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Comparison of differential evolution optimization technique with other techniques in solving multi-objective optimal power flow

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ABSTRACT

Optimal power flow (OPF) is a complex, non-linear optimization problem focused on determining the steady-state operating parameters of power systems for economic and secure operation. The challenge intensifies due to numerous system constraints that must be satisfied simultaneously. Although various evolutionary algorithms (EAs) have been applied to OPF in recent decades, these algorithms often use unconstrained search strategies. A common approach to handle constraint violations is the static penalty function, which penalizes infeasible solutions. However, selecting suitable penalty coefficients typically involves time-consuming trial and error, affecting overall performance. This study explores the integration of advanced constraint handling (CH) techniques within the differential evolution (DE) framework to enhance the performance of optimal power flow (OPF) solutions. In particular, it looks at three approaches: a hybrid ensemble of two CH techniques (ECHT), a self-adaptive penalty method (SP), and superiority of viable solutions (SF). The IEEE 30-bus and IEEE-57 bus benchmark systems are used to evaluate the efficacy of these techniques under a variety of OPF goals, including lowering emissions and generation costs, cutting power losses, and enhancing voltage stability. We took into consideration both weighted-sum multi-objective and single-objective formulations. The simulation outcomes indicate that the proposed CH-DE approaches deliver robust and competitive optimization results, demonstrating improved constraint handling capabilities when compared to contemporary methods in the literature.

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1. INTRODUCTION

The optimal power flow (OPF) problem been a focal point of investigate in power systems for more than fifty years due to its inherent complexity and real-world importance. At its core, OPF involves determining the highest operating condition of a power grid by minimizing objectives such as fuel costs, emissions, active power losses, and voltage deviations, while simultaneously adhering to various engineering and operational constraints. These include generator output limits, voltage bounds, thermal capacities of transmission lines, and power balance requirements. Optimal tuning of control variables-particularly generator voltage settings and real power outputs, is essential not only for cost-effective energy dispatch but also for ensuring safe and reliable system performance [1]. In addition, reactive power support, often provided through shunt capacitor banks, plays a key role in voltage regulation, especially under heavily inductive loading conditions. Traditional mathematical optimization techniques struggled with solving OPF problems due to their dependence on problem convexity and local search capabilities, which made them prone to converging prematurely to local optima in the presence of nonlinear, non-convex constraints [1]. The emergence of evolutionary algorithms (EAs) marked a significant shift, as their stochastic and population-based nature allows for better exploration of complex search landscapes. These methods have shown greater success in escaping local traps and identifying globally competitive solutions. The literature reflects a wide range of evolutionary and swarm intelligence algorithms applied to OPF tasks, each developed to enhance convergence speed, robustness, or constraint handling efficiency. Examples include the differential search algorithm [2], adaptive group search optimization, backtracking search with valve-point effects, and improved colliding bodies.

Further innovations such as the moth swarm algorithm [3], chaotic artificial bee colony, gravitational search algorithm, and adaptive biogeography-based optimization [3], reflect the diversity and creativity in tackling OPF challenges. Other hybrid or nature-inspired methods, including fuzzy harmony search [4], teaching-learning-based with Lévy mutation [4], and Krill Herd algorithms underscore the widespread acceptance. Among these, differential evolution (DE) and its modified forms have gained considerable attention, particularly in real-coded single-objective problems, owing to their strong performance in global optimization benchmarks [5]. Inspired by these successes, this work adopts DE as the core optimization technique for solving various OPF scenarios. Despite advancements in search techniques, one major aspect that remains crucial is constraint handling (CH). Effective CH strategies are essential to ensure that candidate solutions are not only optimal but also feasible under all system constraints. Many past approaches have depended heavily on static penalty functions or discarded infeasible solutions altogether. While easy to implement, these methods come with limitations: improperly tuned penalty parameters can either permit excessive exploration of infeasible space or over-restrict the search, causing early stagnation. On the other hand, eliminating infeasible individuals from the population reduces diversity and makes it harder to find boundaries between feasible and infeasible regions [5]. To overcome these challenges, this study implements and evaluates three modern CH strategies: superiority of feasible solutions (SF), which prioritizes feasible solutions during selection, self-adaptive penalty (SP), which dynamically adjusts penalty weights during the run, and ensemble constraint-handling technique (ECHT), a hybrid approach that combines SF and SP in a dynamic and adaptive framework. The ECHT method is introduced with a practical perspective: since no single CH strategy consistently excels in all scenarios, combining multiple approaches can offer adaptive robustness, reducing the need for manual tuning or algorithm selection by the user. The proposed algorithms are tested across a variety of optimization objectives, including single-objective cases (fuel cost, emissions, losses, voltage stability) and multi-objective cases using a weighted sum approach. Simulation outcomes are thoroughly analyzed and statistically benchmarked against recently published OPF results, with particular attention given to constraint satisfaction and solution reliability [5].

