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An Enhanced Sparrow Search Algorithm for Solving Optimal Power Flow Problem Considering Renewable Energy Systems

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Abstract: In this paper, an enhanced sparrow search algorithm (ESSA) is proposed to solve the optimal power flow (OPF) problem of power systems considering renewable energy systems. Two modifications were introduced to the basic SSA to overcome its weak global search capability. Elite reverse learning strategy for diversifying the population and mutation strategy of firefly algorithm (FA) to achieve a fast convergence rate. The effectiveness of the ESSA is analysed for two types of power systems: conventional power systems with only thermal power plants and modern power systems with thermal and renewable energy power plants. A multi-objective optimisation problem considering the operational cost of power plants and greenhouse gas (GHG) emissions was formulated with multiple power system variables and its operational equal and unequal constraints. The effectiveness of ESSA was verified on standard IEEE 14-bus and IEEE 30-bus test systems without RE plants and compared with the literature. In addition, a real-time Andhra Pradesh, an Indian power system with 14-bus is simulated with RE systems. In the 14-bus test system, the cost is reduced by 89.97 \$/h, the losses are reduced by 4.106 MW, the voltage deviation is reduced by 0.1276 p. u., and GHG emissions are reduced by 8407.86 lb/MWh. In the 30-bus test system, the cost was reduced by 73.1 \$/h, the losses were reduced by 3.962 MW, the voltage deviation was reduced by 0.00459 p. u., and GHG emissions were reduced by 8113 lb/MWh. On the other hand, in a real-time system, the cost is reduced by 114.41 \$/h, the losses are reduced by 1.177 MW, the voltage deviation is reduced by 0.1116 p. u., and GHG emissions are reduced by 75560.13 lb/MWh. The obtained results confirm that the proposed ESSA outperforms the basic SSA and other competitive meta-heuristics, namely the grasshopper optimisation algorithm (GOA), whale optimisation algorithm (WOA), and moth-flame optimisation (MFO), to solve the OPF problem. However, embedding RE plants in the OPF problem has resulted in significant reductions in operating costs and GHG emissions, which are the need of the present world with rising fossil fuel costs and increasing global warming.

Keywords: Elite reverse learning strategy, Firefly algorithm, Multi-objective optimization, Optimal power flow, Renewable energy systems, Sparrow search algorithm.

1. Introduction

In recent times, power system security and reliability optimisation, considering economic and environmental goals, have become increasingly important owing to ever-increasing fossil fuel prices and the dangerous alarm bells of global warming. The primary goal of any power system is to meet the ever-increasing demand for electricity at the lowest possible cost without compromising security and reliability. Optimal power flow (OPF) is one of the solution techniques to achieve this target by determining the generation levels for all power plants and corresponding control variables such as generator voltage magnitudes, reactive power outputs, tap-changing transformer settings, and other volt/VAr controls in the power system by maintaining bus voltage magnitudes within tolerable limits and transmission line currents within their specified limits [1].

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On the other hand, the major pollutants in greenhouse gas (GHG) emissions are carbon dioxide (CO2), nitrogen oxides (NOX), and sulphur dioxide (SO2). Among these, CO2 makes the highest contribution (approximately 70%), followed by particulate matter from conventional power systems with thermal power plants. In this regard, it is essential to adopt various sustainable practices in all sectors, particularly renewable energy (RE) technologies for power systems and electric vehicles (EVs) for the transportation sector.

In light of these aspects, the OPF problem becomes a multi-objective, multi-variable, and multi-constraint optimisation problem. Furthermore, the consideration of RE power plants in the OPF problem becomes more complex and a non-linear, non-convex problem owing to their intermittent nature. The OPF problem is addressed for multiple objectives, such as minimisation of real and reactive power costs, transmission loss reduction, CO_2 emission reduction, maximisation of voltage stability, transmission system loadability, and voltage profile improvement. These objectives are also used to formulate multi-objective functions [2]. In the literature, many methods are used for solving OPF problems, which can be classified as traditional approaches, numerical approaches, and heuristic or meta-heuristic approaches. Considering the drawbacks of traditional approaches, the OPF is potentially addressed by heuristic and meta-heuristic approaches [3].

