



Optimal power flow incorporating wind uncertainty using bald eagle search and transit search optimization algorithms

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ABSTRACT

The optimal power flow (OPF) problem is a key issue in determining the most efficient and secure operating point for a power system. This problem has become particularly complex with the high penetration of renewable energy resources, due to the intermittent and stochastic nature of these resources. In this paper, the OPF is solved using the recently developed algorithms called the Bald Eagle Search (BES) and Transit Search Optimizer (TSO), taking into account the uncertainties associated with the power outputs of the wind generation systems. The paper examines several objective functions, such as minimizing thermal and wind generation costs, transmission losses, voltage deviations, and greenhouse gas emissions. Comparative analyses were carried out on standard and modified IEEE 30-bus and 57-bus test systems, in comparison with recent developed optimization algorithms, including the Equilibrium Optimizer (EO), the Marine Predators Algorithm (MPA), the Artificial Ecosystem-based Optimizer (AEO) and the Slime Mould Algorithm (SMA). The obtained results demonstrate the effectiveness and robustness of the BES and TSO algorithms in solving the OPF problem incorporating renewable energies while optimizing overall system performance and minimizing its environmental impact.

1. INTRODUCTION

The optimal power flow (OPF) solution is a fundamental aspect of power systems, and researchers are constantly striving to improve its efficiency. The main objective of the OPF problem is to optimize the operation of power systems by minimizing fuel costs, transmission losses and environmental emissions, while respecting the operational constraints of generating units, transformers and transmission lines limits (Yoon et al., 2021). Renewable energy resources (RERs), widely integrated into power systems,

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offer an economically, environmentally and technically attractive solution. In other words, the inclusion of RERs significantly reduces dependence on fossil fuels, cuts emissions of greenhouse gases and other pollutants, minimizes production costs and improves overall system performance. Among the technologies most widely deployed to operate RERs are wind generation system. However, the integration of these energy resources poses a number of technical challenges. Essentially, wind speed, which determine wind generation, is inherently intermittent and variable, amplifying uncertainties in the power system, particularly due to fluctuations in load demand (Alsattar et al., 2020).

The OPF problem incorporating wind energy resources has been widely explored in the literature using various metaheuristic optimization methods. In (Amroune, 2022), an artificial bee colony (ABC) algorithm was proposed to solve the OPF problem integrating squirrel-cage induction generators in wind farms. An OPF solution for a wind-thermal generation system, based on a modified bacterial search algorithm (MBFA), was presented in (Biswas et al., 2017). The main objectives of the proposed strategy were to minimize the cost of wind-thermal generation systems and improve voltage stability. (Raj et al., 2014) proposed a hybrid optimization method using particle swarms and artificial physics (PSO-APO) to solve the OPF problem under security constraints while integrating wind generators into the power system. This approach makes it possible to better manage the variability of wind generation while respecting grid security limits. (Liang et al., 2018) developed a new algorithm combining the random black hole model and chaotic maps with the bat algorithm (RCBA) to solve the OPF problem in the presence of random wind generation. This approach takes into account the intermittency and uncertainty of wind power while optimizing the cost of production. (El Attar, 2019) presented and solved the OPF problem for a hybrid wind-thermal system using a modified version of the moth swarm algorithm (MMSA). This method aimed to minimize the total production cost while respecting system constraints and taking into account the random nature of wind generation. (Kaymaz et al., 2021) have proposed a new optimization method combining Lévy flights with the coyote optimization algorithm (COA) to solve the OPF problem in a hybrid wind-thermal system. This approach exploits the exploratory capability of Lévy flights and the robustness of COA to deal with the random nature of wind generation and system constraints. (Ida Evangeline & Rathika, 2021) studied the OPF problem using evolutionary programming (EP) and proposed a framework for optimal real-time power flow, integrating wind power generation. Their approach aims to take into account the intermittency of wind generation and ensure efficient real-time system operation. Recent studies have focused in particular on the development and application of sophisticated optimization algorithms, such as the equilibrium optimizer (EO), the marine predator algorithm (MPA), the artificial ecosystem optimizer (AEO) and the slime mould algorithm (SMA), which have shown good performance in solving complex optimization problems.

This paper presents a structured comparative evaluation of two recently developed metaheuristic algorithms, namely the Bald Eagle Search (BES) and the Transit Search Optimizer (TSO), applied to stochastic wind-integrated OPF. The selection of BES and TSO is motivated by their recent development, distinct exploration-exploitation mechanisms, and promising performance in nonlinear optimization problems, while their application to highly constrained stochastic OPF remains limited. To the best of our knowledge, no prior study has offered a direct and consistent comparison of these two algorithms within a comprehensive wind-integrated OPF framework. Therefore, this work addresses this gap by systematically evaluating their convergence behavior, robustness, and suitability for renewable-integrated power system optimization. The objective function considers fuel costs, costs associated with the intermittency of wind resources, active power losses, system voltage profile deviations, and emissions. Simulations were carried out on standard and modified IEEE 30-bus and 57-bus test systems, and comparative analyses were performed against other optimization algorithms, including the EO, MPA, AEO, SMA and so others.

2. PROBLEM FORMULATION

2.1. Objective functions

2.1.1 Thermal unit cost function

Thermal power plants generate electricity using fossil fuels. The fuel cost per hour as a function of the active power output of a thermal generator is generally represented by a quadratic model, expressed as:

$$f_1 = \sum_{i=1}^{N_{TG}} a_i + b_i P_{Gi} + c_i P_{Gi}^2 \quad (1)$$

where a_i , b_i , c_i are the cost coefficients of the i th thermal generator, P_{Gi} denotes its power output, and N_{TG} is the total number of thermal generators.

2.1.2 Wind farm cost function

The overall operating cost of wind power generation is formulated as:

$$f_2 = \sum_{j=1}^{N_{wg}} (WPCost_{dir.j} + WPCost_{oe.j} + WPCost_{ue.j}) \quad (2)$$

where N_{wg} is the total number of wind generators, $WPCost_{dir.j}$ is the direct cost of wind power generation, $WPCost_{oe.j}$ is the overestimation cost for the j th wind turbine and $WPCost_{ue.j}$ is the underestimated cost for the j th wind turbine.

The direct cost of wind generation is proportional to the produced output and can be modeled as:

$$WPCost_{dir.j} = d_j w_j \quad (3)$$

where d_j is the direct cost coefficient and w_j is the available active power from the j th turbine.

