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Original Research

Generalized Normal Distribution Optimization Algorithm for Economic Dispatch with Renewable Resources Integration

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Abstract

In an electric power system operation, the main goal of economic dispatch (ED) is to schedule the power outputs of committed generating units efficiently. This involves consideration of relevant system equality and inequality constraints to meet the required power demand at the lowest possible operational cost. This is a challenging optimization problem for power system operators that can be dealt with efficient meta-heuristic algorithms. This article uses a recent meta-heuristic approach named the generalized normal distribution optimization (GNDO) algorithm to achieve near-optimal solutions. The efficacy of the proposed GNDO algorithm is validated through experimentation on three distinct test power system networks: one with three thermal units, the second one with six thermal-unit, and the third one with ten thermal units. The algorithm's performance is also assessed on a power network with renewable energy sources. All analyses of the four test cases are conducted on the MATLAB/SIMULINK platform. Finally, this article also compares the obtained results with other literature-reported strategies, genetic algorithm (GA), particle swarm optimization (PSO), whale optimization algorithm (WOA), flower pollination algorithm (FPA), and bald eagle search (BES) algorithm. It is evident from the simulated cases that the employed GNDO algorithm exhibits superior performance for two cases and competitive performance for the remaining cases in achieving the lowest operation costs and power losses.

Keywords
Renewable energy; generalized normal distribution optimization algorithm; economic dispatch; energy management.

1. Introduction

Optimization challenges are prevalent in various scientific and technological domains, posing difficulties due to the practical nature of the target function or model constraints. The ED is one such significant challenge in power systems. The ED tackles the task of determining the best possible combination of power production from various power plants. The objective is to meet the critical power demand while minimizing operational costs and ensuring adherence to system constraints [1]. Enhancing the solution to the ED problem can lead to substantial cost savings, prompting extensive research in this field. Researchers have employed various methodologies to address this optimization challenge, including mathematical, artificial intelligence, and hybrid approaches, each offering unique perspectives and advantages [2].

Today, electric power systems are required to have a significant percentage of renewable energy sources, and there have been numerous initiatives to integrate renewable energy (RE) resources into ED issues [3-5]. Solar, wind, biomass, wave, geothermal, and other energy resources that can be used for power production repeatedly are examples of renewable energy. However, the power generated from RE sources cannot be directly supplied to the utility power grid as most RE sources produce direct current (DC) voltag. In contrast, the electric power transmission system and consumer loads are operated in alternating current (AC) systems [6]. To handle challenges like determining the appropriate operating level for electric power plants to fulfill demand, a variety of conventional and nonconventional optimization techniques are used. Traditional methods, i.e., lambda iteration [7], have failed to solve such a problem. The ED problem has been solved using nonconventional ways, such as artificial bee colony algorithms (ABC) [8], hybrid grey wolf optimizer algorithms (GWO) [9], genetic algorithms (GA) [10], particle swarm optimization (PSO) [11], moth flame optimization, algorithms (MFA) [12], chameleon swarm algorithm (CSA) [13], firefly algorithms (FA) [14]. Also, the woodpecker mating algorithm (WMA) [15], bald eagle search (BES) algorithm [16], whale optimization algorithm (WOA) [17], and bat-inspired algorithm [18] were also explored to solve the ED problems.

As a result, using meta-heuristic optimization methods to resolve the ED problem has become increasingly wideheld in the last two decades, particularly ant colony optimization (ACO), genetic algorithm (GA) [10], and particle swarm optimization (PSO) [11], which have been helpful in a variety of fields of study. Meta-heuristics have become increasingly popular for four reasons: simplicity, adaptability, derivation-free method, and avoidance of local optima [19-22]. This task requires allocating loads to a plant's power generators to achieve the lowest fuel cost while addressing the power demand and transmission loss constraints. Several other versions of this issue model the same goal functions and constraints in different ways. A brief comparison of the proposed model with the noteworthy prior research in this field is provided in Table 1, highlighting the differences and improvements.

Table 1 Comparative study between previous literature and proposed model.

Publishing year	Papers	Contribution and limitation	Proposed model
1995, 2009, 2014, 2015	[23-26]	These papers used GA, PSO, GWO, and ABC for solving ED problems. But these algorithms are relatively old, and their convergence performance is slow compared to recently developed algorithms.	The proposed model uses GNDO algorithm which is developed in 2022, and is faster than GA, PSO, GWO, and ABC.
2016, 2017, 2018, 2022	[8, 9, 12, 13]	Hybrid GWO, ABC, MFO, and CSA are implemented recently to address the ED problem with different modeling technique. However, none of these papers considered the effect of renewable energy integration into power system networks in modern days.	This paper addresses the problem where solar and wind energy are considered for simulation results.

Table 1 shows that the suggested model fixes most of the constraints with the earlier models. On the other hand, traditional methods become exceedingly complicated when dealing with increasingly complex dispatch problems. Their lack of robustness and efficacy further limits them in several practical applications.

A new optimization approach has recently been proposed to address the photovoltaic (PV) module parameter estimations. Since normal distribution theory served as the foundation for this algorithm, it was named the generalized normal distribution optimization algorithm (GNDO) [27]. The efficiency of GNDO in avoiding local minima was demonstrated by its ability to estimate the parameters by minimizing the sum of squared error between the measured and calculated current and voltage values. The most notable quality of GNDO is that it doesn't require any work to fine-tune initial parameters, which makes it superior to most other metaheuristic algorithms now in use. Three photovoltaic model parameters are extracted using GNDO to evaluate its performance. According to experimental findings, GNDO performs better in accuracy and efficiency than the comparison algorithms [27]. Recently, GNDO has been used to solve many recent problems like permutation flow shop scheduling [28], solar PV integration in monopolar DC networks [29], and the medical feature selection Approach [30]. However it has not yet been utilized to solve ED problems. Considering its better performance in solving complex, diverse problems, GNDO is considered in this research to solve ED problems in renewable source integrated power system networks.