In [4], a fuzzy adaptive hybrid approach, namely FAHSPSO-DE, was proposed using self-adaptive particle swarm optimisation (SPSO) and differential evolution (DE) for solving multi-objective OPF focusing on generation cost, real power loss, and GHG emission. The effectiveness of FAHSPSO-DE was tested on IEEE 30-, 57-, and 118-bus test systems. In [5], the whale optimisation algorithm (WOA) and modified moth flame optimisation (MMFO) are hybridised for formulating the WMFO towards the OPF solution. minimisation of cost and voltage deviation is aimed at and verified for its effectiveness in IEEE 14-, 30-, 39-, 57-, and 118-bus test systems. In [6], a modified pigeon-inspired optimisation with the constraint-objective sorting rule (COSR) was proposed to overcome the constraint violation problem in conventional Pareto solutions while solving the OPF problem with respect to generation cost, real power loss, and emission optimisation. Simulations were performed on IEEE 30-, 57-, and 118-bus test systems with valve-point loading. In [7], a gradient-based optimiser for solving multi-objective optimal power-flow problems was presented. In [8], gorilla troop optimisation (GTO) was proposed for the OPF considering the valve-point loading effect. The major objectives are cost optimisation and loss reduction. In [9], an improved Archimedes optimisation algorithm (IAOA) with a dimension-learning-based strategy was introduced for OPF in modern power systems with offshore wind farms. In [10], a hybrid gradient-based and moth-flame algorithm (GMFA) was proposed, considering the optimal placement and sizing of FACTS devices and wind power. In [11], the cost, valve-point loading effect, loss, voltage deviation, and emission were optimised in the multiobjective OPF (MOOPF) problem and solved using a novel approach based on a modified and hybrid flower pollination algorithm to solve multi-objective optimal power flow (MHFPA). In [12], with cost minimisation as the major objective function, the OPF problem is solved using ant colony optimisation (ACO), considering transient stability as the major benefit to the power system.

In a power system, reactive power plays a key role in maintaining the stability and security of the transmission system. Thus, it is essential to optimise the reactive power flow in the entire power system. In [13], hybrid grey wolf optimisation and PSO (GWO-PSO) were proposed for the OPF, considering reactive power optimisation. In [14], a chaotic bat algorithm (CBA) is applied for optimal reactive power dispatch. In [15], the economic, environmental, and technical operation of power networks with high renewable penetration was investigated using a multi-objective coronavirus herd immunity algorithm (MOCHIA).

At this point, it is essential to realise that active and reactive power optimisation via meta-heuristics is a continuous optimisation problem in electrical engineering. However, the modes of operation and control in power systems have changed dramatically owing to the integration of renewable energy (RE) sources. Although they are an alternative and potential solution for pollution reduction in the power sector, their intermittency has become a challenge for power system engineers. In this connection, the reformation of the OPF problem with RE sources and its solution leads to further complicated and nonlinear problems. Recently, some researchers have attempted OPF with RE using meta-heuristics. A modified Rao-2 algorithm (MRao-2) [16], gorilla troops algorithm (GTA) [17], manta ray foraging optimisation (MRFO) [18], an adaptive differential evolutionary algorithm (ADEA) [19], slime mould algorithm (SMA) [20], mixed-integer nonlinear programming (MINLP) [21], an improved grey wolf algorithm [22], an adaptive grasshopper optimization algorithm (AGOA) [23] and modified honey badger algorithm (MHBA) [24] are such recent works. However, according to the no-free-lunch (NFL) theorem [25], most heuristic algorithms suffer from pre-convergence problems owing to their poor exploration and/or exploitation characteristics. Thus, as seen in the above literature, many have proposed improvements and hybridisation to overcome the above-mentioned issues. Moreover, as per NLF, many researchers have been motivated to introduce new algorithms. The extended stochastic coati optimiser (ESCO) [26], swarm magnetic optimiser (SMO) [27], walk-spread algorithm (WSA) [28], four directed search algorithms (FDSA) [29], and migrating walrus algorithm (MWA) [30] are recent meta-heuristics for addressing various real-time optimisation problems. The Sparrow search algorithm (SSA) is a recent and efficient algorithm, but it suffers from slow convergence [31]. Since its introduction, SSA has attracted various real-time optimisation problems and has been subjected to improvements and advancements [32]. In this regard, this study has adapted two modifications to the basic SSA to overcome its weak global search capability. Elite reverse learning strategy for diversifying the population and mutation strategy of the firefly algorithm (FA) to achieve a fast convergence rate [33]. For the first time, SSA with these improvements (ESSA) was adapted to solve OPF problems with RE sources. Compared to the literature, the following are the major contributions of this study.

