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Multi-objective optimal power flow based gray wolf optimization method

Introduction. *One of predominant problems in energy systems is the economic operation of electric energy generating systems. In this paper, one a new evolutionary optimization approach, based on the behavior of meta-heuristic called grey wolf optimization is applied to solve the single and multi-objective optimal power flow and emission index problems.* ***Problem.*** *The optimal power flow are non-linear and non-convex very constrained optimization problems.* ***Goal*** *is to minimize an objective function necessary for a best balance between the energy production and its consumption, which is presented as a nonlinear function, taking into account of the equality and inequality constraints.* ***Methodology.*** *The grey wolf optimization algorithm is a nature inspired comprehensive optimization method, used to determine the optimal values of the continuous and discrete control variables.* ***Practical value.*** *The effectiveness and robustness of the proposed method have been examined and tested on the standard IEEE 30-bus test system with multi-objective optimization problem. The* ***results*** *of proposed method have been compared and validated with hose known references published recently.* ***Originality.*** *The results are promising and show the effectiveness and robustness of proposed approach.* References 35, tables 3, figures 6.

Keywords: **optimization, power networks, optimal power flow, emission index, grey wolf optimization.**

Вступ. *Однією з головних проблем енергетичних системах є економічна експлуатація систем виробництва електроенергії. У цій статті один новий підхід до еволюційної оптимізації, заснований на поведінці метаевристики, яка називається оптимізацією сірого вовка, застосовується для вирішення одно- та багатокритеріальних завдань оптимального потоку потужності та індексу викидів.* ***Проблема***. *Оптимальний потік потужності - це нелінійні та неопуклі задачі оптимізації з дуже обмеженнями.* ***Метою*** *є мінімізація цільової функції, необхідної для найкращого балансу між виробництвом та споживанням енергії, яка представлена у вигляді нелінійної функції з урахуванням обмежень рівності та нерівності.* ***Методологія***. *Алгоритм оптимізації сірого вовка - це натхненний природою комплексний метод оптимізації, що використовується для визначення оптимальних значень безперервних і дискретних змінних, що управляють.* ***Практична цінність***. *Ефективність та надійність запропонованого методу були перевірені та протестовані на стандартній 30-шинній тестовій системі IEEE із завданням багатокритеріальної оптимізації.* ***Результати*** *запропонованого методу були зіставлені та підтверджені нещодавно опублікованими відомими посиланнями.* ***Оригінальність***. *Результати є багатообіцяючими та показують ефективність та надійність запропонованого підходу.* Бібл. 35, табл. 3, рис. 6.

Ключові слова: **оптимізація, енергетичні мережі, оптимальний потік потужності, індекс викидів, оптимізація методом сірого вовка.**

Introduction. The optimal power flow (OPF) problem has a long history of development of more than 60 years. Since the OPF problem was first discussed by Carpenter in 1962, then formulated by Dommel and Tinney in 1968 [1].

Power plants coal-fired contribute a large quantity of polluting gases to the atmosphere, as they produce large amounts of carbon oxides CO_2 and some toxic and dangerous gases such as emissions of sulfur oxides SO_x, and nitrogen oxides NO_x [1, 2].

Over the past few years, various methods have been implemented to solve the OPF and emission index (EI) problems such as: quadratic programming method (QP) [3], Newton and quasi-Newton methods [4, 5], linear and non-linear programming methods [6, 7], and nonlinear internal point methods (IPM) [8].

Several methods of optimization are formulated in the last two decades such as: artificial bee colony (ABC) [9], bacterial foraging algorithms (BFA) [10], artificial neutral networks (ANN) [11], harmony search (HS) [12], Cuckoo search algorithm (CSA) [13], evolution programming (EP) [14], differential evaluation (DE) [15], tabu search (TS) [16], simulated annealing (SA) [17], gravitational search algorithms (GSA) [18], genetic algorithms (GA) [19], particle swarm optimization (PSO) [20], ant colony optimization (ACO) [21], firefly algorithm (FFA) [22], sine-cosine algorithm (SCA) [23], modified imperialist competitive algorithm (MICA) [24], moth swarm algorithm (MSA) [25], electromagnetism-like mechanism method (ELM) [26], wind driven optimization (WDO) method [27], machine learning [28], teaching-learning-studying-based optimization algorithm [29], and more recently grey wolf optimizer (GWO) [30, 31]. Variants of these algorithms were proposed to handle multi-objective functions in electric power systems.

