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A Newly Hybrid Method Based on Cuckoo Search and Sunflower Optimization for Optimal Power Flow Problem

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Abstract: The paper proposes a new hybrid method based on cuckoo search (CSA) and sunflower optimization (SFO) approach (called HCSA-SFO) for improving the performance of solutions in the optimization power system operation problem. In the power system, the optimal power flow (OPF) problem is one of the important factors which usually minimizes total cost and total active power losses while satisfying all constraints of the output power of generators, the voltage at buses, power flow on branches, the capacity of capacitor banks and steps of transformer taps. HCSA-SFO utilizes the mutation and selection mechanism in the SFO algorithm to replace the Lévy flights function in CSA. Hence, this makes HCSA-SFO avoid the fixed step size in the CSA from that can reduce run time and improve the quality of solution for the HCSA-SFO algorithm in the OPF problem. The proposed hybrid technique is simulated on the 30-buses and 118-buses systems. The obtained simulation results from the suggested technique are compared to many other approaches. The result comparisons in different cases showed that the suggested HCSA-SFO can achieve a better result than many other optimization approaches. Therefore, the suggested HCSA-SFO is also an effective approach for dealing with the OPF problem.

Keywords: sunflower optimization; optimal power flow; total fuel cost; cuckoo search algorithm; total active power losses

1. Introduction

Electric companies are constantly striving to find ways for improving effectiveness in the operation of power systems to decrease the production cost while still satisfying all security constraints. The optimal power flow (OPF) problem still plays a major role in power system operation, and it has been continuously studied for enhancing effectiveness in solving the above problems. The OPF is a nonlinear optimization issue with several parameters and numerous equations and also inequality constraints. The parameters of the OPF problem are that power generation outputs, switchable capacitor banks, voltages at buses and tap changers of transformers, while the equations and inequality constraints are real and reactive power balance constrains, the maximum and minimum limits of reactive and real power outputs, the voltage at buses, the capacity of capacitor banks and steps of transformer taps. Therefore, the OPF in power systems is one of a more difficult topic which needs an effective method for solving. Several traditional methods and optimization algorithms have been used to find an OPF solution.

A lot of traditional methods in dealing with the problem of OPF were proposed with aims of minimizing fuel cost, including method of interior point [1], a technique of nonlinear programming [2], a linear programming technique [3], quadratic programming [4] and a newton-based approach [5].

Although the traditional optimization methods have obtained some results in solving the OPF problem, they still show limits for operation in modern power systems which is always a nonlinear optimization issue. Thus, developing an effective optimization method for handling the nonlinear problems of OPF is a vital subject for the research groups of power system optimization.

Recently, many Artificial Intelligence algorithms have been proposed as one alternative promising option for dealing with the problem of OPF. In ref. [6], an improved evolutionary programming (IEP) was introduced in dealing with the OPF problem, in which the mutation and selection techniques were implemented based on Gaussian and Cauchy distributions and the probabilistic. Another search based on differential evolution (DE) to solve the OPF problem has been proposed in [7]. The DE algorithm was tested on power systems with two single-objective functions and a multiobjective function. The results have shown that DE is available to find a performance solution for the OPF problem. A particle swarm optimization (PSO) approach was presented in [8] for dealing with OPF with the multiobjective function. Wherein, a fuzzy membership function was used to choose the best value from the list of Pareto optimal values. Other optimization methods were proposed towards the problem of OPF, such as gravitational search algorithm (GSA) [9–11], differential evolutionary methods [12,13], krill herd algorithm [14], artificial bee colony method [15], an imperialist competitive method [16], an approach of biogeography-based optimization [17], Jaya algorithm [18], a hybrid PSO-GSA approach [19], a technique of improved colliding bodies optimization [20], harmony search method [21], an approach of teaching-learning-optimization [22] and the technique of black-hole-based optimization [23]. In [24], the OPF in a normal and contingent case was solved using the algorithm of improved genetics. Another method based on modified sine-cosine was proposed in [25]. The authors in [26] suggested the method of glowworm swarm optimization to solve the problem of OPF. The problem of OPF with multiobjective function was presented in [27–35].

Recently, the cuckoo search algorithm (CSA) [36,37] and sunflower optimization [38] have been proposed as two other optimization approaches in dealing with the optimization problem in power systems. Although both CSA and SFO were capable of solving the optimization problem, they showed some drawbacks of balancing exploration and exploitation when performing optimization methods in large-scale systems. Finding a suitable balance between exploitation and exploration from a combination CSA and SFO algorithms promises an effective technique for the OPF problem. With this point of view, this paper suggested a hybrid CSA and SFO (HCSA-SFO) technique in dealing with the problem of OPF. The main objective of the suggested technique is to replace the Lévy flight function in CSA using a mutation and selection mechanism in the SFO algorithm to avoid the fixed step size in the CSA, hence increasing the effective global search and improving the quality of the obtained solution. The suggested technique is simulated on the standard 30-buses and 118-buses system. Its results are compared to other methods. The simulation results show that HCSA-SFO is an effective technique to solve the OPF problem in a complex and large-scale system.

The outstanding points of the suggested technique can be listed as follows:

- Dealing with OPF frameworks with several objective functions conditions using a hybrid HCSA-SFO algorithm;
- The HCSA-SFO utilizes the mutation and selection mechanism to follow the best orientation to the sun of sunflowers from the SFO algorithm to replace the Lévy flights function in CSA. This technique helps HCSA-SFO to avoid the fixed step size in the CSA, hence the run time is reduced and the quality of solution for the HCSA-SFO algorithm in the OPF problem is improved;
- The simulation result is validated on the standard 30-buses and 118-buses systems;
- The result is compared to many previous methods, which shows the effectiveness of the suggested HCSA-SFO method in dealing with the OPF problem.

The structure of manuscript are given as follows: Section 2 of manuscript presents the OPF problem formulation, while the original CSA and SFO algorithm is presented in Section 3; Furthermore, Section 3.3 also introduces the HCSA-SFO technique and implementing HCSA-SFO for dealing with the OPF is applied in detail in Sections 3.1 and 3.2. The calculated results and comparisons to other techniques are shown in Section 4. Conclusions are described in Section 5.

2. Problem Formulation

The OPF problem is one of the optimization problems related to the operation of power systems. It is usually used to minimize the objective functions with many controlled variables while satisfying the security constraints of power systems [25]. The OPF problem can be described as follows:

$$\text{Min}\, ff(\text{x, u}) \tag{1}$$

Subject to:
- The constraints of equality and inequality.

$$\text{g(x, u)} = 0 \tag{2}$$

$$\text{h(x, u)} \le 0 \tag{3}$$

where, ff is the goal function which is optimized; g(x,u) and h(x,u) are the constraints of equality and inequality; x is the state variable vector which includes variables of slack bus's active power P_{G1}, the voltage of load bus V_L, reactive generation power Q_G and apparent power at branch S_l as shown in Equation (4); u is the control variable vector which includes variables of active generation power P_G, generator voltages V_G, tap ratio of transformer T and shunt compensation capacitor Q_c as shown in Equation (5).

$$x = [P_{G1}, V_{L1}, \ldots, V_{LN_L}, Q_{G1}, \ldots, Q_{GN_G}, S_{l1}, \ldots, S_{lN_{TL}}] \tag{4}$$

$$u = [P_{G2}, \ldots, P_{GN_G}, V_{G1}, \ldots, V_{GN_G}, T_1, \ldots, T_{N_T}, Q_{c1}, \ldots, Q_{cN_C}] \tag{5}$$

where, N_L, N_G, N_{TL}, N_T and N_C are the number of load nodes, generator nodes, transmission lines, tap transformers and the number of VAR compensators, respectively.

