IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 16 June 2023, accepted 4 July 2023, date of publication 13 July 2023, date of current version 21 July 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3294993

RESEARCH ARTICLE

Improved Sine Cosine Algorithm for Optimization Problems Based on Self-Adaptive Weight and Social Strategy

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This work was supported in part by the National Natural Science Foundation of China under Grant 62106088, in part by the Construction of High-Level Professional Groups in Higher Vocational Education in Jiangsu Province under Grant SJZH [2021] No. 1, and in part by the Jiangsu Higher Vocational Education Industry-Education Integration Platform Construction Plan Project under Grant SJZH [2019] No. 26.

ABSTRACT The Sine Cosine Algorithm (SCA) is a well-known optimization technique that utilizes sine and cosine functions to identify optimal solutions. Despite its popularity, the SCA has limitations in terms of low diversity, stagnation in local optima, and difficulty in achieving global optimization, particularly in complex large-scale problems. In response, we propose a novel approach named the Improved Weight and Strategy Sine Cosine Algorithm (IWSCA). The IWSCA achieves this by introducing novel self-adaptive weight and social strategies that enable the algorithm to efficiently search for optimal solutions in complex large-scale problems. The performance of the IWSCA is evaluated with 23 benchmark test functions and the IEEE CEC 2019 benchmark suite, compare it to a state-of-the-art heuristic algorithm and two improved versions of the SCA. Our experimental results demonstrate that the IWSCA outperforms existing methods in terms of convergence precision and robustness.

INDEX TERMS Sine cosine algorithm, self-adaptive weight, social strategy, complex large-scale problems.

I. INTRODUCTION

In the contemporary epoch, meta-heuristic algorithms (MA) [1], [2], [3] have garnered significant attention across a broad spectrum of application domains. Examples of well-known MA algorithms include Particle Swarm Optimization (PSO) [4], and Artificial Bee Colony Algorithm (ABC) [5]. Additionally, the evolutionary computation and swarm intelligence literature features other algorithms such as Marine Predators Algorithm (MPA) [6], Whale Optimization Algorithm (WOA) [7], Grey Wolf Optimizer (GWO) [8]. It is noteworthy that each of these algorithms has been meticulously crafted to tackle specific optimization challenges that arise in complex real-world scenarios, and researchers relentlessly explore new ways to enhance their performance [9], [10], [11], [12]. The Sine Cosine Algorithm (SCA) has emerged as a promising approach to optimizing population-based optimization problems, which is developed by S. Mirjalili [13]. The SCA is based on simulating the mathematical functions of sine and cosine, and it has demonstrated superior efficiency in comparison to other similar algorithms. The SCA achieves optimization by leveraging the periodic nature of sine and cosine functions to develop a mathematical model.

The Sine Cosine Algorithm (SCA) is a well-known metaheuristic optimization technique used to determine the positions of a population of N individuals through random generation. In this approach, each solution to an optimization problem is associated with the position of the corresponding individual in the search space. In the subsequent iteration, the position of the *i-th* individual is updated based on the following (1):

$$X_i^{t+1} = \begin{cases} X_i^t + r_1 \times \sin(r_2) \times |r_3 P_i^t - X_i^t|, & r_4 < 0.5 \\ X_i^t + r_1 \times \cos(r_2) \times |r_3 P_i^t - X_i^t|, & r_4 \geq 0.5 \end{cases} \quad (1)$$

The associate editor coordinating the review of this manuscript and approving it for publication was Diego Oliva.

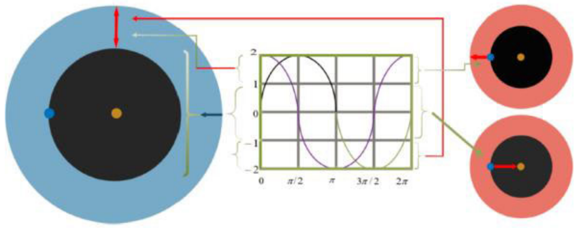

FIGURE 1. The basic principle of SCA.

where t is the current iteration number, X_i^t is the *i-th* position component of individual in the *t-th* iteration, P_i^t is the *i-th* component of the best individual position variable in the *t-th* iteration, r_1 is a linearly decreasing convergence parameter, and its expression is given by (2). Where $a = 2$, and t represents the current iteration number while T represents the maximum number of iterations. r_2, r_3, r_4 are random parameters that are uniformly distributed, $r_2 \in (0, 2\pi)$, $r_3 \in (0, 2)$, $r_4 \in (0, 1)$,

$$r_1 = a - t\frac{a}{T} \tag{2}$$

Fig.1 provides a detailed illustration of the impact of sine and cosine functions on a random number when seeking the next solution. Specifically, it highlights how adjusting the values of sine and cosine functions facilitates the search for the subsequent step in the current solution. The position-update (1) in SCA relies solely on the destination point to determine the distance of the next search region, resulting in a bias towards exploitation.

To tackle this issue, this study proposes an modified version of the SCA, denoted as the Improved Self-adaptive Weight and Social Strategy Sine Cosine Algorithm (IWSCA). Firstly, Self-adaptive weight parameter is employed to update the population's positional information using adaptive weight parameters. The parameter ω is adjusted, and each individual adopts the random values for r1, r2, r3, and r4, thus effectively maintaining population diversity and improving solution accuracy. An adaptive parameter adjustment strategy is implemented to balance global search performance and local exploitation performance. The inclusion of a dynamic inertia weight strategy enables the optimization process to fully utilize individual positional information, enhancing local exploitation performance and accelerating the algorithm's convergence speed.