The main contributions of this paper are listed as follows:

- Development of a generic mathematical formulation of the ED problem of electric power system networks considering renewable energy sources.
- Deployment of a recent effective meta-heuristic algorithm, the GNDO, to find optimal solutions for four test power system networks.
- Comparison of the outcomes of the GNDO algorithm with the literature-reported strategies to demonstrate the effectiveness and superiority of the employed algorithm.

The remaining sections of this paper are organized as follows: the problem formulation is explained in Section 2, and the generalized normal distribution optimization technique is summarized in Section 3. The results and findings are discussed in Section 4, and the conclusions are provided in Section 5.

2. Problem Formulation

The economic dispatch strategy aims to reduce fuel costs while following several equity and inequality criteria. As a result, the problem is stated as follows:

2.1 Objective Function

The quadratic fuel charge equation of the thermal generating units is the cost function of the ED problem, and it is expressed as follows:

$$Min\left(\sum_{i=1}^{N} F_i(p_i)\right) = Min\left(\sum_{i=1}^{N} a_i + b_iP_i + c_iP_i^2\right) \tag{1}$$

Here, a_i, b_i, c_i are i^{th} generating unit's cost coefficients, p_i is the generated power of the unit, and N is the number of generating units.

2.2 Power Balance Constraint

$$P_D + P_L - \sum_{i=1}^{Ng} P_i = 0 \tag{2}$$

Equation (2) is the power balance constraints equation. Here, P_L is Transmission losses and P_D is total load demand. The transmission loss, P_L may be depicted by (3):

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} P_iB_{ij}P_j + \sum_{i=1}^{N} B_{0i}P_i + B_{00} \tag{3}$$

Here, N is the number of generating units and B_{ij} is transmission loss coefficient.

2.3 Power Output Limits

Each generating unit has minimum and maximum limits, i.e.

$$P_i^{min} \le P_i \le P_i^{max} \tag{4}$$

3. Generalized Normal Distribution Optimization

This section describes the GNDO algorithm's specifics [27], divided into sub-sections. The first subsection focuses on the motivations for the GNDO algorithm. The outline of GNDO is then presented in another sub-section. Lastly, the application of GNDO for optimization is explained.

3.1 Description

Based on population location data, a generalized normal distribution approach is used to keep the individual's position current. The normal distribution concept influenced GNDO. The normal distribution, often called the Gaussian distribution, is a helpful tool for characterizing common phenomena. The following is an explanation of a normal distribution. Here, x is assumed as an arbitrary variable that follows a possible arrangement with location and scale parameters, and its probability solidity function can be formulated as below.

$$f(x) = \frac{1}{\sqrt{2\pi\delta}} exp\left(-\frac{(x-\mu)^2}{2\delta^2}\right) \tag{5}$$

The normal distribution has two variables, according to equation (5): the scale parameter δ and the location parameter μ. The mean value and standard variance of random variables are expressed using the location and scale parameters.

Generally, there are three stages to the search procedure for population-based optimization approaches. Firstly, the dispersed distribution contains all initialized persons. Previously, individuals started moving toward the best overall solution while supervised by the planned exploration and exploitation strategies. Finally, everyone gathers around the best solution that has been found. In reality, numerous normal distributions can construct this search procedure.

To put it another way, all people's positions can be considered random variables with a normal distribution. The average position and the ideal location are more comprehensive in the first stage. The ranking standard deviation across all individuals is significantly more significant. The second step steadily reduces the disparity between the mean and optimum positions. The average change in all people's positions is getting smaller and smaller. In addition to the standard change of all individual positions, the space between the mean and optimal positions can be reduced to zero in the final stage.

3.2 The Structure of the Proposed Method

The proposed information exchange process in GNDO is local exploitation and global exploration, and it has a straightforward structure. The present mean and ideal positions guide local exploitation and are built on the generalized normal distribution model. In addition, three randomly chosen persons are linked to global exploration. A detailed explanation of both learning strategies is provided as follows.

3.2.1 Local Exploitation

Local exploitation is locating improved results within a search space that includes all persons' existing places. A GNDO model for optimization can be constructed for the association between a normal distribution and the distribution of people in the population.

$$v_i^t = \mu_i + \delta_i \times \eta, i = 1,2,3,\dots,N \tag{6}$$

Here, δ_i is generalized standard alteration, v^t_i is the trailing vector of the i^{th} individual at time t, μ_i is the generalized mean position of the i^{th} individual, and η is the penalty factor. In addition, μ_i, δ_i, and η can be defined as in (7), (8), and (9).

$$\mu_i = \frac{1}{3}(x_i^t + x_{Best}^t + M) \tag{7}$$

$$\delta_i = \sqrt{\frac{1}{3}[(x_i^t - \mu)^2 + (x_{Best}^t - \mu)^2 + (M - \mu)^2]} \tag{8}$$

$$\eta = \begin{cases} \sqrt{-log(\lambda_1)} \times cos(2\pi\lambda_2), if\ a \le b \\ \sqrt{-log(\lambda_1)} \times cos(2\pi\lambda_2 + \pi), otherwise \end{cases} \tag{9}$$

Here, a, b, λ_1, and λ_2 are unsystematic numbers between 0 and 1, M (10) is the mean position, and x^t_{Best} is the present top position of the existing population. In total, calculating M,

$$M = \frac{\sum_{i=1}^{N} x_i^t}{N} \tag{10}$$

3.2.2 Global Exploration

Global exploration is searching a speech space around the globe for promising places. In GNDO, the global exploration is established on three persons chosen at random, which can be stated as:

$$v_i^t = x_i^t + \beta \times (|\lambda_3| \times v_1) + (1 - \beta) \times (|\lambda_4| \times v_2) \tag{11}$$

In equation (11), $\beta \times (|\lambda_3| \times v_1)$ is local information sharing and $(1-\beta) \times (|\lambda_4| \times v_2)$ is global information sharing.