2.1. OPF Objective Functions

The objectives functions are minimized in the study and include fuel cost, power loss and deviation of voltage.

- Fuel cost:

$$F_C = \sum_{i=1}^{NG} F(P_{Gi}) = \sum_{i=1}^{NG} a_i + b_i P_{Gi} + c_i P_{Gi}^2 \tag{6}$$

- Total real power losses

$$F_{TL} = \sum_{k=1}^{N_{TL}} g_k \left(V_i^2 + V_j^2 - 2V_i V_j \cos\theta_{ij} \right) \tag{7}$$

- Voltage deviation

$$F_V = \sum_{i=1}^{N_L} \left| V_{Li} - V_{ref} \right| \tag{8}$$

where, a_i, b_i and c_i are cost factors of the generator i; g_k is the conductance at k_{th} line; V_i, V_j is voltages amplitude of bus i and j; θ_{ij} is voltage angle difference between bus i and j.

2.2. Constraints

- *Constraints of power balance*

$$P_{Gi} - P_{Di} - \left\{ V_i^2 G_{ii} + \sum_{\substack{j=1 \\ i \neq j}}^{N_B} V_i V_j \left[G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j) \right] \right\} = 0 \quad (9)$$

$$Q_{Gi} - Q_{Di} - \left\{ -V_i^2 B_{ii} - \sum_{\substack{j=1 \\ i \neq j}}^{N_B} V_i V_j \left[G_{ij} \sin(\delta_i - \delta_j) - B_{ij} \cos(\delta_i - \delta_j) \right] \right\} = 0 \quad (10)$$

- *The limits of power generation:*

$$P_{Gi,\min} \leq P_{Gi} \leq P_{Gi,\max},\ i = 1,\ 2,\ \ldots,\ N_G \quad (11)$$

$$Q_{Gi,\min} \leq Q_{Gi} \leq Q_{Gi,\max},\ i = 1,\ 2,\ \ldots,\ N_G \quad (12)$$

- *The limits of generator voltage bus and load voltage bus:*

$$V_{Gi,\min} \leq V_{Gi} \leq V_{Gi,\max},\ i = 1,\ 2,\ \ldots,\ N_G \quad (13)$$

$$V_{Li,\min} \leq V_{Li} \leq V_{Li,\max},\ i = 1,\ 2,\ \ldots,\ N_L \quad (14)$$

- *The limits of switchable capacitor capacity:*

$$Q_{ci,\min} \leq Q_{ci} \leq Q_{ci,\max},\ i = 1,\ 2,\ \ldots,\ N_c \quad (15)$$

- *The limits of transformer tap:*

$$T_{k,\min} \leq T_k \leq T_{k,\max},\ k = 1,\ 2,\ \ldots,\ N_T \quad (16)$$

- *The limits of transmission line:*

$$S_l \leq S_{l,\max},\ l = 1,\ 2,\ \ldots,\ N_{\mathrm{TL}} \quad (17)$$

where, N_B is the total number of nodes; P_{Di}, Q_{Di} are active and reactive power of load at bus i; G_{ij}, B_{ij} are the real and imaginary parts of the admittance between bus i and j; δ_i, δ_j are the voltage angles at bus i and j; $P_{Gi,max}$, $P_{Gi,min,}$ and $Q_{Gi,max,}$ $Q_{Gi,min}$ are the limits of active and reactive capacity outputs of generator i; $V_{Gi,max}$, $V_{Gi,min}$ and $V_{Li,max}$, $V_{Li,min}$ are the limits of the voltage magnitude of generator i and load i, respectively; $Q_{ci,max}$, $Q_{ci,min}$ and $T_{k,max}$, $T_{k,min}$ are the limits of the capacity of switchable capacitor bank and tap changer of transformer i; $S_{l,max}$ is the maximum capacity of transmission line i.

3. Implementation of HCSA-SFO for Dealing with the Problem

3.1. SFO Method

The SFO approach is inspired by nature and was proposed by G. F. Gomes, et al. in 2019 [38]. The SFO algorithm simulates the movement of the sunflower toward the sun. Sunflowers' activity is repeated every morning based on their behavior. These sunflowers search for the best orientation to the sun and move themselves to best catch the sun's radiation. In the morning, the sunflowers move toward the sun and the opposite orientation at the end of the day. The sunflowers' growing rule is repeated for the next morning. The sunflowers which are close to the sun's direction will collect more heat than those far from the sun's direction; hence they remain still in this region. On the contrary, those which are located in the region far from the sun's direction will take larger steps for moving as close to the sun as possible to the global optimum.

The steps of the SFO algorithm are:

1. Generate the population X_i^t randomly, i = 1, ..., n.
2. The fitness function $f(X_i^t)$ of sunflowers is evaluated.
3. Retain the best solutions in the sunflower population X*.
4. Modify all sunflowers headed for the best one (called sun) as Equation (18).

$$\vec{s}_i = \frac{X^* - X_i}{\|X^* - X_i\|},\ \ i = 1, 2 \ldots, n \tag{18}$$

5. Determine the direction for each sunflower by Equation (19).

$$d_i = \lambda \times P_i(\|X_i + X_{i-1}\|) \times \|X_i + X_{i-1}\|, \tag{19}$$

In which,

λ: Inertial displacement of the sunflower plants.
p_i: Pollination probability.
X_i, X_{i-1}: Current position and nearest neighbor position

6. Examine the highest step of individual as Equation (20).

$$d_{max} = \frac{\|X_{max} - X_{\min}\|}{2 \times N_{pop}} \tag{20}$$

where,

X_{min}, X_{max}: The lower and upper limits.
N_{pop}: the number of populations.

The position of new generated individual (sunflower) is updated using the as Equation (21).

$$\vec{X}_{i+1} = X_i + d_i \times \vec{s}_i \tag{21}$$

3.2. CSA Method

The CSA method was developed based on the behavior of some cuckoo breeds. The cuckoo leaves her eggs in the bird nests selected at random from other host birds. The cuckoo's egg will be brooded with a host birds' eggs by the host birds. The processing of laying and moving of cuckoos is performed according to the Lévy flight function. There are two crucial search capabilities in the CSA algorithm, global and local search, which are evaluated by a discovery rate. The Lévy flight function with infinite mean and variance is used for global search rather than the random walk technique.

There are three principle rules that are used in CSA:

- A cuckoo lays its one egg into a bird nest which is selected at random from other host birds.
- The best nests will bear to the next generation.

- A host bird may detect a strange egg by a probability pa ϵ[0, 1]. For this situation, the host bird can throw out the cuckoo's egg or leave the nest and find another place for building a new one (with new random solutions).

