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Single-objective optimal power flow for electric power systems based on crow search algorithm

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Abstract: This paper presents the application of a recent meta-heuristic optimization technique named a crow search algorithm (CSA) in solving the problem of an optimal power flow (OPF) for electric power systems. Various constrained objective functions, total fuel cost, active power loss and pollutant emission are proposed. The generators' output powers, generators' terminal voltages, transmission lines' taps and the shunt capacitors' reactive powers are considered as variables to be designed. The proposed methodology based on the CSA is applied on an IEEE 30-bus system and IEEE 118-bus system. The obtained results via the CSA are compared to others and they ensure the superiority of the CSA in solving the OPF problem in electric power systems.

Key words: crow search algorithm, distribution network, optimal power flow

1. Introduction

In the last decades, the utilities faced a rapid increase in the number of participating consumers with limited expansion of electric generating stations due to financial and political issues. Some aspects must be taken in consideration during the operation of electric power system; minimizing the total fuel cost of generation, reducing the system loss, maximizing the system reliability and security and reducing the pollutant emission released from the generators. An important study of an optimal power flow (OPF) is performed to achieve the previously mentioned issues. The main objective of the OPF study is minimizing the required operational aspects subject to constraints, to obtain a reliable operation of the power system. Many studies have been reported, Frank et al. [1, 2] presented a complete survey on the different methods used in solving the OPF problem; these methods can be classified into two main categories, traditional optimization [3–10]. In [3], a linear programming (LP) to minimize the greenhouse gas-emission from the generation plant has been presented. Alsac et al. solved the problem of the OPF based on non-linear programming (NLP) [4]. In [5], the Newton–Raphson method was presented to solve both constrained and unconstrained OPF problems. Grudinin presented reactive power optimization solved by a quadratic programming method [6]. An integer programming has been presented in [7] to minimize greenhouse-gas emission. In [8] a decomposition method for solving the OPF has been presented. A multi-objective economic dispatch solved by a fast-successive linear programming algorithm has been given in [9]. Sousa et al. [10] presented an interior-point method for solving the OPF problem. These conventional methods are suffering falling in local minimum points. The second category is the meta-heuristic optimization algorithm [11–34], Osman et al. [11] employed a genetic algorithm (GA) to solve the OPF for minimizing the generation fuel cost. Sayah et al. [12] presented a modified differential evolution (MDE) algorithm for solving the OPF with non-smooth and non-convex generator cost curves. A fuzzy rule presented in [13] is employed to vary the crossover and mutation probabilities of the GA to solve the OPF problem. Niknam et al. [14] used honey bee mating optimization (HBMO) and modified honey bee mating optimisation (MHBMO) for solving the OPF to minimize the generator fuel cost with valve-point effects, Abido [15] solved the OPF using Tabu search (TS) which is applied on different objective functions with different forms of the generator cost functions. In [16], the Fuzzy based PSO has been presented to solve the OPF for a system containing wind energy. Hinojosa et al. [17] introduced an algorithm based on the PSO to evaluate the optimum values of generator power, generator voltage, transformer tap position and shunt reactive power so as to minimize the generator fuel cost and system active power loss. Simulated annealing (SA) has been given in [18] to solve the OPF composed by a load flow and economic dispatch problem. An enhanced genetic algorithm (EGA) has been used in [19] to solve the OPF. In [20], a hybrid algorithm that combined the decoupled quadratic load flow solution with the enhanced GA, is presented to solve the problem of the OPF. In [21], ant colony optimization (ACO) has been presented to minimize the total generation cost and evaluate the optimal generators' power. Khorsandi et al. [22] presented a modified artificial bee colony via Fuzzy rules to solve the OPF problem to minimize the total generation cost considering the valve point effect. An evolutionary programming (EP) algorithm has been used in [23] to solve the OPF problem. Reddy et al. [24] presented Glowworm swarm optimization to solve the multi-objective OPF problem of minimization of the total generation cost and emission. In [25], a backtracking search optimization algorithm has been presented to solve the OPF considering different objectives. Pandiarajan et al. [26] used a hybrid algorithm of Fuzzy logic with a harmony search algorithm to obtain the optimal solution for the OPF problem with minimum fuel cost. The harmony search algorithm has been used to solve the multi-objective OPF problem in [27], the Fuzzy based technique is used to select the optimum solution from the Pareto set. In [28], differential evolution and a grey wolf optimizer have been presented to solve the multi-objective and single objective OPF problem. Niknam et al. presented a shuffle frog leaping algorithm (SFLA) and modified the shuffle frog leaping algorithm (MSFLA) in [29] to solve the multi-objective OPF. In [30], a modified teaching-learning based optimization algorithm (MTLBO) has been presented to solve the OPF. Mahdad et al. [31] presented an adaptive flower pollination algorithm (APFPA) for solving the OPF problem to achieve a secure power system, In [32], the multi-objective OPF problem is solved via a modified decomposition algorithm to minimize the fuel cost, emission, power loss and voltage deviation. Mukherjee et al. [33] introduced a krill herd algorithm with opposition based learning to solve the transient stability constrained OPF problem. In [34], a group search optimization (GSA) and its adaptive version has been used for solving the OPF problem. Most of the reported approaches suffer from complexity and consume a lot of time.

