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Greedy Sine-Cosine Non-Hierarchical Grey Wolf Optimizer for Solving Non-Convex Economic Load Dispatch Problems

Ali S. Alghamdi

Department of Electrical Engineering, College of Engineering, Majmaah University, Al-Majmaah 11952, Saudi Arabia; aalghamdi@mu.edu.sa

Abstract: Economic load dispatch (ELD) provides significant benefits to the operation of the power system. It appears to be a complex nonconvex optimization problem subject to several equal and unequal constraints. The greedy sine-cosine nonhierarchical gray wolf optimizer (G-SCNHGWO) is introduced in this study to solve complex nonconvex ELD optimization problems efficiently and robustly. The sine and cosine functions assist the search agents of the grey wolf optimizer (GWO) algorithm in avoiding trapping in a local optimum. In addition, the greedy nonhierarchical concept is integrated into GWO to enrich the optimization power of the conventional GWO algorithm. Simulations are implemented to validate the capability of the suggested algorithm in solving the different ELD problems. According to the results, the algorithm demonstrates very suitable performance compared to other state-of-the-art methods.

Keywords: economic load dispatch; sin-cosine function; optimization; grey wolf optimizer; power system operation

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1. Introduction

Optimal generation planning is an important topic to address in the operation of power systems. One approach to such planning is solving the economic load dispatch (ELD) problem to minimize the cost. The objective function of the ELD problem aims to minimize the fuel cost while observing constraints and limits of generators, prohibited operating zones (POZs), valve point effects (VPE), and power loss in the transmission section [1].

Although significant progressive steps have been taken concerning renewable energy sources (RESs), especially in the field of photovoltaics (PV) and wind turbines (WT), to supply the demand, most of the demand is met using traditional thermal plants [2]. Thermal units operate based on fossil fuels. One way to reduce the operation cost of such units is to apply a suitable planning method and this is known as the ELD problem [3]. In this problem, the power output of generation units (GUs) is scheduled in a planning horizon, and the demand is supplied appropriately. Additionally, the operation limits of GUs and the power system are observed simultaneously [4,5].

The ELD problem is nonlinear, non-smooth, nonconvex, and non-differentiable because of including the VPE, POZs, and multi-fuel (MF) conditions. Hence, the problem becomes so complex that conventional techniques fail to find the global optimum [6,7]. The problem of ELD requires algorithms with superior exploration and exploitation capabilities [8–10]. Popular optimization algorithms inspired by the nature and behavior of animals and plants have been incorporated in recent decades to solve ELD problems. Some of the significant works are briefly reviewed in the following.

Many researchers have focused on developing new modifications to particle swarm optimization (PSO) to solve ELD problems. PSO's algorithmic simplicity and fast convergence are its most attractive features. When applied to a strongly multi-modal optimization problem, PSO tends to suffer premature convergence. PSO algorithms have been enhanced by incorporating a revalued mutation (RVM) operator to enhance global search capability [11]. The Modulated Particle Swarm Optimization (MPSO) has been presented in [12] by modulating the particle velocity of the conventional PSO. In [13], a new PSO (NPSO) method was developed. Additionally, NPSO was coupled with a local random search (LRS) procedure to explore the promising solution region. This new method allows for a thorough exploration of the search space. A novel self-organizing hierarchical particle swarm optimization (SOH_PSO) of nonconvex ELD problems has been proposed in [14] for treating premature convergence. The HICA-PSO method, which uses a combination of the imperialist competitive algorithm (ICA) and imperative stochastic optimization (PSO), can determine the feasible optimal solution to the nonconvex economic dispatch (ED) problem by taking into account valve loading effects [15]. A new PSO, called IODPSO-G, is proposed in [16] for addressing nonconvex/non-smooth problems in singles and multi-areas. A chaotic tent map was used to adapt the acceleration coefficients to improve the proposed algorithm's robustness and global search capabilities. A challenge with the PSO-based methods is determining the control parameters for solving the optimization problems.

The differential evolution (DE) algorithm has been improved using other metaheuristics in hybridization. For example, the hybridization of harmony search (HAS) and DE algorithms (called CSADHS) [17], improved DE (IL-SHADE) [18], a hybrid continuous GRASP and DE algorithms (C-GRASP–SaDE) [19], a hybridization of DE and PSO (DEPSO) [20], a neighborhood search-driven accelerated BBO (aBBOmDE) [21] have been applied to solve ELD problems. The low convergence speed and computational complexity are the main drawbacks of DE-based optimization algorithms.

Teaching-learning-based optimization (TLBO) has shown to be an efficient solution to such complex problems, according to the authors of [22]. In [23], the TLBO's convergence characteristic has been improved by integrating the learning phase into the teaching phase. Up to five students have considered interacting with each other to enhance the local optima avoidance feature of TLBO. In [24], a new method to estimate the Lévy flight in chaotic teaching-learning-based optimization (CTLBO) has been developed. A penalty function was incorporated into this method to address the constraints.

The cuckoo search algorithm (CSA) [25] and its variants have been applied to solve the ELD problems. A clustering cuckoo search optimization (CCSO) [26], an improved version of the cuckoo optimization algorithm (θ-ICO) [27], and one rank cuckoo search algorithm (ORCSA) [28] are some examples of improved SCA-based optimization algorithms. Based on the social behaviors of spiders and humans, a new social spider optimization (ISSO) [29], a modified social spider algorithm (MSSA) [30], and social optimization algorithm (SOA) [31] have been analyzed in solving nonconvex ELD problems.

Other significant kinds of population-based metaheuristic algorithms that were recently developed to solve the ELD problems, whose results are compared with the proposed method, are listed below.

An effective algorithm is based on Franklin's and Coulomb's laws theory (CFA optimizer) [32], a civilized swarm [33], a multi-strategy ensemble biogeography-based optimization (MSEBBO) [34], an improved genetic algorithm (IGA) [35], exchange market algorithm [36], bacterial foraging optimization (BFO) [37], a continuous quick group search optimizer (CQGSO) [38], biogeography-based optimization (BBO) [39], a modified chaotic artificial bee colony (MABC) [40], a fully decentralized approach (DA) [41], an evolutionary simplex adaptive Hooke–Jeeves algorithm (ESAHJ) [42], a new disruption based symbiotic organisms search (DSOS) [43], heat transfer search (HTS) algorithm [44], a new firefly algorithm via non-homogeneous population (NhFA-Rnp) [45], an improved Jaya algorithms IJaya [46], Jaya algorithm with self-adaptive multi-population and Lévy flights (Jaya-SML) [47], a new and effective adaptive charged system search algorithm (ACSSA) [48], a powerful full mixed-integer linear programming (FMILP) model [49], a granular computing method (GrC) [50], an improved chicken swarm optimization (ICSO) [51], a modified ion-motion and crisscross search optimizer (C-MIMO-CSO) [52], a new and powerful consensus-based distributed algorithm (CDA) [53], an improved Big Bang–Big Crunch optimization (HBB-BC) [54], ray optimization (RO) algorithm [55], orthogonal learning competitive swarm optimizer (OLCSO) [56], θ-modified bat algorithm (θ-MBA) [57], ant lion optimization algorithm (ALO) [58], an improved firefly algorithm (IFA) [59], real-coded genetic algorithm (RCGA) [60], several new hybrid algorithms [61], a synergic predator-prey optimization (SPPO) [62], a distributed auction based algorithm (AA) [63], a simplified swarm optimization algorithm (SSOA) [64], a new honey bee mating optimization (CI-HBMO) [65], and krill herd algorithm (KHA-I to KHA-IV) [66].