The proposed GWO approach is tested and illustrated by numerical examples based on IEEE 30-bus test system.

Problem formulation. The OPF and EI are nonlinear optimization problems, represented by a predefined objective function *f*, subject to a set of equality and inequality constraints [27, 32]. Generally, these problems can be expressed as follows:

$$\min f(x, u), \quad (1)$$

subject to

$$h(x, u) = 0; \quad (2)$$

$$g(x, u) \le 0; \quad (3)$$

$$x_{\min} \le x \le x_{\max} \text{ and } u_{\min} \le u \le u_{\max}, \quad (4)$$

where $f(x, u)$ is a scalar objective function to be optimized; and $g(x, u)$ are, respectively, the set of nonlinear equality constraints represented by the load flow equations and inequality constraints consists of state variable limits and functional operating constraints; x and u are the state and control variables vectors respectively; x_{min}, x_{max}, u_{min}, u_{max} are the acceptable limits of the variables.

Hence, x and u can be expressed as given

$$x^t = \left\{P_{G_1}, \left|V_{L_1}\right|, \ldots \left|V_{L_{nL}}\right|, Q_{G_1}, \ldots Q_{G_{ng}}, S_1, \ldots, S_{n_{br}}\right\}, \quad (5)$$

where P_G, Q_G, V_L, and S_k are the generating active power at slack bus, reactive power generated by all generators, magnitude voltage of all load buses and apparent power flow in all branches, respectively; n_g, n_L, and n_{br} are, respectively, the total number of generators, the total number of load buses and the total number of branches.

The set control parameters are represented in terms of the decision vector as follows:

$$u^t = \left\{P_{G_2},...,P_{G_{ng}}, \left|V_{G_1}\right|,...\left|V_{G_{ng}}\right|, Q_{1_{com}},...Q_{n_{com}}, T_1,...,T_{n_T}\right\}, \quad (6)$$

where P_G is the active power generation excluding the slack generator; V_G is the generators magnitude voltage; T is tap settings transformers; Q_{com} is the reactive power compensation by shunt compensator; n_T and n_{com} are the total number of transformers and the total number of compensators units, respectively.

Cost without valve-point optimization. The objective function of cost optimization f_1 of quadratic cost equation for all generators as given below:

$$f_1 = \min \sum_{k=1}^{n_g} C(P_{gk}) = \min \sum_{k=1}^{n_g} a_k + b_k P_{gk} + c_k P_{gk}^2 \quad , \quad (7)$$

where f_1 is the total generation cost in (\$/h); P_{gk} and n_g are the active power output generated by the i^{th} generator and the total number of generators; a_k, b_k, c_k are the cost coefficients of the generator k.

Cost with valve-point optimization. Generally, when every steam valves begins to open, the valve-point shows rippling. However, the characteristics of input-output of generation units make nonlinear and non-smooth of the fuel costs function. To consider the valve-point effect, the sinusoidal function is incorporated into the quadratic function. Typically, this function is represented as follows

$$\begin{aligned} f_2 = \min \sum_{k=1}^{n_g} \left[a_k + b_k P_{gk} + c_k P_{gk}^2\right] + \\ + \left|d_k \sin\left(e_k \left(P_{gk}^{\min} - P_{gk}\right)\right)\right|, \end{aligned} \quad (8)$$

where d_k and e_k are the cost coefficients of unit with valve-point effect.

Active power loss optimization. The active power loss function f_3 in MW to be minimized can be expressed as follows:

$$f_3 = \sum_{k=1}^{n_b} G_{kj}\left[V_k^2 + V_j^2 - 2V_k V_j \cos\theta_{kj}\right], \quad (9)$$

where V_k and V_j are the magnitude voltage at buses k and j, respectively; G_{kj} is the conductance of line kj; θ_{kj} is the voltage angle between buses k and j; n_b is total number of buses.

Emission optimization. The emission function is the sum of exponential and quadratic functions of real power generating. Using a quadratic equation, emission of harmful gases is calculated in (ton/h) as given below

$$\begin{aligned} f_4 = \min \sum_{k=1}^{n_g} 10^{-2}\left(\alpha_k + \beta_k P_{gk} + \gamma_k P_{gk}^2\right) + \\ + \zeta_k \exp\left(\lambda_k P_{gk}\right), \end{aligned} \quad (10)$$

where f_4 is the emission function in (ton/h); α_k, β_k, γ_k, ζ_k, λ_k are the emission coefficients of the generator k.