Meanwhile in order to balance the algorithm's global exploration capability and local exploitation capability, a free social interaction strategy is utilized based on the sine cosine function. This strategy incorporates the guidance of the difference between the global best individual and a random individual, as well as information from other individuals in the population. By updating the positional information of individuals with lower fitness values in the population, the algorithm's exploration and exploitation capabilities are strengthened.

The aforementioned approaches address the deficiencies of the algorithm for function optimization, including slow convergence speed and low convergence accuracy. Through the implementation of adaptive weight parameters and social interaction strategy, the proposed method achieves enhanced solution quality, maintained population diversity, and accelerated convergence speed.

II. BACKGROUND AND RELATED WORK

In the literature, researchers have been exploring various optimization strategies to improve the performance of the Sine Cosine Algorithm (SCA). Li and Wang [14] introduced a method for generating new candidates using Gaussian search equation and exponential decrement strategies, which effectively enhances the diversity of the algorithm. He and Wang [15] also proposed a dynamic selection strategy that is dynamically regulated during the course of evolution. The parent with higher fitness is given higher selection probability, resulting in faster convergence and better exploration. Li and Zhao [16] proposed a dynamic dimension and a greedy strategy by dimension approach, which evaluates the solutions in each dimension. This strategy helps to avoid getting stuck in local optima and improves the overall performance of the algorithm. Gupta and Deep [17] suggested a hybrid Sine Cosine Algorithm with opposition-based learning. This approach combines the use of opposite initial numbers and a self-adaptive component strategy to jump out of the local optima and achieve better convergence. Feng and Duan [18] introduced an enhanced version of SCA, referred to as ESCA, which incorporates several modified strategies to improve its performance. These strategies include opposition learning for expanding the search range, adaptive evolution for enhancing global exploration, neighborhood search for increasing population diversity, and greedy selection for ensuring solution quality. Zhou and Wang [19] proposed a modification to the SCA algorithm by adjusting the conversion parameters from a linear decline to a nonlinear decline, which optimizes the balance between global and local exploration. Gupta and Deep [20] presented a hybrid algorithm that integrates the exploitation skills of crossover with personal best state of individual solutions and self-learning and global search mechanisms. Saha [21] developed a multi-population-based adaptive SCA with a modified mutualism strategy. This algorithm updates solutions using a sine or cosine strategy, and a modified mutualism phase is adopted.

Priya et al. [22] have ingeniously applied an enhanced Sine Cosine Algorithm (SCA) to distribute multimedia content in the cloud. Abdel-Basset et al. [23] have remarkably utilized SCA to tackle multi-objective problems for real-time task scheduling in multiprocessor systems. Khrissi et al. [24] have smartly incorporated SCA with clustering methods to revolutionize the field of image segmentation. Meanwhile, Kumar et al. [25] have judiciously merged SCA, where the Cauchy and Gaussian strategies efficiently optimized global exploration and local exploitation ability, respectively. Elaziz et al. [26] have astutely suggested an improved opposition-based Sine Cosine Algorithm (OBSCA) that leverages the opposition-based learning mechanism to enhance convergence speed by steering away from local optima. Chen et al. [27] have put forth an advanced orthogonal learning-driven multi-swarm sine cosine optimization approach that is highly effective in various optimization problems. Nenavath et al. [28] have deftly combined SCA with a differential evolution algorithm to produce a powerful hybrid algorithm that significantly accelerates the convergence rate. Kaveh et al. [29], have ingeniously proposed an adaptive Sine Cosine Optimization algorithm integrated with Particle Swarm Optimization, where PSO is introduced into ASCA_PSO to enhance the SCA algorithm's exploitation capability.

Regardless of the updating strategy used by SCA, local optima stagnation and insufficient optimization may occur when solving large-scale global optimization problems, Hence, we introduce an enhanced SCA algorithm that utilizes self-adaptive weight and social strategies to overcome local optima:

1.Self-adaptive weight parameter tuning scheme is adopted into the improved SCA. according to the proportion of fitness value;

2.Social mechanism was implemented to balance exploration and exploitation, preventing premature convergence to a local optimal position;

3.The proposed algorithm was tested by 23 benchmark test functions and IEEE CEC 2019 benchmark, compared to state-of-the-art algorithms and different SCA variants.

The remaining part of this paper is organized as follows. Section II briefly introduces the original SCA. Section III describes the proposed sine cosine algorithm in detail. Section IV gives the experimental results and analysis of the benchmark function. Section V concludes this paper and indicates future research.

