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RESEARCH ARTICLE

Solving Optimization Problems of Metamaterial and Double T-Shape Antennas Using Advanced Meta-Heuristics Algorithms

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ABSTRACT This study offers an adaptive dynamic sine cosine fitness grey wolf optimizer (ADSCFGWO) for optimizing the parameters of two types of antennas. The two types of antennas are metamaterial and double T-shape monopoles. The ADSCFGWO algorithm is based on an adaptive dynamic technique and two recently developed and powerful optimization techniques: a modified grey wolf optimization (GWO) based on fitness value and a sine cosine algorithm (SCA). The suggested approach utilizes both algorithms' capabilities to better balance the exploration and exploitation responsibilities of the optimization process while achieving rapid convergence. First, a new feature selection approach is proposed to choose the most significant features from the metamaterial dataset using the suggested ADSCFGWO-based ensemble model for optimal performance. The ADSCFGWO algorithm also optimizes a bidirectional recurrent neural network (BRNN) to estimate the double T-shape monopole antenna characteristics. Several experiments were undertaken to demonstrate the superiority of the suggested algorithms by comparing their results to those of existing optimization algorithms, feature selectors, and regression models. In addition, a statistical analysis is offered to evaluate the algorithm's effectiveness and stability. The findings demonstrate the suggested method's efficacy and superiority over numerous competing algorithms.

INDEX TERMS Grey wolf optimizer, sine cosine optimizer, feature selection, ensemble model, metamaterial antenna, double T-shape antenna.

I. INTRODUCTION

Optimization of the design parameters of antennas is an active research field that has been addressed recently by many machine learning researchers and professionals [1]–[3]. A great deal of interest is paid to this field due to the advances achieved by the currently running fourth industrial revolution and the prevalence of advanced machine learning techniques, and the emergence of a large set of freely available open-source libraries. This enables researchers to customize various machine learning algorithms to realize the ideas inspired by meta-heuristics [4]–[6]. Modern antenna structures are often electromagnetically and topologically complicated, with many design parameters resulting from

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the more demanding specifications required to achieve better performance. The fine-tuning of the material and geometrical aspects of the design structure of antennas to achieve these goals became a common practice in the field of communication [7].

The most common approaches to fine-tune antenna parameters are still based on sweeping few design parameters using the experience-based approaches. This approach, which is often a trial and error process used in designing modern antennas with numerous sensitive parameters, could take a long time with no guarantee of success. As a result, optimization-based design automation is required. Local and/or global numerical optimization approaches are mostly used to increase the performance of antennas through optimization. Even though numerical optimization is superior to parameter sweeping using experience-based approaches, there are still obstacles to overcome [8]–[12].

To get effective results, local optimization approaches frequently necessitate a suitable initial design or starting point for modern antenna designs; this is typically not accessible in practice. On the other hand, global optimization approaches are more appealing due to their resilience and lack of the need for a starting design, but they sometimes need a huge (can be expensive) number of electromagnetic (EM) simulations to get sub-optimal design parameters. Full-wave EM simulations are computationally costly by definition. Full-wave EM simulations based on numerical techniques are unavoidable for comprehensive antenna characterization. The characterization of the design, which is performed once using the standard simulation, is not an issue; the real challenge is that the global optimization approaches usually require a huge number of EM simulations; which represent an unsustainable processing burden [13]–[16].

Machine learning approaches are frequently utilized to enhance numerical optimization methods by including them a priori and/or a posteriori in the optimization kernel to reduce the computing burden of antenna synthesis. Surrogate modeling is one of the most often utilized machine learning tools for assisting numerical optimization methods in antenna synthesis. Surrogate modeling works primarily in the optimization process using computationally inexpensive approximation models instead of computationally expensive function evaluations (i.e., EM simulations with high computations). Surrogate models are a type of approximation modeling that is often built using statistical learning approaches. A variety of surrogate modeling approaches are effective for EM design optimization using modern machine learning techniques [43]–[46].

The high dimensional search space of the current real-world optimization problems makes solving these problems a real challenge [34]. Therefore, heuristic optimization offers a very efficient alternative to the traditional approaches in solving this problem. This results in the prevalence of heuristic optimization as a preferred technique in many research fields such as mechanics, engineering, business processes, machine learning, and many other fields [20], [47]. In general, the main target of optimization is to search the feasible solutions and select the most acceptable one. In specific, the task of optimization becomes a search problem in the space of multi-dimensions that selects the solution with min/max value of a specific objective function [48]. The family of meta-heuristic optimization techniques focuses on finding the best solution quickly and efficiently [49], [50].

The simple concepts of meta-heuristic optimization represent the main factor in making them simple to implement and understand. The main advantages of meta-heuristic optimization algorithms are the flexibility and simplicity that make them superior to other exact and classical optimization techniques such as local search and greedy search. An important feature of meta-heuristic is that they are usually capable of avoiding the local optima due to their search behavior that explores the search space extensively in a stochastic manner that avoids the local optima stagnation. On the other hand, the flexibility of these algorithms makes them convenient to various applications and fields without the need for critical changes in their implementation and design.

Grey Wolf Optimizer (GWO) algorithm is one of the most interesting optimization algorithms that emerged recently in the literature based on a meta-heuristic that mimics the natural behavior of grey wolves [20], [51]. The main characteristics of the GWO algorithm include simplicity, versatility, and the ability to avoid local optima. Much recent research employed the GWO algorithm to train multi-layer perceptron (MLP) network for handling several tasks such as feature selection, solving the optimal reactive power dispatch problem, and financial crisis prediction [52]. As the GWO algorithm is based on many variables in the optimization process, this causes a degradation in its performance. In addition, the algorithm convergence is premature. However, it has a significant advantage that the balance between exploration and exploitation is satisfying. Therefore, the GWO algorithm is adopted in the proposed algorithm to exploit this advantage.

Sine Cosine Algorithm (SCA) is another powerful optimization algorithm that has a greater exploitation rate than other meta-heuristics as it uses a single optimum solution to guide other candidate solutions [23]. Due to its efficiency in memory consumption and convergence time, SCA is employed in a variety of applications [24], [25]. Despite the simplicity and high balance between exploration and exploitation of SCA algorithm, it still has a few drawbacks such as low exploration rate, dependency on a single best solution during the search process, and performance degradation when a large number of local optimal solutions exist. Therefore, in this research, this algorithm is utilized to benefit from its strengths while coping with the drawbacks by utilizing the grey wolf optimizer.

The No-Free-Lunch theorem mentioned that no single meta-heuristic could achieve the best solution for all the optimization problems [53]. Therefore, there is still room

TABLE 1. Review of the popular meta-heuristic optimization for antenna.

Algorithm	Methodology	Strengths	Weaknesses	Applications
Grey wolf optimizer (GWO) [17, 18, 19, 20, 21, 22]	It mimics the behavior of grey wolves in hunting based on social hierarchy and leadership. When hunting prey, three leaders are followed by the individuals of the pack. The steps include prey encircling, attacking the prey, and hunting	Easy and simple to implement, the search precision is high, the balance between exploitation and exploration is satisfying.	A large number of variables in the optimization problem causes degradation in the performance; the convergence is premature as the leaders' position updates depend on each other.	Antenna design, pathfinding and robotics, clustering applications, DC motors parameters adjustments, and feature selection.
Sine cosine algorithm (SCA) [6, 23, 24, 25, 26]	A set of random variables are used to track the direction and distance of movement, emphasize/de-emphasize the effect of destination, and switch between the sine and cosine components. A set of n agents is initially set up randomly, and an objective function is computed for these agents to search for the best solution.	It has a high exploitation rate, efficient in memory usage; convergence speed is high.	Low exploration rate, It depends on a single best solution during the search process, and the performance degrades when a large number of local optimal solutions exist.	Antenna design, Solar radiation forecasting, Signal processing, and filter design.
Particle swarm optimization (PSO) [27, 28, 29, 30, 31]	It is inspired by the behavior of fish and birds flock and their interactions and movements. The best position obtained by the swarm and the best-known position of each individual is used to determine its movements.	Good cooperation model, the implementation is easy, and the convergence is stable.	The convergence is slow, the computational cost is high, and the initial parameters are difficult to determine.	Antenna design, dimensionality reduction, vehicle routing, and gene clustering.
Whale optimization algorithm (WOA) [32, 33, 34, 35, 36]	The humpback whales' bubble-net foraging behavior is the source of inspiration for this algorithm. The spiral movement of whales around a school of fish allows whales to use the resulting bubbles to trap fishes.	Easy and simple to implement, and the search space has a large exploration scale.	The computational cost is high, the potential stagnation in the local optima, and the convergence speed is slow.	Antenna design, controlling systems of laser sensors accurately, task scheduling, route optimization, and minimization of the offset voltage.
Genetic algorithm (GA) [37, 38, 39]	It is based on the biological evolution theory (the fittest is the survival). GA steps include initialization, parent selection, crossover, and mutation. Elitism is another genetic operation that can be applied.	Easy and simple to implement, free of gradient, noisy functions can be handled easily.	The proper scaling with complexity is missing; it is hard to fine-tune the parameters, the convergence is premature, and the convergence speed is slow.	Antenna design, engineering applications, robot path planning, scheduling, and filter design.
Differential evolution (DE) [40, 41, 42]	The fittest is the survival concept that forms the source of inspiration for this algorithm. This algorithm's main steps include starting with a population that is initialized randomly. New candidate solutions are generated using a combination between the mutant and existing solutions, and finally, the solutions achieving the best score are kept alive.	Easy and simple to implement, it allows the diversity of populations, it allows changing circumstances, the convergence is robust.	It is hard to fine-tune its design parameters, the computational cost is high, and the convergence speed is high.	Antenna design, feature extraction, protein folding prediction, capacitive voltage divider, and solution of optical power flow.

for developing new optimization algorithms with more generalization capability. This results in several meta-heuristics that can perform better on some optimization problems than others. A summary of the most popular meta-heuristic-based optimization techniques for the antenna is presented in Table 1. This table shows each algorithm's main idea, strengths, weaknesses, and applications.

This paper proposes an optimization algorithm that can handle the improper balance between the exploration and exploitation tasks and the low convergence of some existing optimization algorithms, such as GWO and SCA. An adaptive dynamic sine cosine fitness grey wolf optimizer (ADSCFGWO) algorithm is proposed based on an adaptive dynamic technique and two recently developed and powerful optimization techniques: a modified grey wolf optimization (GWO) based on fitness value and a sine cosine algorithm (SCA). The new optimization algorithm employs adaptive the modified GWO and SCA algorithms in an adaptive dynamic hybrid and unified framework for the antenna. The main contributions of this work are listed in the following:

- A novel adaptive dynamic sine cosine fitness grey wolf optimizer (ADSCFGWO) algorithm for feature selection and optimized ensembles is proposed.
- A new binary ADSCFGWO algorithm is proposed.
- Application of the ADSCFGWO algorithm to the metamaterial and double T-shape antennas.
- A new ensemble model for robust prediction of the metamaterial antenna parameters is presented.
- Improving the performance of the bidirectional recurrent neural network using the proposed ADSCFGWO for accurate estimation of the parameters of a double T-shape antenna.
- A one-sample two-tailed t-test and ANOVA test are employed to assess the statistical significance of the proposed optimization techniques.

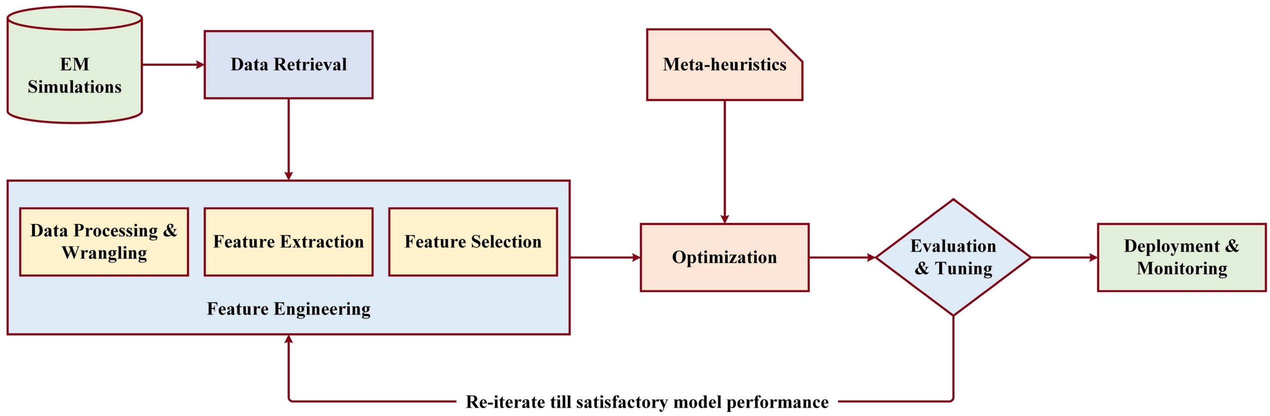


FIGURE 1. Typical process of meta-heuristic optimization for antenna.

