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Noninferior Solution Grey Wolf Optimizer with an Independent Local Search Mechanism for Solving Economic Load Dispatch Problems

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Abstract: The economic load dispatch (ELD) problem is a complex optimization problem in power systems. The main task for this optimization problem is to minimize the total fuel cost of generators while also meeting the conditional constraints of valve-point loading effects, prohibited operating zones, and nonsmooth cost functions. In this paper, a novel grey wolf optimization (GWO), abbreviated as NGWO, is proposed to solve the ELD problem by introducing an independent local search strategy and a noninferior solution neighborhood independent local search technique to the original GWO algorithm to achieve the best problem solution. A local search strategy is added to the standard GWO algorithm in the NGWO, which is called GWOI, to search the local neighborhood of the global optimal point in depth and to guarantee a better candidate. In addition, a noninferior solution neighborhood independent local search method is introduced into the GWOI algorithm to find a better solution in the noninferior solution neighborhood and ensure the high probability of jumping out of the local optimum. The feasibility of the proposed NGWO method is verified on five different power systems, and it is compared with other selected methods in terms of the solution quality, convergence rate, and robustness. The compared experimental results indicate that the proposed NGWO method can efficiently solve ELD problems with higher-quality solutions.

Keywords: grey wolf optimizer (GWO); noninferior solution; local search mechanism; economic load dispatch problems (ELD); optimization algorithms

1. Introduction

Optimization problems widely exist in various fields in real-life. Some of these optimization problems are simple, while others are very complex due to nonconvex objective functions and complex model constraints. For complex optimization problems, a typical characteristic is the minimum or maximum objective function that is subject to heavy equality and/or inequality constraints. The economic load dispatch problem (ELD) is a famous complex power system operation optimization problem. ELD is a computational process, in which the total demanded generation is optimally allocated to each generation unit in operation by minimizing the selected cost criterion while also satisfying the total demand, transmission losses, and a set of physical and operational constraints imposed by the generators and system limitations [1,2]. The optimization study of the ELD problem is implied to be of great significance, because it can effectively save energy and provide a prioritization scheme for the control of real-time energy management power systems to guide power generation companies to implement sustainable development strategies. In addition, ELD is one of the important contents of power grid production and operation activities. Improving the economic production level of power grids can produce significant economic and social benefits. In general, the reasonable allocation of economic burden can save fuel by 0.5~2%, the efficiency of the unit economic combination can reach 1~2.5%, and the network loss correction benefit is 0.05~0.5%. Therefore, it is very important to optimize the economic dispatching of power plants.

Classic mathematical optimization techniques have been employed in previous attempts to solve the ELD problem, such as the fast lambda iteration method [3], quadratic programming [4], the gradient method [5], the interior point technique [6], the linear programming algorithm [7], dynamic programming [8], and the Lagrange relaxation algorithm [9]. However, in these methods, when encountering nonconvex objective function with complex constraints and highly nonlinear, nonconvex, and noncontinuous features with many local optima, the practical constraints of the generating units and the network have to be simplified or ignored, owing to the limits of these methods [10,11]. Faced with the inability to solve complex ELD problems with traditional methods, researchers turned to metaheuristic and evolutionary optimization techniques, such as the genetic algorithm (GA) [12], particle swarm optimization (PSO) [13], the cuckoo search algorithm (CSA) [14], the artificial bee colony algorithm (ABC) [15], the chaotic bat algorithm (CBA) [16], harmony search (HS) [17], grey wolf optimization (GWO) [18], hybrid grey wolf optimization (HGWO) [19], the differential evolution PSO (DE-PSO) method [20], the harmony search DE (HS-DE) method [21], and improved PSO (IPSO) [22], and achieved good expected results as these techniques could handle various complex operating constraints, such as prohibited operating zones (POZ) and generators' ramp-up and ramp-down [11]. The heuristic algorithms that are listed above for solving complex ELD problems can be summarized into three categories [11]: (I) the techniques applied to ELD problems in their original versions; (II) the modified versions of the first category; and, (III) the hybrid methods of the two original versions of the first category. However, except for the GWO algorithm, all of the meta-heuristic or evolutionary optimization techniques that are mentioned above require the algorithm parameters to be artificially set or adjusted to obtain better optimization performance, and once the algorithm-related parameter settings are unreasonable, it is difficult to obtain the desired results. Therefore, it is more advantageous to choose the GWO algorithm to optimize the ELD problem, since good optimization results can be obtained without adjusting any algorithm parameters by GWO algorithm. Moreover, its algorithm principle and structure are very simple and easy to program.

Although metaheuristic and evolutionary algorithms have made considerable progress in solving complex ELD problems when compared with traditional mathematics-based methods, they still face considerable challenges in solving highly nonconvex ELD problems. The no free lunch (NFL) theorem can scientifically explain this phenomenon. According to NFL, it is difficult to find a meta-heuristic that is best suited for solving all optimization problems [23]. In other words, one approach may show very promising results on a particular class of problems, but the same algorithm may show poor results on a different set of problems [24]. Therefore, more researchers improve the current approaches or propose new meta-heuristics for solving different complex problems every year, such as the dragonfly algorithm, is hybridized with the improved Nelder–Mead algorithm (INMDA) for function optimization and multilayer perceptron training [25], the dynamically dimensioned search is improved by embedding with piecewise opposition-based learning (DDS-POBL) for global optimization [26], and this also motivates our attempts in this paper to improve the GWO algorithm for solving complex ELD problems.

The GWO algorithm is a recently proposed, yet advanced, meta-heuristic technique that was inspired by the hierarchy of grey wolf populations and Mirjalilili et al. developed it in 2014 [24]. In GWO, according to the different role of the grey wolf in advancing the hunting process, pack members are divided into four different groups: alpha, beta, delta, and omega. When compared with other algorithms, the GWO has a simpler algorithm structure, and no algorithm parameters need to be adjusted, except for setting the population size and the maximum number of iterations. In addition, two powerful operations parameters are designed to maintain the exploration and exploitation to avoid local optima stagnation [27]. These remarkable advantages make GWO a widely studied and applied technique in practical optimization problems, such as feature selection [28], training multilayer perceptron (MLP) networks [29], optimizing support vector machines [30], clustering applications [31], design and tuning controllers [32], ELD problems [18,19,33], path planning [34], and welding production scheduling [35]. However, as a newly proposed algorithm, the GWO algorithm still has the drawback of the NFL theorem, which states that no optimization algorithm is suitable for all optimization problems. The population diversity may decrease with an increase in the number of iterations, easily falling into local optimal solutions, since all three alpha, beta, and gamma wolves are likely to converge to the same point (solution).

In the standard GWO algorithm, the first three best global optimal solutions (alpha, beta, and gamma wolves) accelerate the convergence rate of the algorithm, but the neglect of the local optimal solution in each iteration weakens the search diversity of the GWO. In addition, the standard GWO has no local search capability for noninferior solution domains, so it easily becomes stuck at a local minimum point, and thus cannot effectively search for other possible global optimal regions. Therefore, an improved novel GWO algorithm (NGWO) that is based on a local optimal search and an independent local search for noninferior solution domains is proposed. In the NGWO algorithm, the first three best wolves in the current iteration are used to replace the first three best wolves that were obtained so far by the standard GWO algorithm for searching the population. In the iterative processes, when the error between the optimal fitness found by some particles and the current optimal fitness of the population is very small, the solution that was found by this particle is a noninferior solution, and there may be a better solution in its field. These individuals no longer move toward the global optimal solution but search for a better solution in their own neighborhood. Therefore, the search mechanism of the NGWO is useful for enhancing the search ability and increasing the chance of the algorithm jumping out of a local optimal solution.

The contributions of this paper are listed, as follows:

1. The first three local optimal solutions of the current iteration are used to replace the alpha, beta, and delta of the standard GWO algorithm for searching the population.
2. A local independent search mechanism for noninferior solutions is introduced in the standard GWO algorithm to avoid local optimization and to find more promising solutions.
3. The NGWO algorithm is proposed based on 1 and 2 and is applied to solve complex ELD problems.

The rest of this paper is structured, as follows: Section 2 presents the proposed NGWO algorithm, Section 3 provides the formulation of the ELD problem, Section 4 addresses the methodology of NGWO for solving ELD problems, and Section 5 presents the conclusions and future work.

2. The Proposed NGWO Algorithm

It is necessary to investigate the relative efficiency of each improved constituent when solving the ELD problem since the proposed NGWO algorithm is an improved version of the standard GWO algorithm, and thus four different algorithm versions are investigated:

- The basic GWO algorithm: The standard GWO algorithm is chosen as a comparison algorithm to compare the performance in solving different ELD cases with the other three improved versions.
- The compared GWOI algorithm: The standard GWO algorithm is improved by changing the strategy of searching the population, but without considering the case of a noninferior solution.
- The compared GWOII algorithm: The standard GWO algorithm is improved by only introducing the local independent search mechanism for the noninferior solution.
- The proposed NGWO algorithm: The standard GWO algorithm integrated with both the GWOI and GWOII methods.

2.1. The Basic GWO Algorithm

GWO is a metaheuristic technique. The inspiration for the basic GWO algorithm is the hunting mechanism and social leadership hierarchy of grey wolves in nature. Grey wolves are considered as the top predators among animals and they have a strict leadership hierarchy. This leadership hierarchy generally consists of four different levels of groups: alpha (α), beta (β), delta (δ), and omega (ω), where α, β, and δ represent the first three best wolves (solutions) and the rest of the wolves (candidate solutions) are ω. In the predation process, the prey is driven to the predation area by encircling under the guidance of the first three optimal grey wolves (α, β, and δ). The encircle mechanism can be described by mathematical equations as [24]:

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_p(t) - \vec{X}(t) \right| \tag{1}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \tag{2}$$

where t is the current iteration, $\vec{C} = 2 \cdot \vec{r}_2$ and $\vec{A} = 2 \cdot \vec{a} \cdot \vec{r}_1 - \vec{a}$ indicates random vectors and they are used for balancing the exploration and exploitation, $\vec{X}_p$ represents the position vector of the prey, $\vec{X}$ is the position vector of a grey wolf, $\vec{a}$ is a control parameter that linearly decreases from 2 to 0, and $\vec{r}$ and $\vec{r}_2$ are the random vectors over the range 0 and 1.

