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Novel Meta-Heuristic Algorithm for Feature Selection, Unconstrained Functions and Engineering Problems

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ABSTRACT This paper proposes a Sine Cosine hybrid optimization algorithm with Modified Whale Optimization Algorithm (SCMWOA). The goal is to leverage the strengths of WOA and SCA to solve problems with continuous and binary decision variables. The SCMWOA algorithm is first tested on nineteen datasets from the UCI Machine Learning Repository with different numbers of attributes, instances, and classes for feature selection. It is then employed to solve several benchmark functions and classical engineering case studies. The SCMWOA algorithm is applied for solving constrained optimization problems. The two tested examples are the welded beam design and the tension/compression spring design. The results emphasize that the SCMWOA algorithm outperforms several comparative optimization algorithms and provides better accuracy compared to other algorithms. The statistical analysis tests, including one-way analysis of variance (ANOVA) and Wilcoxon's rank-sum, confirm that the SCMWOA algorithm performs better.

INDEX TERMS Artificial intelligence, machine learning, optimization, sine cosine algorithm, modified whale optimization algorithm.

I. INTRODUCTION

Stochastic algorithms are traditionally characterized as a heuristic, although current research often labels them meta-heuristics. According to Glover's example, all-natural algorithms are termed metaheuristic [1]. Generally speaking, heuristic refers to the process of finding or detecting through trial and error. Meta- shows a level achieved above and beyond the fundamental heuristic as they are not problem-specific. In his foundational work [1], Fred Glover coined the word "metaheuristics" as "a master technique that drives other heuristics towards the local optimism to generate answers that have to be produced differently" [2]. So, metaheuristics can be considered as randomized local searches. While quality solutions may be found to optimize problems within an acceptable amount of time, there is no guarantee that the optimal solution might be achieved. It is most probable that these techniques will succeed. Yet, this is

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impossible. For high probability global optimization, almost any metaheuristic technique may be used [3].

Meta-heuristics have two characteristics in terms of search behavior: intensification and diversification [4]. Diversifying entails developing various solutions that look at the search field across the globe and intensifying implies restricting the search field to a limited area with superior information. A proper balance between intensity and diversity should be maintained throughout the solution selection process to speed algorithm concordance. The solution is selected for optimum convergence while randomization enhances the search for the location of Optima. A balance between these two components often offers worldwide optimism [5], [6].

Optimization is the process of discovering a solution to a given optimization problem that provides the greatest or least objective function value. It is the subject of a wide variety of machine techniques that are based on artificial neural networks [7], [8]. Several famous optimization algorithms have become accessible for different applications, and many technologies are ready and available in major scientific code libraries. Given an optimization problem, selecting what algorithms can thus be challenging for solving such a problem. Optimization is how a predefined function can have a lowest or highest output for the input parameters of a given problem to be optimized. In machine learning, where the functions' input parameters are numerical, such as the floating-point values, continuous functions optimization arises. The function usually returns parameter evaluation of the real world. Continuous function optimization can be helpful to distinguish between such problems with discrete variables, which is known as combined optimization problems [9].

Various techniques may be determined, organized, and called to optimize the problems involving continuous functions [10], [11]. The needed information about the objective function to be applied throughout the optimization process depends on the technique of optimization classification. The more information about the target function is available and understood, the more accessible it is to be optimized since the needed knowledge can be employed in an effective way. The significant difference between different optimization algorithms is how to identify the destination function in one location. The feature first derivative may be employed to get a possible solution (gradient or route). It can distinguish itself from the other not-calculated gradient data [12].

Metaheuristic optimization means the optimization process that applies metaheuristic techniques. Nearly every area of life can be involved, from holiday preparation to internet travel, engineering to business and other applications [13]–[15]. Using such available resources is maximized because of the continuous scarcity of time, resources, and money. The majority of problems to be optimized are restrictive, multimodal, and non-linear real-world problems. In case of a goal is set, sometimes, the optimal solutions to be obtained are not always available. Usually, a failed or faultless response is not simple to be found. A range of popular metaheuristic algorithms is covered in this article [16], [17].

This paper introduces a hybrid Sine Cosine (SC) Modified Whale Optimization Algorithm (WOA) called SCMWOA. Although the WOA algorithm shows superiority in various single-objective optimization problems, it suffers from local optima stagnation and a low convergence rate. The WOA is considered simple, capable, flexible, and easy to be utilized, and the distinctive advantages of WOA cannot be achieved using traditional optimizers. By increasing the number of random agents in the modified WOA (MWOA), the global search can be more effective and be achieved to avoid local optima. The SCMWOA algorithm is proposed by balancing the updating process of the agents' positions in the search space between the sine cosine and the modified WOA algorithms during iterations to avoid a low convergence rate.

The SCMWOA algorithm evaluation in the experiments is divided into three scenarios. The first scenario is designed to test the ability of the SCMWOA algorithm in feature selection problems based on nineteen different tested datasets from the UCI public machine learning repository. The SCMWOA is compared to original Grey Wolf Optimizer (bGWO) [18], bPSO [19], Stochastic Fractal Search (bSFS) [20], Whale Optimization Algorithm (bWOA) [21], Multiverse Optimization (bMVO) [22], Satin Bowerbird Optimizer (bSBO) [23], Firefly Algorithm (bFA) [24], bGA [25] algorithms, Modified GWO (bMGWO) [26], hybrid of Particle Swarm Optimization (PSO) and GWO (bGWO-PSO) [27], hybrid of Genetic Algorithm (GA) and GWO (bGWO-GA) [26], and hybrid of SCA and PSO (bSCA-PSO) [28] in which *b* at the front of a name denotes the binary variant of the algorithm.

The next scenario examines the SCMWOA algorithm's ability to solve benchmark functions divided into unimodal and multimodal functions. Twenty-three functions are employed in this scenario. The SCMWOA in the second scenario is compared to original GWO [18], PSO [19], WOA [21], Feedforward Error Propagation (FEP) algorithm [29], Gravitational Search Algorithm (GSA) [30], GA [25] algorithms, Enhanced Grey Wolf Optimizer (EGWO) [31], hybrid of Crow Search Algorithm (CSA) and GWO (GWO-CSA) [31], and hybrid of SCA and PSO (bSCA-PSO) [28]. The third and last scenario is designed in this work for testing the ability of the algorithm for solving classical constrained optimization problems of tension/compression spring design (TCSD) [32] and welded beam design [33]. In addition, the SCMWOA algorithm results are compared in the third scenario with the original GWO [18], PSO [19], WOA [21], and GSA [34] algorithms' results to get the minimum cost.

The main contribution of this work can be summarized as follows.

- A Sine Cosine Modified Whale Optimization Algorithm (SCMWOA) is presented.
- A binary SCMWOA is presented.
- Ability of the binary SCMWOA algorithm in feature selection problems is tested.

- Ability of the SCMWOA algorithm to solve twenty-three benchmark functions is tested.
- Ability of the SCMWOA algorithm for solving two constrained optimization problems of Tension/Compression Spring and Welded Beam designs is confirmed.

The following sections are organized as follows. The materials and methods of the WOA, modified WOA, and SCA algorithms are discussed in Section II. Section III and IV present the proposed SCMWOA algorithm in continuous and discrete forms. Section V shows the results and discussion of the designed scenarios of feature selection, benchmark functions, and solving constrained optimization problems. Conclusion and future work are introduced in Section VI.

II. MATERIALS AND METHODS

In this section, the WOA, modified WOA, and SCA optimization algorithms are presented.

A. WHALE OPTIMIZATION ALGORITHM

This algorithm was first proposed in 2016 [21]. It mimics the bubble-net foraging strategy of humpack whales. In this algorithm, a number of n whales in the WOA algorithm can "swim" in an n-dimensional search space. To get the food (global solution), the position of each whale should be updated in the space search during iterations. To achieve this, the following equation was implemented in the WOA algorithm.

$$X(t+1) = X^*(t) - A.|C.X^*(t) - X(t)| \tag{1}$$

where the vector $X(t)$ represents the t^{th} iteration's solution. The vector $X^*(t)$ indicates the prey's possible position. The "." symbol between vectors represents the pairwise multiplication. The A and C vectors are updated during iterations as $A = 2a.r_1 - a$, $C = 2.r_2$. a is decreasing linearly from 2 to 0. r_1 and r_2 are selected randomly between [0, 1].

The exploitation phase of the WOA algorithm is based on a shrinking encircling mechanism that decreases with the value of a, and a spiral updating and is calculated as the distance between whale's location and location of the prey. The process of spiral is expressed as in the following equation.

$$X(t+1) = |X^*(t) - X(t)|.e^{bl}.cos(2\pi l) + X^*(t) \tag{2}$$

where l is selected randomly between $[-1, 1]$. The spiral's shape is represented by the constant b. To simulate the process of prey's encircling and spiral movement, this equation is applied.

$$X(t+1) = \begin{cases} X^*(t) - A.D & \text{if } r_3 < 0.5 \\ D'.e^{bl}.cos(2\pi l) + X^*(t) & otherwise \end{cases} \tag{3}$$

where r_3 is selected randomly in [0, 1] to control switching between a spiral or circular movement.

On the other side, the exploration Phase (searching for a prey) is done based on the vector A. By this process, the agent goes away from the leader. Thus, the agent position will be updated according to a random whale X_r. This allows the optimizer a more global search. This can be achieved by the following equation.

$$X(t+1) = X_r - A.|C.X_r - X| \tag{4}$$

The A vector is used to control switching between exploration and exploitation. The termination criterion of the WOA algorithm will be due to the number of iterations. The pseudo-code of the original WOA algorithm is shown in Algorithm 1.

Algorithm 1 : The WOA Algorithm [21]

Initialize WOA population $X_i (i = 1, 2, \ldots, n)$, size n, maximum iterations Max_{iter}, and objective function F_n.
Initialize WOA parameters $a, A, C, l, r_1, r_2, r_3$
Calculate objective function F_n for each X_i
Find best solution X^*
while $t \leq Max_{iter}$ **do**
  for $(i = 1 : i < n + 1)$ **do**
    if $(r_3 < 0.5)$ **then**
      if $(|A| < 1)$ **then**
        Update current agents' positions by Eq. 1
      else
        Select a random agent X_r
        Update current agents' positions by Eq. 4
      end if
    else
      Update current agents' positions by Eq. 2
    end if
  end for
  Update a, A, C, l, r_3
  Calculate objective function F_n for each X_i
  Find best solution X^*
end while
Return X^*

B. MODIFIED WHALE OPTIMIZATION ALGORITHM

As presented in the original WOA algorithm in the previous section, the position of search agent is changed/updated based on only one random whale, named X_r, that is determined from the population randomly to give the optimizer a more global search capability (exploration ability). By increasing the number of random agents in the modified WOA (MWOA), the global search can be more effective and be achieved. The following equation is applied to replace equation 4 of the original WOA algorithm for increasing the number of random agents up to three agents and give the algorithm more exploration ability.

$$\begin{aligned} X(t+1) = & \; w_1 * X_\alpha \\ & + \zeta * w_2 * (X_\beta - X_\gamma) \\ & + (1 - \zeta) * w_3 * (X(t) - X_\alpha) \end{aligned} \tag{5}$$

where the three random agents are indicated as X_α, X_β, and X_γ which are employed in the MWOA algorithm instead of

Algorithm 2 : The SCMWOA Meta-Heuristic Algorithm

Initialize SCMWOA algorithm population $X_i (i = 1, 2, \ldots, n)$, size n, maximum iterations Max_{iter}, objective function F_n.
Initialize SCMWOA algorithm parameters $a, A, C, l, r_1, r_2, r_3, r_4, r_5, r_6, r_7, w_1, w_2, w_3, t = 1$
Calculate Objective function values F_n for each agent X_i
Find best solution X^* based on F_n
while $t \leq Max_{iter}$ **do**
  for $(i = 1 : i < n + 1)$ **do**
    if $(t\%2 == 0)$ **then**
      if $(r_3 < 0.5)$ **then**
        if $(|A| < 1)$ **then**
          Update current agents' positions based on the following equation
          $X(t + 1) = X^*(t) - A.|C.X^*(t) - X(t)|$
        else
          Select three different random agents X_α, X_β, and X_γ from the population
          Update ζ by the following equation.
          $\zeta = 1 - \left(\frac{t}{Max_{iter}}\right)^2$
          Update current agents' positions based on the following equation using random agents
          $X(t + 1) = w_1 * X_\alpha + \zeta * w_2 * (X_\beta - X_\gamma) + (1 - \zeta) * w_3 * (X(t) - X_\alpha)$
        end if
      else
        Update current agents' positions based on the following equation
        $X(t + 1) = |X^*(t) - X(t)|.e^{bl}.cos(2\pi l) + X^*(t)$
      end if
    else
      if $(r_7 < 0.5)$ **then**
        Update current agents' positions based on the following equation
        $X(t) + r_4 \times \sin(r_5) \times |r_6 X^*(t) - X(t)|$
      else
        Update current agents' positions based on the following equation
        $X(t) + r_4 \times \cos(r_5) \times |r_6 X^*(t) - X(t)|$
      end if
    end if
  end for
  Update parameters a, A, C, l, r_3, r_7
  Calculate objective function F_n for each agent X_i and update old values
  Find best solution X^* based on F_n and update old value
  Set $t = t + 1$
end while
Return best solution X^*

one random agent. The parameter of ζ is computed as follows.

$$\zeta = 1 - \left(\frac{t}{Max_{iter}}\right)^2 \tag{6}$$

where Max_{iter} as maximum number of iterations during the execution process. The w_1, w_2, and w_3 parameters are selected randomly in [0, 1].

