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Flower pollination algorithm to solve combined economic and emission dispatch problems

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ABSTRACT

Economic Load Dispatch (ELD) is the process of allocating the required load between the available generation units such that the cost of operation is minimized. The ELD problem is formulated as a nonlinear constrained optimization problem with both equality and inequality constraints. The dual-objective Combined Economic Emission Dispatch (CEED) problem is considering the environmental impacts that accumulated from emission of gaseous pollutants of fossil-fuelled power plants. In this paper, an implementation of Flower Pollination Algorithm (FPA) to solve ELD and CEED problems in power systems is discussed. Results obtained by the proposed FPA are compared with other optimization algorithms for various power systems. The results introduced in this paper show that the proposed FPA outlasts other techniques even for large scale power system considering valve point effect in terms of total cost and computational time.

1. Introduction

Economic Dispatch (ED) problem has become a crucial task in the operation and planning of power system [1]. It is very complex to solve because of a nonlinear objective function and a large number of constraints. ED in power system deals with the determination of optimum generation schedule of available generators so that the total cost of generation is minimized within the system constraints [2,3]. Well known long-established techniques such as gradient method [4], lambda iteration method [5,6], linear programming [7], quadratic programming [8], Lagrangian multiplier method [9], and classical technique based on co-ordination equations [10] are applied to solve ELD problems. These conventional methods cannot perform satisfactorily for solving such problems as they are sensitive to initial estimates and converge into local optimal solution in addition to its computational complexity.

During the last decades many researches and techniques had dealt with ELD problems. Fuzzy Logic Control (FLC) has attracted the attention in control applications. In contrast with the conventional techniques, FLC formulates the control action in terms of linguistic rules drawn from the behavior of a human operator rather than in terms of an algorithm synthesized from a model of the system [11–14]. However, it requests more fine tuning and simulation before operational. Another technique like Artificial Neural Network (ANN)

Abbreviations: ELD, economic load dispatch; CEED, combined economic emission dispatch; FPA, flower pollination algorithm; ED, economic dispatch; FLC, fuzzy logic control; ANN, artificial neural network; EA, evolutionary algorithm; GA, genetic algorithm; SA, simulated annealing; EP, evolutionary programming; TS, Tabu search; PSO, particle swarm optimization; GSA, gravitational search algorithm; ABC, artificial bee colony; QP, quadratic programming; DE, differential evolution; PPSO, personal best-oriented PSO; APPSO, adaptive personal-best oriented PSO; MPSO, modified particle swarm optimization; ARCGA, adaptive real coded GA; TSAGA, Taguchi self-adaptive real-coded genetic algorithm; CCPSO, PSO with both chaotic sequences and crossover operation; CDE_SQP, combining of chaotic DE and quadratic programming; EDA/DE, estimation of distribution and differential evolution cooperation; SOMA, self-organizing migrating strategy; CSOMA, cultural self-organizing migrating strategy; DE/BBO, combination of differential evolution and biogeography-based optimization; DHS, differential harmony search; BBO, biogeography based optimization; PSO–SQP, integrating PSO with the sequential quadratic programming; GA–PS–SQP, hybrid algorithm consisting of GA, pattern search (PS) and SQP; CPSO, chaotic particle swarm optimization; CPSO–SQP, hybrid algorithm consisting of CPSO and SQP; NPSO_LRS, new PSO with local random search; CDEMD, cultural DE based on measure of population's diversity; HMAPSO, hybrid multi agent based PSO; FAPSO-NM, fuzzy adaptive PSO algorithm with Nelder–Mead; ICA-PSO, improved coordinated aggregation-based PSO; MODE, multiobjective differential evolution; NSGA-II, non-dominated sorting genetic algorithm-II; PDE, Pareto differential evolution; SPEA-2, strength Pareto evolutionary algorithm 2; ABC_PSO, ABC and PSO; EMOCA, enhanced multi-objective cultural algorithm; MABC/D/Cat, modified artificial bee colony with disruptive cat map; MABC/D/Log, modified artificial bee colony with disruptive logistic map; CPU, computational time; NA, not available; PV, photovoltaic.

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has its own advantages and disadvantages. The characteristics of the system is enhanced by ANN, but the main problem of this technique is the long training time, the selecting number of layers and the number of neurons in each layer [6,15–17].

An alternative approach is to employ Evolutionary Algorithm (EA) techniques. Due to its ability to treat nonlinear objective functions, EA is believed to be very effective to deal with ELD problem. Among the EA techniques, Genetic Algorithm (GA) is introduced in References 18 and 19, but it requires a very long run time depending on the size of the system under study. Also, it gives rise to repeat revisiting of the same suboptimal solutions. Simulated Annealing (SA) is illustrated in References 20 and 21, but this technique might fail by getting trapped in one of the local optimal. Evolutionary Programming (EP) is discussed in Reference 22, but it has a slow convergence rate for large problem. Improved Tabu Search (TS) is introduced in Reference 23, but the efficiency of this algorithm is reduced by the use of highly epistatic objective functions and the large number of parameters to be optimized. Also, it is a time-consuming method. Ant swarm optimization is presented in Reference 24, but its theoretical analysis is difficult and probability distribution changes by iteration. Particle Swarm Optimization (PSO) is discussed in References 25–28, but it pains from the partial optimism. Moreover, the algorithm cannot work out the problems of scattering and optimization. Gravitational Search Algorithm (GSA) in illustrated in Reference 29. However, this algorithm appears to be effective for solving ELD problem, it has poor performance at the later search stage due to the lack of agents' diversity in GSA. Artificial Bee Colony (ABC) is developed in Reference 30 to solve the complex non-linear optimization problem, but it is slow to converge and the processes of the exploration and exploitation contradict with each other, so the two abilities should be well balanced for achieving good optimization performance. On the other hand, FPA has only one key parameter *p* (switch probability) which makes the algorithm easier to implement and faster to reach optimum solution. Moreover, this transferring switch between local and global pollination can guarantee escaping from local minimum solution. Thus, FPA is proposed in this paper to overcome the previous drawbacks. In addition, it is clear from the literature survey that the application of FPA to solve ELD and CEED problems has not been discussed. This encourages us to adopt FPA to deal with these problems.

In this paper, a new approach for solving ELD and CEED problems using FPA methodology is discussed considering the power limits of the generator. The purpose of CEED is to minimize both the operating fuel cost and emission level simultaneously while satisfying load demand and operational constraints. This multi-objective CEED problem is converted into a single objective function using a modified price penalty factor approach. FPA is investigated to determine the optimal loading of generators in power systems. Simulations results for small and large scale power system considering the valve loading effect are implemented to indicate the robustness of FPA.

The remainder of this paper is organized as follows: Section 2 provides a brief description and mathematical formulation of ELD and CEED problems. In section 3, the concept of FPA is discussed. Section 4 shows the result on three, ten and forty unit thermal test systems. Finally, the conclusion and future work of research are outlined in section 5.

2. Problem formulation

The CEED problem is to minimize two computing objective functions simultaneously, fuel cost and emission, while satisfying various equality and inequality constraints. Generally the problem is formulated as follows.

2.1. Objective function of ELD

For thermal generating units, the cost of fuel per unit power output varies significantly with the output power of the unit. Fuel costs are usually represented as a quadratic function of output power [31], as shown in equation (1).