The gray wolf optimization algorithm (GWO) [67] has gained the attention of scholars because of its magnificent features. For instance, in [68], the grey wolf optimizer (GWO) has been improved with crossover and mutations, thus enhancing the performance of conventional GWO. Four economic dispatch problems were solved in this work, including prohibited operating zones, valve point loading, and ramp rate limit constraints. The ELD problem with static and dynamic load conditions has been solved in [69] using GWO without improving the algorithm's performance. Nonetheless, as GWO works based on three members with the best values of the objective functions, it may be trapped in local optima. Its application in practical systems will be limited because the diversity of the population becomes lost [70].

The shortcomings of the previous algorithm proposals can be broadly divided into three types. In the first category, control parameters are numerous and computational complexity is high, so they are time-consuming and complex to use, like PSO-based algorithms. Unlike the first category, the second category has a low convergence rate, so it takes longer to achieve an acceptable response range, such as DE-based algorithms. The third group cannot reach a satisfactory outcome and is stuck in optimal local solutions such as gray wolf and cosine sinus. Like the gray wolf, some methods also have these drawbacks simultaneously.

In this paper, a modified sine-cosine function [71] is used to address this defect; this enables a more robust exploration capability of the original greedy nonhierarchical GWO (G-NHGWO); a counter monitors the convergence of the algorithm in order to identify traps when convergent convergence occurs. Next, a learning strategy based on the sine-cosine algorithm is used to find the tuned data of three randomly chosen wolves. It is possible to guide the population to avoid being trapped in the local optimum. Our proposed method in a comparative study has shown that all three defects have been significantly and effectively eliminated.

The great importance of the ELD problem and the incredible complexity of this issue has made us always look for a more robust and faster way to achieve the best choice for the system under study. Therefore, in this article, following the progress of previous work, we have proposed a simple and effective method obtained by combining two very new and well-known algorithms. The proposed method provides a significantly wider population diversity than the basic algorithm; hence, the chance of avoiding the trapping in the local optimal is increased considerably. It also is applied to solve different ELD problems, where different kinds of fuel, POZs, and power loss on transmission lines are considered.

The organization of the paper is summarized here. Section 2 formulates the ELD problem. Section 3 introduces the GWO and G-SCNHGWO algorithms while presenting the latter's flowchart. The procedure of G-SCNHGWO for problem-solving is presented in this section as well. Section 4 provides simulation results and the related discussion. In the end, a summary of conclusions is presented in Section 5 of the paper.

2. Formulation of ELD Problem

An ELD problem tries to perform unit commitment while being subject to some non-linearity limits relevant to the system and power plants. Noting that the objective function used in this problem cannot be differentiated and has a nonconvex nature, traditional algorithms based on gradient fail to solve it [72,73].

2.1. Cost Function

Equation (1) describes the fuel cost function-which should be minimized-used in the objective function of the ELD problem [74]:

$$\text{Min } F_C = \sum_{i=1}^{N} F_i(P_i) = \sum_{i=1}^{N} (a_i P_i^2 + b_i P_i + c_i) \tag{1}$$

where N represents the number of generation units, and P_i denotes the output power of unit i. Cost coefficients a_i, b_i, and c_i are constants and vary concerning generators.

Cost function (1) can be modified as (2) to incorporate the effects of valve points are considered, where the absolute value of a sinusoidal term and the cost function are summed up:

$$F_C = \sum_{i=1}^{N} \left(a_i P_i^2 + b_i P_i + c_i + |e_i \sin(f_i[P_{i,\min} - P_i])| \right) \tag{2}$$

$P_{i,\min}$ shows the lower boundary for output power of generator i, and e_i and f_i denote the effects of valve points of that generator. An optimal plan of units may help reduce power generation costs and enhance the security and efficiency of the power system.

In the cases several types of fuels are adopted for fueling generation units, the cost function can be established using different quadratic equations. Each of the equations is related to one specific type of fuel. Equation (2), as per this fact, is rewritten, as given in (3) [75–78]. In (3), a_{ik}, b_{ik}, and c_{ik} are cost coefficients of generation unit i for fuel type k. e_{ik} and f_{ik} show the coefficients related to valve point effect of generation unit i for fuel type k.

$$F_i(P_i) = \begin{cases} a_{i1} P_i^2 + b_{i1} P_i + c_{i1} + |e_{i1} \sin(f_{i1}[P_{i,\min} - P_i])|; & P_{i,\min} \leq P_i \\ a_{i2} P_i^2 + b_{i2} P_i + c_{i2} + |e_{i2} \sin(f_{i2}[P_{i,\min} - P_i])|; & P_{i2} \leq P_i \leq P_{i2} \\ \vdots & \vdots \\ a_{ik} P_i^2 + b_{ik} P_i + c_{i1} + |e_{ik} \sin(f_{ik}[P_{i,\min} - P_i])|; & P_{ik-1} \leq P_i \leq P_{i,\max} \end{cases} \tag{3}$$

2.2. Constraints of the Problem

System and generation units impose limitations and constraints on the ELD problem [75,76] presented in the following subsections.

2.2.1. Power Balance

Power balance is an equality constraint, stating that the sum of the power output of all generation units must be equal to the power demand on the consumer side and the power loss [75,76]:

$$\sum_{i=1}^{N} P_i = P_D + P_L \tag{4}$$

P_D is the total demand and P_L shows the power loss of the network, which can be calculated as follows:

$$P_L = \sum_{i=1}^{N} \sum_{h=1}^{N} P_i B_{ih} P_h + \sum_{i=1}^{N} B_{0i} + B_{00} \tag{5}$$

In this equation, P_i and P_h represent the power injection into buses i and h, respectively. Additionally, B_{ih}, B_{0i}, and B_{00} are matrices of coefficients used for finding P_L.

