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ORIGINAL ARTICLE

A modified grey wolf optimizer for wind farm layout optimization problem

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Abstract The optimal solution to the wind farm layout optimization problem helps in maximizing the total energy output from the given wind farm. Meta-heuristic algorithms are one of the famous methods for achieving this objective. In this paper, we focus on developing an efficient meta-heuristic based on the grey wolf optimizer for solving the wind farm layout optimization problem. The proposed algorithm is called enhanced chaotic grey wolf optimizer and it is introduced after validating it on a well-known benchmark set of 23 numerical optimization problems. By confirming its efficiency through these benchmarks, it is utilized for wind farm layout optimization. The proposed algorithm is comprised of four search strategies including a modified GWO search mechanism, modified control parameter, chaotic search, and adaptive re-initialization of poor solutions during the search. Two case studies of the wind farm layout optimization problem are considered for numerical experiments. Results are analyzed and compared with other state-of-the-art algorithms. The comparison indicates the efficiency of the proposed algorithm for solving numerical and wind farm layout optimization problems.

Keywords Optimization · Wind farm layout · Wind turbine · Meta-heuristic algorithms · Grey wolf optimizer · Nature-inspired algorithms

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1 Introduction

In the field of renewable energy, the wind farm layout optimization problem (WFLOP) is a popular optimization problem, which is a wind energy system to maximize the total energy output of the farm. The total energy output of the farm depends on the optimal configuration of the wind turbines, such as rotor radius, hub height, and optimal location of the wind turbines. The total energy output of a wind farm is also affected by other factors. However, this paper considers only three wind turbine parameters: wind turbine location, rotor radius, and hub height. All of these have a significant impact on energy production. In this regard, we maximize the total energy output of a wind farm by adjusting these parameters of the problem. In the literature, many traditional and non-traditional algorithms have been applied to solve the wind farm layout optimization problem.

In the work of Mosetti et al. (1994), Grady et al. (2005), Chen et al. (2013), genetic algorithms are used to extract the maximum energy with the minimum installation costs. For the wind turbines, they used 100 square cells as possible locations. In the work of Mittal et al. (2016b), a novel combination of probabilistic genetic algorithms and deterministic gradient-based optimization algorithms, to simultaneously determine the optimum total number of turbines to be placed in a wind farm along with their optimal locations. In the work of Ulku and Alabas-Uslu (2019), a new nonlinear mathematical model for the layout of wind turbines under multiple wake effects is proposed considering two objective functions separately: maximization of total power production and minimization of cost per power. In the work of Patel et al. (2017), a novel algorithm based on teaching-learning-based optimization (TLBO) is proposed for an effective solution for the optimum placement of wind turbines. Biogeographical-based optimization (BBO) (Pouraltafi-Kheljan et al. 2018; Bansal and Farswan 2017; Bansal et al. 2018) and random search (Feng and Shen 2015) are used for the optimal solution of wind farm layout optimization problem. An adaptive genetic algorithm with monte-carlo tree search reinforcement learning (Bai et al. 2022) is used to solve this same problem. In this paper, the exploitation ability in the adaptive genetic algorithm is improved by casting the relocation of multiple wind turbines into a single-player reinforcement learning problem, which is addressed by monte-carlo tree search embedded within the evolutionary algorithm. In the work of Manikowski et al. (2021), a single objective hill-climbing algorithm (HCA) and three multi-objective evolutionary algorithms (NSGA-II, SPEA2, and PESA-II) are applied to solve the similar optimization problem which is used in Mosetti et al. (1994). In the work of Long et al. (2020), Froese et al. (2022), Ju and Liu (2019), Xue and Shen (2020), an adaptive differential evolution algorithm (ADE) is proposed to solve the wind farm layout model. The adaption mechanism of ADE benefits the automatic adjustment of parameters in the mutation and crossover operators to achieve the optimal solution.

In this paper, we apply the modified version of GWO to solve the WFLOP. GWO (Mirjalili et al. 2014) is one of the efficient swarm intelligence-based algorithms. Due to its simplicity and efficiency, it has been used for solving several optimization problems including optimization of PID controller parameters (Das et al. 2015), non-convex economic load dispatch problem (Kamboj et al. 2016), flow shop scheduling problem (Komaki and Kayvanfar 2015), training multi-layer perceptron (MLP) (Mirjalili 2015), wireless sensor networks (Pitchaimanickam 2022; Bera et al. 2021), feature selection (Al-Tashi et al. 2020; Hu et al. 2021; Chantar et al. 2020). It has been observed that in some complex optimization problems, the GWO suffers from premature convergence, and has poor exploration (Bansal and Singh 2021; Meidani et al. 2022; Mittal et al. 2016a; Cai et al. 2019; Mirjalili et al. 2020). To overcome these drawbacks, many researchers have tried to improve the search process of the GWO algorithm using different mechanisms. For example—In the work of Ibrahim et al. (2018), a chaotic opposition-based GWO with DE and disruption operator called COGWO2D is introduced. A chaotic map and the OBL are used to initialize the population, which helps to avoid the drawbacks of the random population. Then, the DE operators are combined with the GWO algorithm, which works as a local search mechanism to improve the exploitation ability. The disruptive operator is used to enhance the exploration ability of the algorithm. To improve the performance of the GWO algorithm, a new version of the GWO, namely mutation-driven modified grey wolf optimizer (MDM-GWO) (Singh and Bansal 2022) is proposed. The MDM-GWO combines a new update search mechanism, modified control parameter, mutation-driven scheme, and greedy approach of selection in the search procedure of the GWO. In the work of Yu et al. (2021), an opposition-based learning (OGWO) is proposed to improve the performance of GWO. In the work of Hu et al. (2022), a new variant of GWO called SCGWO is proposed with an improved spread strategy and a chaotic local search (CLS) mechanism to improve search ability and convergence speed. The first strategy is added to the agents around the current position so that the GWO has more chances to find the global optimal solution and the chances of stagnation at the local optima can be avoided. The second strategy, called CLS with shrinkage characteristics, is used to improve the exploration ability of the GWO. An adaptive grey wolf optimizer (AGWO) (Meidani et al. 2022) is proposed to tune the exploration/exploitation parameters based on the fitness history of the candidate solutions during the optimization. AGWO automatically converges to a sufficiently good optimum in the shortest time by controlling the stopping criteria. To improve the exploration ability of the GWO, an improved covariance matrix evolution GWO (GWOC-MALOL) (Hu et al. 2021) is proposed. In this algorithm, the levy-flight mechanism, orthogonal learning strategy, and CMA-ES are added to improve the search quality of the classical GWO. In the work of (Banaie-Dezfouli et al. 2021), a representative-based grey wolf optimizer (R-GWO) is proposed. In R-GWO, a representative-based hunting search strategy is introduced, which is a combination of three effective trial vectors inspired by the behaviors of alpha wolves.

This paper proposes a new variant of GWO called enhanced chaotic grey wolf optimizer (EC-GWO) which is tested over a set of 23 well-known benchmark problems including unimodal, multimodal, and fixed-dimensional multimodal problems. Moreover, the proposed EC-GWO is applied to solve WFLOP. The main contributions of this paper are summarized as follows:

- A new variant of GWO, named enhanced chaotic grey wolf optimizer (EC-GWO), is proposed for solving WFLOP.
- In the proposed EC-GWO, four search strategies, a modified search mechanism, modified control parameter, chaotic search, and adaptive re-initialization of poor solutions during the search are incorporated with the classical GWO.
- The performance of the proposed EC-GWO on a set of well-known benchmark problems is evaluated and compared with seven other meta-heuristic algorithms.
- EC-GWO is applied to solve the wind farm layout optimization problem (WFLOP).
- The experiment results on benchmark problems and WFLOP indicate that the proposed EC-GWO algorithm is an efficient and reliable solver for WFLOP.

The rest of the paper is organized as follows: Sect. 2 describes the background i.e., wind farm layout optimization problem modelling and GWO working frame work. In Sect. 3, EC-GWO is proposed and analyzed. Section 4 validates the proposed EC-GWO on a well-known set of benchmark problems and compares its performance with other algorithms. EC-GWO is applied to solve the wind farm layout optimization problem in the same section. Finally, Sect. 5 concludes the work and suggests some future research ideas.

2 Background

This section presents the details of the wind farm layout optimization problem (WFLOP) and the classical grey wolf optimizer (GWO).

2.1 Wind farm layout optimization problem (WFLOP)

Wind farm layout optimization (WFLO) is the pattern of wind turbines scheme subject to the constraints related to the position of the turbines, rotor radius, and hub height. In the wind farm layout optimization problem (WFLOP) model, the objective function is the maximization of expected power. The solution of this problem is to find the optimal placement of wind turbines so that the expected energy output of the whole wind farm is maximum. For the WFLOP, two case studies are considered, which include 26 and 30 turbines in the farm size of 2 km × 2 km. The wind farm is subdivided into 100 grids each of size 200 m × 200 m.

In the WFLOP, i^{th} solution is represented by $(p_i^{wt}, q_i^{wt}, r_i^{wt}, h_i^{wt})$, where (p_i^{wt}, q_i^{wt}) is the position of the wt^{th} wind turbine, r_i^{wt} is the radius of the wt^{th} wind turbine, and h_i^{wt} is the height of the wt^{th} wind turbine.

2.1.1 *Jensen's wake model*

Firstly, Jensen's wake model (Mosetti et al. 1994) was used with a genetic algorithm in solving the wind farm optimization problem. Assuming that the momentum is conserved in the wake, the downstream wind speed in j^{th} turbine under the influence of i^{th} turbine is calculated using Eq.(1):

$$u_j = u_{0j}(1 - vd_{ij}) \tag{1}$$

where u_{0j} is the free stream wind speed at j^{th} turbine, and vd_{ij} is the velocity deficit induced on position j by the wake generated by i, which is computed in Eq. (2):

$$vd_{ij} = \left(\frac{ka}{1 + \alpha_i \frac{d_{ij}}{r_i'}} \right) \tag{2}$$

where d_{ij} is the distance between i^{th} and j^{th} turbine. k is a constant value, and a is the induction factor defined in Eq. (3).

$$a = \frac{1 - \sqrt{(1 - C_{wt})}}{2} \tag{3}$$

C_{wt} is the thrust coefficient of the wind turbine, which is fixed for all turbines. α_i is the entrainment constant pertaining to i^{th} turbine and r_i' is the downstream rotor radius of i^{th} turbine, which is find out by the following Eqs. (4)-(5).

$$\alpha_i = \frac{0.5}{\ln\left(\frac{h_i}{z_0}\right)} \tag{4}$$

where h_i is the hub height of i^{th} turbine and z_0 is the surface roughness of wind farm.

$$r_i' = r_i \sqrt{\frac{(1 - a)}{(1 - 2a)}} \tag{5}$$

For the linear wake model, the wake region is conical and represented by the wake influence radius, which is represented in Fig. 1. The wake region is defined in Eq. (6):

$$R_{wi} = \alpha_i d_{ij} + r_i \tag{6}$$

In the instance of a wind turbine encountering multiple wakes, the kinetic energy of the mixed wake can be assumed to be equal to the sum of the kinetic energy deficits. The following Eq. (7) shows the velocity downstream of N_{wt} turbines:

$$u_k = u_{0k}\left[1 - \sqrt{\sum_{m=1}^{N_{wt}} \left(1 - \frac{u_{km}}{u_{0m}}\right)^2}\right] \tag{7}$$

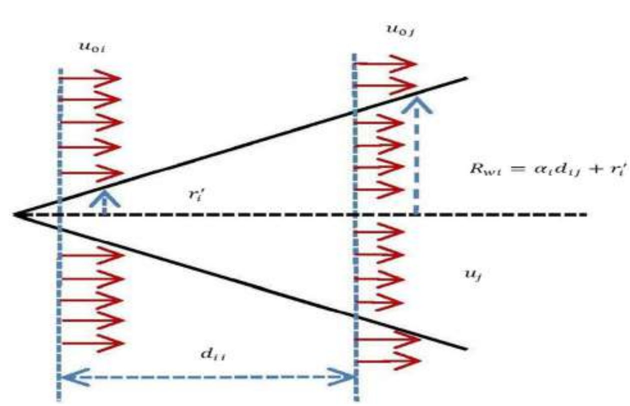

Fig. 1 Linear wake model of wind turbine

where u_{0k} and u_{0m} are the free stream wind velocity without wake effect at *kth* and *mth* turbine, respectively. u_{km} is the wind velocity at *kth* turbine under the wake region of *mth* turbine.

2.1.2 Power output model

P_{total} is the total power output and is given by Eq. (8):

$$P_{total} = \sum_{i=1}^{N_{wt}} P_i \tag{8}$$

Here P_i is the power output from the i^{th} turbine. The detailed calculation of P_i and associated terms are explained in Jensen's wake mode, which is given in the following Eq. (9).

$$P_i = 0.5\rho\pi r_i^2 u_i^3 \frac{C_p}{1000} KW \tag{9}$$

where ρ is the air density and C_p is the rotor efficiency.

The objective of the WFLOP is to find the optimal layout of all the wind turbines to maximize the power output and minimize the cost of a wind farm, given in Eq. (10).

$$Objective = \frac{Cost}{P_{total}} \tag{10}$$

where '*Cost*' represents the cost of the wind farm, which considered Mosetti's cost model (Mosetti et al. 1994) having N_{wt} number of turbines and defined in Eq. (11):

$$Cost = N_{wt}\left(\frac{2}{3} + \frac{1}{3}\exp^{-0.00174N_{wt}^2}\right) \tag{11}$$

In this function, the *Cost* is directly proportional to the number of turbines N_{wt} and consists of two terms: a constant term and a variable term which depends on an exponential function. The variable term decreases as the number of turbines increases.

2.2 Grey wolf optimizer

The Grey wolf optimizer (GWO) algorithm is one of the meta-heuristic algorithms inspired by the leadership hierarchy and social behavior of grey wolves. Within the pack of grey wolves, wolves are divided into four different types of wolves, namely alpha (α), beta (β), delta (δ), and omega (ω). The wolves (α, β, and δ) are known as leading wolves and are used to guide the remaining wolves of the pack to approach the prey. In the GWO, three main steps are performed to complete their search procedure, including encircling, hunting, and attacking the prey. All these steps are explained as follows:

The encircling behavior of grey wolves is modeled mathematically through Eqs. (12) and (13).

$$X_{i,j}^{(t+1)} = X_{prey,j}^t - A_{i,j}^t \times D_{i,j}^t \tag{12}$$

$$D_{i,j}^t = |C_{i,j}^t \times X_{prey,j}^t - X_{i,j}^t| \tag{13}$$

where $X_{i,j}^{(t+1)}$ and $X_{i,j}^{(t)}$ are the j^{th} components of the the updated and current states of wolves X_i. $X_{prey,j}^t$ refers to the j^{th} component of the prey location, t represents the iteration counter. A^t, and D^t are the coefficient vectors which are calculated using Eqs. (14) and (15):

$$A_{i,j}^t = (2 \times rand_1 - 1) \times a^t \tag{14}$$

$$C_{i,j}^t = 2 \times rand_2 \tag{15}$$

where $rand_1$ and $rand_2$ are uniformly random numbers in the range (0, 1). The parameter a is a linearly decreasing variable from 2 to 0 over the iterations, which is calculated by the Eq. (16):

$$a^t = 2 - 2 \times \left(\frac{t}{t_{max}}\right) \tag{16}$$

t_{max} refers to the maximum number of iterations.

