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## **RESEARCH ARTICLE**

# Siberian Tiger Optimization: A New Bio-Inspired Metaheuristic Algorithm for Solving Engineering Optimization Problems

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**ABSTRACT** In this article, a new metaheuristic algorithm called Siberian Tiger Optimization (STO) is designed to deal with optimization applications. The fundamental inspiration of STO is the imitation of the natural behavior of the Siberian tiger during hunting and fighting. First, the whole design of STO and its mathematical model's two phases are explained. Then, the efficiency of the proposed STO approach in optimization tasks is evaluated on sets of various standard benchmark functions from the CEC 2017 test suite. In addition, the CEC 2011 test suite and four engineering design problems are employed to analyze the ability of STO to handle real-world applications. Finally, the quality of the optimization results obtained from the proposed STO approach is compared with the performance of twelve well-known metaheuristic algorithms. The simulation results show that STO, with its high power in exploration and exploitation and creating a balance between them, has provided better results than competitor algorithms and has superior performance in handling optimization applications.

**INDEX TERMS** Optimization, bio-inspired, metaheuristic, Siberian tiger, exploration, exploitation.

## **I. INTRODUCTION**

One of the first to realize the importance of optimization methods was P. L. Chebyshev, who wrote: ''Most practical questions can be reduced to problems of largest and smallest magnitudes. . . and it is only by solving these problems that we can satisfy the requirements of practice which always seeks the best, the most convenient.'' [1]. Optimization refers to the act of searching for the best combination for a set of decision variables to solve a problem [2]. The global optimization of special functions with a lot of local minima occurs in many fields of science and engineering [3]. This is while researchers are looking for more suitable solutions for optimization tasks. Therefore, there is a need for optimization solving methods that are compatible with the complex nature of engineering and scientific optimization challenges [4]. These techniques are developed from traditional approaches based on linear and nonlinear programming [5].

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Many optimization challenges have emerged in real-world applications. These challenges have characteristics such as non-convex, non-linear, high-dimensional, complex, discrete search space, and multiple local optima [6]. Although traditional methods are effective in handling many optimization problems, one of the main disadvantages of these approaches is that they depend on gradient information or a set of initial conditions [7]. Optimization methods can be split into two primary groups: exact and approximate. Exact techniques provide the global optimum for optimization problems in a reasonable time. However, exact techniques are very timeconsuming in dealing with NP-hard and complex problems. Approximate techniques can overcome this difficulty of exact techniques and provide acceptable solutions for optimization problems in a reasonable time. Traditional techniques are able to provide the global optimum in handling simple engineering challenges, linear problems, convex problems, and optimization problems with low complexity [8]. These techniques depend on the complete information and details of the problem, so they may not be effective in dealing with

current and emerging optimization applications. Traditional techniques, when employed in the optimization of complex optimization challenges that are nonlinear in nature, nonconvex, and in a nonlinear and unknown search space, may get stuck in local optima where they have no guarantee to provide the global optima [9]. In addition to achieving the desired solution, the time to accomplish this solution should be within a reasonable and acceptable range [10]. A new concept of approximation algorithms, called metaheuristic methods, has been introduced by [11]. Metaheuristics are often used over the last four decades as they offer simplicity, easy implementation, and the strong ability to avoid a local optima [2]. Metaheuristic algorithms are efficient approaches in providing solutions for optimization applications based on a random search. Although these methods are independent of the type of problem and do not need gradient information, they do not guarantee that they will provide the best solution [12]. To solve these difficulties and to provide optimal solutions in a reasonable time, metaheuristic algorithms have attracted the attention of researchers. Features such as simplicity of concepts, convenient implementation, independence from the type of problem, efficiency in nonlinear and unknown search spaces, and efficiency in handling nonlinear, non-convex, NP-hard, high-dimensional, and complex issues have made metaheuristic algorithms highly popular [13]. Finding a solution in metaheuristic algorithms is based on a random search in the problem-solving space based on the strength of the search agents of these algorithms, which is called the algorithm population. Algorithm populations scan the search space using random operators, unique algorithm steps, and trial and error processes [14]. A metaheuristic algorithm should be able to scan different regions of the search space accurately. This scanning ability can be caused by sudden changes in the position of the population members in the search space. This process, known as exploration, enables metaheuristic algorithms to avoid getting stuck in local optima and move through the search space to discover the original optimal region. In addition, a meta-heuristic algorithm should scan the surroundings of those promising solutions locally to achieve better solutions. This scanning can be achieved by small steps and small changes in the position of the population members. This search process, which is known as exploitation ability, makes metaheuristic algorithms converge to better solutions for optimization problems [15]. Exploration directs the algorithm to better areas of the search space, and exploitation leads the algorithm to better solutions. Therefore, exploration and exploitation pursue contradictory goals. Hence, metaheuristic algorithms must balance these two search abilities with adequate power of exploration and exploitation. They must be able first to discover the original optimal region and then converge to the appropriate solution [16]. The investigation of new metaheuristic methods for a diverse range of applications significantly has influenced the further development of recent search technologies. Unfortunately, many metaheuristic algorithms are relatively knowledge-intensive to be implemented in easy-to-use and cheap computer programs. Hence, users still use simple heuristics that are easy to implement but often perform poorly. Real-world commercial and industrial organizations usually do not need to solve their creating optimization problems to full optimality. Instead, they are only interested in ''good enough—soon enough—cheap enough'' solutions to these problems [17]. One way to solve this problem with the real practical usability of metaheuristic methods is to consider the use of metaheuristic algorithms that do not use any complex ''expertly adjustable parameters'' [14]. The so-called hyper-heuristics, hybrid-metaheuristics, hypermetaheuristics, or metaheuristic methods, in which the main idea is to use a set of heuristics [17], metaheuristics [18], [19] and or a combination of metaheuristic and exact methods [20], respectively, to solve a problem so that we associate each heuristic, metaheuristic or exact method with a different phase of the problem-solving process, belong among other possible ways of solving the problem with ''low applicability in practice.''

Many metaheuristic algorithms have been designed to achieve better and more efficient solutions [21]. These algorithms are employed in various branches of science and realworld applications, e. g., facial expression recognition [22], action recognition [23], internet of things applications [24], object tracking [25]. Therefore, the main research question opened up for researchers, whether there is still a need to continue to search for new metaheuristic algorithms. No Free Lunch (NFL) theorem [26] explicitly answers this question that no metaheuristic algorithm provides the best performance in all optimization tasks. This type of answer is due to the random search nature of metaheuristic algorithms, which does not carry any guarantee of reliably reaching the best solution. Furthermore, according to the NFL theorem, even if a metaheuristic algorithm performs better in a set of optimization problems compared to several algorithms, it may not provide the same performance in handling other optimization applications. Hence, the NFL theorem, by keeping the research area of metaheuristic algorithms open, encourages scientists to introduce metaheuristic algorithms to provide efficient solutions for existing and emerging optimization applications in the real-world and science field.

The novelty of this paper is in the introduction of a new metaheuristic algorithm called Siberian Tiger Optimization (STO), which has applications in dealing with optimization applications in various sciences and real-world problems. The key contributions of this paper are as follows:

- STO is a bio-inspired meta-heuristic algorithm that mimics the behavior of Siberian tigers.
- The fundamental inspiration of STO is simulating the behaviors and strategies of the Siberian tiger when hunting prey and fighting with bears.
- The STO theory is described and then mathematically modeled in two phases (prey hunting and fighting with a bear, respectively).



**FIGURE 1.** Photo of a siberian tiger; downloaded from free media wikimedia commons.

- The efficiency of STO in handling optimization tasks is evaluated on twenty-nine benchmark functions from the CEC-2017 test suite.
- The ability of STO to handle real-world applications is challenged on four engineering design problems and twenty-one real-world optimization problems from the CEC-2011 test suite.
- The quality of the results obtained from STO is compared with the performance of twelve well-known metaheuristic algorithms.

The continuation of the paper is organized as follows: firstly, the literature review is presented in the section II. Then, the proposed Siberian Tiger Optimization (STO) approach is introduced and mathematically modeled in the section III. Next, simulation and evaluation studies on handling optimization tasks are presented in the section IV. The performance of the proposed algorithm in real-world handling applications is evaluated in the section V. Finally, conclusions and prospects for future studies are provided in the section VI.

#### **II. LECTURE REVIEW**

Various sources of inspiration, including natural phenomena, laws of physics, game rules, human interactions, and biological sciences, have been employed in the design of metaheuristic algorithms. Based on the main idea used in the design, metaheuristic algorithms are classified into five groups: swarm-based, evolutionary-based, physics-based, game-based, and human-based approaches.

Swarm-based metaheuristic algorithms simulate swarming phenomena in nature, including the natural behaviors of animals, birds, insects, aquatic animals, and other living organisms. Among the most famous algorithms of this group can mention to Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC) [27], and Ant Colony Optimization (ACO) ()[28]. The design idea of PSO is the searching strategy of birds and fishes to obtain food sources. The concept used in the design of ABC is the activities of the bee colony

searching for food sources. The design idea of ACO is the strategy of the ant colony that seeks to find the shortest path from the nest to the food sources. Living organisms' most common swarming strategies and behaviors are foraging, hunting, and migration. These processes can be seen as searching for an optimal solution. Hence, they have been used in the design of several optimization algorithms, such as the African Vultures Optimization Algorithm (AVOA) [29], Grey Wolf Optimizer (GWO) [30], Golden Jackal Optimization (GJO) [31], Whale Optimization Algorithm (WOA) [32], Honey Badger Algorithm (HBA) [33], Marine Predator Algorithm (MPA) [34], White Shark Optimizer (WSO) [35], Reptile Search Algorithm (RSA) [36], and Tunicate Swarm Algorithm (TSA) [37].

