IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 21 February 2025, accepted 21 March 2025, date of publication 26 March 2025, date of current version 4 April 2025.

Digital Object Identifier 10.1109/ACCESS.2025.3554505

RESEARCH ARTICLE

Development of Random Walks Strategy-Based Dandelion Optimizer and Its Application to Engineering Design Problems

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ABSTRACT The objective of this paper is to enhance the swarm-based metaheuristic dandelion optimizer (DO) algorithm by incorporating various strategies to address early convergence and mitigate the risk of becoming trapped in local optima. This integration is intended to yield optimal and favorable outcomes for real-world optimization problems. To achieve this objective, a novel hybrid algorithm called the random walks dandelion optimizer (RW-DO) was introduced. This new algorithm addresses the limitations of the dandelion optimizer DO when handling optimization problems by incorporating at random walks strategy. By leveraging the random walks strategy, the RW-DO algorithm addresses the issue of premature convergence. This strategy enhances the diversity of solutions, thereby preventing the DO algorithm from becoming trapped in the local optima during the exploitation phase. To assess its performance, the RW-DO algorithm was compared with alternative algorithms by using the CEC 2020 and CEC 2019 function sets. Across all the test sets, the RW-DO algorithm consistently generateds more advantageous solutions. For the CEC 2020 function set, the RW-DO algorithm demonstrated superior performance compared with the DO algorithm from 3% to 11% in 5-dimensional problems. In 30-dimensional problems, the RW-DO algorithm exhibited superior performance compared to the DO algorithm from 14% to 46%. For the CEC 2020 function set in 50-dimensional problems, the RW-DO algorithm demonstrated superior performance compared to the DO algorithm from 11% to 188%. In the CEC 2019 function set, this ratio ranges from 3% to 38%. In engineering problems, the RW-DO algorithm also achieved superiority over the DO algorithm from 2% to 3%. Statistical analyses were performed to validate the superiority of RW-DO. The Kolmogorov-Smirnov normality test was used to select appropriate statistical tests for evaluating the performance of the algorithm based on the CEC 2020 and CEC 2019 function sets. Because the data set is not normally distributed, non-parametric tests such as the Wilcoxon signed-rank test and Kolmogorov-Smirnov for two sample tests were employed. These tests confirm that RW-DO yields distinct and superior solutions compared with the different data sets. Furthermore, the effectiveness of the RW-DO algorithm in solving real-world problems was demonstrated through its application to six engineering design problems. The experimental results highlight its competency in comparison to other algorithms. Overall, this research demonstrates the enhanced capabilities of the RW-DO algorithm in optimizing complex problems and its competitiveness when pitted against alternative methods.

INDEX TERMS Dandelion optimizer, engineering design problem, metaheuristic algorithm, random walk.

I. INTRODUCTION

Mathematical optimization, or programming, seeks optimal solutions under limited resources such as time and materials [1], [2]. A typical problem comprises decision variables,

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

constraints, and an objective function, formally defined as:

$$minf\ (x)\ ,\ g\ (x) \leq 0,\ h\ (x)\ ,\ x \in \mathcal{A}. \quad (1)$$

In Eq. (1), $\mathcal{A}$ is the domain of function f and x is an n dimensional vector in $\mathcal{A}$, g and h are vectors of inequality and equality constraints, respectively. Methods such as linear programming, convex optimization, and interior-point algorithms address numerous problems [3], [4], where NP-hard problems lack efficient deterministic solutions [5]. In such cases, metaheuristic algorithms provide approximate, adaptable solutions without problem-specific modifications [6], [7].

Metaheuristic algorithms represent a class of adaptable, non-derivative, and iterative search methodologies that rely on the stochastic exploration of the solution domain [4], [7], [8]. The optimization procedure initiates with a set of preliminary candidate solutions and cyclically alternates between exploration (diversification) and exploitation (intensification) stages. Although exploration expands the search across the solution landscape, exploitation concentrates on promising areas to refine solutions through memory-based approaches aimed at cost reduction. The competitive nature of these algorithms facilitates the evasion of local optima and efficient identification of near-global solutions. Notably the effectiveness of metaheuristics is contingent upon problem-specific attributes and available computational resources [9], [10]. Notable examples of such algorithms includethe genetic algorithm (GA) [11], particle swarm optimization (PSO) [12], artificial bee colony (ABC) [13], ant colony optimization (ACO) [14], firefly algorithm (FA) [15], sine-cosine algorithm (SCA) [16], grey wolf optimizer (GWO) [17], harris hawks optimization (HHO) [18], and hunger games search (HGS) [19], [20]. These algorithmic approaches find widespread application across diverse domains, including medicine [21], [22], engineering [23], control systems [24], and education [25], [26].

The dandelion optimizer (DO), discussed in this study has previously been used in medicine, control systems and engineering problems [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37]. According to the no-free lunch theorem, even if the DO algorithm performs well, developing and hybridizing it with different algorithms is necessary to solve diverse problems and achieve improved solutions [38]. Therefore, a review of the literature shows that DO has been strengthened by hybridizing different algorithms or developing strategies to make it easier to deal with problems. One of them is the DETDO hybrid algorithm. DETDO combines three strategies: adaptive tent chaotic mapping, differential evolution strategy, and adaptive t-distribution perturbation to address the shortcomings of weak DO development. These enhancements seek to overcome the shortcomings of the initial algorithm, including its limited development potential, susceptibility to becoming trapped in local optima, and a sluggish convergence rate. The mutation rate in differential evolution (DE) is set at 0.9, substantially expanding the search space. While enhancing exploration capabilities, this results in increased computation times for complex optimization problems. The algorithm utilizes fixed parameter settings, such as the mutation rate. This inflexibility limits DETDO's efficiency of DETDOs across the problem domains. Although DETDO demonstrates efficacy in tested engineering optimization problems, its performance in broader, diverse real-world scenarios remains insufficiently investigated [39]. These enhancements seek to overcome the shortcomings of the initial algorithm, including its limited development potential, susceptibility to becoming trapped in local optima, and a sluggish convergence rate. The mutation rate in differential evolution (DE) is set at 0.9, substantially expanding the search space. While enhancing exploration capabilities, this results in increased computation times for complex optimization problems. The algorithm utilizes fixed parameter settings, such as the mutation rate. This inflexibility limits DETDO's efficiency of DETDOs across the problem domains. Although DETDO demonstrates efficacy in tested engineering optimization problems, its performance in broader, diverse real-world scenarios remains insufficiently investigated. Another work is the enhanced DO algorithm called EDO, which incorporates a statistical regeneration mechanism (SRM) to enhance DO's effectiveness of DO. The SRM augments the DO's exploratory capabilities during the initial iterations and improves exploitation in subsequent stages. The researchers evaluated EDO' performance using three benchmark steel frame examples: a 1-bay 10-storey, a 3-bay 15-storey, and a 3-bay 24-storey steel frame. EDO outperformed the original DO and various other metaheuristic optimization algorithms across all examples. In each case, EDO consistently identified superior solutions (lower weight designs) compared to alternative methods, demonstrating its efficacy in structural optimization challenges. The statistical outcomes achieved by EDO generally surpassed those of other optimization techniques, indicating enhanced reliability. The research concludes that EDO exhibits greaterthe reliability and effectiveness than the original DO and other considered optimization methods for steel frame design problems. To substantiate these claims, the authors provided comprehensive comparisons of EDO's performance of EDO against other algorithms, including analyses of stress ratios, evaluations of story drift, and convergence histories for each benchmark problem [40]. EDO was evaluated solely on three steel frame optimization problems, raising questions about its generalizability to other structural optimization problems or domains. The study lacks rigorous mathematical analysis of how the statistical regeneration mechanism (SRM) enhances performance, impeding a comprehensive understanding of its efficacy or limitations. It sets the sigma_i parameter to '3' without a detailed analysis of the algorithm's sensitivity to this parameter, which is potentially crucial for robustness across problem types. The research does not address the computational overhead introduced by SRM. While EDO is compared to other algorithms, the comparison is primarily based on the final optimization results, with limited discussion on convergence speed, consistency, or sensitivity to initial conditions. The paper presents average results and standard deviations but lacks formal statistical tests to confirm whether improvements are statistically significant. Given that the SRM utilizes statistical information from the population, there is a potential risk of premature convergence or overfitting to the specific problems tested.

Another paper presented a hybrid TDOA / AOA localization method based on an improved multi-objective dandelion optimization algorithm for mobile location estimation in non-line-of-sight (NLOS) environments. The authors proposed a hybrid localization method that combines the time difference of arrival (TDOA) and angle of arrival (AOA) techniques, utilizing an improved multi-objective dandelion optimization algorithm. The adaptation of the DO algorithm to the TDOA/AOA hybrid algorithm employed in a previous study demonstrated enhanced localization performance, resulting in improved optimization performance by balancing the convergence speed and, exploration and exploitation capabilities [41]. The paper lacks a comprehensive analysis of the algorithm's sensitivity to various parameters, thereby limiting the understanding of its robustness under different settings. While comparing the proposed method with several algorithms, it does not exhaustively evaluate all possible state-of-the-art localization methods, potentially providing an incomplete assessment of their relative standing.

In another study, a chaos-based version of the DO algorithm, termed the chaotically initialized dandelion optimizer (CIDO), has been proposed. This approach was employed to mitigate the tendency of the algorithm to become trapped at local optima [42]. The paper exhibits a deficiency in comprehensive theoretical analysis regarding the mechanisms by which chaotic initialization enhances performance, thereby limiting the understanding of the circumstances and reasons for CIDO's superior performance compared to classical DO. The presentation of numerical results lacks statistical significance tests, rendering it challenging to ascertain whether the performance disparities are statistically significant or attributable to chance. The investigation solely employed mathematical benchmark functions; the inclusion of real-world problem testing would provide more compelling evidence of CIDO's practical utility of CIDO. The optimization of CIDO's performance on specific benchmark functions raises concerns about potential overfitting, which may consequently restrict its generalization capabilities to other problem types.

As a final illustrative example, to address a classification problem, hybridization was performed using an anti-based system and an improved dandelion optimization algorithm (IDO). The proposed methodology has the potential to enhance the precision of segmenting complex structures and discerning subtle features in breast cancer histopathological images, thereby potentially improving the clinical decision-making processes [43]. The IDO algorithm exhibits superior efficacy in breast cancer image segmentation. However, it does not have potential limitations, particularly the risk of overfitting. The study failed to elucidate the criteria employed for selecting comparison algorithms. Moreover, the research neglects to examine the robustness of the IDO algorithm' to parameter modifications or to provide a comprehensive analysis of the required computational resources.

The local optima problem of the DO algorithm manifests as a tendency to converge on suboptimal solutions, rather than identifying global optima. This issue arises because of several factors. Primarily, despite its effectiveness in various scenarios, the DO algorithm is susceptible to becoming entrapped in local extremum points during the optimization process. Additionally, the problem stems from the algorithm's inadequate global search capabilities, leading to premature convergence of local optima and insufficient exploration of the entire search space. Consequently, the local optima problem imposes limitations on the capacity of the DO to ascertain optimal solutions within complex optimization landscapes, particularly when addressing high-dimensional or multimodal problems. In conclusion, while these studies present various improvements to the DO algorithm, they all exhibit common limitations such as restricted testing scopes, absence of comprehensive theoretical analyses, and potential risks of overfitting.

This paper endeavored to address these limitations to further enhance the reliability and applicability of these optimization techniques. It is evident that the DO algorithm is susceptible to stagnation or premature convergence in the local search domain. Although the aforementioned hybrid algorithms attempted to address this problem, the RW-DO algorithm sought to enhance the solution using diverse benchmark function sets. In this context, the robustness and optimization capability of the RW-DO algorithm have been demonstrated through the utilization of the CEC 2019 and CEC 2020 function sets, which present challenges in identifying global solutions. Furthermore, it has been observed that the algorithm has achieved more optimal outcomes in real-world applications of classical engineering problems. In the current study, the random walks strategy was used to avoid being stuck at local optimum points and to achieve more appropriate global results [44]. The random-walks strategy enhances the diversity of solutions in traversing the local area by simulating stochastic movement and generating irregular steps in contrast to linear and uniform steps [45]. The new algorithm is called the random walks dandelion optimizer (RW-DO).

In this paper, advanced analyses were carried out using the Kolmogorov-Smirnov normality test, parametric or non-parametric tests, and the results were evaluated using, and Kolmogorov-Smirnov and Wilcoxon two-sample non-parametric tests. Signerank tests were also performed [46]. To demonstrate the superiority of the RW-DO algorithm, comparisons were made with other swarm-based algorithms using the test function sets from CEC 2020 [51] and CEC 2019 [52], [53]. The selected alternative algorithms are

TABLE 1. CEC2020 functions.

Functions	feature	Search interval	f_{min}
CEC2020-01: Shifted and Rotated Bent Cigar Function	unimodal	$[-100,100]$	100
CEC2020-02: Shifted and Rotated Schwefel's Function	multimodal	$[-100,100]$	1100
CEC2020-03: Shifted and Rotated Lunacek bi-Rastrigin Function	multimodal	$[-100,100]$	700
CEC2020-04: Expanded Rosenbrok's plus Griewank's Function	multimodal	$[-100,100]$	1900
CEC2020- 05: Hybrid Function 1 (N=3)	hybrid	$[-100,100]$	1700
CEC2020- 06: Hybrid Function 2 (N=4)	hybrid	$[-100,100]$	1600
CEC2020- 07: Hybrid Function 3 (N=5)	hybrid	$[-100,100]$	2100
CEC2020- 08: Composition Function 1 (N=3)	composition	$[-100,100]$	2200
CEC2020- 09: Composition Function 2 (N=4)	composition	$[-100,100]$	2400
CEC2020-10 : Composition Function 3 (N=5)	composition	$[-100,100]$	2500

renowned for their innovative and efficient performance. These include DO [47], sea-horse optimizer (SHO) [48], smell optimization algorithm (SAO) [49], and prairie dog optimization (PDO) [50], all of which are recent and widely utilized in the literature. In this study, local search weaknesses of the DO were noticed through test sets, and these weaknesses were largely eliminated using the random walks strategy. The originality of the random walks strategy used in this study is that it was enriched by considering the average positions of the seeds. The original value of the RW-DO algorithm becomes apparent at the following points.

- In contrast to the hybrid studies incorporating DO and those referenced in this article, which failed to achieve the desired simplicity and comprehensibility when combining more than two algorithms, the RW-DO algorithm demonstrated a remarkably straightforward and intelligible approach to problem-solving, yielding superior results.
- Among all the hybrid studies with DO so far, only the DETDO algorithm analyzed the RMSE values of the CEC 2019 test set. However, the best and worst values were not evaluated. Other hybrid algorithms such as theEDO and, TDOA/AOA algorithms did not include any of the CEC 2020 and CEC 2019 sets. The chaotically ınitialised dandelion optimizer for global optimization (CIDO) algorithm and RW-DO algorithm were employed for the CEC 2019 and CEC 2020 function sets. Although the CIDO algorithm demonstrated efficacy in the CEC2019 set, it exhibited inconsistent performance in the CEC2020 set. The RW-DO algorithm was tested with both sets of functions and was successful.
- Its success in engineering design problems considered in this study has enabled extensive testing of the RW-DO algorithm.

This paper is structured as follows: Subsequent to the summary, the introduction presents the background and foundation of the study. The second section, under the main heading of algorithms, provides the definition and mathematical modelling of the DO and the proposed RW-DO algorithms. The third section, titled Experimental results, presents the statistical analysis and performance outcomes. The fourth section, under the main heading of application to real-world problems, examines six classical engineering problems. As alternatives to the RW-DO algorithm for the optimization of engineering design problems, along with the DO algorithm, harris hawks optimization (HHO) [18], artificial gorilla troop optimizer (GTO) [54], sine-cosine algorithm (SCA) [16], grey wolf optimizer (GWO) [17], weighted mean of vectors (INFO) [55], and whale optimization algorithm (WOA) [56]. All the alternative algorithms used in the comparisons are current and effective. The final section presents our conclusions.