In this paper, a proposed solution methodology based on a crow search algorithm (CSA) is presented to solve the problem of the OPF for an electric power system. The CSA is selected due to its simplicity in programming, requirement of less controlling parameters, less time consumption and guarantee of a global optimum solution. Various forms of constraint objective functions such as total fuel cost, active power loss and pollutant emission are studied. The proposed approach is applied on an IEEE 30-bus system and IEEE 118-bus system. The CSA is compared to other reported approaches; the obtained results encourage the usage of the proposed methodology based on the CSA in solving the OPF.

2. OPF problem formulation

In this work three different objective functions are studied which are total generation fuel cost, active power loss of the network and the pollutant emission from the generators.

2.1. Total fuel cost function

The fuel cost of generators can be expressed in quadratic form as follows [29]:

$$\min \ J_1(x) = \sum_{i=1}^{N_g} \left(a_i P_{gi}^2 + b_i P_{gi} + c_i\right) \quad \text{\$/h}, \tag{1}$$

where: N_g is the number of generators, a_i, b_i, c_i are the fuel cost coefficients of generator i and x is the design variables.

$$x = [P_{g1},\ P_{g2},\ \ldots,\ P_{gi}] \quad \forall i \in N_g\,, \tag{2}$$

where P_{gi} is the MW output from generator i.

2.2. Active power loss

The active power loss of the electric power system can be expressed as given in [28]:

$$\min \ J_2(x) = \sum_{i=1}^{N} \sum_{\substack{j=1\\ j\neq i}}^{N} R_{ij} \frac{\left(|V_i|^2 + |V_j|^2 - 2|V_i|\,|V_j|\cos(\delta_{ij})\right)}{|Z_{ij}|^2} \quad \text{MW}, \tag{3}$$

where: N is the total number of buses, R_{ij} is the resistance of the line between bus i and j, V_i and V_j are the voltage magnitudes at bus i and j, δ_{ij} is the angle between voltages at bus i and j and Z_{ij} is the impedance of the line between bus i and j.

2.3. Pollutant emission

There atmospheric pollution emissions such as nitrogen oxides (NOX) and sulpher oxides (SOX) are caused due to the usage of fossil fuel thermal generation stations. The objective function that represents such emission can be expressed as follows [36]:

$$\min \quad J_3(x) = \sum_{i=1}^{N_g} \left(\gamma_i P_{gi}^2 + \beta_i P_{gi} + \alpha_i + \zeta_i \exp(\lambda_i P_{gi})\right) \quad \text{t/h}, \tag{4}$$

where: γ_i, β_i, α_i, ξ_i and λ_i are the emission coefficients of generator i.

2.4. Constraints

The applied constraints are given as follows:

$$P_{gi} - P_{di} = \sum_{i=1}^{N} |V_i|\,|V_j|\,(G_{ij}\cos(\delta_{ij}) + B_{ij}\sin(\delta_{ij})) \quad \forall i \in N, \tag{5}$$

$$Q_{gi} + Q_{ci} - Q_{di} = \sum_{i=1}^{N} |V_i|\,|V_j|\,(G_{ij}\sin(\delta_{ij}) - B_{ij}\cos(\delta_{ij})) \quad \forall i \in N, \tag{6}$$

$$V_i^{\min} \le V_i \le V_i^{\max} \quad \forall i \in N, \tag{7}$$

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max} \quad \forall i \in N_g\,, \tag{8}$$

$$Q_{gi}^{\min} \le Q_{gi} \le Q_{gi}^{\max} \quad \forall i \in N_g\,, \tag{9}$$

$$t_k^{\min} \le t_k \le t_k^{\max} \quad \forall k \in N_{\text{Trans}}\,, \tag{10}$$

$$Q_{ci}^{\min} \le Q_{ci} \le Q_{ci}^{\max} \quad \forall i \in N_{\text{cap}}\,, \tag{11}$$

where: P_{di} is the load demand at bus i, G_{ij} and B_{ij} are the conductance and susceptance of branch ij, $V_i^{\min}$ and $V_i^{\max}$ are the minimum and maximum voltages at bus i, $P_{gi}^{\min}$ and $P_{gi}^{\max}$ are the minimum and maximum limits of output power from generator i, $Q_{gi}^{\min}$ and $Q_{gi}^{\max}$ are the minimum and maximum limits of reactive power from generator i, $S_{li}^{\max}$ is the maximum allowable capacity of branch i,N_{br} is the total number of branches, $t_k^{\min}$ and $t_k^{\max}$ are the minimum and maximum limits of k^{th} transformer tap, $Q_{ci}^{\min}$ and $Q_{ci}^{\max}$ are the minimum and maximum limits of reactive power of i^{th} compensator capacitor.