Evolutionary-based metaheuristic algorithms simulate biological and genetic sciences by relying on concepts such as natural selection, survival of the fittest, Darwin's theory of evolution, and random operators. Among the most used algorithms of this group are Genetic Algorithm (GA) [38] and Differential Evolution (DE) [39]. Simulating the reproduction process and using random selection, crossover, and mutation operators is the basic idea behind GA and DE. The reaction of the body's immune system against microbes and diseases is the idea used in the design of Artificial Immune Systems (AISs) approaches [40].

Physics-based metaheuristic algorithms model the phenomena, laws, and processes of physics. One of the most famous physics-based approaches is Simulated Annealing (SA) [41]. SA simulates the physical process of metal annealing, in which the metal is melted under heat and then cooled to achieve an ideal crystal. Physical forces have been the source of inspiration for researchers in designing algorithms such as: the Gravitational Search Algorithm (GSA) and Momentum Search Algorithm (MSA) [42]. The gravitational force has been the design idea of GSA, spring tension force has been the design idea of SSA, and the force resulting from the momentum has been the design idea of MSA. Other metaheuristic algorithms based on physics can be mentioned as Water Cycle Algorithm (WCA) [43], Archimedes Optimization Algorithm (AOA) [44], Multi-Verse Optimizer (MVO) [45], Electro-Magnetism Optimization (EMO) [46], Equilibrium Optimizer (EO) [47], and Lichtenberg Algorithm (LA) [48].

Game-based metaheuristic algorithms simulate the rules that govern various individual and group games and the strategies and behaviors of players and other influential people. Simulating the behavior of players and competitions in sports leagues has been the idea of designing algorithms such as Football Game Based Optimization (FGBO) [49] and Volleyball Premier League (VPL) [50]. Mathematical modeling of players' behavior in how to collect points in different games has inspired the design of algorithms such as Tug of War Optimization (TWO) [51], Archery Algorithm (AA) [52], and Puzzle Optimization Algorithm (POA) [53].

Human-based metaheuristic algorithms model the individual and social relations of humans in society. The most



**FIGURE 2.** Flowchart of STO.

famous algorithm in this group is Teaching-Learning Based Optimization (TLBO) [54]. TLBO simulates interactions between students and teachers in the classroom learning environment. The strategies used by doctors to treat patients have inspired the design of Doctor and Patient Optimization [55]. The effort of the members of a team in achieving the set goals has been the basic idea in the design of the Teamwork Optimization Algorithm (TOA) [56]. The most common

### **Algorithm 1** Pseudocode of STO



**End STO.**

human-based metaheuristic algorithms can be mentioned as War Strategy Optimization (WSO) [57], Coronavirus Herd Immunity Optimizer (CHIO) [58], and Ali Baba and the Forty Thieves (AFT) [59].

Based on the best knowledge from our literature review, no metaheuristic algorithm has been designed based on simulating the Siberian tiger's behaviors and strategies. Thus, this paper introduces a new swarm-based algorithm based on mimicking the intelligent natural behavior of Siberian tigers while hunting and fighting other animals to fill this research gap in the existing metaheuristic algorithms. Our proposed algorithm is discussed in the next section.

## **III. SIBERIAN TIGER OPTIMIZATION**

In this section, the proposed Siberian Tiger Optimization (STO) approach is introduced, then its implementation steps are mathematically modeled.

## A. INSPIRATION OF STO

The Siberian tiger or Amur tiger is a species of ''Panthera tigris'' whose habitat is Northeast China, North Korea, and the Russian Far East [60]. Various names have been given for the Siberian tiger, including ''Amur tiger,'' ''Ussurian tiger," "Korean tiger," and "Manchurian tiger," based on the different areas where they live [61]. The color of the Siberian tiger is rusty-yellow or reddish-rusty with narrow

white and black stripes. The minimum body length of this animal is 150 cm, the zygomatic width is 18 cm, the skull length is 25 cm, and the teeth are larger than 26 mm. The Siberian tiger has a flexible body; therefore, it can stand on its hind legs [62]. The weight range of this tiger is between 180 and 306 kg for the male species and between 100 and 167 kg for the female species [63]. A picture of the Siberian tiger is shown in Figure 1. Despite their large size, Siberian tigers are very fast and agile. They are powerful predators whose prey species include: Siberian musk deer (Moschus moschiferus), Manchurian wapiti (Cervus Canadensis xanthopygus), moose (Alces alces), long-tailed goral (Naemorhedus caudatus), sika deer (Cervus nippon), Siberian roe deer (Capreolus pygargus), wild boar (Sus scrofa), and even sometimes brown bears (Ursus arctos) and small size Asiatic black bears (Ursus thibetanus). Smaller prey such as pikas, rabbits, hares, and even salmon are eaten by Siberian tigers, too [64]. During hunting, Siberian tigers select the prey, then attack it, and finally hunt the prey in a chasing process.

Siberian tigers fight with black bears and brown bears due to disputes over prey and defending themselves. In this fight, the Siberian tiger first ambushes and then attacks the bear from above, blocks it from the chin with one forepaw, grabs the bear's throat with the other forepaw, and finally kills it by biting its spine [62].

## **TABLE 1.** Optimization results of the CEC-2017 test suite (dimension  $m = 10$ ).



## **TABLE 1.** (Continued.) Optimization results of the CEC-2017 test suite (dimension  $m = 10$ ).



## **TABLE 1.** (Continued.) Optimization results of the CEC-2017 test suite (dimension  $m = 10$ ).



## **TABLE 2.** Optimization results of the CEC-2017 test suite (dimension  $m = 30$ ).



## **TABLE 2.** (Continued.) Optimization results of the CEC-2017 test suite (dimension  $m = 30$ ).



## **TABLE 2.** (Continued.) Optimization results of the CEC-2017 test suite (dimension  $m = 30$ ).



## **TABLE 3.** Optimization results of the CEC-2017 test suite (dimension  $m = 50$ ).



## **TABLE 3.** (Continued.) Optimization results of the CEC-2017 test suite (dimension  $m = 50$ ).



## **TABLE 3.** (Continued.) Optimization results of the CEC-2017 test suite (dimension  $m = 50$ ).



## **TABLE 4.** Optimization results of the CEC-2017 test suite (dimension  $m = 100$ ).



## **TABLE 4.** (Continued.) Optimization results of the CEC-2017 test suite (dimension  $m = 100$ ).



## **TABLE 4.** (Continued.) Optimization results of the CEC-2017 test suite (dimension  $m = 100$ ).



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**FIGURE 3.** Boxplot diagram of STO and competitor algorithms performances on the CEC-2017 test suite (dimension **m** = **10**).



**FIGURE 3.** (Continued.) Boxplot diagram of STO and competitor algorithms performances on the CEC-2017 test suite (dimension **m** = **10**).

The natural behaviors of Siberian tigers in nature (i.e., their strategy of hunting prey and their approach to fighting brown bears) are intelligent processes, which can be the basis for designing a new metaheuristic algorithm. Therefore, mathematical modeling of these two exciting strategies of the Siberian tiger is employed in creating the proposed STO.

#### B. MATHEMATICAL MODELLING

The process of updating the position of Siberian tigers in the STO is modeled in two different phases based on the natural behaviors of this animal.

#### 1) INITIALIZATION

The proposed STO can provide a suitable solution to the problem by benefiting from the searching power of its population members in an iteration-based process. The STO population consists of Siberian tigers, which seek better solutions by changing their locations in the search space. Each Siberian tiger is a member of the STO population. Thus, it describes a candidate solution to the problem. Its position in the search space represents values for the variables of the problem. Therefore, from a mathematical point of view, each Siberian tiger can be modeled using a vector, and the population of Siberian tigers can be modeled using a matrix according to (1).

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

 $x_{i,j} = lb_j + r_{i,j} \cdot (ub_j - lb_j), \quad i = 1, 2, ..., N,$  $j = 1, 2, \ldots, m,$  (2)

total number of Siberian tigers.

mined using  $(2)$ .

where  $x_{i,j}$  is *j*th dimension of  $X_i$  in the search space (problem variable), *m* is the number of problem variables,  $r_{i,j}$  are random numbers in the interval  $[0, 1]$ ,  $lb_j$ , and  $ub_j$  are the lower bound and upper bound of the *j*th problem variable, respectively.

where *X* is the population matrix of Siberian tigers' locations, *Xi* is the *i*th Siberian tiger (a candidate solution) and *N* is the

The initial position of Siberian tigers in the search space at the beginning of STO implementation is randomly deter-

As mentioned, the position of each Siberian tiger in the search space determines the values of variables of the problem. Therefore, corresponding to each Siberian tiger, a value of the objective function of the problem can be evaluated. The set of calculated values for the objective function can be displayed using a vector called the objective function vector according to (3).

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

where  $F$  is the objective function values vector and  $F_i$  is the obtained objective function value for the *i*th Siberian tiger.

The obtained values for the objective function provide valuable information about the quality of these candidate

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**FIGURE 4.** Boxplot diagram of STO and competitor algorithms performances on the CEC-2017 test suite (dimension **m** = **30**).



