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RESEARCH PAPER

A novel artificial electric field strategy for economic load dispatch problem with renewable penetration

Diwakar Verma[1] · Jatin Soni[1] · Kuntal Bhattacharjee[1]

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Abstract
This article presents an innovative method to address the economic load dispatch (ELD) problem in power systems incorporating renewable energy sources within thermal units. Employing the 2-m point estimation technique for determining renewable energy output power, the proposed approach effectively addresses challenges associated with renewable-based ELD by utilizing the artificial electric field method. Inspired by the electrostatic force principle among charged particles, this approach guides particles toward optimal solutions within the search space. Validation on power systems featuring 3, 5, 6, 15, and 40 units demonstrates superior performance compared to established algorithms, confirmed by the Wilcoxon signed-rank test. The research contributes to the advancement of sustainable and efficient power systems.

Keywords Artificial electric field algorithm · Economic load dispatch · Valve point effect · 2-m point estimation method

List of symbols

a_i, b_i, c_i, e_i, f_i	Cost variable of the i_{th} thermal unit
N	Count of connected generators
Ti	Generated power of i th thermal generator in MW
W_p, S_p	Generated power of wind-solar in MW
C_w	Cost variable of wind in $/h
N_W, N_s	Count of wind and solar unit
Bidl	Bid price of l th solar unit
TL	Transmission loss
TD	Power requirement
B_{ij}, B_{0i}, B_{00}	Loss matrix
T_{imin}, T_{imax}	Boundary limit Minimum-maximum power i th unit
S_{hp}, S_{cp}	Weibull variables
v, v_r	Instant and rated haste of wind unit
v_{in}, v_{out}	Cut in–cut out the haste of wind unit
W_p, W_{pt}	Instant and rated power of wind unit
ω, ψ	Beta variables
Γ	Gamma objectives
$S_{rad(t)}$	Cellular solar radiation at time t
$S_{rad,stc}$	Solar radiation in normal circumstances
$S_{P,stc}$	Solar power in normal circumstances
γ	Temperature variable in %/°C
Tcell	The degree of heat in a solar cell
$T_{cell,stc}$	The solar cell's temperature under the usual test conditions
NOT	The cell's typical operating temperature
N_{sc}, N_{pc}	Number of solar cells in series and parallel
μ, σ	The average and standard deviation
I_k	Input constant
S_e	Total electricity production, including solar and wind
z_l	Uncertainty in the input variable
Qi(t), Qj(t)	Charges of i th and j th fleck
K(t)	Coulomb's variable
E	Modestly positive constant
$R_{ij(t)}$	The distance in Euclid between two particles
α, K_0	Parameter and starting point
F_i, M_i	Force and mass of the i th particle
V_i, X_i	Particle's location and speed

✉ Jatin Soni
20ptphde231@nirmauni.ac.in; sonijatin1995@gmail.com

Diwakar Verma
17bee025@nirmauni.ac.in

Kuntal Bhattacharjee
kuntal.bhattacharjee@nirmauni.ac.in

[1] Institute of Technology, Nirma University, Ahmedabad, Gujarat 382481, India

1 Introduction

Because of the growth of factories and industries, there is a constant increase in the need for electricity. To meet the demand for electricity, the thermal producing units should be run cheaply. Economic Load Dispatch (ELD), a concept coined by researchers and engineers, describes how to distribute load demand across producing units while adhering to all system restrictions. Through mathematical programming and optimization approaches, several traditional methods are utilised to tackle ELD issues, including lambda iteration methods [1], gradient methods [2], linear programming methods [3], and quadratic programming methods [4]. These techniques are only workable for approximate linear cost calculations [5]. By taking into account several practical operating restrictions such generator operating limits and the valve point loading impact, the practical ELD issue becomes very nonlinear after considering Valve Point Loading Effect (VPLE). For nonlinear optimization issues, a variety of heuristic techniques are employed, including Artificial Bee Colony (ABC) [6], Harmony Search Algorithm (HAS) [7], and Flower Pollination Algorithm (FPA) [8]. The aforementioned techniques produce many minima, and obtaining a single global minimum is challenging [9]. The nonlinear ELD issues are solved using evolutionary techniques such as Genetic Algorithm (GA) [10], Differential Evolution (DE) [11], and Particle Swarm Optimization (PSO) [12]. These techniques provide answers regardless of the curve's form. Although the approaches discussed above offer a quick and promising answer, they don't always find the overall ideal solution in a reasonable amount of time [13].

The reason for minimizing load generation cost in Economic Load Dispatch (ELD) is to ensure the most efficient use of resources and to provide electricity to consumers at the lowest possible cost.Electricity generation is a significant contributor to the cost of electricity, and minimizing the cost of generation can result in lower electricity bills for consumers. Additionally, minimizing the cost of generation can help utilities to maximize their profits or minimize their losses, which is important for ensuring the financial sustainability of the power system.Moreover, minimizing the cost of generation can also help to reduce the environmental impact of electricity generation by reducing the need for expensive and polluting power plants, as well as by increasing the utilization of Renewable Energy Sources (RES). Therefore, minimizing load generation cost is a critical objective in ELD, and it is achieved through the optimal allocation of power generation among the available generators in order to meet the system's demand at the lowest possible cost while satisfying all of the operational and physical constraints.

1.1 Research gap

RES and integrated power generating systems have drawn a lot of interest as a result of the increase in global warming and energy demand. Due to the restricted supply of RES electricity, the demand could not be satisfied [14]. It is therefore linked to the grid and integrated with the thermal unit. Because they offer cheaper operational costs, wind and solar energy have been included into ELD. The performance of solar and wind turbines is significantly impacted by the environment and location. [15]. Because they fluctuate with wind velocity and sun irradiance, respectively, wind power and solar power are unreliable sources of energy. Therefore, stochastic ELD issues based on wind and solar energy are solved using a renewable-based ELD model [16]. In this article, the unpredictability of wind-solar energy in ELD is considered. The wind speed and solar irradiance are generated at random using the Weibull and beta distribution functions, respectively [17]. The mean and standard deviation (SD) are computed using the 2-m Point Estimation Method (PEM) [18]. The renewable-based ELD model's goal function has a very complicated and nonlinear nature. It was resolved using a hybrid approach that included PSO and Sequential Quadratic Programming (SQP). Because the issue contains numerous minima, these hybrid techniques produce results too early [19]. In order to extract the best answer from the Pareto set, a fuzzy decision-making approach was used [20]. Sadly, these techniques are quite inefficient and typically become caught in local optima. Biogeography-Based Optimization (BBO) [21] may struggle with high-dimensional problems due to its reliance on migration and mutation operators, which can lead to slow convergence in complex Economic Load Dispatch (ELD) scenarios. Firefly Algorithm (FFA) [22] is sensitive to parameter settings and its vulnerability to premature convergence limit its effectiveness, especially when dealing with non-linear and multimodal ELD problems. Cuckoo Search Algorithm (CSA) [23] has been reliable on a single global nest may lead to suboptimal solutions in large-scale ELD problems, where the algorithm can struggle with effective exploration and exploitation of the solution space. Dragonfly Algorithm (DA) [24] may face challenges in handling dynamic ELD scenarios due to its reliance on predefined mathematical models, potentially hindering adaptability to changing system conditions. Magnetic Optimization Algorithm (MOA) [25] has been dependent on magnetic force modeling may limit its performance in ELD problems with complex constraints, particularly in scenarios where the magnetic interaction model does not adequately capture system dynamics. Charged System Search (CSS) [26] may exhibit slow convergence and limited exploration in high-dimensional Economic Load Dispatch (ELD) problems, impacting its ability to efficiently search for optimal solutions. Oppositional Real-Coded Chemical Reaction Optimization (ORCCRO) [27] is reliable on opposition-based learning may lead to increased computational costs, especially in complex ELD scenarios, where the benefits of oppositional learning may be overshadowed by the associated overhead. Multiple Group Search Optimization (MGSO) [28] may be compromised in dynamic ELD situations due to its susceptibility to premature convergence, hindering its adaptability to changing power system conditionsPlant Grow Simulation Algorithm (PGA) [29] is dependent on a plant growth model may limit its effectiveness in ELD problems with intricate constraints, potentially resulting in suboptimal solutions in scenarios where the model inadequately represents the system dynamics. Gravitational Search Algorithm (GSA) [30] is vulnerable to getting trapped in local optima may impact its performance in complex ELD scenarios, where effective exploration of the solution space is crucial for obtaining optimal results. Teaching-Learning Based Optimization (TLBO) [31] may hinder its performance in highly nonlinear and multimodal ELD problems, where more sophisticated algorithms may provide superior solutions. Artificial Immune System Algorithm (AISA) [32] is reliable on immune system-inspired processes may limit its efficiency in ELD problems with diverse solution spaces, potentially leading to suboptimal solutions.Imperialist Competitive Algorithm (ICA) [33] is sensitive to initial conditions may result in a lack of robustness in ELD scenarios, impacting its reliability in finding optimal solutions, particularly in situations with varying system parameters. Jaya Algorithm's (JA) [34] exploration-exploitation balance may be insufficient for certain ELD problems, particularly in scenarios where a more sophisticated algorithm is needed to navigate complex solution spaces. Ant Lion Optimizer (ALO) [35] may be compromised in large-scale ELD problems due to its reliance on local search mechanisms, potentially limiting its ability to explore and exploit the entire solution space. Bat Algorithm (BA) [36] may struggle with slow convergence and suboptimal solutions in certain ELD scenarios, particularly when faced with complex constraints that challenge its inherent search mechanisms.Adaptive Jaya Algorithm's (AJA) [37] adaptability may be insufficient for dynamic ELD problems, as it may face challenges in adjusting to rapidly changing system conditions.Backtracking Search Algorithm's (BSA) [38] reliance on backtracking mechanisms may introduce computational overhead, particularly in ELD problems with intricate constraints, potentially impacting its efficiency.