The CSA maintains a balance between global and the local search random which is controlled by the parameter Pa∈ [0, 1]. Equations (22) and (23) present the local and global random walks, respectively [36,37]:

$$X_i^{t+1} = X_i^t + \alpha s \otimes H(P_a - \varepsilon) \otimes (X_j^t - X_k^t) \tag{22}$$

$$X_i^{t+1} = X_i^t + \alpha L(s, \lambda) \tag{23}$$

where:

X_i, X_j and X_k: Current positions selected randomly
$\alpha > 0$: Scaling coefficient
X_i^{t+1}: Position i + 1
s: Step size
$\otimes$: Entry-wise product
H: Heaviside function
ε: Random number
L(s, λ): Lévy distribution.

The steps of are in Table 1:

Table 1. Cuckoo search algorithm (CSA) pseudocode.

Generate randomly the n nests
For $Iter$ = 1: $It_{\max}$ do
Get cuckoo (call c1) through Lévy flights technique
Validate its fitness F_{c1}
Select randomly a nest (call $c2$) among n nests
If (F_{c1} is high performance than F_{c2}) then
    Solution $c1$ substitute for $c2$
    Fitness $c1$ substitute for $c2$
End if
Desert P_a of worse nests and build new nests
Retain the best nests
Find the best so far nest $Gbest$
End for
Post processing results.

3.3. Implementation of the Hybrid CSA and SFO Method

The effective solution of the optimization approaches will be improved with a balance between exploitation and exploration. Exploration is used to ensure finding the global solution, while exploitation is performed to search the best optimal values around current good solutions. So, finding a suitable balance between exploitation and exploration from the combination of the CSA and SFO promises to be an effective technique for dealing with the optimization problem. With that viewpoint, this paper suggests a hybrid CSA and SFO (HCSA-SFO) technique for the OPF problem with several objective functions. The main objective of the suggested technique is to replace Lévy flight function in CSA by using mutation and selection mechanism in the SFO algorithm to avoid the fixed step size in CSA, in order to increase the effective global search and improving the quality of candidate solution.

The steps of the suggested HCSA-SFO technique for dealing with the OPF problem are given as below:

Step 1: Set HCSA-SFO parameters

Before performing the procedure, it is necessary to set the control parameters of HCSA-SFO, such as the population size Np, mortality rate m, pollination rate p, maximum number of iterations Nmax, probability Pa∈ [0, 1].

Step 2: Generate a population of solutions

Each solution in the population is initialized by

$$Sol_i^{(0)} = Sol_{ij}^{\min} + rand_1 \times (Sol_{ij}^{\max} - Sol_{ij}^{\min}), i = 1 \ldots n_S; j = 1 \ldots d \tag{24}$$

where Sol_i is the ith solution in population; Sol_{ijmax} and Sol_{ijmin} are upper and lower limits of the jth element in candidate solution; d is the problem's dimension and rand_1 is the random numbers in [0, 1].

Step 3: Evaluate the initial solutions in the population:

The quality of initialized solutions is evaluated by the fitness function Equation (25) via solving the power flow problem. Find the best solution (Sol_{best}) with the corresponding best fitness value $FF_{best.}$

$$FF_i^{(0)} = F + K_p(P_{G1} - P_{G1}^{\lim})^2 + K_q \sum_{i=1}^{N_G} (Q_{Gi} - Q_{Gi}^{\lim})^2 + K_v \sum_{i=1}^{N_L} (V_{Li} - V_{Li}^{\lim})^2 + K_s \sum_{l=1}^{N_{TL}} (S_l - S_{l,\max})^2 \tag{25}$$

where, F is the objective function of each case (F_C, F_{TL}, F_V) that is defined by Equations (6)–(8).
Set the iteration counter n = 1.

Step 4: Generate the first new solutions:

Create new solutions by using the mechanism of SFO. The step of each solution towards the best solution is calculated by Equations (18)–(20). The new solution of the population is updated using Equation (21).

Step 5: Evaluate the first new solutions:

Evaluate the quality of the first new solutions $Sol_i^{new(n)}$ by fitness function Equation (25) via solving the power flow problem. Update the population of the new solutions $Sol_i^{new(n)}$ with the corresponding new fitness function value $FF_i^{new(n)}$. Update the best solution (Sol_{best}) with the corresponding best fitness function value FF_{dbest}

$$Sol_i^{new(n)} = \begin{cases} Sol_i^{(n)} & \text{if} FF_i^{new(n)} \le FF_i^{(0)} \\ Sol_i^{(0)} & otherwise \end{cases} \tag{26}$$

Step 6: Generate a second new solution using fraction (Pa)

The second new solution $Sol'^{new(n)}_i$ is created with probability Pa of CSA. The new solutions of the population are updated using Equation (22).

Step 7: Evaluate the new second solutions:

The quality of the new second solutions is evaluated by fitness function Equation (25) via solving the power flow problem. Update the population of the new second solution $Sol'^{new(n)}_i$ with the corresponding new second fitness function value $FF'^{new(n)}_i$. Update the best solution (Sol_{ibest}) with the corresponding best fitness function value FF_{ibest}

$$Sol_i^{new(n)} = \begin{cases} Sol_i^{(n)} & \text{if} FF_i^{new(n)} \le FF_i^{(0)} \\ Sol_i^{(0)} & otherwise \end{cases} \tag{27}$$

Step 8: Check the sopping condition:

If n < Nmax, $n = n + 1$, the searching process will return to Step 4 for finding the optimal solution. Otherwise, the searching process will stop.

4. Simulation Results

4.1. The IEEE 30-Bus Test System

The system includes six generators, 24 load buses and 41 lines, as in Figure 1. The generator buses are set up voltage value within [0.95–1.1 p.u], while the voltages at load buses are limited [0.95–1.05 p.u]. The regulating transformers have voltage tap settings within [0.9–1.1 p.u]. The rating of shunt capacitors is in the range of [0–5 MVAR]. The system, generator data and operating conditions for the IEEE 30-bus test system are given in Table 2 and in [25,39].

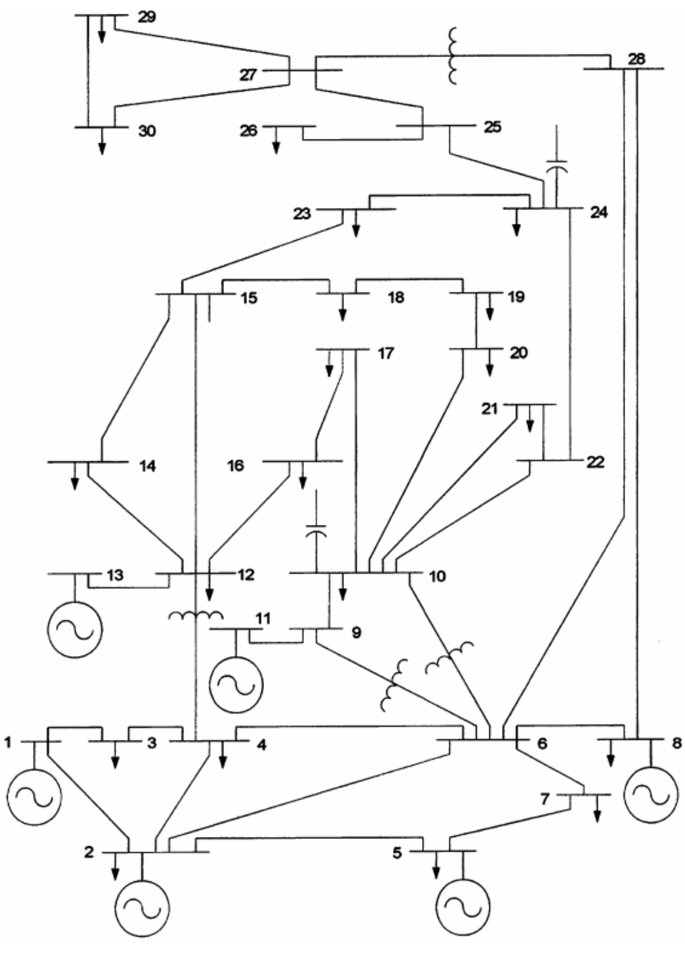

Figure 1. The 30-bus system.

