Enhanced Spider Wasp Optimizer for Function Optimization

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Abstract: **This work introduces a novel Enhanced Spider Wasp Optimizer (ESWO). The proposed ESWO includes a Sobol sequence initialization and Guide-based mutation strategy, coupled with a linear population size reduction technique. The Sobol sequence initialization ensures a more uniform and distributed initial population while the guide-based mutation is designed to improve diversity by incorporating the guidance of two elite solutions. ESWO is compared with some famous algorithms by comparing their outcomes on IEEE CEC 2017 benchmark test suite, comprising twenty-nine diverse functions. Comparative results validate that the ESWO performance is better than that of conventional algorithms.**

Keywords: Metaheuristics, Optimization, Spider Wasp Optimizer, Sobol Initialization, Guide based Mutation

I. INTRODUCTION

Optimization is everywhere, many of our day-to-day decisions are taken by choosing the optimum choice available. Especially engineering and science have inescapable need of optimization. Because metaheuristics optimizations are easy to use and yield reliable results, metaheuristics have become more common than precise approaches for tackling optimization issues. These sectors include engineering, economy, image processing, transportation, and even commerce [1] Bio-inspired algorithms are among the meta-heuristic techniques that have developed the fastest in recent years and are being used to solve engineering problems [2]. Typically, these algorithms optimize mathematical models by imitating the biological functions of living things. These algorithms are of two kinds: single solution and population-based [3]. Methods that utilize a population of individuals are favored over those that rely on a single solution, because they are capable of using information or communicating in between the whole population and efficiently Reveal new sections of the problem's search space [4]. In a population-based metaheuristic, each individual provides a possible solution to the problem. These agents are iteratively updated using various operations. The aim of these operations is to progressively enhance the superiority of the results within the population. Fig. 1 shows the organization of various algorithms.As expressed in the No Free Lunch Theorems [5], no specific optimization technique is best for all problems, which motivates the creation of new algorithms. Every year many nature-inspired optimization algorithms are being introduced in this field. So, to give them a chance to survive, it is necessary to modify their efficiency and robustness. Spider wasp optimizer (SWO) is developed by Mohamed Abdel-Basset et al. [6] in 2023 which is a bio-inspired population-based metaheuristic method. The SWO algorithm is modeled after the searching and nesting behaviors, and the obligate brood parasitism, of several wasp classes that lay a single egg in a spider's belly. Feminine spider wasps first seek for spiders, paralyze them, and then pull them to nests they have prepared in advance; these behaviors serve as the inspiration for the proposed SWO. To improve the execution of SWO, this work uses Sobol initialization, guide-based mutation and linear population size reduction method. This algorithm is abbreviated as ESWO.

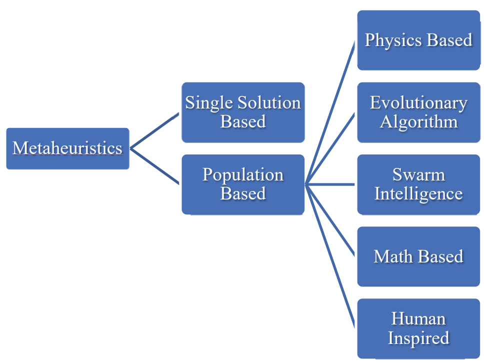

Fig.1 Organization of meta-heuristics

II. SPIDER WASP OPTIMIZER

Grounded in the activities of feminine spider wasps, the SWO algorithm is introduced here with a succinct explanation of its fundamental frameworks.

A. Population initialization

Each spider wasp in SWO may be seen of as a solution to a problem that is expressed by the equation is as follows:

$$\vec{X} = [x_1, x_2, x_3, \dots, x_D] \quad (1)$$

Where X → represents a single female wasp and D stands for the dimension. The following equation (2) is used to start the spider wasp population generation:

$$\vec{X}_i = \vec{L} + \vec{r} \times (\vec{U} - \vec{L}) \quad (2)$$

where is $\vec{r}$ a randomly generated D dimensional vector, in addition, $\vec{L}$ and $\vec{U}$ stands for the inferior and superior limits respectively, of the problem domain.

