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A Comprehensive Study of Parameters Analysis for Galactic Swarm Optimization

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Abstract: The galactic swarm optimization algorithm is a metaheuristic approach inspired by the motion and behavior of stars and galaxies. It is a framework that can use basic metaheuristic search methods. The method, which has a two-phase structure, performs exploration in the first phase and exploitation in the second phase. GSO tries to find the best solution in the search space by repeating these two phases for the specified number of times. In this study, the analysis of maximum epoch number (EP_{max}), the number of iterations in the first phase (L_1), and the number of iterations in the second phase (L_2) parameters, which determine the exploration and exploitation balance in the GSO method, was performed. 15 different parameter sets consisting of different values of these three parameters were created. The methods with 15 different parameter sets were performed at 30 independent runs. The methods were analyzed using 26 benchmark functions. The functions are tested in 30, 60, and 100 dimensions. Detailed results of the analysis were presented in the study, and the results obtained were also evaluated statistically.

Keywords: *galactic swarm optimization, metaheuristic optimization algorithm, parameter analysis*

1. Introduction

Optimization problems are encountered in many different areas such as production, business planning, and transportation in the real world. The main purpose of optimization is to find the parameters that provide the best solution to the problem within the framework of available resources. Mathematical and heuristic methods are used to solve optimization problems. Using mathematical methods in problems where the solution space is very large requires high costs (time, memory, etc.). For this reason, methods that try to find the best solution by scanning the solution space with heuristic approaches are more advantageous in problems with wide solution space [1]. Metaheuristic methods, which are created by combining heuristic approaches, achieve successful results in solving the problems in the literature.

Metaheuristic methods that use different heuristic approaches exist in the literature. These meta-heuristic methods can be examined in different classes such as evolution-based, physics-based, herd-based, human-based algorithms, etc. [2]. Evolution-based algorithms are inspired by the laws of natural evolution. In evolution-based methods, the initial population is generated stochastically. When creating the new generation, which can be named as generation process, the best individuals are chosen for the population until the stopping criteria are met. The most common algorithms of this category are Genetic Algorithms (GA) [3, 4], Evolution Strategy [5], and Differential Evolution (DE) [6]. Physics-based algorithms are developed by simulating the physical laws of the universe. The initial population in this class of algorithms is also generated stochastically, but the individuals interact with each other using physical laws like energy, mass, force, and proximity. Then the evolution proceeds by modifying the physical laws to get better solutions until the stopping criteria are met. Simulated Annealing (SE) [7], Gravitational Search Algorithm (GSA) [8], and Charged System Search (CSS) algorithm [9] can be categorized as physics-based metaheuristic methods. Swarm-based metaheuristic algorithms are inspired by the behaviours of the animal swarms, such as ant or bee colonies, and solutions of algorithms evolve, imitating interactions in the swarm. For this type of method, first, a random new generation is created within the search space. Depending upon the best solution of the individual obtained so far or the best solution of the swarm obtained so far or also both of these achievements, the swarm evolves until the stopping criteria met. The evolution of the swarm is realized by individuals mimicking the movements and interactions of animals within the swarm. Particle Swarm Optimization (PSO) algorithm [10] is one of the most investigated metaheuristic algorithms in this class. There are also many other swarm-based metaheuristic algorithms that exist, including Ant Colony Optimization (ACO) algorithm [11], Artificial Bee Colony (ABC) algorithm [12], Whale Optimization Algorithm (WOA) [13], Cuckoo Search (CS) algorithm [14], Artificial Algae Algorithm (AAA) [15], Bees Algorithm (BEE) [16], Flower Pollination Algorithm (FPA) [17] and Bat Algorithm (BAT) [18]. The last class of metaheuristic algorithms, human-based approaches, developed on human behaviours and characteristics. The most commonly employed algorithms of this class can be given as Tabu Search (TS) algorithm [19, 20], Harmony Search (HS) algorithm [21], and Teaching-Learning-Based Optimization (TLBO) algorithm [22].

GSO is based on the movement and interaction of stars and galaxies. It is not a traditional metaheuristic optimization method; it is a framework that traditional metaheuristic optimization methods. The algorithm consists of two phases, exploration and exploitation. Exploration can be explained as the ability of a search algorithm to explore different areas of the search space to have a high probability of finding reasonable promising solutions.

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Exploitation implies the capacity to focus the search around a promising area to refine a candidate solution. In the exploration phase, independent subpopulations are randomly created, and individuals of these populations are improved with a determined search algorithm. In the second, exploitation phase an initialization population is generated from the best individuals of the subpopulations created in the first phase.

```
Objective function f(x), x={x_1,x_2,...,x_d}
Initialize phase 1 population (x1) in [x_min, x_max]^D
Initialize phase 1 variables (v1_ij, p1_ij, g1_i) in [x_min, x_max]^D
Initialize phase 2 population (x2) in [x_min, x_max]^D
Initialize phase 2 variables (v2_i, p2_i, g2) in [x_min, x_max]^D
for EP = 1 to EP_max
    Start Phase 1
    for i = 1 to Number of Partitions
        for k=1 to Number of Iteration of Phase 1
            for j = 1 to Size of Partitions
                v1_ij ← w_1 v1_ij + c_1r_1(p1_ij − x1_ij) + c_2r_2(g1_i − x1_ij)
                x1_ij ← x1_ij + v1_ij
                if (f(x1_ij) < f(p1_ij)) then
                    p1_ij ← x1_ij
                    if (f(p1_ij) < f(g1_i)) then
                        g1_i ← p1_ij
                        if (f(g1_i) < f(g2)) then
                            g2 ← g1_i
                        end
                    end
                end
            end
        end
    end
    Initialize phase 2 population
    for j = 1 to Number of Partitions
    x2_j ← g1_j
    end

    Start Phase 2
    for k=1 to Number of Iteration of Phase 2
        for i = 1 to Number of Partitions
            v2_i ← w_2 v2_i + c_3r_3(p2_i − x2_i) + c_4r_4(g2 − x2_i)
            x2_i ← x2_i + v2_i
            if (f(x2_i) < f(p2_i)) then
                p2_i ← x2_i
                if (f(p2_i) < f(g2)) then
                    g2 ← p2_i
                end
            end
        end
    end
end
Return g2
```

Fig. 1. Implementation of GSO algorithm with PSO

The search algorithm tries to reach the best solution by using individuals in the generated initialization population and the algorithm repeats these two phases for a certain number of times to get the best solutions. In the base GSO algorithm, PSO was used as a search algorithm in both phases. The primary purpose of the first phase is to perform an effective exploration in the solution space. The second phase is to search for the best solution (exploitation) by developing individuals in the population generated from the first phase. "Exploration" and "Exploitation" are the most critical performance factors of optimization algorithms. A powerful optimization algorithm should optimally balance the two conflicting objectives [4, 23].

In this study, the parameters of the GSO method were analyzed. It tried to determine the most appropriate GSO parameters by using benchmark functions with different characteristics. The parameters analysed are the maximum epoch number, the number of iterations in the first and second phases. The iteration numbers in the first and the second phase are the parameters that directly affect the exploration and exploitation capabilities of the GSO. The main purpose of the study is to determine the most suitable parameters for the GSO method by using different benchmark functions. The results obtained at this point were also analysed statistically.

The paper is organized as follows. The GSO algorithm is clearly mentioned in Section 2. Experimental Setup and Results and Discussion are located in Sections 3 and 4, respectively. Finally, the work is concluded in Section 5.