During the hunting process, wolves' positions are updated based on the three leading wolves, as the algorithm assumes that they have better knowledge about the location of the prey. The mathematical model of the hunting process is described in Eq. (17):

$$X_{i,j}^{(t+1)} = \frac{X_1^{(t+1)} + X_2^{(t+1)} + X_3^{(t+1)}}{3} \tag{17}$$

where

$$X_1^{(t+1)} = X_{\alpha,j}^t - A_{\alpha,j}^t \times D_{\alpha,j}^t \tag{18}$$

$$X_2^{(t+1)} = X_{\beta,j}^t - A_{\beta,j}^t \times D_{\beta,j}^t \tag{19}$$

$$X_3^{(t+1)} = X_{\delta,j}^t - A_{\delta,j}^t \times D_{\delta,j}^t \tag{20}$$

$$D_{\alpha,j}^t = |C_{\alpha,j}^t \times X_{\alpha,j}^t - X_{i,j}^t| \tag{21}$$

$$D_{\beta,j}^t = |C_{\beta,2}^t \times X_{\beta,j}^t - X_{i,j}^t| \tag{22}$$

$$D_{\delta,j}^t = |C_{\delta,3}^t \times X_{\delta,j}^t - X_{i,j}^t| \tag{23}$$

where $A_{\alpha,j}^t$, $A_{\beta,j}^t$, and $A_{\delta,j}^t$ show the uniformly random numbers in the range $(-2, 2)$ at t^{th} iteration and calculated by Eq. (14). $C_{\alpha,j}^t$, $C_{\beta,j}^t$, and $C_{\delta,j}^t$ are uniformly random numbers in the range (0, 2) at t^{th} iteration which is calculated using the Eq. (15). $X^t_{\alpha,j}$, $X^t_{\beta,j}$, and $X^t_{\delta,j}$ are the j^{th} components of leading wolves α, β and δ, respectively which are calculated using Eqs. (18)-(20). The coefficient vectors $D^t_{\alpha,j}$, $D^t_{\beta,j}$, and $D^t_{\delta,j}$ are calculated using Eqs. (21)-(23). The pseudo-code of the classical GWO is presented in Algorithm 1.

this may result premature convergence. In the literature, various position-updated equations have been proposed (Long et al. 2018; Singh and Bansal 2022; Heidari and Pahlavani 2017) to deal with this drawback of GWO. Enhancing the information-exchange mechanism among

Algorithm 1 Pseudo-code of the classical GWO

Input: N, t_{max}, a, A, and C
Output: fittest wolf (α score)
Initialize the position of the wolves X_i, $(i = 1, 2, \dots, N)$
Calculate the fitness value of each grey wolf $f(X_i)$
Select leader wolves from the population
Initialize the iteration counter $t = 0$ and function evaluation $FES = N$
while ($t < t_{max}$ and $FES < FES_{max}$) **do**
  Update the position of each wolf using eq. (17)
  Calculate the fitness value of each wolf
  $FES = FES + 1$
  Update a, A and C
  Update leading wolves of the population
  $t = t + 1$
end while
Return α score

3 Proposed method

3.1 Motivation

As aforementioned in the classical GWO, wolves update their positions with the help of the leader wolves (α, β, and δ). If the leader wolves are not enough good, this behavior may occasionally, mislead the pack towards the local optima which results the algorithm's premature convergence. With this drawback, GWO faces an imbalance between exploration and exploitation. The linear change in the control parameter a is one main factor behind this imbalance. To deal with this situation and improve the search efficiency of the GWO, we have applied four search strategies in GWO namely, a modified search mechanism, modified control parameter, chaotic search, and adaptive re-initialization of poor solutions during the search. A brief description of each applied strategy is provided in the following subsections:

3.2 Modified search mechanism

It is clear from Eq. (17) that the search in GWO significantly relies on the state of leader wolves. This search behavior degrades the exploration or diversity feature of the algorithm, and for complex and multimodal problems, the wolves may reduce this shortcoming more efficiently. Therefore, to improve the exploration ability of the algorithm and to increase the information-exchange mechanism among the wolves, we have introduced a new position update equation in the classical GWO, which is inspired by the weighted center learning method (WCL) (Sun and Chen 2021; Deng et al. 2019). The WCL assigns a weight to each individual based on their fitness so that better solutions can contribute more than poor solutions. In this approach, a new modified search equation in GWO is introduced in Eq. (24):

$$Y^{(t+1)}_{i,j} = X^t_{wcl,j} - A^t_{i,j} \times D^t_{wcl,j} \tag{24}$$

where $X^t_{wcl,j}$ is the j^{th} component of the weighted average vector at t^{th} iteration. The weight is determined by the fitness of each wolf. Since the weight of an individual has a negative correlation with individual fitness, a linear normalization method is used to obtain the weighted average vector. The weighted average vector X^t_{wcl} is calculated using Eq. (25):

$$X^t_{wcl,j} = \sum_{i=1}^{n} \frac{(F^t_{max} - F(X^t_i))}{\sum_{p=1}^{n}(F^t_{max} - F(X^t_i) + \theta)} X^t_{i,j} \tag{25}$$

where F^t_{max} is the fitness of the worst solution in the population, $F(X^t_i)$ is the fitness of the i^{th} wolf and θ is a non-zero positive small real number to prevent the denominator from being zero. n indicates the number of leader wolves which is obtained using the following Eq. (26):

$$n = round\left(N - (N-1) \times \frac{t}{t_{max}}\right) \tag{26}$$

Here N is the total number of grey wolves. t and t_{max} are the current iteration counter and maximum number of iterations, respectively. In Eq. (24), the difference vector $D^t_{wcl,j}$ is obtained using the following Eq. (27).

$$D^t_{wcl,j} = |C^t_{i,j} \times X^t_{wcl,j} - X^t_{i,j}| \tag{27}$$

where $A^t_{i,j}$ and $C^t_{i,j}$ are obtained using Eqs. (14) and (15), respectively. From Eq. (26), it can be seen that the number of leader wolves used to define the weighted average vector is decreased with iteration t. At the initial iteration of the algorithm, the number of leading wolves (n) equals the total number of grey wolves, which supports the exploration. When the number of leading wolves decreases with the iteration, then the exploration phase transits to the exploitation phase. This transition provides a balance between diversity and convergence. Using the WCL approach, in the initial phases of the search procedure, new solutions are discovered using the guidance of each wolf of the population. In contrast, in the later phases of the search, only the best-fitted wolves are used to guide the search procedure by other wolves. In this way, more iterations are being used for exploring the solution space.

After updating the positions of wolves, a greedy selection approach decides whether the obtained new positions of wolves ($Y^{(t+1)}_{i,j}$) will survive in the next iteration or not. Mathematically, considering the optimization problem is minimization, the greedy selection approach can be defined with the help of Eq. (28):

$$X^{(t+1)}_{i,j} = \begin{cases} Y^{(t+1)}_{i,j}, & f(Y^{(t+1)}_i) \leq f(X^t_i) \\ X^t_{i,j}, & otherwise \end{cases} \tag{28}$$

where $f(Y^{(t+1)}_i)$ is the fitness of the i^{th} wolf at $(t+1)^{th}$ iteration and $f(X^t_i)$ is the fitness of the i^{th} wolf at t^{th} iteration.

3.3 Modified control parameter

According to (Mirjalili et al. 2014) the parameters 'A' and 'C' are two parameters that control the flow of exploration and exploitation within the GWO algorithm. The value $|A| > 1$ facilitates the exploration, and the value $|A| < 1$ refers to exploiting the solution space. The control parameter 'a' directly affects the parameter A, which decreases linearly from 2 to 0 through iterations. An appropriate selection of the control parameter 'a' is important to balance exploration and exploitation. In the first half of the search procedure of the GWO, the parameter 'a' with the linearly decreasing strategy is good at exploration but poor for convergence. In contrast, in the next half search procedure, this parameter is good for exploitation but easily trapped in the local optima due to insufficient exploration ability. This approach of parameter 'a' may not be suitable for providing high quality solutions. Hence, a modification in this parameter is required that may provide a sufficient amount of exploitation and exploration for the search procedure of GWO. In this work, we have improved the modification strategy of the control parameter 'a' through iterations. The improved strategy reduces 'a' nonlinearly resulting in more exploitation of identified regions during the exploration process. We have chosen a nonlinear function to select the parameter 'a'. This approach has also been used in other study (Long et al. 2019). The mathematical formulation for the parameter a is given by Eq. (29)

$$a^t = (a_{initial} - a_{final}) \times \exp\left(-\frac{t}{k \times t_{max}}\right)^2 + a_{final} \tag{29}$$

where $a_{initial}$ and a_{final} are the initial and final value of the parameter a which is fixed to 2 and 0, respectively. k is a modulation index that is fixed to be 0.2. Figure (2) shows the comparison graph of the original linearly decreasing strategy and the proposed nonlinear decreasing strategy. From Fig.

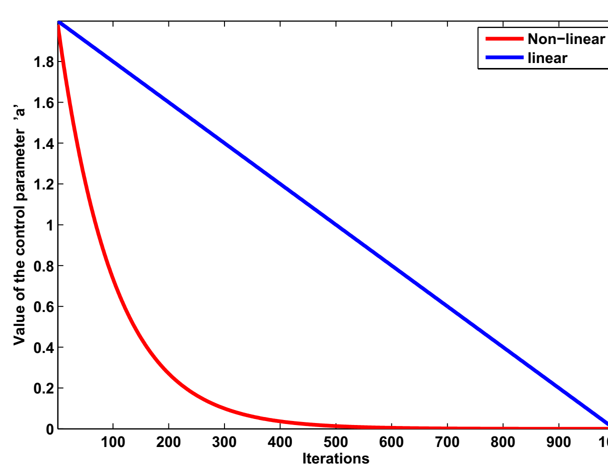

Fig. 2 Comparison of linear and nonlinear control parameter 'a'

(2), it is clear that our approach for setting the parameter 'a' focuses more on exploitation and less on exploration. Thus the proposed 'a' brings early exploitation in the search process. The reason for adopting this setting is to ensure the balance between exploration and exploitation as high exploration has already been achieved in the strategy proposed in Sect. 3.2.

3.4 Chaotic local search

In this subsection, we will define our third strategy called chaotic local search (CLS). The CLS is employed in GWO to improve the local search of the algorithm. Our modified search scheme, as explained in subsection 3.2 has been applied to increase the exploration ability of the algorithm. However, with the exploration of solution space, exploitation of discovered search areas is necessary to prevent skipping promising solutions. Therefore, the CLS scheme has been applied to the proposed algorithm to further exploit the discovered search areas. The chaotic search is an approach to perform the search faster than the ergodic search (dos Santos Coelho and Mariani 2008; Alatas 2010; Jia et al. 2011; Gao et al. 2019). The search process of CLS is based on the regularity of chaos, and it is very sensitive to its initial condition. A huge number of sequences can be obtained by only changing their initial values. The advantage of CLS lies in its randomicity which helps in avoiding the problem of stagnation. Mathematically, CLS is defined by the following Eq. (30):

$$Z_{i,j}^{t+1} = X_{i,j}^{t} + R \times (UB_j - LB_j) \times (C_{no}^{t} - 0.5) \tag{30}$$

where $X_{i,j}^{t}$ is the position of the i^{th} wolf at t^{th} iteration. UB_j and LB_j are the upper and lower bounds of the search space in j^{th} dimension. $R \in (0, 1)$ denotes the chaotic search radius to control the search range. C_{no}^{t} is the logistic chaotic function that is used in t^{th} iteration in the chaotic local search to generate a chaotic sequence (Zhenyu et al. 2006). In this paper, we have taken the initial value of C_{no}^{t} is 0.7. It is defined in the following Eq. (31):

$$C_{no}^{t+1} = \mu \times C_{no}^{t} \times (1 - C_{no}^{t}) \tag{31}$$

After each performance of CLS, if the new fitness is better than the current fitness value, then the solution with new fitness replaces itself to go to the next iteration, while the others stay the same in the next iteration.

3.5 Re-initialization

In the proposed algorithm, we have re-initialized the poor wolves only when they do not improve their states in terms of fitness up to a predefined number of iterations. It can be assumed that these wolves are potentially weak to update their states. Therefore, a restart mechanism is required to pull out these unfit wolves from the optimization procedure, and random solutions distributed in the solution space will be inserted in place of them. To decide whether a particular wolf is unfit or not, we assigned a counter for each wolf of the population. If any wolf cannot achieve its better state, a counter associated with that wolf is increased to 1. This counter value is rechecked in each iteration and compared with the preset threshold limit C_L. If the counter reaches to this limit, the corresponding wolf is re-initialized using the following Eq. (32).

$$X_{i,j}^{(t+1)} = \begin{cases} LB_j + rand \times (UB_j - LB_j), & counter_i > C_L \\ \text{no change}, & otherwise \end{cases} \tag{32}$$

where $X_{i,j}$ is the j^{th} component of the i^{th} wolf, $counter_i$ is counter associated with wolf X_i. LB_j, and UB_j are the j^{th} components of the lower and upper bounds of the search space. $rand(0, 1)$ is a uniformly distributed random number in the range 0 and 1. The proposed strategy is inspired by the artificial bee colony (ABC) (Karaboga et al. 2005). The pseudo-code and flow chart of the proposed EC-GWO are presented in Algorithm 2 and Fig. (3), respectively.