B. Hunting and Nesting behaviour

The female spider wasp begins by doing an initial search, known as an "exploration operator," to identify potential prey. When it locates its target, it sends a signal to its exploitation operator to begin closing in and attacking. Details of these two operators are provided below.

a) Search Stage (Exploration Operator)

As noted above, the female spider wasp initiates this operator at the start of the hunting method in to locate its preferred victim. This behavior can be modelled mathematically using the following expression:

$$\vec{X}_i^{t+1} = \vec{X}_i^t + \mu_1 * \left(\vec{X}_a^t - \vec{X}_b^t\right) \quad (3)$$

where $\vec{X}_a^t$ and $\vec{X}_b^t$ are two arbitrarily nominated solutions from the existing population. The female wasp's steady forward velocity is calculated using an adaptive factor called μ_1, as mathematically defined in the following equation:

$$\mu_1 = |rn| * r_1 \quad (4)$$

where r_1 is an arbitrarily chosen quantity in the interval [0,1] and rn is another arbitrary number drawn from a normal distribution. Prey that falls from the orb may be lost if the female wasps are unable to catch it. To find the lost prey, they employ a different exploring strategy, which is mathematically defined as follows:

$$\vec{X}_i^{t+1} = \vec{X}_c^t + \mu_2 * \left(\vec{L} + \vec{r_2} * (\vec{H} - \vec{L})\right) \tag{5}$$

$$\mu_2 = B * \cos(2\pi l) \tag{6}$$

$$B = \frac{1}{1+e^l} \tag{7}$$

where $\vec{X}_c^t$ is an arbitrarily chosen solution from the existing population representing the location of the fallen prey. $\vec{r_2}$ is a vector including arbitrary values created in the interval $[0,1]$ and l is chosen between -1 and -2 at random.

$$\vec{X}_i^{t+1} = \begin{cases} \text{Eq. (3)} & r_3 < r_4, \\ \text{Eq. (5)} & \text{otherwise}, \end{cases} \tag{8}$$

where r_3 and r_4 are two arbitrary numbers between zero and one.

b) Following and Escaping stage (diversification and intensification operator)

Wasps use the following formula to calculate new positions in relation to the spiders to capture them at this time:

$$\vec{X}_i^{t+1} = \vec{X}_i^t + C * \left|2 * \vec{r}_5 * \vec{X}_a^t - \vec{X}_i^t\right| \tag{9}$$

$$C = \left(2 - 2 * \left(\frac{t}{t_{\max}}\right)\right) * r_6 \tag{10}$$

where t and $t_{\max}$ stand for the current function assessment and greatest function assessment, correspondingly. $\vec{r_5}$ is a vector that has been given numerical values that range between 0 to 1 and are generated in a random fashion according to the uniform distribution. r_6 is a random number that is created lying inside 0 and 1 according to the uniform distribution. Still, there is a likelihood of spiders to flee from the feminine wasps, so the gap among them would progressively grow. The following equation is applied to mimic these actions in SWO:

$$\vec{X}_i^{t+1} = \vec{X}_i^t * \vec{vc}, \tag{11}$$

where $\overrightarrow{vc}$ is a vector of numerical values that are arbitrarily produced inside the bounds k and $-k$ using normal distribution. k is produced by applying the following formula:

$$k = 1 - 1 * \left(\frac{t}{t_{\max}}\right) \tag{12}$$

$$\vec{X}_i^{t+1} = \begin{cases} Eq \cdot (9) & r_3 < r_4 \\ \text{Eq. (11)} & \text{otherwise} \end{cases}. \tag{13}$$

In SWO, the following equation is used to trade-off between (8) and (13):

$$\vec{X}_i^{t+1} = \begin{cases} \text{Eq. (8)} & p < k \\ \text{Eq. (13)} & \text{otherwise} \end{cases} \tag{14}$$

where p is a number picked at random from the range $[0,1]$ based on the characteristics of the uniform distribution.

c) Nesting behaviour (exploitation operator)