2. Galactic Swarm Optimization

The GSO algorithm was introduced by Muthiah-Nakarajan and Noel in 2016 [24]. It is a two-phase optimization method that simulates the movements of the stars, galaxies, and super galaxy clusters in space to find the optimal solution for problems. The first phase is the explorative phase, which can be summed as improving the best solutions of independent subpopulation groups with the pre-determined search methods. Here each independent subpopulation is run a certain number of iterations, determined by the search algorithm. Then a new population, called the super-population, is formed by selecting the best individual of each subpopulation. In the second phase, an optimal solution is searched by using the search method. The first and second phases are repeated for the number of epoch parameters to find the best solution. The PSO algorithm is used as a search method in both the first and second phases of the base GSO algorithm[25].

PSO is an optimization method inspired by the social behavior of bird flocks and fish schools. The best results are obtained by moving the randomly generated starting population in the search space [10, 26]. For a D-dimensional optimization problem $X_i = [x_{i1}, x_{i2}, \dots, x_{id}]$ is a position vector, $V_i = [v_{i1}, v_{i2}, \dots, v_{id}]$ is a velocity vector, $P_i = [p_{i1}, p_{i2}, \dots, p_{id}]$ is the best position vector of the ith particle and is called pbest. The particles move in the solution space according to Eq.1 and Eq.2.

$$v_i(t+1) = w\, v_i(t) + c_1 r_1 (p_i - x_i) + c_2 r_2 (g_i - x_i) \tag{1}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{2}$$

Where w called inertia weight is used to control global and local search ability. r_1 and r_2 are random numbers in the range of [0,1]. c_1 and c_2 are the acceleration coefficients. g_i is the best solution found so far.

Multilayered product of the GSO algorithm is expressed in Eq.3:

$$\begin{aligned} & s_j^i \in S_i : j = 1,2, \dots, N \\ & b_i \in S_i : b_i = best(S_i) \\ & G = \bigcup_{i=1}^{M} b_i \end{aligned} \tag{3}$$

In the base GSO algorithm, the initial M sub-population, which consists of N solutions, is randomly generated. s_j^i represents the jth solution of the ith subpopulation. S_i represents the ith subpopulation. b_i ($best(S_i)$) represents the best solution of the sub-population S_i. Set G represents the super-population that consists of the best solutions that come from subpopulations. The pseudo-code of the GSO framework that is implemented by PSO is given in Fig. 1.

3. Experimental Setup

During the analysis process, 26 numerical optimizations (11 unimodal and 15 multimodal) problems [27-30] with different properties were used. Function No, Name, Search Ranges, Characteristic (C), and mathematical formulations of these benchmark problems are given in Table 1. In column C the characteristic of the function is indicated as M for multimodal functions, U for unimodal functions, S for separable functions, and N non-separable functions.

Table 1. Benchmark functions

No of Funct.	Name	Search Range	C	Function
F1	Sphere	[100,100]	US	$f_1(\vec{X}) = \sum_{i=1}^{n} x_i^2$
F2	Elliptic	[100,100]	UN	$f_2(\vec{X}) = \sum_{i=1}^{n} (10^6)^{\frac{(i-1)}{(n-1)}} x_i^2$
F3	SumSquares	[10,10]	US	$f_3(\vec{X}) = \sum_{i=1}^{n} i x_i^2$
F4	SumPower	[10,10]	MS	$f_4(\vec{X}) = \sum_{i=1}^{n} \lvert x_i \rvert^{(i+1)}$
F5	Schwefel2.22	[10,10]	UN	$f_5(\vec{X}) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$
F6	Schwefel2.21	[100,100]	UN	$f_6(\vec{X}) = max_i\{\lvert x_i \rvert, 1 \le i \le n\}$
F7	Step	[100,100]	US	$f_7(\vec{X}) = \sum_{i=1}^{n} (\lfloor x_i + 0.5 \rfloor)^2$
F8	Quartic	[1.28,1.28]	US	$f_8(\vec{X}) = \sum_{i=1}^{n} i x_i^4$
F9	QuarticWN	[1.28,1.28]	US	$f_9(\vec{X}) = \sum_{i=1}^{n} i x_i^4 + random[0,1)$
F10	Rosenbrock	[10,10]	UN	$f_{10}(\vec{X}) = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$
F11	Rastrigin	[5.12,5.12]	MS	$f_{11}(\vec{X}) = \sum_{i=1}^{n} [x_i^2 - 10\, cos(2\pi x_i) + 10]$
F12	Non-Continuous Rastrigin	[5.12,5.12]	MS	$f_{12}(\vec{X}) = \sum_{i=1}^{n} [y_i^2 - 10\, cos(2\pi y_i) + 10]$ $y_i = \begin{cases} x_i & \lvert x_i \rvert < \frac{1}{2} \\ \frac{round(2x_i)}{2} & \lvert x_i \rvert \ge \frac{1}{2} \end{cases}$
F13	Griewank	[600,600]	MN	$f_{13}(\vec{X}) = \frac{1}{4000} \sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$
F14	Schwefel2.26	[500,500]	UN	$f_{14}(\vec{X}) = 418.98{*}n - \sum_{i=1}^{n} x_i\, sin\left(\sqrt{\lvert x_i \rvert}\right)$
F15	Ackley	[32,32]	MN	$f_{15}(\vec{X}) = -20\, exp\left\{-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right\} - exp\left\{\frac{1}{n}\sum_{i=1}^{n} cos(2\pi x_i)\right\} + 20 + e$
F16	Penalized1	[50,50]	MN	$f_{16}(\vec{X}) = \frac{\pi}{n}\{10\, sin^2(\pi y_1) + \sum_{i=1}^{n-1} (y_i - 1)^2 [1 + 10\, sin^2(\pi y_{i+1})] + (y_n - 1)^2\}$ $+ \sum_{i=1}^{n} u(x_i, 10,100,4)$ $y_i = 1 + \frac{1}{4}(x_i + 1) \quad u_{x_i,a,k,m} = \begin{cases} k(x_i - a)^m & x_i > a \\ 0 & -a \le x_i \le a \\ k(x_i - a)^m & x_i < -a \end{cases}$
F17	Penalized2	[50,50]	MN	$f_{17}(\vec{X}) = \frac{1}{10}\{sin^2(\pi x_1) + \sum_{i=1}^{n-1} (x_i - 1)^2 [1 + sin^2(3\pi x_{i+1})] +$ $(x_n - 1)^2[1 + sin^2(2\pi x_{i+1})]\} + \sum_{i=1}^{n} u(x_i, 5,100,4)$
F18	Alpine	[10,10]	MS	$f_{18}(\vec{X}) = \sum_{i=1}^{n} \lvert x_i \cdot sin(x_i) + 0.1 \cdot x_i \rvert$
F19	Levy	[10,10]	MN	$n-1$

				$\|x_n - 1\|[1 + sin^2(3\pi x_n)]$
F20	Weierstrass	[0.5,0.5]	MN	$f_{20}(\overrightarrow{X}) = \sum_{i=1}^{D} (\sum_{k=0}^{k_{\max}} [a^k \cos(2\pi b^k (x_i + 0.5))]) - D \sum_{k=0}^{k_{\max}} [a^k \cos(2\pi b^k 0.5)]$ $a = 0.5, b = 3, k_{\max} = 20$
F21	Schaffer	[100,100]	MN	$f_{21}(\vec{X}) = 0.5 + \frac{sin^2(\sqrt{\sum_{i=1}^{n} x_i^2}) - 0.5}{(1 + 0.001 * [\sum_{i=1}^{n} x_i^2])^2}$
F22	Shifted Sphere	[100,100]	US	$f_{24}(\vec{X}) = \sum_{i=1}^{n} z_i^2 \quad z = x - o$
F23	Shifted Rastrigin	[5.12,5.12]	MS	$f_{25}(\vec{X}) = \sum_{i=1}^{n} [z_i^2 - 10\, cos(2\pi z_i) + 10] \quad z = x - o$
F24	Shifted Griewank	[600,600]	MN	$f_{26}(\vec{X}) = \frac{1}{4000} \sum_{i=1}^{n} z_i^2 - \prod_{i=1}^{n} cos\left(\frac{z_i}{\sqrt{i}}\right) + 1 \quad z = x - o$
F25	Shifted Ackley	[32,32]	MN	$f_{27}(\vec{X}) = -20\, exp\left\{-0.2 \sqrt{\frac{1}{n} \sum_{i=1}^{n} z_i^2}\right\} - exp\left\{\frac{1}{n} \sum_{i=1}^{n} cos(2\pi z_i)\right\}$ $z = x - o$
F26	Shifted Alpine	[10,10]	MN	$f_{28}(\vec{X}) = \sum_{i=1}^{n} \|z_i \cdot sin(z_i) + 0.1 \cdot z_i\| \quad z = x - o$