- Statistical analysis is performed to evaluate the performance of the proposed ensemble model.
- The proposed algorithm can be generalized to other datasets.

The organization of this research comes as follows. The materials and methods employed in this research are presented in section II. The proposed methodology is explained in section III, followed by a discussion of the achieved results in section IV. The conclusions and future perspectives are presented in section V.

II. METHODS AND MATERIALS

This section presents the main methods and materials employed in the proposed methodology. Figure 1 presents the typical process of antenna optimization based on meta-heuristics. As shown in the figure, the process starts with feature engineering, followed by applying meta-heuristic optimization techniques in an iterative way for achieving the best results. The next sections discuss these steps, focusing on the utilized methods and materials.

A. FEATURE ENGINEERING

Feature engineering is a vital process for all machine learning techniques. This process entails the selection and extraction of the relevant features that are necessary for machine learning pipelines. The words feature selection and feature extraction are used interchangeably in the literature. However, there is a distinction between them in essence. The feature extraction process focuses on processing the raw data to extract additional variables that can help the algorithms of machine learning work properly. On the other hand, the process of feature selection is interested in selecting and identifying the relevant features from the dataset that fulfill certain conditions, such as uniqueness, consistency, and meaningfulness. To realize the feature selection process, binary values (0 and 1) are used to constrain the search space. Consequently, an update must be applied to the continuous values-based optimizers to allow them to work properly with this issue.

The feature selection is the most significant step in feature engineering as it selects the most appropriate features that enable optimizers to achieve the best performance. The Feature selection task can be defined as a binary vector of n-features, with each feature having a value of 1 or 0, depending on whether it is included in the solution or not [21]. A random population of vectors with random features is usually the starting point for the meta-heuristic algorithms that is followed by a series of exploration and exploitation to find the optimum collection of features [22].

B. GREY WOLF OPTIMIZER

The behavior of the grey wolf optimizer (GWO) is inspired by the movements of the real wolves while searching for prey and hunting. The nature of wolves is based on living in groups of varying sizes. The minimum size of a group is five wolves, and the maximum group size is 12 wolves. Based on each wolf's role in the group, they are categorized into four different types. These types are referred to as alpha, beta, omega, and delta [17]. The decision-making regarding the time to walk, the hunting decision, and the sleeping place is usually the role of the alpha-type wolves, whose decisions are usually supported by the beta-type wolves in the group. The alpha wolves are considered the dominant wolves, and the beta wolves are considered the subordinates of the alpha-type wolves. When the alpha wolves pass away, the beta wolves are the best candidate to replace them. The main role of the beta wolves is to reinforce the decisions made by the alpha wolves throughout the group and give feedback to the alpha group. Delta-type wolves usually submit to the alpha and beta-type wolves, but they dominate the omega-type wolves. There are five different delta wolves categories: scouts, sentinels, elders, hunters, and caretakers. Each category has a specific role in the group. The omega-type wolves are considered the group's scapegoats, and they have to submit to all the previous types of wolves in the group.

In the grey wolf optimizer, the first fittest solution of the optimization problem is referred to as the alpha solution.

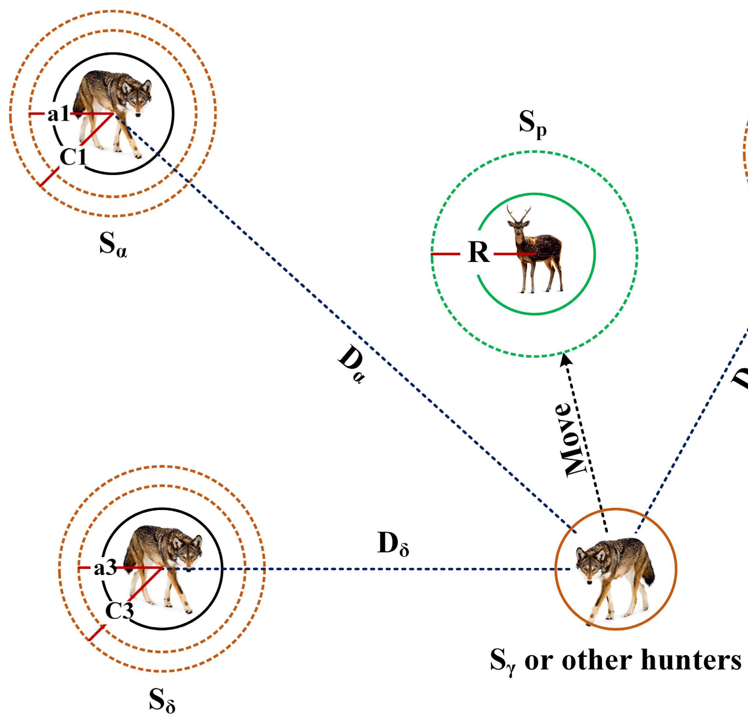


FIGURE 2. Grey wolf position updating process.

However, the second and the third fittest solutions are denoted by the beta and delta solutions. The other solutions are referred to as the omega solutions. In the grey wolf optimizer, the hunting of the best solution is usually guided by alpha, beta, and delta agents, and the omega agents follow these three agents.

From the mathematics perspective, the first fittest solution is denoted by (S_α). The second and third fittest solutions are denoted by (S_β) and (S_δ), respectively. The other solutions are denoted by (S_γ). Figure 2 depicts the updating process of the grey wolves while catching prey. As shown in the figure, the alpha, beta, and delta wolves guide the gamma wolves and other hunters to efficiently hunt their prey. The position updating is performed as follows.

$$S(t+1) = S_p(t) - A.|C.S_p(t) - S(t)| \tag{1}$$

where S denotes the position of the wolf, and t refers to the current iteration of the search algorithm. $S_p(t)$ refers to the prey position and A and C are vectors of coefficients that are defined as follow.

$$A = 2a.r_1 - a \tag{2}$$
$$C = 2r_2 \tag{3}$$

where the values of vectors r_1 and r_2 are randomly selected from the range [0, 1], and the values of the vector a are selected from the range [0, 2] in a linearly decreasing manner. The balance between the exploitation and exploration processes is controlled by the updated values of the vector a [17]. The update of this vector is calculated as follows.

$$a = 2 - t.\frac{2}{M_t} \tag{4}$$

where the number of available iterations is referred as M_t. The estimated positions of the three fittest solutions, S_α, S_β, and S_δ, are used to guide the other solutions, denoted by S_γ, to update their position in the direction of the prey position that is estimated during the search process as shown in Figure 2.

The position updating process of the wolves is described using the following equations by substitution of $S_p(t)$ in equation 1 by S_α, S_β, and S_δ.

$$\begin{aligned} S_1 &= S_\alpha - A_1.D_\alpha, \quad & D_\alpha &= |C_1.S_\alpha - S| \\ S_2 &= S_\beta - A_2.D_\beta, \quad & D_\beta &= |C_2.S_\beta - S| \\ S_3 &= S_\delta - A_3.D_\delta, \quad & D_\delta &= |C_3.S_\delta - S| \end{aligned} \tag{5}$$

The calculations of A_1-A_3 and C_1-C_3 are performed by equation 2 and equation 3, respectively. The population's new position is calculated as follows.

$$S(t+1) = \frac{S_1 + S_2 + S_3}{3} \tag{6}$$

C. SINE COSINE OPTIMIZER

The first introduction of Sine Cosine Algorithm (SCA) was in [23]. The oscillation functions of the sines and cosines form the main factor in identifying the locations of the best solution as shown in Figure 3. A set of random variables are utilized by SCA to denote the following operations [26]:

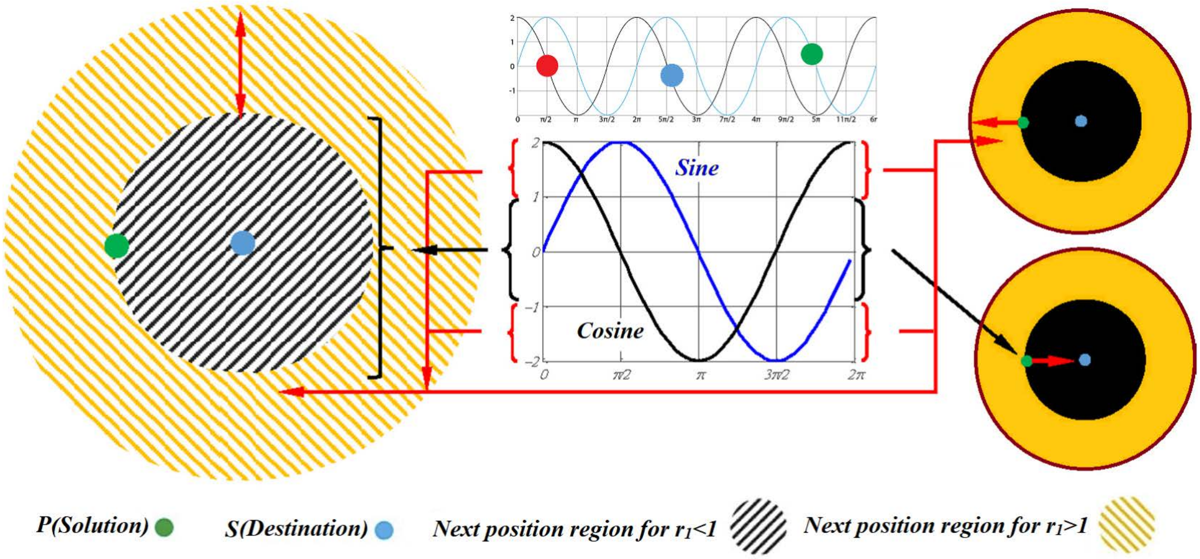


FIGURE 3. Sine cosine position updating process.

- Swapping between the sine and cosine components.
- Emphasizing/de-emphasizing the destination effect.
- The movement location.
- The motion direction.

The update process of the candidate solutions is performed using the following equation.

$$S(t+1) = \begin{cases} S(t) + r_1.sin(r_2).|r_3P(t) - S(t)| & r_4 < 0.5 \\ S(t) + r_1.cos(r_2).|r_3P(t) - S(t)| & r_4 \geq 0.5 \end{cases} \tag{7}$$

where t refers to the iteration number of the search process. P and S refer to the current and destination solutions, respectively. The random variables r_2-r_4 are assigned values in the range $[0-1]$. It can be noted from this equation that the position of the current solution is updated based on the positions of the best solution, which allows the algorithm to reach the optimal solution efficiently. During the running iterations of SCA, the value of r_1 is updated as follows.

$$r_1 = a - \frac{a \times t}{t_{max}} \tag{8}$$

where a is a constant, t and t_{max} represent the current and maximum iterations, respectively.

Due to the utilization of a single best solution to guide the other solutions in the SCA algorithm, this makes it more robust than a wide variety of meta-heuristic techniques in the literature [26]. In addition, the convergence speed and memory consumption of this algorithm are minimal when compared to other competing algorithms. However, the efficiency of this algorithm decreases when the number of local optimal solutions increases. Therefore, in our proposed algorithm, we employed the SCA optimizer to benefit from its fast convergence and memory efficiency properties along with the GWO algorithm to avoid the stagnation in the local optima and to provide a proper balance between exploration and exploitation tasks of the optimization process.

D. BIDIRECTIONAL RECURRENT NEURAL NETWORK (BRNN)

The typical structure of BRNN usually combines RNN that moves forward through time and starts from the beginning of a sequence with another RNN that moves backward through time starting from the end of the sequence [54], [55]. For clarification, Figure 4 depicts the typical structure of a BRNN at three time steps, $t-1$, t, and $t+1$. The information flows in the bottom part from left to right to represent the past information, whereas the information flows from right to left in the top part to represent the future information. Therefore, the result at time t, denoted by O_t is based on the future output denoted by h_t^b in addition to the past output denoted by h_t^f. The training of BRNN uses all available input information in the past and future of a specific time frame.