**FIGURE 4.** (Continued.) Boxplot diagram of STO and competitor algorithms performances on the CEC-2017 test suite (dimension **m** = **30**).

solutions. The best value obtained for the objective function determines the best member *Xbest* (the best candidate solution). Therefore, as new values of the objective function are calculated in each algorithm's iteration, the best member in each iteration must be updated by comparing its value of the objective function with these new values too.

### 2) PHASE 1: PREY HUNTING

Siberian tigers are powerful predators that feed by attacking different prey. Therefore, in the first phase, STO members are updated based on simulating the Siberian tigers' hunting strategy. In this strategy, after selecting the prey, the Siberian tiger attacks it and then kills the prey in a chasing process. Therefore, the prey hunting phase is simulated in two stages.

In the first stage, the position of population members is updated based on the selection and attack on the prey. This stage causes sudden and extensive changes in the position of the STO members, and as a result, it increases the ability of the global search and exploration of the algorithm in the accurate scanning of the search space. In the STO design, the proposed prey positions for each Siberian tiger are selected from other members of the population that have a better objective function value than that member. The set of positions of these proposed preys is shown in (4).

$$
PP_i = \{X_k | k \in \{1, 2, ..., N\} \wedge F_k < F_i\} \cup \{X_{best}\}, \quad (4)
$$

where *Xbest* is the best candidate solution (the best STO member) and *N* is the total number of STO members. Then, one member (we denote it as  $TP_i$ ) from this set  $PP_i$  is randomly selected as the attacked target by the *i*th Siberian tiger (i.e., the *i*th population member), and its new position is calculated

based on the simulation of the attack on the prey using (5).

$$
x_{i,j}^{P1S1} = x_{i,j} + r_{i,j} \cdot (TP_{i,j} - I_{i,j} \cdot x_{i,j}),
$$
  
\n
$$
i = 1, 2, ..., N \text{ and } j = 1, 2, ..., m,
$$
 (5)

where  $TP_{i,j}$  is the *j*th dimension of  $TP_i$ ,  $X_i^{PIS1}$  is the new position of the *i*th member based on the 1st stage of the 1st phase of STO,  $x_{i,j}^{P1S1}$  is its *j*th dimension, *m* is the number of problem variables,  $r_{i,j}$  are random numbers in the interval [0, 1], and  $I_{i,j}$  are random numbers from the set  $\{1, 2\}$ . In the process of updating STO members, the new calculated position is acceptable if it improves the value of the objective function. This process is modeled using (6).

$$
X_i = \begin{cases} X_i^{PIS1}, & F_i^{PIS1} < F_i; \\ X_i, & else, \end{cases} \tag{6}
$$

where  $F_i^{PIS1}$  is objective function value of the *i*th member  $X_i^{P1S1}$ .

In the 2nd stage, the position of the population members is updated based on the chase process. In this process, the Siberian tiger changes its position in the area where it is attacking the prey. This process increases the ability of the algorithm in local search and exploitation to reach better solutions. To simulate the chase process, first, a new position for the Siberian tiger near the attack site is calculated using (7). Then according to (8), if the value of the objective function is improved, this newly calculated position replaces the previous position of the corresponding member.

$$
x_{i,j}^{P1S2} = x_{i,j} + \frac{r_{i,j} \cdot (ub_j - lb_j)}{t}, i = 1, 2, ..., N,
$$
  

$$
j = 1, 2, ..., m, and t = 1, 2, ..., T,
$$
 (7)

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**FIGURE 5.** Boxplot diagram of STO and competitor algorithms performances on the CEC-2017 test suite (dimension **m** = **50**).



**FIGURE 5.** (Continued.) Boxplot diagram of STO and competitor algorithms performances on the CEC-2017 test suite (dimension **m** = **50**).

$$
X_i = \begin{cases} X_i^{PIS2}, & F_i^{PIS2} < F_i; \\ X_i, & else, \end{cases} \tag{8}
$$

where  $X_i^{P1S2}$  is the new position of the *i*th Siberian tiger based on the second stage of the first phase of STO,  $x_{i,j}^{P1S2}$  is its *j*th dimension,  $F_i^{P1S2}$  is its objective function value,  $r_{i,j}$  are random numbers in the interval [0, 1], and *t* is the iteration counter of the algorithm.

#### 3) PHASE 2: FIGHTING WITH A BEAR

Observations of the natural life of Siberian tigers indicate that this animal fights with brown and black bears due to disputes over prey and to protect their lives. Therefore, in the second phase, STO members are updated based on simulating the strategy of Siberian tigers when fighting bears. In this fight, the Siberian tiger first ambushes and then attacks the bear. In the continuation of this fight, the conflicts between these two animals will continue on the battlefield until the Siberian tiger kills the bear. Therefore, the strategy of the Siberian tiger's fight with the bear is simulated in two stages: attack and conflict.

In the 1st stage, to model the attack of the *i*th Siberian tiger on the bear, the other population members are considered the set of bears. From this set of possible bears, the position of the attacked bear is randomly selected (this position is denoted as *k*). This step leads to significant and sudden changes in the position of STO members, which can increase the proposed method's global search and exploration capability. Therefore, to simulate the above concepts, a new position is first calculated for the *i*th STO member,  $i = 1, 2, ..., N$ , based on (9).

$$
x_{i,j}^{P2S1} = \begin{cases} x_{i,j} + r_{i,j} \cdot (x_{k,j} - I_{i,j} \cdot x_{i,j}), & F_k < F_i; \\ x_{i,j} + r_{i,j} \cdot (x_{i,j} - I_{i,j} \cdot x_{k,j}), & else, \end{cases} \tag{9}
$$

where  $x_{k,j}$  is the *j*th dimension of a bear location,  $j =$  $1, 2, \ldots, m$ , where *k* is randomly selected from the set  $\{1, 2, \ldots, i-1, i+1, \ldots, N\}$ ,  $X_i^{P2S1}$  is the new position of the *i*th member based on the 1st stage of the 2nd phase of STO,  $x_{i,j}^{P2S1}$  is its *j*th dimension,  $r_{i,j}$  are random numbers in the interval [0, 1], and  $I_{i,j}$  are random numbers from the set {1, 2}. Then, according to (10), if the value of the objective function is improved, this newly calculated position replaces the previous position of the corresponding member.

$$
X_i = \begin{cases} X_i^{P2S1}, & F_i^{P2S1} < F_i \\ X_i, & \text{else,} \end{cases} \tag{10}
$$

where  $F_k$  is the value of the objective function of the bear (the *k*th member of STO) and  $F_i^{P2S1}$  is objective function value of  $X_i^{P2S1}$ .

In the 2nd stage, the position of the population members is updated based on the simulation of conflicts during combat. This behavior causes small changes in the population members' position, leading to improved the local search of STO and exploitation ability. To model this behavior, first, a random position near the place of the fight is calculated using  $(11)$ .

$$
x_{i,j}^{P2S2} = x_{i,j} + \frac{r_{i,j}}{t} (ub_j - lb_j), i = 1, 2, ..., N,
$$
  

$$
j = 1, 2, ..., m, and t = 1, 2, ..., T,
$$
 (11)

where  $X_i^{P2S2}$  is new position of the *i*th Siberian tiger based on the 2nd stage of the 2nd phase of STO,  $x_{i,j}^{P2S2}$  is its *j*th dimension, and *t* is the iteration counter of the algorithm.

Then, this new position is acceptable for the update process if it improves the value of the objective function

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**FIGURE 6.** Boxplot diagram of STO and competitor algorithms performances on the CEC-2017 test suite (dimension **m** = **100**).



**FIGURE 6.** (Continued.) Boxplot diagram of STO and competitor algorithms performances on the CEC-2017 test suite (dimension **m** = **100**).

according to (12).

$$
X_i = \begin{cases} X_i^{P2S2}, & F_i^{P2S2} < F_i; \\ X_i, & else, \end{cases} \tag{12}
$$

where  $F_i^{P2S2}$  is the objective function value of  $X_i^{P2S2}$ .

## C. REPETITIONS PROCESS, FLOWCHART, AND PSEUDO-CODE OF STO

The first iteration of STO is completed after updating all Siberian tigers based on the first and second phases. Then, the algorithm enters the next iteration with the new values obtained, and the process of updating the position of the Siberian tigers is repeated until the last iteration of the algorithm based on Equations (4) to (12). After the full implementation of STO, the best candidate solution found during all iterations of the algorithm is placed in the output as the solution to the problem. The steps of STO implementation are presented in the form of a flowchart in Figure 2 and the structure of pseudocode in Algorithm 1.