2.2.2. Active Power Limit

The output power of generator i is limited by its lower, $P_{i,\min}$, and upper, $P_{i,\max}$, boundaries, which is expressed as follows:

$$P_{i,\min} \leq P_i \leq P_{i,\max} \tag{6}$$

Such limits prevent the generation units with expensive and inexpensive units from producing less and higher power than their set values.

2.2.3. Prohibit Operating Zones (POZs)

POZs (defined as an inequality constraint) specify those zones or operating ranges a generation unit i can operate within its permitted operation range. The permissible operation zone for generator i is given as follows [78,79]:

$$\begin{cases} P_{i,\min} \le P_i \le P_{i1}^L \\ \ldots \\ P_{im-1}^U \le P_i \le P_{im}^L;\ \forall m = 1,\ 2,\ \ldots,\ n_i \\ \ldots \\ P_{in_i}^U \le P_i \le P_{i,max} \end{cases} \tag{7}$$

where n_i shows the number of POZs for generator i, and P_{ik}^L and P_{ik}^U are the minimum and maximum boundaries of POZ k.

2.2.4. Ramp Rate Limit

A determined ramp rate specifies the amount of change a thermal generator can follow to vary its output power. Ramp rate limit, which is an inequality constraint, is included in the ELD problem [78,79]:

$$\max\left(P_{i,\min}, P_i^0 + D_i\right) \le P_i \le \min\left(P_{i,\max}, P_i^0 + U_i\right) \tag{8}$$

where, P_i^0 is the active power generation by generator i, and D_i and U_i are the downward and upward ramp rates for that generator.

3. The Proposed Algorithm

3.1. GWO Algorithm

The grey wolf optimization (GWO) algorithm imitates the hunting behavior of grey wolves. Grey wolves are categorized as α, β, δ, and ω based on their position and history in their social hierarchy. The dominance descends from α to ω [67]. Several main strategies used in the GWO algorithm include the social hierarchy, encircling, hunting, attacking, and searching strategies [67]. These strategies are mathematically described below.

3.1.1. Social Hierarchy of the Grey Wolves

The fittest solution, the second-best fitting solution, and the third best fit solution within the pool of solutions are named α, β, and δ. These are the initiator members of the hunting strategy in the optimization process. The rest of the solutions are called ω.

3.1.2. Encircling Strategy

The following formulation provides the equations describing the besieging strategy conducted by grey wolves [67]:

$$\vec{D} = |\vec{C}.\vec{X}p(t) - \vec{X}(t)| \tag{9}$$

$$\vec{X}(t+1) = \vec{X}\mathrm{p}(t) - \vec{A}.\vec{D} \tag{10}$$

where t counts the iteration, parameters $\vec{A}$ and $\vec{C}$ are vectors of coefficients, $\vec{X}p(t)$ shows the hunting vector, and $\vec{X}$ denotes the position vector related to wolves. $\vec{A}$ and $\vec{C}$ are found as follows:

$$\vec{A} = 2\vec{a}.\vec{r_1} - \vec{a} \tag{11}$$

$$\vec{C} = 2.\vec{r_2} \tag{12}$$

where $\vec{r}_1$ and $\vec{r}_2$ are random vectors randomly chosen between [0, 1], and $\vec{a}$ changes from 2 and 0 in a linear form while the number of iterations rises.

3.1.3. Hunting Strategy

Grey wolves can identify the place of prey, besiege it, and attack it. α-type wolves start the hunting process, while β and δ types do so from time to time. Assuming that α, β, and δ have the information on the place of prey, the hunting strategy is formulated. Positions of α, β, and δ wolves with the best solutions are stored, and the position of ω wolves are updated accordingly:

$$\begin{aligned} \vec{D}_\alpha &= |\vec{C}_1.\vec{X}_\alpha - \vec{X}| \\ \vec{D}_\beta &= |\vec{C}_2.\vec{X}_\beta - \vec{X}| \\ \vec{D}_\delta &= |\vec{C}_3.\vec{X}_\delta - \vec{X}| \end{aligned} \tag{13}$$

$$\begin{aligned} \vec{X}_1 &= \vec{X}_\alpha - \vec{A}_1.(\vec{D}_1) \\ \vec{X}_2 &= \vec{X}_\beta - \vec{A}_2.(\vec{D}_2) \\ \vec{X}_3 &= \vec{X}_\delta - \vec{A}_3.(\vec{D}_3) \end{aligned} \tag{14}$$

$$\vec{X}_i(t+1) = (\vec{X}_1 + \vec{X}_2 + \vec{X}_3)./3 \tag{15}$$

3.1.4. Attacking Strategy (Exploitation Phase)

To provide a model for how wolves mathematically advance toward the prey, $\vec{a}$ is decreased. $\vec{A}$ in (14) is a vector which randomly generated between $(-2\vec{a}, 2\vec{a})$. In the cases $\vec{A}$ in the range $(-1, 1)$, a searching member (agent) can be placed between its current position and the prey's location. As a result, the wolves embark on attacking when $|\vec{A}| < 1$ [67].

3.1.5. Searching for Prey (Exploration Phase)

The typical approach of grey wolves to attack prey is to search for it separately, gather around, and finally attack the prey. This is called the exploration phase. A random value is assigned to the vector $\vec{A}$ so that $|\vec{A}| > 1$. By doing this, searching wolves are positioned at different points, and the algorithm runs the exploration phase across the solution space.

Vector $\vec{C}$, given in (13), with a value between [0, 2], is a parameter that impacts the exploration phase. Putting this in the hunting stage increases the impact of the prey's location in (13), if $|\vec{C}| > 1$, or decrease it while $|\vec{C}| < 1$. This vector leads to even greater randomness in the GWO; hence, the search space is explored better than before and the algorithm avoids trapping in the local minimum points [67].

The summary of the GWO is as follows. The population is initialized, and the searching stage embarks on. When iterations are carried out, α, β, and δ wolves become aware of the possible location of the prey. Next, the distance between ω wolf and the prey is updated according to the estimated location of the prey. The value of a is decreased from 2 to 0 so that the prey identification and attacking actions are enhanced. $|\vec{A}| < 1$ and $|\vec{A}| > 1$ are adopted in the exploitation and exploration phases, respectively.