C. SINE COSINE ALGORITHM

The SCA algorithm was presented in [35] by switching between the sine and cosine based functions. To know the direction of the movement and how far the movement will be, SCA is based on a set of random variables. The following equation was used to update positions in this optimizer.

$$X(t+1) = \begin{cases} X(t) + r_4 \times \sin(r_5) & \\ \times |r_6 X^*(t) - X(t)| & r_7 < 0.5 \\ X(t) + r_4 \times \cos(r_5) & \\ \times |r_6 X^*(t) - X(t)| & r_7 \geq 0.5 \end{cases} \tag{7}$$

where the position of current solution id represented as $X(t)$, while the best solution is indicated as $X^*(t)$. The r_5, r_6, and r_7 parameters are selected randomly in [0, 1] during iterations. To make a balance between the process of exploration and the process of exploitation, r_4 is changed during iterations as follows.

$$r_4 = a - \frac{a \times t}{Max_{iter}} \tag{8}$$

Algorithm 3 :Binary SCMWOA Meta-Heuristic Algorithm

Initialize the SCMWOA algorithm configuration, including population and parameters
Change to binary solution (0 or 1) the current solutions
Evaluate the objective function
Determine the best solution based on the objective function
Train the model of k-NN and calculate error
while $t \leq iters_{max}$ **do**
  Apply the SCMWOA algorithm
  Update the solutions to binary solutions by the following equation

$$X_d^{(t+1)} = \begin{cases} 1 & \text{if } Sigmoid(X^*) \geq 0.5 \\ 0 & otherwise \end{cases},$$

$$Sigmoid(X^*) = \frac{1}{1 + e^{-10(X^* - 0.5)}}$$

  Evaluate objective function for each agent
  Update parameters
  Update the best solution based on the objective function
end while
Return the optimal solution

TABLE 1. Datasets from UCI repository.

No.	Dataset	# Attributes	# Instances	# Classes
1	Hepatitis	19	155	2
2	Ionosphere	34	351	2
3	Vertebral	6	310	2
4	Seeds	7	210	3
5	Parkinsons	23	197	2
6	Australian	14	690	2
7	Blood	5	748	2
8	Breast_Cancer	10	699	2
9	Diabetes	8	768	2
10	Lymphography	18	148	4
11	Zoo	17	101	7
12	Ring	20	7400	2
13	Titanic	3	2201	2
14	Towonorm	20	7400	2
15	Waveform	21	5000	3
16	Tic-Tac-Toe	9	949	2
17	Mofn	10	1324	2
18	HAR (Smartphones)	561	10299	6
19	ISOLET	617	7797	26

TABLE 2. Binary SCMWOA algorithm configuration.

Parameter	Value
# Agents	10
# Iterations	100
Dimension	# Features in dataset
Domain	[0,1]
# Runs	20
Inertia factor of SC	0.1
h_1 of f_n	0.99
h_2 of f_n	0.01

where t as current iteration, a as constant, and Max_{iter} represents the maximum number of iterations.

III. PROPOSED SCMWOA META-HEURISTIC ALGORITHM

The presented Sine Cosine Modified Whale Optimization (SCMWOA) algorithm is explained in this section. The SCMWOA algorithm is shown in Algorithm 2. The presented algorithm is proposed by balancing the updating process of the agents' positions between the sine cosine and the modified WOA algorithms during iterations.

TABLE 3. Configuration of compared algorithms with 100 iterations and 10 agents for each one.

Algorithm	Parameter (s)	Value (s)
GWO	a	2 to 0
PSO	Inertia W_{max}, W_{min}	[0.9,0.6]
	Acceleration constants C_1, C_2	[2,2]
SFS	Maximum diffusion level	1
WOA	a	2 to 0
	r	[0,1]
MVO	Wormhole existence probability	[0.2,1]
SBO	Step size	0.94
	Mutation probability	0.05
	Upper and lower limit difference	0.02
FA	# fireflies	10
GA	Mutation ratio	0.1
	Crossover	0.9
	Selection mechanism	Roulette wheel
SCA	Parameters $r_2, r_3, r_4,$	[0,1]

The SCMWOA algorithm starts by initializing the population and algorithm parameters, then calculates all agents' objective functions to get the initial best solution in steps from 1 to 4. For iterations $t\%2 = 0$ of current iteration t, the modified WOA algorithm is applied in steps from 8 to 18. As presented in the modified WOA algorithm, the position of the search agent is changed and updated based on three different random whales, named X_α, X_β, and X_γ, that can be determined from the population to give the algorithm more global search capability. While for the rest of the iterations, the cosine algorithm is applied in steps from 20 to 25. Steps from 28 to 30 are applied to update the parameters and find the current best solution X^*.

The SCMWOA algorithm' computational complexity according to Algorithm (2) will be discussed. Let n as number

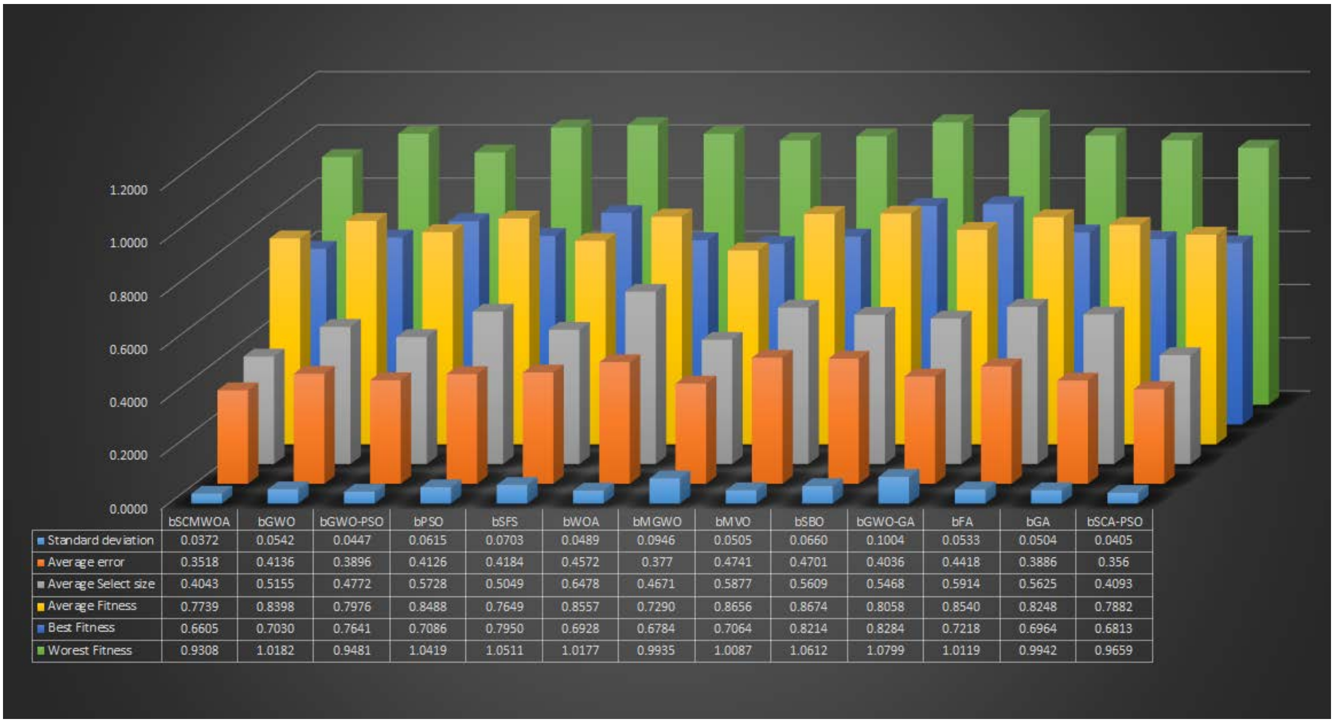

FIGURE 1. Feature selection average results acquired over all the datasets.

TABLE 4. Presented bSCMWOA and compared algorithms' average error.

Dataset	bSCMWOA	bGWO	bGWO-PSO	bPSO	bSFS	bWAO	bMGWO	bMVO	bSBO	bGWO-GA	bFA	bGA	bSCA-PSO
Hepatitis	0.16576	0.17948	0.17262157	0.1698	0.17846471	0.16674	0.176151	0.16674	0.1843863	0.1883078	0.1736	0.16674	0.16942
Ionosphere	0.10314	0.11614	0.11716154	0.14391	0.12325556	0.12896	0.1047342	0.13793	0.1242556	0.1635718	0.13451	0.12383	0.1068
Vertebral	0.17501	0.18812	0.18617573	0.19346	0.19005922	0.1852	0.176801	0.20122	0.207535	0.1939427	0.19977	0.18909	0.17867
Seeds	0.25584	0.26584	0.21918571	0.24941	0.21912857	0.26084	0.2258429	0.24799	0.2272714	0.2272714	0.2587	0.2487	0.2595
Parkinsons	0.10416	0.1221	0.12254615	0.12024	0.10923846	0.11101	0.1202385	0.12255	0.0979308	0.1317769	0.11024	0.11562	0.11782
Australian	0.11892	0.13392	0.12174348	0.12566	0.11926522	0.12805	0.1504391	0.12935	0.1330478	0.1260913	0.13631	0.12392	0.12258
Blood	0.2088	0.2179	0.22331847	0.22513	0.23587309	0.2183	0.2181378	0.21729	0.217696	0.2072542	0.21186	0.22392	0.21246
Breast_Cancer	0.01134	0.0172	0.01848541	0.01334	0.0159103	0.01226	0.0184854	0.01291	0.0159103	0.017627	0.01505	0.01548	0.015
Diabetes	0.23981	0.23706	0.22495	0.24429	0.33510625	0.2437	0.2444813	0.23979	0.2276	0.2272938	0.24311	0.25171	0.24347
Lymphography	3.23427	3.39727	3.284078	3.46564	3.3099	3.56666	3.2245	3.73094	3.52511	3.38749	3.45952	3.15952	3.23793
Zoo	0.10255	0.11485	0.10716154	0.11562	0.12254615	0.13562	0.1148538	0.11408	0.1256231	0.1379308	0.12639	0.12101	0.10621
Ring	0.12594	0.12784	0.13220365	0.1335	0.1362588	0.13202	0.1289595	0.12916	0.1343934	0.1360155	0.13174	0.13383	0.1296
Titanic	0.19087	0.21433	0.20043261	0.20062	0.19071774	0.19817	0.1988236	0.19312	0.183434	0.1899824	0.20028	0.19476	0.19453
Towonorm	0.00092	0.01797	0.01152238	0.03506	0.02887056	0.00313	0.0019463	0.01471	0.0210925	0.0382864	0.02563	0.03766	0.00458
WaveformEW	0.36132	0.37194	0.39727143	0.39493	0.36252941	0.36465	0.4053146	0.38467	0.3834659	0.4051946	0.39184	0.41159	0.36498
Tic-Tac-Toe	0.22575	0.24111	0.24330815	0.23814	0.2324116	0.22513	0.23149	0.22873	0.2690135	0.2583552	0.24425	0.24174	0.22941
Mofn	0.02994	0.08503	0.10634172	0.10158	0.106122	0.095	0.0657295	0.08673	0.0766365	0.1011263	0.10396	0.11031	0.0336
HAR (Smartphones)	0.3823	0.9561	0.8561	0.7878	0.9665	1.5427	0.6339	1.7141	1.8127	0.7456	1.2927	0.8566	0.38596
ISOLET	0.6476	0.8543	0.6583	0.881	0.9675	0.9685	0.7228	0.9368	0.9652	0.7846	0.9338	0.6582	0.65126
Average	0.3518	0.4136	0.3896	0.4126	0.4184	0.4572	0.3770	0.4741	0.4701	0.4036	0.4418	0.3886	0.3560

of population; M_t as total number of iterations. For each part of the algorithm, the time complexity can be defined as:

- Population initialization: $O(1)$.
- Parameters initialization:a, A, C, l, r_1, r_2, r_3, r_4, r_5, r_6, r_7, w_1, w_2, w_3, $t = 1$: $O(1)$.
- Calculating objective function values F_n for each agent X_i: $O(n)$.
- Finding the best solution X^* based on F_n: $O(n)$.
- Position updating: $O(M_t \times n)$.
- Diffusion process calculation: $O(M_t \times n)$.
- Updating $\overrightarrow{a}$ by the exponential form: $O(M_t)$.
- Updating parameters a, A, C, l, r_3, r_7: $O(M_t)$.
- Objective function evaluation: $O(M_t \times n)$.
- Best individual update: $O(M_t \times n)$.
- Iteration counter increment: $O(M_t)$.

The overall complexity of the proposed SCMWOA algorithm is $O(M_t \times n)$. Considering the number of variables as m, the final computational complexity of the algorithm will be $O(M_t \times n \times m)$.

IV. BINARY SCMWOA ALGORITHM

The SCMWOA algorithm has a binary version based on MWOA and SCA. To get a probability value of two discrete classes, an activation function, named Sigmoid, can be employed for binary classification [36]. The classification using this function gives output values between zero or one. The optimizer's outputs are changed to binary values from the

TABLE 5. Average select size of the presented bSCMWOA and compared algorithms.