All multi-objective functions using aggregation weighting function. The function used in the case of weighted aggregation is given as

$$\min F = \sum_{i=1}^{n_f} \omega_i f_i \text{ with } \omega_i \ge 0 \text{ and } \sum_{i=1}^{n_f} \omega_i = 1, \quad (11)$$

where $\sum_{i=1}^{n_f} \omega_i = 1$ and $i = 1 : n_f$, ω_i is the weighting factor; n_f is the number of objective function considered.

Equality constraints. These equality constraints are the sets of nonlinear load flow equations that govern the power system, i.e.:

$$\begin{cases} P_{gk} = P_k + P_{dk}; \\ Q_{gk} - Q_{Comk} = Q_k + Q_{dk}, \end{cases} \quad (12)$$

where P_{gk} and Q_{gk} are, respectively, the scheduled active and reactive power generations at bus k; P_k, Q_k are the active and reactive power injections at bus k; P_{dk}, Q_{dk}, Q_{Comk} are the active and reactive power loads at bus k and the reactive power compensation at bus k.

Inequalitie constraints. The inequality constraints $g(x, u)$ are represented by the system operational and security limits, listed below:

- Active and reactive power generations limits:

$$P_{gk}^{\min} \le P_{gk} \le P_{gk}^{\max} \text{ where } k = 1,...,n_g; \quad (13)$$

$$Q_{gk}^{\min} \le Q_{gk} \le Q_{gk}^{\max} \text{ where } k = 1,...,n_g; \quad (14)$$

- Voltage magnitudes and angles limits:

$$V_k^{\min} \le V_k \le V_k^{\max} \text{ where } k = 1,...,n_b; \quad (15)$$

$$\theta_k^{\min} \le \theta_k \le \theta_k^{\max} \text{ where } k = 1,...,n_b; \quad (16)$$

- Tap settings transformers limits:

$$T_k^{\min} \le T_k \le T_k^{\max} \text{ where } k = 1,...,n_T; \quad (17)$$

- Reactive power compensation limits:

$$Q_{Comk}^{\min} \le Q_{Comk} \le Q_{comk}^{\max} \text{ where } k = 1,.....,n_{Com}; \quad (18)$$

- Security constraint limits:

$$S_{kj} \le S_{kj}^{\max} \text{ where } k = j = 1,.....,n_b, \quad (19)$$

where n_T, n_{Com}, T and Q_{Com} are the total number of transformers, the total number of compensator, the transformers tap settings, the reactive power compensation; $S_{kj}^{\max}$ is the maximum apparent power between buses k and j.

Grey wolf optimization (GWO) is a typical swarm-intelligence based meta-heuristic algorithm proposed by Mirjalili et al. in 2014 [33] which is inspired from the leadership hierarchy and hunting mechanism of Grey Wolves in nature. In nature, Gray Wolf (Canis lupus) belongs to Canidae family. It is considered as a top level of predators and residing at the top in the food chain.

The population hierarchies of grey wolves are separated by 4 layers which are named as, alpha (α) is the fittest solution. Beta (β) is the second optimum solution and delta (δ) is the third one. Omega (ω) is the candidate solutions that are left over [30]. Generally, the populations of grey wolves have average crowd size of 5-12 and the cluster organizes compactly through the hierarchy [30].

The position of the wolves is considered as the variables to be optimized and the distance between prey and grey wolves determine the fitness value of the objective function. The movement of each individual is influenced by 4 processes, namely [30]:

1. Searching for prey (exploration);
2. Encircling prey;
3. Hunting;
4. Attacking prey (exploitation).

The following sub-section explained these operators.

A. Social hierarchy. The grey wolves diverge from each other position for searching a victim. Make use of $\vec{A}_M$ with random values to compel the search agent to diverge from the victim. The component $\vec{C}_M$ provides random weights for searching prey in the search space.