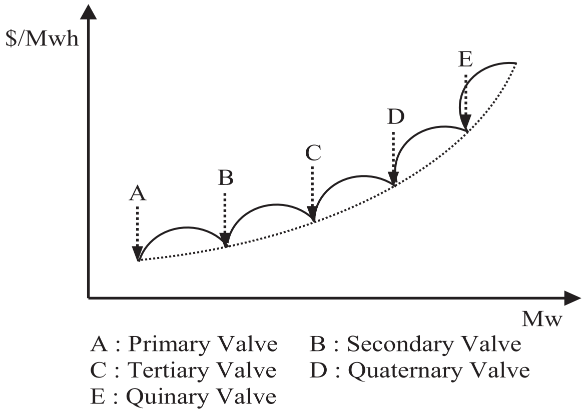

Fig. 1. Valve point effect.

$$F(P)=\gamma P^2+\beta P+\alpha \tag{1}$$

Minimize

$$F_t=\sum_{i=1}^{d}F_i(P_i)=\sum_{i=1}^{d}\left(\gamma_i P_i^2+\beta_i P_i+\alpha_i\right) \tag{2}$$

The minimization is performed subject to the equality constraint that the total generation must equal to the demand plus the loss thus:

$$\sum_{i=1}^{d}P_i=P_D+P_L \tag{3}$$

The total transmission loss using Kron's loss formula is given in equation (4)

$$P_L=\sum_{i=1}^{d}\sum_{j=1}^{d}(P_iB_{ij}P_j)+\sum_{i=1}^{d}B_{0i}P_i+B_{00} \tag{4}$$

It is assumed with little error that these coefficients are constant (as long as operation is near the value where these coefficients are computed).

Based on the maximum and minimum power limits of generators the inequality constraint is

$$P_i^{\min}\le P_i\le P_i^{\max}\quad i=1,2,\ldots\ldots,d \tag{5}$$

2.2. Effect of valve point on fuel cost objective

To be more practical, the valve point effect is taken into account in the cost function of generators. The sharp increase in losses due to the wire drawing effects which occur as each steam admission valve starts to open leads to the nonlinear rippled input output curve [32] as shown in Fig. 1. The obtained cost function based on the rippled curve is more accurate modeling. Thus, the fuel cost function of each fossil fuel generator is given as the sum of a quadratic and a sinusoidal function [33].

$$F_t=\sum_{i=1}^{d}F_i(P_i)=\sum_{i=1}^{d}\left(\gamma_i P_i^2+\beta_i P_i+\alpha_i+e_i*\sin\left(f_i*\left(P_i^{\min}-P_i\right)\right)\right) \tag{6}$$

2.3. Objective function of CEED

The atmospheric pollutants such as sulfur oxides, nitrogen oxides and carbon dioxide caused by fossil fuel fired generator can be modeled separately [34–36]. However, for comparison purposes, the total emission of these pollutants which is the sum of a quadratic and an exponential function can be expressed as [37,38]:

$$E_t = \sum_{i=1}^{d} E_i(P_i) = \sum_{i=1}^{d} \left(a_i P_i^2 + b_i P_i + c_i + \eta_i * \exp(\delta_i * P_i)\right) \tag{7}$$

Optimization of generation cost has been formulated based on classical ELD with emission and line flow constraints. The detailed problem is given as follows [38].

$$\text{Minimize} \quad F = \sum_{i=1}^{d} \{F_i(P_i), E_i(P_i)\} \tag{8}$$

The minimum value of the above objective function has to be found out subject to equality and inequality constraints given by equations (3) and (5). The dual-objective CEED problem is converted into single optimization problem by introducing a price penalty factor h as follows [39].

$$\text{Minimize} \quad F = F_t + h \times E_t \tag{9}$$

Subject to constraints given by equations (3) and (5), the price penalty factor h, which is the ratio between the maximum fuel cost and maximum emission of corresponding generator in \$/Kg [30,33], blends the emission with fuel cost, then F is the total operating cost in \$.

$$h_i = \frac{F_t(P_i^{\max})}{E_t(P_i^{\max})}, \quad \mathrm{i} = 1, 2, \ldots\ldots\ldots, \mathrm{d} \tag{10}$$

The following steps are used to find the price penalty factor for a particular load demand:

A. Find the ratio between maximum fuel cost and maximum emission of each generator.
B. Arrange the values of price penalty factor in ascending order.
C. Add the maximum capacity of each unit ($P_i^{\max}$) one at a time, starting from the smallest h_i, until $\sum P_i^{\max} \geq P_D$.
D. At this point, h_i which associated with the last unit in this process is the approximate price penalty factor value (h) for the given load.

Hence, a modified price penalty factor (h) is used to give the exact value for the particular load demand by interpolating the values of (h), corresponding to their load demand values.

3. Overview of flower pollination algorithm

FPA was developed by Yang in 2012 [40]. It is inspired by the pollination process of flowering plants. Real-world design problems in engineering and industry are usually multiobjective. These multiple objectives often conflict with one another. Also, they have additional challenging issues such as time complexity, inhomogeneity and dimensionality [41]. They are usually more time-consuming. FPA has been adopted in this paper to solve ELD and CEED problems.

3.1. Characteristics of flower pollination

The main purpose of a flower is ultimately reproduction via pollination. Flower pollination is typically correlating with the transfer of pollen, which often associated with pollinators such as birds and insects. Indeed, some flowers and insects have a very specialized flower-pollinator partnership, as some flowers can only attract a specific species of insect or bird for effective pollination. Pollination appears in two major forms: abiotic and biotic. About 90% of flowering plants depend on the biotic pollination process, in which the pollen is transferred by pollinators. About 10% of pollination follows abiotic form that does not require any pollinators [42]. Wind and diffusion help in the pollination process of such flowering plants [43].

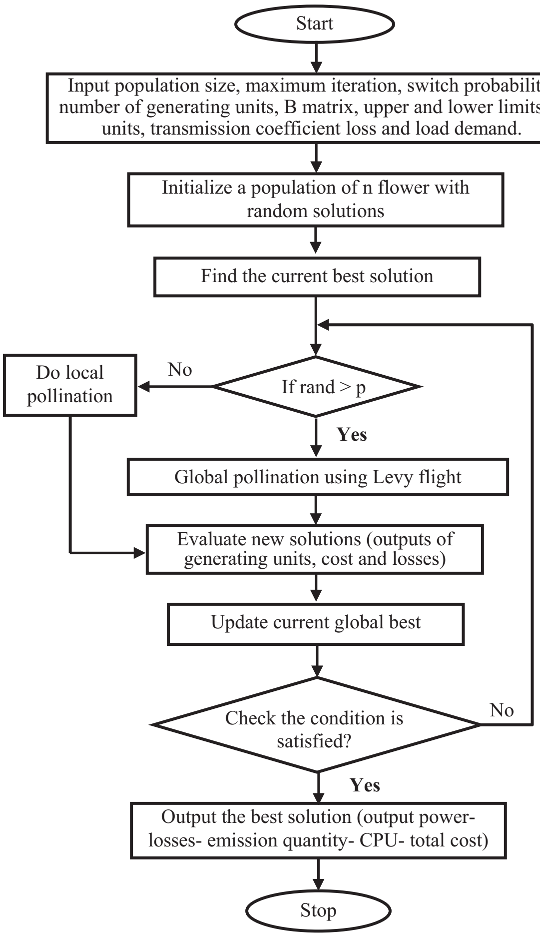

Fig. 2. Flow chart of FPA.

Pollination can be achieved by self-pollination or cross-pollination. Self-pollination is the pollination of one flower from pollen of the same flower. Cross-pollination is the pollination from pollen of a flower of different plants. The objective of flower pollination is the survival of the fittest and the optimal reproduction of plants in terms of numbers as well as the fittest. This can be considered as an optimization process of plant species. All of these factors and processes of flower pollination created optimal reproduction of the flowering plants [43].

3.2. Flower pollination algorithm

For FPA, the following four steps are used:

Step 1: Global pollination represented in biotic and cross-pollination processes, as pollen-carrying pollinators fly following Lévy flight [44].

Step 2: Local pollination represented in abiotic and self-pollination as the process does not require any pollinators.