To train BRNN, the algorithms used in training the conventional RNN can be used in this case since the two types of neurons in the architecture of BRNN have no direct interaction. This results in unfolding the structure of BRNN into a feed-forward structure. However, when the back-propagation is used, the forward and backward steps become more complex as the state and output updates cannot be performed one at a time. Therefore, when the back-propagation through time (BPTT) is employed, the process of forward and backward updates can be performed the same as in the multi-layer perceptron (MLP) network. As the inputs at the forward ($t = 1$) and backward ($t = T$) states are unknown, their values are set arbitrarily to (0.5). On the other hand, the values of the local state derivatives of the forward (at $t = T$) and backward (at $t = 1$) states are set to zero, with an assumption that beyond this point, the

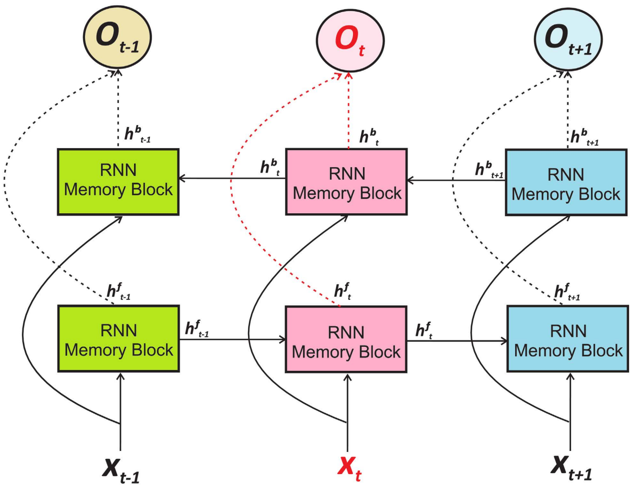


FIGURE 4. Structure of a typical bidirectional recurrent neural network shown at three time steps (i.e. $t-1$, t and $t+1$).

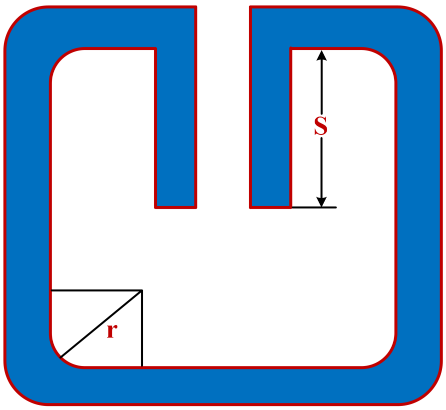


FIGURE 5. The structure of a metamaterial antenna.

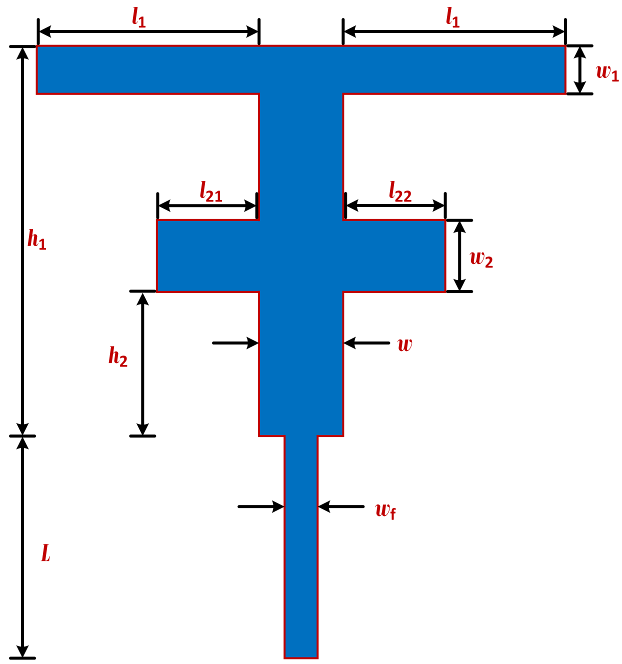


FIGURE 6. The structure of a double T-shape antenna.

information is not significant for the update performed at the current state.

In this research, we employed a proposed optimization algorithm to optimize the parameters of a BRNN for predicting the design parameter of a double T-shape antenna.

E. METAMATERIAL ANTENNA

Rather than the traditional material used in designing antennas, the metamaterial has unusual characteristics that enable manufacturers to design antennas with novel properties. The performance of antennas designed using metamaterial can be improved by setting certain design parameters in addition to providing the antenna substrate with one or more layers of the metamaterial. Figure 5 depicts a sample metamaterial antenna Split Ring Resonator (SRR) unit cell. The surface of the radiation box has a perfect magnetic conductor (PMC) of metamaterial antenna, which is represented by the y-axis [56].

To prove the effectiveness of the proposed optimization algorithm, an ensemble model is proposed, in this research, for estimating the bandwidth of metamaterial antenna based on five regression models. The proposed ensemble model is optimized using the proposed optimization algorithm method to identify the optimum values of the antenna bandwidth. More details about the proposed ensemble model are presented in the next sections. The metamaterial dataset, publicly available on Kaggle [57], employed in the experiments consists of 10 features (namely, Return loss ($S11$), Standing wave ration voltage ($VSWR$), Gain, cell distance (X_a), Array-patch distance (Y_a), Number of cells (SRR_{num}), ring width (T_m), ring distance (D_m), ring gap ($W0_m$), dimensions of the resonator (W_m), and bandwidth) with their values recorded from EM simulators.

F. DOUBLE T-SHAPE ANTENNA

The structure of double T-shape antenna is based on five design parameters referred as w, w_1, w_2, w_f, l_1, l_{21}, and l_{22}, as shown in Figure 6. The function of the T-shape antenna depends mainly on the specified values of these five parameters. On the other hand, there is another set of design parameters (consists of L, h_1, and h_2) whose values are usually retained while varying the values of the aforementioned parameters to fit specific antenna behavior as indicated in [2], [27], [58]–[60]. For instance, a maximum bandwidth can be achieved by removing the amount of value of figure-of-merit (FOM) specified for the antenna performance. The calculation of FOM is performed using the following equation.

$$FOM = \sum_{h=2.3}^{h=3.0} |S_{11}(h)| + \sum_{h=5.15}^{h=5.3} |S_{11}(h)| \tag{9}$$

where the frequency is denoted by h and the value of its reflection coefficient is referred as $S_{11}(h)$.

Algorithm 1 : The Proposed Adaptive Dynamic Sine Cosine Fitness Grey Wolf Optimization (ADSCFGWO) Algorithm

Initialize ADSCFGWO population $X_i (i = 1, 2, \ldots, n)$ with size n, maximum iterations Max_{iter}, fitness function F_n, a, A_1, A_2, A_3, C_1, C_2, r_1, r_2, r_3, r_4
procedure DynamicSearch(F_n)
  if (Best F_n is same for three iterations) **then**
    Increase solutions of exploration group (n_1)
    Decrease solutions of exploitation group (n_2)
  end if
end procedure
Calculate fitness function F_n for each X_i
Find first, second and third best solutions as S_α, S_β, S_δ
Set t = 1
while $t \leq Max_{iter}$ **do**
  Update r_1 by $r_1 = a\left(1 - \frac{t}{Max_{iter}}\right)$
  for $(i = 1 : i < n_1 + 1)$ **do**
    (exploration group update)
    DynamicSearch(F_n)
    Update Fitness $F_\alpha = \frac{F_\alpha}{F_\alpha + F_\beta + F_\delta}$
    Update Fitness $F_\beta = \frac{F_\beta}{F_\alpha + F_\beta + F_\delta}$
    Update Fitness $F_\delta = \frac{F_\delta}{F_\alpha + F_\beta + F_\delta}$
    Calculate $D = |C_1.(F_\alpha * S_\alpha + F_\beta * S_\beta + F_\delta * S_\delta) - X(t)|$
    Calculate $T_1 = S_\alpha - A_1.D$
    Calculate $T_2 = S_\beta - A_2.D$
    Calculate $T_3 = S_\delta - A_3.D$
    Update positions as $X(t+1) = \frac{T_1 + T_2 + T_3}{3}$
    if $(r_4 < 0.5)$ **then**
      $X(t+1) = X(t) + r_1 \times \sin(r_2) \times |r_3 S_\alpha - X(t)|$
    end if
  end for
  for $(i = 1 : i < n_2 + 1)$ **do**
    (exploitation group update)
    DynamicSearch(F_n)
    Update Fitness $F_\alpha = \frac{F_\alpha}{F_\alpha + F_\beta + F_\delta}$
    Update Fitness $F_\beta = \frac{F_\beta}{F_\alpha + F_\beta + F_\delta}$
    Update Fitness $F_\delta = \frac{F_\delta}{F_\alpha + F_\beta + F_\delta}$
    Calculate $D = |C_2.(F_\alpha * S_\alpha + F_\beta * S_\beta + F_\delta * S_\delta) - X(t)|$
    Calculate $T_1 = S_\alpha - A_1.D$
    Calculate $T_2 = S_\beta - A_2.D$
    Calculate $T_3 = S_\delta - A_3.D$
    Update positions as $X(t+1) = \frac{T_1 + T_2 + T_3}{3}$
    if $(r_4 \geq 0.5)$ **then**
      $X(t+1) = X(t) + r_1 \times \cos(r_2) \times |r_3 S_\alpha - X(t)|$
    end if
  end for
  Update the fitness function F_n for each X_i
  Update X_α, X_β, X_δ, a, A_1, A_2, A_3, C_1, C_2, r_2, r_3, r_4
  Find best individual X^*
  Set t = t + 1
end while
Return X^*

In this research, we adopted the double T-shape monopole antenna for verifying the effectiveness of the proposed methodology through estimating its design parameters using optimized BRNN.

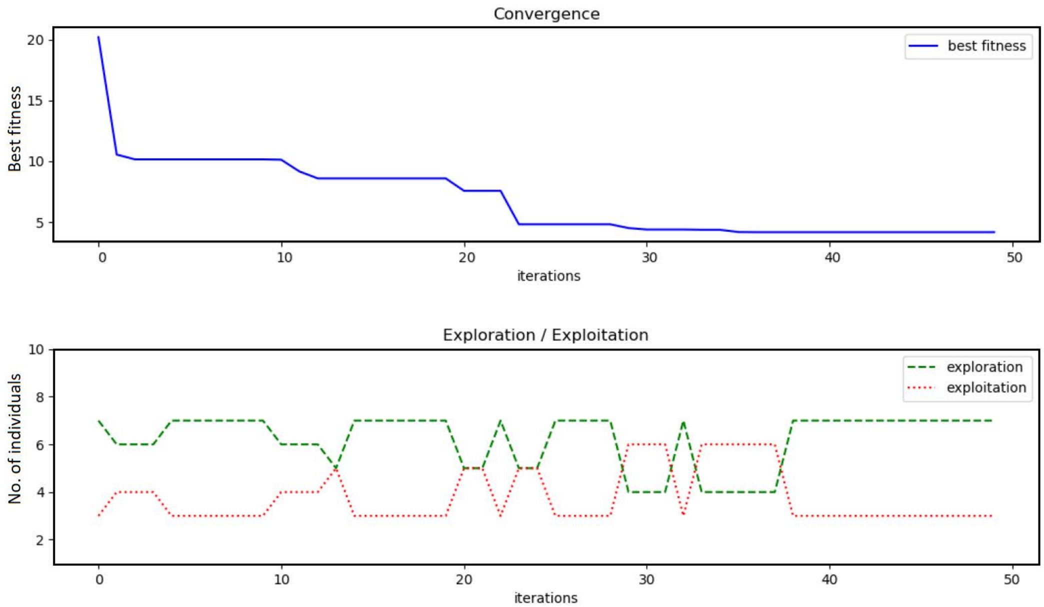


FIGURE 7. **The balance between the exploitation and exploration processes.**

III. THE PROPOSED METHODOLOGY

This section presents and discusses the proposed adaptive dynamic sine cosine fitness grey wolf optimizer (ADSCFGWO). This algorithm is a new hybrid algorithm based on both sine cosine and grey wolf algorithms in an adaptive framework that exploits the advantages of both algorithms. The details of the proposed algorithm are presented in Algorithm 1, and more details are explained in this section.

A. MOTIVATION

In optimization problems, a population refers to a collection of individuals representing the potential solutions to a problem being solved by an algorithm. These individuals usually have parameter vectors for each one of them. The individuals in the candidate solution are divided into two groups, namely, exploitation and exploration groups. The task of the exploitation group is to improve the best solution quality using an objective function. At the same time, the task of the exploration group is to utilize the search space for exploring new areas at which the potential best solution can be found. In the proposed optimization algorithm, these two groups collaborate to exchange duties and necessary information that can help fast retrieve the best solution. The benefits of this collaboration are the efficient avoidance of the local optima and the accurate exploration of the search space. There are two distinct features of the proposed optimization algorithm, firstly, proper control of the balance between the exploitation and exploration groups is maintained by the proposed algorithm; secondly, the avoidance of steady regions in the search space through a dynamic mechanism.

B. BALANCE BETWEEN EXPLORATION AND EXPLOITATION

The proposed algorithm ADSCFGWO automatically balances exploration and exploitation among the population's subgroups. The proposed algorithm employs a 70/30 scheme, where 70% of the population is split into two groups, namely, exploration and exploitation groups. The discovery of fresh and interesting search regions is aided by having a large number of participants in the exploration group early in the optimization process. When more exploitative individuals can boost their fitness values, the overall fitness of individuals rises, but the number of individuals in the exploration group reduces rapidly from 70% to 30%. Using an elitism method ensures convergence by retaining the process leader in succeeding populations if a better solution cannot be found. As long as the leader's fitness hasn't significantly improved over the course of three consecutive iterations, ADSCFGWO can increase the number of members in the exploration group at any time.