2. OPTIMAL POWER FLOW MATHEMATICAL FORMULATION

The OPF problem is a complex task characterized by its non-linear and non-convex nature. It aims to optimize specific performance objectives in a power system while satisfying a set of equality and inequality constraints. Mathematically, the OPF problem can be formulated as (1).

$$Minimize: f(x,u) \tag{1}$$

$g(x,u) \leq 0$ subject to $h(x,u) \leq 0$. In the OPF formulation, u represents the control or independent variables, while x denotes the state or dependent variables. The function $f(x, u)$ corresponds to the objective functions being optimized. The constraints are represented as $g(x, u)$ for inequalities and $h(x, u)$ for equalities [6]-[8].

2.1. Control variables

The variables that actively influence the power flow within the electrical network are termed control variables and are collectively represented as a vector (2).

$$u = [P_G2 \dots P_{GNG}, V_G1 \ldots V_{GNG}, Q_C1 \dots Q_{CNC}, T_1 \dots T_{NT}] \tag{2}$$

Here, PGi represents the active power generated at the i-th generator bus, excluding the slack (swing) generator. Although bus 1 is typically chosen as the swing bus in studies, any generator bus may serve this role. VGi denotes the voltage magnitude at the i-th PV (generator) bus. Tj refers to the tap setting of the j-th transformer branch, and QCk stands for the shunt reactive compensation at the k-th bus. The total number of generators, shunt compensators, and transformers is given by NG, NC, and NT, respectively. Each control variable is allowed to vary within its specified limits. While transformer tap settings are inherently discrete in nature, they are represented here in per-unit (p.u.) values without considering the absolute voltage magnitude. To align with earlier studies and facilitate comparative analysis, these tap settings, as well as all other control variables, are treated as continuous for the majority of simulation scenarios [6]-[8].

2.2. State variables

The state variables that describe the power systems state are represented by vector x as (3). Here, $PG1$ is the generator active power at slack (or swing) bus, QGi is the reactive power of generator connected to bus i, VLp is the bus voltage of p-th load bus (PQ bus), and line loading of q-th line is given by Slq. NL and nl are the number of load buses and transmission lines, respectively [9], [10].

$$x = [P_{G1}, V_{L1} \dots . V_{LNL}, Q_{G1} \dots Q_{GNG}, S_{l1} \dots S_{l_{nl}}] \quad (3)$$

2.3. Constraints

As mentioned before, both equality and inequality constraints must be satisfied in the OPF issue. The following lists these limitations.

2.3.1. Equality constraints

The equality constraints in OPF are power balance equation and those are expressed as (4) and (5).

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j \left[G_{ij} \cos(\delta_{ij}) + B_{ij} \sin(\delta_{ij})\right] = 0 \; \forall \; i \in NB \quad (4)$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j \left[G_{ij} \sin(\delta_{ij}) + B_{ij} \cos(\delta_{ij})\right] = 0 \; \forall \; i \in NB \quad (5)$$

Where $\delta ij = \delta i - \delta j$, is the difference in voltage angles between bus i and bus j, NB is the number of buses, PD and QD are active and reactive load demands, respectively. Gij is the transfer conductance and Bij is the susceptance between bus i and bus j, respectively.

2.3.2. Inequality constraints

In the OPF framework, inequality constraints represent the operational boundaries of system components, as well as the limitations on transmission lines and load buses, ensuring the secure operation of the power network [9].

$$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{mix} \; \forall \; i \in NG \quad (6)$$

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{mix} \; \forall \; i \in NG \quad (7)$$

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{mix} \; \forall \; i \in NG \quad (8)$$

Control variables governed by inequality constraints are inherently restricted within predefined limits. The optimization process identifies suitable values for these variables that remain within their allowable ranges [11]-[13].