Step 3: Flower constancy which can be developed by insects, which is on a par with a reproduction probability that is proportional to the similarity of two flowers involved.

Table 1
ELD Comparison for 40 generators at load of 10,500 MW.

Outputs	PSO [45]	PPSO [45]	APPSO [45]	MPSO [46]	ARCGA [47]	TSAGA [48]	CCPSO [49]	CDE_SQP [50]	EDA/DE [51]	SOMA [52]	CSOMA [52]	DE/BBO [53]	DHS [54]	ICA-PSO [55]	Proposed FPA
P1 (MW)	113.116	111.601	112.579	113.9971	110.8252	114.0000	110.7998	111.7600	111.1110	112.8544	110.8016	110.7998	110.7998	110.8	**72.4810**
P2 (MW)	113.010	111.781	111.553	112.6517	113.9112	111.0400	110.7999	111.5600	110.8299	111.7795	110.8068	110.7998	110.7998	110.8	**103.0314**
P3 (MW)	119.702	118.613	98.751	119.4255	97.4000	97.3000	97.3999	97.3900	97.4122	97.4059	97.4007	97.3999	97.3999	97.41	**83.2726**
P4 (MW)	81.647	179.819	180.384	189.0000	179.7331	179.6000	179.7331	179.7300	179.7443	179.7274	179.7333	179.7331	179.7331	179.74	**182.3106**
P5 (MW)	95.062	92.443	94.389	96.8711	88.6454	90.7210	87.7999	91.6600	88.1510	87.9306	87.8180	87.9576	87.7999	88.52	**76.1669**
P6 (MW)	139.209	139.846	139.943	139.2798	140.0000	140.0000	140.0000	140.0000	139.9959	139.9880	139.9997	140.0000	140.0000	140.00	**126.1346**
P7 (MW)	299.127	296.703	298.937	223.5924	259.6000	260.0600	259.5997	300.0000	259.6065	259.7736	259.6010	259.5997	259.5997	259.60	**258.8452**
P8 (MW)	287.491	284.566	285.827	284.5803	284.6000	285.8700	284.5997	300.0000	284.6045	284.6280	284.6000	284.5997	284.5997	284.60	**297.1636**
P9 (MW)	292.316	285.164	298.381	216.4333	284.6000	284.7700	284.5997	284.5900	284.6149	284.7539	284.6005	284.5997	284.5997	284.60	**290.8899**
P10 (MW)	279.273	203.859	130.212	239.3357	130.0000	130.0000	130.0000	130.0000	130.0002	130.0291	130.0003	130.0000	130.0000	130.00	**274.8232**
P11 (MW)	169.766	94.283	94.385	314.8734	168.7985	94.0000	94.0000	168.7900	168.8029	168.7908	168.7999	168.7998	94.0000	168.80	**356.9806**
P12 (MW)	94.344	94.090	169.583	305.0565	168.7994	168.3800	94.0000	94.0000	94.0000	168.8084	168.7999	94.0000	94.0000	94.00	**124.4054**
P13 (MW)	214.871	304.830	214.617	365.5429	214.7600	214.4500	214.7598	214.7600	214.7591	214.7191	214.7599	214.7598	214.7598	214.76	**493.3764**
P14 (MW)	304.790	304.173	304.886	493.3729	394.2800	394.0100	394.2794	394.2800	394.2716	394.2888	394.2794	394.2794	394.2794	394.28	**344.9029**
P15 (MW)	304.563	304.467	304.547	280.4326	304.5200	394.2700	394.2794	304.5200	304.5206	304.5196	304.5196	394.2794	394.2794	394.28	**372.3864**
P16 (MW)	304.302	304.177	304.584	432.0717	394.2800	304.5700	394.2794	304.5200	394.2834	394.2952	394.2794	394.2794	394.2794	304.52	**345.4624**
P17 (MW)	489.173	489.544	498.452	435.2428	489.2798	489.2800	489.2794	489.2800	489.2912	489.2905	489.2796	489.2794	489.2794	489.28	**422.6378**
P18 (MW)	491.336	489.773	497.472	417.6958	489.2800	489.5600	489.2794	489.2800	489.2877	489.2779	489.2795	489.2794	489.2794	489.28	**434.4065**
P19 (MW)	510.880	511.280	512.816	532.1877	511.2806	511.2900	511.2794	511.2800	511.2977	511.2861	511.2794	511.2794	511.2794	511.28	**461.3107**
P20 (MW)	511.474	510.904	548.992	409.2053	511.2800	511.2700	511.2794	511.2800	511.2791	511.2792	511.2796	511.2794	511.2794	511.28	**434.3828**
P21 (MW)	524.814	524.092	524.652	534.0629	523.2803	523.2300	523.2794	523.2800	523.2958	523.2858	523.2797	523.2794	523.2794	523.28	**545.2846**
P22 (MW)	524.775	523.121	523.399	457.0962	523.2800	523.6300	523.2794	523.2900	523.2849	523.2899	523.2798	523.2794	523.2794	523.28	**490.3572**
P23 (MW)	525.563	523.242	548.895	441.3634	523.2800	523.8200	523.2794	523.2800	523.2856	523.2783	523.2801	523.2794	523.2794	523.28	**506.0639**
P24 (MW)	522.712	524.260	525.871	397.3617	523.2800	523.6200	523.2794	523.2800	523.2979	523.3199	523.2795	523.2794	523.2794	523.28	**467.3109**
P25 (MW)	503.211	523.283	523.814	446.4181	523.2800	523.3300	523.2794	523.2800	523.2799	523.2791	523.2797	523.2794	523.2794	523.28	**488.1203**
P26 (MW)	524.199	523.074	523.565	442.1164	523.2801	523.6800	523.2794	523.2800	523.2910	523.3076	523.2799	523.2794	523.2794	523.28	**486.9019**
P27 (MW)	10.082	10.800	10.575	74.8622	10.0000	10.0000	10.0000	10.0000	10.0064	10.0021	10.0004	10.0000	10.0000	10.00	**16.8002**
P28 (MW)	10.663	10.742	11.177	27.5430	10.0000	10.0000	10.0000	10.0000	10.0018	10.0054	10.0004	10.0000	10.0000	10.00	**39.3475**
P29 (MW)	10.418	10.799	11.210	76.8314	10.0000	10.1600	10.0000	10.0000	10.0000	10.0061	10.0003	10.0000	10.0000	10.00	**23.6359**
P30 (MW)	94.244	94.475	96.178	97.0000	88.7611	87.8700	87.8000	90.3300	96.2132	88.8932	92.7158	97.0000	87.7999	96.39	**86.3295**
P31 (MW)	189.377	189.245	189.999	118.3775	190.0000	190.0000	190.0000	190.0000	189.9996	189.9975	189.9998	190.0000	190.0000	190.00	**165.9924**
P32 (MW)	189.796	189.995	189.924	188.7517	190.0000	190.0000	190.0000	190.0000	189.9998	189.9919	189.9998	190.0000	190.0000	190.00	**174.5707**
P33 (MW)	189.813	188.081	189.714	190.0000	190.0000	190.0000	190.0000	190.0000	189.9981	189.9825	189.9998	190.0000	190.0000	190.00	**184.0570**
P34 (MW)	199.797	198.475	199.284	120.7029	164.8000	165.2300	164.7998	200.0000	164.9126	164.9291	164.8014	164.7998	164.7998	164.82	**193.6668**
P35 (MW)	199.284	197.528	199.599	170.2403	164.8000	200.0000	194.3976	200.0000	199.9941	164.8031	164.8015	200.0000	200.0000	200.00	**191.6152**
P36 (MW)	198.165	196.971	199.751	198.9897	164.8054	200.0000	200.0000	200.0000	200.0000	164.9387	164.8051	200.0000	194.3978	200.00	**196.1763**
P37 (MW)	109.291	109.161	109.973	110.0000	110.0000	110.0000	110.0000	110.0000	109.9988	109.9974	109.9998	100.0000	110.0000	110.00	**90.0101**
P38 (MW)	109.087	109.900	109.506	109.3405	110.0000	110.0000	110.0000	110.0000	109.9994	109.9856	109.9998	110.0000	110.0000	110.00	**37.5421**
P39 (MW)	109.909	109.855	109.363	109.9243	110.0000	110.0000	110.0000	110.0000	109.9974	109.9995	109.9996	110.0000	110.0000	110.00	**89.4239**
P40 (MW)	512.348	510.984	511.261	468.1694	511.2800	510.9800	511.2794	511.2800	511.2800	511.2813	511.2797	511.2794	511.2794	511.28	**471.4405**
Fuel cost * $10^5\$$	**1.22323**	**1.21788**	**1.220446**	**1.216492**	**1.214101**	**1.214630**	**1.214035**	**1.217419**	**1.21412**	**1.214187**	**1.214147**	**1.214208**	**1.214035**	**1.214132**	**1.210745**