3.2. Nonhierarchical GWO (NHGWO)

Imitating the grey wolves' social behavior, the GWO algorithm stores three of the best solutions, i.e., α, β and δ, which help the other population members update their positions. Consequently, it results in premature convergence towards the optimal solution. Such an updating process suffers from some demerits in the filed applications. First, since the best global solutions achieved so far are used, the convergence speed is very high, and the optimization potential is degraded remarkably. Second, the variety decreases in the newly formed population in each iteration. This is addressed by defining the best personal position for each individual wolf i as the best solution obtained so far by the wolf, i.e., $\overrightarrow{X}_i^{best}$. Additionally, we do not choose α, β and δ as the wolves that proceed with the updating process of wolves instead, we select r_1, r_2 and r_3 as randomly chosen members and store their best personal positions given by $\overrightarrow{X}_{r1}^{best}$, $\overrightarrow{X}_{r2}^{best}$, and $\overrightarrow{X}_{r3}^{best}$ so that the population is updated. The equations used for updating the ith member are presented here:

$$\begin{aligned} \overrightarrow{D}_{r1} &= \left| \overrightarrow{C}_1.\overrightarrow{X}_{r1}^{best} - \overrightarrow{X}_i^{best} \right| \\ \overrightarrow{D}_{r2} &= \left| \overrightarrow{C}_2.X_{r2}^{best} - \overrightarrow{X}_i^{best} \right| \\ \overrightarrow{D}_{r3} &= \left| \overrightarrow{C}_3.\overrightarrow{X}_{r3}^{best} - \overrightarrow{X}_i^{best} \right| \end{aligned} \tag{16}$$

$$\begin{aligned} \overrightarrow{X}_{r1} &= \overrightarrow{X}_{r1}^{best} - \overrightarrow{A}_1.(\overrightarrow{D}_{r1}) \\ \overrightarrow{X}_{r2} &= \overrightarrow{X}_{r2}^{best} - \overrightarrow{A}_2.(\overrightarrow{D}_{r2}) \\ \overrightarrow{X}_{r3} &= \overrightarrow{X}_{r3}^{best} - \overrightarrow{A}_3.(\overrightarrow{D}_{r3}) \end{aligned} \tag{17}$$

$$\overrightarrow{X}_i(t+1) = (\overrightarrow{X}_{r1} + \overrightarrow{X}_{r2} + \overrightarrow{X}_{r3})./3 \tag{18}$$

After the calculation of the new position in (18), a comparison is made between $\overrightarrow{X}_i(t+1)$ and $\overrightarrow{X}_i^{best}$ The former gives a better value for the objective function so that it will be assumed as the new best personal position.

3.3. Greedy Sine-Cosine Non-Hierarchical Grey Wolf Optimizer (G-SCNHGWO)

One popular algorithm proposed to solve optimization problems is the Sine Cosine Algorithm (SCA), a metaheuristic algorithm [70]. This algorithm mimics the sine and cosine functions to get the best result. The algorithm determines different solutions, and the searching stage begins. Then, the objective function evaluates the solutions. The algorithm stores the best solution achieved up to the current iteration (the destination point). The rest of the solutions are updated, and new solutions are formed using the sine and cosine functions, as given by (19). Once the maximum number of iterations is reached, the algorithm terminates the operations.

$$\overrightarrow{X}_i(t+1) = \begin{cases} \overrightarrow{X}_i(t) + r_1 \sin(r_2)|r_3 P_i(t) - \overrightarrow{X}_i(t)|;\ if\ \ r_4 < 0.5 \\ \overrightarrow{X}_i(t) + r_1 \sin(r_2)|r_3 P_i(t) - \overrightarrow{X}_i(t)|;\ otherwise \end{cases} \tag{19}$$

In this paper, the sine and cosine functions are used to improve the optimization power of the G-NHGWO algorithm by increasing the variety of populations. The results demonstrate the promising performance of this algorithm in improving the GWO. We call this new algorithm G-SCNHGWO. In this algorithm, the member ith is updated using the following equation:

$$\overrightarrow{D}_{r1} = \begin{cases} \sin(\delta_1) * \left| \overrightarrow{C}_1.\overrightarrow{X}_{r1}^{best} - \overrightarrow{X}_i^{best} \right|;\ if\ rand < 0.5 \\ \cos(\delta_1) * \left| \overrightarrow{C}_1.\overrightarrow{X}_{r1}^{best} - \overrightarrow{X}_i^{best} \right|;\ otherwise \end{cases} \tag{20}$$

$$\vec{D}_{r2} = \begin{cases} \sin(\delta_2) * \left| \vec{C}_2 . \vec{X}_{r2}^{best} - \vec{X}_i^{best} \right| ; \, if \; rand < 0.5 \\ \cos(\delta_2) * \left| \vec{C}_2 . \vec{X}_{r2}^{best} - \vec{X}_i^{best} \right| ; \, otherwise \end{cases} \tag{21}$$

$$\vec{D}_{r3} = \begin{cases} \sin(\delta_3) * \left| \vec{C}_3 . \vec{X}_{r3}^{best} - \vec{X}_i^{best} \right| ; \, if \; rand < 0.5 \\ \cos(\delta_3) * \left| \vec{C}_3 . \vec{X}_{r3}^{best} - \vec{X}_i^{best} \right| ; \, otherwise \end{cases} \tag{22}$$

where δ_1, δ_2, and δ_3 are random numbers that are equal to $rand \times \pi/2$, respectively. By calculating these new modified distances and substituting them in (16), the new position of the search agent ith can be obtained using (17) and (18).

Algorithm 1 depicts the pseudocode of the G-SCNHGWO algorithm in detail.

Algorithm 1: Pseudocode of G-SCNHGWO algorithm.

G-SCNHGWO:

Generate initial grey wolves $X_i(i = 1, 2, \ldots, Npop)$;
Set the initial value of parameters a, $\vec{A}$ *and* $\vec{C}$;
Evaluate the objective value of the initial population;
Initial fitness evolution of grey wolves and save the local position best for any gray wolf;
Set t = 1;
While (t < maximum value of iterations)
For (each member ith)
Update their current position using Equations (17), (18), (21) and (22);
end for
Update parameters a, $\vec{A}$, $\vec{C}$;
Evaluate the objective value of all searching agents members;
Update the value of grey wolves and save the best position for any gray wolf;
Set t = t + 1;
end while
return X_α *as the best solution.*

3.4. Application of G-SCNHGWO in ELD Problem

When G-SCNHGWO is used to solve an ELD problem, population members denote generation units. The value of each member shows the output generation power of that unit. The optimal solution to the problem is achieved through the following steps of the G-SCNHGWO algorithm:

1. **Step (1)** Set the parameters of G-SCNHGWO, the maximum number of iterations ($iter_{\max}$), the population size of grey wolves ($Npop$), B-coefficients, and data of the generation units.
2. **Step (2)** Generate grey wolves.
3. **Step (3)** Calculate the cost function $f_i(P_i)$ for each member in the initial population. The penalty factors (big positive numbers) are used to transform the optimization problem with constraints into a problem with no constraints [32]. The value of penalty factors is determined experimentally for each problem and must be chosen to satisfy the associated constraint.
4. **Step (4)** Use G-SCNHGWO phases to update the obtained solutions.
5. **Step (5)** Calculate the value of $f_i(P_i)$ for new solutions.
6. **Step (6)** Update α, β, and δ wolves by comparing the old and new solutions.
7. **Step (7)** If the termination criterion ($iter_{\max}$) is not satisfied, go to Step 4.