Dataset	bSCMWOA	bGWO	bGWO-PSO	bPSO	bSFS	bWAO	bMGWO	bMVO	bSBO	bGWO-GA	bFA	bGA	bSCA-PSO
Hepatitis	0.3097	0.3737	0.3687	0.5037	0.3286	0.5987	0.4199	0.4737	0.4887	0.4487	0.5087	0.4687	0.31472
Ionosphere	0.10506	0.23537	0.2596	0.45961	0.2827	0.30052	0.2228	0.43991	0.399	0.3929	0.45658	0.35961	0.11008
Vertebral	0.37527	0.4687	0.4687	0.47703	0.4718	0.47703	0.4574	0.48537	0.4017	0.6687	0.47703	0.47703	0.38029
Seeds	0.49727	0.47584	0.5107	0.6687	0.4827	0.65441	0.5299	0.49727	0.5687	0.4827	0.55441	0.5187	0.50229
Parkinsons	0.22488	0.38006	0.3596	0.43688	0.2605	0.45279	0.2777	0.50506	0.4587	0.4687	0.43915	0.41643	0.2299
Australian	0.24084	0.39727	0.42584286	0.50084	0.454414	0.64727	0.340129	0.48299	0.540129	0.4972714	0.4937	0.47584	0.24586
Blood	0.6112	0.6687	0.5687	0.6187	0.5794	0.7437	0.5123	0.7062	0.6187	0.6187	0.7312	0.7437	0.61622
Breast_Cancer	0.4452	0.4937	0.4687	0.56245	0.4937	0.6062	0.4901	0.56245	0.6187	0.6187	0.6062	0.54995	0.45022
Diabetes	0.31195	0.4812	0.4937	0.57495	0.4438	0.6062	0.3937	0.5562	0.4937	0.4937	0.5437	0.5312	0.31697
Lymphography	0.4887	0.3437	0.24647778	0.45203	0.502033	0.47703	0.489822	0.44648	0.502033	0.5020333	0.42703	0.39926	0.49372
Zoo	0.22779	0.33006	0.35051818	0.46188	0.423245	0.4687	0.359609	0.4437	0.459609	0.4505182	0.45961	0.42779	0.23281
Ring	0.2687	0.2887	0.3087	0.3287	0.3008	0.2937	0.2898	0.3037	0.3087	0.2887	0.3237	0.3037	0.27372
Titanic	0.7687	0.7687	0.83536667	0.78537	0.825367	0.8187	0.799833	0.85203	0.7827	0.7687	0.85203	0.8187	0.77372
Towonorm	0.6087	0.8212	0.8187	0.6587	0.7787	0.9462	0.6987	0.8187	0.7587	0.6387	0.7162	0.8387	0.61372
WaveformEW	0.41394	0.49727	0.48298571	0.54965	0.488224	0.86394	0.5687	0.60918	0.5687	0.6544143	0.57584	0.62108	0.41896
Tic-Tac-Toe	0.42981	0.50203	0.44330815	0.57981	0.436412	0.7187	0.44209	0.57981	0.439013	0.5583552	0.60203	0.57981	0.43483
Mofn	0.15037	0.5687	0.16634172	0.6337	0.207022	0.8287	0.175729	0.6137	0.376637	0.4011263	0.6437	0.6537	0.15539
HAR (Smartphones)	0.5358	0.8532	0.7439	0.8481	0.8699	0.8722	0.6674	0.8852	0.9237	0.6808	0.9248	0.7401	0.54082
ISOLET	0.6674	0.8458	0.7472	0.7828	0.9639	0.93384	0.74	0.9043	0.9501	0.7552	0.9019	0.7639	0.67242
Average	0.40428	0.51547	0.47725	0.57282	0.50491	0.64782	0.46714	0.58768	0.56094	0.54677	0.59145	0.56252	0.40930

TABLE 6. Average fitness of the presented bSCMWOA and compared algorithms.

Dataset	bSCMWOA	bGWO	bGWO-PSO	bPSO	bSFS	bWAO	bMGWO	bMVO	bSBO	bGWO-GA	bFA	bGA	bSCA-PSO
Hepatitis	0.19349	0.22938	0.2117	0.21579	0.2297	0.21676	0.1952	0.21676	0.2237	0.1877	0.22355	0.21676	0.1973
Ionosphere	0.11515	0.15012	0.1167	0.17762	0.123	0.16281	0.1468	0.17169	0.1237	0.1627	0.16831	0.15773	0.1189
Vertebral	0.31128	0.35926	0.1857	0.36454	0.213	0.35637	0.1917	0.37223	0.3067	0.2937	0.37079	0.36022	0.3151
Seeds	0.33297	0.36287	0.4227	0.34661	0.4197	0.35792	0.3564	0.34519	0.3967	0.4167	0.3558	0.3459	0.3368
Parkinsons	0.13913	0.13151	0.1217	0.14827	0.132	0.13913	0.14	0.15055	0.1577	0.1317	0.13837	0.1437	0.1429
Australian	0.2817	0.29655	0.12174348	0.28837	0.109265	0.29074	0.150439	0.29203	0.133048	0.1260913	0.29892	0.28665	0.2855
Blood	0.8206	0.8404	0.22331847	0.84756	0.236373	0.8408	0.218138	0.83981	0.217696	0.2072542	0.83245	0.84637	0.8244
Breast_Cancer	0.29214	0.30796	0.31848541	0.30414	0.31531	0.30308	0.315485	0.30371	0.51591	0.317627	0.30584	0.30626	0.2959
Diabetes	0.54537	0.55438	0.55495	0.56153	0.556406	0.56095	0.554481	0.55708	0.5621	0.5546375	0.56037	0.56888	0.5492
Lymphography	3.04226	3.39076	4.3564551	3.45845	4.646251	3.55846	3.458496	3.7211	4.707476	5.2176796	3.45239	3.15539	3.2460
Zoo	0.13075	0.14294	0.14716154	0.1437	0.152546	0.1635	0.134854	0.14218	0.145623	0.1379308	0.15436	0.14903	0.1345
Ring	1.35787	1.35975	0.13220365	1.36535	0.136259	1.36389	0.10896	1.36106	0.134393	0.1360155	1.36361	1.36567	1.3617
Titanic	2.63531	2.65854	2.68602606	2.64497	2.758877	2.64254	2.687936	2.63754	2.91604	2.6899824	2.64463	2.63916	2.6391
Towonorm	1.14447	1.25098	1.41152238	1.2679	1.578806	1.23628	1.316956	1.24775	1.521093	1.6382864	1.25856	1.27047	1.1483
WaveformEW	1.1512	1.16172	1.39727143	1.18448	0.403994	1.1545	1.292315	1.17432	1.383466	0.4051946	1.18142	1.20097	1.1550
Tic-Tac-Toe	0.57874	0.59395	0.75866865	0.591	0.236412	0.57812	0.61249	0.58169	0.589013	0.6583552	0.59705	0.59457	0.5825
Mofn	0.47232	0.52586	0.48663651	0.54225	0.504822	0.53574	0.490103	0.52755	0.548065	0.5011263	0.54461	0.55089	0.4761
HAR (Smartphones)	0.513	0.8254	0.7578	0.8243	0.8799	0.8822	0.7341	0.9035	0.9432	0.7581	0.8912	0.7428	0.5168
ISOLET	0.6458	0.813	0.7443	0.8499	0.9008	0.9143	0.7452	0.8999	0.9543	0.7688	0.88351	0.7699	0.6496
Average	0.7739	0.8398	0.7976	0.8488	0.7649	0.8557	0.7290	0.8656	0.8674	0.8058	0.8540	0.8248	0.7882

TABLE 7. Presented bSCMWOA and compared algorithms' best fitness.

Dataset	bSCMWOA	bGWO	bGWO-PSO	bPSO	bSFS	bWAO	bMGWO	bMVO	bSBO	bGWO-GA	bFA	bGA	bSCA-PSO
Hepatitis	0.09835	0.11776	0.19540588	0.11776	0.178994	0.15658	0.145994	0.17599	0.175994	0.1759941	0.15658	0.11776	0.1849
Ionosphere	0.06339	0.08031	0.10569301	0.11415	0.070115	0.08877	0.113462	0.07185	0.097231	0.1480007	0.06339	0.09723	0.0699
Vertebral	0.2766	0.29582	0.34387799	0.28621	0.334266	0.28621	0.285043	0.30543	0.343878	0.315043	0.30543	0.28621	0.2832
Seeds	0.0687	0.15356	0.21012857	0.12527	0.204129	0.12527	0.135414	0.19599	0.195986	0.2384143	0.21013	0.15356	0.0753
Parkinsons	0.02917	0.04394	0.0743993	0.08963	0.043938	0.05917	0.135322	0.05917	0.059169	0.1200916	0.04394	0.05917	0.1257
Australian	0.2449	0.25781	0.2664205	0.25351	0.269725	0.2492	0.262116	0.26642	0.275029	0.2750292	0.26212	0.25781	0.2515
Blood	0.80045	0.80045	0.80442289	0.8084	0.836302	0.80045	0.825378	0.8084	0.806471	0.7964711	0.79647	0.79647	0.8070
Breast_Cancer	0.27744	0.28119	0.29819034	0.28544	0.285941	0.27695	0.283692	0.28119	0.293941	0.2981903	0.2727	0.28544	0.2840
Diabetes	0.4976	0.51686	0.53233281	0.5246	0.524598	0.50526	0.522898	0.5246	0.516864	0.5207313	0.513	0.513	0.5042
Lymphography	1.93607	1.87546	2.82504921	1.87546	3.090763	1.45117	1.390559	1.63301	3.794845	3.8554574	1.93607	1.71382	1.9426
Zoo	0.05917	0.05917	0.08963007	0.05917	0.120092	0.0744	0.102861	0.05917	0.074399	0.1200916	0.05917	0.0744	0.0657
Ring	1.33793	1.3391	1.35355037	1.35275	1.360375	1.35074	1.35355	1.34913	1.353149	1.3595723	1.3391	1.35435	1.3445
Titanic	2.61256	2.61256	2.60445262	2.61256	2.62066	2.61256	2.605303	2.6058	2.614453	2.6044526	2.61256	2.61256	2.6191
Towonorm	1.16191	1.23954	1.23592263	1.24194	1.253587	1.2303	1.180521	1.23271	1.249171	1.2499737	1.24716	1.25238	1.1685
WaveformEW	1.08577	1.12321	1.17015658	1.11727	1.140547	1.09647	1.176636	1.13629	1.13272	1.1576776	1.10954	1.14223	1.0923
Tic-Tac-Toe	0.53219	0.53219	0.55080728	0.53529	0.558411	0.5477	0.557359	0.53219	0.553911	0.5508073	0.5415	0.5446	0.5387
Mofn	0.41968	0.45335	0.44661837	0.46682	0.48519	0.49152	0.436618	0.45335	0.430904	0.5319245	0.50723	0.48254	0.4262
HAR (Smartphones)	0.4688	0.8019	0.731	0.783	0.8698	0.8791	0.6753	0.8494	0.8694	0.6742	0.8802	0.7306	0.4754
ISOLET	0.579	0.7732	0.6798	0.8143	0.8583	0.881	0.7021	0.8814	0.7683	0.7466	0.858	0.7582	0.6856
Average	0.6605	0.7030	0.7641	0.7086	0.7950	0.6928	0.6784	0.7064	0.8214	0.8284	0.7218	0.6964	0.6813

continuous ones by the following equation.

$$X_d^{(t+1)} = \begin{cases} 1 & \text{if } Sigmoid(X^*) \geq 0.5 \\ 0 & otherwise \end{cases}, \tag{9}$$

where the best position is represented by X^*, The function $Sigmoid$ is mainly scales the continuous values to 0 or 1 values and is calculated as follows.

$$Sigmoid(X^*) = \frac{1}{1 + e^{-10(X^* - 0.5)}} \tag{10}$$

The proposed binary SCMWOA algorithm is discussed step by step in Algorithm 3. The binary SCMWOA algorithm starts by initializing the population and algorithm parameters in step 1. All the solutions are changed to binary ones in step 2. The algorithm calculates the agents' objective function

TABLE 8. Presented bSCMWOA and compared algorithms' worst fitness.

