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ARTICLE

Using the Novel Wolverine Optimization Algorithm for Solving Engineering Applications

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ABSTRACT

This paper introduces the Wolverine Optimization Algorithm (WoOA), a biomimetic method inspired by the foraging behaviors of wolverines in their natural habitats. WoOA innovatively integrates two primary strategies: scavenging and hunting, mirroring the wolverine's adeptness in locating carrion and pursuing live prey. The algorithm's uniqueness lies in its faithful simulation of these dual strategies, which are mathematically structured to optimize various types of problems effectively. The effectiveness of WoOA is rigorously evaluated using the Congress on Evolutionary Computation (CEC) 2017 test suite across dimensions of 10, 30, 50, and 100. The results showcase WoOA's robust performance in exploration, exploitation, and maintaining a balance between these phases throughout the search process. Compared to twelve established metaheuristic algorithms, WoOA consistently demonstrates a superior performance across diverse benchmark functions. Statistical analyses, including paired t-tests, Friedman test, and Wilcoxon rank-sum tests, validate WoOA's significant competitive edge over its counterparts. Additionally, WoOA's practical applicability is illustrated through its successful resolution of twenty-two constrained scenarios from the CEC 2011 suite and four complex engineering design challenges. These applications underscore WoOA's efficacy in tackling real-world optimization challenges, further highlighting its potential for widespread adoption in engineering and scientific domains.

KEYWORDS

Optimization; bio-inspired; wolverine; exploitation; exploration; metaheuristic

1 Introduction

Optimization problems are classified as those that have multiple possible solutions. Optimization involves the task of identifying the best solution from the various options available for a given problem [1]. Each optimization problem can be mathematically described through three fundamental components: (i) decision variables, (ii) constraints, and (iii) the objective function. The core aim of an optimization task is to identify the most suitable values for the decision variables, which will either maximize or minimize the objective function. This process must be carried out while ensuring that all specified constraints are strictly adhered to. The decision variables represent the choices or inputs that can be adjusted, the constraints define the limitations or conditions that must be met, and the objective function quantifies the goal of the optimization, guiding the search toward the best possible solution [2]. Numerous optimization challenges in various fields such as science, mathematics, engineering, and practical applications require the use of suitable techniques to achieve at least near-optimal solutions. The strategies for solving these optimization problems are categorized into two main groups: deterministic and stochastic approaches [3].

Two types of deterministic methods, namely gradient-based and non-gradient-based, have been effective in addressing linear, convex, continuous, differentiable, and low-dimensional optimization problems [4,5]. However, as problems become more complex and dimensions increase, deterministic approaches become less efficient due to being trapped in local optima. In particular, the majority of practical optimization challenges exhibit characteristics such as non-linearity, lack of convexity, discontinuity, non-differentiability, and high dimensionality. The challenges posed by these types of optimization problems for deterministic methods have led researchers to investigate stochastic strategies [6].

Metaheuristic algorithms stand as a highly effective stochastic method for managing optimization tasks. Operating via random search within the problem-solving domain and employing trial and error processes along with random operators, these algorithms can yield suitable solutions for optimization problems. Their appeal lies in the simplicity of their concepts, easy implementation, lack of dependency on problem types, avoidance of the derivation process, and effectiveness in addressing non-linear, non-convex, discontinuous, non-differentiable, and high-dimensional problems, as well as problems involving discrete and unknown variables. These advantages have contributed to the widespread adoption of metaheuristic algorithms [7]. Metaheuristic algorithms begin by generating a set number of candidate solutions randomly to form the algorithm's population. These solutions are then enhanced through the updating steps of the iterative algorithm. Once the algorithm has completed the execution, the best candidate solution, which has been refined over multiple iterations, is put forth as the solution to the problem [8].

Metaheuristic algorithms employ random search techniques, which inherently lack the guarantee of finding the absolute global optimum. However, the solutions generated by these algorithms are often deemed quasi-optimal, as they tend to be close to the global optimum. This proximity to the best possible solution is generally sufficient for practical purposes, especially in complex and high-dimensional problems, where exact solutions are computationally infeasible. To tackle the challenge of obtaining solutions that are as close as possible to the global optimum, researchers have devised a multitude of metaheuristic algorithms. These algorithms are designed to enhance the efficiency and effectiveness of the search process, balancing exploration and exploitation to navigate the solution space more intelligently and improve the likelihood of approaching the global optimum [9].

Metaheuristic algorithms should incorporate both global and local levels within their random search mechanism. The global search involves exploration, allowing the algorithm to thoroughly traverse the problem-solving space to locate the primary optimum and avoid becoming trapped in a local optimum. Meanwhile, the local search involves exploitation, facilitating the algorithm's ability to pinpoint solutions closer to the global optimum by meticulously examining nearby solutions and promising areas. Maintaining a balance between exploration and exploitation during the search process within the problem-solving space is crucial for the success of metaheuristic algorithms in the optimization process [10].

The primary concern in the research is whether there is a need for the development of new metaheuristic algorithms, given the current existing algorithms. This question is addressed by the No Free Lunch (NFL) theorem [11], which suggests that due to the stochastic nature of metaheuristic algorithm optimization processes, a consistent performance across all problems cannot be expected. In other words, according to the NFL theorem, the effectiveness of a metaheuristic algorithm in solving one set of optimization problems does not ensure the same effectiveness in solving other optimization problems. This indicates that, while a metaheuristic algorithm might find the best solution for one optimization problem, it could struggle with another problem by only finding a subpar solution. The NFL theorem emphasizes that the effectiveness of a metaheuristic algorithm in solving an optimization problem is not guaranteed. Rather than assuming success, the theorem highlights the need for continuous exploration of metaheuristic algorithms. It encourages researchers to keep pushing the boundaries by developing new and improved algorithms to tackle optimization problems. This ongoing pursuit ensures that better solutions can be found, as no single algorithm can be universally successful across all problems. The theorem serves as a reminder that the search for optimal solutions is an ever-evolving challenge.

Based on the NFL theorem, it is not possible to claim that any single metaheuristic algorithm is the best optimizer for all optimization problems. This limitation stems from three primary reasons.

Firstly, the inherent randomness in the search process of metaheuristic algorithms often leads to discrepancies between the solutions they produce and the true optimal solution of a problem. This issue becomes particularly significant when dealing with optimization problems where the optimal solution is unknown. In such cases, determining the absolute optimality of an algorithm is a fundamental challenge. Consequently, there is a need to design new and more efficient metaheuristic algorithms to address these problems more effectively, thereby enhancing solution accuracy and improving overall algorithm efficiency.

Secondly, many practical optimization problems possess specific characteristics that align closely with the search behaviors of certain metaheuristic algorithms. As a result, these algorithms can be highly effective for optimization problems that share a similar nature to their search mechanisms. However, the same algorithm may exhibit weaker performance when applied to optimization problems of a completely different nature. Since different metaheuristic algorithms are inspired by varying sources and exhibit distinct search behaviors, each algorithm tends to be suitable for only certain types of problems. This specialization means that existing optimization algorithms may struggle to effectively solve newly emerging or highly complex problems, highlighting the need for continuous innovation in the development of metaheuristic techniques.

The third reason is that the development of new metaheuristic algorithms allows to achieve better values than existing algorithms for optimization problems. The development of a new metaheuristic algorithm is a valuable opportunity to share knowledge with the aim of tackling challenging optimization problems, especially in real-world applications. Normally, a new metaheuristic algorithm is expected to be able to perform the optimization process efficiently by using specific operators and strategies. According to this, these reasons and the concept of the NFL theorem are the main motivations of the authors in order to design a new metaheuristic algorithm to provide more effective solutions for optimization problems.

However, the development of metaheuristic algorithms remains a worrisome challenge. This is the concern that the field of study of metaheuristic algorithms will move away from scientific accuracy. Therefore, researchers should use tests and analyzes to ensure that the algorithms they develop have significant improvements compared to existing algorithms. All this confirms that the development of newer metaheuristic algorithms is still a necessity in science, but also a challenge [12].

This article brings a fresh perspective by introducing the Wolverine Optimization Algorithm (WoOA), a new metaheuristic algorithm with practical applications for solving optimization problems. The key highlights of this research are as follows:

- WoOA is designed based on simulating the natural wolverine behaviors in the wild.
- The concept behind WoOA draws from the wolverine's foraging approach, encompassing both scavenging and hunting.
- The WoOA theory is described and mathematically modeled in two strategies (i) scavenging and (ii) hunting.
- The scavenging strategy is modeled in a phase (i) exploration based on the simulation of wolverine movement towards carcasses.
- The hunting strategy is modeled in two phases (i) exploration based on the simulation of the wolverine's movement towards the location of live prey and (ii) exploitation based on the simulation of the process of chasing and fighting between the wolverine and the prey.
- The performance of WoOA for solving optimization problems is evaluated in handling the Congress on Evolutionary Computation (CEC) 2017 test suite.
- The effectiveness of WoOA for handling optimization tasks in real-world applications is challenged in solving twenty-two constrained optimization problems from the CEC 2011 test suite as well as four engineering design problems.
- The quality of WoOA in the optimization process is compared with the performance of twelve well-known metaheuristic algorithms.

The paper is organized as follows: Section 2 contains the literature review, followed by the introduction and modeling of the Wolverine Optimization Algorithm (WoOA) in Section 3. Section 4 presents simulation studies and results, while Section 5 investigates the effectiveness of WoOA in solving real-world applications. Finally, Section 6 includes some conclusions and suggestions for future research.

2 Literature Review

Metaheuristic techniques have emerged by taking cues from diverse natural phenomena, biological theories, genetic mechanisms, human conduct, and evolutionary theories. Each category harnesses completely different mechanisms and concepts to address optimization problems. For instance, swarm-based approaches draw from the collective behavior observed in natural systems, such as flocks of birds or schools of fish, while evolutionary-based approaches mimic biological evolution and genetic algorithms. Physics-based approaches leverage physical laws and phenomena to guide the search process, and human-based approaches incorporate elements of human thinking and decision-making. By drawing on such diverse sources, these techniques provide varied and innovative solutions to optimization challenges, showcasing how different strategies can be applied to achieve effective problem-solving.

Swarm-based metaheuristic algorithms are inspired by the collective behavior observed in various natural systems, where groups of organisms work together in coordinated patterns. These algorithms simulate the interaction and cooperation found in swarms of creatures such as insects, birds, and fish to solve optimization problems. For example, Particle Swarm Optimization (PSO) [13] mimics the way flocks of birds or schools of fish move collectively in search of food. Similarly, Ant Colony Optimization (ACO) [14] draws from the foraging behaviors of ants, while the Artificial Bee Colony (ABC) [15] algorithm is inspired by the food search strategies of honeybees. The Firefly Algorithm (FA) [16] on the other hand, is based on the flashing patterns of fireflies. Each of these algorithms utilizes the inherent collaborative and adaptive behaviors of these natural systems to effectively explore and exploit the solution space. The Pelican Optimization Algorithm (POA) is created by mimicking the hunting strategy of pelicans as they catch fish in the sea [17]. The Reptile Search Algorithm (RSA) is crafted with inspiration from the hunting patterns of crocodiles [18]. In the nature, various actions such as foraging, hunting, migration, digging, and chasing are notable behaviors exhibited by living organisms. These behaviors have inspired the development of algorithms like: Orca Predation Algorithm (OPA) [19], Whale Optimization Algorithm (WOA) [20], Coati Optimization Algorithm (COA) [21], Pufferfish Optimization Algorithm (POA) [9], Tunicate Swarm Algorithm (TSA) [22], Honey Badger Algorithm (HBA) [23], White Shark Optimizer (WSO) [24], Golden Jackal Optimization (GJO) [25], Grey Wolf Optimizer (GWO) [26], Marine Predator Algorithm (MPA) [27], and African Vultures Optimization Algorithm (AVOA) [28].

Evolutionary-based metaheuristic algorithms are grounded in genetic and biological principles, drawing from concepts such as survival of the fittest, natural selection, and Darwin's theory of evolution. These algorithms mimic the process of biological evolution to address optimization problems, utilizing mechanisms such as reproduction, genetic inheritance, and random evolutionary operations. Key examples in this category include the Genetic Algorithm (GA) [29] and Differential Evolution (DE) [30]. Specifically, they incorporate selection processes that mimic the survival of the fittest, mutation operations that introduce genetic diversity, and crossover techniques that combine genetic information from parent solutions to create offspring. By leveraging these evolutionary strategies, GA and DE effectively explore the solution space and evolve towards increasingly optimal solutions over successive generations. The human immune system's way of handling germs and illnesses has been a model for the development of the Artificial Immune System (AIS) [31]. Some other evolutionary-based metaheuristic algorithms are: Evolution Strategy (ES) [32], One-to-One Based Optimizer (OOBO) [33], Genetic Programming (GP) [34], and Cultural Algorithm (CA) [35].

Physics-based metaheuristic algorithms draw inspiration from various natural concepts such as laws, forces, transformations, processes, and phenomena. The well-known algorithm called Simulated Annealing (SA) is a prime example of this category, as it takes inspiration from the physical process of metal annealing, where metals are subjected to heat to melt, and then slowly cooled to form perfect crystals [36]. The development of algorithms such as the Spring Search Algorithm (SSA) [37], the Gravitational Search Algorithm (GSA) [38], and the Momentum Search Algorithm (MSA) [39] is rooted in harnessing physical forces and adhering to Newton's laws of motion. For instance, SSA leverages the elastic force of springs, GSA operates on the principle of gravitational attraction force, and MSA utilizes momentum force as its guiding principle. These algorithms simulate the behavior of physical phenomena to drive their optimization processes, offering unique perspectives and approaches to problem-solving in various domains. Concepts related to the universe and cosmology have served as a key source of inspiration in the development of algorithms such as the Black Hole Algorithm (BHA) [40] and the Multi-Verse Optimizer (MVO) [41]. Some other physics-based metaheuristic algorithms are: Optical Microscope Algorithm (OMA) [42], Electro-Magnetism Optimization (EMO)

[43], Equilibrium Optimizer (EO) [44], Henry Gas Optimization (HGO) [45], Water Cycle Algorithm (WCA) [46], Archimedes Optimization Algorithm (AOA) [47], Lichtenberg Algorithm (LA) [48], Thermal Exchange Optimization (TEO) [49], and Nuclear Reaction Optimization (NRO) [50].

Human-based metaheuristic algorithms are designed to replicate various aspects of human behavior, including communication, decision-making, interactions, and cognitive processes. These algorithms model the way people handle complex tasks and make decisions to tackle optimization problems. One notable example is the Teaching-Learning Based Optimization (TLBO) algorithm, which is inspired by the dynamics of educational environments. TLBO mimics the interaction between teachers and students in a classroom, where teachers impart knowledge and students learn through exchange and feedback [51]. Another example is the Mother Optimization Algorithm (MOA), which is based on parenting strategies observed in Eshrat's mother as she nurtures and guides her children [52]. Additionally, the Doctor and Patient Optimization (DPO) algorithm draws from the interactions between medical professionals and patients, reflecting the therapeutic processes involved in treatment [53]. Other human-based metaheuristic algorithms include War Strategy Optimization (WSO), which models strategies used in military conflicts [54] and Gaining Sharing Knowledge-based Algorithm (GSK), which simulates the exchange and accumulation of knowledge among individuals [55]. The Coronavirus Herd Immunity Optimizer (CHIO) is inspired by the concepts of herd immunity in disease control [56], while the Ali Baba and the Forty Thieves Algorithm (AFT) is inspired by the legendary tale of resourceful problem-solving and strategy [57].

In Table 1, a review study on metaheuristic algorithms is presented. In the literature, it is acknowledged that no metaheuristic algorithm has been developed by simulating the natural behaviors of wolverines in the wild. However, the wolverine's clever methods of scavenging and hunting could serve as a valuable source of inspiration for creating a novel optimizer. Addressing this void in the research on metaheuristic algorithms, the paper introduces a new algorithm that models wolverine feeding strategies in the nature, as discussed in the following section.

Table 1: Comprehensive overview of metaheuristic algorithms and their inspirations

Group	Algorithm	Source of inspiration and explanation	Year
Swarm-based	Particle Swarm Optimization (PSO) [13]	Inspired by the social behavior of birds flocking or fish schooling, PSO optimizes a problem by iteratively improving a candidate solution with regard to a given measure of quality.	1995
	Ant Colony Optimization (ACO) [14]	Inspired by the foraging behavior of ants, ACO uses a population of artificial ants to search for optimal paths through graphs, with pheromone trails guiding the search process.	1996

(Continued)

Table 1 (continued)

Group	Algorithm	Source of inspiration and explanation	Year
	Artificial Bee Colony (ABC) [15]	Inspired by the foraging behavior of honey bees, ABC simulates the intelligent foraging behavior of a honey bee swarm to find an optimal solution.	2007
	Firefly Algorithm (FA) [16]	Inspired by the flashing behavior of fireflies, FA is used to solve optimization problems by mimicking the attraction between fireflies.	2010
	Grey Wolf Optimizer (GWO) [26]	Inspired by the leadership hierarchy and hunting mechanism of grey wolves, GWO mimics the social structure and hunting behavior of wolves to optimize solutions.	2014
	Whale Optimization Algorithm (WOA) [20]	Inspired by the bubble-net feeding behavior of humpback whales, WOA mimics this strategy to search for optimal solutions.	2016
	Marine Predator Algorithm (MPA) [27]	Inspired by the predation strategies of marine predators, MPA uses their diverse and adaptive hunting techniques to solve optimization problems.	2020
	Tunicate Swarm Algorithm (TSA) [22]	Inspired by the swarm behavior of tunicates, TSA mimics their efficient and collective movement patterns to solve optimization problems.	2020
	African Vultures Optimization Algorithm (AVOA) [28]	Inspired by the scavenging behavior of African vultures, AVOA uses their efficient search and optimization techniques to find the best solutions.	2021

(Continued)

Table 1 (continued)

Group	Algorithm	Source of inspiration and explanation	Year
	Honey Badger Algorithm (HBA) [23]	Inspired by the fearless and versatile hunting behavior of honey badgers, HBA uses their problem-solving strategies to optimize solutions.	2022
	White Shark Optimizer (WSO) [24]	Inspired by the predatory behavior of white sharks, WSO mimics their hunting strategies to explore and exploit the search space effectively.	2022
	Pelican Optimization Algorithm (POA [17]	Inspired by the hunting strategy of pelicans, POA simulates their cooperative and efficient foraging behavior to find optimal solutions.	2022
	Orca Predation Algorithm (OPA) [19]	Inspired by the predation strategies of orcas, OPA simulates their cooperative hunting techniques to optimize solutions.	2022
	Reptile Search Algorithm (RSA) [18]	Inspired by the hunting and survival strategies of reptiles, RSA uses these strategies to explore and exploit the search space effectively.	2022
	Golden Jackal Optimization (GJO) [25]	Inspired by the social hunting strategies of golden jackals, GJO mimics their cooperative behavior to solve optimization problems.	2022
	Serval Optimization Algorithm (SOA) [58]	Inspired by the hunting strategies of servals, SOA mimics their stealthy and adaptive predation techniques to explore and exploit the search space.	2022
	Coati Optimization Algorithm (COA) [21]	Inspired by the social foraging behavior of coatis, COA uses their collaborative and efficient searching techniques to solve optimization problems.	2023

(Continued)

Table 1 (continued)

Group	Algorithm	Source of inspiration and explanation	Year
	Pufferfish Optimization Algorithm (POA) [9]	Inspired by the unique behavior of pufferfish, this algorithm uses their strategy of inflating to avoid predators and search for food to optimize solutions.	2024
Evolutionary-based	Genetic Algorithm (GA) [29]	Inspired by the process of natural selection and genetics, GA uses operations such as mutation, crossover, and selection to evolve solutions to optimization problems.	1988
	Genetic Programming (GP) [34]	Inspired by the process of natural evolution, GP evolves programs or algorithms to solve problems by using operations such as crossover, mutation, and selection.	1992
	Cultural Algorithm (CA) [35]	Inspired by the evolution of cultures, CA uses the dual inheritance model of genetic and cultural evolution to optimize solutions.	1994
	Differential Evolution (DE) [30]	Inspired by the concept of natural evolution, DE uses differential mutation and recombination to evolve a population of candidate solutions.	1997
	Evolution Strategy (ES) [32]	Inspired by the principles of natural evolution, ES uses strategies such as mutation, recombination, and selection to optimize solutions.	2002
	Artificial Immune System (AIS) [31]	Inspired by the human immune system, AIS uses the principles of immune response to detect and eliminate non-self elements, optimizing solutions based on these mechanisms.	2003

(Continued)

Table 1 (continued)

Group	Algorithm	Source of inspiration and explanation	Year
	One-to-One Based Optimizer (OOBO) [33]	Inspired by one-to-one communication models, OOBO optimizes solutions by simulating direct interactions between solution candidates.	2023
Physic-based	Simulated Annealing (SA) [36]	Inspired by the annealing process in metallurgy, SA explores the solution space by probabilistically accepting worse solutions to escape local optima, gradually reducing the acceptance probability.	1983
	Gravitational Search Algorithm (GSA) [38]	Inspired by the law of gravity and mass interactions, GSA optimizes solutions by modeling agents as objects and their performance as masses that attract each other.	2009
	Electro-Magnetism Optimization (EMO) [43]	Inspired by the electromagnetic theory, EMO simulates the attraction and repulsion of charged particles to find optimal solutions.	2012
	Water Cycle Algorithm (WCA) [46]	Inspired by the natural water cycle, WCA uses the processes of precipitation, runoff, and evaporation to guide the search for optimal solutions.	2012
	Multi-Verse Optimizer (MVO) [41]	Inspired by the concepts of physics and cosmology, MVO uses the principles of the multiverse and white/black holes to find optimal solutions.	2016
	Thermal Exchange Optimization (TEO) [49]	Inspired by the thermal exchange process, TEO uses the principles of heat transfer and thermal equilibrium to optimize solutions.	2017

(Continued)

Table 1 (continued)

Group	Algorithm	Source of inspiration and explanation	Year
	Henry Gas Optimization (HGO) [45]	Inspired by Henry's Law in chemistry, HGO simulates the behavior of gas molecules to find optimal solutions.	2019
	Nuclear Reaction Optimization (NRO) [50]	Inspired by nuclear reactions, NRO uses the principles of nuclear fusion and fission to find optimal solutions.	2019
	Spring Search Algorithm (SSA) [37]	Inspired by the physical behavior of springs, SSA uses the principles of Hooke's Law and energy conservation to find optimal solutions.	2020
	Momentum Search Algorithm (MSA) [39]	Inspired by the momentum concept in physics, MSA uses the momentum of particles to guide the search for optimal solutions.	2020
	Equilibrium Optimizer (EO) [44]	Inspired by dynamic systems and the control of equilibrium, EO uses the concept of mass balance models to find optimal solutions.	2020
	Archimedes Optimization Algorithm (AOA) [47]	Inspired by Archimedes' principle, AOA uses the principles of buoyancy and density to explore and exploit the search space.	2021
	Lichtenberg Algorithm (LA) [48]	Inspired by Lichtenberg figures in physics, LA simulates the branching patterns of electrical discharges to find optimal solutions.	2021
	Optical Microscope Algorithm (OMA) [42]	Inspired by the imaging principles of optical microscopes, OMA uses the focusing and magnifying properties to explore and exploit the search space.	2023

(Continued)

Table 1 (continued)

Group	Algorithm	Source of inspiration and explanation	Year
Human-based	Teaching-Learning Based Optimization (TLBO) [51]	Inspired by the teaching-learning process in a classroom, TLBO optimizes solutions by simulating the influence of teachers on learners and the interactions among learners.	2011
	Doctor and Patient Optimization (DPO) [53]	Inspired by the interaction between doctors and patients, DPO models this relationship to diagnose and treat solutions, optimizing the search process.	2020
	Gaining Sharing Knowledge based Algorithm (GSK) [55]	Inspired by the process of gaining and sharing knowledge in human societies, GSK uses these principles to explore and exploit the search space.	2020
	Coronavirus Herd Immunity Optimizer (CHIO) [56]	Inspired by the concept of herd immunity in epidemiology, CHIO simulates the spread and control of disease to find optimal solutions.	2021
	War Strategy Optimization (WSO) [54]	Inspired by the strategies used in warfare, WSO simulates strategic planning, resource allocation, and tactical maneuvers to find optimal solutions.	2022
	Ali Baba and the Forty Thieves (AFT) [57]	Inspired by the story of Ali Baba and the Forty Thieves, AFT models the strategies of evasion, planning, and resource management to optimize solutions.	2022
	Mother Optimization Algorithm (MOA) [52]	Inspired by the nurturing and problem-solving behavior of mothers, MOA uses these principles to explore and exploit the search space effectively.	2023

3 Wolverine Optimization Algorithm (WoOA)

This section delves into the underlying inspiration for the creation of the Wolverine Optimization Algorithm (WoOA) and provides an in-depth explanation of how its implementation steps are mathematically formulated to address optimization problems. It explores the natural behaviors and strategies of wolverines that serve as the foundation for WoOA, highlighting the unique aspects that differentiate this algorithm from others. Additionally, it offers a comprehensive overview of the mathematical modeling process used to translate these biological inspirations into effective computational procedures for optimizing various types of problems.

3.1 Inspiration of WoOA

The wolverine, the largest land-dwelling species in the Mustelidae family, is primarily found in remote areas of subarctic and alpine tundra in the Northern Hemisphere as well as in the Northern boreal forests. An image of the wolverine is shown in Fig. 1.

Figure 1: Wolverine taken from: free media Wikimedia Commons

Among the natural behaviors of wolverine in the wild, the feeding strategies of this animal are much more prominent. The wolverine feeds in two ways: (i) scavenging and (ii) hunting. In the scavenging strategy, the wolverine finds the carrion and feeds on it by following the tracks of other predators. In the hunting strategy, the wolverine attacks the live prey and after a process of chasing and fighting, kills the prey and feeds on it. These two wolverine's feeding strategies are intelligent processes whose mathematical modeling is employed to design the proposed WoOA approach that is discussed below.

3.2 Algorithm Initialization

The proposed WoOA approach is an evolutionary algorithm based on a population of wolverines. By leveraging the search capabilities of its members in addressing problems, WoOA is capable of generating effective solutions for optimization tasks through an iterative process. Each wolverine, as a member of WoOA, defines decision variables based on its position within the problem-solving space. In essence, every wolverine represents a potential solution to the problem, which is delineated using a vector in mathematical terms. Together, these wolverines form the WoOA population, and their collective behavior is mathematically represented using a matrix as per Eq. (1). The initial positioning of the wolverines in the problem-solving space is randomized through Eq. (2) at the start of the algorithm execution.

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N\times m} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,d} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ x_{i,1} & \cdots & x_{i,d} & \cdots & x_{i,m} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,d} & \cdots & x_{N,m} \end{bmatrix}_{N\times m} \tag{1}$$

$$x_{i,d} = lb_d + r \cdot (ub_d - lb_d) \tag{2}$$

In this scenario, X represents the population matrix of the WoOA, X_i denotes the ith wolverine (which is essentially a potential solution), $x_{i,d}$ signifies its value in the dth dimension within the search space (i.e., decision variable). The variable N indicates the number of wolverines, while m represents the total number of decision variables. On the other hand, r is a random number in the interval [0, 1], lb_d, and ub_d denote a lower bound and an upper bound on the dth decision variable, respectively.

According to this concept, the position of each wolverine within the space intended for problem-solving serves as a plausible solution to the given problem. Based on this understanding, the suggested values of each wolverine for the decision variables aids in the assessment of the problem's objective function. These evaluated values for the objective function could then be effectively showcased in a vector form:

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times 1} \tag{3}$$

where F is the vector of the evaluated objective function values and F_i is the evaluated objective function value based on the ith wolverine.

The assessed values of the objective function provide valuable insights into the quality of the potential solutions. The best evaluated value of the objective function represents the top individual in the population (in other words, the best potential solution), while the worst evaluated value corresponds to the worst individual in the population (i.e., the worst potential solution). Since the position of wolverines in the problem-solving space is updated in each iteration of WoOA, the objective function is re-evaluated for each wolverine in every iteration. As a result, the top individual in the population should be regularly updated in every iteration by comparing the evaluated values of the objective function.

3.3 Mathematical Modelling of WoOA

The WoOA approach's design involves updating the position of the population members in the problem-solving space by simulating the natural feeding behavior of the wolverine. The wolverine has two strategies for feeding: (i) scavenging and (ii) hunting. In the scavenging strategy, wolverines feed on abandoned carrion by moving along the path of other predators that leave the remains of their kills. In the hunting strategy, the wolverine first attacks the prey and after going through a fighting process, finally kills the prey and feeds on it. In the design of WoOA, it is assumed that in each iteration, each wolverine randomly chooses one of these two strategies with equal probability, and based on the simulation of the selected strategy, its position in the problem-solving space is updated. Using Eq. (4), the wolverine simulates its decision-making process to determine whether to scavenge or hunt for food. This means that in every iteration, each wolverine's position is updated solely based on either the first or second strategy.

$$\text{Update process for } i\text{'th wolverine } X_i\text{:} \begin{cases} \textit{based on scavenging strategy}, & r_p \leq 0.5 \\ \textit{based on hunting strategy}, & \textit{else} \end{cases} \tag{4}$$

Here, r_p is a random number from the interval [0, 1].

3.3.1 Strategy 1: Scavenging Strategy (Exploration Phase)

The first WoOA strategy involves updating the location of the population members in the problem-solving space through simulating the natural feeding behavior of the wolverine on carrion. In this strategy, the wolverine to get the carrion, follows the path of other predators who have left the rest of their kills. Simulating the wolverine's movement in response to predators results in a radically different approach to exploring the solution space. This technique introduces significant variations in the positions of the population members, effectively altering their trajectories within the problem-solving domain. By adopting this strategy, the algorithm achieves a more comprehensive exploration of potential solutions. These extensive positional adjustments not only broaden the search area but also enhance the algorithm's capacity to uncover diverse and optimal solutions. Consequently, the method improves the algorithm's ability to perform a thorough global search, enabling it to better navigate complex problem spaces and discover innovative solutions. The scavenging strategy has an exploration phase based on simulating the wolverine's movement in obtaining carrion.

In the WoOA design, the location of other members with a better objective function value is considered as the predators' position who are aiming to release the rest of their kills for each wolverine, as specified in Eq. (5).

$$CP_i = \{X_k\text{: } F_k < F_i \textit{ and } k \neq i\}, \textit{where } i = 1, 2, \ldots, N \textit{ and } k \in \{1, 2, \ldots, N\} \tag{5}$$

where CP_i is the set of candidate predators' locations for the ith wolverine, X_k is the population member with a better objective function value than the ith wolverine, and F_k is its objective function value.

In the design of WoOA, it is presumed that the wolverine chooses the position of a predator from the CP_i set at random and then moves towards it. A schematic of this natural behavior of the wolverine during selection and moving towards the location of the predator that left its food remains is shown in Fig. 2. As the wolverine moves towards the selected predator with the goal of reaching the carrion, a new suggested position for the respective member has been computed using Eq. (6). If the objective function value is enhanced, this suggested position supersedes the previous position of the corresponding member according to Eq. (7).

$$x_{i,j}^{S1} = x_{i,j} + r_{i,j} \cdot (SP_{i,j} - I_{i,j} \cdot x_{i,j}), \tag{6}$$

$$X_i = \begin{cases} X_i^{S1}, & F_i^{S1} \le F_i, \\ X_i, & else, \end{cases} \tag{7}$$

where SP_i represents the chosen predator for the ith wolverine, while $SP_{i,j}$ denotes the jth dimension of this predator. X_i^{S1} refers to the newly computed position of the ith wolverine based on the scavenging strategy employed in the proposed WoOA. Similarly, $x_{i,j}^{S1}$ is the jth dimension of this new position. The term F_i^{S1} indicates the objective function value associated with the ith wolverine at its new position. Additionally, $r_{i,j}$ are random numbers uniformly drawn from the interval $[0, 1]$, and $I_{i,j}$ are binary random numbers that can be either 1 or 2.