4. Simulation Results

Four different systems are incorporated here to evaluate the performance of G-SCNHGWO and its efficiency in solving the ELD problems. The four systems include 10, 15, 40, and 140 generation units, and the corresponding number of populations are assumed to be 30, 30, 60, and 90, respectively, for three algorithms. The ELD problems run 25 times, and the costs' best mean, max, and standard deviation values are calculated.

Several cases are considered to run the simulations for the mentioned four sample systems:

1. **Case A-type 1:** A test system with ten thermal units, a demand of 2700 MW, with MF constraints, and neglecting transmission power loss [35].
2. **Case A-type 2:** Similar to Case A-Type 1, considering VPE constraints [35].
3. **Case B-type 1:** A test system with 15 thermal units, a demand of 2630 MW, considering transmission power loss and POZ constraints [32].
4. **Case B-type 2:** Similar to Case B-Type 1, considering ramp rate limits [32].
5. **Case C:** A test system with 40 thermal units, a demand of 10,500 MW, and VPE constraints [65].
6. **Case D:** A large-scale test system with 140 thermal units, a demand of 49,342 MW, and considering VPE and POZ constraints [80].

4.1. CASE A: A Test System with 10 Generation Units

Tables 1 and 2 list the obtained results of Case A-type 1 and Case A-type 2 implemented using various algorithms. As is concluded from the results, the G-SCNHGWO algorithm shows better performance than its counterparts, even better than GWO and SCA, in both study cases. This means that the suggested adaptive learning strategy successfully enhances the performance of GWO and SCA. Figure 1 shows how the results are converged in Case A-type 2 and prove the noticeable ability of the G-SCNHGWO algorithm to reach suitable convergence. Tables 3 and 4 report the best decision variables achieved by the G-SCNHGWO algorithm for Case A-type 1 and Case A-type 2, respectively.

Table 1. The statistical indices of optimal results obtained by different methods for Case A-type 1.

Methods	Min. Cost (USD/h)	Mean Cost (USD/h)	Max. Cost (USD/h)	Std.
RCGA [60]	623.8307	623.8522	623.8908	-
DEPSO [20]	623.8300	623.9000	624.0800	-
ALO [58]	623.8708	625.6935	636.3510	-
ICSO [51]	623.8110	624.0298	-	-
CCEDE [77]	623.8288	623.8574	623.8904	0.0076
SFLA-GHS [61]	623.8406	623.9521	624.7804	-
ORCSA [28]	623.8608	623.8963	623.9353	0.0154
IFA [59]	623.8768	625.2704	629.2765	-
SPPO [62]	623.8279	-	-	-
ISSO [29]	623.8286	623.8490	624.1641	-
SCA	624.3015	624.9862	628.7524	5.93
GWO	624.2521	625.9265	630.1479	7.61
G-SCNHGWO	**623.8092**	**623.8400**	**623.8875**	**0.0055**

Table 2. The statistical indices of optimal results obtained by different methods for Case A-type 2.

Methods	Min. Cost (USD/h)	Mean Cost (USD/h)	Max. Cost (USD/h)	Std.
IFA [59]	624.4950	625.2647	629.3951	-
IGA_MU [35]	624.5178	625.8692	630.8705	-
Jaya-SML [47]	623.9738	624.0468	624.1300	0.0327
CFA [32]	623.9576	623.9702	623.9884	0.0105
CBPSO-RVM [11]	623.9588	624.0816	624.2930	0.0576
CCSO [26]	624.0697	624.2770	624.6282	0.1606
ISSO [29]	624.3477	624.3666	624.8145	-
RO [55]	624.0922	625.2564	627.1189	-

Table 2. *Cont.*

Methods	Min. Cost (USD/h)	Mean Cost (USD/h)	Max. Cost (USD/h)	Std.
ALO [58]	624.3894	625.6773	629.0156	-
AA [63]	623.9500	-	-	-
NPSO-LRS [13]	624.1273	624.9985	626.9981	-
SCA	624.6174	625.5630	628.7001	6.20
GWO	624.5508	626.0128	629.3592	8.73
G-SCNHGWO	**623.9491**	**623.9914**	**624.7415**	**0.0418**

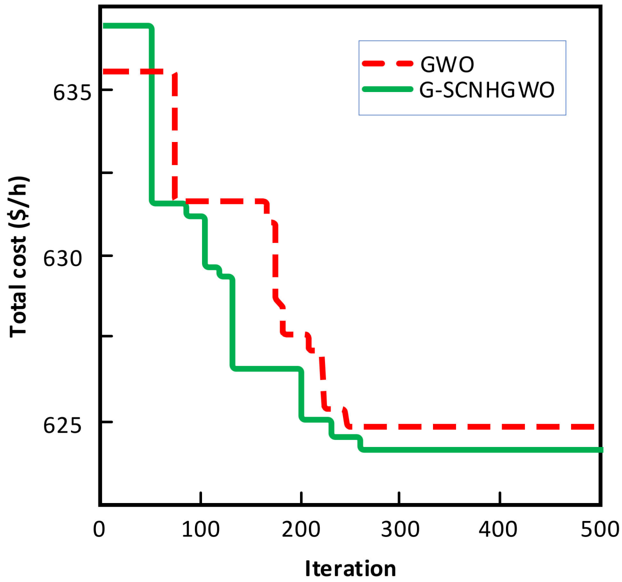

Figure 1. Convergence behavior obtained by GWO and G-SCNHGWO algorithms for Case A-type 2.

Table 3. The best decision variables for Case A-type 1 obtained by G-SCNHGWO algorithm.

Units	Output Power	Fuel Types
P1	218.2500	2
P2	211.6628	1
P3	280.7223	1
P4	239.6312	3
P5	278.4979	1
P6	239.6318	3
P7	288.5849	1
P8	239.6309	3
P9	428.5216	3
P10	274.8666	1
Total cost (USD/h)	623.8092	

Table 4. The best decision variables for Case A-type 2 obtained by G-SCNHGWO algorithm.

Units	Output Power	Fuel Types
P1	219.2079	2
P2	210.2170	1
P3	278.5472	1
P4	239.3705	3
P5	276.4141	1
P6	240.5806	3
P7	292.3230	1
P8	237.7583	3
P9	429.4002	3
P10	276.1812	1
Total cost (USD/h)	623.9491	

4.2. CASE B: A Test System with 15 Generation Units

The results related to optimal solutions of Case B-type 1 and Case B-type 2 are provided in Tables 5 and 6, underlining the superiority and high efficiency of the proposed algorithm. The best control variables for the mentioned cases are given in Tables 7 and 8. The data of this test system is shown in Table 9.