Table 2. Generator data of the 30-bus system.

Bus No	ai ($/h)	bi ($/MWh)	ci ($/MW2h)
1	0.00	2	0.00375
2	0.00	1.75	0.01750
5	0.00	1.00	0.06250
8	0.00	3.25	0.00834
11	0.00	3.00	0.02500
13	0.00	3.00	0.02500

Table 3 presents obtained optimal values using CSA and HCSA-SFO for cases 1–3, consisting of fuel cost, power loss and voltage deviations. In addition, these control parameters are also presented in this table. From this table, the total generator cost obtained is 799.118 ($/h) using the HCSA-SFO technique, while the total generator cost using the CSA approach is 799.129 ($/h) for case 1. For case 1, the total generator cost of the CSA approach approximates that of the HCSA-SFO approach; however, the run time of the suggested HCSA-SFO technique is shorter than that of the CSA approach for all of simulation cases. Wherein, the run time of HCSA-SFO is 9.0261, 7.0549 and 7.3082 s, which are less than those of CSA for solving the problem in case 1, case 2 and case 3, respectively. The convergence curve of the total fuel cost objective function is demonstrated in Figure 2. From this figure, convergence ability to the optimal value of the HCSA-SFO algorithm is better than CSA in terms of optimal value.

Table 3. The results of CSA and hybrid cuckoo search algorithm and sunflower optimization (HCSA-SFO) for the 30-bus system with case 1–3.

Control Parameters (U)	**Initial State**	**Limits**		**Case 1: Total Generator Cost**		**Case 2: Voltage Profile**		**Case 3: Total Active Power Loss**	
		Min	**Max**	**CSA**	**HCSA-SFO**	**CSA**	**HCSA-SFO**	**CSA**	**HCSA-SFO**
P1(MW)	99.221	50	200	177.219	177.148	129.717	117.597	51.2794	51.2795
P2(MW)	80.0	20	80	48.6847	48.7207	60.2810	48.1157	79.9966	79.9964
P5(MW)	50.00	15	50	21.2218	21.3127	39.4447	50.0000	50.0000	50.0000
P8(MW)	20.0	10	35	21.1297	20.9526	18.4269	33.2425	34.9992	34.9995
P11(MW)	20.0	10	30	11.7964	11.9111	19.3629	23.0321	30.0000	30.0000
P13(MW)	20.0	12	40	12.0019	12.0000	23.3748	17.2583	40.0000	39.9995
V1 (p.u)	1.0500	0.95	1.1	1.1000	1.1000	1.0144	1.0075	1.1000	1.1000
V2 (p.u)	1.0400	0.95	1.1	1.0879	1.0878	1.0073	1.0000	1.0977	1.0979
V5 (p.u)	1.0100	0.95	1.1	1.0617	1.0615	1.0189	1.0156	1.0798	1.0804
V8 (p.u)	1.0100	0.95	1.1	1.0704	1.0693	1.0092	1.0142	1.0875	1.0878
V11(p.u)	1.0500	0.95	1.1	1.0998	1.1000	1.0179	1.0377	1.1000	1.1000
V13(p.u)	1.0500	0.95	1.1	1.0999	1.1000	1.0132	1.0176	1.1000	1.0998
T11	1.0780	0.9	1.1	1.0485	1.0596	1.0315	1.0531	1.0681	1.0650
T12	1.0690	0.9	1.1	0.9220	0.9000	0.9009	0.9013	0.9001	0.9000
T15	1.0320	0.9	1.1	1.0023	0.9929	0.9962	0.9911	0.9854	0.9844
T36	1.0680	0.9	1.1	0.9723	0.9687	0.9579	0.9733	0.9754	0.9748
QC10 (MVAR)	0	0	5	5.0000	5.0000	5.0000	2.8273	4.9999	4.9688
QC12 (MVAR)	0	0	5	4.9779	5.0000	4.5504	1.3736	4.9967	4.9994
QC15 (MVAR)	0	0	5	4.8721	5.0000	5.0000	4.9758	4.9991	4.9935
QC17 (MVAR)	0	0	5	4.9764	5.0000	1.1845	1.1102	4.9897	4.9998
QC20 (MVAR)	0	0	5	4.2118	4.4761	5.0000	4.9997	3.8542	4.2219
QC21 (MVAR)	0	0	5	5.0000	5.0000	4.4159	4.7205	4.9989	5.0000
QC23 (MVAR)	0	0	5	3.0770	2.8877	4.6104	4.9371	2.7502	2.8132
QC24 (MVAR)	0	0	5	4.9494	5.0000	4.9751	5.0000	5.0000	4.9994
QC29 (MVAR)	0	0	5	2.5377	2.6939	1.9721	4.0838	2.6171	2.5271
Total cost ($/h)	830.02	-	-	799.129	799.118	842.270	876.855	967.117	967.115
PLoss (MW)	5.8486	-	-	8.6536	8.6456	7.2076	5.8463	2.8752	2.8748
∑Voltage deviation	1.1665	-	-	1.7622	1.8259	0.0961	0.0945	2.0369	2.0554
Run time (s)	-	-	-	86.8238	77.7977	82.1847	75.1298	79.9934	72.6852

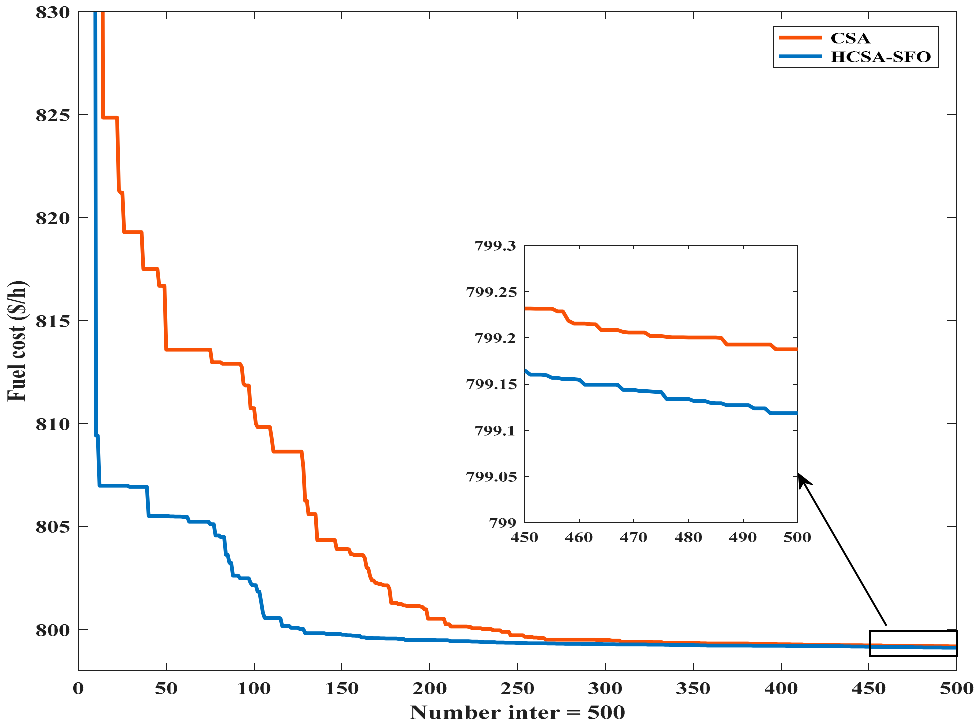

Figure 2. Convergence curves of the CSA and HCSA-SFO for case 1.

