

Seagull optimization algorithm: Theory and its applications for large-scale industrial engineering problems

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ABSTRACT

This paper presents a novel bio-inspired algorithm called Seagull Optimization Algorithm (SOA) for solving computationally expensive problems. The main inspiration of this algorithm is the migration and attacking behaviors of a seagull in nature. These behaviors are mathematically modeled and implemented to emphasize exploration and exploitation in a given search space. The performance of SOA algorithm is compared with nine well-known metaheuristics on forty-four benchmark test functions. The analysis of computational complexity and convergence behaviors of the proposed algorithm have been evaluated. It is then employed to solve seven constrained real-life industrial applications to demonstrate its applicability. Experimental results reveal that the proposed algorithm is able to solve challenging large-scale constrained problems and is very competitive algorithm as compared with other optimization algorithms.

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1. Introduction

Optimization is a process of determining the decision variables of a function to minimize or maximize its values. Most of the real world problems have non-linear constraints, high computational cost, non-convex, complicated, and large number of solution spaces [1]. Therefore, solving such problems with large number of variables and constraints is very tedious and complex [2–6]. Secondly, there are many local optimum solutions that do not guarantee the best solution using classical numerical methods.

To overcome these problems, metaheuristic optimization algorithms are introduced which are capable of solving such complex problems [7,8]. Recently, there is a lot of interest in developing metaheuristic algorithms that are computationally inexpensive, flexible, and simple by nature [9–12].

Metaheuristics are broadly classified into two categories such as single solution and population based algorithms [13]. Single solution based algorithms are in which a solution is randomly generated and improved until the best result is obtained. Population based algorithms are in which a set of solutions is randomly generated in a given search space and solution values are updated during course of iterations until the best solution is found.

However, single solution based algorithms may trap into local optima that preventing us to find global optimum. This is because it reforms only one solution which is randomly generated for a given problem. On the other hand, population based algorithms are able

to find the global optimum. Due to this, researchers have attracted towards population based algorithms nowadays.

The categorization of population based algorithms is done that is based on the theory of evolutionary algorithms, logical behavior of physics algorithms, swarm intelligence of particles, and biological behavior of bio-inspired algorithms. Evolutionary algorithms are inspired by the evolutionary processes such as reproduction, mutation, recombination, and selection. These algorithms are based on the survival fitness of candidate in a population (i.e., a set of solutions) for a given environment [14]. The physics law based algorithms are inspired by physical processes according to some physics rules such as gravitational force, electromagnetic force, inertia force, heating, and cooling of materials. Swarm intelligence based algorithms are inspired by the collective intelligence of swarms. The collective intelligence is found among colonies of flocks, ants, and so on.

Generally, swarm intelligence based algorithms are easy to implement than the evolutionary algorithms due to less number of parameters required. The well-known swarm intelligence based algorithms are Particle Swarm Optimization (PSO) [15] and Ant Colony Optimization [16]. The reason behind the popularity of these algorithms is that only few parameters are required for fine tuning.

Every optimization algorithm needs to address the exploration and exploitation of a search space [17] and maintains a good balance between exploration and exploitation. The exploration phase in an algorithm investigates the different promising regions in a search space whereas exploitation is able to search the optimal

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solutions around the promising regions [18]. Therefore, there is a need for fine tuning of these two phases to achieve the near optimal solutions. Despite the significant number of recently developed optimization algorithms, the question is raised why we need to develop more optimization techniques. The answer lies in No Free Lunch (NFL) theorem [19]. According to this theorem, the performance of one optimization algorithm for a specific set of problems does not guarantee to solve other optimization problems because of their different nature. NFL theorem allows researchers to propose some novel optimization algorithms for solving the problems in different fields [20]. This motivated us to develop a novel technique which is gradient free and effective optimization algorithm to optimize real-life engineering problems.

This paper presents a novel bio-inspired metaheuristic algorithm named as Seagull Optimization Algorithm (SOA) for optimizing the constrained problems. As its name implies, SOA mimics the migration and attacking behaviors of seagulls in nature. The performance of SOA algorithm is evaluated on forty-four well-known benchmark test functions. Further, SOA algorithm is employed to optimize the designs of optical buffer, pressure vessel, speed reducer, welded beam, tension/compression spring, 25-bar truss, and rolling element bearing problems.

The rest of this paper is structured as follows: Section 2 presents the preliminaries of optimization and related work done in the field of single-objective optimization. Section 3 presents the proposed SOA algorithm in detail. The experimental results and discussion is presented in Section 4. In Section 5, the performance of SOA is tested on seven real-life constrained industrial optimization problems and compared it with other well-known algorithms. Finally, the conclusion and some future research directions are discussed in Section 6.

2. Background

This section first describes the definitions of single objective optimization. Further, the literature review and motivation of proposed work are discussed.

2.1. Single-objective optimization problems

Many real-world problems need to achieve several objectives such as minimize risks, maximize reliability, minimize cost, etc. The main goal of optimization process is to find the best optimal solution that combines different objectives into one. In the optimization process, there is a set of equality and inequality constraints which is to be minimized or maximized.

$$\text{Minimize/Maximize: } F(\vec{z}) = f_1(\vec{z}) \quad (1)$$

Subject to:

$$g_j(\vec{z}) \geq 0, j = 1, 2, \dots, p \quad (2)$$

$$h_j(\vec{z}) = 0, j = 1, 2, \dots, q \quad (3)$$

$$lb_j \leq z_j \leq ub_j, j = 1, 2, \dots, r \quad (4)$$

where p is the number of inequality constraints, q is the number of equality constraints, r is the number of variables, lb_j is the lower bound, and ub_j is the upper bound of the j th variable.

Therefore, the presence of local solutions when solving optimization problems is the main challenging task because there is only one best solution in the search space. However, there are many other solutions which are closer to the obtained objective value. These kinds of solutions can be considered as best local solutions, but not the best globally while considering the entire search

space. This may trapped in local optimum due to the presence of local solutions. The convergence speed is another issue because an algorithm that avoids local solutions does not necessarily converge to global optimum. The above-mentioned are the main challenges of metaheuristic algorithm that solves real-life problems.

2.2. Literature review

Population based metaheuristic algorithms are broadly classified into three categories namely Physics-based, Evolutionary-based, and Swarm-based methods.

The first approach is Physics-based algorithms in which search agents can communicate around the search space according to laws of physics such as electromagnetic force, inertia force, gravitational force. The general mechanism of these algorithms is different from other approaches due to the strategy of search agents as per physics rules. The popular Physics-based optimization algorithms are Simulated Annealing (SA) [21] and Gravitational Search Algorithm (GSA) [22]. Simulated Annealing is inspired from annealing in metallurgy that involves heating and controlled cooling attributes of a material. These attributes depend on its thermodynamic free energy. Gravitational Search Algorithm is based on the law of gravity and mass interactions. The population solutions are interact with each other through the gravity force and their performance is measured by its mass. Some of the other popular algorithms are: Big-Bang Big-Crunch (BBCB) [23], Charged System Search (CSS) [24], Black Hole (BH) [25] algorithm, Central Force Optimization (CFO) [26], Small-World Optimization Algorithm (SWOA) [27], and Ray Optimization (RO) algorithm [28].

The second subclass of metaheuristic algorithms is Evolutionary-based algorithms. These algorithms are inspired by theory of natural selection and biological evolution. These algorithms often perform well to find near optimal solutions because they do not make any belief about the basic fitness landscape. The most popular evolutionary algorithm is Genetic Algorithm (GA). GA was first proposed by Holland [29]. The evolution starts with the randomly generated individuals from a population. The fitness value of each individual is calculated in each generation. The crossover and mutation operators are applied on the individuals to create a new population. Thus, the best individuals can generate the new population due to their higher probability during the course of iterations. Differential Evolution (DE) [30] is another Evolutionary-based algorithm which optimizes a problem by maintaining a candidate solutions and creates new candidate solutions by combining the existing ones. It keeps the candidate solution which has best fitness value for optimization problem. Apart from these, some of the other popular evolutionary-based algorithms are Genetic Programming (GP) [31], Evolution Strategy (ES) [32], and Biogeography-Based Optimizer (BBO) [33].

The third main branch in metaheuristics is Swarm-based algorithms which are based on the collective behavior of social creatures. These techniques are generally inspired from natural colonies, flock, and herds. The most popular algorithm is Particle Swarm Optimization (PSO) which was first proposed by Kennedy and Eberhart [15]. In PSO, particles move around the search space using a combination of best solution which they have individually found and the best solution that any particle in their neighborhood has found [34]. The whole process is repeated until the termination criterion is satisfied. Ant Colony Optimization (ACO) is another popular swarm intelligence algorithm which was proposed by Dorigo [16]. The main inspiration behind this algorithm is the social behavior of ants in ant colony. The social intelligence of ants is able to find the shortest path between the source food and nest. Bat-inspired Algorithm (BA) [35] is another intelligence based algorithm that is inspired by the echolocation behavior of bats. The another well-known swarm based technique is Artificial Bee

Table 1
Metaheuristic optimization algorithms.

Algorithms	Abbreviation
Emperor Penguin Optimizer [41]	EPO
Collective Neurodynamic Optimization [1,42–44]	CNO
Artificial Chemical Reaction Optimization Algorithm [45]	ACROA
Galaxy-based Search Algorithm [46]	GbSA
Firefly Algorithm [47]	FA
Exchange Market Algorithm [48]	EMA
Social-Based Algorithm [49]	SBA
Harmony Search [50]	HS
Grey Wolf Optimizer [51]	GWO
Mine Blast Algorithm [52]	MBA
Monkey Search [53]	MS
Bacterial Foraging Optimization Algorithm [54]	BFOA
Fruit fly Optimization Algorithm [55]	FOA
Bird Mating Optimizer [56]	BMO
Krill Herd [57]	KH
Artificial Fish-Swarm Algorithm [58]	AFSA
Dolphin Partner Optimization [59]	DPO
Wolf Pack Search Algorithm [60]	WPSA
Bee Collecting Pollen Algorithm [61]	BCPA
Termite Algorithm [62]	TA
Wasp Swarm Algorithm [63]	WSA
Marriage in Honey Bees Optimization Algorithm [64]	MBO

Colony (ABC) algorithm [36] which is inspired by the collective behavior of bees to find the food sources. Spotted Hyena Optimizer (SHO) [37–39] is a recently developed bio-inspired optimization algorithm that mimics the searching, hunting, and attacking behaviors of spotted hyenas in nature. The main concept of this technique is the social relationship and collective behavior of spotted hyenas for hunting strategy. Cuckoo Search (CS) [40] is another bio-inspired optimization approach which is inspired by the obligate brood parasitism of cuckoo species. These species laying their eggs in the nest of other species. Each egg and a cuckoo egg represent a solution and a new solution, respectively. There are also some of the other metaheuristic techniques which are tabulated in Table 1.

According to the best of our knowledge, there is no Swarm-based technique that mimics the migration and attacking behaviors of seagulls. This motivates us to propose a new Swarm-based technique which is inspired by seagulls and implement its mathematical model for solving various benchmarks and real engineering problems.

3. Seagull optimization algorithm (SOA)

In this section, the inspiration and mathematical modeling of proposed algorithm is discussed in detail.

3.1. Biological paradigm

Seagulls, scientific named as Laridae, are sea birds which can be found all over the planet. There is wide range of seagulls species with different masses and lengths. Seagulls are omnivorous and eat insects, fish, reptiles, amphibians, earthworms, and so on. Body of most seagulls is covered with white plumage. Seagulls are very intelligent birds. They use bread crumbs to attract fish and produce rain-like sound with their feet to attract earthworms hidden under the ground. Seagulls can drink both fresh and salt water. Most of animals are unable to do this. However, seagulls have a special pair of glands right above their eyes which is specifically designed to flush the salt from their systems through openings in the bill.

Generally, seagulls live in colonies. They use their intelligence to find and attack the prey. The most important thing about the seagulls is their migrating and attacking behaviors. Migration is defined as the seasonal movement of seagulls from one place to another to find the richest and most abundant food sources that will provide adequate energy [65]. This behavior is described as follows:

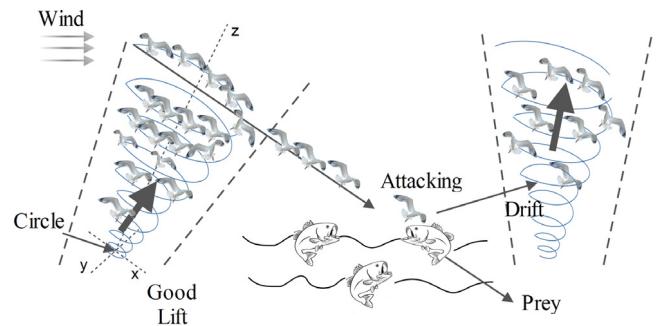


Fig. 1. Migration and attacking behaviors of seagulls.

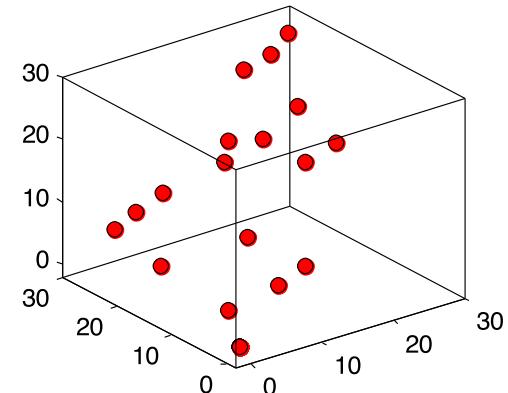


Fig. 2. Collision avoidance between search agents.

- During migration, they travel in a group. The initial positions of seagulls are different to avoid the collisions between each other.
- In a group, seagulls can travel towards the direction of best survival fittest seagull, i.e., a seagull whose fitness value¹ is low as compared to others.
- Based on the fittest seagull, other seagulls can update their initial positions.

Seagulls frequently attack migrating birds over the sea [66] when they migrate from one place to another. They can make their spiral natural shape movement during attacking. A conceptual model of these behaviors is illustrated in Fig. 1. These behaviors can be formulated in such a way that it can be associated with the objective function to be optimized. This makes it possible to formulate a new optimization algorithm. This paper focuses two natural behaviors of seagulls.

3.2. Mathematical model

The mathematical models of migration and attacking the prey are discussed.

3.2.1. Migration (exploration)

During migration, the algorithm simulates how the group of seagulls move towards one position to another. In this phase, a seagull should satisfy three conditions:

- **Avoiding the collisions:** To avoid the collision between neighbors (i.e., other seagulls), an additional variable A is

¹ The term fitness value is defined as a process which evaluates the population and gives a score or fitness. Whereas, the process is a function which measures the quality of the represented solution.

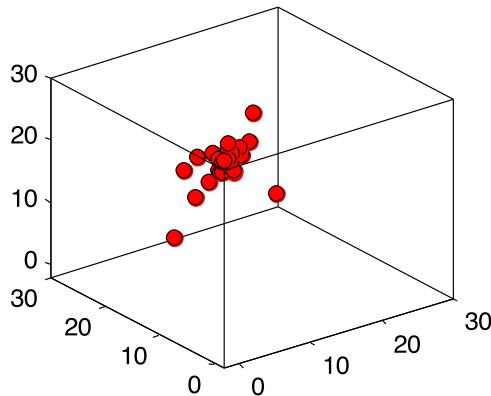


Fig. 3. Movement of search agents towards the best neighbor.

employed for the calculation of new search agent position (see Fig. 2).

$$\vec{C}_s = A \times \vec{P}_s(x) \quad (5)$$

where \vec{C}_s represents the position of search agent which does not collide with other search agent, \vec{P}_s represents the current position of search agent, x indicates the current iteration, and A represents the movement behavior of search agent in a given search space.

$$A = f_c - (x \times (f_c / \text{Max}_{\text{iteration}}))$$

$$\text{where: } x = 0, 1, 2, \dots, \text{Max}_{\text{iteration}} \quad (6)$$

where f_c is introduced to control the frequency of employing variable A which is linearly decreased from f_c to 0. In this work, the value of f_c is set to 2. The detailed sensitivity analysis of f_c has been discussed in Section 4.9.

- **Movement towards best neighbor's direction:** After avoiding the collision between neighbors, the search agents are move towards the direction of best neighbor (see Fig. 3).

$$\vec{M}_s = B \times (\vec{P}_{bs}(x) - \vec{P}_s(x)) \quad (7)$$

where \vec{M}_s represents the positions of search agent \vec{P}_s towards the best fit search agent P_{bs} (i.e., fittest seagull). The behavior of B is randomized which is responsible for proper balancing between exploration and exploitation. B is calculated as:

$$B = 2 \times A^2 \times rd \quad (8)$$

where rd is a random number lies in the range of $[0, 1]$.

- **Remain close to the best search agent:** Lastly, the search agent can update its position with respect to best search agent which is shown in Fig. 4.

$$\vec{D}_s = |\vec{C}_s + \vec{M}_s| \quad (9)$$

where \vec{D}_s represents the distance between the search agent and best fit search agent (i.e., best seagull whose fitness value is less).

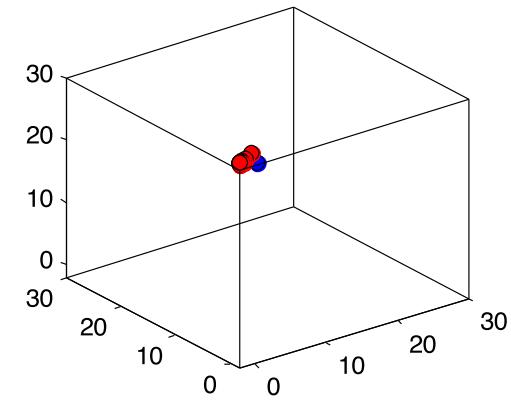


Fig. 4. Convergence towards the best search agent.