For a fair comparison, all experimental studies were performed at 30 independent runs, and the maximum fitness evaluation count was determined as Dimension*5000. In the experimental study, benchmark functions were used in 30, 60, and 100 dimensions. As a result, the maximum fitness evaluation count for 30, 60, and 100 dimensions are calculated as 150000, 300000, and 450000, respectively. In addition, the parameters M (the number of sub-population) and N (the number of solutions in a sub-population) were determined as 10 and 5 as in the original GSO study. Also, the parameters c_1, c_2, c_3, and c_4 of the PSO algorithm used as the search algorithm in the original GSO study were determined as 2.05. The inertial weight w is reduced linearly from one to nearly zero with each iteration. In this experimental study, the parameters of the original study were used for PSO.

In this study, the analysis of the parameters of maximum epoch number (EP_{max}), the number of iterations in the first phase (L_1), and the number of iterations in the second phase (L_2) in the GSO algorithm was performed. In the original GSO study, the EP_{max} parameter was determined as 5, and in cases where the problem dimension is large, it was determined as 9. L_1 and L_2 parameters are determined in such a way that an equal number of fitness evaluations are made in the first and second phases. In other words, the fitness evaluation balance in the first and second phases is %50 - %50. In this study, experimental studies were designed as EP_{max} parameter 3, 5 and 9, the fitness evaluation balance as %20 - %80, %40 - %60, %50 - %50, %60 - %40, and %80 - %20. The name and parameter settings of all methods are given in table 2. The naming of the methods is made in the GSOeb template. Where *e* is the maximum epoch parameter and *b* is the fitness evaluation balance type. 20% - 80%, 40% - 60%, 50% - 50%, 60% - 40%, and 80% - 20% balance parameters are expressed as 1, 2, 3, 4, and 5 types, respectively.

Table 2. The parameters settings of all methods

Method Name	**EP_{max}**	**Balance**	**The count of fitness evaluation in the first phase**			**The count of fitness evaluation in the second phase**			**The number of iterations in the first phase (L_1)**			**The number of iterations in the second phase (L_2)**		
			Dimension			**Dimension**			**Dimension**			**Dimension**		
			30	**60**	**100**	**30**	**60**	**100**	**30**	**60**	**100**	**30**	**60**	**100**
GSO_{31}	3	%20 - %80	30000	60000	90000	120000	240000	360000	200	400	600	4000	8000	12000
GSO_{32}	3	%40 - %60	60000	120000	180000	90000	180000	270000	400	800	1200	3000	6000	9000
GSO_{33}	3	%50 - %50	75000	150000	225000	75000	150000	225000	500	1000	1500	2500	5000	7500
GSO_{34}	3	%60 - %40	90000	180000	270000	60000	120000	180000	600	1200	1800	2000	4000	6000
GSO_{35}	3	%80 - %20	120000	240000	360000	30000	60000	90000	800	1600	2400	1000	2000	3000
GSO_{51}	5	%20 - %80	30000	60000	90000	120000	240000	360000	120	240	360	2400	4800	7200
GSO_{52}	5	%40 - %60	60000	120000	180000	90000	180000	270000	240	480	720	1800	3600	5400
GSO_{53}	5	%50 - %50	75000	150000	225000	75000	150000	225000	300	600	900	1500	3000	4500
GSO_{54}	5	%60 - %40	90000	180000	270000	60000	120000	180000	360	720	1080	1200	2400	3600
GSO_{55}	5	%80 - %20	120000	240000	360000	30000	60000	90000	480	960	1440	600	1200	1800
GSO_{91}	9	%20 - %80	30000	60000	90000	120000	240000	360000	66	133	200	1333	2666	4000
GSO_{92}	9	%40 - %60	60000	120000	180000	90000	180000	270000	133	266	400	999	1999	3000
GSO_{93}	9	%50 - %50	75000	150000	225000	75000	150000	225000	166	333	500	833	1666	2500
GSO_{94}	9	%60 - %40	90000	180000	270000	60000	120000	180000	200	400	600	666	1333	2000
GSO_{95}	9	%80 - %20	120000	240000	360000	30000	60000	90000	266	533	800	333	666	1000