Figure 7 shows the dynamic change in the the number of individuals in exploitation and exploration groups over a set of iterations. The top plot of Figure 7 depicts the convergence curve of the best fitness as an example of finding a point in 2D space in a sample optimization problem. On the other hand, the bottom plot of Figure 7 depicts the number of exploitation and exploration of individuals over the optimization iterations.

C. COMPLEXITY ANALYSIS

The computational complexity of the proposed ADSCFGWO algorithm can be expressed as follows. For population n and iterations t_{max}, the time complexity will be defined as in the following.

- Initialization $X_i (i = 1, 2, \dots, n)$, Maximum iterations Max_{iter}, F_n, t_{max}, c, A_1, A_2, A_3, C_1, C_2, r_1, r_2, r_3, r_4, $t = 1 : O(1)$.
- Calculate objective function F_n for each solution X_i : $O(n)$.
- Finding best solutions $X_{i_{best}}$: $O(n)$.
- Updating position of current grey wolf by fitness: $O(t_{max} \times n)$.
- Updating position of current individual by Sine Cosine: $O(t_{max} \times n)$.
- Updating objective function F_n for each X_i : $O(t_{max}) \times n$.
- Finding best fitness $X_{i_{best}}$: $O(t_{max})$.
- Updating $a, A_1, A_2, A_3, C_1, C_2, r_2, r_3, r_4$: $O(t_{max})$.
- Updating iterations: $O(t_{max})$.
- Producing the best fitness $X_{i_{best}}$: $O(1)$.

From this analysis, the complexity of computations is $O(t_{max} \times n)$ and $O(t_{max} \times n \times d)$ with d dimension.

D. BINARY ADSCFGWO ALGORITHM

The search space of the feature selection problems is limited to the binary values (0 and 1) to decide whether the corresponding feature is significant or not. Therefore, in this section, we propose a binary ADSCFGWO algorithm that converts the continuous values resulting from the continuous ADSCFGWO algorithm into binary [0,1] to match the process of feature selection. The conversion to binary values is performed in terms of the *Sigmoid* function, which is represented by the following equation.

$$X^{(t+1)} = \begin{cases} 1 & \text{if } Sigmoid(X_{best}) \geq 0.5 \\ 0 & otherwise \end{cases},$$
$$Sigmoid(X_{Best}) = \frac{1}{1 + e^{-10(X_{Best} - 0.5)}} \tag{10}$$

where X_{best} refers to best solution solution at iteration t. The main goal of the sigmoid function is to scale the continuous values achieved by Algorithm 1 to become in the range [0-1]. The sigmoid function is shown in Figure 8 and the steps of the proposed binary ADSCFGWO are presented in Algorithm 2.

E. OBJECTIVE FUNCTION

The quality of the retrieved solution based on the the proposed optimization algorithm is measured using the following equation.

$$F_n = \alpha Error(P) + \beta \frac{|S|}{|A|} \tag{11}$$

where P refers to the model parameters. The values of $\alpha \in [0, 1]$, $\beta = 1 - \alpha$ reflect the importance of the selected features in the population. $|S|$ is the number of the selected features, and $|A|$ is the total number of all features in the dataset. The best solution is the one that can employ the minimum number of selected features to achieve the lowest prediction/classification error.

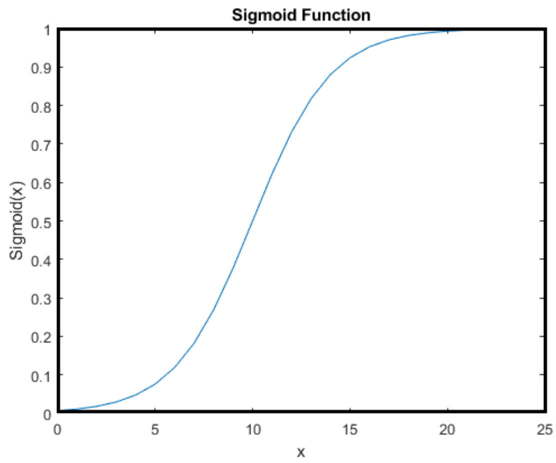


FIGURE 8. Sigmoid function of Eq. 10.

Algorithm 2 : The Proposed Binary ADSCFGWO Algorithm

1: **Initialize** Set ADSCFGWO population, parameters, configuration.
2: **Convert** solutions to binary [0,1].
3: **Calculate** objective function and select best solutions.
4: **Train** k-NN and calculate error
5: **while** $t \leq Max_{iter}$ **do**
6:     **Apply** ADSCFGWO algorithm
7:     **Convert** solutions to binary using Eq. (10)
8:     **Calculate** Fitness
9:     **Update** Positions
10: **end while**
11: **Return** X^*

IV. EXPERIMENTAL RESULTS

The conducted experiments are divided into three scenarios to evaluate the proposed algorithms. In the first scenario, the proposed ADSCFGWO algorithm is tested for seven benchmark functions, from F1 to F7 [61], and on the CEC2017 benchmarks with ten dimensions [62]. The Convergence curves, Mean and standard deviation (StDev), T-test, and ANOVA test results over the benchmark functions are shown in Appendix A. For the CEC2017 benchmark, there are 29 problems across ten dimensions with a 5 percent significance level. The statistical results and the best and standard deviations of error from the optimal solution of the ADSCFGWO and state-of-the-art algorithms over 51 runs for all 29 benchmark functions are shown in Appendix B. The results based on benchmark functions show the performance of the proposed algorithm. The second scenario targets optimizing the parameters of the metamaterial antenna. In contrast, the third scenario is established to optimize the parameters of a double T-shape antenna. The following sections present the details of these scenarios and discuss the achieved results.

A. METAMATERIAL ANTENNA SCENARIO

The set of experiments is conducted in this scenario to measure the effectiveness of the proposed feature selection and optimization algorithms in predicting the bandwidth of metamaterial antenna. In this scenario, the performance of the proposed algorithm is measured in terms of several performance metrics, as presented in the next section.

1) PERFORMANCE METRICS

To measure the effectiveness of the proposed algorithm for predicting the design parameters of metamaterial antenna, we utilized the metrics listed in the following equations. In these metrics, M refers to the number of runs of an optimizer for the process of feature selection. In addition, the best solution at the run number j is denoted by g_j^*, and the number of tested points is referred to as N.

- **Average Error** is calculated to measure the error in predicting the design parameters of the metamaterial antenna. This metric is calculated as follows.

$$\text{Avg Error} = 1 - \frac{1}{M}\sum_{j=1}^{M}\frac{1}{N}\sum_{i=1}^{N} mse(C_i, L_i) \tag{12}$$

  where mse refers to the mean square error of the prediction of the antenna parameters. C_i is the predicted value of the design parameter at point i, and L_i is the corresponding actual value at same point i.
- **Average Select Size** is the average size of the features selected by the feature selection process to the total number of features in the dataset (D). This metric is measured as follows.

$$\text{Avg Select Size} = \frac{1}{M}\sum_{j=1}^{M}\frac{size(g_j^*)}{D} \tag{13}$$

  where the vector g_j^* has a size denoted by $size(g_j^*)$.
- **Average Fitness** is the average of the resulting predictions generated by the proposed optimizer for M times of running. This metric is measured as follows.

$$\text{Avg Fitness} = \frac{1}{M}\sum_{j=1}^{M} g_j^* \tag{14}$$

- **Best Fitness** is a metric that refers to the minimum fitness measured after M runs of the proposed optimizer. This metric is measured as follows.

$$\text{Best Fitness} = Min_{(j\ in\ [M])} g_j^* \tag{15}$$

- **Worst Fitness** is a metric that refers to the worst fitness measured after M runs of the proposed optimizer. This metric is measured as follows.

$$\text{Worst Fitness} = Max_{(j\ in\ [M])} g_j^* \tag{16}$$

- **Standard Deviation** (STD) is the variation of the best predicted values after M runs of the proposed optimizer. This metric is measured as follows.

$$\text{STD} = \sqrt{\frac{1}{M-1}\sum (g_j^* - \text{Avg Fitness})^2} \tag{17}$$

  where Avg Fitness refers to the average fitness measured by equation 14, and M refers to the number of tuns of the optimization algorithm to select the feature subset.

TABLE 2. Performance evaluation metrics.

Metric	Value
RMSE	$\sqrt{\frac{1}{N}\sum_{n=1}^{N}(\hat{V}_n - V_n)^2}$
RRMSE	$\frac{RMSE}{\sum_{n=1}^{N}\hat{V}_n} \times 100$
MAE	$\frac{1}{N}\sum_{n=1}^{N}\lvert\hat{V}_n - V_n\rvert$
MBE	$\frac{1}{N}\sum_{n=1}^{N}(\hat{V}_n - V_n)$
NSE	$1 - \frac{\sum_{n=1}^{N}(V_n - \hat{V}_n)^2}{\sum_{n=1}^{N}(V_n - \bar{\hat{V}}_n)^2}$
WI	$1 - \frac{\sum_{n=1}^{N}\lvert\hat{V}_n - V_n\rvert}{\sum_{n=1}^{N}\lvert V_n - \bar{V}_n\rvert + \lvert\hat{V}_n - \bar{\hat{V}}_n\rvert}$
R2	$1 - \frac{\sum_{n=1}^{N}(V_n - \hat{V}_n)^2}{\sum_{n=1}^{N}(\sum_{n=1}^{N} V_n) - V_n)^2}$
r	$\frac{\sum_{n=1}^{N}(\hat{V}_n - \bar{\hat{V}}_n)(V_n - \bar{V}_n)}{\sqrt{\left(\sum_{n=1}^{N}(\hat{V}_n - \bar{\hat{V}}_n)^2\right)\left(\sum_{n=1}^{N}(V_n - \bar{V}_n)^2\right)}}$

TABLE 3. Configuration parameters of the proposed bADSCFGWO.

Parameter	Value
Dimension	Features count
a	[-10, 10]
b	[-10, 10]
θ	[0, 12π]
α of Eq. (11)	0.99
β of Eq. (11)	0.01
Iterations	80
Agents	10

On the other hand, additional metrics are used to measure the performance of the regression models employed to predict the bandwidth of metamaterial antenna. These metrics include root mean error (RMSE), mean absolute error (MAE), mean bias error (MBE), Pearson's correlation coefficient (r), coefficient of determination (R2), Relative RMSE (RRMSE), Nash Sutcliffe Efficiency (NSE), determine agreement (WI), where N is the number of observations in the dataset; $(\hat{V}_n)$ and (V_n) are the n^{th} estimated and observed bandwidth, and $(\bar{\hat{V}}_n)$ and $(\bar{V}_n)$ are the arithmetic means of the estimated and observed values. The evaluation of these metrics is performed using the equations presented in Table 2.

2) CONFIGURATION PARAMETERS

The configuration parameters of the proposed algorithm are shown in Table 3. As shown in this table, the values of α and β for the employed objective function in Eq. (11), are set to 0.99 and 0.01, respectively. On the other hand, the configuration parameters of the other competing algorithms included in the conducted experiments are shown in Table 4.

3) METAMATERIAL ANTENNA DATASET

To evaluate the proposed algorithm, we adopted the metamaterial dataset that is publicly available on Kaggle [57]

TABLE 4. Configuration parameters of the competing algorithms.

Algorithm	Parameter	Value
FA	Iterations	80
	Fireflies	10
GA	Cross over	0.9
	Mutation ratio	0.1
	Selection mechanism	Roulette wheel
	Iterations	80
	Agents	10
SBO	Mutation probability	0.05
	Step size	0.94
	Limit difference	0.02
	Iterations	80
	Agents	10
PSO	Acceleration constants	[2,2]
	Inertia W_{min}, W_{max}	[0.6, 0.9]
	Iterations	80
	Particles	10
SFS	Max diffusion level	1
	Iterations	80
	Agents	10
WOA	r	[0, 1]
	a	2 to 0
	Iterations	80
	Whales	10
MVO	Probability of wormhole existence	[0.2, 1]
	Iterations	80
	Agents	10
GWO	a	2 to 0
	Wolves	10
	Iterations	80

for the experiments of the second scenario. This dataset consists of a set of 10 features (namely, Return loss ($S11$), Standing wave ration voltage ($VSWR$), Gain, cell distance (X_a), Array-patch distance (Y_a), Number of cells (SRR_{num}), ring width (T_m), ring distance (D_m), ring gap ($W0_m$), dimensions of the resonator (W_m), and bandwidth) with their values recorded from EM simulators. The bandwidth in this dataset is considered one of the most relevant parameters. Therefore, the proposed algorithm is employed to predict the values of the bandwidth based on the features selected using the proposed bADSCFGWO. The correlation among the features of the dataset is depicted in Figure 9.