3. STUDY CASES AND OBJECTIVE FUNCTIONS

Several study cases, including single and multi objective formulations, have been carried out using 30 bus and 57 bus test systems to assess the performance of different constraint handling (CH) techniques. Table 1 provides an overview of main system components, including generators, transformers, and shunt compensators, along with other relevant parameters [14], [15]. In both systems, bus 1 is known as the swing (or slack) bus or δV bus. According to power balance (4) and (5), the swing bus is essential in preserving system power balance analysis by making up for any discrepancy in active and reactive power. The swing bus voltage magnitude and phase angle are adjusted to 1 p.u. and 0 degrees. As output of the load flow analysis, the voltage magnitudes and phase angles of every bus are computed in relation to the swing bus. The next sections [15], [16] address the creation of study cases for these bus systems.

3.1. Problem formulation of study cases

3.1.1. Case 1: Minimization of fuel cost

The relationship between the fuel cost (in \$/h) and the generated power (in MW) is typically modeled using a quadratic function. Therefore, the objective to be minimized is expressed as (9).

$$f(x,u) = \sum a_i + b_i P_{Gi} + c_i P^2 \quad (9)$$

Where a_i, b_i, c_i are cost coefficients of the i-th generator producing power P_{Gi}.

Table 1. Comparative overview of IEEE 30-bus and IEEE 57-bus power network models

System components	30-bus network	57-bus network
Total buses	30 buses [14]	57 buses [15]
Branch count	41 transmission lines	80 transmission links [15]
Swing/slack bus details	Bus 1 designated as swing bus	Buses 1 and 2 configured for swing functions
Generator allocation	6 units at buses 2, 5, 8, 11, and 13	7 units located at buses 3, 6, 8, 9, and 12
Reactive power support	Compensation at 9 buses: 10, 12, 15	Compensation units at 3 locations: buses 18, 25, and 53
Tap-changing transformers	4 transformers connected via branches 11, 12, 15, and 36	17 transformers linked to branches 19, 20, 31, 35, 36, 37, 41, 46, and 54
Tunable control variables	24 adjustable parameters	33 control variables adjusted via buses 58, 59, 65, 66, 71, 73, 76, and 80
Power demand (load)	Total load: 283.4 MW active, 126.2 MVAr reactive	Aggregate demand: 1250.8 MW active, 336.4 MVAr reactive
Permissible voltage band (load buses)	24 buses constrained within [0.95 – 1.05] p.u.	50 load buses maintained between [0.94 – 1.06] p.u.

3.1.2. Case 2: Minimization of cost considering multi-fuels

To produce different power outputs, thermal generating plants use a variety of fuels such as coal, natural gas, and oil. Depending on the kind and amount of fuel used, the petrol function is divided into piecewise quadratic functions. The following represents the expense of using many fuels (10).

$$f\ (x,u) = a_{ik} + b_{ik}P_G + c_{ik}P\ for\ fuel_k \tag{10}$$

Within power output range $P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{mix}$: k being the fuel option.

3.1.3. Case 3: Enhancement of voltage stability of the network

Voltage stability issues have garnered increasing attention in recent years, as several power system blackouts have been attributed to voltage instability. A power system is considered voltage stable if it can reserve all bus voltages within permissible limits under normal operating conditions and following a trouble. Voltage instability arises when a trouble, increased load demand, or a change in system configuration leads to a gradual and uncontainable decline in voltage levels [17]. This problem is particularly prevalent in systems characterized by long transmission lines and heavy loading. Enhancing voltage stability is therefore a critical aspect of power system operation and planning. The L-index has proven to be an effective indicator of voltage stability for each load bus in the network [18]. The index ranges from 0 to 1, where a value of 0 corresponds to a no-load condition and a value of 1 indicates voltage collapse. The L-index is computed for all load buses, and the supreme value among them is used as a global indicator of the system's voltage stability margin. Accordingly, the objective function for assessing system stability can be defined in terms of the maximum L-index value [19], [20].

$$f\ (x,u) = L_{max} = \max(L_j)\ , where\ j = 1,2, \dots, NL \tag{11}$$

3.1.4. Case 4: Minimization of emission

Producing electrical energy from predictable fuel sources leads to the release of environmentally harmful gases. The emission levels of pollutants such as SOx and NOx tend to rise with a surge in generation following the functional relationship presented in (19). Therefore, reducing these emissions is considered one of the primary objectives in the OPF formulation.

$$f\ (x,u) = Emisson = \sum_{I=1}^{NG}[(\alpha_i + \beta_i P_G + \gamma_i P_{G\ i}^{\ 2}) \times 0.01 + \omega_I e^{(\mu i P G_i)}] \tag{12}$$

Where, αi, βi, γi, ωi and μi are all emission coefficients for 30-bus system.

