Flower Pollination Algorithm Applied for Different Economic Load Dispatch Problems

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ABSTRACT

Economic load dispatch (ELD) is the main optimization task in power system operation. Minimizing the fuel cost by optimally setting the real power outputs from generators is the objective of ELD problem. In this work, ELD problem is addressed by considering three different cost functions. Real power generations are adjusted for minimizing the fuel cost by using flower pollination algorithm (FOA). This algorithm works on the basis of pollinating behavior of flowering plants. Unlike the other nature inspired algorithms, it follows only the levy flight mechanism for generating the population for the next generation. Being free from large number of parameters, the algorithm works well and there is no much difficulty in tuning to suit for different problems. The algorithm can be coded easily in any programming language. The proposed algorithm is tested on the standard IEEE-30 bus system and the results are compared with those of the other algorithms reported in the literature. The results are found to be improved and encouraging.

Key words: optimal power flow, economic load dispatch, flower pollination algorithm, generation cost, cost functions.

I. INTRODUCTION

Economic operation of power systems is met by meeting the load demand through optimal scheduling of power generation. Minimization of fuel cost is the main form of optimal power flow (OPF) problems [1]-[2]. Real power generations of different generators are the control variables in ELD problem. Optimal real power scheduling will ensure economic benefits to the power system operators and reduce the release of polluting gases.

ELD primarily aims at optimal scheduling of real power generation from committed units in such a way that it meets the total demand and losses while satisfying the constraints [3]. Achieving minimum cost while satisfying the constraints makes the ELD problem a large-scale highly non-linear constrained optimization problem. The non linearity of the problem is due to non linearity and valve point effects of input–output characteristics of generating units. The objective of cost minimization may have multiple local optima. There is always a demand for an efficient optimization technique for these kinds of highly non linear objective function [4]. Further, the algorithm is expected to produce accurate results for the ELD problem.

In the past, numerous conventional optimization algorithms are exploited for solving the OPF problems [5]. Major drawback of those methods is that they require smooth and convex functions for better results and more likely to trap into local optima. Later, evolutionary algorithms are exploited for ELD problems and improved results were obtained [6]-[8].

In the last decade, several bio inspired algorithms are introduced and attempted for many engineering optimization problems. Some of the notable bio inspired algorithms are particle swarm optimization algorithm (PSO), a well received algorithm and utilized in almost all engineering applications successfully [9]-[10]. Firefly algorithm is another recently introduced algorithm for engineering optimization [11] that has been successfully used to solve the dynamic ELD problem. Theses algorithms are highly efficient and cannot easily trap in to local optima. In addition, they are comfortable with all types of objective functions. Researchers across the world are constantly working to develop still efficient algorithms by copying the behaviour of nature/species. Flower pollination algorithm FPA is one such nature inspired algorithm developed by xin she yang for engineering tasks.

The efficiency of nature/bio inspired algorithms is proved to be outperforming even the evolutionary based algorithms. In this paper, the FPA algorithm [12] is proposed for achieving improved results in the ELD problem. This algorithm is with less number of operators and hence can be easily coded in any programming language. To prove the strength of this algorithm its performance is compared with other algorithms.

II. ECONOMIC DISPATCH PROBLEM FORMULATION

The objective of ELD is to minimize the total fuel cost. Total fuel cost can be calculated by using one of the three cost functions as discussed below.

2.1 *Quadratic cost function*

The total cost of operation of generators includes fuel and maintenance cost but for simplicity only the fuel cost is considered. The fuel cost is Important for thermal power plants. The cost function is assumed to be smooth and taken as a quadratic curve (1).

$$F = \sum_{i=1}^{N_G} C_i(P_{Gi}) = \sum_{i=1}^{N_G} a_{i+} b_i P_{Gi+}\, c_i P_{Gi}^2 \qquad (1)$$

Where N_G is the total number of generation units in the plant, a_i, b_i, c_i are the cost coefficients of generating unit i and P_{Gi} is the real power generation of i^{th} unit.

2.2 *Cost function with sine term*

When a generator is with multiple valve points as is the case in steam turbines the cost curve is not smooth. The assumption that the cost curve function is smooth becomes invalid and the results are erroneous. The effect of valve points can be taken into account by adding a sine term as in equation (2).

$$F_i = a_i + b_i P_{Gi} + c_i P_{Gi}^2 + \left| e_i \times sin\left(f_i \times \left(P_{Gi}^{min} - P_{Gi}\right)\right)\right| \qquad (2)$$

Where, F_i is the fuel cost of i^{th} generator that has multistage valves in its inputs.