B. Encircling prey. As mentioned above, grey wolves encircle prey during the hunt. α, β and δ estimate the position of the 3 best wolves and other wolves updates their positions using the positions of these 3 best wolves. Encircling behavior can be represented by $\vec{D}_M$. When the wolves do hunting, they tend to encircle their prey. The following equations depicted the encircling behavior [33, 34].

$$\vec{D}_M = \left| \vec{C}_M \vec{X}_P(t) - \vec{X}(t) \right|; \tag{20}$$

$$\vec{X}_{(t+1)} = \vec{X}_P(t) - \vec{A}_M . \vec{D}_M , \tag{21}$$

where t is the current iteration; $\vec{X}$ is the position vector of gray wolf; $\vec{X}_P$ is the position of the prey; $\vec{A}_M$ and $\vec{C}_M$ are the coefficient vectors calculated using the following expressions [30, 33]:

$$\vec{A}_M = 2\,\vec{a}\,.\,\vec{r}_1 - \vec{a} \quad \text{and} \quad \vec{C}_M = 2\vec{r}_2 , \tag{22}$$

where $\vec{r}_1$ and $\vec{r}_2$ are random vectors between 0 and 1 and $\vec{a}$ is set to decreased from 2 to 0 over the course of iterations. The 3 best solutions so far are saved and then the other search agents (omega wolves) update their positions according to the current best position [31, 34].

C. Hunting. Conservation of regional habitat connectivity has the potential to facilitate recovery of the grey wolf. After encircling, α wolf guides for hunting. Later, β and δ wolves join in hunting [33]. It is tough to predict about the optimum location of prey. These situations are expressed in the following expressions [33]:

$$\vec{D}_{M\alpha} = \left| \vec{C}_{M\alpha} \cdot \vec{X}_\alpha(t) - \vec{X}(t) \right|; \tag{23}$$

$$\vec{D}_{M\beta} = \left| \vec{C}_{M\beta} \cdot \vec{X}_\beta(t) - \vec{X}(t) \right|; \tag{24}$$

$$\vec{D}_{M\delta} = \left| \vec{C}_{M\delta} \cdot \vec{X}_\delta(t) - \vec{X}(t) \right|; \tag{25}$$

$$\begin{aligned} \vec{X}_{1\alpha} &= \vec{X}_\alpha - \vec{A}_{M1} \vec{D}_{M\alpha}; \\ \vec{X}_{1\beta} &= \vec{X}_\beta - \vec{A}_{M2} \vec{D}_{M\beta}; \\ \vec{X}_{1\delta} &= \vec{X}_\delta - \vec{A}_{M3} \vec{D}_{M\delta}. \end{aligned} \tag{26}$$

The best position of grey wolf is calculated taking average sum of positions and given as

$$\vec{X}_{(t+1)} = \frac{\vec{X}_{1\alpha} + \vec{X}_{1\beta} + \vec{X}_{1\delta}}{3} . \tag{27}$$

D. Attacking prey. The grey wolves stop the hunting by attacking the prey when it stops moving. It depends on the value of a. $\vec{A}_M$ is a random value in the interval [–2a, 2a]. In GWO, search agents update their positions based on the location of α, β and δ and attack towards the prey [32, 33]. However, GWO algorithm is prone to stagnation in local solutions with these operators. It is true that the encircling mechanism proposed shows exploration to some extent, but GWO needs more operators to emphasize exploration [33, 34].

Simulation and results. The 5 generators system, IEEE 30-bus system is used throughout this work to test the proposed algorithm. This system consist 30 buses, 6 generators units and 41 branches, 37 of them are the transmissions lines and 4 are the tap changing transformers. One of these buses is chosen like as a reference bus (slack bus), the buses containing generators are taken the PV buses, the remaining buses are the PQ buses or loads buses. It is assumed that 9 capacitors compensation is available at buses 10, 12, 15, 17, 20, 21, 23, 24 and 29. The network data, the cost and emission coefficients of the five generators are referred in [35]. The one-line diagram IEEE 30-bus system is shown in Fig. 1.