3.1.5. Case 5: Reducing actual power loss

Because the lines in gearbox systems have intrinsic resistance, power loss is inevitable. Use the following formula to reduce the real power loss (in MW) [21].

$$f\ (x,u) = P_{loss} = \sum_{q=1}^{nl} G_{i(if)} \left[V_I^2 + V_j^2 - 2V_I V_j \cos(\vartheta_{ij})\right] \tag{13}$$

Where, $\delta ij = \delta i - \delta j$, is the difference in voltage angles between bus i and bus j, and $Gq(ij)$ is the transfer conductance of branch q connecting buses i and j.

3.1.6. Case 6: Reducing fuel expenses and actual power loss

The voltage quality of the network is measured by voltage deviation. For security, the deviation index is crucial. From the nominal value of unity, the indicator calculates the total change of voltages across all load buses (PQ buses) in the network [22]. The expression is as (14).

$$f\,(x,u) = \sum_{i=1}^{NG} a_i + b_i P_{Gi} + c_i P_{Gi}^2 + \lambda_p \times P_{loss} \tag{14}$$

Where P_{loss} is the real power loss in the network calculated by using (13).

3.1.7. Case 7: Minimization of fuel cost and voltage deviation

The voltage quality of the network is measured by voltage deviation. For security, the deviation index is crucial. From the nominal value of unity, the indicator calculates the total change of voltages across all load buses (PQ buses) in the network [23]. The expression is (15).

$$VD = (\sum_{P=1}^{NL} |V_{l_p} - 1|) \tag{15}$$

The combined objective function of fuel cost and voltage deviation is (16).

$$f(x,u) = (\sum_{i-1}^{NG} ai + biPGi + c_i P^2) + \lambda VD \times VD \tag{16}$$

3.1.8. Case 8: Improving voltage stability and reducing fuel cost

This objective function seeks to improve system voltage stability and lower fuel expenses. A single aim is created by combining several objectives as (17).

$$f(x,u) = (\sum_{i-1}^{NG} ai + biPGi + c_i P^2) + \lambda_L \times L_{max} \tag{17}$$

Where $Lmax$ is calculated using (15).

3.1.9. Case 9: Minimization of fuel cost, emission, voltage deviation, and losses

Reducing fuel cost, lowering pollutants, minimizing voltage deviations, and decreasing real power losses are the four main goals that this case study simultaneously tackles. The following is the formulation of combined objective function (18).

$$f(x,u) = (\sum a_i + b_i P_{Gi} + c_i P^2) + \lambda_E \times Emission + \lambda_{VD} \times VD + \lambda_p + P_{loss} \tag{18}$$

To balance the objectives, the weight factors are selected with λE = 19, λVD = 21, and λP = 22.

3.2. Performance evaluation on IEEE 57-bus test system

The essential configuration and parameter values of the IEEE 57-bus test system are outlined in Table 1. To evaluate algorithm performance under various optimization conditions, four distinct case studies are conducted. These include two single-objective and two multi-objective optimization problems, ensuring a balanced exploration of algorithm effectiveness.

3.2.1. Case 10: Reducing fuel cost

This case addresses a single-objective optimal power flow (OPF) problem focused on minimizing the total generation fuel cost. The mathematical formulation of the cost function and associated coefficients (fuel cost and emission parameters) remain consistent with those employed in the IEEE 30-bus benchmark system, as described in [24], [25].

3.2.2. Case 11: Combined reduction of fuel cost and voltage deviation

In this multi-objective scenario, the objective is to simultaneously reduce the fuel cost and the total voltage deviation across the load buses. These two goals are combined into a scalar objective function by applying a weight factor assigned a value of 100. This scalarization method mirrors the approach used previously in the IEEE 30-bus system to handle conflicting objectives.

3.2.3. Case 12: Combined reduction of fuel cost minimization and voltage stability enhancement

This case considers an objective function that blends economic and operational goals, specifically minimizing fuel cost while enhancing voltage stability. The voltage stability is quantified using the maximum L-index across the system. The formulation parallels the approach used for the 30-bus network, with the stability weight factor set to 100, ensuring balanced trade-offs in optimization.