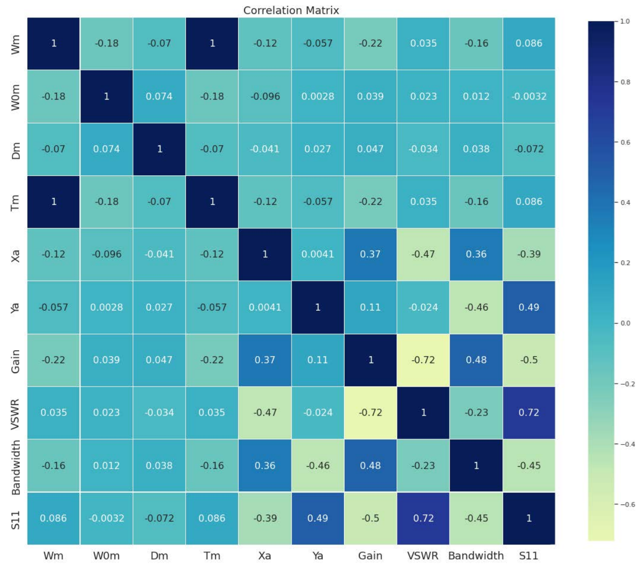


FIGURE 9. Correlation between the features of the metamaterial antenna.

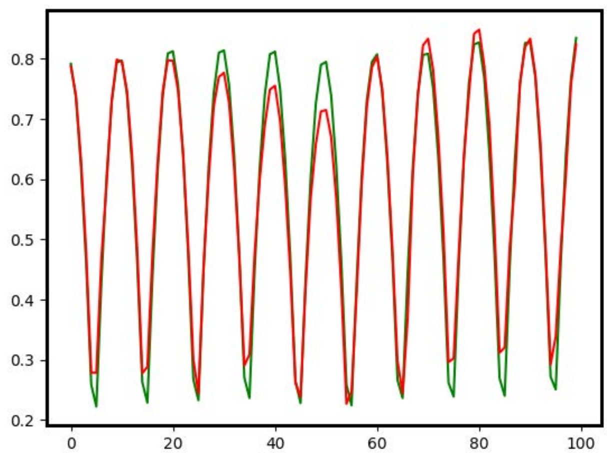


FIGURE 10. The predicted (red color) and actual (green color) values based on the proposed ensemble model.

4) THE PROPOSED ENSEMBLE MODEL

In this section, we proposed a new ensemble model for predicting the bandwidth of metamaterial antenna. The proposed model consists of three main steps: data preprocessing, training base models, and training the proposed ensemble model. In the first step, the given metamaterial dataset is preprocessed to remove the null values and scale the features in the range of [0, 1]. The preprocessed features from the first step are then fed to the proposed bADSCFGWO, shown in Algorithm 2, to select the most significant features. The selected features are used to train a set of five base models to predict the bandwidth of the metamaterial antenna. These base models are support vector regression (SVR), multi-layer perceptron (MLP), decision tree (DT), random forest (RF), and k-nearest neighbors (KNN). The training of these base models is performed in terms of the proposed ADSCFGWO algorithm shown in Algorithm 1. On the other hand, The contribution of each base model in the final prediction result is optimized using the proposed ADSCFGWO algorithm. The predictions using the proposed ensemble model are shown in Figure 10. The detailed steps of the proposed ensemble model are depicted in Figure 11. This ensemble model is compared with the average ensemble and KNN based ensemble models for the same task, and the results are presented and discussed in the next section.

5) ANALYSIS AND DISCUSSION

This section presents and discusses the achieved results based on metamaterial antenna. These results include evaluation of the proposed feature selection algorithm, evaluation of the optimization of the proposed ensemble model using the

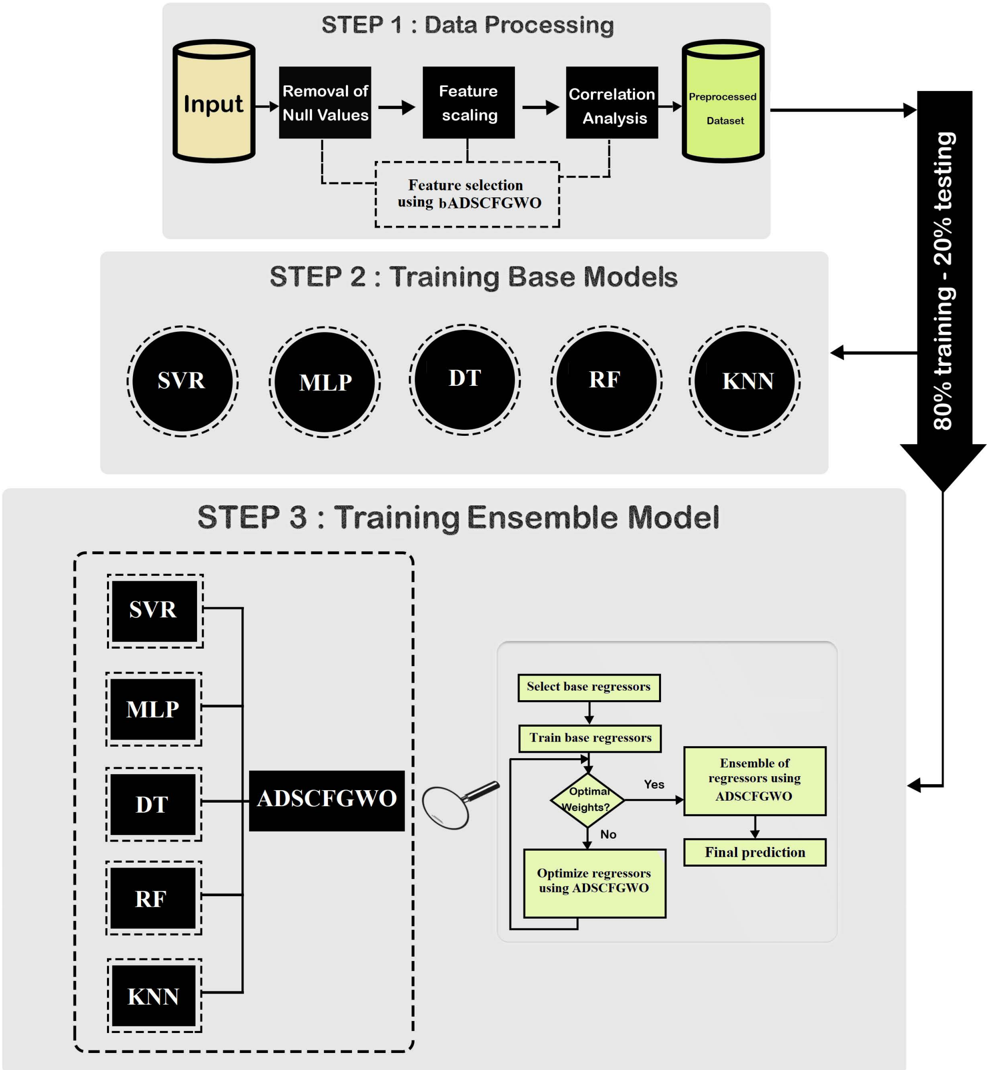
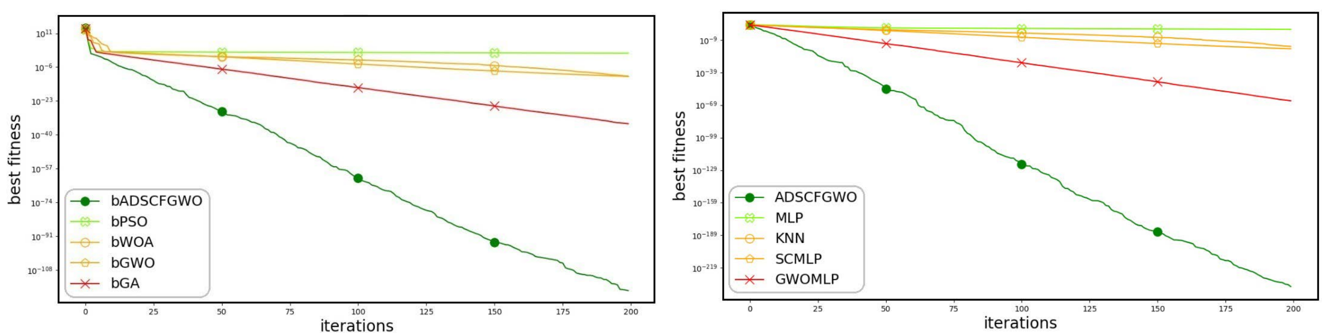


FIGURE 11. The proposed ensemble for optimizing the parameters of metamaterial antenna.



(a) Convergence speed of the proposed bADSCFGWO.

(b) Convergence speed of the proposed ADSCFGWO.

FIGURE 12. Convergence curves of the proposed algorithm and the other competing algorithms.

proposed ADSCFGWO and other optimization algorithms, evaluation of the proposed ensemble model, and finally, statistical analysis of the achieved results.

The feature selection applied to the metamaterial antenna features is performed using the proposed binary ADSCFGWO. The achieved results are compared with

TABLE 5. Performance of the proposed feature selection algorithm compared to other competing algorithms.

	AvgError	AvgSelectSize	Avg Fitness	Best Fitness	Worst Fitness	STD Fitness	Avg Time (S)
bFA	0.9337	0.9018	0.88341	0.8579	0.9057	0.02096	177.6
bGA	0.6581	0.7638	0.7698	0.7581	0.8019	-0.0012	128.1
bSBO	0.9651	0.95	0.9542	0.7682	1.0926	0.0209	183.4
bPSO	0.8809	0.7827	0.8498	0.8142	0.8585	0.0085	132.1
bSFS	0.9674	0.9638	0.9007	0.8582	0.9153	0.0287	176.6
bWOA	0.9684	0.93374	0.9142	0.8809	0.9331	0.0309	245.2
bMVO	0.9367	0.9042	0.8998	0.8813	0.923	0.01983	171.4
bGWO	0.8542	0.8457	0.8129	0.7731	0.8297	0.01	136.1
bMGWO	0.7227	0.7399	0.7451	0.702	0.7832	-0.0013	120.4
bGWO_GA	0.7845	0.7551	0.7687	0.7465	0.8109	0.2926	137.2
bGWO_PSO	0.6582	0.7471	0.7442	0.6797	0.7819	0.00636	135.1
bADSCFGWO	**0.6475**	**0.6673**	**0.6457**	**0.5789**	**0.6485**	**0.00081**	**99.4**

TABLE 6. Statistical analysis of the achieved results based on the proposed feature selection algorithm and other competing algorithms.

	Min	25%	Median	75%	Max	Range	Mean	Std	Std. Error	Sum
SFS	0.0099	0.0111	0.0111	0.0111	0.0121	0.0021	0.0111	0.00046	0.000141	0.1207
PSO	0.0053	0.0061	0.0061	0.0061	0.0077	0.0024	0.0061	0.00057	0.000173	0.0671
GWO	0.0078	0.0096	0.0098	0.0098	0.0098	0.0021	0.0095	0.00064	0.000193	0.1046
GWO_PSO	0.0051	0.0051	0.0051	0.0051	0.0073	0.0023	0.0053	0.00074	0.000223	0.0584
ADSCFGWO	**0.0034**	**0.0036**	**0.0036**	**0.0036**	**0.0038**	**0.0004**	**0.0036**	**0.00011**	**0.000027**	**0.0398**

TABLE 7. Results achieved by the proposed ensemble models and other regression and ensemble models.