Female wasps tug the broken spider into their nest. Spider wasps can dig and create cells in soil, make mud nests, and exploit pre-existing nests or cavities. Spider wasps have many nesting habits, thus SWO uses two equations to model them. The initial equation mimics drawing the spider to the zone with the best spider to create a nest for the immobilized spider and egg on its belly, as specified in the formula:

$$\vec{X}_i^{t+1} = \vec{X}^* + \cos(2\pi l) * \left(\vec{X}^* - \vec{X}_i^t\right) \tag{15}$$

where $\vec{X}^*$ denotes the optimal solution obtained to this point. The subsequent equation creates the shell in the location of a feminine spider, selected arbitrarily from the search agents. This equality also contains an extra step, which helps to ensure that no two nests are built in the same position. This equation is mathematically described below:

$$\vec{X}_i^{t+1} = \vec{X}_a^t + \mathrm{r}_3 * |\gamma| * \left(\vec{X}_a^t - \vec{X}_i^t\right) + (1 - r_3) * \vec{U} * \left(\vec{X}_b^t - \vec{X}_c^t\right) \tag{16}$$

where γ is a random numerical value selected built by the levy flight, U is a vector consisting of binary values that determine whether or not the additional step size is utilized in the process of updating. Whether or not the additional step size is used can be determined by the following defined factor:

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$$\vec{U} = \begin{cases} 1 & \vec{r_4} > \vec{r_5} \\ 0 & \text{otherwise} \end{cases} \tag{17}$$

where $\vec{r_4}$ and $\vec{r_5}$ are two random vectors from a uniform distribution containing numerical values between zero and one. To update each solution during optimization, (15) and (16) are randomly swapped relating to the following procedure:

$$\vec{X}_i^{t+1} = \begin{cases} Eq \cdot (15) & r_3 < r_4 \\ \text{Eq. } (16) & \text{otherwise} \end{cases} \tag{18}$$

At last, during SWO optimization, the following formula is used to swap out the hunting behaviours defined using (14) and the nesting behaviours defined using (18):

$$\vec{X}_i^{t+1} = \begin{cases} \text{Eq.}(14) & i < N * k \\ \text{Eq.}(18) & \text{otherwise} \end{cases} \tag{19}$$

C. Mating behaviour

The method by which SWO generates new wasp eggs is characterized by the following equation:

$$\vec{X}_i^{t+1} = \text{Crossover}\left(\vec{X}_i^t, \vec{X}_m^t, \text{Cr}\right) \tag{20}$$

where $\vec{X}_m^t$ and $\vec{X}_i^t$ are two vectors for the female and male spider wasps, respectively, and Crossover is the uniform crossover operator applied to $\vec{X}_m^t$ and $\vec{X}_i^t$ with a probability, Cr. To identify masculine wasps from feminine, the subsequent method is employed in SWO:

$$\vec{X}_m^{t+1} = \vec{X}_i^t + \boldsymbol{e}^l * |\beta| * \vec{v}_1 + (1 - \boldsymbol{e}^l) * |\beta_1| * \vec{v}_2 \tag{21}$$

where β and β_1 are two arbitrarily selected numbers from the normal distribution, and $\vec{v}_1$ and $\vec{v}_2$ are two vectors generated by the following formula:

$$\vec{v}_1 = \begin{cases} \vec{X}_a - \vec{X}_i & f(\vec{X}_a) < f(\vec{X}_i) \\ \vec{X}_i - \vec{X}_a & \text{otherwise} \end{cases} \tag{22}$$

$$\vec{v}_2 = \begin{cases} \vec{X}_b - \vec{X}_c & f(\vec{X}_b) < f(\vec{X}_c) \\ \vec{X}_c - \vec{X}_b & \text{otherwise} \end{cases} \tag{23}$$

The trade-off factor TR is responsible for the compromise between equations (19) and (20).