In the basic GWO algorithm, the first three best wolves (α, β, and δ) are considered to have better knowledge regarding the potential location of prey and they are responsible for guiding ω to hunt prey, so the other wolves (ω) can update their positions according to α, β, and δ. The following mathematical models are modeled in this regard [23]:

$$\begin{aligned} \vec{D}_\alpha &= \left| \vec{C}_1 \cdot \vec{X}_\alpha - \vec{X} \right| \\ \vec{D}_\beta &= \left| \vec{C}_2 \cdot \vec{X}_\beta - \vec{X} \right| \\ \vec{D}_\delta &= \left| \vec{C}_3 \cdot \vec{X}_\delta - \vec{X} \right| \end{aligned} \tag{3}$$

$$\begin{aligned} \vec{X}_1 &= \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha \\ \vec{X}_2 &= \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta \\ \vec{X}_3 &= \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \end{aligned} \tag{4}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{5}$$

where $\vec{X}_\alpha$, $\vec{X}_\beta$, and $\vec{X}_\delta$ are the positions of the alpha (α), beta (β), and delta (δ), respectively; $\vec{D}_\alpha$, $\vec{D}_\beta$, and $\vec{D}_\delta$ indicate the encircle step sizes of α, β, and δ, respectively; $\vec{C}_1$, $\vec{C}_2$, and $\vec{C}_3$ and $\vec{A}_1$, $\vec{A}_2$, and $\vec{A}_3$ are the random vectors; $\vec{X}$ is the position vector of the current individual, and t represents the number of current iterations.

2.2. The Compared GWOI Algorithm

From the basic GWO algorithm, it can be seen that this algorithm only considers the global search in the search mechanism and lacks the local search for the population. According to Res. [36], the global search is a rough search in the whole search space and the local search is a deep search in the neighborhood of the current optimal solution. If the algorithm only adopts a single global search method, once the particles guiding the global search fall into the local optimal situation (as shown in Figure 1), the algorithm search will easily stop near the local optimal solution.

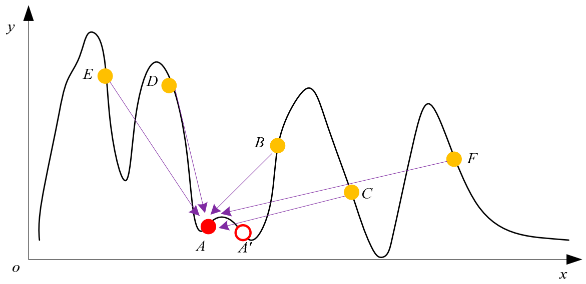

Figure 1. Particle movement in the basic grey wolf optimization (GWO) algorithms.

In the case of solving the minimum value that is shown in Figure 1, when A is the globally optimal particle, the search with only global guidance leads the particles with poor fitness to gather around A rather than A' and easily fall into the local optimum. The main reason for this phenomenon is the lack of a further in-depth search for the neighborhood of the globally optimal particle A. Therefore, this paper adds the local search strategy to this algorithm and proposed an improved version of the GWO, namely, GWOI to improve the search ability of the standard GWO algorithm. As depicted in Figure 2, after adding the local search strategy into the standard GWO algorithm, GWOI can search the local neighborhood of the global optimal point A in depth and it can easily search for a better candidate A'. The direct method for enhancing its local search ability is to replace the alpha, beta, and delta with the first three optimal individuals of the current iteration in its encircling step formulas, since the GWO algorithm search is mainly controlled by the first three best wolves.

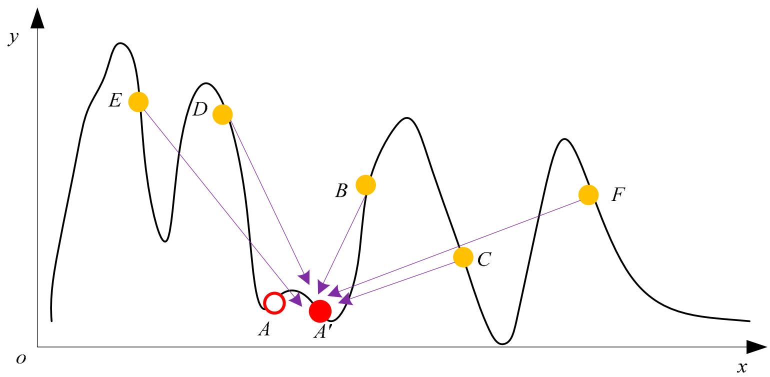

Figure 2. Particle movement in the GWOI.

The improved encircling step formulas are as follows:

$$\begin{aligned} \vec{D}'_{\alpha} &= \left| \vec{C}_1 \cdot \vec{X}'_{\alpha} - \vec{X} \right| \\ \vec{D}'_{\beta} &= \left| \vec{C}_2 \cdot \vec{X}'_{\beta} - \vec{X} \right| \\ \vec{D}'_{\delta} &= \left| \vec{C}_3 \cdot \vec{X}'_{\delta} - \vec{X} \right| \end{aligned} \tag{6}$$

where $\vec{X}'_{\alpha}$, $\vec{X}'_{\beta}$, and $\vec{X}'$ are the first three best locally optimal individuals.

Therefore, the mathematical models of the search agents update their positions, as follows:

$$\begin{aligned} \vec{X}'_1 &= \vec{X}'_{\alpha} - \vec{A}_1 \cdot \vec{D}'_{\alpha} \\ \vec{X}'_2 &= \vec{X}'_{\beta} - \vec{A}_2 \cdot \vec{D}'_{\beta} \\ \vec{X}'_3 &= \vec{X}'_{\delta} - \vec{A}_3 \cdot \vec{D}'_{\delta} \end{aligned} \tag{7}$$

$$\vec{X}(t+1) = \frac{\vec{X}'_1 + \vec{X}'_2 + \vec{X}'_3}{3} \tag{8}$$

2.3. The Compared GWOII Algorithm

Although the local search strategy is added to the GWOI algorithm to enhance its search ability, it only focuses on the local neighborhood search of the first three best particles. Once the globally optimal particles fall into the local optimum, the algorithm loses the ability to jump out of the local optimum, as shown in Figure 2. If the GWO algorithm can conduct an independent local search in the neighborhood of particles with similar fitness to the current optimal fitness, such as points B, C, D, E, and F, the probability of finding a better solution will greatly increase. This paper proposes a noninferior solution neighborhood independent local search technique based on this analysis. The main idea of this method is as follows: if the fitness value error between some particles and the current optimal particles is small, those particles are considered to be a noninferior solution and will no longer move toward the global optimal particle, but conduct a local depth search in their neighborhood to find a better solution that may exist. Figure 3 shows this search situation. In Figure 3, after introducing the noninferior solution neighborhood independent local search strategy and carrying out a certain number of iterative operations, points B, C, D, E, and F find better points B', C', D', E', and F'.

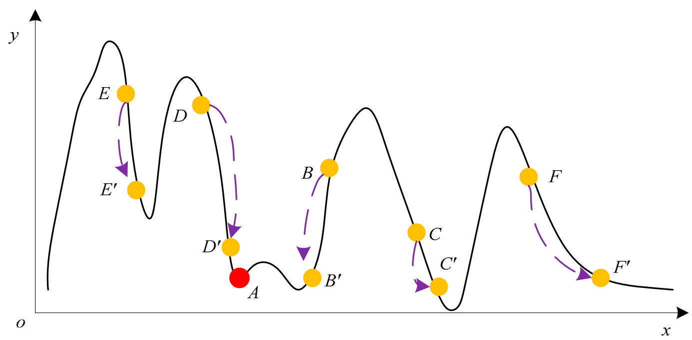

Figure 3. Particle movement under the guidance of the noninferior solution neighborhood independent local search strategy.

To implement the noninferior solution neighborhood independent local search technique, the determination conditions of the noninferior solution are as follows [37]:

$$Fb_i(t) - F_{best}(t) < \lambda\left[\overline{F}b(t) - F_{best}(t)\right] \tag{9}$$

$$\lambda = \log_{0.5}(-t/T) \tag{10}$$

where λ is the adjustment parameter, $Fb_i(t)$, $F_{best}(t)$, and $\overline{F}b(t)$ represents the best fitness value recorded by the ith particle in the ith iteration, the best fitness value searched by the algorithm so far, and the average value of the optimal fitness value searched by each particle, respectively. If the algorithm satisfies the determination condition of Equation (9) during the iteration, then the corresponding particle is a noninferior solution; then, in the $(t+1)$th iteration, the noninferior solution neighborhood independent local search method is executed, and its mathematical expression is as follows:

$$\vec{X}_i(t+1) = \mathrm{pbest}_i(t) + Cauchy(t)\cdot(ub_i - lb_i)\cdot\exp(-2\cdot\frac{t}{T}\cdot\pi)\cdot\cos(\pi\cdot\frac{t}{T}) \tag{11}$$

where $\mathrm{pbest}_i(t)$ is the best position of the ith particle obtained so far, $Cauchy(t)$ is the Cauchy random number in the tth iteration and the reason that we chose this parameter is that it has better stability than the standard normal uniform distribution and is more conducive to the exploration of the algorithms,

ub_i and lb_i are the ith upper boundary and ith lower boundary, respectively, of the search space, and T represents the maximum number of iterations.

Therefore, the GWOII algorithm is proposed by introducing the noninferior solution independent local search strategy into the standard GWO algorithm. As described in Figure 4, this strategy enables the GWOII algorithm to find a better C' in the neighborhood of noninferior solution C. If the fitness value of C' is better than that of the global optimal point A, then the particles in the population will no longer move toward A, but toward C'.