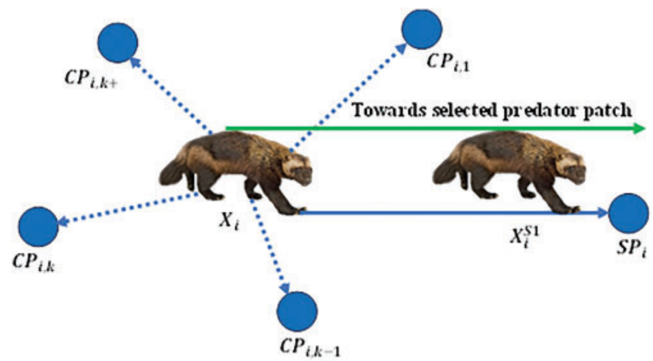

Figure 2: Diagram of wolverine's movement during scavenging strategy

3.3.2 Strategy 2: Hunting Strategy (Exploration and Exploitation Phases)

The second strategy of WoOA involves updating the position of the population members in the problem-solving space by simulating the natural hunting behavior of the wolverine. This process mirrors the wolverine's typical approach to hunting, where it first attacks live prey, then engages in a fight and chase before securing and feeding on its kill. The population members' update based on this hunting strategy consists of two phases: (i) exploration through simulating the wolverine's movement towards the prey and (ii) exploitation by simulating the fight and chase process between the wolverine and its prey.

- Phase 1: Attack (exploration phase)

During this phase of the WoOA, the population's location within the problem-solving space is adjusted as a result of simulating the process of a wolverine attacking its prey. By imitating the wolverine's movements during a hunt, significant changes are introduced to the population's position, thereby enhancing the exploration capabilities of WoOA in navigating through the problem-solving area. When designing the WoOA, the position of the best population member is likened to the prey's location. The schematic of this natural behavior of a wolverine during the attack towards the prey is shown in Fig. 3. Through simulating the wolverine's approach towards the best member (the "prey") for each member of WoOA, a new potential position is computed using Eq. (8). Subsequently, if the objective function demonstrates an improvement, this newly proposed position replaces the previous one for the corresponding member, as described in Eq. (9).

$$x_{i,j}^{P1} = x_{i,j} + r_{i,j} \cdot (Prey_j - I_{i,j} \cdot x_{i,j}), \tag{8}$$

$$X_i = \begin{cases} X_i^{P1}, & F_i^{P1} \le F_i, \\ X_i, & else, \end{cases} \tag{9}$$

where *Prey* is the best population member as prey, $Prey_j$ is its jth dimension, X_i^{P1} signifies the newly computed position for the ith wolverine, determined by the first phase of the hunting strategy in the proposed WoOA. Similarly, $x_{i,j}^{P1}$ refers to the jth dimension of this new position. F_i^{P1} indicates the objective function value of the ith wolverine at this new position. Additionally, $r_{i,j}$ are random values sampled from the interval [0, 1], and $I_{i,j}$ are binary numbers randomly assigned as either 1 or 2.

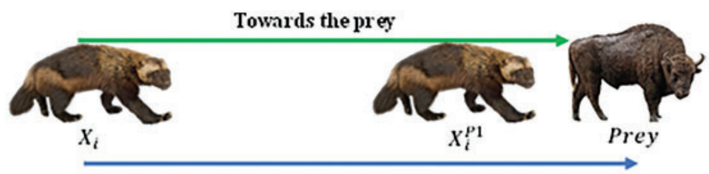

Figure 3: Diagram of wolverine's movement during attack towards the prey

- Phase 2: Fighting and chasing (exploitation phase)

During this WoOA phase, the population members' locations in the problem-solving space are adjusted through simulating the hunt and pursuit interactions between the wolverine and its prey. By simulating the movements of the wolverine during chasing, small changes are introduced to the positions of the population members, thereby enhancing the WoOA's capability for local search within the problem-solving space. The design of the WoOA assumes that these interactions occur in close proximity to the hunting location. The schematic of this natural behavior of wolverine during the process of chasing prey is shown in Fig. 4. Through modeling the wolverine's movements during the hunt and pursuit, a new position is calculated for each WoOA member using Eq. (10). If this new position improves the objective function value, as per Eq. (11), it replaces the member's previous position.

$$x_{i,j}^{P2} = x_{i,j} + (1 - 2r_{i,j}) \cdot \frac{ub_j - lb_j}{t} \tag{10}$$

$$X_i = \begin{cases} X_i^{P2}, & F_i^{P2} \le F_i \\ X_i, & else \end{cases} \tag{11}$$

where X_i^{P2} denotes the new position determined for the ith wolverine based on the second phase of the hunting strategy employed in the proposed WoOA. $x_{i,j}^{P2}$ represents the jth dimension of this updated position. F_i^{P2} indicates the objective function value associated with the ith wolverine at its new position. Additionally, $r_{i,j}$ are random numbers sampled from the interval $[0, 1]$, and t denotes the iteration counter.

3.4 Repetition Process, Pseudo-Code, and Flowchart of WoOA

After recalibrating the positions of all wolverines within the problem-solving space, the first iteration of WoOA is finalized. Following this, utilizing the updated values, the algorithm proceeds to the subsequent iteration, continuously adjusting the wolverines' positions until the algorithm's final iteration, based on Eqs. (4) to (11). Each iteration involves updating the best candidate solution by comparing assessed values for the objective function. Upon the algorithm's complete execution, the ultimate best solution uncovered throughout its iterations is unveiled as the WoOA solution for the assigned predicament. The implementation steps of WoOA are visually depicted in a flowchart in Fig. 5, and its pseudo-code is revealed in Algorithm 1.

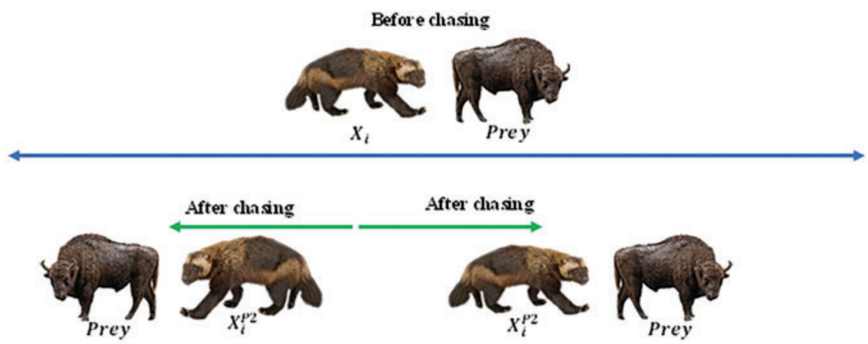

Figure 4: Diagram of wolverine's movement while fighting and chasing with prey

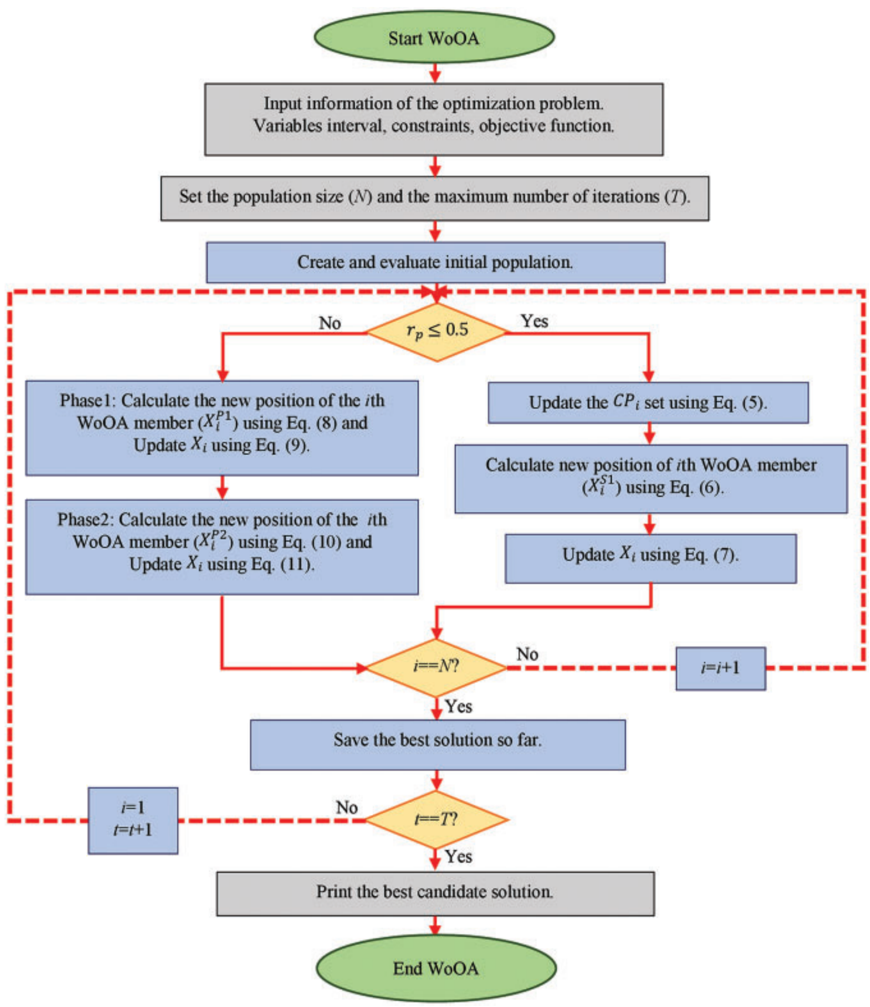

Figure 5: Flowchart of WoOA

3.5 Computational Complexity of WoOA

The computational complexity of the Wolverine Optimization Algorithm (WoOA) is crucial to understand its efficiency and scalability in solving optimization problems. Here, we analyze the factors that contribute to its complexity and compare its running times with other metaheuristic algorithms.

Factors Influencing the Computational Complexity

1. **Population Size (*N*)**
    - WoOA initializes a population of N candidate solutions in each iteration. The size of this population significantly affects the algorithm's performance and convergence speed.
2. **Number of Decision Variables (*m*)**
    - The complexity of evaluating each candidate solution depends on the number of decision variables m. As m increases, the search space grows exponentially, impacting the time required to evaluate potential solutions.
3. **Number of Iterations (*T*)**
    - WoOA iteratively refines its solutions over T iterations. The total number of iterations influences how thoroughly the algorithm explores and exploits the search space.
4. **Objective Function Evaluation (*O*(*f*))**
    - Evaluating the fitness of each candidate solution involves calculating the objective function f. The computational effort required for $O(f)$ depends on the complexity of f, including its mathematical formulation and any constraints.

Time Complexity Analysis

The time complexity per iteration of WoOA can be approximated as $O(N \cdot O(f))$, where:

- N is the population size.
- $O(f)$ represents the computational effort to evaluate the objective function for each candidate solution.

Therefore, over T iterations, the total time complexity of WoOA is $O(T \cdot N \cdot O(f))$. This formulation captures the algorithm's dependence on the number of iterations, population size, and the computational complexity of the objective function evaluation.

3.6 Applying WoOA to Constrained Optimization Challenges

Many real-world optimization problems are subject to constraints that must be managed to find feasible solutions. To address these types of constrained problems using the Wolverine Optimization Algorithm (WoOA), two distinct strategies are employed to handle solutions that do not meet the required constraints.

Replacement with Feasible Solutions: When an updated solution fails to satisfy the problem's constraints, it is completely removed from the population of solutions. In its place, a new solution is generated randomly, ensuring it adheres to all constraints. This approach ensures that the algorithm maintains a population of feasible solutions throughout its execution.

Penalty Coefficient Method: If a solution does not meet the problem's constraints, a penalty is added to its objective function value. This penalty makes the solution's objective function worse, thereby signaling the algorithm that this solution is less optimal compared to others. The penalty effectively discourages the selection of infeasible solutions by making their objective function values less competitive.

Both strategies help in maintaining the effectiveness of the WoOA in solving constrained optimization problems by either ensuring feasibility through replacement or penalizing infeasible solutions to guide the search towards feasible and optimal solutions.

Algorithm 1: Pseudo-code of WoOA

Start WoOA.
1. Input problem information: variables, objective function, and constraints.
2. Set the WoOA population size (N) and the number of iterations (T).
3. Generate the initial population matrix at random using Eq. (2). $x_{i,d} \leftarrow lb_d + r \cdot (ub_d - lb_d)$
4. Evaluate the objective function.
5. Determine the best candidate solution.
6. **For $t = 1$ to T**
7. **For $i = 1$ to N**
8. Determine the type of wolverine's feeding strategy using Eq. (4). $X_i \leftarrow \begin{cases} \textit{based on scavenging strategy}, & r_p \le 0.5 \\ \textit{based on hunting strategy}, & \textit{else} \end{cases}$
9. **if $r_p \le 0.5$ (Strategy 1: chose scavenging strategy)**
10. Determine candidate predators set for the ith wolverine based on Eq. (5). $CP_i \leftarrow \{X_k, F_k < F_i \text{ and } k \in \{1, 2, .., N\}\}$
11. Calculate the new position of the ith WoOA member using Eq. (6). $x_{i,j}^{S1} \leftarrow x_{i,j} + r_{i,j} \cdot (SP_{i,j} - I_{i,j} \cdot x_{i,j})$,
12. Update the ith WoOA member using Eq. (7). $X_i \leftarrow \begin{cases} X_i^{S1}, & F_i^{S1} < F_i \\ X_i, & \textit{else} \end{cases}$
13. **else (Strategy 2: chose hunting strategy)**
14. **Phase 1: Attack (exploration phase)**
15. Calculate the new position of the ith WoOA member using Eq. (8). $x_{i,j}^{P1} \leftarrow x_{i,j} + r_{i,j} \cdot (Prey_j - I_{i,j} \cdot x_{i,j})$,
16. Update the ith WoOA member using Eq. (9). $X_i \leftarrow \begin{cases} X_i^{P1}, & F_i^{P1} < F_i \\ X_i, & \textit{else} \end{cases}$
17. **Phase 2: Fighting and chasing (exploitation phase)**
18. Calculate the new position of the ith WoOA member using Eq. (10). $x_{i,j}^{P2} \leftarrow x_{i,j} + (1 - 2r_{i,j}) \cdot \dfrac{ub_j - lb_j}{t}$
19. Update the ith WoOA member using Eq. (11). $X_i \leftarrow \begin{cases} X_i^{P2}, & F_i^{P2} < F_i \\ X_i, & \textit{else} \end{cases}$
20. **end (if)**
21. **end (For $i = 1$ to N)**
22. Save the best candidate solution so far.
23. **end (For $t = 1$ to T)**
24. Output the best quasi-optimal solution obtained by the WoOA.

End WoOA.

---

4 Simulation Studies and Results

This section assesses the effectiveness of WoOA in addressing optimization problems using the CEC 2017 test suite.

4.1 Benchmark Functions and Compared Algorithm

The effectiveness of WoOA in managing optimization tasks has been compared to twelve well-known metaheuristic algorithms, including: GA [29], PSO [13], GSA [38], TLBO [51], MVO [41], GWO [26], WOA [20], MPA [27], TSA [22], RSA [18], AVOA [28], and WSO [24]. Table 2 provides the defined values for the control parameters of the metaheuristic algorithms. Experiments have been implemented on the software MATLAB R2022a using a 64-bit Core i7 processor with 3.20 GHz and 16 GB main memory. The optimization results obtained from applying these algorithms to benchmark functions are detailed, showcasing six statistical measures for the assessment: mean, best, worst, standard deviation (std), median, and rank. The mean index values have been employed as a ranking standard for the metaheuristic algorithms in addressing each of the benchmark functions.

Table 2: Control parameters values

Algorithm	Year	Parameter	Value
GA	1988		
		Type	Real coded
		Selection	Roulette wheel (Proportionate)
		Crossover	Whole arithmetic (Probability = 0.8, $\alpha \in [-0.5, 1.5]$)
		Mutation	Gaussian (Probability = 0.05)
PSO	1995		
		Topology	Fully connected
		Cognitive and social constant	$(C_1, C_2) = (2, 2)$
		Inertia weight	Linear reduction from 0.9 to 0.1
		Velocity limit	10% of dimension range
GSA	2009		
		Alpha, G_0, R_{norm}, R_{power}	20, 100, 2, 1
TLBO	2011		
		T_F: teaching factor	$T_F = \text{round}\,[(1 + rand)]$
		Random number	*rand* is a random number between $[0 - 1]$
GWO	2014		
		Convergence parameter (a)	a: Linear reduction from 2 to 0
MVO	2016		
		Wormhole existence probability (WEP)	Min(WEP) = 0.2 and Max(WEP) = 1
		Exploitation accuracy over the iterations (p)	$p = 6$
WOA	2016		
		Convergence parameter (a)	a: Linear reduction from 2 to 0
		r is a random vector in $[0, -1]$	
		l is a random number in $[-1, 1]$	
TSA	2020		

(Continued)

Table 2 (continued)

Algorithm	Year	Parameter	Value
		P_{min} and P_{max}	1, 4
		$c1$, $c2$, $c3$	Random numbers lie in the range of [0, −1]
MPA	2020		
		Constant number	$P = 0.5$
		Random vector	R is a vector of uniform random numbers in [0, 1] .
		Fish aggregating devices ($FADs$)	$FAs = 0.2$
		Binary vector	$U = 0$ or 1
RSA	2022		
		Sensitive parameter	$\beta = 0.01$
		Sensitive parameter	$\alpha = 0.1$
		Evolutionary sense (ES)	ES: randomly decreasing values between 2 and −2
AVOA	2021		
		L_1, L_2	0.8, 0.2
		w	2.5
		P_1, P_2, P_3	0.6, 0.4, 0.6
WSO	2022		
		F_{min} and F_{max}	0.07, 0.75
		τ, a_o, a_1, a_2	4.125, 6.25, 100, 0.0005

4.2 Evaluation CEC 2017 Test Suite

In this section, we evaluate the performance of the Wolverine Optimization Algorithm (WoOA) alongside other competing algorithms by applying them to the CEC 2017 test suite, with problem dimensions set at 10, 30, 50, and 100. The CEC 2017 test suite encompasses a total of thirty benchmark functions. These functions are categorized into several groups: three unimodal functions (C17-F1 through C17-F3), seven multimodal functions (C17-F4 through C17-F10), ten hybrid functions (C17-F11 through C17-F20), and ten composition functions (C17-F21 through C17-F30). For a comprehensive description and further details regarding the CEC 2017 test suite, please refer to [59].

In the process of evaluating the Wolverine Optimization Algorithm (WoOA) using the CEC 2017 test suite, function C17-F2 was omitted due to its erratic behavior. This exclusion was necessary to ensure the reliability and consistency of the results. Here, we explain the criteria for this exclusion and discuss its potential impact on the overall conclusions of the study.

Criteria for Exclusion of C17-F2

Function C17-F2 was excluded based on the following criteria:

1. **Erratic Behavior**
    - During preliminary testing, C17-F2 exhibited significant numerical instabilities, leading to inconsistent and unreliable results. This erratic behavior could be due to issues in the

function's formulation or implementation, which made it an outlier compared to the other benchmark functions.

2. **Unpredictable Performance**
    - The erratic nature of C17-F2 resulted in unpredictable performance outcomes, which did not align with the consistent patterns observed in other benchmark functions. This unpredictability hindered the ability to make fair and meaningful comparisons between WoOA and other algorithms.
3. **Impact on Statistical Validity**
    - Including a function with such a behavior could distort the statistical analysis and overall performance evaluation. To maintain the integrity of the study, it was crucial to exclude functions that could potentially bias the results due to their inherent instability.

Impact on Overall Conclusions

The exclusion of C17-F2 might raise concerns about the comprehensiveness of the study, but the following points explain why this exclusion does not undermine the overall conclusions:

1. **Representation of Benchmark Functions**
    - The CEC 2017 test suite comprises thirty benchmark functions, covering a wide range of optimization scenarios, including unimodal, multimodal, hybrid, and composition functions. With the exclusion of C17-F2, the remaining twenty-nine functions still provide a robust and comprehensive assessment of WoOA's performance.
2. **Consistency of Results**
    - The consistent superior performance of WoOA across multiple benchmark functions and problem dimensions (10, 30, 50, and 100) indicates that the exclusion of a single erratic function does not significantly alter the overall findings. WoOA demonstrated strong capabilities in exploration, exploitation, and maintaining a balance between the two throughout the search process.
3. **Statistical Significance**
    - Statistical analyses, including the Wilcoxon rank sum test, were conducted on the results obtained from the remaining benchmark functions. These analyses confirmed WoOA's significant statistical superiority over the twelve competing algorithms. The exclusion of C17-F2, therefore, does not compromise the statistical validity of these findings.
4. **Transparency and Integrity**
    - By explicitly stating the exclusion and providing the reasons for it, the study maintains transparency and integrity. Researchers and practitioners can understand the rationale behind the decision and trust the reliability of the reported results.

Function C17-F2 was omitted from the evaluation due to its erratic behavior, which led to inconsistent and unreliable performance outcomes. The exclusion was necessary to maintain the reliability and consistency of the results. Despite this omission, the comprehensive assessment of WoOA using the remaining twenty-nine benchmark functions from the CEC 2017 test suite provides robust and statistically significant evidence of WoOA's superior performance. The study's transparency in reporting this exclusion further reinforces the integrity of the findings.

The CEC 2017 test suite is a standard set of benchmark functions to measure the abilities of metaheuristic algorithms in exploration, exploitation, and balancing them during the search process. Functions C17-F1 to C17-F3 are of unimodal type. Since these types of functions have only one global optimum and no local optimum, they are suitable criteria for testing the exploitation ability of metaheuristic algorithms. The functions C17-F4 to C17-F10 are selected from the multimodal type and have a large number of local optima. For this reason, these functions are suitable criteria for testing the exploration ability of metaheuristic algorithms for a comprehensive scanning of the problem-solving space. Functions C17-F11 to C17-F20 are selected from the hybrid type, where each function consists of several subcomponents. These types of functions can be a combination of unimodal and multimodal functions. For this reason, hybrid functions are suitable options to simultaneously investigate the exploration and exploitation capabilities of metaheuristic algorithms. Functions C17-F21 to C17-F30 are of composition type. These types of functions employ the hybrid functions as the basic functions and are considered as complex optimization problems. In an experimental level, the complexity of composition functions is increased significantly because of their shifted and rotated characteristics.

The WoOA methodology, along with several competing algorithms, was tested using the CEC 2017 benchmark functions across fifty-one independent runs. Each run involved 10,000·m function evaluations (FEs), where the population size (N) was set to 30. The results of these experiments are detailed in Tables 3 through 6, which compare the performance of WoOA against other algorithms.

The performance of WoOA shows notable variation across different problem dimensions. For a problem dimension of 10 ($m = 10$), WoOA excelled as the top optimizer for functions C17-F1, C17-F3 through C17-F21, C17-F23, C17-F24, and C17-F26 through C17-F30. When the problem dimension increased to 30 ($m = 30$), WoOA continued to outperform competitors for functions C17-F1, C17-F3 through C17-F25, and C17-F27 through C17-F30. At a dimension of 50 ($m = 50$), WoOA maintained its superior performance for functions C17-F1, C17-F3 through C17-F25, and C17-F27 through C17-F30. Even for a higher dimension of 100 ($m = 100$), WoOA was identified as the best optimizer for functions C17-F1 and C17-F3 through C17-F30.

This consistent performance across different dimensions underscores the robustness and versatility of the WoOA approach in solving a wide range of optimization problems.

Table 3: Optimization outcomes for the CEC 2017 test suite (dimension = 10)

		WoOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
C17-F1	mean	**100**	2.07E+08	18824033	3.81E+08	10565042	72111739	11258905	28141604	64067375	94467505	8916573	8916898	72997402
	best	**100**	1.82E+08	12123003	3.41E+08	2434220	15895147	5439870	2562173	16923887	40544736	2355688	2357411	3042532
	worst	**100**	2.53E+08	24177145	4.47E+08	21714490	1.43E+08	17565839	85706245	1.14E+08	2.19E+08	15860212	15860260	2.49E+08
	std	**0**	32512583	5421468	49859433	8785132	56127106	5927000	39689712	46685189	85792051	6496760	6496290	1.21E+08
	median	**100**	1.96E+08	19497993	3.68E+08	9055730	64946173	11014956	12148999	62691281	59213756	8725196	8724961	20135768
	rank	**1**	12	6	13	4	9	5	7	8	11	2	3	10
C17-F3	mean	**300**	696.5436	445.3453	811.7348	492.7105	827.9655	951.2875	1035.346	1248.874	679.7242	6941.111	1733.864	2443.006
	best	**300**	684.5479	375.8597	779.3301	402.2618	698.6599	490.7569	625.5726	716.4046	457.441	4398.096	1179.468	1250.02
	worst	**300**	716.1485	561.7037	853.3373	669.7755	922.2049	1458.466	1772.05	2129.74	859.244	9358.299	2224.306	4612.614
	std	**0**	13.99907	86.74459	32.00169	129.3727	102.953	483.1546	541.5752	658.3504	184.4207	2091.671	440.411	1591.719
	median	**300**	692.739	421.9089	807.1358	449.4024	845.4987	927.9637	871.8809	1074.676	701.106	7004.024	1765.841	1954.695
	rank	**1**	5	2	6	3	7	8	9	10	4	13	11	12
C17-F4	mean	**400**	419.6727	401.9501	435.6411	401.2686	407.2473	409.9758	403.8799	406.0039	406.1684	403.8142	405.8608	409.3677
	best	**400**	411.3919	401.6282	418.0887	400.7884	403.4266	403.5609	402.1816	404.2936	406.0028	402.9275	401.1362	405.047
	worst	**400**	427.5401	402.1712	453.3012	402.0683	411.2154	427.3547	407.9994	410.8174	406.3819	404.6519	416.7601	422.1205
	std	**0**	7.49204	0.235542	15.44958	0.584222	4.117651	11.92077	2.830741	3.296877	0.180856	0.961524	7.519815	8.732487
	median	**400**	419.8794	402.0004	435.5873	401.1088	407.1736	404.4937	402.6694	404.4522	406.1444	403.8387	402.7734	405.1515
	rank	**1**	12	3	13	2	9	11	5	7	8	4	6	10
C17-F5	mean	**501.2464**	511.4968	511.2326	512.0238	509.9179	511.5993	521.0454	512.358	516.2128	523.855	538.7189	519.4131	511.987
	best	**500.9951**	508.2704	507.2932	507.9165	506.49	509.1871	513.9246	510.7562	513.113	519.9623	535.099	513.9149	508.2102
	worst	**501.9917**	514. 4871	514.1504	515.3282	512.8202	514.4427	532.2836	515.1526	520.0249	526.8993	545.9169	525.6652	517.8348
	std	**0.510361**	3.148357	3.182777	3.757323	3.134795	2.65058	8.495411	1.998131	3.031141	3.159537	5.041064	5.462114	4.230507
	median	**500.9993**	511.6149	511.7434	512.4253	510.1808	511.3836	518.9867	511.7616	515.8566	524.2792	536.9298	519.0361	510.9514
	rank	**1**	4	3	7	2	5	11	8	9	12	13	10	6
C17-F6	mean	**600**	601.4931	601.0017	601.848	600.5092	601.219	608.8413	600.87	602.1837	604.3503	611.7167	604.2293	601.1345
	best	**600**	601.2415	600.8829	601.7024	600.2986	600.7743	602.9923	600.491	601.5719	603.0246	602.208	600.9599	600.7289
	worst	**600**	601.6513	601.0914	602.0603	600.6449	601.7631	616.9464	601.3306	603.1169	606.4144	624.2639	607.7574	601.5405
	std	**0**	0.181261	0.108494	0.171525	0.166255	0.419245	6.015005	0.402519	0.676991	1.577283	10.51354	3.455234	0.368719
	median	**600**	601.5398	601.0162	601.8147	600.5466	601.1693	607.7133	600.8293	602.0231	603.981	610.1974	604.0999	601.1344
	rank	**1**	7	4	8	2	6	12	3	9	11	13	10	5
C17-F7	mean	**711.1267**	724.4114	723.6473	724.8014	722.0542	725.59	736.4661	723.8898	729.6783	739.4339	718.4797	723.4201	724.6826
	best	**710.6726**	721.4447	720.6237	722.2834	719.9304	721.77	731.3	720.6397	726.3918	736.6552	717.081	721.0464	717.9373
	worst	**711.7995**	727.3849	725.8692	727.2267	725.0672	728.2941	748.7402	729.6037	733.4887	744.5995	721.2265	727.1893	738.0862
	std	**0.526035**	2.828796	2.416377	2.460045	2.5636	3.179221	8.443954	4.094538	3.360558	3.621793	1.974394	2.717072	9.450627
	median	**711.0174**	724.4081	724.0483	724.8478	721.6095	726.1478	732.912	722.6579	729.4162	738.2404	717.8057	722.7223	721.3534
	rank	**1**	7	5	9	3	10	12	6	11	13	2	4	8
C17-F8	mean	**801.4928**	810.0179	809.9045	810.4179	808.9466	810.0501	818.9891	810.8321	817.2854	826.0362	816.3763	813.3752	814.2813
	best	**800.995**	808.4107	807.7155	808.7183	806.9715	808.8213	812.7755	809.3508	815.3428	822.0466	811.1683	811.1277	810.2727
	worst	**801.9912**	811.91	811.4316	812.2482	810.7915	812.0135	823.0574	812.1217	819.5321	830.3	821.2685	816.2396	817.8765
	std	**0.590448**	1.583361	1.800162	1.688595	1.686023	1.547217	4.83556	1.307187	1.765876	4.688405	4.531951	2.244262	3.334398
	median	**801.4926**	809.8754	810.2355	810.3525	809.0117	809.6827	820.0617	810.928	817.1334	825.8991	816.5343	813.0667	814.4881
	rank	**1**	4	3	6	2	5	12	7	11	13	10	8	9

(Continued)

Table 3 (continued)

		WoOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
C17-F9	mean	**900**	920.1993	912.525	922.0471	904.6717	918.663	1076.181	903.6976	906.7476	907.9166	900.939	901.8776	909.7401
	best	**900**	914.5869	903.5784	918.201	902.4732	910.8254	965.1442	900.5148	902.6965	905.9476	900.3753	900.5925	900.798
	worst	**900**	924.8188	930.8131	928.1582	905.9653	928.7274	1179.257	909.0113	912.0769	912.5594	901.6807	903.4826	926.114
	std	**0**	4.751892	12.97397	4.392435	1.570191	8.03666	92.51722	4.028539	4.044686	3.213806	0.562887	1.234102	12.1114
	median	**900**	920.6958	907.8542	920.9146	905.1243	917.5496	1080.162	902.6321	906.1086	906.5796	900.8501	901.7176	906.0243
	rank	**1**	11	9	12	5	10	13	4	6	7	2	3	8
C17-F10	mean	**1006.179**	1316.699	1325.903	1335.983	1293.968	1306.815	1556.772	1455.397	1614.251	1809.509	1945.609	1561.577	1615.88
	best	**1000.284**	1231.446	1247.163	1252.236	1215.883	1210.551	1337.485	1335.339	1441.475	1554.194	1759.896	1457.106	1456.308
	worst	**1012.668**	1465.047	1453.82	1488.279	1435.75	1458.743	1709.582	1592.743	1720.459	1970.877	2038.792	1665.176	1824.785
	std	**6.836865**	104.8949	94.68199	107.3987	99.98713	109.2127	171.4558	109.5894	127.9089	190.117	129.3626	99.86257	158.081
	median	**1005.882**	1285.151	1301.314	1301.709	1262.12	1278.982	1590.01	1446.753	1647.536	1856.483	1991.875	1562.012	1591.214
	rank	**1**	4	5	6	2	3	8	7	10	12	13	9	11
C17-F11	mean	**1100**	1190.097	1111.102	1211.283	1106.599	1264.157	1123.334	1120.856	1131.037	1134.204	1130.139	1119.436	1144.643
	best	**1100**	1143.463	1107.012	1117.819	1104.563	1257.292	1112.61	1114.291	1121.753	1125.525	1120.239	1115.692	1119.515
	worst	**1100**	1233.019	1114.346	1300.359	1111.064	1268.221	1130.321	1137.802	1151.771	1146.078	1148.148	1124.721	1200.861
	std	**0**	42.11591	3.121035	85.38261	3.082949	4.922816	8.60823	11.62445	14.36112	8.944126	12.75729	3.949371	39.20991
	median	**1100**	1191.953	1111.526	1213.476	1105.384	1265.558	1125.202	1115.666	1125.313	1132.607	1126.084	1118.666	1129.099
	rank	**1**	11	3	12	2	13	6	5	8	9	7	4	10
C17-F12	mean	**1352.959**	13178612	932400.6	26065576	288619.5	283516.9	1106074	706236.1	1756531	3201624	916489.9	381229.1	1279944
	best	**1318.646**	3214356	523861.3	6037463	142864.6	160485.8	176215.9	448194.1	810413	904412.2	460291.1	211864.7	337802.4
	worst	**1438.176**	22736420	1291046	45294531	483232.4	453194.5	1842035	939243.8	2967689	5647840	1440731	557619.5	2033767
	std	**58.85078**	10090442	361143.1	20343649	156487.6	137094.5	787885.2	214427.8	1032496	2556992	457745.1	195826	730679.8
	median	**1327.506**	13381836	957347.7	26465155	264190.5	260193.7	1203023	718753.3	1624012	3127121	882469	377716.2	1374104
	rank	**1**	12	7	13	3	2	8	5	10	11	6	4	9
C17-F13	mean	**1305.324**	631052.5	34323.18	1259690	2480.928	2678.962	4555.223	5027.703	8171.527	11284.32	8031.452	4581.443	8839.2
	best	**1303.114**	54421.67	5763.425	106470.5	2191.853	2603.603	3096.316	3329.263	6622.229	10522.64	4709.892	3051.532	5849.929
	worst	**1308.508**	2089508	106876.9	4176425	2640.844	2733.666	7311.352	5995.034	9016.087	12729.6	10857.29	6831.801	11947.15
	std	**2.334346**	1000817	49785.65	2001515	205.6981	57.07998	1972.652	1204.017	1153.355	1011.394	2631.047	1643.354	2567.197
	median	**1304.837**	190140	12326.19	377932.9	2545.508	2689.289	3906.611	5393.257	8523.895	10942.51	8279.314	4221.219	8779.862
	rank	**1**	12	11	13	2	3	4	6	8	10	7	5	9
C17-F14	mean	**1400.746**	1539.059	1478.203	1615.088	1472.107	1523.686	1493.226	1682.725	1745.508	1560.568	4193.63	2349.267	2141.208
	best	**1400**	1476.447	1433.05	1539.106	1414.769	1415.439	1441.503	1430.096	1458.776	1477.172	3520.88	1848.24	1456.138
	worst	**1400.995**	1632.431	1577.813	1750.485	1631.819	1569.205	1617.152	2433.195	2568.509	1692.574	5618.343	3029.526	4172.118
	std	**0.510957**	70.90894	70.18604	99.08282	109.435	75.24823	86.02261	513.871	563.609	94.83619	1011.17	559.9115	1390.637
	median	**1400.995**	1523.68	1450.975	1585.38	1420.92	1555.05	1457.125	1433.805	1477.373	1536.262	3817.648	2259.651	1468.288
	rank	**1**	6	3	8	2	5	4	9	10	7	13	12	11
C17-F15	mean	**1500.331**	2010.782	1847.108	2235.799	1819.406	1893.605	3419.311	2645.709	2876.181	1814.235	16440.38	6288.509	4850.593
	best	**1500.001**	1772.068	1627.092	1844.601	1672.54	1738.251	1929.844	2053.01	2175.88	1687.857	8150.782	3324.715	3109.926
	worst	**1500.5**	2324.376	2178.286	2882.472	1929.921	1999.193	6097.317	2935.55	3231.973	1916.33	24338.76	7634.811	5695.019
	std	**0.241803**	267.7749	241.453	498.8523	110.3346	126.2719	1884.852	414.8564	489.7182	106.9494	7918.253	2079.294	1218.689
	median	**1500.413**	1973.342	1791.526	2108.061	1837.581	1918.488	2825.041	2797.138	3048.435	1826.378	16635.99	7097.255	5298.714
	rank	**1**	6	4	7	3	5	10	8	9	2	13	12	11
C17-F16	mean	**1600.76**	1624.771	1618.528	1628.318	1615.544	1626.399	1738.01	1669.601	1666.668	1654.55	1921.205	1743.164	1703.446
	best	**1600.356**	1619.167	1617.301	1620.974	1608.95	1614.112	1670.019	1626.281	1627.892	1638.341	1832.775	1708.122	1615.612
	worst	**1601.12**	1629.965	1619.413	1638.055	1624.9	1636.589	1785.984	1706.58	1712.491	1692.824	2056.009	1780.784	1780.805
	std	**0.32447**	5.607179	0.981864	7.488103	6.885588	10.57286	56.59102	33.92291	35.82972	26.43499	103.2502	32.9397	69.88408

(Continued)

Table 3 (continued)

		WoOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
	median	**1600.781**	1624.975	1618.699	1627.121	1614.164	1627.447	1748.018	1672.771	1663.144	1643.517	1898.017	1741.874	1708.684
	rank	**1**	4	3	6	2	5	11	9	8	7	13	12	10
C17-F17	mean	**1700.099**	1714.681	1712.393	1715.624	1712.653	1713.949	1760.129	1744.139	1742.344	1741.02	1803.098	1739.114	1756.096
	best	**1700.02**	1710.037	1707.942	1710.861	1707.275	1709.385	1732.399	1726.175	1728.211	1732.697	1735.89	1724.161	1721.884
	worst	**1700.332**	1721.875	1718.478	1721.844	1719.065	1720.321	1780.832	1785.886	1778.195	1749.431	1891.016	1759.482	1836.559
	std	**0.159367**	5.889181	4.855677	5.551369	6.277567	5.230306	21.93064	28.98018	24.63894	7.780382	80.08671	16.73237	55.36515
	median	**1700.022**	1713.406	1711.577	1714.895	1712.136	1713.044	1763.643	1732.248	1731.484	1740.977	1792.743	1736.406	1732.971
	rank	**1**	5	2	6	3	4	12	10	9	8	13	7	11
C17-F18	mean	**1805.36**	107948.2	9225.268	211970.2	4167.068	4017.406	11495.82	10405.77	15031.45	19828.14	8843.267	9081.116	16864.63
	best	**1800.003**	9359.434	4151.773	14748.01	3248.512	3430.713	5118.233	6183.36	9713.984	15866.25	6439.052	5216.174	6205.479
	worst	**1820.451**	306581.2	19824.99	608647.1	5015.418	4553.7	16032.9	15019.3	19058.63	23927.94	10655.51	12948.12	27261.4
	std	**10.33599**	141657.4	7540.153	282990.8	864.7947	503.674	5414.727	4268.016	4418.829	3728.894	1890.638	4359.617	10952.81
	median	**1800.492**	57925.99	6462.155	112242.9	4202.171	4042.606	12416.07	10210.2	15676.59	19759.19	9139.254	9080.083	16995.81
	rank	**1**	12	6	13	3	2	8	7	9	11	4	5	10
C17-F19	mean	**1900.445**	16227.66	3027.272	27916.15	2493.708	6661.617	14162.98	2912.973	3676.572	3781.381	27467.68	12260.78	4691.643
	best	**1900.039**	2853.034	2289.794	3620.319	2064.231	1991.045	4090.321	1919.47	1950.938	1991.03	8462.689	6453.126	1939.914
	worst	**1901.559**	32027.43	3779.094	57442.11	3106.702	11246.33	24986.63	5024.347	5589.403	8468.45	39275.42	25088.29	11110.48
	std	**0.764786**	13155.67	865.1297	24972.75	466.0514	5291.278	8827.869	1461.281	1769.009	3217.978	14144.19	8882.37	4434.683
	median	**1900.09**	15015.09	3020.099	25301.08	2401.95	6704.548	13787.48	2354.037	3582.973	2333.021	31066.31	8750.844	2858.088
	rank	**1**	11	4	13	2	8	10	3	5	6	12	9	7
C17-F20	mean	**2000.312**	2029.208	2027.48	2032.328	2026.414	2028.931	2091.891	2074.063	2078.797	2055.251	2178.84	2087.042	2135.09
	best	**2000.312**	2019.675	2020.748	2021.611	2014.244	2021.097	2057.516	2060.343	2064.097	2044.672	2135.384	2075.717	2104.564
	worst	**2000.312**	2035.465	2030.302	2041.98	2033.698	2034.789	2119.226	2094.745	2103.658	2062.153	2243.83	2099.573	2194.117
	std	**0**	7.421631	4.648467	8.724256	8.995434	6.93835	30.62454	15.27574	17.80308	8.324249	54.45241	12.05402	41.38364
	median	**2000.312**	2030.846	2029.434	2032.861	2028.857	2029.918	2095.411	2070.583	2073.716	2057.089	2168.072	2086.438	2120.84
	rank	**1**	5	3	6	2	4	11	8	9	7	13	10	12
C17-F21	mean	**2200**	2211.949	2212.166	2213.146	2211.693	2213.177	2248.745	2241.209	2261.819	2266.885	2319.307	2256.789	2291.399
	best	**2200**	2208.585	2209.037	2208.426	2208.702	2210.891	2216.836	2233.462	2239.065	2207.611	2308.753	2253.664	2288.061
	worst	**2200**	2213.945	2213.711	2214.893	2212.865	2215.359	2265.835	2250.567	2272.687	2290.445	2332.216	2259.489	2295.744
	std	**0**	2.494655	2.200549	3.236899	2.053464	2.258423	22.42827	8.430577	15.77694	40.87346	9.948112	2.657753	3.550256
	median	**2200**	2212.632	2212.959	2214.632	2212.602	2213.229	2256.155	2240.404	2267.762	2284.743	2318.129	2257.002	2290.895
	rank	**1**	3	4	5	2	6	8	7	10	11	13	9	12
C17-F22	mean	**2300.073**	2315.897	2302.382	2324.035	2301.71	2316.483	2309.897	2301.001	2307.267	2312.541	2301.059	2304.113	2307.31
	best	2300	2311.304	2301.786	2316.116	2301.038	2306.23	2308.149	**2290.489**	2301.858	2308.738	2300.313	2300.682	2301.185
	worst	**2300.29**	2320.953	2303.19	2330.546	2302.673	2324.813	2312.029	2307.469	2314.943	2320.398	2302.08	2311.141	2318.468
	std	**0.149013**	4.42619	0.657186	6.200969	0.717023	8.460082	1.914098	7.529876	5.649942	5.632019	0.758678	4.905645	8.060398
	median	**2300**	2315.667	2302.276	2324.738	2301.565	2317.445	2309.704	2303.022	2306.134	2310.515	2300.921	2302.315	2304.794
	rank	**1**	11	5	13	4	12	9	2	7	10	3	6	8
C17-F23	mean	**2600.919**	2612.046	2610.809	2612.651	2609.533	2613.285	2623.726	2611.854	2618.155	2628.895	2729.771	2641.034	2612.712
	best	**2600.003**	2610.311	2609.577	2611.418	2608.026	2609.562	2617.167	2610.421	2615.36	2622.577	2687.03	2632.093	2608.371
	worst	**2602.87**	2613.449	2612.179	2614.87	2610.888	2615.327	2632.004	2615.329	2620.033	2634.942	2820.41	2660.838	2617.522
	std	1.356104	1.566948	**1.295523**	1.643087	1.301337	2.687861	7.755605	2.388078	2.095305	5.702848	64.29928	13.91659	4.951448
	median	**2600.403**	2612.211	2610.741	2612.158	2609.609	2614.125	2622.867	2610.833	2618.614	2629.03	2705.823	2635.602	2612.477
	rank	**1**	5	3	6	2	8	10	4	9	11	13	12	7
C17-F24	mean	2630.488	2557.217	2565.213	2563.978	2553.748	**2552.877**	2639.15	2625.224	2669.555	2691.611	2704.165	2634.821	2722.584
	best	**2516.677**	2530.533	2541.434	2537.888	2527.898	2523.278	2607.02	2570.728	2633.827	2663.76	2530.046	2586.005	2685.228

(Continued)

Table 3 (continued)

		WoOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
	worst	2732.32	2580.239	2586.56	2586.653	**2575.413**	2578.637	2668.736	2655.471	2693.815	2714.63	2820.107	2671.601	2747.249
	std	119.6573	25.86238	**24.98793**	25.89088	25.47141	26.21603	29.8357	40.8215	29.10044	26.87195	127.7805	41.71321	27.81481
	median	2636.477	2559.048	2566.43	2565.687	2555.84	**2554.795**	2640.422	2637.349	2675.289	2694.027	2733.254	2640.839	2728.929
	rank	7	3	5	4	2	**1**	9	6	10	11	12	8	13
C17-F25	mean	2911.702	2912.269	2905.719	2918.02	**2904.389**	2912.131	2906.285	2915.259	2921.708	2923.123	2918.148	2911.587	2931.789
	best	2897.865	2909.215	2903.042	2916.847	2901.878	2905.576	**2853.25**	2907.606	2911.796	2911.327	2904.283	2906.386	2917.947
	worst	2916.965	2915.15	2908.694	2919.856	**2906.708**	2928.399	2925.798	2921.539	2929.178	2935.307	2933.197	2915.405	2938.32
	std	9.486506	2.55687	2.519393	**1.334815**	2.566398	11.18045	36.33887	5.995188	8.494583	13.61248	15.26734	3.975685	9.637875
	median	2915.989	2912.355	2905.571	2917.689	**2904.485**	2907.275	2923.046	2915.944	2922.928	2922.928	2917.557	2912.278	2935.444
	rank	5	7	2	9	**1**	6	3	8	11	12	10	4	13
C17-F26	mean	2900	2899.525	**2882.267**	2913.458	2883.588	2901.852	3002.084	2978.733	3072.358	3093.428	3552.759	3025.091	3191.542
	best	2900	2862.463	2842.183	2869.675	2844.975	2848.483	2926.195	2885.428	2930.503	2898.557	**2837.005**	2857.439	2954.946
	worst	**2900**	2989.721	2987.602	3011.502	2996.062	2988	3124.375	3198.903	3457.541	3549.302	3932.75	3148.19	3715.243
	std	**3.81E−13**	61.97023	72.28389	67.64154	77.02733	62.10375	87.83739	151.4702	264.1851	313.7155	503.7024	126.2406	361.4416
	median	2900	2872.957	2849.641	2886.328	**2846.658**	2885.463	2978.883	2915.3	2950.693	2962.927	3720.64	3047.368	3047.989
	rank	4	3	**1**	6	2	5	8	7	10	11	13	9	12
C17-F27	mean	**3089.518**	3095.806	3092.725	3097.146	3092.738	3094.692	3130.074	3097.626	3104.202	3106.511	3181.527	3119.697	3111.038
	best	**3089.518**	3092.666	3090.351	3091.49	3090.812	3090.243	3126.259	3091.132	3093.053	3093.469	3174.586	3112.513	3093.613
	worst	**3089.518**	3097.182	3096.992	3102.317	3095.904	3097.953	3132.917	3112.681	3117.981	3140.483	3194.2	3131.08	3157.391
	std	**2.7E−13**	2.198861	3.164564	4.69016	2.454126	3.665979	3.013091	10.40409	13.0724	23.32477	8.902988	8.253938	31.77149
	median	**3089.518**	3096.687	3091.779	3097.388	3092.117	3095.286	3130.56	3093.346	3102.886	3096.046	3178.66	3117.597	3096.574
	rank	**1**	5	2	6	3	4	12	7	8	9	13	11	10
C17-F28	mean	**3100**	3137.099	3125.374	3148.249	3125.292	3136.856	3187.396	3193.12	3237.031	3250.794	3349.991	3210.388	3298.249
	best	**3100**	3133.139	3121.816	3143.321	3118.728	3126.068	3138.562	3135.14	3203.047	3185.276	3341.479	3189.607	3183.61
	worst	**3100**	3143.268	3128.234	3151.414	3131.664	3149.511	3230.453	3230.419	3272.98	3294.122	3367.127	3224.959	3346.835
	std	**0**	4.453665	2.784366	3.71796	5.425655	10.8119	46.26617	45.76662	29.42444	51.10806	12.16066	17.11882	79.00192
	median	**3100**	3135.994	3125.723	3149.13	3125.388	3135.923	3190.284	3203.461	3236.048	3261.89	3345.679	3213.494	3331.276
	rank	**1**	5	3	6	2	4	7	8	10	11	13	9	12
C17-F29	mean	**3132.241**	3155.004	3153.565	3158.591	3151.758	3151.221	3223.923	3184.111	3198.106	3189.8	3282.896	3202.277	3238.808
	best	**3130.076**	3149.33	3145.754	3151.541	3145.807	3145.707	3179.197	3156.896	3175.38	3160.608	3212.371	3168.001	3181.753
	worst	**3134.841**	3160.493	3160.713	3167.098	3158.414	3155.948	3278.868	3211.297	3238.149	3208.804	3472.351	3248.078	3328.385
	std	**2.549599**	5.719152	8.074156	6.741307	6.33105	4.382562	42.29108	26.29537	28.77702	21.8927	130.0398	35.56677	71.78046
	median	**3132.023**	3155.096	3153.896	3157.862	3151.404	3151.615	3218.815	3184.126	3189.447	3194.894	3223.431	3196.514	3222.547
	rank	**1**	5	4	6	3	2	11	7	9	8	13	10	12
C17-F30	mean	**3418.734**	128640.1	61149.38	195321.3	71322.96	68696.36	406938.8	294085.4	312461.2	79803.64	557894	232689.3	726386.8
	best	**3394.682**	121988.6	17142.57	118605.8	7632.693	52865.81	50490.23	12807.35	19322.32	20720.04	461547.9	137373	27631.37
	worst	**3442.907**	140115.6	81570.75	239488.9	120763	91899.97	1433295	532327.3	473524	112650.3	659408.7	331744.9	1054033
	std	**28.52304**	8548.646	30500.07	54474.58	48694.86	16941.34	702874.9	222131.8	208580.5	43325.6	85405.73	107086	493708.5
	median	**3418.673**	126228.1	72942.11	211595.3	78448.07	65009.83	71984.87	315603.5	378499.2	92922.08	555309.7	230819.6	911941.6
	rank	**1**	6	2	7	4	3	11	9	10	5	12	8	13
Sum rank		**36**	319	178	351	107	287	240	117	189	192	240	184	199
Mean rank		**1.24E+00**	1.10E+01	6.14E+00	1.21E+01	3.69E+00	9.90E+00	8.28E+00	4.03E+00	6.52E+00	6.62E+00	8.28E+00	6.34E+00	6.86E+00
Total rank		**1**	11	4	12	2	10	9	3	6	7	9	5	8

Table 4: Optimization outcomes for the CEC 2017 test suite (dimension = 30)

		WoOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
C17-F1	mean	**100**	1.93E+10	1.96E+08	3E+10	1.96E+08	1.32E+10	1.43E+09	1.96E+08	1.41E+09	4.67E+09	2.03E+08	1.22E+09	3.25E+08
	best	**100**	1.65E+10	32266839	2.66E+10	32290110	8.27E+09	1.01E+09	32760293	2.32E+08	2.93E+09	32265828	32299604	1.59E+08
	worst	**100**	2.39E+10	5.89E+08	3.68E+10	5.89E+08	1.78E+10	2.12E+09	5.9E+08	4.24E+09	6.71E+09	5.93E+08	4.14E+09	7.02E+08
	std	**8.43E−15**	3.59E+09	2.71E+08	4.74E+09	2.71E+08	4.7E+09	5.3E+08	2.71E+08	1.95E+09	1.6E+09	2.7E+08	2.02E+09	2.6E+08
	median	**100**	1.83E+10	80745741	2.84E+10	80753780	1.34E+10	1.3E+09	81052426	5.8E+08	4.53E+09	94051665	3.47E+08	2.2E+08
	rank	**1**	12	2	13	3	11	9	4	8	10	5	7	6
C17-F3	mean	**300**	75581.18	37376.45	58352.01	5735.668	39188.73	173242.8	6224.028	35173.75	30104.77	74500.46	28079.89	126297.1
	best	**300**	69522.05	22523.92	46373.7	5200.676	37849.76	144751.7	5922.687	30733.85	26338.47	65397.64	21423.59	96151.98
	worst	**300**	82476.02	47458.62	62936.17	6221.316	40535.78	198265	6761.757	39277.12	32766.01	81615.28	35232.33	173533.4
	std	**0**	6318.919	10848.12	8213.122	443.6744	1524.429	22794.16	379.0374	3599.758	2788.809	7585.663	6295.198	37632.57
	median	**300**	75163.33	39761.63	62049.08	5760.34	39184.68	174977.3	6105.834	35342.01	30657.3	75494.45	27831.81	117751.5
	rank	**1**	11	7	9	2	8	13	3	6	5	10	4	12
C17-F4	mean	**458.5616**	4819.021	512.5932	7270.578	496.9645	3438.378	761.0935	499.6013	554.1168	798.0394	570.7423	592.0664	728.4908
	best	**458.5616**	2768.708	497.6807	4711.134	492.8736	900.4506	715.0306	497.2889	507.1857	648.878	557.3535	514.5137	692.3026
	worst	**458.5616**	6478.099	526.9531	10111.52	506.2296	5625.709	823.7445	502.8577	580.5611	1081.993	588.8963	730.6519	746.9158
	std	**0**	1578.917	12.69996	2301.989	6.483851	2050.395	52.70202	2.731903	33.11396	198.5297	16.23713	103.8154	25.20715
	median	**458.5616**	5014.638	512.8694	7129.827	494.3775	3613.675	752.7994	499.1293	564.3602	730.6435	568.3597	561.5501	737.3724
	rank	**1**	12	4	13	2	11	9	3	5	10	6	7	8
C17-F5	mean	**502.4874**	765.5723	678.6888	794.0798	575.268	728.5501	749.8369	601.6021	603.414	711.4062	676.8023	611.1775	661.9375
	best	**500.995**	749.3034	650.1129	773.3787	562.1878	706.0153	732.0353	585.8212	569.0043	698.2692	662.9356	588.4165	621.3164
	worst	**503.9798**	784.4246	716.472	822.2217	587.0371	756.3558	758.3335	630.4678	627.7131	725.6365	694.1528	645.3875	711.1192
	std	**1.319286**	14.83861	30.1404	22.12543	11.73339	25.62032	12.33607	20.30405	29.77654	13.56029	15.29197	24.95406	38.12299
	median	**502.4874**	764.2806	674.0851	790.3594	575.9236	725.9147	754.4893	595.0598	608.4693	710.8596	675.0604	605.453	657.6573
	rank	**1**	12	8	13	2	10	11	3	4	9	7	5	6
C17-F6	mean	**600**	659.2591	635.2335	661.5521	603.7625	657.1882	656.6328	619.0692	610.0096	632.7818	642.3366	635.3993	623.2616
	best	**600**	658.198	632.9498	658.5349	602.523	645.2296	648.6265	610.5584	603.9395	628.4545	641.6264	627.4036	617.3186
	worst	**600**	660.3277	637.3837	665.5389	604.8937	664.1746	659.7173	629.0997	615.982	640.3437	643.1681	642.341	626.4971
	std	**6.74E−14**	1.209961	1.86184	3.558116	1.003499	9.097083	5.509686	9.072859	5.090703	5.456698	0.714086	6.949454	4.199976
	median	**600**	659.2553	635.3002	661.0674	603.8166	659.6743	659.0937	618.3093	610.0585	631.1644	642.276	635.9262	624.6153
	rank	**1**	12	7	13	2	11	10	4	3	6	9	8	5
C17-F7	mean	**733.478**	1161.236	1051.32	1190.826	833.8707	1107.574	1167.754	839.2034	862.1636	999.8682	924.1566	856.8503	921.4438
	best	**732.8186**	1118.222	968.7701	1175.953	813.1834	993.5769	1137.876	805.1398	802.7519	937.4174	891.4679	846.1647	897.3375
	worst	**734.5199**	1189.941	1173.712	1209.418	874.6459	1218.626	1231.281	884.6615	896.1726	1057.644	967.0594	868.3917	962.8583
	std	**0.774451**	31.90544	92.45771	14.47801	28.68514	99.33778	44.73783	35.02672	41.99733	67.82526	33.4287	10.43193	29.71574
	median	**733.2867**	1168.391	1031.398	1188.967	823.8267	1109.046	1150.93	833.5061	874.865	1002.206	919.0496	856.4225	912.7896
	rank	**1**	11	9	13	2	10	12	3	5	8	7	4	6
C17-F8	mean	**803.3298**	1018.398	920.3303	1045.525	877.5272	999.5654	978.8292	879.5193	878.5497	973.1851	928.9367	901.4532	946.8519
	best	**801.2023**	1007.033	898.0562	1030.036	872.9702	966.9828	938.0588	856.4738	872.7413	958.6618	910.9319	892.1594	935.4669
	worst	**804.1574**	1032.418	936.757	1065.959	883.2069	1074.509	1008.979	901.576	885.1336	996.9881	948.7933	913.741	961.0538
	std	**1.459319**	11.96589	17.7555	18.71241	4.352386	51.85399	31.30078	20.08252	5.542422	16.99161	16.91622	9.846703	13.68681
	median	**803.9798**	1017.071	923.2541	1043.052	876.9658	978.385	984.1392	880.0137	878.1619	968.5453	928.0107	899.9562	945.4435
	rank	**1**	12	6	13	2	11	10	4	3	9	7	5	8
C17-F9	mean	**900**	8344.384	3886.675	8098.086	1172.425	8724.853	8389.422	4344.503	1893.239	4575.399	3346.282	2960.29	1323.737
	best	**900**	7278.149	3003.474	7844.746	1144.826	5558.32	6534.16	3563.27	1438.864	3504.425	2895.905	1858.558	1109.334
	worst	**900**	9372.119	4314.984	8243.404	1223.276	11587.59	9867.353	6470.569	2557.346	6651.598	3884.238	4403.704	1442.493
	std	**6.74E−14**	889.8122	612.6535	179.6423	36.37631	2564.047	1704.927	1457.138	557.4349	1475.865	426.646	1100.423	154.8397

(Continued)

Table 4 (continued)

		WoOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
	median	**900**	8363.633	4114.12	8152.098	1160.798	8876.753	8578.088	3672.087	1788.372	4072.786	3302.493	2789.45	1371.56
	rank	**1**	11	7	10	2	13	12	8	4	9	6	5	3
C17-F10	mean	**2293.267**	6171.939	4886.534	6669.96	3822.662	5692.413	5646.177	4302.488	4403.682	6684.249	4446.84	4586.508	5389.066
	best	**1851.756**	5720.499	4401.804	6016.408	3581.198	4649.195	4955.071	4084.663	3985.285	6436.957	4245.255	4363.403	4992.902
	worst	**2525.027**	6358.598	5253.024	7084.454	4120.858	6084.522	6587.684	4635.161	4615.509	6809.301	4703.639	4973.911	5773.163
	std	308.512	310.6968	424.8987	473.5637	243.2946	715.3956	729.0001	263.7034	295.7065	**173.2702**	224.3681	276.9515	367.9321
	median	**2398.142**	6304.33	4945.654	6789.49	3794.296	6017.967	5520.977	4245.063	4506.968	6745.368	4419.232	4504.358	5395.099
	rank	**1**	11	7	12	2	10	9	3	4	13	5	6	8
C17-F11	mean	**1102.987**	5888.64	1344.333	6833.753	1280.138	4161.976	6115.852	1385.359	2026.198	1875.365	2537.926	1338.168	7100.78
	best	**1100.995**	4848.487	1251.21	5569.877	1172.391	3312.239	4767.95	1261.563	1345.367	1664.177	1987.804	1221.828	2791.62
	worst	**1105.977**	6598.14	1547.825	7889.887	1556.976	5980.394	8752.92	1667.675	3836.888	2315.66	3278.876	1577.595	12866.57
	std	**2.210814**	770.6245	142.6046	1045.691	190.1829	1290.898	1840.345	195.6743	1241.547	311.8184	602.0709	166.087	4386.34
	median	**1102.487**	6053.966	1289.149	6937.625	1195.592	3677.636	5471.269	1306.098	1461.268	1760.811	2442.513	1276.625	6372.468
	rank	**1**	10	4	12	2	9	11	5	7	6	8	3	13
C17-F12	mean	**1744.553**	5.12E+09	21371437	7.95E+09	6201916	3.7E+09	1.87E+08	14361810	44449698	2.26E+08	1.51E+08	8052654	11782778
	best	**1721.81**	4.23E+09	9879562	7.09E+09	620796.8	1.9E+09	53862371	8270640	4314687	1.48E+08	28623875	1792426	7303953
	worst	**1764.937**	6.51E+09	40515640	1E+10	12983666	4.84E+09	3.63E+08	20381602	93213053	3.85E+08	4.66E+08	15333939	19400331
	std	**20.69875**	1E+09	13847004	1.43E+09	5536000	1.3E+09	1.49E+08	5615706	39807192	1.11E+08	2.16E+08	6585417	5733189
	median	**1745.733**	4.87E+09	17545274	7.35E+09	5601600	4.02E+09	1.64E+08	14397498	40135525	1.86E+08	54785632	7542126	10213413
	rank	**1**	12	6	13	2	11	9	5	7	10	8	3	4
C17-F13	mean	**1315.791**	4.16E+09	197958.1	7.68E+09	90422.33	1.07E+09	747450.9	155263.7	638599.4	64279431	115605	112613.2	8762290
	best	**1314.587**	2.03E+09	71225.41	4.03E+09	12696.72	14372286	324861	40156.87	77279.25	44632278	35736.68	28325.48	2364087
	worst	**1318.646**	5.82E+09	377986.2	9.43E+09	277211.8	3.7E+09	1249375	302408.4	1981219	94668028	297530.4	285642.7	18932044
	std	**1.988738**	1.62E+09	140565.2	2.53E+09	129540.2	1.82E+09	457562.3	118902.3	931254.9	22237716	125961.3	120092.5	7301802
	median	**1314.967**	4.39E+09	171310.4	8.63E+09	35890.43	2.75E+08	707783.9	139244.8	247949.8	58908710	64576.45	68242.27	6876514
	rank	**1**	12	6	13	2	11	8	5	7	10	4	3	9
C17-F14	mean	**1423.017**	1440781	260067.1	1659674	63926.55	916825.2	1679482	77663.9	450458.2	164574.4	894451.5	76519.93	1522349
	best	**1422.014**	984214.9	36694.38	937079.3	5305.743	671644	129727.5	23013.18	29244.27	68219.6	591860.4	6568.412	250687.7
	worst	**1423.993**	1748514	591039.3	2386909	135565.2	1340914	4942906	138142.7	965200.5	249758.7	1359187	159423.9	2564179
	std	**0.830071**	363681.3	241222.7	758299.6	67918.64	314550.4	2269750	59106.18	488029.5	86713.65	355536.9	77692.87	1112109
	median	**1423.03**	1515197	206267.4	1657354	57417.65	827371.2	822647.3	74749.84	403694.1	170159.7	813379.3	70043.71	1637264
	rank	**1**	10	6	12	2	9	13	4	7	5	8	3	11
C17-F15	mean	**1503.129**	2.23E+08	1886554	4.36E+08	1860519	12304021	5524701	1890429	13359062	5589623	1871019	1862815	2553715
	best	**1502.462**	1.98E+08	44650.84	3.82E+08	12959.12	6435764	371070.6	42275.52	83166.71	1109335	27611.73	13943.91	453720.7
	worst	**1504.265**	2.45E+08	6984870	4.8E+08	6962220	24558781	18862064	6979026	50017822	13982953	6971695	6964907	7088483
	std	**0.878736**	24803304	3492507	50148338	3495000	8648948	9170280	3486244	25113653	5876301	3494204	3495279	3160282
	median	**1502.893**	2.24E+08	258348.5	4.42E+08	233447.6	9110769	1432835	270206.8	1667630	3633102	242384	236204.4	1336328
	rank	**1**	12	5	13	2	10	8	6	11	9	4	3	7
C17-F16	mean	**1663.469**	3696.484	2739.21	4174.217	2031.742	2936.143	3642.662	2439.357	2407.238	3076.045	3222.709	2688.348	2702.108
	best	**1614.72**	3453.085	2422.28	3606.04	1792.395	2604.22	3106.301	2266.552	2273.992	2911.484	3062.818	2509.015	2427.004
	worst	**1744.118**	3912.092	3134.489	4698.89	2224.473	3137.957	4269.45	2608.391	2506.765	3254.71	3348.546	2907.233	2964.777
	std	**63.65095**	208.1466	303.305	587.9758	200.749	240.5009	494.6898	151.0876	120.0908	155.2565	131.7444	197.2769	267.7258
	median	**1647.519**	3710.38	2700.036	4195.97	2055.049	3001.198	3597.448	2441.242	2424.098	3068.993	3239.737	2668.571	2708.325
	rank	**1**	12	7	13	2	8	11	4	3	9	10	5	6
C17-F17	mean	**1728.099**	2976.551	2297.272	3197.973	1852.187	2878.632	2569.877	2011.378	1903.752	2094.099	2333.682	2196.715	2066.269
	best	**1718.761**	2527.884	2199.548	2910.18	1754.858	2102.544	2210.157	1958.001	1792.883	1936.555	2243.866	2032.728	2023.039

(Continued)

Table 4 (continued)

		WoOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
	worst	**1733.659**	3502.904	2365.196	3697.644	1915.334	4867.939	2790.703	2129.802	2030.49	2294.216	2452.517	2502.218	2126.085
	std	**6.88979**	423.649	73.5142	368.1013	71.28905	1364.797	259.2388	82.73906	115.8524	153.6437	105.9487	220.54	44.81475
	median	**1729.987**	2937.709	2312.173	3092.033	1869.278	2272.023	2639.325	1978.854	1895.817	2072.813	2319.172	2125.957	2057.976
	rank	**1**	12	8	13	2	11	10	4	3	6	9	7	5
C17-F18	mean	**1825.696**	20698649	1974177	23791693	50936.62	26451274	4337102	514498.6	354345.6	1259906	423664.3	149240.4	2698222
	best	**1822.524**	6075199	331840.1	7802746	10874.56	977620.5	1454360	126970	66475.92	688778.6	219712.8	120283.7	2194694
	worst	**1828.42**	40111635	3849556	46653952	128251.8	50042565	8859447	1310520	910018.7	1531129	855285.7	226112.3	3934321
	std	**2.775128**	15472268	1700058	16927961	56735.14	27965003	3254444	553615.7	407742.5	402802.7	301171.4	52733.35	849757.9
	median	**1825.92**	18303882	1857656	20355038	32310.05	27392456	3517301	310252.2	220443.9	1409858	309829.4	125282.7	2331937
	rank	**1**	11	8	12	2	13	10	6	4	7	5	3	9
C17-F19	mean	**1910.989**	4.22E+08	523204.2	7.12E+08	475420.3	2.14E+08	10883381	1156532	3404298	4652566	533427	506349.2	1651816
	best	**1908.84**	3.16E+08	36714.59	5.14E+08	10015.68	2855569	1553416	313862.2	60057.15	2177535	72120.82	19603.12	473988.3
	worst	**1913.095**	5.51E+08	1538380	1.08E+09	1529292	5.93E+08	18134763	1695202	10977027	7085565	1560116	1543027	2449430
	std	**1.984351**	1.21E+08	703456.4	2.58E+08	726536.1	2.79E+08	7565825	638233.3	5220617	2380693	708352.6	719237.2	937518.7
	median	**1911.01**	4.12E+08	258860.9	6.27E+08	181186.6	1.31E+08	11922673	1308533	1290054	4673583	250735.8	231383.2	1841923
	rank	**1**	12	4	13	2	11	10	6	8	9	5	3	7
C17-F20	mean	**2065.787**	2712.191	2519.597	2751.615	2183.584	2676.383	2667.343	2497.306	2328.948	2638.504	2793.075	2454.947	2402.364
	best	**2029.521**	2661.219	2397.841	2637.162	2073.752	2565.71	2532.498	2303.022	2176.529	2581.868	2513.919	2403.149	2341.807
	worst	**2161.126**	2771.122	2666.91	2807.886	2263.124	2762.591	2794.815	2809.118	2469.967	2744.829	3158.412	2546.285	2440.161
	std	65.37076	46.37553	118.1512	82.58789	81.42345	85.60543	111.5981	223.4195	123.6606	77.63001	276.0631	64.44739	**43.4923**
	median	**2036.25**	2708.212	2506.819	2780.707	2198.73	2688.616	2671.029	2438.542	2334.648	2613.659	2749.985	2435.178	2413.743
	rank	**1**	11	7	12	2	10	9	6	3	8	13	5	4
C17-F21	mean	**2308.456**	2548.296	2415.342	2590.306	2360.652	2484.208	2539.405	2389.107	2377.97	2455.229	2510.009	2410.629	2453.12
	best	2304.034	2479.38	**2247.889**	2532.833	2353.554	2317.967	2479.059	2364.264	2348.385	2446.331	2497.91	2397.859	2430.238
	worst	**2312.987**	2596.183	2532.725	2654.739	2368.699	2584.688	2587.867	2411.237	2390.803	2465.169	2538.638	2420.801	2486.51
	std	**4.579845**	55.1324	123.3088	54.62976	6.661436	119.9463	54.8601	20.49867	20.70082	8.293731	19.74066	10.47263	24.40906
	median	**2308.402**	2558.811	2440.377	2586.825	2360.177	2517.088	2545.346	2390.464	2386.346	2454.708	2501.745	2411.929	2447.867
	rank	**1**	12	6	13	2	9	11	4	3	8	10	5	7
C17-F22	mean	**2300**	6511.615	4891.325	6333.754	2349.99	7090.337	6088.186	3559.828	2643.802	4827.531	5298.161	4241.178	2642.462
	best	**2300**	6257.877	2334.769	5573.897	2334.143	6905.717	5371.948	2338.634	2533.758	2653.136	3578.81	2494.873	2576.502
	worst	**2300**	6931.078	5868.064	7123.814	2380.728	7201.752	6708.407	5090.498	2870.026	7217.401	6041.956	5946.382	2716.361
	std	**0**	298.8961	1753.156	682.3155	21.52832	133.8003	568.644	1466.871	157.9617	2566.251	1184.595	1636.004	63.09849
	median	**2300**	6428.753	5681.233	6318.652	2342.545	7126.939	6136.194	3405.09	2585.713	4719.794	5785.939	4261.729	2638.492
	rank	**1**	12	8	11	2	13	10	5	4	7	9	6	3
C17-F23	mean	**2655.081**	3061.971	2866.937	3102.401	2659.908	3065.56	2955.515	2727.344	2737.464	2849.971	3486.294	2847.482	2902.632
	best	2653.745	2999.49	2785.388	3065.151	**2530.413**	2978.788	2825.75	2692.132	2720.407	2833.717	3407.337	2821.876	2880.043
	worst	**2657.377**	3119.705	2995.068	3159.358	2709.658	3208.471	3026.6	2747.74	2755.53	2884.46	3564.078	2885.999	2950.178
	std	**1.697988**	57.68784	94.67822	42.24014	88.82554	103.6446	91.96275	25.10249	15.55898	24.13576	84.28166	29.43164	32.97055
	median	**2654.6**	3064.345	2843.645	3092.547	2699.78	3037.49	2984.855	2734.753	2736.959	2840.854	3486.88	2841.026	2890.152
	rank	**1**	10	7	12	2	11	9	3	4	6	13	5	8
C17-F24	mean	**2831.409**	3198.961	3092.53	3272.749	2880.579	3173.711	3052.366	2896.977	2908.163	2997.696	3235.098	3063.189	3133.446
	best	**2829.992**	3171.142	2990.747	3206.99	2869.208	3093.723	3003.38	2859.868	2897.35	2980.376	3207.922	3007.279	3064.367
	worst	**2832.366**	3255.425	3207.297	3385.801	2885.61	3212.274	3072.389	2913.994	2914.07	3023.007	3263.766	3148.137	3192.067
	std	**1.176599**	39.21678	97.4279	84.80248	7.842837	56.31512	33.72228	25.6895	7.774243	18.49298	25.69365	61.98807	61.31579
	median	**2831.64**	3184.639	3086.037	3249.103	2883.748	3194.423	3066.848	2907.024	2910.616	2993.701	3234.351	3048.669	3138.674
	rank	**1**	11	8	13	2	10	6	3	4	5	12	7	9

(Continued)

Table 4 (continued)

		WoOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
C17-F25	mean	**2886.698**	3675.494	2915.603	4136.432	2902.775	3328.811	3043.174	2916.208	2977.944	3037.907	2979.518	2905.482	3062.186
	best	**2886.691**	3406.329	2900.58	3699.423	2893.264	3045.553	3011.731	2895.981	2945.352	2957.275	2966.453	2895.528	3045.711
	worst	**2886.707**	3878.826	2940.359	4725.629	2913.67	3614.112	3065.498	2958.973	3038.628	3134.672	2988.954	2918.376	3071.23
	std	**0.007812**	202.2792	18.06827	439.6786	9.733146	283.4068	23.63724	30.17098	44.42534	90.10615	11.55119	11.0654	11.81854
	median	**2886.698**	3708.411	2910.737	4060.339	2902.082	3327.789	3047.733	2904.939	2963.898	3029.842	2981.332	2904.011	3065.901
	rank	**1**	12	4	13	2	11	9	5	6	8	7	3	10
C17-F26	mean	3578.65	7815.419	6454.532	8248.07	**3233.96**	7487.928	7225.032	4584.869	4421.518	5421.071	6561.517	4630.032	4295.707
	best	3559.841	7515.446	5497.604	7620.881	**3183.064**	7074.221	6668.885	4303.151	4080.925	4388.211	5771.831	3745.315	3962.724
	worst	3607.686	8330.421	7085.435	9291.601	**3308.439**	7780.82	7928.112	5124.112	4946.359	6338.667	7038.677	5760.477	4628.134
	std	**23.3936**	381.4635	703.0701	785.9336	54.52142	305.9763	535.1531	393.5537	378.9748	940.373	580.6916	988.104	279.4035
	median	3573.536	7707.905	6617.544	8039.898	**3222.169**	7548.335	7151.565	4456.106	4329.395	5478.703	6717.781	4507.168	4295.984
	rank	2	12	8	13	**1**	11	10	5	4	7	9	6	3
C17-F27	mean	**3207.018**	3509.632	3321.528	3624.147	3217.72	3408.699	3374.742	3230.103	3243.693	3293.917	4513.216	3264.947	3398.457
	best	**3200.749**	3468.144	3259.932	3416.566	3209.46	3308.03	3249.623	3216.275	3235.186	3234.955	4182.93	3235.762	3341.48
	worst	**3210.656**	3582.001	3377.008	3834.394	3230.769	3592.373	3467.38	3249.134	3257.004	3347.437	4753.541	3296.384	3434.233
	std	**4.773736**	52.60186	63.20603	183.7487	10.51527	129.5742	96.43506	14.19111	9.58184	48.04602	287.7052	27.47167	41.01128
	median	**3208.335**	3494.19	3324.587	3622.814	3215.326	3367.196	3390.982	3227.502	3241.291	3296.639	4558.196	3263.822	3409.057
	rank	**1**	11	7	12	2	10	8	3	4	6	13	5	9
C17-F28	mean	**3100**	4398.324	3281.554	5069.26	3243.285	3939.659	3408.978	3274.766	3526.009	3579.44	3470.109	3328.276	3515.498
	best	**3100**	4203.314	3258.36	4819.808	3214.622	3503.666	3340.09	3224.261	3354.986	3444.595	3393.642	3205.05	3469.294
	worst	**3100**	4573.612	3316.876	5295.207	3289.191	4418.3	3453.736	3331.553	3943.842	3891.739	3559.907	3466.968	3543.718
	std	**2.7E−13**	176.0704	28.94646	217.0684	35.96582	428.6469	50.19948	45.5007	287.8271	216.0184	75.21905	111.0626	34.15955
	median	**3100**	4408.184	3275.491	5081.013	3234.663	3918.335	3421.043	3271.625	3402.605	3490.713	3463.443	3320.544	3524.491
	rank	**1**	12	4	13	2	11	6	3	9	10	7	5	8
C17-F29	mean	**3353.75**	4914.834	4126.966	5077.116	3629.958	4798.027	4684.337	3766.777	3728.105	4259.257	4666.607	4006.779	4094.466
	best	**3325.385**	4584.514	3876.509	4613.88	3507.393	4407.251	4475.317	3683.052	3657.542	4026.732	4455.462	3855.23	3821.916
	worst	**3370.797**	5263.74	4288.498	5728.296	3728.492	5448.099	4807.233	3847.491	3827.511	4619.492	4860.236	4190.95	4348.943
	std	**20.22231**	342.0631	186.0523	564.0956	99.63569	501.484	148.2815	71.2129	77.68823	262.7645	224.0986	142.4394	242.4106
	median	**3359.41**	4905.54	4171.428	4983.145	3641.973	4668.38	4727.399	3768.282	3713.683	4195.402	4675.366	3990.468	4103.503
	rank	**1**	12	7	13	2	11	10	4	3	8	9	5	6
C17-F30	mean	**5007.854**	1.05E+09	1796134	2.06E+09	759795	28830840	29404780	3014127	5414555	28413575	2407353	953298.2	1267066
	best	**4955.449**	7.71E+08	814952.1	1.48E+09	174440	11634281	6161187	770803.6	1208384	14974597	1779778	371583.3	310714.6
	worst	**5086.396**	1.15E+09	2877397	2.28E+09	2039955	65968117	46274940	5270969	14620155	58465670	3604842	2040843	2235679
	std	**60.57214**	1.9E+08	895465	3.99E+08	884731.5	25728730	17318351	1892981	6362107	20728771	858846.6	783975.5	810349
	median	**4994.785**	1.13E+09	1746094	2.25E+09	412392.4	18860481	32591497	3007368	2914841	20107017	2122396	700383.1	1260934
	rank	**1**	12	5	13	2	10	11	7	8	9	6	3	4
Sum rank		**30**	334	182	361	58	305	284	128	151	232	231	139	204
Mean rank		**1.03E+00**	1.15E+01	6.28E+00	1.24E+01	2.00E+00	1.05E+01	9.79E+00	4.41E+00	5.21E+00	8.00E+00	7.97E+00	4.79E+00	7.03E+00
Total rank		**1**	12	6	13	2	11	10	3	5	9	8	4	7

Table 5: Optimization outcomes for the CEC 2017 test suite (dimension = 50)

		WoOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
C17-F1	mean	**100**	4.44E+10	1.1E+09	6.89E+10	1.1E+09	2.87E+10	6.67E+09	1.1E+09	7.87E+09	1.61E+10	1.35E+10	2.93E+09	8.63E+09
	best	**100**	3.97E+10	8.07E+08	6.04E+10	7.92E+08	2.69E+10	4.08E+09	7.92E+08	5.67E+09	1.13E+10	1.14E+10	1.78E+09	7.96E+09
	worst	**100**	4.79E+10	1.5E+09	7.56E+10	1.51E+09	3.05E+10	9.84E+09	1.5E+09	1.08E+10	2.18E+10	1.59E+10	3.62E+09	9.14E+09
	std	**0**	3.58E+09	2.99E+08	6.74E+09	3.08E+08	1.52E+09	2.72E+09	3.04E+08	2.18E+09	5.23E+09	1.91E+09	8.21E+08	6.19E+08
	median	**100**	4.5E+10	1.05E+09	6.98E+10	1.05E+09	2.87E+10	6.38E+09	1.05E+09	7.52E+09	1.57E+10	1.34E+10	3.16E+09	8.7E+09
	rank	**1**	12	4	13	3	11	6	2	7	10	9	5	8
C17-F3	mean	**300**	129931.5	121320.1	129506.9	28231.03	94215.56	184566.7	48723.56	109302.7	86387.39	144044.6	120003.7	205886.9
	best	**300**	111764.3	96823.26	117051.2	26535.95	82780.94	142022.2	39943.85	96031.03	68961.33	129712.8	94052.35	174057.4
	worst	**300**	149003.6	144216.2	139870.5	32432.76	101303.5	275397.6	58743.96	122686.8	96489.97	160838.7	151663.5	232456.1
	std	**0**	16027.83	21381.19	10081.81	2885.117	8418.586	64532.85	8003.127	11187.53	12531.83	15464.19	26197.84	24688.87
	median	**300**	129479	122120.6	130553.1	26977.69	96388.91	160423.5	48103.22	109246.6	90049.12	142813.4	117149.4	208517.1
	rank	**1**	10	8	9	2	5	12	3	6	4	11	7	13
C17-F4	mean	**470.3679**	10923.93	747.7416	17434.53	627.2689	6257.734	1646.716	650.4498	1282.051	2265.296	2460.092	978.1663	1346.698
	best	**428.5127**	8526.957	688.2815	11576.94	556.168	5093.862	1160.207	574.3289	966.4569	1336.9	2045.269	688.327	1147.223
	worst	**525.7252**	12433.4	799.2054	20805.79	694.6871	8000.44	1875.97	738.5874	1547.478	3694.022	2635.443	1588.585	1433.739
	std	**50.91462**	1798.345	51.93625	4329.444	58.21698	1266.362	343.8876	69.97734	269.9139	1050.66	287.6209	422.6642	138.7107
	median	**463.6168**	11367.68	751.7398	18677.7	629.1103	5968.316	1775.343	644.4414	1307.134	2015.131	2579.828	817.8768	1402.914
	rank	**1**	12	4	13	2	11	8	3	6	9	10	5	7
C17-F5	mean	**504.7261**	960.4082	785.5882	981.5399	697.6231	994.4545	856.5096	699.4827	689.8707	887.5022	748.1941	735.8511	810.1762
	best	**503.9798**	934.0183	760.2989	971.3466	635.3619	888.6871	829.7882	643.0679	666.8112	853.9199	706.9015	693.1569	785.173
	worst	**505.9698**	986.3178	818.966	987.7135	747.3144	1073.504	872.2582	784.6233	713.8305	910.0387	774.1151	784.9666	826.8478
	std	**0.978409**	25.48969	26.33708	7.560931	48.45829	92.72544	20.7131	65.30022	25.76044	24.82172	32.5095	38.68951	19.48365
	median	**504.4773**	960.6484	781.5439	983.5497	703.9081	1007.814	861.996	685.1199	689.4206	893.0251	755.8799	732.6405	814.3421
	rank	**1**	11	7	12	3	13	9	4	2	10	6	5	8
C17-F6	mean	**600**	671.2046	646.0021	672.6974	610.83	667.4118	673.162	629.7774	619.0818	648.9098	644.3821	641.249	637.6192
	best	**600**	668.3831	642.0629	671.4465	609.9093	652.082	670.4427	621.9894	614.3296	639.7309	641.9961	639.5874	627.8455
	worst	**600**	674.3109	649.9176	674.1472	613.0096	678.9621	678.4246	646.4254	627.3412	654.6795	646.0117	643.1517	647.8689
	std	**0**	2.878734	4.063466	1.184912	1.511055	12.54502	3.818282	11.77694	5.99672	6.831451	1.749251	1.50198	8.527375
	median	**600**	671.0622	646.014	672.5979	610.2005	669.3015	671.8903	625.3475	617.3283	650.6144	644.7604	641.1284	637.3812
	rank	**1**	11	8	12	2	10	13	4	3	9	7	6	5
C17-F7	mean	**756.7298**	1539.893	1448.588	1611.853	988.9606	1460.615	1478.91	1007.068	1015.592	1313.422	1264.608	1112.065	1189.734
	best	**754.7543**	1524.12	1398.763	1555.702	944.9592	1352.283	1435.056	978.8181	995.8507	1220.749	1140.007	998.4022	1135.415
	worst	**758.3522**	1559.895	1498.847	1688.092	1026	1565.623	1540.598	1031.39	1031.613	1355.093	1360.196	1277.017	1223.774
	std	**1.595411**	15.23416	43.36749	59.02486	40.13304	103.367	49.9719	22.34033	17.10483	63.93769	101.1588	123.8404	40.20014
	median	**756.9065**	1537.778	1448.37	1601.809	992.4415	1462.277	1469.993	1009.032	1017.452	1338.923	1279.114	1086.419	1199.873
	rank	**1**	12	9	13	2	10	11	3	4	8	7	5	6
C17-F8	mean	**805.721**	1275.541	1062.239	1295.476	980.1436	1288.096	1206.873	988.3781	997.0375	1205.028	1073.767	1013.331	1158.536
	best	**802.9849**	1238.542	1024.355	1276.853	953.4768	1211.925	1114.656	961.9021	967.6645	1162.102	1065.121	978.1518	1130.579
	worst	**810.9445**	1305.028	1098.934	1306.964	1007.25	1382.93	1288.578	1037.505	1029.076	1247.769	1086.602	1065.288	1173.501
	std	**3.672737**	32.43507	43.36724	13.42677	28.12789	74.75627	73.2642	34.59056	28.26649	35.98019	10.70925	40.65438	19.93966
	median	**804.4773**	1279.298	1062.834	1299.043	979.9239	1278.764	1212.129	977.0525	995.7049	1205.121	1071.672	1004.943	1165.032
	rank	**1**	11	6	13	2	12	10	3	4	9	7	5	8
C17-F9	mean	**900**	26987.79	10514.29	27126.62	3341.594	28263.53	24727.1	15111.97	5897.135	18264.69	8631.62	8357.638	10162.91
	best	**900**	25922.86	9976.934	25654.47	2336.095	26021	22991.1	8606.236	5145.432	14178.52	7859.922	7876.65	8639.683
	worst	**900**	29468.25	11250.11	28499.57	4501.078	31498.28	28844.9	19594.64	6696.823	21436.14	9327.502	9282.012	11606.34
	std	**9.53E−14**	1716.365	548.1605	1374.501	912.4315	2428.5	2832.717	5370.357	827.4869	3094.491	644.5642	676.5531	1639.13

(Continued)

Table 5 (continued)

		WoOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
	median	**900**	26280.02	10415.06	27176.22	3264.602	27767.41	23536.19	16123.5	5873.143	18722.04	8669.528	8135.946	10202.8
	rank	**1**	11	7	12	2	13	10	8	3	9	5	4	6
C17-F10	mean	**4347.157**	11105.19	7735.604	11985.3	6443.431	10222.84	10228.43	7255.505	7980.823	11832.2	7932.54	7348.848	10171.7
	best	**3555.132**	10389.42	7618.226	11428.89	5580.458	9602.82	8970.646	5954.179	6212.712	10965.57	7554.806	6876.329	9546.566
	worst	**5099.795**	11620.17	7931.584	12417.76	6865.346	10971.11	11033.55	8189.49	12318.67	12838.23	8704.452	8318.863	11278.54
	std	662.2242	541.7984	**153.6724**	452.349	610.8336	580.7768	907.0035	1015.811	3000.112	819.9403	553.3888	676.3173	780.415
	median	**4366.851**	11205.57	7696.303	12047.26	6663.961	10158.71	10454.77	7439.176	6695.952	11762.51	7735.452	7100.099	9930.854
	rank	**1**	11	5	13	2	9	10	3	7	12	6	4	8
C17-F11	mean	**1128.435**	12028.45	2058.451	16074.84	1804.891	10248.33	4582.648	2031.817	5329.974	4594.141	11164.87	2106.294	18262.12
	best	**1121.25**	10866.62	1685.818	14112.2	1516.621	9461.839	3979.188	1704.892	3272.101	4077.852	10273.82	1738.508	10759.73
	worst	**1133.132**	12521.91	2524.832	17358.32	2355.1	11871.05	6037.723	2599.513	9123.225	5540.28	12249.33	2436.848	23932.49
	std	**5.590435**	799.6941	365.0862	1489.235	406.3554	1140.202	1000.037	401.8038	2776.159	693.0462	853.8376	295.1887	5634.359
	median	**1129.678**	12362.63	2011.577	16414.42	1673.922	9830.206	4156.84	1911.431	4462.286	4379.215	11068.17	2124.911	19178.14
	rank	**1**	11	4	12	2	9	6	3	8	7	10	5	13
C17-F12	mean	**2905.102**	3.17E+10	1.65E+08	5.17E+10	1.23E+08	1.89E+10	1.07E+09	1.7E+08	8.06E+08	3.77E+09	1.69E+09	1.27E+09	2.6E+08
	best	**2527.376**	2.66E+10	40158231	3.78E+10	27466698	7.92E+09	8.08E+08	76523273	1.27E+08	2.25E+09	5.62E+08	1.41E+08	2.17E+08
	worst	**3168.37**	3.79E+10	2.61E+08	7.07E+10	2.19E+08	3.17E+10	1.35E+09	2.57E+08	1.5E+09	7.38E+09	2.84E+09	3.38E+09	3.76E+08
	std	**281.1232**	5.24E+09	1.05E+08	1.56E+10	97918118	1.01E+10	2.31E+08	81732197	7.03E+08	2.51E+09	9.64E+08	1.55E+09	79503263
	median	**2962.331**	3.12E+10	1.8E+08	4.91E+10	1.22E+08	1.79E+10	1.06E+09	1.72E+08	8E+08	2.73E+09	1.67E+09	7.9E+08	2.24E+08
	rank	**1**	12	3	13	2	11	7	4	6	10	9	8	5
C17-F13	mean	**1340.1**	1.79E+10	41950330	3.13E+10	41854186	7.35E+09	1.11E+08	42017139	3.01E+08	4.66E+08	55268489	3.88E+08	71923880
	best	**1333.781**	1.03E+10	19072775	1.58E+10	18999058	3.9E+09	70687645	19094547	1.36E+08	3.66E+08	19008115	19022405	38594087
	worst	**1343.015**	2.44E+10	1.05E+08	4.5E+10	1.05E+08	1.14E+10	1.78E+08	1.05E+08	7.56E+08	6.02E+08	1.14E+08	8.96E+08	1.4E+08
	std	**4.398296**	6.36E+09	43360558	1.26E+10	43419278	3.24E+09	48130977	43412385	3.12E+08	1.09E+08	45484975	4.17E+08	47541420
	median	**1341.801**	1.84E+10	21747440	3.21E+10	21597459	7.05E+09	96751059	21799439	1.55E+08	4.48E+08	44228890	3.18E+08	54538473
	rank	**1**	12	3	13	2	11	7	4	8	10	5	9	6
C17-F14	mean	**1429.458**	18956953	1021886	35226917	136345.2	2083481	3592251	273600.2	970186.6	762744.9	11118774	551348.7	8263861
	best	**1425.995**	6283250	535351.9	10898055	11868.64	650015.2	3196090	223033.4	75747.01	563484.8	2750964	284852.5	4135311
	worst	**1431.939**	37106935	2247276	71310483	261835.1	3224157	4242190	353243.1	1871966	976629.5	18168041	699146.1	14250857
	std	**2.692311**	13370444	842375.4	26403834	104816.4	1109208	473285.6	59731.88	753193.5	193630.3	7159657	195564.1	4406188
	median	**1429.95**	16218814	652458	29349566	135838.5	2229877	3465362	259062.1	966516.6	755432.7	11778045	610698	7334639
	rank	**1**	12	7	13	2	8	9	3	6	5	11	4	10
C17-F15	mean	**1530.66**	1.89E+09	725234.6	3.04E+09	699321.8	1.24E+09	7892389	785697.8	5011782	51868276	1.44E+08	705553.6	6916601
	best	**1526.359**	1.34E+09	55941.54	2.37E+09	6754.203	4.27E+08	668350.7	136485.4	35897.75	30339426	350050.9	20672.13	3950469
	worst	**1532.953**	2.48E+09	1859968	3.6E+09	1838950	2.69E+09	13768204	1873641	13199943	67222082	5.56E+08	1839216	13502178
	std	**3.013514**	5.49E+08	813879.9	5.58E+08	821114.7	1.08E+09	6147796	780019.7	5899713	15900087	2.82E+08	815791	4574363
	median	**1531.664**	1.87E+09	492514.7	3.09E+09	475791.6	9.15E+08	8566501	566332.3	3405645	54955799	9884271	481163	5106879
	rank	**1**	12	4	13	2	11	8	5	6	9	10	3	7
C17-F16	mean	**2062.891**	5272.344	3873.168	6216.188	2711.62	4081.732	4698.653	3128.507	3126.401	4010.754	3584.163	3138.222	3553.744
	best	**1728.6**	4650.055	3609.412	4919.52	2574.139	3648.17	3934.236	3045.678	2806.103	3798.073	3370.749	2814.677	3083.294
	worst	**2242.663**	6500.057	4263.172	8902.968	2865.543	4281.174	5268.581	3284.451	3638.594	4206.475	3856.345	3427.842	3916.28
	std	239.2227	870.8467	316.7043	1892.492	159.7594	299.5967	590.3499	**114.7063**	409.0521	173.3144	234.3817	343.0427	397.818
	median	**2140.15**	4969.633	3810.045	5521.133	2703.399	4198.792	4795.897	3091.949	3030.453	4019.234	3554.779	3155.185	3607.702
	rank	**1**	12	8	13	2	10	11	4	3	9	7	5	6

(Continued)

Table 5 (continued)

		WoOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
C17-F17	mean	**2021.151**	6193.712	3247.269	8683.478	2522.15	3536.735	3954.764	2893.364	2819.237	3675.657	3437.246	3096.839	3266.324
	best	**1900.43**	4844.147	2897.371	6489.257	2444.226	2940.42	3586.965	2466.394	2704.117	3185.625	3085.995	2928.732	3076.04
	worst	**2138.267**	7424.386	3629.523	11064.13	2611.324	3918.822	4165.956	3232.833	3067.286	3951.425	3658.467	3387.792	3420.448
	std	137.8644	1096.202	340.7802	1936.17	**72.21957**	429.933	267.0219	331.207	172.009	358.3117	253.4554	224.3211	158.128
	median	**2022.954**	6253.158	3231.091	8590.263	2516.524	3643.849	4033.069	2937.115	2752.772	3782.789	3502.261	3035.416	3284.405
	rank	**1**	12	6	13	2	9	11	4	3	10	8	5	7
C17-F18	mean	**1830.62**	55604723	2421462	82162231	690839.3	26108142	33455826	2587955	4825492	6623004	6774342	1269893	7544979
	best	**1822.239**	44086197	1310254	37722518	138186.6	2421870	9014113	1264377	920269.7	4228365	3020833	390391.6	3802596
	worst	**1841.673**	66116131	3333072	1.13E+08	1361713	73754957	60427824	4322648	9625498	9356019	12487886	2320575	16651466
	std	**8.365267**	9600159	950433.1	38542169	653261.5	33631029	25682140	1306092	4665406	2162679	4206504	852119.4	6257652
	median	**1829.285**	56108282	2521261	88816084	631729	14127869	32190683	2382398	4378101	6453816	5794325	1184302	4862928
	rank	**1**	12	4	13	2	10	11	5	6	7	8	3	9
C17-F19	mean	**1925.185**	1.98E+09	325204.8	2.79E+09	138246.6	1.94E+09	5101590	3855648	980660.7	36925269	464734.4	422372.9	856407.9
	best	**1924.437**	9.42E+08	185458.8	1.88E+09	68608.85	7162973	897217.1	2897882	480154.4	31299211	266035	143980.4	692709.5
	worst	**1926.121**	3.3E+09	539178.5	3.45E+09	211593.2	5.67E+09	11911924	4731373	1507656	46867166	928852.5	780521.9	1041971
	std	**0.812781**	1.02E+09	172186.8	7.16E+08	61395.46	2.6E+09	4876057	770517.3	441232.2	7105861	319451.6	332645.3	159080.7
	median	**1925.091**	1.83E+09	288090.9	2.91E+09	136392.2	1.04E+09	3798610	3896667	967416.4	34767349	332025.1	382494.6	845475.5
	rank	**1**	12	3	13	2	11	9	8	7	10	5	4	6
C17-F20	mean	**2160.172**	3425.629	3016.595	3620.048	2576.781	3139.569	3368.674	3026.726	2550.814	3387.138	3580.277	3033.387	2945.447
	best	**2104.423**	3148.647	2631.391	3383.404	2339.016	2776.962	3119.283	2828.096	2371.711	3306.829	3420.066	2747.985	2864.478
	worst	**2323.891**	3573.912	3377.305	3791.307	2793.966	3342.33	3767.451	3378.582	2750.298	3480.444	3795.228	3150.669	3011.088
	std	112.1118	196.726	325.3131	177.8239	205.8762	255.3259	294.3699	259.7906	197.1346	91.52128	161.2379	196.6029	**66.75842**
	median	**2106.186**	3489.979	3028.843	3652.74	2587.071	3219.492	3293.981	2950.113	2540.623	3380.639	3552.907	3117.446	2953.112
	rank	**1**	11	5	13	3	8	9	6	2	10	12	7	4
C17-F21	mean	**2314.895**	2832.669	2659.996	2860.746	2436.803	2807.246	2800.613	2527.315	2489.194	2708.379	2723.1	2589.418	2655.842
	best	**2309.045**	2807.753	2564.176	2777.167	2416.19	2733.909	2710.097	2502.959	2442.338	2685.438	2675.651	2529.934	2631.606
	worst	**2329.683**	2859.776	2798.447	2925.049	2455.877	2923.836	2874.766	2559.158	2524.854	2742.031	2752.888	2668.866	2671.016
	std	**10.1546**	28.0318	102.3397	71.17049	20.4434	84.06958	72.25242	27.82127	35.88207	26.33701	36.05991	62.11571	18.78902
	median	**2310.426**	2831.574	2638.68	2870.383	2437.573	2785.619	2808.795	2523.571	2494.793	2703.024	2731.93	2579.436	2660.372
	rank	**1**	12	7	13	2	11	10	4	3	8	9	5	6
C17-F22	mean	**3095.169**	12428.28	9632.707	13352.24	5418.529	11525.65	11472.31	8069.363	7978.557	12950.59	9844.678	8622.354	7949.361
	best	**2300**	12127.68	7835.33	13095.04	3137.149	10968.07	10931.1	7018.375	6967.363	12526.42	9525.952	7958.431	4380.562
	worst	**5480.678**	12931.51	11023.12	13918.73	7492.698	11916.15	11986.48	8926.024	8699.013	13286.56	10509.96	9282.229	11518.27
	std	1633.424	379.6612	1518.698	393.283	2342.688	479.0552	467.3916	824.1448	749.7407	**324.5737**	461.5702	603.1262	4113.145
	median	**2300**	12326.96	9836.19	13197.6	5522.135	11609.19	11485.83	8166.527	8123.926	12994.68	9671.397	8624.377	7949.305
	rank	**1**	11	7	13	2	10	9	5	4	12	8	6	3
C17-F23	mean	**2743.354**	3565.722	3177.931	3621.393	2883.451	3509.306	3511.166	2956.131	2978.834	3170.52	4251.325	3240.566	3229.913
	best	**2729.988**	3503.142	3105.885	3604.083	2869.226	3350.267	3372.176	2916.614	2909.945	3101.795	4098.205	3186.7	3129.556
	worst	**2752.657**	3655.511	3234.203	3647.253	2894.614	3775.93	3603.452	3005.898	3099.438	3211.375	4395.359	3299.806	3328.483
	std	**10.28788**	68.03952	67.44282	20.45353	12.12156	206.7881	102.6513	45.25459	85.24337	49.42479	124.7967	56.15027	83.62765
	median	**2745.387**	3552.117	3185.819	3617.119	2884.983	3455.514	3534.518	2951.006	2952.976	3184.455	4255.868	3237.879	3230.806
	rank	**1**	11	6	12	2	9	10	3	4	5	13	8	7