Dataset	bSCMWOA	bGWO	bGWO-PSO	bPSO	bSFS	bWAO	bMGWO	bMVO	bSBO	bGWO-GA	bFA	bGA	bSCA-PSO
Hepatitis	0.29288	0.31188	0.273052941	0.33129	0.253641	0.33129	0.311876	0.29246	0.292465	0.2924647	0.3507	0.29246	0.29955
Ionosphere	0.21462	0.22415	0.173385315	0.23262	0.256322	0.24954	0.232616	0.21569	0.19877	0.2580007	0.26646	0.27492	0.22129
Vertebral	0.41838	0.40155	0.363101294	0.43038	0.392325	0.43038	0.439994	0.46883	0.468829	0.4111595	0.57456	0.46883	0.46505
Seeds	0.478643	0.62027	0.408128571	0.57784	0.408129	0.57784	0.388129	0.50713	0.408129	0.4081286	0.52127	0.59199	0.485313
Parkinsons	0.20988	0.19625	0.211476224	0.24194	0.226707	0.22671	0.226707	0.22671	0.211476	0.2419378	0.21148	0.21148	0.21655
Australian	0.31557	0.36542	0.309463975	0.3482	0.287942	0.33099	0.40416	0.31377	0.30516	0.3051596	0.46442	0.32238	0.32224
Blood	0.90382	0.90382	0.887916867	0.90382	0.931652	0.88394	0.887917	0.90382	0.887917	0.8879169	0.86406	0.90382	0.91049
Breast_Cancer	0.32883	0.34493	0.327932833	0.32368	0.327933	0.31943	0.336431	0.32368	0.323684	0.3151861	0.33218	0.33643	0.3355
Diabetes	0.5966	0.62515	0.547801563	0.59034	0.567138	0.60968	0.594208	0.61354	0.555536	0.5632703	0.60194	0.67542	0.60327
Lymphography	5.2512	5.20913	5.007090023	5.89607	6.409131	5.43138	5.59607	5.45158	6.623417	7.2699472	5.0677	5.08791	5.25787
Zoo	0.19758	0.24194	0.196245455	0.25717	0.211476	0.28763	0.236707	0.21148	0.226707	0.2471685	0.21148	0.25717	0.20425
Ring	1.37042	1.37242	1.379243796	1.38366	1.384463	1.37965	1.356601	1.37684	1.381653	1.3744263	1.38486	1.38085	1.37709
Titanic	2.45443	3.07717	2.646321646	2.7017	2.73006	2.74897	2.620605	2.68684	2.655776	2.6584772	2.83001	2.70035	2.9611
Towonorm	1.1344	1.26724	1.251579562	1.30899	1.272878	1.2564	1.264426	1.26443	1.261215	1.2816891	1.27246	1.30899	1.14107
WaveformEW	1.15733	1.25929	1.218884074	1.23731	1.245625	1.17966	1.213536	1.22423	1.228392	1.2135359	1.24562	1.26048	1.164
Tic-Tac-Toe	0.6277	0.66253	0.653221073	0.71839	0.628393	0.62839	0.656325	0.65012	0.674945	0.659428	0.65012	0.6377	0.63437
Mofn	0.54888	0.59703	0.540904082	0.60825	0.621516	0.57458	0.569476	0.59703	0.552129	0.5498837	0.57009	0.59703	0.55555
HAR (Smartphones)	0.5363	0.8351	0.8365	0.8463	0.9002	0.9564	0.7568	0.9142	0.8143	0.7691	0.9011	0.7787	0.54297
ISOLET	0.6486	0.8298	0.782	0.8586	0.9154	0.9332	0.7833	0.9231	1.0927	0.811	0.9058	0.802	0.65527
Average	0.9308	1.0182	0.9481	1.0419	1.0511	1.0177	0.9935	1.0087	1.0612	1.0799	1.0119	0.9942	0.9659

TABLE 9. Standard deviation fitness of the presented bSCMWOA and compared algorithms.

Dataset	bSCMWOA	bGWO	bGWO-PSO	bPSO	bSFS	bWAO	bMGWO	bMVO	bSBO	bGWO-GA	bFA	bGA	bSCA-PSO
Hepatitis	0.00157	0.02059	0.004182095	0.02827	0.020597	0.01494	0.011148	0.00848	0.016249	0.01296563	0.01927	0.01904	0.0239
Ionosphere	0.00167	0.01122	0.007017724	0.00204	0.043341	0.01104	0.006416	0.00835	0.006256	0.01519998	0.01668	0.01624	0.0043
Vertebral	-0.00532	-0.00248	-0.00270308	0.00867	0.017188	0.00639	0.006275	0.00906	0.019832	0.00427609	0.03273	0.01366	-0.0040
Seeds	0.06171	0.08493	0.050190353	0.07245	0.057824	0.07587	0.063834	0.04811	0.068077	0.05459854	0.05181	0.07438	0.0640
Parkinsons	0.00059	0.01001	0.020350051	0.01157	0.045158	0.0212	0.004124	0.02146	0.026296	0.01637985	0.01306	0.00616	0.0029
Australian	-0.01587	0.00073	-0.01243929	-0.00936	-0.00448	-0.00767	0.002753	-0.01591	-0.01455	-0.0119742	0.01422	-0.01341	-0.0136
Blood	-0.01099	-0.00624	0.002506873	-0.0028	0.013276	-0.00655	-0.00867	-0.00629	0.008953	0.00476914	-0.01044	5E-05	-0.0087
Breast_Cancer	-0.01856	-0.0171	-0.01869565	-0.02201	0.001796	-0.02025	-0.02063	-0.01984	-0.01966	-0.0248562	-0.01811	-0.01801	-0.0163
Diabetes	-0.01554	-0.00111	-0.01376146	-0.01435	0.005523	-0.00884	0.000307	-0.00464	-0.01483	-0.012276	-0.00584	0.00375	-0.0132
Lymphography	0.80947	0.87009	0.849143714	1.10514	1.063027	0.81593	1.731152	0.94078	1.100886	1.33560729	0.87009	0.90668	0.8118
Zoo	0.00941	0.01412	0.013104941	0.01823	0.027531	0.02445	0.013343	0.01518	0.031866	0.02466142	0.01412	0.01633	0.0117
Ring	-0.02459	-0.02295	-0.02137493	-0.02352	-0.02111	-0.02194	-0.02456	-0.0235	-0.02055	-0.0253889	-0.0196	-0.02496	-0.0223
Titanic	-0.01646	0.06839	-0.01591841	-0.00432	0.013285	0.00077	0.013505	-0.01197	-0.01264	-0.0084112	0.01478	-0.00977	-0.0142
Towonorm	-0.02534	-0.02264	-0.02482292	-0.01502	-0.01951	-0.02466	-0.02059	-0.02303	-0.02287	-0.0187496	-0.02376	-0.01664	-0.0230
WaveformEW	-0.01007	0.00033	-0.01073646	-0.00193	0.01053	-0.00583	5.76E-05	4E-05	0.011222	-0.0082914	0.0021	0.00236	-0.0078
Tic-Tac-Toe	-0.01087	0.0032	0.008261358	-0.00762	0.013249	-0.00188	-0.0092	-0.01087	0.012115	0.0106023	-0.00168	-0.00136	-0.0086
Mofn	-0.00136	0.00706	0.009529998	0.01493	-0.00015	0.00221	0.037771	-0.01024	0.017822	-0.024454	0.00825	-0.01472	0.0009
HAR (Smartphones)	-0.0144	0.0021	-0.0014	-0.0001	0.0199	0.0231	-0.0091	0.0143	0.01883	0.2698	0.0132	-0.0012	-0.0121
ISOLET	-0.008	0.0101	0.00646	0.0086	0.0288	0.031	-0.0012	0.01993	0.021	0.2927	0.02106	-0.0011	-0.0057
Average	0.0372	0.0542	0.0447	0.0615	0.0703	0.0489	0.0946	0.0505	0.0660	0.1004	0.0533	0.0504	0.0405

TABLE 10. The p-values of the presented bSCMWOA against compared algorithms for the nineteen datasets.

Dataset	bGWO	bGWO-PSO	bPSO	bSFS	bWAO	bMGWO	bMVO	bSBO	bGWO-GA	bFA	bGA	bSCA-PSO
Hepatitis	2.03E-04	2.03E-04	2.03E-04	2.03E-04	**0.2433**	2.03E-04	**0.2560**	2.03E-04	2.03E-04	2.03E-04	**0.0881**	2.03E-04
Ionosphere	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	**0.0613**	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04
Vertebral	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	**0.0814**	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04
Seeds	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04
Parkinsons	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04
Australian	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04
Blood	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	**0.0899**	2.03E-04	2.03E-04	**0.0669**
Breast_Cancer	2.03E-04	2.03E-04	2.03E-04	2.03E-04	**0.0756**	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04
Diabetes	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	**0.0893**	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04
Lymphography	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	**0.0712**	2.03E-04
Zoo	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04
Ring	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04
Titanic	2.03E-04	2.03E-04	2.03E-04	**0.0833**	2.03E-04	2.03E-04	2.03E-04	2.03E-04	**0.0651**	2.03E-04	2.03E-04	2.03E-04
Towonorm	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	**0.0587**	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04
WaveformEW	2.03E-04	2.03E-04	2.03E-04	**0.0834**	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04
Tic-Tac-Toe	2.03E-04	2.03E-04	2.03E-04	2.03E-04	**0.0658**	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04
Mofn	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04
HAR (Smartphones)	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04
ISOLET	2.03E-04	**0.0788**	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	2.03E-04	**0.0621**	2.03E-04

values to get the initial best solution in steps 3 and 4. The k-NN model training and the error are calculated to adjust the performance at step 5. The SCMWOA algorithm is then applied in step 7, and the output solutions are updated to binary ones in step 8. Steps from 9 to 11 evaluate the objective function redetermining the best solution and update the algorithm parameters for the next iteration.

V. EXPERIMENTAL RESULTS AND DISCUSSION

The experimental results section is divided into three scenarios. The first scenario is designed to test the ability of the SCMWOA algorithm in feature selection problems based on nineteen different tested datasets from the UCI public machine learning repository. The next scenario examines the presented algorithm's ability to solve twenty-three

TABLE 11. Mean and standard deviation (StDev) of the suggested and compared algorithms over the benchmark functions (f_1 to f_{23}).

		SCMWOA	PSO	WOA	GWO	FEP	GSA	GA	EGWO	GWO-CSA	SCA-PSO
f_1	Mean	0.00E+00	0.000136	1.41E-30	6.59E-28	0.00057	2.53E-16	4.6E-172	1.74E-16	1.01E-28	1.11014E-20
	StDev	0.00E+00	0.000202	4.91E-30	6.34E-05	0.00013	9.67E-17	0.00E+00	3.69E-16	1.26E-28	1.83289E-20
f_2	Mean	2.1E-182	0.042144	1.06E-21	7.18E-17	0.0081	0.055655	3.44E-90	5.16E-11	1.50E-17	4.09460E-11
	StDev	0.00E+00	0.045421	2.39E-21	0.029014	0.00077	0.194074	6.13E-90	8.54E-11	1.25E-17	5.68981E-11
f_3	Mean	0.00E+00	70.12562	5.39E-07	3.29E-06	0.016	896.5347	1.7E-127	1.27E-01	5.18E-04	2.16858E-12
	StDev	0.00E+00	22.11924	2.93E-06	79.14958	0.014	318.9559	8.6E-127	2.83E-01	1.07E-03	1.03815E-11
f_4	Mean	1E-194	1.086481	0.072581	5.61E-07	0.3	7.35487	1.15E-75	1.55E+00	2.07E-07	8.47410E-08
	StDev	0.00E+00	0.317039	0.39747	1.315088	0.5	1.741452	2.45E-75	3.95E+00	3.00E-07	1.23324E-07
f_5	Mean	0.00E+00	96.71832	27.86558	26.81258	5.06	67.54309	28.37287	2.80E+01	2.70E+01	21.97646
	StDev	0.00E+00	60.11559	0.763626	69.90499	5.87	62.22534	0.582802	9.83E-01	5.00E-01	0.54774
f_6	Mean	0.121209	0.000102	3.116266	0.816579	0.00E+00	2.5E-16	3.932626	3.19E+00	1.23E+00	7.13998E-12
	StDev	0.154425	8.28E-05	0.532429	0.000126	0.00E+00	1.74E-16	0.431755	5.08E-01	2.62E-01	3.65884E-11
f_7	Mean	0.000225	0.122854	0 .001425	0.002213	0.1415	0.089441	0.022992	1.19E-02	1.92E-03	0.00012
	StDev	0.000267	0.044957	0.001149	0.100286	0.3522	0.04339	0.021966	5.87E-03	9.88E-04	0.00010
f_8	Mean	-6514.05	-4841.29	-5080.76	-6123.1	-12554.5	-2821.07	-4080.18	-6.34E+03	-3.57E+03	-12569.486
	StDev	1077.84	1152.814	695.7968	-4087.44	52.6	493.0375	551.6504	6.13E+02	4.42E+02	2.39996E-07
f_9	Mean	0.00E+00	46.70423	0.00E+00	0.310521	0.046	25.96841	0.00E+00	1.87E+02	1.19E+00	0.00E+00
	StDev	0.00E+00	11.62938	0.00E+00	47.35612	0.012	7.470068	0.00E+00	5.25E+01	3.32E+00	0.00E+00
f_{10}	Mean	4.33E-17	0.276015	7.4043	1.06E-13	0.018	0.062087	7.99E-16	1.30E-01	1.37E-14	2.24609E-11
	StDev	0.00E+00	0.50901	9.897572	0.077835	0.0021	0.23628	1.07E-15	5.83E-01	3.53E-15	2.33547E-11
f_{11}	Mean	0.00E+00	0.009215	0.000289	0.004485	0.016	27.70154	0.00E+00	9.89E-03	0.00E+00	0.00E+00
	StDev	0.00E+00	0.007724	0.000289	0.006659	0.022	5.040343	0.00E+00	1.18E-02	0.00E+00	0.00E+00
f_{12}	Mean	0.144417	0.006917	0.339676	0.053438	9.2E-06	1.799617	0.556173	3.00E+00	4.92E-02	8.46465E-14
	StDev	0.343144	0.026301	0.214864	0.020734	3.6E-06	0.95114	0.063582	3.55E+00	8.54E-03	2.79106E-13
f_{13}	Mean	1.14E-34	0.006675	1.889015	0.654464	0.00016	8.899084	2.132497	2.70E+00	9.39E-01	0.00399
	StDev	2.54E-49	0.008907	0.266088	0.004474	0.000073	7.126241	0.174792	5.52E-01	2.09E-01	0.00928
f_{14}	Mean	0.9663	3.627168	2.111973	4.042493	1.22	5.859838	0.998004	6.42E+00	9.98E-01	1.13027
	StDev	2.13E-13	2.560828	2.498594	4.252799	0.56	3.831299	1.37E-09	5.03E+00	2.21E-05	0.50338
f_{15}	Mean	0.000523	0.000577	0.000572	0.000337	0.0005	0.003673	0.002318	7.58E-03	3.38E-04	3.13244E-04
	StDev	0.000237	0.000222	0.000324	0.000625	0.00032	0.001647	0.010072	9.76E-03	2.22E-05	2.17489E-05
f_{16}	Mean	-1.02163	-1.03163	-1.03163	-1.03163	-1.03	-1.03163	-1.03163	-1.03E+00	-1.03E+00	-1.0316
	StDev	1.64E-07	6.25E-16	4.2E-07	-1.03163	4.9E-07	4.88E-16	4.44E-06	2.26E-08	5.57E-06	4.40244E-16
f_{17}	Mean	0.387895	0.397887	0.397914	0.397889	0.398	0.397887	0.398223	3.98E-01	3.98E-01	0.39788
	StDev	7.99E-06	0.00E+00	2.7E -05	0.397887	1.5E-07	0.00E+00	0.001395	3.02E-07	2.93E-04	3.66527E-15
f_{18}	Mean	3.000023	3.00E+00	3.00E+00	3.000028	3.02	3.00E+00	3.000029	7.05E+00	3.00E+00	3.00E+00
	StDev	0.000157	1.33E-15	4.22E -15	3.00E+00	0.11	4.17E-15	4.22E-05	9.89E+00	1.97E-05	5.96540E-13
f_{19}	Mean	-3.86247	-3.86278	-3.85616	-3.86263	-3.86	-3.86278	-3.86272	-3.86E+00	-3.86E+00	-3.86278
	StDev	0.000488	2.58E-15	0.002706	-3.86278	0.000014	2.29E-15	9.02E-05	2.15E-03	2.52E-03	8.31755E-15
f_{20}	Mean	-3.25476	-3.26634	-2.98105	-3.28654	-3.27	-3.31778	-3.25066	-3.24E+00	-3.31E+00	-3.27168
	StDev	0.063134	0.060516	0.376653	-3.25056	0.059	0.023081	0.081811	7.11E-02	5.58E-03	0.06371
f_{21}	Mean	-5.5369	-6.8651	-7.04918	-10.1514	-5.52	-5.95512	-6.03721	-5.26E+00	-6.80E+00	-10.15319
	StDev	1.518415	3.019644	3.629551	-9.14015	1.59	3.737079	1.998973	3.08E+00	2.23E+00	4.46227E-15
f_{22}	Mean	-6.53255	-8.45653	-8.18178	-10.4015	-5.53	-9.68447	-6.76809	-7.56E+00	-8.76E+00	-10.40294
	StDev	2.168117	3.087094	3.829202	-8.58441	2.12	2.014088	2.628446	3.61E+00	6.47E-01	1.80672E-15
f_{23}	Mean	-6.66653	-9.95291	-9.34238	-10.534	-6.57	-10.5364	-5.79459	-7.02E+00	-8.82E+00	-10.53640
	StDev	2.434882	1.782786	2.414737	-8.55899	3.14	2.6E-15	2.643454	4.02E+00	5.52E-01	4.84794E-15