Here, λ_3 and λ_4 are arbitrary figures dependent on the standard normal distribution. Modify parameter (β) is a random quantity between 0 and 1, and v_1 and v_2 are two trail vectors. Furthermore, v_1 and v_2 can be determined by:

$$v_1 = \begin{cases} x_i^t - x_{p1}^t, if\ f(x_i^t) < f(x_{p1}^t) \\ x_{p1}^t - x_i^t, otherwise \end{cases} \tag{12}$$

$$v_2 = \begin{cases} x_{p2}^t - x_{p3}^t, if\ f(x_{p2}^t) < f(x_{p3}^t) \\ x_{p3}^t - x_{p2}^t, otherwise \end{cases} \tag{13}$$

Here, $p1$, $p2$, and $p3$ are three different numbers ranging from 1 to N, which come across $i \neq p1$

≠ *p2* ≠ *p3.* Equations (12) and (13), the subsequent term on the right of (11) can be termed local knowing term, which signifies that the result *p1* has information in common with the resolution *i*; global information sharing is the third term on the right of (11) that defines the individual *i* is specified information by those *p2* and *p3*. Furthermore, λ_3 and λ_4 are casual numbers with the usual normal distribution, which can sort GNDO has more excellent search space in acting out the global exploration. The adjustment parameter (*β)* equates the two information distribution approaches. The total sign in (11) is to stay steady with the showing mechanism in (12) and (13).

3.2.3 The GNDO Implementation for Optimization

The operation of GNDO is discussed in this section. The suggested GNDO is founded on local exploitation and global exploration tactics that have been established. The two strategies are equally crucial to GNDO and have the same chance of being chosen. Furthermore, like with other population-based optimization techniques, GNDO's population is initialized by

$$x_{i,j}^{t} = I_j + \left(u_j - I_j\right) \times \lambda_5 \tag{14}$$

Here, *i* is 1, 2, 3, 4, …, N, and *j* is 1, 2, 3, 4, …, D.

Where λ_5 is an arbitrary digit between 0 and 1, *D* is the number of design variables, the upper and lower limits of the j^{th} design variables are u_j and I_j, respectively. Reminder that the i^{th} specific may not discover a good result through global exploration or local exploitation strategies. To carry the improved solution into the following generation population, a showing mechanism (15) is considered; it can be denoted as:

$$x_i^{t+1} = \begin{cases} v_i^t, if\ f(v_i^t) < f(x_i^t) \\ x_i^t, otherwise \end{cases} \tag{15}$$

3.2.4 The Computation Difficulty of the Proposed Algorithm

Computation difficulty is an essential statistic for estimating the execution time of an algorithm. The computational complexity of GNDO comprises the period spent comparing and updating positions, which depends on the number of participants, iterations, and variables. *N* individuals must update their locations in each cycle, and *N* comparisons must be made. As a result, GNDO's overall computing complexity can be expressed as $O\ (NDT_{max} + NT_{max})$. The proposed GNDO algorithm's flowchart is shown in Figure 1. A flow chart illustrating the simulation process approach is displayed in Figure 2.

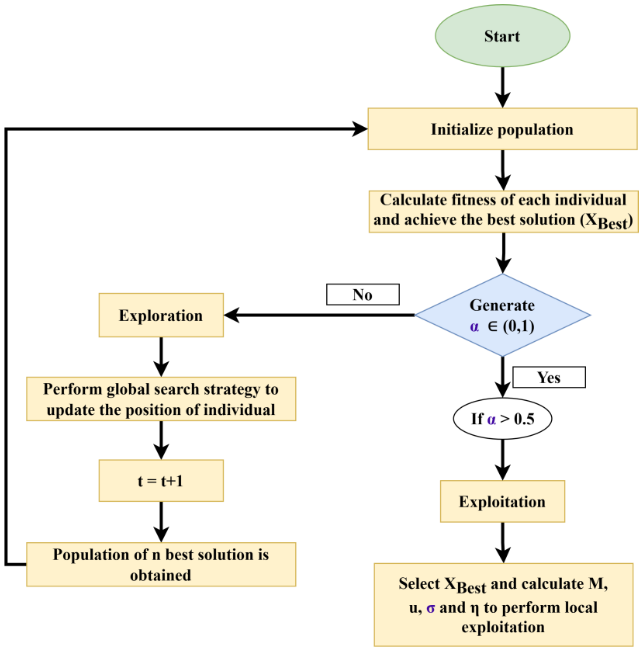

Figure 1 GNDO algorithm flowchart.