- Formulation and solution of OPF incorporating important real-world factors. Advances in solving OPF with high renewable penetration.
- Novel metaheuristics are proposed to overcome the limitations of the existing algorithms. Improvements to the sparse search algorithm to accelerate convergence for OPF.
- Elite reverse learning and firefly mutation strategies were incorporated for the first time to enhance the global search ability.
- Simulations were performed on standard IEEE 14-bus, 30-bus, and a real-time 14-bus Andhra Pradesh power system with renewable sources.

The remainder of the paper is structured as follows: the problem formulation is explained in section 2, the solution methodology is covered in section 3, the results of OPF without RE sources are explained in section 4, the results of OPF with RE sources are explained in section 5, and the important research findings are presented in section 6 in detail.

2. Problem formulation

The OPF is mainly non-convex and non-linear problem and that can be represented as minimization problem, mathematically,

$$\min F\,(x,u) \tag{1}$$

Subjected to:

$$g(x,u) = 0, p = 1,2,\dots,m \tag{2}$$

$$h(x,u) \leq 0, p = 1,2,\dots,n \tag{3}$$

In the OPF problem, active and reactive power generations at slack buses, reactive power generations at generator buses, voltage magnitudes of load buses, and branch power flows are the state variables. On the other hand, real power generation and voltage magnitudes of generators, tap-changer controls, and shunt VAr controls are the major control or independent variables.

$$x = \begin{bmatrix} P_{g,1} \\ Q_{g,1}, Q_{g,2}, \dots, Q_{g,ng} \\ V_{l,1}, V_{l,2}, \dots, V_{l,nl} \\ S_{l,1}, S_{l,2}, \dots, S_{l,ntr} \end{bmatrix} \tag{4}$$

$$u = \begin{bmatrix} P_{g,2}, P_{g,3}, \dots, Q_{g,ng} \\ V_{g,1}, V_{g,2}, \dots, V_{g,ng} \\ a_{t,1}, a_{t,2}, \dots, a_{t,ntap} \\ Q_{sh,1}, Q_{sh,2}, \dots, Q_{sh,nsh} \end{bmatrix} \tag{5}$$

2.1 Objective functions

Minimization of generation cost (f_1), loss (f_2), and voltage deviation (f_3) are considered in this paper to formulate multi-objective problem while solving OPF in conventional power systems consisting of only thermal power plants. On the other hand, reduction of emission (f_4) is also considered while solving OPF in modern power systems consisting of both thermal and RE power plants.

$$f_1 = P_{cost} = \sum_{k=1}^{ng}\left[a_k P_{g,k}^2 + b_k P_{g,k} + c_k\right] \tag{6}$$

$$f_2 = P_{loss} = \sum_{k=1}^{ntr}\left[P_{k(i,j)} + P_{k(j,i)}\right] \tag{7}$$

$$f_3 = V_{dev} = \sum_{k=1}^{nb}\left[1 - V_{l,k}\right] \tag{8}$$

$$f_4 = GHG_{em} = (CO_2 + SO_2 + NO_x) \times P_{g,1} \tag{9}$$

2.2 Equality constraints

The real and reactive power balances are the major equality constraints in OPF problem.

$$\sum_{k=1}^{ng} P_{g,k} + \sum_{k=1}^{nrg} P_{rg,k} = P_{loss} + \sum_{k=1}^{nl} P_{l,k} \quad (10)$$

$$\sum_{k=1}^{ng} Q_{g,k} + + \sum_{k=1}^{nrg} Q_{rg,k} + \sum_{k=1}^{nsh} Q_{sh,k} = Q_{loss} + \sum_{k=1}^{nl} Q_{l,k} \quad (11)$$

2.3 Inequality constraints

The real power generation, reactive power generation and voltage magnitude limits at thermal power plants, tap-changer limits, shunt VAr limits, and line power flow limits are the major inequality constraints in OPF problem.