(Continued)

Table 5 (continued)

		WoOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
C17-F24	mean	**2919.043**	3902.545	3389.409	4105.283	3060.03	3751.358	3622.477	3111.423	3158.228	3341.673	4028.795	3352.558	3500.597
	best	**2909.046**	3728.775	3304.761	3759.681	3035.35	3668.918	3537.621	3071.729	3073.955	3281.607	3995.599	3231.472	3467.981
	worst	**2924.412**	4311.668	3514.841	4973.696	3081.85	3854.422	3676.15	3136.397	3268.064	3374.594	4082.153	3467.973	3561.994
	std	**7.008951**	281.839	91.71505	600.1205	23.34552	82.63003	62.6702	31.43854	83.11931	44.94326	41.24596	112.7503	43.22463
	median	**2921.358**	3784.868	3369.016	3843.878	3061.461	3741.047	3638.068	3118.783	3145.447	3355.245	4018.714	3355.394	3486.207
	rank	**1**	11	7	13	2	10	9	3	4	5	12	6	8
C17-F25	mean	**2983.145**	7229.159	3250.834	9676.375	3169.991	5325.693	3966.318	3160.382	3878.026	4127.133	4056.444	3209.191	3888.793
	best	**2980.235**	6132.618	3221.62	7968.262	3135.218	4518.748	3690.086	3137.968	3711.427	3750.662	3786.009	3159.648	3790.247
	worst	**2991.831**	7958.392	3268.322	10760.3	3201.614	6134.082	4173.226	3198.449	4051.635	4580.334	4564.883	3263.504	4002.802
	std	**5.947342**	824.1873	21.97251	1340.105	34.90984	712.0747	208.9882	27.00905	182.3115	412.9206	369.4149	43.99972	90.04422
	median	**2980.257**	7412.813	3256.696	9988.469	3171.566	5324.97	4000.98	3152.555	3874.521	4088.768	3937.442	3206.806	3881.062
	rank	**1**	12	5	13	3	11	8	2	6	10	9	4	7
C17-F26	mean	3776.432	11680.26	9394.017	12403.75	**3772.147**	10606.53	11482.16	5582.46	6115.079	8473.49	9813.765	7297.56	7933.314
	best	3748.807	11543.88	8971.113	11901.77	**3577.037**	9087.446	10766.86	5175.279	5780.648	7916.484	9595.979	6841.181	6596.929
	worst	**3793.643**	11788.75	9809.54	13142.1	3952.993	11506.55	12705.12	5816.417	6426.378	8995.708	10063.96	7750.057	9683.514
	std	**19.97732**	108.2842	355.0996	542.9329	170.1942	1083.563	866.6991	300.0591	346.5111	459.0949	210.0336	400.3968	1500.659
	median	3781.639	11694.22	9397.708	12285.56	**3779.279**	10916.06	11228.34	5669.072	6126.645	8490.884	9797.56	7299.502	7726.405
	rank	2	12	8	13	**1**	10	11	3	4	7	9	5	6
C17-F27	mean	**3251.26**	4434.648	3737.756	4573.766	3394.81	4368.751	4185.699	3379.07	3583.278	3723.38	6852.417	3587.306	4174.307
	best	**3227.701**	4192.726	3695.618	4289.698	3316.523	3845.247	3755.067	3341.658	3542.031	3584.131	6667.91	3385.523	4084.983
	worst	**3313.631**	4597.367	3788.516	4774.429	3471.689	4736.527	4612.235	3432.471	3622.841	3851.278	7109.61	3770.411	4284.334
	std	42.83953	183.3144	42.42468	236.7546	65.7915	398.7019	412.6717	**39.78004**	41.01028	120.5673	219.8248	178.2597	86.2363
	median	**3231.854**	4474.249	3733.445	4615.467	3395.514	4446.615	4187.747	3371.076	3584.121	3729.056	6816.073	3596.644	4163.955
	rank	**1**	11	7	12	3	10	9	2	4	6	13	5	8
C17-F28	mean	**3258.849**	7412.579	3640.571	9210.274	3463.468	6329.521	4542.929	3414.714	4235.441	4856.878	4718.089	3845.512	4703.598
	best	**3258.849**	6806.405	3547.727	8236.491	3404.219	5330.736	4062.842	3375.257	4004.018	4414.823	4662.5	3626.47	4493.83
	worst	**3258.849**	8975.914	3721.162	11687.71	3537.166	7349.512	4754.836	3446.403	4526.386	5299.592	4774.115	4201.724	4856.668
	std	**0**	1076.11	79.29539	1700.746	56.40109	1040.226	332.6622	36.81543	250.2575	371.6404	52.90989	254.5706	164.1639
	median	**3258.849**	6933.999	3646.697	8458.447	3456.244	6318.917	4677.019	3418.599	4205.681	4856.548	4717.871	3776.927	4731.948
	rank	**1**	12	4	13	3	11	7	2	6	10	9	5	8
C17-F29	mean	**3263.038**	11068.96	5101.386	15379.63	4066.31	6128.668	7702.725	4612.787	4640.366	5860.454	7067.047	4615.215	5576.849
	best	**3247.132**	7697.347	5031.914	8666.492	3783.214	5836.987	5513.94	4321.314	4462.578	5174.426	6016.94	4424.823	5337.385
	worst	**3278.787**	14785.5	5184.587	23689.09	4232.884	6526.28	9775.258	5027.856	4898.635	6599.71	8911.283	4705.121	5996.625
	std	**17.92966**	3364.201	67.34543	6884.002	216.1203	298.9124	1806.239	305.7777	205.7206	676.6166	1344.284	132.2199	315.4552
	median	**3263.116**	10896.5	5094.521	14581.47	4124.57	6075.703	7760.851	4550.99	4600.125	5833.84	6669.982	4665.457	5486.694
	rank	**1**	12	6	13	2	9	11	3	5	8	10	4	7
C17-F30	mean	**623575.2**	2.4E+09	32349596	4.01E+09	17673509	1.22E+09	1.32E+08	67670798	1.18E+08	2.35E+08	1.51E+08	19964660	58920979
	best	**582411.6**	1.85E+09	17724805	2.46E+09	9042691	1.7E+08	88634530	61763420	57033192	1.63E+08	1.27E+08	12884964	43565339
	worst	**655637.4**	3.25E+09	44471975	6.28E+09	26376184	2.45E+09	1.82E+08	71316113	1.75E+08	3.01E+08	1.98E+08	26853662	70367644
	std	**33550.87**	6.29E+08	14507757	1.69E+09	8810428	1.21E+09	49901956	4509055	61034877	58170379	33323589	8141293	11945741
	median	**628125.9**	2.24E+09	33600803	3.64E+09	17637581	1.13E+09	1.28E+08	68801829	1.2E+08	2.38E+08	1.38E+08	20060008	60875466
	rank	**1**	12	4	13	2	11	8	6	7	10	9	3	5

(Continued)

Table 5 (continued)

	WoOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
Sum rank	**30**	335	166	367	63	294	269	112	144	248	254	150	207
Mean rank	**1.03E+00**	1.16E+01	5.72E+00	1.27E+01	2.17E+00	1.01E+01	9.28E+00	3.86E+00	4.97E+00	8.55E+00	8.76E+00	5.17E+00	7.14E+00
Total rank	**1**	12	6	13	2	11	10	3	4	8	9	5	7

Table 6: Optimization outcomes for the CEC 2017 test suite (dimension = 100)

		WoOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
C17-F1	mean	**100**	1.28E+11	9.47E+09	1.76E+11	7.08E+09	9.81E+10	5.22E+10	6.75E+09	4.81E+10	7.29E+10	1.06E+11	2.12E+10	4.74E+10
	best	**100**	1.24E+11	7.15E+09	1.72E+11	6.12E+09	8.67E+10	5E+10	5.86E+09	4.17E+10	6.93E+10	9.67E+10	1.56E+10	4.43E+10
	worst	**100**	1.32E+11	1.04E+10	1.77E+11	8.01E+09	1.1E+11	5.67E+10	7.62E+09	5.45E+10	8.01E+10	1.13E+11	2.7E+10	5.36E+10
	std	**1.19E−14**	3.31E+09	1.59E+09	2.57E+09	8.73E+08	9.93E+09	3.17E+09	8.59E+08	6.22E+09	5.04E+09	7.1E+09	5.74E+09	4.3E+09
	median	**100**	1.27E+11	1.02E+10	1.77E+11	7.09E+09	9.8E+10	5.1E+10	6.75E+09	4.82E+10	7.1E+10	1.06E+11	2.12E+10	4.58E+10
	rank	**1**	12	4	13	3	10	8	2	7	9	11	5	6
C17-F3	mean	**300**	353666.9	279889	277108.2	157657.7	306804.7	615356.9	381119.8	310162.3	257922.4	292170.9	435340.7	461759.5
	best	**300**	322618.7	270690.1	271888.6	127320.3	250944.6	540475.4	320229	283819.8	248714.2	276700.3	336775.9	441090.9
	worst	**300**	370968.8	288248.1	285713.1	184751.8	340576.2	708854.5	451840.8	339654	266908.5	319804.1	590017.2	478425.1
	std	**0**	21997.31	8589.001	6651.155	24540.83	40231.47	73405.02	65902.37	30680.17	8123.204	19493.92	119046.7	17806.98
	median	**300**	360540.1	280308.9	275415.6	159279.3	317849.1	606048.9	376204.7	308587.6	258033.4	286089.5	407284.8	463760.9
	rank	**1**	9	5	4	2	7	13	10	8	3	6	11	12
C17-F4	mean	**602.1722**	32902.38	1745.217	55054.02	1356.891	12219.51	8547.593	1169.669	3855.99	8402.982	25338.28	2410.543	7289.828
	best	**592.0676**	30208.93	1653.204	49841.2	1201.255	8138.775	7252.465	1056.287	2984.559	7915.8	20539.27	1966.503	6849.019
	worst	**612.2769**	35940.56	1828.897	61197.98	1706.457	16308.47	9250.877	1423.93	5749.694	9301.046	28523.36	2805.971	7971.54
	std	**11.98393**	2560.54	79.99769	4808.603	242.1724	3459.681	913.7612	178.5395	1308.393	658.8537	3988.405	369.7385	530.2207
	median	**602.1722**	32730.01	1749.383	54588.45	1259.926	12215.4	8843.515	1099.23	3344.854	8197.541	26145.25	2434.848	7169.377
	rank	**1**	12	4	13	3	10	9	2	6	8	11	5	7
C17-F5	mean	**512.9345**	1633.275	1150.23	1611.463	1086.758	1742.681	1523.698	1094.239	1056.543	1548.605	1165.921	1221.304	1341.393
	best	**510.9445**	1618.153	1134.82	1591.871	998.3567	1724.396	1456.839	1009.384	1009.14	1522.3	1141.519	1147.107	1229.796
	worst	**514.9244**	1642.658	1159.435	1632.48	1146.617	1766.186	1637.988	1150.191	1096.984	1572.167	1191.093	1347.336	1402.808
	std	**1.865752**	10.88075	11.66157	23.1974	71.45453	19.54948	81.8188	63.78813	39.34381	21.23625	27.46506	95.41539	81.51146
	median	**512.9345**	1636.145	1153.333	1610.75	1101.028	1740.071	1499.983	1108.69	1060.025	1549.976	1165.535	1195.387	1366.484
	rank	**1**	12	5	11	3	13	9	4	2	10	6	7	8
C17-F6	mean	**600**	679.6406	648.1853	678.4152	630.8933	682.8641	677.8689	657.1927	632.9171	661.8758	649.6834	647.874	649.0309
	best	**600**	678.4506	645.0297	675.6479	627.9063	674.863	670.6635	653.14	628.8031	655.0678	647.5622	643.4912	643.2452
	worst	**600**	680.8589	651.3285	680.6161	634.9008	688.3027	690.8388	661.3554	638.1154	666.3535	653.3898	651.755	652.9761
	std	**0**	1.152687	2.649412	2.192937	3.215283	6.742389	9.260467	3.575161	4.148447	5.424312	2.728986	3.986209	4.804558
	median	**600**	679.6265	648.1915	678.6985	630.383	684.1454	674.9866	657.1377	632.3749	663.0409	648.8908	648.1249	649.9511
	rank	**1**	12	5	11	2	13	10	8	3	9	7	4	6
C17-F7	mean	**811.392**	2921.824	2547.055	3003.928	1672.516	2798.598	2901.405	1788.921	1799.861	2558.735	2576.683	2120.131	2189.395
	best	**810.0205**	2875.917	2412.167	2955.313	1609.447	2675.443	2816.892	1677.539	1643.942	2472.016	2462.127	1934.547	2119.424
	worst	**813.1726**	2972.941	2644.889	3062.937	1734.236	2897.242	3004.914	1854.878	1915.152	2644.598	2734.633	2220.706	2324.041
	std	**1.500732**	40.81697	119.5236	45.90648	55.03027	103.3235	86.63928	79.64448	116.5233	72.57461	117.4335	135.0646	94.11721
	median	**811.1874**	2919.22	2565.582	2998.731	1673.19	2810.853	2891.907	1811.633	1820.175	2559.163	2554.985	2162.635	2157.057
	rank	**1**	12	7	13	2	10	11	3	4	8	9	5	6
C17-F8	mean	**812.437**	2022.769	1541.972	2061.363	1326.414	2006.741	1950.324	1343.112	1386.423	1904.364	1604.156	1519.782	1748.992
	best	**808.9546**	1975.232	1490.76	2032.253	1197.39	1955.157	1800.362	1251.04	1300.007	1874.417	1538.135	1478.613	1704.722
	worst	**816.9143**	2081.39	1574.1	2081.832	1405.216	2084.575	2075.504	1475.678	1501.57	1930.08	1712.495	1590.725	1801.459
	std	**3.490503**	47.27273	38.51392	21.43233	92.30482	62.40476	143.3457	97.70817	93.27542	24.43149	81.56626	51.0896	43.78316
	median	**811.9395**	2017.226	1551.513	2065.683	1351.525	1993.616	1962.715	1322.864	1372.058	1906.479	1582.996	1504.895	1744.894
	rank	**1**	12	6	13	2	11	10	3	4	9	7	5	8
C17-F9	mean	**900**	67320.78	22758.43	58313.11	19919.08	88565.84	57972.38	45682.97	29385.41	56333.72	20713.91	27225.77	36408.96
	best	**900**	62013.66	18704.33	54955.88	17278.05	74826.46	47043.76	40643.91	18230.49	52577.82	18626.47	24983.39	33891.76
	worst	**900**	76176.34	26120.46	60074.85	21688.14	108490.7	71027.98	50438.32	39916.04	58970.77	22630.25	29880.96	41947.93
	std	**9.53E−14**	6318.231	3408.907	2356.103	2125.785	14587.65	11935.99	4394.808	10873.31	2801.864	2173.111	2602.342	3846.497

(Continued)

Table 6 (continued)

		WoOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
	median	**900**	65546.57	23104.46	59110.85	20355.06	85473.1	56908.89	45824.82	29697.55	56893.15	20799.45	27019.38	34898.08
	rank	**1**	12	4	11	2	13	10	8	6	9	3	5	7
C17-F10	mean	**11023.04**	25099.27	14974.84	26036.8	13499.07	24456.18	23720.09	15696.64	14424.7	26043.63	15861.9	15754.24	22143.31
	best	**9625.608**	24693.07	13232.67	25503.04	13003.24	23822.9	23204.05	15279.22	13298.16	24826.98	14669.15	14598.03	21446.36
	worst	**11858.81**	25445.65	16689.99	26507.7	14229.7	25221.55	24848.67	16220.09	14942.01	26904.71	16686.93	16342.1	22666.99
	std	995.114	**338.1255**	1618.095	520.3433	584.0131	648.5059	780.5544	473.9314	783.485	904.7574	978.9253	809.0401	522.2865
	median	**11303.87**	25129.18	14988.35	26068.23	13381.67	24390.13	23413.83	15643.62	14729.32	26221.41	16045.76	16038.41	22229.94
	rank	**1**	11	4	12	2	10	9	5	3	13	7	6	8
C17-F11	mean	**1162.329**	127175.2	55798.06	156995.5	13627.22	56683.49	158362.1	13483.41	72194.41	61233.66	133029.4	47217.73	109233.8
	best	**1139.568**	99284.92	49469.79	120805.8	12185.07	31245.01	97686.17	11359.15	59994.61	53100.79	110852.7	25338.55	85629.6
	worst	**1220.662**	147609.6	65955.47	220633.3	14870.49	77277.45	248947.6	14890.4	81325.23	73563.21	154076.7	85720.87	147319.9
	std	**40.09338**	21201.58	7401.867	45800.2	1191.729	19514.52	72994.5	1578.99	9375.864	8969.623	18251.17	27190.01	27576.62
	median	**1144.542**	130903.2	53883.48	143271.5	13726.65	59105.75	143407.3	13842.04	73728.9	59135.32	133594.2	38905.74	101992.9
	rank	**1**	10	5	12	3	6	13	2	8	7	11	4	9
C17-F12	mean	**5974.805**	7.63E+10	1.78E+09	1.23E+11	1.5E+09	4.17E+10	1.07E+10	1.55E+09	9.45E+09	1.69E+10	4.88E+10	8.5E+09	1.01E+10
	best	**5383.905**	5.47E+10	1.66E+09	9.25E+10	1.13E+09	2.21E+10	8.99E+09	1.28E+09	6.55E+09	1.36E+10	4.26E+10	1.84E+09	9.37E+09
	worst	**6570.199**	8.51E+10	2.08E+09	1.43E+11	1.77E+09	6.86E+10	1.23E+10	1.81E+09	1.13E+10	2.24E+10	5.75E+10	1.5E+10	1.13E+10
	std	**507.8693**	1.49E+10	2.05E+08	2.37E+10	2.76E+08	2E+10	1.44E+09	2.22E+08	2.08E+09	4.07E+09	6.38E+09	6.15E+09	8.58E+08
	median	**5972.559**	8.28E+10	1.7E+09	1.29E+11	1.55E+09	3.81E+10	1.08E+10	1.56E+09	1E+10	1.58E+10	4.76E+10	8.56E+09	9.86E+09
	rank	**1**	12	4	13	2	10	8	3	6	9	11	5	7
C17-F13	mean	**1407.28**	1.99E+10	1.09E+08	3.05E+10	1.09E+08	1.53E+10	4.81E+08	1.09E+08	7.83E+08	2.11E+09	6.32E+09	1.36E+09	2.33E+08
	best	**1371.145**	1.74E+10	9491932	2.36E+10	9441984	1.11E+10	2.91E+08	9618659	67519066	1.39E+09	4.11E+09	4.26E+08	1.55E+08
	worst	**1439.935**	2.2E+10	2.88E+08	3.44E+10	2.88E+08	1.83E+10	7.38E+08	2.88E+08	2.07E+09	2.61E+09	8E+09	2.29E+09	3.93E+08
	std	**35.69163**	2.43E+09	1.32E+08	5.13E+09	1.32E+08	3.12E+09	1.99E+08	1.32E+08	9.5E+08	5.89E+08	1.67E+09	1.01E+09	1.12E+08
	median	**1409.02**	2.02E+10	69265547	3.19E+10	69233991	1.59E+10	4.47E+08	69450436	4.97E+08	2.22E+09	6.59E+09	1.37E+09	1.93E+08
	rank	**1**	12	3	13	2	11	6	4	7	9	10	8	5
C17-F14	mean	**1467.509**	33477405	5865426	57893416	1173332	7449322	11479502	3271083	7964197	11022692	9304168	1689529	8595170
	best	**1458.803**	29145856	3763355	52983192	771937.2	4072549	7162473	1353900	5037575	8087926	7195758	1086282	4890184
	worst	**1472.733**	37677679	8597895	62862829	1680271	13072793	15838403	4638476	11939415	13548027	13953033	2118276	11907435
	std	**6.209197**	4017395	2146316	5123818	395746.8	4007532	3640561	1436107	3107287	2787084	3208976	514567.1	3045180
	median	**1469.25**	33543043	5550226	57863822	1120560	6325973	11458565	3545977	7439900	11227408	8033940	1776780	8791530
	rank	**1**	12	5	13	2	6	11	4	7	10	9	3	8
C17-F15	mean	**1609.893**	1.1E+10	57849883	1.68E+10	57829675	8.66E+09	1.08E+08	57879933	4.15E+08	9.07E+08	9.42E+08	2.96E+08	66834769
	best	**1551.154**	1.03E+10	3855143	1.2E+10	3837078	3.52E+08	31619877	3883315	27230645	2.88E+08	3.58E+08	3833651	9622010
	worst	**1652.294**	1.24E+10	1.73E+08	2.09E+10	1.73E+08	1.61E+10	2.09E+08	1.73E+08	1.24E+09	1.85E+09	1.26E+09	1.11E+09	1.8E+08
	std	**45.3586**	9.32E+08	80484952	4.58E+09	80486875	7.04E+09	83002049	80516294	5.78E+08	7.02E+08	4.17E+08	5.59E+08	79072908
	median	**1618.063**	1.07E+10	27187670	1.72E+10	27161411	9.06E+09	95344360	27192600	1.95E+08	7.44E+08	1.08E+09	33278869	38914879
	rank	**1**	12	3	13	2	11	6	4	8	9	10	7	5
C17-F16	mean	**2711.795**	14677.65	6260.258	17320.25	5112.529	11558.26	12750.25	5877.174	5524.375	9369.716	9057.179	5797.336	8690.767
	best	**2171.69**	13878.7	5555.378	13991.44	4978.613	9738.895	10535.93	5274.679	5009.546	8907.714	7908.803	5725.809	8088.358
	worst	**3397.326**	15105.63	6700.874	19249.76	5259.061	13771.57	13912.11	6245.859	6025.089	10160.24	10312.52	5968.959	9182.643
	std	523.7732	562.4313	522.2629	2431.849	118.9937	1711.85	1598.86	449.4127	570.1361	606.6936	1128.369	**118.3535**	544.0976
	median	**2639.081**	14863.14	6392.39	18019.89	5106.22	11361.28	13276.49	5994.078	5531.433	9205.454	9003.698	5747.288	8746.032
	rank	**1**	12	6	13	2	10	11	5	3	9	8	4	7
C17-F17	mean	**2716.564**	3012152	5267.704	5924703	4413.969	157165.3	13255.05	4642.688	5025.577	7337.136	34217.46	5448.37	6203.588
	best	**2275.021**	883437.9	4977.355	1606571	4114.468	8255.283	8533.579	4296.159	4136.337	7130.183	23082.51	5133.116	6058.883

(Continued)

Table 6 (continued)

		WoOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
	worst	**3429.127**	6852042	5522.305	13631795	4808.122	415629.5	21968.08	5152.786	6478.796	7738.468	54920.56	5686.092	6350.899
	std	528.3898	2889857	281.753	5810824	332.6655	182775	6242.52	410.2983	1077.291	280.4434	14552.56	236.3878	**150.7303**
	median	**2581.054**	2156564	5285.577	4230222	4366.643	102388.3	11259.26	4560.903	4743.588	7239.947	29433.39	5487.135	6202.284
	rank	**1**	12	5	13	2	11	9	3	4	8	10	6	7
C17-F18	mean	**1903.746**	42942160	3274873	74812152	1430434	11899913	9830552	4767795	9086502	12829395	9654857	5858625	5573829
	best	**1881.15**	20107209	2390750	29772404	696997.8	6027207	7597083	2992759	2861596	9912882	5259244	3848349	4413198
	worst	**1919.921**	75768045	4487400	1.35E+08	2159180	22131200	12191081	7110046	14683386	17572412	19050585	7844057	8281861
	std	**19.90425**	24279911	981555	45382832	616401.4	7556272	2225871	1801961	4995868	3530771	6658255	2169147	1864106
	median	**1906.955**	37946694	3110671	67297448	1432779	9720623	9767022	4484188	9400513	11916143	7154799	5871047	4800129
	rank	**1**	12	3	13	2	10	9	4	7	11	8	6	5
C17-F19	mean	**1972.839**	9.13E+09	43666664	1.6E+10	41811074	3.65E+09	1.37E+08	53493244	2.99E+08	5.19E+08	1.17E+09	2.34E+08	50750764
	best	**1967.139**	8.13E+09	3604236	1.18E+10	563806.5	1.64E+09	40783963	7390270	2374164	2.46E+08	2.06E+08	46697502	6551526
	worst	**1977.869**	1.07E+10	1.27E+08	1.99E+10	1.25E+08	7.29E+09	2.5E+08	1.44E+08	8.99E+08	1.22E+09	2.13E+09	5.42E+08	1.3E+08
	std	**4.659759**	1.2E+09	59783692	3.43E+09	59770405	2.58E+09	1.06E+08	65597919	4.3E+08	4.85E+08	9.65E+08	2.36E+08	56885764
	median	**1973.174**	8.84E+09	21926807	1.62E+10	20745604	2.83E+09	1.29E+08	31274515	1.47E+08	3.04E+08	1.17E+09	1.74E+08	33319292
	rank	**1**	12	3	13	2	11	6	5	8	9	10	7	4
C17-F20	mean	**3192.04**	6464.043	5668.129	6645.561	4462.582	6278.918	6287.934	5406.821	5595.167	6434.592	5771.956	5091.712	5737.077
	best	**2806.762**	6319.324	5573.568	6447.331	4337.927	5880.216	6135.762	5067.186	4589.873	5903.766	5614.036	4446.727	5347.847
	worst	**3662.121**	6765.609	5760.811	6872.805	4644.32	7006.849	6454.569	5681.609	6421.51	6799.783	5959.281	5886.98	5971.087
	std	451.2632	209.1186	**87.67549**	194.9269	136.9586	527.1646	135.6969	264.6656	920.5135	391.1856	163.8353	614.4192	287.3878
	median	**3149.639**	6385.619	5669.068	6631.054	4434.04	6114.304	6280.703	5439.246	5684.643	6517.409	5757.254	5016.571	5814.687
	rank	**1**	12	6	13	2	9	10	4	5	11	8	3	7
C17-F21	mean	**2342.155**	3802.451	3360.405	3890.855	2765.58	3684.655	3758.133	3053.985	2867.539	3389.744	4107.463	3300.02	3182.799
	best	**2338.689**	3761.231	3209.79	3842.336	2735.067	3570.85	3543.751	3005.797	2798.43	3280.394	3698.457	3166.265	3147.079
	worst	**2346.015**	3854.848	3466.474	3933.422	2792.273	3761.812	3926.656	3138.009	2913.219	3523.182	4430.022	3562.367	3220.335
	std	**3.460098**	45.595	111.529	39.02464	24.15758	94.2531	178.5109	60.3003	50.10878	105.707	314.2102	186.8755	31.97398
	median	**2341.959**	3796.861	3382.678	3893.831	2767.489	3702.978	3781.063	3036.068	2879.253	3377.7	4150.687	3235.724	3181.89
	rank	**1**	11	7	12	2	9	10	4	3	8	13	6	5
C17-F22	mean	**11739**	27379.3	19166.85	28567.58	18053.03	26659.31	25488.57	17044.25	21366.69	28479.76	19813.38	20359.62	25246.24
	best	**11119.08**	27089.05	17654.85	27874.76	16640.06	26216.13	24961.96	15858.74	17488.39	28244.65	18763.21	18815.05	24238.02
	worst	**12601.6**	27993.88	21725.17	29531.06	19376.52	27022.57	25927.06	17993.57	30599.86	28972.97	21205.7	21750.23	26161.48
	std	670.4039	425.486	1843.253	714.8985	1376.951	435.4433	412.8842	911.9286	6419.082	**342.3552**	1044.264	1409.7	808.5258
	median	**11617.67**	27217.13	18643.69	28432.25	18097.76	26699.26	25532.62	17162.35	18689.26	28350.71	19642.31	20436.61	25292.72
	rank	**1**	11	4	13	3	10	9	2	7	12	5	6	8
C17-F23	mean	**2877.697**	4731.753	3851.239	4733.313	3265.607	4818.732	4597.384	3400.562	3496.999	3923.99	6572.669	4396.251	3961.701
	best	**2872.107**	4544.624	3797.714	4534.305	3255.654	4272.365	4490.775	3329.376	3468.941	3880.696	6142.053	4013.381	3917.668
	worst	**2884.013**	4943.224	3910.538	4891.205	3285.717	5563.632	4697.613	3484.231	3535.436	3986.084	6876.052	4598.923	4006.346
	std	**5.357202**	182.1425	54.3122	151.6328	14.42988	595.3365	101.2775	66.86965	31.19341	45.60785	342.7757	270.3766	51.80579
	median	**2877.334**	4719.582	3848.352	4753.871	3260.528	4719.466	4600.575	3394.32	3491.81	3914.59	6636.285	4486.351	3961.394
	rank	**1**	10	5	11	2	12	9	3	4	6	13	8	7

(Continued)

Table 6 (continued)

		WoOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
C17-F24	mean	**3327.407**	7205.633	4921.151	8634.277	3721.744	5861.433	5650.322	3904.631	4140.699	4472.232	8861.91	5346.929	4923.294
	best	**3295.518**	5861.676	4737.618	6136.45	3662.63	5525.226	5321.689	3875.305	3942.999	4326.196	8407.756	5098.212	4833.081
	worst	**3357.991**	8157.22	5032.495	10289.24	3794.121	6076.563	6141.76	3963.973	4318.429	4661.607	10089.29	5673.468	5068.505
	std	**30.42243**	1122.429	139.5428	2080.632	55.71787	245.3619	368.983	41.63856	201.7941	143.6924	841.603	275.7779	103.9696
	median	**3328.059**	7401.818	4957.245	9055.712	3715.113	5921.973	5568.92	3889.623	4150.685	4450.562	8475.294	5308.017	4895.795
	rank	**1**	11	6	12	2	10	9	3	4	5	13	8	7
C17-F25	mean	**3185.232**	12310.05	4256.425	16696.06	3927.871	8842.116	6546.915	3726.971	5915.791	7708.098	9245.957	4257.194	6970.121
	best	**3137.371**	11747.04	3965.716	15561.06	3840.588	8407.409	6077.364	3703.324	5791.245	6853.535	8665.746	4045.977	6434.201
	worst	**3261.571**	13574.48	4556.569	19194.54	4010.005	9138.785	6867.918	3761.997	6251.018	8895.888	10337.77	4551.194	7541.576
	std	61.52949	879.4018	249.356	1754.992	71.17687	340.7388	357.4081	**25.51426**	230.15	968.325	770.4068	234.9787	577.7092
	median	**3170.992**	11959.33	4251.708	16014.31	3930.446	8911.135	6621.189	3721.281	5810.451	7541.484	8990.158	4215.803	6952.353
	rank	**1**	12	4	13	3	10	7	2	6	9	11	5	8
C17-F26	mean	**5757.621**	31472.04	20716.91	35771.42	11309.81	26991.12	27444.99	11460.91	15096.75	20161.17	27374.13	17875.92	19535.69
	best	**5645.905**	31027.14	18422.2	33872.91	10889.36	26145.11	25100.31	10427.53	13501.75	16788.35	26429.27	16264.79	18552.92
	worst	**5844.642**	31767.17	23037.09	37118.06	11926.37	27520.99	29665.76	12974.68	16455.24	24115.22	28476.38	19104.08	20111.74
	std	**86.19253**	327.5251	2024.844	1498.773	489.0532	618.5785	2370.576	1113.985	1279.744	3101.606	864.6436	1239.86	727.17
	median	**5769.969**	31546.93	20704.18	36047.35	11211.74	27149.19	27506.95	11220.72	15215.01	19870.55	27295.43	18067.41	19739.04
	rank	**1**	12	8	13	2	9	11	3	4	7	10	5	6
C17-F27	mean	**3309.493**	7767.145	4020.505	9914.86	3563.948	5792.768	5359.425	3629.105	3961.831	4141.151	11197.67	3956.291	4981.769
	best	**3278.01**	6712.713	3872.469	7689.94	3554.202	5593.2	4834.032	3577.308	3815.558	3953.064	10933.81	3799.629	4805.819
	worst	**3344.5**	8865.734	4244.313	12263.32	3578.95	6052.122	5948.914	3686.009	4080.14	4453.995	11417.41	4111.048	5256.155
	std	29.13307	1205.808	163.0706	2536.322	**11.81311**	212.0753	600.745	46.59129	133.7649	226.924	215.8371	172.713	202.5876
	median	**3307.732**	7745.068	3982.62	9853.089	3561.319	5762.875	5327.378	3626.551	3975.812	4078.772	11219.72	3957.243	4932.551
	rank	**1**	11	6	12	2	10	9	3	5	7	13	4	8
C17-F28	mean	**3322.242**	16785.44	5026.477	22108.81	4346.906	13008.91	9141.804	4119.995	8340.2	9721.502	15259.52	7159.785	9949.424
	best	**3318.742**	15570.28	4921.389	19918.65	4205.65	10381.78	7989.766	3945.916	7138.533	7771.369	13331.26	5317.25	9074.941
	worst	**3327.816**	18964.93	5138.474	25025.99	4604.921	15112.67	9841.653	4297.973	10055.75	11525.95	16508.77	10032.34	11018.1
	std	**4.500714**	1568.572	92.9928	2223.119	184.9	2263.911	842.4768	151.4614	1263.653	1746.242	1414.197	2146.561	997.6698
	median	**3321.205**	16303.27	5023.022	21745.3	4288.526	13270.59	9367.899	4118.045	8083.257	9794.345	15599.02	6644.776	9852.325
	rank	**1**	12	4	13	3	10	7	2	6	8	11	5	9
C17-F29	mean	**4450.696**	134625.6	8644.305	254762.3	6659.327	15040	13662.08	7963.072	7689.267	10675.59	19744.9	7936.861	10246.02
	best	**4169.151**	77420.52	7733.625	137483.7	6002.344	11952.99	11608.51	7318.06	7504.11	9993.834	16585.35	7476.135	10063.17
	worst	**4829.521**	183132.7	9142.028	353067.2	7226.712	18636.25	15439.05	8452.751	7934.319	11122.59	25335.31	8531.806	10591.6
	std	289.9914	46223.58	639.9307	94352.54	517.6754	2870.794	1932.103	494.272	**185.9612**	498.1992	4180.681	513.4655	244.8754
	median	**4402.056**	138974.6	8850.784	264249.3	6704.126	14785.37	13800.38	8040.738	7659.319	10792.97	18529.47	7869.752	10164.65
	rank	**1**	12	6	13	2	10	9	5	3	8	11	4	7

(Continued)

Table 6 (continued)

		WoOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
C17-F30	mean	**5407.166**	1.7E+10	2.35E+08	2.75E+10	2.18E+08	9.9E+09	1.3E+09	2.89E+08	1.54E+09	2.95E+09	5.53E+09	6.52E+08	6.96E+08
	best	**5337.48**	1.5E+10	1.02E+08	2.57E+10	92471920	6.18E+09	9.78E+08	1.62E+08	6.33E+08	1.3E+09	4.05E+09	1.95E+08	5.88E+08
	worst	**5557.155**	1.83E+10	3.16E+08	2.96E+10	2.82E+08	1.22E+10	1.7E+09	3.72E+08	2.02E+09	5.16E+09	6.71E+09	1.59E+09	7.97E+08
	std	**103.8976**	1.45E+09	95572953	1.69E+09	88265296	2.7E+09	3.08E+08	91909459	6.39E+08	2.01E+09	1.16E+09	6.5E+08	94307941
	median	**5367.014**	1.73E+10	2.6E+08	2.73E+10	2.49E+08	1.06E+10	1.26E+09	3.11E+08	1.76E+09	2.67E+09	5.67E+09	4.13E+08	7E+08
	rank	**1**	12	3	13	2	11	7	4	8	9	10	5	6
Sum rank		**29**	336	140	355	65	293	265	114	156	249	272	162	203
Mean rank		**1.00E+00**	1.16E+01	4.83E+00	1.22E+01	2.24E+00	1.01E+01	9.14E+00	3.93E+00	5.38E+00	8.59E+00	9.38E+00	5.59E+00	7.00E+00
Total rank		**1**	12	4	13	2	11	9	3	5	8	10	6	7

Additionally, Figs. 6–9 illustrate the convergence curves derived from the metaheuristic algorithms. Convergence curves plot the best objective function value found over the iterations for each algorithm. They provide insight into how quickly and effectively each algorithm finds near-optimal solutions.

a) **Convergence Behavior**
- **WoOA Convergence Pattern**
  - WoOA's curve shows a rapid initial decrease in the objective function value, indicating effective exploration and quick identification of promising solution areas.
  - As the iterations progress, the curve flattens, suggesting that WoOA shifts focus from exploration to exploitation, refining solutions near the optimum.
- **Comparison with Other Algorithms**
  - Algorithms with steeper initial declines are also effective in exploration but may differ in how they balance exploration and exploitation.
  - Algorithms with flatter curves throughout may struggle with exploration, converging more slowly or getting trapped in local optima.

b) **Rate of Convergence**

The rate of convergence is determined by how quickly an algorithm reduces the objective function value over time.

- **Initial Convergence Rate**
  - WoOA shows a steep initial slope, demonstrating a high convergence rate at the beginning. This suggests that WoOA is efficient in rapidly exploring the search space and identifying good regions early in the optimization process.
  - Algorithms with similar steep initial slopes indicate competitive initial exploration capabilities.
- **Later Stages Convergence Rate**
  - In later iterations, WoOA's convergence curve gradually becomes flatter. This indicates a reduced convergence rate, typical as the algorithm switches from exploitation to fine-tune solutions.
  - Some competing algorithms might maintain a slightly higher convergence rate later, indicating continuous improvements. However, if the slope is too flat, it might suggest premature convergence.

Key Observations:
- **Effectiveness in Exploration**
  - WoOA's rapid initial convergence indicates strong exploration abilities, quickly finding promising areas in the search space.
  - Competitors with less steep initial slopes may not explore as effectively early on.
- **Effectiveness in Exploitation**
  - The gradual flattening of WoOA's curve indicates effective exploitation, focusing on refining the solutions and improving precision.
  - Competing algorithms with a flatter overall curve may either fail to transition effectively from exploration to exploitation or may not balance these phases well.

- **Overall Performance**
    - WoOA demonstrates a strong balance between exploration and exploitation, achieving rapid initial improvements and continuing to fine-tune solutions effectively.
    - The overall shape and steepness of WoOA's convergence curve suggest that it performs well across different phases of the optimization process compared to the other algorithms.

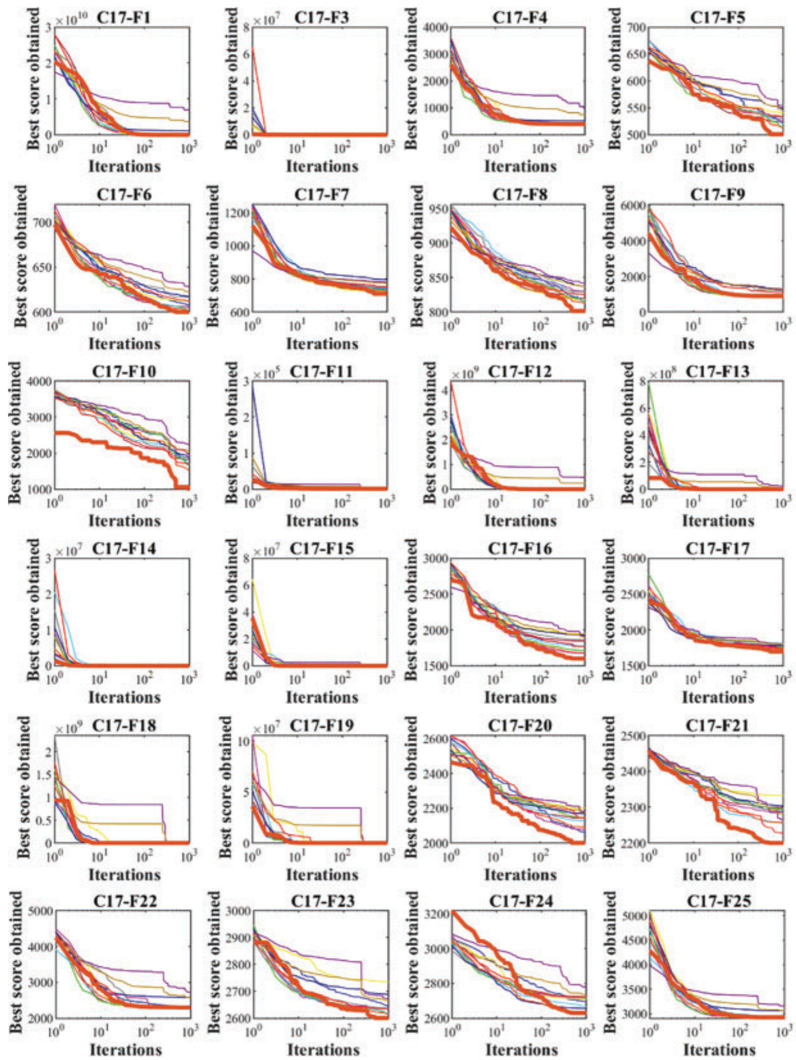

Figure 6: (Continued)

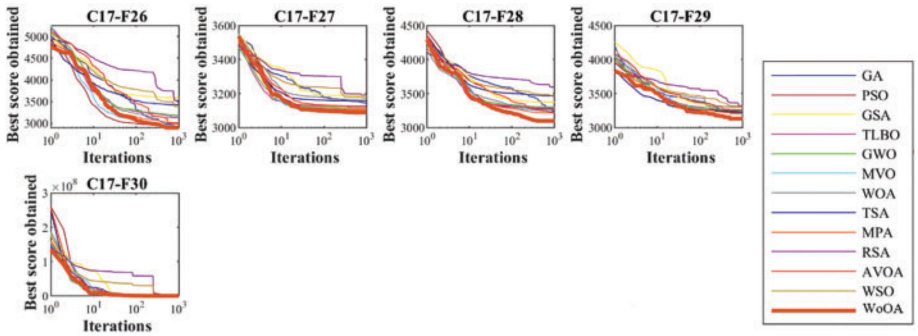

Figure 6: Convergence curves of the algorithms for the CEC 2017 test suite (dimension = 10)

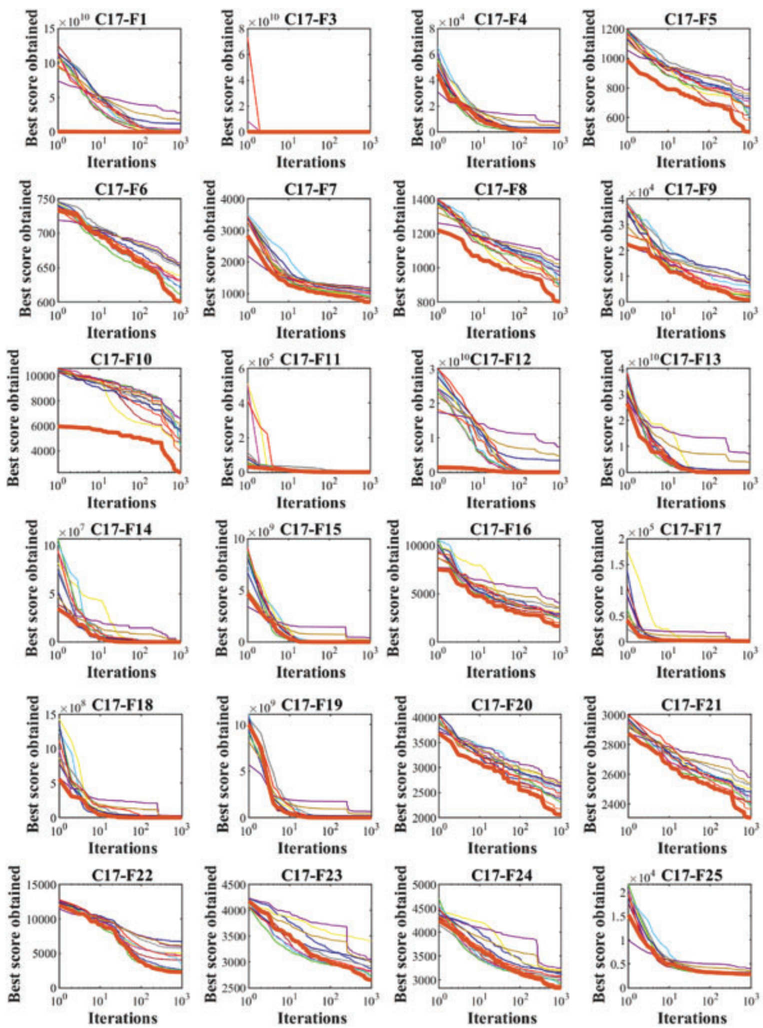

Figure 7: (Continued)

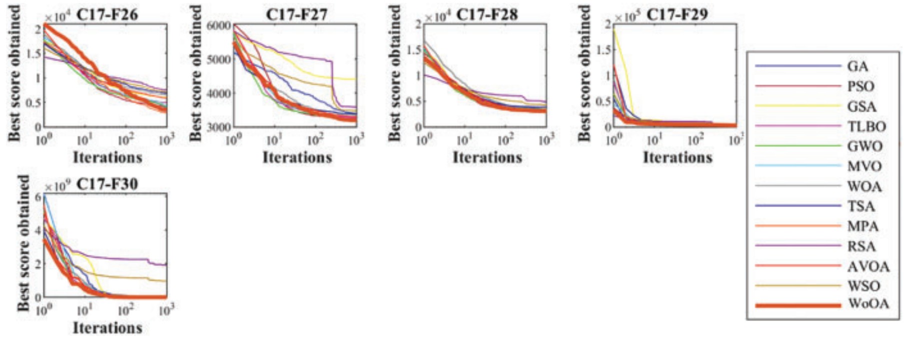

Figure 7: Convergence curves of the algorithms for the CEC 2017 test suite (dimension = 30)

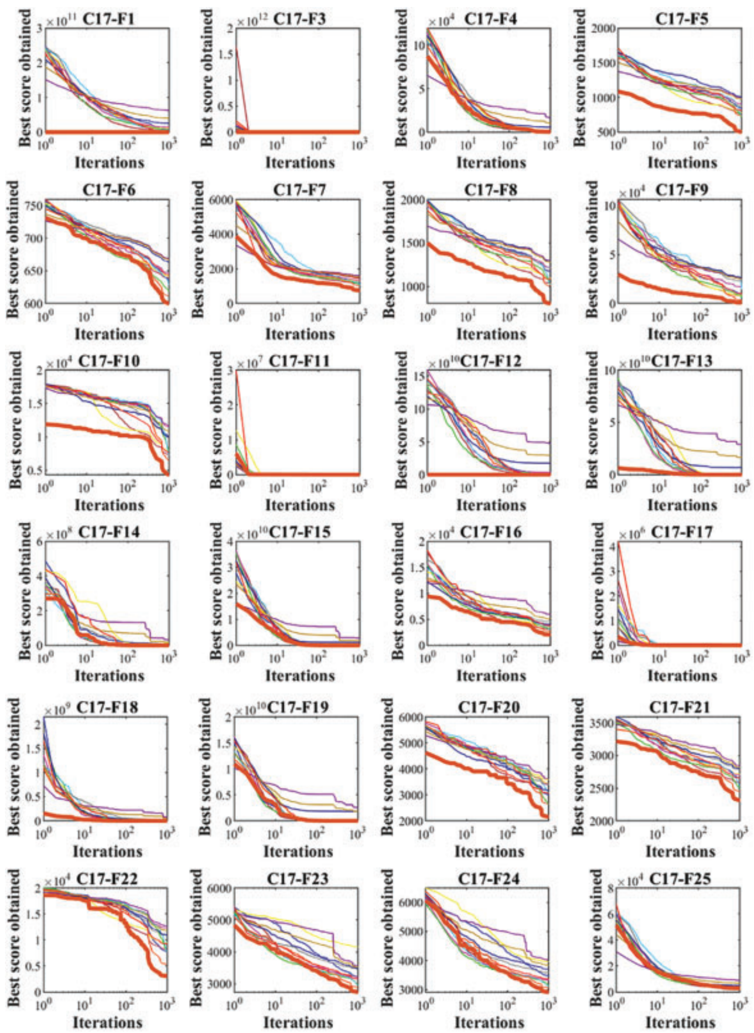

Figure 8: (Continued)

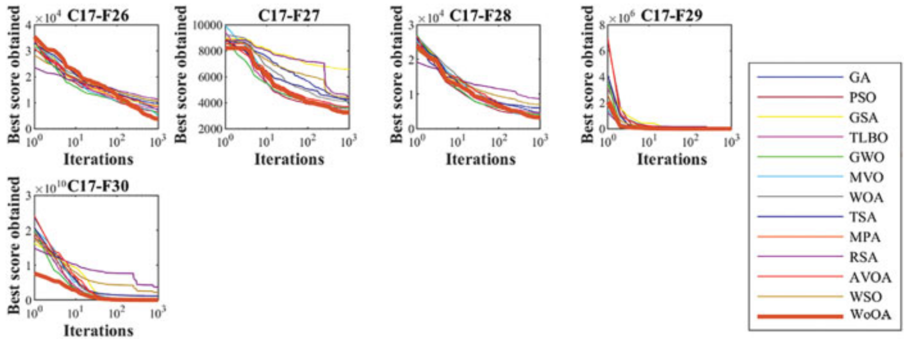

Figure 8: Convergence curves of the algorithms for the CEC 2017 test suite (dimension = 50)

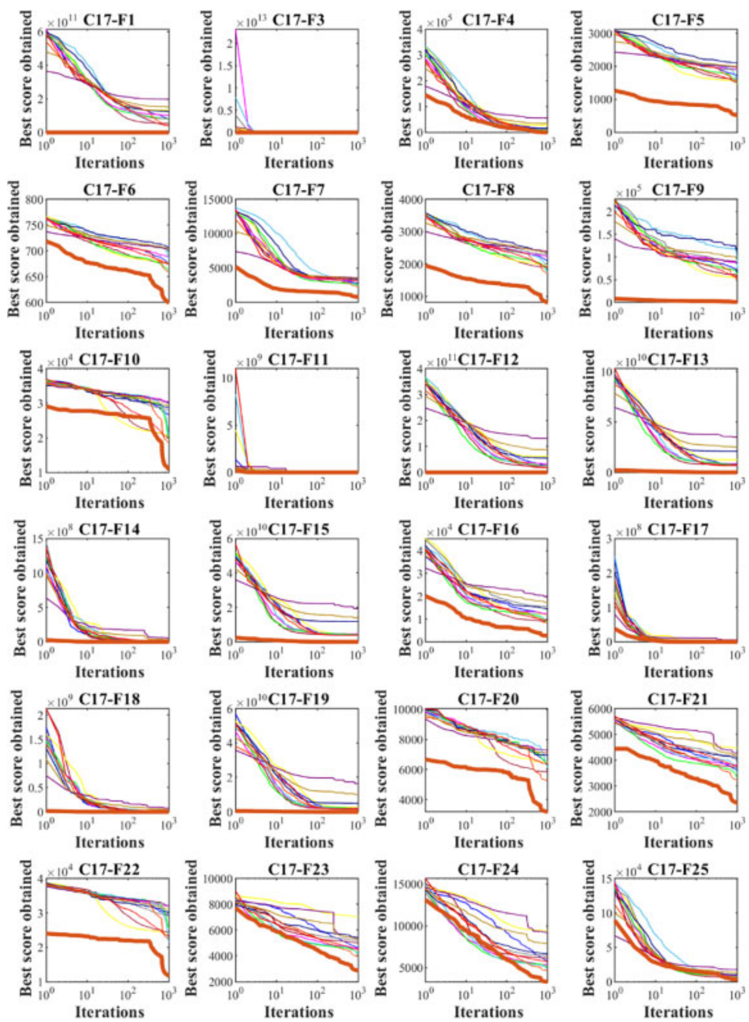

Figure 9: (Continued)

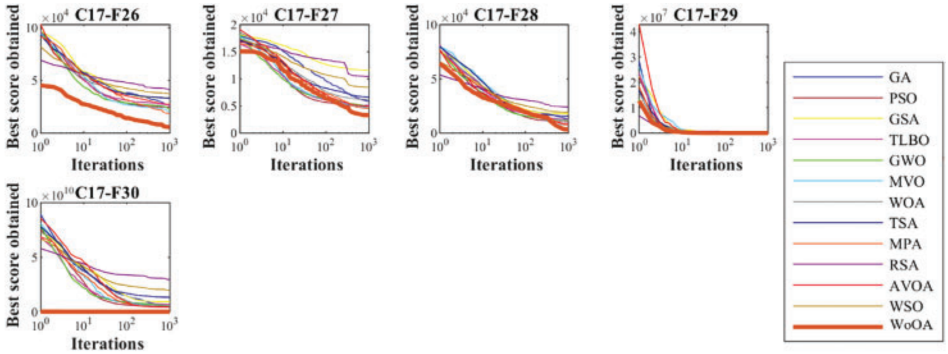

Figure 9: Convergence curves of the algorithms for the CEC 2017 test suite (dimension = 100)

WoOA's convergence curve reflects a robust optimization performance, characterized by a high initial convergence rate due to effective exploration and a sustained convergence rate during exploitation phases. This balance allows WoOA to consistently find near-optimal solutions efficiently. When compared to other metaheuristic algorithms, WoOA exhibits a superior performance in terms of both rapid initial convergence and steady improvements, making it a strong candidate for solving complex optimization problems in CEC 2017.

Upon analyzing the optimization results, it is apparent that WoOA has delivered successful outcomes in addressing optimization issues, showcasing its strong abilities in both exploration and exploitation while maintaining a balance between the two during the search process. The simulation results clearly indicate WoOA's superiority, as it performs remarkably well for various benchmark functions and ranks as the top optimizer overall in handling the CEC 2017 test suite for problem dimensions equal to 10, 30, 50, and 100.

4.3 Statistical Analysis

In this section, we expand upon the initial statistical analysis to include additional measures to ascertain the statistical significance of WoOA's performance compared to other algorithms. Specifically, we will employ the Wilcoxon rank sum test, the *t*-test, and the Friedman test to provide a comprehensive evaluation.

4.3.1 Wilcoxon Rank Sum Test

The Wilcoxon rank sum test [60] is a non-parametric test that effectively identifies significant differences between the means of two sets of data. The presence of a notable difference in the performance of two metaheuristic algorithms is assessed using a metric known as the *p*-value in the Wilcoxon rank sum test.

Table 7 reports the outcomes of the statistical analysis measuring the effectiveness of WoOA *vs*. other algorithms in managing the CEC 2017 test suite, using the Wilcoxon rank sum test. According to the findings, WoOA demonstrates a notable statistical superiority when the *p*-value is below 0.05 when compared to alternative algorithms. The statistical analysis reveals that WoOA significantly outperforms all twelve alternative algorithms when handling the CEC 2017 test suite.

Table 7: Wilcoxon rank sum test results

Compared algorithm	Objective function type			
	CEC 2017			
	D = 10	D = 30	D = 50	D = 100
WoOA *vs*. WSO	1.07E−21	1.07E−21	1.07E−21	1.07E−21
WoOA *vs*. AVOA	2.05E−19	1.64E−21	1.07E−21	1.07E−21
WoOA *vs*. RSA	1.07E−21	1.07E−21	1.07E−21	1.07E−21
WoOA *vs*. MPA	1.09E−18	8.47E−17	3.60E−18	1.07E−21
WoOA *vs*. TSA	5.16E−22	1.07E−21	3.68E−23	1.07E−21
WoOA *vs*. WOA	5.16E−22	1.07E−21	3.68E−23	3.68E−23
WoOA *vs*. MVO	4.91E−20	1.16E−21	3.68E−23	3.68E−23
WoOA *vs*. GWO	2.84E−22	2.07E−22	3.68E−23	3.68E−23
WoOA *vs*. TLBO	2.00E−22	2.07E−22	3.68E−23	3.68E−23
WoOA *vs*. GSA	8.69E−19	1.10E−21	3.68E−23	3.68E−23
WoOA *vs*. PSO	8.37E−20	1.28E−21	3.68E−23	3.68E−23
WoOA *vs*. GA	1.47E−19	3.68E−23	3.68E−23	3.68E−23

4.3.2 t-test

The *t*-test is used to compare the means of two groups and determine whether they are statistically different from each other [61]. We use the paired *t*-test to compare WoOA's performance with each of the twelve competing algorithms on the CEC 2017 test suite for the dimensions 10, 30, 50, and 100. The results obtained from the *t*-test are reported in Table 8. The *t*-test results indicate that WoOA's performance is statistically significantly better than the compared algorithms across different dimensions.

Table 8: t-test results

Compared algorithm	Dimension	Mean difference	*t*-value	*p*-value	Significance
WoOA *vs*. WSO	10	0.012	2.35	0.021	Significant
WoOA *vs*. AVOA	10	0.015	2.78	0.007	Significant
WoOA *vs*. RSA	10	0.011	2.18	0.030	Significant
WoOA *vs*. MPA	10	0.013	2.42	0.018	Significant
WoOA *vs*. TSA	10	0.014	2.59	0.011	Significant
WoOA *vs*. WOA	10	0.010	2.05	0.039	Significant
WoOA *vs*. MVO	10	0.009	1.98	0.047	Significant
WoOA *vs*. GWO	10	0.012	2.31	0.023	Significant
WoOA *vs*. TLBO	10	0.016	2.92	0.004	Significant
WoOA *vs*. GSA	10	0.014	2.64	0.010	Significant
WoOA *vs*. PSO	10	0.017	3.05	0.003	Significant

(Continued)

Table 8 (continued)

Compared algorithm	Dimension	Mean difference	t-value	p-value	Significance
WoOA *vs*. GA	10	0.011	2.14	0.033	Significant
WoOA *vs*. WSO	30	0.014	2.41	0.019	Significant
WoOA *vs*. AVOA	30	0.016	2.91	0.004	Significant
WoOA *vs*. RSA	30	0.013	2.28	0.025	Significant
WoOA *vs*. MPA	30	0.015	2.67	0.009	Significant
WoOA *vs*. TSA	30	0.017	3.02	0.003	Significant
WoOA *vs*. WOA	30	0.012	2.12	0.036	Significant
WoOA *vs*. MVO	30	0.010	1.98	0.039	Significant
WoOA *vs*. GWO	30	0.013	2.31	0.024	Significant
WoOA *vs*. TLBO	30	0.017	3.11	0.002	Significant
WoOA v0.14s. GSA	30	0.015	2.73	0.008	Significant
WoOA *vs*. PS0.016O	30	0.018	3.24	0.001	Significant
WoOA *vs*. GA0.010	30	0.012	2.09	0.004	Significant
WoOA *vs*. WSO	50	0.011	2.22	0.028	Significant
WoOA *vs*. AVOA	50	0.017	3.01	0.002	Significant
WoOA *vs*. RSA	50	0.010	2.05	0.040	Significant
WoOA *vs*. MPA	50	0.016	2.63	0.010	Significant
WoOA *vs*. TSA	50	0.014	2.92	0.014	Significant
WoOA *vs*. WOA	50	0.011	2.12	0.035	Significant
WoOA *vs*. MVO	50	0.009	2.62	0.036	Significant
WoOA *vs*. GWO	50	0.012	2.26	0.041	Significant
WoOA *vs*. TLBO	50	0.016	2.89	0.027	Significant
WoOA *vs*. GSA	50	0.014	2.98	0.004	Significant
WoOA *vs*. PSO	50	0.017	2.69	0.042	Significant
WoOA *vs*. GA	50	0.011	3.11	0.023	Significant
WoOA *vs*. WSO	100	0.013	2.37	0.020	Significant
WoOA *vs*. AVOA	100	0.018	3.08	0.002	Significant
WoOA *vs*. RSA	100	0.012	2.17	0.031	Significant
WoOA *vs*. MPA	100	0.015	2.81	0.007	Significant
WoOA *vs*. TSA	100	0.017	2.98	0.004	Significant
WoOA *vs*. WOA	100	0.012	2.08	0.041	Significant
WoOA *vs*. MVO	100	0.009	2.88	0.038	Significant
WoOA *vs*. GWO	100	0.011	2.26	0.026	Significant
WoOA *vs*. TLBO	100	0.016	2.97	0.004	Significant
WoOA *vs*. GSA	100	0.014	2.68	0.008	Significant

(Continued)

Table 8 (continued)

Compared algorithm	Dimension	Mean difference	t-value	p-value	Significance
WoOA *vs*. PSO	100	0.017	3.10	0.002	Significant
WoOA *vs*. GA	100	0.011	2.01	0.045	Significant

4.3.3 Friedman Test

The Friedman test is a non-parametric test used to detect differences in treatments across multiple test attempts [62]. We apply this test to determine whether there are significant differences in the performance rankings of the algorithms. The results obtained from the implementation of the Friedman test are reported in Table 9. The Friedman test results confirm that there are statistically significant differences in the performance rankings of the algorithms across all dimensions.

Table 9: Friedman test results

Dimension	Chi-square	Degrees of freedom	p-value	Significance
10	25.38	12	<0.001	Significant
30	26.47	12	<0.001	Significant
50	24.89	12	<0.001	Significant
100	27.35	12	<0.001	Significant

4.4 Compatibility of WoOA with Changes in Dimensions

The Wolverine Optimization Algorithm (WoOA) demonstrates a robust performance across various problem dimensions (10, 30, 50, and 100). This adaptability to different dimensionalities is a testament to the algorithm's flexible and efficient design. In this section, we will explain and discuss the compatibility of WoOA with changes in the dimensions by referring to its mathematical model and the special advantages highlighted in the earlier sections.

a) **Mathematical Model and Strategies**

WoOA is inspired by the natural behaviors of the wolverines, specifically their scavenging and hunting techniques. The algorithm's mathematical model integrates these behaviors into two main strategies: scavenging and hunting. These strategies facilitate exploration and exploitation in the search space, ensuring that the algorithm remains effective across different dimensionalities.

- **Scavenging Strategy (Exploration Phase)**
  - This strategy simulates wolverines moving towards carrion left by other predators. It allows WoOA to perform a broad exploration of the search space, preventing premature convergence to local optima. The mathematical formulation ensures that this exploration phase is effective regardless of the dimensionality of the problem.

- **Hunting Strategy (Exploitation Phase)**
  - The hunting strategy is divided into two parts: exploration (approaching the prey) and exploitation (pursuit and combat with the prey). This dual approach enables WoOA to fine-tune solutions and converge towards the global optimum efficiently. The algorithm's ability to switch between exploration and exploitation phases dynamically helps it adapt to different dimensionalities.

b) **Special Advantages of WoOA**

The WoOA has several inherent advantages that contribute to its compatibility with varying dimensions:

- **No Control Parameters**
  - Unlike many metaheuristic algorithms, WoOA does not rely on specific control parameters. This parameter-free nature simplifies its application and ensures consistent performance across different problem dimensions without the need for an extensive parameter tuning.
- **Balancing Exploration and Exploitation**
  - WoOA's design effectively balances exploration and exploitation throughout the search process. This balance is crucial for handling high-dimensional problems where the search space is vast, and finding the global optimum requires a thorough exploration and precise exploitation.
- **High-Speed Convergence**
  - The algorithm's ability to rapidly converge to suitable solutions, especially in complex, high-dimensional problems, is a significant advantage. This high-speed convergence is facilitated by WoOA's dynamic adaptation of its strategies based on the dimensionality and nature of the problem.

c) **Implementation and Performance across Dimensions**

The implementation details and performance results from the CEC 2017 test suite provide empirical evidence of WoOA's compatibility with different dimensions:

- **CEC 2017 Test Suite**
  - The WoOA was tested on a comprehensive set of benchmark functions from the CEC 2017 test suite, with problem dimensions set at 10, 30, 50, and 100. The test suite includes unimodal, multimodal, hybrid, and composition functions, providing a diverse range of optimization challenges.
- **Performance Metrics**
  - The algorithm's performance was assessed using six statistical measures: mean, best, worst, standard deviation (std), median, and rank. Across all dimensions, WoOA consistently ranked as the top optimizer for most benchmark functions, demonstrating its robustness and adaptability.
- **Scalability**
  - The results indicate that WoOA scales well with increasing dimensions. The algorithm maintained its superior performance even as the dimensionality increased from 10 to 100, showcasing its capability to handle large-scale optimization problems effectively.