II. ALGORITHMS

A. DANDELION OPTIMIZER ALGORITHM

DO is a new biologically inspired swarm intelligence algorithm inspired by the process by which Dandelion seeds travel long distances under the influence of the wind. It consists of three phases: ascent, descent, and land in. During the ascension phase, seeds are filtered through a local community by the action of air circulation or rise spirally upwards. During the descending and landing stages, the flying seeds descend and land in respectively in global space by adjusting their direction with a route drawn according to Lévy random walks and Brownian motion rules [47]. The DO algorithm uses an evolutionary strategy that provides the advantage of a simple computation. It provides better convergence to local minima owing to its self-adaptive feature and takes steps for a better solution using a memory-based mechanism to avoid premature convergence. The DO has the ability to determine the best global solution by referencing the entire population, which is different from other metaheuristic algorithms. Finally, DO divides Dandelion seeds into two main groups as core and auxiliary seeds, expanding the search range and increasing the probability of reaching the optimal

TABLE 2. Performance of algorithm with five dimensional CEC2020.

Dimension=5						
Function	Metric	SHO	SAO	PDO	DO	**RW-DO**
CEC2020-01	Mean	8.3507E+03	6.1953E+08	4.1697E+08	3.8371E+03	**3.3646E+03**
	Std	7.5458E+03	5.4509E+08	2.7372E+08	3.7953E+03	**2.2187E+03**
	Best	7.8576E+02	5.6759E+06	7.1931E+06	2.4420E+02	**1.0223E+02**
	Worst	3.7280E+04	2.3647E+09	1.1113E+09	1.3233E+04	**6.9627E+03**
CEC2020-02	Mean	1.3359E+03	1.6736E+03	1.5299E+03	1.3287E+03	**1.2438e+03**
	Std	1.2185E+02	1.9666E+02	1.4050E+02	9.7422E+01	**8.7137E+01**
	Best	1.1164E+03	1.2440E+03	1.1666E+03	1.1135E+03	**1.1002e+03**
	Worst	1.5610E+03	2.1103E+03	1.7661E+03	1.5215E+03	**1.4570e+03**
CEC2020-03	Mean	7.1518E+02	7.3295E+02	7.2718E+02	7.1262E+02	**7.1004E+02**
	Std	4.4634E+00	1.3250E+01	5.8867E+00	4.1864E+00	**3.1811E+00**
	Best	7.0829E+02	7.0747 E+02	7.1325E+02	7.0599E+02	**7.0497E+02**
	Worst	7.2553E+02	7.6797E+02	7.3684E+02	7.2022 E+02	**7.1676E+02**
CEC2020-04	Mean	1.9000E+03	1.9010E+03	1.9000E+03	1.9002E+03	**1.9000E+03**
	Std	0.0000E+03	0.7323E+00	0.0000E+03	2.6280E-01	**4.3700E-02**
	Best	1.9000E+03	1.9000E+03	1.9000E+03	1.9000E+03	**1.9000E+03**
	Worst	**1.9000E+03**	1.9030E+03	1.9000E+03	1.9009E+03	1.9002E+03
CEC2020-05	Mean	1.8063E+03	3.6038E+03	1.0348E+04	1.8130E+03	**1.7282E+03**
	Std	1.1200E+02	2.7789E+03	8.0148E+03	1.0466E+01	**3.4145E-01**
	Best	1.7062E+03	1.7749E+03	2.0257E+03	1.7030E+03	**1.7006E+03**
	Worst	2.0820E+03	1.6246E+04	2.7714E+04	2.1339E+03	**1.8433E+03**
CEC2020-06	Mean	1.6015E+03	1.6443E+03	1.6249E+03	1.6010E+03	**1.6006E+03**
	Std	8.9460E-01	6.7657E-01	1.8671E+01	5.3920E-01	**3.6020E-01**
	Best	1.6005E+03	1.6012E+03	1.6015E+03	1.6000E+03	**1.6000E+03**
	Worst	1.6031E+03	1.8427E+03	1.6628E+03	1.6025E+03	**1.6013E+03**
CEC2020-07	Mean	2.4411E+03	6.0369E+03	2.2184E+04	2.2257E+03	**2.1835E+03**
	Std	5.7975E+02	3.5294E+03	6.0627E+04	8.9490E+01	**7.4538E+01**
	Best	2.1017E+03	2.1615E+03	2.4719E+03	2.1005E+03	**2.1000E+03**
	Worst	4.4139E+03	9.9159E+03	3.4015E+05	2.4188E+03	**2.3992E+03**
CEC2020-08	Mean	2.2788E+03	2.4062E+03	2.3501E+03	2.2736E+03	**2.2497E+03**
	Std	4.5080E+01	1.5121E+02	7.8115E+01	**4.4615E+01**	4.9048E+01
	Best	2.2002E+03	2.2172E+03	2.2191E+03	2.2000E+03	**2.2000E+03**
	Worst	2.3366E+03	2.8338E+03	2.5157E+03	2.3034E+03	**2.3016E+03**
CEC2020-09	Mean	2.5075E+03	2.6312E+03	2.8307E+03	2.5567E+03	**2.4967E+03**
	Std	3.8896E+01	3.6389E+01	4.6895E+01	1.0794E+02	**1.8257E+01**
	Best	2.4277E+03	2.5528E+03	2.6204E+03	2.4000E+03	**2.4000E+03**
	Worst	2.6106E+03	2.7036E+03	2.8817E+03	2.7309E+03	**2.5000E+03**
CEC2020-10	Mean	2.8501E+03	2.8928E+03	2.8913E+03	**2.8458E+03**	2.8474E+03
	Std	1.5543E+01	2.9999E+01	2.4379E+01	8.6523E+00	**7.7000E-02**
	Best	2.8028E+03	2.8510E+03	2.8527E+03	**2.8000E+03**	2.8474E+03
	Worst	2.8893E+03	2.9617E+03	2.9715E+03	2.8475E+03	**2.8474E+03**

position. In addition, this separation strategy allows the algorithm to reduce the risk of failure by creating a protection mechanism for the dispersal of seeds that go through these three stages causing an increase in the dandelion population. Furthermore, these three stages also explain the Dandelion optimizer modeling process, where each dandelion seed is a candidate solution. The mathematical model of DO is provided below [28], [30], [32].

Initialization: The DO algorithm is initialized with an initial set of candidate solutions, modeled by an iteratively updated population matrix. Each dandelion seed is a member of the solution set. The DO population can be expressed as following matrix.

$$population = \begin{bmatrix} x_1^1 \ldots x_1^{dim} \\ x_N^1 \ldots x_N^{dim} \end{bmatrix} \tag{2}$$

TABLE 3. Performance of algorithm with thirty dimensional CEC2020.

				Dimension = 30		
Function	Metric	SHO	SAO	PDO	DO	**RW-DO**
CEC2020-01	Mean	1. 9336E+10	6. 9344E+10	5. 1737E+10	8. 8804E+05	**4. 7722E+04**
	Std	5. 0222E+09	8. 3332E+09	9. 6071E+09	5. 2037E+05	**1. 2768E+05**
	Best	1. 2555E+10	4. 7234E+10	3. 4146E+10	2. 9195E+05	**3. 6947E+02**
	Worst	3. 1630E+10	7. 9651E+10	7. 0084E+10	2. 2296E+06	**6. 0156E+05**
CEC2020-02	Mean	5. 5313E+03	9. 1170E+03	8. 4166E+03	5. 1486E+03	**4. 5616E+03**
	Std	5. 3145E+02	5. 8211E+02	6. 1389E+02	6. 8075E+02	**5. 4236E+02**
	Best	4. 3909E+03	8. 1087E+03	6. 9046E+03	3. 9931E+03	**3. 4368E+03**
	Worst	6. 4476E+03	1. 1012E+04	9. 4343E+03	6. 3229E+03	**5. 6677E+03**
CEC2020-03	Mean	1. 1798E+03	1. 5612E+03	1. 3539E+03	1. 0291E+03	**9.7077E+02**
	Std	6. 7772E+01	6. 8889E+01	6. 9861E+01	6. 9480E+01	**5. 8978E+01**
	Best	1. 0826E+03	1. 4394E+03	1. 2318E+03	9. 1766E+02	**8. 7783E+02**
	Worst	1. 3225E+03	1. 7355E+03	1. 5251E+03	1. 1861E+03	**1. 1344E+03**
CEC2020-04	Mean	1. 9000E+03	1. 9096E+03	1. 9000E+03	1. 9061E+03	1. 9005E+03
	Std	**0.0000E+00**_	8. 0122E+00	**0.0000E+03**_	2. 4383E+00	1. 2005E+00
	Best	1. 9000E+03	1. 9000E+03	1. 9000E+03	1. 9025E+03	**1. 9000E+03**
	Worst	1. 9000E+03	1. 9212E+03	1. 9000E+03	1. 9109E+03	1. 9057E+03
CEC2020-05	Mean	1. 4851E+07	1. 3804E+08	6. 6357E+07	1. 4026E+06	**1. 7282E+03**
	Std	1. 1911E+07	7. 4724E+07	3. 3385E+07	9. 7730E+05	**3. 4145E+01**
	Best	3. 5930E+06	2. 9130E+07	2. 5445E+07	4. 4106E+05	**1. 7006E+03**
	Worst	4. 4892E+07	3. 0444E+08	1. 6292E+08	4. 5015E+06	**1. 8433E+03**
CEC2020-06	Mean	2. 3509E+03	7. 6310E+03	5. 2627E+03	2. 2849E+03	**2. 0400E+03**
	Std	2. 5293E+02	2. 0409E+03	8. 0357E+02	2. 8799E+02	**1. 4445E+02**
	Best	1. 9690E+03	4. 2928E+03	3. 5039E+03	1. 8255E+03	**1. 7828E+03**
	Worst	2. 8955E+03	1. 2332E+04	7. 2217E+03	2. 9756E+03	**2. 3365E+03**
CEC2020-07	Mean	2. 1026E+06	1. 0451E+08	3. 3932E+07	6. 4284E+05	**1. 3995E+05**
	Std	2. 5451E+06	7. 9823E+07	1. 9659E+07	2. 9835E+05	**1. 2942E+05**
	Best	1. 0432E+05	1. 2771E+07	8. 2081E+06	6. 5656E+04	**1. 2241E+04**
	Worst	1. 0091E+07	2. 7944E+08	8. 2708E+07	1. 1112E+06	**5. 6507E+05**
CEC2020-08	Mean	6. 2806E+03	1. 0368E+04	9. 3764E+03	5. 9171E+03	**5. 2383E+03**
	Std	1. 4380E+03	9. 4576E+02	**9. 1012E+02**	1. 8132E+03	1. 9125E+03
	Best	4. 2332E+03	7. 3784E+03	5. 9726E+03	2. 3075E+03	**2. 3000E+03**
	Worst	8. 9706E+03	1. 1963E+04	1. 0814E+04	8. 6759E+03	**8. 1295E+03**
CEC2020-09	Mean	3. 3485E+03	3. 9946E+03	**2. 8165E+03**	3. 0778E+03	3. 0543E+03
	Std	5. 8609E+01	2. 4742E+02	**5. 7305E+01**	6. 2952E+01	5. 9519E+01
	Best	3. 2153E+03	3. 5711E+03	2. 6740E+03	2. 9367E+03	**2. 9328E+03**
	Worst	3. 4712E+03	4. 7376E+03	2. 8730E+03	3. 2241E+03	**3. 1989E+03**
CEC2020-10	Mean	3. 4619E+03	6. 0318E+03	4. 8231E+03	2. 9136E+03	**2. 8891E+03**
	Std	2. 0359E+01	6. 1257E+02	8. 5522E+02	1. 7235E+01	**1. 0186E+01**
	Best	3. 1810E+03	5. 0924E+03	3. 4724E+03	2. 8843E+03	**2. 8836E+03**
	Worst	3. 9935E+03	8. 2095E+03	7. 0849E+03	2. 9468E+03	**2. 9348E+03**

In this matrix, N, *dim* represents the number of seeds in the swarm, and the number of variables in the problem. In the initial phase, candidate positions are ($lb = [lb_1, \ldots, lb_{dim}]$) randomly selected between the lower (*rand*) and upper bounds of the problem ($ub = [ub_1, \ldots, ub_{dim}]$) and the individual x_i is modeled by the following equation.

$$x_i = lb + rand \times (ub - lb) \tag{3}$$

Eq. (3) is expressed as the best position in the initial stage and x_{elite} starts the process with the individual with the best

TABLE 4. Performance of algorithm with fifty dimensional CEC2020.

		Dimension = 50				
Function	Metric	SHO	SAO	PDO	DO	**RW-DO**
CEC2020-01	Mean	6. 0950E+10	1. 2592E+11	1. 0572E+11	1. 7857E+07	**3. 3731E+05**
	Std	1. 1855E+10	5. 9469E+09	8. 9205E+09	9. 5013E+06	**4. 8617E+05**
	Best	4. 1385E+10	1. 0983E+11	8. 5812E+10	6. 6100E+06	**1. 3080E+04**
	Worst	8. 2164E+10	1. 3608E+11	1. 1991E+11	4. 0265E+07	**1. 4790E+06**
CEC2020-02	Mean	1. 1168E+04	1. 6246E+04	1. 5179E+04	8. 8099E+03	**7. 8698E+03**
	Std	8. 2991E+02	7. 1396E+02	**6. 3376E+02**	9. 7513E+02	7. 7639E+02
	Best	9. 4443E+03	1. 4891E+04	1. 3676E+04	6. 6248E+03	**6. 4035E+03**
	Worst	1. 3061E+04	1. 8048E+04	1. 6180E+04	1. 0625E+04	**9. 2260E+03**
CEC2020-03	Mean	1. 6609E+03	2. 2079E+03	1. 9643E+03	1. 3742E+03	**1. 2855E+03**
	Std	**7. 909E+01**	9. 0314E+01	1. 3510E+02	1. 4477E+02	1. 0538E+02
	Best	1. 4914E+03	2. 0829E+03	1. 7390E+03	**1. 0579E+03**	1. 1286E+03
	Worst	1. 8315E+03	2. 5294E+03	2. 2129E+03	1. 6824E+03	**1. 5595E+03**
CEC2020-04	Mean	**1. 9000E+03**	1. 9196E+03	1. 9000E+03	1. 9231E+03	1. 9012E+03
	Std	**0.0000E+03**	1. 5664E+01	**0.0000E+00**	7. 9563E+00	2. 7380E+00
	Best	1. 9000E+03	1. 9000E+03	1. 9000E+03	1. 9040E+03	**1. 9000E+03**
	Worst	**1. 9000E+03**	1. 9440E+03	1. 9000E+03	1. 9376E+03	1. 9121E+03
CEC2020-05	Mean	7. 2574E+07	9. 7519E+08	4. 7420E+08	4. 3897E+06	**7. 2111E+05**
	Std	4. 0368E+07	2. 8767E+08	1. 5809E+08	2. 5013E+06	**4. 8375E+05**
	Best	1. 2691E+07	3. 5010E+08	2. 6380E+08	8. 5485E+05	**2. 1776E+05**
	Worst	1. 5415E+08	1. 7495E+09	8. 4579E+08	1. 1366E+07	**2. 4568E+06**
CEC2020-06	Mean	4. 4451E+03	1. 3097E+04	8. 9899E+03	3. 6712E+03	**2. 7183E+03**
	Std	4. 9691E+02	2. 6453E+03	1. 5806E+03	4. 7807E+02	**3. 2334E+02**
	Best	3. 4676E+03	8. 6614E+03	6. 8206E+03	2. 9350E+03	**2. 1107E+03**
	Worst	5. 5517E+03	1. 8846E+04	1. 3031E+04	4. 8169E+03	**3. 2762E+03**
CEC2020-07	Mean	1. 1005E+07	1. 7215E+08	9. 3796E+07	2. 9672E+06	**4. 3393E+05**
	Std	6. 8254E+06	1. 0372E+08	5. 5059E+07	1. 5521E+06	**2. 9320E+05**
	Best	3. 2381E+06	5. 4095E+07	2. 5876E+07	4. 3516E+05	**6. 7726E+04**
	Worst	3. 0355E+07	4. 8758E+08	2. 5912E+08	7. 3330E+06	**1. 0756E+06**
CEC2020-08	Mean	1. 3119E+04	1. 7512E+04	1. 6873E+04	9. 8705E+03	**9. 6358E+03**
	Std	1. 0248E+03	**8. 2673E+02**	6. 2170E+02	8. 7509E+02	8. 8718E+02
	Best	9. 1130E+03	1. 5604E+04	1. 5689E+04	**7. 6433E+03**	7. 7370E+03
	Worst	1. 4907E+04	1. 8887E+04	1. 7732E+04	1. 1845E+04	**1. 1342E+04**
CEC2020-09	Mean	4. 1549E+03	5. 1688E+03	**2. 8283E+03**	3. 4567E+03	3. 4295E+03
	Std	1. 4193E+02	3. 3570E+02	4. 4022E+01	1. 2371E+02	**1. 0329E+02**
	Best	3. 9390E+03	4. 4652E+03	**2. 6788E+03**	3. 2459E+03	3. 2624E+03
	Worst	4. 5788E+03	5. 7616E+03	**2. 8732E+03**	3. 6998E+03	3. 6139E+03
CEC2020-10	Mean	7. 6756E+03	1. 7723E+04	1. 4509E+04	3. 1332E+03	**3. 0737E+03**
	Std	1. 0289E+03	1. 2073E+03	1. 6055E+03	4. 4005E+01	**4. 2534E+01**
	Best	5. 4593E+03	1. 4807E+04	1. 0742E+04	3. 0398E+03	**2. 9641E+03**
	Worst	9. 7338E+03	1. 9405E+04	1. 6871E+04	3. 2109E+03	**3. 1224E+03**

fitness value. x_{elite} is modeled by the following Eq. (4).

$$x_{elite} = min\left(f\left(x_i\right)\right) \tag{4}$$

$$x_{elite} = x\left(find\left(f_{best} == f\left(x_i\right)\right)\right) \tag{5}$$

find represents two indices with the same value in Eq. (5).