III. IMPROVED SINE COSINE ALGORITHM

A. SELF-ADAPTIVE WEIGHT

In this paper, we propose an approach that incorporates an adaptive weight parameter into the optimization process. By fully leveraging the adaptive variation of the parameter, our approach enhances the global exploration capability of the algorithm and improves the ability of individuals to escape from local optima, while still maintaining strong performance in local development when the optimization is relatively stable. Specifically, in the early stages of the optimization, our approach accelerates the global exploration of the solution space. In more stable situations, it increases the ability to develop solutions locally, achieving a balance between global and local exploration. We aim to make full use of the position information of the destination point to increase exploration through the design of a self-adaptive weight position-update (1), which is described by (3):

$$X_i^{t+1} = \begin{cases} \omega X_i^t + r_1 \times \sin(r_2) \times \left|r_3 P_i^t - X_i^t\right|, & r_4 < 0.5 \\ \omega X_i^t + r_1 \times \cos(r_2) \times \left|r_3 P_i^t - X_i^t\right|, & r_4 \geq 0.5 \end{cases} \tag{3}$$

Weight parameter ω is the balance factor and described by (4), whose function is to adjust the weight between the destination point and the current individual in (4). This study proposes a self-adaptive weight that guides the update formula for dynamic correction. P_i^t denotes the best fitness value of the current iteration of position variable, while G_{best} signifies the global optimal fitness value. r_5 are random parameters that are uniformly distributed between 0 and 1.

$$\omega = (\omega_{init} - \omega_{end}) \times r_5 \times \frac{(n-i)P_i^t}{nG_{best}}, \quad \omega_{init} = 0.9, \omega_{end} = 0.4 \tag{4}$$

In instances where the fitness value of the current position variable surpasses the global fitness value, the inertia weight assumes a larger value, is advantageous in terms of global exploration capabilities and expands the search space for feasible solutions. Conversely, self-adaptive weight generates a smaller value to facilitate faster convergence rates, which promotes healthy development of the region. The self-adaptive weight is thus advantageous in aiding particles in the SCA to automatically select global or local phases, thereby improving accuracy and convergence speed and reducing the possibility of falling into local optima.

B. SOCIAL STRATEGY

In this section, we present another part of the Improved Algorithm, which can optimize the search space and speed up the effectiveness of the search process in the IWSCA. The modified search (5), introduced in the IWSCA is expressed as follows:

$$X_i^{t+1} = \begin{cases} \omega X_i^t + r_1 \times \sin(r_2) \times \left|r_3 P_i^t - X_i^t\right| + (G_{best} - P_i^t), \\ \quad r_4 < 0.5 \\ \omega X_i^t + r_1 \times \cos(r_2) \times \left|s r_3 P_i^t - X_i^t\right| + (G_{best} - P_i^t), \\ \quad r_4 \geq 0.5 \end{cases} \tag{5}$$

In this optimization methodology, the current solution at iteration t is denoted as X_i^t, while the current best position attained by the solution is represented as P_i^t. Furthermore, G_{best} denotes the best position among the population of solutions, and parameters r_1, r_2, r_3, r_4 are consistent with those used in classical SCA.

The second crucial component in the search process is the social component which is represented by $(G_{best} - P_i^t)$ on the right-hand side. This strategy improves the ability to develop solutions locally while still maintaining the ability to escape from local optima. The solution updated may have a chance to diverge from the current state of a solution to avoid falling into the local optimal when the search area provided by the coefficient is very large.

The social components and self-adaptive weight provide a direction to the current solution by combining the directions of the best solution state and the best population state. The newly developed algorithm can be summarized in the following steps:

Algorithm 1 The Improved Sine Cosine Algorithm

Initialize population N and *Max iterations*
Initialize fitness optimal P_i^t and global optimal G_{best} according to X_i^t
While($t <$ *Max iterations*)
    for $i = 1: N$
        Update r_1 by the (3),
        Update r_2, r_3, r_4, r_5
        Update self-adaptive weight ω according to (4)
        Update each individual of both the sub population by (5)
    if $(f(x_i^{t+1}) < f(P_i^t))$
        Update the current best position P_i^t
      End if
    End for
      if $(f(P_i^t) < f(G_{best}))$
Update the global best position G_{best}
          End if
End while
      Return G_{best}

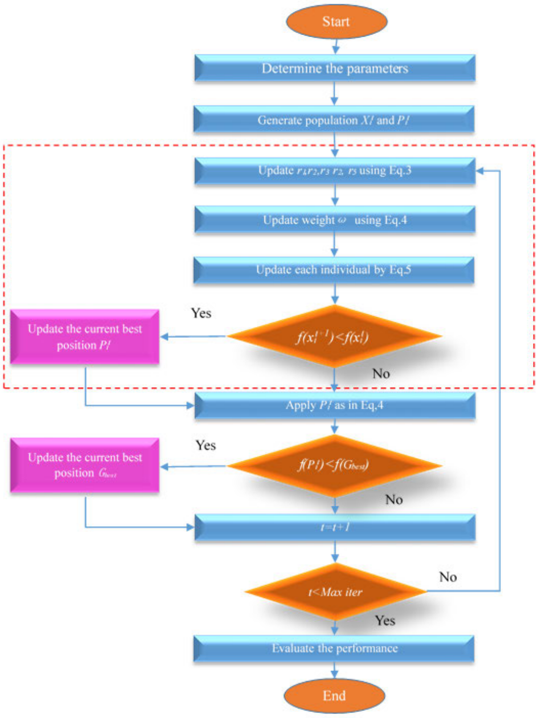

FIGURE 2. Framework of IWSCA.

Thus the phase of opposition based weight and self-adaptive strategy provides an enhanced global and local search which helps in increasing appropriate diversity and avoids the skipping of true solutions. The flow of search process of proposed Sine Cosine Algorithm is presented in Fig.2 A detailed analysis off enhanced diversity of solutions and exploitation of search space has been done in experimental section.