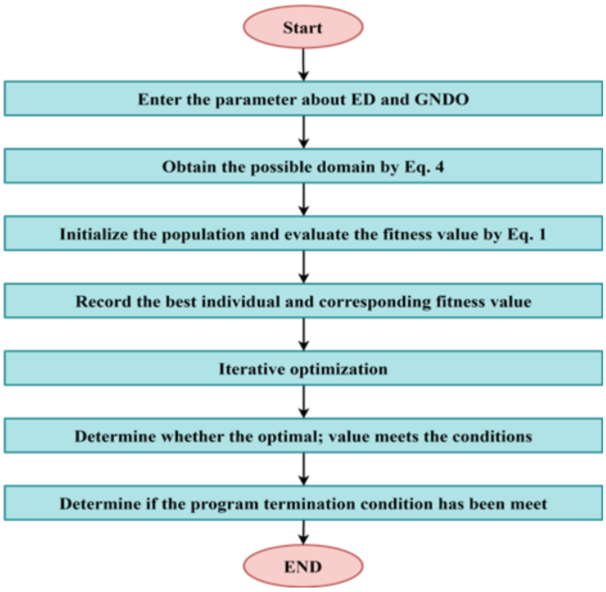

Figure 2 Methodology for the simulation process.

4. Results and Discussion

The proposed approach has undergone verification in four distinct power systems, encompassing three thermal units, six thermal units, ten thermal units, and three thermal units with two renewable resources power systems. In each of these setups, the cost function for the system's units is represented by a quadratic function. To address the economic dispatch problems, various techniques, including GNDO, GA, WOA, PSO, and other methods, are employed, and their outcomes are thoroughly analyzed. To conduct a comparative study, all algorithms are implemented using MATLAB to tackle ED problems effectively. The primary objective is to use GNDO to optimize power generation costs.

4.1 First Case: Three Thermal-Unit System

Table 2 provides the fuel cost coefficients for three thermal-unit systems. The results acquired for the system employing the GNDO are shown in Table 3 and compared with GA [31] ,BES [16], and WOA [17]. Figure 3 shows the convergence curve of three thermal fuel costs using the GNDO algorithm for 1000 iterations. It gives the optimum value within 40 iterations. Table 3 shows the fuel costs for the three-unit system at 400MW using different algorithms, where the GNDO algorithm provides minimum fuel cost compared to GA, BES, and WOA. Also, compared to GA, BES, and WOA, power loss is reduced while utilizing the GNDO algorithm. In this case, the computation time for 1000 iterations is 9.44 seconds.

Table 2 Coefficients of fuel cost for three thermal-unit systems [32].

	a	**b**	**c**	P_{min} **(MW)**	P_{max} **(MW)**
1	1243.5311	38.30553	0.03546	35	210
2	1658.5696	36.32782	0.02111	130	325
3	1356.6592	38.27041	0.01799	125	315

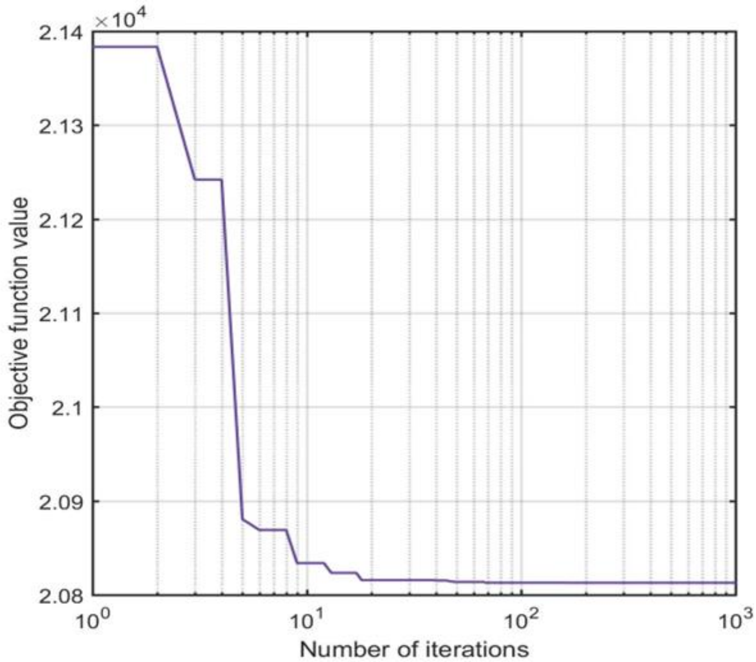

Figure 3 Cost convergence characteristics of GNDO for three thermal-unit systems.

Table 3 Comparison of three thermal-unit systems at a power demand of 400MW.

Power Output (MW)	**GA** [31]	**BES** [16]	**WOA** [17]	**GNDO**
P_1	102.61	83.091	110.59	87.99
P_2	153.82	182.349	130	174.97
P_3	151.01	142.129	166.91	144.56
Total generation	407.41	407.41	407.45	407.35
Loss	7.41	7.571	7.45	7.35
Total cost ($/h)	**20840**	**20815.54**	**20897.63**	**20814.9075**

4.2 Second Case: Six Thermal-Unit System

Table 4 for the six thermal-unit systems shows the fuel cost coefficients. The results acquired for the six thermal-unit systems by the GNDO are shown in Table 5 and are compared with GA and WOA.

Table 4 Coefficients of fuel cost for six thermal-unit systems [33].

Power Output (MW)	P_{min} **(MW)**	P_{max} **(MW)**	**a**	**b**	**c**
P_1	100	500	240	7	0.007
P_2	50	200	200	10	0.0095
P_3	80	300	220	8.5	0.009
P_4	50	150	200	11	0.009
P_5	50	200	220	10.5	0.008
P_6	50	120	120	12	0.0075

Table 5 Comparison of a six thermal-unit system at P_D = 1263 MW.