Table 2
Statistical comparison between FPA and different algorithms.

Algorithm	Best cost ($)	Mean cost ($)	Worst cost ($)	Time (s)
ARCGA [47]	121410.1038	121462.1502	121536.8745	15.67
TSAGA [48]	121463.07	122928.31	124296.54	696.01
CCPSO [49]	121403.5362	121445.3269	121535.4934	19.3
CDE_SQP [50]	121741.9793	122295.1278	122839.2941	14.26
EDA/DE [51]	121412.50	121460.70	121517.80	NA
BBO [52]	121426.66	121508.03	121688.66	NA
SOMA [52]	121418.7856	121449.8796	121508.3757	NA
CSOMA [52]	121414.6978	121415.0479	121417.8045	NA
DE/BBO [53]	121420.89	121420.90	121420.90	60.00
DHS [54]	121403.5355	121410.5967	121417.2274	1.32
ICA-PSO [55]	121413.2	121428.14	121453.56	139.92
EP [56]	122624.35	123382.00	125740	1167.35
EP–SQP [56]	122323.97	122379.63	NA	997.73
PSO [56]	123930.45	124154.49	NA	933.39
PSO–SQP [56]	122094.67	122245.25	NA	733.97
GA–PS–SQP [57]	121458	122039	NA	46.98
CPSO [58]	121865.23	122100.87	NA	114.65
CPSO–SQP [58]	121458.54	122028.16	NA	98.49
NPSO_LRS [59]	121664.4308	122209.3185	122981.5913	16.81
APSO [60]	121663.5222	122153.6730	122912.3958	5.05
DE [61]	121416.29	121422.72	121431.47	NA
CDEMD [62]	121423.4013	121526.7330	121696.9868	44.3
HMAPSO [63]	121586.90	121586.90	21586.90	NA
FAPSO-NM [64]	121418.3	121418.803	121419.8	40
FPA	**121074.5**	**121095.7**	**121196.3**	**0.89**

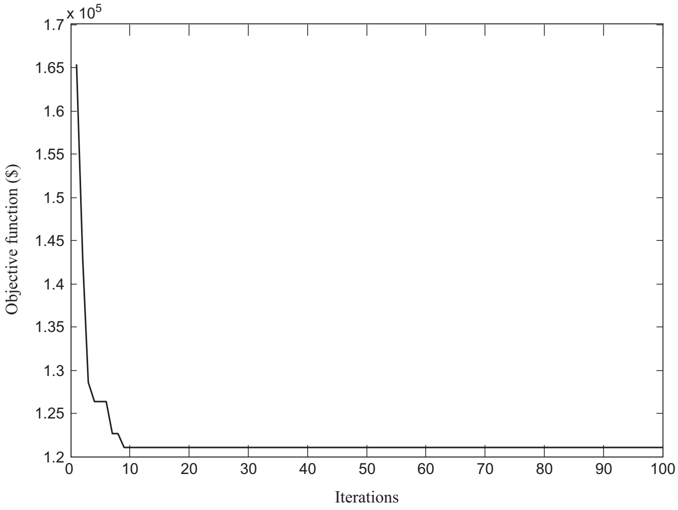

Fig. 4. Objective function for forty unit system.

Step 4: The interaction of local pollination and global pollination is controlled by a switch probability $p \in [0, 1]$, lightly biased toward local pollination.

To generate the updating formulas, the above rules have to be converted into proper updating equations. For example at the global pollination step, the pollinators such as insects carry the flower pollen gametes, so the pollen can travel over a long distance because of the ability of these insects to fly and move in much longer ranges. Therefore, global pollination step and flower constancy step can be represented by:

$$x_i^{t+1} = x_i^t + \gamma L(\lambda)(g_* - x_i^t) \tag{11}$$

In fact, $L(\lambda)$ is the Lévy flights based step size that corresponds to the strength of the pollination. Since long distances can be covered by insects using various distance steps, a Lévy flight can be used to mimic this behavior efficiently. That is, $L > 0$ from a Lévy distribution.

$$L \sim \frac{\lambda \Gamma(\lambda) \sin(\pi\lambda/2)}{\pi} \left(\frac{1}{s^{1+\lambda}} \right) \quad (s \gg s_0 > 0) \tag{12}$$

This distribution is valid for large steps $s > 0$.

For the local pollination, both Step 2 and Step 3 can be represented as

$$x_i^{t+1} = x_i^t + \varepsilon \left(x_j^t - x_k^t \right) \tag{13}$$

Table 3
Results for the best simulations with 3-unit system considering emission.

P_D	h	Power outputs	GA [38]	PSO [38]	FPA
400 (MW)	43.55981	P1 (MW)	102.617	102.612	102.4468
		P2 (MW)	153.825	153.809	153.8341
		P3 (MW)	151.011	150.991	151.1321
		P_L (MW)	7.41324	7.41173	7.4126
		Fuel Cost ($)	20840.1	20838.3	**20838.1**
		Emission (Kg)	200.256	200.221	**200.2238**
		Total Cost ($)	29563.2	29559.9	**29559.81**
		CPU (Sec)	0.282	0.235	**0.175**

The bold values are obtained using the proposed FPA algorithm.

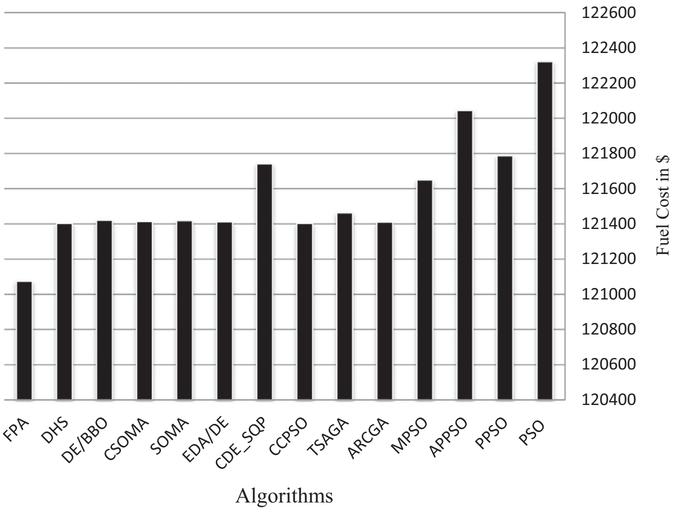

Fig. 3. Fuel cost for various algorithms for case 1.

