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Application of Meta-Heuristic Algorithm for Finding the Best Solution for the Optimal Power Flow Problem

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Abstract: Optimal power flow (OPF) is an important problem in the power system operation. The purpose of the OPF problem is to optimize a defined objective function by modifying variables of control such as real power at generator buses except slack bus generator, voltages at all generator buses, reactive power of compensators and tap ratio of transformers while all constraints are satisfied. This paper is proposed an approach based on the artificial ecosystem optimization (AEO) to solve problem of optimal power flow. The suggested algorithm is tested on the IEEE-30 bus systems with five target functions consisting of fuel cost, emission, power loss, voltage deviations and L_index. The results obtained of the suggested AEO approach compared with equilibrium optimizer (EO), particle swarm optimization (PSO), sunflower optimization (SFO), genetic algorithm (GA) and other exiting methods. The results simulation shows that, standard deviation obtained value after 50 independent runs by the proposed AEO algorithm is better compared with EO, PSO, SFO and GA method. The fuel cost, emissions, active power loss and voltage deviations levels are reduced by 11.21%, 44.06%, 46.44%, and 92.13% respectively, compared to the initial case. Furthermore, for other exiting methods the improvement level percentage (IL) of the proposed AEO algorithm can be up to 0.2285 % for fuel cost objective, 0.137% for emission objective, 7.618% for total power loss objective, 89.85% for voltage deviation objective and 0.652% for L_index objective. Thus, the proposed AEO method is also one of effective and reliable algorithms for handling OPF problem.

Keywords: Artificial ecosystem optimization, Optimal power flow, Power loss, Generator cost.

1. Introduction

Optimal power flow (OPF) plays important role in operating and planning of power system. The OPF aims to optimize a defined objective by modifying variables of control such as real power at generator buses except slack bus generator, voltages at all generator buses, reactive power of compensators and tap ratio of transformers while satisfying constraints.

Many conventional approaches have been implemented for handling the OPF problem such as linear programming (LP) [1], nonlinear programming (NLP) [2], newton-based technique [3], quadratic programming (QP) [4], and interior point (IP) methods [5]. However, the objective functions of the OPF problem, which was solved by these conventional methods, is simple and differentiable. In fact, the OPF problem in modern power systems is always a nonlinear optimization problem and may be a non-differentiable one, thus it is an actual challenge for optimization methods for dealing with, especially the conventional methods

To over the limitations of classical methods, heuristic methods have been considered as alternative approaches to solve the OPF problem with the advantages of obtaining nearly optimum solution whether the problem is differentiable or not. Many heuristic optimization methods have applied for solving OPF problem such as tabu search (TS) [6], evolutionary programming (EP) [7], differential evolution (DE) [8], biogeography optimization (BOA) [9], teaching learning optimization algorithm (TLOA) [10], stud krill herd algorithm (SKHA) [11], water wave optimization algorithm (WWOA) [12], gravitational search algorithm (GSA) [13], artificial bee colony approach (ABCA) [14], moth swarm algorithm (MSA) [15], Jaya algorithm [16]. Besides, number of improved version of heuristic optimization algorithms have been proposed to improve the performance as well as robustness such as self-adaptive differential evolution (SADE) [17], modified differential evolution algorithm (MDEA) [18], enhanced genetic algorithm (EGA) [19], adaptive real coded biogeography-based optimization (ARCBOA) [20], improved stud krill herd algorithm (ISKHA) [21], improved grey wolf optimization (IGWO) [22], modified shuffle frog leaping algorithm (MSFLA) [23], modified imperialist competitive algorithm (MICA) [24], modified artificial bee colony approach (MABCA) [25], improved electromagnetism mechanism approach (IEMA) [26], modified of sine-cosine approach (MSCA) [27], hybrid particle swarm optimization and differential evolution (HPSO-DE) [28], hybrid particle swarm optimization and gravitational search approach (HPSO-GSA) [29].

In generally, these methods have successfully applied for the OPF problem, however they have always been a trade-off exploration and exploitation problem. Therefore, it might be challenging for many algorithms to obtain balance between exploration and exploitation abilities. Recently, an artificial ecosystem optimization (AEO) approach developed based on the flow of energy in the ecosystem is introduced in [30, 31]. The AEO method utilizes three mechanisms in the ecosystem to keep a problem of balancing exploration and exploitation ability that can over local minima. The ecosystem is considered as a population containing of a production organism, a decomposition organism and consumption organisms. The exploration mission is performed during the processing of consumption organisms via updating new solution and selecting the smallest energy level value. Unlike different many algorithms, the AEO does not need special control parameters in the calculation process. The AEO only requires two external parameters to control is that population size and maximum iterations number, so it is simple to implement and smooth execution. From this viewpoint, this paper proposed the AEO technique for dealing with the OPF problem with five different objective functions. The suggested technique is simulated on IEEE-30 bus system. The achieved result values of suggested technique compared with different techniques that shows the AEO also is an effective method to solve OPF problem in large scale and complex systems.