	RMSE	MAE	MBE	r	R2	RRMSE	NSE	WI
SVR	0.045	0.034	0.005	0.982	0.964	12.048	0.963	0.920
MLP Regressor	0.047	0.035	0.001	0.980	0.959	12.716	0.959	0.916
KNN Regressor	0.019	0.013	-0.002	0.997	0.994	5.041	0.994	0.969
Decision Tree Regressor	0.064	0.047	-0.002	0.963	0.927	17.087	0.926	0.887
Random Forest Regressor	0.102	0.079	0.000	0.901	0.811	27.423	0.811	0.812
Average Ensemble	0.044	0.032	0.000	0.983	0.966	5.041	0.964	0.922
Ensemble using KNN Regressor	0.013	0.009	-0.001	0.998	0.997	3.487	0.997	0.979
Ensemble using ADSCFGWO	**0.004**	**0.002**	**0.000**	**1.000**	**1.000**	**0.626**	**1.000**	**0.993**

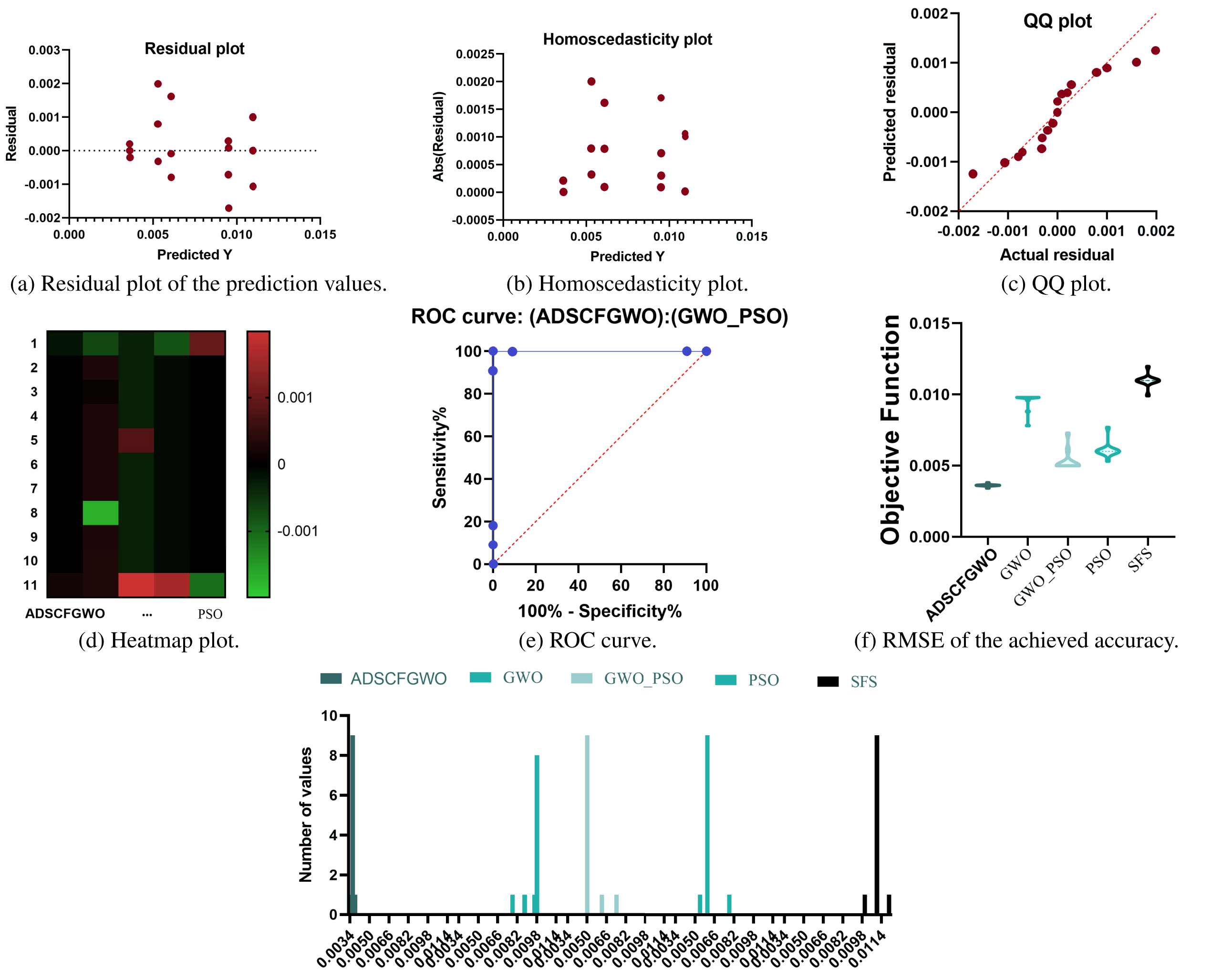
TABLE 8. The results of the ANOVA test based on the achieved results on the metamaterial antenna.

ANOVA table	SS	DF	MS	F (DFn, DFd)	P value
Treatment (between columns)	0.0004087	4	0.0001022	F (4, 50) = 338.8	P<0.0001
Residual (within columns)	0.00001508	50	3.016E-07		
Total	0.0004238	54			

TABLE 9. Two-tailed t-test of the achieved results using the proposed algorithm and other algorithms for the metamaterial antenna.

	ADSCFGWO	GWO	GWO_PSO	PSO	SFS
Theoretical mean	0	0	0	0	0
Actual mean	0.003619	0.009509	0.005308	0.006091	0.01097
Number of values	11	11	11	11	11
One sample t test					
t, df	t=134.2, df=10	t=49.20, df=10	t=23.84, df=10	t=35.22, df=10	t=78.59, df=10
P value (two tailed)	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
P value summary	****	****	****	****	****
Significant (alpha=0.05)?	Yes	Yes	Yes	Yes	Yes
How big is the discrepancy?					
Discrepancy	0.003619	0.009509	0.005308	0.006091	0.01097
SD of discrepancy	0.00008944	0.000641	0.0007386	0.0005735	0.0004631
SEM of discrepancy	0.00002697	0.0001933	0.0002227	0.0001729	0.0001396
95% confidence interval	0.0036 to 0.0037	0.0091 to 0.0099	0.0048 to 0.0058	0.0057 to 0.0065	0.0107 to 0.0113
R squared (partial eta squared)	0.9994	0.9959	0.9827	0.992	0.9984

other state-of-the-art binary optimization techniques, namely, Firefly Algorithm (FA) [63], Genetic Algorithm (GA) [37], Satin Bowerbird Optimizer (SBO) [64], Particle swarm optimization (PSO) [28], Stochastic Fractal Search (SFS) [65], Whale optimization algorithm (WOA) [36], Multiverse Optimization (MVO) [66], Grey Wolf Optimizer



(a) Residual plot of the prediction values.
(b) Homoscedasticity plot.
(c) QQ plot.
(d) Heatmap plot.
(e) ROC curve.
(f) RMSE of the achieved accuracy.
(g) Histogram of the RMSE values of the predicted bandwidth of metamaterial antenna.

FIGURE 13. Evaluation results of the proposed algorithm for optimizing metamaterial antenna parameters.

TABLE 10. The results of the ANOVA test based on the achieved results on the T-shape antenna.

ANOVA table	SS	DF	MS	F (DFn, DFd)	P value
Treatment (between columns)	2.027E-08	4	5.068E-09	F (4, 100) = 1621	P<0.0001
Residual (within columns)	3.126E-10	100	3.126E-12		
Total	2.059E-08	104			

(GWO) [29], Modified binary grey wolf optimizer (MbGWO) [67], hybrid GWO and PSO (bGWO_PSO) [68], hybrid GWO and GA (bGWO_GA). The evaluation results are presented in Table 5. As shown in this table, the proposed bADSCFGWO achieves an average error of (0.6475), which is the best among the values achieved by the other algorithms. In addition, other metrics such as achieving better values of average select size, average fitness, best fitness, worst fitness, and standard deviation, the proposed algorithm achieves the best values when compared to the other competing algorithms. Moreover, the convergence speed of the proposed algorithm, shown in the last column of the figure, is the smallest among the average time spent by the other algorithms in selecting the appropriate features from the metamaterial dataset. These results confirm the effectiveness of the proposed algorithm in selecting the proper features that are used to predict the parameters of the metamaterial antenna accurately.

On the other hand, four optimization algorithms, namely, SFS, PSO, GWO, and GWO_PSO, along with the proposed ADSCFGWO, are used to optimize the parameters of the proposed ensemble model to prove the efficiency of the proposed ADSCFGWO algorithm in optimizing the ensemble parameters. The results of this evaluation are

TABLE 11. Two-tailed t-test of the achieved results using the proposed algorithm and other algorithms for optimizing the parameters of double T-shape antenna.

	MLP	KNN	SCA BRNN	GWO BRNN	ADSCFGWO BRNN
Theoretical mean	0	0	0	0	0
Actual mean	0.00003562	0.000002958	6.905E-07	2.857E-07	2.905E-100
Number of values	21	21	21	21	21
One sample t test					
t, df	t=42.49, df=20	t=14.64, df=20	t=41.18, df=20	t=20.00, df=20	t=24.70, df=20
P value (two tailed)	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
P value summary	****	****	****	****	****
Significant (alpha=0.05)?	Yes	Yes	Yes	Yes	Yes
How big is the discrepancy?					
Discrepancy	0.00003562	0.000002958	6.905E-07	2.857E-07	2.905E-100
SD of discrepancy	0.000003842	9.261E-07	7.684E-08	6.547E-08	5.39E-101
SEM of discrepancy	8.384E-07	2.021E-07	1.677E-08	1.429E-08	1.176E-101
95% confidence interval	3.3e-5 to 3.7e-5	2.5e-6 to 3.4e-6	6.6e-7 to 7.3e-7	2.6e-7 to 3.2e-7	2.7e-100 to 3.20e-100
R squared (partial eta squared)	0.989	0.9146	0.9883	0.9524	0.9683

presented in Table 6. This table presents a statistical analysis of the achieved results when compared with the other algorithms. As shown in this table, the minimum value achieved by the proposed algorithm is (0.0034), which is smaller than that of the corresponding metric achieved by the other algorithms. In addition, the mean, standard deviation, and standard deviation error of the mean achieved by the proposed algorithm are better than those values achieved by the other algorithms.

Moreover, the proposed ensemble model is evaluated and compared with other ensemble and regression models, namely, average ensemble and KNN-based ensemble, along with the separate application of regression models. The results of these models are presented in Table 7. These results are measured in terms of the eight evaluation criteria, presented in Table 2, to examine the performance of the proposed ensemble model with comparison to the other models. The presented results in Table 7 show the efficiency and superiority of the proposed ensemble model in predicting the bandwidth of metamaterial antenna when compared to the other ensembles and separate regression models.

The one-way analysis of variance (ANOVA) test results, based on the proposed ensemble models and other models, is presented in Table 8. In this table, it can be noted that the proposed algorithm and other competing algorithms are statistically similar. However, deciding which algorithm is better is not obvious in the results of the ANOVA test. Therefore, we conducted another test between every two approaches. The results of a one-tailed t-test at 0.05 significance level are shown in Table 9 for eleven values. In this kind of testing, when the p-value has a value <0.05, this represents a significant superiority of the approach and vice versa. As shown in Table 9, the measured value of p-value between the proposed approach and the other approaches is <0.05, which indicates the superiority of the proposed approach and proves it's significant statistically.

On the other hand, the plots shown in Figure 13 depict an in-depth investigation of the performance of the proposed optimization algorithm. This figure shows the seven types of plots, namely, residual plot, homoscedasticity plot, QQ plot, heatmap, ROC curve, root-mean-square-error (RMSE) plot, and histogram of RMSE values.

The residual plot in Figure 13a shows the mapping between the predicted values of the metamaterial antenna parameters and the prediction error values. As shown in the figure, the prediction errors are within the range of (0.002) to (-0.002), which indicates the accuracy of the proposed algorithm in predicting the parameters of the metamaterial antenna. These results are also confirmed by the homoscedasticity shown in Figure 13b. In addition, the QQ plot depicted in Figure 13c shows the mapping between the predicted and actual values metamaterial antenna parameters. In this figure, the mapping approximately fits a straight line, which emphasizes the effectiveness of the proposed algorithm. A comparison between the proposed feature selection algorithm other algorithms is presented in Figure 13d. The white-green color in the figure refers to better performance, which is shown in the figure with the proposed algorithm.

In addition, the results presented in Figure 13e and Figure 13f confirm the superiority of the proposed feature selection algorithm and the achieved prediction results. The ROC curve shows promising performance of the proposed feature selection algorithm. In addition, the RMSE plot shows the smallest value of the objective function for the proposed algorithm compared to other existing feature selection algorithms that have been recently published in the literature. Figure 13g depicts the histogram of the RMSE values achieved using the proposed algorithm and other algorithms. In this figure, the majority of the predicted values have the smallest RMSE values among the corresponding predictions using the other feature selection algorithms. Most of the achieved RMSE values are in the range of (0.0034) to (0.004), which outperforms those achieved by the other algorithms. These results prove the proposed algorithm's

TABLE 12. Statistical analysis of the achieved results based on T-shape antenna and using the optimized BRNN.