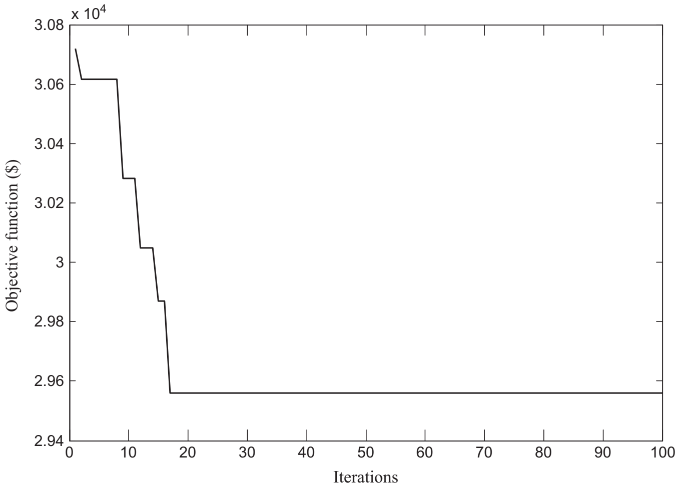

Fig. 5. Objective function for 3-unit system with demand = 400 MW.

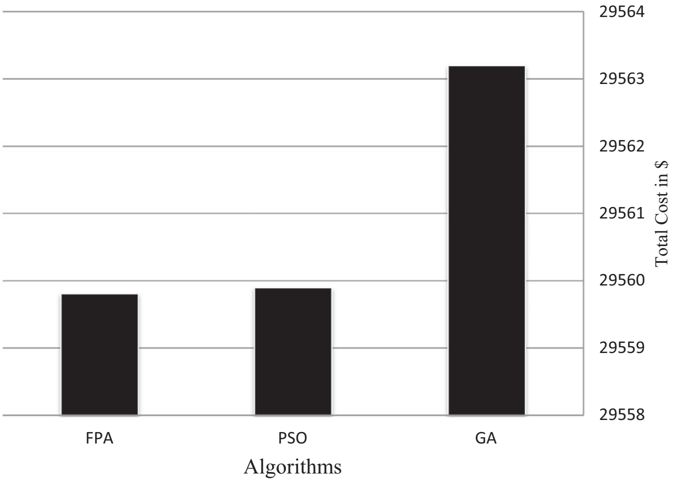

Fig. 6. Total cost for various algorithms with demand = 400 MW.

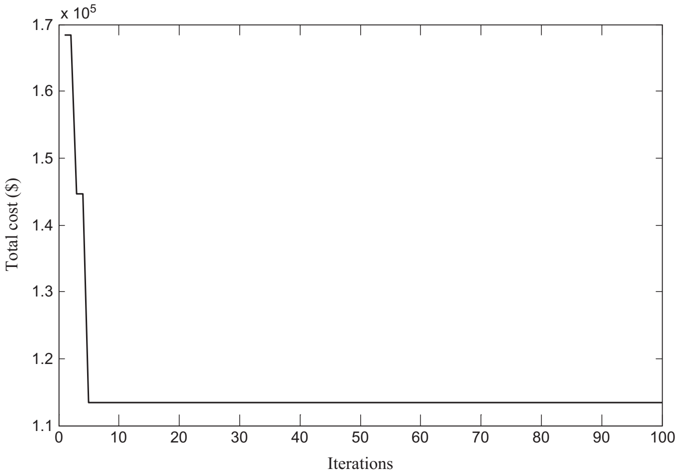

Fig. 7. Change of objective function with iterations for ten units.

where x_j^t and x_k^t are pollen from different flowers of the same plant species mimicking the flower constancy in a limited neighborhood. For a local random walk, x_j^t and x_k^t come from the same species, then ε is drawn from a uniform distribution as [0, 1].

In principle, flower pollination activities can occur at all scales. But in reality, adjacent flower patches are more likely to be pollinated by a local flower pollen than those far away. In order to mimic this, one can effectively use a switch probability (Step 4) to switch between common global pollination to intensive local pollination. To start with, one can use a naive value of $p = 0.5$. A preliminary parametric showed that $p = 0.8$ might work better for most applications. The flow chart of FPA is given in Fig. 2. The data of FPA are shown in Appendix A.

4. Results and discussion

FPA is employed to solve ELD and CEED problems for different cases to assure its optimization efficiency, where the objective function is limited by the output limits of generation units and transmission losses. The performance of FPA is compared with various optimization algorithms. Simulations were done under the Matlab environment.

4.1. Case study 1

This case considers 40 generators as a large scale power system to confirm the superiority of FPA over other algorithms in reaching optimum solution. Moreover, the effect of valve loading point is taken into account to complete the analysis [45–55]. The data of this system are given in Appendix B.

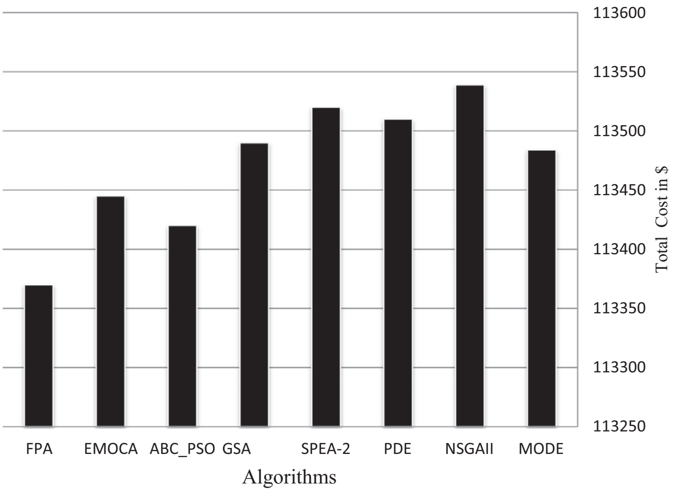

Fig. 8. Total cost for various algorithms for case 3.

Table 1 outlines the outputs of each unit for 10,500 MW load demand and the cost for each algorithm. It can be noticed that the suggested FPA achieves lower cost compared with other algorithms while achieving the constraints of generations. Therefore, these algorithms have trapped in local minimum solutions. Thus,

Table 4
CEED comparison for ten unit system at demand of 2000 MW.

Outputs	MODE [65]	NSGAII [65]	PDE [65]	SPEA-2 [65]	GSA [66]	ABC_PSO [67]	EMOCA [68]	Proposed FPA
P1 (MW)	54.9487	51.9515	54.9853	52.9761	54.9992	55	55	**53.188**
P2 (MW)	74.5821	67.2584	79.3803	72.813	79.9586	80	80	**79.975**
P3 (MW)	79.4294	73.6879	83.9842	78.1128	79.4341	81.14	83.5594	**78.105**
P4 (MW)	80.6875	91.3554	86.5942	83.6088	85.0000	84.216	84.6031	**97.119**
P5 (MW)	136.8551	134.0522	144.4386	137.2432	142.1063	138.3377	146.5632	**152.74**
P6 (MW)	172.6393	174.9504	165.7756	172.9188	166.5670	167.5086	169.2481	**163.08**
P7 (MW)	283.8233	289.4350	283.2122	287.2023	292.8749	296.8338	300	**258.61**
P8 (MW)	316.3407	314.0556	312.7709	326.4023	313.2387	311.5824	317.3496	**302.22**
P9 (MW)	448.5923	455.6978	440.1135	448.8814	441.1775	420.3363	412.9183	**433.21**
P10 (MW)	436.4287	431.8054	432.6783	423.9025	428.6306	449.1598	434.3133	**466.07**
Fuel cost * 10^5\$	1.13484	1.13539	1.1351	1.1352	1.1349	1.1342	1.13445	**1.1337**
Emission (Ib)	4124.9	4130.2	4111.4	4109.1	4111.4	4120.1	4113.98	**3997.7**
Losses (MW)	84.33	84.25	83.9	84.1	83.9869	84.1736	83.56	**84.3**
CPU (s)	3.82	6.02	4.23	7.53	NA	NA	2.90	**2.23**

FPA performs better than these algorithms in terms of fuel cost even for large scale power system with valve loading effect. Also, Table 2 lists the statistical comparison between FPA and different algorithms reported in [47–64] in terms of the best, mean, worst cost and computational (CPU) time through 50 trials. It is clear that the fuel cost obtained by the proposed FPA is better than other algorithms. Fig. 3 shows the total cost for each algorithm. On the other hand, a graph for convergence rate of the objective function is given in Fig. 4. It can be seen that the objective function is stabilized after 9 iterations. Also, the mean CPU time of FPA is the shortest one.