3.2.4. Case 13: Reducing voltage deviation

The fourth case addresses a single-objective problem where the goal is to minimize the overall voltage deviation of load buses from their nominal per-unit value (1.0 p.u.). The objective function used here is structurally similar to the expression applied in the IEEE 30-bus test system, ensuring methodological consistency while adapting to the scale of the 57-bus network.

4. ALGORITHM FOR DIFFERENTIAL EVOLUTION (DE) ALGORITHM

The resilient, stochastic population-based optimization method known as DE, which was first introduced by [26], [27], has become popular for solving complicated and nonlinear optimization problems. A population of potential solutions is iteratively refined by the algorithm through a cycle of mutation, crossover, and selection. A fitness function is used to assess each member of the population, and those that do better are retained to affect the makeup of the following generation. An overview of the main steps in the DE process is given in this section.

4.1. Initialization of population

Each candidate solution (or decision vector) is given a random value within the specified bounds of the corresponding decision variables. At the start of the DE process, that starts with the random generation of an initial population. The initialization guarantees that the search begins in the solution space viable region. The starting values of the kth decision vector and jth component are as (19).

$$X_{k.0}(j) = X_{min}(j) + rand_{k,j}\ [0,1] \times [x_{\max}(j) - x_{min}(j)] \tag{19}$$

Where $randk$, j[0,1] is a random number lying between 0 and 1; j = 1,2, …, D where D is the dimension of the decision vector.

4.2. Mutation

In the second step of the DE algorithm, a mutation operation is applied to generate a mutant (or donor) vector Vk, G for each individual in the population, referred to as the target vector Xk, G where the subscript 'G' denotes the current generation. The mutation strategy employed in this work follows the "DE/rand/1" scheme, where the mutant vector is formed by adding the weighted difference of two randomly selected population vectors to a third randomly chosen vector (20).

$$V_{k,G} = X_{Rk1,G} + F(X_{Rk2,G} - X_{Rk3,G} \tag{20}$$

The indices $Rk1$, $Rk2$, and $Rk3$ are distinct and randomly selected from the entire population range. The mutation factor F is a positive parameter used to scale the difference between vectors.

4.3. Crossover

The trial or offspring vector Uk, G = [Uk, G (1), Uk, G (2), ..., Uk, $G(D)$] is generated by joining elements of the donor vector with those of the target vector Xk, G through a crossover process. In this approach, binomial crossover is employed, where each component is nominated based on a comparison between a randomly generated number (ranging from 0 to 1) and a predefined crossover rate CR. The procedure for determining each element is outlined as (21).

$$U_{k,G}{}^{V_{k,G}(j)\ if\ j=j_{rand}\ or\ rand_{k,j}\ [0,1]\leq CR}_{(j)=\{\ X^{k,G}\ (j) otherwise, where\ j=1,\ldots,D} \tag{21}$$

Where, $rand$ is a randomly chosen natural number in {1, 2, …, D}. The offspring vector Uk, GU {k, G} Uk, G is evaluated and compared with the parent vector Xk, GX {k, G} Xk, G based on fitness and constraint violation. In computationally intensive real-world problems like OPF, trial-and-error to identify a suitable CH method can be inefficient. To address this, the ECHT method combines multiple CH techniques (SF and SP) with DE [19] as the base optimization algorithm. Each CH technique maintains its own population and parameters, producing offspring that not only compete within their own group but also across the populations of other CH methods. This cross-competition ensures that even if an offspring is rejected within its own group, it may still be accepted elsewhere—thus maximizing the utility of each function evaluation. ECHT dynamically adapts, allowing the most effective CH technique at any stage to dominate and influence the evolutionary process. This removes the need for manual tuning and method selection. For the OPF problem, the decision variable dimensions (D) are 24, 33, and 130 for the 30- and 57-bus systems.

The population size (NP) and the maximum number of function evaluations (maxeval) vary by case. The algorithms were implemented in MATLAB and simulations were performed on an Intel Core i5 CPU @ 2.7 GHz with 4 GB RAM. Simulation results are discussed in Figure 1, that shows the flowchart of the ECHT-DE algorithm [26], [27].