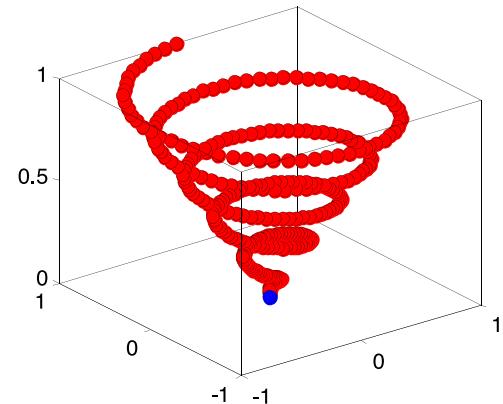


Fig. 5. Natural attacking behavior of seagull.

$$y' = r \times \sin(k) \quad (11)$$

$$z' = r \times k \quad (12)$$

$$r = u \times e^{kv} \quad (13)$$

where r is the radius of each turn of the spiral, k is a random number in range $[0 \leq k \leq 2\pi]$. u and v are constants to define the spiral shape, and e is the base of the natural logarithm. The updated position of search agent is calculated using Eqs. (9)–(13).

$$\vec{P}_s(x) = (\vec{D}_s \times x' \times y' \times z') + \vec{P}_{bs}(x) \quad (14)$$

where $\vec{P}_s(x)$ saves the best solution and updates the position of other search agents.

The proposed SOA starts with a random generated population. The search agents can update their positions with respect to best search agent during the iteration process. A is linearly decreased from f_c to 0. For smooth transition between exploration and exploitation, variable B is responsible. Hence, SOA is considered as a global optimizer (see Algorithm 1) because of its better exploration and exploitation capability.

3.3. Computational complexity

The complexity of an algorithm is an important metric to judge its performance. The population initialization process of proposed SOA and other competitor algorithms (i.e., SHO, GWO, PSO, MFO, MVO, SCA, GSA, GA, and DE) requires $\mathcal{O}(n_o \times n_p)$ time, where n_o represents the number of objectives and n_p represents the number

3.2.2. Attacking (exploitation)

The exploitation intends to exploit the history and experience of the search process. Seagulls can change the angle of attack continuously as well as speed during migration. They maintain their altitude using their wings and weight. While attacking the prey, the spiral movement behavior occurs in the air (see Fig. 5). This behavior in x , y , and z planes is described as follows.

$$x' = r \times \cos(k) \quad (10)$$

Algorithm 1 Seagull Optimization Algorithm

```

Input: Seagull population  $\vec{P}_s$ 
Output: Optimal search agent  $\vec{P}_{bs}$ 
1: procedure SOA
2: Initialize the parameters  $A$ ,  $B$ , and  $Max_{iteration}$ 
3: Set  $f_c \leftarrow 2$ 
4: Set  $u \leftarrow 1$ 
5: Set  $v \leftarrow 1$ 
6: while ( $x < Max_{iteration}$ ) do
7:    $\vec{P}_{bs} \leftarrow \text{ComputeFitness}(\vec{P}_s)$  /* Calculate the fitness values of each search agent using ComputeFitness function*/
  /* Migration behavior */
8:    $rd \leftarrow Rand(0, 1)$  /* To generate the random number in range [0, 1] */
9:    $k \leftarrow Rand(0, 2\pi)$  /* To generate the random number in range [0,  $2\pi$ ] */
  /* Attacking behavior */
10:   $r \leftarrow u \times e^{kv}$  /* To generate the spiral behavior during migration */
11:  Calculate the distance  $D_s$  using Eq. (9)
12:   $P \leftarrow x' \times y' \times z'$  /* Compute x, y, z planes using Eqs. (10)–(13) */
13:   $\vec{P}_s(x) \leftarrow (D_s \times P) + \vec{P}_{bs}$ 
14:   $x \leftarrow x + 1$ 
15: end while
16: return  $P_{bs}$ 
17: end procedure

1: procedure COMPUTEFITNESS( $\vec{P}_s$ )
2:   for  $i \leftarrow 1$  to  $n$  do /* Here,  $n$  represents the dimension of a given problem */
3:      $FIT_s[i] \leftarrow \text{FitnessFunction}(P_s(i, :))$  /* Calculate the fitness of each individual */
4:   end for
5:    $FIT_{sbest} \leftarrow \text{BEST}(FIT_s[])$  /* Calculate the best fitness value using BEST function */
6: return  $FIT_{sbest}$ 
7: end procedure

1: procedure BEST( $FIT_s[]$ )
2:    $Best \leftarrow FIT_s[0]$ 
3:   for  $i \leftarrow 1$  to  $n$  do
4:     if( $FIT_s[i] < Best$ ) then
5:        $Best \leftarrow FIT_s[i]$ 
6:     end if
7:   end for
8: return  $Best$  /* Return the best fitness value */
9: end procedure

```

of population size. The complexity of calculating the fitness of search agents for all algorithms needs $\mathcal{O}(Max_{iteration} \times o_f)$, where o_f represents the objective function for a given problem. For simulate the whole procedure, it requires $\mathcal{O}(N)$ time.

The computational complexity of proposed SOA algorithm is $\mathcal{O}(N \times Max_{iteration} \times n_o \times n_p \times o_f)$. The computational complexity of SHO algorithm is $\mathcal{O}(N \times G \times Max_{iteration} \times n_o \times n_p \times o_f)$ since it requires $\mathcal{O}(G)$ time to define the group of spotted hyenas. The computational complexities corresponding to GWO, PSO, MFO, MVO, SCA algorithms are $\mathcal{O}(N \times Max_{iteration} \times n_o \times n_p \times o_f)$. The GSA algorithm needs $\mathcal{O}(f^2)$ time for calculating the force component and overall requires $\mathcal{O}(N \times f^2 \times Max_{iteration} \times n_o \times n_p \times o_f)$. Finally, the computational complexities of GA, and DE algorithms are $\mathcal{O}(N \times Max_{iteration} \times n_o \times n_p \times o_f \times (c_s + m_t))$, where c_s and m_t represent the crossover and mutation operators, respectively.

Whereas, the space complexity of all algorithms are the maximum amount of utilized space at any one time which is considered during its initialization process. In this work, the space complexity for all approaches are considered as $\mathcal{O}(n_o \times n_p)$.

However, the average running time of proposed SOA and other algorithms is given in [Table 2](#) and [Fig. 6](#). It can be seen that SOA takes less time than other approaches in terms of seconds.

Since, SOA is a bio-inspired optimization algorithm so there is no need of evolutionary processes, i.e., crossover and mutation. Therefore, it can be concluded that the computational efficiency of proposed algorithm is much better than the other competitor approaches.

4. Experimental results and discussion

In this section, the proposed algorithm is tested on 44 well-known benchmark test functions (see [Appendix A](#)) and the results are compared with the other competitor methods. These test functions are categorized into five categories such as unimodal, multimodal, fixed-dimension multimodal, CEC 2005 [[37](#)], and CEC 2015 special session test functions [[67](#)]. To demonstrate the efficiency of SOA algorithm, seven real-life constrained industrial optimization applications are also employed.

To validate the performance of the proposed algorithm, the nine well-known metaheuristics are chosen for comparison. These are Spotted Hyena Optimizer (SHO) [[7,37](#)], Grey Wolf Optimizer (GWO) [[51](#)], Particle Swarm Optimization (PSO) [[15](#)], Moth-Flame Optimization (MFO) [[68](#)], Multi-Verse Optimizer (MVO) [[69](#)], Sine Cosine Algorithm (SCA) [[70](#)], Gravitational Search Algorithm (GSA) [[22](#)], Genetic Algorithm (GA) [[71](#)], and Differential Evolution (DE) [[30](#)].

Table 2

Average running time of proposed and competitive approaches.

Algorithms	Average time (in seconds)
Seagull Optimization Algorithm (SOA)	1.2245
Spotted Hyena Optimizer (SHO)	1.3269
Grey Wolf Optimizer (GWO)	1.2536
Particle Swarm Optimization (PSO)	2.0241
Moth-Flame Optimization (MFO)	2.2362
Multi-Verse Optimizer (MVO)	1.5236
Sine Cosine Algorithm (SCA)	1.4452
Gravitational Search Algorithm (GSA)	1.2965
Genetic Algorithm (GA)	1.3668
Differential Evolution (DE)	1.6354



Fig. 6. Average running time of metaheuristics algorithms.

4.1. Experimental setup

The parameter settings of SOA and other competitor algorithms are given in Table 3. The experimentation and algorithms are implemented in MATLAB R2018b (version 9.5.0) software. The simulations are performed in the environment of Microsoft Windows 8.1 (64 bit) on Core i5 processor with 3.2 GHz and 8 GB main memory. The proposed algorithm utilizes 30 independent runs to generate the results.

4.2. Exploitation analysis

The unimodal test functions are suitable to assess and evaluate the exploitation capability of the algorithm. Table 4 shows the optimal values obtained by the proposed and above-mentioned algorithms for unimodal benchmark test functions. It can be seen that SOA and SHO algorithms provide better results on F_1 (Sphere) test function. GWO and GSA are the second and third best algorithms in terms of average and standard deviation. For F_2 (Schwefel's Problem 2.22) test function, SOA and SHO algorithms are significantly better than the other competitor algorithms. After these, GWO and GA are the second and third best algorithms for this benchmark test function, respectively. SHO algorithm obtains the best results on F_3 (Schwefel's Problem 1.2) test function whereas SOA and GWO algorithms become second and third best optimizer, respectively. For F_4 (Schwefel's Problem 2.21) test function, GWO obtains better results than the other algorithms. SHO is the second best and SOA is the third best optimizer on this benchmark test function. The results obtained by SOA algorithm are better than the other approaches on F_5 (Generalized Rosenbrock's) test function. For F_5 test function, SHO and GWO are the second and third best optimization algorithm. GSA algorithm obtains competitive results than the other metaheuristics on F_6 (Step) test function. On this benchmark test function, PSO and MFO algorithms are the second and third most best optimization algorithms. For F_7 (Quartic) test function, the results obtained by SOA algorithm are superior than others. Whereas, SHO and GA algorithms outperform over other

Table 3

Parameter setting values for algorithms.

Algorithms	Parameters	Values
# For all algorithms	Population	100
	Maximum iterations	1000
Seagull Optimization Algorithm (SOA)	Control Parameter (A) f_c	[2, 0] 2
Spotted Hyena Optimizer (SHO)	Control Parameter (\bar{h}) \bar{M} Constant	[5, 0] [0.5, 1]
Grey Wolf Optimizer (GWO)	Control Parameter (\bar{a})	[2, 0]
Particle Swarm Optimization (PSO)	Inertia Coefficient Cognitive and Social Coeff	0.75 1.8, 2
Moth-Flame Optimization (MFO)	Convergence Constant Logarithmic Spiral	[-1, -2] 0.75
Multi-Verse Optimizer (MVO)	Wormhole Existence Prob. Traveling Distance Rate	[0.2, 1] [0.6, 1]
Sine Cosine Algorithm (SCA)	Number of Elites	2
Gravitational Search Algorithm (GSA)	Gravitational Constant Alpha Coefficient	100 20
Genetic Algorithm (GA)	Crossover Mutation	0.9 0.05
Differential Evolution (DE)	Crossover Scale factor (F)	0.9 0.5

algorithms as a second and third best algorithm, respectively. Therefore, it has been concluded that the proposed SOA algorithm is able to find the best results on most of the test functions. In particular, SOA reveals the robustness for functions F_1 , F_2 , F_5 , and F_7 which show the capability for exploitation around the optimum point.

4.3. Exploration analysis

These functions have a capability to avoid local optima problem. Multimodal and fixed-dimension multimodal test functions are suitable for better exploration of a proposed algorithm. Tables 5 and 6 depict the results of different methods on multimodal and fixed-dimension multimodal benchmark test functions, respectively. For F_8 (Generalized Schwefel's Problem 2.26) function, SOA algorithm outperforms than the existing competitive approaches. MFO and MVO are the second and third best optimization algorithms, respectively. For F_9 (Generalized Rastrigin's Function) function, SHO becomes the best optimizer than others. GWO and GA are the second and third best optimization algorithms on F_9 test function. For F_{10} (Ackley's Function) function, the average value of SOA algorithm is best as compared to other approaches whereas the standard deviation of GWO algorithm is better than the other metaheuristics. For F_{11} (Generalized Griewank Function) function, the performance of SOA and SHO algorithms are same whereas the performance of GA and DE algorithms are the second and third best than competitive optimizers. The results obtained by PSO algorithm are superior than other metaheuristics on F_{12} (Generalized Penalized Function) function. For F_{13} (Generalized Penalized Function) function, GSA is the best optimization algorithm while PSO and GA obtain better results than the others.

For F_{14} (Shekel's Foxholes Function) function, MVO provides better results. SCA and MFO are second and third best optimization algorithms, respectively. For F_{15} (Kowalik's Function) and F_{16} (Six – Hump Camel – Back Function) functions, the results of SOA are superior than the other algorithms. DE and SHO algorithms are the second and third best optimizers, respectively. For F_{17} (Branin Function) and F_{18} (Goldstein – Price Function) functions, the results produced from SOA algorithm are better than others. For F_{19} (Hartman's) function, the average value obtained by PSO algorithm is better while the standard deviation value obtained by MFO algorithm is better than the other competitive approaches. For F_{20} (Hartman's)

Table 4

Results of SOA on unimodal benchmark test functions.

F	SOA		SHO		GWO		PSO		MFO		MVO		SCA		GSA		GA		DE	
	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std
F_1	0.00E+00	0.00E+00	0.00E+00	0.00E+00	4.69E−47	4.50E−48	4.98E−09	1.41E−10	3.15E−04	5.00E−05	2.81E−01	1.10E−02	3.55E−02	1.07E−02	1.16E−16	6.10E−17	1.95E−12	2.04E−13	3.10E−10	3.21E−11
F_2	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.20E−24	1.00E−24	7.29E−04	1.57E−05	3.71E+01	2.16E+01	3.96E−01	1.41E−01	3.23E−05	8.28E−06	1.70E−01	5.29E−02	6.53E−18	4.00E−19	4.99E−13	4.81E−14
F_3	4.62E−19	2.30E−27	0.00E+00	0.00E+00	1.00E−14	4.18E−15	1.40E+01	7.13E+00	4.42E+03	3.71E+03	4.31E+01	8.97E+00	4.91E+03	3.89E+03	4.16E+02	1.56E+02	7.70E−10	5.46E−12	5.58E−02	1.50E−03
F_4	7.35E−05	3.11E−06	7.78E−12	5.06E−12	2.02E−14	2.95E−15	6.00E−01	1.72E−01	6.70E+01	1.06E+01	8.80E−01	2.50E−01	1.87E+01	8.21E+00	1.12E+00	9.89E−01	9.17E+01	5.67E+01	5.21E+01	1.01E−01
F_5	7.00E+00	1.13E−01	8.59E+00	5.53E−01	2.79E+01	1.84E+00	4.93E+01	3.89E+01	3.50E+03	2.83E+03	1.18E+02	1.00E+02	7.37E+02	1.90E+02	3.85E+01	3.47E+01	5.57E+02	4.16E+01	2.10E+02	1.73E+02
F_6	3.47E−02	1.31E−04	2.46E−01	1.78E−01	6.58E−01	3.38E−01	9.23E−09	8.48E−10	1.66E−04	2.49E−05	3.15E−01	9.98E−02	4.88E+00	9.75E−01	1.08E−16	4.00E−17	3.15E−01	9.98E−02	9.77E−02	5.13E−02
F_7	3.35E−06	7.51E−06	3.29E−05	2.43E−05	7.80E−04	3.85E−04	6.92E−02	2.87E−02	3.22E−01	2.93E−01	2.02E−02	7.43E−03	3.88E−02	1.15E−02	7.68E−01	5.70E−01	6.79E−04	5.21E−04	4.00E−03	2.27E−03

Table 5

Results of SOA on multimodal benchmark test functions.

F	SOA		SHO		GWO		PSO		MFO		MVO		SCA		GSA		GA		DE	
	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std
F_8	−8.50E+03	4.57E+02	−1.16E+03	2.72E+02	−6.14E+03	9.32E+02	−6.01E+03	1.30E+03	−8.04E+03	8.80E+02	−6.92E+03	9.19E+02	−3.81E+03	2.83E+02	−2.75E+03	5.72E+02	−5.11E+03	4.37E+02	−3.94E+03	5.81E+02
F_9	3.12E+02	2.85E+01	0.00E+00	0.00E+00	4.34E−01	2.68E−01	4.72E+01	1.03E+01	1.63E+02	3.74E+01	1.01E+02	1.89E+01	2.23E+01	1.28E+01	3.35E+01	1.19E+01	1.23E+01	1.01E+01	8.50E+01	1.00E+01
F_{10}	4.22E−16	4.09E−13	2.48E+00	1.41E+00	1.63E−14	3.14E−15	3.86E−02	2.91E−04	1.60E+01	6.18E+00	1.15E+01	7.87E−01	1.55E+01	8.11E+00	8.25E−09	1.90E−09	5.31E−11	9.10E−12	7.40E−06	5.44E−07
F_{11}	0.00E+00	0.00E+00	0.00E+00	0.00E+00	2.29E−03	1.21E−03	5.50E−03	4.32E−04	5.03E−02	1.29E−02	5.74E−01	1.12E−01	3.01E−01	2.89E−01	8.19E+00	3.70E+00	3.31E−06	1.43E−06	7.09E−04	5.58E−04
F_{12}	5.80E−01	4.71E−02	3.68E−02	1.15E−02	3.93E−02	2.42E−02	1.05E−10	2.86E−11	1.26E+00	1.83E+00	1.27E+00	1.02E+00	5.21E+01	2.19E+01	2.65E−01	1.13E−01	9.16E−08	2.80E−08	1.06E−06	1.00E−06
F_{13}	8.48E−02	4.32E−04	9.29E−01	9.52E−02	4.75E−01	2.38E−01	4.03E−03	3.01E−03	7.24E−01	1.59E−01	6.60E−02	4.33E−02	2.81E+02	5.62E+01	5.73E−32	1.30E−32	6.39E−02	4.49E−02	9.78E−02	3.42E−02

Table 6

Results of SOA on fixed-dimension multimodal benchmark test functions.