4.2. Case study 2

This case studies a 3-unit generating thermal system considering emission impact. The generator cost coefficients, emission coefficients, generation limits and the transmission loss coefficient matrix are given in Appendix B. Table 3 summarizes the results of solving CEED using the proposed FPA compared with GA and PSO [38]. As shown from Table 3, FPA donates superior result in terms of fuel cost, total cost and CPU compared with other algorithms. Moreover, the equality and inequality constraints are accomplished. The proposed FPA gives better results in terms of minimum total cost and smaller CPU time than other algorithms. Fig. 5 shows the total cost associated with FPA for 400 MW demand. The superiority of the proposed algorithm in decreasing the total cost can be verified as shown in Fig. 6.

4.3. Case study 3

This case involves a ten unit generating thermal system with valve point effects. The fuel cost coefficients, generators constraint, emission coefficients and transmission loss coefficient matrix are shown in Appendix B. Table 4 outlines the results of solving CEED for 2000 MW load demand using FPA and comparing with other algorithms [65–68]. The result of the suggested algorithm is highlighted here. The suggested FPA yields a lower cost than ABC_PSO, GSA, EMOCA, MODE, PDE, SPEA-2 and NSGA-II by 50$, 120$, 75$, 114$, 140$, 150$ and 169$ respectively while achieving the constraints of system. Also, its emission is also lower than SPEA-2, PDE, GSA, EMOCA, ABC_PSO, MODE and NSGA-II. Thus, FPA succeeds in achieving the global minimum solution. Moreover, the CPU time is smaller than other algorithm. Hence, FPA outperforms and outlasts other algorithms in reducing the net cost with minimum time. In addition, the cost convergence for this demand is given in Fig. 7. The objective function is convergent after 5 iterations. Finally, the total cost for every algorithm is given in Fig. 8.

4.4. Case study 4

This test system consists of forty generating units with non-smooth fuel cost and emission functions. Unit data and loss coefficients have been found in Appendix B. Table 5 summarizes the results of solving CEED for 10,500 MW load demand using FPA and

Table 5
CEED comparison for 40 generators at load of 10,500 MW.

Outputs	MODE [65]	PDE [65]	NSGA-II [65]	SPEA-2 [65]	GSA [66]	MABC/D/Cat [69]	MABC/D/Log [69]	Proposed FPA
P1 (MW)	113.5295	112.1549	113.8685	113.9694	113.9989	110.7998	110.7998	43.405
P2 (MW)	114	113.9431	113.6381	114	113.9896	110.7998	110.7998	113.95
P3 (MW)	120	120	120	119.8719	119.9995	97.3999	97.3999	105.86
P4 (MW)	179.8015	180.2647	180.7887	179.9284	179.7857	174.5504	174.5486	169.65
P5 (MW)	96.7716	97	97	97	97	87.7999	97	96.659
P6 (MW)	139.2760	140	140	139.2721	139.0128	105.3999	105.3999	139.02
P7 (MW)	300	299.8829	300	300	299.9885	259.5996	259.5996	273.28
P8 (MW)	298.9193	300	299.0084	298.2706	300	284.5996	284.5996	285.17
P9 (MW)	290.7737	289.8915	288.8890	290.5228	296.2025	284.5996	284.5996	241.96
P10 (MW)	130.9025	130.5725	131.6132	131.4832	130.3850	130	130	131.26
P11 (MW)	244.7349	244.1003	246.5128	244.6704	245.4775	318.1921	318.2129	312.13
P12 (MW)	317.8218	318.2840	318.8748	317.2003	318.2101	243.5996	243.5996	362.58
P13 (MW)	395.3846	394.7833	395.7224	394.7357	394.6257	394.2793	394.2793	346.24
P14 (MW)	394.4692	394.2187	394.1369	394.6223	395.2016	394.2793	394.2793	306.06
P15 (MW)	305.8104	305.9616	305.5781	304.7271	306.0014	394.2793	394.2793	358.78
P16 (MW)	394.8229	394.1321	394.6968	394.7289	395.1005	394.2793	394.2793	260.68
P17 (MW)	487.9872	489.3040	489.4234	487.9857	489.2569	399.5195	399.5195	415.19
P18 (MW)	489.1751	489.6419	488.2701	488.5321	488.7598	399.5195	399.5195	423.94
P19 (MW)	500.5265	499.9835	500.8	501.1683	499.2320	506.1985	506.1716	549.12
P20 (MW)	457.0072	455.4160	455.2006	456.4324	455.2821	506.1985	506.2206	496.7
P21 (MW)	434.6068	435.2845	434.6639	434.7887	433.4520	514.1472	514.1105	539.17
P22 (MW)	434.5310	433.7311	434.15	434.3937	433.8125	514.1455	514.1472	546.46
P23 (MW)	444.6732	446.2496	445.8385	445.0772	445.5136	514.5237	514.5664	540.06
P24 (MW)	452.0332	451.8828	450.7509	451.8970	452.0547	514.5386	514.4868	514.5
P25 (MW)	492.7831	493.2259	491.2745	492.3946	492.8864	433.5196	433.5195	453.46
P26 (MW)	436.3347	434.7492	436.3418	436.9926	433.3695	433.5195	433.5196	517.31
P27 (MW)	10	11.8064	11.2457	10.7784	10.0026	10	10	14.881
P28 (MW)	10.3901	10.7536	10	10.2955	10.0246	10	10	18.79
P29 (MW)	12.3149	10.3053	12.0714	13.7018	10.0125	10	10	26.611
P30 (MW)	96.9050	97.	97	96.2431	96.9125	97	87.8042	59.581
P31 (MW)	189.7727	190.0000	189.4826	190.0000	189.9689	159.733	159.733	183.48
P32 (MW)	174.2324	175.3065	174.7971	174.2163	175	159.733	159.7331	183.39
P33 (MW)	190	190	189.2845	190	189.0181	159.733	159.733	189.02
P34 (MW)	199.6506	200	200	200	200	200	200	198.73
P35 (MW)	199.8662	200	199.9138	200	200	200	200	198.77
P36 (MW)	200	200	199.5066	200	199.9978	200	200	182.23
P37 (MW)	110	109.9412	108.3061	110	109.9969	89.1141	89.1141	39.673
P38 (MW)	109.9454	109.8823	110	109.6912	109.0126	89.1141	89.1141	81.596
P39 (MW)	108.1786	108.9686	109.7899	108.5560	109.4560	89.1141	89.1141	42.96
P40 (MW)	422.0628	421.3778	421.5609	421.8521	421.9987	506.1879	506.1951	537.17
Total cost * 10^5 $	**1.2579**	**1.2573**	**1.2583**	**1.2581**	**1.2578**	**1.24490903**	**1.24491161**	**1.23170**
Emission * 10^5 ton	**2.1119**	**2.1177**	**2.1095**	**2.1110**	**2.1093**	**2.56560267**	**2.56560267**	**2.0846**
CPU (s)	**5.39**	**6.15**	**7.32**	**8.57**	**NA**	**NA**	**NA**	**4.92**