#### D. COMPUTATIONAL COMPLEXITY

This subsection discussed the computational complexity analysis of the proposed STO. Since the most time-consuming step in the entire algorithm is calculating the values of the objective function, which are very complicated in most real applications, the computational complexity of STO can be estimated based on the number of needed function evaluations FEs. The initialization process of STO has the complexity FEs  $=N$ , where *N* is the number of Siberian tigers. In each iteration, each STO member is updated in two different phases. Each of these phases has two stages of calculating the objective function. Therefore, the process of

updating population members in the proposed STO has the complexity FEs =  $4N \cdot T$ , where *T* is the total number of iterations of the algorithm. Hence, the total computational complexity of STO by the total number of function evaluations MFEs is equal to  $(4T + 1) \cdot N$ . Thus, we get the following formula

$$
MFEs = (4T + 1) \cdot N \Longleftrightarrow T = \left\lceil \frac{MFEs - N}{4N} \right\rceil. \quad (13)
$$

#### **IV. SIMULATION STUDIES AND DISCUSSION**

In this section, the ability of the proposed STO approach to solving optimization problems is tested on twenty-nine standard benchmark functions from CEC 2017 test suite. CEC-2017 test suite has thirty objective functions, of which C17-F1 to C17-F3 are unimodal, C17-F4 to C17-F10 are multimodal, C17-F11 to C17-F20 are hybrid, and C17-F21 to C17-F30 are composition. From this set, the C17-F2 function has been removed from the simulations due to its unbalanced behavior. Precise details of CEC-2017 test suite are provided in [65]. Twelve well-known metaheuristic algorithms: LSHADE-SPACMA [66], FDB-SOS [67], FDB-SFS [68], FDB-RUN [69], FDB-AGDE [70], WSO, AVOA, RSA, TSA, WOA, GWO, GSA are employed in order to compare with the performance of the proposed approach in optimizing the benchmark functions. In the implementation of competitor algorithms on benchmark functions, the population size for LSHADE-SPACMA, FDB-SOS, FDB-SFS, FDB-RUN, FDB-AGDE, and GSA approaches is considered equal to 50 and for WSO, AVOA, RSA, TSA, WOA, and GWO approaches is considered equal to 30. The experimentation has been done on MATLAB R2020a version using 64-bit Core i7 processor with 3.20 GHz and 16 GB main memory.

The proposed STO approach and competitor algorithms are employed in the optimization of the mentioned benchmark functions. Simulation results are reported using four statistical indicators: mean, best, standard deviation (std), and rank. In order to better present and display the tables and figures, the competitor algorithm of LSHADE-SPACMA is specified with the symbol L-S.

## A. EVALUATION OF CEC 2017 TEST SUITE

The proposed algorithm and competitor algorithms are implemented on the CEC 2017 test suite for dimensions  $m =$ 10, 30, 50, and 100 to analyze the efficiency of the proposed STO approach in solving optimization problems. For all test functions in the CEC 2017 test suite, STO has employed a population of 30 Siberian tigers (thus,  $N = 30$ ) along with a maximum number of FEs equal to  $10000 \cdot m$  (thus, MFEs = 10000*m*), where *m* is the number of variables (dimensions of the problem). The stop criterion for the proposed STO is set to the maximum number of function evaluations MFEs. To get statistical results on the behavior of the proposed STO, we ran 51 times independently the computation of STO for each benchmark function in each experiment. The optimization results of the CEC-2017 test suite are reported in Tables 1 to 4.

Based on the results obtained for the number of dimensions *m* equal to 10, the proposed approach STO is the best optimizer in solving functions C17-F1, C17-F3 to C17-F11, C17- F14 to C17-F17, C17-F19 to C17-F21, C17-F23, C17-F28, and C17-F29. For dimensions *m* equal to 30, the proposed approach STO is the best optimizer for handling functions C17-F1, C17-F3, C17-F5 to C17-F11, C17-F13, C17-F16, C17-F17, C17-F20, C17-F21, C17-F24, C17-F25, C17-F28, and C17-F29. For the number of dimensions *m* equal to 50, the proposed approach STO is the best optimizer in handling functions C17-F1, C17-F3, C17-F5 to C17-F13, C17-F15 to C17-F18, C17-F20 to C17-F25, and C17-F28 to C17-F30. For the number of dimensions *m* equal to 100, the proposed approach STO is the best optimizer for optimizing functions C17-F1, C17-F3, C17-F5 to C17-F13, C17-F15 to C17-F17, and C17-F20 to C17-F29.

The analysis of the optimization results shows that the proposed STO approach has performed better than the competitor algorithms in most of the CEC-2017 test suite functions. Overall, it has obtained the first rank as the best optimizer in handling the CEC-2017 test suite. The performance boxplot of STO and competitor algorithms in handling the CEC-2017 test suite for different dimensions  $m = 10, 30, 50,$  and 100 are drawn in Figures 3 to 6.

## B. STATISTICAL ANALYSIS

In this subsection, the statistical analysis of the performance of the proposed STO approach against competitor algorithms is presented to check whether the superiority of STO is significant from a statistical point of view. For this purpose, Wilcoxon rank sum test [71] is used. Wilcoxon rank sum test is a non-parametric statistical test that shows whether





there is a significant difference between the average of two data samples. The results obtained from the implementation of the Wilcoxon rank sum test on the performance of STO compared to each of the competitor metaheuristic algorithms are published in Table 5. Based on the simulation results, it is clear that in cases where the *p*-value is less than 0.05, STO has a significant superiority over the corresponding competitor algorithm from a statistical point of view.

### **V. STO FOR REAL-WORLD APPLICATION**

In this section, to evaluate the proposed STO approach in dealing with real-world applications, its efficiency in the optimization of the CEC-2011 test suite and four engineering design problems is challenged.

### A. EVALUATION OF CEC 2011 TEST SUITE

The CEC 2011 test suite includes twenty-two real-world problems, of which CEC11-F3 is excluded from the simulations. Full details and information on the CEC-2011 test suite are provided [72]. For all test functions in the CEC 2011 test suite, STO is employed 30 Siberian tigers along with a maximum number of FEs of 150,000. The stop criterion for the proposed STO is set to the maximum number of FEs, where it ran 25 times independently for each function in each experiment. The implementation results of the STO and competitor algorithms on the CEC-2011 test suite are published in Table 6.

Based on the simulation results, it is evident that the proposed approach is the best optimizer in solving C11-F1, C11- F2, C11-F4 to C11-F10, C11-F12 to C11-F14, and C11-F16 to C11-F22. Furthermore, analysis of the simulation results shows that the proposed STO approach is acceptable for dealing with real-world applications. Therefore, compared to the competitor algorithms, it has won the first rank for the CEC-2011 test suite. Also, the results of p-values obtained from the Wilcoxon statistical analysis show that the proposed STO approach has a significant statistical advantage over competitor algorithms in dealing with the CEC2011 test suite. The boxplots of the performance of STO and competitor