The ELD problem in power systems has gained significant attention, especially with the increasing integration of RES. However, a comprehensive review of the existing literature reveals a notable research gap in addressing the dynamic nature of ELD while considering the penetration of RES. Many existing studies focus on static ELD, neglecting the temporal variations introduced by RES such as wind and solar power. The temporal dynamics of these RES, along with their uncertain and intermittent nature, pose significant challenges to achieving optimal ELD in real-time power system operations. Additionally, the literature lacks a unified and effective methodology that considers both the economic aspects and dynamic characteristics of the power system with a high penetration of RES. Most existing methods either oversimplify the dynamics or neglect the economic factors, leading to sub-optimal solutions that may not be suitable for practical implementation.

The Artificial Electric Field Algorithm (AEFA) is suggested in this publication to get the lowest likely cost of produced electricity while taking wind and solar uncertainty into account [39]. Coulomb's law of electrostatic force and Newton's law of motion serve as the foundation for AEFA. The agents in this algorithm are seen as point charge particles. Each particle has the same weight. The best charge particle locates the ideal solution in the search space and attracts additional low charge particles. The algorithm is memory-based. To update the location and velocity, it used the particle's local best and global best fitness history. It is observed that AEFA's performance in the various optimization issues is wholly satisfactory. The current authors are using this recently created method to tackle non-convex and extremely complicated renewable-based ELD issues because of the benefits of AEFA. To prevent underestimating and overestimating the cost of RES, the probabilities of wind velocity and solar irradiation are computed using PDF. Accuracy is increased and premature convergence at local optima is avoided by using the initial parameter of AEFA. the research gap in the ELD Problem considering RES penetration calls for a methodology that combines adaptability, consideration of economic objectives, and efficient exploration of the solution space. The AEFA method stands out as a promising approach to bridge this gap, offering a robust and effective solution to achieve optimal economic load dispatch in power systems with a significant share of RES.

These are crucial contributions and novelties of this research work: (a) Yadav et al. recently proposed AEFA, an effective soft computing approach [40]. Yadav et al. improved the 15 benchmark functions to demonstrate the resilience of the technique [40]. It's been observed that AEFA produces significantly better outcomes than the majority of newly created algorithms. For the first time, the AEFA has been employed in this study to address extremely challenging and non-linear economic load dispatch concerns since RES are becoming more prevalent in electrical power networks. (b) The unknown values of wind speed and solar irradiation have been obtained using well-known probability density functions. To estimate the output power of RES like wind and solar energy, the 2-m point estimation approach has been promoted. Because of this, this specific ELD issue can be classified as a probabilistic economic load dispatch issue. (c) Test systems of various sizes, including small, medium, and big ones, have been used to validate the proposed work. (d) The Wilcoxon signed-rank test, a well-known static data analytic method, was used to validate the results. (e) The evaluation of the proposed AEFA algorithm in comparison to certain current methodologies demonstrates its superiority and efficacy.

A comprehensive exploration of probabilistic ELD problems is detailed in Sect. 2, which includes an in-depth examination of mathematical models for wind and solar energy in Sect 2.3. Section 3 outlines the PEM and their procedural steps. Additionally, Section 4 introduces the AEFA approach, providing a detailed description in its original form. The adaptation of AEFA to address the challenges posed by renewable-based ELD is extensively discussed in Sect 4.1. The simulation results and their analysis are presented in Sect 5, shedding light on the efficacy of the proposed methodologies. Finally, Sect 6 encapsulates the study with conclusions drawn from the findings, emphasizing the ongoing need for further advancements in optimizing renewable energy integration within ELD frameworks.

2 Problem formulation

The development of a renewable-based ELD formulation takes into account the erratic nature of sun irradiation and wind velocity. The primary goal of the objective function is to meet load demand while minimising the overall cost of generating while taking into account wind, solar, and thermal units. The objective function equation is written as follows.

2.1 Main purpose

2.1.1 The cost function including wind-solar power without VPLE

An equation with a quadratic solution represents the thermal unit's goal function of cost. The objective function of cost for a wind-solar ELD without VPLE is displayed as follows:

$$Total\ cost = min\left[\sum_{i=1}^{N} a_i + b_i T_i + c_i T_i^2 + \sum_{k=1}^{N_w} W_{p,k} C_{w,k} + \sum_{l=1}^{N_s} S_{pl} Bidl\right] \quad (1)$$

where a_i, b_i and c_i are cost constant of ith thermal generator; N is count of thermal generators; T_i is output power of each thermal generator; T_{imin}, T_{imax} are boundary of minimum-maximum power; W_p, S_p are generated power of wind-solar in MW; C_w is cost constant of wind in \$/h; N_w, N_s is count of wind and solar plant; Bidl is Bid price of lth solar plant;

2.1.2 The cost function incorporating with wind-solar with VPLE

In the problem's use-case scenario, the VPLE is taken into account. Thus, the goal function now includes the sinusoidal phrase. The wind-solar ELD's cost function with VPLE is stated as

$$\text{Total cost} = \min\left[\sum_{i=1}^{N} a_i + b_i T_i + c_i T_i^2 e_i sin\{f_i(T_i^{min} - T_i^{max})\} + \sum_{k=1}^{N_w} W_{p,k} C_{w,k} + \sum_{l=1}^{N_s} S_{pl} Bidl\right] \quad (2)$$

where e_i and f_i are cost constant ith thermal generator representing VPLE

2.2 Constraints

ELD's objective function is optimised while taking into account a number of restrictions, including equality and inequality. Below are the restrictions for the thermal, wind, and solar units. Economic Load Dispatch (ELD) is a method used in power systems to determine the optimal allocation of power generation among the available generators in order to meet the system's demand at the lowest possible cost while satisfying various operational and physical constraints.