III. PROPOSED ENHANCED SWO

In metaheuristic algorithms, initialization of population in the search domain is an important factor. Here, random initialization may generate bulk of populations in one portion of search space, for this Sobol sequence initialization is used to generate equally distributed random solutions. Exploration and exploitation are another two important factor of metaheuristics algorithm, looking towards these factors good exploitation is necessary to get optimal solution. In SWO, exploitation is not good because of choosing randomly one spider wasp. So, to overcome this problem authors introduced guide-based mutation. For better exploration in initial iterations and exploitation in later iterations, population reduction over iterations is justified. In this proposed ESWO, we incorporated linear population size reduction method to achieve this.

A. *Sobol initialization*

The Sobol sequence was mainly suggested by Russian mathematician Ilya M. Sobol. The Sobol sequence is a quasi-random number generator that is used to create a more evenly distributed set of initial candidate solutions [7]. Compared to traditional random number generators, Sobol initialization annihilates the problem of biased or uneven distribution. Due to this Sobol initialization, no region of the search space will be left completely unexplored, which is a great benefit for the algorithm to start with.

B. *Guide based mutation*

Guide based Mutation is an idea that uses the top solutions observed to this point (the "guides") to guide the mutation process. In SWO, the authors have used random individuals to perform mutation as shown in equation (9).

The proposed guide-based mutation which replaces equation (9) in this algorithm is

$$\vec{X}_i^{t+1} = \vec{X}_i^t + |C| * ((\mathrm{r}_7 * \vec{X}_i^{Best} - \vec{X}_i^t) + (\mathrm{r}_8 * \vec{X}_i^{SecondBest} - \vec{X}_i^t)) \tag{24}$$

Here, the random individuals are replaced by the two best scoring individuals. These two best scoring individuals will guide the next position of the individual towards some optimal points. This mutation ultimately ensures good exploitation.

C. *Linear population size reduction*

In SWO, the authors have used the 'fix' function to reduce the population size over iterations, which is an inbuilt MATLAB function. But this reduction is very rapid and reduces the population to its minimum in a few initial iterations only. This results in poor initial exploration, which is a drawback. To rectify this issue, we instead added the linear population size reduction (LPSR). LPSR was used to make LSHADE by Tanabe and Fukunaga [8]. The LPSR technique employs a function that constantly decreases the size of

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the search agents. The population size that is employed has a big impact on regulating the pace of convergence. Although smaller populations lead to quicker convergence, there is a greater chance of reaching a local optimum. Large population numbers, on the other hand, tend to slow down the rate of convergence but can promote more thorough investigation of the domain. In the primary phases of the exploration route, the LPSR aids in exploration; in later iterations, it gradually moves toward exploitation. At generation 1, there are Ninit individuals, and at the end of the run, there are $Nmin$ individuals. Following each generation G, the subsequent generation's size, N(G+1), is calculated using the following method:

$$N_{G+1} = \ round\left[\left(\frac{N^{min}-N^{init}}{NFE_{MAX}}\right).NFE + N^{init}\right] \tag{25}$$

N^{min} is set to the minimum possible value, N^{min} = 4. NFE is the present number of fitness assessments, and NFE_{MAX} represents the maximum number of function assessments. When $N_{G+1} < N_G$, the (N_G – N_{G+1}) lowest-grade agents are removed from the existing search agents.

IV. EXPERIMENTAL SETUP

We study the strength and ability of the projected ESWO by comparing it with some renowned algorithms such as: DE (Differential evolution) [9], GWO (Grew Wolf Optimizer) [10], PSO (Particle Swarm Optimization) [11], WOA (Whale Optimization algorithm) [12], TLBO (Teaching Learning Based Optimization) [13] and PO (Puma Optimizer) [14] and SWO. The IEEE CEC 2017 test functions [15] for Single Objective Real-Parameter Numerical Optimization with dimension 10 was used for our comparisons. The tests were carried out on a Windows 11 Pro PC with Intel(R) Core (TM) i7-12700 CPU (2.10 GHz), 8 GB of RAM, and RAM. MATLAB R2022b was used to evaluate the algorithm results. Every algorithm was allocated 50 thousand function assessments for each run, starting with a population of 50, in order to maintain fairness. The simulated outcomes are displayed in Table 1.