In the rising phase, two situations were evaluated as clear or rainy weather. The process is operated by assuming that the wind speed $lnY \sim N\left(\pi, \sigma^2\right)$ on days when the weather is clear is suitable for the normal distribution in expression. At this stage, which represents the exploration phase of the algorithm, the seeds are distributed according to the height and speed Y of the wind along their axis. The turbulences that form around the seeds are updated throughout the process to force them to spiral upwards continuously according to the equations below

$$x_{t+1} = x_t + \alpha \times v_x \times v_y \times lnY \times (x_t - x_s) \tag{6}$$

$$x_s = rand\,(1, dim) \times (ub - lb) + lb \tag{7}$$

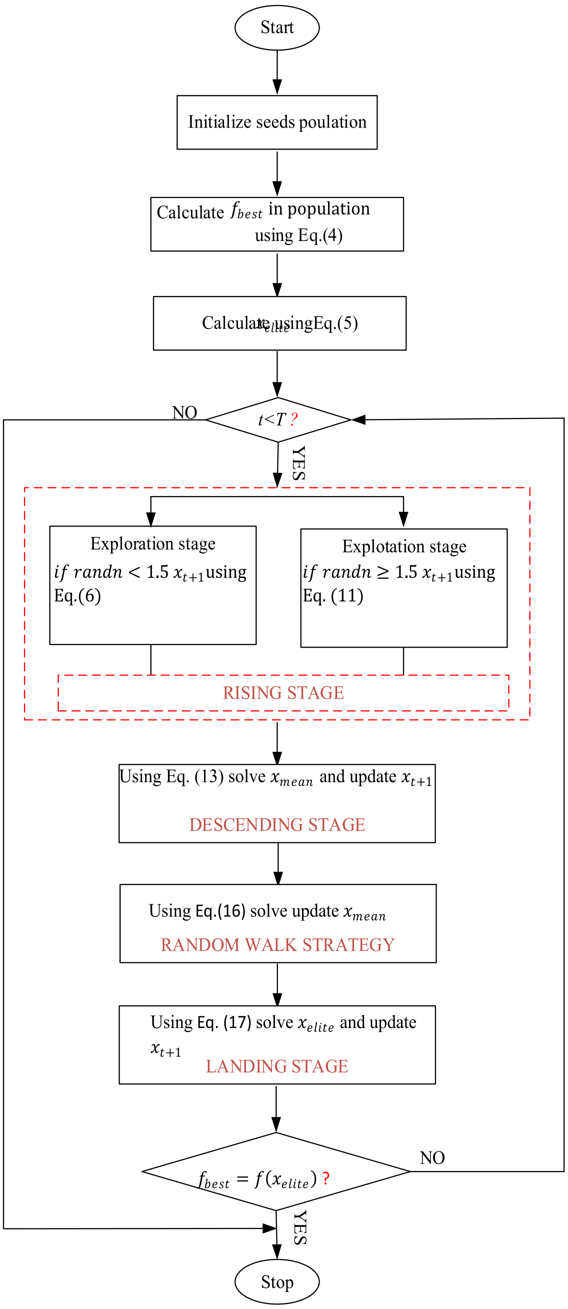

FIGURE 1. Flowchart of RW-DO.

$$lnY = \begin{cases} \frac{1}{y\sqrt{2\mu}} exp\left[-\frac{1}{2\sigma^2}(lny)^2\right] & y \geq 0 \\ 0 & y < 0 \end{cases} \tag{8}$$

In Eq. (6), x_t, the position of the dandelion seed and, x_s indicates the randomly chosen position of the dandelion seed. In Eq. (8), lnY represents the lognormal distribution $(\mu = 0, \sigma^2 = 1)$. It is an adaptive nonlinear control parameter that decreases by showing a random fluctuation behavior in the parameter range [0, 1] expressed in the Eq.(9) α [47].

$$\alpha = rand \times \left(\frac{1}{T^2}t^2 - \frac{2}{T}t + 1\right) \tag{9}$$

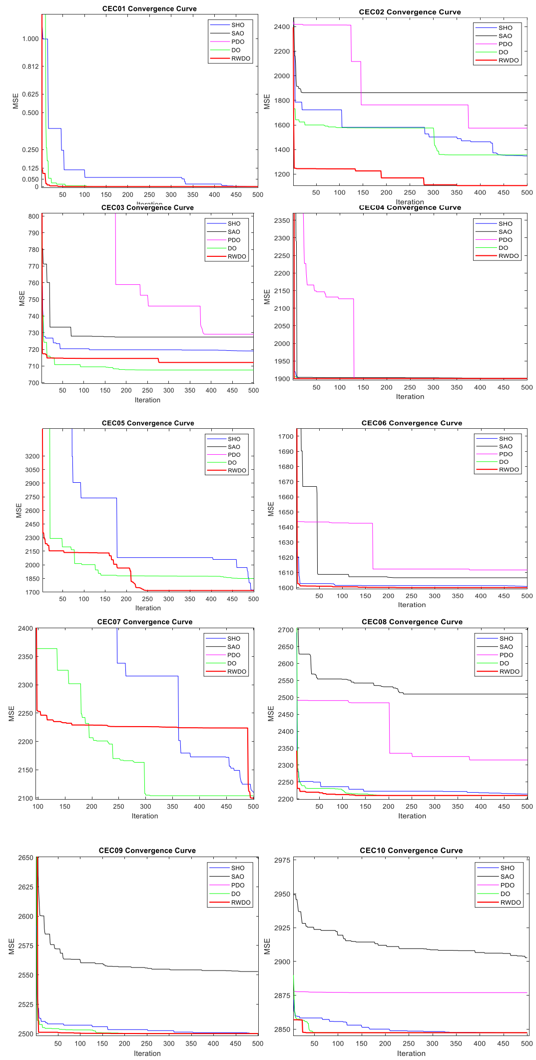

FIGURE 2. Convergence curve of CEC 2020 D = 5.

v_x and v_y are expressed as parameter coefficients that express the lifting ability of the dandelion seed under the hurricane effect. θ denotes $[-\mu, \mu]$ a randomly chosen angle in the range.

$$\left.\begin{aligned} r &= \frac{1}{exp\theta} \\ v_x &= r \times cos\theta \\ v_y &= r \times sin\theta \end{aligned}\right\} \tag{10}$$

On rainy days, dandelion seeds struggle with the wind to rise properly owing to limitations in their buoyancy. It also uses the control parameter to regulate the search in k the local area.

$$\left.\begin{aligned} x_{t+1} &= x_t \times k \\ k &= 1 - rand \times q \\ q &= \left(\frac{t-1}{T-1}\right)^2 + 1 \end{aligned}\right\} \tag{11}$$

The mathematical modeling of dandelion seeds in the rising stage is given in the Eq. (12).

$$x_{t+1} = \begin{cases} x_t + \alpha \times v_x \times v_y \times lny \times (x_s - x_t) & randn < 1.5 \\ x_t \times k & otherwise \end{cases} \tag{12}$$

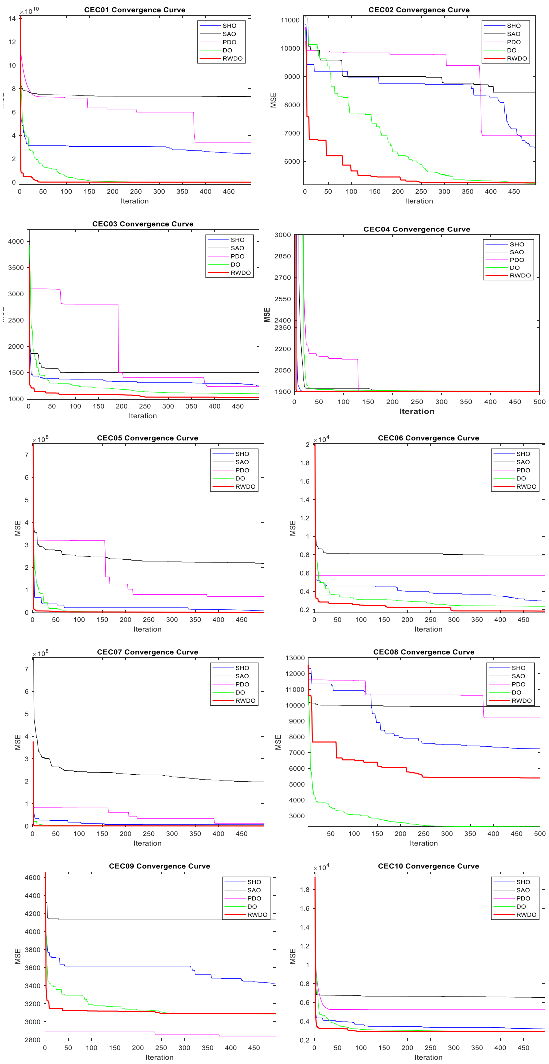

FIGURE 3. **Convergence curve of CEC 2020 D = 30.**

in Eq. (12) *randn* express generates a random number.

In the descending phase, the seed descent process starts with the help of Brownian motion to improve the exploration phase of the DO algorithm. Brownian motion adapts every change in seeds to a normal distribution. The algorithm evaluates the average positions (x_{mean}) using Brownian motion after the rising stage of the seeds. β_t represents Brownian motion and the mathematical modelling of the descent phase is given by Eq. (13)

$$\left.\begin{array}{r} x_{mean} = \frac{1}{N}\sum_{i=1}^{N} x_i \\ \beta_t = \frac{2t}{T} \\ x_{t+1} = x_t - \alpha \times \beta_t \times (x_{mean} - \alpha \times \beta_t \times x_t) \end{array}\right\} \quad (13)$$

During the landing phase, Dandelion seeds land randomly in indeterminate areas. However, as the iterations increase, the algorithm converges to the global optimal solution, adopting a path of information gathering by exploiting local elites so that dandelion seeds can sustain their life cycle and germinate. Search agents borrow the most relevant information from real elites to exploit their local location in their neighborhood, thereby converging to the optimal solution globally. In Eq.14 x_{elite}, is the optimum position of the dandelion seed during the ith iteration. B, [0, 2] is a random value in the range, $s = 0.01$, and w and t values are [0, 1] random values in the range.

$$\left.\begin{array}{c} \sigma = \left(\frac{\Gamma(1+B)\times sin\left(\frac{\pi B}{2}\right)}{\Gamma\left(\frac{1+B}{2}\right)\times B\times sin^{\left(\frac{B+1}{2}\right)}}\right) \\ Levy\,(\lambda) = s \times \frac{w\times\sigma}{|t|^{\frac{1}{B}}} \\ \hline x_{t+1} = x_{elite} + Levy\,(\lambda) \times \alpha \times (x_{elite} - x_t \times \sigma) \end{array}\right\} \quad (14)$$

The algorithm introduces several parameters, such as α and k; however, there is limited discussion regarding the sensitivity

Algorithm 1 Pseudocode of Proposed RW-DO Algorithm

Input: Population size: N=*30*, maximum number of iterations: *Max_iter*=*500*, variable dimension: *Dim*.
Output:
The optimal dandelion seed: *Bestposition* and its fitness value: *Bestfitness*

1. **Initialize** dandelion seeds X
2. **Calculate** the fitness value f for each dandelion seed.
3. **Select** the optimum dandelion seed X_{elite} according to fitness values.
4. **while** (t<T) **do**

Rise Stage:

5. **if** randn()<1.5 **do**
6. The adaptive parameters are generated using

Eq. (9).

7. Update the dandelion seeds using Eq. (6).
8. **else if do**
9. The adaptive parameters are generated using

Eq. (11).

10. Update the dandelion seeds using Eq. (11).
11. **end if**

Decline Stage:

12. Update the dandelion seeds using Eq. (13).
13. Update dandelion seeds according to random walks strategy using Eq. (16)

Land Stage:

13. Update the dandelion seeds using Eq. (14).
14. Arrange dandelion seeds from good to bad according to their fitness values.
15. Update X_{elite}
16. **if** f(X_{elite}) <f(X_{best}) **then**
17. $X_{best} = X_{elite}$, f_{best} =f(X_{elite})
18. **end if**

end while
Return X_{best} and f_{best}

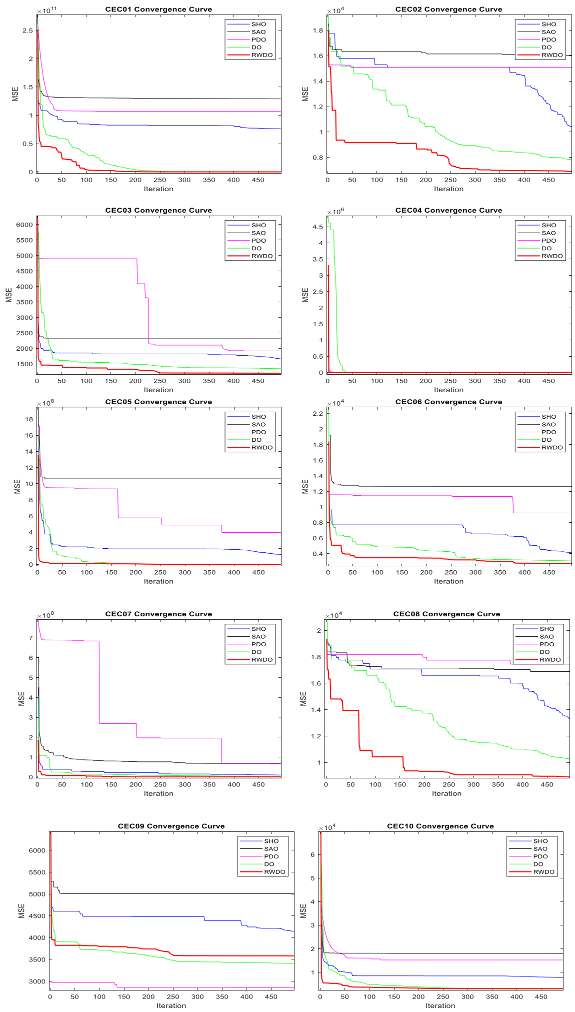

FIGURE 4. Converge curve of CEC 2020 D = 50.