When solving an ELD problem, there are typically a number of parameters that need to be minimized. These include:

Fuel cost: The primary objective of ELD is to minimize the total cost of generating electricity, which is mainly driven by the fuel costs of the power plants. Each power plant has its own fuel cost curve, which specifies the cost of generating a unit of electricity as a function of the plant's output.

Transmission losses: As power flows through the transmission lines, some of it is lost due to resistance in the lines. These losses can be significant, particularly for long-distance transmission. Therefore, ELD must consider the impact of transmission losses on the cost of generation.

Emissions: With increasing concerns about the environment, it has become important to minimize the emissions of greenhouse gases and other pollutants from power generation. Therefore, ELD may also include constraints on emissions levels.

Operating constraints: There are various operational constraints that need to be considered when solving ELD, such as minimum and maximum generation limits for each power plant, ramp rate limits (i.e., the rate at which a power plant can change its output), and transmission line capacity limits.

By considering all of these parameters and constraints, ELD can determine the optimal allocation of power generation among the available generators in order to meet the system's demand at the lowest possible cost while satisfying all of the operational and physical constraints.

2.2.1 Equality constraints

Thermal, wind, and solar power plants should have output active powers that are equivalent to the load demand.

$$\sum_{i=1}^{N} T_i + \sum_{k=1}^{N_w} W_{p,k} + \sum_{l=1}^{N_s} S_{pl} - T_D = 0 \tag{3}$$

2.2.2 Inequality constraints

For consistently steady functioning, the output active and reactive powers from each wind and solar unit should be between their minimum and maximum limitations.

$$T_i^{min} \leq T_i \leq T_i^{max}; \quad i = 1, 2, 3, \dots, N \tag{4}$$

$$0 \leq w_j \leq w_{r,j}; \quad j = 1, 2, 3, \dots, N_w \tag{5}$$

$$0 \leq S_k \leq S_{r,k}; \quad k = 1, 2, 3, \dots, N_s \tag{6}$$

where Wpkmin and Wpkmax are boundary of minimum-maximum wind turbine respectively. Splmin and Splmax are boundary of minimum-maximum solar plant respectively. The operational limit (i.e. maximum or minimum) has been taken into consideration as the output power of the corresponding unit if the generated power from wind-solar plant exceeds the limit.

2.3 Modelling of wind and solar power

Researchers have given the renewable energy source a lot of consideration. To reduce the usage of fossil fuels, these renewable sources are combined with traditional sources.

2.3.1 Wind power modelling

The key factor affecting wind power generation is wind speed. Numerous techniques were computed to demonstrate the unpredictability of wind speed features [41]. Using the Weibull Probability Density Function (PDF), wind speed profiles are described. The PDF is written as for wind speed [42].

$$f_v(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} \exp\left[1 - \left(\frac{v}{c}\right)^k\right]; for\ 0 < v < \infty \tag{7}$$

where Sshf and Sscf are shape -scale constant of wind unit; v is instant speed of wind turbine. After the uncertainty of wind speed has been established as an arbitrary parameter, the output of the wind plant is next computed as an arbitrary variable by a conversion from output power to wind speed. The speed-power curve is used to calculate the wind power as

$$W_p = \begin{cases} 0; & : \ v < v_{in}, v > v_{out} \\ W_{pt}\left(\frac{v-v_i}{v_r-v_i}\right) & : \ v_r < v < v_{out} \\ W_{pr}; & : \ v_r < v < v_{out} \end{cases} \tag{8}$$

where v and vr are instant-rated speed of wind turbine; vin and vout are cut in-cut out speed of wind turbine; Wp and Wpt are generated-rated power of wind plant.

2.3.2 Modelling of solar power

Irradiance and temperature have the most effects on the solar system's output power. The term "unpredictability of solar irradiance" (beta PDF) is used [43]. The formula for the beta distribution is

$$PDF(ir) = \begin{cases} \frac{\omega+\psi}{\omega\psi} \times ir^{\omega-1}(1 - ir^{\psi-1}) & : \ 0 \leqslant ir \leqslant 1, \omega \geq 0, \psi \geq 0 \\ 0 & : \ otherwise \end{cases} \tag{9}$$

where ω are ψ beta constant; Γ is the gamma objective. The grid receives solar energy with a power factor of one. As a result, it is considered that solar energy has no reactive power [17]. Temperature and sun radiation both affect how much electricity a solar cell can produce. The formula for their relationship is as follows:

$$S_p(t) = \left[S_{p,st} \times \frac{S_{rad}(t)}{S_{rad,st}} \times \left\{ 1 - \gamma \times (T_{cell} - T_{cell,st}) \right\} \right] \times N_s \times N_p \tag{10}$$

where Srad(t) is Cellular sun irradiation at time t; Srad,stc is sun irradiation in ideal circumstances; SP,stc is solar generated power in ideal circumstances; γ is constant of temperature in %/°C; Tcell is the degree of heat in a solar cell; Tcell,stc is the solar cell's heat is within acceptable test parameters; Nsc are Npc number of solar cells in series and parallel. The following formula may be used to compute the temperature of cell Tcell:

$$T_{cell} = T_{amb} + \frac{S_{rad}(t)}{S_{rad,stc}} \times (NTC - 20) \tag{11}$$

where Tcell is normal heat in °C and NTC is the typical solar cell heat.

3 Point estimation method

To tackle probabilistic issues, PEM is utilised. However, in order to employ the suggested approach, numerous simulations are required for PEM to function. In order to ascertain the probabilistic property of the arbitrary variable, Hongs introduced the 2-m PEM. The mathematical notation for the probabilistic ELD issue for RES is

$$Se = f(Q_k) \tag{12}$$

where Se is the overall power production-including solar-wind and Q_k are the input variables. In a deterministic problem, the anticipated value may differ from the actual values. The equation is changed to read as follows if m is the value of an arbitrary variable.

$$PDFf(zl) = f(b, g_1, g_2, \dots, g_a) \tag{13}$$

The PDF f(zl) of each arbitrary variable zl is changed to a two-point system utilising three moments -average μ, divergence σ, and imbalance λ constant. The function f moments must be computed 2-m times. The modified expression is given below:

$$PDFf(zl) = f(b, \mu_{g1}, \mu_{g2}, \dots, \mu_{ga}); \quad d = 1, 2; y = 1, 2, \dots, b \tag{14}$$

The 2-m PEM process is broken down into the following phases.

1. Pick any random input variable
2. The output random variable's first and second moments $E_x(Exp^t)$ should all be set to zero.

$$E_x(Exp^t) = 0; k = 1, 2 \tag{15}$$

3. Choose a hazard parameter g_y
4. Determine skewness β_{gy}

$$\beta_{gy,a} = \frac{E_x[(g_y - \mu_{gy})^3]}{(\sigma_{gy})^3} \tag{16}$$

where

$$E_x[(g_y - \mu_{gy})^3] = \sum_{j=1}^{N} (g_{y,j} - \mu_{gy})^3 \times prob(g_{yj}) \tag{17}$$

5. Add two regular locations together

$$\psi = \frac{\beta_{gy,3}}{2} + (-1)^{3-d} \sqrt{\left(b + \left(\frac{\beta_{gy,3}}{2} \right)^2 \right)}; \quad d = 1, 2 \tag{18}$$

6. Calculate two projected locations

$$g_{y,k} = \mu_{gy} + \psi_{gy,k} \sigma_{gy}; \quad d = 1, 2 \tag{19}$$

7. Calculate probabilistic ELD for two far-off locations

$$Exp_{yd} = f(\mu_{g1}, \mu_{g2}, \dots, g_{yd}, \dots, \mu_{ga}; \quad d = 1, 2; y = 1, 2, \dots, b \tag{20}$$