Table 5. The statistical indices of optimal results obtained by different algorithms in Case B-type 1.

Methods	Min. Cost (USD/h)	Mean Cost (USD/h)	Max. Cost (USD/h)	Std.
CSA [25]	32,544.9704	32,545.0068	32,546.6734	0.238
CSO [33]	32,588.9189	32,679.8775	32,796.7792	-
SSOA [64]	32,731.6903	32,845.5416	32,930.9734	-
ESAHJ [42]	32,568.1200	-	-	-
KHA-IV [66]	32,547.3700	32,548.1348	32,548.9326	-
CIHBMO [65]	32,548.5858	32,548.5858	32,548.5858	-
SCA	32,564.9641	32,585.5542	32,727.5931	142.3
GWO	32,562.7306	32,580.1590	32,872.6039	322.4
G-SCNHGWO	**32,543.2943**	**32,544.8824**	**32,545.7109**	**0.097**

Table 6. The statistical indices of optimal results obtained by different algorithms in Case B-type 2.

Methods	Min. Cost (USD/h)	Mean Cost (USD/h)	Max. Cost (USD/h)	Std.
CCSO [26]	32,706.6400	32,706.6400	32,706.6400	0.00070
C-MIMO-CSO [52]	32,701.2100	32,701.2100	32,701.2200	0.00580
TLBO [22]	32,697.2151	32,697.2151	32,697.2151	0.00000
DSOS [43]	32,706.7610	32,706.8993	32,709.9665	0.45737
SPPO [62]	32,708.0000	32,732.0000	32,789.0000	18.0250
IODPSO-L [16]	32,692.3900	32,692.3900	32,692.3900	0.00000
SSOA [64]	32,819.1554	32,902.1631	32,999.4008	-
CIHBMO [65]	32,548.5858	32,548.5858	32,548.5858	-
KHA-IV [66]	32,547.3700	32,548.1348	32,548.9326	-
MsEBBO [34]	32,692.3972	32,692.3973	32,692.3975	0.00006
SOH-PSO [14]	32,751.0000	32,878.0000	32,945.0000	-
EMA [36]	32,704.4503	32,704.4504	32,704.4506	-
BFO [37]	32,784.5024	32,976.8100	-	85.77430
NhFA-Rnp [45]	32,697.9100	32,700.5600	32,709.9400	2.640000
SCA	32,759.0206	32,889.4720	32,954.3356	285.6200
GWO	32,748.6935	32,900.2007	32,986.0753	415.4700
G-SCNHGWO	**32,687.1014**	**32,690.0745**	**32,692.7422**	**0.004200**

Table 7. The best decision variables for Case B-type 1 obtained by G-SCNHGWO algorithm.

Units	Output Power
P_1	454.9909
P_2	455.0000
P_3	130.0000
P_4	130.0000
P_5	231.3200
P_6	460.0000
P_7	465.0000
P_8	60.0000
P_9	25.0000
P_{10}	35.5300
P_{11}	74.4800
P_{12}	80.0000
P_{13}	25.0000
P_{14}	15.0000
P_{15}	15.0000
P_L (MW)	26.3207
Total cost (USD/h)	32,543.2943

Table 8. The best decision variables for Case B-type 2 obtained by G-SCNHGWO algorithm.

Units	Output Power
P_1	455.0000
P_2	380.0000
P_3	130.0000
P_4	130.0000
P_5	170.0000
P_6	460.0000
P_7	430.0000
P_8	67.9593
P_9	58.0137
P_{10}	159.9999
P_{11}	80.0000
P_{12}	80.0000
P_{13}	25.0007
P_{14}	17.9118
P_{15}	15.0000
P_L (MW)	28.8854
Total cost (USD/h)	32,687.1014

Table 9. Unit's data for the 15-unit power system.

Unit	P_{min} (MW)	P_{max} (MW)	a	b	c	Prohibited Operating Zones (MW)
1	150	455	0.0003	10.1	671	-
2	150	455	0.0002	10.2	574	[185 255] [305 335] [420 450]
3	20	130	0.0011	8.8	374	-
4	20	130	0.0011	8.8	374	-
5	150	470	0.0002	10.4	461	[180 200] [305 335] [390 420]
6	135	460	0.0003	10.1	630	[230 255] [365 395] [430 455]
7	135	465	0.0004	9.8	548	-
8	60	300	0.0003	11.2	227	-
9	25	162	0.0008	11.2	173	-
10	25	160	0.0012	10.7	175	-
11	20	80	0.0036	10.2	186	-
12	20	80	0.0055	9.9	230	[30 40] [55 65]
13	25	85	0.0004	13.1	225	-
14	15	55	0.0019	12.1	309	-
15	15	55	0.0044	12.4	323	-

Figure 2 depicts the convergence characteristics of the total fuel cost for Case B-type 1, which again validates the efficacy and superiority of the proposed G-SCNHGWO algorithm in showing appropriate convergence behavior.

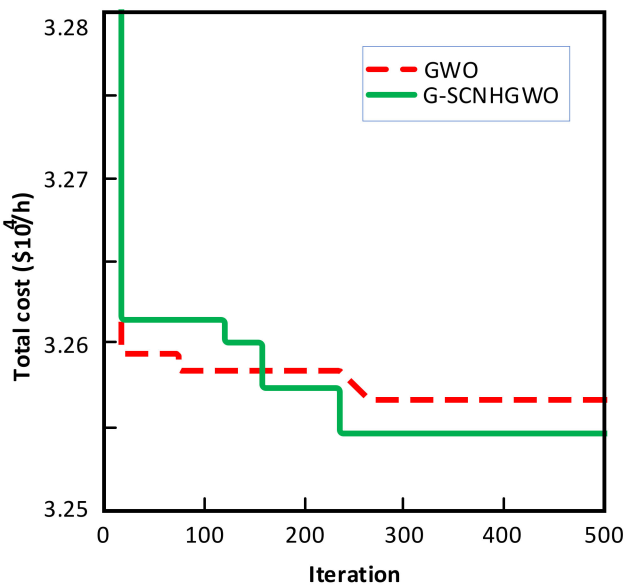

Figure 2. Convergence behavior obtained by GWO and G-SCNHGWO algorithms for Case B-type 2.

4.3. Case C: A Test System with 40 Generation Units

Table 10 provides the optimal solutions obtained by different algorithms for Case C. As per the results, the G-SCNHGWO algorithm proves its outstanding potential in reaching the optimal solution compared to its counterparts. Figure 3 illustrates the convergence curve related to objective function values in Case C, which again validates the superior convergence of the suggested algorithm. Table 11 lists the best values for decision variables obtained using the G-SCNHGWO in Case C.