$$P_{g,k(min)} \leq P_{g,k} \leq P_{g,k(max)}, k = 1{:}ng \quad (12)$$

$$Q_{g,k(min)} \leq Q_{g,k} \leq Q_{g,k(max)}, k = 1{:}ng \quad (13)$$

$$V_{g,k(min)} \leq V_{g,k} \leq V_{g,k(max)}, k = 1{:}ng \quad (14)$$

$$a_{t,k(min)} \leq a_{t,k} \leq a_{t,k(max)}, k = 1{:}ntap \quad (15)$$

$$Q_{sh,k(min)} \leq Q_{sh,k} \leq Q_{sh,k(max)}, k = 1{:}nsh \quad (16)$$

$$S_{l,k} \leq S_{l,k(max)}, \quad k = 1{:}ntr \quad (17)$$

For satisfying each constraint, a penalty function is introduced to the multi-objective function.

$$F = \sum_{k=1}^{nf} f_k + \sum_{k=1}^{nx} \gamma_k \left[x_k - x_{k(lm)}\right]^2 \quad (18)$$

$$x_{k(lm)} = x_{k(max)} - 0.25\left[x_{k(max)} - x_{k(min)}\right] r_k \quad (19)$$

3. Solution methodology

In this section, the proposed OPF is solved by adapting sparrow search algorithm (SSA) with elite reverse learning strategy and mutation strategy of firefly algorithm (FA).

3.1 Basic sparrow search algorithm

The sparrow search algorithm (SSA) optimises swarm intelligence based on sparrow eating and predator avoidance. The sparrows who discover better food behave as finders, and the others follow. The initial position of sparrows and their respective fitness functions are given in Eq. (20) and (21), respectively.

$$S = \begin{bmatrix} s_{1,1} & s_{1,2} & \cdots & s_{1,d} \\ s_{2,1} & s_{2,2} & \cdots & s_{2,d} \\ \vdots & \vdots & \ddots & \vdots \\ s_{n,1} & s_{n,2} & \cdots & s_{n,d} \end{bmatrix} \quad (20)$$

$$F(S) = \begin{bmatrix} F[s_{1,1} & s_{1,2} & \cdots & s_{1,d}] \\ F[s_{2,1} & s_{2,2} & \cdots & s_{2,d}] \\ & \vdots & & \\ F[s_{n,1} & s_{n,2} & \cdots & s_{n,d}] \end{bmatrix} \quad (21)$$

where *n* and *d* represent the number of sparrows and dimension of search variables in the problem, respectively, $s_{i,j}$ represents the *i*th sparrow position in *j*th dimension, $F(S)$ is the fitness of each sparrow, At the stage, the minimum fitness function and corresponding sparrow population will be treated as pre-iterative best fitness and solution variables, respectively.

The finders guide the populace with greater fitness levels and prioritise food during the search. Thus, the discoverers can search a larger region for food than the participants. The sparrow sings to alert predators. The finder will take players to safer foraging sites if the alarm value exceeds the safety value. Each iteration updates the sparrow finder location:

$$s_{i,j}^{k+1} = \begin{cases} s_{i,j}^{k} \times exp^{(-i/r_1 k_{max})} & if\ r_3 < \delta \\ s_{i,j}^{k} + r_2 \propto & if\ r_3 \geq \delta \end{cases} \quad (22)$$

where $r_1 \in (0,1]$, $r_1 \in [0,1]$, $r_3(\in [0,1])$ and $\delta(\in [0.5,1])$ are the random numbers, respectively; k and k_{max} represent the iteration number and maximum iterations, respectively; If every item in a dimensioned matrix is 1, then $\propto$ is set to 1.

There are no predators if $r_3 < \delta$, and the finder enters extensive search mode. All sparrows must depart for safety if $r_3 \geq \delta$ because some sparrows have come into contact with predators.

Energy loss in an entry group leads to decreased foraging opportunities, potentially causing immigrants to flee. Sparrows can locate locators and forage near or collect food from them. Some observe finders to intensify predation and engage in competition, with winners receiving the finder's meal immediately. The formula for updating the enrolee position is:

$$s_{i,j}^{k+1} = \begin{cases} r_2 \times exp^{\left(\frac{s_{worst}^{k} - s_{i,j}^{k}}{k^2}\right)} & if\ i < \frac{n}{2} \\ s_{i,j}^{k+1} + \left|s_P^{k} - s_P^{k+1}\right| r_4^{+} \propto & else \end{cases} \quad (23)$$

where s_{worst}^{k} is the worst position in iteration k, r_4^{+} is a *d*-dimensional random number between [1, -1];

$r_4^+ = r_4^T(r_4 r_4^T)^{-1}$. $if\ i < \frac{n}{2}$, it implies that the ith competitor is unfit and is going to starve.