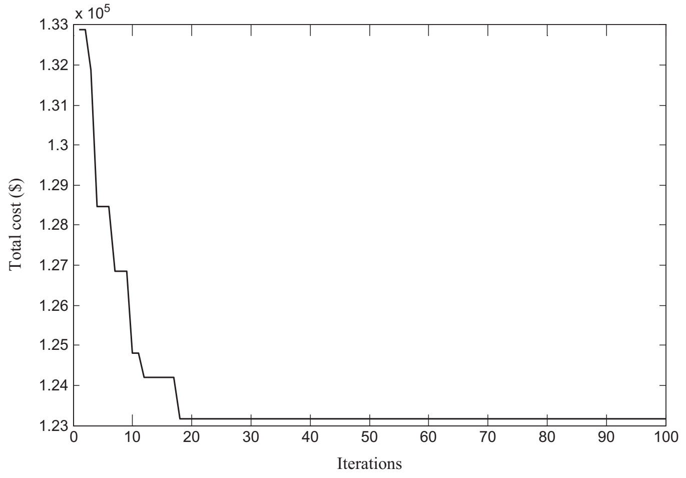

Fig. 9. Change of objective function with iterations for forty units.

comparing with MODE, PDE, NSGA-II, SPEA-2 [65], GSA [66], MABC/D/Cat [69] and MABC/D/Log [69]. The result of the suggested algorithm yields to a lower fuel cost than others as shown in Table 5. Therefore, these algorithms have trapped in local minimum solutions. On the other hand, the objective function representing the total cost decreases gradually and converges after 18 iterations as given in Fig. 9. Moreover, the average CPU time of the proposed FPA is the smallest one compared with other algorithms. The superiority of the proposed FPA in reaching the global minimum cost is detected by examining Fig. 10.

4.5. Comparison and discussion

The superiority of the proposed FPA is investigated here by comparison with other optimization algorithms in terms of economic effects and computation efficiency.

4.5.1. Economic effects

As seen in Figs. 3, 6, 8 and 10, the proposed FPA can get the best solution among other algorithms in the literatures. From Table 2, it is obvious that the mean cost value obtained by the proposed FPA is comparatively less compared with other algorithms. Therefore, the proposed FPA can result in better economic effects than other algorithms. Moreover, it leads to higher quality solution than other algorithms.

4.5.2. Convergence property and computation efficiency

From Figs. 4, 5, 7 and 9, one can get that the descending speeds at the beginning are high; this indicates the high convergence of the proposed algorithm based on evolution search. FPA can be convergent quickly and get the optimum results in very small iteration numbers. It is confirmed to have a good convergence property. As seen in Tables 1–5, CPU times of the proposed FPA are smaller than other algorithms since FPA has only one key parameter. Thus, it can get better computation efficiency than other algorithms.

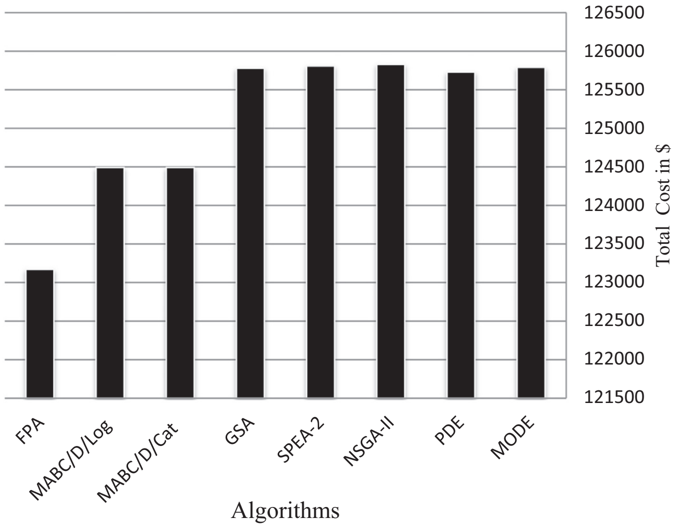

Fig. 10. Total cost for various algorithms for case 4.

5. Conclusions

In this paper, FPA has been developed to solve ELD and CEED problems in power systems. The performance of the FPA was tested for various test cases and compared with the reported cases in recent literatures. The superiority of FPA over other algorithms for settling ELD and CEED problems even for large scale power system with valve point effect is confirmed. Moreover, the economic effect, computation efficiency and convergence property of FPA are demonstrated. Therefore FPA optimization is a promising technique for solving complicated problems in power systems. Applications of the proposed algorithm to multi-area power system integrated with wind farms and PV system are the future scope of this work.

Appendix A

[a] Parameters of FPA for case 40 generators: Maximum number of iterations = 500, population size = 20, probability switch = 0.8.

[b] Parameters of FPA for case 3, 10 generators: Maximum number of iterations = 500, population size = 25, probability switch = 0.75.

Appendix B

See Tables B1–B3 and the transmission line losses coefficient.

Table B1
Generator cost coefficients for the three unit system considering emission.

Unit	γ \$/MW^{2}h	β \$/MWh	α \$/h	a (Kg/MW^{2}h)	b (Kg/MWh)	c (Kg/h)	P^{min} (MW)	P^{max} (MW)
1	0.03546	38.30553	1243.5311	0.00683	–0.54551	40.2669	35	210
2	0.02111	36.32782	1658.5696	0.00461	–0.5116	42.89553	130	325
3	0.01799	38.27041	1356.6592	0.00461	–0.5116	42.89553	125	315

The transmission line losses coefficient of three units system.

$$B_{ij} = 0.0001 * \begin{bmatrix} 0.71 & 0.3 & 0.25 \\ 0.3 & 0.69 & 0.32 \\ 0.255 & 0.32 & 0.8 \end{bmatrix},$$

Table B2
Ten unit generator characteristics.

Unit	γ \$/MW^{2}h	β (\$/MWh)	α (\$/h)	e (\$/h)	f (rad/MW)	$P^{\min}$ (MW)	$P^{\max}$ (MW)	a (Ib/MW^{2}h)	b (Ib/MWh)	c (Ib/h)	η (Ib/h)	δ (1/MW)
P1	0.12951	40.5407	1000.403	33	0.0174	10	55	0.04702	–3.9864	360.0012	0.25475	0.01234
P2	0.10908	39.5804	950.606	25	0.0178	20	80	0.04652	–3.9524	350.0056	0.25475	0.01234
P3	0.12511	36.5104	900.705	32	0.0162	47	120	0.04652	–3.9023	330.0056	0.25163	0.01215
P4	0.12111	39.5104	800.705	30	0.0168	20	130	0.04652	–3.9023	330.0056	0.25163	0.01215
P5	0.15247	38.539	756.799	30	0.0148	50	160	0.0042	0.3277	13.8593	0.2497	0.012
P6	0.10587	46.1592	451.325	20	0.0163	70	240	0.0042	0.3277	13.8593	0.2497	0.012
P7	0.03546	38.3055	1243.531	20	0.0152	60	300	0.0068	–0.5455	40.2669	0.248	0.0129
P8	0.02803	40.3965	1049.998	30	0.0128	70	340	0.0068	–0.5455	40.2669	0.2499	0.01203
P9	0.02111	36.3278	1658.569	60	0.0136	135	470	0.0046	–0.5112	42.8955	0.2547	0.01234
P10	0.01799	38.2704	1356.659	40	0.0141	150	470	0.0046	–0.5112	42.8955	0.2547	0.01234

The transmission line losses coefficient of ten units system.