## **TABLE 6.** Optimization results of the CEC-2011 test suite.



**TABLE 6.** (Continued.) Optimization results of the CEC-2011 test suite.

														$+05$
				worst <b>1.40E+04</b> 1.34E+05 3.89E+04 1.80E+05		8.31E+04	$1.80E + 0.5$			7.00E+05 4.49E+05 1.38E+06 9.20E+04 7.00E+05 8.25E+04 9.78E+05				
	std			<b>3.70E+03</b> 2.26E+04 1.20E+04 2.92E+04		$2.12E + 04$	$2.89E + 04$			1.18E+05 3.52E+04 2.77E+05 1.70E+04 2.15E+05 2.66E+04 8.97E+04				
						$6.06E + 04$	$1.65E + 05$			$6.10E+05$ $4.25E+05$   $1.27E+06$   $7.25E+04$   $3.62E+05$ $4.22E+04$   $9.40E+05$				
		1	6	2	7	4	8		10	13	5	9	3	12
	rank							11						
	mean						$-1.30E+01$ $-1.34E+01$							
				2.15E+01 1.33E+01 1.26E+01 1.34E+01						.75E+01  1.64E+01  1.13E+01  1.37E+01  1.20E+01  1.33E+01  1.23E+01				
	best						$-1.53E+01$ $-1.39E+01$							
$C11-$				2.18E+01 1.36E+01 1.28E+01 1.39E+01						.94E+01 1.66E+01 1.17E+01 1.86E+01 1.28E+01 1.38E+01 1.28E+01				
F10	worst						$-1.15E+01$ $-1.29E+01$							
				$2.08E+01$  1.30E+01 1.20E+01 1.30E+01						.58E+01 1.61E+01 1.10E+01 1.10E+01 1.14E+01 1.20E+01 1.14E+01				
	std			4.74E-01 2.91E-01 3.78E-01 4.59E-01		$1.62E + 00$	4.94E-01			1.75E+00 <b> 2.43E-01 </b> 2.97E-01 <b> </b> 3.39E+00 <b> </b> 5.78E-01 <b> </b> 8.68E-01 <b> </b> 6.81E-01				
							$-1.26E+01$ $-1.34E+01$							
				median 2.17E+01 1.33E+01 1.28E+01 1.34E+01						l.74E+01 1.65E+01 1.13E+01 1.25E+01 1.19E+01 1.37E+01 1.25E+01				
	rank	$\mathbf{1}$	8	10	5	9	6	2	$\mathfrak{Z}$	13	$\overline{4}$	12	7	-11
$C11-$ F11				mean 5.72E+05 8.60E+04 1.86E+06 5.49E+05		$1.81E + 06$	7.75E+05			3.35E+05 1.03E+06 9.72E+06 6.50E+06 1.28E+06 4.17E+06 1.50E+06				
	best			$2.61E+05$ 6.14E+04 1.77E+06 5.32E+05		$1.54E + 06$	7.47E+05			1.42E+05 8.25E+05 9.42E+06 5.41E+06 1.17E+06 3.97E+06 1.34E+06				
				worst 8.29E+05 1.10E+05 2.06E+06 5.67E+05		$2.22E+06$	$8.18E + 0.5$			5.14E+05 1.21E+06 9.90E+06 7.86E+06 1.43E+06 4.60E+06 1.68E+06				
	std			$[2.48E+05]2.00E+04]1.37E+05$ 1.80E+04		$3.02E + 05$	$3.19E + 04$			1.52E+05 1.66E+05 2.06E+05 1.01E+06 1.11E+05 2.90E+05 1.39E+05				
				median 5.99E+05 <b>8.63E+04</b> 1.80E+06 5.49E+05		$1.74E + 06$	$7.67E + 05$			3.42E+05 1.05E+06 9.77E+06 6.37E+06 1.26E+06 4.06E+06 1.48E+06				
	rank	$\overline{4}$	1	10	3	9	5	$\overline{2}$	6	13	12	$\tau$	11	8
$C11-$ F12				mean 1.20E+06 1.50E+06 1.23E+06 1.68E+06		$1.27E + 06$	$1.70E + 06$			3.37E+06 3.60E+06 1.45E+07 5.43E+06 6.29E+06 1.45E+06 6.26E+06				
	best			$1.16E+06$ 1.47E+06 1.16E+06 1.64E+06		$1.22E + 06$	$1.66E + 06$			3.19E+06 3.49E+06 1.34E+07 5.12E+06 5.83E+06 1.27E+06 5.94E+06				
				worst <b>1.25E+06</b> 1.53E+06 1.30E+06 1.71E+06		$1.32E + 06$	$1.73E + 06$			3.51E+06 3.67E+06 1.54E+07 5.59E+06 6.53E+06 1.59E+06 6.50E+06				
										1.43E+05 7.81E+04 7.98E+05 2.16E+05 3.22E+05 1.35E+05 2.39E+05				
	std			$[4.49E+04]$ 2.73E+04 5.81E+04 3.05E+04		$5.66E + 04$	$3.01E + 04$							
						$1.28E + 06$	$1.71E + 06$			$3.39E+06$ 3.62E+06 1.45E+07 5.50E+06 6.41E+06 1.46E+06 6.31E+06				
$C11-$ F13	rank	$\mathbf{1}$	5	2	6	$\overline{3}$	$\overline{7}$	8	9	13	10	12	$\overline{4}$	-11
				mean 1.54E+041.54E+041.55E+041.55E+04		$1.55E + 04$	$1.55E + 04$			1.55E+04 1.54E+04 1.64E+04 1.55E+04 1.55E+04 1.55E+04 1.40E+05				
	best			$[1.54E+04]1.54E+04]1.55E+04]1.55E+04$		$1.55E + 04$	$1.55E + 04$			1 <b>.54E+04 1.54E+04 </b> 1.59E+04 1.55E+04 1.55E+04 1.55E+04 1.01E+05				
				worst   1.54E+04  1.54E+04  1.55E+04  1.55E+04		$1.55E + 04$	$1.55E + 04$			1.55E+04 <b> 1.54E+04 </b> 1.75E+04 <b> </b> 1.55E+04 <b> 1.56E+04 1.55E+04 1.93E+05</b>				
	std			$\left  8.65E - 03 \right  1.68E + 00 \left  3.72E + 00 \right  1.65E + 00$		$6.92E + 00$	$1.68E + 00$			1.25E+01 9.78E-01 7.67E+02 1.23E+01 5.27E+01 9.25E+00 4.16E+04				
				median <b>1.54E+04 1.54E+04</b> 1.55E+04 1.55E+04		$1.55E + 04$	$1.55E + 04$			1.54E+04 1.54E+04 1.61E+04 1.55E+04 1.55E+04 1.55E+04 1.33E+05				
	rank	-1	2	$7^{\circ}$	5	8	- 6	$\overline{4}$	$\mathbf{3}$	12	9	-11	10	-13
$C11-$ F14				mean   1.83E + 04   1.83E + 04   1.88E + 04   1.84E + 04		$1.90E + 04$	$1.85E + 04$			$1.84E+04$ $1.85E+04$ $2.51E+05$ $1.97E+04$ $1.93E+04$ $1.93E+04$ $1.92E+04$				
				best $[1.82E+04]1.83E+04]1.86E+04]1.84E+04$		$1.89E + 04$	$1.84E + 04$			$1.82E+04$   1.84E+04   1.84E+05   1.94E+04   1.92E+04   1.92E+04   1.89E+04				
				worst <b>1.84E+04 1.84E+04</b> 1.89E+04 1.85E+04		$1.91E + 04$	$1.86E + 04$			1.85E+04 1.86E+04 3.63E+05 2.03E+04 1.95E+04 1.95E+04 1.94E+04				
	std			6.81E+016.88E+019.65E+014.88E+01		$9.14E + 01$	$4.75E + 01$			$[9.42E+01]1.05E+02]7.99E+04$ 4.11E+02  1.37E+02  1.61E+02  2.39E+02				
				median <b>1.83E+04 1.83E+04 1</b> .88E+04 1.84E+04		$1.90E + 04$	$1.85E + 04$			1.84E+04 1.86E+04 2.29E+05 1.95E+04 1.93E+04 1.93E+04 1.92E+04				
	rank	$\mathbf{1}$	2	$7\phantom{.0}$	$\overline{4}$	8	$5^{\circ}$	3	6	13	12	10	11	9
$C11-$ F15				mean 3.29E+043.29E+043.29E+043.29E+04		$3.30E + 04$	3.29E+04 3.30E+04 1.16E+05 2.11E+06 5.68E+04 2.38E+05 3.31E+04 3.28E+05							
				best $3.28E+043.28E+043.29E+043.28E+04$		$3.30E + 04$								
				worst 3.30E+04 3.29E+04 3.30E+04 3.29E+04		$3.30E + 04$	3.28E+04 [3.29E+04] $4.42E+04$ [8.81E+05] $3.31E+04$ [3.30E+04] $3.31E+04$ [2.90E+05] $3.30E + 04$			3.31E+04 1.96E+05 5.52E+06 1.28E+05 3.42E+05 3.32E+04 3.54E+05				
	std			7.32E+01 6.95E+01 5.93E+01 6.76E+01		$4.62E+01$	$6.61E+01$			1.00E+028.14E+042.28E+064.73E+041.40E+054.64E+012.98E+04				
				median 3.29E+04 3.29E+04 3.29E+04 3.29E+04		$3.30E + 04$	$3.29E+04$			$3.30E+04$ 1.11E+05 1.02E+06 3.32E+04 2.89E+05 3.31E+04 3.34E+05				
	rank	$\overline{2}$	1	5	3	7	$\overline{4}$	6	10	13	9	11	8	12
$C11-$ F16				mean   1.34E+05  1.35E+05  1.40E+05  1.36E+05		$1.41E + 05$	$1.37E + 0.5$			1.39E+05 1.35E+05 2.14E+06 1.46E+05 1.43E+05 1.47E+05 2.07E+07				
	best			1.31E+05 1.32E+05 1.37E+05 1.34E+05		$1.36E + 05$	$1.34E + 05$			1.34E+05 1.34E+05 5.09E+05 1.44E+05 1.37E+05 1.44E+05 1.05E+07				
				worst   1.36E+05  1.37E+05  1.41E+05  1.39E+05		$1.44E + 05$	$1.40E + 05$							
	std			2.28E+03 2.59E+03 1.63E+03 2.55E+03		$3.31E+03$	$2.44E + 03$			5.89E+03 1.02E+03 2.17E+06 2.51E+03 5.08E+03 3.95E+03 1.16E+07				
				median <b>1.33E+05</b> 1.35E+05 1.40E+05 1.37E+05		$1.41E + 05$	$1.37E + 05$	1.38E+05		1.36E+05 1.36E+06 1.47E+05 1.44E+05 1.46E+05 1.74E+07				
	rank	$\mathbf{1}$	$\overline{2}$	7	$\overline{4}$	8	5	6	3	12	10	9	11	13
$C11-$ F17	mean			$1.93E+06$ 2.33E+06 2.52E+06 2.56E+06		$2.76E + 06$	$2.62E + 06$			3.65E+06 2.56E+09 1.71E+10 1.42E+09 1.07E+10 3.13E+06 1.24E+10				
	best			$1.92E+06$ 1.93E+06 1.99E+06 1.98E+06		$2.52E+06$	$2.01E + 06$			1.93E+06 2.32E+09 1.23E+10 1.17E+09 7.64E+09 2.05E+06 1.09E+10				
				worst <b>1.94E+06</b> 3.41E+06 3.38E+06 3.85E+06		$3.32E + 06$	$3.89E + 06$			8.19E+062.80E+092.09E+101.62E+091.42E+105.19E+061.31E+10				
	std			$1.14E+04$ 7.21E+05 6.22E+05 8.72E+05		$3.81E + 0.5$	$8.68E + 05$			3.04E+06 2.09E+08 3.71E+09 2.32E+08 2.78E+09 1.42E+06 1.01E+09				
				median 1.92E+06 1.99E+06 2.35E+06 2.20E+06		$2.60E + 06$	$2.29E + 06$			2.24E+06 2.55E+09 1.77E+10 1.44E+09 1.05E+10 2.65E+06 1.28E+10				
	rank	1	2	3	4	6	5	8	10	13	9	11	7	12
				mean 9.42E+05 1.05E+06 9.88E+05 1.09E+06		$9.92E + 05$	$1.10E + 06$			1.48E+06 7.15E+06 1.31E+08 2.17E+06 1.05E+07 1.04E+06 1.22E+07				
$C11-$														
F18				best $ 9.38E+05 9.67E+05 9.55E+05 9.78E+05$		$9.69E + 05$	$9.80E + 0.5$			1.06E+06 4.26E+06 9.03E+07 1.88E+06 4.46E+06 9.70E+05 9.08E+06				

## **TABLE 6.** (Continued.) Optimization results of the CEC-2011 test suite.



#### **TABLE 7.** Performance of optimization algorithms on pressure vessel design problem.



algorithms in the CEC-2011 test suite optimization are drawn in Figure 7.