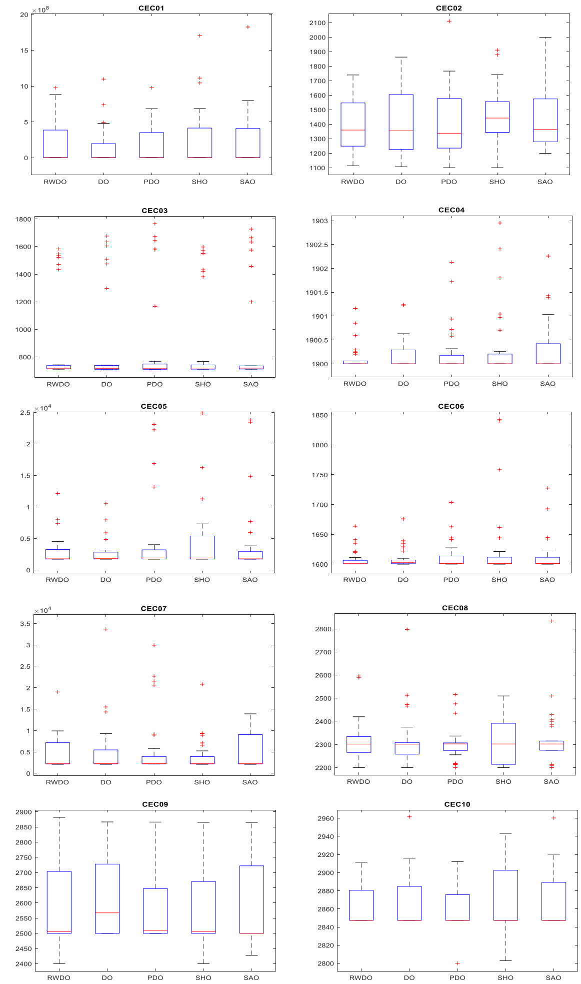

FIGURE 5. Boxplot of CEC 2020 D = 5.

of the performance to these parameters or the optimal method for setting them across different problems. For instance, the algorithm exhibits reduced optimization speed when solving complex problems. It is susceptible to becoming trapped in local optima, particularly when addressing complex optimization problems. Owing to the limitations of its own population, the dandelion algorithm demonstrates an inadequate global search capability. Furthermore, the dandelion optimization algorithm does not possess sufficient convergence accuracy for solving complex optimization problems.

B. RANDOM WALKS SEARCH STRATEGY AND RW-DO ALGORITHM

A random variable is a function that generates a sample space by mapping objects or events into numbers. This process, which consists of taking a sequential series of random steps, is called the random walks strategy [44]. The correlation between any two consecutive random walking steps is expressed in the following equation [2], [45], [57].

$$W_{NP} = \sum_{i=1}^{NP} S_i = \sum_{i=1}^{NP-1} S_i + X_{NP} = W_{NP-1} + S_{NP} \tag{15}$$

In the Eq. (15) W_{NP} is the sum of each consecutive random step, S_i is the consecutive random steps taken from a random distribution. NP and S_{NP} indicates the number of steps and the random variables respectively.

The random walks method proposed in the paper was developed by considering the Eq. (15). It was enriched by the addition of the random walks strategy tackled $x_{mean} = \frac{1}{N}\sum_{i=1}^{N} x_i$ in Eq. (13). In this strategy, each search agent in the swarm attempts to overcome local obstacles in different and random steps (W = 300). The random walks strategy involves creating a deviation by disrupting the stable gait by interfering with the next iteration so as not to get stuck in the local optimum. Thus, the exit process from the local is facilitated without reaching the local optimum early. Subsaquently, in the exploration phase, progress is achieved in which the deviation decreases in the next iterations, with a less effective deviation, and stable results are achieved. The mathematical model of the random walks strategy applied in this paper is expressed by the equation below.

$$x_{mean} = x_{mean} + (W \times \sum_{i=1}^{N} X_N) \times (0.5 - rand\,(1)) \tag{16}$$

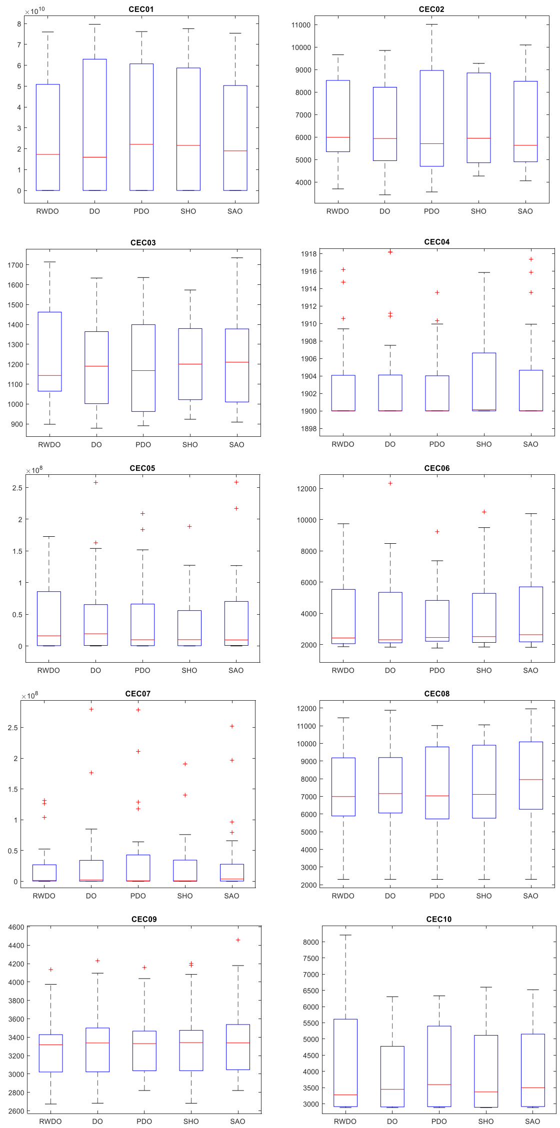

FIGURE 6. Boxplot of CEC 2020 (Dim = 30).

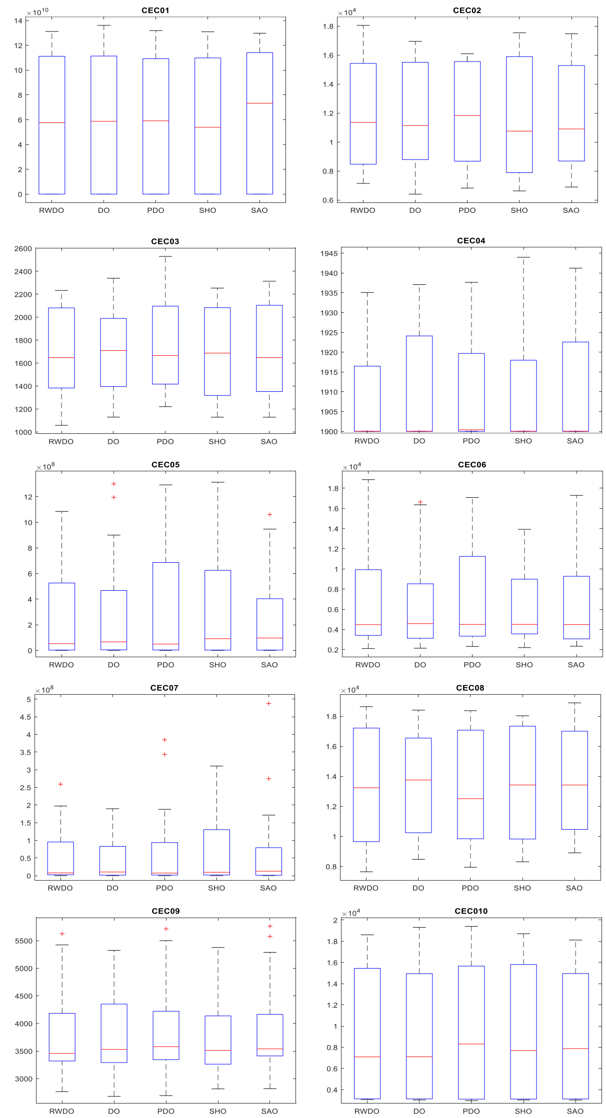

FIGURE 7. Boxplot of CEC 2020 (Dim = 50).

Given $(0.5 - rand\ (1))$ in Eq. (16) allows us to obtain different results for each iteration. Because of this expression, the number of random steps actively changes. The relationship between this dynamism and the fact that the results are more optimal can be explained by an increase in diversity within certain limits. The pseudocode for the proposed RW-DO algorithm is given in Algorithm and at flowchart is provided in Figure 1.

III. EXPERIMENTAL RESULTS

In this section, performance comparisons of the RW-DO algorithm with alternative algorithms and their statistical positions are evaluated using statistical test methods, and the solution to engineering design problems is presented in the second part of the section. The MATLAB R2021a package program was used for the experimental studies, 500 iterations were performed in each study, and 30 search agents were used. Thirty independent runs were performed to achieve more objective results, 30 independent runs were performed. The best results are shown in bold fonts. In addition to demonstrating the superior performance of the proposed RW-DO metaheuristic algorithm through the CEC2019 and CEC2020 function sets, it has been stated that it is a superior and different algorithm when non-parametric tests applied too.

A. MEASURING PERFORMANCE RW-DO AND ALTERNATIVE ALGORITHMS VIA CEC 2020

The CEC 2020 function set offers a distinguished benchmark for measuring the quality of optimization algorithms, as functions are shifted, rotated, expanded, and combined variables of the most complex mathematical optimization problems as shown in Table 1. They have features that make it difficult for algorithms to determine the global optimum point [58].

TABLE 5. Wilcoxon and KS test for 2 samples for CEC 2020 (D = 5).

FUNC	TEST	METRIC	SHO	SAO	PDO	DO
CEC 2020-01	Wilcoxon	p - value	9. 7110E-05	1. 7344E-06	1. 7344E-06	0.7499E+00
		W/T/L	W	W	W	L
	Kolmogorov- Smirnov	p - value	0. 7000E-03	1. 7973E-14	1. 7973E-14	0.5372E+00
		W/T/L	W	W	W	L
CEC 2020-02	Wilcoxon	p - value	0.0087E+00	1. 7344E-06	3. 1817E-06	0.0017E+00
		W/T/L	W	W	W	W
	Kolmogorov- Smirnov	p - value	0.0017E+00	8. 3836E-12	3. 5202E-10	0.0017E+00
		W/T/L	W	W	W	W
CEC 2020-03	Wilcoxon	p - value	4. 0715E-05	2. 1266E-06	1. 7344E-06	0.0175E+00
		W/T/L	W	W	W	W
	Kolmogorov- Smirnov	p - value	6. 1740E-05	1. 1615E-12	1. 7973E-14	0. 1088E+00
		W/T/L	W	W	W	T
CEC 2020-04	Wilcoxon	p - value	0.0078E+00	1. 7344E-06	0.0078E+00	2. 1417E-04
		W/T/L	W	W	W	W
	Kolmogorov- Smirnov	p - value	0.2003	1. 1615E-12	0.2003	0.0046
		W/T/L	T	W	T	W
CEC 2020-05	Wilcoxon	p - value	0.0012E+00	1. 9209E-06	1. 7344E-06	5. 2872E-04
		W/T/L	W	W	W	W
	Kolmogorov- Smirnov	p - value	0.0113E+00	1. 4977E-13	1. 7973E-14	6. 1578E-04
		W/T/L	W	W	W	W
CEC 2020-06	Wilcoxon	p - value	2. 1630E-05	1. 7344E-06	1. 7344E-06	0.0166E+00
		W/T/L	W	W	W	W
	Kolmogorov- Smirnov	p - value	1. 1433E-06	1. 4977E-13	1. 7973E-14	0.0259E+00
		W/T/L	W	W	W	W
CEC 2020-07	Wilcoxon	p - value	0.0157E+00	1. 0246E-05	1. 7344E-06	0. 1359E+00
		W/T/L	W	W	W	T
	Kolmogorov- Smirnov	p - value	0.0046E+00	5. 5870E-08	1. 7973E-14	0.0550E+00
		W/T/L	W	W	W	T
CEC 2020-08	Wilcoxon	p - value	8. 1878E-05	1. 7988E-05	2. 3704E-05	0.0032E+00
		W/T/L	W	W	W	W
	Kolmogorov- Smirnov	p - value	2. 6199E-07	2. 6199E-07	4. 6436E-06	2. 0212E-04
		W/T/L	W	W	W	W
CEC 2020-09	Wilcoxon	p - value	1. 8910E-04	1. 7344E-06	1. 7344E-06	6. 8923E-05
		W/T/L	W	W	W	W
	Kolmogorov- Smirnov	p - value	1. 1615E-12	1. 7973E-14	1. 7973E-14	5. 6313E-11
		W/T/L	W	W	W	W
CEC 2020-10	Wilcoxon	p - value	8. 1878E-05	1. 7344E-06	1. 7344E-06	8. 3071E-04
		W/T/L	W	W	W	W
	Kolmogorov- Smirnov	p - value	1. 1088E-08	1. 7973E-14	1. 7973E-14	2. 0212E-04
		W/T/L	W	W	W	W

In this study, the CEC 2020 test set is organized in 5, 30 and 50 dimensions respectively.

When considering the five dimensional CEC 2020 function, as presented in Table 2, the results of DO-RW's best value and mean value for function CEC 2020-10 are optimal among all functions, although they rank second after the DO algorithm. Despite the low number of variables in five-dimensional functions, and the proximity of performance values among competing algorithms, the RW-DO algorithm demonstrated stability and superior performance compared to alternative algorithms across the entire test set.

In Table 3, for dimension = 30, DO-RW had the best results, but ranked second in terms of mean values in the functions CEC2020-04 and CEC2020-09. It has maintained its position as an advantageous algorithm owing to its superior performance in all statistical results for all other functions. As the RW-DO algorithm shows superiority in five-dimensional problems, it has maintained its

TABLE 6. Wilcoxon and KS test for 2 samples for CEC 2020 (D = 30).

FUNC	TEST	METRIC	SHO	SAO	PDO	DO
CEC 2020-01	Wilcoxon	p - value	1. 7344E-06	1. 7344E-06	1. 7344E-06	1. 7344E-06
		W/T/L	W	W	W	W
	Kolmogorov-Smirnov	p - value	1. 7973E-14	1. 7973E-14	1. 7973E-14	1. 1615E-12
		W/T/L	W	W	W	W
CEC 2020-02	Wilcoxon	p - value	5. 2165E-06	1. 7344E-06	1. 7344E-06	9. 6266E-04
		W/T/L	W	W	W	W
	Kolmogorov-Smirnov	p - value	1. 1433E-06	1. 7973E-14	1. 7973E-14	0.0046E+00
		W/T/L	W	W	W	W
CEC 2020-03	Wilcoxon	p - value	1. 7344E-06	1. 7344E-06	1. 7344E-06	0.0016E+00
		W/T/L	W	W	W	W
	Kolmogorov-Smirnov	p - value	1. 1615E-12	1. 7973E-14	1. 7973E-14	0.0017E+00
		W/T/L	W	W	W	W
CEC 2020-04	Wilcoxon	p - value	2. 4414E-04	1. 7988E-05	2. 4414E-04	1. 7344E-06
		W/T/L	W	W	W	W
	Kolmogorov-Smirnov	p - value	0.0046	1. 1433E-06	0.0046	1. 1615E-12
		W/T/L	W	W	W	W
CEC 2020-05	Wilcoxon	p - value	1. 7344E-06	1. 7344E-06	1. 7344E-06	1. 7344E-06
		W/T/L	W	W	W	W
	Kolmogorov-Smirnov	p - value	1. 7973E-14	1. 7973E-14	1. 7973E-14	1. 4977E-13
		W/T/L	W	W	W	W
CEC 2020-06	Wilcoxon	p - value	1. 2506E-04	1. 7344E-06	1. 7344E-06	3. 0650E-04
		W/T/L	W	W	W	W
	Kolmogorov-Smirnov	p - value	1. 1433E-06	1. 7973E-14	1. 7973E-14	2. 0212E-04
		W/T/L	W	W	W	W
CEC 2020-07	Wilcoxon	p - value	5. 2165E-06	1. 7344E-06	1. 7344E-06	2. 3534E-06
		W/T/L	W	W	W	W
	Kolmogorov-Smirnov	p - value	5. 5870E-08	1. 7973E-14	1. 7973E-14	2. 0480E-09
		W/T/L	W	W	W	W
CEC 2020-08	Wilcoxon	p - value	0.0082E+00	1. 7344E-06	1. 7344E-06	0. 1779E+00
		W/T/L	W	W	W	L
	Kolmogorov-Smirnov	p - value	0. 1088E+00	1. 4977E-13	1. 4977E-13	0. 1088E+00
		W/T/L	T	W	W	T
CEC 2020-09	Wilcoxon	p - value	2. 6134E-04	1. 7344E-06	1. 7344E-06	1. 7344E-06
		W/T/L	W	W	W	W
	Kolmogorov-Smirnov	p - value	2. 0212E-04	1. 4977E-13	1. 7973E-14	1. 7973E-14
		W/T/L	W	W	W	W
CEC 2020-10	Wilcoxon	p - value	1. 7344E-06	1. 7344E-06	1. 7344E-06	3. 1123E-05
		W/T/L	W	W	W	W
	Kolmogorov-Smirnov	p - value	1. 7973E-14	1. 7973E-14	1. 7973E-14	3. 5202E-10
		W/T/L	W	W	W	W

advantageous position with its stability and superior performance compared with alternative algorithms in almost every function for thirty-dimensional problems.