Table 3: The experimental results for D=30

F.No	GSO_{31}	GSO_{32}	GSO_{33}	GSO_{34}	GSO_{35}	GSO_{51}	GSO_{52}	GSO_{53}	GSO_{54}	GSO_{55}	GSO_{91}	GSO_{92}	GSO_{93}	GSO_{94}	GSO_{95}
F1	2.980E-02	8.760E-02	**0.000E+00**	1.215E-06	**0.000E+00**	**0.000E+00**	7.056E-04	6.417E-01	1.510E-03	3.100E-01	2.165E-03	**0.000E+00**	**0.000E+00**	1.114E-03	**0.000E+00**
F2	1.817E+06	3.838E+05	3.576E+05	7.262E+05	3.111E+05	9.481E+02	1.110E+05	1.661E+04	3.152E+04	5.461E+04	2.226E+04	4.048E+03	1.554E+06	**0.000E+00**	7.656E+05
F3	3.333E+00	**0.000E+00**	**0.000E+00**	1.513E-01	4.726E-04	1.649E-06	1.155E-01	4.338E-04	**0.000E+00**	**0.000E+00**	8.234E-06	**0.000E+00**	1.040E-01	5.267E-05	1.911E-02
F4	1.070E-08	5.870E+06	3.333E+04	3.367E+05	3.333E+01	**0.000E+00**	**0.000E+00**	**0.000E+00**	3.485E-11	3.806E-11	3.333E+04	3.367E+04	6.002E-11	4.153E-08	1.361E-03
F5	8.236E-01	2.750E-03	7.305E-01	3.019E-01	4.934E-01	**0.000E+00**	3.333E-01	**0.000E+00**	1.767E-02	3.117E-02	4.833E-01	**0.000E+00**	2.537E-01	3.333E-01	4.019E-07
F6	7.780E-02	1.084E-02	**0.000E+00**	4.276E-03	1.468E-01	**0.000E+00**	**0.000E+00**	7.899E-03	**0.000E+00**	**0.000E+00**	1.030E-02	**0.000E+00**	1.604E-02	**0.000E+00**	1.113E-02
F7	**0.000E+00**	**0.000E+00**	**0.000E+00**	**0.000E+00**	**0.000E+00**	**0.000E+00**	**0.000E+00**	**0.000E+00**	**0.000E+00**	3.345E+02	2.000E-01	2.000E-01	**0.000E+00**	3.333E-02	**0.000E+00**
F8	8.305E-13	6.024E-11	**0.000E+00**	5.090E-11	1.882E-06	**0.000E+00**	1.369E-11	6.316E-20	**0.000E+00**	1.459E-10	**0.000E+00**	8.399E-17	2.378E-09	**0.000E+00**	**0.000E+00**
F9	1.073E-04	1.598E-04	1.258E-04	1.804E-04	2.942E-04	9.798E-05	8.993E-05	2.347E-04	2.618E-04	6.484E-04	1.073E-04	**8.279E-05**	1.565E-04	1.599E-04	4.944E-04
F10	2.499E+01	3.147E+01	2.778E+01	2.491E+01	2.874E+01	1.459E+01	2.924E+01	2.295E+01	2.390E+01	2.879E+01	**1.358E+01**	1.361E+01	1.541E+01	1.538E+01	2.158E+01
F11	1.661E-02	2.825E+00	3.344E-03	3.443E+00	2.773E+00	5.839E+00	4.382E+00	2.241E-01	1.759E+00	1.559E+00	**0.000E+00**	1.232E+00	4.085E+00	2.092E+00	2.816E+00
F12	2.929E-04	4.016E+00	3.467E+00	1.934E+00	5.054E+00	7.965E+00	5.819E+00	2.667E-01	2.136E+00	1.290E+00	3.334E+00	6.667E-02	5.004E+00	**0.000E+00**	8.032E-03
F13	2.954E-02	4.351E-02	1.650E-02	1.962E-02	2.601E-02	**0.000E+00**	2.954E-03	5.782E-03	7.365E-03	1.732E-03	5.524E-03	7.580E-03	8.399E-02	9.653E-04	**0.000E+00**
F14	3.595E+03	3.148E+03	3.076E+03	2.942E+03	3.303E+03	3.072E+03	2.793E+03	**2.567E+03**	3.541E+03	3.550E+03	2.981E+03	2.837E+03	3.223E+03	3.088E+03	3.174E+03
F15	9.200E-01	5.774E-01	1.665E+00	1.003E+00	1.008E+00	**0.000E+00**	1.118E-01	9.400E-03	1.372E-01	5.808E-02	3.491E-04	2.409E-04	9.698E-03	1.020E+00	8.764E-01
F16	1.118E-01	8.577E-02	7.273E-02	9.708E-02	1.225E-01	9.211E-02	6.357E-02	6.383E-02	7.991E-02	1.078E-01	3.949E-02	**3.377E-02**	3.519E-02	7.355E-02	9.143E-02
F17	1.627E+00	1.568E+00	1.529E+00	1.557E+00	1.691E+00	1.409E+00	1.453E+00	1.318E+00	1.528E+00	1.507E+00	1.120E+00	**1.109E+00**	1.209E+00	1.281E+00	1.573E+00
F18	2.962E-01	2.380E-03	1.895E-03	**0.000E+00**	3.185E-03	4.769E-03	2.746E-03	9.914E-02	**0.000E+00**	1.512E-01	9.881E-03	2.387E-02	1.917E-03	2.380E-01	8.841E-03
F19	1.136E+01	1.087E+01	1.215E+01	9.612E+00	1.329E+01	6.978E+00	8.510E+00	8.475E+00	1.136E+01	1.136E+01	5.701E+00	**3.746E+00**	6.869E+00	6.679E+00	8.803E+00
F20	4.354E-01	6.870E-01	3.163E-01	4.474E-01	5.592E-01	2.657E-01	1.127E-02	**0.000E+00**	5.370E-01	7.188E-02	1.333E-01	5.264E-02	3.019E-01	**0.000E+00**	3.279E-01
F21	1.777E-02	1.241E-03	3.847E-03	3.221E-02	3.239E-04	1.914E-02	**0.000E+00**	6.265E-03	1.565E-03	4.557E-03	1.565E-03	**0.000E+00**	**0.000E+00**	**0.000E+00**	2.415E-02
F22	1.669E+04	1.224E+04	7.641E+03	5.026E+03	8.572E+03	1.076E+04	3.610E+03	4.742E+03	7.172E+03	6.272E+03	7.897E+03	7.624E+03	6.138E+03	6.408E+03	**1.635E+03**
F23	1.835E+02	1.691E+02	1.734E+02	1.630E+02	2.012E+02	1.865E+02	1.640E+02	1.747E+02	1.635E+02	1.909E+02	1.765E+02	2.229E+02	1.847E+02	**1.585E+02**	1.892E+02
F24	1.321E+02	6.712E+01	5.126E+01	6.351E+01	2.221E+01	1.094E+02	3.245E+01	6.395E+01	2.379E+01	5.172E+01	6.547E+01	8.856E+01	5.714E+01	**2.156E+01**	4.643E+01
F25	1.458E+01	1.222E+01	1.311E+01	1.341E+01	1.357E+01	1.239E+01	**1.112E+01**	1.174E+01	1.299E+01	1.248E+01	1.342E+01	1.138E+01	1.262E+01	1.137E+01	1.209E+01
F26	1.652E+01	1.589E+01	1.833E+01	1.900E+01	1.959E+01	1.663E+01	1.682E+01	1.812E+01	1.940E+01	2.020E+01	**1.554E+01**	1.668E+01	1.772E+01	2.018E+01	2.170E+01
Avg.	11.0192	9.5769	8.0577	9.3654	11.1731	6.6346	6.3846	6.3654	7.4038	9.2692	6.8269	**5.4423**	7.9615	6.1154	8.4038
Winner	1/26	2/26	5/26	2/26	2/26	8/26	5/26	5/26	5/26	2/26	4/26	**9/26**	3/26	8/26	5/26