Power Output (MW)	**GA** [33]	**WOA** [17]	**GNDO**
P_1	447.80	499.98	487.68
P_2	178.63	188.19	141.31
P_3	262.20	299.98	295.86
P_4	134.28	101.26	110.90
P_5	151.90	68.06	162.39
P_6	74.18	119.99	78.58
Total generation (MW)	1276.03	1277.49	1276.74
Loss (MW)	13.02	14.49	13.75
Total cost ($/h)	**15459.0**	**15603.95**	**15490.40**

Table 4 shows the fuel costs for six thermal-unit systems at 1263MW using different algorithms, where the GNDO algorithm provides the lowest fuel cost and less power loss compared to the WOA algorithm. And nearly identical fuel costs and power loss compared to GA [33], a well-established methodology. Figure 4 indicates the cost convergence curve of six thermal-unit systems using the GNDO algorithm for 1000 iterations. It provides optimum value within 60 iterations. In this instance, the process takes 9.56 seconds to complete 1000 iterations.

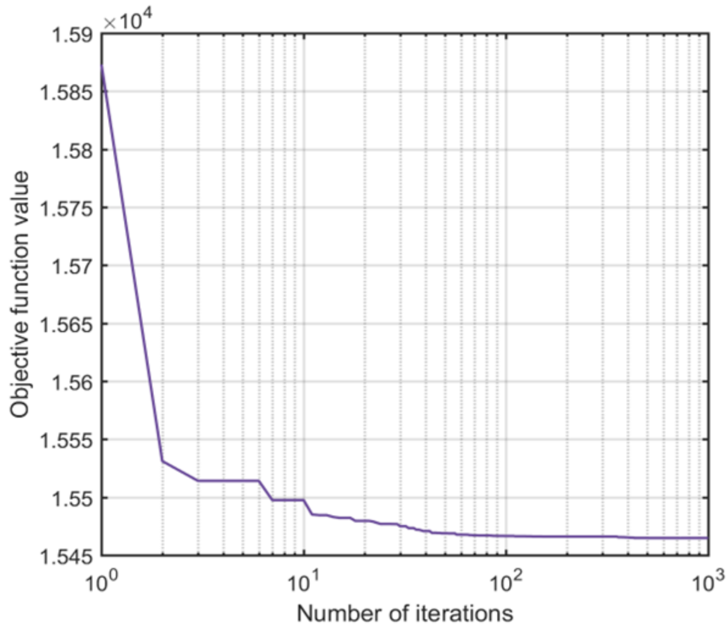

Figure 4 Cost convergence characteristics of GNDO for six thermal-unit system.

4.3 Third Case: Ten Thermal-Unit System

The results acquired for the ten generator systems for ten thermal-unit coefficients [32] by the GNDO are given in Table 6 and compared with other algorithms.

Table 6 Comparison of ten thermal-unit systems at P_D = 2000MW.

Power Output (MW)	**FPA** [17]	**WOA** [17]	**GNDO**
P_1	53.18	20.26	52.33
P_2	79.97	61.61	71.22
P_3	78.10	112.57	97.79
P_4	97.11	111.15	74.79
P_5	152.74	139.17	58.40
P_6	163.08	222.07	220.32
P_7	258.61	263.29	293.93
P_8	302.22	301.35	297.49
P_9	433.21	415.20	461.97
P_{10}	466.07	435.69	458.24
Loss (MW)	84.3	82.17	85.49
Total cost ($/h)	**113370.01**	**115345.37**	**113921.95**

Figure 5 illustrates the cost convergence curve of ten thermal units using the GNDO algorithm for 1000 iterations. It offers optimum value within 110 iterations. Table 6 shows the fuel costs for ten thermal-unit systems at 2000 MW using different algorithms, where the GNDO algorithm provides less fuel cost than the WOA algorithms and almost similar fuel cost compared to a well-established algorithm, FPA. In this case, 1000 iterations are completed in 9.48 seconds.

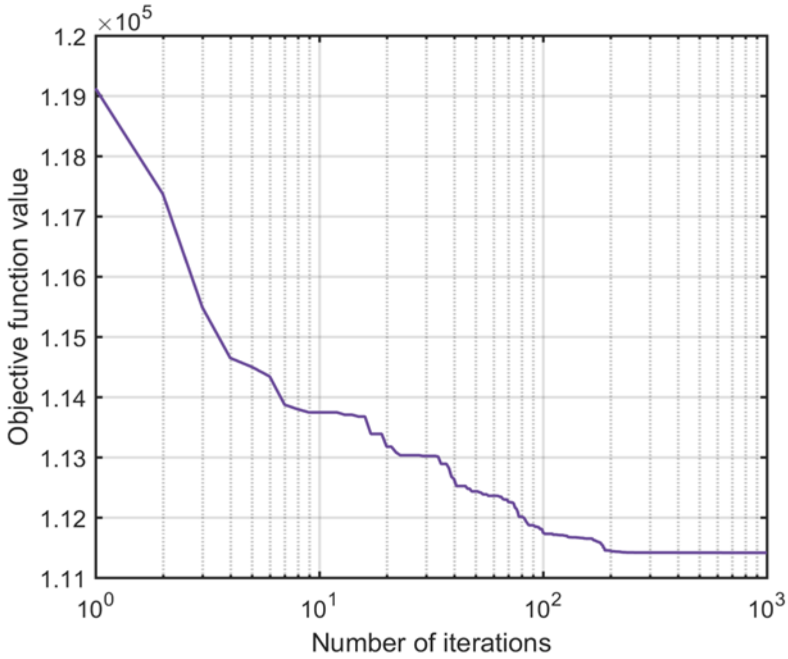

Figure 5 Cost convergence characteristics of GNDO for ten thermal-unit systems.