Algorithm 2 Pseudo-code of the proposed EC-GWO

```
Input: N, t_max, FES_max, a_initial, a_final, A, C, C_L, C_no^0, k
Output: fittest wolf (α score)
Initialize the position of the wolves X_i, (i = 1, 2, ..., N)
Calculate the fitness value of each wolf f(X_i)
Select the fittest wolf (α score) of the current population
Initialize the iteration counter t = 0, function evaluation FES = N, and counter = 0
while (t < t_max and FES < FES_max) do
  Update the control parameter 'a' using eq. (29)
  for i=1:N do
    Obtain the position Y_i^{t+1} of wolf X_i^t using eq. (24)
    Calculate the fitness value f(Y_i^{t+1}) at Y_i^{t+1}
    FES = FES + 1
    Apply greedy selection:
    if f(Y_i^{t+1})<f(X_i^t) then
      X_i^{t+1}=Y_i^{t+1}
      counter(i)=0
    else
      X_i^{t+1}=X_i^t
      counter(i) = counter(i) + 1
      Obtain the position Z_i^{t+1} of wolf X_i^t using eq. (30)
      Calculate the fitness value f(Z_i^{t+1}) at Z_i^{t+1}
      FES = FES + 1
      Apply greedy selection:
      if f(Z_i^{t+1})<f(X_i^t) then
        X_i^{t+1}=Z_i^{t+1}
        counter(i)=0
      else
        X_i^{t+1}=X_i^t
        counter(i) = counter(i) + 1
      end if
    end if
    if counter(i) ≥ C_L then
      Re-initialize the position of the wolf using eq. (32)
      Calculate the fitness value f(X_i^{(t+1)}) of the wolf
      FES = FES + 1
      counter(i) = 0
    end if
  end for
  t = t + 1
end while
Return: α score
```

4 Experimental results

The proposed EC-GWO is first tested over a set of 23 well-known benchmark problems in Sect. 4.1 and then applied to solve the WFLOP in Sect. 4.2.

4.1 Testing on benchmark problems

4.1.1 Benchmark problems and parameters settings

To evaluate the performance of the EC-GWO, a set of 23 well-known benchmark problems (Bäck and Schwefel 1993; Fogel 1991; Long et al. 2018; Bansal and Singh 2021) is selected. Many researchers have used these benchmark problems in the literature to evaluate the performance of various meta-heuristic algorithms (Li et al. 2021; Yu et al. 2021; Dong et al. 2022; Lakshmi and Mohanaiah 2021; Teng et al. 2019; Heidari et al. 2019; Li et al. 2020, 2021). The details of these problems are reported in Table 1. In this table, according to the characteristics, problems are divided into three categories: unimodal, multimodal, and fixed-dimensional multimodal problems. In Table 1, D indicates the number of decision variables and *Range* refers to the search range for the decision variables. The F_i^* represents the true optima of the problem.

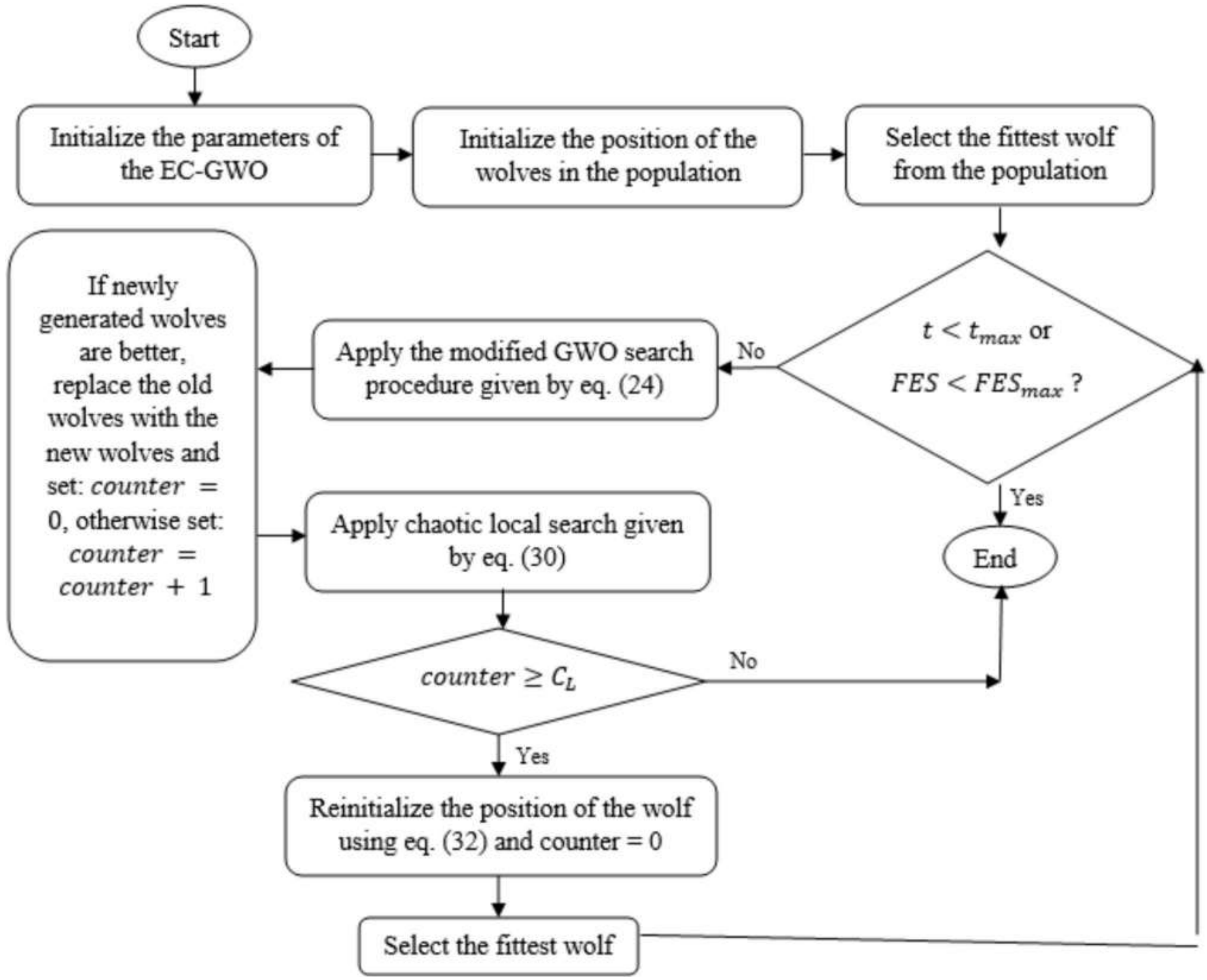

Fig. 3 Flow Chart of the proposed EC-GWO

A fair parameter setting is important to compare the performance of the meta-heuristic algorithms. The population size (N), maximum number of iterations (t_{max}), and maximum number of function evaluations (FES_{max}) are set to 50, 1000, and 5×10^4, respectively for all the algorithms. The algorithm ran 30 times independently. The parameter setting of the compared meta-heuristic algorithms, namely ABC (Karaboga and Basturk 2007), BBO (Simon 2008), SCA (Mirjalili 2016), WOA (Mirjalili and Lewis 2016)), GWO (Mirjalili et al. 2014) and variants of the GWO (MGWO (Mittal et al. 2016a), and RWGWO (Gupta and Deep 2019)) is derived from their original papers. A detailed parameter setting for all the compared algorithms is given in Table 2. These algorithms are very competitive or have recently been published in the literature. Hence, they have been chosen for the performance comparison of the EC-GWO.

The simulation environment is MATLAB 2014a, the operating system is Windows 10, 8GB RAM, and the processor is Intel(R) Core(TM) i5-8250U CPU @ 1.60GHz 1.80 GHz with 8 GB RAM.

4.1.2 *Comparison with classical GWO and other meta-heuristic algorithms*

To evaluate the advantages of the proposed algorithm, the EC-GWO is compared with GWO and other meta-heuristic algorithms on a set of problems given in Table 1. These algorithms are ABC, BBO, SCA, WOA, GWO, and variants of the GWO, namely MGWO, and RWGWO. We have used four statistics; namely, *average*, *best*, *worst*, *median*,

Table 1 Benchmark problems

Problem	Types	*D*	Range	F_i^*
F1(x)=$\sum_{i=1}^{D} x_i^2$	Unimodal	30	[−100,100]	0
F2(x)=$\sum_{i=1}^{D} \lvert x_i^2\rvert + \prod_{i=1}^{D} \lvert x_i\rvert$	Unimodal	30	[−10,10]	0
F3(x)=$\sum_{i=1}^{D} \left(\sum_{j-1}^{i} x_j\right)^2$	Unimodal	30	[−100,100]	0
F4(x)=$\max_i \left\{\lvert x_i\rvert, 1 \le i \le D\right\}$	Unimodal	30	[−100,100]	0
F5(x)=$\sum_{i=1}^{D-1} \left[100\left(x_{i+1} - x_i^2\right)^2 + \left(x_i - 1\right)^2\right]$	Unimodal	30	[−30,30]	0
F6(x)=$\sum_{i=1}^{D} \left(\left[x_i + 0.5\right]\right)^2$	Unimodal	30	[−100,100]	0
F7(x)=$\sum_{i=1}^{D} ix_i^4 + random[0, 1)$	Unimodal	30	[−1.28,1.28]	0
F8(x)=$\sum_{i=1}^{D} -x_i \sin\left(\sqrt{\lvert x_i\rvert}\right)$	Multimodal	30	[−500,500]	−418.9829×*n*
F9(x)=$\sum_{i=1}^{D} \left[x_i^2 - 10\cos\left(2\pi x_i\right) + 10\right]$	Multimodal	30	[−5.12,5.12]	0
F10(x)=$-20\exp(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}) - \exp\left(\frac{1}{D}\sum_{i=1}^{D}\cos\left(2\pi x_i\right)\right) + 20 + e$	Multimodal	30	[-32,32]	0
F11(x)=$\frac{1}{4000}\sum_{i=1}^{D} x_i^2 - \prod_{i=1}^{D}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	Multimodal	30	[−600,600]	0
F12(x)=$\frac{\pi}{D}\left\{10\sin\left(\pi y_1\right) + \sum_{i=1}^{D-1}(y_i - 1)^2\left[1 + 10\sin^2(\pi y_{i+1})\right] + (y_D - 1)^2\right\} + \sum_{i=1}^{D} u(x_i, 10, 100, 4)$ $y_i = 1 + \frac{x_i+1}{4} u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m & x_i > a \\ 0 & -a < x_i < a \\ k(-x_i - a)^m & x_i < -a \end{cases}$	Multimodal	30	[−50,50]	0
F13(x)=$0.1\left\{\sin^2(3\pi x_1) + \sum_{i=1}^{D}\left(x_i - 1\right)^2\left[1 + \sin^2(3\pi x_i + 1)\right] + (x_D - 1)^2\left[1 + \sin^2(2\pi x_D)\right]\right\} + \sum_{i=1}^{D} u(x_i, 5, 100, 4)$	Multimodal	30	[−50,50]	0
F14(x)=$\left(\frac{1}{500} + \sum_{j=1}^{25}\frac{1}{j+\sum_{i=1}^{2}\left(x_i - a_{ij}\right)^6}\right)^{-1}$	Fixed-dimensional multimodal	2	[−65, 65]	0.998
F15(x)=$\sum_{i=1}^{11}\left[a_i - \frac{x_1\left(b_i^2 + b_i x_2\right)}{b_i^2 + b_i x_3 + x_4}\right]^2$	Fixed-dimensional multimodal	4	[−5, 5]	0.00030
F16(x)=$4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1x_2 - 4x_2^2 + 4x_2^4$	Fixed-dimensional multimodal	2	[−5, 5]	−1.0316
F17(x)=$\left(x_2 - \frac{5.1}{4\pi^2}x_1^2 + \frac{5}{\pi}x_1 - 6\right)^2 + 10\left(1 - \frac{1}{8\pi}\right)\cos x_1 + 10$	Fixed-dimensional multimodal	2	[−5, 5]	0.398
F18(x)=$\left[1 + \left(x_1 + x_2 + 1\right)^2\left(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1x_2 + 3x_2^2\right)\right]$ $\left[30 + \left(2x_1 - 3x_2\right)^2\left(18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1x_2 + 27x_2^2\right)\right]$	Fixed-dimensional multimodal	2	[−2, 2]	3
F19(x)=$-\sum_{i=1}^{4} c_i\exp\left(-\sum_{j=1}^{3} a_{ij}\left(x_j - p_{ij}\right)^2\right)$	Fixed-dimensional multimodal	3	[1, 3]	−3.86
F20(x)=$-\sum_{i=1}^{4} c_i\exp\left(-\sum_{j=1}^{6} a_{ij}\left(x_j - p_{ij}\right)^2\right)$	Fixed-dimensional multimodal	6	[0, 1]	−3.32
F21(x)=$-\sum_{i=1}^{5}\left[\left(X - a_i\right)\left(X - a_i\right)^T + c_i\right]^{-1}$	Fixed-dimensional multimodal	4	[0, 10]	−10.1532
F22(x)=$-\sum_{i=1}^{7}\left[\left(X - a_i\right)\left(X - a_i\right)^T + c_i\right]^{-1}$	Fixed-dimensional multimodal	4	[0, 10]	−10.4028
F23(x)=$-\sum_{i=1}^{10}\left[\left(X - a_i\right)\left(X - a_i\right)^T + c_i\right]^{-1}$	Fixed-dimensional multimodal	4	[0.10]	−10.5363

and *standard deviation* (*Std*) to compare the optimization results. Here, '*average*', *best*, *worst*, *median*, and *standard deviation* (*Std*) are the mean, best, worst, median, and standard deviation of the fitness values which are obtained in 30 runs. The results are shown in Tables 3, 4, 5, where the better results are highlighted in boldface.

Table 2 Parameter setting for comparing meta-heuristic optimization algorithms

Algorithms	Parameter setting
GWO	a is linearly decreased from 2 to 0
ABC	Food sources (SN) is 50, Limit is $SN \times D$
BBO	Habitat modification probability is 1, initial mutation probability is 0.1 number of best habitats is 2
SCA	a is 2, r_1 is linearly decreased from 2 to 0, r_2 is $(2 \times \pi) \times$ rand(), r_3 is random number in the range [0,2], and r_4 is random number in the range [0,1]
WOA	a_1 is linearly decreased from 2 to 0 and a_2 is linearly decreased from - 1 to - 2, $r_1 =$ rand(), $r_2 =$ rand(), $b = 1$, $p =$ rand()
MGWO	a is non-linearly decreased from 2 to 0
RWGWO	a is linearly decreased from 2 to 0
EC-GWO	a is non-linearly decreased from 2 to 0, $C_L = 50$, $k = 0.2$

For the unimodal benchmark promlems (F1-F7), results are given in Table 3. In this table, the EC-GWO has achieved an optimal value (0) for the problems F1-F4. The proposed strategies provide solutions with higher precision to each problem. As compared to other algorithms, the proposed EC-GWO has provided better results for the problem F5. However, ABC has outstanding performance for problem F6 as compared to the proposed EC-GWO, BBO, SCA, WOA, GWO, MGWO, and RWGWO. Moreover, for problem F7, the results obtained by EC-GWO are very close to the results of the MGWO algorithm and performed better than ABC, BBO, SCA, WOA, GWO, and RWGWO. It can be verified from the results of unimodal problems that the EC-GWO has performed overall better than other compared algorithms, which proves its strong exploitation ability. Hence, the modified control parameter and chaotic local search have proven their efficiency in enhancing the exploitation abilities of the classical GWO.