3. Crow search algorithm

A crow search algorithm (CSA) is a novel metaheuristic optimization algorithm presented by Askarzadeh [34]. The main idea of the CSA is derived from the social behavior of crows, which are characterized by extreme intelligence. The process of getting food is based on observing other crows hide their foods in the hive, pending the departure of the crows (food-owners) and then on the theft of the food. After that the thief crow tries to hide the food obtained, to prevent being a victim of other crows in the future. In the search process followed in the CSA, it is assumed that in a flock of N crows, each one has a position x_i^k at an iteration number k. The primary mission of each crow is to evaluate the best food in the search plane which is defined as m_i^k via two probable scenarios. The first one is based on the assumption that the crow j, owner of the food source m_j^k

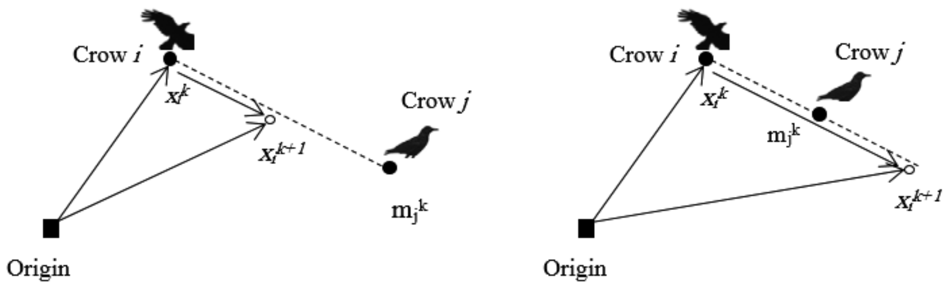
doesn't know that the thief crow i follows it; therefore, the theft process takes place successfully. The updating process of the thief crow position can be performed as follows:

$$x_i^{k+1} = x_i^k + r_i \times fl_i^k \times \left(m_j^k - x_i^k\right). \tag{12}$$

where: r_i is a random number in the range from 0 to 1, fl_i^k is the flight length of the crow i at an iteration k. The second probable scenario is that the owner crow j knows that the thief crow i follows it; therefore, the owner crow will trick the crow i by transferring the food to another position. The position of the crow i is updated by a random position. In CSA the scenario is determined by the following expression:

$$\begin{array}{c} if \;\; r_j \geq \rho_j^k \;\; \text{Update postion by Equation 10} \\ \text{Else} \\ \text{Update to random position} \end{array}, \tag{13}$$

where: ρ_j^k is the probability of awareness of the crow j at an iteration k, the parameter fl_i^k plays an important role in catching the global optimal solution, as a small value of fl_i^k leads to a local minimum, while a large value leads to a global minimum, Fig. 1 shows the effect of fl_i^k in the searching process.



(a) (b)

Fig. 1. The effect of fl on search process: (a) $fl < 1$; (b) $fl > 1$

The main steps followed in the CSA are shown in Fig. 2(a). At recent days, the CSA has gained great attention in the application of the power system analysis due to its simplicity in construction and consuming less time in operation. In [37], the CSA has been used in allocating the capacitors in the power system to reduce the network power loss and improve the voltage profile of buses.

4. The proposed solution methodology

The proposed algorithm that incorporated a CSA is shown in Fig. 2(b). The algorithm starts by defining the data of the electrical power system including line data, bus data, generators'