The main contributions of the study can be briefed as follows:

(i) The AEO is successfully adjusted for handling the OPF problem with five other target functions.

(ii) The OPF method based on AEO have been successfully implemented for finding the optimal solution on IEEE 30-bus systems.

(iii) The effectiveness of the AEO technique is compared to the implemented methods and different exiting methods that prove the effectiveness of AEO for the problem of OPF.

2. Problem formulation

OPF is an optimization issue in electric power system operation which minimizes the defined objective functions by adjusting controlled variables while satisfying all security constraints of electric power system [11]. The problem of OPF is mathematically presented as below

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

Subject to

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

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

Where F is the objective function; $g(x, u)$ and $h(x, u)$ are equality and inequality constraints, respectively. The state variables vector x and control variables vector u can be described as Eq. (4) and Eq. (5) respectively.

$$x = [P_{G,slack}, V_{L1}, \dots, V_{LN_L}, Q_{G1}, \dots, Q_{GN_G}, S_l \dots, S_{N_l}] \tag{4}$$

$$u = [P_{Gi}, \dots, P_{GN_G}, V_{G1}, \dots, V_{GN_G}, T_1, \dots, T_{N_T}, Q_{c1}, \dots, Q_{cN_c}] \tag{5}$$

2.1. OPF objective functions

In this study, five target functions including of fuel cost, emission cost, power loss, voltage deviations and L_index are considered as follows

2.1.1. Fuel cost

$$OF_F = f_i(P_{Gi}) = \sum_{i=1}^{N_G} a_i + b_i P_i + c_i P_{Gi}^2 \tag{6}$$

Where a_i, b_i, c_i are the fuel cost coefficients of the i_{th} generator.

2.1.2. Emission

Two important types SOx and NOx of emission gasses are calculated as the pollutant gasses. The emission gasses generated by each generating unit may be approximated by a combination of a quadratic cost and an exponential function of generator active power output. The emission is defined as Eq. (7)

$$OF_E = \sum_{i=1}^{N_G} (\alpha_i + \beta_i P_i + \gamma_i P_{Gi}^2 + \xi_i (\lambda_i P_{Gi})) \quad (7)$$

Where β_i, γ_i, ξ_i are the emission coefficients of the i_{th} generator

2.1.3. Total transmission loss

Total power loss is presented as Eq. (8)

$$OF_L = \sum_{i=1}^{N_G} P_{Gi} - \sum_{j=1}^{N_L} P_{Dj} \quad (8)$$

2.1.4. Voltage deviation

This objective is to minimize voltage deviation at all load buses and is described as Eq. (9)

$$OF_V = \sum_{i=1}^{N_L} |V_{Li} - 1.0| \quad (9)$$

2.1.5. Voltage stability enhancement

Voltage stability is one of the important problems which needs to consider for operating of electric power system. To evaluate voltage stability, L-index known as voltage collapse proximity indicator. The bus with the highest L-index value will be the most vulnerable bus in the system. The L-index calculation for a power system is presented as follow [14].

$$\begin{bmatrix} I_G \\ I_L \end{bmatrix} = \begin{bmatrix} Y_{GG} & Y_{GL} \\ Y_{LG} & Y_{LL} \end{bmatrix} \begin{bmatrix} V_G \\ V_L \end{bmatrix} \quad (10)$$

In which:

I_G: Current at generator bus
I_L: Load bus load
V_G: Generator bus voltage
V_L: Load bus voltage

Rearrange Eq. (10)

$$\begin{bmatrix} V_L \\ I_G \end{bmatrix} = \begin{bmatrix} Z_{LL} & F_{LG} \\ K_{GL} & Y_{GG} \end{bmatrix} \begin{bmatrix} I_L \\ V_G \end{bmatrix} \quad (11)$$

With

$$F_{LG} = -[Y_{LL}]^{-1}[Y_{LG}]$$

L index at load bus j can be calculated as follows

$$L_j = \left| 1 - \sum_{i=1}^{N_G} F_{ji} \frac{V_i}{V_j} \angle \theta_{ij} + \theta_i - \theta_j \right|, \quad (12)$$
$$j = 1, \ldots, N_L$$

Where V_i , δ_i are voltage and voltage angle at generator bus i; V_j, δ_j are voltage and voltage angle at load bus j; θ_{ij} is the phase-angle of F_{ji}, N_L is the load buses. The objective function can be given as

$$OF_{IL} = max(L_j) \quad (13)$$

2.2 Constraints

2.2.1. Equality constraints

Constraints on real and reactive power balance

$$P_i = P_{Gi} - P_{Di} = V_i \sum_{j=1}^{N} |Y_{ij}||V_j| \cos(\delta_i - \delta_j - \theta_{ij}) \quad (14)$$

$$Q_i = Q_{Gi} - Q_{Di} = V_i \sum_{j=1}^{N} |Y_{ij}||V_j| \sin(\delta_i - \delta_j - \theta_{ij}) \quad (15)$$