F	SOA		SHO		GWO		PSO		MFO		MVO		SCA		GSA		GA		DE	
	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std
F ₁₄	3.35E+00	1.15E+00	9.68E+00	3.29E+00	3.71E+00	2.15E+00	2.77E+00	2.20E+00	2.21E+00	1.80E+00	9.98E-01	4.13E-02	1.26E+00	6.86E-01	3.61E+00	2.96E+00	4.39E+00	4.41E-02	3.97E+00	1.42E+00
F ₁₅	4.11E-04	4.26E-05	9.01E-04	1.06E-04	3.66E-03	3.48E-04	9.09E-04	2.38E-04	1.58E-03	2.48E-04	7.15E-03	1.40E-03	1.01E-03	3.75E-04	6.84E-03	2.77E-03	7.36E-03	2.39E-04	5.01E-04	1.00E-04
F ₁₆	-1.08E+01	6.48E-12	-1.06E+01	2.86E-11	-1.03E+00	7.02E-09	-1.03E+00	0.00E+00	-1.03E+00	0.00E+00	-1.03E+00	4.74E-08	-1.03E+00	3.23E-05	-1.03E+00	0.00E+00	-1.04E+00	4.19E-07	-1.03E+00	3.60E-04
F ₁₇	3.98E-01	1.36E-03	3.98E-01	2.46E-01	3.98E-01	2.42E-02	3.98E-01	4.11E-02	3.98E-01	1.13E-03	3.98E-01	2.15E-02	3.99E-01	7.61E-04	3.98E-01	1.74E-04	3.98E-01	1.00E-04	3.98E-01	8.40E-02
F ₁₈	3.00E+00	5.49E-05	3.00E+00	8.15E-05	3.00E+00	7.16E-06	3.00E+00	6.59E-05	3.00E+00	1.42E-07	5.70E+00	8.40E-04	3.00E+00	2.25E-05	3.01E+00	3.24E-02	3.01E+00	6.33E-07	3.00E+00	9.68E-04
F ₁₉	-3.88E+00	3.00E-10	-3.75E+00	4.39E-01	-3.86E+00	1.57E-03	3.90E+00	3.37E-15	-3.86E+00	3.16E-15	-3.86E+00	3.53E-07	-3.86E+00	2.55E-03	-3.22E+00	4.15E-01	-3.30E+00	4.37E-10	-3.40E+00	6.56E-06
F ₂₀	-3.32E+00	1.23E-02	-1.44E+00	5.47E-01	-3.27E+00	7.27E-02	-3.32E+00	2.66E-01	-3.23E+00	6.65E-02	-3.23E+00	5.37E-02	-2.84E+00	3.71E-01	-1.47E+00	5.32E-01	-2.39E+00	4.37E-01	-1.79E+00	7.07E-02
F ₂₁	-1.00E+01	3.47E+00	-1.00E+01	3.80E-01	-1.01E+01	1.54E+00	-1.00E+01	2.77E+00	-1.00E+01	3.52E+00	-1.00E+01	2.91E+00	-1.00E+01	1.80E+00	-1.00E+01	1.30E+00	-1.00E+01	2.34E+00	-1.00E+01	1.91E+00
F ₂₂	-1.04E+01	2.00E-04	-1.04E+01	2.04E-04	-1.03E+01	2.73E-04	-1.04E+01	3.08E+00	-1.04E+01	3.20E+00	-1.01E+01	3.02E+00	-1.04E+01	1.99E+00	-1.04E+01	2.64E+00	-1.04E+01	1.37E-02	-1.04E+01	5.60E-03
F ₂₃	-1.05E+01	1.32E-01	-1.05E+01	2.64E-01	-1.01E+01	8.17E+00	-1.05E+01	2.52E+00	-1.05E+01	3.68E+00	-1.03E+01	3.13E+00	-1.05E+01	1.96E+00	-1.05E+01	2.75E+00	-1.05E+01	2.37E+00	-1.05E+01	1.60E+00

Table 7

Results of SOA on CEC 2005 special session benchmark test functions.

F	SOA		SHO		GWO		PSO		MFO		MVO		SCA		GSA		GA		DE	
	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std	Ave	Std
CF1	2.52E+01	2.11E+00	2.30E+02	1.37E+02	8.39E+01	6.02E+01	6.00E+01	5.05E+01	1.18E+02	7.40E+01	1.40E+02	1.00E+02	1.20E+02	3.11E+01	1.81E+01	1.05E+01	5.97E+02	1.34E+02	4.41E+02	3.57E+02
CF2	6.21E+01	1.30E+00	4.08E+02	9.36E+01	1.48E+02	3.78E+01	2.44E+02	1.73E+02	9.20E+01	1.84E+01	2.50E+02	1.44E+02	1.14E+02	1.84E+00	2.03E+02	1.99E+01	4.09E+02	2.10E+01	6.01E+02	1.14E+02
CF3	3.01E+02	2.35E+01	3.39E+02	3.14E+01	3.53E+02	5.88E+01	3.39E+02	8.36E+01	4.19E+02	1.15E+02	4.05E+02	1.67E+02	3.89E+02	5.41E+01	3.67E+02	8.38E+01	9.30E+02	8.31E+01	3.70E+02	2.11E+02
CF4	3.35E+02	2.63E+01	7.26E+02	1.21E+02	4.23E+02	1.14E+02	4.49E+02	1.42E+02	3.31E+02	2.09E+01	3.77E+02	1.28E+02	4.31E+02	2.94E+01	5.32E+02	1.01E+02	4.97E+02	3.24E+01	5.00E+02	2.12E+02
CF5	5.61E+01	1.15E+01	1.06E+02	1.38E+01	1.36E+02	2.75E+01	2.40E+02	7.49E+01	1.13E+02	9.27E+01	2.45E+02	9.96E+01	1.56E+02	8.30E+01	1.44E+02	1.09E+02	1.90E+02	5.03E+01	4.06E+02	3.45E+01
CF6	4.55E+02	3.73E+00	5.97E+02	4.98E+00	8.26E+02	1.74E+02	8.22E+02	1.80E+02	8.92E+02	2.41E+01	8.33E+02	1.68E+02	6.06E+02	1.66E+02	8.13E+02	1.13E+02	6.65E+02	3.37E+02	9.55E+02	6.04E+02

function, SOA algorithm performs superior whereas PSO and GWO are the second and third best optimizers. The average value of GWO algorithm is best on F_{21} (Shekel's Foxholes Function) test function while the standard deviation value of SHO algorithm is better on this test instance. The results obtained by SOA algorithm are superior than the competitor approaches on F_{22} (Shekel's Foxholes Function) and F_{23} (Shekel's Foxholes Function) benchmark test functions. It can be seen that SOA algorithm has good exploration capability and competitive on seven test problems (i.e., F_{15} , F_{16} , F_{17} , F_{18} , F_{20} , F_{22} , and F_{23}) out of ten test functions.

4.4. Escape local minima with CEC 2005 test functions

Table 7 depicts the results obtained by all algorithms in terms of average and standard deviation. For CF_1 test function, GSA algorithm outperforms than the other competitor metaheuristics. For CF_2 test function, the results of SOA are superior than others whereas MFO and SCA algorithms are second and third best optimizers, respectively. For CF_3 test function, the performance of SOA algorithm is better than the above-mentioned algorithms. The performance of SHO and PSO are very much similar on this test function. For CF_4 test function, the results obtained by MFO algorithm are better than the existing metaheuristics. For CF_5 and CF_6 test functions, SOA algorithm outperforms the other optimization algorithms. SHO and MFO algorithms are the second and third most best optimizers on CF_5 and CF_6 test functions. It has been concluded that the proposed SOA algorithm provides prominent results for the majority of test functions (i.e., CF_2 , CF_3 , CF_5 , and CF_6).

4.5. Global minima finding with CEC 2015 test functions

For proper exploration and exploitation, the proposed algorithm is tested on fifteen CEC 2015 special session benchmark test functions. **Table 8** shows the best obtained optimal solutions by all algorithms in terms of average and standard deviation. For $CEC - 1$ test function, the average value of SOA algorithm is better than other approaches. The standard deviation value of PSO algorithm is superior on this test instance. For $CEC - 2$ test function, the performance of GSA algorithm is better as compared to other metaheuristics. The average value obtained by SOA algorithm on $CEC - 3$ test instance is better while the standard deviation value of GSA algorithm is best than other approaches. For $CEC - 4$, $CEC - 5$, and $CEC - 6$ test functions, PSO generates optimal solutions and very competitive than other optimizers. The optimal values obtained by proposed SOA algorithm in terms of average is superior than all of the other optimization algorithms on $CEC - 7$, $CEC - 8$, $CEC - 9$, $CEC - 10$, $CEC - 11$, $CEC - 12$, $CEC - 13$, $CEC - 14$, and $CEC - 15$ benchmark test instances. Despite, the standard deviation values of PSO algorithm on $CEC - 8$, $CEC - 9$, $CEC - 10$, and $CEC - 15$ test functions are better than others. The standard deviation obtained by GSA algorithm on $CEC - 14$ test instance is superior as compared to other metaheuristic techniques. **Fig. 11** shows the box plot for the proposed SOA and other competitor algorithms on CEC 2015 benchmark test functions. The results reveal that the SOA algorithm is the best optimizer for most of the test functions.

4.6. Analysis of SOA algorithm

The convergence analysis of metaheuristic algorithm is another feature for better understanding of explorative and exploitative mechanisms. Seagulls tend to explore the different promising regions of the search space. During the initial generation of optimization process, the search agents can change rapidly. **Fig. 8** shows the convergence curves of SOA and other competitor methods. While optimizing the test functions, SOA shows the three different

convergence behaviors. In the initial step of iterations, SOA converges more rapidly towards the promising regions because of its adaptive mechanism. This behavior is shown in F_1 , F_3 , F_7 , F_9 and F_{11} test functions. GSA encourages good convergence and achieves better performance on F_5 test function during the initial steps of iterations. Whereas, MFO converges towards the optimum for F_{21} and F_{23} test functions. In second step, SOA converges towards the optimum during the final iteration which is observed in F_{21} and F_{23} test functions. GA and MFO algorithms are also converge on F_1 , F_3 and F_{11} test functions, SCA and MVO on F_5 test function, and PSO algorithm on F_7 and F_9 test functions towards the optimum during final iterations. The last step is the explicit convergence. This behavior is shown for SOA algorithm on F_{21} and F_{23} test functions, for MFO, GA, and DE on F_9 test function.

In order to demonstrate the convergence analysis of SOA algorithm, three metrics are also employed in 2D environment which are shown in **Fig. 7**. The employed metrics are discussed as follows:

- **Search history** shows the location history of seagulls during optimization. It is observed from **Fig. 7** that SOA explores most promising area in the given search space for benchmark test functions. For unimodal test functions, the sample points are sparsely distributed in the non-promising area. Whereas, the most of sample points are distributed around the promising area for multimodal and fixed-dimension multimodal test functions. This is due to the difficulty level of these test functions. SOA does not stuck in local optima and explores the entire search space. The distribution of sample points is around the true optimal solution, which ensures its exploitation capability. Therefore, SOA has both exploration and exploitation capability.
- **Trajectory** of the first seagull shows the value of the first variable in each iteration. The trajectory curves show that the seagulls exhibit large and abrupt changes in the initial steps of optimization. According to Berg et al. [72], this behavior can guarantees that a Swarm-based method eventually converges to a point in search space.
- **Average fitness** indicates the average objective value of all seagulls in each iteration. The curves show descending behavior on all of the test functions. This proves that SOA algorithm improves the accuracy of the approximated optimum during simulation runs.

Therefore, the success rate of SOA algorithm is computationally high for solving optimization problems.

4.7. Scalability study

The proposed algorithm is performed on highly scalable environment to solve the large-scale optimization problems. The dimensionality of the various test functions is varied from 30 to 50, 50 to 80, and 80 to 100. In **Fig. 9**, the performance of SOA algorithm provides different behaviors which shows the robustness of proposed algorithm. It is also observed that the performance degradation is not too much that making its applicability on the highly scalable environment.

4.8. Statistical testing

The comparison of algorithms does not guarantee the efficacy and superiority of the proposed algorithm. The possibility of getting good results, by chance, cannot be ignored. For this, Wilcoxon statistical test [73] is performed at 5% level of significance and the p -values are tabulated in **Table 9**. During statistical testing, the best algorithm is chosen and compared with other competitor algorithms.

Table 8

Results of SOA on CEC 2015 benchmark test functions.

F	SOA	SHO	GWO	PSO	MFO	MVO	SCA	GSA	GA	DE
CEC-1	2.55E+05 (2.45E+05)	2.28E+06 (2.18E+06)	2.02E+06 (2.01E+06)	4.37E+05 1.81E+05 (1.00E+06)	1.47E+06 (5.02E+05)	6.06E+05 (3.07E+06)	7.65E+06 (2.98E+06)	3.20E+07 (6.95E+06)	8.89E+06 (5.11E+06)	6.09E+06
CEC-2	5.53E+06 (8.37E+04)	3.13E+05 (2.10E+05)	5.65E+06 (2.19E+06)	9.41E+03 (4.82E+03)	1.97E+04 (1.46E+04)	1.43E+04 (1.03E+04)	7.33E+08 (2.33E+08)	4.58E+03 1.09E+03 (1.09E+03)	2.97E+05 (2.85E+03)	4.40E+04 (2.75E+04)
CEC-3	3.20E+02 (3.71E−03)	3.20E+02 (3.76E−02)	3.20E+02 (7.08E−02)	3.20E+02 (8.61E−02)	3.20E+02 (9.14E−02)	3.20E+02 (3.19E−02)	3.20E+02 (7.53E−02)	3.20E+02 1.02E+03 (1.02E+03)	3.20E+02 (2.78E−02)	3.20E+02 (1.15E−03)
CEC-4	4.10E+02 (5.32E+01)	4.11E+02 (1.71E+01)	4.16E+02 (1.03E+01)	4.09E+02 3.96E+00 (3.96E+00)	4.26E+02 (1.17E+01)	4.18E+02 (1.03E+01)	4.42E+02 (7.72E+00)	4.39E+02 (7.25E+00)	6.99E+02 (6.43E+00)	4.91E+06 (6.03E+00)
CEC-5	9.54E+02 (2.12E+02)	9.13E+02 (1.85E+02)	9.20E+02 (1.78E+02)	8.65E+02 (2.16E+02)	1.33E+03 (3.45E+02)	1.09E+03 (2.81E+02)	1.76E+03 (2.30E+02)	1.75E+03 (2.79E+02)	1.26E+03 (1.86E+02)	3.34E+03 (3.01E+02)
CEC-6	2.47E+03 (1.40E+03)	1.29E+04 (1.15E+04)	2.26E+04 (2.07E+04)	1.86E+03 1.28E+03 (1.28E+03)	7.35E+03 (3.82E+03)	3.82E+03 (2.44E+03)	2.30E+04 (1.91E+04)	3.91E+06 (2.70E+06)	2.91E+05 (1.67E+05)	5.39E+04 (2.40E+04)
CEC-7	7.02E+02 (5.76E−01)	7.02E+02 (6.76E−01)	7.02E+02 (7.07E−01)	7.02E+02 (7.75E−01)	7.02E+02 (1.10E+00)	7.02E+02 (9.40E−01)	7.06E+02 (9.07E−01)	7.08E+02 (1.32E+00)	7.08E+02 (2.97E+00)	7.06E+02 (3.87E+00)
CEC-8	1.65E+03 (2.12E+03)	1.86E+03 (1.98E+03)	3.49E+03 (2.04E+03)	3.43E+03 (2.77E+03)	9.93E+03 (8.74E+03)	2.58E+03 (1.61E+03)	6.73E+03 (3.36E+03)	6.07E+05 (4.81E+05)	5.79E+04 (2.76E+04)	5.60E+03 (5.15E+04)
CEC-9	1.00E+03 (7.35E−01)	1.00E+03 (1.43E−01)	1.00E+03 (1.28E−01)	1.00E+03 (7.23E−02)	1.00E+03 (2.20E−01)	5.29E+02 (5.29E+02)	1.00E+03 (9.79E−01)	1.00E+03 (5.33E+00)	1.00E+03 (3.97E+00)	1.00E+03 (4.05E+00)
CEC-10	1.97E+03 (1.21E+03)	2.00E+03 (1.79E+03)	4.00E+03 (2.82E+03)	3.27E+03 (1.84E+03)	8.39E+03 (3.82E+03)	2.62E+03 (1.18E+03)	9.91E+03 (8.83E+03)	3.42E+05 (8.83E+03)	4.13E+04 (1.74E+05)	3.10E+04 (2.39E+04)
CEC-11	1.32E+03 (1.34E+01)	1.38E+03 (2.42E+01)	1.40E+03 (5.81E+01)	1.35E+03 (1.12E+02)	1.37E+03 (8.97E+01)	1.39E+03 (5.42E+01)	1.35E+03 (1.11E+02)	1.41E+03 (7.73E+01)	1.36E+03 (5.39E+01)	1.65E+03 (3.00E+01)
CEC-12	1.30E+03 (3.54E+00)	1.30E+03 (7.89E−01)	1.30E+03 (6.69E−01)	1.30E+03 (6.94E−01)	1.30E+03 (9.14E−01)	1.30E+03 (8.07E−01)	1.31E+03 (1.54E+00)	1.31E+03 (2.05E+00)	1.31E+03 (1.65E+00)	1.30E+03 (9.36E−01)
CEC-13	1.30E+03 (9.13E−07)	1.30E+03 (2.76E−04)	1.30E+03 (1.92E−04)	1.30E+03 (5.44E−03)	1.30E+03 (1.04E−03)	1.30E+03 (2.43E−04)	1.30E+03 (3.78E−03)	1.35E+03 (4.70E+01)	1.35E+03 (3.97E+01)	1.30E+03 (4.96E−02)
CEC-14	3.78E+03 (2.32E+03)	4.25E+03 (1.73E+03)	7.29E+03 (2.45E+03)	7.10E+03 (3.12E+03)	7.60E+03 (1.29E+03)	7.34E+03 (2.47E+03)	7.51E+03 (1.52E+03)	9.30E+03 (1.94E+03)	8.96E+03 (6.32E+03)	6.08E+03 (5.83E+03)
CEC-15	1.60E+03 (6.56E−02)	1.60E+03 (3.76E+00)	1.61E+03 (4.94E+00)	1.60E+03 (1.06E−02)	1.61E+03 (1.13E+01)	1.60E+03 (1.80E−02)	1.62E+03 (3.64E+00)	1.64E+03 (1.12E+01)	1.63E+03 (3.67E+01)	1.61E+03 (1.08E+00)

Table 9

p-values obtained from Wilcoxon ranksum test for CEC 2015 benchmark functions.

