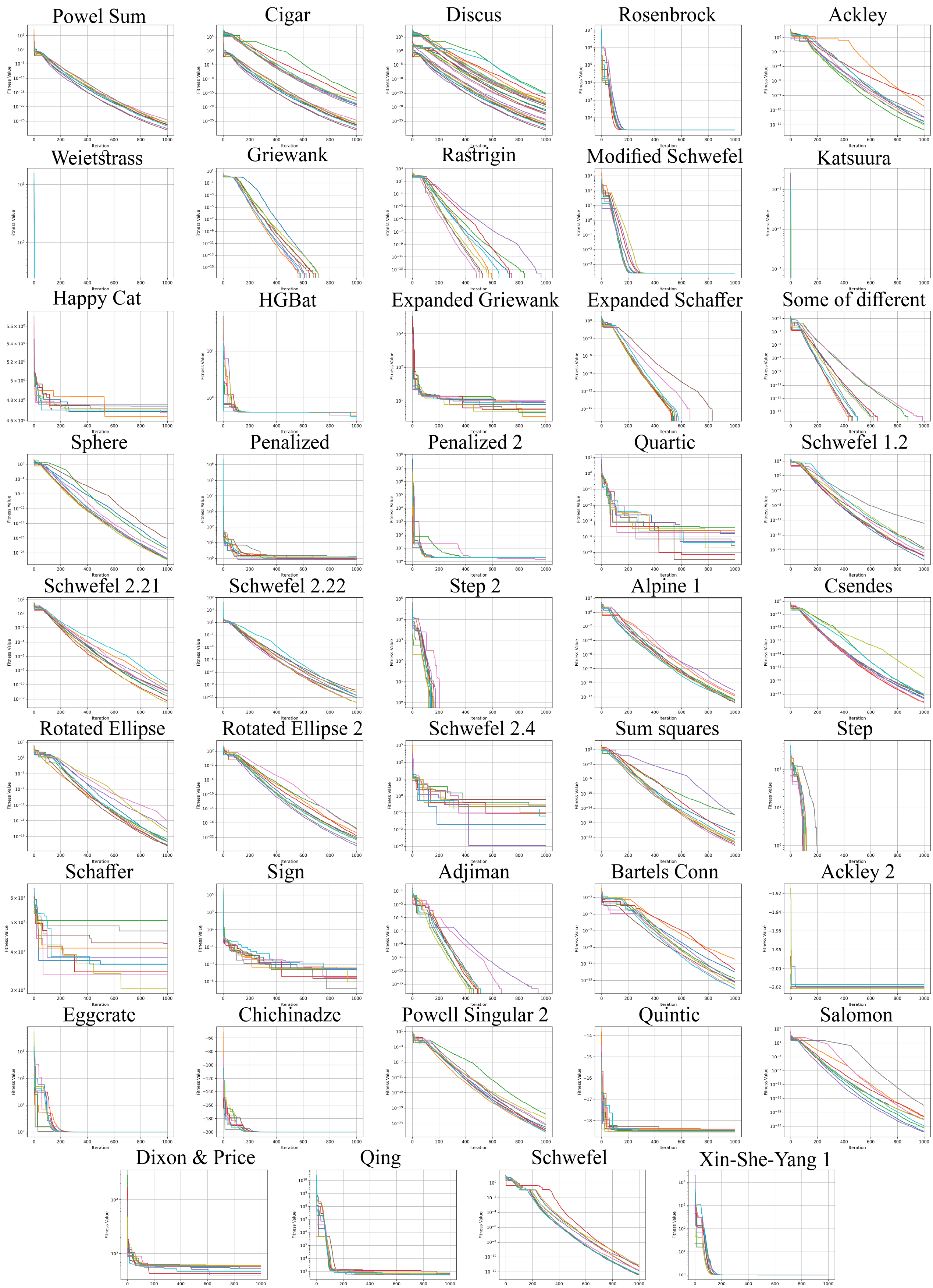

Figure 4. Convergence curves of 10 trials for each of the 44 benchmark functions (dimension: 20, iterations: 1000, population: 150) with our proposed ISUD optimization algorithm.