Table 10. Comparing the best results obtained by different algorithms in Case C.

Method	Min. Cost (USD/h)	Mean Cost (USD/h)	Max. Cost (USD/h)	Std.
CTLBO [24]	121,553.83	121,790.23	122,116.18	150.000
SOH_PSO [14]	121,501.14	121,853.57	122,446.30	-
RCGA [60]	121,418.72	121,685.99	121,921.65	-
IJaya [46]	121,454.37	121,770.32	122,109.01	173.700
BF [37]	121,423.63	121,814.94	-	-
BBO [39]	121,426.95	121,508.03	121,688.66	-
CCSO [26]	121,414.43	121,686.59	122,288.96	193.080
ABCTend [40]	121,418.51	-	122,831.22	-
CIHBMO [65]	121,412.57	121,412.59	121,412.63	-
OLCSO [56]	121,415.81	121,460.77	121,504.04	21.7993
CSADHS [17]	121,414.87	121,415.44	121,415.92	0.30040
MSSA [30]	121,413.46	121,466.61	121,521.73	28.6932
aBBOmDE [21]	121,414.87	121,487.85	121,568.32	-
IODPSO-G [16]	121,414.93	121,416.54	121,426.42	17.7500
DEPSO [20]	121,412.560	121,419.31	121,468.25	-
SOA [31]	124,295.4	126,033.2	-	-
CQGSO [38]	121,412.55	121,412.55	121,438.68	-
θ-MBA [57]	121,491.06	121,491.06	121,491.06	0.23300
COA [27]	122,003.74	122,072.97	122,159.59	-
SMPSO [12]	121,412.57	121,938.24	122,265.56	169.740
HBB-BC [54]	121,471.72	121,984.24	122,137.42	-
ESAHJ [42]	121,412.70	-	-	-
KHA-IV [66]	121,412.59	121,413.14	121,415.00	-
DA [41]	121,412.680	121,439.89	121,479.63	-
SCA	121,506.58	121,857.90	122,056.15	347.26
GWO	121,490.72	122,108.21	122,800.33	935.620
G-SCNHGWO	**121,412.54**	**121,412.58**	**121,412.63**	**0.00850**

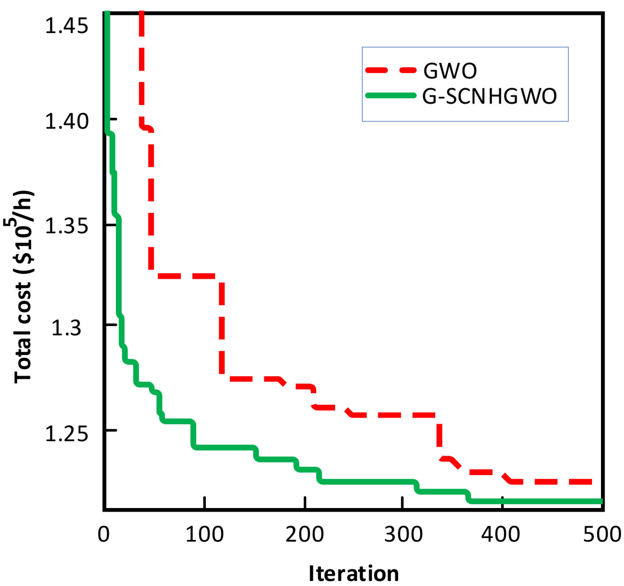

Figure 3. Convergence behavior of GWO and G-SCNHGWO algorithms in Case C.

Table 11. The best decision variables obtained by G-SCNHGWO algorithm in Case C.

Units	Output Power	Units	Output Power
P_1	110.7995	P_{21}	523.2794
P_2	110.7995	P_{22}	523.2794
P_3	97.4000	P_{23}	523.2794
P_4	179.7329	P_{24}	523.2794
P_5	87.7999	P_{25}	523.2794
P_6	140.0000	P_{26}	523.2794
P_7	259.5997	P_{27}	10.0000
P_8	284.5997	P_{28}	10.0000
P_9	284.5997	P_{29}	10.0000
P_{10}	130.0000	P_{30}	87.7999
P_{11}	94.0000	P_{31}	190.0000
P_{12}	94.0000	P_{32}	190.0000
P_{13}	214.7598	P_{33}	190.0000
P_{14}	394.2794	P_{34}	164.7998
P_{15}	394.2794	P_{35}	194.3978
P_{16}	394.2794	P_{36}	200.0000
P_{17}	489.2794	P_{37}	110.0000
P_{18}	489.2794	P_{38}	110.0000
P_{19}	511.2794	P_{39}	110.0000
P_{20}	511.2794	P_{40}	511.2794
Total cost (USD/h)	121,412.5425		

4.4. Case D: A Test System with 140 Generation Units

Table 12 gives the optimization results obtained in Case D. According to the results, and the G-SCNHGWO demonstrates its power and efficiency. Figure 4 shows the convergence curve obtained in Case D. Table 13 lists the best values of decision variables obtained by G-SCNHGWO algorithm for Case D. The data of this test system is shown in Table 14.

Table 12. Comparison of best results obtained by different algorithms for Case D.

Algorithm	Min. Cost (USD/h)	Mean Cost (USD/h)	Max. Cost (USD/h)	Std.
C-GRASP–SaDE [19]	1,657,962.7	1,658,006.2	1,658,583.52	-
HPSO-ICA [15]	1,747,466.0	-	1,783,367.0	17,168
CCEDE [77]	1,657,962.7	1,657,963.0	1,657,965.18	1.1466
CCPSO [80]	1,657,962.73	1,657,962.7	1,657,962.73	0.0
CQGSO [38]	1,657,962.72	1,657,962.7	1,657,962.77	-
IL-SHADE [18]	1,657,962.73	1,657,965.3	1,658,090.54	-
SCA	1,680,904.41	1,698,895.23	1,751,427.09	754.31
GWO	1,678,795.41	1,702,255.9	1,803,546.78	150,000
G-SCNHGWO	1,657,954.70	1,657,957.5	1,657,961.16	3.62

Table 13. The best decision variables obtained for Case D by the proposed G-SCNHGWO.