CEC	SHO	GWO	PSO	MFO	MVO	SCA	GSA	GA	DE
1	0.0045	0.0002	0.0004	0.0002	0.0017	0.0003	0.0001	0.0005	0.0060
2	0.0010	0.0001	0.0001	0.0060	0.0001	0.0075	0.0038	0.0021	0.0065
3	0.0001	0.0211	0.0104	0.0179	0.0001	0.0043	0.0001	0.0101	0.0001
4	0.0065	0.0280	0.0264	0.0051	0.0039	0.0045	0.0002	0.0097	0.0001
5	0.0006	0.0480	0.0001	0.0687	0.0001	0.2413	0.0001	0.0009	0.0498
6	0.0001	0.0004	0.0033	0.0050	0.8930	0.4726	0.0001	0.0046	0.0557
7	0.0092	0.0082	0.0001	0.0033	0.0037	0.0028	0.0001	0.0072	0.0013
8	0.0093	0.0052	0.0001	0.0859	0.0031	0.0001	0.0233	0.0064	0.0087
9	0.0008	0.0011	0.0001	0.0211	0.0001	0.0001	0.0096	0.0192	0.0001
10	0.0001	0.0003	0.0001	0.0807	0.0001	0.0097	0.0001	0.0550	0.0043
11	0.0027	0.0113	0.0002	0.0001	0.0008	0.0490	0.0041	0.0005	0.0110
12	0.0001	0.0093	0.0001	0.0001	0.0008	0.0001	0.0001	0.0010	0.0259
13	0.0001	0.0048	0.0001	0.0001	0.0393	0.0001	0.0030	0.0022	0.0847
14	0.0001	0.0009	0.0045	0.0001	0.0896	0.0003	0.0001	0.0068	0.0036
15	0.0024	0.0012	0.0025	0.0497	0.0055	0.0001	0.0001	0.0032	0.0092

Whereas, p-values are less than 0.05 to demonstrate the statistical superiority of proposed SOA. The test functions are taken from CEC 2015 special session which are most challenging test functions in the literature. Besides, the Mann–Whitney U rank sum test [74] has also been conducted on the average values of CEC 2015 special session test functions. Table 10 shows the results of the Mann–Whitney U rank sum test for statistical superiority of proposed SOA at 0.05 significance level. First, the significant difference between two data sets has been observed by Mann–Whitney U rank sum test. If there is no significant difference then sign '-' appears and when significant difference is observed then signs '+' or '-' appears for the case where SOA takes less or more function evaluations than the other competitor algorithms, respectively. In Table 10, '+' shows that SOA is significantly better and '-' shows that SOA is worse. As Table 10 includes 120 '+' signs out of 135 comparisons. Therefore, it can be concluded that the results of SOA is significantly effective than competitive approaches (i.e., SHO, GWO, PSO, MFO, MVO, SCA, GSA, GA, and DE) over CEC 2015 benchmark test suite. Overall, the results reveal that SOA outperforms other algorithms.

4.9. Investigating the influence of hyperparameters on SOA

The hyperparameter tuning of metaheuristics is one of the major challenge. Different values of hyperparameter might yield different results as reported from the exiting literature. SOA algorithm involves three hyperparameters namely Maximum number of iterations, number of search agents, and parameter f_c .

The sensitivity investigation of these hyperparameters has been discussed by varying their values.

1. Maximum number of iterations: SOA algorithm was run for different number of iterations. The values of $Max_{iteration}$ used in experimentation are 100, 500, 800, and 1000. Fig. 10(a) reveals that SOA converges towards the optimum when the number of iterations is increased. The detailed analysis related to iterations process is given in Table 11.
2. Number of search agents: To investigate the effect of number of search agents on all test functions, SOA algorithm was executed for 50, 80, 100, and 200. For brevity, the F11 test

Table 10

Mann–Whitney U rank sum test at 0.05 significance level (where '+' indicates SOA is significantly better, '-' indicates SOA is significantly worst and '=' indicates that there is no significant difference).

F	SHO	GWO	PSO	MFO	MVO	SCA	GSA	GA	DE
CEC-1	+	+	+	+	+	+	+	+	+
CEC-2	-	+	-	-	-	+	-	-	-
CEC-3	+	+	+	+	+	=	+	=	=
CEC-4	+	+	-	+	+	+	+	+	+
CEC-5	-	-	-	+	+	+	+	+	+
CEC-6	+	+	-	+	+	+	+	+	+
CEC-7	+	+	+	+	+	+	+	+	+
CEC-8	+	+	+	+	+	+	+	+	+
CEC-9	+	+	+	+	-	+	+	+	+
CEC-10	+	+	+	+	+	+	+	+	+
CEC-11	+	+	+	+	+	+	+	+	+
CEC-12	+	+	+	+	+	+	+	+	+
CEC-13	+	+	+	+	+	+	+	+	+
CEC-14	+	+	+	+	+	+	+	+	+
CEC-15	+	+	+	+	+	+	+	+	+

Table 11

The obtained optimal values on unimodal, multimodal, fixed-dimension multimodal, CEC 2005, and CEC 2015 benchmark test functions using different simulation runs. The best results are in bold.

Functions	Iterations	Optimal values
F_1	100	3.42E+00
	500	9.12E-17
	800	2.54E-30
	1000	0.00E+00
F_5	100	3.81E+12
	500	7.37E+10
	800	1.15E+08
	1000	5.18E+03
F_{11}	100	8.14E+00
	500	6.14E-04
	800	5.70E-04
	1000	0.00E+00
F_{17}	100	1.19E+05
	500	1.52E+02
	800	6.93E-02
	1000	1.14E-05
F_{23}	100	-2.01E+00
	500	-9.81E+00
	800	-1.02E+01
	1000	-1.10E+01
$CF1$	100	1.80E+08
	500	3.13E+05
	800	4.91E+03
	1000	7.15E+02
$CEC - 1$	100	7.30E+12
	500	1.51E+09
	800	9.03E+05
	1000	2.22E+05

function is chosen for analysis. Fig. 10(b) shows the effect of number of search agents. It was found that SOA provides best optimal solutions when the number of search agent is set to 100. The detailed results are given in Table 12.

- Variation in parameter f_c : SOA algorithm was run for different values of parameter f_c keeping other parameters fixed, i.e., maximum number of iterations and number of search agents. The values of f_c used in experimentation are 1, 2, 3, 4, and 5. Fig. 10(c) shows that the function $F1$ obtains best optimal solution when the value of f_c is set to 2. It is observed that $f_c = 2$ is a reasonable value for most of the test functions. The detailed sensitivity results related to f_c are given in Table 13.

Table 12

The obtained optimal values on unimodal, multimodal, fixed-dimension multimodal, CEC 2005, and CEC 2015 benchmark test functions where number of iterations is fixed as 1000. The number of search agents are varied from 50 to 200. The best results are in bold.

Functions	Search agents	Optimal values
F_1	50	0.00E+00
	80	0.00E+00
	100	0.00E+00
	200	0.00E+00
F_5	50	1.31E+01
	80	3.42E+02
	100	5.10E+00
	200	9.19E+00
F_{11}	50	0.00E+00
	80	0.00E+00
	100	0.00E+00
	200	0.00E+00
F_{17}	50	5.71E-03
	80	9.80E-03
	100	5.27E-04
	200	7.00E-02
F_{23}	50	-2.41E+00
	80	-7.90E+00
	100	-2.72E+01
	200	-4.11E+00
$CF1$	50	6.41E+01
	80	8.37E+01
	100	2.72E+01
	200	5.77E+01
$CEC - 1$	50	1.23E+06
	80	3.50E+06
	100	1.34E+05
	200	8.57E+05

5. Real industrial engineering applications

In this section, the efficiency of proposed SOA algorithm should be investigated in solving seven real-life constrained optimization problems and compared with other state-of-the-art algorithms. These problems have several equality and inequality constraints. SOA algorithm should be equipped with a constraint handling method to optimize these problems.

5.1. Constraint handling

Constraint handling is one of the biggest challenges in solving optimization problems using metaheuristic techniques. There are five constraint handling techniques [75]: penalty functions, hybrid methods, separation of objective functions and constraints, repair algorithms, and special operators. Among these techniques, the penalty functions are simple and easy to implement. There are numerous penalty functions such as static, annealing, adaptive, co-evolutionary, and death penalty. These approaches convert constraint problems into unconstraint problem by adding some penalty values. In this paper, a static penalty approach is employed to handle constraints in optimization problems.

$$\zeta(z) = f(z) \pm \left[\sum_{i=1}^m l_i \cdot \max(0, t_i(z))^\alpha + \sum_{j=1}^n o_j \cdot |U_j(z)|^\beta \right] \quad (15)$$

where $\zeta(z)$ is the modified objective function, l_i and o_j are positive penalty values, $t_i(z)$ and $U_j(z)$ are constraint functions, and l_i and o_j are positive constants. The values of α and β are 1 and 2, respectively. This approach assigns the penalty value for each infeasible solution. In death penalty approach, a large value is assigned to objective function of infeasible solution. Therefore, the static penalty function is employed which helps the search agents to move towards the feasible search space of the problem.

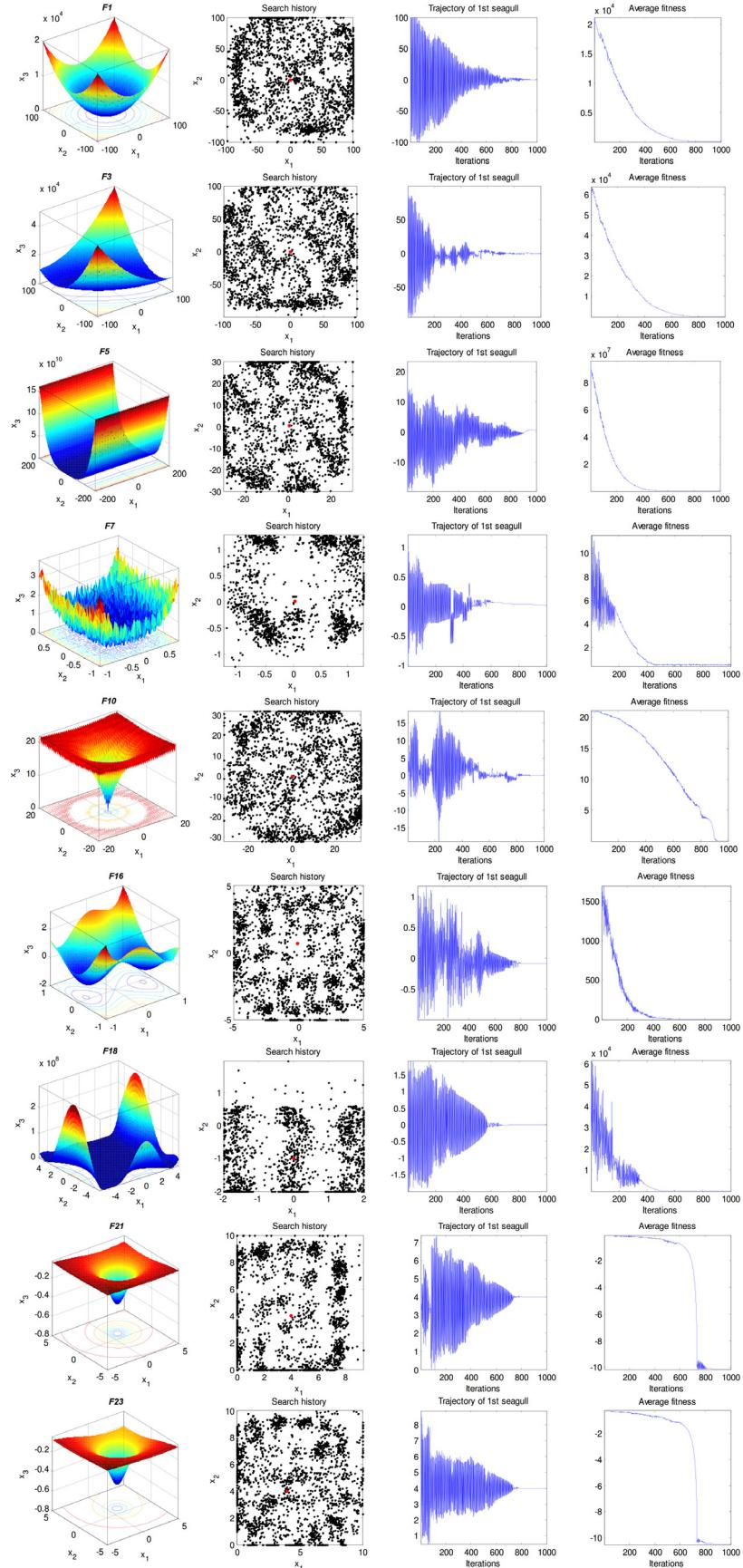


Fig. 7. Search history, trajectory, and average fitness of SOA algorithm on 2D benchmark test problems.

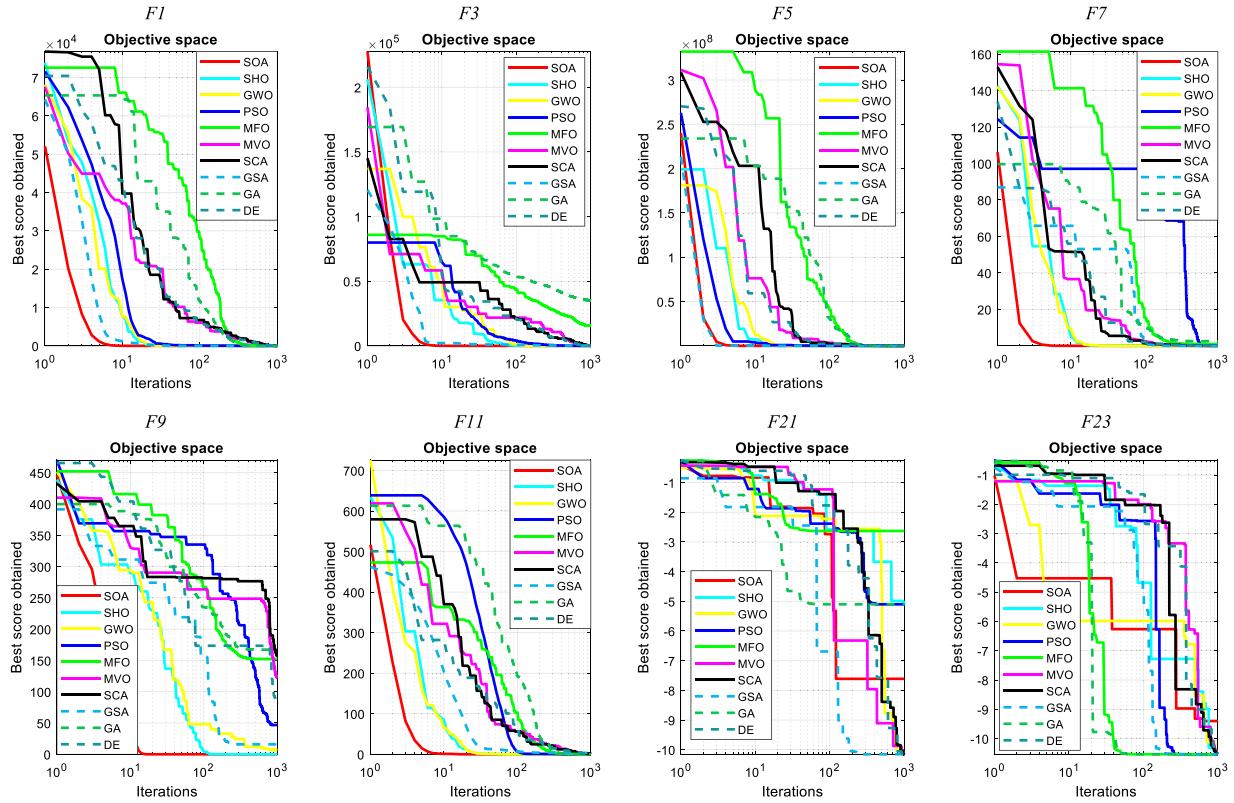


Fig. 8. Convergence analysis of proposed SOA and competitor algorithms on some of the benchmark test functions.

5.2. Optical buffer design problem

The optical buffer permits the optical CPUs to measure different optical packets during slow down the group velocity of light. This whole process is executed using most popular device known as Photonic Crystal Waveguide (PCW). Generally, PCWs have a lattice-shaped structure with a line defect and holes with different radii which yield the characteristics of slow light. In this subsection, the structure of PCW called a Bragg Slot Photonic Crystal Waveguide (BSPCW) is optimized to achieve these characteristics by SOA algorithm.

The performance of slow light devices is compared using Delay Bandwidth Product (DBP) and Normalized DBP (NDBP) metrics which are formulated as follows [76]:

$$DBP = \Delta d \cdot \Delta b \quad (16)$$

where Δd and Δb indicates the delay and bandwidth of slow light device, respectively.

$$NDBP = \bar{m}_g \cdot \Delta \omega / \omega_0 \quad (17)$$

where \bar{m}_g is the average of group index, $\Delta \omega$ is the bandwidth, and ω_0 is the central frequency of light wave. However, NDBP has a relation with group index (m_g) as:

$$m_g = \frac{V}{v_g} = C \frac{dv}{d\omega} \quad (18)$$

where ω is the dispersion, v defines the wave vector, C indicates the velocity of light, and m_g is responsible for changing in the bandwidth range. The average of m_g is calculated as follows:

$$\bar{m}_g = \int_{\omega_L}^{\omega_H} m_g(\omega) \frac{d\omega}{\Delta \omega} \quad (19)$$

Since, m_g has a constant value with maximum fluctuation of $\pm 10\%$ [77]. The detailed information about PCWs can be found

in [78]. The mathematical formulation of this problem is described as follows:

$$\vec{z} = [z_1 z_2 z_3 z_4 z_5 z_6 z_7 z_8] = \left[\frac{R_1}{a} \frac{R_2}{a} \frac{R_3}{a} \frac{R_4}{a} \frac{R_5}{a} \frac{l}{a} \frac{w_h}{a} \frac{w_l}{a} \right],$$

$$\text{Maximize: } f(\vec{z}) = NDBP,$$

Subject to:

$$\max(|\beta_2(\omega)|) < 10^6 a / 2\pi c^2,$$

$$\omega_H < \min(\omega_{upband}),$$

$$\omega_L > \max(\omega_{lowband}),$$

$$k_n > k_{nH} = \omega_{guidedmode} > \omega_H,$$

$$k_n < k_{nL} = \omega_{guidedmode} < \omega_L,$$

where,

$$\omega_H = \omega(k_{nH}) = \omega(1.1m_{g0}), v\omega_L = \omega(k_{nL}) = \omega(0.9m_{g0}),$$

$$vk_n = \frac{ka}{2\pi}, \Delta\omega = \omega_H - \omega_L, a = \omega_0 \times 1550 \text{ nm},$$

$$0 \leq z_{1-5} \leq 0.5, \quad 0 \leq z_6 \leq 1, \quad 0 \leq z_{7,8} \leq 1. \quad (20)$$

There are five constraints in this problem for SOA algorithm. The algorithm is tested and run 30 times on this problem and the results obtained are tabulated in Table 14. The results reveal that there is a substantial 99% and 10% improvements achieved in bandwidth through proposed approach as compared with Wu et al. [79] and GWO [51], respectively. The similar behavior has been observed in NDBP. The improvements achieved in NDBP are 90% and 14% as compared with Wu et al. [79] and GWO [51] approaches, respectively. The optimized super cell is shown in Fig. 12. It shows that the optimized structure has a very good bandwidth without band mixing. The results demonstrate that SOA algorithm proved its merit for solving optical buffer optimization problem.