Table 4: The experimental results for D=60

F.No	GSO$_{31}$	GSO$_{32}$	GSO$_{33}$	GSO$_{34}$	GSO$_{35}$	GSO$_{51}$	GSO$_{52}$	GSO$_{53}$	GSO$_{54}$	GSO$_{55}$	GSO$_{91}$	GSO$_{92}$	GSO$_{93}$	GSO$_{94}$	GSO$_{95}$
F1	3.783E-02	3.334E+02	1.684E+03	3.341E+02	4.116E-02	0.000E+00	1.532E-05	**0.000E+00**	3.337E-02	8.722E-02	6.930E+00	1.148E-03	7.070E+00	3.302E+02	5.293E-03
F2	8.721E+05	1.189E+05	4.630E+06	1.571E+06	3.531E+06	2.507E+06	2.810E+05	1.654E+06	1.242E+04	5.298E+05	1.664E+04	2.129E+06	2.149E+05	**1.125E+04**	1.777E+05
F3	1.182E-04	5.453E-03	1.754E-05	1.286E-05	6.815E+00	2.944E+01	**0.000E+00**	6.546E-04	**0.000E+00**	1.251E-02	6.233E-04	4.638E-02	1.777E-05	2.485E-08	**0.000E+00**
F4	3.370E+15	3.333E+00	3.333E+19	3.333E+21	3.334E+18	3.333E+20	7.033E+05	3.333E+02	3.333E+27	2.891E+02	**6.046E-11**	3.667E+09	2.400E-08	5.633E-09	5.388E-04
F5	2.340E+00	1.689E+00	3.469E-01	3.802E+00	3.105E+00	3.355E-01	**0.000E+00**	1.886E-02	3.413E+00	1.060E+00	3.333E-01	1.889E+00	7.591E-01	3.520E-01	3.573E-01
F6	2.519E-04	1.020E-03	7.579E-02	**0.000E+00**	**0.000E+00**	**0.000E+00**	4.345E-03	7.258E-05	8.537E-03	1.646E-03	**0.000E+00**	4.372E-04	2.683E-05	2.209E-01	1.895E-03
F7	**0.000E+00**	**0.000E+00**	3.333E+02	3.333E+02	1.157E+01	**0.000E+00**	**0.000E+00**	**0.000E+00**	**0.000E+00**	**0.000E+00**	**0.000E+00**	**0.000E+00**	**0.000E+00**	**0.000E+00**	**0.000E+00**
F8	**0.000E+00**	2.865E-14	3.846E-13	6.366E-07	3.675E-11	**0.000E+00**	9.115E-09	5.973E-09	1.852E-13	1.937E-05	**0.000E+00**	7.119E-13	7.179E-16	1.536E-19	8.948E-02
F9	4.325E-05	**1.265E-04**	7.460E-05	9.232E-05	1.724E-04	7.587E-05	1.727E-04	7.377E-05	3.739E-04	4.340E-04	1.033E-04	7.708E-05	1.790E-01	9.661E-05	1.965E-04
F10	6.236E+01	7.397E+01	7.527E+01	5.864E+01	5.868E+01	5.843E+01	5.856E+01	5.859E+01	5.870E+01	5.863E+01	**5.262E+01**	5.449E+01	5.654E+01	5.852E+01	5.860E+01
F11	1.846E+01	1.344E+01	**0.000E+00**	6.749E+00	1.246E+01	4.116E+00	3.446E-01	7.791E+00	4.536E+00	1.121E-03	3.857E+00	3.110E-02	5.093E+00	6.635E+00	1.928E+00
F12	9.201E+00	1.948E+00	7.734E+00	1.755E+01	1.417E+01	5.200E+00	1.185E+00	**2.511E-03**	6.120E+00	8.333E-01	5.333E-01	4.225E+00	9.175E-01	6.568E-01	6.363E+00
F13	2.065E-02	**0.000E+00**	3.430E-03	2.129E-02	4.346E-03	8.607E-04	1.751E-02	2.472E-02	3.891E-03	7.032E-03	1.024E-01	**0.000E+00**	4.461E-02	1.176E-02	2.330E-02
F14	9.655E+03	8.655E+03	9.518E+03	8.694E+03	8.460E+03	7.996E+03	7.500E+03	7.699E+03	8.325E+03	8.520E+03	8.324E+03	7.856E+03	8.032E+03	**7.268E+03**	8.157E+03
F15	2.419E+00	1.977E+00	2.408E+00	4.603E-01	1.556E+00	3.762E-01	9.143E-01	8.350E-01	1.042E+00	7.386E-01	**1.300E-04**	7.563E-01	2.208E-02	1.074E-03	6.088E-01
F16	1.317E-01	1.476E-01	1.739E-01	1.614E-01	2.105E-01	9.697E-02	1.029E-01	1.231E-01	1.678E-01	1.615E-01	**6.150E-02**	8.101E-02	9.936E-02	8.553E-02	1.309E-01
F17	4.663E+00	4.575E+00	4.611E+00	4.760E+00	4.999E+00	4.518E+00	4.493E+00	4.708E+00	4.705E+00	4.756E+00	4.114E+00	4.266E+00	**4.057E+00**	4.473E+00	4.778E+00
F18	1.558E-01	5.713E-04	1.188E+00	3.057E-01	7.349E-01	3.427E-03	8.095E-01	3.108E-03	2.283E-01	1.630E-01	2.279E-04	8.670E-01	**0.000E+00**	6.857E-01	2.653E-02
F19	4.747E+01	4.558E+01	4.773E+01	5.154E+01	4.611E+01	4.031E+01	4.367E+01	4.264E+01	4.859E+01	4.672E+01	**3.553E+01**	3.836E+01	3.834E+01	4.103E+01	4.323E+01
F20	4.756E-01	3.372E-02	1.433E-01	3.069E-01	1.224E+00	1.294E+00	**5.333E-01**	1.256E-03	9.671E-01	1.333E-01	5.630E-01	8.050E-01	7.315E-01	4.175E-01	2.849E-01
F21	1.653E-02	1.653E-02	3.239E-04	1.810E-02	2.805E-03	2.267E-05	4.992E-02	4.557E-03	1.565E-03	3.847E-03	**0.000E+00**	**0.000E+00**	1.777E-02	1.686E-02	2.262E-02
F22	5.765E+04	4.009E+04	4.300E+04	**1.555E+04**	3.080E+04	4.191E+04	5.004E+04	3.843E+04	3.577E+04	4.048E+04	3.298E+04	5.748E+04	4.463E+04	3.310E+04	1.987E+04
F23	5.614E+02	4.985E+02	**5.833E+02**	6.080E+02	6.370E+02	5.609E+02	5.025E+02	5.525E+02	5.454E+02	5.933E+02	5.685E+02	5.081E+02	5.514E+02	5.554E+02	6.206E+02
F24	5.585E+02	3.255E+02	4.429E+02	3.573E+02	2.679E+02	3.195E+02	**2.276E+02**	5.130E+02	2.973E+02	2.912E+02	6.806E+02	4.343E+02	2.944E+02	4.039E+02	3.972E+02
F25	1.765E+01	1.686E+01	1.756E+01	1.841E+01	1.784E+01	1.734E+01	1.707E+01	1.768E+01	1.842E+01	1.879E+01	1.654E+01	**1.583E+01**	1.727E+01	1.651E+01	1.797E+01
F26	6.148E+01	5.747E+01	6.313E+01	5.997E+01	6.886E+01	5.567E+01	6.029E+01	5.972E+01	5.978E+01	7.007E+01	**5.427E+01**	5.797E+01	6.237E+01	6.025E+01	6.642E+01
Avg.	9.8077	7.6346	10.1731	10.3462	10.7115	6.2885	7.1346	6.9231	8.9423	9.0577	**4.9423**	6.6346	6.7885	6.1346	8.4808
Winner	3/26	3/26	1/26	2/26	1/26	4/26	4/26	4/26	2/26	1/26	**10/26**	4/26	3/26	3/26	2/26