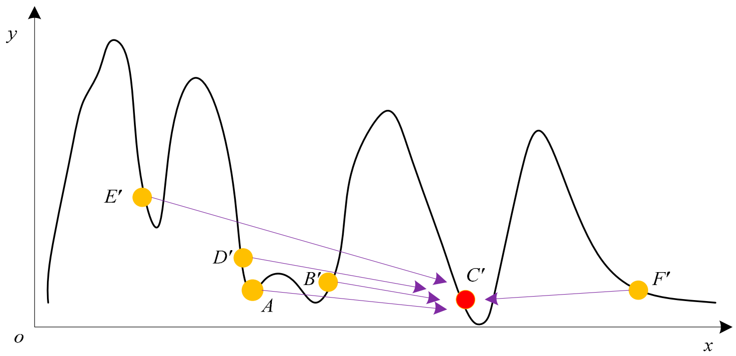

Figure 4. Particle movement in the GWOII.

2.4. The Proposed NGWO Algorithm

In this subsection, the GWOI algorithm is combined with the GWOII algorithm to form the proposed NGWO algorithm. The NGWO algorithm not only retains the strong search performance of the GWOI algorithm, but it also has the strong ability to jump out of the local optimal solution, as in the GWOII algorithm. Figure 5 shows the superiority of NGWO over GWO, GWOI, and GWOII in terms of optimization performance under certain optimization conditions.

In Figure 5, the local depth search method is used to search the neighborhood of the global optimal particle A and to then find a better potential solution A'; the noninferior solution neighborhood independent local search technique is adapted to search the noninferior solution B, C, D, E, and F, and better particles B', C', D', E', and F' are found. Moreover, among these better particles, the fitness of C' is better than that of the global optimal particle A'. Therefore, the particles in the population move toward particle C' instead of toward particle A', and particle C' becomes the globally optimal particle.

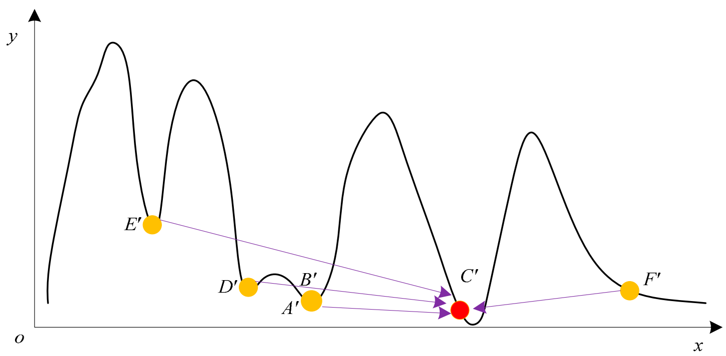

Figure 5. Particle movement in the novel GWO (NGWO) algorithms.

Figure 6 details the flowchart of the proposed NGWO algorithm, and Algorithm 1 presents the pseudocode of the proposed NGWO.

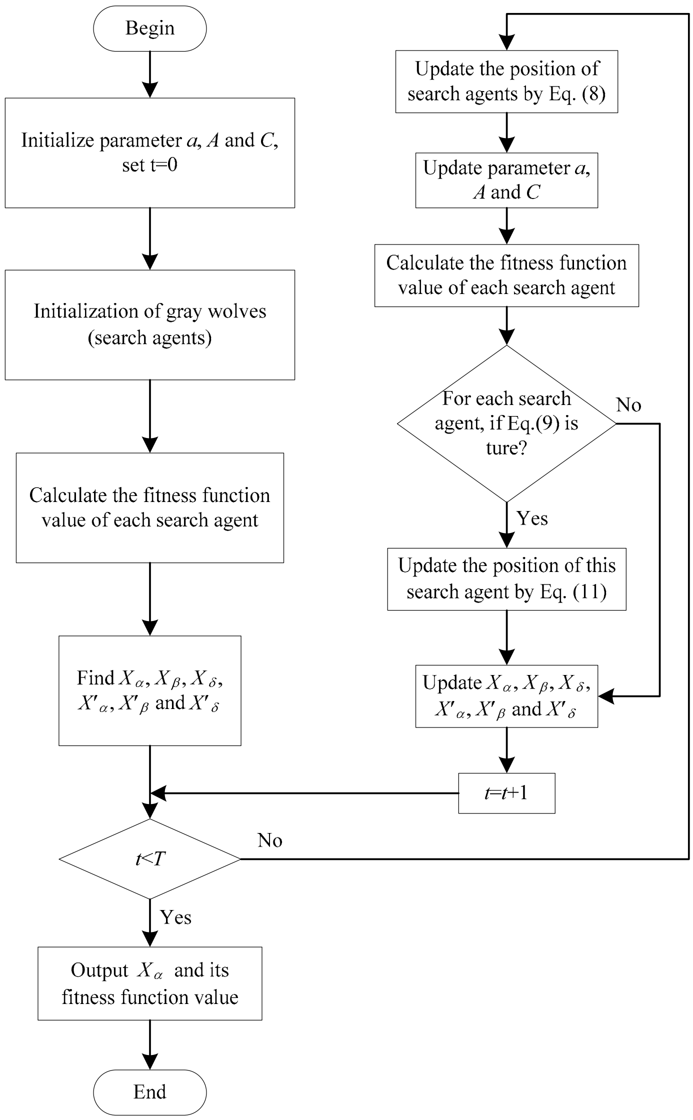

Figure 6. Flow chart of the proposed NGWO algorithm.

Algorithm 1. Pseudo code of the NGWO algorithm

Begin
Initialize the prey wolf population X_i (i = 1, 2, ... , n) and set the maximum number of iterations T.
Initialize a, A, and C
Calculate fitness function value of each search agent $f(X_i)$
X_α = the global best search agent; X'_α = the local best search agent
X_β = the global second search agent; X'_β = the local second search agent
X_δ = the global third search agent; X'_δ = the local third search agent
while $t < T$ **do**
  for each search agent
    Update the position of the current search agent by Equation (8)
  end for
Update a, A, and C
  Calculate the fitness function value of all search agents
  for each search agent
    if Equation (9) is ture
    Update the position of the current search agent by Equation (11)
    end if
  end for
Update X_α, X_β, X_δ, X'_α, X'_β and X'_δ
$t = t + 1$
end while
return X_α and $f(X_\alpha)$

3. Economic Load Dispatch Formulations

The ELD problem can be described as an optimization problem to minimize the total fuel cost of the individual dispatchable generating power while being subject to different constraints. We adopt the problem descriptions and formulations from refs. [38,39].

3.1. Objective Function

The ELD problem sums all the costs of the committed generators. Mathematically, this problem can be modeled in Equation (12), as:

$$F = \sum_{i=1}^{n} F_i(P_i) \tag{12}$$

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i \tag{13}$$

where F is the total cost function of n committed generating units, $F_i(P_i)$ is the generating cost function of the ith generator with the generation output P_i, and a_i, b_i, and c_i are the smooth cost fuel coefficients of the ith generator, which are constants.

In real-life, the valve-point loading effects are modeled by adding a higher-order nonlinearity rectified sinusoid contribution to the power generating systems and they are represented using Equation (13), as follows:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i + \left| e_i \times \sin\left(f_i \times \left(P_i^{\min} - P_i\right)\right) \right| \tag{14}$$

where e_i and f_i represent the nonsmooth cost fuel coefficients of the ith generator; and, $P_i^{\min}$ is the minimum generating capacity of the ith generator.

According to the description above, the objective function of the ELD problem with the valve-point effect can be formulated as:

$$\min F = \sum_{i=1}^{n} (a_i P_i^2 + b_i P_i + c_i + \left| e_i \times \sin(f_i \times (P_i^{\min} - P_i)) \right|) \tag{15}$$

3.2. Constraints and Variables

The constraints and variables of Equation (15) are listed, as follows [40–43]:

3.2.1. Power Balance Constraints and Variables

The whole power demand must equal to the total power generated by available units minus the total transmission loss, which can be modeled as:

$$\sum_{i=1}^{n} P_i - P_{\text{loss}} = P_{\text{demand}} \tag{16}$$

where P_{loss} and P_{demand} are the value of power demand and whole transmission loss, respectively, in the system. Generally, P_{loss} is calculated by Kron's loss formula, as shown in Equation (17).

$$P_{\text{loss}} = \sum_{i=1}^{n} \sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{i0} P_i + B_{00} \tag{17}$$

where B_{ij}, B_{i0}, and B_{00} are the loss coefficients, which are assumed to be constants under normal circumstances.

3.2.2. Generating Capacity Limits and Variables

The actual output P_i that is generated by the ith available unit should range between its minimum generation capacity and maximum generation capacity:

$$P_i^{\min} \leq P_i \leq P_i^{\max} \tag{18}$$

where $P_i^{\min}$ and $P_i^{\max}$ are the minimum and maximum generating capacity of the ith generator, respectively.

3.2.3. Ramp Rate Limits and Variables

In real circumstances, the operating range of each unit is restricted by its ramp-rate limit constraint:

$$\max(P_i^{\min}, P_i^0 - DR_i) \leq P_i \leq \min(P_i^{\max}, P_i^0 + UR_i) \tag{19}$$

where P and P_i^0 are the current and previous power output, respectively, and UR_i and DR_i are the ramp-up and ramp-down limits of generator i, respectively.

3.2.4. Prohibited Operating Zones Constraints and Variables

In the actual situation, the valve-point loading effects affect the power system, and each generator contains some discontinuous POZs where the generator cannot work. Therefore, the feasible operating zones of each unit should be avoided in these prohibited zones and they can be demonstrated, as follows:

$$\begin{array}{c} P_i^{\min} \leq P_i \leq P_{i,1}^{\text{lower}} \\ P_{i,j-1}^{\text{upper}} \leq P_i \leq P_{i,j}^{\text{lower}} \\ P_{i,n_i}^{\text{upper}} \leq P_i \leq P_i^{\max} \end{array} \tag{20}$$

where $P_{i,j}^{\text{lower}}$ and $P_{i,j}^{\text{upper}}$ are the lower and upper bounds, respectively, of the jth POZs of the ith generating unit, where $j \in [1, n_i]$, and n_i is the total number of POZs of unit number i.