## B. APPLICATION OF STO IN FOUR ENGINEERING DESING OPTIMIZATION PROBLEM

In this subsection, the performance of STO in solving four engineering design problems from real-world applications is evaluated. animal. For each engineering design problems, STO is employed 25 Siberian tigers along with a maximum number of FEs of 100,000. The stop criterion for the proposed STO and competitor algorithms is set to the maximum number of FEs equal to 100,000, where it ran 20 times independently for each design problem in each experiment.

#### **TABLE 8.** Statistical results of optimization algorithms on pressure vessel design problem.



#### **TABLE 9.** Performance of optimization algorithms on speed reducer design problem.



**TABLE 10.** Statistical results of optimization algorithms on speed reducer design problem.



#### 1) PRESSURE VESSEL DESIGN PROBLEM

Pressure vessel design is a minimization problem whose object is to reduce the design cost. Pressure vessel design schematic is presented in Figure 8. The mathematical model of this problem is presented in [73]. This problem has four design variables:

$$
X = [x_1, x_2, x_3, x_4] = [T_s, T_h, R, L]. \tag{14}
$$

#### where:

## $0 \le x_1, x_2 \le 100$  and  $10 \le x_3, x_4 \le 200$ .

The results of implementing STO and competitor algorithms on pressure vessel design are presented in tables 7 and 8. Based on the obtained results, STO has presented the optimal design of this problem with the values of the design variables equal to (0.778027075, 0.384579186, 40.3122837, 200) and the value of the corresponding objective function equal to 5882.895451. The results of statistical indicators



**FIGURE 7.** Boxplot diagram of STO and competitor algorithms performances on the CEC-2011 test suite.

show that STO has provided superior performance in dealing with the problem of pressure vessel design compared to competitor algorithms. The convergence curve of STO in handling this design is plotted in Figure 9.



**FIGURE 8.** Schematic view of pressure vessel design problem.



**FIGURE 9.** Convergence analysis of the STO for the pressure vessel design optimization problem.

#### 2) SPEED REDUCER DESIGN PROBLEM

Speed reducer design is a minimization problem whose object is to reduce the weight of the speed reducer. Speed reducer design schematic is presented in Figure 10. The mathematical model of this problem is presented in [74] and [75]. This problem has seven design variables:

$$
X = [x1, x2, x3, x4, x5, x6, x7] = [b, m, p, l1, l2, d1, d2].
$$
\n(15)

Where:

$$
2.6 \le x_1 \le 3.6, 0.7 \le x_2 \le 0.8, 17 \le x_3
$$
  
\n
$$
\le 28, 7.3 \le x_4 \le 8.3, 7.8 \le
$$
  
\n
$$
x_5 \le 8.3, 2.9 \le x_6 \le 3.9, \text{ and } 5 \le x_7 \le 5.5.
$$

The results of optimizing the design of speed reducer using STO and competitor algorithms are presented in Tables 9 and 10. Based on the obtained results, STO has presented the optimal design of this problem with the values of the design variables equal to (3.5, 0.7, 17, 7.3, 7.8, 3.350215, 5.286683) and the value of the corresponding objective function equal to 2996.348165. Comparing the results of statistical indicators shows that STO has performed better in optimizing speed reducer design compared to competitor algorithms. The STO convergence driver while reaching the solution is plotted in Figure 11.

## 3) WELDED BEAM DESIGN PROBLEM

Welded beam design is a minimization problem whose object is to reduce the fabrication cost of the welded beam. Welded



**FIGURE 10.** Schematic view of speed reducer design problem.



**FIGURE 11.** Convergence analysis of the STO for the speed reducer design optimization problem.

beam design schematic is presented in Figure 12. The mathematical model of this problem is presented in [32]. This problem has four design variables:

$$
X = [x_1, x_2, x_3, x_4] = [h, l, t, b].
$$
 (16)

Where:

$$
0.1 \le x_1, x_4 \le 2 \text{and} 0.1 \le x_2, x_3 \le 10.
$$

The results of employing STO and competitor algorithms in dealing with the welded beam design problem are presented in Tables 11 and 12. Based on the obtained results, STO has presented the optimal design of this problem with the values of the design variables equal to (0.20572964, 3.470488666, 9.03662391, 0.20572964) and the value of the corresponding objective function equal to 1.724679823. From the analysis of the statistical results, it is concluded that STO has provided superior performance in solving the welded beam design problem compared to competitor algorithms. The STO convergence curve during the optimization of this design is drawn in Figure 13.

#### 4) TENSION/COMPRESSION SPRING DESIGN PROBLEM

Tension/compression spring design is a minimization problem whose object is to reduce the weight of tension/compression spring. Tension/compression spring design schematic is presented in Figure 14. The mathematical model of this problem is presented in [32]. This problem has three design variables:

$$
X = [x_1, x_2, x_3] = [d, D, P].
$$

## **TABLE 11.** Performance of optimization algorithms on welded beam design problem.



**TABLE 12.** Statistical results of optimization algorithms on welded beam design problem.





**FIGURE 12.** Schematic view of the welded beam design problem.

where:

 $0.05 \le x_1 \le 2, 0.25 \le x_2 \le 1.3$  and  $2 \le x_3 \le 15$ .

The simulation results of tension/compression spring design problem are presented in tables 13 and 14. Based on the obtained results, STO has presented the optimal design of this problem with the values of the design variables equal to (0.051689061, 0.356717736, 11.28896595) and the value of the corresponding objective function equal to 0.012601907. Based on the analysis of statistical



**FIGURE 13.** Convergence analysis of the STO for the welded beam design optimization problem.



**FIGURE 14.** Schematic view of tension/compression spring problem.

results, STO has been more effective in handling the tension/compression spring design problem compared to competitor algorithms. The convergence curve of STO while achieving the optimal design of this problem is drawn in Figure 15.

#### **TABLE 13.** Performance of optimization algorithms on tension/compression spring design problem.



**TABLE 14.** Statistical results of optimization algorithms on tension/compression spring design problem.





**FIGURE 15.** Convergence analysis of the STO for the tension/compression spring design optimization problem.

#### **VI. CONCLUSION AND FUTURE WORKS**

This paper introduced a new swarm-based metaheuristic algorithm called the Siberian Tiger Optimization (STO), which imitates the natural life of Siberian tigers in nature. The basis of the proposed STO is the mathematical modeling of the strategy of Siberian tigers during hunting (in two stages: attack and chase), as well as the modeling of the strategy of the Siberian tiger fighting with bears (in two stages: attack and conflict). The proposed STO was tested on twentynine standard benchmark functions from the CEC 2017 test suite. In addition, the optimization results of the proposed STO were compared with the results of twelve well-known metaheuristic algorithms. Analysis of the simulation results showed that the proposed STO approach, having high ability in exploration, exploitation, and balance in exploration and exploitation, compared to competitor algorithms, has provided better results and has superior performance. Also, the implementation of the proposed STO approach on the CEC-2011 test suite and four engineering design problems indicated the acceptable ability of STO to handle real-world applications.

Following the introduction of the STO approach, several research tasks are activated for further studies in the future. The development of binary and multi-objective versions of the proposed STO approach is this paper's most extraordinary research potential. Employing the STO approach in optimization tasks in various sciences and other real-world applications are among other suggestions of the authors for future works.

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#### **REFERENCES**

[1] V. M. Tikhomirov, *Stories About Maxima and Minima*. Providence, RI, USA: American Mathematical Society, 1990.