Table 5: The experimental results for D=100

F.No	GSO_{31}	GSO_{32}	GSO_{33}	GSO_{34}	GSO_{35}	GSO_{51}	GSO_{52}	GSO_{53}	GSO_{54}	GSO_{55}	GSO_{91}	GSO_{92}	GSO_{93}	GSO_{94}	GSO_{95}
F1	1.000E+03	1.000E+03	2.000E+03	1.335E+03	2.750E+00	**0.000E+00**	6.974E-04	3.333E+02	1.027E-01	7.761E-02	3.178E-04	3.089E-03	1.126E-03	1.483E-02	3.901E-02
F2	4.483E+07	1.797E+07	2.939E+06	7.666E+06	2.289E+07	1.761E+06	1.055E+06	2.539E+06	**8.160E+04**	9.640E+06	1.120E+06	8.818E+05	3.244E+07	1.277E+06	9.608E+04
F3	7.400E+02	5.797E+02	3.300E+02	2.337E+02	2.631E+02	6.966E+00	3.334E+00	2.173E+02	4.151E+02	3.060E+00	**0.000E+00**	7.017E-08	3.392E-02	1.014E-03	5.871E-02
F4	3.667E+27	3.333E+66	3.337E+61	3.333E+62	3.333E+63	3.333E+18	7.000E+17	3.333E+36	3.333E+47	5.264E+35	**7.994E-15**	3.333E+19	3.333E+38	3.367E+02	3.333E+34
F5	5.020E+00	2.745E+00	2.050E+00	1.340E+00	5.336E+00	3.007E+00	1.669E+00	2.711E+00	4.250E-01	9.699E-01	7.025E-02	5.341E-01	4.537E-01	**4.073E-02**	2.020E+00
F6	**0.000E+00**	**0.000E+00**	1.348E-03	**0.000E+00**	3.705E-05	1.051E-03	**0.000E+00**	2.509E-04	**0.000E+00**	7.542E-04	8.711E-04	**0.000E+00**	**0.000E+00**	**0.000E+00**	**0.000E+00**
F7	1.667E+03	1.333E+03	2.333E+03	**0.000E+00**	3.588E+03	**0.000E+00**	**0.000E+00**	**0.000E+00**	3.333E+02	**0.000E+00**	**0.000E+00**	**0.000E+00**	**0.000E+00**	**0.000E+00**	6.667E+02
F8	**0.000E+00**	**0.000E+00**	3.943E-07	3.579E-01	3.786E-08	3.178E-13	3.866E-12	2.833E-06	**0.000E+00**	**0.000E+00**	2.869E-13	1.687E-10	2.870E-16	1.734E-11	**0.000E+00**
F9	3.798E-05	**6.442E-05**	4.474E-01	6.968E-05	8.949E-01	6.306E-05	6.236E-05	1.799E-04	2.366E-04	2.129E-03	3.580E-01	4.909E-05	1.757E-04	1.157E-04	1.537E-04
F10	9.845E+01	9.865E+01	9.980E+01	9.863E+01	9.873E+01	9.838E+01	9.849E+01	9.853E+01	9.873E+01	9.866E+01	1.001E+02	**9.837E+01**	9.838E+01	9.845E+01	9.872E+01
F11	1.529E+01	1.197E+01	2.078E+01	1.735E+01	7.969E+00	1.298E+01	7.098E+00	3.795E+00	2.928E+00	9.996E+00	**0.000E+00**	1.465E+00	9.700E+00	2.883E+00	5.156E+00
F12	2.135E+01	2.834E+01	1.480E+01	5.533E+01	1.238E+01	9.479E+00	2.618E+00	1.731E+01	4.606E+00	1.540E+01	**1.721E+00**	1.110E+01	7.314E+00	1.681E+01	3.218E+00
F13	3.908E+01	6.029E+00	2.115E+01	3.018E+00	6.048E+00	4.895E-02	8.618E-05	1.176E-05	1.309E+00	5.870E-02	**0.000E+00**	**0.000E+00**	4.920E-03	1.051E-03	4.665E-02
F14	1.772E+04	1.851E+04	1.797E+04	1.842E+04	1.871E+04	1.647E+04	1.682E+04	1.696E+04	1.685E+04	1.715E+04	1.603E+04	1.569E+04	**1.502E+04**	1.645E+04	1.656E+04
F15	2.938E+00	1.762E+00	2.933E+00	1.592E+00	2.419E+00	1.177E+00	7.454E-01	2.411E+00	2.355E+00	1.256E+00	1.083E+00	**3.231E-01**	9.943E-01	8.454E-01	6.589E-01
F16	2.055E-01	1.974E-01	2.539E-01	3.385E-01	3.582E-01	**1.385E-01**	1.956E-01	1.862E-01	1.710E-01	2.835E-01	1.791E-01	1.569E-01	1.622E-01	1.738E-01	1.858E-01
F17	8.724E+00	8.777E+00	8.919E+00	8.896E+00	9.093E+00	8.516E+00	8.655E+00	8.699E+00	8.828E+00	8.977E+00	**8.081E+00**	8.110E+00	8.229E+00	8.406E+00	8.762E+00
F18	1.153E+00	9.453E-01	2.353E+00	7.587E-01	2.346E+00	6.133E-03	**4.614E-03**	7.386E-01	6.609E-01	3.795E-01	3.189E-01	1.964E-01	6.183E-01	3.940E-01	1.498E-01
F19	8.593E+01	8.716E+01	8.838E+01	8.686E+01	9.012E+01	9.107E+01	8.600E+01	8.796E+01	8.394E+01	8.536E+01	**7.801E+01**	8.066E+01	8.658E+01	8.105E+01	9.456E+01
F20	2.267E+00	3.068E+00	1.847E+00	1.109E+00	4.224E-01	4.572E-01	8.623E-01	2.756E-01	1.099E+00	4.360E-01	1.057E+00	8.498E-01	6.847E-01	**2.533E-02**	8.765E-01
F21	3.774E-02	3.316E-02	1.686E-02	3.933E-02	5.018E-02	3.239E-04	1.842E-02	8.237E-03	2.553E-02	2.567E-02	**0.000E+00**	1.695E-02	2.482E-03	2.193E-02	3.315E-02
F22	1.635E+05	1.435E+05	8.280E+04	1.376E+05	1.140E+05	1.574E+05	9.661E+04	1.010E+05	1.365E+05	1.110E+05	1.207E+05	1.334E+05	1.377E+05	1.164E+05	**7.613E+04**
F23	1.164E+03	1.107E+03	1.188E+03	1.182E+03	1.141E+03	1.205E+03	**1.055E+03**	1.085E+03	1.080E+03	1.222E+03	1.163E+03	1.159E+03	1.076E+03	1.128E+03	1.120E+03
F24	1.075E+03	9.720E+02	1.227E+03	7.509E+02	7.966E+02	1.452E+03	1.181E+03	1.343E+03	7.020E+02	8.397E+02	1.151E+03	8.962E+02	1.097E+03	**6.644E+02**	9.050E+02
F25	1.995E+01	2.000E+01	**1.980E+01**	2.033E+01	2.041E+01	2.042E+01	2.027E+01	2.004E+01	2.031E+01	2.026E+01	2.031E+01	2.018E+01	2.023E+01	1.997E+01	2.031E+01
F26	1.384E+02	1.414E+02	1.428E+02	1.470E+02	1.487E+02	1.392E+02	1.421E+02	1.320E+02	1.420E+02	1.464E+02	1.410E+02	**1.314E+02**	1.414E+02	1.373E+02	1.449E+02
Avg.	10.0769	10.2692	11.6154	10.7692	11.7885	7.5577	5.7308	7.9615	7.6346	8.6923	5.6346	**4.2885**	6.1154	4.8269	7.0385
Winner	3/26	2/26	1/26	2/26	0/26	3/26	4/26	1/26	3/26	2/26	**9/26**	6/26	3/26	5/26	3/26

4. Results and Discussion

In this chapter, 15 parameter sets designed in chapter 3 are tested using 26 benchmark functions and their results analyzed. Experimental study results were obtained by taking the mean of 30 independent runs. The mean test results in 30, 60, and 100 dimensions are presented in Tables 3, 4, and 5, respectively. In addition, in the last two rows of the tables, the average of the results obtained by the average of the means (Avg.) and the number of the best results (Winner) are given. The best results obtained in the tables are shown in bold.

When the results obtained for 30 dimensions were analyzed, the GSO_{92} method reached more successful results in terms of both Average and Winner than other methods. The GSO_{92} method achieved the best value in 9 out of 26 benchmark functions. In addition, it obtained the best Avg value with 5.4423. When the results in Table 5 are examined, the best method for 60 dimensions is GSO_{91}. The GSO_{91} method reached the best value in 10 benchmark functions, and its average value is 4.9423. In the results obtained for 100 dimensions, the GSO_{92} method reached the best result in terms of Average, while the GSO_{91} method obtained a better result in terms of winner. The average value of the GSO_{92} method is 4.2885. The GSO_{91} method achieved the best results in 9 out of 26 benchmark functions. When the Average and Winner results obtained from all methods are analyzed, it is seen that the results of some methods are the same or very close. Therefore, determining which method is more successful becomes a complicated situation. At this point, the results obtained should be analyzed statistically. Friedman test is often used in the literature [31-33] to rank the results of multiple methods. The Friedman test [34] is a nonparametric statistical test. It is particularly suitable for situations where the results of more than one classifier are evaluated. The level of significance is set at 0.05 for the Friedman test. This means that if the p-Value is less than 0.05, there is a statistically significant difference between the results. Otherwise, there is no significant difference. In this study, the 15 methods were ranked by using the Friedman ranking test for the mean values. The mean rank, final rank, and p-Value values obtained in the Friedman ranking test result are given in Table 6. Mean ranking histograms of all dimensions are shown in Fig. 2.