4. Implementation of NGWO Method in Solving the ELD Problem

In this subsection, the connection between the NGWO algorithm and the ELD problem was developed to obtain an efficient and high-quality solution. The NGWO algorithm was primarily employed to determine the optimal power generation for each unit that was operational during a particular period to minimize the total power generation cost. Two following definitions should be described in detail before using the proposed NGWO method to solve the ELD problem.

4.1. Constraints Handling in ELD Problems with NGWO Approache

The key point in applying the NGWO method to optimizing the ELD problem is how the NGWO algorithm handles the constraints that exist in the problem. In general, most of the researchers are more likely to employ the penalty function methods to treat the constrained optimization problems [44]. The introduction of a penalty function can transform a constrained problem into an unconstrained problem and build a single objective function, so using an unconstrained optimization method can minimize it. When using the NGWO algorithm to solve a constrained ELD problem, it is common to handle constraints using principles of penalty functions, as follows [44]:

$$\min f = \begin{cases} f(P_i), & \text{if} P_i \in Fl \\ f(P_i) + \text{penalty}(P_i), & \text{otherwise} \end{cases} \tag{21}$$

where, $\text{penalty}(P_i)$ is 0 if no constraint is violated; otherwise it is positive value, Fl indicates the feasible region.

4.1.1. ELD Problem without the Valve-Point Loading Effects

In our work, when using the NGWO algorithm to handle the ELD problem without considering the valve-point loading effects, the map methods is built, as in Equation (22).

$$P_i^j(t+1) = P_i^{\min} + x_i(P_i^{\max} - P_i^{\min}) \tag{22}$$

where, x_i is a value between 0 and 1 obtained by the NGWO method, and the meanings of $P_i^{\min}$ and $P_i^{\max}$ are shown in Section 3.2.

After establishing the map method, Equation (13) is rewritten as:

$$\min F = \sum_{i=1}^{n} F_i(P_i) \cdot \left(1 - q \cdot \max\left(\sum_{i=1}^{n} P_i - P_{\text{demand}}, 0\right)\right) \tag{23}$$

where, q is a positive constants (penalty factors).

4.1.2. ELD Problem with Considering the Valve-Point Loading Effects

In this article, the map method used for handling the valve-point loading effects in NGWO approaches is according to Equations (22)–(24), as follows:

$$P_{\text{lower},i} = \max(P_i^{\min}, P_i^0 - DR_i) \tag{24}$$

$$P_{\text{upper},i} = \min(P_i^{\max}, P_i^0 + UR_i) \tag{25}$$

$$P_i^j(t+1) = P_{\text{lower},i} + x_i \cdot (P_{\text{upper},i} - P_{\text{lower},i}) \tag{26}$$

where, t is the current iteration, the meanings of $P_i^{\min}$, $P_i^{\max}$, P_i^0, DR_i, and UR_i are shown in Section 3.2, x_i is a value between 0 and 1 that is obtained by the NGWO method.

Next, if the equality Equation (16) and inequality Equations (19) and (20) are not solved, then Equation (15) is rewritten as:

$$\min F = \sum_{i=1}^{n} F_i(P_i) + q \cdot \max\left(1 - \frac{\sum\limits_{i=1}^{n} P_i - P_{\text{loss}}}{P_{\text{demand}}}, 0\right) \tag{27}$$

where, q is a positive constant (penalty factors), the meanings of P_{loss} and P_{demand} are shown in Section 3.2.

4.2. Implementation Steps of NGWO to ELD Problem

This work presents a quick solution to the ELD problem while utilizing the NGWO algorithm to obtain global optimal or near global optimal generation quantity of each generator unit. The development steps of the proposed technique to solve the ELD problem were detailed, as below.

Step 1: Initialize the population size N and the maximum number of iteration T, and randomly generate the grey individuals of the population between 0 and 1.

Step 2: Calculate the fitness value.

Step 2.1 If it is the ELD problem without the valve-point loading effects, map these initialized grey wolf individuals to the feasible domain of the practical operation constraints according to Equation (22). Calculate the total cost function of n committed generating units by using Equation (23) as the fitness value.

Step 2.2 If the valve-point loading effects are considered in the ELD problem, then map these initialized grey wolf individuals to the feasible domain of the practical operation constraints according to Equation (26), and employ the loss coefficients B, B_0, and B_{00} to calculate the transmission loss P_{loss} while using Equation (17). Calculate the total cost function of n committed generation units using Equation (27) as the fitness value.

Step 3: Compare each individual's fitness value to find out X_a, X_β, X_δ, X'_α, X'_β, and X'_δ.

Step 4: Update the position of the current search agent by Equation (8).

Step 5: Update parameters a, A, and C.

Step 6: Calculate Equation (9). If Equation (9) is satisfied, then update the position of the current search agent by Equation (11).

Step 7: Use Step 2 to calculate fitness function value for each individual search agents.

Step 8: Update X_α, X_β, X_δ, X'_α, X'_β, and X'_δ.

Step 9: If the number of iterations t reaches the maximum T, then go to Step 10. Otherwise, go to Step 3.

Step 10: The latest generated individual X_α is the optimal and then maps X_α according to Step 2 to obtain $P(X_\alpha)$. $P(X_\alpha)$ is the optimal generation power of each unit, and its fitness value $F(P(X_\alpha))$ is the minimum total generation cost.

Based on above analysis, the pseudocode of the NGWO algorithm employed to solve the ELD problem is shown in Algorithm 2.

Algorithm 2. Pseudo code of NGWO algorithm employed to solve the ELD problem

Begin
Initialize the prey wolf population X_i ($I = 1, 2, \ldots, n$) and set the maximum number of iterations T.
Input the relevant constraint parameters of the generator unit.
If the ELD problem has no valve-point loading effects, then map the initialized grey wolf individuals to the feasible domain according to Equation (22) to obtain $P(X_{\mathrm{i}})$. Otherwise, map the initialized grey wolf individuals to the feasible domain according to Equation (26) to obtain $P(X_{\mathrm{i}})$, and then calculate the transmission loss P_{loss} by using Equation (17).
Initialize a, A, and C
Calculate fitness function value of each search agent $F(P(X_{\mathrm{i}}))$ according to Equation (27) for considering the valve-point loading effects. Otherwise, calculate $F(P(X_{\mathrm{i}}))$ by using Equation (23).
X_α = the global best search agent; X'_α = the local best search agent
X_β = the global second search agent; X'_β = the local second search agent
X_δ = the global third search agent; X'_δ = the local third search agent
while $t < T$ **do**
  for each search agent
    Update the position of the current search agent by Equation (8)
  end for
Update a, A, and C
  Calculate the fitness function value for each search agents according to Equation (27) for considering the valve-point loading effects. Otherwise calculate the fitness function value of all search agents by utilizing Equation (23).
  for each search agent
    if Equation (9) is satisfied
    Update the position of the current search agent by Equation (11)
    end if
  end for
Update X_α, X_β, X_δ, X'_α, X'_β and X'_δ
$t = t + 1$
end while
return $P(X_\alpha)$ and $F(P(X_\alpha))$

5. Numerical Simulation Results and Analysis

To verify the applicability of NGWO for solving the ELD problem, the performance of the basic GWO, the compared GWOI, the compared GWOII, and the proposed NGWO algorithms are assessed on the following ELD cases:

Case I. A 3-generator system for load demand of 850 MW, and valve-point loading effects are considered.
Case II. A 13-generator system for a load demand of 2520 MW, and valve-point loading effects are considered.
Case III. A 40-generator system for a load demand of 10500 MW, and valve-point loading effects are considered.
Case IV. A 6-generator system with a quadratic cost function, POZs and transmission loss, and a load demand of 1263 MW.
Case V. A 15-generator system with a quadratic cost function, POZs and transmission loss, and a load demand of 2630 MW.

In this paper, the parameters set for each case study mentioned above are listed below. Each optimization technique was coded in MATLAB 2015a and executed on a Windows 10, 4-GHz, 2-GB RAM processor. In addition, the numbers of 50 independent runs were recorded for the compared GWOI, GWOII, and the proposed NGWO algorithms to validate the robustness of the proposed optimization technique. Furthermore, the population size was set to 30 for each case. Finally, for each ELD case, the maximum number of iterations was set to 500.

5.1. Case I: 3-Generator System

This case study consists of three generating units with quadratic cost functions and the effects of valve-point loadings are considered [45]. Table 1 provides the data of the generating units. In this case study, NGWO is compared with GWO, GWOI, GWOII, GA, and PSO [46], CJAYA and MP-CJAYA [37], and EP [47], in terms of the mean (F_{mean}) and the best (F_{best}) total generation cost. Table 2 records the comparison results. Figure 7 shows the convergence curve of the total generation cost for the mean solution, and Figure 8 explicitly shows the robustness of GWO, GWOI, GWOII, and NGWO in 30 trials.

Table 1. Generating units' parameters for Case I with value-point loading.

Generator	$P_{i\min}$ (MW)	$P_{i\max}$ (MW)	a_i	b_i	c_i	e_i	f_i
1	100	600	0.001562	7.92	561	300	0.0315
2	50	200	0.004820	7.97	78	150	0.063
3	100	400	0.001940	7.85	310	200	0.042

As shown in Table 2, GWO, GWOI, GWOII, and NGWO continuously decrease the values of F_{best} and F_{mean}, and NGWO achieves the very competitive minimum value of 8223.104 $/h relative to that of GA of 8222.07 $/h, as well as the very close minimum F_{mean} value 8233.567 $/h relative to that of MP-CJAYA of 8232.06 $/h. Therefore, the NGWO could obtain the second best results when compared to the above eight mentioned algorithms. The convergence curve in Figure 7 shows that the convergence rates of GWO, GWOI, GWOII, and NGWO continuously improved, and NGWO had the fastest convergence rate. Figure 8 confirms that NGWO achieved the best robustness.