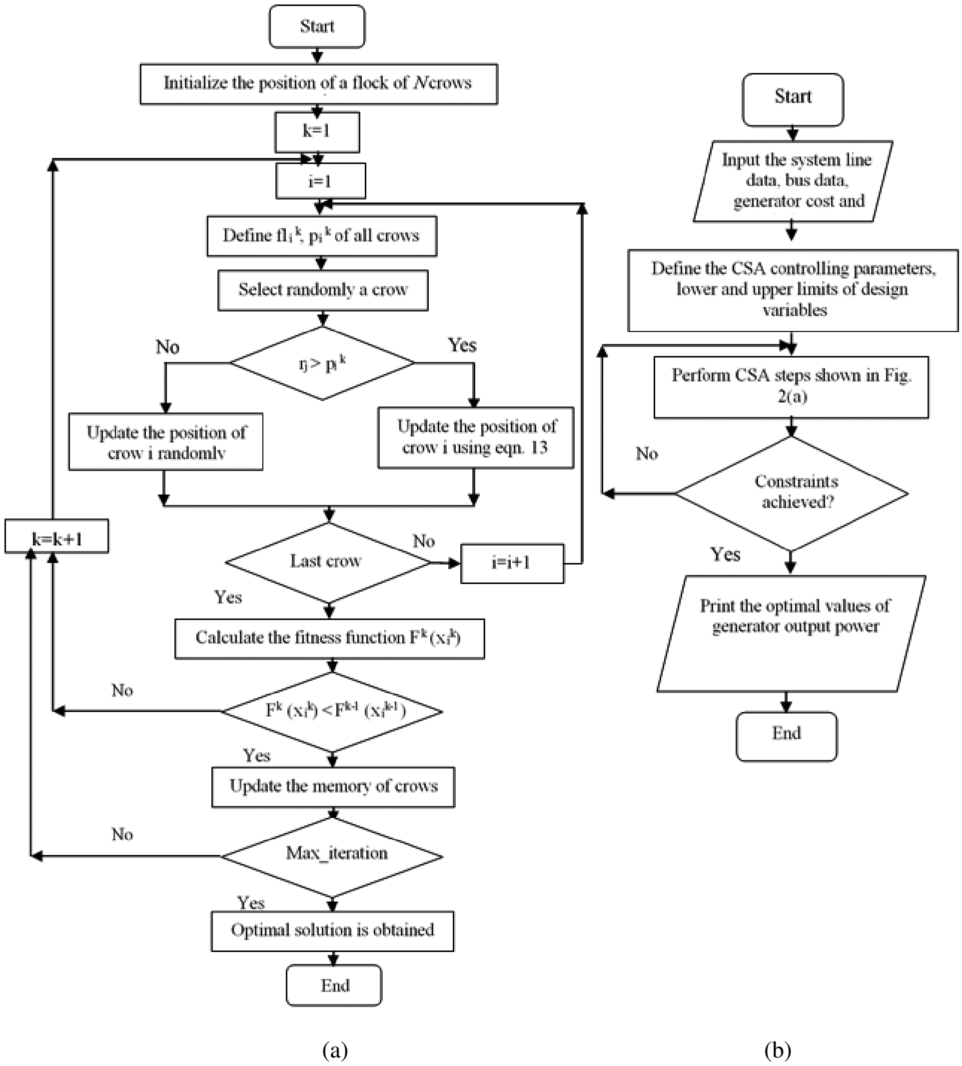


Fig. 2. (a) The flowchart of CSA; (b) the proposed methodology steps

cost data and generators' emission data. The second step defines the controlling parameters of the CSA and the lower and upper limits of the variables to be designed, then performing the flow chart steps given in Fig. 2(a). After that, the constraints are checked to ensure a reliable operation of the power system. In the case of achieving the constraints, the optimal solution is obtained, else the steps of the CSA shown in Fig. 2(a) are repeated. The updating process takes place based on comparing the obtained objective function with that obtained in the previous iteration. The steps are repeated until the last iteration is reached and then the optimal solution is obtained.

5. Simulation results

The proposed CSA algorithm is programmed in the MATLAB R2013a environment and applied on two systems, an IEEE 30-bus network and an IEEE 118-bus network. The analysis is performed on the Intel ®Core i3 CPU M370 @ 2.40 GHz processor, 4.00 GB RAM, 64-bit operating system, PC. Four scenarios are studied, as the three presented objective functions are studied on the IEEE 30-bus system while the only objective function of the total generation fuel cost is applied on the IEEE 118-bus system. The controlling parameters of the CSA for both systems are given in Table 1.

Table 1. Controlling parameters of CSA

Parameter	Value
Flock (population) size	50
Awareness probability	0.1
Flight length	2
Max. iteration	500

5.1. Scenario (1)

In this section, the minimization of the total generation fuel cost is the main target that is applied on an IEEE 30-bus system; the data of this system is given in [38]. The IEEE 30-bus system has 6 generators, 41 branches and 4 transformers to serve about 21 customers of 310.2289 MVA. The fuel cost coefficients and the generator limits are tabulated in Table 2 [14], the minimum and maximum generator voltages are considered as 0.9 and 1.1 pu, respectively. The obtained results via the proposed CSA are compared to others as given in Table 3. It is clear that a minimum cost of 801.728 $/h. is obtained via the proposed CSA with minimum total loss of 9.3953 MW with a consuming time of 18.26 s. The CSA response is shown in Fig. 3. Additionally, the variables

Table 2. The cost coefficients and generation limitation of IEEE 30-bus system [14]

Unit number	Installed bus	a	b	c	P_g^{min} (MW)	P_g^{max} (MW)	Q_g^{min} (MVAr)	Q_g^{max} (MVAr)
G1	1	0.00375	2.00	0.00	50	200	−20	200
G2	2	0.01750	1.75	0.00	20	80	−20	100
G3	5	0.06250	1.00	0.00	15	50	−15	80
G4	8	0.00830	3.25	0.00	10	35	−15	60
G5	11	0.02500	3.00	0.00	10	30	−10	50
G6	13	0.02500	3.00	0.00	11	40	−15	60

obtained via the CSA compared with the others are given in Table 4. In order to guarantee good results obtained via the CSA, several runs are performed and the obtained results are tabulated in Table 5. It is derived that the CSA gives the best solution for several runs. Statistical parameters (mean, standard division and median) of the objective function evaluated by the CSA after several runs are given in Table 6. The responses of objective functions after several runs are given in Fig. 4.

Table 3. Results obtained via CSA compared to others for minimizing fuel cost

Method	Pg1 (MW)	Pg2 (MW)	Pg5 (MW)	Pg8 (MW)	Pg11 (MW)	Pg13 (MW)	Total generation (MW)	Loss (MW)	CPU time (s)	Fuel cost ($/h)
NLP [4]	176.26	48.84	21.51	22.15	12.14	12	292.9	9.48	–	802.4
GA [11]	170.1	53.9	20.6	18.8	12	17.7	293.1	–	–	805.94
DE [12]	176.009	48.801	21.334	22.262	12.46	12	292.866	9.466	36.61	802.394
MDE [12]	175.974	48.884	21.51	22.24	12.251	12	292.859	9.459	23.07	802.376
GA-Fuzzy[13]	175.137	50.353	21.451	21.176	12.667	12.11	–	9.494	–	802.0003
HBMO [14]	178.4646	46.274	21.4596	21.446	13.207	12.0134	292.8646	9.466164	28.56	802.211
MHBMO [14]	177.0431	49.209	21.5135	22.648	10.4146	12	292.8242	9.49	21.34	801.985
SA [18]	192.5105	48.3951	19.5506	11.6204	10	12	294.0766	–	–	804.1072
EGA [19]	176.2	48.75	21.44	21.95	12.42	12.02	292.7800	–	–	802.06
ACO [21]	181.945	47.001	20.553	21.146	10.433	12.173	293.2510	9.852	–	802.578
GSO [34]	176.033	48.6549	21.1301	22.2710	12.6965	12.0202	292.8057	–	–	802.188
AGSO [34]	178.704	46.712	20.756	22.252	12.025	12.342	292.7910	–	–	801.75
CSA	177.1066	48.9171	21.4972	21.8525	12.1700	11.2469	292.7903	9.3953	18.26	801.7280