2.2.2. Inequality constraints

The limits of power generation

$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max}, i = 1,2,\ldots,N_G \quad (16)$$

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max}, i = 1,2,\ldots,N_G \quad (17)$$

The voltage limits of generator buses and load buses

$$V_{Gi}^{min} \le V_{Gi} \le V_{Gi}^{max}, i = 1,2,\ldots,N_G \quad (18)$$

$$V_{Li}^{min} \le V_{Li} \le V_{Li}^{max}, i = 1,2,\ldots,N_L \quad (19)$$

The capacity of switchable capacitor

$$Q_{ci}^{min} \le Q_{ci} \le Q_{ci}^{max}, i = 1,2,\ldots,N_c \quad (20)$$

The limits of transformer tap

$$T_k^{min} \le T_k \le T_k^{max}, k = 1,2,\ldots,N_T \quad (21)$$

The line flow limits of transmission line

$$S_l \leq S_l^{max}, l = 1,2,\ldots,N_l \quad (22)$$

3. Implementation of AEO for solving the OPF problem

AEO is a method that are inspired by the flow of energy in a food chain. The AEO utilizes three mechanisms in the ecosystem to keep a problem balancing exploration and exploitation ability. The ecosystem is considered as a population containing of a production organism, a decomposition organism and consumption organisms. The energy level of each organism is based on its fitness value. The organism with better fitness value has higher energy level. The step by step of applying of AEO for the OPF problem is presented as follow

Step 1: Choose control parameter: Ecosystem size n, max iteration t_{max}

Step 2: Initialize the ecosystem

Each solution (sol) is considered as an organism in the ecosystem and is initialized as follows

$$sol_{i,d} = sol_{d,min} + rand(0,1)(sol_{d,max} - sol_{d,min}) \quad (23)$$

Where, $sol_{d,min}$ is the ith solution, d is the number of control variables, $sol_{d,max}$ and $sol_{d,min}$ are the upper and lower limits of dth control variable which are defined as Eq. (4).

$$\begin{cases} sol_{d,min} = [P_{G2}^{min},\ldots,P_{GN_G}^{min},V_{G1}^{min},\ldots,V_{GN_G}^{min}, \\ \quad T_1^{min},\ldots,T_{N_T}^{min},Q_{c1}^{min},\ldots,Q_{cN_c}^{min}] \\ sol_{d,max} = [P_{G2}^{max},\ldots,P_{GN_G}^{max},V_{G1}^{max},\ldots,V_{GN_G}^{max} \\ \quad T_1^{max},\ldots,T_{N_T}^{max},Q_{c1}^{max},\ldots,Q_{cN_c}^{max}] \end{cases} \quad (24)$$

Step 3: Solve power flow and evaluate the fitness function using Eq. (25) based on the energy level of the organism sol_i. The organism with the smallest fitness value is considered as the best organism in the ecosystem (sol_{best}).

$$OF_i^{(0)} = OF + I_P(P_{G1} - P_{G1}^{lim})^2 + I_q\sum_{i=1}^{N_G}(Q_{Gi} - Q_{Gi}^{lim})^2 + I_v\sum_{i=1}^{N_L}(V_{Li} - V_{Li}^{lim})^2 + I_s\sum_{i=1}^{N_{TL}}(S_l - S_{l,max})^2 \quad (25)$$

Where, OF is the objective function of each case (OF_F, OF_E, OF_L, OF_V, OF_{IL}) that is defined by equation (6)-(9) and (13). I_p, I_q, I_v, and I_s are the penalty coefficients for the inequality constraints of the state variables.

Step 4: Update the production organism

All rearrange organisms in direction of increasing energy level. The first organism which has lowest energy level is chosen as production organism. The production organism is updated as below

$$sol_1^{new} = rand_1(0,1).\left[1 - (1 - \frac{t}{t_{max}})\right].sol_{best} + (1 - \frac{t}{t_{max}}).\left[rand_2(0,1).(sol_d^{max} - sol_d^{min}) + sol_d^{min}\right] \quad (26)$$

Step 5: Update the consumption organisms

Update the consumption organisms is based on three types of herbivores, carnivore and omnivorous. If the consumption organism is an herbivore, it will update with the production organism as Eq. (27)

$$sol_i^{new} = sol_i + \beta_c.(sol_i - sol_1^{new})\,; i \in [2,\ldots,n] \quad (27)$$

Where, β_c is the consumption coefficient determined based on the Levy distribution as follow

$$\beta_c = \frac{1}{2}.\frac{u_1}{u_2}; u_1, u_2 \sim \mathrm{N}(0,1) \quad (28)$$