In table 4, the CEC2020 50-dimensional problem set is a highly multivariate complex test set, and solving such non-linear problems at the best level demonstrates the superiority of the algorithm in solving difficult problems. It has been observed that the RW-DO algorithm has superior performance when compared with alternative algorithms in all functions except the CEC2020-04 function. The results for all dimensions were evaluated collectively, and the RW-DO algorithm was evaluated by selecting the problems in the CEC2020 test set, which is a widely used and effective algorithm quality measure, in small, medium, and large dimensions, namely, 5, 30, and 50 dimensions, respectively. The results show that, it is best for almost all sizes and functions. When the results were analyzed, the best value in almost all dimensions and functions outperformed all alternative algorithms, and the RW-DO algorithm, which overcame the obstacle of being stuck at the local optimum point owing to the random walk strategy, had a 93.33% performance advantage in capturing the best value. Similar results were obtained for the mean and worst value. The fact that the standard deviation values are not high indicates the resolute structure of the algorithm. When Figure 2, Figure 3, Figure 4 are examined, the algorithms tested with the CEC2020 function set in all dimensions are compared with alternative algorithms. In particular, for dim = 5, 1, 2,3,4, 5, 6, 8, and 10, for dim = 30, all the functions, and for dim = 50, all the functions except 4 gradually converge slowly and evenly. When the proposed RW-DO algorithm and alternative algorithms are considered in the CEC2020 function set and selected dimensions, the results of the performance tables and convergence curve graphs show that it is not caused by coincidence but iteratively creates a balanced and stable structure.

TABLE 7. Wilcoxon and KS test for 2 samples for CEC 2020 (D = 50).

FUNC	TEST	METRIC	SHO	SAO	PDO	DO
CEC 2020-01	Wilcoxon	p - value	1. 7344E-06	1. 7344E-06	1. 7344E-06	1. 7344E-06
		W/T/L	W	W	W	W
	Kolmogorov-Smirnov	p - value	1. 7973E-14	1. 7973E-14	1. 7973E-14	1. 7973E-14
		W/T/L	W	W	W	W
CEC 2020-02	Wilcoxon	p - value	1. 7344E-06	1. 7344E-06	1. 7344E-06	8. 1878E-05
		W/T/L	W	W	W	W
	Kolmogorov-Smirnov	p - value	1. 7344E-06	1. 7344E-06	1. 7344E-06	0.0017E+00
		W/T/L	W	W	W	W
CEC 2020-03	Wilcoxon	p - value	1. 7344E-06	1. 7344E-06	1. 7344E-06	0.0024E+00
		W/T/L	W	W	W	W
	Kolmogorov-Smirnov	p - value	1. 4977E-13	1. 7973E-14	1. 7973E-14	0.0259E+00
		W/T/L	W	W	W	W
CEC 2020-04	Wilcoxon	p - value	6. 1035E-05	2. 1630E-05	6. 1035E-05	2. 3534E-06
		W/T/L	W	W	W	W
	Kolmogorov-Smirnov	p - value	6. 1578E-04	4. 6436E-06	6. 1578E-04	8. 3836E-12
		W/T/L	W	W	W	W
CEC 2020-05	Wilcoxon	p - value	1. 7344E-06	1. 7344E-06	1. 7344E-06	1. 7344E-06
		W/T/L	W	W	W	W
	Kolmogorov-Smirnov	p - value	1. 7973E-14	1. 7973E-14	1. 7973E-14	8. 3836E-12
		W/T/L	W	W	W	W
CEC 2020-06	Wilcoxon	p - value	1. 7344E-06	1. 7344E-06	1. 7344E-06	1. 9209E-06
		W/T/L	W	W	W	W
	Kolmogorov-Smirnov	p - value	1. 7973E-14	1. 7973E-14	1. 7973E-14	3. 5202E-10
		W/T/L	W	W	W	W
CEC 2020-07	Wilcoxon	p - value	1. 7344E-06	1. 7344E-06	1. 7344E-06	1. 9209E-06
		W/T/L	W	W	W	W
	Kolmogorov-Smirnov	p - value	1. 7973E-14	1. 7973E-14	1. 7973E-14	1. 4977E-13
		W/T/L	W	W	W	W
CEC 2020-08	Wilcoxon	p - value	1. 9209E-06	1. 7344E-06	1. 7344E-06	0. 3709E+00
		W/T/L	W	W	W	L
	Kolmogorov-Smirnov	p - value	1. 4977E-13	1. 7973E-14	1. 7973E-14	0.0550E+00
		W/T/L	W	W	W	T
CEC 2020-09	Wilcoxon	p - value	1. 7344E-06	1. 7344E-06	1. 7344E-06	0.4284E+00
		W/T/L	W	W	W	L
	Kolmogorov-Smirnov	p - value	1. 4977E-13	1. 7973E-14	1. 7973E-14	0.9360E+00
		W/T/L	W	W	W	L
CEC 2020-10	Wilcoxon	p - value	1. 7344E-06	1. 7344E-06	1. 7344E-06	2. 1630E-05
		W/T/L	W	W	W	W
	Kolmogorov-Smirnov	p - value	1. 7973E-14	1. 7973E-14	1. 7973E-14	2. 6199E-07
		W/T/L	W	W	W	W

The results are presented in Figures 5, 6 and 7 using boxplot analysis, a robust statistical approach that captures the essential characteristics of the data distribution and central tendency. This method calculates the interquartile range (IQR) between the first (Q1) and third (Q3) quartiles, with the median at its center, while also showing the minimum and maximum limits of the dataset. It also highlights outliers beyond certain thresholds. Boxplot analysis proves invaluable

TABLE 8. CEC 2019 functions.

Functions	Dimension	Features	Bounds	Fitting Value
CEC2019-01: Storn's Chebyshev Polynomial Fitting Problem	9	multimodal	[−8192, 8192]	1
CEC2019-02: Inverse Hilbert Matrix Problem (F2)	16	multimodal	[−16384, 16384]	1
CEC2019-03: Lennard–Jones Minimum Energy Cluster (F3)	18	multimodal	[-4.4]	1
CEC2019-04: Rastrigin's Function (F4)	10	multimodal shifted and rotated	[−100, 100]	1
CEC2019-05: Griewangk's Function (F5)	10	multimodal shifted and rotated	[−100, 100]	1
CEC2019-06: Weierstrass Function (F6)	10	multimodal shifted and rotated	[−100, 100]	1
CEC2019-07: Modified Schwefel's Function(F7)	10	multimodal shifted and rotated	[−100, 100]	1
CEC2019-08: Expanded Schafer's F6 Function (F8)	10	multimodal shifted and rotated	[−100, 100]	1
CEC2019-09: Happy Cat Function (F9)	10	multimodal shifted and rotated	[−100, 100]	1
CEC2019-10: Ackley Function (F10)	10	multimodal shifted and rotated	[−100, 100]	1

for evaluating the consistency of outputs from independently applied algorithms. By comparing the outputs of the different algorithms, the width and symmetry of the distribution provide crucial insights into their performance and reliability. Specifically, a narrow variance and symmetrical distribution suggest that the algorithm produces consistent and trustworthy results, whereas a wide variance with numerous outliers indicates unstable performance or failure in certain cases.

The analyses conducted on the 5, 30, and 50-dimensional function sets of CEC 2020 show that the RW-DO algorithm exhibits the least number of outliers. This observation suggests that the outputs of the RW-DO algorithm are more uniform and stable.

Moreover, the closeness of the obtained results and the more balanced distribution support the assertion that the RW-DO algorithm effectively performs in these processes.

B. STATISTICAL ANALYSIS

The Smirnov (KS) test was used to select parametric or non-parametric statistical tests, considering the mathematical test functions and alternative metaheuristic algorithms on the collected dataset. The KS test shows whether the data obtained when the algorithms optimize each function are normal, if the p value of the KS test is less than 0.05, the data set is not normally distributed and non-parametric testing should be considered. If the p- value is > 0.05, parametric testing is performed [64], [65].

The Wilcoxon signed rank test, it is determined whether the variables are taken from two different datasets by considering the mean value of the variable ranks. A p value less than 0.05 means that the data were taken from two different sets. In this test, a dataset with a lower rank mean represents better statistical behavior [51], [66]. the Kolmogorov-Smirnov test for two samples is sensitive to any distribution difference, such as measures of central tendency, kurtosis, skewness, and variability for two independent samples [67]. When the normal distribution of the datasets generated by the CEC2020 functions of RW-DO and alternative algorithms are examined through the Kolmogorov-Smirnov test, it is appropriate to use Wilcoxon and two-sample Kolmogorov-Smirnov non-parametric statistical tests because $p = 6.9688E-28$ for all algorithms. The Wilcoxon signed-rank test and Kolmogorov-Smirnov test results for the two samples are shown in Table 5, Table 6, and Table 7. When evaluated together with the $W = 229$, $T = 5$, and $L = 6$ results, the Wilcoxon signed cross validation of Kolmogorov-Smirnov tests for the rank test and two samples showed the superiority of the RW-DO algorithm with low mean ranking and that it is a unique algorithm that creates different datasets.

C. MEASURING PERFORMANCE RW-DO AND ALTERNATIVE ALGORITHMS VIA CEC 2019

Compared with other test sets, the CEC2019 test set is more challenging owing to its variable dimensional structure and multimodal testing features; however, it is more accurate in measuring the optimization results. The properties are listed in Table 8. The CEC 2019 function set is examined, and it is observed that it is a set of functions consisting of shifted, rotated, extended and combined versions of classical

TABLE 9. Performance of RW-DO and alternative meta heuristic algorithms.

Function_	Metric	SHO	SAO	PDO	DO	**RW-DO**
CEC2019-01	Mean	**1. 8622E+11**	1. 0833E+12	3. 7721E+12	4. 9082E+11	1. 0048E+12
	Std	**6. 4228E+11**	8. 1450E+11	2. 8727E+12	1. 3106E+12	5. 4781E+12
	Best	6. 2719E+04	2. 1644E+11	2. 9820E+11	2. 8503E+09	**4. 3931E+04**
	Worst	**2. 6012E+12**	4. 0708E+12	9. 8953E+12	6. 4801E+12	3. 0010E+13
CEC2019-02	Mean	6. 1541E+03	**5. 8464E+02**	1. 3570E+04	1. 2104E+03	7. 5361E+02
	Std	4. 1713E+03	**2. 1669E+03**	6. 4590E+03	3. 5999E+03	4. 0324E+03
	Best	1. 3673E+02	1. 7448E+01	3. 9421E+03	1. 7573E+01	**1. 7343E+01**
	Worst	1. 5601E+04	**1. 1608E+04**	2. 7757E+04	1. 6155E+04	2. 2104E+04
CEC2019-03	Mean	1. 2704E+01	1. 2703E+01	1. 2703E+01	1. 2704E+01	**1. 2702E+01**
	Std	1. 1259E-03	9. 4919E-04	1. 3963E-03	1. 6337E-03	**3. 2369E-04**
	Best	1. 2703E+01	1. 2702E+01	1. 2702E+01	1. 2702E+01	**1. 2702E+01**
	Worst	1. 2707E+01	1. 2706E+01	1. 2708E+01	1. 2708E+01	**1. 2704E+01**
CEC2019-04	Mean	2. 0796E+04	7. 2611E+03	1. 8611E+04	6. 1619E+03	**2. 0009E+03**
	Std	7. 5384E+03	**4. 9338E+03**	7. 9509E+03	5. 4593E+03	5. 1776E+03
	Best	6. 5357E+03	2. 2004E+03	5. 3621E+03	6. 0998E+02	**5. 6584E+01**
	Worst	3. 7454E+04	2. 5748E+04	3. 8917E+04	**2. 6467E+04**	2. 8801E+04
CEC2019-05	Mean	6. 1987E+00	3. 3391E+00	5. 4913E+00	3. 0046E+00	**2. 2237E+00**
	Std	1. 2076E+00	6. 9401E-01	1. 1963E+00	**1. 0548E+00**	1. 1210E+00
	Best	3. 6833E+00	2. 6030E+00	3. 7985E+00	2. 0240E+00	**1. 3039E+00**
	Worst	9. 3730E+00	**5. 6252E+00**	8. 4927E+00	6. 6712E+00	7. 7344E+00
CEC2019-06	Mean	1. 2808E+01	1. 2974E+01	1. 3024E+01	1. 3503E+01	**1. 1329E+01**
	Std	1. 3123E+00	1. 3490E+00	1. 3382E+00	**1. 0758E+00**	1. 5504E+00
	Best	9. 7767E+00	9. 5166E+00	9. 9443E+00	1. 1948E+01	**6. 8661E+00**
	Worst	1. 6056E+01	1. 5328E+01	1. 6630E+01	1. 6353E+01	**1. 4512E+01**
CEC2019-07	Mean	1. 5598E+03	1. 4532E+03	1. 2275E+03	1. 2715E+03	**5. 8500E+02**
	Std	3. 4528E+02	**3. 2489E+02**	4. 4976E+02	4. 9316E+02	3. 8092E+02
	Best	1. 0046E+03	9. 9957E+02	4. 9502E+02	4. 9997E+02	**1. 4078E+02**
	Worst	2. 5597E+03	2. 1448E+03	2. 1197E+03	2. 4336E+03	**1. 9391E+03**
CEC2019-08	Mean	7. 3781E+00	7. 0011E+00	7. 1053E+00	7. 3588E+00	**6. 0281E+00**
	Std	6. 0237E-01	**5. 3599E-01**	5. 6243E-01	6. 3675E-01	8. 8749E-01
	Best	6. 5025E+00	5. 8901E+00	6. 0446E+00	6. 0330E+00	**3. 8049E+00**
	Worst	9. 0993E+00	8. 3485E+00	**8. 1346E+00**	9. 1522E+00	8. 5721E+00
CEC2019-09	Mean	3. 4653E+03	8. 0776E+02	3. 3500E+03	9. 3837E+02	**2. 5812E+02**
	Std	**1. 0649E+03**	7. 1064E+02	1. 2935E+03	1. 2713E+03	1. 2291E+03
	Best	1. 1115E+03	1. 5476E+02	1. 9484E+03	6. 0949E+00	**3. 6549E+00**
	Worst	5. 8735E+03	**3. 2915E+03**	7. 6441E+03	6. 9416E+03	6. 7510E+03
CEC2019-10	Mean	2. 0732E+01	2. 0801E+01	2. 0725E+01	2. 0798E+01	**2. 0505E+01**
	Std	2. 1579E-01	**1. 5560E-01**	1. 9691E-01	2. 1101E-01	2. 1654E-01
	Best	2. 0266E+01	2. 0400E+01	2. 0257E+01	2. 0395E+01	**2. 0214E+01**
	Worst	**2. 1113E+01**	2. 1146E+01	2. 1132E+01	2. 1273E+01	2. 1305E+01

functions [68]. When the superiority of the algorithms was examined using the CEC2019 function set given by Table 9, the superiority of the RW-DO algorithm was observed in all functions except the mean value results of the CEC2019-01 and CEC2019-02 functions. The main reason for this advantage is the deviation created by the random walk strategy to overcome the local area. Through this deviation, the stable walk is broken and an exit is achieved. In the exploration phase, this deviation decreases iteratively and more stable results are obtained.

D. STATISTICAL ANALYSIS FOR CEC 2019 RESULTS

Table 10. is examined two determine whether the data sets generated with the CEC2019 functions of RW-DO and alternative algorithms are normally distributed or not, it is appropriate to use Wilcoxon and Kolmogorov-Smirnov non-parametric statistical tests for two samples as $p< 0.5$ is reached for all algorithms.

Table 11. shows the comparison results of the algorithms using the Wilcoxon signed-rank test and two sample Kolmogorov-Smirnov tests. When taken together with the

TABLE 10. Normality test results via KS test.