$$B_{ij} = 0.0001 * \begin{bmatrix} 0.49 & 0.14 & 0.15 & 0.15 & 0.16 & 0.17 & 0.17 & 0.18 & 0.19 & 0.20 \\ 0.14 & 0.45 & 0.16 & 0.16 & 0.17 & 0.15 & 0.15 & 0.16 & 0.18 & 0.18 \\ 0.15 & 0.16 & 0.39 & 0.10 & 0.12 & 0.12 & 0.14 & 0.14 & 0.16 & 0.16 \\ 0.15 & 0.16 & 0.10 & 0.40 & 0.14 & 0.10 & 0.11 & 0.12 & 0.14 & 0.15 \\ 0.16 & 0.17 & 0.12 & 0.14 & 0.35 & 0.11 & 0.13 & 0.13 & 0.15 & 0.16 \\ 0.17 & 0.15 & 0.12 & 0.10 & 0.11 & 0.36 & 0.12 & 0.12 & 0.14 & 0.15 \\ 0.17 & 0.15 & 0.14 & 0.11 & 0.13 & 0.12 & 0.38 & 0.16 & 0.16 & 0.18 \\ 0.18 & 0.16 & 0.14 & 0.12 & 0.13 & 0.12 & 0.16 & 0.40 & 0.15 & 0.16 \\ 0.19 & 0.18 & 0.16 & 0.14 & 0.15 & 0.14 & 0.16 & 0.15 & 0.42 & 0.19 \\ 0.20 & 0.18 & 0.16 & 0.15 & 0.16 & 0.15 & 0.18 & 0.16 & 0.19 & 0.44 \end{bmatrix}.$$

Table B3
Forty unit generator characteristics.

Unit	$P^{\min}$ (MW)	$P^{\max}$ (MW)	α \$/h	β \$/MWh	γ \$/MW^{2}h	e (\$/h)	f (rad/MW)	c (Ib/h)	b (Ib/MWh)	a (Ib/MW^{2}h)	η (Ib/h)	δ (1/MW)
P1	36	114	94.705	6.73	0.00690	100	0.084	60	–2.22	0.0480	1.3100	0.05690
P2	36	114	94.705	6.73	0.00690	100	0.084	60	–2.22	0.0480	1.3100	0.05690
P3	60	120	309.540	7.07	0.02028	100	0.084	100	–2.36	0.0762	1.3100	0.05690
P4	80	190	369.030	8.18	0.00942	150	0.063	120	–3.14	0.0540	0.9142	0.04540
P5	47	97	148.890	5.35	0.01140	120	0.077	50	–1.89	0.0850	0.9936	0.04060
P6	68	140	222.330	8.05	0.01142	100	0.084	80	–3.08	0.0854	1.3100	0.05690
P7	110	300	287.710	8.03	0.00357	200	0.042	100	–3.06	0.0242	0.6550	0.02846
P8	135	300	391.980	6.99	0.00492	200	0.042	130	–2.32	0.0310	0.6550	0.02846
P9	135	300	455.760	6.60	0.00573	200	0.042	150	–2.11	0.0335	0.6550	0.02846
P10	130	300	722.820	12.9	0.00605	200	0.042	280	–4.34	0.4250	0.6550	0.02846
P11	94	375	635.200	12.9	0.00515	200	0.042	220	–4.34	0.0322	0.6550	0.02846
P12	94	375	654.690	12.8	0.00569	200	0.042	225	–4.28	0.0338	0.6550	0.02846
P13	125	500	913.400	12.5	0.00421	300	0.035	300	–4.18	0.0296	0.5035	0.02075
P14	125	500	1760.400	8.84	0.00752	300	0.035	520	–3.34	0.0512	0.5035	0.02075
P15	125	500	1760.400	8.84	0.00752	300	0.035	510	–3.55	0.0496	0.5035	0.02075
P16	125	500	1760.400	8.84	0.00752	300	0.035	510	–3.55	0.0496	0.5035	0.02075
P17	220	500	647.850	7.97	0.00313	300	0.035	220	–2.68	0.0151	0.5035	0.02075
P18	220	500	649.690	7.95	0.00313	300	0.035	222	–2.66	0.0151	0.5035	0.02075
P19	242	550	647.830	7.97	0.00313	300	0.035	220	–2.68	0.0151	0.5035	0.02075
P20	242	550	647.810	7.97	0.00313	300	0.035	220	–2.68	0.0151	0.5035	0.02075
P21	254	550	785.960	6.63	0.00298	300	0.035	290	–2.22	0.0145	0.5035	0.02075
P22	254	550	785.960	6.63	0.00298	300	0.035	285	–2.22	0.0145	0.5035	0.02075
P23	254	550	794.530	6.66	0.00284	300	0.035	295	–2.26	0.0138	0.5035	0.02075
P24	254	550	794.530	6.66	0.00284	300	0.035	295	–2.26	0.0138	0.5035	0.02075
P25	254	550	801.320	7.10	0.00277	300	0.035	310	–2.42	0.0132	0.5035	0.02075
P26	254	550	801.320	7.10	0.00277	300	0.035	310	–2.42	0.0132	0.5035	0.02075
P27	10	150	1055.100	3.33	0.52124	120	0.077	360	–1.11	1.8420	0.9936	0.04060
P28	10	150	1055.100	3.33	0.52124	120	0.077	360	–1.11	1.8420	0.9936	0.04060
P29	10	150	1055.100	3.33	0.52124	120	0.077	360	–1.11	1.8420	0.9936	0.04060
P30	47	97	148.890	5.35	0.01140	120	0.077	50	–1.89	0.0850	0.9936	0.04060
P31	60	190	222.920	6.43	0.00160	150	0.063	80	–2.08	0.0121	0.9142	0.04540
P32	60	190	222.920	6.43	0.00160	150	0.063	80	–2.08	0.0121	0.9142	0.04540
P33	60	190	222.920	6.43	0.00160	150	0.063	80	–2.08	0.0121	0.9142	0.04540
P34	90	200	107.870	8.95	0.00010	200	0.042	65	–3.48	0.0012	0.6550	0.02846
P35	90	200	116.580	8.62	0.00010	200	0.042	70	–3.24	0.0012	0.6550	0.02846
P36	90	200	116.580	8.62	0.00010	200	0.042	70	–3.24	0.0012	0.6550	0.02846
P37	25	110	307.450	5.88	0.01610	80	0.098	100	–1.98	0.0950	1.4200	0.06770
P38	25	110	307.450	5.88	0.01610	80	0.098	100	–1.98	0.0950	1.4200	0.06770
P39	25	110	307.450	5.88	0.01610	80	0.098	100	–1.98	0.0950	1.4200	0.06770
P40	242	550	647.830	7.97	0.00313	300	0.035	220	–2.68	0.0151	0.5035	0.02075

Nomenclature

F_t	The total fuel cost of generation in \$
$F_i(P_i)$	The fuel cost function of i^{th} generator in \$
$\gamma_i, \beta_i, \alpha_i$	The cost coefficients of i^{th} generator in \$/MW^2, \$/MW and \$ respectively
P_i	The real power generation of i^{th} generator in MW
d	The number of generators connected in the network
P_D	The total load of the system in MW
P_L	The transmission losses of the system in MW
P_i, P_j	The real power injections at i^{th} and j^{th} buses respectively
B_{ij}, B_{0i}, B_{00}	The loss-coefficients of transmission loss formula
$P_i^{\min}$, $P_i^{\max}$	The minimum and maximum values of real power allowed at generator i
e_i, f_i	The coefficients of i^{th} generator due to valve point effect in \$ and MW^{-1} respectively
F	The optimal cost of total generation and emission
$F_i(P_i), E_i(P_i)$	The total fuel cost and total emission of generators respectively
a, b, c	The emission coefficients of generators in Kg/MW^2, Kg/MW and Kg respectively
η_i, δ_i	The emission coefficients of i^{th} generator in Ton and MW^{-1} respectively
h	The price penalty factor value in \$/Kg
x_i^t	The pollen i
g^*	The current best solution found at the current generation
γ	The scaling factor controlling the step size
$\Gamma(\lambda)$	The standard gamma function
p	Switch probability

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