Where, $N(0,1)$ is a standard normal distribution. If the consumption organism is a carnivore, it will update with another carnivore with higher energy level as Eq. (29)

$$sol_i^{new} = sol_i + \beta_c.(sol_i - sol_j) \quad (29)$$

If the consumption organism is omnivorous, it will update with a producer and a carnivore with higher energy level as Eq. (30)

$$sol_i^{new} = sol_i + \beta_c.[rand_2(0,1).(sol_i - sol_1^{new}) + 1 - rand_2(0,1).(sol_i - sol_j)] \quad (30)$$

Step 6: Solve power flow and evaluate the fitness function using Eq. (25) based on the energy level of the new organisms sol_i^{new}

Step 7: Replace all organisms if new organisms have better fitness values

If new organisms have the better quality than the corresponding ones in the ecosystem, the selective mechanism is used to update the ecosystem and the

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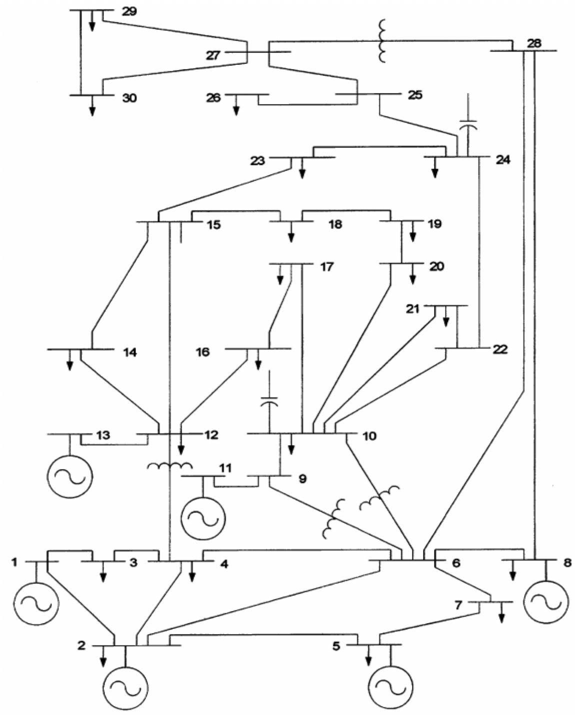

Figure. 1 The IEEE 30-bus system

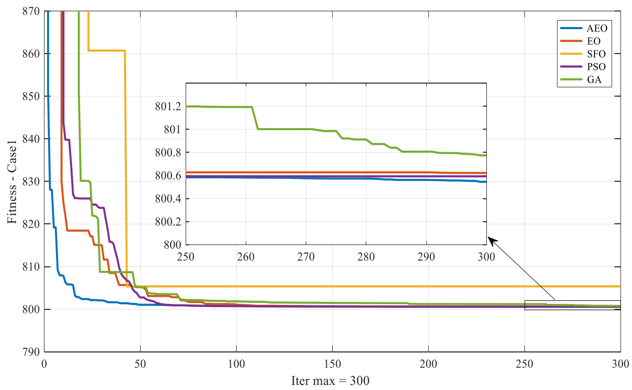

Figure 2. Convergence rate of the AEO and other methods for case 1

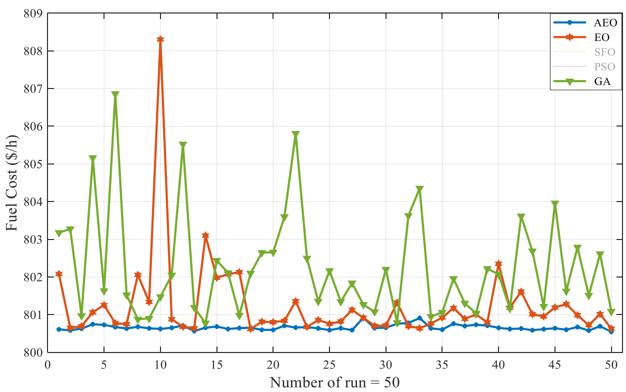

Figure 3. Fuel cost obtained in 50 runs using AEO and other approaches

best organism sol_{best} is also updated after the ecosystem updated.

Step 8: Update the whole ecosystem by decomposition mechanism

Organisms that die will be decomposed by a decomposition organism. Therefore, each organism in the ecosystem will update with the decomposition organism as follows

$$sol_i^{new} = sol_i + 3.\beta_{dr}.(\sigma_1.sol_{best} - \sigma_2.sol_i) \tag{31}$$

Where, β_{dr} is the decomposition rate determined by $\beta_{dr} \sim N(0,1)$. σ_1 and σ_2 are weight factors which are determined by the below equations

$$\begin{cases} \sigma_1 = rand_3(0,1).randi([1,2]) - 1 \\ \sigma_2 = 2.rand_3(0,1) - 1 \end{cases} \tag{32}$$

Step 9: Solve power flow and evaluate the fitness function using Eq. (25). The ecosystem and the best organism sol_{best} are also updated.

Step 10: Check stopping criteria. If $(t < t_{max})$ return to step 5 with $t = t + 1$, otherwise go to next step.