For the multimodal problems (F8-F13), results are shown in Table 4. The proposed EC-GWO has obtained optimal solution for the problems F8, F9, and F11. As Compared with ABC, BBO, SCA, WOA, GWO, MGWO, and RWGWO, the proposed EC-GWO has achieved better results for problem F10. For problems F12 and F13, ABC has provided good results as compared to the other algorithms. Hence, the results on multimodal problems indicate that the proposed EC-GWO has more advantages of jumping out from the local optimal regions than other compared algorithms.

For the fixed-dimensional multimodal problems (F14-F23), results are indicated in Table 5. ABC has performed better than BBO, SCA, WOA, GWO, MGWO, RWGWO, and EC-GWO for the problem F14. For the same function, RWGWO is the second best algorithm. For problem F15, RWGWO has provided better results in terms of average, best, and median values, and the proposed EC-GWO has obtained better results in terms of worst and std values. For problems F16-F19, all the algorithms have provided better and similar results in terms of average, best, worst, and median values than the BBO algorithm. The ABC algorithm has performed better in all the statistics for problems F16-F19. For problem F20, ABC has provided better results than the other compared algorithms. The proposed EC-GWO and the ABC have performed very well on problems F21-F23, but in these problems, ABC has provided better results in terms of all the statistics. As compared to the multimodal problems, these problems have less local optima. Therefore, the ability to maintain a comparatively better balance between exploration and exploitation is verified in the EC-GWO through these problems. Thus, it can be concluded that all the employed strategies have shown their impact on improving the search mechanism of the GWO for better solution accuracy.

4.1.3 Convergence analysis

This subsection compares and analyzes the convergence feature of the proposed EC-GWO and other compared algorithms. Fig. 4, 5, 6 plots the convergence curves for the selected benchmark problems F1, F4, F5, F6, F8, F10, F11, F13, F14, F15, F20, and F23 of the EC-GWO, and compares them with the convergence curves of the other compared algorithms. In these curves, the horizontal axis represents the function evaluations, and the fitness values are depicted on the vertical axis. These curves show that the proposed EC-GWO achieved a faster convergence rate than other algorithms for most of the problems. For problems F1, F4, and F5, the convergence speed of the proposed EC-GWO is very fast compared to other algorithms. For some problems, such as F6, F13, F15, and F20, the convergence speed of EC-GWO is worse than ABC, but its convergence speed is better than the speed of the other algorithms. It can be concluded that the proposed EC-GWO also has the highest convergence speed.

Table 3 Comparison results obtained by EC-GWO and ABC, BBO, SCA, WOA, GWO, MGWO, and RWGWO on a set of unimodal benchmark problems

Problem	Algorithm	Average	Best	Worst	Median	Std
F1	ABC	2.80E−11	2.70E−12	1.89E−10	1.27E−11	4.26E−11
	BBO	5.94E+00	2.76E+00	1.34E+01	5.25E+00	2.46E+00
	SCA	2.60E−03	9.59E−07	2.22E−02	4.24E−04	5.00E−03
	WOA	1.60E−172	2.43E−185	3.24E−171	9.05E−180	0.00E+00
	GWO	3.14E−76	5.30E−80	4.69E−75	3.62E−77	8.73E−76
	MGWO	2.07E−99	2.54E−103	1.68E−98	2.58E−100	3.82E−99
	RWGWO	6.02E−75	1.08E−77	6.11E−74	3.53E−75	1.14E−74
	EC-GWO	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**
F2	ABC	9.80E−07	4.21E−07	2.11E−06	9.08E−07	3.86E−07
	BBO	8.52E−01	6.01E−01	1.26E+00	8.25E−01	1.58E−01
	SCA	7.61E−06	9.51E−10	8.10E−05	1.02E−06	1.69E−05
	WOA	1.43E−109	1.31E−118	2.39E−108	2.07E−113	4.73E−109
	GWO	4.70E−45	2.35E−46	3.81E−44	2.66E−45	7.14E−45
	MGWO	1.84E−57	6.99E−59	1.35E−56	7.61E−58	2.87E−57
	RWGWO	1.99E−43	1.56E−44	4.70E−43	1.53E−43	1.43E−43
	EC-GWO	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**
F3	ABC	1.25E+04	7.89E+03	1.68E+04	1.27E+04	2.30E+03
	BBO	8.91E+03	4.21E+03	1.41E+04	8.56E+03	2.35E+03
	SCA	2.87E+03	1.77E+02	1.18E+04	1.98E+03	3.00E+03
	WOA	8.61E+03	2.82E+02	2.99E+04	8.53E+03	6.48E+03
	GWO	2.04E−21	9.02E−29	5.82E−20	6.38E−25	1.06E−20
	MGWO	1.13E−19	3.66E−28	1.30E−18	3.25E−24	3.47E−19
	RWGWO	4.53E−12	4.53E−17	3.51E−11	1.31E−13	1.02E−11
	EC-GWO	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**
F4	ABC	2.16E+01	1.05E+01	2.63E+01	2.27E+01	3.81E+00
	BBO	6.31E+00	4.58E+00	9.27E+00	6.36E+00	1.00E+00
	SCA	1.24E+01	1.36E+00	3.06E+01	1.11E+01	7.84E+00
	WOA	3.76E+01	1.16E−02	8.18E+01	3.62E+01	2.70E+01
	GWO	5.90E−17	2.84E−19	5.96E−16	9.86E−18	1.23E−16
	MGWO	2.99E−23	2.08E−25	1.37E−22	1.26E−23	4.02E−23
	RWGWO	9.66E−14	1.67E−15	3.91E−13	3.56E−14	1.23E−13
	EC−GWO	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**
F5	ABC	2.38E+00	7.24E−02	1.12E+01	1.77E+00	2.41E+00
	BBO	3.26E+02	1.72E+02	6.80E+02	3.06E+02	1.25E+02
	SCA	9.48E+01	2.77E+01	7.13E+02	3.15E+01	1.55E+02
	WOA	2.67E+01	2.58E+01	2.74E+01	2.67E+01	3.22E−01
	GWO	2.66E+01	2.53E+01	2.72E+01	2.66E+01	5.34E−01
	MGWO	2.64E+01	2.50E+01	2.87E+01	2.62E+01	9.19E−01
	RWGWO	2.58E+01	2.49E+01	2.71E+01	2.60E+01	5.45E−01
	EC−GWO	**1.85E−02**	**5.41E−03**	**3.40E−02**	**1.87E−02**	**7.27E−03**
F6	ABC	**2.06E−11**	**2.16E−12**	**1.07E−10**	**1.29E−11**	**2.40E−11**
	BBO	5.70E+00	2.01E+00	9.96E+00	5.40E+00	2.28E+00
	SCA	4.27E+00	3.50E+00	4.95E+00	4.24E+00	3.10E−01
	WOA	1.07E−02	1.10E−03	1.90E−01	3.70E−03	3.39E−02
	GWO	5.26E−01	1.49E−05	9.92E−01	5.00E−01	2.56E−01
	MGWO	3.81E−01	3.08E−05	7.57E−01	2.57E−01	2.42E−01
	RWGWO	4.96E−02	5.45E−06	3.22E−01	9.75E−06	9.46E−02
	EC-GWO	3.31E−04	1.03E−04	1.29E−03	2.69E−04	2.47E−04

Table 3 (continued)

Problem	Algorithm	Average	Best	Worst	Median	Std
F7	ABC	1.10E−01	5.48E−02	1.59E−01	1.12E−01	2.54E−02
	BBO	2.47E−02	1.19E−02	6.31E−02	2.16E−02	1.12E−02
	SCA	2.96E−02	2.00E−03	1.03E−01	2.21E−02	2.51E−02
	WOA	1.20E−03	1.74E−05	6.60E−03	7.86E−04	1.30E−03
	GWO	7.69E−04	2.63E−04	2.80E−03	6.58E−04	4.85E−04
	MGWO	4.39E−04	1.66E−04	**9.92E−04**	**3.84E−04**	**2.29E−04**
	RWGWO	1.21E−03	3.85E−04	2.64E−03	1.20E−03	6.09E−04
	EC-GWO	**4.29E−04**	**1.38E−04**	1.24E−03	4.10E−04	2.33E−04

4.1.4 Statistical analysis

The Wilcoxon rank-sum test (Derrac et al. 2011) statistically, at a significance level of 5% has been used to evaluate EC-GWO. It is a pairwise test that tries to find significant differences between two independent groups. It ensures that significant results for algorithms do not occur by chance. The results of the Wilcoxon rank-sum test for a set of 23 well-known benchmark problems are listed in Table 6. In table 6, "$+/-/\approx$" are used to indicate that the EC-GWO is significantly better, worse, or the same as the ABC, BBO, SCA, WOA, GWO, MGWO, and RWGWO. As can be seen from the results the proposed EC-GWO is significantly better than the ABC for 17 problems, BBO for 23 problems, SCA for 21 problems, WOA for 17 problems, classical GWO for 17 problems, MGWO for 17 problems, and RWGWO for 15 problems out of 23 problems. Conclusively, EC-GWO has better exploration capability and better synergy between exploitation and exploration than other algorithms. Moreover, we have also ranked the average values obtained by EC-GWO and other algorithms for each problem, as shown in Table 7. In Table 7, EC-GWO gets the first rank in all the problems. The complete ranking order is EC-GWO, ABC, WOA, RWGWO, MGWO, GWO, BBO, and SCA.

Overall, we can conclude that as compared with ABC, BBO, SCA, WOA, GWO, MGWO, and RWGWO, the proposed EC-GWO has the best performance and robustness when solving global optimization problems. Thus, the EC-GWO is suitable for solving global optimization problems.

4.2 The proposed EC-GWO for wind farm layout optimization problem (WFLOP)

4.2.1 Numerical experiment results and discussion

This subsection is devoted to numerical investigations while solving the WFLOP using various meta-heuristics. To verify and validate the performance of the proposed EC-GWO, its simulation results are compared with ABC, BBO, SCA, WOA, GWO, MGWO, and RWGWO. The parameters setting of these algorithms are the same as in Table 2. For the considered wind farm (2 km × 2 km), air density (ρ) is 1.2254 kg/m^3, rotor efficiency (C_p) is 0.4, thrust coefficient (C_{wt}) is 8/9 and the surface roughness of wind farm (z_0) is 0.3 m. For all the compared algorithms, the population size and the maximum function evaluations are set to 50 and 5×10^4, respectively. In this paper, we have considered two cases, namely case 1 for 26 wind turbines and case 2 for 30 wind turbines. For case 1 and case 2, the numerical results for all compared algorithms over 30 independent runs in terms of the average, minimum, maximum, median, std, and cost, and corresponding optimal positions, rotor radius, and hub height are presented in Tables 8, 9, 10, 11, 12, 13.

For case 1 and case 2, Tables 8 and 11 report the average, minimum, maximum, median, and std of the total power obtained over 30 runs of all the compared algorithms and also, the statistical analysis through the Wilcoxon rank-sum test at a significance level of 5% are reported in the same Tables 8 and 11. Moreover, Cost indicates the objective function value. In these tables, "+" indicates that the EC-GWO is significantly better than the ABC, BBO, SCA, WOA, MGWO, and RWGWO while "≈" shows that the EC-GWO is the same as ABC, BBO, SCA, WOA, MGWO, and RWGWO. From the results of Table 8, it can be observed that the proposed EC-GWO has provided a better solution as it gives a maximum value for a total power that is 13792.53138 KW as well as the minimum value for a total cost is 0.0014549 obtained by case 1. Referring to Table 8, it can be seen that BBO has also performed better than ABC, SCA, WOA, GWO, MGWO, and RWGWO. Overall, the proposed EC-GWO has provided better results for case 1. For case 2, the proposed EC-GWO has performed better than ABC, BBO, SCA, WOA, MGWO, and RWGWO. The proposed EC-GWO has obtained a maximum power 15787.08 KW and the corresponding objective value is 0.00140418. BBO

Table 4 Comparison results obtained by EC-GWO and ABC, BBO, SCA, WOA, GWO, MGWO, and RWGWO on a set of multimodal benchmark problems