IV. EXPERIMENTS AND DISCUSSION

A. BENCHMARK PROBLEM EXPERIMENTS

Within the framework of optimization research, a key aspect of assessing the efficacy of newly proposed algorithms is the utilization of a rigorous evaluation process. To this end, we conducted an extensive examination of the IWSCA on a diverse set of benchmark problems. These classical 23 benchmark functions test can be categorized into three distinct categories, namely unimodal, multimodal, and fixed dimension problems [30], [31]. Due to space limitations, we only provide an overview of the 16 benchmark function problems.

In the evaluation of the classical set of problems, we utilized a population size of 50 solutions, and the termination criterion for all algorithms was fixed at 1000 iterations. To ensure the robustness and validity of our results, we conducted a comprehensive comparison across two distinct evaluation criteria, namely mean and standard deviation, This evaluation was conducted 20 independent runs on each function in order to provide a thorough and comprehensive assessment of the algorithm's efficacy. To facilitate these experiments, we utilized MATLAB 2020a on a personal computer with a 3.2 GHz CPU and 16 GB RAM.

The IWSCA has demonstrated superior optimization performance compared to classical Sine Cosine Algorithm (SCA) and other popular population-based optimization algorithms, including MPA, WOA,GWO,PSO,ABC, (Differential Evolution, DE) [32], (Gravitational Search Algorithm, GSA) [33] and (Cuckoo Search Algorithm, CS) [34]. The obtained results are presented in Table 1.

We compared the experimental results of algorithms on the F1-F23 function. Due to the length issue of the paper, Table 2 only shows the experimental results of the test function F1-F16. Upon careful examination of the data presented in Table 1, it is evident that the IWSCA outperform other state-of-the-art optimization techniques. Our proposed algorithm, IWSCA, consistently achieved the theoretical global optimum for 12 of these functions (F1-F5, F7-F11, and F13-F14). Although IWSCA did not achieve the theoretical global optimum for functions F6 and F12, the obtained solutions were superior to those obtained by the other compared algorithms. In comparison, MPA perform better than IWSCA on only two functions (F6 and F12) and worse on the remaining functions.

The performance of PSO, WOA, ABC, GWO, SCA DE, GSA and CS were considerably worse than the superior performance of IWSCA for any of the 16 benchmark functions. These results highlight the superior performance of IWSCA in terms of global exploration and the ability to escape from local optima compared to the other compared algorithms.

In this study, we present the convergence curves of the nine optimization algorithms tested in Fig.3. The results show that IWSCA perform exceptionally well in achieving the theoretical global minimum for the Unimodal functions F1-F5, requiring only around 600 and 800 iterations, respectively. Furthermore, it converged faster than other algorithms on the Multimodal functions F9, F10, F11, and F16, achieving the theoretical global minimum with only a few iterations. In fixed-dimension problems, IWSCA also exhibited superior convergence speed and accuracy compared to other heuristic algorithms, indicating significant characteristics.

TABLE 1. Comparison results for benchmark functions.