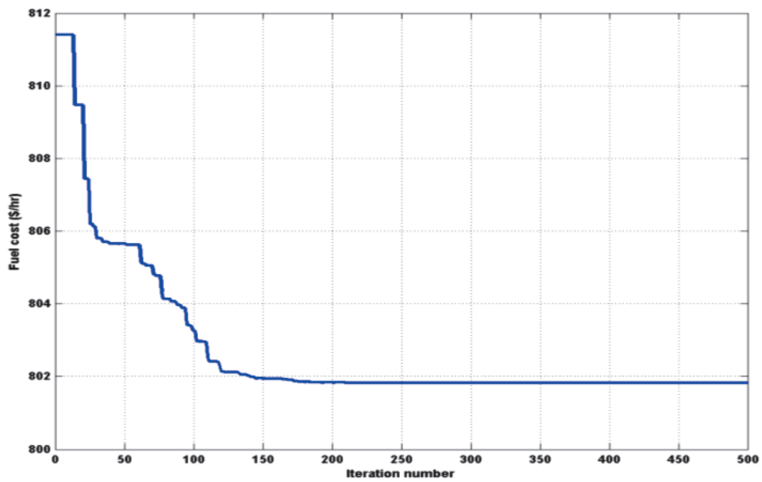


Fig. 3. Convergence plot of generation fuel cost for IEEE 30-bus system

Table 4. The CSA results for IEEE 30-bus system compared to others for scenario (1)

Method	**Vg1 (p.u.)**	**Vg2 (p.u.)**	**Vg5 (p.u.)**	**Vg8 (p.u.)**	**Vg11 (p.u.)**	**Vg13 (p.u.)**	**T6-9 (p.u.)**	**T6-10 (p.u.)**	**T4-12 (p.u.)**	**T27-28 (p.u.)**	**QC10 (MVAr)**	**QC24 (MVAr)**
NLP [4]	1.05	1.0382	1.0114	1.0194	1.0912	1.0913	0.275	−3.98	0.474	−5.837	–	–
MDE [12]	1.05	1.0382	1.0113	1.0191	1.0951	1.0837	0.9866	0.9714	0.9972	0.9413	–	–
GA-Fuzzy [13]	1.05	1.034	1.006	1.003	1.071	1.048	1.0032	0.9645	1.0161	0.9645	–	–
HBMO [14]	1.05	1.0394	1.0117	1.0235	1.0482	1.0437	0.99	0.98	0.98	0.97	12.784	13.975
MHBMO [14]	1.05	1.0421	1.0119	1.0274	1.0496	1.0435	0.99	0.96	0.99	0.98	13.074	18.942
EGA [19]	1.05	1.038	1.012	1.02	1.082	1.067	1.0125	0.95	1	0.9625	–	–
CSA	1.06	1.0430	1.0100	1.0100	1.0820	1.0710	0.978	0.969	0.932	0.968	19	4.3

Table 5. Results obtained via CSA after several runs for minimizing fuel cost

No. of runs	**Pg1 (MW)**	**Pg2 (MW)**	**Pg5 (MW)**	**Pg8 (MW)**	**Pg11 (MW)**	**Pg13 (MW)**	**Loss (MW)**	**Fuel cost ($/h)**
100	178.6176	48.5076	21.5911	19.2988	12.8959	11.0001	9.3991	801.8267
200	177.2012	49.0161	21.3159	20.4346	12.8361	11.0217	9.3956	801.8215
300	176.7943	49.0212	21.3751	21.3335	12.2566	11.0107	9.3934	801.8209
400	177.2048	49.1105	21.6367	20.5652	12.2048	11.0001	9.3922	801.8194
500	177.5115	49.3159	21.3962	20.0901	12.4964	11.0510	9.3911	801.8189