Problem	Algorithm	Average	Best	Worst	Median	Std
F8	ABC	−1.22E+04	−1.25E+04	−1.19E+04	−1.22E+04	1.27E+02
	BBO	−1.26E+04	−1.26E+04	−1.25E+04	−1.26E+04	6.55E+00
	SCA	−4.01E+03	−4.60E+03	−3.44E+03	−3.99E+03	2.80E+02
	WOA	−1.13E+04	−1.26E+04	−8.17E+03	−1.23E+04	1.65E+03
	GWO	−6.35E+03	−7.36E+03	−3.64E+03	−6.37E+03	7.39E+02
	MGWO	−6.22E+03	−7.74E+03	−3.57E+03	−6.62E+03	1.28E+03
	RWGWO	−8.80E+03	−1.00E+04	−7.86E+03	−8.79E+03	5.12E+02
	EC-GWO	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**	**4.28E−03**
F9	ABC	2.78E−01	5.25E−09	1.55E+00	6.09E−05	4.84E−01
	BBO	2.48E+00	6.04E−01	4.81E+00	2.25E+00	9.19E−01
	SCA	1.32E+01	1.36E−06	1.33E+02	4.66E−02	2.87E+01
	WOA	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	GWO	1.39E+00	0.00E+00	1.31E+01	0.00E+00	3.39E+00
	MGWO	6.95E−02	0.00E+00	2.08E+00	0.00E+00	3.81E−01
	RWGWO	1.17E+01	0.00E+00	2.56E+01	1.19E+01	6.23E+00
	EC-GWO	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**
F10	ABC	1.42E−05	4.30E−06	4.10E−05	1.21E−05	8.59E−06
	BBO	1.28E+00	6.31E−01	1.93E+00	1.22E+00	3.19E−01
	SCA	1.25E+01	7.50E−05	2.03E+01	1.98E+01	9.60E+00
	WOA	4.80E−15	8.88E−16	7.99E−15	4.44E−15	2.16E−15
	GWO	8.11E−15	4.44E−15	1.51E−14	7.99E−15	1.47E−15
	MGWO	6.10E−15	4.44E−15	7.99E−15	4.44E−15	1.80E−15
	RWGWO	8.23E−15	7.99E−15	1.51E−14	7.99E−15	1.30E−15
	EC-GWO	**8.88E−16**	**8.88E−16**	**8.88E−16**	**8.88E−16**	**0.00E+00**
F11	ABC	7.15E−04	4.76E−11	1.22E−02	1.29E−07	2.74E−03
	BBO	1.05E+00	1.02E+00	1.09E+00	1.04E+00	1.85E−02
	SCA	1.66E−01	2.26E−06	7.90E−01	8.14E−02	2.16E−01
	WOA	1.30E−03	0.00E+00	3.89E−02	0.00E+00	7.10E−03
	GWO	3.90E−03	0.00E+00	2.12E−02	0.00E+00	6.60E−03
	MGWO	8.04E−04	0.00E+00	1.37E−02	0.00E+00	3.10E−03
	RWGWO	2.70E−03	0.00E+00	2.89E−02	0.00E+00	6.69E−03
	EC-GWO	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**
F12	ABC	**1.31E−12**	**6.75E−14**	**5.39E−12**	**6.94E−13**	**1.47E−12**
	BBO	3.97E−02	8.30E−03	1.27E−01	2.28E−02	3.65E−02
	SCA	4.34E+00	3.09E−01	6.02E+01	7.25E−01	1.21E+01
	WOA	2.00E−03	1.70E−04	1.37E−02	5.55E−04	3.40E−03
	GWO	3.40E−02	1.32E−02	7.85E−02	2.91E−02	1.67E−02
	MGWO	2.01E−02	7.17E−06	4.05E−02	1.97E−02	9.20E−03
	RWGWO	1.08E−02	6.01E−07	1.16E−01	3.55E−03	2.33E−02
	EC-GWO	1.35E−04	8.08E−06	1.72E−03	4.49E−05	3.36E−04
F13	ABC	**7.73E−11**	**1.68E−12**	**1.81E−09**	**1.15E−11**	**3.27E−10**
	BBO	2.76E−01	1.11E−01	4.50E−01	2.90E−01	8.92E−02
	SCA	3.18E+00	2.02E+00	1.33E+01	2.57E+00	2.11E+00
	WOA	3.75E−02	4.10E−03	2.07E−01	2.58E−02	4.30E−02
	GWO	4.79E−01	1.96E−01	7.79E−01	4.46E−01	1.62E−01
	MGWO	2.81E−01	3.46E−05	6.24E−01	3.04E−01	1.49E−01
	RWGWO	7.92E−02	8.11E−06	3.08E−01	7.72E−02	8.32E−02
	EC-GWO	2.85E−04	1.66E−05	9.32E−04	2.71E−04	1.96E−04

Table 5 Comparison results obtained by EC-GWO and ABC, BBO, SCA, WOA, GWO, MGWO, and RWGWO on a set of fixed-dimensional multimodal problems

Problem	Algorithm	Average	Best	Worst	Median	Std
F14	ABC	9.98E-01	9.98E-01	9.98E-01	9.98E-01	1.40E-16
	BBO	9.98E-01	9.98E-01	1.00E+00	9.98E-01	7.56E-04
	SCA	1.20E+00	9.98E-01	2.98E+00	9.98E-01	6.05E-01
	WOA	1.88E+00	9.98E-01	1.08E+01	9.98E-01	2.49E+00
	GWO	3.42E+00	9.98E-01	1.27E+01	2.98E+00	3.65E+00
	MGWO	2.51E+00	9.98E-01	1.27E+01	9.98E-01	2.69E+00
	RWGWO	9.98E-01	9.98E-01	9.98E-01	9.98E-01	7.17E-12
	EC-GWO	**9.98E-01**	**9.98E-01**	**9.98E-01**	**9.98E-01**	4.95E-10
F15	ABC	6.30E-04	3.65E-04	8.42E-04	6.41E-04	1.11E-04
	BBO	4.70E-03	9.94E-04	2.11E-02	2.00E-03	6.00E-03
	SCA	8.58E-04	3.91E-04	1.30E-03	7.35E-04	3.25E-04
	WOA	6.14E-04	3.08E-04	1.40E-03	3.91E-04	3.90E-04
	GWO	5.70E-03	3.07E-04	2.04E-02	3.07E-04	9.00E-03
	MGWO	1.80E-03	3.07E-04	2.04E-02	3.08E-04	5.10E-03
	RWGWO	**3.38E-04**	**3.07E-04**	1.22E-03	**3.07E-04**	1.67E-04
	EC-GWO	7.05E-04	5.70E-04	**7.47E-04**	7.15E-04	**3.81E-05**
F16	ABC	-1.03E+00	-1.03E+00	-1.03E+00	-1.03E+00	5.05E-16
	BBO	-1.03E+00	-1.03E+00	-1.02E+00	-1.03E+00	2.80E-03
	SCA	-1.03E+00	-1.03E+00	-1.03E+00	-1.03E+00	1.28E-05
	WOA	-1.03E+00	-1.03E+00	-1.03E+00	-1.03E+00	1.22E-11
	GWO	-1.03E+00	-1.03E+00	-1.03E+00	-1.03E+00	1.46E-09
	MGWO	-1.03E+00	-1.03E+00	-1.03E+00	-1.03E+00	1.42E-08
	RWGWO	-1.03E+00	-1.03E+00	-1.03E+00	-1.03E+00	1.01E-09
	EC-GWO	**-1.03E+00**	**-1.03E+00**	**-1.03E+00**	**-1.03E+00**	1.42E-09
F17	ABC	3.98E-01	3.98E-01	3.98E-01	3.98E-01	0.00E+00
	BBO	4.00E-01	3.98E-01	4.10E-01	3.99E-01	2.50E-03
	SCA	3.98E-01	3.98E-01	4.01E-01	3.98E-01	5.62E-04
	WOA	3.98E-01	3.98E-01	3.98E-01	3.98E-01	1.14E-07
	GWO	3.98E-01	3.98E-01	3.98E-01	3.98E-01	6.49E-08
	MGWO	3.98E-01	3.98E-01	3.98E-01	3.98E-01	3.97E-07
	RWGWO	3.98E-01	3.98E-01	3.98E-01	3.98E-01	5.58E-08
	EC-GWO	**3.98E-01**	**3.98E-01**	**3.98E-01**	**3.98E-01**	5.65E-08
F18	ABC	3.00E+00	3.00E+00	3.02E+00	3.00E+00	3.19E-03
	BBO	6.00E+00	3.00E+00	3.42E+01	3.02E+00	9.11E+00
	SCA	3.00E+00	3.00E+00	3.00E+00	3.00E+00	4.55E-06
	WOA	3.00E+00	3.00E+00	3.00E+00	3.00E+00	3.80E-06
	GWO	3.00E+00	3.00E+00	3.00E+00	3.00E+00	1.89E-06
	MGWO	3.00E+00	3.00E+00	3.00E+00	3.00E+00	1.79E-06
	RWGWO	3.00E+00	3.00E+00	3.00E+00	3.00E+00	9.12E-07
	EC-GWO	**3.00E+00**	**3.00E+00**	**3.00E+00**	**3.00E+00**	1.81E-06
F19	ABC	-3.00E-01	-3.00E-01	-3.00E-01	-3.00E-01	2.26E-16
	BBO	-2.80E-01	-2.97E-01	-2.45E-01	-2.87E-01	1.35E-02
	SCA	-3.01E-01	-3.01E-01	-3.01E-01	-3.01E-01	2.26E-16
	WOA	-3.01E-01	-3.01E-01	-3.01E-01	-3.01E-01	2.26E-16
	GWO	-3.01E-01	-3.01E-01	-3.01E-01	-3.01E-01	2.26E-16
	MGWO	-3.01E-01	-3.01E-01	-3.01E-01	-3.01E-01	2.26E-16
	RWGWO	-3.00E-01	-3.00E-01	-3.00E-01	-3.00E-01	2.26E-16
	EC-GWO	**-3.00E-01**	**-3.00E-01**	**-3.00E-01**	**-3.00E-01**	**2.26E-16**

Table 5 (continued)

Problem	Algorithm	Average	Best	Worst	Median	Std
F20	ABC	**-3.32E+00**	**-3.32E+00**	**-3.32E+00**	**-3.32E+00**	**1.65E-15**
	BBO	-3.29E+00	-3.32E+00	-3.20E+00	-3.32E+00	5.36E-02
	SCA	-2.95E+00	-3.13E+00	-1.92E+00	-3.01E+00	2.51E-01
	WOA	-3.27E+00	-3.32E+00	-3.14E+00	-3.32E+00	6.83E-02
	GWO	-3.25E+00	-3.32E+00	-3.13E+00	-3.26E+00	7.26E-02
	MGWO	-3.26E+00	-3.32E+00	-3.09E+00	-3.32E+00	7.42E-02
	RWGWO	-3.25E+00	-3.32E+00	-3.20E+00	-3.20E+00	6.07E-02
	EC-GWO	-3.29E+00	-3.32E+00	-3.20E+00	-3.32E+00	5.17E-02
F21	ABC	-1.02E+01	-1.02E+01	-1.02E+01	-1.02E+01	**5.16E-15**
	BBO	-4.62E+00	-1.01E+01	-2.62E+00	-2.68E+00	3.13E+00
	SCA	-2.86E+00	-7.69E+00	-4.97E-01	-1.77E+00	2.32E+00
	WOA	-9.22E+00	-1.02E+01	-2.63E+00	-1.02E+01	2.15E+00
	GWO	-9.06E+00	-1.02E+01	-2.68E+00	-1.02E+01	2.26E+00
	MGWO	-8.97E+00	-1.02E+01	-5.06E+00	-1.02E+01	2.18E+00
	RWGWO	-9.48E+00	-1.02E+01	-5.10E+00	-1.02E+01	1.75E+00
	EC-GWO	**-1.02E+01**	**-1.02E+01**	**-1.02E+01**	**-1.02E+01**	4.16E-05
F22	ABC	-1.04E+01	-1.04E+01	-1.04E+01	-1.04E+01	1.40E-15
	BBO	-5.76E+00	-1.04E+01	-2.75E+00	-3.72E+00	3.34E+00
	SCA	-4.49E+00	-7.88E+00	-9.07E-01	-4.92E+00	1.95E+00
	WOA	-1.02E+01	-1.04E+01	-5.09E+00	-1.04E+01	9.70E-01
	GWO	-1.00E+01	-1.04E+01	-5.09E+00	-1.04E+01	1.35E+00
	MGWO	-1.04E+01	-1.04E+01	-1.04E+01	-1.04E+01	7.21E-04
	RWGWO	-1.02E+01	-1.04E+01	-5.09E+00	-1.04E+01	9.70E-01
	EC-GWO	**-1.04E+01**	**-1.04E+01**	**-1.04E+01**	**-1.04E+01**	7.36E-05
F23	ABC	-1.05E+01	-1.05E+01	-1.05E+01	-1.05E+01	1.11E-06
	BBO	-6.20E+00	-1.05E+01	-2.42E+00	-3.83E+00	3.60E+00
	SCA	-4.31E+00	-8.86E+00	-9.44E-01	-4.85E+00	2.21E+00
	WOA	-9.92E+00	-1.05E+01	-2.81E+00	-1.05E+01	1.92E+00
	GWO	-1.01E+01	-1.05E+01	-2.42E+00	-1.05E+01	1.75E+00
	MGWO	-1.04E+01	-1.05E+01	-5.13E+00	-1.05E+01	9.87E-01
	RWGWO	-1.02E+01	-1.05E+01	-5.12E+00	-1.05E+01	1.37E+00
	EC-GWO	**-1.05E+01**	**-1.05E+01**	**-1.05E+01**	**-1.05E+01**	3.43E-05

has also performed approximately the same as the proposed EC-GWO. For all the compared algorithms, corresponding to maximum total power, the optimal position of the turbines (OP), Rotor radius (RR), and hub height (RH) are given in Tables 9 and 10 for case 1 and Tables 12 and 13 for case 2. Figures 7 and 9 represent the optimal configuration of case 1 and case 2, respectively for the ABC, BBO, SCA, WOA, GWO, MGWO, RWGWO, and the proposed EC-GWO. Figures 8 and 10 show the convergence rate of ABC, BBO, SCA, WOA, GWO, MGWO,