The underestimation cost refers to the economic penalty incurred when the scheduled or forecasted wind generation is lower than the actual available wind power, leading to unused renewable energy or inefficient dispatch planning. This cost can be mathematically expressed as follows:

$$WPCost_{ue.j} = \sum_{j=1}^{N_{wg}} (C_{pwj} \times E(Y_{ue.j})) \quad (4)$$

where C_{pwj} is the underestimation cost coefficient and $E(Y_{ue.j})$ is the expected value of unutilized wind energy for the j th turbine.

$$E(Y_{ue.j}) = \begin{cases} w_j \{1 - \exp(-(v_{IN}/c)^k) + \exp(-(v_{OUT}/c)^k)\} \\ + ((\frac{w_R v_{IN}}{v_R - v_{IN}}) + w_j) (\exp(-\frac{v_{IN}^k}{c^k}) - \exp(-\frac{v_j^k}{c^k})) \\ + ((\frac{w_R c}{v_R v_{IN}}) (\Gamma[1 + \frac{1}{K}, (\frac{v_{IN}}{c})^k] - \Gamma[1 + \frac{1}{K}, (\frac{v_j}{c})^k]) \end{cases} \quad (5)$$

where w_j is the available active power from the j th wind power source; w_R is the rated wind power output; v_R is the rated velocity of wind; v_{IN} is the cut-in velocity of wind; v_{OUT} is the cut-out velocity of the wind, k and c are the shape and scaling coefficients for the j th wind generator, respectively. $\Gamma(x)$ is the gamma function.

The overestimation cost is associated with the situation where the scheduled wind generation is higher than what is actually available. This results in a generation shortfall that necessitates compensation from

pricier conventional units or reserve power. The overestimation cost can be calculated using the following equation:

$$WPCost_{oe,j} = \sum_{j=1}^m (C_{rwj} \times E(Y_{oe,j})) \quad (6)$$

where C_{rwj} is the reserve cost coefficient and $E(Y_{oe,j})$ is the expected overestimated wind generation:

$$E(Y_{oe,j}) = \begin{cases} 1 - \exp(-(v_{IN}/c)^k) + \exp(-(v_{OUT}/c)^k) \\ + \left(\left(\frac{w_R v_{IN}}{v_R - v_{IN}} \right) + w_j \right) \left(\exp\left(-\frac{v_{IN}^k}{c^k}\right) - \exp\left(-\frac{v_j^k}{c^k}\right) \right) \\ + \left(\left(\frac{w_R c}{v_R v_{IN}} \right) \right) \left(T \left[1 + \frac{1}{K} \left(\frac{v_{IN}}{c} \right)^k \right] - T \left[1 + \frac{1}{K} \left(\frac{v_j}{c} \right)^k \right] \right) \end{cases} \quad (7)$$

It is important to clarify that the uncertainty treatment adopted in this study is probabilistic in nature but does not constitute a distributionally robust or chance-constrained optimization framework. The Weibull-based modeling approach is used to analytically capture the statistical variability of wind speed and to integrate its expected impact into the OPF objective function through penalty and reserve cost terms. Therefore, the formulation accounts for wind variability in expectation, rather than guaranteeing feasibility under worst-case or multi-scenario realizations.

2.1.3 Active power loss

Transmission line power losses (P_{loss}) in the power system can be calculated as follows:

$$P_{loss} = \sum_{i=1}^{NL} \sum_{j \neq i}^{NL} G_{ij} [V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j)] \quad (8)$$

where G_{ij} is the conductance between buses i and j , δ_i and δ_j are the corresponding voltage angles. The combined cost including both fuel and losses is:

$$f_3 = \sum_{i=1}^{NG} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) + \lambda_{loss} * P_{loss} \quad (9)$$

with λ_{loss} as the weighting factor (set to 40 in this study (Mohamed et al., 2017)).

2.1.4 Voltage deviation

Voltage deviation (VD) quantifies the deviation of bus voltages from the nominal value (1.0 p.u.), and is given by:

$$VD = (\sum_{i=1}^{Nb} |V_i - 1.0|) \quad (10)$$

The combined objective of minimizing both generation cost and VD is:

$$f_4 = \sum_{i=1}^{NG} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) + \lambda_{VD} * VD \quad (11)$$

where λ_{VD} is set to 100 (Mohamed et al., 2017).

2.1.5 Emission cost

Reducing emissions such as NO_x , SO_x and CO_2 is another critical objective. The emissions from thermal units are modeled as:

$$E = \sum_{i=1}^{N_G} [10^{-2} (\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2) + (\omega_i e^{(\mu * P_{Gi})})] \quad (12)$$

where $\alpha, \beta, \gamma, \omega$ and μ are the emission coefficients corresponding to the i th thermal generator.

The emission-related objective function is then:

$$f_5 = \sum_{i=1}^{N_G} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) + \lambda_E * E \quad (13)$$

where λ_E is the emission weight factor, chosen as 1000 (Boucekara et al., 2018).

2.2 Constraints

The equality constraints enforce power balance:

$$P_{gi} - P_{di} - V_i \sum_{j=1}^{N_B} V_j [G_{ij} \cos(\delta_{ij}) + B_{ij} \sin(\delta_{ij})] = 0 \quad (14)$$

$$Q_{gi} - Q_{di} - V_i \sum_{j=1}^{N_B} V_j [G_{ij} \sin(\delta_{ij}) + B_{ij} \cos(\delta_{ij})] = 0 \quad (15)$$

where P_{gi} and Q_{gi} are the active and reactive powers of the i th generator, P_{di} and Q_{di} are the active and reactive loads of the i th bus, $\delta_{ij} = \delta_i - \delta_j$ is the voltage angle difference between buses i and j , and G_{ij} and B_{ij} are the ij branch conductance and susceptance, respectively.

The inequality constraints are device limits and system security limits:

- Generator voltage limits:

$$V_{gi}^{min} \leq V_{gi} \leq V_{gi}^{max} \quad i = 1, 2, \dots, N_G \quad (16)$$

where V_{gi} represents the voltage magnitude of the i th generator bus and N_G is the number of thermal generators.

- Generator active/reactive power limits:

$$P_{gi}^{min} \leq P_{gi} \leq P_{gi}^{max} \quad i = 1, 2, \dots, N_G \quad (17)$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max} \quad i = 1, 2, \dots, N_G \quad (18)$$

- Transformer tap settings:

$$T_i^{min} \leq T_i \leq T_i^{max} \quad i = 1, 2, \dots, N_T \quad (19)$$

where T^{min} and T^{max} are the limits of tap changer transformers and N_T is the number of tap changers.

- Shunt compensators:

$$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max} \quad i = 1, 2, \dots, N_C \quad (20)$$

where Q_c^{min} and Q_c^{max} are the limits of shunt compensators and N_C represents the number of shunt compensators.

3. OPTIMIZATION ALGORITHMS

3.1 Bald eagle search algorithm

The bald eagle, recognized for its intelligence and efficiency in locating prey, serves as a biologically inspired foundation for the Bald Eagle Search (BES) optimization algorithm. Primarily piscivorous, bald eagles exhibit exceptional hunting and fishing capabilities, though their diet may also include birds, small mammals, and carrion. The BES algorithm emulates the strategic foraging behavior of bald eagles, offering a robust and efficient framework for addressing complex optimization problems (Panda & Tripathy, 2015). It operates through three distinct phases: searching, swooping, and attacking, as depicted in Figure 1.