8. Compute two weighting factors

$$w_{yd} = \frac{(-1)^d}{b} \times \frac{\psi_{y,3-d}}{\psi_{y,1} - \psi_{y,2}}; \quad d = 1, 2 \tag{21}$$

9. Update each output arbitrary variable's moment

$$E_x(Exp^t) = E_x(Exp^t) + \sum_{d=1}^{2} w_{y,d} (S_{exp}(y, d))^t; \quad k = 1, 2 \tag{22}$$

10. Steps 3 through 9 should be repeated until all variables are computed.
11. Calculate mean. SD

$$mean(\mu) = E_x(Exp^t); \quad std(\sigma) = \sqrt{E_x(Exp^2) - E_x(Exp^1)^2} \tag{23}$$

4 Artificial electric field algorithm

The Newton law of motion and Coulomb's law of electrostatic force are the driving forces behind the AEFA algorithm. In this method, the idea of the electrostatic force between two charged particles is utilised. A pair of objects' electrostatic attraction is directly proportional to the total of their charges and inversely related to the square of the distance separating them. We assume the search agents to be charged particles. Charges are a gauge of an agent's strength. Between charged particles, there is an attraction and repulsion force. The agents then travel throughout the search area. Charge placement gives the answer to the issue. Based on the population's fitness, these charges are determined. The only force taken into account in this method is attraction. Since all other lower charge particles are drawn to the highest charge particle, the search space is gradually traversed by this particle.

In d-dimensional search space, a system of N charged particles is taken into consideration. The location of the ith particle in the d-dimensional search space be Xi= (xi1,x2,.....,xid) for i =1,2,3,.....,N, where xid is the position of ith particle in dth dimension. The locale of the ith particle at any time t is provided by the following equation:

$$X_i^d(t+1) = \begin{cases} X_i^d(t); & : \ f(X_i(t)) < f(X_i(t+1)) \\ X_i^d(t+1) & : \ f(X_i(t+1)) \le f(X_i(t)) \end{cases} \quad (24)$$

where f(Xi (t)) is strength of the ith fleck at tth repetition in dth element and f(Xi (t+1)) is strength of the ith fleck at (t+1)th repetition in dth element. Each particle's charge is determined by its fitness function and calculated as follows.

$$q_i(t) = exp\frac{f(X_i(t)) - f(worst(t))}{f(best(t)) - f(worst(t))} \quad (25)$$

$$Q_i(t) = \frac{q_i(t)}{\sum_{i=1}^{N} q_i(t)} \quad (26)$$

$$Q_i(t) = Q_j(t); i, j = 1, 2, 3, \dots, N \quad (27)$$

where f(worst(t)) and f(best(t)) are local worst-best strength at tth iteration. Based on the charges of the particles and their separation from one another, the force is used to calculate the total force exerted on any charged particle. The force between the charges I and j at any moment t is:

$$F_{ij}^d(t) = K(t)\frac{Q_i(t)Q_j(t)(P_j^d(t) - X_i^d(t))}{R_{ij}(t) + \varepsilon} R_{ij})(t)\left\|X_i(t), X_j(t)\right\| \quad (28)$$

where Rij (t) is given a definition by the equation as the Euclidian separation between fleck i and j.

$$R_{ij})(t)\left\|X_i(t), X_j(t)\right\| \quad (29)$$

K(t) is a measure of the coulomb's constant that depends on the number of maximal iterations and is calculated as follows:

$$K(t) = K_0 \times e^{-\alpha \times \frac{iteration}{maxiteration}} \quad (30)$$

where K0 and α are starting point and variable respectively. Iteration and maxiteration are terms used to describe the current iteration and the maximum number of iterations. The total electric force exerted by all other charges at any one time, if N is the total number of charges, is:

$$F_i^d(t) = \sum_{j=1,i}^{N} rand()F_{ij}^d(t) \quad (31)$$

where rand() is an count between 0 and1. The electricity field of the ith fleck at time t is:

$$E_i^d(t) = \frac{F_i^d(t)}{Q_i(t)} \quad (32)$$

Newton's second law of motion (F=ma) and the equation provide the acceleration of charge (27)

$$a_i^d(t) = \frac{Q_i(t)E_i^d(t)}{M_i(t)} \quad (33)$$

The particle's location and velocity are updated as illustrated below:

$$V_i^d(t+1) = rand() \times V_i^d(t) + a_i^d(t) \quad (34)$$

$$X_i^d(t+1) = X_i^d(t) + V_i^d(t+1) \quad (35)$$

In the metaheuristic optimization method, the learning component is crucial. This phrase raises the effectiveness of optimization methods. The force specified in Equation (24) is regarded as a learning term in AEFA. Term Pjd (t) refers to the historical data of the local best fitness value. The Qi term, as shown in Equation, uses the prior history of the global best fitness value (28). Consequently, using these two concepts, the best particle draws other particles to it in the search area. Each particle moves in the direction of the best particle due to the force term.

4.1 AEFA used in renewable based ELD problem

The steps for applying AEFA to solve the renewable-based ELD challenge are described. Figure 1 shows the AEFA flowchart that was utilised to resolve the renewable-based ELD issue. The steps to solving the issue are as follows:

Fig. 1 The flowchart of AEFA used in solving renewable-based ELD problem

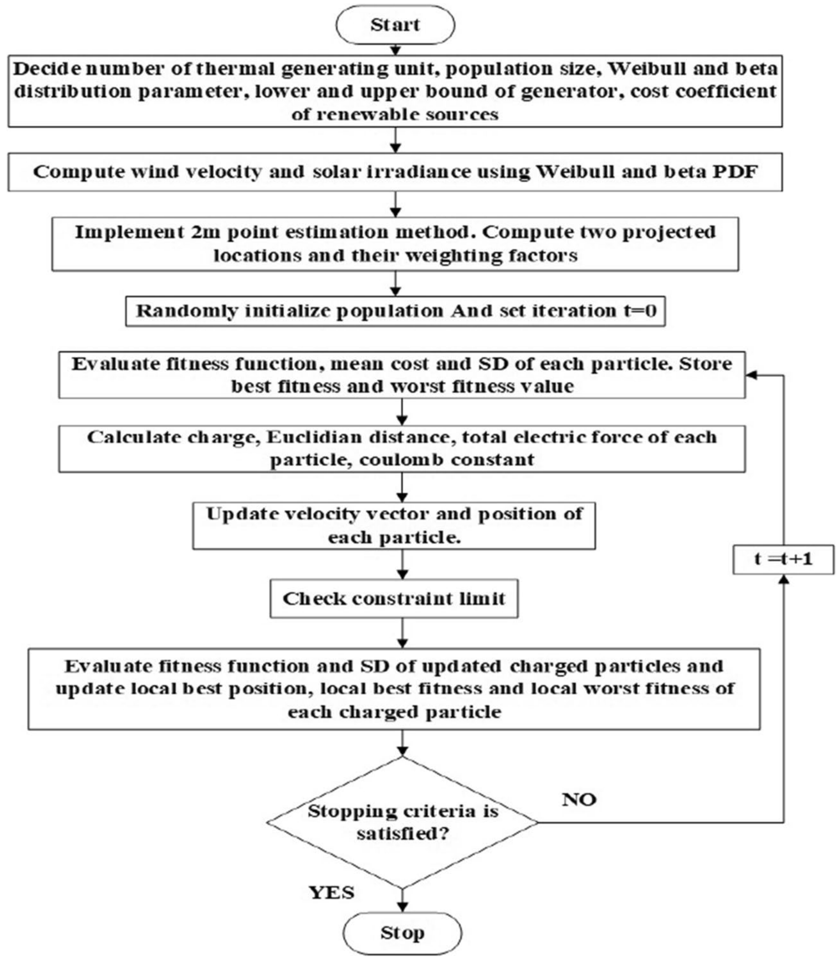

Table 1 Specifics of the test system

Case	1	2	3	4	5
No. of thermal units	3	5	6	15	40
No. of wind plant	2	2	2	2	2
No. of solar plant	2	2	2	2	2
Total demand (MW)	1050	730	1263	2630	10,500
Valve point loading	Yes	Yes	No	No	Yes