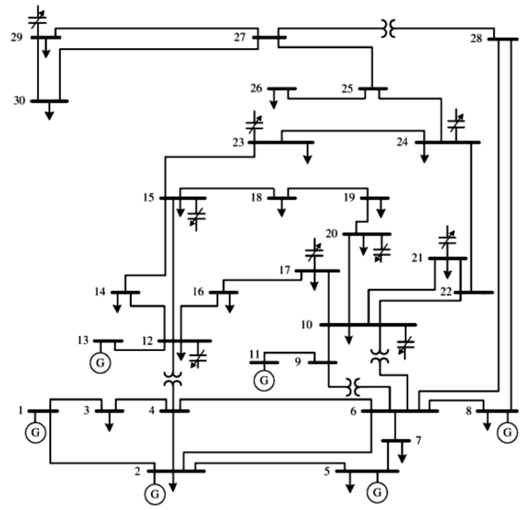

Fig. 1. One-line diagram of IEEE 30-bus system

The total loads of active and reactive powers are 283.4 MW and 126.2 MVAr, respectively, with 24 control variables. The basis apparent power used in this paper is 100 MVA. The simulation results of load flow problem of test system are summarized in Table 1.

A. Case 1: Cost optimization without valve-point effect. The cost function f_1 given in (7) is optimized. Therefore, in this case, the cost has resulted in 801.65 \$/h, which is considered 8.301 % lower than the initial case (load flow). Figure 2 shows the convergence of cost using GWO algorithm. Table 1 summarizes the optimal control variables of this case.

B. Case 2: Cost optimization with valve-point effect. The cost function f_2 is optimized. Therefore, in this case, the cost has resulted in 836.73 \$/h, which is considered 4.288 % lower than the initial case. The convergence characteristic of cost for this case is introduced in Fig. 2. The optimal control variables of this case are presented in Table 1.

C. Case 3: Active power loss optimization. The optimal control variables of this case are introduced in Table 1. Figure 3 shows the trend for convergence characteristics of active power losses using GWO algorithm. The active power loss minimization has dramatically decreased to 5.072 MW.

Table 1

Results of case 1, 2 and 3 for test system

Control variables	Optimal values			
	Base	Case 1	Case 2	Case 3
P_{G2}, MW	40	46.53	36.57	66.930
P_{G5}, MW	0	21.71	17.06	50
P_{G8}, MW	0	18.36	18.44	13.533
P_{G11}, MW	0	15.03	12.64	22.466
P_{G13}, MW	0	15.26	12.45	29.854
V_1, pu	1.060	1.085	1.087	1.071
V_2, pu	1.045	1.066	1.064	1.061
V_5, pu	1.050	1.035	1.032	1.040
V_8, pu	1.070	1.038	1.036	1.040
V_{11}, pu	1.090	1.088	1.047	1.068
V_{13}, pu	1.090	1.022	1.027	1.064
Q_{com10}, MVAr	0	2.372	1.185	2.083
Q_{com12}, MVAr	0	0.330	4.804	2.198
Q_{com15}, MVAr	0	3.462	3.158	0.934
Q_{com17}, MVAr	0	1.139	4.612	1.319
Q_{com20}, MVAr	0	1.667	3.320	0.864
Q_{com21}, MVAr	0	2.321	2.095	1.756
Q_{com23}, MVAr	0	1.962	2.136	1.516
Q_{com24}, MVAr	0	4.765	3.672	1.586
Q_{com29}, MVAr	0	3.180	2.985	3.012
$T_{6\text{-}9}$	0.978	1.046	1.000	0.985
$T_{6\text{-}10}$	0.969	0.971	0.995	0.975
$T_{4\text{-}12}$	0.966	0.974	0.996	0.991
$T_{27\text{-}28}$	0.932	0.993	0.999	0.973
Cost, \$/h	**874.22**	**801.65**	**836.73**	–
Losses, MW	**17.56**	–	–	**5.072**
Emission, ton/h	**4.100**	–	–	–
Slack, MW	260.96	175.43	196.4	105.687
CPU time, s	19.820	79.710	83.77	91.791

D. Case 4: Emission optimization. In this case, the emission reduction yielded 0.215 ton/h. The optimal control variables settings for this case are detailed in Table 1. The convergence characteristics of emission is shown in Fig. 4.

E. Case 5: Cost and active loss optimization. The control variables of this case are tabulated in detail in Table 2. The cost and the power losses has resulted in 814.45 \$/h and 7.4 MW, respectively. The convergence result of this case is presented in Fig. 5.

F. Case 6: Cost and emission optimization. The control variables of this case are tabulated in detail in Table 2. The cost and emission has resulted, respectively, in 801.88 \$/h and 0.267 ton/h. Figure 6 shows the convergence algorithm obtained in case 5.