In order to evaluate the effectiveness of the suggested HCSA-SFO technique in dealing with the OPF problem, simulations results of the HCSA-SFO technique is compared with many other approaches as demonstrated in Table 4. For case 1, it can be seen from the Table 4, total fuel cost obtained by HCSA-SFO is 799.11 ($/h), which is better than many other methods in the literature. This is the demonstration of the robustness of the hybrid HCSA-SFO technique in dealing with OPF.

Table 4. Compared results of HCSA-SFO and other methods for cases 1, 2 and 3.

Method	Case 1	Case 2	Case 3
	Total Generator Cost	**Voltage Profile**	**Total Active Power Loss**
Gradient method [17]	804.853	NR	10.486
DE-OPF [35]	802.394	NR	9.466
MDE-OPF [35]	802.375	NR	9.459
MSFLA [34]	802.287	NR	9.6991
IGA [16]	800.805	NR	NR
ABC [15]	800.66	0.1381	3.1078
GSA [9]	798.675143	NR	NR
SCA [25]	800.1018	0.1082	2.9425
Hybrid PSO-GSA [19]	800.49859	0.12674	9.0339
Jaya [18]	800.4794	0.1243	3.1035
EGA-DQLF [27]	799.56	0.111	3.2008
MSCA [25]	799.31	0.1031	2.9334
SPEA [24]	NR	0.1247	NR
HS [21]	NR	0.1006	2.9678
BBO [17]	NR	0.09803	NR
CSA	799.1292	0.0961	2.8752
HCSA-SFO proposed	799.1185	0.0945	2.8748

The simulation results of the HCSA-SFO technique compared with many other approaches for case 2 is also shown in Table 4. As observed from Table 4, the voltage deviation of the suggested HCSA-SFO technique is better than those of many other methods. Moreover, the voltage deviation obtained by HCSA-SFO is 0.0945 pu, which is also better than that of CSA as shown in Table 4.

For case 3, the total active power loss achieved using HCSA-SFO is 2.8748 (MW), while the total active power loss reduces to 2.8752 (MW) using CSA as shown in Table 4. From Table 4, it can be observed that the total power loss of the suggested HCSA-SFO technique obtains a better minimum value compared with other approaches. Besides, the results of fuel cost, voltage deviation and active power loss using CSA and HCSA-SFO also are given in Figures 3–5. From the figures, the results of HCSA-SFO are better than those of CSA for all three cases. In addition, the statistical results of HCSA-SFO and CSA in Table 5 show that HCSA-SFO outperforms CSA in terms of the best, average and the worst fitness values as well as the standard deviation. The analytical results show that HCSA-SFO is also an effective method to find an optimized solution with fast convergence ability.

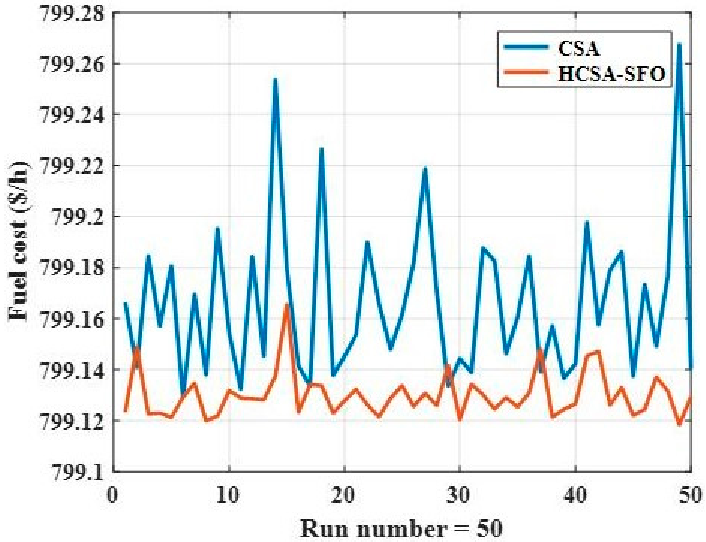

Figure 3. Comparison of fuel cost of the CSA and HCSA-SFO for case 1.

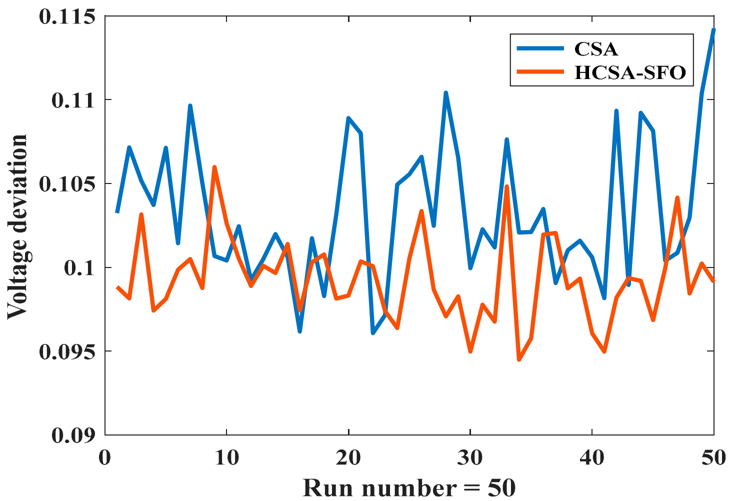

Figure 4. Comparison of voltage deviation of the CSA and HCSA-SFO for case 2.

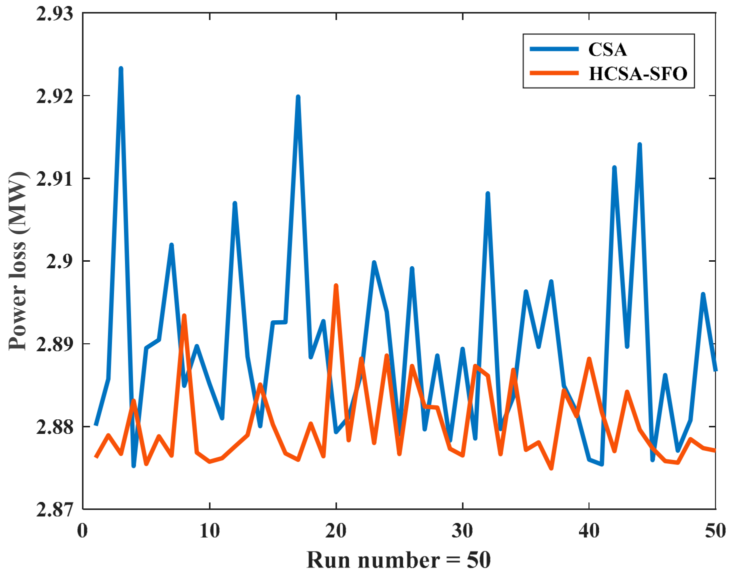

Figure 5. Comparison of active power loss of the CSA and HCSA-SFO for case 3.