- [2] A. W. Mohamed, A. A. Hadi, and A. K. Mohamed, "Gaining-sharing knowledge based algorithm for solving optimization problems: A novel nature-inspired algorithm,'' *Int. J. Mach. Learn. Cybern.*, vol. 11, no. 7, pp. 1501–1529, Jul. 2020.
- [3] H. Rocha, J. M. Dias, B. C. Ferreira, and M. C. Lopes, "Incorporating radial basis functions in pattern search methods: Application to beam angle optimization in radiotherapy treatment planning,'' in *Computational Science and Its Applications—ICCSA 2012*. Berlin, Germany: Springer, 2012, pp. 1–16.
- [4] M. S. Braik, "Chameleon swarm algorithm: A bio-inspired optimizer for solving engineering design problems,'' *Expert Syst. Appl.*, vol. 174, Jul. 2021, Art. no. 114685.
- [5] T. Ommen, W. B. Markussen, and B. Elmegaard, ''Comparison of linear, mixed integer and non-linear programming methods in energy system dispatch modelling,'' *Energy*, vol. 74, pp. 109–118, Sep. 2014.
- [6] E. Sandgren, ''Nonlinear integer and discrete programming in mechanical design optimization,'' *J. Mech. Des.*, vol. 112, no. 2, pp. 223–229, Jun. 1990.
- [7] L. Abualigah, D. Yousri, M. A. Elaziz, A. A. Ewees, M. A. A. Al-Qaness, and A. H. Gandomi, ''Aquila optimizer: A novel meta-heuristic optimization algorithm,'' *Comput. Ind. Eng.*, vol. 157, Jul. 2021, Art. no. 107250.
- [8] J. Xue and B. Shen, "A novel swarm intelligence optimization approach: Sparrow search algorithm,'' *Syst. Sci. Control Eng.*, vol. 8, no. 1, pp. 22–34, Jan. 2020.
- [9] S. Mirjalili, A. H. Gandomi, S. Z. Mirjalili, S. Saremi, H. Faris, and S. M. Mirjalili, ''Salp swarm algorithm: A bio-inspired optimizer for engineering design problems,'' *Adv. Eng. Softw.*, vol. 114, pp. 163–191, Dec. 2017.
- [10] C. Aktemur and I. Gusseinov, "A comparison of sequential quadratic programming, genetic algorithm, simulated annealing, particle swarm optimization and hybrid algorithm for the design and optimization of Golinski's speed reducer,'' *Int. J. Energy Appl. Technol.*, vol. 4, no. 2, pp. 34–52, 2017.
- [11] F. Glover, "Future paths for integer programming and links to artificial intelligence,'' *Comput. Oper. Res.*, vol. 13, no. 5, pp. 533–549, Jan. 1986.
- [12] F. A. Zeidabadi, A. Dehghani, M. Dehghani, Z. Montazeri, Š. Hubálovský, P. Trojovský, and G. Dhiman, ''SSABA: Search step adjustment based algorithm,'' *Comput., Mater. Continua*, vol. 71, no. 3, pp. 4237–4256, 2022
- [13] M. Cavazzuti, ''Deterministic optimization,'' in *Optimization Methods: From Theory to Design Scientific and Technological Aspects in Mechanics*. Berlin, Germany: Springer, 2013, pp. 77–102.
- [14] P. Trojovský and M. Dehghani, ''Pelican optimization algorithm: A novel nature-inspired algorithm for engineering applications,'' *Sensors*, vol. 22, no. 3, p. 855, Jan. 2022.
- [15] S. S. Mohar, S. Goyal, and R. Kaur, "Localization of sensor nodes in wireless sensor networks using bat optimization algorithm with enhanced exploration and exploitation characteristics,'' *J. Supercomput.*, vol. 78, no. 9, pp. 11975–12023, Jun. 2022.
- [16] G. Brunetti, C. Stumpp, and J. Šimunek, "Balancing exploitation and exploration: A novel hybrid global-local optimization strategy for hydrological model calibration,'' *Environ. Model. Softw.*, vol. 150, Apr. 2022, Art. no. 105341.
- [17] N. Pillay and W. Banzhaf, "A study of heuristic combinations for hyperheuristic systems for the uncapacitated examination timetabling problem,'' *Eur. J. Oper. Res.*, vol. 197, no. 2, pp. 482–491, Sep. 2009.
- [18] A. Potluri and A. Singh, ''Hybrid metaheuristic algorithms for minimum weight dominating set,'' *Appl. Soft Comput.*, vol. 13, no. 1, pp. 76–88, Jan. 2013.
- [19] M. Ramachandran, S. Mirjalili, M. Nazari-Heris, D. S. Parvathysankar, A. Sundaram, and C. A. R. Charles Gnanakkan, ''A hybrid grasshopper optimization algorithm and Harris hawks optimizer for combined heat and power economic dispatch problem,'' *Eng. Appl. Artif. Intell.*, vol. 111, May 2022, Art. no. 104753.
- [20] M. Gonzalez, J. J. López-Espín, J. Aparicio, and E.-G. Talbi, ''A hypermatheuristic approach for solving mixed integer linear optimization models in the context of data envelopment analysis,'' *PeerJ Comput. Sci.*, vol. 8, p. e828, Jan. 2022.
- [21] M. Dehghani, Z. Montazeri, E. Trojovská, and P. Trojovský, ''Coati optimization algorithm: A new bio-inspired metaheuristic algorithm for solving optimization problems,'' *Knowl.-Based Syst.*, vol. 259, Jan. 2023, Art. no. 110011.
- [22] S. Liu, S. Huang, W. Fu, and J. C.-W. Lin, "A descriptive human visual cognitive strategy using graph neural network for facial expression recognition,'' *Int. J. Mach. Learn. Cybern.*, early access, pp. 1–17, Oct. 2022, doi: [10.1007/s13042-022-01681-w.](http://dx.doi.org/10.1007/s13042-022-01681-w)
- [23] S. Liu, Y. Li, and W. Fu, ''Human-centered attention-aware networks for action recognition,'' *Int. J. Intell. Syst.*, early access, Aug. 2022, doi: [10.1002/int.23029.](http://dx.doi.org/10.1002/int.23029)
- [24] S. Liu, S. Wang, X. Liu, J. Dai, K. Muhammad, A. H. Gandomi, W. Ding, M. Hijji, and V. H. C. de Albuquerque, ''Human inertial thinking strategy: A novel fuzzy reasoning mechanism for IoT-assisted visual monitoring,'' *IEEE Internet Things J.*, early access, Jan. 11, 2022, doi: [10.1109/JIOT.2022.3142115.](http://dx.doi.org/10.1109/JIOT.2022.3142115)
- [25] S. Liu, D. Liu, G. Srivastava, D. Połap, and M. Woźniak, ''Overview and methods of correlation filter algorithms in object tracking,'' *Complex Intell. Syst.*, pp. 1895–1917, Jun. 2020.
- [26] D. H. Wolpert and W. G. Macready, "No free lunch theorems for optimization,'' *IEEE Trans. Evol. Comput.*, vol. 1, no. 1, pp. 67–82, Apr. 1997.
- [27] D. Karaboga and B. Basturk, ''Artificial bee colony (ABC) optimization algorithm for solving constrained optimization problems,'' in *Foundations of Fuzzy Logic and Soft Computing*, vol. 4529. Berlin, Germany: Springer, 2007, pp. 789–798.
- [28] M. Dorigo, V. Maniezzo, and A. Colorni, ''Ant system: Optimization by a colony of cooperating agents,'' *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 26, no. 1, pp. 29–41, Feb. 1996.
- [29] B. Abdollahzadeh, F. S. Gharehchopogh, and S. Mirjalili, ''African vultures optimization algorithm: A new nature-inspired metaheuristic algorithm for global optimization problems,'' *Comput. Ind. Eng.*, vol. 158, Aug. 2021, Art. no. 107408.
- [30] S. Mirjalili, S. M. Mirjalili, and A. Lewis, ''Grey wolf optimizer,'' *Adv. Eng. Softw.*, vol. 69, 46-61, Mar. 2014.
- [31] N. Chopra and M. M. Ansari, "Golden jackal optimization: A novel nature-inspired optimizer for engineering applications,'' *Expert Syst. Appl.*, vol. 198, Jul. 2022, Art. no. 116924.
- [32] S. Mirjalili and A. Lewis, ''The whale optimization algorithm,'' *Adv. Eng. Softw.*, vol. 95, pp. 51–67, May 2016.
- [33] F. A. Hashim, E. H. Houssein, K. Hussain, M. S. Mabrouk, and W. Al-Atabany, ''Honey badger algorithm: New Metaheuristic algorithm for solving optimization problems,'' *Math. Comput. Simul.*, vol. 192, pp. 84–110, Feb. 2022.
- [34] A. Faramarzi, M. Heidarinejad, S. Mirjalili, and A. H. Gandomi, ''Marine predators algorithm: A nature-inspired metaheuristic,'' *Expert Syst. Appl.*, vol. 152, Aug. 2020, Art. no. 113377.
- [35] M. Braik, A. Hammouri, J. Atwan, M. A. Al-Betar, and M. A. Awadallah, ''White shark optimizer: A novel bio-inspired meta-heuristic algorithm for global optimization problems,'' *Knowl.-Based Syst.*, vol. 243, May 2022, Art. no. 108457.
- [36] L. Abualigah, M. A. Elaziz, P. Sumari, Z. W. Geem, and A. H. Gandomi, ''Reptile search algorithm (RSA): A nature-inspired meta-heuristic optimizer,'' *Expert Syst. Appl.*, vol. 191, Apr. 2022, Art. no. 116158.
- [37] S. Kaur, L. K. Awasthi, A. L. Sangal, and G. Dhiman, ''Tunicate swarm algorithm: A new bio-inspired based metaheuristic paradigm for global optimization,'' *Eng. Appl. Artif. Intell.*, vol. 90, Apr. 2020, Art. no. 103541.
- [38] D. E. Goldberg and J. H. Holland, "Genetic algorithms and machine learning,'' *Mach. Learn.*, vol. 3, no. 2, pp. 95–99, 1988.
- [39] R. Storn and K. Price, ''Differential evolution—A simple and efficient heuristic for global optimization over continuous spaces,'' *J. Global Optim.*, vol. 11, no. 4, pp. 341–359, 1997.
- [40] L. N. D. Castro and J. I. Timmis, ''Artificial immune systems as a novel soft computing paradigm,'' *Soft Comput.*, vol. 7, no. 8, pp. 526–544, Aug. 2003.