Step 11: End. Export best organism

The best organism sol_{best} corresponding to the value of the fitness function F_{best} is considered as the result of the OPF problem.

4. Numerical results

The OPF problem with five different objective functions based on AEO method is developed on Matlab software to determine the optimal solution for IEEE-30 bus system. Furthermore, the obtained results using AEO are also compared with other studies to prove the effectiveness of the OPF problem method based on AEO.

The IEEE 30-bus system consist of six generators, 24 load buses and 41 lines as Fig 1. Bus 1, 2, 5, 8, 11 and 13 are generator buses. Line 6–9, 6–10, 4–12 and 27–28 is tap changer of transformers. In addition, bus 10, 12, 15, 17, 20, 21, 23, 24 and 29 are reactive power sources. System data is given in [25, 32]. The generator buses voltage bound is within 0.95 and 1.1 p.u, while load bus voltage limits are 0.95 and 1.05 p.u, the tap ratio bound is 0.9 and 1.1 p.u, the reactive power sources capacity is [0-5] MVAr. The generation cost and emission coefficients of IEEE-30 bus system given in Table 1.

The Table 2 is presented the control parameters and optimal value obtained using AEO method with five targets including of fuel cost, emission, active power loss, voltage deviations and L_index. The values obtained of AEO method compared with EO, PSO, SFO and GA methods for every the objective

Table 1. IEEE 30-bus system: fuel cost and emissions constants [25, 32]

Generator	Bus	a	b	c	α	β	γ	ζ	λ
G1	1	0	2	0.00375	4.091	−5.554	6.490	0.0002	2.857
G2	2	0	1.75	0.0175	2.543	−6.047	5.638	0.0005	3.333
G5	5	0	1	0.0625	4.258	−5.094	4.586	0.000001	8
G8	8	0	3.25	0.00834	5.326	−0.0355	3.380	0.002	2
G11	11	0	3	0.025	4.258	−0.05094	4.586	0.000001	8
G13	13	0	3	0.025	6.131	−0.05555	5.151	0.00001	6.667

Table 2. The control parameters and optimal value obtained using AEO method for five targets in IEEE 30-bus system

Control parameters	**Limits**		**Proposed AEO Method**				
	Min	**Max**	Fuel cost **Case 1**	Emissions **Case 2**	Power Loss **Case 3**	Voltage deviation **Case 4**	L_index **Case 5**
P1(MW)	50	200	177.1564	64.2336	51.6600	100.6993	162.9103
P2(MW)	20	80	49.1070	67.4432	79.9791	77.6726	45.1485
P5(MW)	15	50	21.3021	49.9976	49.9995	38.9237	19.8578
P8(MW)	10	35	21.0267	34.9994	34.9861	20.4162	24.8632
P11(MW)	10	30	11.8464	29.9978	29.9344	22.4628	18.5628
P13(MW)	12	40	12.0188	40.0000	39.9635	29.4494	20.6263
V1 (p.u)	0.95	1.1	1.0847	1.0600	1.0641	1.0065	1.0775
V2 (p.u)	0.95	1.1	1.0654	1.0565	1.0584	1.0027	1.0617
V5 (p.u)	0.95	1.1	1.0335	1.0376	1.0363	1.0177	1.0708
V8 (p.u)	0.95	1.1	1.0381	1.0434	1.0437	1.0098	1.0535
V11(p.u)	0.95	1.1	1.0843	1.0998	1.0959	1.0289	1.0873
V13(p.u)	0.95	1.1	1.0453	1.0650	1.0533	1.0102	1.0413
T11	0.9	1.1	1.0279	1.0733	1.0479	1.0387	1.0166
T12	0.9	1.1	0.9361	0.9315	0.9307	0.9060	0.9579
T15	0.9	1.1	0.9757	0.9999	0.9923	0.9910	0.9472
T36	0.9	1.1	0.9756	0.9825	0.9860	0.9714	0.9608
QC10 (MVAR)	0	5	2.3262	2.7505	1.4101	4.8911	1.6256
QC12 (MVAR)	0	5	3.9324	0.7183	3.6882	4.3993	0.2223
QC15 (MVAR)	0	5	4.4115	2.6664	3.2613	4.7698	0.9287
QC17 (MVAR)	0	5	2.9116	1.6783	2.7524	1.7478	0.7723
QC20 (MVAR)	0	5	4.6717	3.7098	1.5721	4.9801	3.6823
QC21 (MVAR)	0	5	4.9008	1.9602	4.9354	4.8403	2.6649
QC23 (MVAR)	0	5	3.5063	3.8141	4.7714	4.9578	1.9901
QC24 (MVAR)	0	5	4.8725	4.9986	4.6153	4.9911	0.6793
QC29 (MVAR)	0	5	2.6080	2.9194	3.1888	3.5958	0.1264
Total cost ($/h)	-	-	**800.5454**	944.2521	967.4142	874.4066	807.3090
Emissions	-	-	0.3664	**0.2048**	0.2073	0.2366	0.3264
PLoss (MW)	-	-	9.0574	3.2715	**3.1225**	6.2241	8.5690
VD	-	-	0.9215	0.8260	0.8736	**0.0924**	0.8711
L_index	-	-	0.1384	0.1394	0.1394	0.1491	**0.1370**