Table 2. Best outputs of different methods for three-units system (PD = 850 MW).

Unit	GA [46]	PSO [46]	MP-CJAYA [37]	CJAYA [37]	EP [47]	GWO	GWOI	GWOII	NGWO
1	398.700	300.268	350.2464	350.0254	300.264	299.838	300.618	300.248	300.562
2	399.600	400.000	400.000	400.000	400.000	399.600	399.600	399.600	399.600
3	50.100	149.732	99.7576	99.9511	149.736	150.57	149.803	150.153	149.843
P_{total}(MW)	848.400	850.000	850.004	849.977	850.000	850.011	850.021	850.010	850.005
F_{mean} ($/h)	8234.72	8234.09	8232.06	8289.41	8234.16	8305.91	8284.772	8240.313	8233.567
F_{best} ($/h)	8222.07	8234.07	8223.29	8226.18	8234.07	8223.61	8223.367	8223.197	8223.104

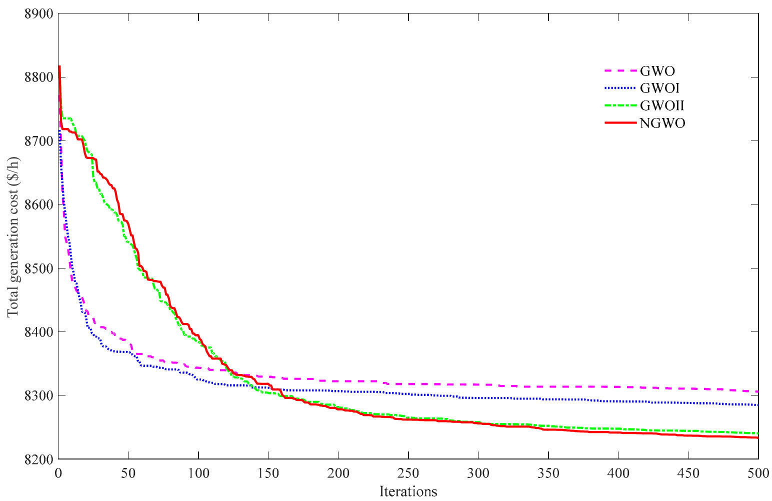

Figure 7. Convergence curve of the total generation cost for the mean solution in Case 1.

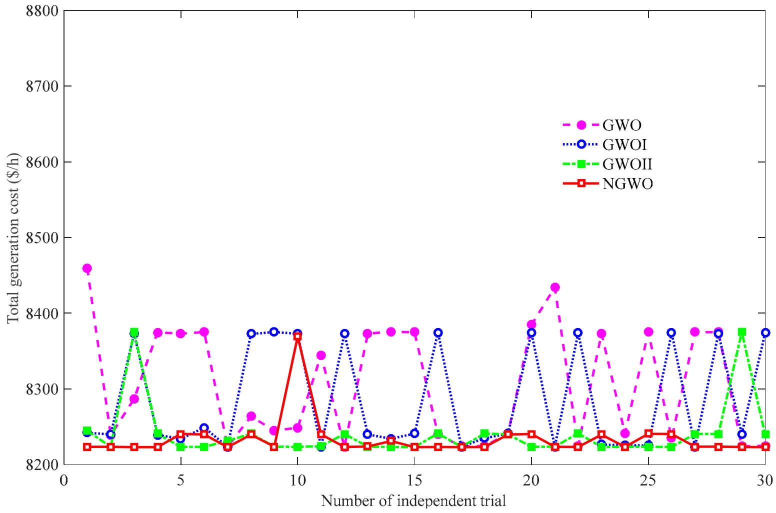

Figure 8. Total generation cost obtained by GWO, GWOI, GWOII, and NGWO for 30 trials in Case 1.

5.2. Case II: 13-Generator System

This case study is the second system with both valve-point loading effects and multiple fuel options and it comprises 13 generating units with quadratic cost functions. Table 3 shows all detailed data, which are taken from refs. [38,43]. The total power demand is 2520 MW. With an increasing number of generators, this system becomes more nonlinear and complex when compared to Case I. The results obtained by GWO, GWOI, GWOII, and NGWO were compared with GA [46], CPSO [48], JAYA and CJAYA [37], and SA [48], as listed in Table 4. The comparison results confirm that NGWO achieved the optimum total generation cost of both F_{mean} and F_{best} among the other algorithms, which were 24,366.12 $/h and 24,185.45 $/h, respectively. Figure 9 shows the convergence curves of GWO, GWOI, GWOII, and NGWO for the mean value of the total generation cost in 30 trials. From Figure 9, GWO and GWOI have better convergence rates in the early iteration than GWOII and NGWO, but they easily fall into the local optimal solution, and GWOII and NGWO more easily obtain the global optimal solution in the later iteration. Figure 10 describes the distribution of the total generation cost of GWO, GWOI, GWOII, and NGWO in 30 trials. NGWO was more robust than GWO, GWOI, and GWOII.

Table 3. Generating units' parameters for Case II with value-point loading.

Generator	$P_{i\min}$ (MW)	$P_{i\max}$ (MW)	a_i	b_i	c_i	e_i	f_i
1	00	680	0.00028	8.10	550	300	0.035
2	00	360	0.00056	8.10	309	200	0.042
3	00	360	0.00056	8.10	307	200	0.042
4	60	180	0.00324	7.74	240	150	0.063
5	60	180	0.00324	7.74	240	150	0.063
6	60	180	0.00324	7.74	240	150	0.063
7	60	180	0.00324	7.74	240	150	0.063
8	60	180	0.00324	7.74	240	150	0.063
9	60	180	0.00324	7.74	240	150	0.063
10	40	120	0.00284	8.6	126	100	0.084
11	40	120	0.00284	8.6	126	100	0.084
12	55	120	0.00284	8.6	126	100	0.084
13	55	120	0.00284	8.6	126	100	0.084

Table 4. Best outputs of different methods for 13-units system (PD = 2520 MW).

Unit	GA [46]	CPSO [48]	CJAYA [37]	JAYA [37]	SA [46]	GWO	GWOI	GWOII	NGWO
1	627.05	628.32	628.3185	628.3185	668.40	647.3842	645.5569	630.9811	630.9951
2	359.40	299.83	299.1992	299.2009	359.78	306.3995	306.9539	300.8038	297.9355
3	358.95	299.17	299.1993	306.9105	358.20	309.6117	306.5356	302.7475	299.9253
4	158.93	159.70	159.7330	159.7339	104.28	175.1400	169.6878	160.1702	157.9267
5	159.73	159.64	159.7331	159.7337	60.36	66.8791	168.4922	161.0252	159.6433
6	159.68	159.67	159.7331	159.7338	110.64	162.7466	174.9721	160.9845	159.2335
7	159.53	159.64	159.7330	109.8673	162.12	174.3111	167.1394	159.1231	159.7630
8	158.89	159.65	159.7330	159.7342	163.03	61.2250	116.8800	110.4278	159.6615
9	110.15	159.78	159.7331	159.7340	161.52	175.1400	116.8800	159.7720	159.4265
10	77.27	112.46	110.0403	114.8012	117.09	116.7600	116.8800	116.8577	76.8790
11	75.00	74.00	114.7994	114.8001	75.00	116.7600	109.9096	77.0418	79.5038
12	60.00	56.50	55.0000	92.4018	60.00	99.9167	59.0347	91.4990	86.8040
13	55.41	91.64	55.0000	55.0027	119.58	108.5598	66.5129	88.6915	94.1941
P_{total} (MW)	2520	2520	2519.96	2519.97	2520	2520.83	2521.74	2520.13	2520.21
F_{mean} ($/h)	–	–	24,385.7604	24,476.2547	–	24,442.08	24,471.53	24,395.58	24,366.12
F_{best} ($/h)	24,418.99	24,211.56	24,178.8040	24,220.7529	24,970.91	24,231.18	24,244.69	24,198.47	24,185.45

"–" indicates the cost value is missing.

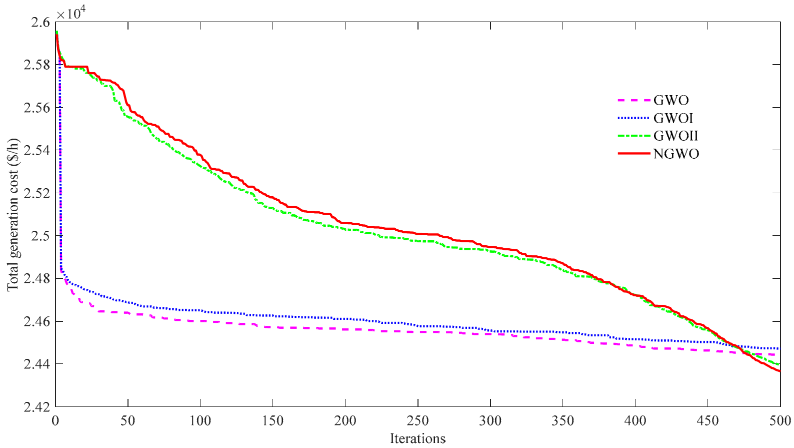

Figure 9. Convergence curve of the total generation cost for the mean solution in Case II.