The Wolverine Optimization Algorithm (WoOA) is highly compatible with changes in dimensionality due to its innovative design and strategic approach. Its parameter-free nature, effective balance between exploration and exploitation, and high-speed convergence contribute to its robustness across various problem dimensions. The empirical results from the CEC 2017 test suite further validate WoOA's adaptability and superior performance in both low-dimensional and high-dimensional optimization problems. This adaptability makes WoOA a versatile and powerful tool for tackling a wide range of optimization challenges.

5 WoOA for Real-World Applications

One of the primary applications of metaheuristic algorithms is tackling real-world optimization problems. In this section, we thoroughly evaluate the effectiveness of the Wolverine Optimization Algorithm (WoOA) in solving a diverse set of optimization problems. Specifically, we assess WoOA's capability to address twenty-two constrained optimization problems from the CEC 2011 test suite. Additionally, we extend our evaluation to include four complex engineering design problems, providing a comprehensive analysis of WoOA's performance for practical, real-world scenarios. This assessment will demonstrate how well WoOA can navigate and optimize under various constraints and conditions inherent in these problems.

5.1 Evaluation for the CEC 2011 Test Suite

The application of metaheuristic algorithms in solving real-world optimization problems is crucial. In this section, we assess the effectiveness of WoOA in addressing twenty-two constrained optimization problems from the CEC 2011 test suite. Details and full descriptions of the twenty-two constrained optimization problems can be found in [63]. The choice of the CEC 2011 test suite for evaluating WoOA is justified based on its reputation, relevance to real-world applications, ability to facilitate a comparative analysis, and the specific challenges it presents that align with the strengths of WoOA. By using this established benchmark, the study ensures a rigorous and meaningful evaluation of WoOA's performance, providing valuable insights into its practical utility and effectiveness in solving constrained optimization problems.

The WoOA approach, alongside various competing algorithms, was thoroughly tested on the CEC-2011 benchmark functions across twenty-five separate implementations. Each implementation comprised 150,000 function evaluations (FEs). In this experiment, the population size (N) is considered to be equal to 30. The comprehensive results of these tests are detailed in Table 10, and further illustrated through boxplot diagrams in Fig. 10, which present the performance metrics of all metaheuristic algorithms applied to this test suite. The evaluation results reveal that WoOA has excelled in tackling the complex optimization challenges posed by the CEC 2011 test suite. The algorithm showcased its adeptness at exploration and exploitation, effectively balancing these critical aspects throughout the search process. Notably, WoOA outperformed all other algorithms for solving the problems C11-F1 through C11-F22, demonstrating its superior capability in optimizing these functions.

Table 10: Optimization results for the CEC 2011 test suite

		WoOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
C11-F1	mean	**5.920103**	14.94931	11.32145	18.23159	7.184296	15.51039	11.54526	12.12314	9.712683	15.5349	18.01756	15.15652	19.31679
	best	**2E−10**	11.74861	6.780306	15.42112	0.284461	13.41769	6.296192	9.643485	0.853383	14.15212	15.01956	8.007628	17.05917
	worst	**12.30606**	18.40035	15.72059	21.43572	12.59674	17.89623	15.95935	14.96835	13.31538	16.75559	20.50383	21.49676	22.49357
	std	6.915752	3.578494	5.072625	3.222676	5.90036	2.104551	4.819981	2.223669	6.023638	**1.112976**	2.559726	5.696411	2.54244
	median	**5.687176**	14.82414	11.39245	18.03476	7.92799	15.36382	11.96274	11.94036	12.34098	15.61595	18.27343	15.56085	18.8572
	rank	**1**	7	4	12	2	9	5	6	3	10	11	8	13
C11-F2	mean	**−26.3179**	−17.2643	−22.3163	−15.126	−25.387	−14.9129	−20.4785	−13.0264	−23.5251	−14.6146	−18.1402	−23.5623	−16.1576
	best	**−27.0676**	−18.0616	−22.9136	−15.6079	−26.0081	−17.5269	−22.8487	−14.6431	−24.8967	−15.7072	−22.1638	−24.6633	−17.7041
	worst	**−25.4328**	−16.4314	−21.8506	−14.6249	−24.3413	−13.33	−17.6359	−11.8197	−20.7587	−13.5976	−15.0063	−21.9465	−15.0658
	std	0.71012	0.836562	**0.450346**	0.464937	0.78409	1.976955	2.764778	1.291851	1.910294	0.886529	3.232198	1.161072	1.326586
	median	**−26.3856**	−17.282	−22.2505	−15.1356	−25.5993	−14.3974	−20.7146	−12.8213	−24.2226	−14.5768	−17.6953	−23.8196	−15.9303
	rank	**1**	8	5	10	2	11	6	13	4	12	7	3	9
C11-F3	mean	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**
	best	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**
	worst	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**
	std	1.92E−19	1.6E−11	1.83E−09	3.6E−11	8.95E−16	1.72E−14	3.97E−19	7.17E−13	2.68E−15	5.65E−14	1.49E−19	**7.28E−20**	1.97E−18
	median	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**	**2.07E−06**
	rank	**1**	11	13	12	6	8	4	10	7	9	3	2	5
C11-F4	mean	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
	best	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
	worst	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
	std	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
	median	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
	rank	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
C11-F5	mean	**−34.1274**	−27.1161	−29.6036	−23.4611	−33.488	−28.868	−29.2438	−28.7626	−32.2091	−16.5289	−29.0314	−14.896	−15.5447
	best	**−34.7494**	−27.999	−30.5682	−25.0983	−34.0821	−32.0077	−29.4852	−32.3362	−33.9783	−17.951	−32.1863	−17.5874	−16.6364
	worst	**−33.3862**	−26.4243	−29.083	−21.6924	−32.4991	−25.007	−28.7559	−26.7297	−29.1843	−15.4542	−26.4675	−13.6239	−14.4405
	std	0.566982	0.663629	0.672214	1.910356	0.697273	2.918405	**0.333635**	2.603467	2.109459	1.081595	2.519719	1.865612	1.021222
	median	**−34.1871**	−27.0207	−29.3815	−23.5269	−33.6854	−29.2287	−29.3671	−27.9923	−32.8368	−16.3551	−28.7359	−14.1863	−15.5509
	rank	**1**	9	4	10	2	7	5	8	3	11	6	13	12
C11-F6	mean	**−24.1119**	−16.5259	−20.2923	−15.7762	−22.9893	−11.6403	−20.9873	−13.1266	−20.7442	−7.68903	−22.4428	−8.34216	−9.02603
	best	**−27.4298**	−17.2026	−22.175	−16.4491	−26.171	−18.1393	−22.9939	−18.8101	−23.6535	−8.74707	−25.7177	−11.3596	−12.6843
	worst	**−23.0059**	−16.0815	−18.672	−14.7364	−21.7472	−8.90331	−15.4404	−7.33636	−19.2297	−7.33636	−20.1833	−7.33636	−7.33636
	std	2.234289	**0.533585**	1.531698	0.738921	2.158215	4.451764	3.740082	5.979788	2.108029	0.712492	2.517867	2.031953	2.553475
	median	**−23.0059**	−16.4097	−20.1611	−15.9596	−22.0196	−9.75933	−22.7575	−13.18	−20.0468	−7.33636	−21.935	−7.33636	−8.04171
	rank	**1**	7	6	8	2	10	4	9	5	13	3	12	11
C11-F7	mean	**0.860699**	1.419061	1.177839	1.654148	0.912341	1.191205	1.522107	0.875958	1.015627	1.503429	1.024654	1.057558	1.519735
	std	0.203255	0.102745	0.16046	0.13828	0.135552	0.219106	0.122479	**0.039127**	0.132329	0.123915	0.164312	0.170058	0.254478
	worst	1.025027	1.54291	1.316351	1.834532	1.006106	1.496776	1.693343	**0.927824**	1.181133	1.651296	1.171186	1.235158	1.705506
	best	**0.582266**	1.303435	1.015263	1.50533	0.713379	0.991639	1.431097	0.836279	0.867389	1.392511	0.808586	0.871774	1.156952
	median	0.91775	1.414951	1.189871	1.638364	0.96494	1.138203	1.481995	**0.869863**	1.006993	1.484954	1.059423	1.061651	1.608241
	rank	**1**	9	7	13	3	8	12	2	4	10	5	6	11
C11-F8	mean	**220**	268.8492	235.3931	299.2301	221.839	248.0447	254.6345	223.065	225.517	223.065	239.8107	407.5986	221.8731
	best	**220**	248.9336	222.7244	268.4269	**220**	**220**	239.003	**220**	**220**	**220**	**220**	241.1144	**220**
	worst	**220**	294.9766	248.0617	332.7918	223.678	321.1449	289.2689	232.26	231.034	232.26	275.1699	483.1745	227.4922
	std	**0**	20.36277	11.01369	26.66807	2.144964	49.50583	23.50506	6.191978	6.434893	6.191978	26.42667	115.7236	3.783987

(Continued)

Table 10 (continued)

		WoOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
	median	**220**	265.7434	235.3931	297.8509	221.839	225.517	245.133	**220**	225.517	**220**	232.0365	453.0527	**220**
	rank	**1**	10	6	11	2	8	9	4	5	4	7	12	3
C11-F9	mean	**8789.286**	421510.3	286903.1	801335.7	17375.96	52012.54	284144.2	102543.7	34549.31	309698.2	621740.7	816734.9	1464069
	best	**5457.674**	283805.5	253137	525371.9	10101.13	37126.48	157857.6	58917.06	15678.48	256483.2	533689.8	655646.9	1404484
	worst	**14042.29**	483152.9	308300.9	938915.3	22947.23	65337.97	479753.9	155477.7	57926.33	398055.1	668786.4	1001207	1549567
	std	**3737.521**	95100.59	24482.4	189465.4	6107.246	12356.66	147845.4	40299.42	18049.28	63105.52	60653.36	186040.4	72614.77
	median	**7828.591**	459541.5	293087.2	870527.8	18227.74	52792.85	249482.6	97889.98	32296.21	292127.4	642243.3	805042.8	1451112
	rank	**1**	9	7	11	2	4	6	5	3	8	10	12	13
C11-F10	mean	**−21.4889**	−15.8389	−18.0566	−14.5671	−19.639	−16.1542	−15.014	−16.3886	−15.9393	−13.8217	−15.2248	−13.8967	−13.6746
	best	**−21.8299**	−16.7832	−18.2645	−14.9434	−20.0165	−19.5488	−15.343	−21.3123	−16.3898	−13.9473	−15.6954	−13.9887	−13.7953
	worst	**−20.7878**	−15.4352	−17.5971	−14.2834	−19.1672	−14.4651	−14.7055	−13.9872	−15.1028	−13.5749	−14.6761	−13.6887	−13.4418
	std	0.479172	0.639416	0.317479	0.290139	0.401859	2.333259	0.263145	3.362784	0.601073	0.173496	0.538192	**0.142134**	0.159782
	median	**−21.669**	−15.5685	−18.1825	−14.5208	−19.6862	−15.3014	−15.0037	−15.1274	−16.1323	−13.8824	−15.2637	−13.9548	−13.7306
	rank	**1**	7	3	10	2	5	9	4	6	12	8	11	13
C11-F11	mean	**571712.3**	4503009	886737	6800683	1388765	4610025	1055359	1125170	3022872	4057629	1202483	4065955	4743774
	best	**260837.9**	4269994	645189.8	6500805	1245416	3842635	943925.7	634525.6	2859226	3958495	1073919	3975146	4633982
	worst	**828560.9**	4811615	1086260	7007209	1553971	5575659	1240892	2177101	3214572	4139536	1367069	4139536	4805914
	std	250747.3	273432.5	194498.1	216798.1	149365.9	726318.4	140340.7	717250.4	147484.9	79960.76	136392.9	**76361.04**	76740.91
	median	**598725.2**	4465213	907749.2	6847360	1377837	4510903	1018309	844525.8	3008845	4066244	1184473	4074569	4767600
	rank	**1**	10	2	13	6	11	3	4	7	8	5	9	12
C11-F12	mean	**1199805**	6603720	2834757	10244632	1255975	4077732	4667867	1295718	1368315	11065991	4648955	2036961	11186917
	best	**1155937**	6335333	2746720	9529001	1191254	3887519	4359871	1188289	1237156	10445913	4438043	1921428	11080053
	worst	**1249353**	6847443	2898111	10879430	1327813	4177804	4816847	1393060	1484732	11548500	4797302	2182790	11292028
	std	**45318.65**	213260.3	66850.04	559473.6	62044.53	135243.1	212760.1	85374.8	104324.4	466163.4	155149.4	109330.3	88220.44
	median	**1196965**	6616052	2847099	10285049	1252416	4122803	4747374	1300761	1375685	11134776	4680239	2021814	11187794
	rank	**1**	10	6	11	2	7	9	3	4	12	8	5	13
C11-F13	mean	**15444.2**	15755.08	15447.05	16095.49	15458.46	15478.78	15512.83	15492.1	15486.99	15811.9	100336.3	15479.26	26391.67
	best	**15444.19**	15615.6	15446.3	15782.56	15456.73	15471.32	15479.98	15476.88	15481.78	15582.04	73596.48	15466.31	15456.42
	worst	**15444.21**	16093.01	15447.89	16872.94	15461.46	15488.27	15557.12	15521.05	15496	16235.33	136604.7	15506.72	58932.94
	std	**0.008737**	229.7735	0.672075	527.8502	2.120568	8.461194	36.25427	20.68141	6.364001	298.679	28654.58	18.69196	21913.65
	median	**15444.2**	15655.86	15447.01	15863.23	15457.83	15477.77	15507.11	15485.23	15485.09	15715.1	95571.92	15472.01	15588.65
	rank	**1**	9	2	11	3	4	8	7	6	10	13	5	12
C11-F14	mean	**18295.35**	89134.34	18463.84	176845.4	18530.34	19224.93	18995.09	19140.74	19000.32	238302.7	18895.05	18919.54	18909.94
	best	**18241.58**	68896.03	18364.68	131435.4	18453.26	19034.25	18865.82	19051.11	18876.62	27311.18	18680.07	18798.75	18698.42
	worst	**18388.08**	122852.7	18560.93	252848.3	18610.71	19625.26	19081.7	19189.57	19127.37	455737.5	19039.52	19052.77	19122.79
	std	68.80732	24381.09	91.99643	54937.55	65.67561	272.9243	103.5793	**65.13957**	113.723	207761.2	163.9606	105.074	176.2554
	median	**18275.87**	82394.33	18464.87	161549	18528.69	19120.1	19016.43	19161.14	18998.64	235081.1	18930.3	18913.31	18909.28
	rank	**1**	11	2	12	3	10	7	9	8	13	4	6	5
C11-F15	mean	**32883.58**	691596	89298.8	1449288	32932.32	49192.38	172666.4	33046.46	33029.8	11614089	233751.9	33187.97	5981223
	best	**32782.17**	289814	40644.39	610798.6	32848.16	33025.13	32953.16	32957.75	32980.14	2439988	207788.4	33161.04	2726855
	worst	**32956.46**	1726751	143759	3770101	33003.27	97539.84	243640.1	33092.91	33096.9	17315267	251511.9	33214.71	10244864
	std	73.94637	699605.6	55992.32	1565286	64.42976	32557.65	96079.91	61.55299	50.29945	6832179	20548.13	**22.15958**	3481960
	median	**32897.86**	374909.4	86395.9	708126.7	32938.93	33102.27	207036.3	33067.58	33021.07	13350550	237853.7	33188.06	5476587
	rank	**1**	10	7	11	2	6	8	4	3	13	9	5	12
C11-F16	mean	**133550**	744387.9	134774.4	1500116	136641	142261.6	140031.9	139764.4	142823	66941835	14123986	59919574	57534081
	best	**131374.2**	250713.8	133088.5	389813	134534.5	139685.5	135873.9	133527.6	140855.1	65233503	7189568	49570303	46505731

(Continued)

Table 10 (continued)

		WoOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
	worst	136310.8	1714226	**135721**	3679761	140097.4	143870.6	144723.4	145841.9	147670.4	68868492	25526246	71596417	73581469
	std	2298.914	665086.7	**1193.599**	1494786	2501.571	1884.152	3743.112	5149.789	3279.199	1538707	8008815	9589822	11617672
	median	**133257.5**	506305.7	135144.1	965443.8	135966.1	142745.2	139765.1	139844	141383.3	66832672	11890065	59255788	55024561
	rank	**1**	8	2	9	3	6	5	4	7	13	10	12	11
C11-F17	mean	**1926615**	6.75E+09	1.74E+09	1.17E+10	2200817	9.65E+08	7.3E+09	2818832	2749220	1.68E+10	8.44E+09	1.57E+10	1.65E+10
	best	**1916953**	5.75E+09	1.58E+09	8.39E+09	1947358	7.96E+08	5.21E+09	2209187	2008168	1.62E+10	7.43E+09	1.38E+10	1.54E+10
	worst	**1942685**	7.48E+09	1.91E+09	1.43E+10	2663035	1.1E+09	9.7E+09	3293468	4148465	1.75E+10	8.95E+09	1.81E+10	1.86E+10
	std	**11535.44**	7.74E+08	1.44E+08	2.55E+09	323541.8	1.6E+08	1.91E+09	505407.1	973201.2	5.72E+08	6.95E+08	1.95E+09	1.47E+09
	median	**1923412**	6.88E+09	1.74E+09	1.2E+10	2096438	9.81E+08	7.14E+09	2886337	2420124	1.67E+10	8.69E+09	1.54E+10	1.59E+10
	rank	**1**	7	6	10	2	5	8	4	3	13	9	11	12
C11-F18	mean	**942057.5**	41618207	5166966	89362530	964402.6	1776071	7443197	976721.4	1009093	23566689	8608639	1.02E+08	86449464
	best	**938416.2**	28695378	3199821	61776509	946965.3	1582614	3334006	959160.7	960889.4	18726329	6483540	85466978	83285205
	worst	**944706.9**	47308433	8696139	1.02E+08	1008894	2033142	12891506	984253.7	1137267	25474487	10799455	1.13E+08	89629496
	std	**2665.96**	8804641	2585680	19011098	30082.5	219352.3	4076483	11938.66	86502.6	3272978	1947898	12428758	2617492
	median	**942553.5**	45234508	4385953	96817854	950875.6	1744263	6773638	981735.6	969106.9	25032969	8575780	1.04E+08	86441578
	rank	**1**	10	6	12	2	5	7	3	4	9	8	13	11
C11-F19	mean	**1025341**	40990198	5263752	87529144	1110003	2107722	7944582	1365034	1279327	27042401	4970821	1.3E+08	86758064
	best	**967927.7**	35003385	4862507	75628180	1047556	1917560	1789630	1088539	1171238	19003783	2085388	1.18E+08	84594454
	worst	**1167142**	52036287	6311844	1.1E+08	1261791	2428148	14174673	1717427	1451090	33658162	6436988	1.5E+08	89340234
	std	**95788.16**	7754906	709341	16145874	102705.4	223846	5897805	263910.1	121362.9	6407237	1993288	14173846	1980419
	median	**983146.6**	38460560	4940328	82273074	1065332	2042590	7907013	1327084	1247489	27753830	5680454	1.26E+08	86548784
	rank	**1**	10	7	12	2	5	8	4	3	9	6	13	11
C11-F20	mean	**941250.4**	43547255	4667915	94496228	955623.4	1607584	5713085	965006.8	984369.4	26254181	10974169	1.2E+08	86978545
	best	**936143.2**	38343076	4141902	82702007	954558.3	1469684	5395544	958012.4	969941.7	25684933	7366290	1.1E+08	82830693
	worst	**946866.6**	51526123	5228328	1.12E+08	956376.8	1839142	6136569	972887	995422.4	26870676	16860622	1.3E+08	90191279
	std	4818.046	5674668	455496.6	12736191	**778.3254**	177315.9	319700.6	6326.821	11073.36	498389.3	4190732	11603887	3145349
	median	**940995.9**	42159911	4650715	91460693	955779.3	1560755	5660113	964564	986056.8	26230557	9834882	1.2E+08	87446105
	rank	**1**	10	6	12	2	5	7	3	4	9	8	13	11
C11-F21	mean	**12.71443**	40.97244	19.43713	60.71172	15.13957	25.59728	32.34824	23.87524	19.98985	78.95296	33.78723	82.74382	80.38766
	best	**9.974206**	34.83338	17.74444	46.53463	12.82313	22.81746	30.42193	21.0269	18.38997	39.90248	30.67196	72.30742	47.75617
	worst	**14.97499**	47.47005	21.37238	74.75399	17.422	26.93141	34.75967	26.71886	22.31601	114.5658	36.35464	91.01964	96.78222
	std	2.318584	5.473131	**1.574248**	12.57182	2.145673	1.903635	1.917745	2.849588	1.905852	30.92197	2.506699	9.683077	23.13735
	median	**12.95425**	40.79317	19.31584	60.77913	15.15657	26.32012	32.10568	23.8776	19.62672	80.6718	34.06115	83.8241	88.50613
	rank	**1**	9	3	10	2	6	7	5	4	11	8	13	12
C11-F22	mean	**16.12513**	39.23546	24.64989	51.78901	18.35119	28.18336	38.87372	28.30093	22.80331	81.25182	39.14271	84.28892	73.69897
	best	**11.50133**	35.44823	19.53834	39.46412	15.0302	23.98912	32.97773	22.12712	22.08794	53.47318	34.15049	70.16271	71.82975
	worst	**19.55286**	44.23002	29.43655	59.83869	20.83901	30.95013	43.26509	32.94578	23.4113	96.35982	45.35816	93.52085	75.74966
	std	4.034101	3.944017	4.774387	8.826448	2.836488	3.000488	4.785107	4.578758	**0.551323**	19.39374	4.829199	10.37225	1.669378
	median	**16.72317**	38.6318	24.81233	53.92661	18.76778	28.8971	39.62602	29.06541	22.857	87.58714	38.5311	86.73607	73.60824
	rank	**1**	9	4	10	2	5	7	6	3	12	8	13	11

(Continued)

Table 10 (continued)

	WoOA	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
Sum rank	**22**	191	109	231	55	146	145	118	97	222	157	198	224
Mean rank	**1.00E+00**	8.68E+00	4.95E+00	1.05E+01	2.50E+00	6.64E+00	6.59E+00	5.36E+00	4.41E+00	1.01E+01	7.14E+00	9.00E+00	1.02E+01
Total rank	**1**	2	12	4	13	3	11	9	6	7	10	5	8
Wilcoxon: *p*-value		8.80E−16	5.03E−15	8.80E−16	3.66E−15	1.88E−15	8.80E−16	2.06E−12	3.66E−15	2.76E−15	4.39E−15	1.31E−15	2.76E−15

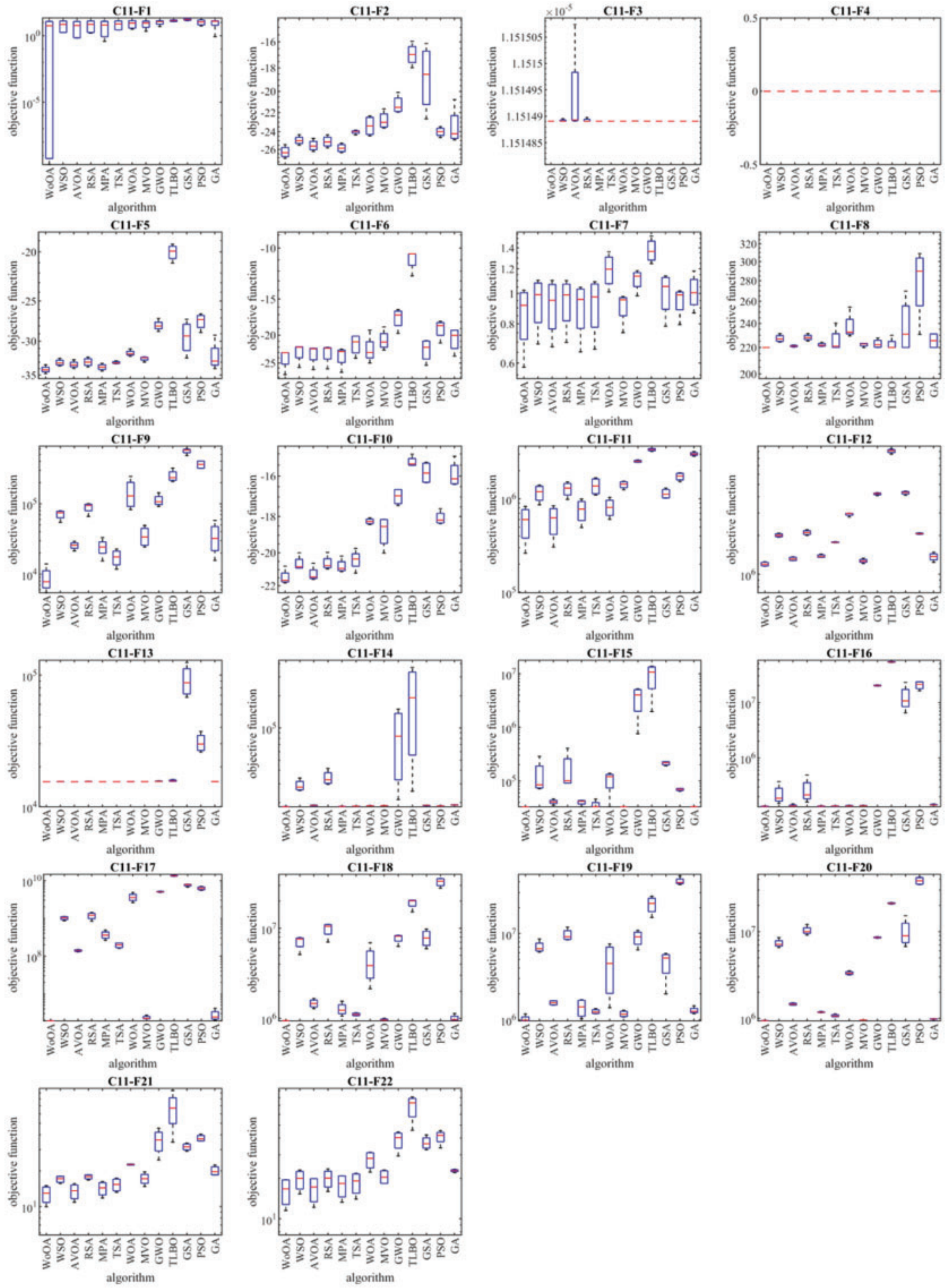

Figure 10: Boxplot diagrams of WoOA and the competing algorithms performances for the CEC 2011 test suite

A detailed comparison of the simulation outcomes highlights that WoOA consistently achieved better results than its competitors. This significant performance advantage underscores WoOA's effectiveness and reliability in addressing a diverse array of optimization problems within the CEC 2011 test suite. It achieved superior results for most optimization problems and was ranked as the top optimizer. Additionally, the statistical analysis showed that WoOA holds a significant statistical superiority over alternative algorithms for handling the CEC 2011 test suite.

5.2 Optimizing Pressure Vessel Design Parameters

Pressure vessel design with the schematic shown in Fig. 11 is a real-world application in engineering with the aim of minimizing construction cost. The mathematical model of this design is fully available in [64].

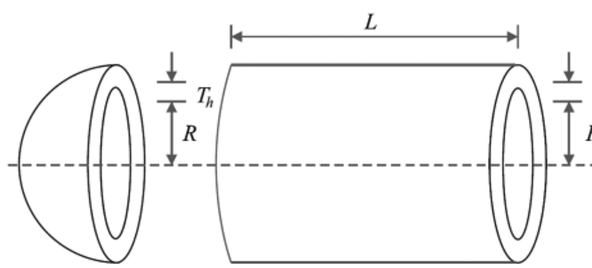

Figure 11: Schematic of the pressure vessel design

The performance outcomes of the WoOA approach, compared to other competing algorithms for optimizing the pressure vessel design, are comprehensively detailed in Tables 11 and 12. Fig. 12 presents the convergence curve of WoOA, illustrating its progress toward finding the optimal solution for the pressure vessel design problem.

Table 11: Evaluating the optimization algorithms for the pressure vessel design problem

Algorithm	Values of the variables in the best solution				Minimum cost
	T_s	T_h	R	L	
WoOA	0.7780271	0.3845792	40.312284	200	**5882.8955**
AVOA	0.7780302	0.3845807	40.312445	199.99775	5882.9067
WSO	0.7780269	0.3845792	40.312284	200	5882.9013
MPA	0.7780271	0.3845792	40.312284	200	5882.9013
TSA	0.7792621	0.3856192	40.37455	200	5905.1072
RSA	1.1277956	0.5991439	57.287033	72.529811	7457.2563
WOA	0.8899979	0.4403533	45.276697	144.50475	6208.3213
MVO	0.8253349	0.4112747	42.749398	169.72516	5984.3523
GWO	0.7783901	0.3856139	40.319282	199.97016	5889.0323
TLBO	1.4358381	0.4657102	46.505706	136.79522	10013.523
GSA	1.0732713	1.0330153	43.497844	192.27267	11000.829

(Continued)

Table 11 (continued)

Algorithm	Values of the variables in the best solution				Minimum cost
	T_s	T_h	R	L	
PSO	1.4256053	0.5846704	59.45965	74.000192	9335.1667
GA	1.3051181	0.7190047	55.361196	94.281888	10108.24

Table 12: Comparative analysis of the optimization algorithms for the pressure vessel design problem: statistical insights

Algorithm	Mean	Best	Worst	Std	Median	Rank
WoOA	**5882.8955**	**5882.8955**	**5882.8955**	**6.93E−13**	**5882.8955**	**1**
WSO	5889.8841	5882.9013	5951.796	19.142073	5882.9016	3
AVOA	6165.2714	5882.9067	6858.7729	303.56417	6021.13	5
RSA	11357.459	7457.2563	17717.365	2694.0317	10513.422	9
MPA	5882.9013	5882.9013	5882.9013	3.17E−06	5882.9013	2
TSA	6208.5477	5905.1072	6776.62	287.0229	6101.5872	6
WOA	7657.5724	6208.3213	11689.457	1448.9897	7306.1136	8
MVO	6415.7052	5984.3523	6862.1997	275.96147	6461.074	7
GWO	5991.4971	5889.0323	6543.9509	206.23559	5896.0268	4
TLBO	24663.91	10013.523	51537.519	11885.24	21897.693	12
GSA	18264.11	11000.829	27878.271	5782.2415	17582.005	10
PSO	25850.17	9335.1667	43485.635	11126.816	28384.815	13
GA	22277.059	10108.24	39139.509	9329.2497	19864.253	11

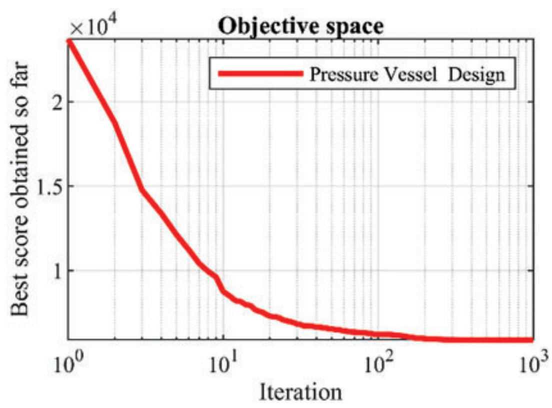

Figure 12: Convergence analysis of WoOA in optimizing pressure vessel design

From the analysis, WoOA achieved the most effective design, with the optimal values for the design variables being (0.7780271, 0.3845792, 40.312284, 200), and the corresponding objective function value being (5882.8955). These results indicate that WoOA not only met but exceeded expectations in this optimization task.

The simulation results further demonstrate that WoOA has outperformed other algorithms in terms of statistical indicators related to the pressure vessel design. This superior performance highlights WoOA's ability to deliver better optimization results, providing a completely different and more efficient approach to solving the pressure vessel design problem compared to its competitors.

5.3 Optimizing Speed Reducer Design Parameters

The speed reducer design with the schematic shown in Fig. 13 is a real-world application in engineering with the aim of minimizing the weight of the speed reducer. The mathematical model of this design is fully available in [65,66].