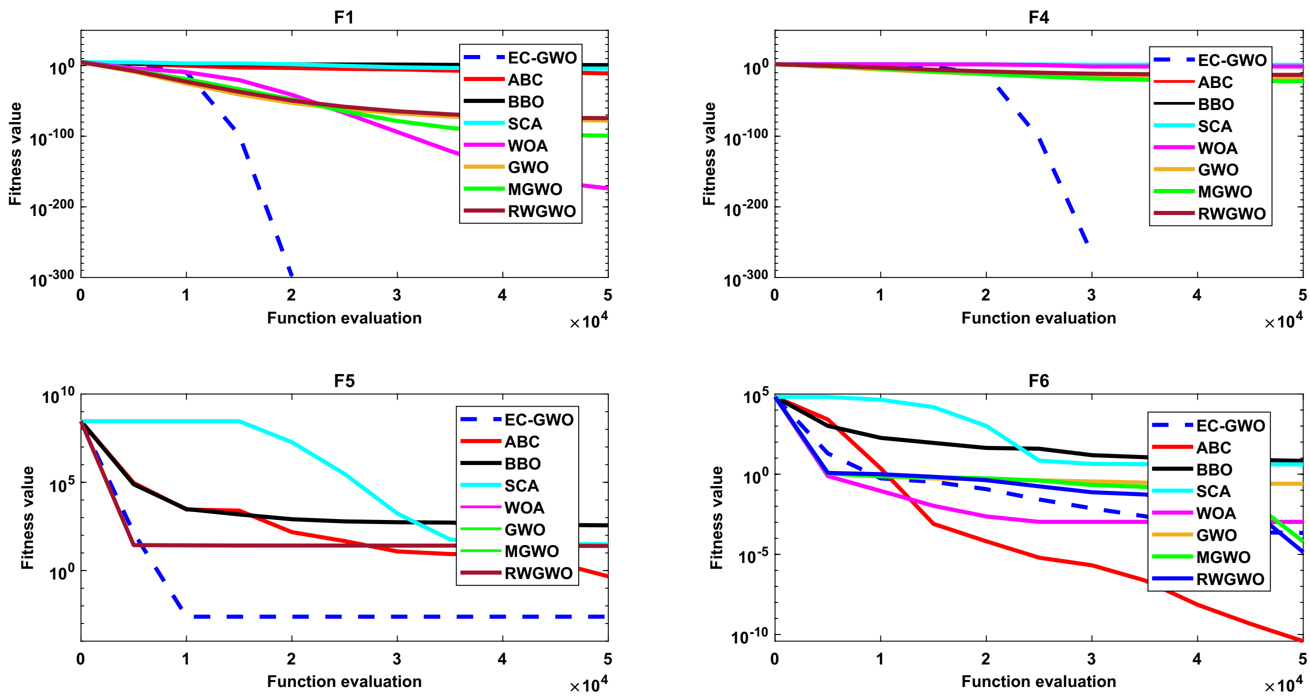

Fig. 4 Convergence curves for selected benchmark problems

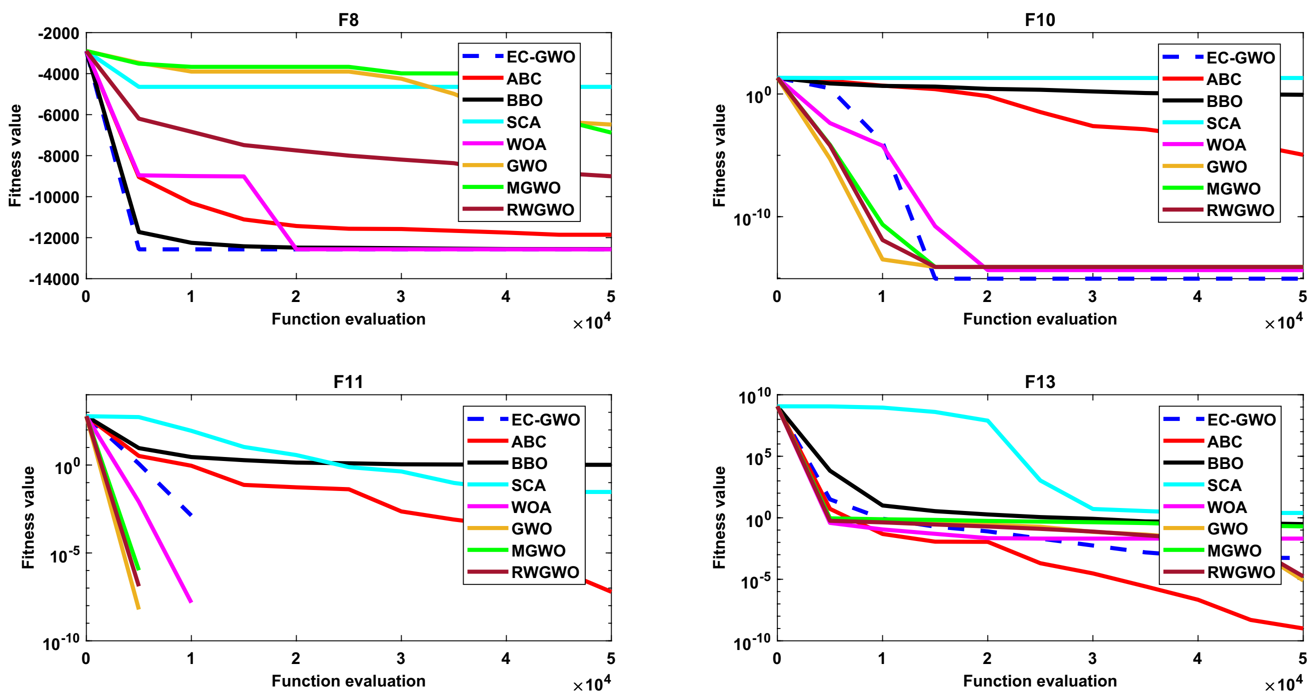

Fig. 5 Convergence curves for selected benchmark problems

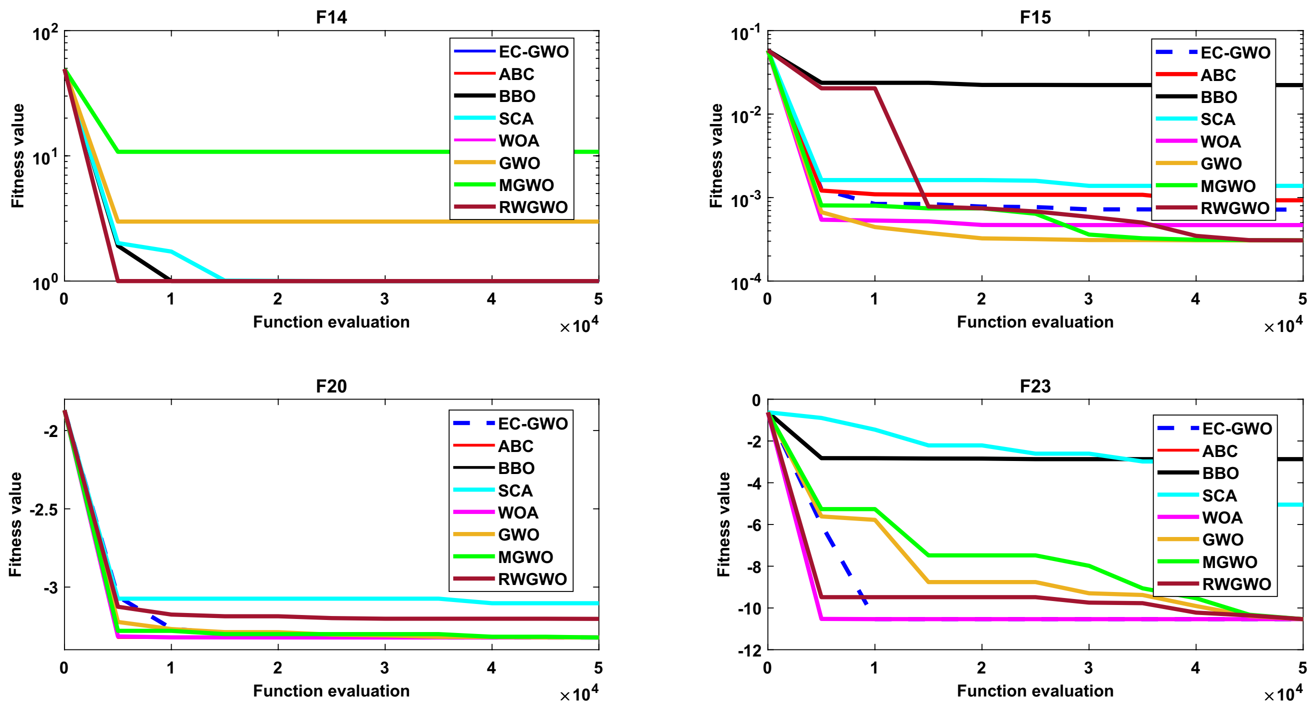

Fig. 6 Convergence curves for selected benchmark problems

RWGWO, and the proposed EC-GWO, respectively. From these curves, it can be concluded that the EC-GWO algorithm has the fastest convergence rate. Hence, based on different performance measures, it is obvious that the proposed EC-GWO is more efficient than other compared algorithms for solving the WFLOP.

Table 6 *p*-values and statistical conclusion calculated by Wilcoxon rank-sum test for a set of 23 well-known benchmark problems

Function	ABC		BBO		SCA		WOA		GWO		MGWO		RWGWO	
	p value	Conclusion	*p* value	Conclusion	*p* value	Conclusion	*p* value	Conclusion	*p* value	Conclusion	*p* value	Conclusion	*p* value	Conclusion
F1	1.21E−12	+	1.21E−12	+	1.21E−12	+	1.21E−12	+	1.21E−12	+	1.21E−12	+	1.21E−12	+
F2	1.21E−12		1.21E−12		1.21E−12		1.21E−12	+	1.21E−12	+	1.21E−12	+	1.21E−12	+
F3	1.21E−12	+	1.21E−12	+	1.21E−12	+	1.21E−12	+	1.21E−12	+	1.21E−12	+	1.21E−12	+
F4	1.21E−12	+	1.21E−12	+	1.21E−12	+	1.21E−12	+	1.21E−12	+	1.21E−12	+	1.21E−12	+
F5	3.02E−11	+	3.02E−11	+	3.02E−11	+	3.02E−11	+	3.02E−11	+	3.02E−11	+	3.02E−11	+
F6	3.02E−11	−	3.02E−11	+	3.02E−11	+	3.34E−11	+	8.48E−09	+	1.11E−06	+	1.95E−03	−
F7	3.02E−11	+	3.02E−11	+	3.02E−11	+	8.31E−03	+	7.74E−06	+	NA	≈	8.48E−09	+
F8	3.02E−11	+	3.02E−11	+	3.02E−11	+	3.02E−11	+	3.02E−11	+	3.02E−11	+	3.02E−11	+
F9	1.21E−12	+	1.21E−12	+	1.21E−12	+	NA	≈	1.37E−03	+	NA	≈	2.67E−11	+
F10	1.21E−12	+	1.21E−12	+	1.21E−12	+	8.04E−11	+	4.16E−14	+	4.63E−13	+	2.71E−14	+
F11	1.21E−12	+	1.21E−12	+	1.21E−12	+	NA	≈	8.81E−03	+	NA	≈	2.16E−02	+
F12	3.02E−11	−	3.02E−11	+	3.02E−11	+	3.82E−09	+	3.02E−11	+	5.57E−10	+	1.03E−02	+
F13	3.02E−11	−	3.02E−11	+	3.02E−11	+	3.02E−11	+	3.02E−11	+	6.52E−09	+	2.71E−02	+
F14	5.20E−12	+	6.70E−11	+	3.34E−11	+	2.51E−02	+	NA	≈	8.12E−04	+	2.28E−05	+
F15	1.06E−03	−	3.02E−11	+	NA	≈	2.16E−03	−	7.96E−03	+	6.77E−05	−	5.57E−10	−
F16	6.32E−12	+	3.02E−11	+	3.02E−11	+	3.02E−11	+	NA	≈	3.47E−10	+	NA	+
F17	1.21E−12	+	3.02E−11	+	3.02E−11	+	NA	≈	NA	≈	1.86E−06	+	NA	≈
F18	NA	≈	3.02E−11	+	3.77E−04	+	NA	≈	3.92E−02	+	NA	≈	NA	≈
F19	NA	≈	1.21E−12	+	NA	≈	NA	≈	NA	≈	NA	≈	NA	≈
F20	1.57E−11	−	3.18E−04	+	3.02E−11	+	1.53E−05	+	NA	≈	3.51E−02	+	NA	+
F21	5.14E−12	+	3.02E−11	+	3.02E−11	+	5.07E−10	+	4.20E−10	+	3.02E−11	+	5.46E−06	+
F22	1.93E−11	+	3.02E−11	+	3.02E−11	+	2.07E−02	+	1.27E−02	+	1.09E−10	+	3.15E−02	+
F23	2.57E−11	+	3.02E−11	+	3.02E−11	+	2.96E−05	+	NA	+	5.07E−10	+	NA	≈

Table 7 Ranking on algorithms based on their performances on a set of 23 well-known benchmark problems

Algorithm ⇒	ABC	BBO	SCA	WOA	MGWO	RWGWO	GWO	Proposed GWO
Average Rank	3.3	6.61	6.91	3.93	4.26	3.96	5.13	**1.89**
Rank	2	7	8	3	5	4	6	**1**

Bold values indicate the best result

Table 8 Comparison results obtained by EC-GWO and other meta-heuristic algorithms on 26 turbines

	ABC	BBO	SCA	WOA	GWO	MGWO	RWGWO	EC-GWO
Average	6634.2	13582.77	7797.006	10890	11535.56	11512.4259	12655.30082	13573.04987
Minimum	5961.676	13503.97	7321.713	9860.269578	10650.76	10484.5509	11367.26817	13380.6456
Maximum	6997.555	13622.37	8357.669	12414.83983	12131.47	12152.7529	13037.66957	**13792.53138**
Median	6617.683	13595.46	7840.819	10829.95817	11640.46	11615.78979	12851.75888	13583.31962
Std	286.2216	41.94022	349.4201	775.741274	470.1764	526.6938	508.0193608	132.4547915
Cost	0.002867(+)	0.001473(≈)	0.002401(+)	0.001616421(+)	0.00165411(+)	0.00165121(+)	0.00153914(+)	**0.0014549**

Bold values indicate the best result

Table 9 Optimal positions, hub heights, and rotor radii obtained by ABC, BBO, SCA, and WOA for 26 turbines

ABC			BBO			SCA			WOA		
OP	RR	HH	OP	RR	HH	OP	RR	HH	OP	RR	HH
(1600,1400)	20.00	23.78	(1000,1800)	19.69	43.34	(1200,1200)	20.00	60.00	(1200,1000)	20.00	29.85
(400,1800)	20.00	54.95	(1400,1400)	19.78	45.32	(800,1600)	20.00	31.90	(1400,1000)	20.00	42.04
(600,1800)	18.03	32.37	(1800,1600)	19.85	26.68	(200,1000)	20.00	38.03	(200,800)	0.00	50.88
(200,800)	52.90	36.11	(400,1200)	19.93	50.13	(1000,600)	0.00	7.909	(600,400)	17.37	26.38
(1400,200)	12.37	38.07	(1400,1200)	19.92	25.78	(800,800)	16.39	60.00	(1600,1600)	20.00	30.78
(600,1200)	19.44	50.34	(200,400)	20.00	47.61	(1400,1200)	20.00	60.00	(200,1200)	20.00	36.41
(1200,1400)	6.496	27.42	(600,1600)	19.87	23.60	(1000,1000)	20.00	60.00	(1800,1000)	20.00	52.00
(1600,1800)	38.33	41.30	(1000,1600)	19.96	20.29	(200,200)	20.00	38.94	(1400,600)	20.00	59.97
(1400,1400)	7.937	10.18	(1800,1400)	19.93	53.80	(1800,1000)	20.00	60.00	(600,400)	20.00	35.16
(1800,600)	2.577	3.045	(1600,1200)	20.00	20.33	(400,800)	0.000	26.17	(200,1000)	20.00	34.28
(400,1000)	14.24	37.78	(1800,1000)	19.89	47.67	(400,1200)	3.243	60.00	(600,600)	0.000	24.72
(1000,1600)	13.65	58.04	(800,1200)	19.79	58.79	(800,200)	0.000	51.68	(200,800)	19.66	47.52
(800,1800)	8.135	18.67	(1600,1000)	19.64	28.50	(200,1000)	0.000	60.00	(1600,800)	20.00	31.39
(1200,400)	17.56	22.75	(600,1000)	19.97	30.48	(800,1000)	20.00	34.29	(800,1800)	20.00	23.73
(200,200)	19.74	48.13	(600,800)	19.96	27.92	(200,400)	16.37	47.90	(200,600)	20.00	25.09
(1000,1200)	17.98	34.15	(1200,400)	19.77	46.93	(800,1600)	14.00	31.66	(1800,800)	18.87	31.66
(1000,200)	97.21	31.73	(1800,400)	19.90	52.40	(1800,600)	0.2126	60.00	(200,1800)	18.73	49.24
(400,600)	17.56	21.08	(1400,600)	19.96	33.69	(1800,200)	20.00	23.86	(1600,600)	20.00	54.70
(200,1600)	3.119	34.57	(1400,400)	19.59	32.81	(1800,1600)	20.00	40.57	(600,1800)	20.00	40.37
(600,600)	5.331	13.69	(1000,800)	19.99	36.50	(200,1200)	19.02	60.00	(800,600)	20.00	35.65
(1800,1200)	8.741	45.84	(600,600)	19.85	44.76	(1200,200)	20.00	60.00	(200,200)	20.00	26.57
(1400,1000)	6.631	56.62	(400,600)	19.92	36.54	(800,800)	20.00	41.41	(1200,200)	20.00	54.64
(1200,1000)	19.06	2764	(800,200)	19.95	58.88	(1400,400)	0.000	20.00	(1600,600)	20.00	42.39
(1000,1000)	18.43	55.89	(1600,200)	19.20	45.78	(1800,1600)	0.000	60.00	(1800,800)	19.91	44.19
(600,800)	19.87	48.36	(400,400)	19.66	31.52	(1000,1000)	20.00	60.00	(400,1200)	19.44	57.62
(600,200)	18.95	54.83	(1800,200)	19.98	55.28	(400,1200)	14.43	60.00	(200,1600)	20.00	43.04