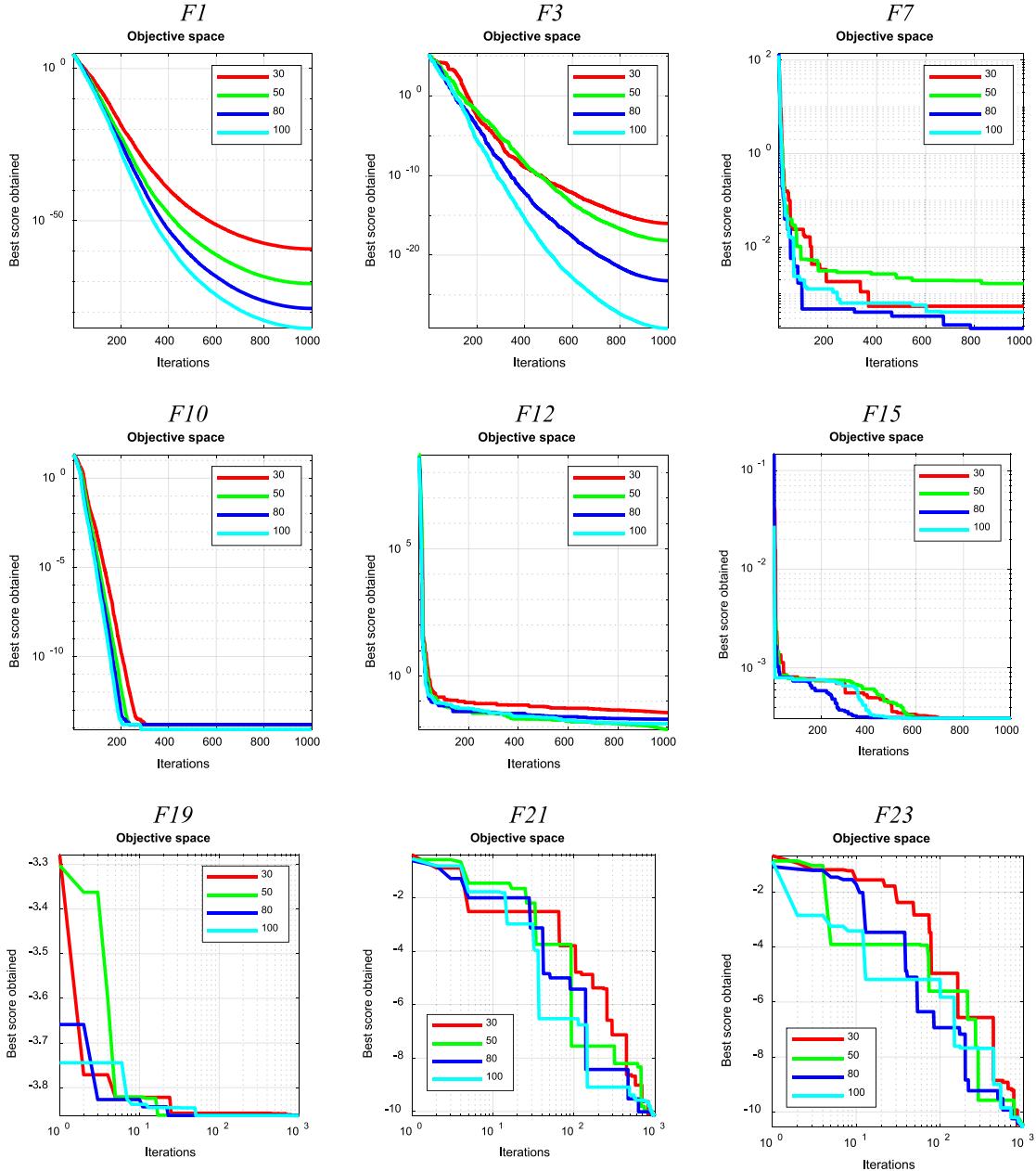


Fig. 9. Scalability analysis of proposed SOA algorithm on some of the benchmark test functions.

5.3. Pressure vessel design problem

This problem was first proposed by Kannan and Kramer [80] to minimize the total cost consisting of material, forming, and welding of a cylindrical vessel. Fig. 13 shows the schematic view of pressure vessel which are capped at both ends by hemispherical heads. There are four variables in this problem:

- T_s (z_1 , thickness of the shell).
- T_h (z_2 , thickness of the head).
- R (z_3 , inner radius).
- L (z_4 , length of the cylindrical section without considering the head).

Among these four design variables, R and L are continuous variables. T_s and T_h are integer values which are multiples of 0.0625 in.

The mathematical formulation of this problem is given below:

$$\text{Consider } \vec{z} = [z_1 \ z_2 \ z_3 \ z_4] = [T_s \ T_h \ R \ L],$$

$$\begin{aligned} \text{Minimize } f(\vec{z}) &= 0.6224z_1z_3z_4 + 1.7781z_2z_3^2 + 3.1661z_1^2z_4 \\ &+ 19.84z_1^2z_3, \end{aligned}$$

Subject to:

$$g_1(\vec{z}) = -z_1 + 0.0193z_3 \leq 0,$$

$$g_2(\vec{z}) = -z_3 + 0.00954z_3 \leq 0,$$

$$g_3(\vec{z}) = -\pi z_3^2 z_4 - \frac{4}{3}\pi z_3^3 + 1296,000 \leq 0,$$

$$g_4(\vec{z}) = z_4 - 240 \leq 0,$$

where,

$$1 \times 0.0625 \leq z_1, z_2 \leq 99 \times 0.0625, 10.0 \leq z_3, z_4 \leq 200.0. \quad (21)$$

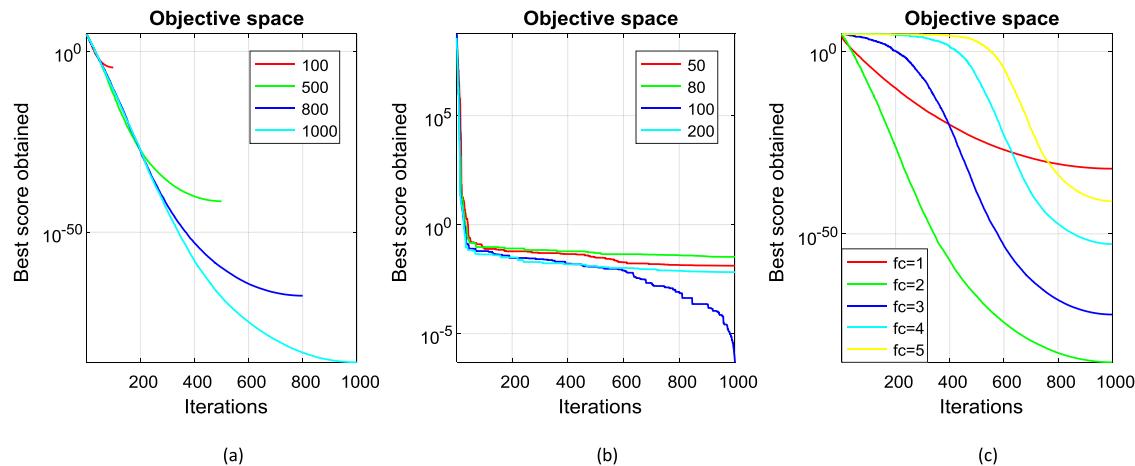


Fig. 10. Hyperparameters analysis of proposed SOA algorithm, (a) Effect of iterations on F_1 function; (b) Effect of search agents on F_{11} function; (c) Effect of parameter f_c on F_1 function.

Table 13

The obtained optimal values on unimodal, multimodal, fixed-dimension multimodal, CEC 2005, and CEC 2015 benchmark test functions where number of iterations and search agents are fixed as 1000 and 100, respectively. The parameter f_c is varied from 1 to 5. The best results are in bold.

Functions	f_c	Optimal values
F_1	1	$2.45E-10$
	2	$0.00E+00$
	3	$7.74E-11$
	4	$4.30E-24$
	5	$4.00E-18$
F_5	1	$4.40E+04$
	2	$8.00E+00$
	3	$2.01E+02$
	4	$3.98E+02$
	5	$3.00E+04$
F_{11}	1	$4.00E-12$
	2	$0.00E+00$
	3	$1.73E-20$
	4	$4.38E-23$
	5	$3.60E-14$
F_{17}	1	$1.21E+04$
	2	$8.90E-02$
	3	$4.11E+02$
	4	$9.78E+04$
	5	$2.09E+01$
F_{23}	1	$-2.41E+00$
	2	$-2.20E+02$
	3	$-1.12E+01$
	4	$-8.41E+00$
	5	$-4.80E+01$
$CF1$	1	$1.11E+03$
	2	$1.27E+01$
	3	$7.23E+02$
	4	$2.12E+03$
	5	$7.40E+03$
$CEC - 1$	1	$1.00E+07$
	2	$3.57E+03$
	3	$3.00E+07$
	4	$2.68E+10$
	5	$4.71E+08$

The comparison of obtained optimal solution from proposed SOA and other algorithms, i.e., SHO, GWO, PSO, MVO, SCA, GSA, GA, and DE is depicted in Table 15. The proposed SOA provides optimal solution at $z_{1-4} = (0.778080, 0.383247, 40.315120, 200.000000)$ with corresponding fitness value equal to $f(z_{1-4}) = 5879.5241$. It

Table 14

Comparison results for optical buffer design problem.

Parameters	SOA	GWO [51]	Wu et al. [79]
R_1	0.31348a	0.33235a	–
R_2	0.22374a	0.24952a	–
R_3	0.23400a	0.26837a	–
R_4	0.27680a	0.29498a	–
R_5	0.30217a	0.34992a	–
l	0.7263a	0.7437a	–
w_h	0.2052a	0.2014a	–
w_l	0.60026a	0.60073a	–
$a(nm)$	327	343	430
\bar{m}_g	17.3	19.6	23
Bandwidth	37.1	33.9	17.6
$\beta_2(a/2\pi c^2)$	10^3	10^3	10^3
NDBP	0.49	0.43	0.26

can be concluded that SOA is able to find best optimal design with minimum cost.

The statistical results of pressure vessel design problem are provided in Table 16. The results show that SOA performs better than the other competitor algorithms in terms of best, mean, and median. Fig. 14 shows the convergence behavior of optimal solution obtained from proposed SOA.

5.4. Speed reducer design problem

The speed reducer design problem is a challenging benchmark due to its seven design variables [81] as shown in Fig. 15. The main objective of this problem is to minimize the weight of speed reducer with subject to constraints [82]:

- Bending stress of the gear teeth.
- Surface stress.
- Transverse deflections of the shafts.
- Stresses in the shafts.

There are seven design variables ($z_1 - z_7$) which can represent as the face width (b), module of teeth (m), number of teeth in the pinion (p), length of the first shaft between bearings (l_1), length of the second shaft between bearings (l_2), the diameter of first (d_1) shafts, and the diameter of second shafts (d_2). The third variable i.e., number of teeth in the pinion (p) is of integer values.

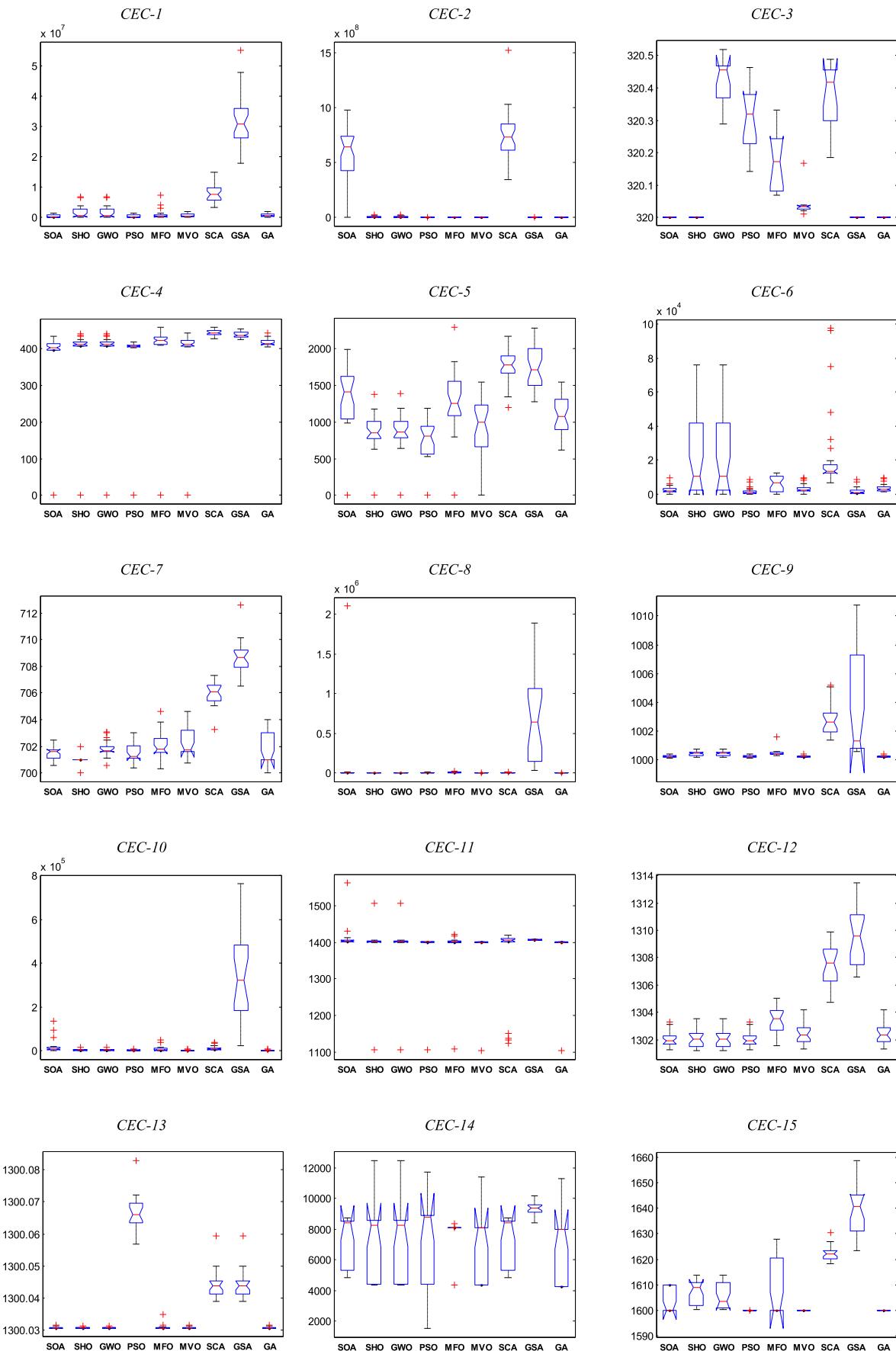


Fig. 11. Box plot obtained from proposed SOA and other competitor algorithms on CEC 2015 benchmark test functions.

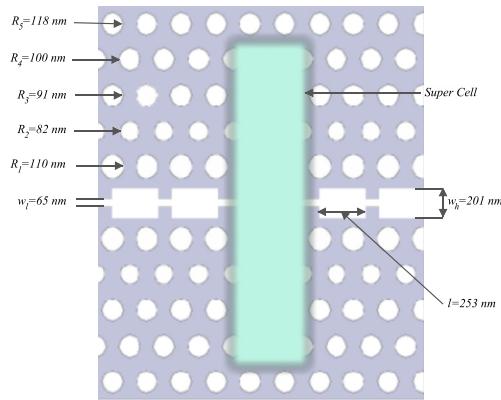


Fig. 12. Optimized super cell using proposed SOA algorithm.

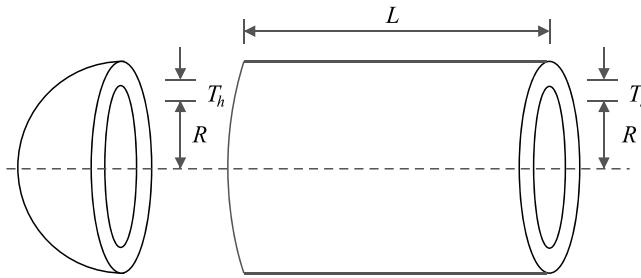


Fig. 13. Schematic view of pressure vessel problem.

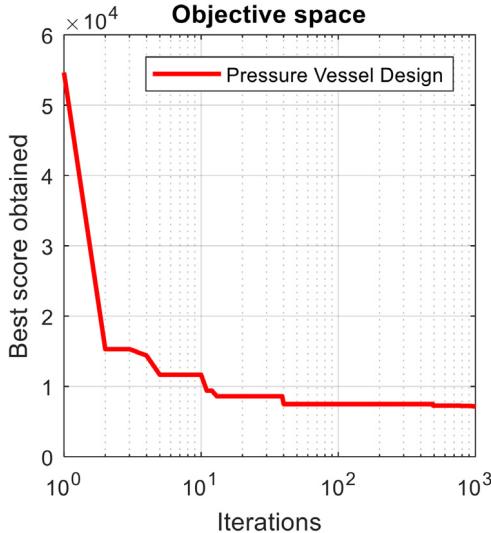


Fig. 14. Convergence analysis of SOA for pressure vessel design problem.