are detail descibled in Table 3. From Table 3, it can be noted that, the total generator cost (case 1) is achieved 800.5454 ($/h) using AEO algorithm, which is better than EO, PSO, SFO and GA methods. The total generator achieved of EO method is 800.6220 ($/h), PSO method is 800.5924 ($/h), SFO method is 805.3635 ($/h) and GA method is 800.7742 ($/h). The convergence rate of the fuel cost function and obtained value in 50 runs using the AEO and other methods are demonstrated in Fig. 2, Fig.3. As observed from those Figure, ability convergence and standard deviation of AEO algorithm is better than compared with EO, PSO, SFO and GA methods in term of optimal value. For case 2, total emission of AEO approach is approximate EO, PSO approach and is reduced than SFO, GA method as shown in Table 3. The AEO, EO, PSO approaches are total emission 0.2048 (ton/h), while SFO and GA algorithm is 0.2163 (ton/h) and 0.2050 (ton/h) respectively. As noted in Fig. 4, the standard deviation in 50 runs of the AEO algorithm is better than compared with the PSO, SFO and GA method and similar as the EO method.

With case 3, as shown in Table 3, the active power losses is decreased to 3.1225 (MW) using the AEO. From Table 3, it can be seen that, the total

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Table 3. The results obtained of AEO method compared with EO, PSO, SFO and GA method with case 1-5

Case 1	**Fuel Cost ($/h)**			
Algorithm	Min	Average	Max	Standard deviation
AEO	800.5454	800.6614	800.9169	0.0742
EO	800.6220	801.2520	808.3032	1.1501
PSO	800.5924	3.8412×10^{7}	1.2888×10^{8}	3.1887×10^{15}
SFO	805.3635	909.4241	5.2008×10^{3}	619.4435
GA	800.7742	802.2623	806.8618	1.4086
Case 2	**Emission (Ton/h)**			
AEO	0.2048	0.2049	0.2052	6.1577×10^{-5}
EO	0.2048	0.2049	0.2051	4.5183×10^{-5}
PSO	0.2048	3.6719×10^{7}	1.2698×10^{7}	5.4718×10^{7}
SFO	0.2163	0.2525	0.3101	0.0238
GA	0.2050	0.2060	0.2076	6.6487×10^{-4}
Case 3	**Power Loss (MW)**			
AEO	3.1225	3.1980	3.3315	0.0505
EO	3.1048	3.3008	4.6138	0.2358
PSO	3.1012	3.1781×10^{7}	1.2789×10^{8}	5.2204×10^{7}
SFO	4.8875	2.0842×10^{3}	1.0389×10^{5}	1.4691×10^{4}
GA	3.1847	3.4366	5.2477	0.2927
Case 4	**Voltage deviation**			
AEO	0.0924	0.1000	0.1149	0.0060
EO	0.1018	0.1207	0.1564	0.0140
PSO	0.0904	4.1989×10^{7}	1.3034×10^{8}	5.6051×10^{7}
SFO	0.2108	8.8620×10^{3}	4.4308×10^{5}	6.2661×10^{4}
GA	0.1183	6.7222×10^{4}	3.3611×10^{6}	4.7533×10^{5}
Case 5	**L_index**			
AEO	0.1370	0.1376	0.1388	4.0761×10^{-4}
EO	0.1372	0.1388	0.1408	8.2925×10^{-4}
PSO	0.1373	4.0918×10^{7}	1.2667×10^{8}	5.5296×10^{7}
SFO	0.1399	0.1454	0.1562	0.0043
GA	0.1380	0.1406	0.1474	0.0017