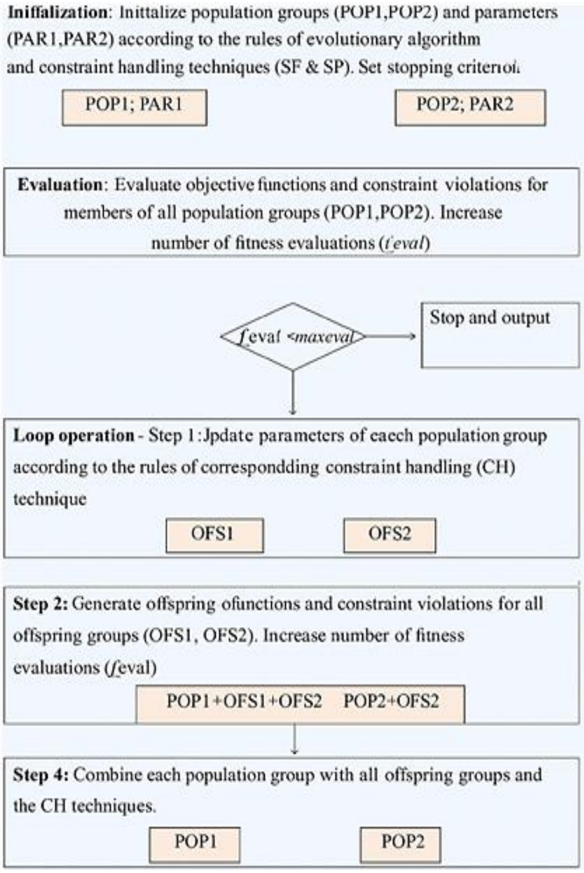

Figure 1. Flowchart for ECHT-DE algorithm

5. RESULTS AND COMPARISON

The 30-bus system underwent optimization across 09 different cases, each targeting specific objectives such as fuel cost minimization, emission reduction, loss minimization, voltage stability, and valve-point effects. SP-DE consistently outperforms in multi-objective cases, especially in emission and power loss optimization (Cases 2 and 5). ECHT-DE provides robust solutions in voltage stability and emission-focused cases (Cases 3 and 4). SF-DE performs reliably under complex conditions like valve-point loading and delivers competitive results in cost-centric cases (Cases 1, 6, 9). Table 2 represents summary of case studies. For the 57-bus system, Cases 10 through 13 evaluate the system based on fuel cost, losses, emissions, voltage deviation, and L-index, focusing on overall system reliability and economic performance. SP-DE clearly dominates the IEEE 57-bus system, achieving the lowest fuel cost, best voltage regulation, lowest emissions, and shortest CPU time. SF-DE marginally outperforms in power loss reduction in Case 13, indicating its strength in electrical efficiency. SP-DE is the most versatile algorithm, showing superior performance in minimizing fuel costs, emissions, voltage deviation, and computation time across both IEEE systems. ECHT-DE proves effective for voltage stability and emission-centric cases, especially in the 30-bus system. SF-DE, while slightly less dominant overall, excels in loss minimization and valve-point handling, indicating suitability for realistic and non-linear scenarios. The 30-bus system, being smaller, exhibits lower absolute power losses and emissions, whereas the 57-bus system emphasizes scalability and voltage control. Tables 3 and 4 show simulation results of best solutions for 30 and 57-bus systems. Figures 2 and 3 represent the 30-bus system - voltage profiles of load buses for the best solutions of cases 1 to 9. Figure 4 (see Appendix) shows the 57-bus system - voltage profiles of load buses for the best solutions of cases 10 to 13. Figure 5 (see Appendix) depicts convergence graphs for different parameters of proposed and other algorithms.

Table 2. Overview of the case study scenarios

Case No.	Valve-point effect	Emission	IEEE 30-bus system: Basic fuel cost (dup)	Power loss	Voltage deviation (dup)	Voltage stability	Multi-fuel cost	IEEE 57-bus system: Voltage deviation	Voltage stability (dup)	Basic fuel cost
1			Yes			Yes			Yes	Yes
2				Yes	Yes		Yes			
3					Yes	Yes		Yes	Yes	
4		Yes	Yes			Yes				Yes
5				Yes			Yes		Yes	
6	Yes	Yes	Yes							Yes
7			Yes	Yes	Yes		Yes			Yes
8		Yes	Yes			Yes			Yes	Yes
9					Yes	Yes	Yes		Yes	Yes
10	Yes	Yes	Yes	Yes	Yes	Yes		Yes	Yes	Yes
11	Yes						Yes			
12	Yes	Yes	Yes		Yes			Yes		
13	Yes				Yes		Yes	Yes	Yes	Yes