4.4 Fourth Case: Three Thermal-Unit with Two Renewable-Unit System

In this case, solar and wind generation data are considered renewable energy, as given in Table 7, where Table 8 provides the fuel price coefficients. The GNDO's three thermal-unit and two renewable-unit system results are presented in Table 9 and distinguished with WOA. The wind and solar generation values in Table 7 are plotted in Figure 6. These wind and solar power are added to the load. In this case, total fuel cost is reduced as they are renewable energy.

Table 7 The data of solar and wind generation (24-hour) [34].

Time (h)	Solar (MW)	Wind (MW)	Time (h)	Solar (MW)	Wind (MW)
1	0	1.7	13	31.94	14.35
2	0	8.5	14	26.81	10.35
3	0	9.27	15	10.08	8.26
4	0	16.66	16	5.30	13.71
5	0	7.22	17	9.57	3.44
6	0.03	4.91	18	2.31	1.87
7	6.27	14.66	19	0	0.75
8	16.18	26.56	20	0	0.17
9	24.05	20.58	21	0	0.15
10	39.37	17.85	22	0	0.31
11	7.41	12.80	23	0	1.07
12	3.65	18.65	24	0	0.58

Table 8 Fuel cost coefficients for three thermal-unit and two renewable-unit system [34].

Unit	P_{min} (MW)	P_{max} (MW)	a	b	c

1	37	150	1530	21	0.024
2	40	160	992	20.16	0.029
3	50	190	600	20.4	0.021

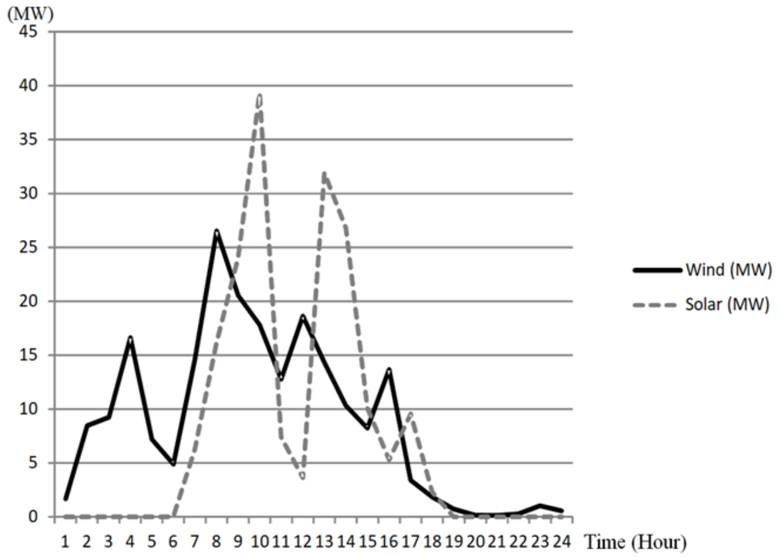

Figure 6 Wind and solar power generation for 24 hours.

Figure 7 shows the changes in fuel cost concerning time, considering the power demand variations over 24 hours. Table 9 shows the fuel costs for three thermal-unit and two renewable-unit systems using WOA and GNDO algorithms, where the GNDO algorithm provides the lowest fuel cost compared to the WOA algorithms. One thousand iterations are completed in this case in 14.98 seconds.

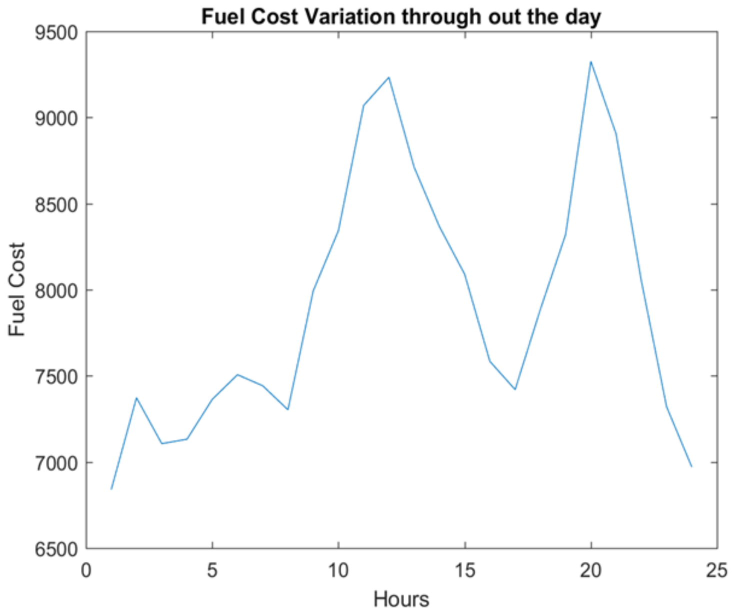

Figure 7 Hourly operation cost with GNDO for three thermal-unit and two renewable-unit systems.

Table 9 Data of fuel cost of three thermal-unit and two renewable-unit systems for 24 hours.