		MPA	WOA	GWO	PSO	ABC	SCA	DE	GSA	CS	**IWSCA**
F1	Mean	7.54E-46	9.40E-167	9.21E-52	0.39866	3265.836	7267.898	6.414023	79024.94	3.50E-06	**1.70E-298***
	Std	1.07E-45	0	1.09E-51	0.142735	548.2128	7923.763	9.790549	8764.662	9.98E-07	**0***
F2	Mean	3.13E-26	1.50E-108	9.64E-31	10.48455	30039243	7.44E+13	3.997803	4.05E+13	0.002039	**2.40E-151***
	Std	4.16E-26	6.10E-108	6.12E-31	3.696955	1.30E+08	1.79E+14	2.524376	9.98E+13	0.0011	**5.40E-151***
F3	Mean	1.69E-08	98017.16	5.44E-09	104.4392	228642.6	114698.5	31160.49	118340.2	0.004853	**2.20E-284***
	Std	4.49E-08	23781.28	2.17E-08	31.13618	37225.62	20286.39	20898.1	10688.53	0.002153	**0***
F4	Mean	1.53E-17	55.67727	1.41E-11	14.99226	84.74267	0.018369	1.091698	1.10E-154	0.026983	**2.90E-149***
	Std	1.24E-17	31.27014	1.76E-11	4.265669	5.337355	0.010034	1.162554	5.10E-154	0.010158	**1.00E-148***
F5	Mean	43.22485	46.94949	46.74938	401.7574	1.17E+08	2.59E+08	179.259	2.57E+08	47.99563	**8.86E-05***
	Std	0.343717	0.440857	0.954943	190.535	37239093	24625841	176.5258	24578278	0.206831	**0.000128***
F6	Mean	**2.83E-08***	0.043204	1.715824	0.443087	3201.68	2.660999	7.597723	75263.38	5.18021	0.035051
	Std	**9.98E-09**	0.030777	0.572322	0.174453	853.0752	0.616291	9.741876	8704.553	0.336491	0.034116
F7	Mean	0.00444	0.010402	0.015403	1.422255	64.03542	9.34E-05	0.099127	136.3595	2.67E-05	**7.76E-05***
	Std	0.002991	0.013818	0.009075	0.417288	15.53781	9.40E-05	0.067416	29.77889	2.03E-05	**8.26E-05***
F8	Mean	-11350.1	-12238.2	-5926.76	-12119.3	0*	-10564.6	-11733	-9801.27	-8571.77	**-8934.27**
	Std	1070.481	3374.572	1587.646	1063.36	5.40E+120	757.2572	612.2045	889.0292	341.2866*	**3083.643**
F9	Mean	0.443087	0.572322	8.53E-15	137.0864	529.265	9.40E-05	60.68836	515.6887	1.58E-06	**0****
	Std	0.174453	0.015403	2.08E-14	21.15038	25.43619	-10564.6	34.56928	91.61236	3.72E-07	**0***
F10	Mean	4.26E-15	4.09E-15	2.79E-14	10.37497	15.04883	8.88E-16	1.073177	18.49346	0.000322	**8.88E-16***
	Std	7.94E-16	2.55E-15	2.92E-15	1.455791	1.419373	2.073727	0.812259	0.416341	3.97E-05	**0***
F11	Mean	0.01821	0.301811	0.00112	0.061535	28.90602	3.004474	0.43706	420.275	0.001368	**0***
	Std	1.096175	0.002469	0.003533	0.026127	3.765943	0	0.423649	43.37559	0.006065	**0***
F12	Mean	**1.68E-09**	0.00287	0.06385	12.54503	3.38E+08	0.067932	0.098869	5.20E+08	0.773784	0.002929
	Std	**8.11E-10**	0.003487	0.023304	4.727356	71812393	0.01821	0.177061	48910785	0.03604	0.004314
F13	Mean	0.004732	0.235976	1.353243	60.53125	6.23E+08	1.096175	0.495329	1.06E+09	4.940395	**3.86E-07***
	Std	0.007889	0.168206	0.284081	18.10671	1.43E+08	0.262581	0.601246	1.08E+08	0.012609	**5.23E-07***
F14	Mean	0.998004	2.073727	3.645475	2.086115	0.998015	0.99843	1.12275	2.404934	8.316944	**1.437598***
	Std	0	3.004474	3.761364	1.632594	4.32E-05	0.00179	0.301811	1.202665	4.611669	**0.655936***
F15	Mean	0.000307	0.0007	0.002365	0.077502	0.002563	0.000723	0.002469	0.001949	0.006641	**0.000797***
	Std	3.67E-19	0.000412	0.006159	0.114014	0.000911	0.00028	0.001246	0.000963	0.026256	**0.000335***
F16	Mean	-1.03163	-1.02203	-1.02747	189.2388	-1.00819	-0.92615	-1.01343	-1.021	-1.00741	**-0.84757***
	Std	1.89E-12	0.017563	0.010413	246.5158	0.018152	0.316792	0.018449	0.010392	0.013849	**0.315569***

* represent the optimal solution of the function

In contrast, the other nine algorithms, including MPA, PSO, ABC, WOA, GWO, and SCA, converged prematurely in all benchmark functions, and the obtained solutions were consistently inferior to those obtained by IWSCA. MPA perform better than IWSCA in only two functions (F6 and F12) but perform worse in other functions. In all other tested functions, MPA failed to converge to the theoretical global minimum after 1000 iterations and produced solutions that deviated significantly from the theoretical values, indicating that the algorithm became trapped in local optima.

The convergence curves demonstrate that IWSCA consistently found the theoretical global minimum for the majority