- [41] S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi, "Optimization by simulated annealing,'' *Science*, vol. 220, no. 4598, pp. 671–680, 1983.
- [42] M. Dehghani and H. Samet, ''Momentum search algorithm: A new metaheuristic optimization algorithm inspired by momentum conservation law,'' *Social Netw. Appl. Sci.*, vol. 2, no. 10, pp. 1–15, Oct. 2020.
- [43] H. Eskandar, A. Sadollah, A. Bahreininejad, and M. Hamdi, "Water cycle algorithm—A novel metaheuristic optimization method for solving constrained engineering optimization problems,'' *Comput. Struct.*, vols. 110–111, pp. 151–166, Nov. 2012.
- [44] F. A. Hashim, K. Hussain, E. H. Houssein, M. S. Mabrouk, and W. Al-Atabany, ''Archimedes optimization algorithm: A new metaheuristic algorithm for solving optimization problems,'' *Int. J. Speech Technol.*, vol. 51, no. 3, pp. 1531–1551, Mar. 2021.
- [45] S. Mirjalili, S. M. Mirjalili, and A. Hatamlou, ''Multi-verse optimizer: A nature-inspired algorithm for global optimization,'' *Neural Comput. Appl.*, vol. 27, no. 2, pp. 495–513, Feb. 2016.
- [46] E. Cuevas, D. Oliva, D. Zaldivar, M. Pérez-Cisneros, and H. Sossa, ''Circle detection using electro-magnetism optimization,'' *Inf. Sci.*, vol. 182, no. 1, pp. 40–55, Jan. 2012.
- [47] A. Faramarzi, M. Heidarinejad, B. Stephens, and S. Mirjalili, "Equilibrium optimizer: A novel optimization algorithm,'' *Knowl.-Based Syst.*, vol. 191, Mar. 2020, Art. no. 105190.
- [48] J. L. J. Pereira, M. B. Francisco, C. A. Diniz, G. A. Oliver, S. S. Cunha, and G. F. Gomes, ''Lichtenberg algorithm: A novel hybrid physics-based metaheuristic for global optimization,'' *Expert Syst. Appl.*, vol. 170, May 2021, Art. no. 114522.
- [49] M. Dehghani, M. Mardaneh, J. M. Guerrero, O. Malik, and V. Kumar, ''Football game based optimization: An application to solve energy commitment problem,'' *Int. J. Intell. Eng. Syst.*, vol. 13, no. 5, pp. 514–523, Oct. 2020.
- [50] R. Moghdani and K. Salimifard, ''Volleyball premier league algorithm,''
- *Appl. Soft Comput.*, vol. 64, pp. 161–185, Mar. 2018. [51] A. Kaveh and A. Zolghadr, ''A novel meta-heuristic algorithm: Tug of war optimization,'' *Int. J. Optim. Civil Eng.*, vol. 6, no. 4, pp. 469–492, 2016.
- [52] F. A. Zeidabadi, M. Dehghani, P. Trojovský, Š. Hubálovský, V. Leiva, and G. Dhiman, ''Archery algorithm: A novel stochastic optimization algorithm for solving optimization problems,'' *Comput., Mater. Continua*,
- vol. 72, no. 1, pp. 399–416, 2022. [53] F. A. Zeidabadi and M. Dehghani, ''POA: Puzzle optimization algorithm,'' *Int. J. Intell. Eng. Syst.*, vol. 15, no. 1, pp. 273–281, 2022.
- [54] R. V. Rao, V. J. Savsani, and D. P. Vakharia, ''Teaching–learning-based optimization: A novel method for constrained mechanical design optimization problems,'' *Comput.-Aided Des.*, vol. 43, no. 3, pp. 303–315, Mar. 2011.
- [55] M. Dehghani, M. Mardaneh, J. M. Guerrero, O. P. Malik, R. A. Ramirez-Mendoza, J. Matas, J. C. Vasquez, and L. Parra-Arroyo, "A new 'doctor and patient' optimization algorithm: An application to energy commitment problem,'' *Appl. Sci.*, vol. 10, no. 17, p. 5791, Aug. 2020.
- [56] M. Dehghani and P. Trojovský, ''Teamwork optimization algorithm: A new optimization approach for function minimization/maximization,'' *Sensors*, vol. 21, no. 13, p. 4567, Jul. 2021.
- [57] T. S. L. V. Ayyarao, N. S. S. Ramakrishna, R. M. Elavarasan, N. Polumahanthi, M. Rambabu, G. Saini, B. Khan, and B. Alatas, ''War strategy optimization algorithm: A new effective metaheuristic algorithm for global optimization,'' *IEEE Access*, vol. 10, pp. 25073–25105, 2022.
- [58] M. A. Al-Betar, Z. A. A. Alyasseri, M. A. Awadallah, and I. A. Doush, ''Coronavirus herd immunity optimizer (CHIO),'' *Neural Comput. Appl.*, vol. 33, no. 10, pp. 5011–5042, May 2021.
- [59] M. Braik, M. H. Ryalat, and H. Al-Zoubi, ''A novel meta-heuristic algorithm for solving numerical optimization problems: Ali Baba and the forty thieves,'' *Neural Comput. Appl.*, vol. 34, no. 1, pp. 409–455, Jan. 2022.
- [60] D. G. Miquelle, ''The Amur tiger: A case study of living on the edge,'' in *Biology and Conservation of Wild Felids*. Oxford, U.K.: Oxford Univ. Press, 2010, pp. 325–339.
- [61] H. Yang, H. Dou, R. K. Baniya, S. Han, Y. Guan, B. Xie, G. Zhao, T. Wang, P. Mou, L. Feng, and J. Ge, ''Seasonal food habits and prey selection of Amur tigers and Amur leopards in northeast China,'' *Sci. Rep.*, vol. 8, no. 1,
- p. 6930, Dec. 2018. [62] V. G. Heptner, ''Carnivora (hyenas and cats),'' in *Mammals of the Soviet Union*, vol. 2. Leiden, The Netherlands: Brill, 1989.
- [63] V. Mazák, ''Panthera tigris,'' *Mammalian Species*, no. 152, pp. 1–8, 1981, doi: [10.2307/3504004.](http://dx.doi.org/10.2307/3504004)
- [64] D. G. Miquelle, E. N. Smirnov, T. W. Merrill, A. E. Myslenkov, H. B. Quigley, M. G. Hornocker, and B. Schleyer, ''Hierarchical spatial analysis of Amur tiger relationships to habitat and prey,'' in *Riding the Tiger: Tiger Conservation in Human-Dominated Landscapes*. Cambridge, U.K.: Cambridge Univ. Press, 1999, pp. 71–99. [65] N. Awad, M. Ali, J. Liang, B. Qu, P. Suganthan, and P. Definitions,
- ''Evaluation criteria for the CEC 2017 special session and competi tion on single objective real-parameter numerical optimization,'' Technol. Rep., Sep. 2017. [Online]. Available: https://www.researchgate.net/ profile/Guohua-Wu-5/publication/317228117\_Problem\_Definitions\_and\_ Evaluation\_Criteria\_for\_the\_CEC\_2017\_Competition\_and\_Special\_Sess ion\_on\_Constrained\_Single\_Objective\_Real-Parameter\_Optimization/lin ks/5982cdbaa6fdcc8b56f59104/Problem-Definitions-and-Evaluation-Crit eria-for-the-CEC-2017-Competition-and-Special-Session-on-Constra ined-Single-Objective-Real-Parameter-Optimization.pdf
- [66] A. W. Mohamed, A. A. Hadi, A. M. Fattouh, and K. M. Jambi, "LSHADE with semi-parameter adaptation hybrid with CMA-ES for solving CEC 2017 benchmark problems,'' in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jun. 2017, pp. 145–152.
- [67] H. T. Kahraman, S. Aras, and E. Gedikli, "Fitness-distance balance (FDB): A new selection method for meta-heuristic search algorithms,'' *Knowl.- Based Syst.*, vol. 190, Feb. 2020, Art. no. 105169.
- [68] S. Duman, H. T. Kahraman, and M. Kati, ''Economical operation of modern power grids incorporating uncertainties of renewable energy sources and load demand using the adaptive fitness-distance balance-based stochastic fractal search algorithm,'' *Eng. Appl. Artif. Intell.*, vol. 117, Jan. 2023, Art. no. 105501.
- [69] E. Cengiz, C. Yilmaz, H. Kahraman, and C. Suicmez, ''Improved Runge Kutta optimizer with fitness distance balance-based guiding mechanism for global optimization of high-dimensional problems,'' *Düzce Üniversitesi Bilim ve Teknoloji Dergisi*, vol. 9, no. 6, pp. 135–149, 2021.
- [70] U. Guvenc, S. Duman, H. T. Kahraman, S. Aras, and M. Katı, "Fitnessdistance balance based adaptive guided differential evolution algorithm for security-constrained optimal power flow problem incorporating renewable energy sources,'' *Appl. Soft Comput.*, vol. 108, Sep. 2021, Art. no. 107421.
- [71] F. Wilcoxon, ''Individual comparisons by ranking methods,'' *Biometrics*
- *Bull.*, vol. 1, no. 6, p. 80, Dec. 1945.<br>[72] S. Das and P. N. Suganthan, "Problem definitions and evaluation criteria for CEC 2011 competition on testing evolutionary algorithms on real world optimization problems,'' Jadavpur Univ., Nanyang Technol. Univ., Kolkata, India, Tech. Rep., Dec. 2010, pp. 341–359. [Online]. Available: https://sci2s.ugr.es/sites/default/files/files/TematicWebSites/EAMHCO/ contributionsCEC11/RealProblemsTech-Rep.pdf
- [73] B. K. Kannan and S. N. Kramer, ''An augmented Lagrange multiplier based method for mixed integer discrete continuous optimization and its applications to mechanical design,'' *J. Mech. Des.*, vol. 116, no. 2,
- pp. 405–411, Jun. 1994. [74] A. H. Gandomi and X.-S. Yang, ''Benchmark problems in structural optimization,'' in *Computational Optimization, Methods and Algorithms* (Studies in Computational Intelligence), vol. 356. Berlin, Germany: Springer, 2011, pp. 259–281.
- [75] E. Mezura-Montes and C. A. C. Coello, ''Useful infeasible solutions in engineering optimization with evolutionary algorithms,'' in *MICAI 2005: Advances in Artificial Intelligence*, vol. 3789. Berlin, Germany: Springer, 2005, pp. 652–662.



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