Table 15

Comparison results for pressure vessel design problem.

Algorithms	Optimum variables				Optimum cost
	T_s	T_h	R	L	
SOA	0.778080	0.383247	40.315120	200.00000	5879.5241
SHO	0.778210	0.384889	40.315040	200.00000	5885.5773
GWO	0.779035	0.384660	40.327793	199.65029	5889.3689
PSO	0.778961	0.384683	40.320913	200.00000	5891.3879
MVO	0.845719	0.418564	43.816270	156.38164	6011.5148
SCA	0.817577	0.417932	41.74939	183.57270	6137.3724
GSA	1.085800	0.949614	49.345231	169.48741	11550.2976
GA	0.752362	0.399540	40.452514	198.00268	5890.3279
DE	1.099523	0.906579	44.456397	179.65887	6550.0230

Table 16

Statistical results obtained from different algorithms for pressure vessel design problem.

Algorithms	Best	Mean	Worst	Std. Dev.	Median
SOA	5879.5241	5883.0052	5893.4521	256.415	5881.4486
SHO	5885.5773	5887.4441	5892.3207	002.893	5886.2282
GWO	5889.3689	5891.5247	5894.6238	013.910	5890.6497
PSO	5891.3879	6531.5032	7394.5879	534.119	6416.1138
MVO	6011.5148	6477.3050	7250.9170	327.007	6397.4805
SCA	6137.3724	6326.7606	6512.3541	126.609	6318.3179
GSA	11550.2976	23342.2909	33226.2526	5790.625	24010.0415
GA	5890.3279	6264.0053	7005.7500	496.128	6112.6899
DE	6550.0230	6643.9870	8005.4397	657.523	7586.0085

The mathematical formulation of this problem is formulated as follows:

$$\text{Consider } \vec{z} = [z_1 \ z_2 \ z_3 \ z_4 \ z_5 \ z_6 \ z_7] = [b \ m \ p \ l_1 \ l_2 \ d_1 \ d_2], \\ \text{Minimize } f(\vec{z}) = 0.7854z_1z_2^2(3.3333z_3^2 + 14.9334z_3 - 43.0934) \\ - 1.508z_1(z_6^2 + z_7^2) + 7.4777(z_6^3 + z_7^3) + 0.7854(z_4z_6^2 + z_5z_7^2), \quad (22)$$

Subject to:

$$g_1(\vec{z}) = \frac{27}{z_1z_2^2z_3} - 1 \leq 0, \\ g_2(\vec{z}) = \frac{397.5}{z_1z_2^2z_3^2} - 1 \leq 0, \\ g_3(\vec{z}) = \frac{1.93z_4^3}{z_2z_6^4z_3} - 1 \leq 0, \\ g_4(\vec{z}) = \frac{1.93z_5^3}{z_2z_7^4z_3} - 1 \leq 0, \\ g_5(\vec{z}) = \frac{[(745(z_4/z_2z_3))^2 + 16.9 \times 10^6]^{1/2}}{110z_6^3} - 1 \leq 0, \\ g_6(\vec{z}) = \frac{[(745(z_5/z_2z_3))^2 + 157.5 \times 10^6]^{1/2}}{85z_7^3} - 1 \leq 0, \\ g_7(\vec{z}) = \frac{z_2z_3}{40} - 1 \leq 0, \\ g_8(\vec{z}) = \frac{5z_2}{z_1} - 1 \leq 0, \\ g_9(\vec{z}) = \frac{z_1}{12z_2} - 1 \leq 0, \\ g_{10}(\vec{z}) = \frac{1.5z_6 + 1.9}{z_4} - 1 \leq 0, \\ g_{11}(\vec{z}) = \frac{1.1z_7 + 1.9}{z_5} - 1 \leq 0,$$

where,

$$2.6 \leq z_1 \leq 3.6, \quad 0.7 \leq z_2 \leq 0.8, \quad 17 \leq z_3 \leq 28, \quad 7.3 \leq z_4 \leq 8.3, \\ 7.3 \leq z_5 \leq 8.3, \quad 2.9 \leq z_6 \leq 3.9, \quad 5.0 \leq z_7 \leq 5.5.$$

The comparison of the obtained optimal solution with various competitor optimization algorithms is tabulated in Table 17. SOA provides optimal solution at $z_{1-7} = (3.50128, 0.7, 17, 7.3, 7.8, 3.33416, 5.24160)$ with corresponding fitness value equal to $f(z_{1-7}) = 2992.9985$. However, the statistical results of proposed and competitive optimization algorithms including SHO, GWO, PSO, MVO, SCA, GSA, GA, and DE are given in Table 18.

The results indicate that SOA outperforms than other metaheuristics. Fig. 16 reveals that SOA algorithm converges towards the best optimal solution for speed reducer design problem.

Table 17

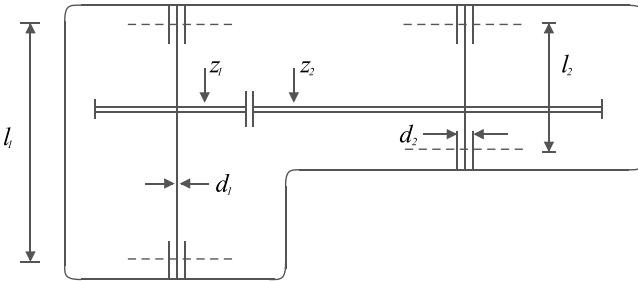
Comparison results for speed reducer design problem.

Algorithms	Optimum variables						Optimum cost	
	b	m	p	l_1	l_2	d_1	d_2	
SOA	3.50128	0.7	17	7.3	7.8	3.33416	5.24160	2992.9985
SHO	3.50159	0.7	17	7.3	7.8	3.35127	5.28874	2998.5507
GWO	3.506690	0.7	17	7.380933	7.815726	3.357847	5.286768	3001.288
PSO	3.500019	0.7	17	8.3	7.8	3.352412	5.286715	3005.763
MVO	3.508502	0.7	17	7.392843	7.816034	3.358073	5.286777	3002.928
SCA	3.508755	0.7	17	7.3	7.8	3.461020	5.289213	3030.563
GSA	3.600000	0.7	17	8.3	7.8	3.369658	5.289224	3051.120
GA	3.510253	0.7	17	8.35	7.8	3.362201	5.287723	3067.561
DE	3.520124	0.7	17	8.37	7.8	3.366970	5.288719	3029.002

Table 18

Statistical results obtained from different algorithms for speed reducer design problem.

Algorithms	Best	Mean	Worst	Std. Dev.	Median
SOA	2992.9985	2996.756	2997.795	1.78075	2991.997
SHO	2998.5507	2999.640	3003.889	1.93193	2999.187
GWO	3001.288	3005.845	3008.752	5.83794	3004.519
PSO	3005.763	3105.252	3211.174	79.6381	3105.252
MVO	3002.928	3028.841	3060.958	13.0186	3027.031
SCA	3030.563	3065.917	3104.779	18.0742	3065.609
GSA	3051.120	3170.334	3363.873	92.5726	3156.752
GA	3067.561	3186.523	3313.199	17.1186	3198.187
DE	3029.002	3295.329	3619.465	57.0235	3288.657

**Fig. 15.** Schematic view of speed reducer problem.

5.5. Welded beam design problem

The main objective of this design problem is to minimize the fabrication cost of welded beam (see Fig. 17). The optimization constraints of welded beam are shear stress (τ) and bending stress (θ) in the beam, buckling load (P_c) on the bar, end deflection (δ) of the beam. There are four design variables of this problem which are described as follows:

- h (z_1 , thickness of weld)
- l (z_2 , length of the clamped bar)
- t (z_3 , height of the bar)
- b (z_4 , thickness of the bar)

The mathematical formulation is described as follows:

Consider $\vec{z} = [z_1 \ z_2 \ z_3 \ z_4] = [h \ l \ t \ b]$,

$$\text{Minimize } f(\vec{z}) = 1.10471z_1^2z_2 + 0.04811z_3z_4(14.0 + z_2),$$

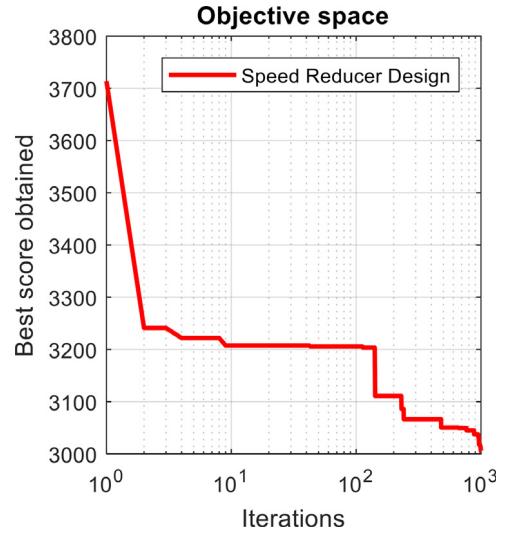
Subject to:

$$g_1(\vec{z}) = \tau(\vec{z}) - 13,600 \leq 0, \quad (23)$$

$$g_2(\vec{z}) = \sigma(\vec{z}) - 30,000 \leq 0,$$

$$g_3(\vec{z}) = \delta(\vec{z}) - 0.25 \leq 0,$$

$$g_4(\vec{z}) = z_1 - z_4 \leq 0,$$

**Fig. 16.** Convergence analysis of SOA for speed reducer design problem.

$$g_5(\vec{z}) = 6000 - P_c(\vec{z}) \leq 0,$$

$$g_6(\vec{z}) = 0.125 - z_1 \leq 0,$$

$$g_7(\vec{z}) = 1.10471z_1^2 + 0.04811z_3z_4(14.0 + z_2) - 5.0 \leq 0,$$

where,

$$0.1 \leq z_1, 0.1 \leq z_2, z_3 \leq 10.0, z_4 \leq 2.0,$$

$$\tau(\vec{z}) = \sqrt{(\tau')^2 + (\tau'')^2 + (l\tau'\tau'')/\sqrt{0.25(l^2 + (h+t)^2)}},$$

$$\tau' = \frac{6000}{\sqrt{2hl}}, \quad \sigma(\vec{z}) = \frac{504,000}{t^2 b}, \quad \delta(\vec{z}) = \frac{65,856,000}{(30 \times 10^6)bt^3},$$

$$\tau'' = \frac{6000(14 + 0.5l)\sqrt{0.25(l^2 + (h+t)^2)}}{2[0.707hl(l^2/12 + 0.25(h+t)^2)]},$$

$$P_c(\vec{z}) = 64,746.022(1 - 0.0282346t)tb^3.$$

The comparison for best solution obtained from proposed SOA and other algorithms is depicted in Table 19. SOA provides optimal solution at $z_{1-4} = (0.205408, 3.472316, 9.035208, 0.201141)$ with corresponding fitness value equal to $f(z_{1-4}) = 1.723485$. The results indicate that SOA converges towards the best design and provides better solutions. The statistical comparison of the proposed SOA with other competitor algorithms is depicted in Table 20. It can be seen that SOA outperforms than other approaches in terms of best, mean, and median. Fig. 18 reveals the convergence analysis of best optimal solution obtained from proposed SOA algorithm.

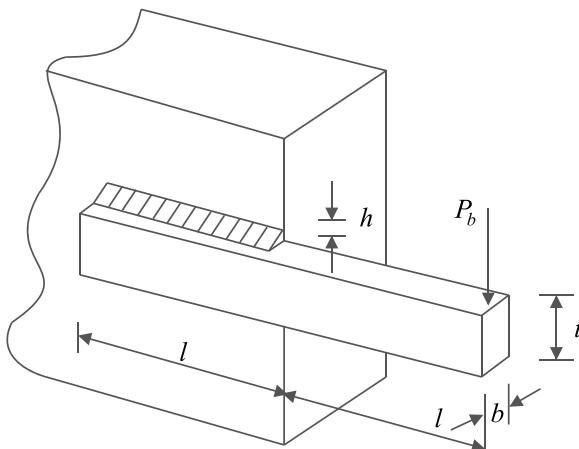


Fig. 17. Schematic view of welded beam problem.

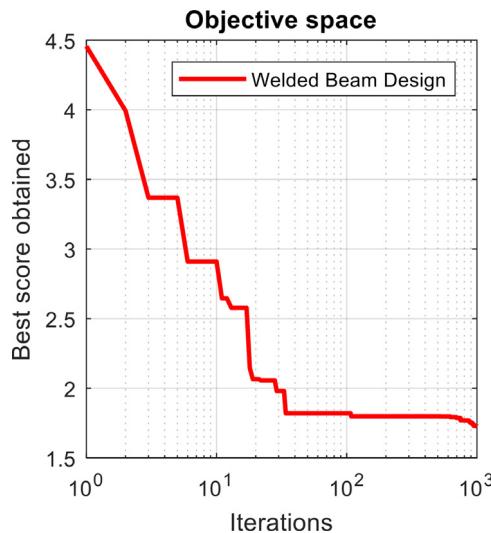


Fig. 18. Convergence analysis of SOA for welded beam design problem.

5.6. Tension/compression spring design problem

The objective of this problem is to minimize the tension/compression spring weight as shown in Fig. 19. The optimization constraints of this problem are described as follows:

- Shear stress.
- Surge frequency.
- Minimum deflection.

There are three design variables such as wire diameter (d), mean coil diameter (D), and the number of active coils (P).

The mathematical representation of this problem is described as follows:

Consider $\vec{z} = [z_1 z_2 z_3] = [d D P]$,

Minimize $f(\vec{z}) = (z_3 + 2)z_2z_1^2$,

Subject to:

$$g_1(\vec{z}) = 1 - \frac{z_2^3 z_3}{71785 z_1^4} \leq 0, \quad (24)$$

$$g_2(\vec{z}) = \frac{4z_2^2 - z_1 z_2}{12566(z_2 z_1^3 - z_1^4)} + \frac{1}{5108 z_1^2} \leq 0,$$

Table 19
Comparison results for welded beam design problem.

Algorithms	Optimum variables			Optimum cost
	h	l	t	
SOA	0.205408	3.472316	9.035208	0.201141
SHO	0.205563	3.474846	9.035799	0.205811
GWO	0.205678	3.475403	9.036964	0.206229
PSO	0.197411	3.315061	10.00000	0.201395
MVO	0.205611	3.472103	9.040931	0.205709
SCA	0.204695	3.536291	9.004290	0.210025
GSA	0.147098	5.490744	10.00000	0.217725
GA	0.164171	4.032541	10.00000	0.223647
DE	0.206487	3.635872	10.00000	0.203249
				1.836250

Table 20
Statistical results obtained from different algorithms for welded beam design problem.

Algorithms	Best	Mean	Worst	Std. Dev.	Median
SOA	1.723485	1.724251	1.727102	0.005967	1.724007
SHO	1.725661	1.725828	1.726064	0.000287	1.725787
GWO	1.726995	1.727128	1.727564	0.001157	1.727087
PSO	1.820395	2.230310	3.048231	0.324525	2.244663
MVO	1.725472	1.729680	1.741651	0.004866	1.727420
SCA	1.759173	1.817657	1.873408	0.027543	1.820128
GSA	2.172858	2.544239	3.003657	0.255859	2.495114
GA	1.873971	2.119240	2.320125	0.034820	2.097048
DE	1.836250	1.363527	2.035247	0.139485	1.9357485

Table 21
Comparison results for tension/compression spring design problem.

Algorithms	Optimum variables			Optimum cost
	d	D	P	
SOA	0.051065	0.342897	12.0885	0.012645217
SHO	0.051144	0.343751	12.0955	0.012674000
GWO	0.050178	0.341541	12.07349	0.012678321
PSO	0.05000	0.310414	15.0000	0.013192580
MVO	0.05000	0.315956	14.22623	0.012816930
SCA	0.050780	0.334779	12.72269	0.012709667
GSA	0.05000	0.317312	14.22867	0.012873881
GA	0.05010	0.310111	14.0000	0.013036251
DE	0.05025	0.316351	15.23960	0.012776352

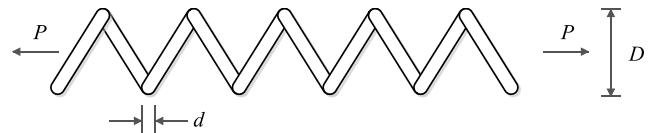


Fig. 19. Schematic view of tension/compression spring problem.

$$g_3(\vec{z}) = 1 - \frac{140.45z_1}{z_2^2 z_3} \leq 0,$$

$$g_4(\vec{z}) = \frac{z_1 + z_2}{1.5} - 1 \leq 0,$$

where,

$$0.05 \leq z_1 \leq 2.0, 0.25 \leq z_2 \leq 1.3, 2.0 \leq z_3 \leq 15.0.$$

The comparison between proposed SOA and other competitor algorithms is given in Table 21. SOA obtains best solution at design variables $z_{1-3} = (0.051065, 0.342897, 12.0885)$ with an objective function value of $f(z_{1-3}) = 0.012645217$. The results show that the proposed SOA again performs better than the other metaheuristic algorithms. The statistical results of tension/compression spring design are compared and tabulated in Table 22. It can be seen that SOA provides better statistical results than the other metaheuristics in terms of best, mean, and median.

The convergence analysis of best optimal solution obtained from SOA is shown in Fig. 20.

Table 22

Statistical results obtained from different algorithms for tension/compression spring design problem.