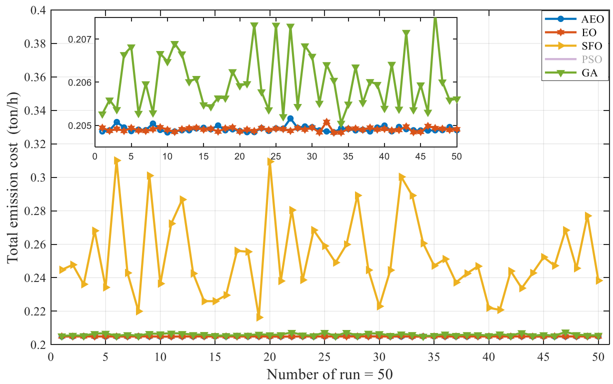

Figure 4. Emission obtained in 50 runs using AEO and other methods

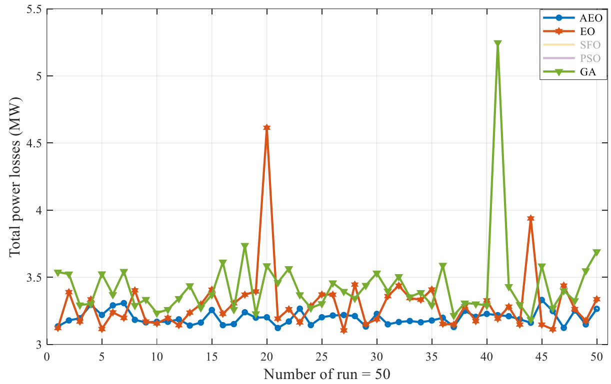

Figure 5. Power loss obtained in 50 runs using AEO and other methods

power loss of the AEO technique achieves better minimum compared with the SFO and GA methods. Although power loss obtained from AEO is less than EO and PSO method, however the AEO algorithm has better average and standard deviation values compared with EO and PSO method. This shows the suggested method's effective wih ability to obtain optimized solution as shown in Fig. 5. Also, Fig. 6, Fig. 7 are presented obtained values in 50 runs of the AEO method for case 4 and case 5, respectively. It can be observed that from the Table 3 and those Fig, the AEO algorithm can obtained better voltage deviation and L_index values with smaller standard deviation compared to EO, PSO, SFO and GA methods. Furthermore, the results simulation show that application of the AEO for the OPF problem that

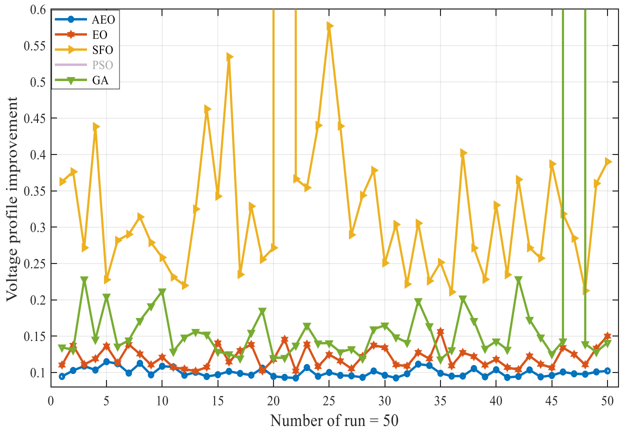

Figure 6. Voltage profile obtained in 50 runs using AEO and other methods

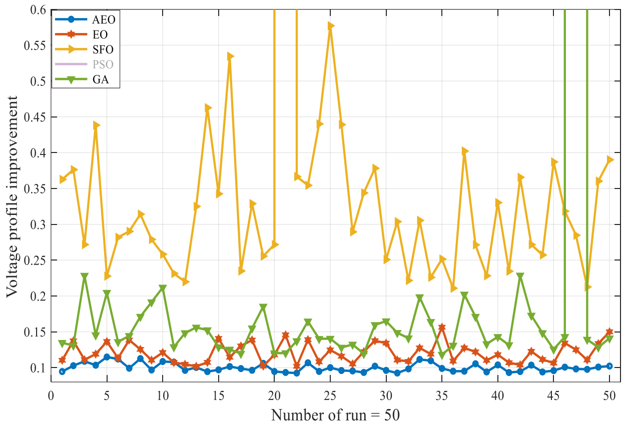

Figure 7. L_index obtained in 50 runs using AEO and other methods

Table 4. The solution obtained from AEO for fuel cost objective compared with different algorithms

Method	Fuel Cost ($/h)	IL (%)
Initial	901.6391	11.21
TS [6]	802.29	0.217
EP [7]	802.62	0.258
DE [8]	801.23	0.085
TLOA [10]	800.7257	0.022
SKHA [11]	801.4675	0.115
MDEA [18]	802.375	0.228
IGWO [22]	801.259	0.089
MSFLA [23]	802.287	0.217
HPSO-DE [28]	802.248	0.212
Proposed AEO	800.5454	-

Table 5. The solution obtained from AEO for emission objective compared with different algorithms

Method	Emission (Ton/h)	IL (%)
Initial	0.3661	44.06
SKHA [11]	0.20508	0.136
ABCA [14]	0.204826	0.127
MSA [15]	0.20482	0.010
ARCBOA [20]	0.2048	0
ISKHA [21]	0.204818	0.009
Proposed AEO	0.2048	-

Table 6. The solution obtained from AEO for TPL objective compared with different algorithms

Method	TPL (MW)	IL (%)
Initial	5.830	46.44
DE [8]	3.38	7.618
SKHA [11]	3.1409	0.586
ABCA [14]	3.1078	0
EGA [19]	3.2008	2.446
ARCBOA [20]	3.1009	0
Proposed AEO	3.1225	-

Table 7. The solution obtained from AEO for voltage deviation objective compared with different algorithms