TABLE 1: RESULTS OF ESWO WITH BASIC ALGORITHMS ON IEEE CEC 2017 BENCHMARK WITH D=10

Test Functions		SWO	ESWO	DE	GWO	PSO	WOA	TLBO	PO
F1	Mean	**1.0000E+02**	**1.0000E+02**	**1.0000E+02**	4.5508E+06	2.5916E+03	9.9676E+05	1.1474E+03	1.9469E+02
	Best	**1.0000E+02**	**1.0000E+02**	**1.0000E+02**	7.3568E+03	1.0754E+02	2.2255E+04	1.0070E+02	1.0007E+02
	std	**4.1036E-09**	**4.2476E-08**	**0.0000E+00**	1.0544E+07	2.1667E+03	1.1722E+06	1.1581E+03	1.8053E+02
F2	Mean	**3.0000E+02**	**3.0000E+02**	**3.0000E+02**	1.3505E+03	3.0000E+02	1.8481E+03	**3.0000E+02**	3.0000E+02
	Best	**3.0000E+02**	**3.0000E+02**	**3.0000E+02**	3.0191E+02	3.0000E+02	4.1221E+02	**3.0000E+02**	3.0000E+02
	std	**1.3099E-13**	**1.1802E-13**	**0.0000E+00**	1.3875E+03	6.0550E-06	1.7451E+03	**7.0800E-14**	7.7242E-05