Table 5. The statistical results of HCSA-SFO and CSA for case 1, 2 and 3.

Item	Case 1		Case 2		Case 3	
Method	CSA	HCSA-SFO	CSA	HCSA-SFO	CSA	HCSA-SFO
Best fitness	799.1292	799.1185	0.0961	0.0945	2.8752	2.8748
Average fitness	799.1661	799.1301	0.1034	0.0993	2.8894	2.8803
Worst fitness	799.2675	799.1655	0.1143	0.1060	2.9233	2.8970
Standard deviation	0.0302	0.0089	0.0041	0.0025	0.0116	0.0051

4.2. The IEEE 118-Bus Test System

The larger power system with the standard IEEE 118-bus is used to test the robustness of HCSA-SFO for dealing with the OPF problem. Parameters of the 118-bus system are given in [25,39]. The 118-bus system includes 118 buses, which are 99 load buses, 54 thermal units, 186 branches, 9 transformers and 12 reactive compensations with size within (0–30) MVAr each. The system is considered as a large-scale OPF problem which is usually used to test the robustness of many other algorithms.

The optimal value of objective function and control optimal parameters for the IEEE 118-bus system using CSA and suggested HCSA-SFO is presented in Table 6. From Table 6, the total generator cost achieved is 129,619.848 ($/h) using HCSA-SFO, while the total generator cost achieved by CSA is 129,847.86 ($/h). Moreover, Table 6 also shows that the run time to the obtained optimal value of the suggested HCSA-SFO method is 234.2190 s, which is 44.2609 s less than of CSA. Besides, the variation of the total generator cost is also presented in Figure 6. From this figure, the convergence ability of the HCSA-SFO technique for the OPF problem with large scale systems can be demonetized. For additional effective confirmation, the results of HCSA-SFO are also compared with many other approaches, as shown in Table 7. From Table 7, HCSA-SFO achieved the solution better than many other methods. Table 8 presents the values of optimal objective functions for cases 2 and 3 obtained by HCSA-SFO compared to CSA. As observed, the suggested HCSA-SFO achieved better optimal results than the CSA algorithm. The voltage deviation decreases to 0.3836 in case 2 and the power loss of 11.2784 MW in case 3 using HCSA-SFO, while the voltage deviation is 0.6117 in case 2 and the power loss 21.3664 MW in case 3 using CSA.

Table 6. The solution of optimal power flower (OPF) achieved for IEEE 118-bus system with case 1.

	Control Parameter	CSA	HCSA-SFO	Control Parameter	CSA	HCSA-SFO	Control Parameter	CSA	HCSA-SFO
4	PG01 (MW)	26.8831	25.7191	V01 (p.u.)	1.0496	1.06	T5_8 (p.u.)	0.9819	0.9588
6	PG04 (MW)	0.0011	0	V04 (p.u.)	1.0196	1.0583	T25_26 (p.u.)	1.0544	1.0599
8	PG06 (MW)	0.0036	0.0006	V06 (p.u.)	1.0107	1.0511	T17_30 (p.u.)	0.994	0.9792
10	PG08 (MW)	0	0	V08 (p.u.)	1.0248	1.0343	T37_38 (p.u.)	0.9994	0.9704
12	PG010 (MW)	398.447	401.4037	V10 (p.u.)	1.0499	1.0599	T59_63 (p.u.)	1.0144	0.9855
15	PG012 (MW)	85.7506	85.6885	V12 (p.u.)	1.0065	1.0486	T61_64 (p.u.)	1.0234	0.9992
18	PG015 (MW)	22.1625	20.3813	V15 (p.u.)	1.0007	1.0486	T65_66 (p.u.)	0.9771	0.9853
19	PG018 (MW)	12.943	12.9764	V18 (p.u.)	1.0024	1.0506	T68_69 (p.u.)	0.9	0.9548
24	PG019 (MW)	22.3069	21.4271	V19 (p.u.)	0.9985	1.0481	T80_81 (p.u.)	0.9985	0.9888
25	PG24 (MW)	0.0005	0	V24 (p.u.)	1.0111	1.0501	QC34 (MVAR)	4.9211	0.034
26	PG25 (MW)	193.8773	194.4536	V25 (p.u.)	1.0398	1.06	QC44 (MVAR)	3.0739	4.1145
27	PG26 (MW)	280.7126	280.6595	V26 (p.u.)	1.05	1.06	QC45 (MVAR)	27.4402	19.3306
31	PG27 (MW)	10.114	11.1432	V27 (p.u.)	0.9974	1.0455	QC46 (MVAR)	2.3706	0
32	PG31 (MW)	7.3274	7.2506	V31 (p.u.)	0.9924	1.0411	QC48 (MVAR)	2.0481	7.637
34	PG32 (MW)	17.6087	15.656	V32 (p.u.)	0.9969	1.0446	QC74 (MVAR)	24.7779	30
36	PG34 (MW)	5.2681	5.7499	V34 (p.u.)	1.0015	1.0566	QC79 (MVAR)	29.722	30
40	PG36 (MW)	7.9528	0	V36 (p.u.)	0.999	1.0547	QC82 (MVAR)	20.7679	29.9971
42	PG40 (MW)	55.5105	49.6176	V40 (p.u.)	0.9899	1.0446	QC83 (MVAR)	30	9.8588
46	PG42 (MW)	39.0042	41.3484	V42 (p.u.)	0.9916	1.0445	QC105 MVAR)	21.1656	30
49	PG46 (MW)	19.1381	19.061	V46 (p.u.)	0.9961	1.0447	QC107 (MVAR)	2.1189	0.0008

Table 6. *Cont.*

	Control Parameter	CSA	HCSA-SFO	Control Parameter	CSA	HCSA-SFO	Control Parameter	CSA	HCSA-SFO
54	PG49 (MW)	193.6385	193.8593	V49 (p.u.)	1.0136	1.0577	QC110 (MVAR)	29.3622	25.541
55	PG54 (MW)	49.7253	49.4907	V54 (p.u.)	0.9923	1.0395	Fuel cost ($/h)	129,847.9	129,619.8
56	PG55 (MW)	35.8876	31.7237	V55 (p.u.)	0.9905	1.0395	Plosses (MW)	81.0879	76.8078
59	PG56 (MW)	37.6324	32.0909	V56 (p.u.)	0.9906	1.0392	$\sum$Voltage deviation	1.7266	2.6842
61	PG59 (MW)	148.637	149.6631	V59 (p.u.)	0.9927	1.0572	Run time (s)	278.4798	234.219
62	PG61 (MW)	147.0241	148.5939	V61 (p.u.)	1.0039	1.06			
65	PG62 (MW)	0.0019	0	V62 (p.u.)	1.0023	1.0559			
66	PG65 (MW)	351.1325	353.3149	V65 (p.u.)	1.0281	1.06			
69	PG66 (MW)	348.2007	350.0869	V66 (p.u.)	1.0239	1.06			
70	PG69 (MW)	454.8334	455.0162	V69 (p.u.)	1.0309	1.06			
72	PG70 (MW)	0.0002	0	V70 (p.u.)	0.9968	1.0369			
73	PG72 (MW)	0.0112	0	V72 (p.u.)	1	1.0407			
74	PG73 (MW)	1.0773	0	V73 (p.u.)	0.9975	1.0365			
76	PG74 (MW)	0.003	17.4254	V74 (p.u.)	0.9809	1.0277			
77	PG76 (MW)	28.817	23.2027	V76 (p.u.)	0.969	1.0122			
80	PG77 (MW)	0.0001	0	V77 (p.u.)	1.0015	1.0448			
82	PG80 (MW)	429.1381	431.9109	V80 (p.u.)	1.015	1.0584			
85	PG85 (MW)	0.001	0	V85 (p.u.)	1.0108	1.0507			
87	PG87 (MW)	3.7636	3.6263	V87 (p.u.)	1.0072	1.0537			
89	PG89 (MW)	498.3809	502.6848	V89 (p.u.)	1.0248	1.06			