G. Case 7: Cost, active power loss and emission. The control variables of this case are presented in detail in Table 2. The cost optimization obtained in this case is presented in Fig. 2.

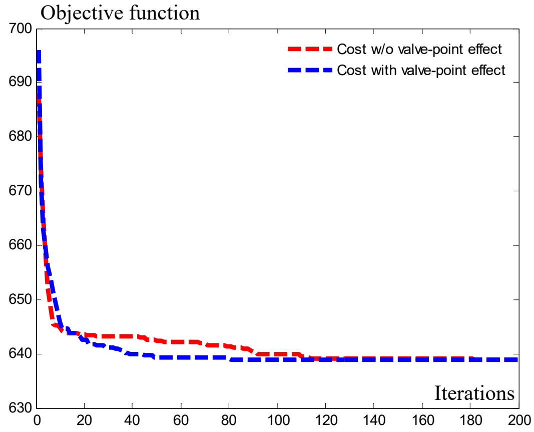

Fig. 2. Convergence algorithm for cases 1 and 2

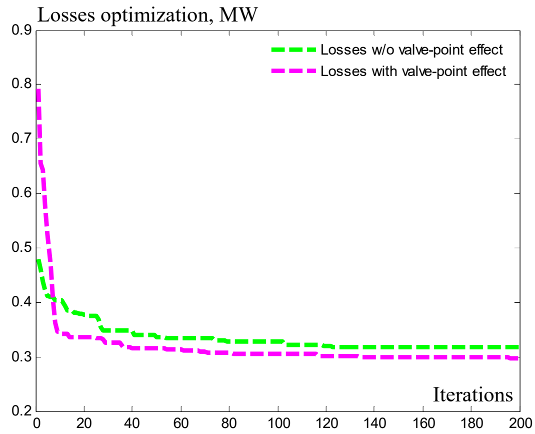

Fig. 3. Convergence algorithm for case 3

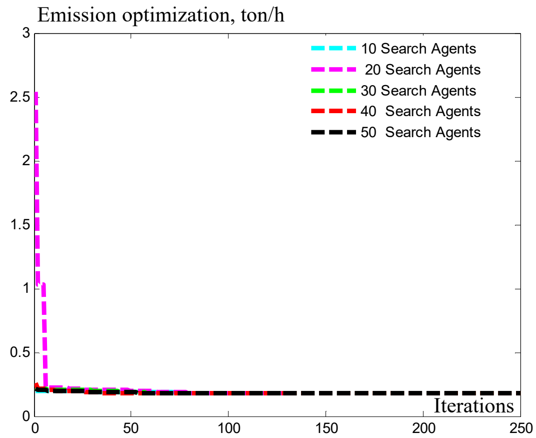

Fig. 4. Convergence algorithm for case 4

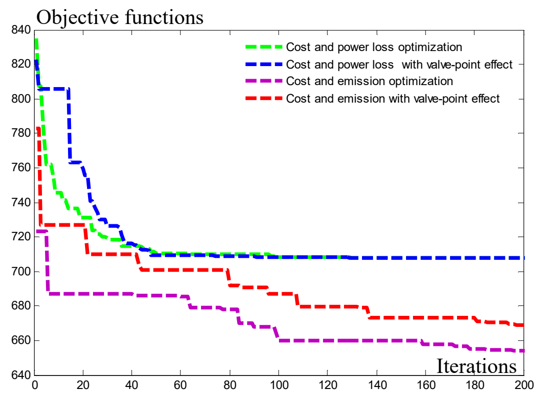

Fig. 5. Convergence algorithm for cases 5 and 6

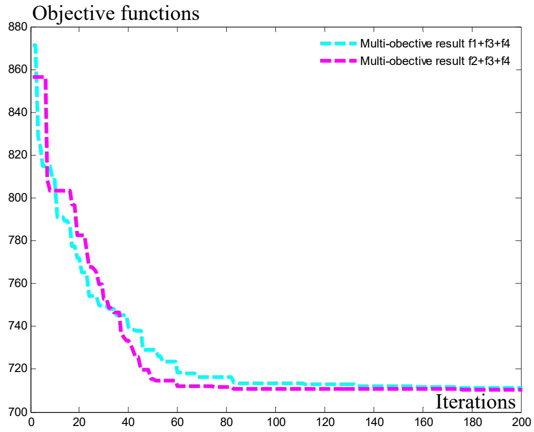

Fig. 6. Convergence algorithm for case 7

Table 2

Results of cases 4, 5, 6 and 7 for test system

Control variables	Optimal values			
	Case 4	Case 5	Case 6	Case 7
P_{G2}, MW	76.762	60.385	47.081	53.489
P_{G5}, MW	50	26.084	20.674	30.009
P_{G8}, MW	26.991	15.136	21.764	34.998
P_{G11}, MW	30	20.436	13.838	18.426
P_{G13}, MW	40	23.063	15.590	23.746
V_1, pu	1.042	1.078	1.083	1.073
V_2, pu	1.032	1.064	1.065	1.060
V_5, pu	1.003	1.034	1.033	1.032
V_8, pu	0.999	1.038	1.040	1.039
V_{11}, pu	1.004	1.098	1.069	1.082
V_{13}, pu	1.011	1.049	1.045	1.051
Q_{com10}, MVAr	2.887	3.674	2.488	2.286
Q_{com12}, MVAr	2.193	3.143	1.277	1.414
Q_{com15}, MVAr	1.092	2.047	2.774	1.749
Q_{com17}, MVAr	1.771	2.508	1.688	4.259
Q_{com20}, MVAr	3.213	2.539	2.294	2.561
Q_{com21}, MVAr	2.972	1.584	1.297	3.274
Q_{com23}, MVAr	3.749	1.330	3.604	1.828
Q_{com24}, MVAr	3.506	4.274	1.192	2.970
Q_{com29}, MVAr	3.247	0.313	2.277	2.971
$T_{6\text{-}9}$	1.078	1.036	1.041	1.010
$T_{6\text{-}10}$	0.939	0.940	0.922	0.995
$T_{4\text{-}12}$	1.006	0.971	0.974	0.994
$T_{27\text{-}28}$	0.924	0.980	0.973	0.982
Cost, \$/h	**–**	**814.45**	**801.88**	**823.00**
Losses, MW	–	**7.40**	–	**6.038**
Emission, ton/h	**0.215**	–	**0.267**	**0.227**
Slack, MW	63.681	145.69	173.28	128.768
CPU time, s	74.987	81.601	86.01	99.374

For the IEEE-30 bus system, 24 control variables (5 generators excluding slack bus, 6 generators magnitude voltages, 4 transformers taps and 9 reactive powers compensators) were optimized. Tables 3 shows a comparison between the obtained results.