Units	Output Power									
$P_1 \sim P_{10}$	118.9999	163.9999	190.0	190.0	168.5400	190.0	490.0	489.9990	495.9990	496.0
$P_{11} \sim P_{20}$	496.0	496.0	506.0	508.9999	506.0	505.0	506.0	505.9999	504.9999	505.0
$P_{21} \sim P_{30}$	505.0	505.0	504.9999	505.0	537.0	536.9995	549.0	549.0	501.0	499.0
$P_{31} \sim P_{40}$	505.9999	506.0	506.0	506.0	499.9998	500.0	241.0	241.0	774.0	769.0
$P_{41} \sim P_{50}$	3.0	3.0	249.9999	250.0	250.0	249.9998	250.0	250.0	250.0	250.0
$P_{51} \sim P_{60}$	165.0	165.0	165.0	165.0	180.0	180.0	103.0	198.0	312.0	308.9987
$P_{61} \sim P_{70}$	163.0	95.0	511.0	511.0	490.0	256.0664	490.0	490.0	130.0	339.8395
$P_{71} \sim P_{80}$	141.0082	388.3274	195.0004	200.6508	194.9314	257.1706	398.9960	330.0	530.9999	531.0
$P_{81} \sim P_{90}$	542.0	56.0	115.0	115.0	115.0	207.0	207.0	175.0	175.0	180.0
$P_{91} \sim P_{100}$	175.0	575.9758	547.2990	836.8	837.5	682.0	720.0	717.9999	720.0	964.0
$P_{101} \sim P_{110}$	957.9999	947.9	934.0	935.0	876.4999	880.8999	873.7	877.4	871.7	864.8
$P_{111} \sim P_{120}$	882.0	94.0	94.0	94.0	244.0	244.0	244.0	95.0	95.0	116.0
$P_{121} \sim P_{130}$	175.0	2.0	4.0	15.0	9.0	12.0	10.0	112.0	4.0	5.0
$P_{131} \sim P_{140}$	5.0	50.0	5.0	42.0	42.0	41.0	17.0	7.0	7.0	26.0
Total power output		**49,342.0 MW**				**Fuel total cost**			**1,657,954.708 USD/h**	

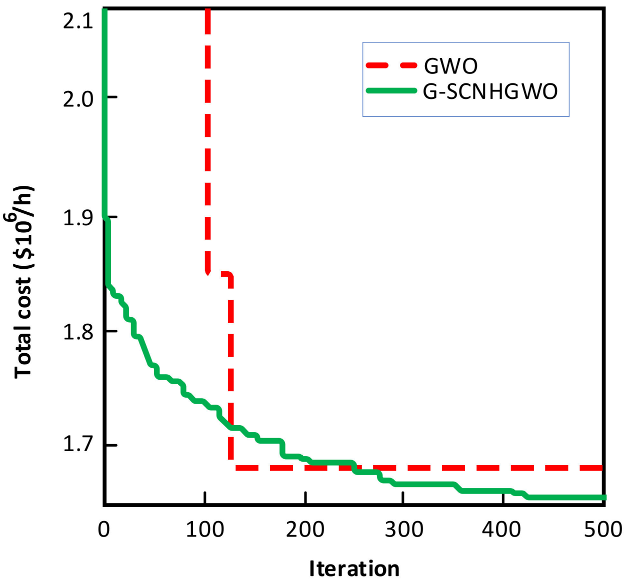

Figure 4. Convergence behavior obtained by GWO and G-SCNHGWO algorithms for Case D.

Table 14. Unit's data for the 40-unit large-scale power system.

Units	P_{min} (MW)	P_{max} (MW)	a	b	c	e	f
1	36	114	0.0069	6.7300	94.705	100	0.0840
2	36	114	0.0069	6.7300	94.705	100	0.0840
3	60	120	0.0203	7.0700	309.540	100	0.0840
4	80	190	0.0094	8.1800	369.030	150	0.0630
5	47	97	0.0114	5.3500	148.890	120	0.0770
6	68	140	0.0114	8.0500	222.330	100	0.0840
7	110	300	0.0036	8.0300	287.710	200	0.0420
8	135	300	0.0049	6.9900	391.980	200	0.0420
9	135	300	0.0057	6.6000	455.760	200	0.0420
10	130	300	0.0060	12.9000	722.820	200	0.0420
11	94	375	0.0052	12.9000	635.200	200	0.0420
12	94	375	0.0057	12.8000	654.690	200	0.0420
13	125	500	0.0042	12.5000	913.400	300	0.0350
14	125	500	0.0075	8.8400	1760.4	300	0.0350
15	125	500	0.0071	9.1500	1728.3	300	0.0350
16	125	500	0.0071	9.1500	1728.3	300	0.0350
17	220	500	0.0031	7.9700	647.850	300	0.0350
18	220	500	0.0031	7.9500	649.690	300	0.0350
19	242	550	0.0031	7.9700	647.830	300	0.0350
20	242	550	0.0031	7.9700	647.810	300	0.0350
21	254	550	0.0030	6.6300	785.960	300	0.0350
22	254	550	0.0030	6.6300	785.960	300	0.0350
23	254	550	0.0028	6.6600	794.530	300	0.0350
24	254	550	0.0028	6.6600	794.530	300	0.0350
25	254	550	0.0028	7.1000	801.320	300	0.0350
26	254	550	0.0028	7.1000	801.320	300	0.0350
27	10	150	0.5212	3.3300	1055.1	120	0.0770
28	10	150	0.5212	3.3300	1055.1	120	0.0770
29	10	150	0.5212	3.3300	1055.1	120	0.0770
30	47	97	0.0114	5.3500	148.890	120	0.0770
31	60	190	0.0016	6.4300	222.920	150	0.0630
32	60	190	0.0016	6.4300	222.920	150	0.0630
33	60	190	0.0016	6.4300	222.920	150	0.0630
34	90	200	0.0001	8.9500	107.870	200	0.0420
35	90	200	0.0001	8.6200	116.580	200	0.0420
36	90	200	0.0001	8.6200	116.580	200	0.0420
37	25	110	0.0161	5.8800	307.450	80	0.0980
38	25	110	0.0161	5.8800	307.450	80	0.0980
39	25	110	0.0161	5.8800	307.450	80	0.0980
40	242	550	0.0031	7.9700	647.830	300	0.0350

5. Conclusions

Non-hierarchical grey wolf optimizer (NHGWO) was employed as the basis of a novel algorithm named G-SCNHGWO. The aim was to modify the GWO algorithm so that it could escape local optima. To validate the suggested algorithm, the ELD problem was incorporated. The amounts of output power generation by a generation unit were used as the decision variables in the ELD problem. The objective function attempted to adjust the variables optimally to minimize the overall cost of generation units while being limited by system constraints. Simulations on four different systems with 10, 15, 40, and 140 generation units proved the efficacy and high potential of the suggested G-SCNHGWO algorithm. This algorithm can be implemented in the real world for field applications; this will be addressed in future studies. The suggested method will be used in other nonlinear and complex optimization problems prevalent in the industry.

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