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F3	Mean	4.0006E+02	**4.0001E+02**	4.0247E+02	4.0973E+02	4.0380E+02	4.2574E+02	4.0026E+02	4.0136E+02
	Best	4.0000E+02	**4.0000E+02**	4.0041E+02	4.0283E+02	4.0099E+02	4.0393E+02	4.0000E+02	4.0016E+02
	std	7.3679E-02	**9.6746E-03**	9.7071E-01	1.0304E+01	9.9336E-01	2.5719E+01	9.2665E-01	6.1758E-01
F4	Mean	5.0726E+02	**5.0604E+02**	5.1581E+02	5.1709E+02	5.0869E+02	5.4596E+02	5.1035E+02	5.1588E+02
	Best	5.0199E+02	**5.0298E+02**	5.0298E+02	5.0797E+02	5.0298E+02	5.2002E+02	5.0497E+02	5.0199E+02
	std	3.3374E+00	**2.3067E+00**	9.6514E+00	7.5419E+00	3.3238E+00	1.4984E+01	3.1243E+00	7.9779E+00
F5	Mean	6.0000E+02	6.0000E+02	**6.0000E+02**	6.0040E+02	6.0000E+02	6.3717E+02	6.0007E+02	6.0000E+02
	Best	6.0000E+02	6.0000E+02	**6.0000E+02**	6.0005E+02	6.0000E+02	6.1128E+02	6.0000E+02	6.0000E+02
	std	2.0808E-06	2.7041E-07	**6.6759E-14**	5.7121E-01	3.7758E-07	1.4416E+01	2.0525E-01	6.7038E-03
F6	Mean	7.1715E+02	**7.1659E+02**	7.3261E+02	7.2954E+02	7.2002E+02	7.8109E+02	7.1810E+02	7.2735E+02
	Best	7.0543E+02	**7.1060E+02**	7.1656E+02	7.1696E+02	7.0991E+02	7.4652E+02	7.1169E+02	7.1577E+02
	std	4.2952E+00	**2.3842E+00**	6.3728E+00	1.0224E+01	6.0393E+00	2.3647E+01	3.6548E+00	5.4848E+00
F7	Mean	8.0892E+02	**8.0647E+02**	8.1587E+02	8.1471E+02	8.1014E+02	8.4202E+02	8.0807E+02	8.1529E+02
	Best	8.0199E+02	**8.0298E+02**	8.0398E+02	8.0445E+02	8.0300E+02	8.2091E+02	8.0199E+02	8.0398E+02
	std	4.1353E+00	**2.2133E+00**	9.1359E+00	7.4208E+00	3.6730E+00	1.1610E+01	3.5205E+00	5.8803E+00
F8	Mean	**9.0000E+02**	**9.0000E+02**	**9.0000E+02**	9.0956E+02	**9.0000E+02**	1.4393E+03	9.0020E+02	9.0014E+02
	Best	**9.0000E+02**	**9.0000E+02**	**9.0000E+02**	9.0004E+02	**9.0000E+02**	9.9200E+02	9.0000E+02	9.0000E+02
	std	**5.9711E-14**	**4.2222E-14**	**0.0000E+00**	1.6371E+01	**1.0556E-13**	4.7446E+02	3.4227E-01	3.4902E-01
F9	Mean	1.2766E+03	**1.1979E+03**	1.9237E+03	1.5969E+03	1.3859E+03	2.0853E+03	1.3525E+03	1.5036E+03
	Best	1.0070E+03	**1.0004E+03**	1.0153E+03	1.0198E+03	1.1219E+03	1.2594E+03	1.0035E+03	1.0153E+03
	std	1.6713E+02	**1.0378E+02**	2.9889E+02	3.0892E+02	2.0156E+02	3.8831E+02	2.3435E+02	2.5000E+02
F10	Mean	1.1024E+03	1.1019E+03	**1.1009E+03**	1.1413E+03	1.1049E+03	1.1858E+03	1.1085E+03	1.1056E+03
	Best	1.1000E+03	1.1000E+03	**1.1000E+03**	1.1023E+03	1.1005E+03	1.1167E+03	1.1021E+03	1.1000E+03
	std	1.5420E+00	1.3291E+00	**8.1571E-01**	4.3252E+01	3.0561E+00	7.1020E+01	5.8367E+00	4.1877E+00
F11	Mean	1.3961E+03	1.3868E+03	**1.2391E+03**	6.2867E+05	2.6239E+04	5.3821E+06	8.7877E+03	1.4424E+04
	Best	1.2057E+03	1.2003E+03	**1.2000E+03**	3.8132E+03	2.1793E+03	2.3858E+04	2.4453E+03	1.3625E+03
	std	1.3764E+02	1.1518E+02	**6.4326E+01**	8.0130E+05	1.7875E+04	5.7884E+06	4.3596E+03	1.4193E+04
F12	Mean	1.3072E+03	1.3068E+03	**1.3026E+03**	9.1735E+03	8.2310E+03	1.5069E+04	2.4339E+03	1.3105E+03
	Best	1.3000E+03	1.3000E+03	**1.3000E+03**	1.8643E+03	1.3065E+03	1.9326E+03	1.3930E+03	1.3048E+03
	std	4.6781E+00	4.7082E+00	**2.4316E+00**	5.4338E+03	8.5080E+03	1.1483E+04	8.0213E+02	3.4858E+00
F13	Mean	1.4017E+03	**1.4011E+03**	1.4012E+03	2.5902E+03	1.4379E+03	2.0170E+03	1.4303E+03	1.4084E+03
	Best	1.4000E+03	**1.4000E+03**	1.4000E+03	1.4485E+03	1.4033E+03	1.4811E+03	1.4109E+03	1.4008E+03
	std	1.0500E+00	**9.1824E-01**	3.6201E+00	1.7178E+03	1.4662E+01	1.0311E+03	7.8767E+00	2.6976E+01
F14	Mean	1.5008E+03	1.5008E+03	**1.5002E+03**	4.6724E+03	1.5782E+03	6.8455E+03	1.5407E+03	1.5022E+03
	Best	1.5000E+03	1.5000E+03	**1.5000E+03**	1.5539E+03	1.5051E+03	1.7301E+03	1.5169E+03	1.5001E+03
	std	7.3255E-01	5.8398E-01	**2.9798E-01**	4.1920E+03	7.8523E+01	4.3677E+03	2.0784E+01	1.4091E+00
	Mean	1.6163E+03	1.6008E+03	**1.6006E+03**	1.7288E+03	1.6198E+03	1.8974E+03	1.6157E+03	1.6767E+03