3.1.1 Select space

At this stage, the eagles establish their initial positions. The appropriate search space can be expressed by the following relation:

$$P_{new,i} = P_{best} + \alpha \times r(P_{mean} - P_i) \quad (21)$$

Here, P_{best} denotes the best position identified by the eagles, α is a control factor ranging between [1.5 2], and r is a random value within [0 1]. The term P_{mean} represents the average position derived from all previous search experiences, while P_i refers to the current location of the eagle.

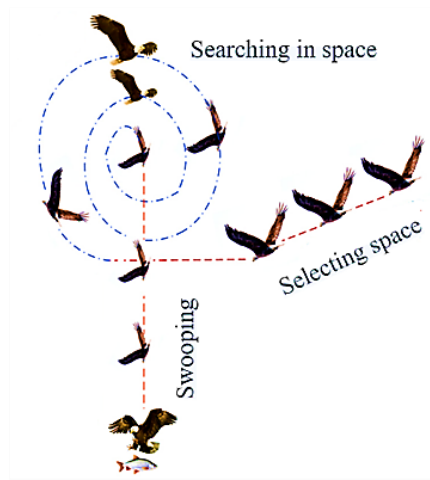


Fig 1. Phases of the BES algorithm (Amroune, 2022).

3.1.2 Search in the space

In this phase, the eagle modifies its position according to the following formula:

$$P_{new,i} = P_i + y(i) \times (P_i - P_{i+1}) + x(i) \times (P_i - P_{mean}) \quad (22)$$

3.1.3 Swooping

The swooping behavior of eagles can be modeled as follows:

$$P_{new,i} = rand \times P_{best} + x_1(i) \times (P_i - P_i \times P_{mean}) + y_i(i) \times (P_i - c_2 \times P_{best}) \quad (23)$$

where $c_1, c_2 \in [1, 2]$.

After these stages, the set of initially generated candidate solutions is progressively refined through multiple iterations until the global optimum is reached. The pseudocode of the complete procedure is presented in **Algorithm 1**.

Algorithm 1: BES algorithm

Start

Generate initial population of BES P_i ($i = 1, 2, 3, \dots, n$)

Calculate the fitness values of the initial population: $f(P_i)$

Iteration $t = 1$

while $t < \text{Max iteration}$

Select space

for (each point i in the population)

$$P_{new} = P_{best} + \alpha \times r (P_{mean} - P_i)$$

if $f(P_{new}) < f(P_i)$

$$P_i = P_{new}$$

end if

if $f(P_{new}) < f(P_{best})$

$$P_{best} = P_{new}$$

end if

end for

Search in space

for (each point i in the population)

$$P_{new} = P_i + y(i) \times (P_i - P_{i+1}) + x(i) \times (P_i - P_{mean})$$

if $f(P_{new}) < f(P_i)$

$$P_i = P_{new}$$

end if

if $f(P_{new}) < f(P_{best})$

$$P_{best} = P_{new}$$

end if

end for

Swoop

for (each point i in the population)

$$P_{new} = rand \times P_{best} + x_1(i) \times (P_i - c_1 \times P_{mean})$$

$$+ y_1(i) \times (P_i - c_2 \times P_{best})$$

if $f(P_{new}) < f(P_i)$

$$P_i = P_{new}$$

end if

if $f(P_{new}) < f(P_{best})$

$$P_{best} = P_{new}$$

end if

end for

$t = t + 1$

end while

end

3.2 Transit search optimizer

Transit searching method is used to detect exoplanets, i.e. planets outside our solar system. It is based on the observation of small, periodic decreases in the brightness of a star caused by the passage of a planet in front of it, in the manner of a mini-eclipse. Inspired by this astronomical principle, the Transit Search Optimizer (TSO) is an optimization algorithm that reproduces the process of discovering planets by observing the variations in light caused by their transit in front of stars (Mirrashid & Naderpour, 2022).

3.2.1 Key components of the TSO

In the structure of the algorithm, two main parameters are defined: the number of host stars (ns) and the signal-to-noise ratio (S/N). The latter is evaluated according to the transit model, while the noise estimate is based on the standard deviation of observations made outside transit periods. When receiving images of stars, photon noise is an unavoidable occurrence (Mirrashid & Naderpour, 2022).

3.2.2 TSO phases

The Transit Search (TS) process can be compared to a journey of space exploration, structured in five main stages: galaxy, star, transit, planet, neighbor and exploitation. Each of these stages represents a phase of exploration, like a game in which you progress by discovering new entities. This progressive approach simulates the search for exoplanets through the analysis of starlight, while structuring optimization into coherent, exploratory stages (Mirrashid & Naderpour, 2022).

The steps of the TSO algorithm are summarized in the **Algorithm 2**, while the mathematical equations used are presented in the corresponding reference (Mirrashid & Naderpour, 2022).

Algorithm 2: TSO algorithm

Inputs:

Number of host stars (ns), Signal-to-noise ratio (SN), Location of the best planet for each star i ($L_{p,i}$)

Outputs:

Global best planet location with corresponding fitness

Initialization:

Set the initial global best planet location

for $i = 1:ns$

for $j = 1:NS$

 Modify the properties of the current planet to compute a new candidate location

if L_E is better than $L_{p,i}$

 Save the L_E as $L_{p,i}$

end

end

if Planet i is the best ever planet detected

 Save the L_p as L_B

end

end

Return L_p and its corresponding fitness (for each star)

Return L_B and its corresponding fitness

4. RESULTS AND DISCUSSIONS

The primary aim of this section is to assess the efficacy and efficiency of the BES and TSO algorithms in the OPF incorporating stochastic wind power generation. To ensure a fair and consistent comparison between the investigated algorithms, a unified parameter tuning strategy was adopted. The control parameters of both the BES and TSO algorithms were selected based on preliminary sensitivity analyses and established guidelines from the literature to achieve a balanced trade-off between exploration and exploitation capabilities. Furthermore, both algorithms were implemented and evaluated under identical computational conditions, including the same population size, maximum number of iterations, stopping criteria, and simulation environment. The algorithms are evaluated using the modified IEEE 30-bus and IEEE 57-bus test systems (Zimmerman et al., 2011). Figures 2 and 3 illustrate the single line schematics of both test systems. The modified IEEE 30-bus system has three thermal generators located at buses 1, 2, and 8, and three wind farms of 60 MW placed in buses 5, 11 and 13. This system has four tap changer transformers, and nine shunt capacitors situated at buses 10, 12, 15, 17, 20, 21, 23, 24, and 29. The

system's base real power is 283.4 MW, whereas the reactive power demand is 126.2 MVar. The minimum and maximum voltage limitations for PV buses are set between [0.95, 1.1] p.u., but for the remaining PQ buses, the limits are established between [0.95, 1.05] p.u. The capacity of VAR sources is estimated to range from 0 to 5 MVar. The second test system consists of five thermal units located at buses 1, 2, 3, 8 and 12 and two wind farms of 60 MW are placed in buses 6 and 9. It consists of 17 tap changer transformers, and 3 shunt VAR compensators situated at buses 18, 25, and 53. The system's base real power is 1250.8 MW, whereas the reactive power demand is 336.4 MVar. The minimum and maximum voltage limitations for PV and PQ buses are set at [0.95, 1.1] and [0.94, 1.06] per unit, respectively. The capacity of shunt VAR compensators is believed to range from 0 to 20 MVar. The fuel costs and emission coefficients of the thermal generators for both test systems are presented in Table 1. The parameters associated with integrated wind turbines, (Kaymaz et al., 2021), are reported in Table 2.