FUNCTION	SHO	SAO	PDO	DO	RW-DO
CEC2019-01	6. 9688E-28	6. 9688E-28	6. 9688E-28	6. 9688E-28	6. 9688E-28
CEC2019-02	6. 9688E-28	6. 9688E-28	6. 9688E-28	6. 9688E-28	6. 9688E-28
CEC2019-03	6. 9688E-28	6. 9688E-28	6. 9688E-28	6. 9688E-28	6. 9688E-28
CEC2019-04	6. 9688E-28	6. 9688E-28	6. 9688E-28	6. 9688E-28	6. 9688E-28
CEC2019-05	1. 2482E-27	7. 0709E-28	7. 0332E-28	1. 0244E-26	7. 3910E-23
CEC2019-06	6. 9688E-28	6. 9688E-28	6. 9688E-28	6. 9688E-28	6. 9688E-28
CEC2019-07	6. 9688E-28	6. 9688E-28	6. 9688E-28	6. 9688E-28	6. 9688E-28
CEC2019-08	6. 9688E-28	6. 9688E-28	6. 9688E-28	6. 9688E-28	7.0315E-28
CEC2019-09	6. 9688E-28	6. 9688E-28	6. 9688E-28	6. 9688E-28	7. 0831E-28
CEC2019-10	6. 9688E-28	6. 9688E-28	6. 9688E-28	6. 9688E-28	6. 9688E-28

results of W = 78, T = 0, L = 2, Wilcoxon signed rank test, and cross-validation of Kolmogorov–Smirnov tests for two samples, the RW-DO algorithm has a low mean rank, which shows its superiority and that it is a unique algorithm that creates different datasets. When Figure 8 is examined, testing the RW-DO algorithm through the CEC2019 function set, how it iteratively converges to the solution, and its effectiveness can be evaluated by comparing it with the alternative algorithms. The RW-DO algorithm exhibited the best optimization performance for all functions. It can be observed that the optimization process is completed in a gradual manner for all functions. Through the convergence curves, the strength of the random-walk strategy provides a balance between the exploitation and exploration phases by increasing the diversity of the solutions at the local optimum point and converging to the global solution by providing a certain amount of deviation from the current solution. The fact that the RW-DO algorithm reaches the best global solution for all functions informs the reader whether the DO algorithm of the random walk strategy is stuck at the local optimum.

The boxplot analysis of the CEC 2019 Function Set, as depicted in Fig. 9, revealed that despite the presence of two outliers in the first function, the proposed RW-DO algorithm demonstrated the most equilibrated relationship between the median and upper limit values. Notably, the algorithm's resilience and consistent performance in the face of outliers underscore its reliability as an optimization tool. The RW-DO algorithm's efficacy is further evidenced by its low variance and centrally positioned median within the distribution, indicating its capacity to yield stable and dependable solutions. Moreover, the absence of substantial deviations towards extreme interquartile ranges (IQR) or outliers suggests that the algorithm produces uniform outputs across various iterations. These findings collectively support the assertion that RW-DO exhibits robust performance in complex optimization scenarios, maintaining its effectiveness particularly when confronted with diverse functional structures.

E. SENSITIVITY ANALYSIS

This document describes a sensitivity analysis conducted to determine the optimal values for the parameter beta in the RW-DO algorithm. CEC 2019 benchmark set 1, 2, 4, and 9, and CEC 2020 benchmark set 1, 3, 5, and 8, including eight different functions, were selected. Beta has the status of receiving numbers within the range of Beta parameter [0, 2]. Four different values (0.5, 1, 1.5, and 2.0) were assigned to the beta. The sensitivity of the DO algorithm to this change is also measured. As a result, we observed that the CEC 2020, 8. Function and CEC 2019 1.2 and 4. These functions yielded the most favorable results as seen Table 12.

IV. ENGINEERING DESIGN PROBLEM

Real-world engineering design problems are widely used in the industry. The optimization processes of these problems may contain various design constraints depending on the type of non-linear material, geometric shape of the structure, and body dynamics. The main purpose of the optimization process is to achieve optimal results by minimizing the technological and economic difficulties and costs.

TABLE 11. Wilcoxon and KS test for two samples.

func _	Test	metric	SHO	SAO	PDO	DO
CEC2019-01	Wilcoxon	p - value	0. 4653E+00	3. 1123E-05	3. 1123E-05	3. 5202E-10
		W/T/L	L	W	W	W
	Kolmogorov-smirnov	p - value	0.5372E+00	1. 4977E-13	1. 4977E-13	3. 1123E-05
		W/T/L	L	W	W	W
CEC2019-02	Wilcoxon	p - value	3. 1123E-05	1. 1265E-05	1. 9209E-06	2. 8434E-05
		W/T/L	W	W	W	W
	Kolmogorov-smirnov	p - value	3. 5202E-10	1. 4977E-13	1. 4977E-13	1. 1615E-12
		W/T/L	W	W	W	W
CEC2019-03	Wilcoxon	p - value	1. 7344E-06	1. 7344E-06	1. 1265E-05	1. 7344E-06
		W/T/L	W	W	W	W
	Kolmogorov-smirnov	p - value	1. 1615E-12	1. 4977E-13	6. 1740E-05	8. 3836E-12
		W/T/L	W	W	W	W
CEC2019-04	Wilcoxon	p - value	3. 1817E-06	2. 3534E-06	4. 2857E-06	5. 7517E-06
		W/T/L	W	W	W	W
	Kolmogorov-smirnov	p - value	3. 5202E-10	1. 4977E-13	1. 4977E-13	2. 6199E-07
		W/T/L	W	W	W	W
CEC2019-05	Wilcoxon	p - value	2. 8434E-05	1. 9209E-06	1. 9209E-06	5. 3070E-05
		W/T/L	W	W	W	W
	Kolmogorov-smirnov	p - value	3. 5202E-10	1. 4977E-13	1. 4977E-13	1. 1433E-06
		W/T/L	W	W	W	W
CEC2019-06	Wilcoxon	p - value	3. 1123E-05	6. 3198E-05	1. 6046E-04	1. 9209E-06
		W/T/L	W	W	W	W
	Kolmogorov-smirnov	p - value	1. 7552E-05	2. 0212E-04	6. 1740E-05	5. 5870E-08
		W/T/L	W	W	W	W
CEC2019-07	Wilcoxon	p - value	2. 3534E-06	1. 7344E-06	1. 3595E-04	4. 2857E-06
		W/T/L	W	W	W	W
	Kolmogorov-smirnov	p - value	8. 3836E-12	8. 3836E-12	1. 1433E-06	1. 1433E-06
		W/T/L	W	W	W	W
CEC2019-08	Wilcoxon	p - value	3. 7243E-05	2. 8786E-06	6. 3198E-05	1. 7344E-06
		W/T/L	W	W	W	W
	Kolmogorov-smirnov	p - value	1. 1433E-06	1. 1088E-08	1. 7552E-05	1. 1088E-08
		W/T/L	W	W	W	W
CEC2019-09	Wilcoxon	p - value	3. 4053E-05	1. 9209E-06	1. 4936E-05	3. 1817E-06
		W/T/L	W	W	W	W
	Kolmogorov-smirnov	p - value	5. 6313E-11	1. 4977E-13	1. 4977E-13	3. 5202E-10
		W/T/L	W	W	W	W
CEC2019-10	Wilcoxon	p - value	6. 3391E-06	1. 4773E-04	1. 1433E-06	3. 5152E-06
		W/T/L	W	W	W	W
	Kolmogorov-smirnov	p - value	1. 1088E-08	1. 7552E-05	1. 7552E-05	1. 1433E-06
		W/T/L	W	W	W	W

TABLE 12. Wilcoxon and KS test for two samples.

Function	Metric	Beta=0.5;	Beta=1.0	Beta=1.5	Beta=2.0
		CEC 2020 (Dim=30)			
CEC 2020-01	Mean	5.7723e+04	2.6885e+04	4. 7722E+04	2.0886e+04
	Std	1.7409e+05	4.9424e+04	1. 2768E+05	4.5359e+04
	Best	8.2043e+02	**2.6797e+02**	3. 6947E+02	7.6340e+02
	Worst	8.2694e+05	2.3950e+05	6. 0156E+05	2.3899e+05
CEC 2020-03	Mean	9.7712e+02	9.6946e+02	9.7077E+02	9.9889e+02
	Std	5.1931e+01	6.5056e+01	5. 8978E+01	7.4456e+01
	Best	**8.5047e+02**	8.6876e+02	8. 7783E+02	8.7909e+02
	Worst	1.0874e+03	1.1558e+03	1. 1344E+03	1.1793e+03
CEC 2020-05	Mean	2.0492e+05	2.2227e+05	2.6258e+05	2.4439e+05
	Std	1.3014e+05	1.4125e+05	1.5497e+05	1.4457e+05
	Best	**1.6389e+04**	8.2571e+04	6.8060e+04	4.9211e+04
	Worst	5.7559e+05	6.5417e+05	5.8551e+05	5.5652e+05
CEC 2020-08	Mean	4.7008e+03	6.0228e+03	5. 2383E+03	5.2111e+03
	Std	1.8979e+03	9.4595e+02	1. 9125E+03	1.7167e+03
	Best	2.3002e+03	2.3074e+03	**2. 3000E+03**	2.3001e+03
	Worst	7.2044e+03	7.3256e+03	8. 1295E+03	7.1507e+03
		CEC 2019			
CEC 2019-01	Mean	1.8076e+11	1.8076e+11	1. 0048E+12	8.8068e+10
	Std	9.8688e+11	9.8688e+11	5. 4781E+12	4.7167e+11
	Best	5.0890e+04	5.0890e+04	**4. 3931E+04**	4.4213e+04
	Worst	5.4060e+12	5.4060e+12	3. 0010E+13	2.5852e+12
CEC 2019--02	Mean	4.4258e+02	5.4590e+02	7. 5361E+02	4.0606e+02
	Std	2.3289e+03	2.8949e+03	4. 0324E+03	2.1285e+03
	Best	1.7344e+01	1.7343e+01	**1. 7343E+01**	1.7343e+01
	Worst	1.2773e+04	1.5873e+04	2. 2104E+04	1.1676e+04
CEC 2019-04	Mean	2.2162e+03	2.4826e+03	2. 0009E+03	2.6740e+03
	Std	3.6666e+03	5.8229e+03	5. 1776E+03	3.3938e+03
	Best	7.0170e+01	7.0139e+01	**5. 6584E+01**	7.9404e+01
	Worst	2.0015e+04	3.2105e+04	2. 8801E+04	1.8740e+04
CEC 2019--09	Mean	1.2990e+02	3.7340e+02	2. 5812E+02	1.9688e+02
	Std	4.4838e+02	1.4822e+03	1. 2291E+03	7.7057e+02
	Best	**3.1784e+00**	3.8804e+00	3. 6549E+00	3.4678e+00
	Worst	2.4400e+03	8.1570e+03	6. 7510E+03	4.1742e+03

Metaheuristic optimization algorithms have been preferred in recent years owing to their simplicity and non-adherence to local optimum points [69], [70]. The most commonly used pressures in this study vessel, tension/compression string, three bar truss, gear train, cantilever beam, and welded beam design problems are included. The MATLAB R2021a package program was used for the application of the design problems, 500 iterations were performed in each study, and 30 search agents were used. Thirty independent runs were performed to achieve more objective results, 30 independent runs were performed. The best results are shown in bold font.

A. PRESSURE VESSEL DESIGN PROBLEM

The purpose of the pressure vessel design problem (PVD) is to minimize the total cost of the raw materials, forming, and welding of the pressure vessel.

As shown in Figure 10, this problem comprises four decision parameters the pressure (R), thickness

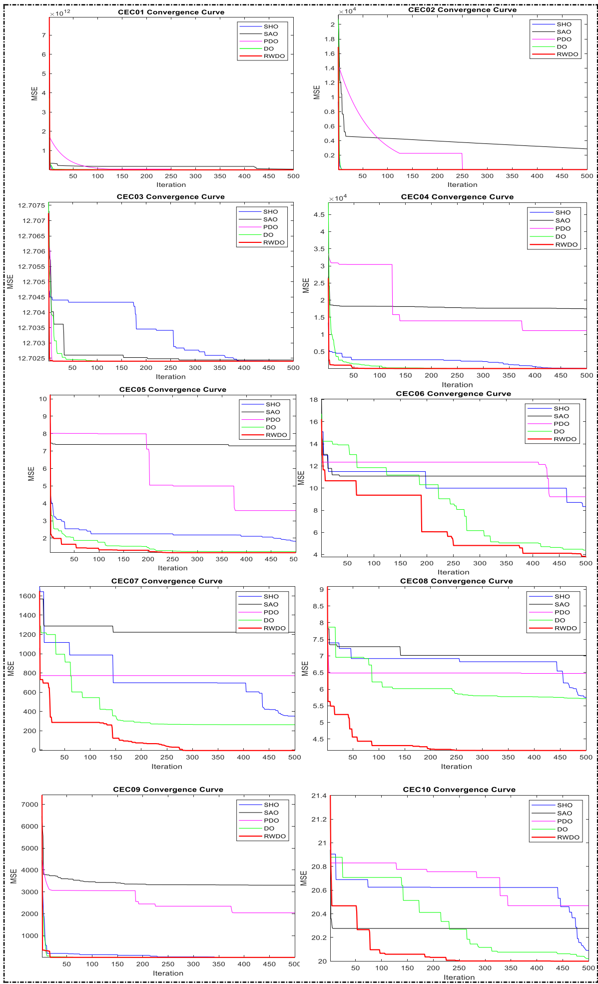

FIGURE 8. Convergence curve of CEC 2019.

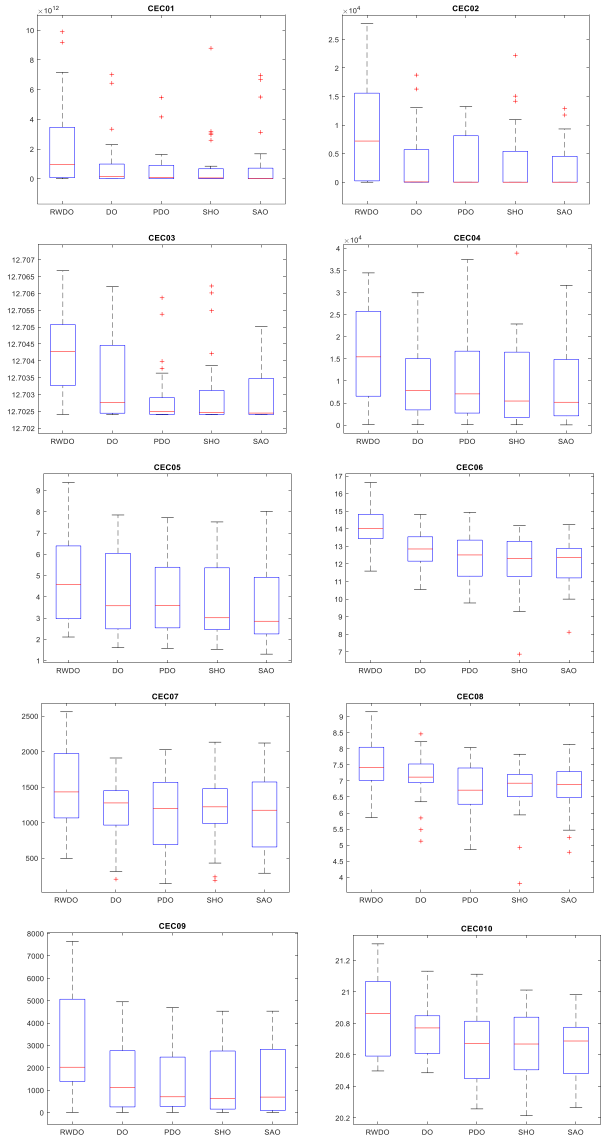

FIGURE 9. Boxplot of CEC 2019.

of the head (T_h), length of the cylindrical section of the vessel (L), and thickness of the shell (T_s). The mathematical model of the PVD is given by Eq. 17 [52], [55].

$$
\begin{aligned}
minf_x &= 0.6224x_1x_3x_4 + 1.7781x_2x_3^2 + 3.1661x_1^2x_4 \\
&\quad + 9.8400x_1^2x_3 \\
\vec{x} &= [\mathrm{T_s}, \mathrm{T_h}, R, L] = [x_1, x_2, x_3, x_4] \\
g_1(\vec{x}) &= -x_1 + 0.0193x_3 \leq 0, \\
g_2(\vec{x}) &= -x_3 + 0.000954x_3 \leq 0, \\
g_3(\vec{x}) &= \pi x_3^2 x_4 - \frac{4}{3}\pi x_3^3 + 1296000 \leq 0, \\
g_4(\vec{x}) &= x_4 - 240 \leq 0. \\
&0 \leq x_1 \leq 99, 10 \leq x_2 \leq 99, \\
&10 \leq x_3 \leq 200, 0 \leq x_4 \leq 200. \qquad (17)
\end{aligned}
$$

Table 13. shows that the proposed RW-DO algorithm in the process of optimizing the PVD problem was compared with alternative algorithms, and it achieved the best results in all statistical results. This proves that the success of the RW-DO algorithm in reaching the The purpose of the

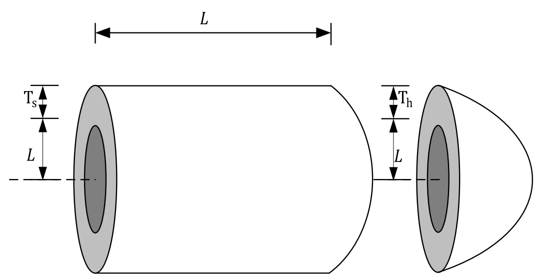

FIGURE 10. PVD model.

tension/compression sequence design problem (SDP) is to minimize the weight of parameters such as wire diameter (x_1), average coil diameter (x_2), and active coil count (x_3). optimal result depends on its success in demonstrating the exploitation-exploration balance.