1. Determine the population size, the number of thermal producing units, the Weibull and beta distribution parameters, the lower and upper bounds of the generators, and the cost coefficient of RES.
2. Equations (5) and (6) should be used to generate the wind speed and solar irradiance using the Weibull distribution and beta distribution function, respectively (7).
3. Use the 2-m-point estimation technique as described in Sect. 3 to determine wind and solar power production. Use Eq. (13) to determine two predicted sites and their weighting factors (18).
4. To adhere to all ELD problem restrictions, randomly start the population.
5. Equation should be used to assess each AEFA charged particle search agent's fitness function, mean cost, and SD (20). Store the fitness values with the lowest mean cost and the highest mean cost, respectively.
6. Use Eqs. (21)–(25) for determining charge, Euclidian distance, and each particle's overall electric force.
7. Using Equation, get the coulomb constant (27)
8. Equations (31) and (32) are used to update the velocity vector and location of each particle (32).
9. Using Eqs. (3) and (4), verify the constraint limit (4).
10. Update the best and worst fitness by evaluating the mean cost and SD of the revised charged particles' fitness function.
11. Up until the halting requirement is met, go to step 5 and repeat the procedure.

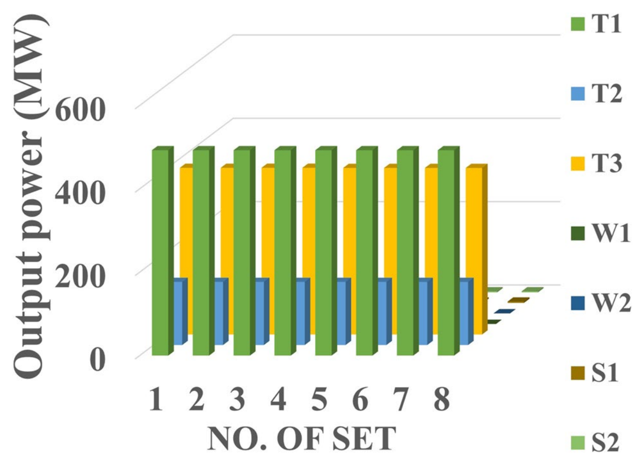

Fig. 2 The 2-m set of maximum output power obtained for test scenario 1

Table 2 Performance evaluation of popular techniques for test case 1

Methods	Mean cost ($/h)	Simulation time (s)	SD
AEFA	10028.59	2.4371	0.0336
DA	10049.19	8.00	0.53
CSA	10065.70	10.00	1.23
ALO	10079.23	12.00	3.02
OCCRO	10080.80	14.60	8.74
BBO	10088.85	17.80	13.25
PSO	10089.00	20.50	15.33
GA	10096.19	24.20	18.36

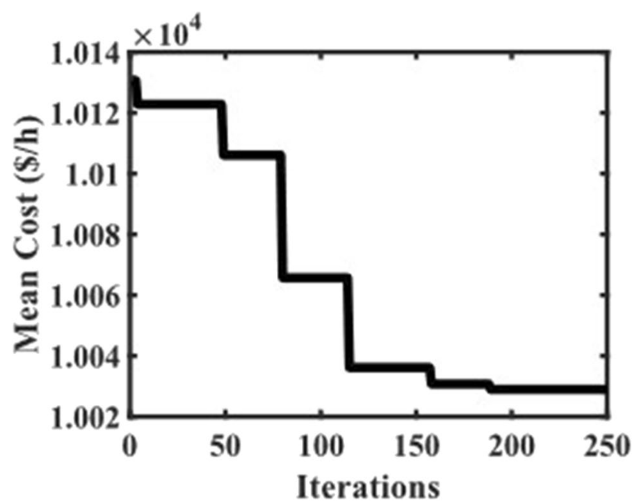

Fig. 3 Convergence characteristic by AEFA algorithm for case 1

5 Results and discussion

The AEFA algorithm is evaluated on five distinct types of test systems, which comprise two wind and two solar units in addition to modest and large numbers of heat producing units. The many types of operating settings are picked to test the resilience and efficacy of the suggested method, which is described in Table 1. Other well-known algorithms including DA, CSA, ALO, BBO, PSO, GA, and ORCCRO are used to compare the results. A 1.7GHz Intel core, 4GB RAM personal computer is utilised to model the issue and evaluate it using MATLAB 2021a software. You can find the input data for solar and wind units in [24]. [36] provides the input data for thermal units. Each solar and wind turbine has a maximum capacity of 10 MW and 0.8 MW, respectively.

5.1 Test system 1

Along with two wind and two solar farms, three thermal producing units are taken into account. This scenario takes into account the VPLE. The system's overall load is 1050 MW. In 250 iterations and 2.4371 s, the algorithm finds the best option. Figure 2 displays the 2-m sets with the highest obtained output power. As shown in Table 2, the mean cost and standard deviation achieved by AEFA are compared with DA, ALO, OCCRO, PSO, GA, and CSA. From this Table 3, it can be seen that AEFA's cost of 10028.59 $/h is significantly lower than that of DA, ALO, BBO, OCCRO, PSO, GA, and CSA. Additionally, it has been found that AEFA takes a lot shorter time than other strategies to arrive to the best answer. In Fig. 3, the AEFA convergence characteristic is displayed.

5.1.1 Tuning of parameters for AEFA algorithms

To find the best solution with less iterations, the different AEFA algorithm parameters like fper, Rnorm, Rpower, alfa, and k0 should be tweaked. For each test system, the minimal fuel cost has been determined using various parameter settings. Through the selection of a single value for one parameter, the other parameters have been altered. For instance, fper has been adjusted from 3 to 7 in the appropriate stages when Rpower = 1. The alfa value has been changed simultaneously from 10 to 90. Rnorm and k0 have also been altered, with ranges of 1–4.2 and 1–600, respectively. Table 3 displays the findings of the minimal gasoline cost for various parameter values in a succinct manner. In order to determine the minimal fuel cost for each test system, a 50-trial run was performed. Therefore, for Test System 1, the ideal values of these adjusted parameters are fper = 5, Rnorm = 2.6, Rpower = 0.6, alfa = 50, and k0 = 1.

Table 3 The lowest fuel cost for Test System 1 at various parameter values

fper	Rnorm	Rpower	alpha	k0						
				1	100	200	300	400	500	600
7	4.2	1	90	10029.08	10031.61	10029.21	10029.71	10031.16	10028.79	10029.36
6.5	3.8	0.9	80	10032.37	10030.79	10031.53	10030.41	10033.06	10030.67	10028.95
6	3.4	0.8	70	10032.89	10029.81	10033.07	10033.03	10030.42	10029.60	10028.53
5.5	3	0.7	60	10028.75	10031.28	10032.65	10030.25	10031.77	10032.57	10029.10
5	2.6	0.6	50	10028.39	10030.66	10031.29	10033.33	10032.26	10031.59	10032.03
4.5	2.2	0.5	40	10028.54	10029.73	10031.74	10029.21	10031.83	10028.45	10029.49
4	1.8	0.4	30	10033.00	10031.84	10029.61	10029.40	10029.28	10030.23	10031.25
3.5	1.4	0.3	20	10029.30	10030.80	10031.91	10031.08	10029.48	10028.97	10031.68
3	1	0.2	10	10029.69	10032.58	10030.97	10031.88	10031.30	10032.13	10032.59