Threat alertness affects 10%–20% of sparrows, which randomly determines where they land at the beginning. The sparrows in the midst of the group will wander around randomly to get close to other sparrows, while the sparrows on the edge of the group that are aware of danger will quickly fly to the safe region to better their position. The mathematical model of scout is:

$$s_{i,j}^{k+1} = \begin{cases} s_{best}^k + \tau.\left|s_P^k - s_{best}^k\right| & if\ F_i > F_g \\ s_{i,j}^k + r_5\left[\frac{s_{i,j}^k - s_{worst}^k}{(F_i - F_w) + \varepsilon}\right] & if F_i = F_g \end{cases} \tag{23}$$

where r_5 is the sparrow movement direction as a random number [1, 1], s_{best}^k is the current global ideal position, and τ is a step size control parameter represented by a normal distribution of random numbers with a mean of 0 and a variance of 1. The global, worst and current fitness values for the optimisation problem are represented by F_g, F_w and F_i. Here ε is used as the smallest constant to prevent zero division error. For ease of understanding, when it is safe, s_{best}^k, around the middle, $F_i > F_g$ indicates that sparrows are towards the edge of the group; otherwise, $F_i = F_g$ shows that sparrows in the population are aware of the danger sparrow.

3.2. Enhanced sparrow search algorithm

According to elite learning strategy, the opposite sparrows of a vector S_i in d-dimensional space may be stated as follows if it is in the range $[a_i, b_i]$. The original forward solution set and the reverse solution set are regarded as fitness values according to the forward sparrow and reverse sparrow taken together, and the inverse vectors of all solutions in the optimisation space are calculated. By using direct screening or other optimisation techniques, it is possible to quickly converge to the optimal solution by selecting the sparrows in the d-dimensional solution space with the highest fitness value as a new optimisation group.

3.2.1. Elite reverse learning strategy

The new optimisation group is created by the elite strategy, which gathers the original and inverse solution vectors and produces new solutions at a specific rate to join the original and inverse solution set. The mathematical form that was optimised produces $S_{i,new}$:

$$S_i = a_i + b_i - S_i \tag{24}$$

$$S_{i,new} = S_i \times \varphi \times \frac{rand(-0.5,\ 0.5)}{d} \tag{25}$$

where φ is the Euclidean distance between the best answer and the next-closest solution is S_i. The 20% and d-dimension solutions $s_{i,worst}^k$ with the worst fitness values are deleted to create a new optimisation group after sorting the fitness values of the solution vectors in the new set.

3.2.2 Mutation strategy of firefly algorithm

The firefly algorithm (FA) [34] draws in additional fireflies by using light. The FA demonstrates how SSA's performance can be enhanced by optimisation processing's mutations, quick convergence, and few parameters. To create new solutions, the SSA's update formula in Eq. (26) is hybridised with the FA's mutation strategy equation.

$$s_{i,j}^{k+1} = \begin{cases} s_{best}^k + \tau_1.\left|s_{i,j}^k - s_{best}^k\right| + \rho(r_6 - 0.5) & if\ F_i > F_g \\ s_{i,j}^k + r_7\left[\frac{s_{i,j}^k - s_{worst}^k}{(F_i - F_w) + \varepsilon}\right] & if F_i = F_g \end{cases} \tag{23}$$

where τ_1 and ρ are the step-size control parameters, r_6 and r_7 are random numbers. By increasing search accuracy and convergence speed, these two changes considerably improve the performance of basic SSA [31].

4. Results on standard IEEE test systems and comparison study

In order to validate the effectiveness of proposed ESSA, the simulation results are performed on IEEE 14-bus and IEEE 30-bus test systems. The data of the test systems are taken from MATPOWER [35].

4.1 IEEE 14-bus system

In basic 14-bus system, there are two thermal power plants at buses 1 and 2 are scheduled for supplying total active and reactive power loads of 259 MW and 73.5 MVAr, respectively. The total transmission losses are 13.393 MW and 54.54 MVAr, respectively.