TABLE 13. PVD analysis results.

algorithm	Basic Parameters				Statistical Results			
	T_s	T_h	R	L	Mean	Std . Dev.	Best v.	Worst v.
HHO	1.0216E+00	4. 7671E-01	4.9904E+01	9.9111E+01	6.6700E+03	4.2427E+02	5.9754E+03	7.7097E+03
GTO	1.2588E+00	6. 1962E-01	6.5223E+01	1.0008E+01	6.3925E+03	5.7068E+02	5.8807E+03	7.2993E+03
SCA	1.3379E+00	6. 3529E-01	6.5348E+01	1.3038E+01	7.4640E+03	7.6054E+02	6.4965E+03	9.0739E+03
GWO	7. 7849E-01	3. 8748E-01	4.0323E+01	2.0000E+02	6.1048E+03	4.1521E+02	5.8888E+03	7.2620E+03
INFO	1.0965E+00	5. 3984E-01	5.6812E+01	5.2065E+01	6.3460E+03	3.6818E+02	5.8807E+03	7.2993E+03
WOA	1.0803E+00	2.9657E+00	4.1207E+01	1.8800E+02	9.3496E+03	2.4017E+03	6.3346E+03	1.5812E+04
DO	0.7782E+00	3. 8310E-01	4.0320E+01	1.9999E+02	6.5013E+03	5.4863E+02	5.8808E+03	7.2863E+03
RW-DO	7.7830 E-01	3. 8309E-01	4.0327E+01	1.9989E+02	**6.1096E+03**	**2.7880E+02**	**5.8806E+03**	**6.9366E+03**

B. TENSION / COMPRESSION STRING DESIGN PROBLEM

mathematical model of the SDP shown in Figure 11 is given by Equation 18 [52], [55].

$$
\begin{aligned}
minf_x &= (x_3+2)\, x_2 x_1^2 \\
\vec{x} &= [W, d, N] = [x_1, x_2, x_3] \\
g_1(\vec{x}) &= 1 - \frac{x_2^3 x_3}{71785 x_1^4}, \\
g_2(\vec{x}) &= \frac{4x_2^2 - x_1 x_2}{12566\left(x_2 x_1^3 - x_1^4\right)} + \frac{1}{5108 x_1^2} - 1 \le 0, \\
g_3(\vec{x}) &= 1 - \frac{140.45 x_1}{x_2^2 x_3} \le 0, \\
g_4(\vec{x}) &= \frac{x_1 + x_2}{1.5} - 1 \le 0 \\
& 0.05 \le x_1 \le 2, \\
& 0.25 \le x_2 \le 1.30, \\
& 2 \le x_3 \le 15.
\end{aligned} \tag{18}
$$

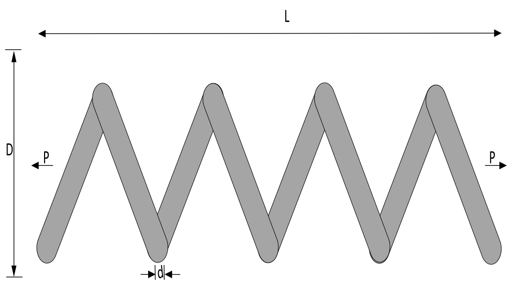

FIGURE 11. SDP model.

Table 14 shows at comparison of the proposed RW-DO algorithm in the optimization process of the SDP design problem with alternative algorithms. It was observed that all the results favored RW-DO, except for the best value in the statistical results. This proves that the success of the RW-DO algorithm in reaching the optimal result depends on its success in demonstrating the exploitation-exploration balance.

C. THREE BAR TRUSS DESIGN PROBLEM

As shown Figure 12, The goal of Three Bar Truss design problem (TBT) is to design a truss structure that minimizes the maximum node displacement without violating constraints such as skew, stress, and deflection.as shown given by Eq 19. [71]

$$
\begin{aligned}
minf\,(x) &= \left(2\sqrt{2}x_1 + x_2\right).l \\
g_1 &= \frac{2\sqrt{2}\,x_1 + x_2}{\sqrt{2}\,x_1^2 + 2x_1 x_2} P \le \sigma, \\
g_2 &= \frac{x_2}{\sqrt{2}\,x_1^2 + 2x_1 x_2} P \le \sigma \\
g_3 &= \frac{1}{x_1 + \sqrt{2}\,x_2} P \le \sigma \\
& 0 \le x_1 \le 1,\ 0 \le x_2 \le 1,\ l = 100cm, \\
& \sigma = 2KN \big/ cm^2,\ and\ P = 2KN \big/ cm^2
\end{aligned} \tag{19}
$$

Table 15 shows at comparison of the proposed RW-DO algorithm in the optimization process of the TBT design problem has been compared with alternative algorithms, and it has been determined that all RW-DO algorithms reach more optimal results in statistical results. According to these results, the RW-DO algorithm proved that its success in reaching the optimal result compared to alternative algorithms depends on its success in showing the exploitation-exploration balance.

TABLE 14. SDP analysis results.

algorithm	Basic Parameters			Statistical Results			
	W	d	N	mean	Std . Giant.	best v.	Worst v.
HHO	5. 6728E-02	4. 9050E-01	6. 2998E+00	1. 3634E-02	9. 2358E-04	1. 2665E-02	1. 6434E-02
GTO	5. 3643E-02	4. 0558E-01	8. 9097E+00	1. 2724E-02	9. 5930E-05	1. 2665E-02	1. 3167E-02
SCA	5. 0000E-02	3. 1091E-01	1. 5000E+01	1. 3283E-02	8. 1156E-04	1. 2761E-02	1. 7287E-02
GWO	5. 0000E-02	3. 1718E-01	1. 4064E+01	1. 2789E-02	1. 5509E-04	1. 2690E-02	1. 3413E-02
INFO	5. 6685E-02	4. 8913E-01	6. 3340E+00	1. 2900E-02	2. 7053E-04	**1. 2666E-02**	1. 3610E-02
WOA	6. 3540E-02	7. 1450E-01	3. 2079E+00	1. 3869E-02	1. 1433E-03	1. 2670E-02	1. 5884E-02
DO	5.0012E-02	3.1740E-01	1. 4029E+01	0.0136E+00	1.1001E-03	1.2700E-02	1.7100E-02
RW-DO	5. 0509E-02	3. 3910E-01	1. 2404E+01	**1. 2700E-02**	**2. 7082E-05**	1. 2700E-02	**1. 2800E-02**

TABLE 15. TBT analysis results.

algorithm	Basic Parameters		Statistical Results			
	A1	A2	mean	Std . Giant.	best v.	Worst v.
HHO	7. 8365E-01	4. 2265E-01	2. 6403E+02	1. 7224E-01	2. 6390E+02	2. 6443E+02
GTO	7. 8868E-01	4. 0824E-01	2. 6390E+02	8. 5564E-05	2. 6390E+02	2. 6390E+02
SCA	7. 9894E-01	3. 8045E-01	2. 6792E+02	7. 5915E+00	2. 6395E+02	2. 8284E+02
GWO	7. 8616E-01	4. 1544E-01	2. 6516E+02	4. 8055E+00	2. 6390E+02	2. 8284E+02
INFO	7. 8864E-01	4. 0834E-01	2. 6390E+02	3. 1691E-05	2. 6390E+02	2. 6390E+02
WOA	8. 4950E-01	2. 5867E-01	2. 6549E+02	1. 8910E+00	2. 6390E+02	2. 7119E+02
DO	7.8740E-01	4.1180E-01	2.6389E+02	2.0000E-03	2.6390E+02	2.6390E+02
RW-DO	7. 8749E-01	4. 1159E-01	2.6389E+02	**2. 0346E-05**	**2.6389E+02**	**2.6389E+02**

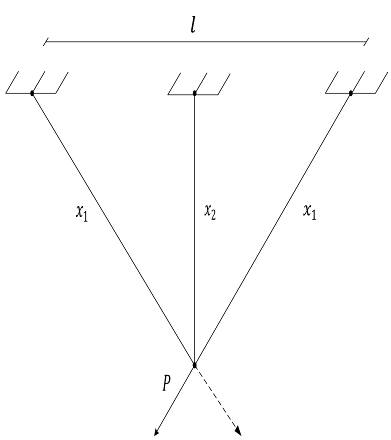

FIGURE 12. TBT model.

D. GEAR TRAIN DESIGN PROBLEM

The goal of the Gear Train design problem (GTD) is to minimize the ratio of the output and input angular velocity variation, as shown in Figure 13. of A, B, C, and D, namely the teeth of the gears. The mathematical model of the GTD is given by Eq.20 [55], [72].

$$
\begin{aligned}
minf\ (x) &= \left(\frac{1}{6.931} - \frac{x_1 x_2}{x_3 x_4}\right)^2 \\
&\vec{x} = [A, B, C, D] = [x_1, x_2, x_3, x_4], \\
&12 \leq x_i \leq 60, \\
&(x_i = x_1, x_2, x_3, x_4)
\end{aligned} \tag{20}
$$

Table 16 shows that the proposed RW-DO algorithm is compared with alternative algorithms in the optimization process of the GTD design problem, and it is observed that it reaches the best value together with GTO and INFO algorithms, but it cannot compete in other statistical results.

E. CANTILEVER BEAM DESIGN PROBLEM

The objective of the cantilever beam design problem (CBD) is to minimize the volume of the beam given by the decision variables for the width or height of the five hollow square blocks with a constant thickness. The mathematical model of the CBD shown in Figure 14 is expressed by

TABLE 16. GTD analysis results.

Algorithm	Basic Parameters				Statistical Results			
	A	B	C	D	mean	Std . Giant.	best v.	Worst v.
HHO	2.0418E+01	2.0050E+01	5.0971E+01	5.5668E+01	2. 5679E-35	1. 4065E-34	**0.0000E+00**	7. 7037E-34
GTO	1.3184E+01	1.3027E+01	2.0339E+01	5.8525E+01	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
SCA	2.3161E+01	2.0577E+01	6.0000E+01	5.5064E+01	8. 5197E-10	1. 1798E-09	1. 2735E-13	4. 5085E-09
GWO	3.3588E+01	1.5432E+01	5.9876E+01	6.0000E+01	3. 0298E-12	6. 8544E-12	1. 1543E-16	3. 0587E-11
INFO	2.6382E+01	1.3840E+01	5.2097E+01	4.8577E+01	**0.0000E+00** _	**0.0000E+00** _	**0.0000E+00** _	**0.0000E+00** _
WOA	1.6561E+01	1.5722E+01	3.3154E+01	5.4435E+01	3. 0026E-20	1. 6446E-19	**0.0000E+00** _	9. 0079E-19
DO	1.3880E+01	2. 4420E+01	3. 9642+01	5. 6993E+01	4. 1159E-03	8. 7326 E-03	1. 6937E-06	4. 6752E-02
RW-DO	1.5452E+01	1.7530E+01	3.3812E+01	5.5527E+01	4. 0760E-22	1. 1361E-21	**0.0000E+00** _	4. 7218E-21

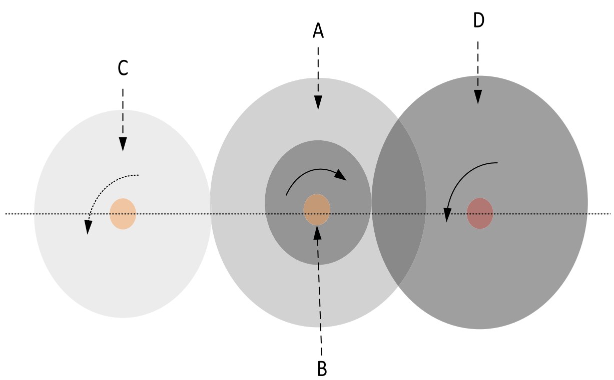

FIGURE 13. GTD model.

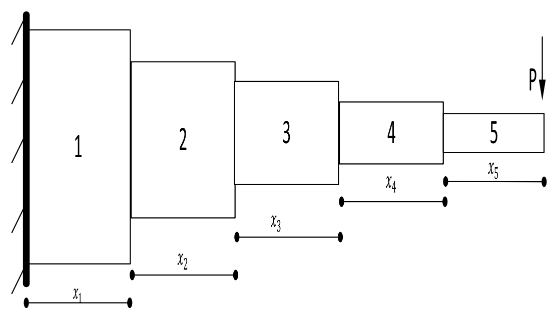

FIGURE 14. CBD model.

Eq. (21) [72].

$$\begin{aligned} minf\ (x) &= 0.0624\,(x_1 + x_2 + x_3 + x_4 + x_5) \\ \vec{x} &= [1, 2, 3, 4, 5] = [x_1, x_2, x_3, x_4, x_5] \\ g_1\,(x_1, x_2, x_3, x_4, x_5) &= \frac{61}{x_1^2} + \frac{37}{x_2^2} + \frac{19}{x_3^2} + \frac{7}{x_4^2} + \frac{1}{x_5^2} \\ &-1 \leq 0, 0.01 \leq x_i \leq 100,\ \ i = 1, 2, 3, 4, 5 \end{aligned} \tag{21}$$

Table 17 shows at comparison of the proposed RW-DO algorithm in the optimization process of the CBD design problem has been compared with alternative algorithms, and it was determined that the entire RW-DO algorithm achieves more optimal results in the statistical results. According to these results, the RW-DO algorithm proved that its success in reaching the optimal result compared to alternative algorithms depends on its success in showing the exploitation-exploration balance.