Table 3. System 1 (30-bus) results of optimal simulation runs

Case No.	T11 (p.u.)	V8 (p.u.)	Emission (t/h)	PG8 (MW)	PG2 (MW)	Qc29 (MVAr)	Fuel cost ($/h)	V13 (p.u.)	T36 (p.u.)	Ploss (MW)	Algorithm
1	1.0582	1.0391	0.3734	20.7681	48.1202	2.4321	813.9912	1.0451	0.9731	9.2248	SF-DE
2	1.0264	1.0423	0.27761	33.7593	56.8025	2.2953	651.2234	1.0579	0.9799	6.5553	SP-DE
3	1.0497	1.0572	0.2307	33.1893	79.1742	0.0327	926.1824	1.0721	0.9642	4.5103	ECHT-DE
4	1.0723	1.0458	0.21715	35.0	66.3093	2.4801	935.1349	1.0533	0.9712	3.2247	ECHT-DE
5	1.0689	1.0465	0.20998	34.9921	80.0000	2.3024	956.8823	1.0567	0.9735	3.1029	SP-DE
6	1.0131	1.0371	0.44420	11.0029	44.9991	2.3034	843.1888	1.0542	0.9752	10.7891	SF-DE
7	1.0673	1.0415	0.22421	35.0000	52.0913	2.2219	872.3123	1.0538	0.9707	4.5182	SF-DE
8	1.0684	1.0435	0.37233	23.4531	48.2191	2.5192	815.3323	1.0481	0.9711	9.7713	ECHT-DE
9	1.0302	1.0361	0.37098	21.7234	47.1912	2.0457	810.7987	1.0401	0.9663	8.8033	SF-DE

Table 4. System 2 (57-bus) results of optimal simulation runs

Performance parameter	Minimum	Maximum	Test case 10	Test case 11	Test case 12	Test case 13
Optimization procedure	—	—	SP-DE	SP-DE	SF-DE	SP-DE
Fuel cost (in $/h)	—	—	41,778.82	42,567.50	42,168.53	45,549.49
Active power loss (MW)	—	—	14.9090	15.5897	14.8963	18.4275
Voltage deviation (p.u.)	—	—	1.54367	0.78253	1.61174	0.60267
Emission (t/h)	—	—	1.3500	1.3550	1.3576	1.2898
Maximum L-index	—	—	0.28123	0.29228	0.29022	0.30052
Computation time (seconds)	—	—	219.9	203.6	214.4	212.5

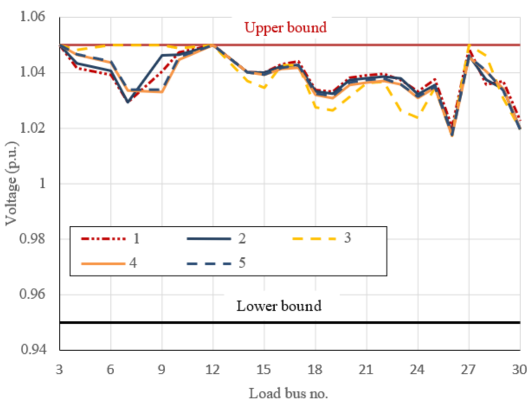

Figure 2. 30-bus system - voltage profiles of load buses for the best solutions of case 1 to case 5

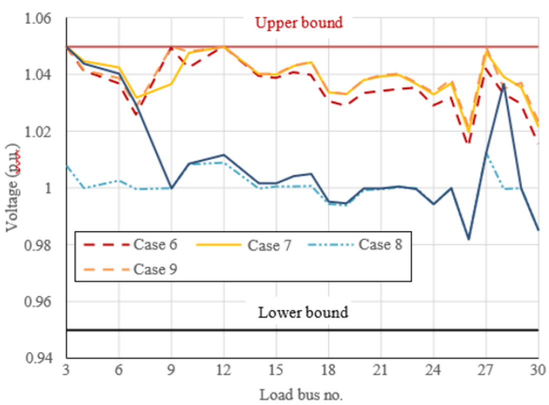

Figure 3. 30-bus system - voltage profiles of load buses for the best solutions of case 6 to case 9