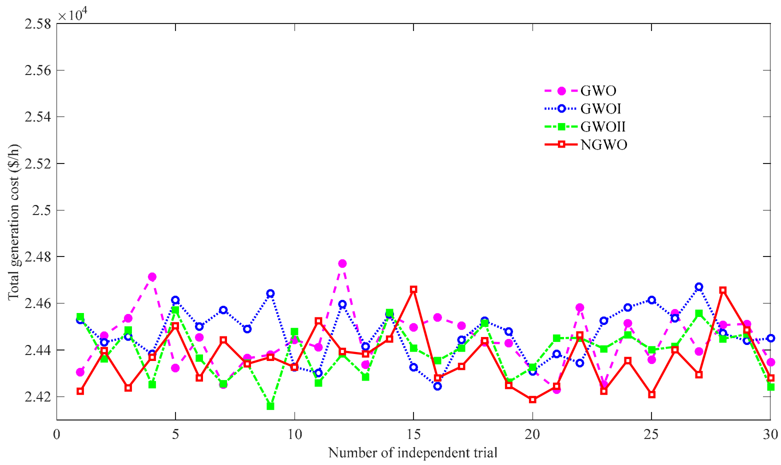

Figure 10. Total generation cost obtained by GWO, GWOI, GWOII, and NGWO for 30 trials in Case II.

5.3. Case III: 40-Generator System

In this subsection, the largest ELD problem system consisting of 40 generators, in which the valve-point effect is considered, with a total load demand of 10,500 MW, is selected to investigate the effectiveness of the NGWO algorithm. Table 5 provides the test data for this case study, in which the valve-point loading has also been included in the fuel cost functions [47]. Due to the large number of generator units in this test system, it has a much more complex solution when compared to the previous solution; therefore, the test system is very suitable for testing the difference in the optimization performance of different improvement strategies for the same algorithm. Table 6 reports the comparison results of the proposed NGWO method with NPSO [49], PSO-LRS [37], MPSO [13], CJAYA [37], IGA [50], GWO, GWOI, and GWOII. The table shows that NGWO solved the large-scale ELD problem with a high-quality optimum, and its optimization ability was slightly worse than that of CJAYA, but was better than that of the other methods. In these eight comparison algorithms, NGWO achieved the second optimization results. In Figure 11, the convergence curves of four different GWO versions are compared, and it can be observed that NGWO and GWOII dramatically accelerated the convergence rate. However, GWO and GWOI were easily trapped in the local optimum. Figure 12 is the distribution of the optimal total generation cost values that were obtained by GWO, GWOI, and GWOII in 30 runs. This figure demonstrates that these three algorithms show poor stability when optimizing this large-scale power system. However, the stability of the NGWO algorithm is relatively better. All of the above comparisons provide strong evidence demonstrating the effectiveness of NGWO in solving large-scale ELD problems.

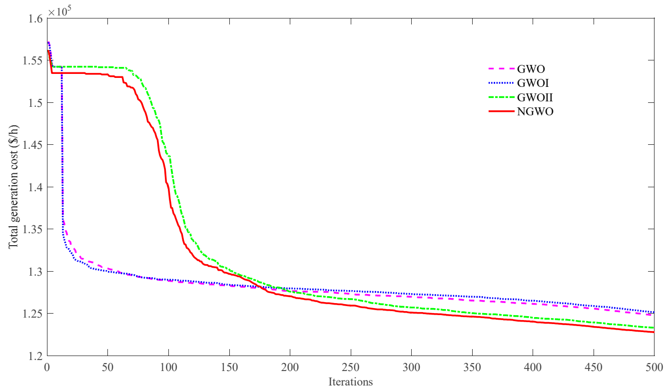

Figure 11. Convergence curve of total generation cost for the mean solution in Case III.

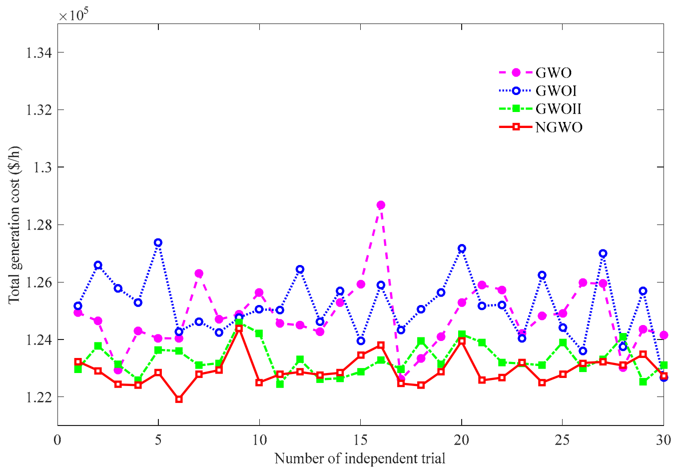

Figure 12. Total generation cost obtained by GWO, GWOI, GWOII, and NGWO for 30 trials in Case III.

Table 5. Generating units' parameters for Case III with value-point loading.

Generator	$P_{i\min}$ (MW)	$P_{i\max}$ (MW)	a_i	b_i	c_i	e_i	f_i
1	36	114	0.00690	6.73	94.705	100	0.084
2	36	114	0.00690	6.73	94.705	100	0.084
3	60	120	0.02028	7.07	309.54	100	0.084
4	80	190	0.00942	8.18	369.03	150	0.063
5	46	97	0.01140	5.35	148.89	120	0.077
6	68	140	0.01142	8.05	222.33	100	0.084
7	110	300	0.00357	8.03	287.71	200	0.042
8	135	300	0.00492	6.99	391.98	200	0.042
9	135	300	0.00573	6.60	455.76	200	0.042
10	130	300	0.00606	12.9	722.82	200	0.042
11	94	375	0.00515	12.9	635.20	200	0.042
12	94	375	0.00569	12.8	654.69	200	0.042
13	125	500	0.00421	12.5	913.40	300	0.035
14	125	500	0.00752	8.84	1760.4	300	0.035
15	125	500	0.00708	9.15	1728.3	300	0.035
16	125	500	0.00708	9.15	1728.3	300	0.035
17	220	500	0.00313	7.97	647.85	300	0.035
18	220	500	0.00313	7.95	649.69	300	0.035
19	242	550	0.00313	7.97	647.83	300	0.035
20	242	550	0.00313	7.97	647.81	300	0.035
21	254	550	0.00298	6.63	785.96	300	0.035
22	254	550	0.00298	6.63	785.96	300	0.035
23	254	550	0.00284	6.66	794.53	300	0.035
24	254	550	0.00284	6.66	794.53	300	0.035
25	254	550	0.00277	7.10	801.32	300	0.035
26	254	550	0.00277	7.10	801.32	300	0.035
27	10	150	0.52124	3.33	1055.1	120	0.077
28	10	150	0.52124	3.33	1055.1	120	0.077
29	10	150	0.52124	3.33	1055.1	120	0.077
30	47	97	0.01140	5.35	148.89	120	0.077
31	60	190	0.00160	6.43	222.92	150	0.063
32	60	190	0.00160	6.43	222.92	150	0.063
33	60	190	0.00160	6.43	222.92	150	0.063
34	90	200	0.0001	8.95	107.87	200	0.042
35	90	200	0.0001	8.62	116.58	200	0.042
36	90	200	0.0001	8.62	116.58	200	0.042
37	25	110	0.0161	5.88	307.45	80	0.098
38	25	110	0.0161	5.88	307.45	80	0.098
39	25	110	0.0161	5.88	307.45	80	0.098
40	242	550	0.00313	7.97	647.83	300	0.035

Table 6. Best outputs of different methods for 40-units system.

Unit	NPSO [49]	PSO-LRS [37]	MPSO [50]	CJAYA [37]	IGA [50]	GWO	GWOI	GWOII	NGWO
1	113.9891	111.9858	114.000	114.0000	110.97	109.0947	109.7268	107.6544	111.3177
2	113.6334	110.5273	114.000	111.6651	110.88	112.0471	111.7342	109.2161	112.7551
3	97.5500	98.5560	120.000	119.9876	98.17	115.4584	119.2197	94.7874	118.6377
4	180.0059	182.9622	182.222	188.2606	178.85	179.8333	181.6041	182.3441	183.3649
5	97.0000	87.7254	97.000	96.9763	87.78	46.1649	89.8836	86.9731	91.8097
6	140.0000	139.9933	140.000	139.9488	140.00	83.1571	125.1816	109.1907	104.3697
7	300.0000	259.6628	300.000	264.0949	260.37	261.6345	265.0775	259.4910	297.6533
8	300.0000	297.7912	299.021	299.9814	286.83	292.4025	290.2216	284.1803	289.4349
9	284.5797	284.8459	300.000	284.9042	285.14	284.7149	285.2586	285.1526	298.4044
10	130.0517	130.0000	130.000	130.0908	204.86	132.9049	134.9231	129.3500	129.3500
11	243.7131	94.6741	94.000	94.0011	165.98	101.6726	167.9983	317.4787	241.9702
12	169.0104	94.3734	94.000	94.0000	167.75	319.8174	183.6314	157.3563	166.9113
13	125.0000	214.7369	125.000	125.1028	214.31	215.0746	219.5396	300.6095	214.8490
14	393.9662	394.1370	304.485	394.2529	305.65	394.9259	394.9259	305.0848	215.6690
15	304.7586	483.1816	394.607	484.1262	393.66	398.1829	212.7154	395.3099	305.6922
16	304.5120	304.5381	305.323	304.5950	394.60	304.1546	484.5572	203.9544	394.6479
17	489.6024	489.2139	490.272	490.8265	489.22	490.0842	494.3478	489.6721	494.7618
18	489.6087	489.6154	500.000	489.3438	489.25	493.2515	491.2367	492.3490	493.1559
19	511.7903	511.1782	511.404	511.3775	511.23	511.4229	514.3755	514.3882	512.7416
20	511.2624	511.7336	512.174	512.1395	510.69	511.9422	514.3755	511.7323	520.8929
21	523.3274	523.4072	550.000	523.6621	524.74	532.3762	522.6016	532.2046	526.1137
22	523.2196	523.4599	523.655	523.3534	525.52	532.2484	523.6988	527.3193	532.1443
23	523.4707	523.4756	534.661	524.9677	522.98	530.7732	523.6988	527.3193	536.8421
24	523.0661	523.7032	550.000	524.2850	522.22	526.1112	536.1385	539.9336	524.4669
25	523.3978	523.7854	525.057	522.9279	523.26	524.4545	523.5451	526.6306	525.2461
26	523.2897	523.2757	549.155	523.2298	523.32	523.4934	524.0780	524.8658	529.3289
27	10.0208	10.0000	10.000	10.0000	10	11.5028	14.8568	9.9500	9.9500
28	10.0927	10.6251	10.000	10.0047	10	9.9541	21.0962	9.9500	9.9500
29	10.0621	10.0727	10.000	10.0000	10	10.3272	13.1286	9.9500	9.9500
30	88.9456	51.3321	97.000	97.0000	88.86	91.6019	88.5089	90.3385	88.4106
31	189.9951	189.8048	190.000	190.0000	162.30	188.8475	188.0180	159.6875	188.9088
32	190.0000	189.7386	190.000	189.9503	177.94	165.2531	166.2968	188.9923	188.8126
33	190.0000	189.9122	190.000	190.0000	160.18	188.9197	182.0808	173.1974	186.9624
34	165.9825	199.3258	200.000	169.8860	166.54	189.2968	164.9636	189.6808	195.0897
35	172.4153	199.3065	200.000	199.8549	164.80	180.4605	172.6948	192.1671	171.5047
36	191.2978	192.8977	200.000	199.9896	170.68	184.2693	191.0765	157.5027	176.1085
37	109.9893	110.0000	110.000	109.9712	108.17	89.6748	108.8942	104.4095	89.5297
38	109.9521	109.8628	110.000	109.9977	100.68	90.1485	100.8804	86.74132	89.3589
39	109.8733	92.8751	110.000	109.9871	109.34	57.0464	27.8744	100.2970	109.3222
40	511.5671	511.6883	512.964	511.2250	511.28	514.3622	511.7717	512.43873	512.5412
P_{total} (MW)	10,499.9989	10,499.9452	10,500	10,499.97	10,500	10,499.97	10,499.96	10,499.97	10,499.93
F_{mean} ($/h)	122,221.3697	122,558.4565	–	122,581.85	122,811.41	124,796.61	125,155.07	123,314.39	122,787.77
F_{best} ($/h)	121,704.7391	122,035.7946	122,252.265	121,799.88	121,915.93	122,602.37	122,678.91	122,430.74	121,881.81