Algorithms	Best	Mean	Worst	Std. Dev.	Median
SOA	0.012645217	0.012665871	0.012665417	0.001108	0.012655241
SHO	0.012674000	0.012684106	0.012715185	0.000027	0.012687293
GWO	0.012678321	0.012697116	0.012720757	0.000041	0.012699686
PSO	0.013192580	0.014817181	0.017862507	0.002272	0.013192580
MVO	0.012816930	0.014464372	0.017839737	0.001622	0.014021237
SCA	0.012709667	0.012839637	0.012998448	0.000078	0.012844664
GSA	0.012873881	0.013438871	0.014211731	0.000287	0.013367888
GA	0.013036251	0.014036254	0.016251423	0.002073	0.013002365
DE	0.012776352	0.013069872	0.015214230	0.000375	0.012952142

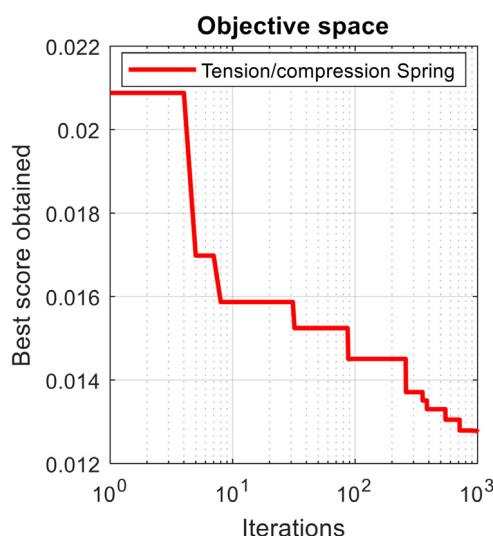


Fig. 20. Convergence analysis of SOA for tension/compression spring design problem.

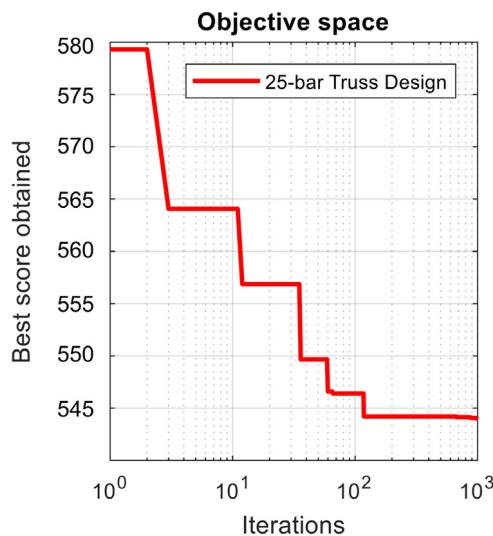


Fig. 21. Convergence analysis of SOA for 25-bar truss design problem.

Table 24

Two loading conditions for the 25-bar truss design problem.

Node	Case 1			Case 2		
	P_x Kips(kN)	P_y Kips(kN)	P_z Kips(kN)	P_x Kips(kN)	P_y Kips(kN)	P_z Kips(kN)
1	0.0	20.0 (89)	-5.0 (22.25)	1.0 (4.45)	10.0 (44.5)	-5.0 (22.25)
2	0.0	-20.0 (89)	-5.0 (22.25)	0.0	10.0 (44.5)	-5.0 (22.25)
3	0.0	0.0	0.0	0.5 (2.22)	0.0	0.0
6	0.0	0.0	0.0	0.5 (2.22)	0.0	0.0

Table 23

Member stress limitations for 25-bar truss design problem.

Element group	Compressive stress limitations Ksi (MPa)	Tensile stress limitations Ksi (MPa)
Group 1	35.092 (241.96)	40.0 (275.80)
Group 2	11.590 (79.913)	40.0 (275.80)
Group 3	17.305 (119.31)	40.0 (275.80)
Group 4	35.092 (241.96)	40.0 (275.80)
Group 5	35.092 (241.96)	40.0 (275.80)
Group 6	6.759 (46.603)	40.0 (275.80)
Group 7	6.959 (47.982)	40.0 (275.80)
Group 8	11.082 (76.410)	40.0 (275.80)

5.7. 25-bar truss design problem

The truss design problem is a popular optimization problem as shown in Fig. 22. There are 10 nodes which are fixed and 25 bars cross-sectional members which are grouped into eight categories.

- Group 1: A_1
- Group 2: A_2, A_3, A_4, A_5
- Group 3: A_6, A_7, A_8, A_9
- Group 4: A_{10}, A_{11}
- Group 5: A_{12}, A_{13}
- Group 6: A_{14}, A_{15}, A_{17}
- Group 7: $A_{18}, A_{19}, A_{20}, A_{21}$
- Group 8: $A_{22}, A_{23}, A_{24}, A_{25}$

The other variables which affects on this problem are as follows:

- $p = 0.0272 \text{ N/cm}^3 (0.1 \text{ lb/in.}^3)$
- $E = 68947 \text{ MPa (10000 Ksi)}$
- Displacement limitation = 0.35 in.
- Maximum displacement = 0.3504 in.
- Design variable set = $\{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1, 1.2, 1.3, 1.4, 1.5, 1.6, 1.7, 1.8, 1.9, 2.0, 2.1, 2.2, 2.3, 2.4, 2.6, 2.8, 3.0, 3.2, 3.4\}$

Table 23 shows the member stress limitations for this truss problem.

The loading conditions for 25-bar truss is presented in Table 24. The comparison of best solutions between several optimization algorithms is tabulated in Table 25. The proposed SOA is better than other competitor optimization algorithms in terms of best, average, and standard deviation. SOA converges towards the best optimal design using low computational efforts (see Fig. 21).

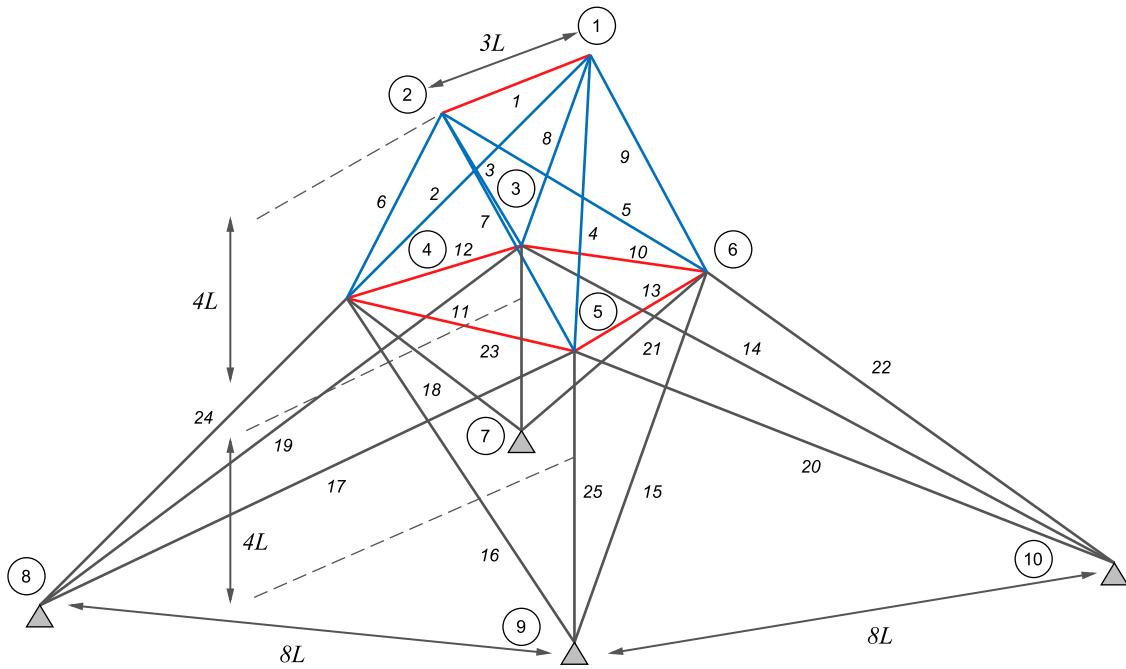


Fig. 22. Schematic view of 25-bar truss problem.

5.8. Rolling element bearing design problem

The objective of this problem is to maximize the dynamic load carrying capacity of a rolling element bearing as demonstrated in Fig. 23. There are 10 decision variables such as pitch diameter (D_m), ball diameter (D_b), number of balls (Z), inner (f_i) and outer (f_o) raceway curvature coefficients, K_{Dmin} , K_{Dmax} , ε , e , and ζ . The mathematical representation of this problem is given below:

$$\text{Maximize } C_d = \begin{cases} f_c Z^{2/3} D_b^{1.8}, & \text{if } D < 25.4 \text{ mm} \\ C_d = 3.647 f_c Z^{2/3} D_b^{1.4}, & \text{if } D > 25.4 \text{ mm} \end{cases}$$

Subject to:

$$g_1(\vec{z}) = \frac{\phi_0}{2\sin^{-1}(D_b/D_m)} - Z + 1 \leq 0,$$

$$g_2(\vec{z}) = 2D_b - K_{Dmin}(D - d) \geq 0,$$

$$g_3(\vec{z}) = K_{Dmax}(D - d) - 2D_b \geq 0,$$

$$g_4(\vec{z}) = \zeta B_w - D_b \leq 0,$$

$$g_5(\vec{z}) = D_m - 0.5(D + d) \geq 0,$$

$$g_6(\vec{z}) = (0.5 + e)(D + d) - D_m \geq 0,$$

$$g_7(\vec{z}) = 0.5(D - D_m - D_b) - \varepsilon D_b \geq 0,$$

$$g_8(\vec{z}) = f_i \geq 0.515,$$

$$g_9(\vec{z}) = f_o \geq 0.515,$$

where,

$$x = [(D - d)/2 - 3(T/4)]^2 + [D/2 - T/4 - D_b]^2 - \{d/2 + T/4\}^2$$

$$y = 2\{(D - d)/2 - 3(T/4)\}\{D/2 - T/4 - D_b\}$$

$$f_c = 37.91 \left[1 + \left\{ 1.04 \left(\frac{1 - \gamma}{1 + \gamma} \right)^{1.72} \left(\frac{f_i(2f_o - 1)}{f_o(2f_i - 1)} \right)^{0.41} \right\}^{10/3} \right]^{-0.3} \times \left[\frac{\gamma^{0.3}(1 - \gamma)^{1.39}}{(1 + \gamma)^{1/3}} \right] \left[\frac{2f_i}{2f_i - 1} \right]^{0.41} \quad (25)$$

Table 25

Statistical results obtained from different algorithms for 25-bar truss design problem.

Groups	SOA	ACO [83]	PSO [84]	CSS [85]	BB-BC [86]
A1	0.01	0.01	0.01	0.01	0.01
A2-A5	1.897	2.042	2.052	2.003	1.993
A6-A9	3.002	3.001	3.001	3.007	3.056
A10-A11	0.01	0.01	0.01	0.01	0.01
A12-A13	0.01	0.01	0.01	0.01	0.01
A14-A17	0.663	0.684	0.684	0.687	0.665
A18-A21	1.621	1.625	1.616	1.655	1.642
A22-A25	2.671	2.672	2.673	2.66	2.679
Best weight	544.85	545.03	545.21	545.10	545.16
Average weight	545.08	545.74	546.84	545.58	545.66
Std. dev.	0.391	0.94	1.478	0.412	0.491

$$\phi_0 = 2\pi - 2\cos^{-1}\left(\frac{x}{y}\right)$$

$$\gamma = \frac{D_b}{D_m}, \quad f_i = \frac{r_i}{D_b}, \quad f_o = \frac{r_o}{D_b}, \quad T = D - d - 2D_b$$

$$D = 160, \quad d = 90, \quad B_w = 30, \quad r_i = r_o = 11.033$$

$$0.5(D + d) \leq D_m \leq 0.6(D + d), \quad 0.15(D - d) \leq D_b \leq 0.45(D - d), \quad 4 \leq Z \leq 50, \quad 0.515 \leq f_i \text{ and } f_o \leq 0.6, \\ 0.4 \leq K_{Dmin} \leq 0.5, \quad 0.6 \leq K_{Dmax} \leq 0.7, \quad 0.3 \leq e \leq 0.4, \\ 0.02 \leq \zeta \leq 0.1, \quad 0.6 \leq \zeta \leq 0.85.$$

Table 26 reveals the performance comparison between the proposed SOA and other competitor algorithms. SOA provides optimal solution at $z_{1-10} = (125, 21.41892, 10.94123, 0.515, 0.515, 0.4, 0.7, 0.3, 0.02, 0.6)$ with corresponding fitness value equal to $f(z_{1-10}) = 85068.052$. The statistical results obtained for rolling element bearing design problem are compared and given in **Table 27**. **Fig. 24** shows the convergence analysis of SOA algorithm. The results reveals that SOA is capable to achieve a best optimal solution.

Table 26

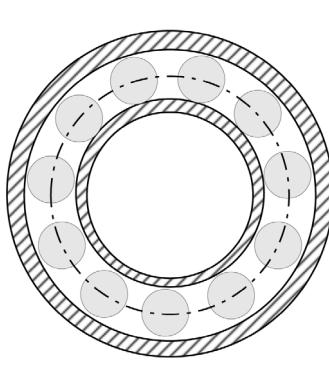
Comparison results for rolling element bearing design problem.

Algorithms	Optimum variables									Opt. cost	
	D_m	D_b	Z	f_i	f_o	$K_{D\min}$	$K_{D\max}$	ε	e	ζ	
SOA	125	21.41892	10.94123	0.515	0.515	0.4	0.7	0.3	0.02	0.6	85068.052
SHO	125	21.40732	10.93268	0.515	0.515	0.4	0.7	0.3	0.02	0.6	85054.532
GWO	125.6199	21.35129	10.98781	0.515	0.515	0.5	0.68807	0.300151	0.03254	0.62701	84807.111
PSO	125	20.75388	11.17342	0.515	0.515000	0.5	0.61503	0.300000	0.05161	0.60000	81691.202
MVO	125.6002	21.32250	10.97338	0.515	0.515000	0.5	0.68782	0.301348	0.03617	0.61061	84491.266
SCA	125	21.14834	10.96928	0.515	0.515	0.5	0.7	0.3	0.02778	0.62912	83431.117
GSA	125	20.85417	11.14989	0.515	0.517746	0.5	0.61827	0.304068	0.02000	0.624638	82276.941
GA	125	20.77562	11.01247	0.515	0.515000	0.5	0.61397	0.300000	0.05004	0.610001	82773.982
DE	125	20.87123	11.16697	0.515	0.516000	0.5	0.61951	0.301128	0.05024	0.614531	81569.527

Table 27

Statistical results obtained from different algorithms for rolling element bearing design problem.

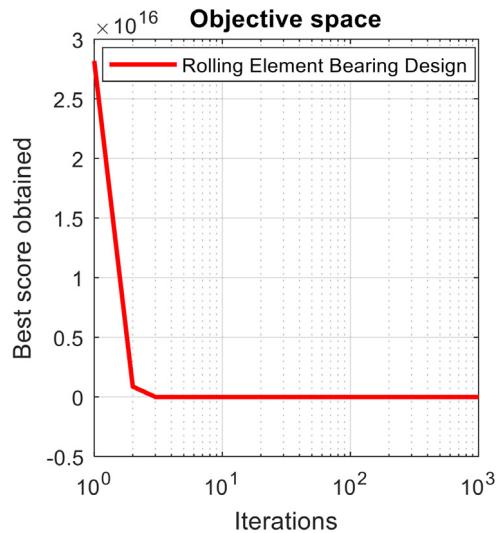
Algorithms	Best	Mean	Worst	Std. Dev.	Median
SOA	85068.052	85044.954	86540.853	1523.76	85055.421
SHO	85054.532	85024.858	85853.876	0186.68	85040.241
GWO	84807.111	84791.613	84517.923	0137.186	84960.147
PSO	81691.202	50435.017	32761.546	13962.150	42287.581
MVO	84491.266	84353.685	84100.834	0392.431	84398.601
SCA	83431.117	81005.232	77992.482	1710.777	81035.109
GSA	82276.941	78002.107	71043.110	3119.904	78398.853
GA	82773.982	81198.753	80687.239	1679.367	8439.728
DE	81569.527	80397.998	79412.779	1756.902	8347.009

**Fig. 23.** Schematic view of rolling element bearing problem.

In summary, these results show that SOA is an effective optimizer for solving large-scale constrained engineering design problems with low computational cost and fast convergence speed.

6. Conclusion and future works

This paper presents a novel bio-inspired based optimization algorithm called Seagull Optimization Algorithm (SOA). In this work, SOA is tested on forty-four benchmark test functions to validate its efficiency. The results reveal that SOA provides very competitive results as compared with nine well-known optimization algorithms. The results on the unimodal and multimodal test functions show the exploration and exploitation capabilities of SOA algorithm, respectively. Whereas, results of the CEC 2005 and CEC 2015 benchmark test functions show that SOA is able to solve challenging and high dimensionality bound constrained real problems. The statistical testing has been performed to demonstrate the statistical significance of proposed SOA over benchmark test functions. In addition, SOA is employed to seven real-life industrial applications (i.e., Optical buffer design, Pressure vessel design, Speed reducer design, Welded beam design, Tension/compression

**Fig. 24.** Convergence analysis of SOA for rolling element bearing design problem.

spring design, 25-bar truss design, and Rolling element bearing design problems) to verify and demonstrate its performance.

For future works, parallel seagull optimization algorithm can be developed to automatically detects the number of available processors and divides the workload among them to accomplish the effective utilization of the available resources. OpenMP library is used to speed up the performance and efficiency of traditional seagull optimization algorithm. The binary and multi-objective versions of SOA algorithm can also be developed to solve large-scale real-life engineering problems.

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Appendix A. Unimodal, multimodal, and fixed-dimension multimodal benchmark test functions

A.1. Unimodal benchmark test functions

A.1.1. Sphere model

$$F_1(z) = \sum_{i=1}^{30} z_i^2$$

$$-100 \leq z_i \leq 100, \quad f_{\min} = 0, \quad \text{Dim} = 30$$

Table 28Shekel's Foxholes Function F_{14} .