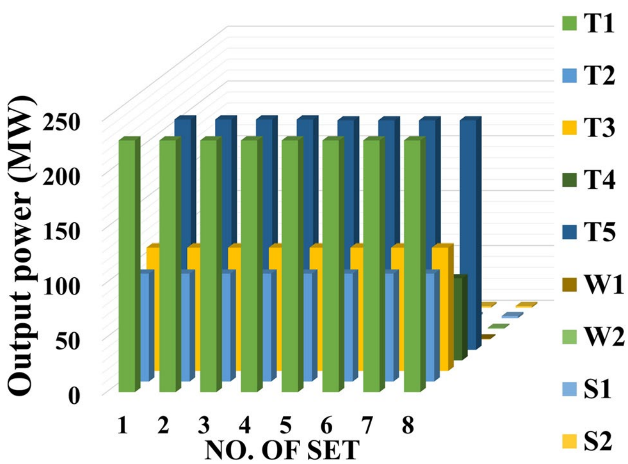

Fig. 4 The 2-m set of maximum output power obtained for test scenario 2

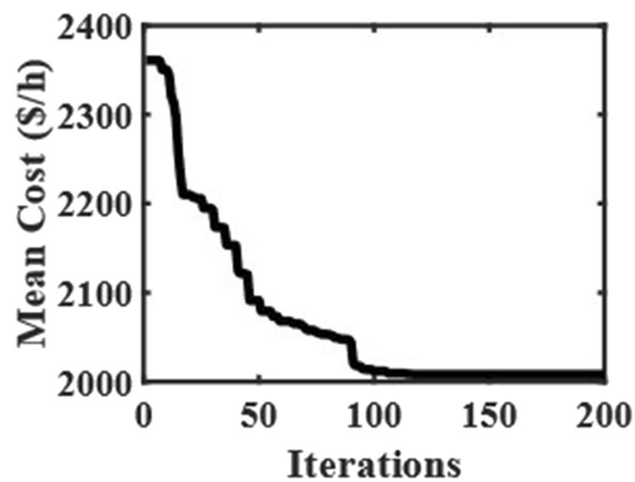

Fig. 5 Convergence characteristic by AEFA algorithm for case 2

Table 4 Performance analysis of popular techniques for test case 2

Methods	Mean cost ($/h)	Simulation time (s)	SD
AEFA	2006.63	2.30	0.51
DA	2018.07	12.00	2.51
CSA	2021.52	12.60	4.22
ALO	2025.82	14.50	6.32
OCCRO	2046.63	17.20	9.88
BBO	2058.52	21.00	14.25
PSO	2060.80	25.00	18.73
GA	2073.89	28.00	23.18

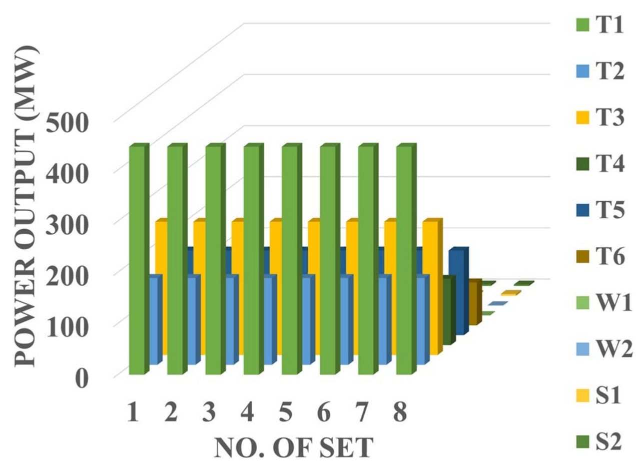

Fig. 6 The 2-m set of maximum output power obtained for test scenario 3

Table 5 Performance evaluation of well-liked methods for test case 3

Methods	Mean cost ($/h)	Simulation time (s)	SD
AEFA	15195.46	2.56	4.91
DA	15268.83	15.00	13.12
CSA	15277.23	18.00	15.33
ALO	15278.21	19.20	16.91
OCCRO	15280.11	23.90	18.21
BBO	15284.97	24.00	21.47
PSO	15286.36	27.60	26.98
GA	15287.83	28.00	28.77

Table 6 Performance analysis of popular techniques for test case 4

Methods	Mean cost ($/h)	Simulation time (s)	SD
AEFA	32222.81344	2.22	3.6156
DA	32,310.2922	20	10.5017
CSA	32,318.1056	24.3	14.2357
ALO	32,329.5536	26.8	16.6912
OCCRO	32,358.0926	29	19.7439
BBO	32,260.2696	31.4	21.3321
PSO	32,365.9862	35	24.9874
GA	32,388.5473	36.7	26.1234

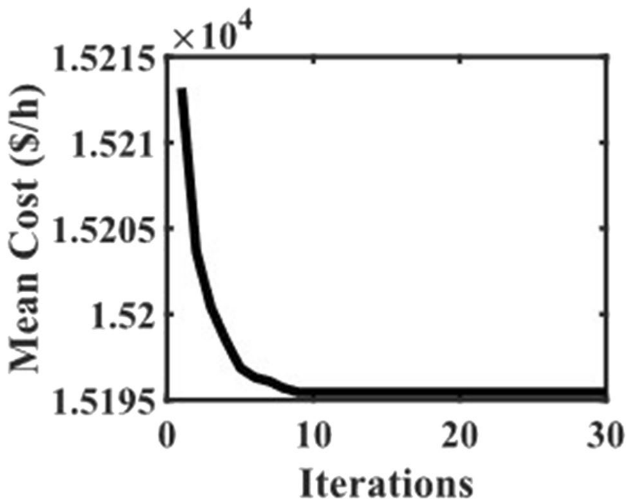

Fig. 7 Convergence characteristic by AEFA algorithm for case 3

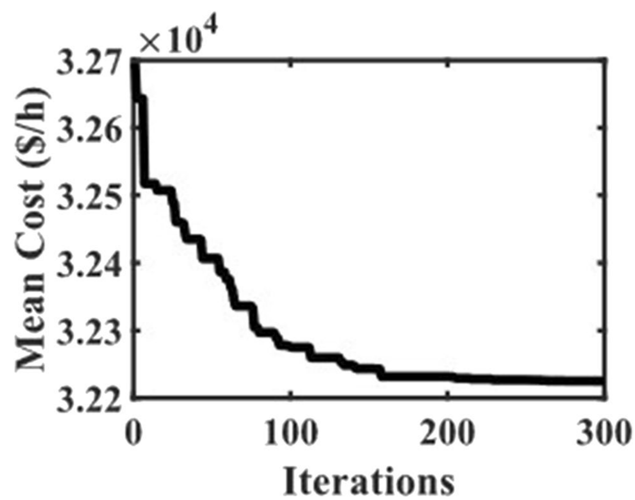

Fig. 9 Convergence characteristic by AEFA algorithm for case 4

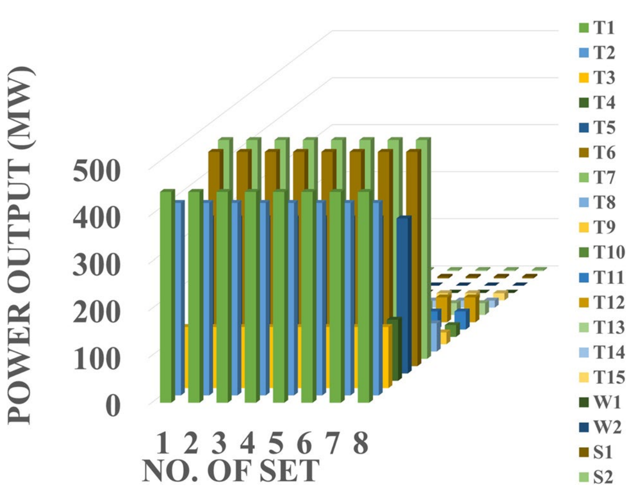

Fig. 8 The 2-m set of maximum output power obtained for test scenario 4

5.2 Test system 2

With two wind and two solar farms, five thermal producing units are taken into consideration. This scenario takes into account the VPLE. There is a 730 MW overall electricity demand. In 2.30 s and 200 iterations, the algorithm finds the best option. Figure 4 displays the 2-m sets of highest output power attained in this scenario. The AEFA algorithm's mean cost, which is demonstrated in Table 4 to be quite low compared to other algorithms like DA, ALO, BBO, OCCRO, PSO, GA, and CSA, is 2006.631 $/h. Figure 5 depicts the AEFA algorithm's convergence characteristic. Using various parameter values from Test System 1, the Minimum Fuel Cost for Test System 2 has been computed. The tuned parameters' acquired optimal values for test system 2 are identical to those for test system 1.