Table 1. Generators and emission coefficients of the IEEE 30-bus and IEEE 57-bus system (Biswas et al., 2018).

Test system	Generator bus	Fuel cost coefficients			Emission coefficients				
		a	b	c	α	β	γ	ω	μ
IEEE 30-bus	1	0	2	0.00375	4.091	-5.554	6.49	0.0002	2.857
	2	0	1.75	0.0175	2.543	-6.047	5.638	0.0005	3.333
	8	0	3.25	0.00834	5.326	-3.55	3.38	0.002	2
IEEE 57-bus	1	0	20	0.0775795	4.0910	-5.5540	6.4900	0.0002	0.2860
	2	0	40	0.01	2.5430	-6.0470	5.6380	0.0005	0.3330
	3	0	20	0.25	6.1310	-5.5550	5.1510	0.0000	0.6670
	8	0	20	0.0222222	4.2580	-5.0940	4.5860	0.0000	0.8000
	12	0	20	0.0322581	5.3260	-3.5550	3.3800	0.0020	0.2000

Table 2. Data for wind generators (Kaymaz et al., 2021).

Test system	IEEE 30-bus		IEEE 57-bus		
	Wind turbine_5	Wind turbine_11	Wind turbine_13	Wind turbine_6	Wind turbine_9
Cut-in speed (m/s)	3	3	3	3	3
Cut-out speed (m/s)	30	30	30	25	25
Rated output speed (m/s)	12	12	12	16	16
Direct cost coefficient (\$/MWh)	1.75	2	2.25	1.6	1.75
Reserve cost coefficient (\$/MWh)	3	3	3	3	3
Penalty cost coefficient (\$/MWh)	1.5	1.5	1.5	1.5	1.5
Shape factor (k)	1	2	2	2	2
Scale factor (c)	15	15	25	9	10

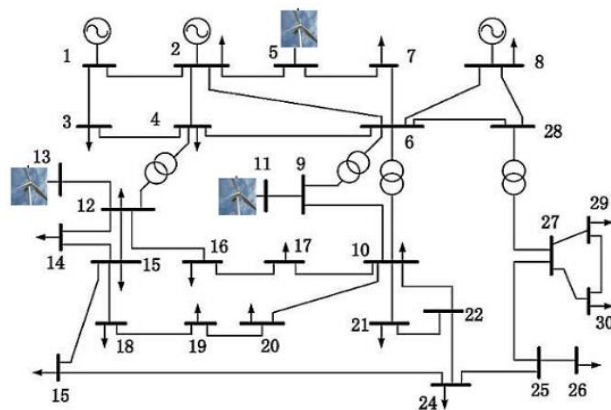


Fig 2. Single line diagram of the modified IEEE 30-bus test system.

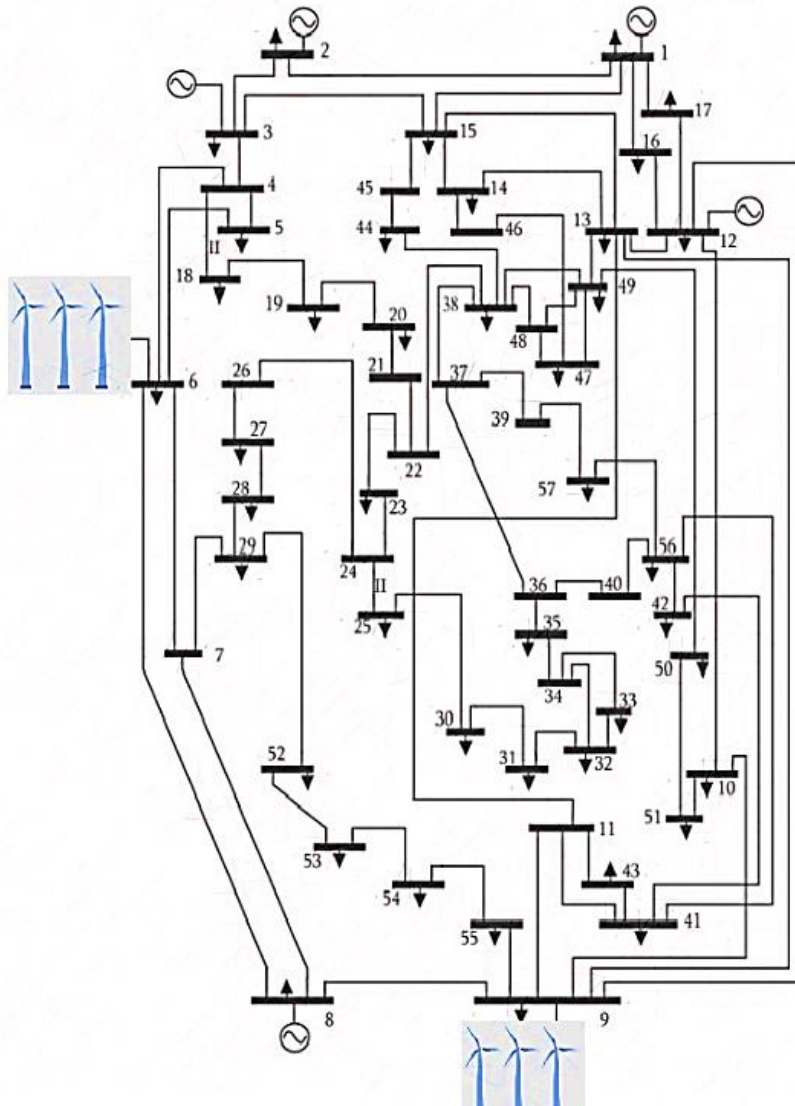


Fig 3. Single line diagram of the modified IEEE 57-bus test system

4.1 Case study 1: Optimizing total generation cost

The aim of this case is to use the BES and TSO algorithms to minimize the total cost of power generation, while also maintaining system constraints within their predetermined limits. The original formulations of the BES and TSO algorithms were preserved without structural modifications. Both methods were implemented in accordance with their initial descriptions, and only their control parameters were tuned to ensure a fair and consistent benchmarking comparison.