	MLP	KNN	SCA BRNN	GWO BRNN	ADSCFGWO BRNN
Number of values	21	21	21	21	21
Minimum	0.0000261	0.00000261	0.0000005	0.0000001	1E-100
25% Percentile	0.0000361	0.00000261	0.0000007	0.0000003	3E-100
Median	0.0000361	0.00000261	0.0000007	0.0000003	3E-100
75% Percentile	0.0000361	0.00000261	0.0000007	0.0000003	3E-100
Maximum	0.0000461	0.00000561	0.0000009	0.0000004	4E-100
Range	0.00002	0.000003	0.0000004	0.0000003	3E-100
10% Percentile	0.0000281	0.00000261	0.00000054	0.00000014	2.2E-100
90% Percentile	0.0000361	0.00000527	0.0000007	0.0000003	3E-100
Mean	0.00003562	0.000002958	6.905E-07	2.857E-07	2.905E-100
Std. Deviation	0.000003842	9.261E-07	7.684E-08	6.547E-08	5.39E-101
Std. Error of Mean	8.384E-07	2.021E-07	1.677E-08	1.429E-08	1.176E-101
Coefficient of variation	10.79%	31.31%	11.13%	22.91%	18.55%
Geometric mean	0.00003541	0.000002862	6.861E-07	2.739E-07	2.831E-100
Geometric SD factor	1.121	1.272	1.126	1.406	1.301
Harmonic mean	0.00003518	0.000002797	6.813E-07	2.545E-07	2.71E-100
Quadratic mean	0.00003582	0.000003093	6.945E-07	2.928E-07	2.952E-100
Skewness	-0.5612	2.604	-0.5612	-2.219	-2.232
Kurtosis	5.325	5.681	5.325	5.87	8.718
Sum	0.0007481	0.00006211	0.0000145	0.000006	6.1E-99

TABLE 13. Estimated parameters of the double T-shape antenna.

algorithm	l_{21}	l_{22}	w_1	w_2	w	Time (s)
MLP	7.3	6.3	1	3.5	3.5	297.7
KNN	7.3	6.3	1	3.5	3.5	284.8
SCA BRNN	7.3	6.3	1	3.5	3.5	275.6
GWO BRNN	7.3	6.3	1	3.5	3.5	273.9
ADSCFGWO BRNN	**7.3**	**6.3**	**1.2**	**3.3**	**3.1**	**233.1**

TABLE 14. Unimodal benchmark functions (F1 to F7).

Function	**D**	**Range**
$F1(w) = \sum_{i=1}^{n} w^2$	30	[-100, 100]
$F2(w) = \sum_{i=1}^{n} \lvert w_i\rvert + \prod_{i=1}^{n} \lvert w_i\rvert$	30	[-10, 10]
$F3(w) = \sum_{i=1}^{n}(\sum_{j=1}^{i} w_i)^2$	30	[-100, 100]
$F4(w) = max_i\{\lvert w_i\rvert, 1 \leq i \leq D\}$	30	[-100, 100]
$F5(w) = \sum_{i=1}^{D-1}[100(w_{i+1} - w_i^2)^2 - (w_i - 1)^2]$	30	[-30, 30]
$F6(w) = \sum_{i=1}^{D}(w_i + 0.5)^2$	30	[-100, 100]
$F7(w) = \sum_{i=1}^{D} iw_i^4 + rand[0, 1]$	30	[-1.28, 1.28]

effectiveness for predicting the bandwidth of metamaterial antenna.

B. DOUBLE T-SHAPE ANTENNA SCENARIO

The third scenario of the conducted experiments targets optimizing the parameters of a double T-shape antenna. In this scenario, we employed the proposed ADSCFGWO algorithm to optimize the bidirectional recurrent neural network (BRNN) parameters to estimate the design parameters of a double T-shape monopole antenna. The performance of the proposed approach is compared with the performance of four other machine learning and optimization models, namely, MLP, KNN, SCA BRNN, and GWO BRNN. More details about the achieved results are presented in the following.

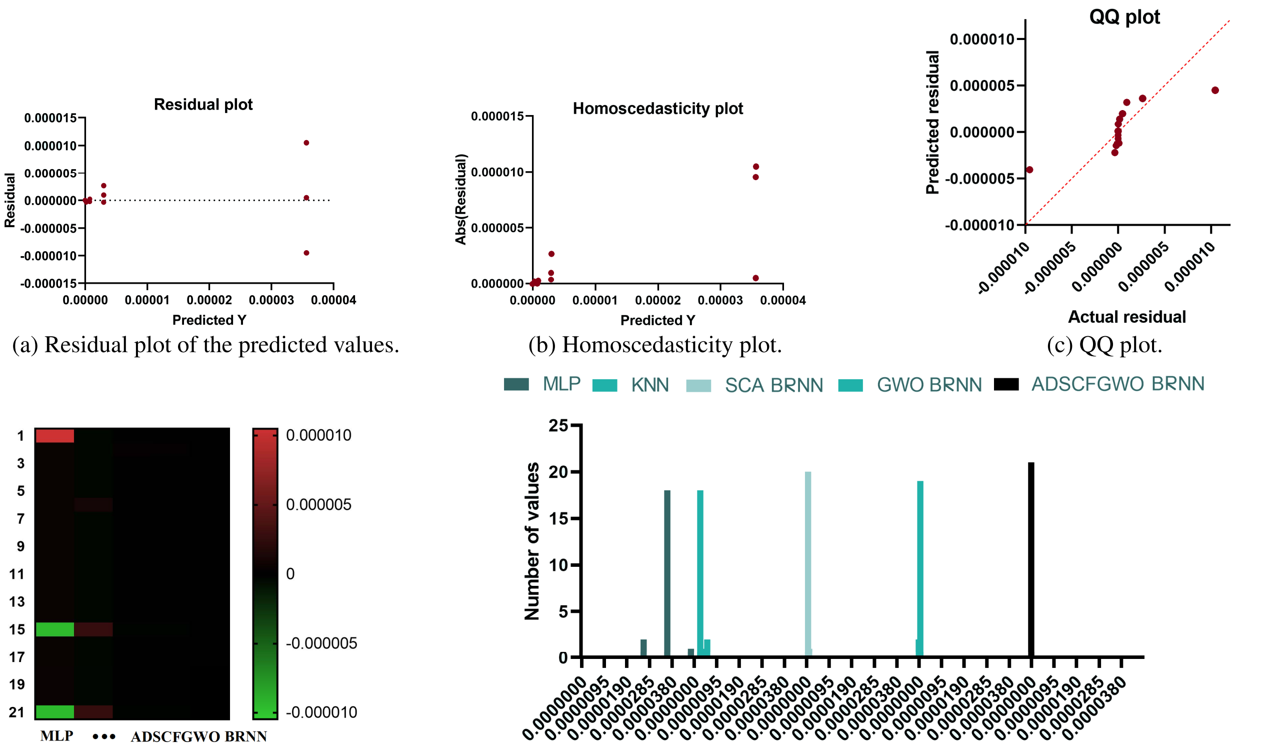
1) ANALYSIS AND DISCUSSION

The results of the ANOVA test based on the proposed optimized BRNN, in comparison with other algorithms, are presented in Table 10. As shown in the table, the proposed approach and other approaches are statistically significant. To clearly show the superiority of the proposed approach, we conducted another test between every two algorithms in terms of the two-tailed t-test. The results of this test at 0.05 significance level are shown in Table 11 for 21 samples. When the p-value has a value <0.05, this reflects the significance of the algorithm and vice versa. As shown in Table 11, the measured value of p-value matches the condition and reflects their significance. However, the proposed approach could achieve the minimum discrepancy among the experimented models, which indicates the superiority of the proposed algorithm and proves its greater statistical significance.

Another statistical analysis is presented in Table 12 for comparing the accuracy of the estimated parameters of T-shape using the proposed optimized BRNN and other approaches for 21 runes. As shown in the table, the proposed approach achieves a minimum error of (1E-100) based on

TABLE 15. Mean and standard deviation (StDev) of the suggested and compared algorithms over the benchmark functions (F1 to F7).

Func	Algorithm	ADSCFGWO	PSO	WOA	GWO	GA
F1	Mean	0	0.000136	1.41E30	6.59E-28	4.6E-172
	StDev	0	0.000202	4.91E30	6.34E-05	0
F2	Mean	0	0.042144	1.06E21	7.18E-17	3.44E-90
	StDev	0	0.045421	2.39E21	0.029014	6.13E-90
F3	Mean	0	70.12562	5.39E07	3.29E-06	1.7E-127
	StDev	0	22.11924	2.93E06	79.14958	8.6E-127
F4	Mean	0	1.086481	0.072581	5.61E-07	1.15E-75
	StDev	0	0.317039	0.39747	1.315088	2.45E-75
F5	Mean	0	96.71832	27.86558	26.81258	28.37287
	StDev	0	60.11559	0.763626	69.90499	0.582802
F6	Mean	0	0.000102	3.116266	0.816579	3.932626
	StDev	0	8.28E-05	0.532429	0.000126	0.431755
F7	Mean	0	0.122854	0 .001425	0.002213	0.022992
	StDev	0	0.044957	0.001149	0.100286	0.021966



(a) Residual plot of the predicted values. (b) Homoscedasticity plot. (c) QQ plot. (d) Heatmap plot. (e) Histogram of the RMSE values of the optimized parameters of the double T-shape antenna.

FIGURE 14. Evaluation of the proposed ADSCFGWO algorithm in optimizing the parameters of a double T-shape antenna.

the fitness score concerning the global optimizer, which is the minimum value among the results achieved by the other algorithms. In addition, all other metrics in the table show the superiority of the proposed algorithm for the task of T-shape antenna parameter optimization.

Table 13 shows the estimated parameters using the proposed optimized model and the other models. In this table, the time consumed by the proposed approach (233.1) to find the estimated values of T-shape antenna parameters is the smallest while accurately estimating these values. This reflects the accuracy of the proposed model and its fast convergence, which indicates the superiority and efficiency of the proposed approach.

On the other hand, the plots shown in Figure 14 depict an in-depth investigation of the performance of the proposed optimization algorithm in terms of estimating the parameters of a T-shape antenna. This figure shows five types of plots, namely, residual plot, homoscedasticity plot, QQ plot, heatmap, ROC curve, RMSE plot, and histogram of RMSE. The residual plot, in Figure 14a, shows the mapping between the predicted values of the T-shape antenna parameters and the prediction error. As shown in the figure, the residuals are close to the x-axis, which indicates the accuracy of the proposed algorithm in predicting the parameters of a T-shape antenna. This finding is also confirmed by the homoscedasticity shown in Figure 14b. In addition, the QQ

TABLE 16. ANOVA test over the benchmark functions (F1 to F7).

F1

	SS	DF	MS	F (DFn, DFd)	P value
Treatment (between columns)	2.42E-07	4	6.05E-08	F (4, 145) = 12.04	P<0.0001
Residual (within columns)	7.29E-07	145	5.03E-09		
Total	9.71E-07	149			

F2

	SS	DF	MS	F (DFn, DFd)	P value
Treatment (between columns)	269.7	4	67.43	F (4, 145) = 7.730	P<0.0001
Residual (within columns)	1265	145	8.723		
Total	1535	149			

F3

	SS	DF	MS	F (DFn, DFd)	P value
Treatment (between columns)	4.25E+10	4	1.06E+10	F (4, 145) = 186.8	P<0.0001
Residual (within columns)	8.24E+09	145	56830905		
Total	5.07E+10	149			

F4

	SS	DF	MS	F (DFn, DFd)	P value
Treatment (between columns)	61550	4	15387	F (4, 145) = 92.40	P<0.0001
Residual (within columns)	24147	145	166.5		
Total	85697	149			

F5

	SS	DF	MS	F (DFn, DFd)	P value
Treatment (between columns)	59376	4	14844	F (4, 145) = 42.46	P<0.0001
Residual (within columns)	50691	145	349.6		
Total	110067	149			

F6

	SS	DF	MS	F (DFn, DFd)	P value
Treatment (between columns)	355.2	4	88.79	F (4, 145) = 1261	P<0.0001
Residual (within columns)	10.21	145	0.07039		
Total	365.4	149			

F7

	SS	DF	MS	F (DFn, DFd)	P value
Treatment (between columns)	566.5	4	141.6	F (4, 145) = 16.82	P<0.0001
Residual (within columns)	1221	145	8.422		
Total	1788	149			

TABLE 17. T-test for the benchmark functions (from F1 to F7) based on the suggested algorithm against the compared algorithms.

	ADSCFGWO vs PSO	ADSCFGWO vs GWO	ADSCFGWO vs WOA	ADSCFGWO vs GA
F1	3.17E-05	3.17E-05	3.17E-05	3.17E-05
F2	3.17E-05	3.17E-05	3.17E-05	3.17E-05
F3	3.17E-05	3.17E-05	3.17E-05	3.17E-05
F4	3.17E-05	3.17E-05	3.17E-05	3.17E-05
F5	3.17E-05	3.17E-05	3.17E-05	3.17E-05
F6	3.17E-05	3.17E-05	3.17E-05	3.17E-05
F7	3.17E-05	3.17E-05	3.17E-05	3.17E-05

plot depicted in Figure 14c shows the mapping between the predicted and actual values of T-shape antenna parameters. In this figure, the mapping approximately fits a straight line, which emphasizes the effectiveness of the proposed approach. A comparison between the proposed feature selection algorithm and other algorithms is presented in Figure 14d. The dark regions in the figure refer to better performance. Most of these regions are associated with the proposed ADSCFGWO BRNN approach. Moreover, the histogram of RMSE values is shown in Figure 14e. It is clearly shown in the figure that most of the achieved RMSE values using the proposed approach are approximately close to zero. These results prove the accuracy of the proposed approach when compared to the other approaches.