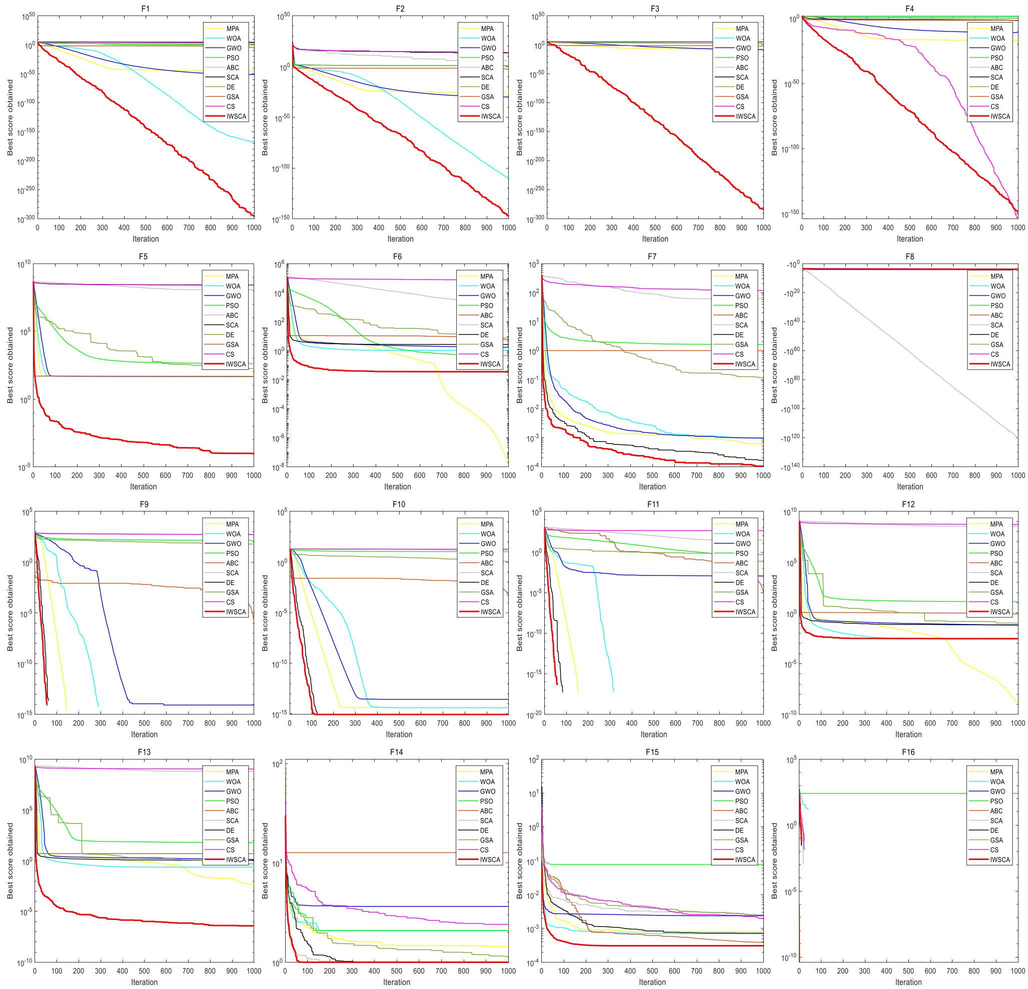

FIGURE 3. Convergence curves for benchmark functions.

TABLE 2. CEC2019 function.

Function	Dim	Range	f_{min}
CEC01: Storn's Chebyshev Polynomial Fitting Problem	9	[−8192, 8192]	1
CEC02: Inverse Hilbert Matrix Problem	16	[−16384, 16384]	1
CEC03: Lennard-Jones Minimum Energy Cluster	18	[−4, 4]	1
CEC04: Rastrigin's Function	10	[−100, 100]	1
CEC05: Griewangk's Function	10	[−100, 100]	1
CEC06: Weierstrass Function	10	[−100, 100]	1
CEC07: Modified Schwefel's Function	10	[−100, 100]	1
CEC08: Expanded Schaffer's CEC06	10	[−100, 100]	1
CEC09: Happy Cat Function	10	[−100, 100]	1
CEC10: Ackley Function	10	[−100, 100]	1

of the benchmark functions, further highlighting its superior optimization performance. The excellent convergence speed of the IWSCA ensured that it could effectively reduce the computational complexity of the optimization problem.

Fig.4 shows box-plot test of the global optimal solutions of comparison algorithms in 20 independent experiments on different test functions. It can be seen that IWSCA can converge to the theoretical extreme value of the function on different test functions with a stable distribution of optimal values and good robustness of the algorithm. The results obtained from other algorithms have significant deviations from the theoretical extreme values of the function, and exhibit strong volatility, indicating poor robustness of the algorithm.

B. IEEE CEC2019 LARGE-SCALE GLOBAL OPTIMIZATION PROBLEMS EXPERIMENTS

In order to further evaluate and compare the performance of the IWSCA on Large-Scale Global Optimization (LSGO) problems, IEEE CEC2019 were employed in this study. A detailed description of these problems is presented in Table 2, which elucidate the complexity of the optimization landscape for these problems [35], [36]. We tested 20 independent runs on each function with the similar populations and iterations with previous experiments, ensuring a rigorous evaluation of the algorithms.

The function values are summarized in Table 3, which provide an in-depth analysis of the performance of the IWSCA and its comparison to other algorithms, including other improved versions of SCA, MSCA [30] and ISCA [37]. It shows that the IWSCA get closer to the minimum values