OP: best position of turbines obtained by algorithms, RR: rotor radius, HH: hub height

Table 10 Optimal positions, hub heights, and rotor radii obtained by GWO, MGWO, RWGWO, and the proposed EC-GWO for 26 turbines

GWO			MGWO			RWGWO			EC-GWO		
OP	RR	HH	OP	RR	HH	OP	RR	HH	OP	RR	HH
(800,1200)	1.734	34.14	(200,1400)	15.88	46.00	(1800,1600)	19.05	58.54	(1200,1600)	20.00	60.00
(600,1800)	18.96	51.00	(1600,1800)	20.00	55.83	(1800,1200)	20.00	29.81	(600,1600)	20.00	60.00
(400,1200)	19.48	36.88	(800,1200)	19.35	48.24	(1600,1800)	19.86	42.22	(1200,1400)	20.00	60.00
(200,1200)	19.45	33.40	(1800,1000)	20.00	38.67	(1400,600)	19.71	28.19	(1800,1200)	20.00	60.00
(1800,800)	19.89	36.47	(1600,200)	19.50	26.35	(200,1400)	18.66	35.33	(1800,1000)	20.00	60.00
(400,400)	20.00	43.54	(1200,400)	19.39	33.63	(1600,600)	20.00	22.71	(1600,1000)	20.00	60.00
(1200,1800)	19.78	47.68	(800,800)	19.50	26.46	(400,800)	20.00	50.67	(1400,1600)	20.00	60.00
(600,1600)	19.36	52.01	(1400,600)	18.11	58.03	(600,600)	19.57	39.97	(600,1000)	20.00	60.00
(1400,800)	19.21	42.51	(1800,1000)	18.15	50.88	(1200,1400)	18.75	44.44	(200,1800)	20.00	60.00
(400,400)	19.51	51.97	(1600,600)	19.89	35.76	(200,1200)	19.21	33.78	(1600,600)	20.00	60.00
(1600,400)	19.50	30.72	(1400,400)	18.64	38.96	(1400,400)	20.00	27.38	(1400,1000)	20.00	60.00
(1600,1600)	19.78	23.98	(200,1200)	20.00	34.28	(1000,200)	20.00	44.78	(200,400)	20.00	60.00
(1200,400)	18.86	49.41	(1200,400)	20.00	52.11	(1800,1000)	20.00	33.37	(1600,400)	20.00	60.00
(1000,1600)	19.40	44.57	(1200,200)	19.63	21.42	(800,1400)	20.00	36.29	(1200,400)	20.00	60.00
(1000,800)	16.14	54.14	(400,1600)	18.42	35.15	(1600,1600)	19.99	20.00	(1400,800)	20.00	60.00
(1800,600)	19.91	44.28	(1000,1600)	19.11	24.78	(1000,1600)	20.00	36.15	(600,800)	20.00	60.00
(1000,800)	20.00	21.27	(400,1600)	19.26	51.81	(600,400)	19.01	30.70	(1000,1800)	20.00	60.00
(1600,200)	19.31	31.63	(1600,400)	0.03669	45.32	(600,400)	20.00	26.43	(800,400)	20.00	60.00
(400,1200)	13.29	32.26	(800,200)	19.36	29.97	(1200,1000)	20.00	28.96	(800,200)	20.00	60.00
(1200,400)	19.33	36.24	(600,1200)	20.00	43.91	(1200,800)	19.67	21.75	(600,600)	20.00	60.00
(1600,1600)	19.97	56.09	(1200,1600)	19.01	36.70	(800,800)	17.16	41.35	(1000,1200)	20.00	60.00
(1200,200)	18.71	38.31	(400,1200)	19.93	23.78	(200,1200)	19.36	27.24	(1600,200)	20.00	60.00
(1200,200)	19.12	35.25	(400,800)	19.39	34.29	(1600,1600)	18.61	47.25	(1400,600)	20.00	60.00
(400,400)	19.34	26.71	(200,800)	19.76	30.37	(1800,600)	19.44	48.01	(800,1800)	20.00	60.00
(600,400)	19.72	46.12	(1200,200)	18.89	52.94	(400,200)	20.00	39.48	(400,1800)	20.00	60.00
(800,200)	19.74	41.36	(1600,800)	19.31	30.14	(1000,1600)	18.96	51.20	(1000,1000)	19.66	31.62

OP: best position of turbines obtained by algorithms, RR: rotor radius, HH: hub height

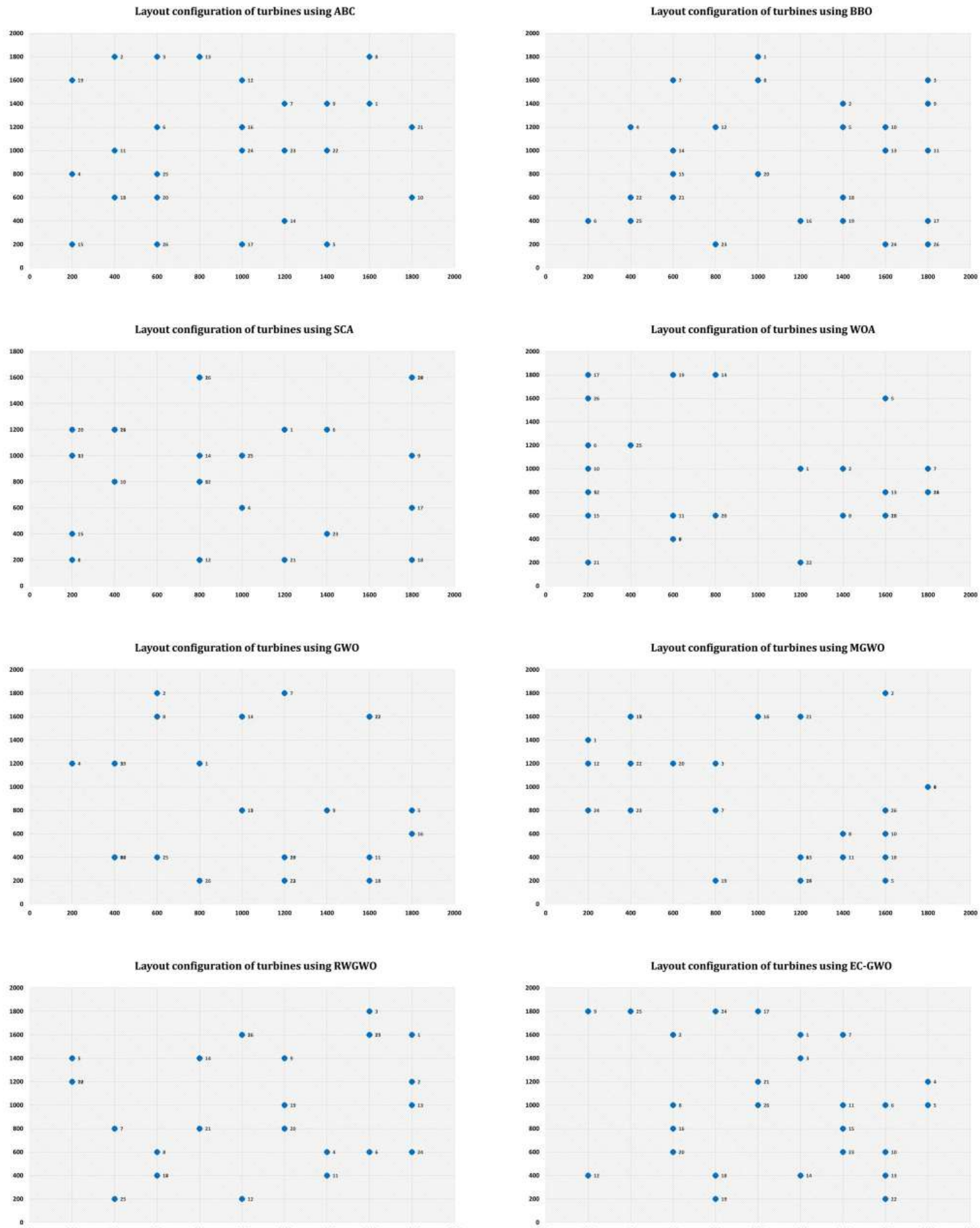

Fig. 7 Optimal configurations of 26 wind turbines

Fig. 8 Convergence curves for WFLOP with 26 turbines

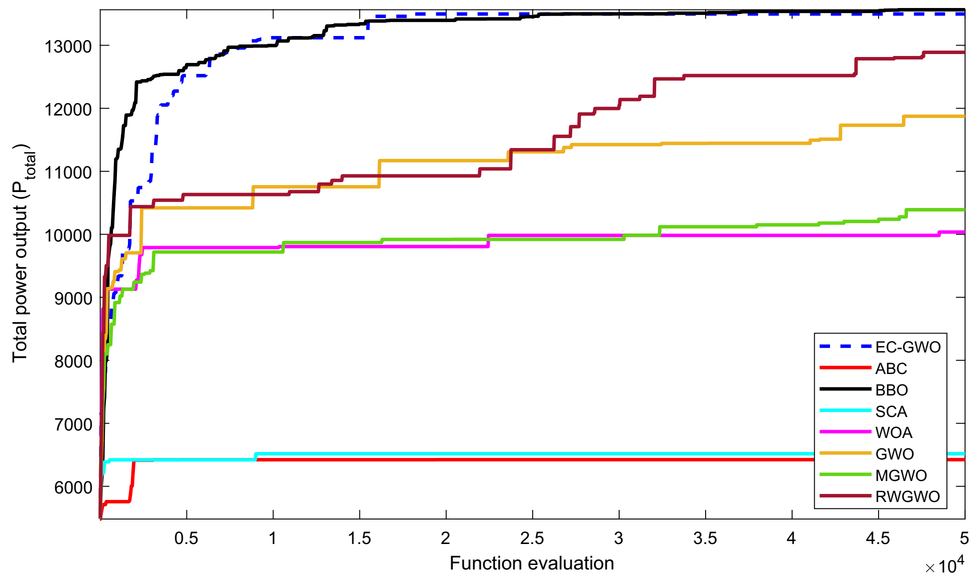

Table 11 Comparison results obtained by EC-GWO and other meta-heuristic algorithms on 30 turbines

	ABC	BBO	SCA	WOA	GWO	MGWO	RWGWO	EC-GWO
Average	7512.327	15457.39	8393.217	11562.7	12746.41	12663.71	13951.93	15535.19
Minimum	7300.36	15317.01	7489.006	10662.78	12091.47	11869.33	13317.5	15215.84
Maximum	7898.162	15560.09	9119.794	13514.58	13398.93	13497.38	14419.16	15787.08
Median	7458.713	15457.55	8334.575	11355.78	12674.76	12636.83	14070.37	15487.3
Std	229.4362	70.23642	457.5484	904.0591	465.1145	450.1876	419.1293	184.6043
Cost	0.0028067(+)	0.0014247(≈)	0.00243074(+)	0.0016403(+)	0.0016545(+)	0.00164238(+)	0.00153739(+)	0.00140418

Table 12 Optimal positions, hub heights and rotor radii obtained by ABC, BBO, SCA, and WOA for 30 turbines. (OP: best position of turbines obtained by algorithms, RR: rotor radius, HH: hub height)