Table 7 Performance analysis of popular techniques for test case 5

Methods	Mean cost ($/h)	Simulation time (s)	SD
AEFA	1,21,395.1	11.98	27.83
OCCRO	1,21,823.1	19	29.44
TLBO [26]	1,21,924.2	21.6	32.56
PSO	1,22,051.3	24	33.53
GA	1,22,165.6	27	35.41

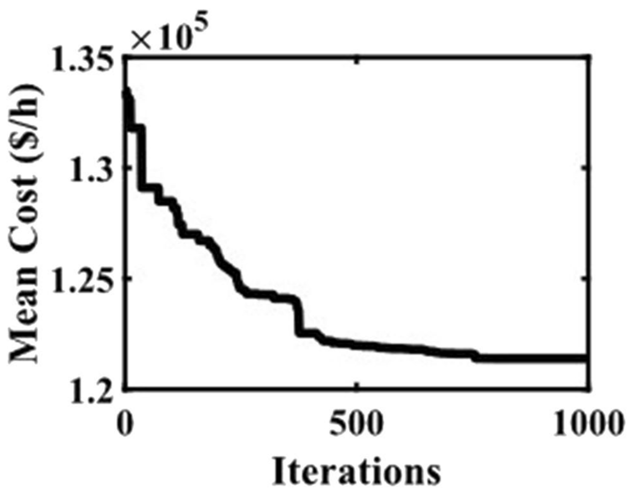

Fig. 10 Convergence characteristic by AEFA algorithm for case 5

5.3 Test system 3

Two solar and two wind power plants are linked with six thermal generating units. There is a 1263 MW load demand. 30 iterations and 2.5662 s are needed by the algorithm to arrive at the best result. Figure 6 displays the 2-m sets of highest output power attained in this scenario. The AEFA algorithm's mean cost is 15,195.46 $/h, which is significantly less expensive than the mean costs of other algorithms including the DA, ALO, BBO, OCCRO, PSO, GA, and CSA as shown in Table 5. Additionally, it has been shown that AEFA takes a lot shorter time than other strategies to arrive to the ideal answer. Figure 7 depicts the AEFA algorithm's convergence characteristic. For test system 3, the minimal fuel cost has been estimated for various parameter values that are listed for test system 1. The tuned parameters' attained optimal values for test system 3 are identical to those for test system 1.

5.4 Test system 4

Two solar power plants and two wind farms are linked to the 15 thermal producing units. There is a 2630 MW energy demand. The algorithm needs 300 iterations and 2.22 s to arrive at the best result. In this instance, the 2-m sets of highest output power obtained are depicted in Fig. 8. The AEFA algorithm's mean cost is 32222.81 $/h, which is extremely low when compared to other algorithms like DA, ALO, BBO, OCCRO, PSO, GA, and CSA, which are listed in Table 6. As seen in Fig. 9, the AEFA algorithm's convergence characteristic. At various values of the parameter as specified in test system 1, the minimal fuel cost for test system 4 has been determined. The test system 4's optimised tuned parameter values were identical to those in test system 1's results.

5.5 Test system 5

The authors' system, which consists of forty huge thermal producing units, is combined with two solar and two wind power plants. Thermal units take into account the VPLE. 10,500 MW are needed for electricity. The optimal result is reached by the algorithm after 1000 iterations and 11.98 s. As shown in Table 7, the AEFA algorithm's mean cost is 1,21,395.1 $/h, which is incredibly low when compared to other algorithms as OCCRO, TLBO [31], PSO, and GA. Additionally, it has been found that AEFA takes a lot shorter time than other strategies to arrive to the best answer. Figure 10 displays the AEFA algorithm's convergence characteristic. At various values of the parameter as specified in test system 1, the minimal fuel cost for test system 5 has been computed. The optimised tuned parameter values found for test system 5 are identical to those found for test system 1.

5.6 Discussion

Table 8 illustrates the outcomes of the AEFA across diverse test systems, featuring 3, 5, 6, 15, and 40 thermal units. The table details the average cost, electricity output per unit, total thermal, wind, and solar generation, total iterations, and mean cost. The average cost column represents economic efficiency, while the unit-specific electricity outputs offer insights into power distribution. Total generation values summarize cumulative outputs, and total iterations indicate computational effort. The mean cost column provides a comprehensive metric. This

Table 8 The mean cost determined by AEFA and the producing unit's output power

	3 Conventional unit with renewable energy	5 Conventional unit with renewable energy	6 Conventional unit with renewable energy	15 Conventional unit with renewable energy	40 Conventional unit with renewable energy		
T_1	492.7149	229.5216	445.7938	448.0375	110.8433	T_{21}	523.3266
T_2	151.4709	98.5392	169.8037	409.04	110.7814	T_{22}	523.2969
T_3	399.6829	112.6709	260.4783	130	97.47112	T_{23}	523.2729
T_4		75	129.5184	130	179.7505	T_{24}	523.3586
T_5		209.3155	165.6152	329.322	87.85648	T_{25}	523.2506
T_6			83.9509	455.3519	139.9602	T_{26}	523.3343
T_7				465	259.5864	T_{27}	10.03139
T_8				60	284.5891	T_{28}	10.01151
T_9				25	284.6134	T_{29}	10.00819
T_{10}				25	130.0459	T_{30}	87.91745
T_{11}				38.5568	168.6465	T_{31}	190
T_{12}				52.8616	94.02922	T_{32}	190
T_{13}				25	214.7651	T_{33}	189.9807
T_{14}				15	394.2813	T_{34}	164.8205
T_{15}				15	394.044	T_{35}	164.8813
T_{16}					394.2755	T_{36}	164.798
T_{17}					489.2801	T_{37}	109.9783
T_{18}					489.2551	T_{38}	94.21626
T_{19}					511.0952	T_{39}	109.8646
T_{20}					511.2812	T_{40}	510.9194
Total thermal generation	1043.869	725.0472	1255.16	2623.17	10493.72		
Total wind and solar generation	6.131359	4.952806	7.839547	6.830158	6.281573		
Iteration	250	200	30	300	1000		
Mean cost ($/h)	10028.592	2006.6314	15195.455	32222.813	1,21,395.1		

Table 9 For all test systems, Wilcoxon signed-rank test

Test systems	Best solution	Mean solution	Worst solution	No. of trail run	Standard deviation	p Value
1	10028.39328	10030.8879	10035.3256	50	61.05	1.45E−05
2	2006.631	2008.3917	2010.1256	50	46.25	1.12E−05
3	15195.46	15204.698	15212.9632	50	94.50	1.10E−05
4	32222.8134	32239.53614	32256.9678	50	103.59	1.15E−05
5	121395.1	121423.2432	121459.1258	50	103.59	1.68E−05

structured breakdown enhances understanding and evaluation of AEFA's performance in varying test scenarios. Figures 11, 12, 13, 14 and 15 display the system's total power output and total load demand for various test systems. The total power produced by thermal units in examples 1, 2, 3, 4, and 5 is 1043.869 MW, 725.0472 MW, 1255.16 MW, 2623.17 MW, and 10493.72 MW, respectively. It has been noted that the load sharing of renewable sources has decreased the overall generation of thermal units. The incorporation of RES reduces the consumption of fossil fuels. The greenhouse impact is thereby diminished. In comparison to other well-known optimization approaches, the results show that AEFA provides a promising and adequate performance in terms of quality and efficiency of the optimum solution.