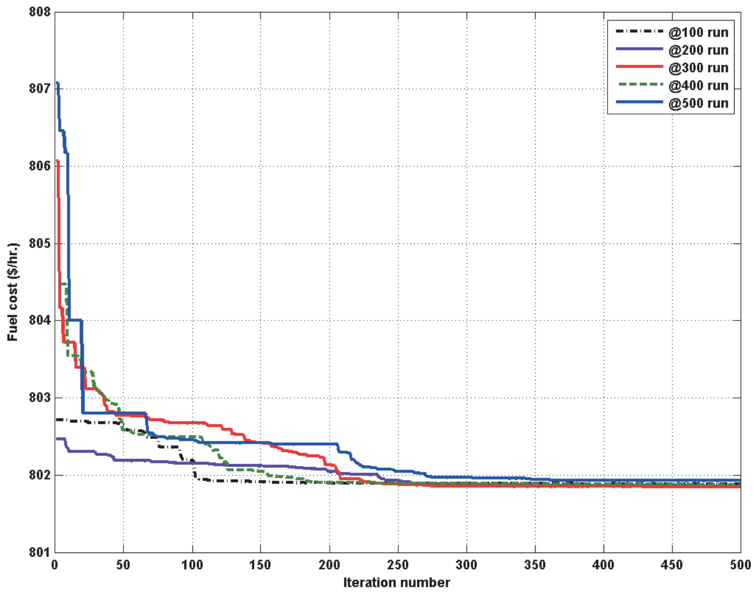


Fig. 4. Convergence plot of generation fuel cost after several runs

Table 6. Statistical analysis of the CSA after several runs

No. of runs	Mean	Std. dev.	Median
100	802.3	0.6873	802
200	802.1	0.4927	801.9
300	802.2	0.3371	801.9
400	802.0	0.2551	801.9
500	802.0	0.1747	801.9

5.2. Scenario (2)

In this section, the focus is on minimizing the system active power loss; the obtained results compared to other optimization algorithms are given in Table 7.

Table 7. Results obtained via CSA compared to other optimization algorithms for minimizing power loss

Method	Pg1 (MW)	Pg2 (MW)	Pg5 (MW)	Pg8 (MW)	Pg11 (MW)	Pg13 (MW)	Total generation (MW)	Loss (MW)	CPU time (s)	Fuel cost ($/h)
NSGA-II [27]	–	79.06	50	35	29.53	36.134	–	3.6294	–	956.45
HSA [27]	66.2759	79.6413	46.8835	34.8880	29.1213	30.0558	286.8658	3.5165	–	928.5099
CSA	51.8973	80.0000	50.0000	35.0000	30.0000	40.0000	286.8973	3.4973	9.1300	1072.1

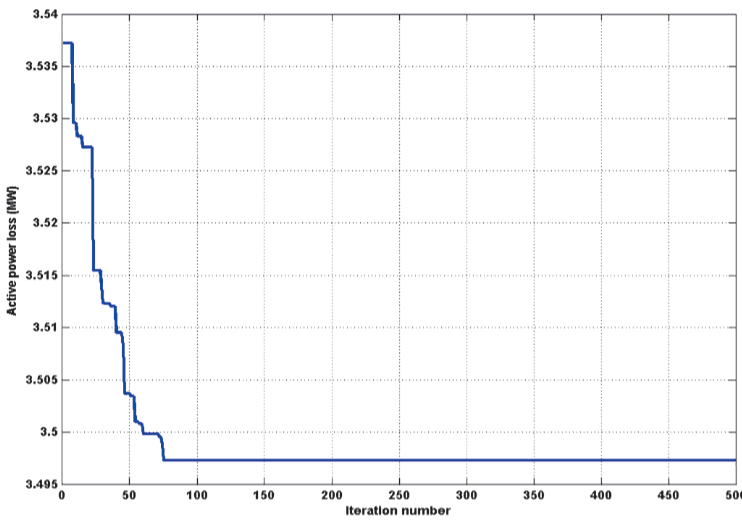


Fig. 5. Convergence plot of Active power loss for IEEE 30-bus system

The system active loss obtained via the proposed CSA is 3.4973 MW, which is the best compared to the other optimization algorithms, this solution is obtained after 9.13 s. The convergence curve obtained in this case is shown in Fig. 5 and the obtained variables are given in Table 8.

Table 8. The obtained variables of IEEE 30-bus system for scenario (2)

Vg1 (p.u.)	Vg2 (p.u.)	Vg5 (p.u.)	Vg8 (p.u.)	Vg11 (p.u.)	Vg13 (p.u.)	T6-9 (p.u.)	T6-10 (p.u.)	T4-12 (p.u.)	T27-28 (p.u.)	QC10 (MVAr)	QC24 (MVAr)
1.0068	1.0179	1.0294	1.0482	1.0820	1.0541	1.0572	1.0134	1.0143	1.0717	5.9332	11.8417

5.3. Scenario (3)

Minimizing the total pollutant emission is an important issue in power system operation, in this section the proposed CSA is applied for minimizing the pollution emitted from the generators for an IEEE 30-bus system. The emission coefficients are given in Table 9.

Table 9. Emission coefficients of IEEE 30-bus system [30]

Unit number	γ	β	α	ξ	λ
G1	0.0649	−0.0555	0.0409	0.0002	2.8570
G2	0.05638	−0.0605	0.0254	0.0005	3.3330
G3	0.04586	−0.0509	0.0426	0.0000	8.0000
G4	0.0338	−0.0355	0.0533	0.0020	2.0000
G5	0.04586	−0.0509	0.0426	0.0000	8.0000
G6	0.05151	−0.0556	0.0613	0.0000	6.6670

The obtained results via the proposed CSA are tabulated in Table 10, it is clear that the less emission is 0.2010 t/h. obtained via the proposed methodology. The CSA response curve for the

Table 10. Results obtained via CSA compared to other optimization algorithms for minimizing emission