Table 6. *Cont.*

	Control Parameter	CSA	HCSA-SFO	Control Parameter	CSA	HCSA-SFO	Control Parameter	CSA	HCSA-SFO
90	PG90 (MW)	0.0293	0	V90 (p.u.)	0.9967	1.0407			
91	PG91 (MW)	0.0137	0	V91 (p.u.)	0.9967	1.0435			
92	PG92 (MW)	0.0006	0	V92 (p.u.)	1.0056	1.0488			
99	PG99 (MW)	0.0008	0	V99 (p.u.)	1.001	1.0509			
100	PG100 (MW)	230.6961	231.4663	V100 (p.u.)	1.0077	1.0548			
103	PG103 (MW)	38.1507	38.2706	V103 (p.u.)	1.0033	1.0467			
104	PG104 (MW)	0.0086	0.0003	V104 (p.u.)	0.9938	1.0372			
105	PG105 (MW)	7.8782	5.5612	V105 (p.u.)	0.9923	1.0345			
107	PG107 (MW)	32.89	29.3361	V107 (p.u.)	0.9853	1.0284			
110	PG110 (MW)	12.0952	7.1166	V110 (p.u.)	0.998	1.0347			
111	PG111 (MW)	35.1675	35.2286	V111 (p.u.)	1.0063	1.0422			
112	PG112 (MW)	33.2392	36.6019	V112 (p.u.)	0.99	1.0271			
113	PG113 (MW)	0.0001	0	V113 (p.u.)	1.0099	1.056			
116	PG116 (MW)	0	0	V116 (p.u.)	1.0249	1.06			

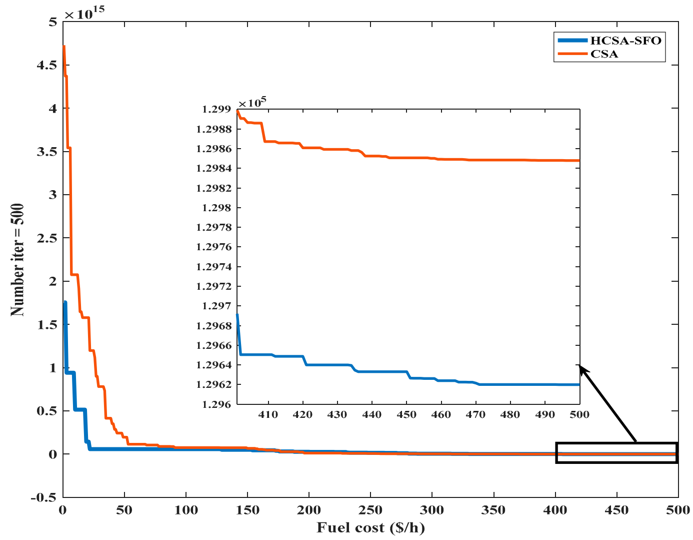

Figure 6. Convergence characteristics of the HCSA-SFO algorithm of IEEE 118 for case 1.

Table 7. Comparison of the results achieved for IEEE 118-bus system with case 1.

Approach	Total Generator Cost ($/h)
DE [20]	142,751.1178
BSO [33]	135,333.5
BBO [20]	135,272.1959
ECBO [20]	135,172.266
ABC [20]	135,145.1889
Improved ICBO [20]	135,121.570
CBO [20]	135,072.999
GWO [7]	129,720.000
BBO [17]	129,686.000
TLBO [22]	129,682.844
SCA [25]	129,622.650
MSCA [25]	129,620.220
CSA proposed	129,847.86
HCSA-SFO proposed	129,619.848

Table 8. The results for IEEE 118 bus system with case 1, case 2 and case 3.

Approach Proposed	Case 1	Case 2	Case 3
	Generator Cost ($/h)	Voltage Deviation	Total Power Loss (MW)
CSA	129,847.86	0.6117	21.3664
HCSA—SFO	129,619.848	0.3836	11.2784

5. Conclusions

In the next years, OPF problems will still be one of the important issues of power system operation, especially in the electricity market. Many research teams still continue developing other methods to enhance the performance solution of the OPF problem. This is a nonlinear issue with many control parameters that requires an effective technique in dealing with it. A newly robust hybrid technique, which is successfully applied for dealing with OPF for large-scale systems, is presented in this paper. In order to evaluate the ability to find an optimal solution of the suggested technique, the hybrid HCSA-SFO technique is compared with CSA and many other approaches. The simulation results are tested and evaluated for the IEEE 30- and IEEE 118-bus system with the objective function of minimizing generator costs, power loss and voltage deviation. For both of the testing systems, HCSA-SFO reaches better solutions and faster convergence than CSA for all of cases of the objective functions in each independent run as well as in 50 runs. In comparison with other methods, the proposed HCSA-SFO method outperforms other methods. The simulation results achieved show that HCSA-SFO can be a potential approach for dealing with large-scale OPF problems or the OPF problems considering to distributed generation sources and FACTS devices.