By implementing OPF with ESSA, the network performance is changed as follows: the total transmission losses are reduced to 9.287 MW and

Table 1. Generation schedule in IEEE 14-bus

Gen #	Schedule (MW + j MVAr)	
	Base case	OPF
1	232.39 – j 16.55	194.33 + j 0.00
2	40.00 + j 43.56	36.72 + j 23.69
3	0.00 + j 25.08	28.74 + j 24.13
6	0.00 + j 12.73	0.00 + j 11.55
8	0.00 + j 17.62	8.50 + j 8.27
f_1	8171.6	8081.64
f_2	13.393 + j 54.54	9.287 + j 39.16
f_3	0.6786	0.5511
f_4	557779.15	549371.29

Table 2. Comparison of ESSA with literature for IEEE 14-bus system

Method	f_1	f_2	f_3	f_4
WMFO [6]	8082.128	9.379	0.621	–
GOA	8082.24	9.299	0.001	549395.9
WOA	8083.66	9.324	0.553	549447.1
MFO	8084.38	9.336	0.553	549471.6
SSA	8085.10	9.348	0.554	549496.2
ESSA	8081.637	9.287	0.551	549371.3

39.16 MVAr, respectively. The generation schedule before and after OPF are given in Table 1. In base case schedule, generators at buses 3, 6 and 8 are scheduled for only reactive power to maintain specified voltage magnitudes. On the other hand, OPF has resulted for schedule at all generators except at bus-6. The operating cost (f_1) in \$/h, loss (f_2) in (MW + j MVAr), and voltage deviation (f_3) in p.u and emission (f_4) in lb/MWh for both the cases are given in the same table. The cost is reduced by 89.97 \$/h, the losses are reduced by 4.106 MW, the voltage deviation reduced by 0.1276 p.u and GHG emissions are reduced by 8407.86 lb/MWh.

The simulation results obtained by ESSA are compared with literature in Table 2. The effectiveness of ESSA is compared with GOA, WOA, MFO, SSA and WMFO [6]. The results of ESSA are very competitive to WMFO [6] and GOA, where as they are very superior to WOA, MFO and SSA with low objective functions.

4.2 IEEE 30-bus system

In basic 30-bus system, there are two thermal power plants at buses 1 and 2 are scheduled for supplying total active and reactive power loads of 283.4 MW and 126.2 MVAr, respectively. The total transmission losses are 17.557 MW and 54.54 MVAr, respectively.

Table 3. Generation schedule in IEEE 30-bus

Gen #	Schedule (MW + j MVAr)	
	Base case	OPF
1	260.96 – j 20.42	176.29 + j 0.20
2	40.00 + j 56.07	48.79 + j 19.02
5	0.00 + j 35.66	21.50 + j 29.30
8	0.00 + j 36.11	22.04 + j 44.63
11	0.00 + j 16.06	12.20 + j 6.72
13	0.00 + j 10.45	12.01 + j 4.22
f_1	875.3	802.2
f_2	13.393 + j 54.54	9.431 + j 37.67
f_3	0.9082	0.9036
f_4	607743.03	599630.04

Table 4. Comparison of ESSA with literature for IEEE 30-bus system

Method	f_1	f_2	f_3	f_4
WMFO [6]	804.209	9.956	0.099	–
MHFPA [11]	867.8159	5.6303	–	–
ESSA	802.20	9.431	0.551	

By implementing OPF with ESSA, the network performance is changed as follows: the total transmission losses are reduced to 9.431 MW and 37.67 MVAr, respectively. The generation schedule before and after OPF are given in Table 3. In base case schedule, generators at buses 3, 6 and 8 are scheduled for only reactive power to maintain specified voltage magnitudes. On the other hand, OPF has resulted for schedule at all generators except at bus-6. The cost is reduced by 73.1 \$/h, the losses are reduced by 3.962 MW, the voltage deviation reduced by 0.00459 p.u and GHG emissions are reduced by 8113 lb/MWh.

The simulation results obtained by ESSA are compared with literature in Table 4. The effectiveness of ESSA is compared with GOA, WOA, MFO, SSA and WMFO [6], and MHFPA [11]. The results of ESSA are very competitive to WMFO [6], where as they are very superior to MHFPA [11] with low objective functions.

5. Results on modified IEEE test systems with renewable energy systems

In this scenario, some of the generator locations are treated as PV and WT systems and correspondingly, OPF is solved in real-time Andhra Pradesh, Indian power system. The data of Andhra Pradesh 14-bus system is taken from [36].