ABC			BBO			SCA			WOA		
OP	RR	HH	OP	RR	HH	OP	RR	HH	OP	RR	HH
(600,600)	18.05	24.48	(1200,1000)	19.86	45.83	(1200,600)	0.000	60.00	(1400,1400)	20.00	23.96
(1400,1400)	18.84	43.94	(800,800)	19.91	31.51	(800,200)	20.00	55.86	(200,200)	17.28	41.91
(1000,800)	19.05	36.14	(1000,1600)	19.52	24.88	(1600,1000)	0.000	60.00	(800,1800)	20.00	55.14
(400,1400)	18.16	29.92	(600, 1400)	19.21	29.85	(400,600)	20.00	60.00	(1400,1200)	19.25	19.62
(1200,1000)	16.16	57.87	(400,1800)	19.91	39.41	(1000,1000)	16.83	60.00	(800,1800)	19.20	52.99
(400,200)	3.506	21.81	(1800,1800)	19.96	59.59	(200,600)	20.00	60.00	(1400,1800)	20.00	35.96
(1600,1400)	27.01	34.12	(1600,800)	19.73	23.79	(1600,400)	20.00	60.00	(400,1000)	20.00	60.00
(1200,200)	9.250	16.95	(1400,1400)	19.68	40.81	(600,800)	20.00	60.00	(800,400)	20.00	48.28
(600,1200)	18.16	40.73	(200,1400)	19.85	58.45	(1800,1600)	20.00	22.61	(1200,1200)	0.4356	17.11
(800,1600)	15.28	30.97	(200,800)	19.98	50.19	(1200,800)	0.000	60.00	(1400,600)	20.00	50.83
(800,800)	16.13	23.51	(1000,800)	19.90	34.22	(400,1400)	1.377	53.21	(600,600)	17.41	18.18
(1200,1200)	15.14	39.46	(800,600)	19.98	22.34	(600,1200)	4.513	60.00	(400,800)	19.83	23.48
(400,1200)	16.28	52.68	(1200,400)	19.86	50.08	(600,1000)	0.000	44.75	(1600,1800)	19.91	34.96
(1800,200)	17.19	32.02	(1000,600)	19.62	28.53	(200,1800)	0.000	60.00	(1200,1000)	18.96	33.51
(200,1600)	13.42	54.03	(1400,1000)	19.86	33.68	(1400,1800)	20.00	60.00	(600,400)	0.000	59.83
(1600,1800)	8.403	35.41	(200,400)	19.98	32.55	(1400,800)	0.000	4.199	(1400,1400)	20.00	36.07
(200,1800)	11.43	13.76	(1600,600)	19.99	30.48	(200,1400)	6.914	60.00	(1200,200)	20.00	22.08
(1600,200)	15.38	22.06	(800,400)	18.91	57.87	(1800,1400)	20.00	51.66	(200,1800)	20.00	33.01
(1200,800)	2.013	46.38	(1600,400)	19.65	45.44	(800,400)	20.00	55.52	(1800,400)	17.75	59.50
(1000,1000)	14.67	47.16	(1200,200)	19.20	20.14	(600,800)	6.924	60.00	(400,200)	0.000	60.00
(1200,600)	18.67	40.55	(800,200)	19.54	29.47	(1000,1800)	20.00	48.95	(200,1000)	20.00	60.00
(400,1800)	4.450	13.03	(400,1200)	19.99	51.11	(1400,1000)	0.000	3.931	(1200,1600)	18.52	60.00
(1200,400)	16.15	50.48	(1800,1400)	19.43	42.59	(1800,600)	18.32	33.23	(800,200)	19.87	60.00
(1400,1600)	18.33	37.88	(1400,400)	19.88	43.53	(400,1800)	20.00	60.00	(400,1600)	20.00	44.54
(1000,400)	8.695	31.38	(1000,200)	19.95	55.83	(1800,1200)	0.000	60.00	(600,800)	20.00	52.53
(1600,800)	8.396	46.99	(1800,1200)	19.98	39.23	(1200,1600)	20.00	49.29	(1400,200)	20.00	22.00
(1600,1200)	15.28	23.78	(1800,1000)	19.93	27.51	(1200,1600)	20.00	34.17	(1000,1000)	20.00	53.66
(400,1000)	18.29	47.57	(400,800)	19.35	35.34	(1000,200)	20.00	43.21	(400,1200)	19.91	59.90
(1600,600)	16.10	23.37	(400,200)	19.71	44.39	(1200,800)	20.00	60.00	(1000,600)	20.00	50.09
(1800,1800)	11.40	55.83	(1600,200)	19.96	43.47	(1600,200)	20.00	60.00	(1600,1000)	20.00	51.26

Table 13 Optimal positions, hub heights, and rotor radii obtained by GWO, MGWO, RWGWO, and the proposed EC-GWO for 30 turbines

GWO			MGWO			RWGWO			EC-GWO		
OP	RR	HH	OP	RR	HH	OP	RR	HH	OP	RR	HH
(1600,1600)	18.86	50.10	(200, 1200)	14.82	47.94	(1000,400)	19.90	48.84	(600,1600)	20.00	60.00
(1400,800)	19.84	30.68	(1400, 1000)	19.16	30.95	(200,1800)	20.00	37.35	(200,800)	20.00	60.00
(200,1200)	20.00	44.80	(1400, 1400)	19.61	53.23	(600,600)	19.60	48.48	(1600,1400)	20.00	60.00
(1200,400)	19.70	35.47	(400, 1200)	19.70	60.00	(200,800)	20.00	40.02	(1800,800)	20.00	60.00
(600, 1400)	20.00	48.76	(1000, 200)	20.00	54.55	(1600,1800)	20.00	49.59	(1600,1000)	20.00	60.00
(1000,1400)	19.57	34.06	(1400, 200)	17.47	23.26	(1600,800)	20.00	33.09	(1000,1600)	20.00	60.00
(200,1000)	18.77	32.06	(1800, 1800)	0.000	45.21	(1800,1800)	18.68	31.80	(1200,1000)	20.00	60.00
(1400,600)	0.7639	25.34	(800, 1200)	19.42	30.72	(200,600)	19.79	30.24	(1000,1200)	20.00	60.00
(1200,1000)	5.810	20.54	(600, 400)	19.15	25.26	(800,400)	18.37	48.33	(400,1800)	20.00	60.00
(200,400)	18.53	47.67	(1400, 1600)	18.97	28.74	(600,600)	19.63	50.95	(1200,400)	20.00	60.00
(1800,1200)	19.13	31.37	(1000, 200)	20.00	25.59	(400,600)	19.36	33.51	(1200,1600)	20.00	60.00
(1800,1200)	18.98	35.70	(1200, 1800)	19.10	22.38	(600,600)	20.00	39.17	(1400,800)	20.00	60.00
(1800,400)	14.97	43.72	(1400, 1600)	20.00	36.88	(1200,200)	18.24	34.45	(1400,200)	20.00	60.00
(1000,1000)	20.00	27.92	(800, 800)	0.7677	19.87	(400,600)	19.13	55.36	(1800,400)	20.00	60.00
(1000,600)	20.00	56.26	(800, 400)	19.95	49.77	(400,400)	19.23	26.94	(200,600)	20.00	60.00
(800,1400)	20.00	34.51	(1200, 1800)	20.00	41.02	(600,200)	20.00	39.21	(1200,200)	20.00	60.00
(1400,200)	19.73	40.48	(1600, 800)	20.00	51.46	(1600,400)	18.70	38.98	(200,400)	20.00	60.00
(1600,1200)	19.99	22.72	(1600, 400)	19.56	50.55	(1000,200)	19.88	46.46	(1600,200)	20.00	60.00
(600, 1400)	18.49	39.08	(200, 1200)	19.43	20.16	(1000,200)	19.63	54.53	(1000,800)	20.00	60.00
(1200,1800)	16.38	27.69	(1000, 1800)	20.00	53.04	(800,200)	20.00	29.34	(600,1000)	20.00	60.00
(200,400)	18.52	42.17	(1200, 1000)	19.86	50.90	(1800,1600)	19.24	52.30	(200,200)	20.00	60.00
(1000,1200)	18.66	39.97	(1000, 1800)	20.00	50.76	(1600,1800)	17.02	58.54	(800,200)	20.00	60.00
(1800,1600)	18.36	41.94	(1600, 1800)	20.00	25.67	(400,400)	18.74	35.56	(1000,400)	20.00	60.00
(1200,1600)	18.21	26.24	(400, 800)	16.95	23.67	(600,200)	19.44	24.86	(1000,200)	20.00	60.00
(400,1000)	20.00	31.04	(1400, 200)	18.99	24.90	(1800,400)	19.57	23.96	(400,1600)	20.00	60.00
(600, 1400)	16.93	35.64	(1400, 200)	19.38	41.77	(1800,1000)	18.45	56.36	(200,1800)	20.00	60.00
(1400,800)	20.00	22.13	(400, 600)	20.00	29.61	(1000,1800)	18.74	22.62	(1800,200)	20.00	60.00
(800,400)	20.00	36.34	(200, 600)	19.06	28.86	(1600,400)	12.27	53.43	(600,400)	20.00	60.00
(1600,1000)	20.00	25.36	(200, 200)	19.26	46.84	(200,600)	19.26	57.38	(400,1400)	20.00	60.00
(1400,200)	20.00	59.26	(1600, 1800)	16.33	51.02	(1000,1000)	19.22	48.61	(400,1200)	17.83	38.53

OP: best position of turbines obtained by algorithms, RR: rotor radius, HH: hub height

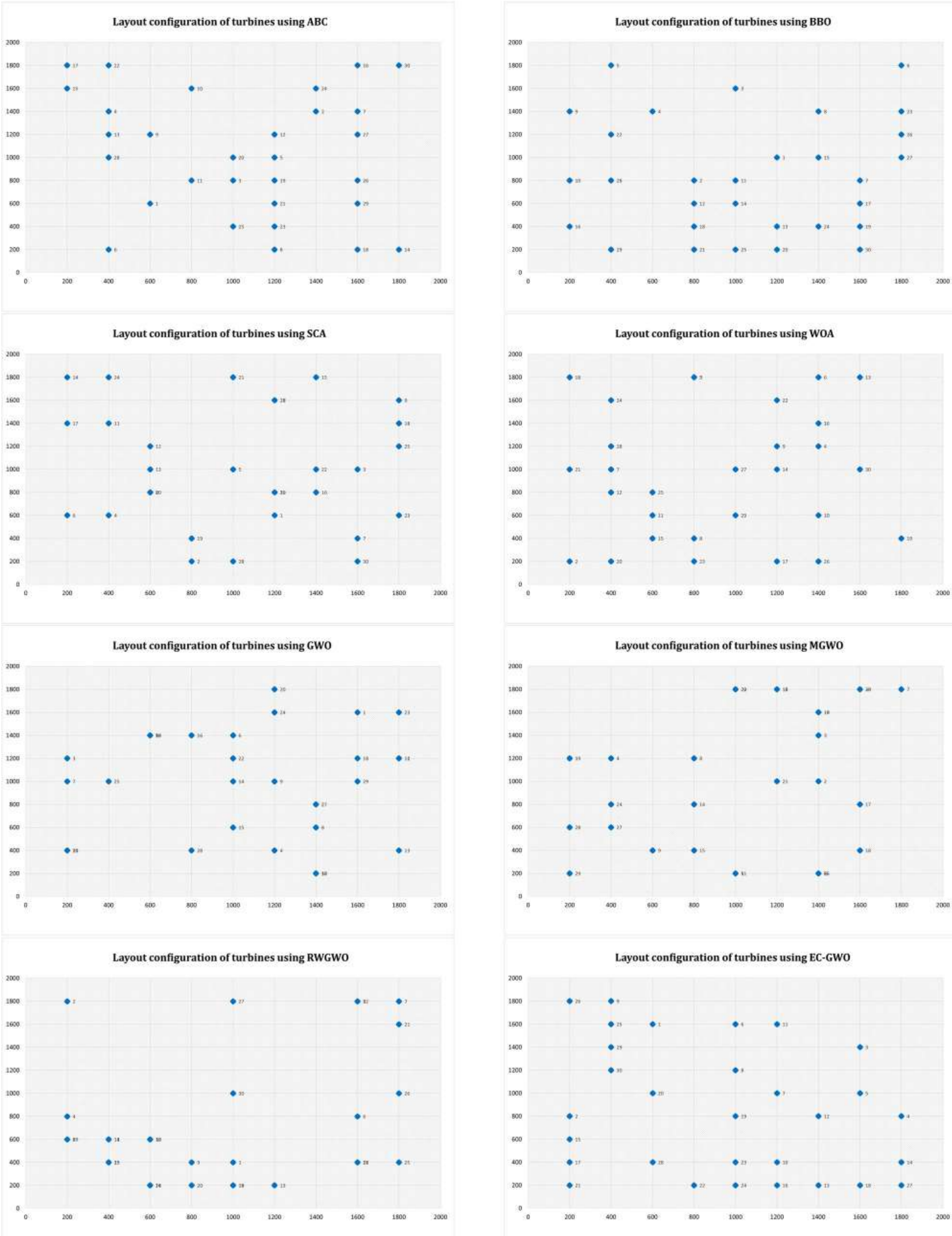

Fig. 9 Optimal configurations of 30 wind turbines

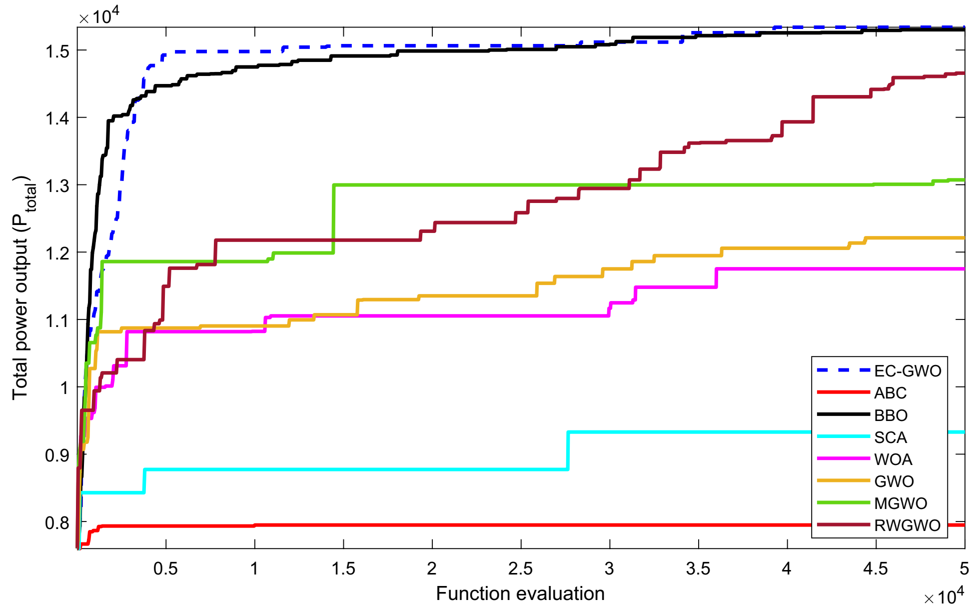

Fig. 10 Convergence curves for WFLOP with 30 turbines

5 Conclusion

This paper proposes a modified grey wolf optimizer, namely an enhanced chaotic grey wolf optimizer (EC-GWO), for the solution of the wind farm layout optimization problem. The EC-GWO is combined with four different strategies, including a modified GWO search mechanism, modified control parameter, chaotic search, and adaptive re-initialization of poor solutions. The modified control parameter is used to enhance the exploitation ability of the proposed EC-GWO algorithm, and chaotic search and adaptive re-initialization strategies have been combined with the EC-GWO to improve the exploration ability of the algorithm. The remaining strategy is the modification of the search scheme of the GWO, which includes the weighted average vector as a base vector for the search process. This strategy helps to provide a better transition from the exploration to the exploitation phase. The proposed algorithm EC-GWO, together with all these strategies, is validated on a well-known benchmark set of 23 numerical optimization problems. This set contains the problems of various difficulty levels such as unimodal, multimodal, and low-dimensional multimodal, which have verified that the proposed EC-GWO has an appropriate efficiency to manage and balance the exploration and exploitation levels during the optimization process. By confirming its efficiency through these benchmarks, it is applied to solve the wind farm layout optimization problem with a square wind farm of 2 km × 2 km. The numerical results for two cases with 26 and 30 turbines are obtained and compared with that of other meta-heuristic algorithms. From the obtained results, it can be concluded that the proposed EC-GWO is not only a better optimizer for WFLOP but also performs best on test problems. Thus, the proposed EC-GWO is recommended as an efficient solver for the WFLOP. The utility of EC-GWO can further be explored for other real-world problems.

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Declarations

Conflict of interest The authors declare no Conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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