6. CONCLUSION

To solve the OPF problem, a non-linear and multi-constrained optimization challenge essential to the safe and cost-effective operation of power systems, this study has investigated the integration of sophisticated constraint handling approaches with DE. Conventional methods such as static penalty functions are constrained by their sensitivity to manually chosen penalty coefficients, which frequently necessitate significant tuning and have poor generalization across various system conditions. Superiority of feasible solutions, self-adaptive penalty and a hybrid ensemble approach termed ensemble constraint handling technique were the three unique constraint-handling mechanisms that the study constructed and compared to get around these restrictions. These tactics were applied methodically to both 30-bus and 57-bus test systems, addressing a variety of OPF objectives including cost minimization, emission reduction, power loss minimization, and voltage stability enhancement. Simulation results indicate that the proposed methods, particularly the ensemble approach (ECHT), significantly enhance the DE algorithm’s ability to converge to high-quality, feasible solutions across both single-objective and multi-objective optimization scenarios. The ECHT method exhibited robust performance in balancing the trade-offs among competing OPF objectives while consistently maintaining feasibility under strict operational constraints. Furthermore, the adaptive and dynamic nature of the proposed constraint handling techniques reduces the dependency on problem-specific parameter tuning and enhances the algorithm’s generalizability to different OPF settings. Compared to existing techniques in the literature, the proposed methods offer a more reliable and automated framework for solving the OPF problem under practical power system constraints. In summary, this work contributes a meaningful advancement in the field of evolutionary optimization for power systems by addressing the critical issue of constraint satisfaction in OPF problems. Future work may extend this framework by integrating other metaheuristics with hybrid constraint handling or exploring real-time OPF in smart grid environments involving renewable integration and demand-side participation.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [SKC], upon reasonable request.

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APPENDIX

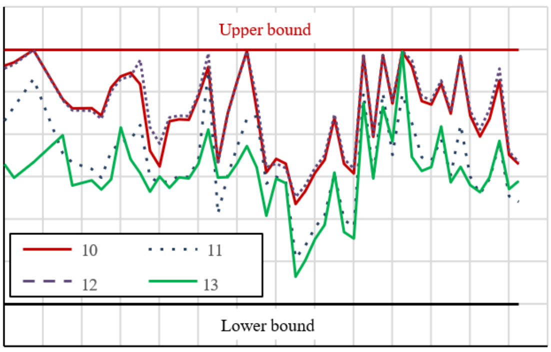

Figure 4. 57-bus system - voltage profiles of load buses for the best solutions of case 10 to case 13

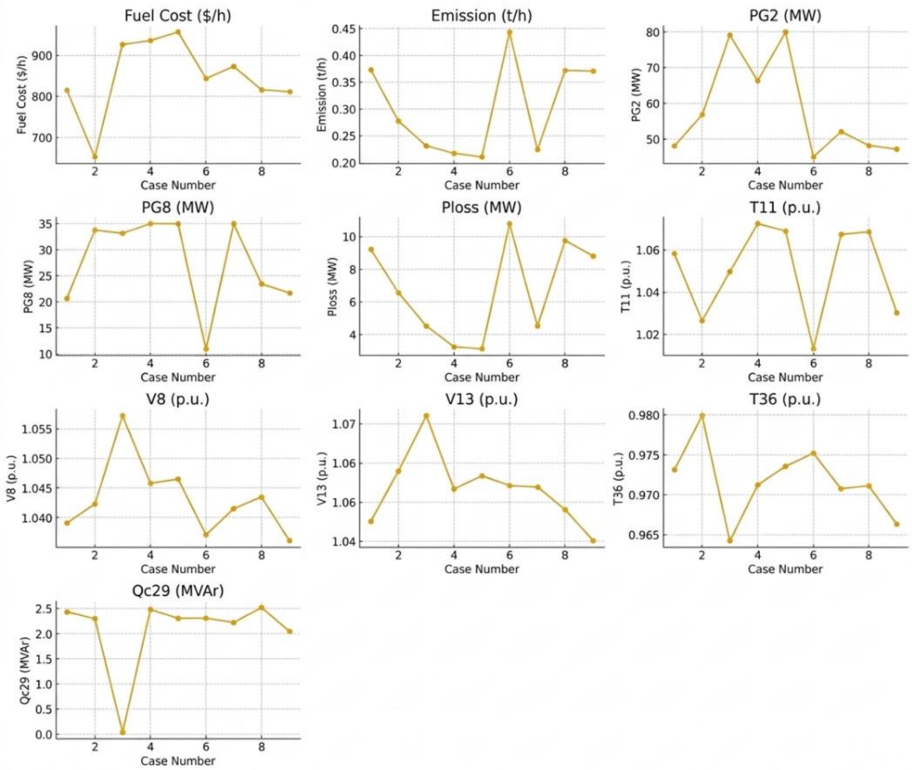

Figure 5. Convergence graphs for different parameters of proposed and other algorithms

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