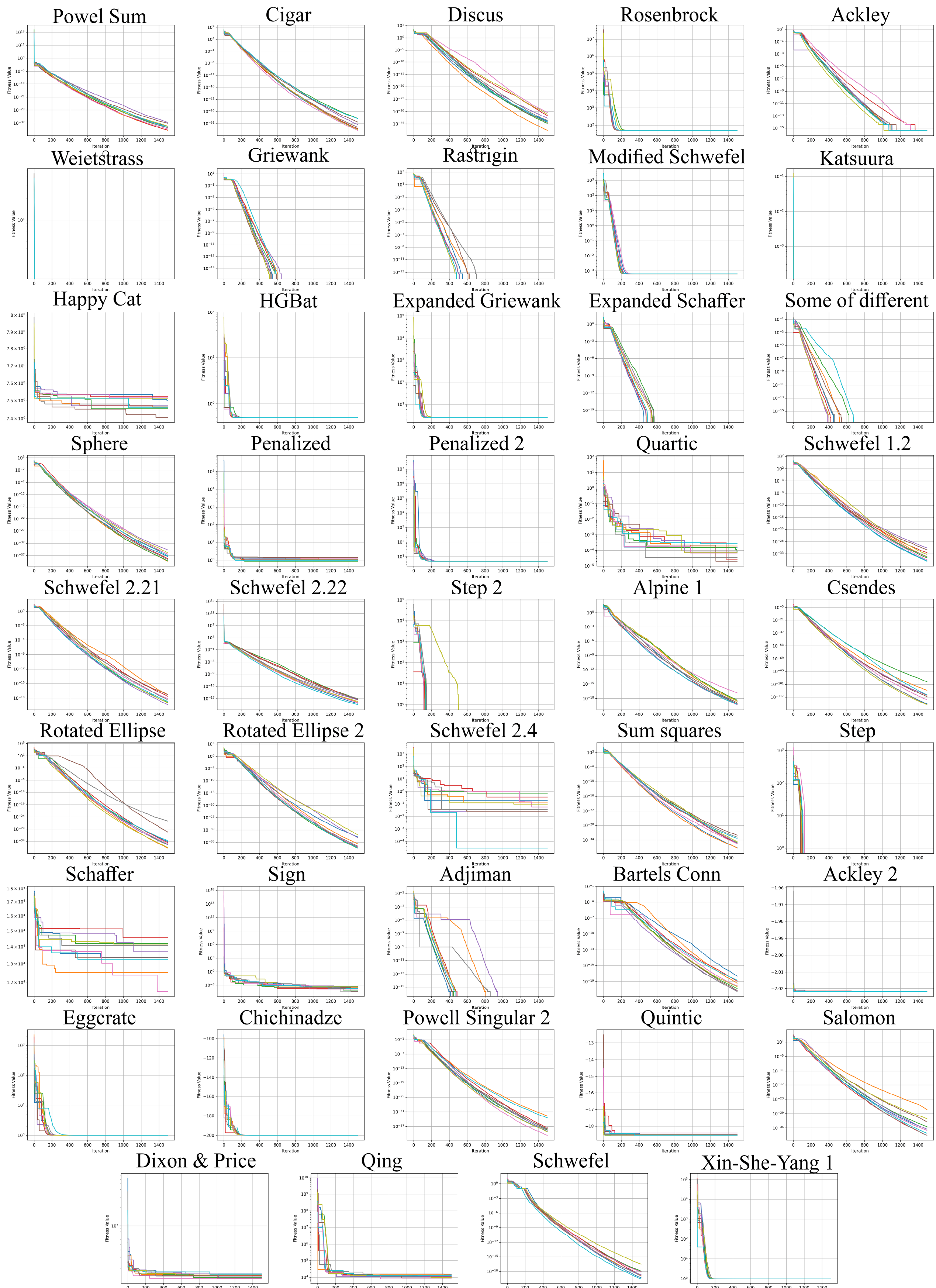

Figure 5. Convergence curves of 10 trials for each of the 44 benchmark functions (dimension: 50, iterations: 1500, population: 200) with our proposed ISUD optimization algorithm.