F15	Best	1.6000E+03	1.6000E+03	**1.6000E+03**	1.6108E+03	1.6001E+03	1.6213E+03	1.6005E+03	1.6004E+03
	std	4.0988E+01	2.1223E+00	**2.9305E-01**	1.1890E+02	4.7409E+01	1.5655E+02	3.6705E+01	7.5036E+01
F16	Mean	1.7018E+03	**1.7010E+03**	1.7011E+03	1.7625E+03	1.7309E+03	1.8030E+03	1.7314E+03	1.7191E+03
	Best	1.7000E+03	**1.7000E+03**	1.7000E+03	1.7271E+03	1.7013E+03	1.7408E+03	1.7069E+03	1.7013E+03
	std	3.0278E+00	**6.4800E-01**	2.2144E+00	3.4427E+01	2.7316E+01	5.0738E+01	1.0791E+01	1.2878E+01
F17	Mean	1.8006E+03	**1.8006E+03**	1.8010E+03	2.8626E+04	8.4125E+03	1.8583E+04	5.3550E+03	1.8049E+03
	Best	1.8000E+03	**1.8000E+03**	1.8000E+03	6.1444E+03	2.1688E+03	2.3437E+03	2.1756E+03	1.8003E+03
	std	5.0743E-01	**4.7703E-01**	3.6493E+00	1.1761E+04	6.1995E+03	1.1676E+04	3.1249E+03	6.6232E+00
F18	Mean	1.9001E+03	1.9000E+03	**1.9000E+03**	7.1497E+03	2.0170E+03	3.9507E+04	1.9196E+03	1.9010E+03
	Best	1.9000E+03	1.9000E+03	**1.9000E+03**	1.9100E+03	1.9067E+03	2.0008E+03	1.9057E+03	1.9000E+03
	std	2.5504E-01	3.9250E-02	**2.1490E-02**	5.8295E+03	1.4184E+02	6.9628E+04	1.0398E+01	6.0578E-01
F19	Mean	2.0002E+03	**2.0002E+03**	2.0004E+03	2.0744E+03	2.0188E+03	2.1871E+03	2.0182E+03	2.0042E+03
	Best	2.0000E+03	**2.0000E+03**	2.0000E+03	2.0125E+03	2.0003E+03	2.0636E+03	2.0016E+03	2.0000E+03
	std	4.3746E-01	**4.2602E-01**	3.9643E-01	5.7300E+01	3.2534E+01	7.8040E+01	8.6357E+00	5.8583E+00
F20	Mean	2.2445E+03	**2.2070E+03**	2.2864E+03	2.3086E+03	2.2806E+03	2.3390E+03	2.2190E+03	2.2227E+03
	Best	2.2000E+03	**2.2000E+03**	2.2000E+03	2.2041E+03	2.2001E+03	2.2079E+03	2.2000E+03	2.2000E+03
	std	5.5505E+01	**2.6684E+01**	5.3768E+01	2.8906E+01	5.2400E+01	3.8074E+01	4.0540E+01	4.4844E+01
F21	Mean	2.2945E+03	**2.2770E+03**	2.2970E+03	2.3303E+03	2.3022E+03	2.3886E+03	2.2979E+03	2.2991E+03
	Best	2.2112E+03	**2.2000E+03**	2.2000E+03	2.3011E+03	2.3006E+03	2.3054E+03	2.2060E+03	2.2156E+03
	std	2.2590E+01	**3.9591E+01**	1.8321E+01	1.2375E+02	1.0959E+00	2.8301E+02	1.7373E+01	1.5806E+01
F22	Mean	2.6095E+03	2.6080E+03	**2.6046E+03**	2.6163E+03	2.6083E+03	2.6495E+03	2.6137E+03	2.6198E+03
	Best	2.6041E+03	2.6046E+03	**2.6000E+03**	2.6060E+03	2.6000E+03	2.6126E+03	2.6050E+03	2.6067E+03
	std	3.4291E+00	2.4530E+00	**3.2380E+00**	7.7164E+00	4.1550E+00	2.2169E+01	5.9850E+00	8.4433E+00
F23	Mean	2.6262E+03	**2.5628E+03**	2.7026E+03	2.7457E+03	2.7013E+03	2.7733E+03	2.6274E+03	2.7253E+03
	Best	2.4000E+03	**2.4000E+03**	2.5000E+03	2.7261E+03	2.5000E+03	2.5559E+03	2.5000E+03	2.5000E+03
	std	1.2311E+02	**1.1233E+02**	8.1105E+01	1.1004E+01	9.1672E+01	4.8304E+01	1.1644E+02	7.7553E+01
F24	Mean	2.9059E+03	**2.8997E+03**	2.9042E+03	2.9373E+03	2.9244E+03	2.9437E+03	2.9162E+03	2.9263E+03
	Best	2.8977E+03	**2.8977E+03**	2.8977E+03	2.8992E+03	2.8981E+03	2.8999E+03	2.8977E+03	2.8977E+03
	std	1.7175E+01	**8.2860E+00**	1.5888E+01	2.1799E+01	2.4810E+01	2.2530E+01	2.2132E+01	2.2965E+01
F25	Mean	2.8958E+03	**2.8700E+03**	2.9000E+03	3.1176E+03	3.0885E+03	3.4287E+03	2.8905E+03	2.9116E+03
	Best	2.6000E+03	**2.6000E+03**	2.9000E+03	2.8112E+03	2.9000E+03	2.6061E+03	2.8000E+03	2.8000E+03
	std	6.0008E+01	**9.1539E+01**	0.0000E+00	3.9887E+02	3.8430E+02	5.0386E+02	3.8898E+01	5.6222E+01
F26	Mean	3.0929E+03	3.0913E+03	**3.0912E+03**	3.0967E+03	3.0990E+03	3.1267E+03	3.0956E+03	3.0930E+03
	Best	3.0886E+03	3.0873E+03	**3.0890E+03**	3.0895E+03	3.0918E+03	3.0950E+03	3.0900E+03	3.0893E+03
	std	2.7293E+00	1.9897E+00	**2.3448E+00**	9.1075E+00	1.0992E+01	3.2341E+01	2.3754E+00	2.8792E+00
F27	Mean	3.1133E+03	**3.0800E+03**	3.1284E+03	3.3645E+03	3.2535E+03	3.3889E+03	3.1905E+03	3.1921E+03
	Best	3.1000E+03	**2.8000E+03**	3.1000E+03	3.1763E+03	3.1000E+03	3.1036E+03	2.8000E+03	2.8000E+03