V. CONCLUSION AND FUTURE WORK

In this research, we proposed a new optimization algorithm referred to as adaptive dynamic sine cosine fitness grey wolf optimizer (ADSCFGWO) algorithm. The main motivation of this algorithm is to achieve a better balance between the exploration and exploitation tasks of the optimization process and achieving fast convergence. To verify the effectiveness of the proposed algorithm, two sets of experimental results were conducted based on two types of antennas. The publicly

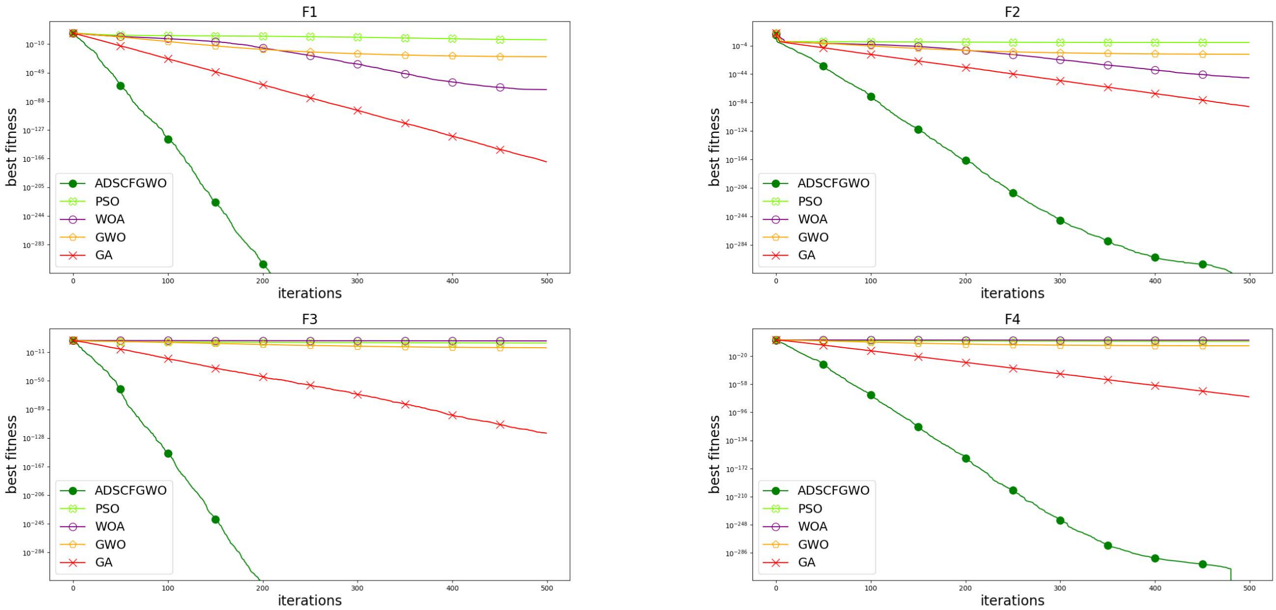


FIGURE 15. Convergence curves of the proposed algorithm and the other competing algorithms for F1, F2, F3, and F4 benchmark functions.

TABLE 18. Results of ADSCFGWO in 10D.

	Best	Worst	Median	Mean	Std
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0
5	0	0	0	0	0
6	0	6.071588	4.641829	7.045341	11.30094
7	0	13.57012	14.56004	14.57174	14.74524
8	0	0	0	0	0
9	0.122722	187.359	0.310514	8.96641	20.16131
10	0	0	0	0	0
11	0.102308	221.3217	0	14.8196	41.23888
12	0	9.780877	10.71786	11.94317	13.63467
13	0	0	0	0	0
14	6.45E-05	0	0	0	0
15	0.102847	115.7061	0	0	2.846899
16	1.001688	19.19553	6.196043	4.366698	7.836576
17	0.00216	8.87959	0.349836	0	5.891857
18	0	0	0	0	0
19	0	7.429979	4.444986	-2.39046	6.355141
20	103.7882	190.9678	187.3449	182.344	2.234339
21	0	84.445	84.445	76.96873	10.42859
22	102.1191	295.565	289.8828	290.1827	13.98651
23	180	322.8577	317.5574	314.6461	3.472153
24	307.6947	427.8222	382.454	385.1424	4.782208
25	230	331.5944	284.445	285.3695	8.95277
26	189.0055	377.1299	373.963	373.9771	14.76841
27	200	596.2668	355.6332	382.7575	99.88764
28	115.4603	262.7932	219.8455	223.0598	5.89391
29	194.5008	817562.5	427.5714	32477.66	160173.8

available metamaterial antenna dataset was employed for the first set of experiments. Meanwhile, the second set of experiments targets utilizing the proposed algorithm to optimize the design parameters of a double T-shape antenna. We proposed a new ensemble model based on five regression models for the first set of experiments, namely SVR, MLP, DT, RF, and KNN. The parameters of this ensemble model are optimized using the proposed ADSCFGWO algorithm. In addition, we proposed a new binary optimizer for selecting the significant features for classification and regression tasks. This binary optimizer is employed for selecting the significant features in the metamaterial antenna dataset to boost the prediction accuracy of the antenna bandwidth. The proposed ensemble model and the proposed feature selection algorithm were tested and compared with other competing approaches to verify their effectiveness, and the results confirmed our expectations.

On the other hand, the second set of experiments targeted optimizing the parameters of a BRNN that was used to classify the design parameters of a double T-shape antenna. Moreover, additional experiments were conducted to verify the stability and robustness of the proposed algorithm. The results achieved by the proposed algorithm were also compared with the results of other optimization algorithms to prove their superiority. The future perspectives of this research can be testing the proposed algorithm in other optimization problems in different domains.

APPENDIX A

In this appendix, the proposed ADSCFGWO algorithm is tested for seven benchmark functions, from F1 to F7 [61] as shown in Table 14. Figure 15 shows the Convergence curves of the proposed algorithm and the other competing algorithms for F1, F2, F3, and F4 benchmark functions. Table 15 shows the T-test for the benchmark functions (from F1 to F7) based on the suggested algorithm against the compared algorithms. Table 16 shows the ANOVA test results over the benchmark functions (F1 to F7). Table 17 presents the mean and standard deviation (StDev) of the suggested and compared algorithms over the benchmark functions (F1 to F7). The results show the performance of the proposed algorithm.

TABLE 19. Experimental results of GWO, PSO, SFS and ADSCFGWO over 51 independent runs on 29 test functions of 10 variables with 100,000 FES.

	GWO	PSO	SFS	ADSCFGWO
1	1.50E+08 ± 6.50E+07	2.30E+03 ± 3.05E+03	5.60E+03 ± 3.26E+03	0.00E+00 ± 0.00E+00
2	5.28E+02 ± 7.98E+02	0.00E+00 ± 0.00E+00	2.05E02 ± 1.17E02	0.00E+00 ± 0.00E+00
3	1.84E+01 ± 1.62E+01	2.82E+00 ± 1.21E+00	9.37E01 ± 6.74E01	0.00E+00 ± 0.00E+00
4	3.01E+01 ± 4.85E+00	1.59E+01 ± 7.08E+00	8.68E+00 ± 3.30E+00	0.00E+00 ± 0.00E+00
5	7.81E+00 ± 1.09E+00	8.27E02 ± 3.36E01	5.35E03 ± 1.59E03	0.00E+00 ± 0.00E+00
6	4.35E+01 ± 5.14E+00	1.72E+01 ± 4.46E+00	2.33E+01 ± 3.60E+00	0.00E+00 ± 0.00E+00
7	2.38E+01 ± 4.44E+00	1.23E+01 ± 5.33E+00	7.42E+00 ± 2.76E+00	4.01E+01 ± 3.08E+00
8	1.10E+01 ± 3.79E+00	0.00E+00 ± 0.00E+00	6.68E06 ± 4.34E06	2.14E+01 ± 2.33E+00
9	8.53E+02 ± 2.50E+02	6.30E+02 ± 2.64E+02	3.63E+02 ± 1.91E+02	0.00E+00 ± 0.00E+00
10	4.03E+01 ± 9.91E+00	1.10E+01 ± 7.27E+00	4.61E+00 ± 1.25E+00	0.00E+00 ± 0.00E+00
11	2.58E+06 ± 3.10E+06	1.33E+04 ± 1.24E+04	5.04E+03 ± 2.11E+03	9.93E+01 ± 7.46E+01
12	1.16E+04 ± 8.11E+03	6.45E+03 ± 5.72E+03	4.55E+01 ± 9.83E+00	5.56E+00 ± 1.11E+00
13	5.91E+02 ± 1.21E+03	4.57E+01 ± 1.93E+01	2.20E+01 ± 3.82E+00	6.18E+00 ± 3.06E+00
14	8.04E+02 ± 1.12E+03	5.62E+01 ± 5.89E+01	1.00E+01 ± 2.14E+00	0.00E+00 ± 0.00E+00
15	8.52E+01 ± 9.41E+01	2.05E+02 ± 1.19E+02	4.17E+00 ± 3.16E+00	4.77E+00 ± 4.75E+00
16	5.42E+01 ± 8.45E+00	4.56E+01 ± 2.30E+01	2.34E+01 ± 5.66E+00	1.27E+01 ± 7.18E+00
17	3.68E+04 ± 2.11E+04	5.10E+03 ± 5.76E+03	5.22E+01 ± 1.05E+01	3.34E01 ± 2.2E01
18	1.75E+03 ± 3.81E+03	9.57E+01 ± 2.95E+02	5.84E+00 ± 8.94E01	2.19E+00 ± 4.89E+00
19	7.76E+01 ± 3.83E+01	5.51E+01 ± 5.42E+01	1.21E+01 ± 3.31E+00	0.00E+00 ± 0.00E+00
20	2.03E+02 ± 4.93E+01	1.79E+02 ± 5.65E+01	1.00E+02 ± 5.06E02	1.98E+02 ± 6.07E+01
21	1.25E+02 ± 6.03E+00	9.38E+01 ± 2.55E+01	9.24E+01 ± 3.00E+01	1.00E+02 ± 4.17E01
22	3.33E+02 ± 3.86E+00	3.28E+02 ± 1.24E+01	3.03E+02 ± 4.35E+01	3.11E+02 ± 3.82E+00
23	3.63E+02 ± 4.56E+00	3.24E+02 ± 8.33E+01	2.18E+02 ± 1.18E+02	3.14E+02 ± 1.17E+01
24	4.42E+02 ± 1.56E+01	4.25E+02 ± 2.29E+01	4.21E+02 ± 2.30E+01	5.73E+02 ± 2.65E+01
25	4.09E+02 ± 1.47E+02	2.74E+02 ± 7.63E+01	2.92E+02 ± 4.40E+01	3.02E+02 ± 0.13E+00
26	3.96E+02 ± 1.15E+00	4.03E+02 ± 1.97E+01	3.92E+02 ± 1.85E+00	3.82E+02 ± 1.17E01
27	5.39E+02 ± 9.99E+01	4.54E+02 ± 1.57E+02	3.06E+02 ± 3.97E+01	3.19E+02 ± 4.23E+01
28	2.94E+02 ± 3.04E+01	3.05E+02 ± 4.50E+01	2.59E+02 ± 1.18E+01	2.81E+02 ± 3.96E+00
29	4.84E+05 ± 7.31E+05	2.00E+05 ± 3.79E+05	2.03E+03 ± 1.63E+03	4.42E+02 ± 3.12E+01

APPENDIX B

The proposed ADSCFGWO algorithm is tested for the CEC2017 benchmarks with ten dimensions [62]. For the CEC2017 benchmark, there are 29 problems across ten dimensions with a 5 percent significance level. Table 18 summarizes the statistical results of the proposed ADSCFGWO algorithm on the CEC2017 benchmarks with ten dimensions. Table 19 presents a statistical results of the benchmark comparisons with ten dimensions, best and standard deviations of error, from the optimal solution of ADSCFGWO and other state-of-the-art algorithms over 51 runs for all 29 benchmark functions. The results based on CEC 2017 also show the performance of the proposed algorithm.

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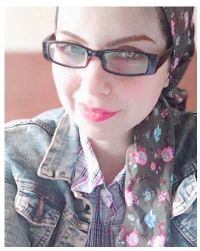

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