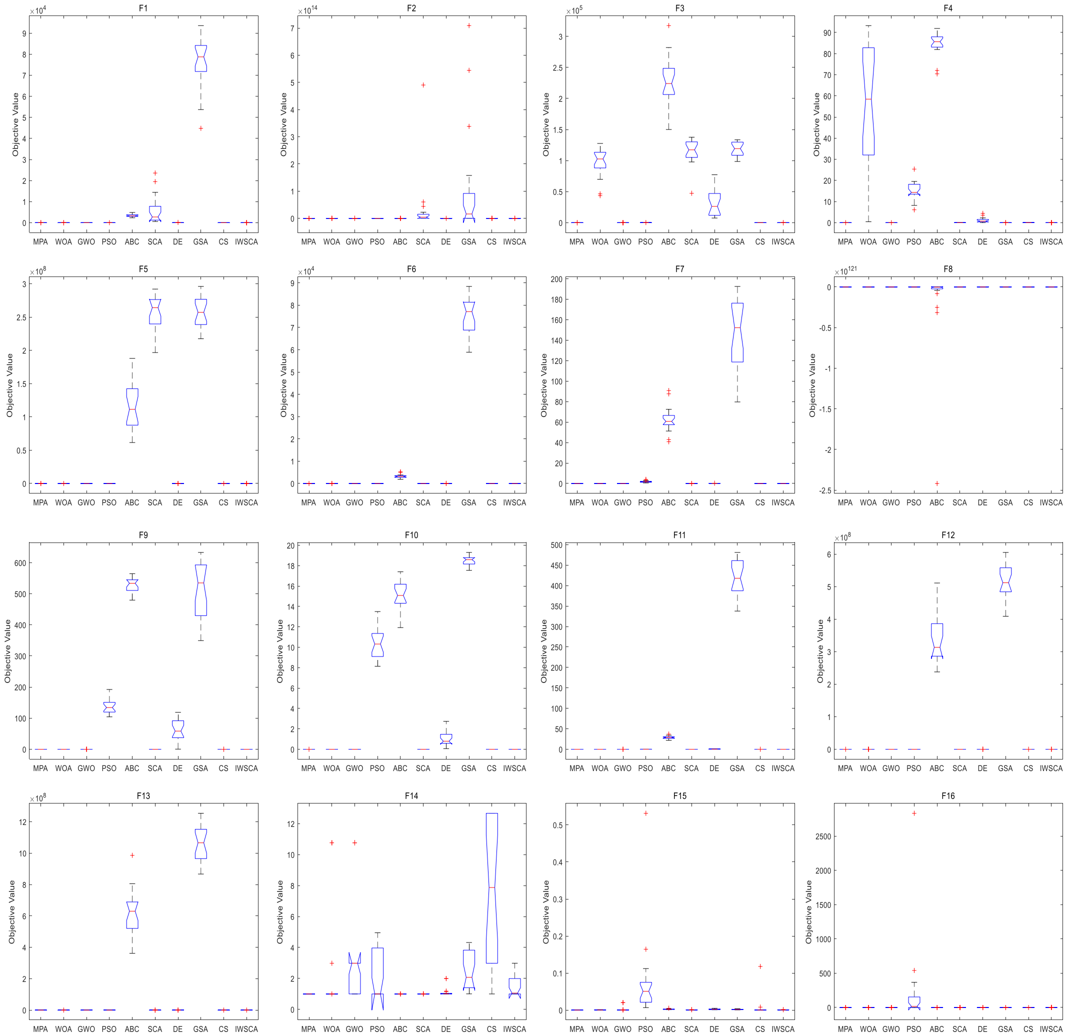

FIGURE 4. Box-plot for benchmark functions.

than other algorithms. The IWSCA obtain the remarkable performances, which outperforms other algorithms in solving LSGO problems with a significant improvement in accuracy and convergence speed for most of CEC2019 functions.

The convergence curve algorithms shown in Fig.5, which clearly shows that the IWSCA generates a smaller value to facilitate faster convergence rates than other algorithms. It converged faster than other algorithms on the functions CEC01-CEC03, which is achieving the theoretical global minimum with only a few iterations. On the functions CEC04-CEC10, the IWSCA also exhibited superior convergence speed and accuracy compared to other heuristic algorithms, indicating significant characteristics.

C. IWSCA FOR THE ENGINEERING PROBLEM

In this section, we investigate the efficacy of the IWSCA in the pressure vessel design (PVD) (Yang et al., 2020). When we design pressure vessels, the demand for required raw materials should be minimized to significantly reduce production costs. The pressure vessel design is shown in Fig.6 with covers on both sides and a hemispherical head shape. L is the height of the remaining part after removing the hemispherical head, R is the inner radius of the cylindrical part, Ts and Th represent the difference between the outer and inner radii of the cylindrical part and the head, respectively. The mathematical model is described as follows:

$$
\begin{aligned}
f(x) &= 0.6224x_1x_3x_4 + 1.7781x_2x_3^2 \\
&\quad + 19.84x_1^2x_3 + 3.1661x_1^2x_4 \\
x &= (x_1, x_2, x_3, x_4) = (T_s, T_h, R, L) \\
g_1(x) &= 0.0193x_3 - x_1 \leq 0 \\
g_2(x) &= 0.00954x_3 - x_2 \leq 0 \\
g_3(x) &= 1296000 - 4/3\pi x_3^3 - \pi x_3^2 x_4 \leq 0 \\
g_4(x) &= x_4 - 240 \leq 0
\end{aligned}
$$

The cost optimization achieved by IWSCA is significantly lower compared to SCA, as evidenced by Table 4. In fact, IWSCA demonstrates more pronounced advantages over widely known algorithms such as MPA, WOA,GWO,PSO and ABC when solving this specific problem. Furthermore,

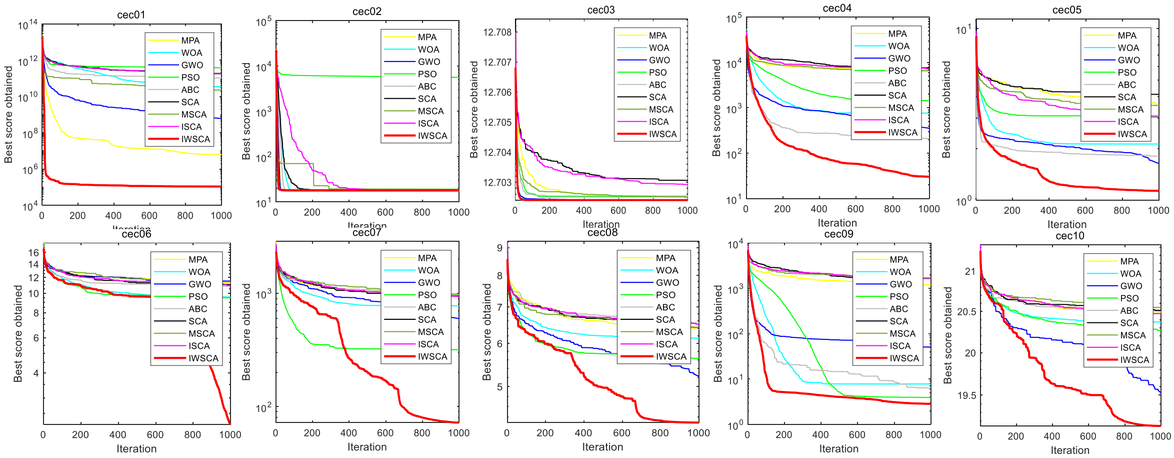

FIGURE 5. Convergence curves for CEC 2019 functions.