$(a_{ij}, i = 1, 2 \text{ and } j = 1, 2, \dots, 25)$								
$i \setminus j$	1	2	3	4	5	6	...	25
1	-32	-16	0	16	32	-32	...	32
2	-32	-32	-32	-32	-32	-16	...	32

A.1.2. Schwefel's Problem 2.22

$$F_2(z) = \sum_{i=1}^{30} |z_i| + \prod_{i=1}^{30} |z_i|$$

$$-10 \leq z_i \leq 10, \quad f_{\min} = 0, \quad \text{Dim} = 30$$

A.1.3. Schwefel's Problem 1.2

$$F_3(z) = \sum_{i=1}^{30} \left(\sum_{j=1}^i z_j \right)^2$$

$$-100 \leq z_i \leq 100, \quad f_{\min} = 0, \quad \text{Dim} = 30$$

A.1.4. Schwefel's Problem 2.21

$$F_4(z) = \max_i \{|z_i|, 1 \leq i \leq 30\}$$

$$-100 \leq z_i \leq 100, \quad f_{\min} = 0, \quad \text{Dim} = 30$$

A.1.5. Generalized Rosenbrock's function

$$F_5(z) = \sum_{i=1}^{29} [100(z_{i+1} - z_i^2)^2 + (z_i - 1)^2]$$

$$-30 \leq z_i \leq 30, \quad f_{\min} = 0, \quad \text{Dim} = 30$$

A.1.6. Step function

$$F_6(z) = \sum_{i=1}^{30} (\lfloor z_i + 0.5 \rfloor)^2$$

$$-100 \leq z_i \leq 100, \quad f_{\min} = 0, \quad \text{Dim} = 30$$

A.1.7. Quartic function

$$F_7(z) = \sum_{i=1}^{30} iz_i^4 + \text{random}[0, 1]$$

$$-1.28 \leq z_i \leq 1.28, \quad f_{\min} = 0, \quad \text{Dim} = 30$$

A.2. Multimodal benchmark test functions**A.2.1. Generalized Schwefel's Problem 2.26**

$$F_8(z) = \sum_{i=1}^{30} -z_i \sin(\sqrt{|z_i|})$$

$$-500 \leq z_i \leq 500, \quad f_{\min} = -12569.5, \quad \text{Dim} = 30$$

A.2.2. Generalized Rastrigin's function

$$F_9(z) = \sum_{i=1}^{30} [z_i^2 - 10 \cos(2\pi z_i) + 10]$$

$$-5.12 \leq z_i \leq 5.12, \quad f_{\min} = 0, \quad \text{Dim} = 30$$

Table 29Hartman Function F_{19} .

i	$(a_{ij}, j = 1, 2, 3)$			c_i	$(p_{ij}, j = 1, 2, 3)$		
1	3	10	30	1	0.3689	0.1170	0.2673
2	0.1	10	35	1.2	0.4699	0.4387	0.7470
3	3	10	30	3	0.1091	0.8732	0.5547
4	0.1	10	35	3.2	0.038150	0.5743	0.8828

Table 30Shekel Foxholes Functions F_{21}, F_{22}, F_{23} .

i	$(a_{ij}, j = 1, 2, 3, 4)$				c_i
1	4	4	4	4	0.1
2	1	1	1	1	0.2
3	8	8	8	8	0.2
4	6	6	6	6	0.4
5	3	7	3	7	0.4
6	2	9	2	9	0.6
7	5	5	3	3	0.3
8	8	1	8	1	0.7
9	6	2	6	2	0.5
10	7	3.6	7	3.6	0.5

A.2.3. Ackley's function

$$F_{10}(z) = -20 \exp \left(-0.2 \sqrt{\frac{1}{30} \sum_{i=1}^{30} z_i^2} \right)$$

$$- \exp \left(\frac{1}{30} \sum_{i=1}^{30} \cos(2\pi z_i) \right) + 20 + e$$

$$-32 \leq z_i \leq 32, \quad f_{\min} = 0, \quad \text{Dim} = 30$$

A.2.4. Generalized Griewank function

$$F_{11}(z) = \frac{1}{4000} \sum_{i=1}^{30} z_i^2 - \prod_{i=1}^{30} \cos \left(\frac{z_i}{\sqrt{i}} \right) + 1$$

$$-600 \leq z_i \leq 600, \quad f_{\min} = 0, \quad \text{Dim} = 30$$

A.2.5. Generalized penalized functions

- $F_{12}(z) = \frac{\pi}{30} \{ 10 \sin(\pi x_1) + \sum_{i=1}^{29} (x_i - 1)^2 [1 + 10 \sin^2(\pi x_{i+1})] + (x_n - 1)^2 \} + \sum_{i=1}^{30} u(z_i, 10, 100, 4)$
- $F_{13}(z) = 0.1 \{ \sin^2(3\pi z_1) + \sum_{i=1}^{29} (z_i - 1)^2 [1 + \sin^2(3\pi z_i + 1)] + (z_n - 1)^2 [1 + \sin^2(2\pi z_{30})] \} + \sum_{i=1}^N u(z_i, 5, 100, 4)$

$$-50 \leq z_i \leq 50, \quad f_{\min} = 0, \quad \text{Dim} = 30$$

$$-50 \leq z_i \leq 50, \quad f_{\min} = 0, \quad \text{Dim} = 30$$

where, $x_i = 1 + \frac{z_i + 1}{4}$

$$u(z_i, a, k, m) = \begin{cases} k(z_i - a)^m & z_i > a \\ 0 & -a < z_i < a \\ k(-z_i - a)^m & z_i < -a \end{cases}$$

Table 31Hartman Function F_{20} .

i	$(a_{ij}, j = 1, 2, \dots, 6)$						c_i	$(p_{ij}, j = 1, 2, \dots, 6)$			
1	10	3	17	3.5	1.7	8	1	0.1312	0.1696	0.5569	0.0124
2	0.05	10	17	0.1	8	14	1.2	0.2329	0.4135	0.8307	0.3736
3	3	3.5	1.7	10	17	8	3	0.2348	0.1415	0.3522	0.2883
4	17	8	0.05	10	0.1	14	3.2	0.4047	0.8828	0.8732	0.5743

Table 32

Composite benchmark test functions.

Functions	Dim	Range	f_{min}
$F_{24}(CF1)$: $f_1, f_2, f_3, \dots, f_{10} = \text{Sphere Function}$ $[\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_{10}] = [1, 1, 1, \dots, 1]$ $[\beta_1, \beta_2, \beta_3, \dots, \beta_{10}] = [5/100, 5/100, 5/100, \dots, 5/100]$	10	$[-5, 5]$	0
$F_{25}(CF2)$: $f_1, f_2, f_3, \dots, f_{10} = \text{Griewank's Function}$ $[\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_{10}] = [1, 1, 1, \dots, 1]$ $[\beta_1, \beta_2, \beta_3, \dots, \beta_{10}] = [5/100, 5/100, 5/100, \dots, 5/100]$	10	$[-5, 5]$	0
$F_{26}(CF3)$: $f_1, f_2, f_3, \dots, f_{10} = \text{Griewank's Function}$ $[\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_{10}] = [1, 1, 1, \dots, 1]$ $[\beta_1, \beta_2, \beta_3, \dots, \beta_{10}] = [1, 1, 1, \dots, 1]$	10	$[-5, 5]$	0
$F_{27}(CF4)$: $f_1, f_2 = \text{Ackley's Function}$ $f_3, f_4 = \text{Rastrigin's Function}$ $f_5, f_6 = \text{Weierstrass Function}$ $f_7, f_8 = \text{Griewank's Function}$ $f_9, f_{10} = \text{Sphere Function}$ $[\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_{10}] = [1, 1, 1, \dots, 1]$ $[\beta_1, \beta_2, \beta_3, \dots, \beta_{10}] = [5/32, 5/32, 1, 1, 5/0.5, 5/0.5, 5/100, 5/100, 5/100, 5/100]$	10	$[-5, 5]$	0
$F_{28}(CF5)$: $f_1, f_2 = \text{Rastrigin's Function}$ $f_3, f_4 = \text{Weierstrass Function}$ $f_5, f_6 = \text{Griewank's Function}$ $f_7, f_8 = \text{Ackley's Function}$ $f_9, f_{10} = \text{Sphere Function}$ $[\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_{10}] = [1, 1, 1, \dots, 1]$ $[\beta_1, \beta_2, \beta_3, \dots, \beta_{10}] = [1/5, 1/5, 5/0.5, 5/0.5, 5/100, 5/100, 5/32, 5/100, 5/100, 5/100]$	10	$[-5, 5]$	0
$F_{29}(CF6)$: $f_1, f_2 = \text{Rastrigin's Function}$ $f_3, f_4 = \text{Weierstrass Function}$ $f_5, f_6 = \text{Griewank's Function}$ $f_7, f_8 = \text{Ackley's Function}$ $f_9, f_{10} = \text{Sphere Function}$ $[\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_{10}] = [0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1]$ $[\beta_1, \beta_2, \beta_3, \dots, \beta_{10}] = [0.1 * 1/5, 0.2 * 1/5, 0.3 * 5/0.5, 0.4 * 5/0.5, 0.5 * 5/100, 0.6 * 5/100, 0.7 * 5/32, 0.8 * 5/32, 0.9 * 5/100, 1 * 5/100]$	10	$[-5, 5]$	0

A.3. Fixed-dimension multimodal benchmark test functions

$$-5 \leq z_i \leq 5, \quad f_{min} = -1.0316285, \quad \text{Dim} = 2$$

A.3.1. Shekel's foxholes function

See Table 28.

$$F_{14}(z) = \left(\frac{1}{500} + \sum_{j=1}^{25} \frac{1}{j + \sum_{i=1}^2 (z_i - a_{ij})^6} \right)^{-1}$$

$$-65.536 \leq z_i \leq 65.536, \quad f_{min} \approx 1, \quad \text{Dim} = 2$$

A.3.2. Kowalik's function

$$F_{15}(z) = \sum_{i=1}^{11} \left[a_i - \frac{z_1(b_i^2 + b_i z_2)}{b_i^2 + b_i z_3 + z_4} \right]^2$$

$$-5 \leq z_i \leq 5, \quad f_{min} \approx 0.0003075, \quad \text{Dim} = 4$$

A.3.3. Six-Hump Camel-Back function

$$F_{16}(z) = 4z_1^2 - 2.1z_1^4 + \frac{1}{3}z_1^6 + z_1 z_2 - 4z_2^2 + 4z_2^4$$

A.3.4. Branin function

$$F_{17}(z) = \left(z_2 - \frac{5.1}{4\pi^2} z_1^2 + \frac{5}{\pi} z_1 - 6 \right)^2 + 10 \left(1 - \frac{1}{8\pi} \right) \cos z_1 + 10$$

$$-5 \leq z_1 \leq 10, \quad 0 \leq z_2 \leq 15, \quad f_{min} = 0.398, \quad \text{Dim} = 2$$

A.3.5. Goldstein-Price function

$$F_{18}(z) = [1 + (z_1 + z_2 + 1)^2(19 - 14z_1 + 3z_1^2 - 14z_2 + 6z_1 z_2 + 3z_2^2)] \times [30 + (2z_1 - 3z_2)^2]$$

$$\times (18 - 32z_1 + 12z_1^2 + 48z_2 - 36z_1 z_2 + 27z_2^2)]$$

$$-2 \leq z_i \leq 2, \quad f_{min} = 3, \quad \text{Dim} = 2$$

Table 33

CEC 2015 benchmark test functions.

No.	Functions	Related basic functions	Dim	f_{min}
CEC – 1	Rotated Bent Cigar Function	Bent Cigar Function	30	100
CEC – 2	Rotated Discus Function	Discus Function	30	200
CEC – 3	Shifted and Rotated Weierstrass Function	Weierstrass Function	30	300
CEC – 4	Shifted and Rotated Schwefel's Function	Schwefel's Function	30	400
CEC – 5	Shifted and Rotated Katsuura Function	Katsuura Function	30	500
CEC – 6	Shifted and Rotated HappyCat Function	HappyCat Function	30	600
CEC – 7	Shifted and Rotated HGBat Function	HGBat Function	30	700
CEC – 8	Shifted and Rotated Expanded Griewank's plus Rosenbrock's Function Rosenbrock's Function	Griewank's Function	30	800
CEC – 9	Shifted and Rotated Expanded Scaffer's F6 Function	Expanded Scaffer's F6 Function	30	900
CEC – 10	Hybrid Function 1 ($N = 3$) Rastrigin's Function High Conditioned Elliptic Function	Schwefel's Function	30	1000
CEC – 11	Hybrid Function 2 ($N = 4$) Weierstrass Function Rosenbrock's Function Scaffer's F6 Function	Griewank's Function	30	1100
CEC – 12	Hybrid Function 3 ($N = 5$) HappyCat Function Expanded Griewank's plus Rosenbrock's Function Schwefel's Function Ackley's Function	Katsuura Function	30	1200
CEC – 13	Composition Function 1 ($N = 5$) High Conditioned Elliptic Function Bent Cigar Function Discus Function High Conditioned Elliptic Function	Rosenbrock's Function	30	1300
CEC – 14	Composition Function 2 ($N = 3$) Rastrigin's Function High Conditioned Elliptic Function	Schwefel's Function	30	1400
CEC – 15	Composition Function 3 ($N = 5$) Rastrigin's Function Schwefel's Function Weierstrass Function High Conditioned Elliptic Function	HGBat Function	30	1500

A.3.6. Hartman's family

See Tables 29 and 31.

$$\bullet F_{19}(z) = - \sum_{i=1}^4 c_i \exp\left(- \sum_{j=1}^3 a_{ij}(z_j - p_{ij})^2\right)$$

$$0 \leq z_j \leq 1, \quad f_{min} = -3.86, \quad Dim = 3$$

$$\bullet F_{20}(z) = - \sum_{i=1}^4 c_i \exp\left(- \sum_{j=1}^6 a_{ij}(z_j - p_{ij})^2\right)$$

$$0 \leq z_j \leq 1, \quad f_{min} = -3.32, \quad Dim = 6$$

A.3.7. Shekel's foxholes function

$$\bullet F_{21}(z) = - \sum_{i=1}^5 [(X - a_i)(X - a_i)^T + c_i]^{-1}$$

$$0 \leq z_i \leq 10, \quad f_{min} = -10.1532, \quad Dim = 4$$

$$\bullet F_{22}(z) = - \sum_{i=1}^7 [(X - a_i)(X - a_i)^T + c_i]^{-1}$$

$$0 \leq z_i \leq 10, \quad f_{min} = -10.4028, \quad Dim = 4$$

$$\bullet F_{23}(z) = - \sum_{i=1}^{10} [(X - a_i)(X - a_i)^T + c_i]^{-1} \text{ (see Table 30)}$$

$$0 \leq z_i \leq 10, \quad f_{min} = -10.536, \quad Dim = 4$$

A.4. Basic composite benchmark test functions

A.4.1. Weierstrass function

$$F(z) = \sum_{i=1}^{30} \left(\sum_{k=0}^{20} [0.5^k \cos(2\pi 3^k (z_i + 0.5))] \right) - 30 \sum_{k=0}^{20} [0.5^k \cos(2\pi 3^k \times 0.5)]$$

Note that the Sphere, Rastrigin's, Griewank's, and Ackley's functions in composite benchmark suite are same as above mentioned F_1 , F_9 , F_{11} , and F_{10} benchmark test functions.

A.5. Basic CEC 2015 benchmark test functions

A.5.1. Bent Cigar function

$$F(z) = z_1^2 + 10^6 \sum_{i=2}^{30} z_i^2$$

A.5.2. Discus function

$$F(z) = 10^6 z_1^2 + \sum_{i=2}^{30} z_i^2$$

A.5.3. Modified Schwefel's function

$$F(z) = 418.9829 \times 30 - \sum_{i=1}^{30} g(y_i),$$

$$y_i = z_i + 4.209687462275036e + 002$$

$$g(y_i) = \begin{cases} y_i \sin(|y_i|^{1/2}) & \text{where, if } |y_i| \leq 500, \\ (500 - \text{mod}(y_i, 500)) \sin(\sqrt{|500 - \text{mod}(y_i, 500)|}) \\ - \frac{(y_i - 500)^2}{10000 \times 30} & \text{where, if } y_i > 500, \\ (mod(|y_i|, 500) - 500) \sin(\sqrt{|mod(|y_i|, 500) - 500|}) \\ - \frac{(y_i + 500)^2}{10000 \times 30} & \text{where, if } y_i < -500 \end{cases}$$

A.5.4. Katsuura function

$$F(z) = \frac{10}{30^2} \prod_{i=1}^{30} \left(1 + i \sum_{j=1}^{32} \frac{|2^j z_i - \text{round}(2^j z_i)|}{2^j} \right)^{\frac{10}{30^{1.2}}} - \frac{10}{30^2}$$

A.5.5. HappyCat function

$$F(z) = \left| \sum_{i=1}^{30} z_i^2 - 30 \right|^{1/4} + (0.5 \sum_{i=1}^{30} z_i^2 + \sum_{i=1}^{30} z_i) / 30 + 0.5$$

A.5.6. HGBat function

$$F(z) = \left| \left(\sum_{i=1}^{30} z_i^2 \right)^2 - \left(\sum_{i=1}^{30} z_i \right)^2 \right|^{1/2} + (0.5 \sum_{i=1}^{30} z_i^2 + \sum_{i=1}^{30} z_i) / 30 + 0.5$$

A.5.7. Expanded Griewank's plus Rosenbrock's function

$$F(z) = F_{39}(F_{38}(z_1, z_2)) + F_{39}(F_{38}(z_2, z_3)) + \dots + F_{39}(F_{38}(z_{30}, z_1))$$

A.5.8. Expanded Scaffer's F6 function

Scaffer's F6 Function:

$$g(z, x) = 0.5 + \frac{(\sin^2(\sqrt{z^2 + x^2}) - 0.5)}{(1 + 0.001(z^2 + x^2))^2}$$

$$F(z) = g(z_1, z_2) + g(z_2, z_3) + \dots + g(z_{30}, z_1)$$

A.5.9. High conditioned elliptic function

$$F(z) = \sum_{i=1}^{30} (10^6 \frac{i-1}{30-1} z_i^2)$$

Note that the Weierstrass, Rosenbrock's, Griewank's, Rastrigin's, and Ackley's functions in CEC 2015 benchmark test suite are same as above mentioned Weierstrass, F_5 , F_{11} , F_9 , and F_{10} benchmark test functions.

A.6. Composite benchmark functions

The detailed description of six well-known composite benchmark test functions ($F_{24} - F_{29}$) are mentioned in Table 32.

A.7. CEC 2015 benchmark test functions

The detailed description of fifteen well-known CEC 2015 benchmark test functions (CEC1 — CEC15) are mentioned in Table 33.

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