The comparative convergence profile of the minimum total cost value obtained using the BES and TSO algorithms is depicted in Figures 4 and 5. It can be observed that the total cost function value, for both test systems, converges more smoothly and with fewer iteration cycles for BES compared to TSO, demonstrating its superior ability to approach the global optimal solution. Tables 3 and 4 display the optimal results derived from the BES and TSO algorithms under case 1 for IEEE 30-bus and IEEE 57-bus systems. The simulation results clearly indicate that the BES method attains a minimal total cost which is inferior than the TSO algorithm's cost for both test systems.

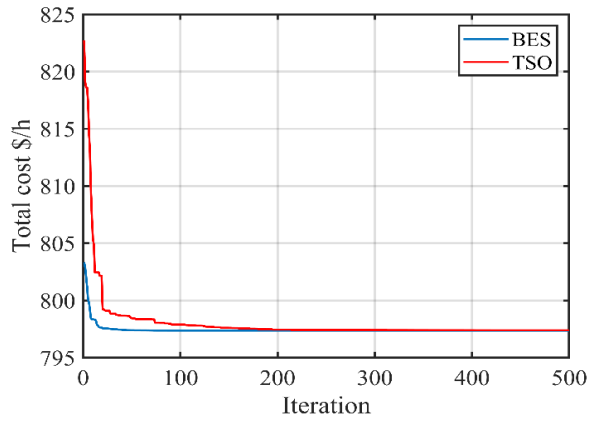


Fig 4. The convergence behavior of the proposed algorithms for IEEE 30-bus (Case 1).

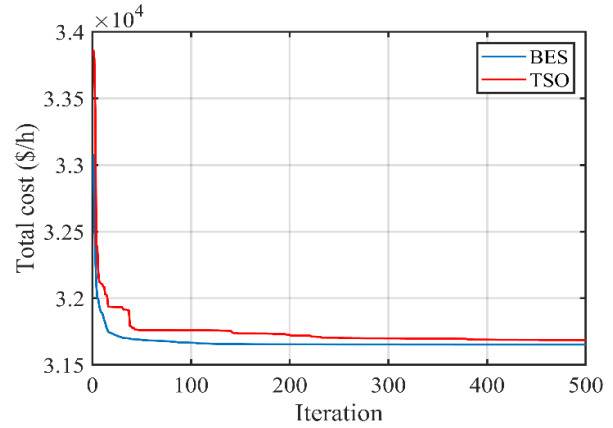


Fig 5. The convergence behavior of the proposed algorithms for IEEE 57-bus (Case 1).

4.2 Case study 2: Optimizing total generation cost with transmission losses

Minimization of transmission loss along with fuel and stochastic wind power costs is considered here. The convergence curves for BES and TSO algorithms in solving this case, for both test systems, are depicted in Figures 6 and 7. BES algorithm appears to have converged faster than the TSO algorithm. The obtained optimal values of control variables yielded by both BES and TSO algorithms are reported in Tables 3 and 4. The minimum active power loss obtained using the BES algorithm for the IEEE 30-bus system is 2.3913 MW, while the TSO algorithm yields a slightly lower value of 2.3394 MW. Although TSO achieves a lower transmission loss, the best fitness value obtained by BES remains superior. Similarly, for the IEEE 57-bus system (as shown in Table 5), the comparison of results further demonstrates the superiority of the BES algorithm over the TSO algorithm.

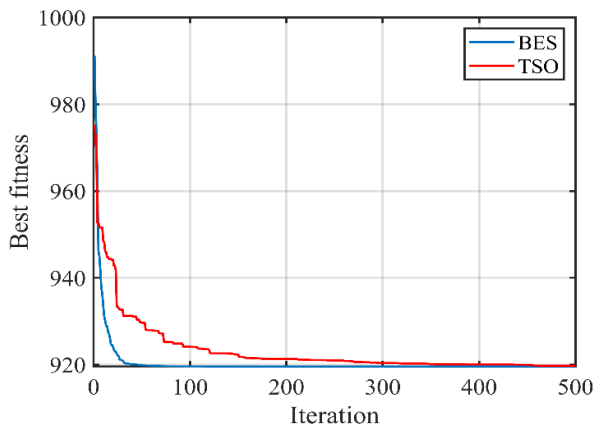


Fig 6. The convergence behavior of the proposed algorithms for IEEE 30-bus (Case 2).

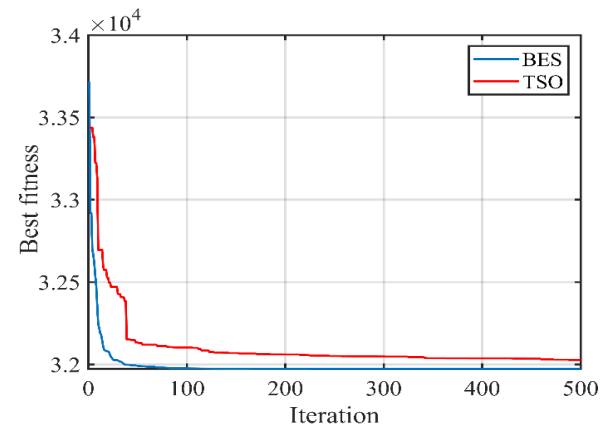


Fig 7. The convergence behavior of the proposed algorithms for IEEE 57-bus (Case 2).

4.3 Case study 3: Optimizing total generation cost with voltage deviation

This case addresses the minimization of fuel and stochastic wind power costs and voltage deviation. The convergence curves for best fitness obtained by BES and TSO algorithms in the IEEE 30-bus and IEEE 57-bus systems are presented in Figures 8 and 9. As shown after 100 iterations, solution convergence

takes place in BES quicker than that of TSO. Tables 3 and 4 show the results of the BES and TSO algorithms, with BES achieving the minimum fitness function value in both test systems. Therefore, the BES algorithm demonstrated higher efficiency and optimization compared to the TSO algorithm.

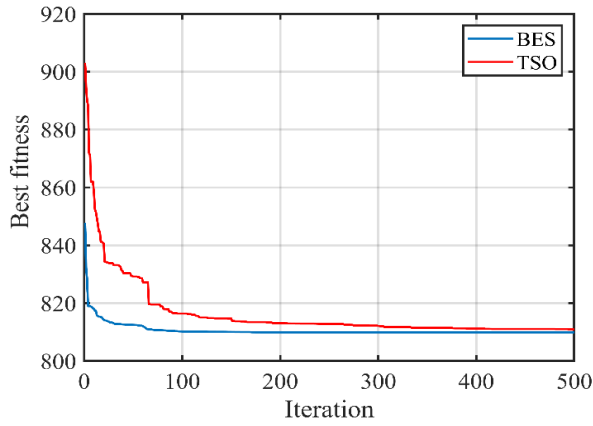


Fig 8. The convergence behavior of the proposed algorithms for IEEE 30-bus (Case 3).