TABLE 3. Comparison results for CEC2019 functions.

		MPA	WOA	GWO	SCA	MSCA	ISCA	IWSCA
CEC01	Mean	11397059	2.8E+10	2.3E+08	2.33E+11	1.35E+10	1.87E+11	**94986.55***
	Std	29176575	3.75E+10	5.23E+08	1.09E+11	2.2E+10	8.45E+10	**35307.83***
CEC02	Mean	17.64495	17.34385	17.34326	17.96891	18.43388	17.78252	**17.34286***
	Std	0.146312	0.001262	0.000116	0.204346	0.37005	0.130733	**4.72E-11***
CEC03	Mean	12.70253	12.7024	12.70253	12.70299	12.70252	12.70295	**12.7024***
	Std	9.36E-05	6.18E-07	0.000537	0.000293	4.32E-05	0.000154	**3.65E-15***
CEC04	Mean	6095.935	729.7574	709.5172	7733.907	6290.736	6669.683	**31.64105***
	Std	2164.833	761.7323	929.551	1318.525	1489.423	2140.749	**15.12766***
CEC05	Mean	3.614644	1.857695	1.492529	4.080605	3.460237	3.1734	**1.127013***
	Std	0.449521	0.279215	0.326804	0.329035	0.369453	0.284602	**0.10726***
CEC06	Mean	11.11903	9.703693	11.35634	11.25945	11.43866	11.32952	**3.220508***
	Std	0.752064	1.09774	0.481888	0.693017	0.649028	0.606436	**1.025882***
CEC07	Mean	886.5872	789.2073	572.842	913.2191	935.9098	1032.292	**34.86555***
	Std	160.4639	390.1973	324.6597	183.3852	187.3558	144.9208	**81.66029***
CEC08	Mean	6.497835	6.076865	5.439884	6.23651	6.454703	6.460085	**4.361781***
	Std	0.289402	0.444666	0.908896	0.376494	0.22846	0.293716	**0.506573***
CEC09	Mean	1182.569	7.888396	35.53668	1873.635	1743.04	1602.365	**2.657349***
	Std	540.5359	5.503818	96.22807	259.5559	431.7092	436.8081	**0.196024***
CEC10	Mean	20.49161	20.33912	20.13028	20.5171	20.54297	20.51822	**20.01243***
	Std	0.119621	0.157203	1.865928	0.105897	0.087757	0.075413	**0.020527***

* represent the optimal solution of the function

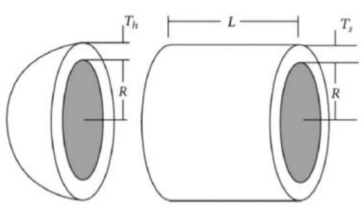

FIGURE 6. Pressure vessel design.

IWSCA exhibits a lower optimum cost than enhanced SCA variants such as Modified SCA (MSCA) and Improved SCA (ISCA). Based on the presented case study, the final results demonstrate that IWSCA excels in both exploration and exploitation, outperforming its competitors in obtaining solutions. Consequently, it can be concluded that the proposed IWSCA holds great promise for practical applications in real-world scenarios and engineering challenges with constraints.

TABLE 4. Comparison results for pressure vessel design.

Algorithm	x_1	x_2	x_3	x_4	$f(x)$
MPA	0.8125	0.4375	42.0650	180.8232	6151.1441
WOA	0.8125	0.4375	42.04861	177.7078	6538.8530
GWO	0.8250	0.6250	55.987	184.4542	6288.7450
PSO	0.9375	0.4375	42.0913	176.7465	6410.3810
ABC	0.8125	0.4345	40.3239	112.6790	6126.1041
SCA	0.9375	0.5000	48.3290	117.7110	6176.3051
MSCA	0.8125	0.4125	42.0913	176.7465	6121.5431
ISCA	0.8125	0.5220	41.3239	152.1234	6108.8120
IWSCA	0.8125	0.4375	42.0984	176.6382	6059.7457

V. CONCLUSION

The study presents an innovative approach to the Sine Cosine Algorithm by incorporating a social strategy and self-adaptive weight setting. This approach aims to overcome the limitations by avoiding local optima and improving overall performance. The experimental results clearly demonstrate that the IWSCA significantly enhances search efficiency, solution accuracy, and convergence speed compared state-of-the-art heuristic algorithms and other improved versions of SCA. These findings suggest that the IWSCA is a superior optimization method in solving LSGO problems with promising practical applications in various fields that require optimization.

Future research should focus on implementing IWSCA on multi-objective optimization. This would allow for more extensive testing of the algorithm's capabilities and provide a better understanding of its potential in real-world applications.

ACKNOWLEDGMENT

Data used in this study are available upon reasonable request to the corresponding author. The authors are grateful to the Jiangsu Vocational College of Information Technology for a partial financial sponsorship and their facility support in this research. The authors declare no conflict of interest.

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