Method	Pg1 (MW)	Pg2 (MW)	Pg5 (MW)	Pg8 (MW)	Pg11 (MW)	Pg13 (MW)	Total generation (MW)	Loss (MW)	Fuel cost ($/h)	Emission (t/h)
MSLFA[29]	65.7798	68.2688	50	34.9999	29.9982	39.9970	289.0437	–	951.5106	0.2056
SLFA [29]	64.4840	71.3807	49.8573	35.0000	30.0000	39.9729	290.6949	–	960.1911	0.2063
MTLBO[30]	64.2924	67.625	50.0000	35.0000	30.0000	40.0000	286.9174	–	–	0.20493
GSO [34]	66.3163	68.7716	49.9998	34.9994	29.9995	39.9998	290.0864	–	–	0.206
AGSO [34]	67.004	68.036	50	35	30	40	290.0400	–	–	0.2059
CSA	61.0193	70.9515	50.0000	35.0000	30.0000	40.0000	286.9708	3.5708	950.9308	0.2010

emission obtained from the generators is shown in Fig. 6. The obtained variables after minimizing the pollutant emission are given in Table 11.

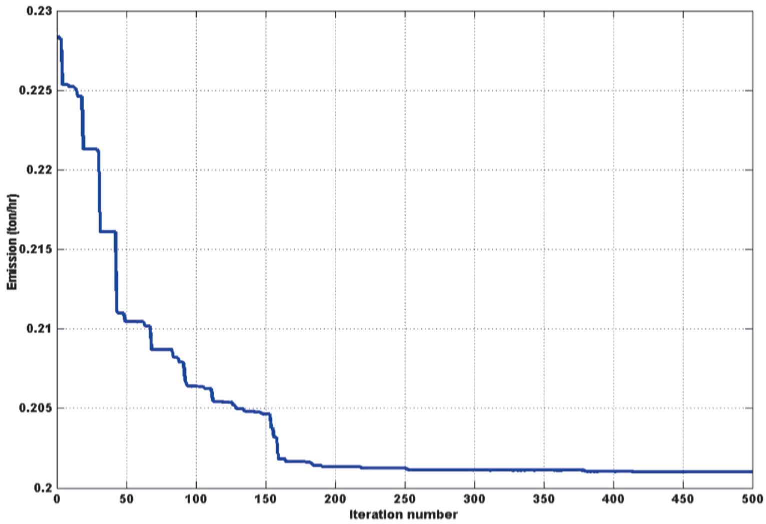


Fig. 6. Convergence plot of pollutant emission for IEEE 30-bus system

Table 11. The obtained variables of IEEE 30-bus system for scenario (3)

Vg1 (p.u.)	**Vg2 (p.u.)**	**Vg5 (p.u.)**	**Vg8 (p.u.)**	**Vg11 (p.u.)**	**Vg13 (p.u.)**	**T6-9 (p.u.)**	**T6-10 (p.u.)**	**T4-12 (p.u.)**	**T27-28 (p.u.)**	**QC10 (MVAr)**	**QC24 (MVAr)**
1.0600	1.0430	1.0100	1.0100	1.0820	1.0710	0.8492	1.0947	1.0097	1.0137	6.8629	5.36789

5.4. Scenario (4)

In order to check the validity of the proposed CSA in solving the OPF for any system, the algorithm is applied on a large-scale power system of the IEEE 118-bus. In this scenario, the minimization of the total generation fuel cost is the main target to be achieved. The data of this system is given in [38]; the system has 54 generators, 186 branches, 9 transformers to serve about 99 customers of 4479.1 MVA. The CSA is performed and the optimal generated power and the corresponding controlling variables are tabulated in Table 12. It is shown that the total generation fuel cost is 129400 \$/h. with system active power loss of 77.401 MW. A comparison to other optimization algorithms is given in Table 13, as the best solution is obtained via the proposed CSA. From the presented analysis, one can derive that the proposed methodology incorporated the CSA is efficient, reliable in solving the problem of the optimal power flow compared to others as it gives the best optimal solution for minimizing the total fuel cost, active power loss and pollutant emission for both studied systems.

Table 12. Results obtained via CSA for IEEE 118-bus system for minimizing the fuel cost