Time (h)	**PD (MW)**	**P1 (MW)**	**P2 (MW)**	**P3 (MW)**	**WOA ($/h)** [17]	**GNDO ($/h)**
1	140	45.39	43.03	50.71	6838.75	6838.65
2	150	48.76	40.08	53.54	6997.13	6994.11
3	155	53.88	42.18	50.60	7103.87	7104.28
4	160	38.12	52.42	53.72	7133.74	7131.59
5	165	40.39	62.05	56.45	7376.64	7359.40
6	170	51.46	42.11	72.72	7530.84	7503.32
7	175	48.13	40.00	67.02	7447.30	7433.21
8	180	39.37	48.64	50.08	7305.53	7302.37
9	210	49.56	61.37	55.65	7992.54	7983.71
10	230	39.85	45.04	89.31	8339.31	8325.35
11	240	77.75	92.74	51.47	9047.65	9046.33
12	250	39.40	63.87	127.0	9360.27	9270.65
13	240	38.16	55.83	101.5	8770.22	8699.37
14	220	57.96	40.03	86.39	8316.87	8318.85
15	200	82.19	41.60	59.35	8111.73	8083.25
16	180	46.00	40.53	75.66	7595.14	7574.98
17	170	44.93	61.77	51.38	7418.9	7410.38
18	185	49.95	44.15	88.25	7923.13	7874.25
19	200	77.01	50.53	73.49	8376.48	8279.83
20	240	92.64	41.93	107.9	9344.58	9302.71
21	225	40.91	90.46	95.87	9044.12	8916.91
22	190	77.37	40.29	73.65	8110.03	8054.18
23	160	42.75	65.94	51.36	7329.17	7319.09
24	145	37.00	58.31	50.03	6970.52	6970.43
Total Cost	**4580 MW**	**1260.8 MW**	**1266.9 MW**	**1695.2 MW**	**189780.1 ($/day)**	**189100.1 ($/day)**

5. Conclusions

This paper employed GNDO to solve the ED problem for four electric power system networks: three thermal units, six thermal units, ten thermal units, and three thermal units with two renewable resources under load and generator limit constraints. The placement of each individual is rearranged using the GNDO. The key feature of the GNDO, connected to the most recent metaheuristic algorithms, is that it does not require a contest for suitable initial parameter adjustment. The employed algorithm significantly outperformed WOA in all scenarios. Considering the availability of solar and wind power demonstrated that the proposed method could boost convergence and pursue the ideal global solution.

In most cases, the simulation results have shown that the proposed algorithm outperforms other selected algorithms concerning determining the minimum generation cost and power losses. Besides, the employed strategy exhibited competitive performances for the remaining test cases.

However, it is worth noting that this article does not consider network constraints, such as transmission congestion. Including these constraints couldcan be considered regarded for future research and analysis.

Author Contributions

Conceptualization, S.H., M.S., M.R.I.; methodology, S.H., S.A., M.S.A.; software, S.A., M.S.; investigation, S.A., M.S.,A., M.R.I.; data curation, M.R.I., M.S.; writing—original draft preparation, S.H., S.A., M.S.A.; writing—review and editing, M.R.I., M.S.

Competing Interests

The authors have declared that no competing interests exist.

Abbreviations

ABC	Artificial Bee Colony
AOC	Ant Colony Optimization
BES	Bald Eagle Search Optimization Algorithm
BIT	Bat-Inspired Algorithm
CEED	Combining Economic and Emission Dispatch
CSA	Chameleon Swarm Algorithm
ED	Economic Dispatch
FA	Firefly Algorithms
FPA	Flower Pollination Algorithm
GA	Genetic Algorithm
GNDO	Generalized Normal Distribution Optimization
HGWO	Hybrid Grey Wolf Optimizer Algorithms
MFOA	Moth Flame Optimization Algorithms
PSO	Particle Swarm Optimization
RE	Renewable Energy
WMA	Woodpecker Mating Algorithm
WOA	Whale Optimization Algorithm

References

1. Sinha N, Chakrabarti R, Chattopadhyay PK. Evolutionary programming techniques for economic load dispatch. IEEE Trans Evol Comput. 2003; 7: 83-94.
2. Chowdhury BH, Rahman S. A review of recent advances in economic dispatch. IEEE Trans Power Syst. 1990; 5: 1248-1259.
3. Aghaei J, Alizadeh MI. Demand response in smart electricity grids equipped with renewable energy sources: A review. Renew Sustain Energy Rev. 2013; 18: 64-72.
4. Azam MS, Islam MR, Shafiullah M, Islam MS. Robust Design of PSS for Multimachine Networks using Jellyfish Search Algorithm. Conference of Open Innovations Association FRUCT (FRUCT31); 2022 April 27-29; Helsinki, Finland. Genève, Switzerland: Zenodo, CERN.