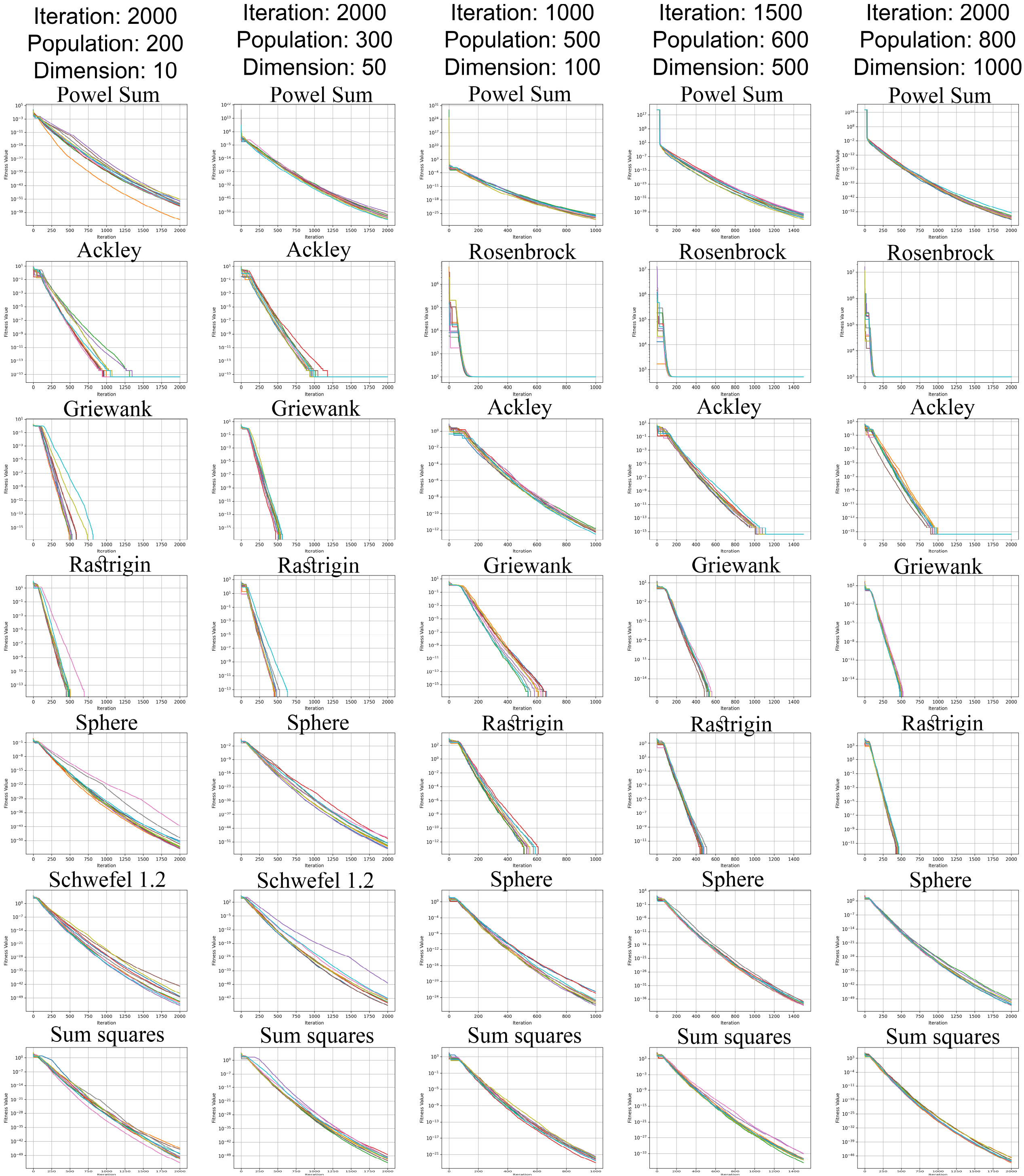

Figure 6. Convergence curves of 10 trials on 7 benchmark functions with different dimension, iterations, and population with our proposed ISUD optimization algorithm.

افراد با اختلال مصرف مواد مخدر: یک روش فراابتکاری جدید برای حل مسائل بهینه‌سازی

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ارسال ۲۰۲۴/۱۰/۰۵؛ بازنگری ۲۰۲۵/۰۱/۱۹؛ پذیرش ۲۰۲۵/۰۳/۰۴

چکیده:

در زمینه بهینه‌سازی، الگوریتم‌های فراابتکاری سهم قابل توجهی را به خود اختصاص داده‌اند. این الگوریتم‌ها که از انتخاب طبیعی، تکامل و استراتژی‌های حل مسأله الهام می‌گیرند، یک رویکرد جایگزین برای حل مسائل پیچیده بهینه‌سازی ارائه می‌دهند. برخلاف روش‌های متداول مهندسی نرم‌افزار، فراابتکاری بر محاسبات مشتق در فضای جستجو متکی نیست. در عوض، آنها راه‌حل‌ها را با اصلاح و تطبیق مکرر فرآیند جستجوی خود بررسی می‌کنند. قضیه "ناهار غیر رایگان" ثابت می‌کند که یک طرح بهینه‌سازی نمی‌تواند در مواجهه با تمام چالش‌های بهینه‌سازی عملکرد خوبی داشته باشد. در طول دو دهه گذشته، تعداد زیادی از الگوریتم‌های فراابتکاری ظهور کرده‌اند که هر کدام ویژگی‌ها و محدودیت‌های منحصر به فردی دارند. در این مقاله، ما یک الگوریتم فراابتکاری جدید به نام "افراد با اختلال مصرف مواد" برای حل مسائل بهینه‌سازی، با بررسی رفتارهای بالینی افرادی که مجبور به استفاده از مواد مخدر هستند، پیشنهاد می‌کنیم. ما اثربخشی الگوریتم پیشنهادی خود را با مقایسه آن با چندین الگوریتم اکتشافی معروف در ۴۴ تابع معیار با ابعاد مختلف ارزیابی می‌کنیم. نتایج نشان می‌دهد که الگوریتم معرفی شده از این روش‌های موجود بهتر عمل می‌کند و راه‌حل‌های برتر برای مسائل بهینه‌سازی ارائه می‌دهد.

کلمات کلیدی: بهینه‌سازی، الگوریتم‌های فراابتکاری، هوش ازدحامی.