benchmark functions divided into unimodal and multimodal functions. The third and last scenario is designed in this work for testing the ability of the algorithm for solving two constrained optimization problems of Tension/Compression Spring and Welded Beam designs.

A. FEATURE SELECTION SCENARIO

Nineteen UCI repository datasets are tested in this work to analyze the ability of the proposed algorithm for feature selection problems. The nineteen datasets, shown in Table 1, are determined with various number of features/attributes, instances, and classed that the algorithms may be evaluated on working with various concerns. In this scenario, the presented algorithm of binary SCMWOA (bSCMWOA) is compared to the original bGWO [18], bPSO [19], bSFS [20], bWOA [21], bMVO [22], bSBO [23], bFA [24], bGA [25] algorithms, Modified GWO (bMGWO) [26], hybrid of PSO and GWO (bGWO-PSO) [27], hybrid of GA and GWO (bGWO-GA) [26], and hybrid of SCA and PSO (bSCA-PSO) [28] in which b denotes the binary variant of the algorithm. Configuration of the presented SCMWOA and compared algorithms during the experiments are discussed in Tables 2 and 3 with 100 iterations and 10 agents initiated at the start of each algorithm.

For evaluating the feature selection ability of the proposed algorithm, the following metrics are employed in experiments. For M as the number repetitions, g_* represents the optimal solution, and N be the total number of points. The following equation can compute the Average Error for L as a class for point, C as classifier output for that point, and $Match$ to represent the matching between the two inputs.

$$AvgError = 1 - \frac{1}{M}\sum_{j=1}^{M}\frac{1}{N}\sum_{i=1}^{N} Match(C_i, L_i) \tag{11}$$

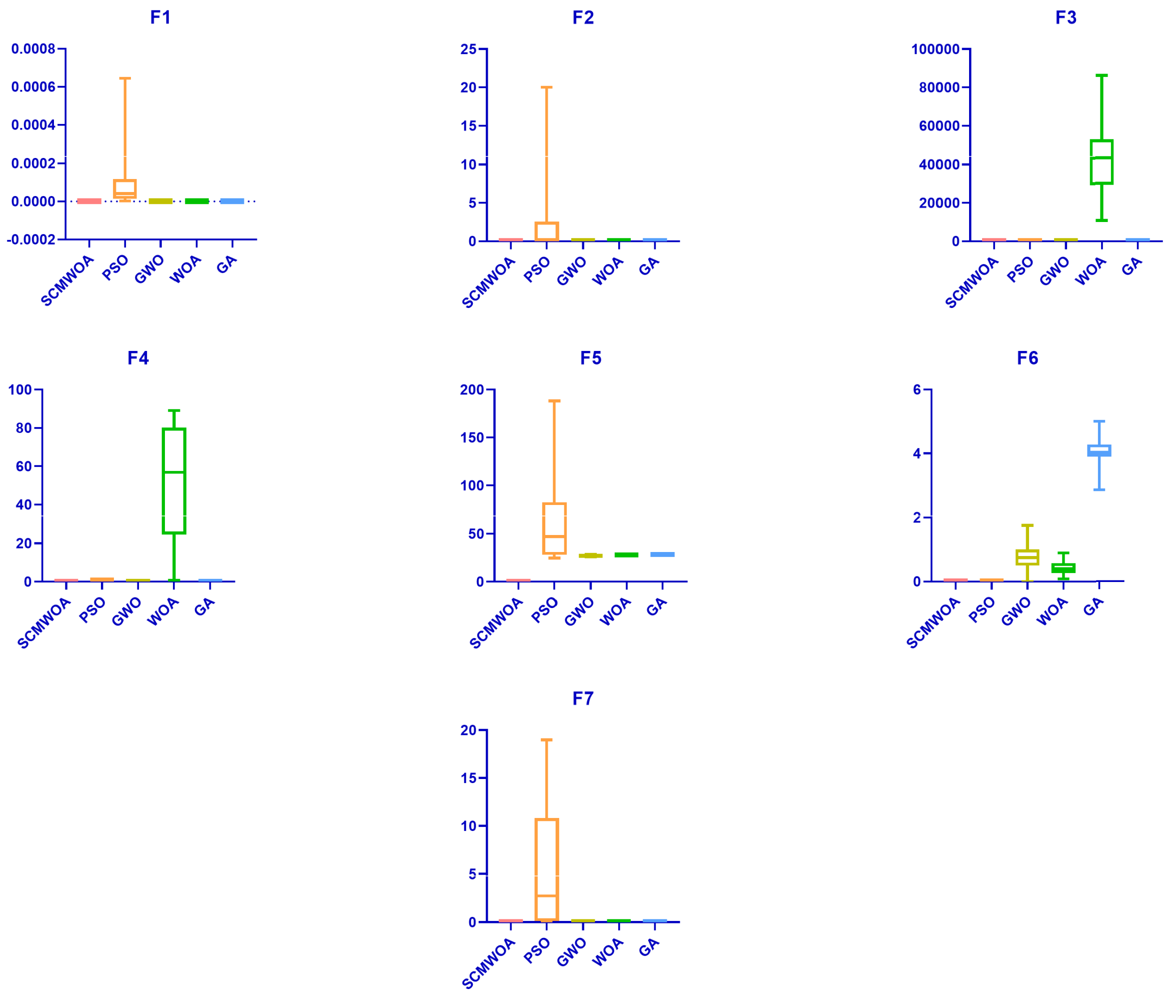

FIGURE 2. Box plot of the suggested and compared algorithms for benchmark function (f_1 to f_7).

The Average Fitness can be computed, for $size(g_j^*)$ as the vector g_j^* size and D represents the size of dataset, as follows.

$$AvgSelectSize = \frac{1}{M}\sum_{j=1}^{M}\frac{size(g_j^*)}{D} \tag{12}$$

The Best Fitness and the Worst Fitness are computed as in the following equations.

$$BestF_n = Min_{j=1}^{M} g_j^* \tag{13}$$

$$WorstF_n = Max_{j=1}^{M} g_j^* \tag{14}$$

The Mean and the Standard Deviation (SD) are represented as in the following equations.

$$SD = \sqrt{\frac{1}{M-1}\sum(g_j^* - Mean)^2} \tag{15}$$

$$Mean = \frac{1}{M}\sum_{j=1}^{M} g_j^* \tag{16}$$

The results of the presented and compared algorithms based on average error for the nineteen datasets are shown in Table 4. Average selected size-based results are presented in Table 5. The average fitness, best fitness, and worst fitness-based evaluation results are introduced in Tables 6, 7, and 8, respectively. The standard deviation fitness results of the tested algorithms are shown in Table 9. Tables 10 presented the p-values of the proposed and other tested algorithms for the nineteen datasets, which reflects the performance of the suggested algorithm with a p-value less than 0.005 for all datasets. Figure 1 shows the feature selection average results acquired over all the datasets, summary results, to measure the performance of the bSCMWOA algorithm. The results shown in tables from Table 4 to Table 10 and Figure 1 confirm the performance of the binary SCMWOA algorithm for feature selection problem.

B. BENCHMARK FUNCTIONS SCENARIO

This scenario tests the ability of the presented algorithm to get the best solution for the benchmark functions. Twenty-three functions, divided into seven unimodal, six multimodal, and ten multimodal-based fixed-dimension benchmark functions,

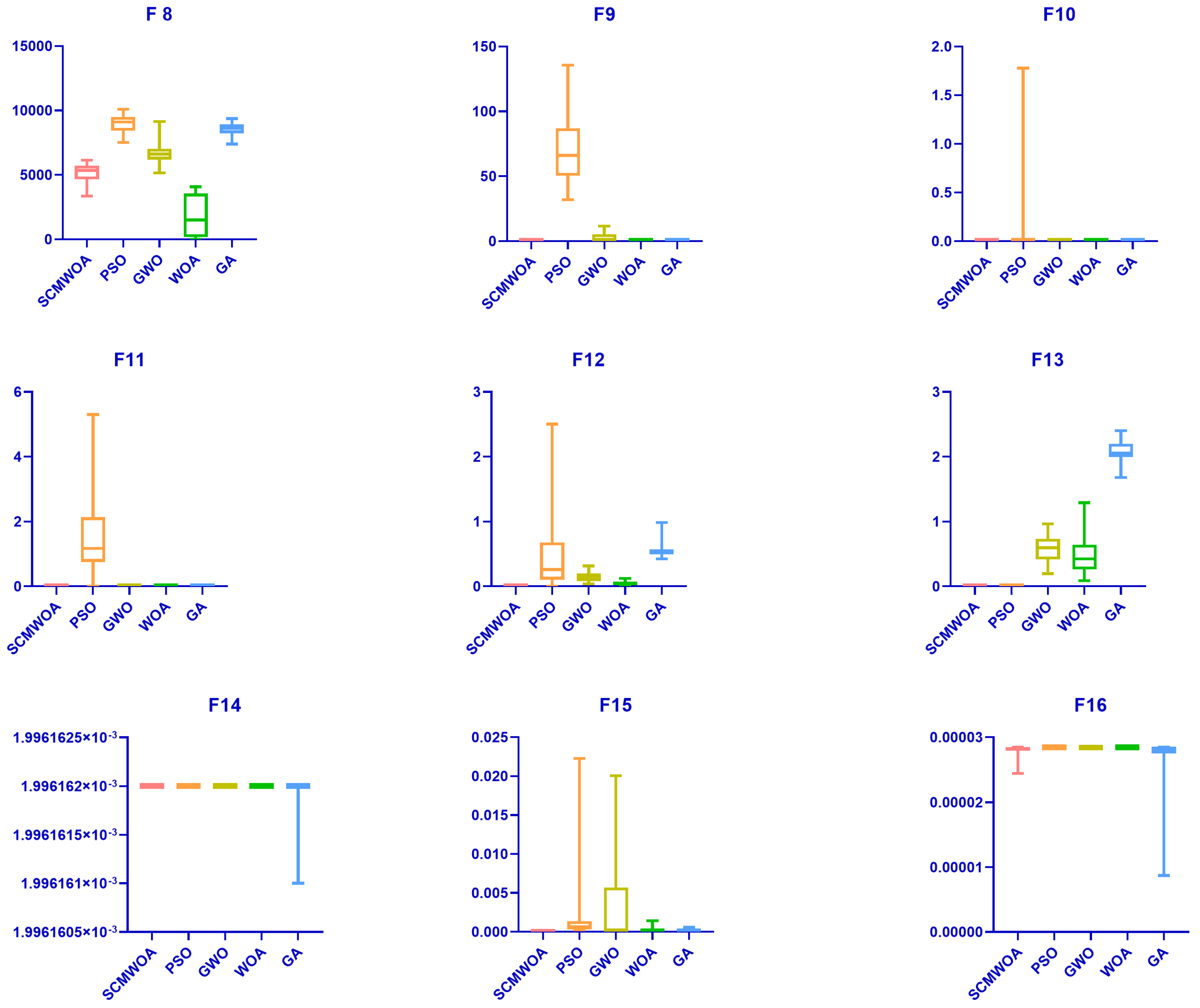

FIGURE 3. Box plot of the suggested and compared algorithms for benchmark function (f_8 to f_{16}).

are employed in this sub-section. Figure 21 describe the unimodal functions parameters and range. The multimodal and multimodal-based fixed dimension functions description of the range and minimum values are shown in Figures 22 and 23. The SCMWOA in the second scenario is compared to original GWO [18], PSO [19], WOA [21], FEP [29], GSA [30], GA [25] algorithms, EGWO [31], hybrid of CSA and GWO (GWO-CSA) [31], and hybrid of SCA and PSO (bSCA-PSO) [28].