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	std	5.5269E+01	**7.6112E+01**	8.6578E+01	8.7630E+01	1.6689E+02	1.9039E+02	1.7374E+02	1.5736E+02
F28	Mean	3.1542E+03	3.1443E+03	**3.1327E+03**	3.1765E+03	3.1891E+03	3.3558E+03	3.1668E+03	3.1959E+03
	Best	3.1360E+03	3.1324E+03	**3.1275E+03**	3.1384E+03	3.1404E+03	3.1769E+03	3.1430E+03	3.1440E+03
	std	1.5248E+01	7.1428E+00	**4.2300E+00**	2.6499E+01	4.5008E+01	1.3400E+02	1.4520E+01	5.5147E+01
F29	Mean	3.9096E+03	3.7256E+03	**3.5171E+03**	8.0506E+05	5.9183E+05	7.7360E+05	1.1597E+05	2.4775E+05
	Best	3.4948E+03	3.4767E+03	**3.3958E+03**	5.7584E+03	3.9942E+03	8.3548E+03	4.1138E+03	3.7322E+03
	std	4.3791E+02	2.6664E+02	**1.7346E+02**	1.4349E+06	9.0342E+05	1.2016E+06	3.0208E+05	3.8135E+05

V. DISCUSSION

The best performing results are boldfaced in the Table 1. From Table1, it is inferred that ESWO performs better than SWO, GWO, PSO, WOA, TLBO and PO in 26 benchmark suite and the performance is identical to some algorithms for 3 benchmark suites. It also performs better than DE, in 15 benchmark suite of CEC 2017 and it performs identical with 3 benchmark suites. Notably, this improvement in the outcome is due to the three features that we enhanced or modified in SWO. The outcomes show that the suggested ESWO can handle complex optimization problems and might be applied to resolve engineering challenges in the real world.

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