F. WELDED BEAM DESIGN PROBLEM

The goal of the Welded Beam Design problem (WBD) is to minimize the thickness and length of the welds in the connections. The WBD contains four constraints: shear (τ), beam blending stress(θ), bar-buckling load beam(P_c), and

TABLE 17. **CBD analysis results.**

algorithm	Basic Parameters					Statistical Results			
	one	2	3	4	5	mean	Std . Giant.	best v.	Worst v.
HHO	5.9577E+00	5.2864E+00	4.6978E+00	3.3000E+00	2.2921E+00	1.3443E+00	2.8797E-03	1.3403E+00	1.3527E+00
GTO	5.9990E+00	5.2976E+00	4.4766E+00	3.4898E+00	2.2144E+00	1.3401E+00	3.3789E-04	1.3400E+00	1.3418E+00
SCA	5.7505E+00	7.1043E+00	4.1655E+00	3.5025E+00	1.9848E+00	1.4133E+00	3.0013E-02	1.3525E+00	1.4890E+00
GWO	5.9568E+00	5.3720E+00	4.4890E+00	3.5088E+00	2.1506E+00	1.3401E+00	1.3762E-04	1.3400E+00	1.3406E+00
INFO	5.9754E+00	5.2708E+00	4.5193E+00	3.5243E+00	2.1865E+00	1.3400E+00	7.9641E-05	1.3400E+00	1.3403E+00
WOA	1.0539E+01	7.2551E+00	4.1648E+00	2.6079E+00	1.7295E+00	1.6404E+00	2.8705E-01	1.3601E+00	2.4698E+00
DO	6.0419E+00	5.3048E+00	4.5052E+00	3.4902E+00	2.1323E+00	1.3400E+00	3.7865E-05	1.3400E+00	1.3401E+00
RW-DO	6.0078E+00	5.3278E+00	4.4607E+00	3.4840E+00	2.1959E+00	**1.3400E+00**	**4.7776E-07**	**1.3400E+00**	**1.3400E+00**

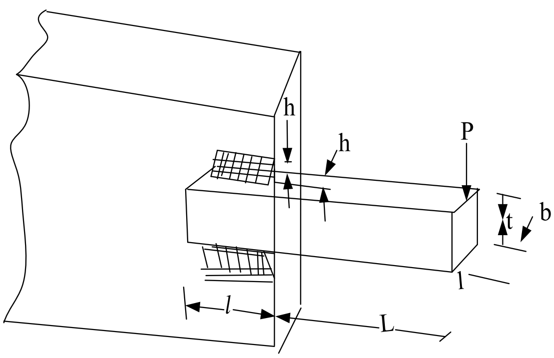

FIGURE 15. **WBD model.**

deflection(δ) of the beam end. The shown in Figure 15 mathematical model of the WBD is given by Eq.22 [52], [55], [72].

$$
\begin{aligned}
&minf\ (x) = 1.10471x_1^2x_2 + 0.04811x_3x_4\,(14 + x_2)\\
&\quad 0.1 \le x_1 \le 2.00,\ 0.1 \le x_2, x_3 \le 10,\\
&\quad 0.1 \le x_4 \le 2.00\\
&\quad \vec{x} = [h, l, t, b] = [x_1, x_2, x_3, x_4]\\
&g_1(\vec{x}) = \tau(x) - \tau_{max} \le 0,\\
&g_2(\vec{x}) = \sigma(x) - \sigma_{max} \le 0,\\
&g_3(\vec{x}) = \delta(x) - \delta_{max} \le 0,\\
&g_4(\vec{x}) = x_1 - x_{max} \le 0,\\
&g_5(\vec{x}) = P - P_c(\vec{x}) \le 0,\\
&g_6(\vec{x}) = 0.125 - x_1 \le 0\\
&g_7(\vec{x}) = 1.10471x_1^2 + 0.04811x_3x_4\,(14 + x_2) - 5 \le 0,\\
&\tau(\vec{x}) = \sqrt{(\tau')^2 + 2\tau'\tau''\frac{x_2}{2R} + (\tau'')^2}\\
&\tau' = \frac{P}{\sqrt{2}\,x_1x_2},\ \tau'' = \frac{MR}{J} M = P\left(L + \frac{x_2}{2}\right)\\
&R = \sqrt{\frac{x_2^3}{4} + \left(\frac{x_1+x_3}{2}\right)^2}\\
&J = 2\left\{\sqrt{2}\,x_1x_2\left[\left(\frac{x_2^2}{4}\right) + \left(\frac{x_1+x_3}{2}\right)^2\right]\right\}\\
&\sigma(\vec{x}) = \left(\frac{6PL}{x_3^2x_4}\right)\\
&\delta(\vec{x}) = \left(\frac{6PL^3}{Ex_3^2x_4}\right)\\
&P_c(\vec{x}) = \frac{4.013E\sqrt{\frac{x_3^2x_4^6}{36}}}{L^2}\left(1 - \frac{x_3}{2L}\sqrt{\frac{E}{4G}}\right),
\end{aligned}
$$

TABLE 18. WBD analysis results.

algorithm	Basic Parameters				Statistical Results			
	h	l	t	b	Mean	Std . Giant.	best v.	Worst v.
HHO	1.2743E-01	5.5663E+00	9.7046E+00	1.8221E-01	1.8116E+00	3.9472E-01	1.5069E+00	3.3980E+00
GTO	2.3219E-01	1.9581E+00	8.5061E+00	2.3219E-01	1.5219E+00	9.4941E-02	1.4730E+00	1.8318E+00 _
SCA	1.4884E-01	3.8373E+00	9.5882E+00	1.8615E-01	1.5952E+00	4.1934E-02	1.5179E+00	1.6963E+00
GWO	1.7582E-01	2.5267E+00	9.5835E+00	1.8303E-01	1.4782E+00	3.0679E-03	1.4745E+00	1.4872E+00
INFO	1.8298E-01	2.4073E+00	9.5818E+00	1.8298E-01	1.4941E+00	1.1067E-01	1.4730E+00	2.0795E+00
WOA	1.3432E-01	3.9653E+00	9.9788E+00	1.8053E-01	2.2776E+00	7.4221E-01	1.5259E+00	3.8609E+00
DO	1.8600E-01	2.3721E+00	9.5016E+00	1.8600E-01	1.4951E+00	5.4900E-02	1.4731E+00	1.7177E+00
RW-DO	1.8280E-01	2.4101E+00	9.5818E+00	1.8300E-01	**1.4731E+00**	**3.4190E-05**	**1.4730E+00**	**1.4731E+00**

$$L = 14in,\ P = 6000lb,\ \delta_{max} = 0.25in,$$
$$E = 3.00E + 06psi,\ G = 1.20E + 07psi$$
$$\tau_{max} = 1.36E + 04psi$$
$$\sigma_{max} = 3.00E + 04psi \quad (22)$$

Table 18 compares the proposed RW-DO algorithm with alternative algorithms in the optimization process of the WBD design problem, and the statistical results show that all RW-DO algorithms achieve more optimal results. According to these results, the RW algorithm has proven its success in reaching the optimal result compared to alternative algorithms, depending on its success in showing the exploration-exploitation balance. Figure 12 shows whether the RW-DO algorithm maintains the exploration-exploitation balance by overcoming the problem of being stuck at the local optimum point in the DO algorithm in the optimization of design problems. It can be seen that the global solutions obtained from 30 independent runs for all problems are more optimal than the DO algorithm solutions. In addition, it can be stated that more stable solutions are produced because the closeness between the results is greater. The RW-DO algorithm improves the DO algorithm in problem solving and leads to more effective use in the industry.

In general, when all the tables from Tables 10 to 15 and Figure 16 are examined, it can be observed that the RW-DO algorithm is the most successful because of the optimization process in all engineering problems. The fact that the results

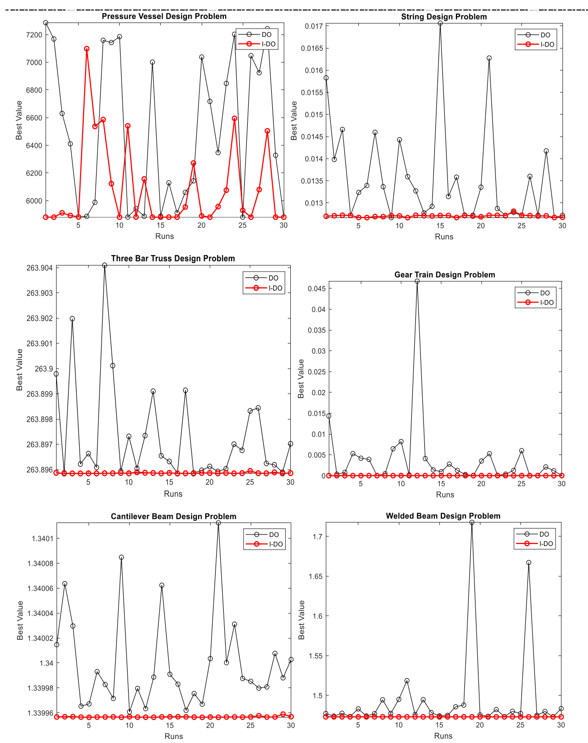

FIGURE 16. Convergence curve of engineering design problem.

of the DO algorithm are more stable and move to the closest vicinity to the best result indicates that the RW-DO algorithm

TABLE 19. Wilcoxon and KS test for 2 samples.

Engineering problem	Test	Metric	PressureVessel Design	String Design	Three bar truss Design	GearTrain Design	CantileverBeam Design	WeldedBeam Design
DO	Wilcoxon	p - value	2.3000E-03	1.9729E-05	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
		W/T/L	W	W	W	W	W	W
	Kolmogorov- smirnov	p - value	4.6000E-03	3.5202E-10	5.6313E-11	1.7973E-14	1.7973E-14	1.4977E-13
		W/T/L	W	W	W	W	W	W
SAO	Wilcoxon	p - value	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
		W/T/L	W	W	W	W	W	W
	Kolmogorov- smirnov	p - value	1.7973E-14	1.7973E-14	1.7973E-14	1.7973E-14	1.7973E-14	1.7973E-14
		W/T/L	W	W	W	W	W	W
SHO	Wilcoxon	p - value	1.4000E-03	4.2857E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
		W/T/L	W	W	W	W	W	W
	Kolmogorov- smirnov	p - value	6.1740E-05	5.6313E-11	1.7973E-14	1.7973E-14	1.7973E-14	1.7973E-14
		W/T/L	W	W	W	W	W	W
SCA	Wilcoxon	p - value	1.9209E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
		W/T/L	W	W	W	W	W	W
	Kolmogorov- smirnov	p - value	8.3836E-12	1.4977E-13	1.7973E-14	1.7973E-14	1.7973E-14	1.7973E-14
		W/T/L	W	W	W	W	W	W
CapSA	Wilcoxon	p - value	2.4000E-03	1.7988E-05	1.7344E-06	8.7000E-03	2.3534E-06	1.4000E-02
		W/T/L	W	W	W	W	W	W
	Kolmogorov- smirnov	p - value	4.6000E-03	2.6199E-07	1.7973E-14	5.5870E-08	1.1088E-08	6.1578E-04
		W/T/L	W	W	W	W	W	W
GTO	Wilcoxon	p - value	2.4300E-02	5.4400E-01	1.7000E-03	2.0000E-03	1.7344E-06	2.1000E-03
		W/T/L	W	L	W	W	W	W
	Kolmogorov- smirnov	p - value	1.0880E-01	7.6000E-01	2.0212E-04	5.5000E-02	1.7973E-14	6.1578E-04
		W/T/L	L	L	W	T	W	W
HHO	Wilcoxon	p - value	4.8603E-05	2.3534E-06	1.9209E-06	2.9000E-03	1.7344E-06	1.7344E-06
		W/T/L	W	W	W	W	W	W
	Kolmogorov- smirnov	p - value	2.3000E-03	1.9729E-05	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
		W/T/L	W	W	W	W	W	W
GWO	Wilcoxon	p - value	4.6000E-03	3.5202E-10	5.6313E-11	1.7973E-14	1.7973E-14	1.4977E-13
		W/T/L	W	W	W	W	W	W
	Kolmogorov- smirnov	p - value	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
		W/T/L	W	W	W	W	W	W
INFO	Wilcoxon	p - value	1.7973E-14	1.7973E-14	1.7973E-14	1.7973E-14	1.7973E-14	1.7973E-14
		W/T/L	W	W	W	W	W	W
	Kolmogorov- smirnov	p - value	1.4000E-03	4.2857E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
		W/T/L	W	W	W	W	W	W
WOA	Wilcoxon	p - value	6.1740E-05	5.6313E-11	1.7973E-14	1.7973E-14	1.7973E-14	1.7973E-14
		W/T/L	W	W	W	W	W	W
	Kolmogorov- smirnov	p - value	1.9209E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
		W/T/L	W	W	W	W	W	W

surpasses the local algorithm with good performance and approaches the best global point. Based on these results, it can be predicted that the RW-DO algorithm will improve the DO algorithm in addressing industrial design problem-solving tasks and provide a more efficient use in various industries.

G. STATISTICAL ANALYSIS

In this paper, the innovative nature and superior performance of the RW-DO algorithm were rigorously evaluated in the previous section through Wilcoxon and Kolmogorov-Smirnov two-sample tests on the CEC 2019 and CEC 2020 function sets. Furthermore, the unique characteristics and superior performance of the RW-DO algorithm in optimizing engineering design problems are listed Table 19. When compared with alternative algorithms, the proposed RW-DO algorithm achieved 56 wins, one till, and three losses in a total of 60 evaluations. These findings highlight the distinctive features of the algorithm and demonstrate its efficacy in practical applications.

V. CONCLUSION AND DISCUSSION

This paper proposes a new algorithm, the random walk dandelion optimizer (RW-DO) algorithm, by hybridizing the DO algorithm with a local search strategy using a random walk style called the random walk. The main advantage of the proposed RW-DO algorithm is that it overcomes the weaknesses of the DO algorithm, which cannot achieve better global results because it is stuck in the local optimum. In this manner, a good balance between the exploration and exploitation phases can be achieved, and solutions closer to the global optimum can be produced.

The performance of the proposed RW-DO algorithm is tested using the CEC2020 and CEC2019 algorithms. In comparison with alternative algorithms selected from current and effective algorithms, it is shown with the help of performance tables and convergence curve graphs that the RW-DO algorithm achieves optimal results in global solutions and shows stable convergence.

When the statistical table results and convergence curve plots of the CEC2020 and CEC2019 functions are evaluated, it is seen that the proposed RW-DO algorithm, thanks to its slow convergence feature and the fact that it prevents the random walks strategy from getting stuck at the local optimum point with the maneuver of diversifying and deviating the solution, the global best solution found converges around the global minimum point.

Considering this evidence, the proposed RW-DO algorithm proved to be the best optimizer compared to the current, efficient, and competitive alternative algorithms presented in this paper.

To examine whether the RW-DO algorithm is a different and superior algorithm for both CEC2020 and CEC2019, normality analysis with the Kolmogorov-Smirnov test was first performed. It was determined that the RW-DO algorithm was not normally distributed. Therefore, that non-parametric tests should be applied. RW-DO was cross-tested using Kolmogorov-Smirnov and Wilcoxon signed-rank tests for two samples, and it was found that RW-DO is a unique algorithm with a separate dataset. At the same time, it is found to be more advantageous than alternative algorithms that produce stable results owing to its good exploration-exploitation balance.

Six engineering design problems were solved to observe the success of applying RW-DO to real-world problems. The results returned by RW-DO were compared with those of alternative metaheuristic algorithms, and it was observed that it achieved the most optimal results. The results of 30 independent runs of the RW-DO and DO algorithms for solving engineering design problems were monitored using convergence curve plots, and it was observed that the algorithm achieved the best global results and provided stable results. Based on these results, it is concluded that the RW-DO algorithm overcomes the weaknesses of the DO algorithm and has a more effective structure.

This paper examined the algorithm's parameter sensitivity, facilitating a more comprehensive understanding of the optimal settings in diverse problem domains. The algorithm may experience a reduction in speed of optimization when adapting to complex problems; however, this can be attributed to the provision of in-depth solutions for more challenging tasks. This characteristic is advantageous in scenarios requiring a meticulous solution process. With enhancements to the original dandelion optimizer, the RW-DO algorithm demonstrates superior performance, particularly in complex optimization problems. The risk of entrapment in local optima can be addressed to increase the potential of the algorithm to attain the global optimum, further enhancing its efficiency. Population limitations can be mitigated through the implementation of novel strategies for exploring large solution spaces, enabling the effective utilization of larger and more diverse optimization problems. The capabilities of the algorithm can be augmented to ensure sufficient convergence accuracy, facilitating greater success in complex real-world optimization tasks. These potential improvements will enhance the performance of the algorithm, enabling it to effectively solve larger and more diverse optimization problems, thereby increasing its efficiency in future applications.

In future research, based on the solution success of the RW-DO algorithm, the random walk strategy can be hybridized with other algorithms to obtain more useful and powerful new structures. Similarly, for the DO algorithm, new hybrid structures can be obtained by using other strategies. It is clear from the changes in the solution graphs that the DO algorithm has a flexible structure that is compatible with new structures. This study can also be evaluated in different studies for the random walk local search strategy and the DO algorithm and can serve as a source of inspiration for real-world problems. Flexible structure that is compatible with new structures. This study can also be evaluated in different studies for the random walk local search strategy and the DO algorithm and can serve as a source of inspiration for real-world problems. the DO algorithm and can serve as a source of inspiration for real-world problems.

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