The mean and standard deviation (StDev) results of the suggested and compared algorithms over the benchmark functions (f_1 to f_{23}) are shown in Table 11. This table shows that the proposed SCMWOA algorithm achieved zero values in Mean and StDev in some cases and better results than the compared single and hybrid algorithms in other cases. Table 12 shows the ANOVA test for sample functions (f_1,f_2,f_3,f_9,f_{11},f_{23}). The T-test analysis test for all benchmark functions (f_1 to f_{23}) using the suggested algorithm against the compared algorithms is presented in Table 13.The histogram interpolation of a sample function (f_{11}) based on the SCMWOA algorithm and PSO, GWO, WOA, and GA algorithms is discussed in Table 14.

Box plot of the suggested and compared algorithms for benchmark function (f_1 to f_7), (f_8 to f_{16}), and ($f_1$7 to f_{23}) are shown in Figures 2, 3, and 4, respectively. The histogram of the suggested and compared algorithms for benchmark function (f_1, f_2, f_3, f_9, f_{11}, and f_{23}) are tested and shown in Figure 5. The Quantile-Quantile (QQ) plot of the suggested and compared algorithms for benchmark function (f_1, f_2, f_3, f_9, f_{11}, and f_{23}) and the convergence curves based on the benchmark functions (f_1, f_2, f_3, f_9, f_{11}, and f_{23}) are presented in Figures 6 and 7.

The results of the proposed continuous SCMWOA algorithm in this scenario, compared to the state-of-the-art algorithms, confirm the performance of the algorithm for the benchmark functions.

TABLE 12. ANOVA test for sample functions (f_1, f_2, f_3, f_9, f_{11}, f_{23}).

f_1

	SS	DF	MS	F (DFn, DFd)	P value
Row Factor	1.46E-07	29	5.03E-09	F (29, 116) = 1.000	P = 0.4765
Column Factor	2.42E-07	4	6.05E-08	F (4, 116) = 12.04	P < 0.0001
Residual	5.83E-07	116	5.03E-09	-	-

f_2

	SS	DF	MS	F (DFn, DFd)	P value
Row Factor	253	29	8.723	F (29, 116) = 1.000	P = 0.4765
Column Factor	269.7	4	67.43	F (4, 116) = 7.730	P < 0.0001
Residual	1012	116	8.723	-	-

f_3

	SS	DF	MS	F (DFn, DFd)	P value
Row Factor	1.65E+09	29	56882271	F (29, 116) = 1.001	P = 0.4750
Column Factor	4.25E+10	4	1.06E+10	F (4, 116) = 186.8	P < 0.0001
Residual	6.59E+09	116	56818063	-	-

f_9

	SS	DF	MS	F (DFn, DFd)	P value
Row Factor	3700	29	127.6	F (29, 116) = 0.9840	P = 0.4982
Column Factor	117171	4	29293	F (4, 116) = 225.9	P < 0.0001
Residual	15041	116	129.7	-	-

f_{11}

	SS	DF	MS	F (DFn, DFd)	P value
Row Factor	8.828	29	0.3044	F (29, 116) = 1.001	P = 0.4754
Column Factor	56.84	4	14.21	F (4, 116) = 46.72	P < 0.0001
Residual	35.28	116	0.3041	-	-

f_{23}

	SS	DF	MS	F (DFn, DFd)	P value
Row Factor	145.3	29	5.011	F (29, 116) = 1.037	P = 0.4274
Column Factor	561.1	4	140.3	F (4, 116) = 29.04	P < 0.0001
Residual	560.4	116	4.831	-	-

TABLE 13. T-test for the benchmark functions (*from*f_1 to f_{23}) based on the suggested SCMWOA algorithm against the compared algorithms.

	PSO	GWO	WOA	GA
f_1	<0.0001	<0.0001	<0.0001	<0.0001
f_2	<0.0001	<0.0001	<0.0001	<0.0001
f_3	<0.0001	< 0.0001	<0.0001	<0.0001
f_4	<0.0001	<0.0001	<0.0001	0.0887
f_5	<0.0001	<0.0001	<0.0001	<0.0001
f_6	0.0103	<0.0001	<0.0001	<0.0001
f_7	0.0003	<0.0001	<0.0001	<0.0001
f_8	<0.0001	<0.0001	<0.0001	<0.0001
f_9	<0.0001	<0.0001	0.3256	1
f_{10}	0.1388	<0.0001	<0.0001	<0.0001
f_{11}	<0.0001	<0.0001	<0.0001	1
f_{12}	<0.0001	<0.0001	<0.0001	<0.0001
f_{13}	<0.0001	<0.0001	<0.0001	0.0001
f_{14}	<0.0001	<0.0001	<0.0001	<0.0001
f_{15}	0.0077	0.0049	<0.0001	0.0002
f_{16}	<0.0001	<0.0001	<0.0001	<0.0001
f_{17}	<0.0001	<0.0001	<0.0001	<0.0001
f_{18}	<0.0001	0.3256	0.0007	<0.0001
f_{19}	<0.0001	<0.0001	0.0006	<0.0001
f_{20}	<0.0001	<0.0001	<0.0001	<0.0001
f_{21}	0.0007	0.0021	0.0008	<0.0001
f_{22}	<0.0001	0.0077	<0.0001	<0.0001
f_{23}	0.1233	0.1233	<0.0001	<0.0001

C. SOLVING CONSTRAINED OPTIMIZATION PROBLEMS SCENARIO

This section is designed to validate the SCMWOA algorithm to solve two constrained optimization example of tension/compression spring and welded beam designs. The two engineering problems are described mathematically in equations 17-23. In addition, the SCMWOA algorithm results are compared with GWO [18], WOA [21], GSA [34], and PSO [19] algorithms result to get the minimum cost.

1) TENSION/COMPRESSION SPRING DESIGN PROBLEM

Figure 8 shows the schematic diagram of tension/compression spring design (TCSD) [32]. TCSD is considered as a continuous constrained problem. The algorithm aims to minimize the volume of a coil spring under a constant tension/compression load. The TCSD has three design variables which are the number of spring's active coils, L, the diameter of the winding, d, and the diameter of the wire, w. The mathematical formulation of the TCSD can be described as follows:

Minimize

$$f(w, d, L) = (L+2)w^2 d \tag{17}$$

Subject to the following constraints

$$g_1 = 1 - \frac{d^3 + L}{71785w^4} \leq 0$$
$$g_2 = \frac{d(4d-w)}{w^3(12566d-w)} + \frac{1}{5108w^2} - 1 \leq 0$$
$$g_3 = 1 - \frac{140.45w}{d^2 L} \leq 0$$

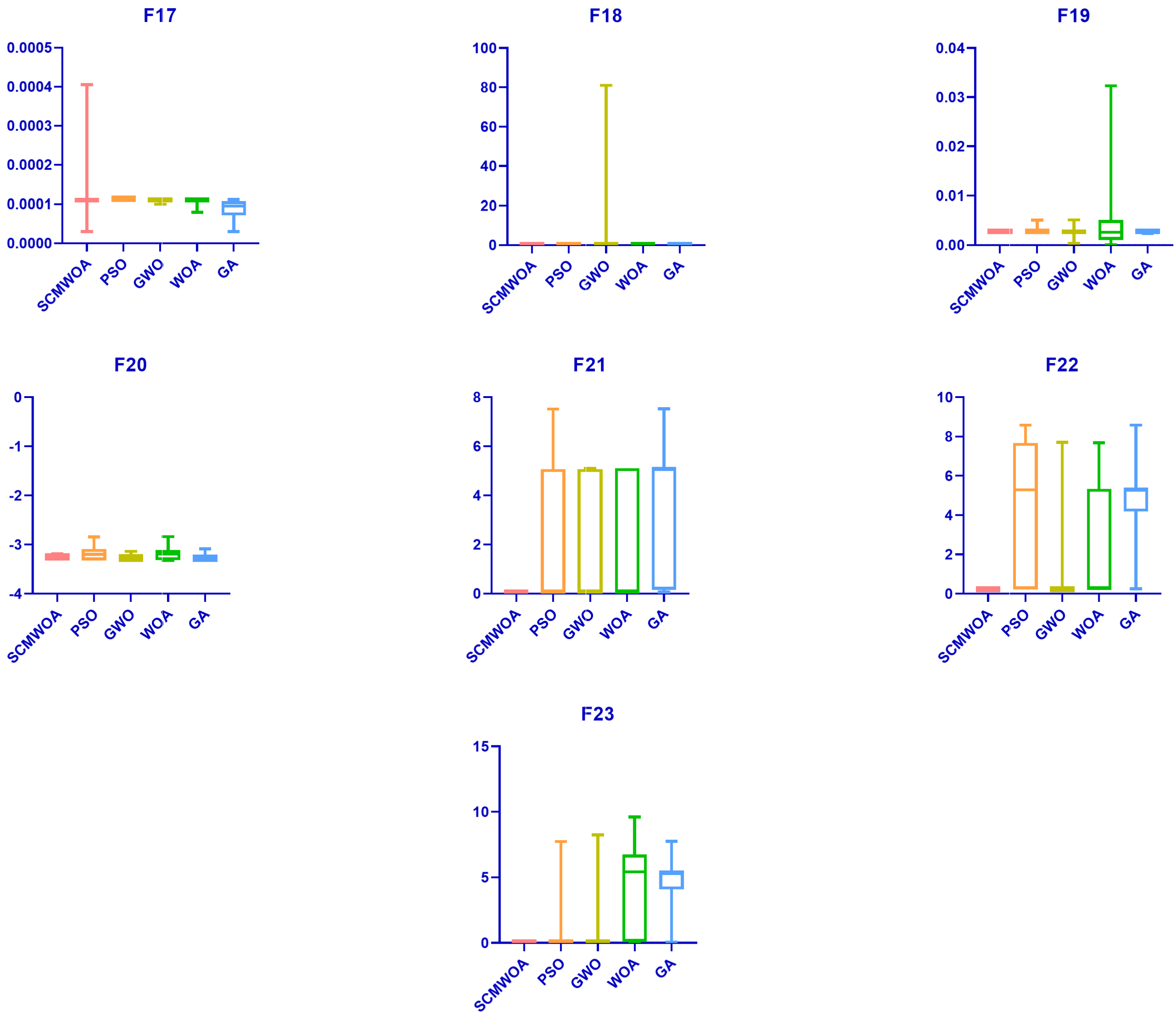

FIGURE 4. Box plot of the suggested and compared algorithms for benchmark function (f_{17} to f_{23}).

$$g_4 = \frac{2(w+d)}{3} - 1 \leq 0 \tag{18}$$

where the three variables range are as follows:

$$\begin{aligned} 0.05 &\leq w \leq 2.0, \\ 0.25 &\leq d \leq 1.3, \\ 2.0 &\leq L \leq 15 \end{aligned} \tag{19}$$

The box plot results of Tension/Compression Spring design based on different algorithms are shown in Figure 9. The histogram results of Tension/Compression Spring design based on different algorithms are discussed in Figure 10. Table 17 shows the comparison of one sample t-test analysis of the tension/compression spring design among other algorithms.

Tables 15 and 16 presents the best solution and the statistical results of proposed and compared algorithms for Tension/Compression Spring design Problem, respectively. The results of the proposed SCMWOA algorithm in this scenario compared to the state-of-the-art algorithms confirm the performance of the algorithm for solving the Tension/Compression Spring design.