Method	VD (Pu)	IL (%)
Initial	1.1747	92.13
GWO [8]	0.118736	22.18
BOA [9]	0.0951	2.839
GSA [13]	0.0932	0.858
Jaya [16]	0.1273	27.41
EGA [19]	0.911	89.85
ARCBOA [20]	0.092	0
ISKHA [21]	0.1029	10.20
MICA [24]	0.0952	2.941
MABC [25]	0.1017	9.145
IEMA [26]	0.1063	13.07
SCA [27]	0.1082	14.60
MSCA [27]	0.103	10.29
HPSO-GSA [29]	0.1267	27.07
Proposed AEO	0.0924	-

Table 8. The solution obtained from AEO for L_index objective compared with different algorithms

Method	L index (Pu)	IL (%)
ABCA [14]	0.1379	0.652
ARCBOA [20]	0.1369	0
Proposed AEO	0.1370	-

significantly enhances the performance of power systems. The fuel cost, emissions, active power loss and voltage deviations levels are reduced by 11.21%, 44.06%, 46.44%, and 92.13% respectively, compared to the initial case.

With the purpose of evaluate effective of the susgested AEO method, the authors compare the objective functions including of fuel cost, emission, power loss, voltage deviations and L_index from the suggested AEO approach to those other methods. The best values achieved for the objectives using the proposed technique and other technique are listed in Table 4-8.

As observed in the Table 4, total fuel cost achieved using the AEO method is reduced insignificantly as compared with TS [6], EP [7], DE [8], TLOA [10], SKHA [11], MDEA [18], IGWO [22], MSFLA [23], and HPSO-DE [28] approaches. The improvement level (IL) in % can be up to 0.2285 % for fuel cost objective. The four other objectives including emission, power loss, voltage deviation and L_index using the AEO have obtained value better or equal compared with diffrent approaches as seen in Table 5-7, respectively. The improvement level percentage of the proposed AEO algorithm to 0.137% for emission objective, 7.618% for total power loss objective, 89.85% for voltage deviation objective and 0.652% for L_index objective. The comparison results indicates that the ability quickly convergence of AEO technique with the optimal value. This is demonstration the robust of the AEO technique in dealing with OPF problem.

5. Conclusion

OPF is one of important issues for operating of power system and it might be challenging for many algorithms to handle with OPF problem, especially in complex systems. In this paper, the AEO is successfully adjusted for handling the problem of OPF with five other target functions. The optimal values and success rate obtained by the proposed AEO algorithm are the better or same ompared with EO, PSO, SFO and GA method. Furthermore, the fuel cost, emissions, active power loss and voltage deviations levels are reduced by 11.21%, 44.06%, 46.44%, and 92.13% respectively, compared to the initial case. For other exiting methods, the improvement level percentage (IL) of the proposed AEO algorithm can be up to 0.2285 % for fuel cost objective, 0.137% for emission objective, 7.618% for total power loss objective, 89.85% for voltage deviation objective and 0.652% for L_index objective. The simulation results demonstrate that, the AEO also is one of effective and reliable methods for dealing problem of OPF in large scale and complex systems such as the OPF problem incorporting renewable rnergy, FACTS.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization, T.L.D; methodology, T.L.D; software, N.A.N; validation, T.L.D, N.A.N, and T.T.N; formal analysis, T.L.D and T.T.N; investigation, N.A.N; writing-original draft preparation, T.L.D; writing-review and editing, T.L.D; visualization, N.A.N; supervision, T.L.D

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Appendix

Nomenclature and abbreviations	
$P_{G,slack}$	active power of the slack generator
V_L	magnitude voltage of the load bus

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Q_G	reactive power of the generators
S_l	transparent power flow in line
P_G	active power of the generator
T_k	tap changer of the transformer
Q_C	reactive power of shunt compensator
V_G	magnitude voltage of the generator bus
N	Toal number of buses
N_L	number of load buses.
N_G	number of generating units
N_T	number of regulating transformers.
N_l	number of line.
N_c	number of shunt compensators
V_i,V_j	magnitude voltages of the buses i, j .
P_i	active power injection into $i\ th$ bus
Q_i	reactive power injection into $i\ th$ bus
P_{Gi}	active generated at bus i
Q_{Gi}	reactive power generated at bus i
P_{Dj}	load active power at bus j
Q_{Dj}	load reactive power at bus i
$P_{Gi,min}$	min. active power limit of generator
$Q_{Gi,min}$	min. reactive power limit of generator
$P_{Gi,max}$	max. active power limit of generator
$Q_{Gi,max}$	max. reactive power limit of generator
$V_{Gi,min}$	min. voltage of the generator bus i
$V_{Gi,max}$	max. voltage of the generator bus i
$V_{Li,min}$	min. voltage of the load bus i
$V_{Li,max}$	max. voltage of the load bus i
$Q_{ci,min}$	min. reactive power compensative devise at load bus i
$Q_{ci,max}$	max. reactive power compensative devise at load bus i
$T_{i,min}$	min. tap changer of the transformer
$T_{i,max}$	max. tap changer of the transformer
$S_{l,max}$	max. line flow limits of transmission line