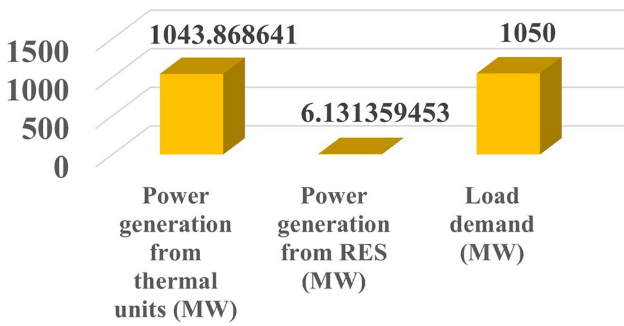

Fig. 11 The power requirement for case 1 and the system's total power output

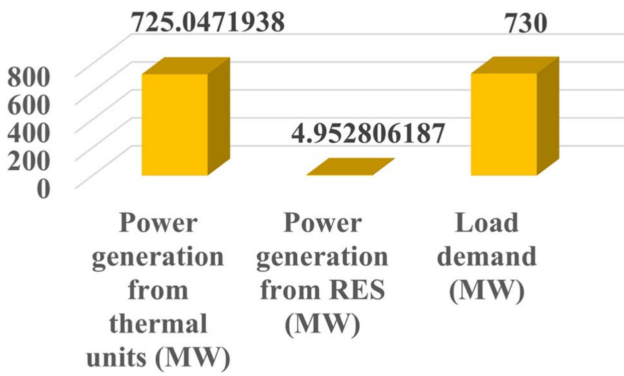

Fig. 12 The power requirement for case 2 and the system's total power output

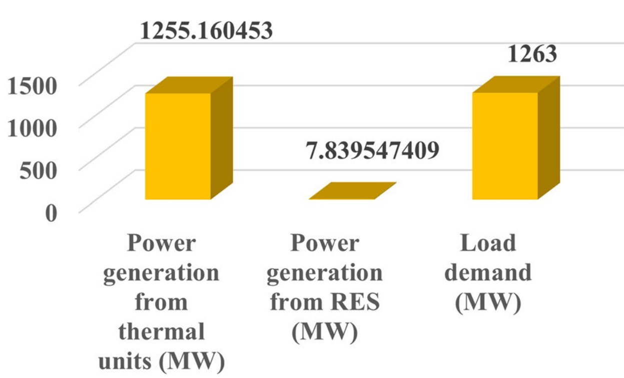

Fig. 13 The power requirement for case 3 and the system's total power output

5.6.1 Wilcoxon signed-rank test

A statistical way to examine outcomes from any algorithm is the Wilcoxon signed-rank test [44]. A robust algorithm has been defined as one that can demonstrate its statistical value. As a result, the method must provide adequate evidence to refute the null hypothesis. It has been decided to use 50 trials

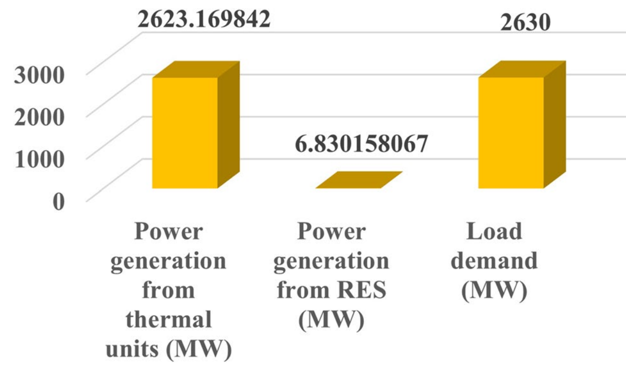

Fig. 14 The power requirement for case 4 and the system's total power output

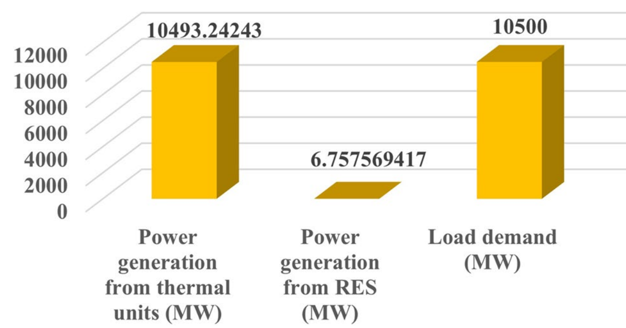

Fig. 15 The power requirement for case 5 and the system's total power output

for the suggested algorithm (n = 50). The Wilcoxon signed-rank test's stages are described below.

1. The null-hypothesis H0 has been removed from the 50 trail run findings. Each trail run result has been given a signed-rank from smallest to largest.
2. Compute T+ and T−. where T+ is the sum of positive signed rank and T− is the sum of negative signed-rank. Compute T which is the minimum of T+ and T−.
3. Compute mean T, σ, and z.

$$mean\,T = \frac{n(n+1)}{4} \tag{36}$$

$$\sigma = \sqrt{\frac{n(n+1)(2n+1)}{24}} \tag{37}$$

$$z = \frac{T - mean\,T}{\sigma} \tag{38}$$

4. The probability value (p value) should be considered strong evidence against the null hypothesis.

Table 9 contains the Wilcoxon signed-rank test p values at the 5% level of significance for all test systems, together with their best and worst values for the mean and standard deviation. All of the test systems' p values are substantially lower than the necessary level of 0.05. As a result, from the standpoint of statistical analysis, the suggested method may be regarded as reliable and significant.

6 Conclusion

In addressing the renewable-based Economic Load Dispatch challenge, the AEFA is employed, accommodating the unpredictability of wind and solar energy. The AEFA algorithm considers various constraints, including VPLE and generator running restrictions. The 2-m point estimation method is implemented to compute generation from RES such as wind and solar. Through rigorous testing across multiple scenarios, including systems with 3, 5, 6, 15, and 40 thermal generating units alongside two wind and two solar plants, AEFA's performance has been evaluated against other well-known algorithms, including DA, ALO, BBO, GA, ORCCRO, PSO, and CSA. The results consistently demonstrate AEFA's superiority, showcasing enhanced optimal solutions with rapid convergence. While the AEFA algorithm proves to be a powerful and effective technique for addressing complex and nonlinear ELD issues, we acknowledge that there is room for further improvement and exploration in this domain. Future research directions could include:

Integration of Energy Storage Systems and Plug-in Electric Vehicle (PEVs): Exploring the incorporation of energy storage systems and PEVs into the ELD problem to mitigate RES variability and uncertainty, thereby enhancing power system reliability and flexibility.

Multi-Objective Optimization: Considering multi-objective optimization to simultaneously address conflicting objectives, such as minimizing costs and emissions while maximizing the penetration level of renewable energy.

Author contributions Diwakar Verma: Methodology, software, writing original Draft, data curation, conceptualization, investigation, validation, resources, project administration, format analysis, visualization, supervision. Jatin Soni: Writing original Draft, data curation, conceptualization, investigation, validation, format analysis, visualization, supervision. Kuntal Bhattacharjee: Investigation, validation, format analysis, visualization, supervision.

Availability of data and materials Data available within the article or its supplementary materials.

Declarations

Competing interests The authors declare no competing interests.

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