2) WELDED BEAM DESIGN PROBLEM

The next constrained problem is the welded beam design [33]. The schematic diagram of the welded beam design is shown in Figure 11. It is considered as an important benchmark to test different optimization methods. The main objective is to minimize the fabricating cost of the welded beam which comprised of the setup, welding labor, and material costs. The properties constraints are on the shear stress, bending stress, buckling load, end deflection, and the side constraint. Four design variables of w, L, d, and h are considered here. The

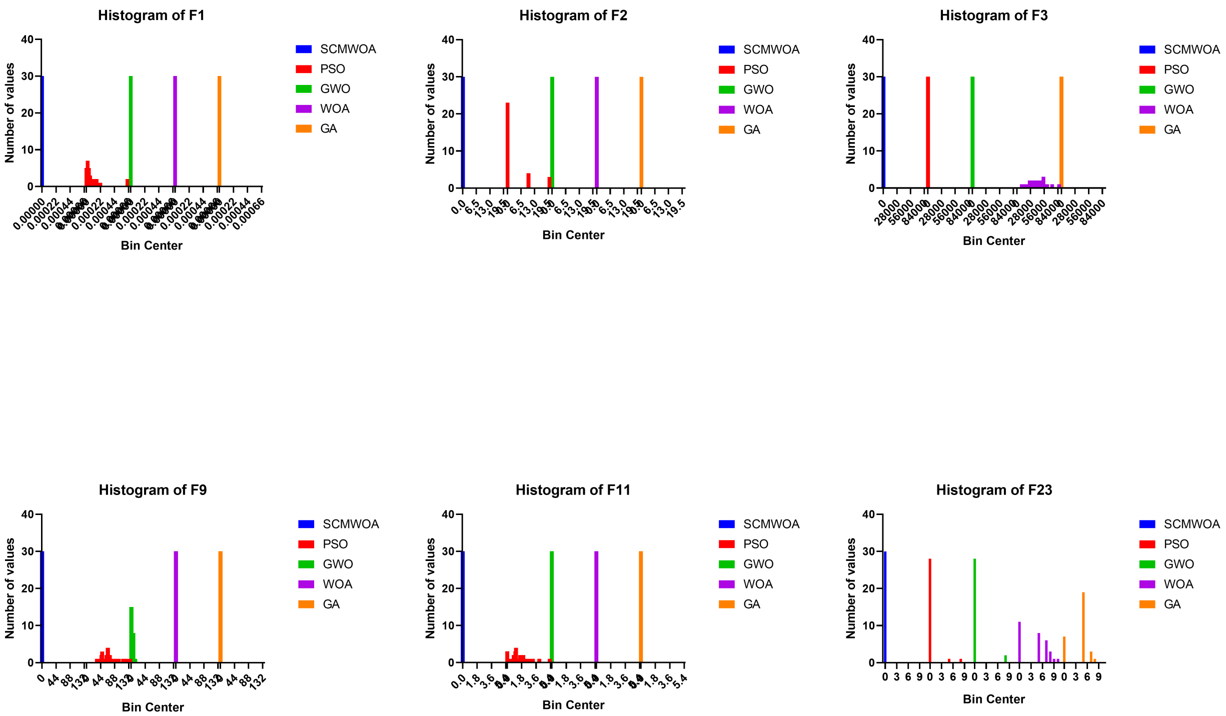

FIGURE 5. Histogram of the suggested and compared algorithms for benchmark function (f_1, f_2, f_3, f_9, f_{11}, and f_{23}).

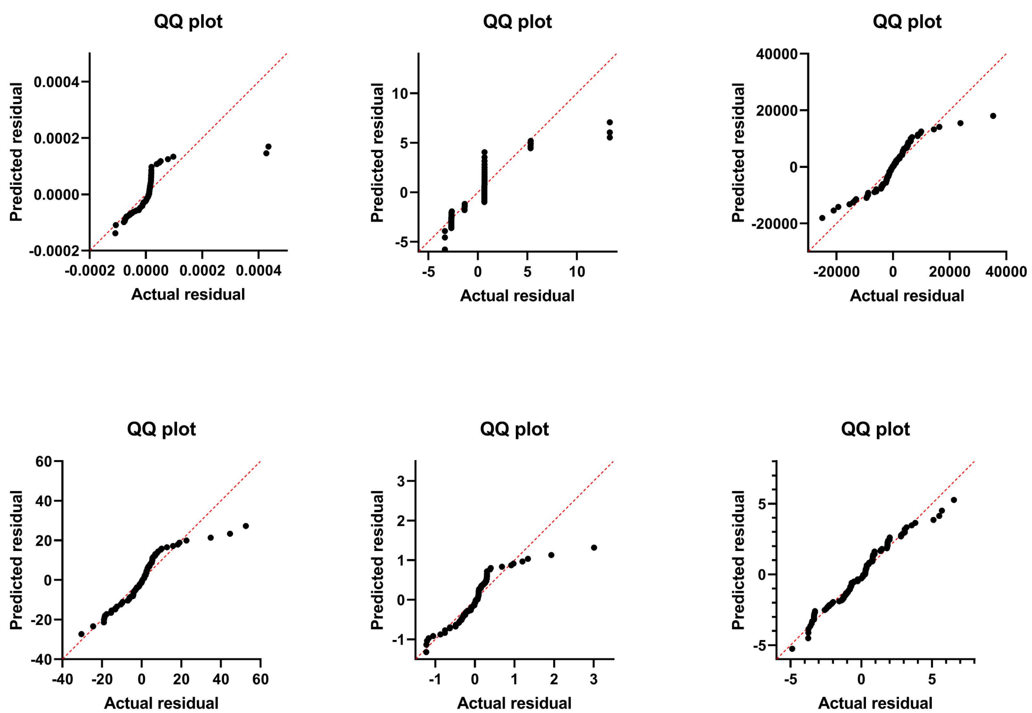

FIGURE 6. QQ plot of the suggested and compared algorithms for benchmark function (f_1, f_2, f_3, f_9, f_{11}, and f_{23}).

mathematical formulation of the problem can be described as follows:

Minimize

$$f(w, L, d, h) = 1.10471w^2L + 0.04811dh(14.0 + L) \tag{20}$$

Subject to the following constraints

$$g_1 = w - h \leq 0$$
$$g_2 = \delta - 0.25 \leq 0$$
$$g_3 = \tau - 13,600 \leq 0$$
$$g_4 = \sigma - 30,000 \leq 0$$

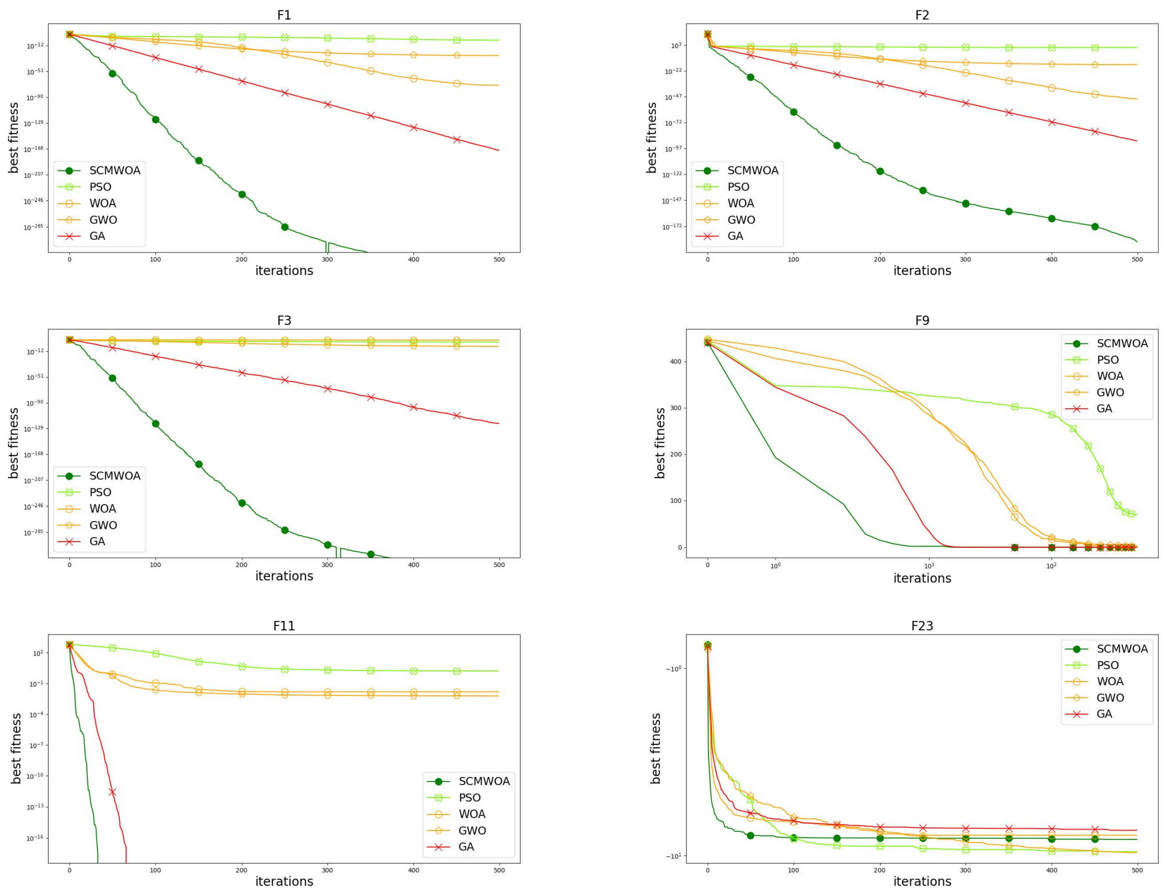

FIGURE 7. Convergence curves of the suggested and compared algorithms based on the benchmark functions (f_1, f_2, f_3, f_9, f_{11}, and f_{23}).

TABLE 14. Interpolation of Histogram of a sample function (f_{11}).

Asymmetric Sigmoidal, 5PL, X is log(concentration)	SCMWOA	PSO	GWO	WOA	GA
Best-fit values					
LogEC50	-3.4		-3.4	-3.4	-3.4
HillSlope	-4.564		-4.564	-4.564	-4.564
S	-1.815		-1.815	-1.815	-1.815
Top	115.5		115.5	115.5	115.5
Bottom	0.5455		0.5455	0.5455	0.5455
EC50	0.000398		0.000398	0.000398	0.000398
95% CI (asymptotic)					
Bottom	-0.5931 to 1.684	-0.5931 to 1.684	-0.5931 to 1.684	-0.5931 to 1.684	
EC50					
Goodness of Fit					
Degrees of Freedom	50		50	50	50
R squared	0		0	0	0
Adjusted R squared	-0.08		-0.08	-0.08	-0.08
Sum of Squares	883.6		883.6	883.6	883.6
Runs test					
Points above curve	1		1	1	1
Points below curve	54		54	54	54
Number of runs	2		2	2	2
P value (runs test)	0.0364		0.0364	0.0364	0.0364
Deviation from Model	Significant		Significant	Significant	Significant
Number of points					
# of X values	55	55	55	55	55
# Y values analyzed	55	55	55	55	55

$$
\begin{aligned}
g_5 &= 0.125 - w \leq 0 \\
g_6 &= 6000 - P \leq 0 \\
g_7 &= 0.10471w^2 + 0.04811hd(14 + L) - 0.5 \leq 0 \quad (21)
\end{aligned}
$$

where

$$
\delta = \frac{65856}{30000\,h.D^3}, \tau = \sqrt{\alpha^2 + \left(\frac{\alpha.\beta.L}{D}\right) + \beta^2}
$$

TABLE 15. **Best solution of proposed and compared algorithms for Tension/Compression Spring design problem.**

Algorithm	Design Variables			Optimal Cost
	w	d	L	
PSO	0.051728	0.357644	11.244543	0.0126747
GSA	0.050276	0.323680	13.525410	0.0127022
WOA	0.051207	0.345215	12.004032	0.0126763
SCMWOA	0.051232	0.345805	11.959020	0.0126696

TABLE 16. **Statistical results of proposed and compared algorithms for Tension/Compression Spring design problem.**

Algorithm	Optimal Cost	Average	Standard Deviation	Function Evaluations
PSO	0.0126747	0.0139	0.0033	5460
GSA	0.0127022	0.0136	0.0026	4980
GWO	0.0126763	0.0135	0.0024	4820
SCMWOA	0.0126696	0.0134	0.0013	2460

TABLE 17. **One sample t-test analysis of the Tension/Compression Spring design problem based on different algorithms.**

	SCMWOA	PSO	GSA	GWO
Theoretical mean	0	0	0	0
Actual mean	0.01267	0.0128	0.01277	0.01282
Number of values	19	19	19	19
One sample t test				
t, df	t=1657, df=18	t=120.7, df=18	t=239.2, df=18	t=152.8, df=18
P value (two tailed)	0.0001	0.0001	0.0001	0.0001
P value summary	****	****	****	****
Significant (alpha=0.05)?	Yes	Yes	Yes	Yes
How big is the discrepancy?				
Discrepancy	0.01267	0.0128	0.01277	0.01282
SD of discrepancy	0.00003333	0.0004622	0.0002328	0.0003657
SEM of discrepancy	0.000007647	0.000106	0.0000534	0.0000839
95% confidence interval	0.01265 to 0.01269	0.01258 to 0.01303	0.01266 to 0.01288	0.01265 to 0.01300
R squared (partial eta squared)	1	0.9988	0.9997	0.9992

TABLE 18. **Best solution of proposed and compared algorithms for Welded beam design problem.**

Algorithm	Design Variables				Optimal Cost
	w	L	d	h	
PSO	0.202369	3.544214	9.048210	0.205723	1.728024
GSA	0.182129	3.856979	10.00000	0.203760	1.879952
WOA	0.205396	3.484293	9.037426	0.206276	1.730499
SCMWOA	0.205604	3.479712	9.041001	0.205739	1.726738

TABLE 19. **Statistical results of proposed and compared algorithms for Welded beam design problem.**

Algorithm	Optimal Cost	Average	Standard Deviation	Function Evaluations
PSO	1.728024	1.7422	0.01275	13770
GSA	1.879952	3.5761	1.28740	10750
WOA	1.730499	1.7320	0.02260	9900
SCMWOA	1.726738	1.7273	0.10162	8740

$$\alpha = \frac{6000}{\sqrt{2}wL}, \beta = \frac{QD}{J}$$
$$Q = 6000\left(14 + \frac{L}{2}\right), D = \frac{1}{2}\sqrt{L^2 + (w+d)^2}$$
$$J = \sqrt{2}wL\left(\frac{L^2}{6} + \frac{(w+d)^2}{2}\right)$$
$$\sigma = \frac{504,000}{hd^2}$$

$$P = 0.61432 \times 10^6 \frac{dh^3}{6}\left(1 - \frac{d\sqrt{30/48}}{28}\right) \tag{22}$$

where the four variables range are as follows:

$$\begin{aligned} 0.1 &\leq w, h \leq 2.0,\\ 0.1 &\leq L, d \leq 10 \end{aligned} \tag{23}$$

The box plot results of the Welded Beam design problem based on different algorithms are shown in Figure 12.