Table 6: The Friedman ranking results of all methods

D		GSO_{31}	GSO_{32}	GSO_{33}	GSO_{34}	GSO_{35}	GSO_{51}	GSO_{52}	GSO_{53}	GSO_{54}	GSO_{55}	GSO_{91}	GSO_{92}	GSO_{93}	GSO_{94}	GSO_{95}
30	*Mean Rank*	11.0192	9.5769	8.0577	9.3654	11.1731	6.6346	6.3846	6.3654	7.4038	9.2692	6.8269	**5.4423**	7.9615	6.1154	8.4038
	Final Rank	14	13	9	12	15	5	4	3	7	11	6	**1**	8	2	10
	p-Value	**1.63E-07**														
60	*Mean Rank*	9.8077	7.6346	10.1731	10.3462	10.7115	6.2885	7.1346	6.9231	8.9423	9.0577	**4.9423**	6.6346	6.7885	6.1346	8.4808
	Final Rank	12	8	13	14	15	3	7	6	10	11	**1**	4	5	2	9
	p-Value	**1.96E-07**														
100	*Mean Rank*	10.0769	10.2692	11.6154	10.7692	11.7885	7.5577	5.7308	7.9615	7.6346	8.6923	5.6346	**4.2885**	6.1154	4.8269	7.0385
	Final Rank	11	12	14	13	15	7	4	9	8	10	3	**1**	5	2	6
	p-Value	**2.47E-17**														

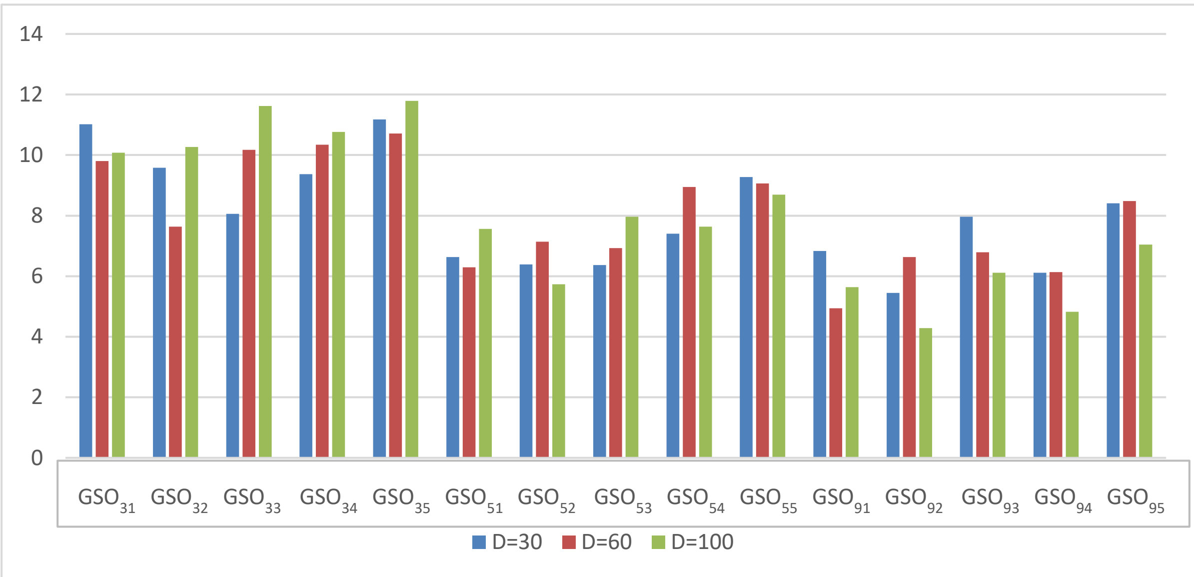

Fig. 2. The Friedman ranking results of all dimensions

When Table 6 is examined, all the p-Value values obtained from the Friedman test performed for each dimension all are smaller than the level of significance (0.05). It shows that there is a statistically significant difference between all results obtained. Final Ranking values also indicate that GSO_{91} and GSO_{92} are more successful than other methods. While the GSO_{92} method reached the best ranking in 30 and 100 dimensions, the GSO_{91} method achieved the best ranking value in 60 dimensions.

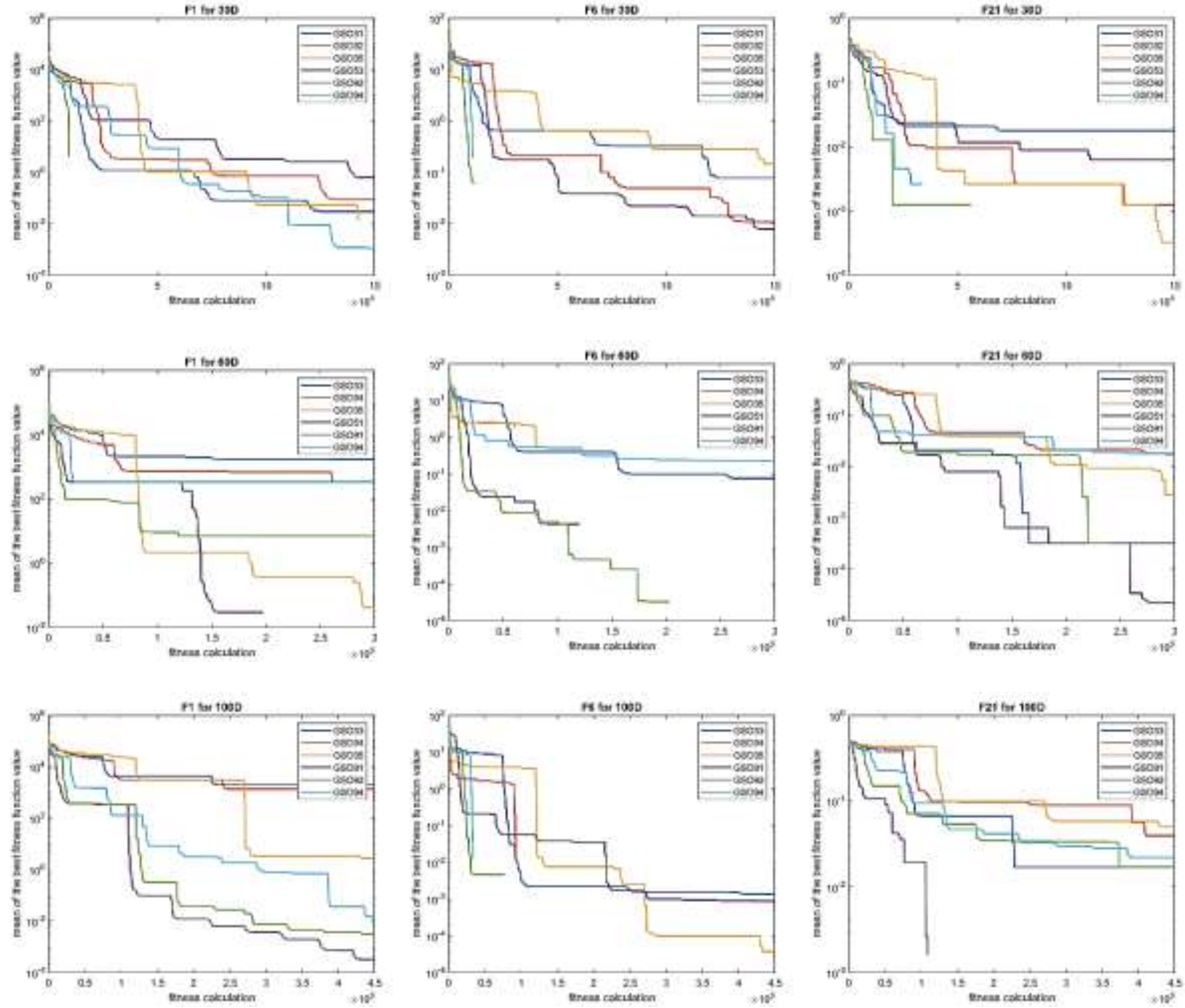

Fig. 3. Convergence curves of F1, F6 and F21 functions in 30, 60 and 100 dimensions

It is not possible to show convergence curves of all methods in all dimensions and functions. For this reason, 6 methods with the best and worst 3 Friedman rank for each dimension were used in the creation of the convergence curves. In Fig. 3, convergence curves have been presented for 30, 60 and 100 dimensions of F1, F6 and F21 functions which have different characteristic. When the convergence graphs are examined, the methods with the EP_{max} parameter of 9 show a better convergence to the optimum solution.