5.4. Case IV: 6-Generator System

This case study comprises six generating units with constraints of transmission loss, together with two POZs with ramp-up and ramp-down. The generator data and two POZs are recorded in Table 7, and Table 8 shows the loss B-coefficients [11]. The algorithm used to find the global optima for this problem always encounters challenging complexity, owing to the decision spaces being nonconvex and the cost functions being convex and represented by quadratic functions.

To validate the effectiveness of our method on this test system, NGWO is compared with SA [46], GA [51], MTS [52], NPSO [49], PSO [46], JAYA [37], GWO, GWOI, and GWOII in terms of the total generation cost. Table 9 provides the comparison confirming that GWOI obtained the lowest best total generation cost (F_{best}) of 15,443.25 $/h among all of the techniques, while JAYA and NGWO achieved the second and third lowest F_{best} of 15,447.09 $/h and 15,449.17 $/h, respectively. In addition, Table 10 summarizes the best total generation cost (F_{best}), worst total generation cost (F_{worst}), and mean total generation cost (F_{mean}) of the four versions of GWO. From Table 10, we can observe that NGWO provided the lowest F_{best} and F_{mean} of 15,449.17 $/h and 15,449.86 $/h, respectively, and GWOII obtained the lowest F_{worst} of 15,452.41 $/h. Figure 13 plots the distribution of the total generation cost for the mean solution, which shows that NGWO is the fastest among the four versions of GWO in terms of the convergence rate and it approaches the global optimum. In addition, NGWO has the most robust characteristics, as described in Figure 14.

Table 7. Ramp rate limits and prohibited zones of units for Case IV.

Generator	$P_{i\min}$ (MW)	$P_{i\max}$ (MW)	a_i	b_i	c_i	P_i^0	UR_i	DR_i	Prohibited Zones
1	100	500	0.0070	7.0	240	440	80	120	[210, 240], [350, 380]
2	50	200	0.0095	10.0	200	170	50	90	[90, 110], [140, 160]
3	80	300	0.0090	8.5	220	200	65	100	[150, 170], [210, 240]
4	50	150	0.0090	11.0	200	150	50	90	[80, 90], [110, 120]
5	50	200	0.0080	10.5	220	190	50	90	[90, 110], [140, 150]
6	50	120	0.0075	12.0	190	110	50	90	[75, 85], [100, 105]

Table 8. Transmission loss coefficients for Case IV.

$\mathbf{B = 1 \times 10^{-2}}$	**0.0017**	**0.0012**	**0.0007**	**−0.0001**	**−0.0005**	**−0.0002**
	0.0012	0.0014	0.0009	0.0001	−0.0006	−0.0001
	0.0007	0.0009	0.0031	0	−0.001	−0.0006
	−0.0001	0.0001	0	0.0024	−0.0006	−0.0008
	−0.0005	−0.0006	−0.001	−0.0006	0.0129	−0.0002
	−0.0002	−0.0001	−0.0006	−0.0008	−0.0002	0.015
$\mathbf{B_0}$ = 1×10^{-3}	−0.3908	−0.1297	0.7047	0.0591	0.2161	−0.6635
$\mathbf{B_{00}}$ = 10×	0.0056					

Table 9. Best outputs of different methods for 6-units system.

Generator	SA [46]	GA [51]	MTS [52]	NPSO [49]	PSO [46]	JAYA [37]	GWO	GWOI	GWOII	NGWO
1	478.1258	462.0444	448.1277	447.4734	447.5823	457.9858	446.6281	447.2399	446.9060	448.7973
2	163.0249	189.4456	172.8082	173.1012	172.8387	176.8785	171.7686	175.0336	172.1000	174.4309
3	261.7146	254.8535	262.5932	262.6804	261.3300	250.0717	264.6710	262.6065	263.8918	262.9964
4	125.7665	127.4296	136.9605	139.4156	138.6812	129.3748	141.3356	138.8324	139.8172	138.2484
5	153.7056	151.5388	168.2031	165.3002	169.6781	172.8886	166.5389	167.2797	164.4018	164.9710
6	93.7965	90.7150	87.3304	87.9761	85.8963	88.4618	85.0000	85.0000	88.8170	86.46551
P_{total} (MW)	1276.1339	1276.0270	1276.0232	1275.96	1276.0066	1275.6611	1276.3156	1276.0229	1276.0155	1275.4658
P_{loss} (MW)	13.1317	13.0268	13.0205	12.9470	13.0066	12.6665	13.3099	13.0222	13.0066	12.8486
F_{best} ($/h)	15,461.10	15,457.96	15,450.06	15,450.00	15,450.14	15,447.09	15,450.07	15,443.25	15,449.96	15,449.17

Table 10. Comparison results of 6-units system.

Algorithm	F_{best} ($/h)	F_{worst} ($/h)	F_{mean} ($/h)
SA [46]	15,461.10	15,545.50	15,488.98
GA [51]	15,457.96	15,524.69	15,477.71
MTS [52]	15,450.06	15,453.64	15,451.17
NPSO [49]	15,450.00	15,454.00	15,452.00
PSO [46]	15,450.14	15,491.71	15,465.83
JAYA [37]	15,477.09	15,622.16	15,500.11
GWO	15,450.07	15,487.14	15,453.41
GWOI	15,450.15	15,455.17	15,451.13
GWOII	15,449.96	15,452.41	15,450.48
NGWO	15,449.17	15,460.10	15,449.86

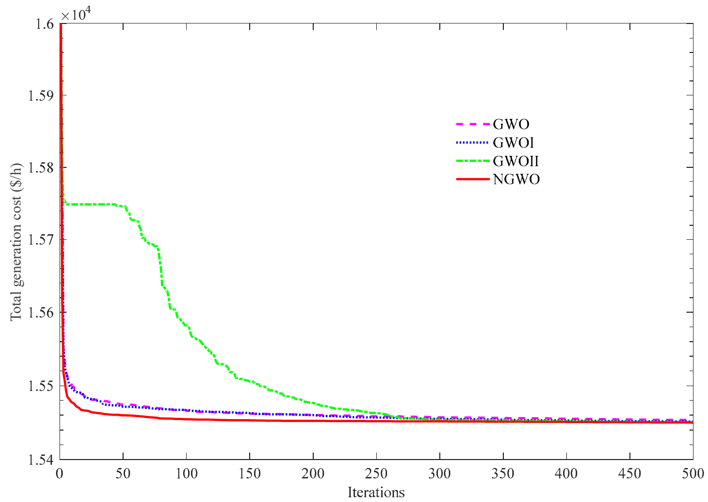

Figure 13. Convergence curve of the total generation cost for the mean solution in Case IV.

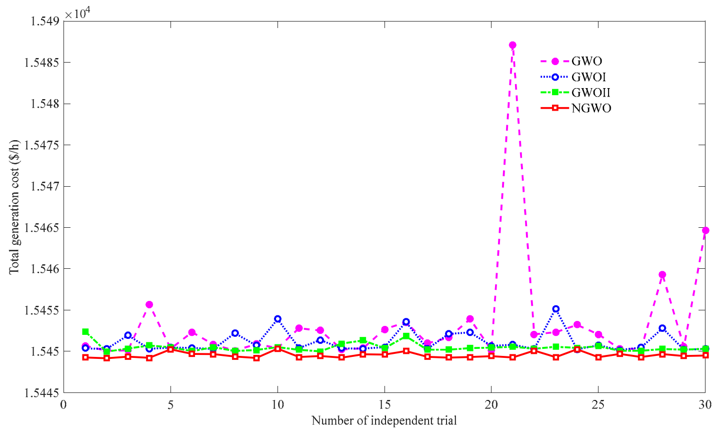

Figure 14. Total generation cost obtained by GWO, GWOI, GWOII, and NGWO for 30 trials in Case IV.