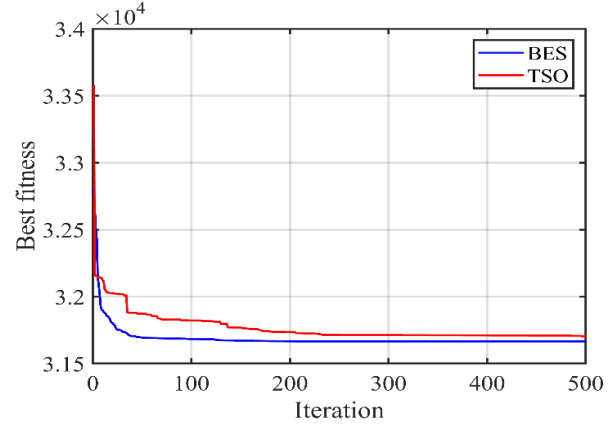


Fig 9. The convergence behavior of the proposed algorithms for IEEE 57-bus (Case 3).

4.4 Case study 4: Optimizing total generation cost with emission

This study aims to optimize the total generation cost and associated emissions from conventional thermal power plants. The optimal solutions and control variable values for both test systems are presented in Tables 3 and 4. Additionally, Figures 10 and 11 show that the BES algorithm achieves a faster convergence rate compared to the TSO method. These results highlight the superiority of the BES heuristic algorithm over TSO in terms of both optimality and convergence performance. The superior performance of BES can be attributed to its structured three-phase search mechanism, which progressively transitions from global exploration to focused exploitation. This mechanism appears particularly effective in the highly nonlinear and constrained OPF problem, where gradual refinement improves feasibility preservation and local intensification. In contrast, TSO demonstrates competitive exploration capability but comparatively slower fine-tuning near the optimum, which explains the small but consistent performance gap observed across test systems.

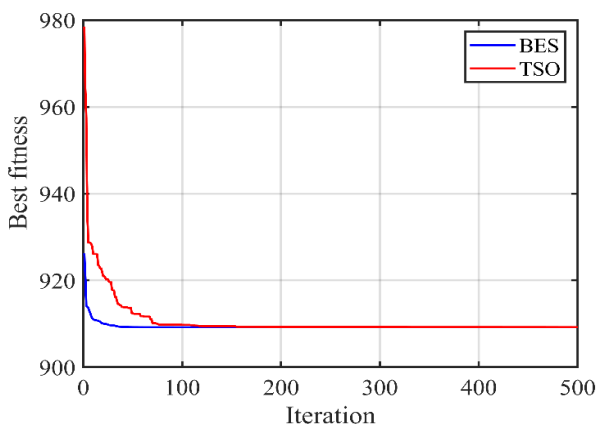


Fig 10. The convergence behavior of the proposed algorithms for IEEE 30-bus (Case 4).

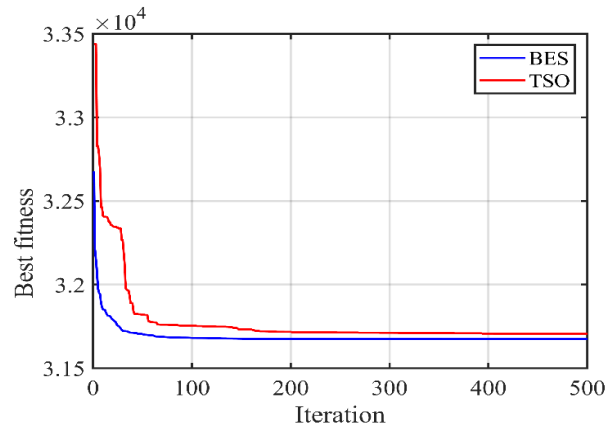


Fig 11. The convergence behavior of the proposed algorithms for IEEE 57-bus (Case 4).

Table 3. Optimal results for the IEEE 30-bus system.

Control variables	Min	Max	Optimal values							
			BES				TSO			
			Case 1	Case 2	Case 3	Case 4	Case 1	Case 2	Case 3	Case 4
P ₁ (MW)	50	200	200.0000	200.0000	179.7365	156.8560	106.7928	58.3428	106.9605	78.6957
P ₂ (MW)	20	80	28.4195	23.7490	26.6763	36.2151	32.8822	34.7978	32.8105	41.9153
P ₅ (MW)	0	60	13.7948	12.1500	30.2586	41.2595	40.4845	59.9999	41.2563	51.5590
P ₈ (MW)	10	30	10.0000	20.4652	10.0000	10.2775	10	22.9780	10	12.3652
P ₁₁ (MW)	0	60	18.7175	28.1560	22.7918	15.1650	38.1303	49.9013	38.0454	42.7722
P ₁₃ (MW)	0	60	15.1947	18.0619	25.845	33.5963	59.9999	60	59.9987	60
Total cost (\$/h)	-	-	797.3691	823.9334	800.2974	806.0785	797.4061	826.1544	800.5517	806.0030
Thermal cost (\$/h)	-	-	367.3336	286.9317	365.5029	324.3238	367.3393	286.7449	357.2473	323.2232
Wind cost (\$/h)	-	-	430.0355	537.0017	434.7945	481.7547	430.0668	539.4095	443.3044	482.7798
P _{loss} (Mw)	-	-	4.4626	2.3913	5.3904	3.2719	4.4747	2.3394	5.2276	3.2768
VD (p.u.)	-	-	1.9614	2.0249	0.0946	1.9900	1.8988	2.0355	0.1039	1.9919
Emission (t/h)	-	-	0.1267	0.0946	0.1258	0.1031	0.1267	0.0941	0.1232	0.1032
CPU time (s)			429.48	477.20	444.29	441.25	436.76	488.52	464.12	456.85

Table 4. Optimal results for the IEEE 57-bus system.

Control variables	Min	Max	BES				TSO			
			Case 1	Case 2	Case 3	Case 4	Case 1	Case 2	Case 3	Case 4
P ₁ (MW)	0	576	575.88	575.88	575.88	575.88	88.8733	210.6952	148.0704	141.3550
P ₂ (MW)	30	100	30.2554	30	30	35.4356	55.0966	45.5360	35.0694	64.7676
P ₃ (MW)	40	140	40	40	40	40	40.6529	55.2440	45.8873	40
P ₆ (MW)	0	150	108.1066	42.7103	54.7052	74.1088	149.9998	131.7982	149.9999	149.9999
P ₈ (MW)	100	550	100	100	199.4280	249.11	476.4043	359.4247	435.1710	410.1304
P ₉ (MW)	0	120	3.5584	73.1433	101.2903	105.4829	119.999	105.4392	119.9993	119.9995
P ₁₂ (MW)	100	410	206.4987	190.5680	105.3457	100	348.1698	357.9730	342.2948	343.3636
Total cost (\$/h)	-	-	31653.28	31663.20	31653.07	31653.33	31686.733	31691.14	31690.56	31695.88
Thermal cost (\$/h)	-	-	30618.23	30628.15	30618.02	30618.28	0654.4610	30656.09	30655.51	30660.83
Wind cost (\$/h)	-	-	1035.051	1035.051	1035.051	1035.051	35.05	1035.05	1035.05	1035.05
P _{loss} (Mw)	-	-	15.03	14.0850	15.0508	15.0272	16.3915	15.2777	15.5299	16.2865
VD (pu.)	-	-	1.1323	1.0963	1.1288	1.1254	1.1574	1.1098	1.0920	1.1317
Emission (t/h)	-	-	0.6409	0.6342	0.6217	0.6299	0.6788	0.6744	0.6851	0.6757
CPU time (s)			901.24	944.85	987.80	992.09	910.25	973.19	982.64	992.09