Control variables	**CSA**	**Control variables**	**CSA**	**Control variables**	**CSA**	**Control variables**	**CSA**	**Control variables**	**CSA**
P_{G1} (MW)	11.4	P_{G65} (MW)	220.1947	V_1 (p.u.)	1.0296	V_{61} (p.u.)	1.0364	V_{111} (p.u.)	1.0527
P_{G4} (MW)	2.5189	P_{G66} (MW)	201.0445	V_4 (p.u.)	1.0418	V_{62} (p.u.)	1.0502	V_{112} (p.u.)	1.1063
P_{G6} (MW)	11.4936	P_{G69} (MW)	436.1827	V_6 (p.u.)	1.0358	V_{65} (p.u.)	1.0521	V_{113} (p.u.)	1.0801
P_{G8} (MW)	0.0619	P_{G70} (MW)	59.7256	V_8 (p.u.)	1.0869	V_{66} (p.u.)	1.0597	V_{116} (p.u.)	1.0417
P_{G10} (MW)	0.0023	P_{G72} (MW)	24.3827	V_{10} (p.u.)	1.0976	V_{69} (p.u.)	1.0504	T_{5-8} (p.u.)	0.985
P_{G12} (MW)	124.5337	P_{G73} (MW)	74.5509	V_{12} (p.u.)	1.0269	V_{70} (p.u.)	1.0900	T_{25-26} (p.u.)	0.96
P_{G15} (MW)	19.5939	P_{G74} (MW)	8.3226	V_{15} (p.u.)	1.0253	V_{72} (p.u.)	1.0520	T_{17-30} (p.u.)	0.96
P_{G18} (MW)	24.8812	P_{G76} (MW)	34.6640	V_{18} (p.u.)	1.0379	V_{73} (p.u.)	1.1055	T_{37-38} (p.u.)	0.935
P_{G19} (MW)	7.7568	P_{G77} (MW)	74.6901	V_{19} (p.u.)	1.0269	V_{74} (p.u.)	1.0722	T_{59-63} (p.u.)	0.96
P_{G24} (MW)	48.7838	P_{G80} (MW)	147.4332	V_{24} (p.u.)	1.0547	V_{76} (p.u.)	1.0627	T_{61-64} (p.u.)	0.985
P_{G25} (MW)	107.1875	P_{G85} (MW)	99.4061	V_{25} (p.u.)	1.0907	V_{77} (p.u.)	1.0720	T_{65-66} (p.u.)	0.935
P_{G26} (MW)	195.5876	P_{G87} (MW)	17.0301	V_{26} (p.u.)	1.0708	V_{80} (p.u.)	1.0978	T_{68-69} (p.u.)	0.935
P_{G27} (MW)	37.2393	P_{G89} (MW)	299.9715	V_{27} (p.u.)	1.0441	V_{85} (p.u.)	1.0762	T_{80-81} (p.u.)	0.935
P_{G31} (MW)	50.8580	P_{G90} (MW)	53.3827	V_{31} (p.u.)	1.0364	V_{87} (p.u.)	1.0836	Q_{C34} (MVAr)	1.0002
P_{G32} (MW)	99.3890	P_{G91} (MW)	10.8769	V_{32} (p.u.)	1.0502	V_{89} (p.u.)	1.0730	Q_{C44} (MVAr)	1.0280
P_{G34} (MW)	94.9050	P_{G92} (MW)	55.1368	V_{34} (p.u.)	1.0521	V_{90} (p.u.)	1.1256	Q_{C45} (MVAr)	1.0454
P_{G36} (MW)	100.0000	P_{G99} (MW)	55.5188	V_{36} (p.u.)	1.0597	V_{91} (p.u.)	1.0680	Q_{C46} (MVAr)	1.0109
P_{G40} (MW)	51.9858	P_{G100} (MW)	204.5296	V_{40} (p.u.)	1.0504	V_{92} (p.u.)	1.0255	Q_{C48} (MVAr)	0.9849
P_{G42} (MW)	42.9328	P_{G103} (MW)	23.0027	V_{42} (p.u.)	1.0900	V_{99} (p.u.)	1.0374	Q_{C74} (MVAr)	1.0222
P_{G46} (MW)	47.2488	P_{G104} (MW)	25.1934	V_{46} (p.u.)	1.0520	V_{100} (p.u.)	1.0338	Q_{C79} (MVAr)	1.0178
P_{G49} (MW)	74.3148	P_{G105} (MW)	67.7487	V_{49} (p.u.)	1.1055	V_{103} (p.u.)	1.0048	Q_{C82} (MVAr)	1.9167
P_{G54} (MW)	148.0000	P_{G107} (MW)	33.5919	V_{54} (p.u.)	1.0722	V_{104} (p.u.)	1.0089	Q_{C83} (MVAr)	0.99432
P_{G55} (MW)	16.4742	P_{G110} (MW)	23.2359	V_{55} (p.u.)	1.0627	V_{105} (p.u.)	1.0807	Q_{C105} (MVAr)	1.0535
P_{G56} (MW)	32.1441	P_{G111} (MW)	41.7063	V_{56} (p.u.)	1.0720	V_{107} (p.u.)	1.0884	Q_{C107} (MVAr)	1.00394
P_{G59} (MW)	161.0960	P_{G112} (MW)	59.3044	V_{59} (p.u.)	1.0441	V_{110} (p.u.)	1.0608	Q_{C110} (MVAr)	994560
P_{G61} (MW)	208.2879	P_{G113} (MW)	78.4926						
P_{G62} (MW)	37.1254	P_{G116} (MW)	4.0774						
Fuel cost ($/h)		**129400**							
P_{loss} (MW)		**77.401**							
Q_{loss} (MW)		**483.52**							

Table 13. Comparison between the CSA results and other optimization algorithms for IEEE 118-bus

Algorithm	*P*losses (MW)	Fuel cost ($/h)
DE [28]	79.41	129582
GWO [28]	79.58	129720
CSA	77.401	129400

Finally, one can derive that the proposed CSA is efficient in solving the OPF for the three presented objective functions for both the IEEE-30 system and IEEE-118 bus system.

6. Conclusions

The optimal power flow problem acts as one of the most important issues that must be taken in consideration during the operation of the electrical power systems. This paper proposes a new solution methodology based on a recent meta-heuristic algorithm of crow search (CSA) to solve the problem of the OPF. Different case studies are performed on the IEEE 30-bus system and IEEE 118-bus network with minimization of generation fuel cost, system active power loss and emission injected from the generators. The obtained results are compared to other meta-heuristic optimization algorithms. The comparison ensures the validity and efficiency of the proposed methodology via the CSA in solving the OPF in electrical power systems.

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