5. Islam MS, Islam MR, Shafiullah M, Azam MS. Dragonfly algorithm for robust tuning of power system stabilizers in multimachine networks. 2022 International Conference on Advancement in Electrical and Electronic Engineering (ICAEEE); 2022 February 24-26; Gazipur, Bangladesh. Piscateville, NJ, USA: IEEE.
6. Islam MR. Operation planning of a microgrid incorporating hydrogen energy and RE technology. 2020 International Conference on System, Computation, Automation and Networking (ICSCAN); 2020 Jul 3; Pondicherry, India. Piscateville, NJ, USA: IEEE.
7. Gaing ZL. Particle swarm optimization to solving the economic dispatch considering the generator constraints. IEEE Trans Power Syst. 2003; 18: 1187-1195.
8. Mouassa S, Bouktir T. Artificial bee colony algorithm for solving economic dispatch problems with non-convex cost functions. Int J Power Energy Convers. 2017; 8: 146-165.
9. Jayabarathi T, Raghunathan T, Adarsh BR, Suganthan PN. Economic dispatch using hybrid grey wolf optimizer. Energy. 2016; 111: 630-641.
10. Lee JC, Lin WM, Liao GC, Tsao TP. Quantum genetic algorithm for dynamic economic dispatch with valve-point effects and including wind power system. Int J Electr Power Energy Syst. 2011; 33: 189-197.
11. Mirjalili S, Song Dong J, Lewis A, Sadiq AS. Particle swarm optimization: Theory, literature review, and application in airfoil design. In: Nature-inspired optimizers: Theories, literature reviews and applications. Cham, Switzerland: Springer; 2020.
12. Sulaiman MH, Mustaffa Z, Rashid MI, Daniyal H. Economic dispatch solution using moth-flame optimization algorithm. MATEC Web Conf. 2018; 214: 03007.
13. Rizk Allah RM, Hassanien AE, Snášel V. A hybrid chameleon swarm algorithm with superiority of feasible solutions for optimal combined heat and power economic dispatch problem. Energy. 2022; 254: 124340.
14. Wadhwani S. Economic load dispatch problem using firefly algorithm. Int J Sci Eng Res. 2013; 4: 2155-2160.
15. Karimzadeh Parizi M, Keynia F, Khatibi Bardsiri A. Woodpecker mating algorithm for optimal economic load dispatch in a power system with conventional generators. Int J Ind Electron Control Optim. 2021; 4: 221-234.
16. Adnan S, Islam MR, Shafiullah M, Hoque S, Azam MS. Bald Eagle Search Optimization Algorithm for Economic Dispatch Problem with Renewable Energy Integration. 2023 XIX International Scientific Technical Conference Alternating Current Electric Drives (ACED); 2023 May 23; Ekaterinburg, Russian Federation. Piscateville, NJ, USA: IEEE.
17. Touma HJ. Study of the economic dispatch problem on IEEE 30-bus system using whale optimization algorithm. Int J Eng Technol Sci. 2016; 3: 11-18.
18. Tariq F, Alelyani S, Abbas G, Qahmash A, Hussain MR. Solving renewables-integrated economic load dispatch problem by variant of metaheuristic bat-inspired algorithm. Energies. 2020; 13: 6225.
19. Mirjalili S, Mirjalili SM, Lewis A. Grey wolf optimizer. Adv Eng Software. 2014; 69: 46-61.
20. Shafiullah M, Abido MA, Al Mohammed AH. Chapter 2 - Metaheuristic optimization techniques. In: Power System Fault Diagnosis. Elsevier; 2022. pp. 27-68.
21. Shafiullah M, Hossain MI, Abido MA, Abdel Fattah T, Mantawy AH. A modified optimal PMU placement problem formulation considering channel limits under various contingencies. Measurement. 2019; 135: 875-885.

22. Shafiullah M, Abido MA, Coelho LS. Design of robust PSS in multimachine power systems using backtracking search algorithm. 2015 18th International Conference on Intelligent System Application to Power Systems (ISAP); 2015 Sep 11; Porto, Portugal. Piscateville, NJ, USA: IEEE.
23. Chen PH, Chang HC. Large-scale economic dispatch by genetic algorithm. IEEE Trans Power Syst. 1995; 10: 1919-1926.
24. Mahor A, Prasad V, Rangnekar S. Economic dispatch using particle swarm optimization: A review. Renewable Sustainable Energy Rev. 2009; 13: 2134-2141.
25. Wong LI, Sulaiman MH, Mohamed MR, Hong MS. Grey Wolf Optimizer for solving economic dispatch problems. 2014 IEEE international conference on power and energy (PECon); 2014 Dec 1; Kuching, Malaysia. Piscateville, NJ, USA: IEEE.
26. Secui DC. A new modified artificial bee colony algorithm for the economic dispatch problem. Energy Convers Manage. 2015; 89: 43-62.
27. Zhang Y, Jin Z, Mirjalili S. Generalized normal distribution optimization and its applications in parameter extraction of photovoltaic models. Energy Convers Manage. 2020; 224: 113301.
28. Abdel Basset M, Mohamed R, Abouhawwash M, Chang V, Askar SS. A local search-based generalized normal distribution algorithm for permutation flow shop scheduling. Appl Sci. 2021; 11: 4837.
29. Montoya OD, Gil González W, Grisales Noreña LF. Solar photovoltaic integration in monopolar DC networks via the GNDO algorithm. Algorithms. 2022; 15: 277.
30. Abdel Basset M, Mohamed R, Chakrabortty RK, Ryan MJ, Nam Y, Abouhawwash M. Medical feature selection approach based on generalized normal distribution algorithm. Comput Mater Contin. 2021; 69: 2883-2901.
31. Devi AL, Krishna OV. Combined economic and emission dispatch using evolutionary algorithms-a case study. ARPN J Eng Appl Sci. 2008; 3: 28-35.
32. Abdelaziz AY, Ali ES, Abd Elazim SM. Flower pollination algorithm to solve combined economic and emission dispatch problems. Eng Sci Technol Int J. 2016; 19: 980-990.
33. Fu C, Zhang S, Chao KH. Energy management of a power system for economic load dispatch using the artificial intelligent algorithm. Electronics. 2020; 9: 108.
34. Trivedi IN, Bhoye M, Bhesdadiya RH, Jangir P, Jangir N, Kumar A. An emission constraint environment dispatch problem solution with microgrid using Whale Optimization Algorithm. 2016 National Power Systems Conference (NPSC); 2016 Dec 19; Bhubaneswar, India. Piscateville, NJ, USA: IEEE.