TABLE 20. One sample t-test analysis of the welded beam design problem based on different algorithms.

	SCMWOA	PSO	GSA	WOA
Theoretical mean	0	0	0	0
Actual mean	1.727	1.73	1.893	1.734
Number of values	19	19	19	19
One sample t test				
t, df	t=1346, df=18	t=1508, df=18	t=238.2, df=18	t=921.5, df=18
P value (two tailed)	0.0001	0.0001	0.0001	0.0001
P value summary	****	****	****	****
Significant (alpha=0.05)?	Yes	Yes	Yes	Yes
How big is the discrepancy?				
Discrepancy	1.727	1.73	1.893	1.734
SD of discrepancy	0.005591	0.005	0.03464	0.008201
SEM of discrepancy	0.001283	0.001147	0.007948	0.001881
95% confidence interval	1.724 to 1.729	1.727 to 1.732	1.876 to 1.910	1.730 to 1.738
R squared (partial eta squared)	1	1	0.9997	1

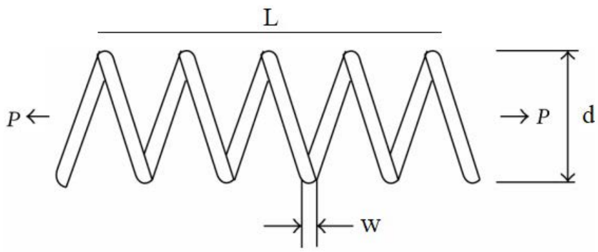

FIGURE 8. Tension/compression spring design problem [32].

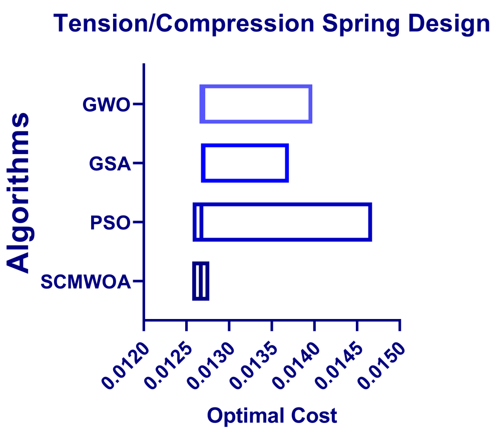

FIGURE 9. Box plot results of tension/compression spring design based on different algorithms.

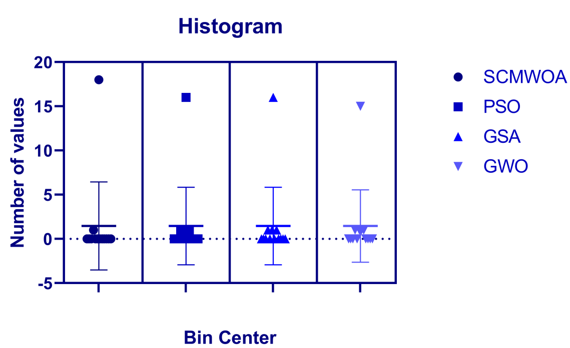

FIGURE 10. Histogram results of tension/compression spring design based on different algorithms.

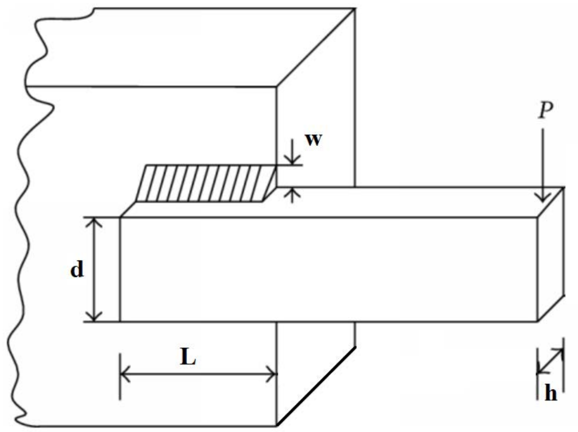

FIGURE 11. Welded beam design problem [33].

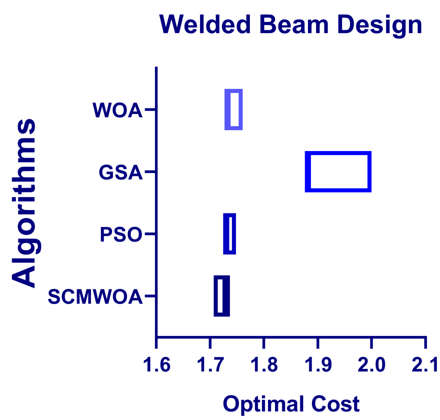

FIGURE 12. Box plot results of Welded Beam design problem based on different algorithms.

The histogram results of the Welded Beam design problem based on different algorithms are shown in Figure 13. Table 20 shows the comparison of the one sample t-test analysis of the welded beam design problem among other algorithms.

Tables 18 and 19 presents the best solution and the statistical results of proposed and compared algorithms for Welded Beam design problem, respectively. The results of the proposed SCMWOA algorithm in this scenario compared to the state-of-the-art algorithms confirm the performance of the algorithm for solving the Welded Beam design.

TABLE 21. Description of the unimodal benchmark functions.

Function	D	Range
$f_1(w) = \sum_{i=1}^{n} w^2$	30	[-100, 100]
$f_2(w) = \sum_{i=1}^{n} \lvert w_i \rvert + \prod_{i=1}^{n} \lvert w_i \rvert$	30	[-10, 10]
$f_3(w) = \sum_{i=1}^{n} (\sum_{j=1}^{i} w_i)^2$	30	[-100, 100]
$f_4(w) = max_i\{\lvert w_i \rvert, 1 \leq i \leq D\}$	30	[-100, 100]
$f_5(w) = \sum_{i=1}^{D-1} [100(w_{i+1} - w_i^2)^2 - (w_i - 1)^2]$	30	[-30, 30]
$f_6(w) = \sum_{i=1}^{D} (w_i + 0.5)^2$	30	[-100, 100]
$f_7(w) = \sum_{i=1}^{D} iw_i^4 + rand[0, 1]$	30	[-1.28, 1.28]

TABLE 22. Description of the multimodal benchmark functions.

Function	D	Range	f_{min}
$f_{08}(w) = \sum_{i=1}^{D} -w_i \sin\ (\sqrt{\lvert w_i \rvert})$	30	[-500, 500]	-12569.487
$f_{09}(w) = \sum_{i=1}^{D} [w_i^2 - 10\cos(2\pi w_i) + 10]$	30	[-5.12, 5.12]	0
$f_{10}(w) = -20\exp(-0.2\sqrt{\sum_{i=1}^{D} w_i^2}) - \exp(\frac{1}{d}\sum_{i=1}^{D} \cos(2\pi w_i)) + 20 + \eta$	30	[-32, 32]	0
$f_{11}(w) = \frac{1}{4000}\sum_{i=1}^{D} w_i^2 - \prod_{i=1}^{D} \cos(\frac{w_i}{\sqrt{i}}) + 1$	30	[-600, 600]	0
$f_{12}(w) = \frac{\pi}{D}\{10\sin^2(\pi y_i) + \sum_{i=1}^{D-1} (y_i - 1)^2[1 + 10\sin^2(\pi y_i + 1) + (yD - 1)^2 + \sum_{i=1}^{D} u(w_i, 10, 100, 4)]\}$	30	[-50, 50]	0
$y_i = 1 + \dfrac{w_i + 1}{4}, \quad u(w_i, h, k, m) = \begin{cases} k(w_i - h)^m & w_i > h \\ 0 & -h < w_i < h \\ k(-w_i - h)^m & w_i < -h \end{cases}$			
$f_{13}(w) = 0.1\{10\sin^2(3\pi y_i) + \sum_{i=1}^{D-1} (w_i - 1)^2[1 + 10\sin^2(3\pi y_i + 1)] + (w_n - 1)^2[1 + \sin^2(2\pi w_n)]\} + \sum_{i=1}^{n} u(w_i, 5, 100, 4)$	30	[-50, 50]	0

TABLE 23. Description of multimodal based fixed-dimension benchmark functions.

Function	D	Range	f_{min}
$f_{14}(w) = \left(\frac{1}{500} + \sum_{j=1}^{25} \frac{1}{j + \sum_{i=1}^{2} (w_i - h_{ij})^6}\right)^{-1}$	2	[-65, 65]	1
$f_{15}(w) = \sum_{i=1}^{11} \left[h_i - \frac{w_1(b_i^2 + b_i w_2)}{b_i^2 + b_i w_3 + w_4}\right]^2$	4	[-5, 5]	0.00030
$f_{16}(w) = 4w_1^2 - 2.1w_1^4 + \frac{1}{3}w_1^6 + w_1 w_2 - 4w_2^2 + 4w_2^4$	2	[-5, 5]	-1.0316
$f_{17}(w) = \left(w_2 - \frac{5.1}{4\pi^2}w_1^2 + \frac{5}{\pi}w_1 + -6\right)^2 + 10\left(1 - \frac{1}{8\pi}\right)\cos w_1 + 10$	2	[-5, 5]	0.398
$f_{18}(w) = [1 + (w_1 + w_2 + 1)^2(19 - 14w_1 + 3w_1^2 - 14w_2 + 6w_1 w_2 + 3w_2^2)] \times [30 + (2w_1 - 3w_2)^2 w(18 - 32w_1 + 12w_1^2 + 48w_2 - 36w_1 w_2 + 27w_2^2)]$	2	[-2, 2]	3
$f_{19}(w) = -\sum_{i=1}^{4} b_i \exp(-\sum_{j=1}^{3} h_{ij}(w_j - p_{ij})^2)$	3	[1, 3]	-3.86
$f_{20}(w) = -\sum_{i=1}^{4} b_i \exp(-\sum_{j=1}^{6} h_{ij}(w_j - p_{ij})^2)$	6	[0, 1]	-3.32
$f_{21}(w) = -\sum_{i=1}^{5} \left[(w - h_i)(w - h_i)^T + b_i\right]^{-1}$	4	[0, 10]	-10.1532
$f_{22}(w) = -\sum_{i=1}^{7} \left[(w - h_i)(w - h_i)^T + b_i\right]^{-1}$	4	[0, 10]	-10.4028
$f_{23}(w) = -\sum_{i=1}^{10} \left[(w - h_i)(w - h_i)^T + b_i\right]^{-1}$	4	[0, 10]	-10.5363

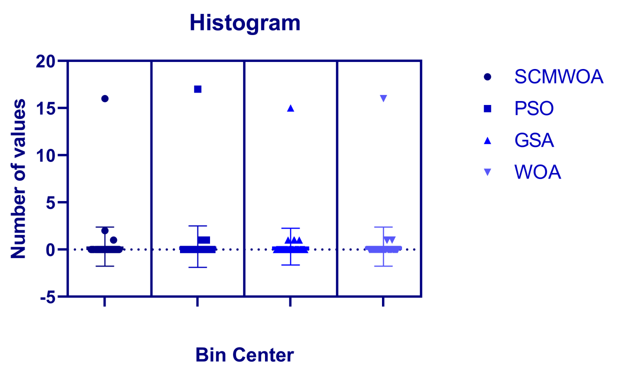

FIGURE 13. Histogram results of Welded Beam design problem based on different algorithms.

VI. CONCLUSION

This paper proposed an optimization algorithm called Sine Cosine hybrid with Modified Whale Optimization Algorithm (SCMWOA). The SCMWOA algorithm is tested using nineteen datasets, from the UCI Machine Learning Repository, with different number attributes, instances, and classes for feature selection. The SCMWOA algorithm is also tested for twenty-three benchmark functions. The functions include seven unimodal, six multimodal, and ten multi modal based fixed-dimension functions. The two tested engineering problems are the tension/compression spring design and the welded beam design. The results emphasize that the SCMWOA algorithm outperforms several comparative optimization algorithms and provides high accuracy. Statistical analysis tests, including one-way analysis of variance (ANOVA) and Wilcoxon's rank-sum, confirm that the SCMWOA algorithm has better performance. The SCMWOA algorithm will be tested for more classical engineering design problems in future work since the algorithm perform well only in the two mentioned problems in this paper. Other benchmark functions, such as CEC 2015 and CEC 2017, will also be considered in future work.

APPENDIX

This appendix includes three tables of benchmark functions. Table 21 shows the description of the unimodal benchmark functions. Table 22 shows the description of the multimodal benchmark functions. Table 23 shows the description of the multimodal based fixed-dimension benchmark functions.

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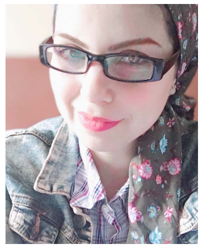

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