When evaluated as total, methods in which the EP_{max} parameter is determined to be 9 achieve more successful results than other methods. Good results were not obtained in cases where the maximum number of epochs was 3. In general, more fitness evaluation methods in the second phase are more successful than others.

5. Conclusion

In this study, EP_{max}, L_1 and L_2 parameters, which are important parameters of the GSO method, were analyzed. 3, 5, and 9 values for EP_{max} and 5 different balance values for parameters L_1 and L_2 were created. Finally, 15 different parameter sets were analyzed. 26 benchmark functions with different properties were used in the analysis study. For detailed analysis, functions are tested in 30, 60, and 100 dimensions. Successful parameters were revealed by examining the obtained results. Statistical analysis of the results was also concluded in the study.

GSO is an effective framework that can be used as a search method for optimization methods available in the literature. By using different optimization methods under the umbrella of GSO, effective models can be put forward in solving different optimization problems. At this point, the parameter analysis made in this study can be the basis for these studies.

References

[1] Dokeroglu, T., et al., *A survey on new generation metaheuristic algorithms.* Computers & Industrial Engineering, 2019. **137**.

[2] Korkmaz, S. and M.S. Kiran, *An artificial algae algorithm with stigmergic behavior for binary optimization.* Applied Soft Computing, 2018. **64**: p. 627-640.

[3] Holland, J.H., *Genetic Algorithms.* Scientific American, 1992. **267**(1): p. 66-72.

[4] Cheng, S., Y.H. Shi, and Q.D. Qin, *Population Diversity of Particle Swarm Optimizer Solving Single- and Multi-Objective Problems.* Emerging Research on Swarm Intelligence and Algorithm Optimization, 2015: p. 71-98.

[5] Rechenberg, I. *Evolutionsstrategien*. in *Simulationsmethoden in der Medizin und Biologie*. 1978. Berlin, Heidelberg: Springer Berlin Heidelberg.

[6] Storn, R. and K. Price, *Differential Evolution – A Simple and Efficient Heuristic for global Optimization over Continuous Spaces.* Journal of Global Optimization, 1997. **11**(4): p. 341-359.

[7] Kirkpatrick, S., C.D. Gelatt, and M.P. Vecchi, *Optimization by Simulated Annealing.* Science, 1983. **220**(4598): p. 671-680.

[8] Rashedi, E., H. Nezamabadi-Pour, and S. Saryazdi, *GSA: A Gravitational Search Algorithm.* Information Sciences, 2009. **179**(13): p. 2232-2248.

[9] Kaveh, A. and S. Talatahari, *A novel heuristic optimization method: charged system search.* Acta Mechanica, 2010. **213**(3-4): p. 267-289.

[10] Kennedy, J. and R. Eberhart, *Particle swarm optimization.* 1995 Ieee International Conference on Neural Networks Proceedings, Vols 1-6, 1995: p. 1942-1948.

[11] Dorigo, M., V. Maniezzo, and A. Colorni, *Ant system: Optimization by a colony of cooperating agents.* Ieee Transactions on Systems Man and Cybernetics Part B-Cybernetics, 1996. **26**(1): p. 29-41.

[12] Karaboğa, D., *An idea based on honey bee swarm for numerical optimization*, in *Technical Report-TR06*. 2005, Erciyes University, Engineering Faculty, Comput. Eng.Dep.

[13] Mirjalili, S. and A. Lewis, *The Whale Optimization Algorithm.* Advances in Engineering Software, 2016. **95**: p. 51-67.

[14] Yang, X.S. and S. Deb, *Cuckoo Search via Levey Flights.* 2009 World Congress on Nature & Biologically Inspired Computing (Nabic 2009), 2009: p. 210-214.

[15] Uymaz, S.A., G. Tezel, and E. Yel, *Artificial algae algorithm (AAA) for nonlinear global optimization.* Applied Soft Computing, 2015. **31**: p. 153-171.

[16] Pham, D.T., et al., *The Bees Algorithm and mechanical design optimisation.* Icinco 2008: Proceedings of the Fifth International Conference on Informatics in Control, Automation and Robotics, Vol Icso, 2008: p. 250-+.

[17] Yang, X.-S. *Flower Pollination Algorithm for Global Optimization*. 2012. Berlin, Heidelberg: Springer Berlin Heidelberg.

[18] Yang, X.S. and A.H. Gandomi, *Bat algorithm: a novel approach for global engineering optimization.* Engineering Computations, 2012. **29**(5-6): p. 464-483.

[19] Glover, F., *Tabu Search—Part I.* ORSA Journal on Computing, 1989. **1**(3): p. 190-206.

[20] Glover, F., *Tabu Search—Part II.* ORSA Journal on Computing, 1990. **2**(1): p. 4-32.

[21] Geem, Z.W., J.H. Kim, and G.V. Loganathan, *A new heuristic optimization algorithm: Harmony search.* Simulation, 2001. **76**(2): p. 60-68.

[22] Rao, R.V., V.J. Savsani, and D.P. Vakharia, *Teaching-Learning-Based Optimization: An optimization method for continuous non-linear large scale problems.* Information Sciences, 2012. **183**(1): p. 1-15.

[23] Cheng, S., Y.H. Shi, and Q.D. Qin, *Population Diversity Based Study on Search Information Propagation in Particle Swarm Optimization.* 2012 Ieee Congress on Evolutionary Computation (Cec), 2012.

[24] Muthiah-Nakarajan, V. and M.M. Noel, *Galactic Swarm Optimization: A new global optimization metaheuristic inspired by galactic motion.* Applied Soft Computing, 2016. **38**: p. 771-787.

[25] Kaya, E., S.A. Uymaz, and B. Kocer, *Boosting galactic swarm optimization with ABC.* International Journal of Machine Learning and Cybernetics, 2019. **10**(9): p. 2401-2419.

[26] Eberhart, R.C. and Y.H. Shi, *Particle swarm optimization: Developments, applications and resources.* Proceedings of the 2001 Congress on Evolutionary Computation, Vols 1 and 2, 2001: p. 81-86.

[27] Yao, X., Y. Liu, and G.M. Lin, *Evolutionary programming made faster.* Ieee Transactions on Evolutionary Computation, 1999. **3**(2): p. 82-102.

[28] Digalakis, J.G. and K.G. Margaritis, *On benchmarking functions for genetic algorithms.* International Journal of Computer Mathematics, 2001. **77**(4): p. 481-506.

[29] Derrac, J., et al., *A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms.* Swarm and Evolutionary Computation, 2011. **1**(1): p. 3-18.

[30] Gao, W.F., S.Y. Liu, and L.L. Huang, *A Novel Artificial Bee Colony Algorithm Based on Modified Search Equation and Orthogonal Learning.* Ieee Transactions on Cybernetics, 2013. **43**(3): p. 1011-1024.

[31] Wong, G.Y., F.H. Leung, and S.-H. Ling, *A hybrid evolutionary preprocessing method for imbalanced datasets.* Information Sciences, 2018. **454**: p. 161-177.

[32] Babalik, A., A.C. Cinar, and M.S. Kiran, *A modification of tree-seed algorithm using Deb's rules for constrained optimization.* Applied Soft Computing, 2018. **63**: p. 289-305.

[33] Gungor, I., et al., *Integration search strategies in tree seed algorithm for high dimensional function optimization.* International Journal of Machine Learning and Cybernetics, 2020. **11**(2): p. 249-267.

Friedman, M., *A Comparison of Alternative Tests of Significance for the Problem of m Rankings.* Ann. Math. Statist., 1940. **11**(1): p. 86-92.