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Table 5. Generation schedule in IEEE 14-bus

Gen # (Type)	**Schedule (MW + j MVAr)**	
	Without RES	**With RES**
1 (T)	158.45 + j 10.00	145.92 + j 10.01
2 (T)	44.45 + j 10.45	41.77 + j 16.76
3 (T)	20.02 + j 23.4	19.47 + j 20.66
6 (T)	33.63 + j 2.09	5.00 – j 6.00
8 (T)	9.99 + j 11.48	17.56 + j 11.72
f_1	711.19	596.78
f_2	7.541 + j 28.73	6.364 + j 24.02
f_3	0.5245	0.412943399
f_4	545793.96	470233.83

5.1 OPF without RES systems

In this case, the ESSA OPF is performed without considering any RES systems and the results are given in Table 5.

5.2. OPF with RES systems

In this case, a 10 MW photovoltaic system at Karnool (bus-11) and a 30 MW onshore Wind Power Plant at Anantapur (bus-13) are considered. Excluding peak generations of (7.87 + j 5.1) MVA at bus-11 and (27.85 – j 4.96) at bus-13 due to PV and WT, respectively, the OPF is performed. The simulation results of ESSA are given in Table 5.

The cost is reduced by 114.41 $/h, the losses are reduced by 1.177 MW, the voltage deviation reduced by 0.1116 p.u and GHG emissions are reduced by 75560.13 lb/MWh.

6. Conclusions

This paper proposes an extended sparrow search algorithm (ESSA) for power system optimal power flow (OPF), including renewable energy systems. A multi-objective optimisation problem with numerous power system variables and equal and unequal operational constraints considers power plant operating costs and GHG emissions. The effectiveness ESSA is verified on standard IEEE 14-bus and IEEE 30-bus test systems without RE plants and compared with literature. Also, a re-time Andhra Pradesh, Indian power system with 14-bus is simulated with RE systems. The results show that the proposed ESSA outperforms the standard SSA, GOA, WOA, and MFO for addressing the OPF problem. However, incorporating RE plants into OPF problems has reduced operating costs and GHG emissions, which are needed in a world with rising fossil fuel prices and global warming.

Notations

u	Independent (control) variable vector
x	Dependent (state) variable vector
g	Equality constraints
h	Inequality constraints
m	Number of equality constraints
n	Number of inequality constraints
$P_{g,1}$	Real power generation by slack bus
$Q_{g,1}$	Reactive power generation by slack bus
$P_{g,ng}$	Real power generation by other generator buses
$Q_{g,ng}$	Reactive power generation by other generator buses
$V_{l,nl}$	Load bus voltage magnitudes
$S_{l,ntr}$	Apparent power flows of transmission lines
$a_{t,nt}$	Tap-settings of transformers
$V_{g,ng}$	Generator bus voltage magnitudes,
$Q_{sh,nsh}$	Shunt VAr controls
ng	Number of generator buses
nl	Number of load buses,
ntr	Number of transmission lines
$ntap$	Number of tap-changers
nsh	Number shunt var control buses
nrg	Number of RE power plants
a_k, b_k, c_k	Cost curve coefficients of *k*th thermal power plant
$P_{k(i,j)}$	Real power flows in *k*th transmission line from bus-*i* to bus-*j*
$P_{k(j,i)}$	Real power flows in *k*th transmission line from bus-*j* to bus-*i*
$P_{rg,k}$	Real power generations by RE power plant at bus-*k*
$Q_{rg,k}$	Reactive power generations by RE power plant at bus-*k*
$P_{l,k}$	Real power loads of bus-*k*
$Q_{l,k}$	Reactive power loads of bus-*k*
P_{loss}	Real power loss
Q_{loss}	Reactive power loss
min	Minimum limit of control variable
max	Maximum limit of control variable
γ_k	Penalty factors
r_k	Random number between 0 and 1
nf	Number of objective functions
x_k	Limit violated control variable
nx	Number of limit violated control variables
$x_{k(min)}$	Minimum limits of control variables
$x_{k(max)}$	Maximum limits of control variables

Conflicts of interest

The authors declare no conflict of interest.

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Author contributions

Conceptualization, methodology, software and original draft preparation are done by Narendra Babu Kattepogu; supervision, review, and formal analysis are done by G Saravanan and A Rama Koteswara Rao.

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