Table 5 shows the performance comparison of the BES and TSO algorithms, for IEEE 30-bus system, with several state-of-the-art algorithms, namely the Equilibrium Optimizer (EO), Marine Predators Algorithm (MPA), Artificial Ecosystem-Based Optimization (AEO), and Slim Mould Algorithm (SMA) (Amroune, 2022). The evaluation was based solely on the fitness value obtained, which reflects the quality of the solution with respect to the defined objective function. In Case 1, the BES algorithm demonstrated the best performance, achieving the lowest fitness value of 797.3691. This result suggest that BES is highly effective in converging toward the optimal solution. TSO ranked third with a fitness of 797.3876, indicating competitive performance but slightly less efficient optimization than BES and EO. The remaining algorithms showed higher fitness values compared to BES and TSO. In Case 2, BES continued to outperform the other algorithms, achieving the lowest fitness value of 919.5846, followed closely by TSO at 919.7324. In Case 3, BES maintained its leading position with a fitness of 809.7623. TSO showed a slightly higher fitness value of 810.9260, indicating that its performance in this case was not as effective as BES and MPA algorithms. In Case 4, the BES algorithm again achieved the best fitness value of 909.1923. TSO ranked fourth with 909.2154, indicating that BES is more effective in this scenario. Across all four test cases, BES consistently achieved the best fitness value, demonstrating

its superior ability to converge toward the optimal solution. TSO showed competitive performance, particularly in Case 1 and Case 2, but was generally outperformed by BES.

Comparison analysis of BES and TSO, in the case of IEEE 57-bus system, with EO, MPA, AEO, and SMA algorithms was also performed and its results are illustrated in Table 6. In Case 1, the BES algorithm achieved a fitness value of 31653.2848, which was the best among all the algorithms. TSO followed with a fitness of 31686.7372, indicating slightly less effective optimization compared to BES. In Case 2, BES again achieved the best fitness value of 31973.0772, slightly ahead of TSO at 32027.2558. In Case 3, BES again showed superior performance with a fitness value of 31666.1274. TSO ranked second with 31704.4709, while EO achieved a fitness of 31696.1040. MPA (Amroune, 2022) (31694.7374), AEO (Amroune, 2022) (31699.0802), and SMA (Amroune, 2022) (31696.8172) had very similar fitness values, indicating that the optimization performance of these algorithms was almost identical in this case. In Case 4, BES maintained its leadership with a fitness value of 31674.6323, followed by TSO at 31716.9827. Across all four cases, BES consistently achieved the best fitness value, demonstrating its robust optimization capability. TSO showed competitive performance but was slightly outperformed by BES in most cases.

Table 5. Comparison of the obtained results for the IEEE 30-bus system

Case #	Algorithm	Fitness	Total cost (\$/h)	Fuel cost (\$/h)	Wind power cost (\$/h)	P_{loss} (MW)	VD (p.u.)	Emission (t/h)
Case 1	BES	797.3691	797.3691	367.3336	430.0355	4.4626	1.9614	0.1267
	TSO	797.3876	797.3876	367.3393	430.0668	4.4747	1.8988	0.1267
	EO (Amroune, 2022)	797.3691	797.3691	367.3351	430.0341	4.4627	1.9632	0.1267
	MPA (Amroune, 2022)	797.3798	797.3798	367.4523	429.9320	4.4689	1.9688	0.1266
	AEO (Amroune, 2022)	797.4245	797.4245	367.640	427.7838	4.4875	1.9730	0.1268
	SMA (Amroune, 2022)	797.5397	797.5397	367.4709	430.0688	4.5188	1.8231	0.1266
Case 2	BES	919.5846	823.9334	286.9317	537.0017	2.3913	2.0249	0.0946
	TSO	919.7324	826.1544	286.7449	539.4095	2.3394	2.0355	0.0941
	EO (Amroune, 2022)	919.6928	824.5102	288.4463	536.0639	2.3796	2.0487	0.0943
	MPA (Amroune, 2022)	919.6319	824.3706	285.6551	538.7155	2.3818	2.0256	0.0946
	AEO (Amroune, 2022)	919.7517	824.5134	286.6954	537.8180	2.3810	2.0505	0.0944
	SMA (Amroune, 2022)	920.1276	824.5868	287.6572	536.9296	2.3885	2.0274	0.0944
Case 3	BES	809.7623	800.2974	365.5029	434.7945	5.3904	0.0946	0.1258
	TSO	810.9260	800.5517	357.2473	443.3044	5.2276	0.1039	0.1232
	EO (Amroune, 2022)	810.0825	800.2323	366.1098	434.1225	5.3873	0.0985	0.1261
	MPA (Amroune, 2022)	809.8394	801.2906	363.6851	437.6055	5.2916	0.0955	0.1247
	AEO (Amroune, 2022)	810.3387	800.2900	366.5951	433.6949	5.4027	0.1005	0.1257
	SMA (Amroune, 2022)	810.2878	800.2581	360.3164	439.9417	5.2557	0.1003	0.1245
Case 4	BES	909.1923	806.0785	324.3238	481.7547	3.2719	1.9900	0.1031
	TSO	909.2154	806.0030	323.2232	482.7798	3.2768	1.9919	0.1032
	EO (Amroune, 2022)	909.1960	806.0748	324.3218	481.7530	3.2739	1.9934	0.1031
	MPA (Amroune, 2022)	909.1980	806.0861	324.1114	481.9747	3.2714	1.9991	0.1033
	AEO (Amroune, 2022)	909.2117	806.2652	324.9920	481.2732	3.2661	1.9736	0.1029
	SMA (Amroune, 2022)	909.4127	806.2848	325.7623	480.5225	3.3526	1.7481	0.1031

5. CONCLUSION

Integrating wind power into OPF problem presents significant challenges due to the stochastic and intermittent nature of wind energy. Addressing these challenges has driven the development of innovative methodologies that optimize power flow while ensuring system reliability, stability, and efficiency. Recent advancements have introduced sophisticated algorithms and models that incorporate wind power uncertainty, emissions reduction, and operational constraints. This study focuses on solving

the OPF problem with a detailed representation of wind power uncertainty. It introduces the BES and TSO algorithms as effective tools for optimizing OPF in wind-thermal systems. These algorithms address multiple objectives, including minimizing costs of fossil and wind power generation, reducing power losses, improving voltage profiles, and lowering emissions. Simulations conducted on IEEE 30-bus and 57-bus test systems validate the superior performance of BES and TSO algorithms compared to other advanced optimization techniques.