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References

1. Monoh, J.A.; El-Hawary, M.E.; Adapa, R. A review of selected optimal power flow literature to 1993 Part II: Newton, linear programming and Interior Point Methods. *IEEE Trans. Power Syst.* **1999**, *14*, 105–111. [CrossRef]
2. Alsac, O.; Scott, B. Optimal load flow with steady state security. *IEEE Trans. Power Appar. Syst.* **1974**, *93*, 745–751. [CrossRef]
3. Alsac, O.; Bright, J.; Prais, M.; Stott, B. Further developments in LP-based optimal power flow. *IEEE Trans. Power Syst.* **1990**, *5*, 697–711. [CrossRef]
4. Burchett, R.C.; Happ, H.H.; Vierath, D.R. Quadratically convergent optimal power flow. *IEEE Trans. Power Appar. Syst.* **1984**, *103*, 3267–3276. [CrossRef]
5. Sun, D.I.; Ashley, B.; Brewer, B.; Hughes, A.; Tinney, W.F. Optimal power flow by Newton approach. *IEEE Trans. Power Appar. Syst.* **1984**, *103*, 2864–2880. [CrossRef]
6. Ongsakul, W.; Tantimaporn, T. Optimal power flow by improved evolutionary programming. *Electr. Power Compon. Syst.* **2006**, *34*, 79–95. [CrossRef]
7. El-Fergany, A.A.; Hasanien, H.M. Single and multi-objective optimal power flow using grey wolf optimizer and differential evolution algorithms. *Electr. Power Compon. Syst.* **2015**, *43*, 1548–1559. [CrossRef]
8. Hazra, J.; Sinha, A.K. A multi-objective optimal power flow using particle swarm optimization. *Eur. Trans. Electr. Power* **2011**, *21*, 1028–1045. [CrossRef]
9. Duman, S.; Güvenç, U.; Sönmez, Y.; Yörükeren, N. Optimal power flow using gravitational search algorithm. *Energy Convers. Manag.* **2012**, *59*, 86–95. [CrossRef]
10. Bhattacharya, A.; Roy, P.K. Solution of multi-objective optimal power flow using gravitational search algorithm. *IET Gener. Transm. Distrib.* **2012**, *6*, 751–763. [CrossRef]
11. Jahan, M.S.; Amjady, N. Solution of large-scale security constrained optimal power flow by a new bi-level optimisation approach based on enhanced gravitational search algorithm. *IET Gener. Transm. Distrib.* **2013**, *7*, 1481–1491. [CrossRef]
12. El-Sehiemy, R.A.; Shaheen, A.M.; Farrag, S.M. Solving multi-objective optimal power flow problem via forced initialised differential evolution algorithm. *IET Gener. Transm. Distrib.* **2016**, *10*, 1634–1647.
13. Varadarajan, M.; Swarup, K.S. Solving multi-objective optimal power flow using differential evolution. *IET Gener. Transm. Distrib.* **2008**, *2*, 720–730. [CrossRef]
14. Pulluri, H.; Naresh, R.; Sharma, V. A solution network based on stud krill herd algorithm for optimal power flow problems. *Soft Comput.* **2016**, *5*, 1–18. [CrossRef]
15. Adaryani, M.R.; Karami, A. Artificial bee colony algorithm for solving multi-objective optimal power flow problem. *Int. J. Electr. Power Energy Syst.* **2013**, *53*, 219–230. [CrossRef]
16. Ghanizadeh, A.J.; Mokhtar, G.; Abedi, M.; Gharehpetian, G.B. Optimal power flow based on imperialist competitive algorithm. *Int. Rev. Electr. Eng.* **2011**, *6*, 1847–1852.
17. Bhattacharya, A.; Chattopadhyay, P.K. Application of biogeography-based optimisation to solve different optimal power flow problems. *IET Gener. Transm. Distrib.* **2011**, *5*, 70–80. [CrossRef]

18. Warid, W.; Hizam, H.; Mariun, N.; Abdul-Wahab, N.I. Optimal power flow using the Jaya algorithm. *Energies* **2016**, *9*, 678. [CrossRef]
19. Radosavljević, J.; Klimenta, D.; Jevtić, M.; Arsić, N. Optimal power flow using a hybrid optimization algorithm of particle swarm optimization and gravitational search algorithm. *Electr. Power Compon. Syst.* **2015**, *43*, 1958–1970. [CrossRef]
20. Bouchekara, H.R.; Chaib, A.E.; Abido, M.A.; El-Sehiemy, R.A. Optimal power flow using an improved colliding bodies optimization algorithm. *Appl. Soft Comput.* **2016**, *42*, 119–131. [CrossRef]
21. Arul, R.; Ravi, G.; Velusami, S. Solving optimal power flow problems using chaotic selfadaptive differential harmony search algorithm. *Electr. Power Compon. Syst.* **2013**, *41*, 782–805. [CrossRef]
22. Bouchekara, H.R.E.H.; Abido, M.A.; Boucherma, M. Optimal power flow using teaching learning- based optimization technique. *Electr. Power Syst. Res.* **2014**, *114*, 49–59. [CrossRef]
23. Bouchekara, H.R. Optimal power flow using black-hole-based optimization approach. *Appl. Soft Comput.* **2014**, *24*, 879–888. [CrossRef]
24. Lai, L.L.; Ma, J.T.; Yokoyama, R.; Zhao, M. Improved genetic algorithms for optimal power flow under both normal and contingent operation states. *Int. J. Electr. Power Energy Syst.* **1997**, *19*, 287–292. [CrossRef]
25. Attia, A.-F.; Sehiemy, R.A.E.; Hasanien, H.M. Optimal power flow solution in power systems using a novel Sine-Cosine. *Int. J. Electr. Power Energy Syst.* **2018**, *99*, 331–343. [CrossRef]
26. Surender, R.S.; Srinivasa, R.C. Optimal power flow using glowworm swarm optimization. *Int. J. Electr. Power Energy Syst.* **2016**, *80*, 128–139. [CrossRef]
27. Kumari, M.S.; Maheswarapu, S. Enhanced genetic algorithm based computation technique for multi-objective optimal power flow solution. *Int. J. Electr. Power Energy Syst.* **2010**, *32*, 736–742. [CrossRef]
28. Surender, R.S. Solution of multi-objective optimal power flow using efficient meta-heuristic algorithm. *Electr. Eng.* **2017**, *100*, 401–413.
29. Surender, R.S.; Abhyankar, A.R.; Bijwe, P.R. Reactive power price clearing using multi-objective optimization. *Energy* **2011**, *36*, 3579–3589.
30. Surender, R.S. Security constrained optimal power flow with FACTS controllers using hybrid differential evolution and harmony search algorithm. *Int. J. Appl. Eng. Res.* **2016**, *11*, 10939–10944.
31. Surender, R.S.; Bijwe, P.R. Differential evolution-based efficient multi-objective optimal power flow. *Neural Comput. Appl.* **2017**, *31*, 509–522. [CrossRef]
32. Abhishek, R.; Malakar, T. Optimal reactive power dispatch using hybrid Nelder- Mead simplex based firefly algorithm. *Int. J. Electr. Power Energy Syst.* **2015**, *66*, 9–24.
33. Chaib, A.E.; Bouchekara, H.R.; Mehasni, R.; Abido, M.A. Optimal power flow with emission and non-smooth cost functions using backtracking search optimization algorithm. *Int. J. Electr. Power Energy Syst.* **2016**, *81*, 64–77. [CrossRef]
34. Niknam, T.; Narimani, M.; Jabbari, M.; Malekpour, A.R. A modified shuffle frog leaping algorithm for multi-objective optimal power flow. *Energy* **2011**, *36*, 6420–6432. [CrossRef]
35. Sayah, S.; Zehar, K. Modified differential evolution algorithm for optimal power flow with non-smooth cost functions. *Energy Convers. Manag.* **2008**, *49*, 3036–3042. [CrossRef]
36. Yang, X.S.; Deb, S. Cuckoo search via Lévy flights. In Proceedings of the 2009 World Congress on Nature & Biologically Inspired Computing, Coimbatore, India, 9–11 December 2009; pp. 210–214.
37. Yang, X.S.; Deb, S. Engineering optimisation by cuckoo search. *Int. J. Math. Model. Num. Optim.* **2010**, *1*, 330–343. [CrossRef]
38. Gomes, G.F.; Cunha, S.S.A.; Ancelotti, A.C. A sunflower optimization (SFO) algorithm applied to damage identification on laminated composite plates. *Eng. Comput.* **2018**, *35*, 619–626. [CrossRef]
39. MATPOWER A MATLAB Power System Simulation Package Version 4.1. Available online: http://www.pserc.cornell.edu//matpower/ (accessed on 1 June 2020).