Conclusions. In this paper, the grey wolf optimization approach is implemented and applied successfully to solve the multi-objective optimal power flow. The obtained results with proposed method in all cases are much better. Therefore, in the multi-objective case, taking into account generation cost, the active power losses optimization and emission optimization all results were significantly decreased to 823 \$/h, 6.038 MW and 0.227 ton/h, which are considered 5.85 %, 61.61 % and 44.63 %, respectively, lower than the initial case (load flow). With comparison, the obtained results validate the advantage of the proposed approach over many other methods used to solve the optimal power flow in terms of solution quality. It is concluded that the proposed method has the ability to obtain near global solution with stable convergence characteristics. Thus, the may be recommended the proposed approach as a promising algorithm for solving some more complex engineering problems. The versatility of optimization is illustrated by various tests by changing the parameters of proposed approach such as number of population size and control parameter α_0 coefficient. The simulation results demonstrated the effectiveness and robustness of the proposed methodology.

Table 3

Comparison of obtained results for cases 5, 6 and 7

Methods		Cost, \$/h	Losses, MW	Emission, \$/ton
Methods	Reference			
Case 5				
Proposed	–	**814.45**	**7.40**	**0.2524**
MSA	[25]	859.191	4.540	–
ABC	[9]	854.913	4.982	–
PSO	[20]	878.873	7.810	–
DE	[15]	820.880	5.594	–
Case 6				
Proposed	–	**801.88**	**–**	**0.267**
GA	[19]	820.166	–	0.271
MICA	[24]	865.066	–	0.222
Case 7				
Proposed	–	**823.00**	**6.038**	**0.227**
GA	[19]	793.605	8.450	0.187
IABC	[9]	851.611	4.873	0.223
ABC	[9]	854.916	4.982	0.228
DE	[15]	867.980	5.563	0.266

Conflict of interest. The authors declare that they have no conflicts of interest.

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