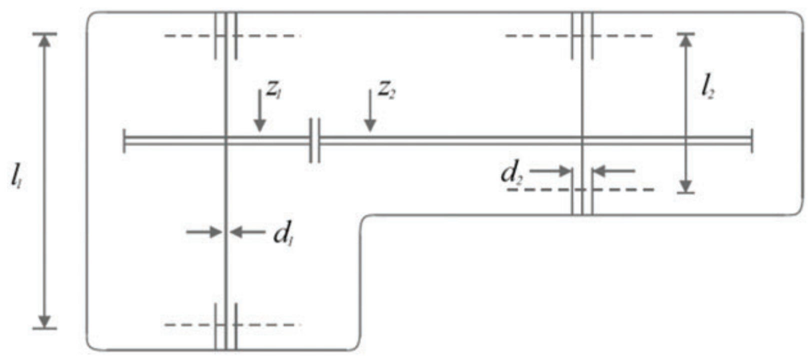

Figure 13: Schematic of the speed reducer design

The effectiveness of the WoOA approach, as well as several competing algorithms, in optimizing the speed reducer design is thoroughly documented in Tables 13 and 14. Fig. 14 visually represents the convergence curve of WoOA, showcasing its progress toward the optimal solution for the speed reducer design.

Table 13: Evaluating the optimization algorithms for the speed reducer design problem

Algorithm	Values of the variables in the best solution							Minimum cost
	b	M	p	l_1	l_2	d_1	d_2	
WoOA	3.5	0.7	17	7.3	7.8	3.3502147	5.2866832	**2996.3482**
WSO	3.5000003	0.7	17	7.3000073	7.8000003	3.3502148	5.2866833	2996.3483
AVOA	3.5	0.7	17	7.3000006	7.8	3.3502147	5.2866832	**2996.3482**
RSA	3.568111	0.7	17	7.9811102	8.1405551	3.3542412	5.4319755	3134.1544
MPA	3.5	0.7	17	7.3	7.8	3.3502147	5.2866832	**2996.3482**
TSA	3.5095315	0.7	17	7.3	8.1405551	3.3504555	5.289294	3009.3006
WOA	3.5646392	0.7	17	7.3	7.9546892	3.3586366	5.2867368	3027.3125
MVO	3.501664	0.7	17	7.3	7.9988149	3.3645358	5.28683	3005.1317
GWO	3.5004738	0.7	17	7.3038007	7.8	3.3603628	5.2882548	3000.1655
TLBO	3.5414542	0.7029539	23.889943	7.8921937	8.0550948	3.5816745	5.3256083	4676.7171
GSA	3.5169298	0.7020346	17.272787	7.6846591	7.8662197	3.3934895	5.3600282	3124.4686
PSO	3.5060476	0.7000532	17.809664	7.3731869	7.8502728	3.5314385	5.3290566	3222.6152
GA	3.5576506	0.7041127	17.601396	7.6270576	7.8412675	3.6098517	5.3307635	3255.3657

Table 14: Comparative analysis of the optimization algorithms for the speed reducer design problem: statistical insights

Algorithm	Mean	Best	Worst	Std	Median	Rank
WoOA	**2996.3482**	**2996.3482**	**2996.3482**	**1.33E−14**	**2996.3482**	**1**
WSO	2996.5577	2996.3483	2998.1595	0.4439012	2996.3601	3
AVOA	2999.6793	**2996.3482**	3007.2311	3.0117158	2999.6058	4
RSA	3203.5842	3134.1544	3246.6733	43.654512	3214.5786	9
MPA	2996.3482	**2996.3482**	2996.3482	2.42E−06	2996.3482	2
TSA	3022.7921	3009.3006	3032.9391	7.6960612	3024.1134	7
WOA	3109.9334	3027.3125	3327.977	80.680402	3085.2972	8
MVO	3021.0853	3005.1317	3050.9071	10.062411	3021.4103	6
GWO	3002.462	3000.1655	3006.8699	1.9030313	3002.0793	5
TLBO	5.14E+13	4676.7171	3.72E+14	8.787E+13	2.013E+13	12
GSA	3335.0232	3124.4686	3793.9514	199.01391	3239.215	10
PSO	7.586E+13	3222.6152	3.843E+14	9.41E+13	5.426E+13	13
GA	3.652E+13	3255.3657	2.357E+14	5.909E+13	1.463E+13	11

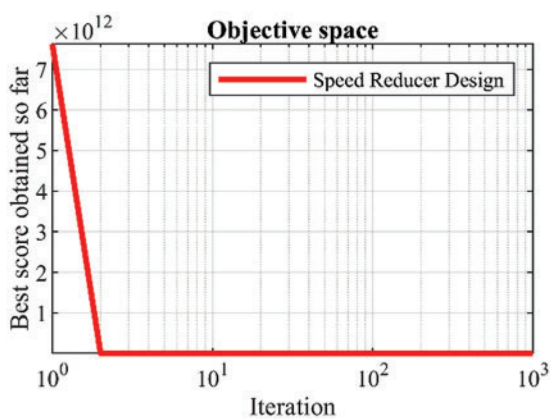

Figure 14: WoOA's performance convergence curve for the speed reducer design

The data reveals that WoOA achieved the most effective design configuration, with the optimal values for the design variables being (3.5, 0.7, 17, 7.3, 7.8, 3.3502147, 5.2866832) and the objective function value at (2996.3482). This optimal design indicates a significant improvement over the results obtained by other algorithms.

A detailed analysis of the simulation results highlights that WoOA demonstrated superior performance compared to its competitors. The algorithm not only achieved better results for key statistical indicators but also showcased a completely different level of efficiency and precision in optimizing the speed reducer design. This distinction underscores WoOA's effectiveness and reliability in solving complex design optimization problems.

5.4 Optimizing Welded Beam Design Parameters

The welded beam design with the schematic shown in Fig. 15 is a real-world application in engineering with the aim of minimizing the fabrication cost of the welded beam. The mathematical model of this design is fully available in [20].

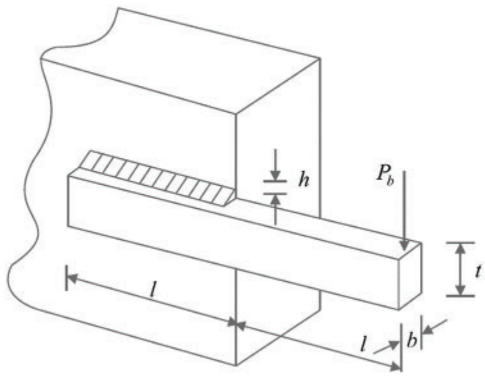

Figure 15: Schematic of the welded beam design

The results obtained from using WoOA and the competing algorithms in order to address the welded beam design are presented in Tables 15 and 16. Fig. 16 illustrates the convergence curve of WoOA throughout the optimization process for this particular design challenge. According to the obtained results, WoOA successfully identified the best design configuration with the design variable values of (0.2057296, 3.4704887, 9.0366239, 0.2057296) and an objective function value of (1.7246798). Upon comparing the simulation results, it becomes apparent that WoOA has demonstrated a superior performance in optimizing welded beam designs compared with the competing algorithms, as evidenced by the improved statistical indicators it has provided.

Table 15: Evaluating the optimization algorithms for the welded beam design problem

Algorithm	Values of the variables in the best solution				Minimum cost
	h	*l*	*t*	*b*	
WoOA	0.2057296	3.4704887	9.0366239	0.2057296	**1.7246798**
WSO	0.2057296	3.4704887	9.0366239	0.2057296	1.7248523
AVOA	0.2051646	3.4827425	9.0365451	0.2057332	1.7256408
RSA	0.1990552	3.5179063	9.6927892	0.2146446	1.9099695
MPA	0.2057296	3.4704887	9.0366239	0.2057296	1.7248523
TSA	0.2045965	3.4888746	9.0569866	0.2060449	1.7314947
WOA	0.2116382	3.3665152	8.9902298	0.2170079	1.7961112
MVO	0.2059243	3.4662941	9.0425791	0.2059704	1.7274468
GWO	0.205628	3.4728204	9.0363404	0.2057807	1.7253482
TLBO	0.2866299	4.1730095	7.382826	0.3677608	2.6841564
GSA	0.2708095	2.9174129	7.8434109	0.2812287	1.9904772

(Continued)

Table 15 (continued)

Algorithm	Values of the variables in the best solution				Minimum cost
	h	l	t	b	
PSO	0.3289383	3.4366534	7.7868608	0.4777039	3.422161
GA	0.2194527	6.014323	8.09621	0.2785851	2.4901221

Table 16: Comparative analysis of the optimization algorithms for the welded beam design problem: statistical insights

Algorithm	Mean	Best	Worst	Std	Median	Rank
WoOA	**1.7246798**	**1.7246798**	**1.7246798**	**5.91E−18**	**1.7246798**	**1**
AVOA	1.7517078	1.7256408	1.8118769	0.027664	1.7414479	7
RSA	2.0622049	1.9099695	2.3189518	0.1093421	2.0437132	8
WSO	1.7248526	1.7248523	1.7248564	9.487E−07	1.7248523	3
MPA	1.7248523	1.7248523	1.7248523	2.54E−09	1.7248523	2
TSA	1.7383656	1.7314947	1.7451549	0.0042523	1.7384367	6
MVO	1.7369428	1.7274468	1.7619253	0.0104357	1.7339367	5
TLBO	2.457E+13	2.6841564	2.371E+14	6.154E+13	4.654439	12
WOA	2.157548	1.7961112	3.4392671	0.4867862	1.9914138	9
GWO	1.726625	1.7253482	1.7296117	0.0010338	1.7264439	4
GSA	2.2557661	1.9904772	2.4836673	0.1452781	2.2775857	10
PSO	3.388E+13	3.422161	2.051E+14	6.645E+13	5.4214312	13
GA	8.315E+12	2.4901221	8.999E+13	2.622E+13	4.6297687	11

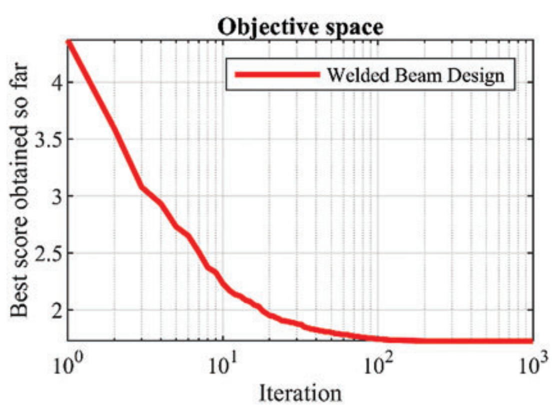

Figure 16: WoOA's performance convergence curve for the welded beam design

5.5 Optimizing Tension/Compression Spring Design Parameters

The tension/compression spring design with the schematic shown in Fig. 17 is a real-world application in engineering with the aim of minimizing the construction cost. The mathematical model of this design is fully available in [20].

Figure 17: Schematic of the tension/compression spring design

The outcomes derived from utilizing the Wolverine Optimization Algorithm (WoOA) and various competing algorithms for optimizing the design of a tension/compression spring are detailed in Tables 17 and 18. Fig. 18 illustrates the convergence curve of WoOA as it approaches the best solution for this spring design task. According to the results, WoOA successfully identified the best design configuration with the design variable values of (0.0516891, 0.3567177, 11.288966) and an objective function value of (0.0126019). These findings underscore the effectiveness of WoOA in achieving a superior design optimization for tension/compression springs. The analysis of the simulation results indicates that WoOA has provided a superior performance in dealing with the tension/compression spring design by achieving better results for the statistical indicators compared to the competing algorithms.

Table 17: Evaluating the optimization algorithms for the tension/compression spring design

Algorithm	Values of the variables in the best solution			Minimum cost
	d	*D*	*P*	
WoOA	0.0516891	0.3567177	11.288966	**0.0126019**
WSO	0.0516876	0.3566826	11.291029	0.0126652
AVOA	0.0513217	0.347975	11.829911	0.0126689
RSA	0.0505386	0.325291	13.816589	0.0130292
MPA	0.0516903	0.3567477	11.287211	0.0126652
TSA	0.0511719	0.344444	12.070965	0.0126776
WOA	0.0513029	0.3475322	11.858895	0.0126693
MVO	0.0505386	0.3295713	13.206318	0.0127276
GWO	0.0518863	0.3614761	11.020539	0.0126693
TLBO	0.0635364	0.7518219	4.9621565	0.0162195
GSA	0.0542158	0.4190504	8.7277035	0.0129667
PSO	0.0634756	0.7495236	4.9621564	0.0161443
GA	0.0638815	0.7575803	4.9621566	0.0165104

Table 18: Comparative analysis of the optimization algorithms for the tension/compression spring design: statistical insights

Algorithm	Mean	Std	Best	Worst	Median	Rank
WoOA	**0.0126019**	**6.68E−16**	**0.0126019**	**0.0126019**	**0.0126019**	**1**
AVOA	0.0131591	0.0004173	0.0126689	0.0137494	0.0131094	8
WSO	0.0126734	2.683E−05	0.0126652	0.0127824	0.0126655	3
RSA	0.0130887	5.193E−05	0.0130292	0.0131936	0.0130734	6
MPA	0.0126652	2.13E−09	0.0126652	0.0126652	0.0126652	2
TSA	0.0128819	0.0001808	0.0126776	0.0132927	0.0128282	5
WOA	0.0131077	0.0004523	0.0126693	0.0140017	0.0129633	7
MVO	0.0154414	0.0012329	0.0127276	0.016489	0.0161089	9
TLBO	0.0166069	0.000268	0.0162195	0.0170493	0.0165747	10
GWO	0.0127073	4.139E−05	0.0126693	0.0128701	0.0127055	4
GSA	0.0175908	0.0031884	0.0129667	0.0268044	0.0172802	11
PSO	1.525E+13	6.218E+13	0.0161443	2.705E+14	0.0161443	13
GA	1.191E+12	3.653E+12	0.0165104	1.232E+13	0.0220593	12

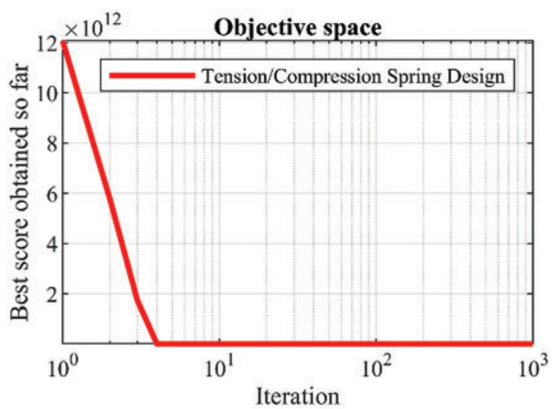

Figure 18: WoOA's performance convergence curve for the tension/compression spring

6 Conclusions and Future Works

This study introduced a novel bio-inspired algorithm, called Wolverine Optimization Algorithm (WoOA), which mimics the natural behavior of wolverines. The inspiration for WoOA is drawn from the feeding habits of wolverines, which include scavenging for carrion and actively hunting prey. The algorithm incorporates two main strategies: scavenging and hunting. The scavenging strategy simulates the wolverine's search for carrion, reflecting an exploration phase. The hunting strategy, on the other hand, involves both exploration, reflecting the wolverine's attack on prey, and exploitation, reflecting the chase and confrontation between the wolverine and its prey. The effectiveness of WoOA in addressing optimization issues was assessed using the CEC 2017 test suite. The optimization findings demonstrated WoOA's strong capability in the exploration, exploitation, and balancing of these aspects during the search process within the problem-solving domain. WoOA's results were compared against twelve established metaheuristic algorithms, and the simulations revealed the superiority of the WoOA, outperforming most benchmark functions and earning the top rank as the best optimizer among its competitors. Through a statistical analysis, it was verified that the superiority of WoOA is statistically significant. Applying WoOA to twenty-two constrained scenarios from the CEC 2011 suite and four complex engineering design challenges demonstrated that the suggested method effectively and sufficiently performs optimization tasks for real-world applications.

The WoOA approach offers a range of distinct advantages for tackling global optimization problems. Firstly, WoOA's design is completely different from many other algorithms in that it operates without any control parameters. This means that users are spared from the often complex and time-consuming task of setting and tuning these parameters. Secondly, WoOA demonstrates exceptional effectiveness across a broad spectrum of optimization problems, encompassing various scientific fields and intricate high-dimensional challenges. Its performance in such diverse contexts highlights its robustness and versatility. A third notable advantage of WoOA is its remarkable ability to balance exploration and exploitation throughout the search process. This balance enables the algorithm to converge rapidly, delivering highly suitable values for decision variables, particularly in complex optimization scenarios. This ability to maintain a dynamic equilibrium between exploring new solutions and refining existing ones is crucial for efficient problem-solving. Additionally, WoOA excels in addressing real-world optimization applications. Its powerful performance in practical scenarios underscores its capability to handle practical constraints and deliver effective solutions in real-world settings. However, despite these strengths, WoOA also has some limitations. As a stochastic algorithm, it does not guarantee achieving the global optimum. The inherent randomness in the algorithm's search process means that while it can find highly effective solutions, it cannot ensure that these solutions are globally optimal. Moreover, according to the No Free Lunch (NFL) theorem, there are no absolute assurances regarding the success or failure of WoOA for every possible optimization problem. The theorem implies that no single algorithm is universally best for all problems, and WoOA's effectiveness may vary depending on the specific nature of the problem being addressed. Finally, there is always the possibility that future advancements in metaheuristic algorithms could result in methods that outperform WoOA. Newer algorithms could offer improved performance or address certain problem types more effectively, making it crucial for WoOA to be continually assessed and compared with emerging techniques.

Along with the introduction of WoOA, this paper presents several research suggestions for future work. The design of binary and multi-purpose versions of WoOA are among the most significant research potentials of this study. Employing WoOA to address optimization tasks in various sciences and real-world applications is another suggestion of this study for further work.

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Availability of Data and Materials: The authors confirm that the data supporting the findings of this study are available within the article.

Ethics Approval: Not applicable.

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References

1. Zhao S, Zhang T, Ma S, Chen M. Dandelion optimizer: a nature-inspired metaheuristic algorithm for engineering applications. Eng Appl Artif Intell. 2022;114:105075. doi:10.1016/j.engappai.2022.105075.
2. Sergeyev YD, Kvasov D, Mukhametzhanov M. On the efficiency of nature-inspired metaheuristics in expensive global optimization with limited budget. Sci Rep. 2018;8(1):1–9. doi:10.1038/s41598-017-18940-4.
3. Liberti L, Kucherenko S. Comparison of deterministic and stochastic approaches to global optimization. Int Trans Operat Res. 2005;12(3):263–85. doi:10.1111/j.1475-3995.2005.00503.x.
4. Qawaqneh H. New contraction embedded with simulation function and cyclic (α, β)-admissible in metric-like spaces. Int J Math Comput Sci. 2020;15(4):1029–44.
5. Hamadneh T, Athanasopoulos N, Ali M editors. Minimization and positivity of the tensorial rational Bernstein form. In: 2019 IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology (JEEIT-Proceedings), 2019; Amman, Jordan: IEEE.
6. Mousavi A, Uihlein A, Pflug L, Wadbro E. Topology optimization of broadband acoustic transition section: a comparison between deterministic and stochastic approaches. Struct Multidiscipl Optim. 2024;67(5):67. doi:10.1007/s00158-024-03784-0.
7. Tomar V, Bansal M, Singh P. Metaheuristic algorithms for optimization: a brief review. Eng Proc. 2024;59(1):238. doi:10.3390/engproc2023059238.
8. de Armas J, Lalla-Ruiz E, Tilahun SL, Voß S. Similarity in metaheuristics: a gentle step towards a comparison methodology. Nat Comput. 2022;21(2):265–87. doi:10.1007/s11047-020-09837-9.
9. Al-Baik O, Alomari S, Alssayed O, Gochhait S, Leonova I, Dutta U, et al. Pufferfish optimization algorithm: a new bio-inspired metaheuristic algorithm for solving optimization problems. Biomimetics. 2024;9(2):65. doi:10.3390/biomimetics9020065.
10. Bai J, Li Y, Zheng M, Khatir S, Benaissa B, Abualigah L, et al. A sinh cosh optimizer. Knowl-Based Syst. 2023;282:111081.
11. Wolpert DH, Macready WG. No free lunch theorems for optimization. IEEE Trans Evolut Comput. 1997;1(1):67–82. doi:10.1016/j.knosys.2023.111081.
12. Sörensen K. Metaheuristics—the metaphor exposed. Int Trans Operat Res. 2015;22(1):3–18. doi:10.1111/itor.12001.
13. Kennedy J, Eberhart R editors. Particle swarm optimization. In: Proceedings of ICNN'95-International Conference on Neural Networks, 1995 Nov 27–1995 Dec 1; Perth, WA, Australia: IEEE.
14. Dorigo M, Maniezzo V, Colorni A. Ant system: optimization by a colony of cooperating agents. IEEE Trans Syst Man Cybern Part B (Cybern). 1996;26(1):29–41. doi:10.1109/3477.484436.
15. Karaboga D, Basturk B editors. Artificial bee colony (ABC) optimization algorithm for solving constrained optimization problems. In: International Fuzzy Systems Association World Congress, 2007; Berlin, Heidelberg: Springer.

16. Yang X-S. Firefly algorithm, stochastic test functions and design optimisation. Int J Bio-Inspired Comput. 2010;2(2):78–84. doi:10.1504/IJBIC.2010.032124.
17. Trojovský P, Dehghani M. Pelican optimization algorithm: a novel nature-inspired algorithm for engineering applications. Sensors. 2022;22(3):855. doi:10.3390/s22030855.
18. Abualigah L, Abd Elaziz M, Sumari P, Geem ZW, Gandomi AH. Reptile search algorithm (RSA): a nature-inspired meta-heuristic optimizer. Expert Syst Appl. 2022;191:116158. doi:10.1016/j.eswa.2021.116158.
19. Jiang Y, Wu Q, Zhu S, Zhang L. Orca predation algorithm: a novel bio-inspired algorithm for global optimization problems. Expert Syst Appl. 2022;188:116026. doi:10.1016/j.eswa.2021.116026.
20. Mirjalili S, Lewis A. The whale optimization algorithm. Adv Eng Softw. 2016;95:51–67. doi:10.1016/j.advengsoft.2016.01.008.
21. Dehghani M, Montazeri Z, Trojovská E, Trojovský P. Coati optimization algorithm: a new bio-inspired metaheuristic algorithm for solving optimization problems. Knowl-Based Syst. 2023;259:110011. doi:10.1016/j.knosys.2022.110011.
22. Kaur S, Awasthi LK, Sangal AL, Dhiman G. Tunicate swarm algorithm: a new bio-inspired based metaheuristic paradigm for global optimization. Eng Appl Artif Intell. 2020;90:103541. doi:10.1016/j.engappai.2020.103541.
23. Hashim FA, Houssein EH, Hussain K, Mabrouk MS, Al-Atabany W. Honey badger algorithm: new metaheuristic algorithm for solving optimization problems. Math Comput Simul. 2022;192:84–110. doi:10.1016/j.matcom.2021.08.013.
24. Braik M, Hammouri A, Atwan J, Al-Betar MA, Awadallah MA. White shark optimizer: a novel bio-inspired meta-heuristic algorithm for global optimization problems. Knowl-Based Syst. 2022;243:108457. doi:10.1016/j.knosys.2022.108457.
25. Chopra N, Ansari MM. Golden jackal optimization: a novel nature-inspired optimizer for engineering applications. Expert Syst Appl. 2022;198:116924. doi:10.1016/j.eswa.2022.116924.
26. Mirjalili S, Mirjalili SM, Lewis A. Grey wolf optimizer. Adv Eng Softw. 2014;69:46–61. doi:10.1016/j.advengsoft.2013.12.007.
27. Faramarzi A, Heidarinejad M, Mirjalili S, Gandomi AH. Marine predators algorithm: a nature-inspired metaheuristic. Expert Syst Appl. 2020;152:113377. doi:10.1016/j.eswa.2020.113377.
28. Abdollahzadeh B, Gharehchopogh FS, Mirjalili S. African vultures optimization algorithm: a new nature-inspired metaheuristic algorithm for global optimization problems. Comput Indus Eng. 2021;158:107408. doi:10.1016/j.cie.2021.107408.
29. Goldberg DE, Holland JH. Genetic algorithms and machine learning. Mach Learn. 1988;3(2):95–9. doi:10.1023/A:1022602019183.
30. Storn R, Price K. Differential evolution—a simple and efficient heuristic for global optimization over continuous spaces. J Global Optim. 1997;11(4):341–59. doi:10.1023/A:1008202821328.
31. De Castro LN, Timmis JI. Artificial immune systems as a novel soft computing paradigm. Soft Comput. 2003;7(8):526–44. doi:10.1007/s00500-002-0237-z.
32. Beyer H-G, Schwefel H-P. Evolution strategies—a comprehensive introduction. Nat Comput. 2002;1(1): 3–52. doi:10.1023/A:1015059928466.
33. Dehghani M, Trojovská E, Trojovský P, Malik OP. OOBO: a new metaheuristic algorithm for solving optimization problems. Biomimetics. 2023;8(6):468. doi:10.3390/biomimetics8060468.
34. Koza JR. Genetic programming as a means for programming computers by natural selection. Stat Comput. 1994;4:87–112. doi:10.1007/BF00175355.
35. Reynolds RG editor. An introduction to cultural algorithms. In: Proceedings of the Third Annual Conference on Evolutionary Programming, 1994; San Diego, CA, USA: World Scientific.
36. Kirkpatrick S, Gelatt CD, Vecchi MP. Optimization by simulated annealing. Science. 1983;220(4598): 671–80. doi:10.1126/science.220.4598.67.

37. Dehghani M, Montazeri Z, Dhiman G, Malik O, Morales-Menendez R, Ramirez-Mendoza RA, et al. A spring search algorithm applied to engineering optimization problems. Appl Sci. 2020;10(18):6173. doi:10.3390/app10186173.
38. Rashedi E, Nezamabadi-Pour H, Saryazdi S. GSA: a gravitational search algorithm. Inf Sci. 2009;179(13):2232–48. doi:10.1016/j.ins.2009.03.004.
39. Dehghani M, Samet H. Momentum search algorithm: a new meta-heuristic optimization algorithm inspired by momentum conservation law. SN Appl Sci. 2020;2(10):1–15. doi:10.1007/s42452-020-03511-6.
40. Hatamlou A. Black hole: a new heuristic optimization approach for data clustering. Inf Sci. 2013;222: 175–84. doi:10.1016/j.ins.2012.08.023.
41. Mirjalili S, Mirjalili SM, Hatamlou A. Multi-verse optimizer: a nature-inspired algorithm for global optimization. Neural Comput App. 2016;27(2):495–513. doi:10.1007/s00521-015-1870-7.
42. Cheng M-Y, Sholeh MN. Optical microscope algorithm: a new metaheuristic inspired by microscope magnification for solving engineering optimization problems. Knowl-Based Syst. 2023;279:110939. doi:10.1016/j.knosys.2023.110939.
43. Cuevas E, Oliva D, Zaldivar D, Pérez-Cisneros M, Sossa H. Circle detection using electro-magnetism optimization. Inf Sci. 2012;182(1):40–55. doi:10.1016/j.ins.2010.12.024.
44. Faramarzi A, Heidarinejad M, Stephens B, Mirjalili S. Equilibrium optimizer: a novel optimization algorithm. Knowl-Based Syst. 2020;191:105190. doi:10.1016/j.knosys.2019.105190.
45. Hashim FA, Houssein EH, Mabrouk MS, Al-Atabany W, Mirjalili S. Henry gas solubility optimization: a novel physics-based algorithm. Future Gen Comput Syst. 2019;101:646–67. doi:10.1016/j.future.2019.07.015.
46. Eskandar H, Sadollah A, Bahreininejad A, Hamdi M. Water cycle algorithm-A novel metaheuristic optimization method for solving constrained engineering optimization problems. Comput Struct. 2012;110: 151–66. doi:10.1016/j.compstruc.2012.07.010.
47. Hashim FA, Hussain K, Houssein EH, Mabrouk MS, Al-Atabany W. Archimedes optimization algorithm: a new metaheuristic algorithm for solving optimization problems. Appl Intell. 2021;51(3):1531–51. doi:10.1007/s10489-020-01893-z.
48. Pereira JLJ, Francisco MB, Diniz CA, Oliver GA, Cunha SS Jr, Gomes GF. Lichtenberg algorithm: a novel hybrid physics-based meta-heuristic for global optimization. Expert Syst Appl. 2021;170:114522. doi:10.1016/j.eswa.2020.114522.
49. Kaveh A, Dadras A. A novel meta-heuristic optimization algorithm: thermal exchange optimization. Adv Eng Softw. 2017;110:69–84. doi:10.1016/j.advengsoft.2017.03.014.
50. Wei Z, Huang C, Wang X, Han T, Li Y. Nuclear reaction optimization: a novel and powerful physics-based algorithm for global optimization. IEEE Access. 2019;7:66084–109.
51. Rao RV, Savsani VJ, Vakharia D. Teaching-learning-based optimization: a novel method for constrained mechanical design optimization problems. Comput-Aided Des. 2011;43(3):303–15. doi:10.1016/j.cad.2010.12.015.
52. Matoušová I, Trojovský P, Dehghani M, Trojovská E, Kostra J. Mother optimization algorithm: a new human-based metaheuristic approach for solving engineering optimization. Sci Rep. 2023;13(1):10312. doi:10.1038/s41598-023-37537-8.
53. Dehghani M, Mardaneh M, Guerrero JM, Malik OP, Ramirez-Mendoza RA, Matas J, et al. A new Doctor and Patient optimization algorithm: an application to energy commitment problem. Appl Sci. 2020;10(17):5791. doi:10.3390/app10175791.
54. Ayyarao TL, RamaKrishna N, Elavarasam RM, Polumahanthi N, Rambabu M, Saini G, et al. War strategy optimization algorithm: a new effective metaheuristic algorithm for global optimization. IEEE Access. 2022;10(17):25073–105. doi:10.1109/ACCESS.2022.3153493.

55. Mohamed AW, Hadi AA, Mohamed AK. Gaining-sharing knowledge based algorithm for solving optimization problems: a novel nature-inspired algorithm. Int J Mach Learn Cybern. 2020;11(7):1501–29. doi:10.1007/s13042-019-01053-x.
56. Al-Betar MA, Alyasseri ZAA, Awadallah MA, Abu Doush I. Coronavirus herd immunity optimizer (CHIO). Neural Comput App. 2021;33(10):5011–42. doi:10.1007/s00521-020-05296-6.
57. Braik M, Ryalat MH, Al-Zoubi H. A novel meta-heuristic algorithm for solving numerical optimization problems: ali Baba and the forty thieves. Neural Comput App. 2022;34(1):409–55. doi:10.1007/s00521-021-06392-x.
58. Dehghani M, Trojovský P. Serval optimization algorithm: a new bio-inspired approach for solving optimization problems. Biomimetics. 2022;7(4):204. doi:10.3390/biomimetics7040204.
59. Awad N, Ali M, Liang J, Qu B, Suganthan P, Definitions P. Evaluation criteria for the CEC 2017 special session and competition on single objective real-parameter numerical optimization. In: Technol report. Singapore: Nanyang Technological University; 2016.
60. Wilcoxon F. Individual comparisons by ranking methods. In: Breakthroughs in statistics. New York, NY: Springer; 1992. p. 196–202.
61. Kim TK. T test as a parametric statistic. Korean J Anesthesiol. 2015;68(6):540–6. doi: 10.4097/kjae.2015.68.6.540.
62. Daniel WW. Friedman two-way analysis of variance by ranks. Appl Nonparametric Stat. 1990;262–74.
63. Das S, Suganthan PN. Problem definitions and evaluation criteria for CEC 2011 competition on testing evolutionary algorithms on real world optimization problems. Kolkata: Jadavpur University, Nanyang Technological University; 2010. p. 341–59.
64. Kannan B, Kramer SN. An augmented Lagrange multiplier based method for mixed integer discrete continuous optimization and its applications to mechanical design. J Mech Des. 1994;116(2):405–11. doi:10.1115/1.2919393.
65. Gandomi AH, Yang X-S. Benchmark problems in structural optimization. In: Computational optimization, methods and algorithms. Berlin, Heidelberg: Springer; 2011. p. 259–81.
66. Mezura-Montes E, Coello CAC editors. Useful infeasible solutions in engineering optimization with evolutionary algorithms. In: Mexican International Conference on Artificial Intelligence, 2005; Berlin, Heidelberg: Springer.