5.5. Case V: 15-Generator System

This case study comprises a larger 15-unit system with quadratic cost functions and it has the same constraints as those in case IV. Table 11 shows the generator data and POZs, in which three POZs exist in generators 2, 5, and 6, and generator 12 has two POZs. The transmission loss coefficient data are taken directly from Ref. [53]. The best output results that were achieved by GWO, GWOI, GWOII, and NGWO are compared with those of SA [46], GA [47], MTS [52], TSA [54], PSO [46], and AIS [55], as recorded in Table 12. The table shows that NGWO obtained the lowest best generation cost among all of the abovementioned methods. Table 13 compares the F_{best}, F_{worst}, and F_{mean} of the four versions of GWO with those of the techniques that are listed above. As shown in Table 13, NGWO achieved the best F_{best} and F_{mean} and the third best F_{worst}. GWOII provided the best F_{worst}, and MTS obtained the second best F_{best}, F_{worst}, and F_{mean}. Figure 15 shows the convergence curves of average evaluation values of the 15-generator systems while using the four versions of the GWO method. The NGWO was the fastest algorithm to converge to the global optimal solution as can be seen from the simulation. Figure 16 displays the distribution outline of the best solution in 30 runs and, in most of the trials, the NGWO method obtained a better-quality solution and strong, robust characteristics.

Table 11. Ramp rate limits and prohibited zones of units for Case V.

Generator	$P_{i\min}$ (MW)	$P_{i\max}$ (MW)	a_i	b_i	c_i	P_i^0	UR_i	DR_i	Prohibited Zones
1	150	455	0.000299	10.1	671	400	80	120	
2	150	455	0.000183	10.2	574	300	80	120	[185, 225], [305, 335], [420, 450]
3	20	130	0.001126	8.8	374	105	130	130	
4	20	130	0.001126	8.8	374	100	130	130	
5	150	470	0.000205	10.4	461	90	80	120	[180, 200], [305, 335], [390, 420]
6	135	460	0.000301	10.1	630	400	80	120	[230, 255], [365, 395], [430, 455]
7	135	465	0.000364	9.8	548	350	80	120	
8	60	300	0.000338	11.2	227	95	65	100	
9	25	162	0.000807	11.2	173	105	60	100	
10	25	160	0.001203	10.7	175	110	60	100	
11	20	80	0.003586	10.2	186	60	80	80	
12	20	80	0.005513	9.9	230	40	80	80	[30, 40], [55, 65]
13	25	85	0.000371	13.1	225	30	80	80	
14	15	55	0.001929	12.1	309	20	55	55	
15	15	55	0.004447	12.4	323	20	55	55	

Table 12. Best outputs of different methods for 15-units system.

Generator	SA [46]	GA [47]	MTS [53]	TSA [54]	PSO [46]	AIS [55]	SPSO [48]	GWO	GWOI	GWOII	NGWO
1	453.6646	445.5619	453.9922	440.500	454.7167	441.159	439.12	455.0000	455.0000	455.0000	455.0000
2	377.6091	380.0000	379.7434	346.800	376.2002	409.587	407.97	380.0000	380.0000	380.0000	380.0000
3	120.3744	129.0605	130.0000	110.880	129.5547	117.298	119.63	130.0000	130.0000	130.0000	130.0000
4	126.2668	129.5250	129.9232	122.460	129.7083	131.258	129.99	130.0000	130.0000	130.0000	130.0000
5	165.3048	169.9659	168.0877	177.740	169.4407	151.011	151.07	170.0000	165.3122	167.8379	160.5430
6	459.2455	458.7544	460.0000	459.110	458.8153	466.258	460.00	159.0815	460.0000	460.0000	460.0000
7	422.8619	417.9041	429.2253	406.410	427.5733	423.368	425.56	430.0000	430.0000	430.0000	430.0000
8	126.4025	97.8230	104.3097	107.550	67.2834	99.948	98.57	102.8806	60.8698	78.4634	84.1915
9	54.4742	54.2933	35.0358	107.270	75.2673	110.684	113.49	43.5154	69.1738	48.3551	57.7845
10	149.0879	144.2214	155.8829	140.560	155.5899	100.229	101.11	125.8636	158.4501	148.3092	146.7789
11	77.9594	77.3302	79.8994	78.470	79.9522	32.057	33.91	80.0000	80.0000	80.0000	80.0000
12	93.9489	77.0371	79.9037	74.170	79.8947	78.815	79.96	80.0000	80.0000	80.0000	80.0000
13	25.0022	31.1537	25.0220	31.950	25.2744	23.568	25.00	33.2702	30.1938	30.5576	32.7497
14	16.0636	15.0233	15.2586	37.380	16.7318	40.258	41.41	26.4876	17.6755	18.5833	17.2977
15	15.0196	33.6125	15.0796	22.470	15.1967	36.906	35.61	15.0116	15.1082	23.69718	15.4832
P_{total} (MW)	2663.29	2661.23	2661.36	2663.70	2661.19	2662.04	2662.4	2662.2318	2662.1458	2660.96	2660.54
P_{loss} (MW)	33.2737	31.2363	31.3523	33.8110	31.1697	32.4075	32.431	32.2317	31.0156	30.8550	30.0148
F_{best} ($/h)	32,786.40	32,779.81	32,716.87	32,918.00	32,724.17	32,854.00	32,858	32,743.2959	32,733.8961	32,734.6249	32,712.6131

Table 13. Comparison results of 15-units system.

Algorithm	F_{best} ($/h)	F_{worst} ($/h)	F_{mean} ($/h)
SA [46]	32,786.40	33,028.95	32,869.51
GA [47]	32,779.81	33,041.64	32,841.21
MTS [53]	32,716.87	32,796.15	32,767.21
TSA [54]	32,917.87	33,245.54	33,066.76
PSO [46]	32,724.17	32,841.38	32,807.45
SPSO [48]	32,858.00	33,331.00	33,039.00
AIS [55]	32,854.00	32,892.00	32,873.25
GWO	32,743.30	32,857.96	32,784.96
GWOI	32,733.90	32,889.63	32,783.22
GWOII	32,734.62	32,817.91	32,774.82
NGWO	32,712.61	32,830.61	32,752.78

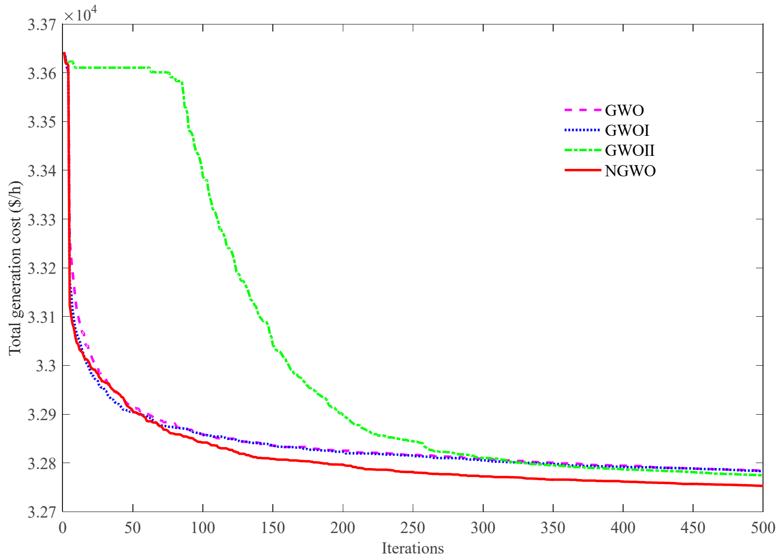

Figure 15. Convergence curve of the total generation cost for the mean solution in Case V.

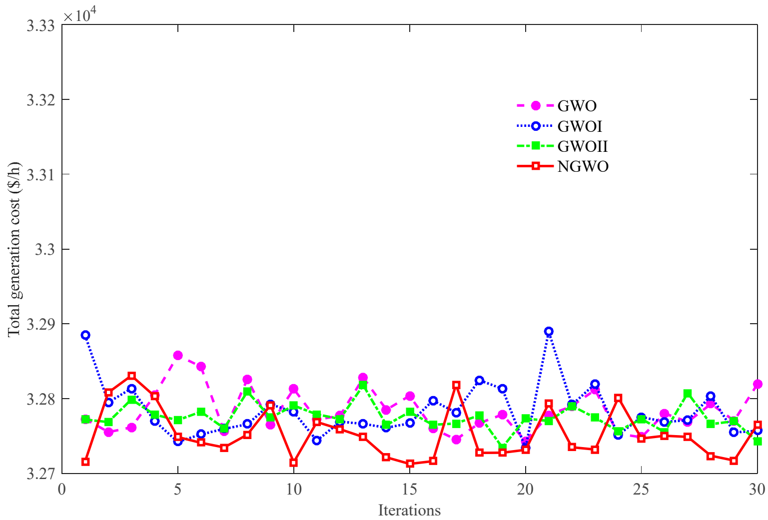

Figure 16. Total generation cost obtained by GWO, GWOI, GWOII, and NGWO for 30 trials in Case V.

6. Conclusions and Future Work

In this paper, we successfully applied the proposed NGWO technique to solve the ELD problem by considering the ramp rate limits, POZ constraints, and nonsmooth cost functions. The NGWO algorithm was validated to improve both the global exploration capability and the convergence rates and it had the best robustness when compared to the other three versions of the GWO algorithms. Furthermore, the results, when compared to all the other compared algorithms in five cases, demonstrated the outstanding superiority of the NGWO method in solving the ELD problem.

The superiority of the NGWO algorithm in solving ELD problems was proven. Although our research has not been yet applied to any utility companies or energy providers, we believe that the application of this algorithm in the future will surely improve the operational level of these companies. Next, an interesting application would be to apply the algorithm to training neural networks, optimizing restrictive engineering structures, and solving multiobjective optimization problems. However, for the large-scale power systems of Cases II, III, and V, the robustness of the NGWO algorithm in solving these problems is not as perfect as in solving Cases I and IV, so the optimization performance of the NGWO algorithm can still be improved.

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