A key limitation of this study lies in the reliance on the Weibull distribution to model wind speed uncertainty. While this distribution is widely adopted due to its simplicity and effectiveness, the choice of its shape and scale parameters has a direct impact on the estimation of wind power variability. In particular, these parameters significantly influence the expected reserve requirements and associated penalty costs resulting from wind power deviations. An inaccurate representation may lead to either overestimation of reserve allocation, increasing operational costs, or underestimation, potentially compromising system reliability. Future research should investigate alternative uncertainty modeling approaches, including empirical distributions derived from real wind data, as well as hybrid and data-driven models that better capture temporal and spatial correlations. Additionally, integrating scenario-based stochastic formulations and distributional robust optimization frameworks could provide a more accurate and resilient representation of uncertainty, ultimately improving decision-making in OPF problems with high renewable penetration. Moreover, the proposed approach has been validated on the IEEE 30-bus and 57-bus test systems, which are widely used benchmarks for OPF studies. Validation on larger practical power systems remains an important extension to further confirm scalability, computational efficiency, and applicability under realistic large-scale operating conditions.

Table 6. Comparison of the results obtained for the IEEE 57-bus system

Case #	Algorithm	Fitness	Total cost (\$/h)	Fuel cost (\$/h)	Wind power cost (\$/h)	P_{loss} (MW)	VD (p.u.)	Emission (t/h)
Case 1	BES	31653.2848	31653.2848	30618.2337	1035.0511	15.03	0.6409	1.1323
	TSO	31686.7372	31686.7372	30654.4646	1035.0518	16.3915	0.6788	1.1574
	EO (Amroune, 2022)	31589.1037	31589.1037	30663.09	925.7431	16.0990	1.5544	1.1352
	MPA (Amroune, 2022)	31593.4077	31593.4077	30668.32	925.7431	16.0473	1.6418	1.1208
	AEO (Amroune, 2022)	31603.2534	31603.2534	30678.25	925.7407	16.4772	1.4074	1.1366
	SMA (Amroune, 2022)	31609.8821	31609.8821	30690.07	925.4033	16.5407	1.3353	1.1320
Case 2	BES	31973.0772	31663.2068	30628.1551	1035.0517	14.0850	0.6342	1.0963
	TSO	32027.2558	31691.1446	30656.0928	1035.0518	15.2777	0.6744	1.1098
	EO (Amroune, 2022)	32190.3406	31621.0727	30695.33	925.7427	14.2352	1.7383	1.0746
	MPA (Amroune, 2022)	32201.3907	31626.1730	30700.43	925.7430	14.3818	1.6722	1.0577
	AEO (Amroune, 2022)	32215.6634	32630.9430	31705.20	925.7430	14.6316	1.1586	1.0860
	SMA (Amroune, 2022)	32198.4505	31626.2803	30700.54	925.7403	14.3170	1.5874	1.0714
Case 3	BES	31666.1274	31653.0712	30618.0201	1035.0511	15.0508	0.6217	1.1288
	TSO	31704.4709	31690.5627	30655.5109	1035.0518	15.5299	0.6851	1.0920
	EO (Amroune, 2022)	31696.1040	31621.9631	30696.22	925.7431	16.5111	0.7534	1.1414
	MPA (Amroune, 2022)	31694.7374	31618.1730	30692.43	925.7430	16.6794	0.7710	1.1259
	AEO (Amroune, 2022)	31699.0802	31623.8749	30698.14	925.7349	16.7252	0.7570	1.1140
	SMA (Amroune, 2022)	31696.8172	31624.1885	30698.45	925.7385	16.7858	0.7348	1.1346
Case 4	BES	31674.6323	31653.3318	30618.2801	1035.0517	15.0272	0.6299	1.1254
	TSO	31716.9827	31695.8846	30660.8328	1035.0518	16.2865	0.6757	1.1317
	EO (Amroune, 2022)	31615.9700	31593.8331	30668.09	925.7431	16.1703	1.5718	1.1359
	MPA (Amroune, 2022)	31620.0766	31598.1731	30672.43	925.7431	16.0919	1.4497	1.1107
	AEO (Amroune, 2022)	31624.9099	31602.9922	30677.25	925.7422	16.3273	1.2340	1.1228
	SMA (Amroune, 2022)	31624.8453	32601.6123	31675.87	925.7423	16.3186	1.4107	1.1345

NOMMENCLATURE

a_i, b_i, c_i	Cost coefficients of the i th thermal generator		
B_{ij}	Susceptance between buses i and j		
c	Scale parameter of Weibull distribution		
C_{pwj}	Underestimation cost coefficient		
C_{rwj}	Reserve cost coefficient		
d_j	Direct cost coefficient		
E	Total emission		
$E(Y_{oe,j})$	Expected overestimated wind energy		
$E(Y_{ue,j})$	Expected unutilized wind energy		
f_1	Total thermal generation cost		
f_3, f_4, f_5	Combined objective functions		
G_{ij}	Conductance between buses i and j		
k	Shape parameter of Weibull distribution		
N_b	Number of buses		
N_C	Number of shunt compensators		
N_G	Number of generators		
N_T	Number of transformers		
N_{TG}	Number of thermal generators		
N_{wg}	Number of wind generators		
P_{best}	Best solution found		
P_{mean}	Mean population position		
P_{Gi}	Active power output of the i th thermal generator		
P_{di}, Q_{di}	Active and reactive load demand		
P_{gi}, Q_{gi}	Active and reactive power generation		
P_i	Current solution position		
P_{loss}	Transmission power loss		
$P_{new,i}$	Updated solution position		
V_i, V_j	Voltage magnitudes at buses i and j		
VD	Voltage deviation index		
v_{IN}	Cut-in wind speed		
v_{OUT}	Cut-out wind speed		
v_R	Rated wind speed		
w_j	Available active wind power of the j th turbine		
$WPCost_{dir,j}$	Direct wind power cost of the j th turbine		
$WPCost_{oe,j}$	Overestimation cost of the j th wind turbine		
$WPCost_{ue,j}$	Underestimation cost of the j th wind turbine		
w_r	Rated wind power		
$x_i(i), y_i(i)$	Control functions in search phase		
<i>Greek letters</i>			
$\alpha, \beta, \gamma, \omega, \mu$	Emission coefficients	λ_E	Weight factor for emissions
δ_i, δ_j	Voltage angles at buses i and j	λ_{VD}	Weight factor for voltage deviation
δ_{ij}	Voltage angle difference	λ_{loss}	Weight factor for power loss

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