2.3 *NOx Emission Objective*

The minimum emission dispatch optimizes the above classical economic dispatch including NO_x emission objective, which can be modeled by using a second order polynomial functions.

$$E_{NO_x} = \sum_{i=1}^{N_G} (a_{iN} + b_{iN} P_{Gi} + c_{iN} P_{Gi}^2 + d_{iN} \sin(e_{iN} P_{Gi})) \quad \text{ton/hr} \qquad (3)$$

Economic load dispatch is subject to equality constraints like power flow equations and inequality constraints like generator power, voltage magnitude and line power flow.

Equality Constraints**:**

$$P_{gi} - P_{di} - \sum_{j=1}^{N} |V_i||V_j||Y_{ji}| cos\left(\delta_i - \delta_j - \theta_{ij}\right) = 0 \qquad (4)$$

$$Q_{gi} - Q_{di} - \sum_{j=1}^{N} |V_i||V_j||Y_{ji}| sin\left(\delta_i - \delta_j - \theta_{ij}\right) = 0 \qquad (5)$$

$$\sum P_{gi} - P_D - P_L = 0 \qquad (6)$$

Where P_D is the demand power and P_L is the total transmission network losses.

Inequality Constraints

Branch power flow limit:

$$|Si| \leq |S_i^{max}| \quad i = 1, \ldots N_L \qquad (7)$$

Generator MVAR outputs:

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{min} \quad i = 1, \ldots N_G \qquad (8)$$

Real power generation output:

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \quad i = 1, \ldots N_G \qquad (9)$$

III. POLLINATION IN FLOWERING PLANTS

It is estimated that 80% of plants use pollination for reproduction. Flower pollination is the transfer of pollen from a male flower to a female flower. Pollination may take place in the form of biotic or abiotic. 90% of pollination is through insects and animals only the remaining 10 % is by wind and other natural causes.

Biotic pollination may be of self-pollination or cross-pollination. Cross-pollination means pollination occurring between two different flowers, while self-pollination takes place in the same flower between its male and female parts. Biotic and cross type pollinations occur between flowers far away from each other hence they are equivalent to global optimization. As the pollinating agents like insects follow the Levy flight movement, it can be employed for global optimization. Abiotic and self pollinations can be thought of local optimization since it occurs in the same flower.

3.1 *Flower Pollination Algorithm*

Based on the concept of flower pollination, Flower pollination algorithm is (FPA) is developed.

The following are the four rules employed to copy the pollination characteristics of flowers [12]

Rule 1. Biotic and cross-pollination are considered as global pollination process and pollen is carried by a movement which obeys Levy flight movement.

Rule 2. Abiotic and self-pollination are equivalent to local pollination process.

Rule 3. Pollinators can develop flower constancy, which is like reproduction probability and proportional to the similarity of two flowers involved.

Rule 4. Changing from local pollination to global pollination or vice versa can be controlled by a probability p $\in$ [0, 1].

For implementation of this FPA algorithm, a set of updating formulae are developed by converting the rules into updating equations. In the global pollination step, flower pollen gametes are carried by pollinators such as insects over longer distances.

Therefore, the mathematical equivalent of Rule 1 and flower constancy is written as

$$x_i^{t+1} = x_i^t + \gamma L(\lambda)(x_i^t - x_*) \tag{10}$$

Where, x_i^{t+1} is the solution vector (pollen) x_i at iteration t, $x_*$is the current best solution, γ is a scaling factor to control the step size. $L(\lambda)$ is the parameter that corresponds to the strength of the pollination, which essentially is also the step size. Since insects may move over a long distance with various distance steps, we can use a Levy flight to mimic this characteristic efficiently. That is, we draw L > 0 from a Levy distribution

$$L \simeq \frac{\lambda \Gamma(\lambda) sin(\pi\lambda/2)}{\pi} \frac{1}{s^{1+\lambda}} \quad (s \gg s_0 > 0) \tag{11}$$

Here, $\Gamma(\lambda)$ is the standard gamma distribution valid for large steps. i.e. for s > 0.

Then, to model the local pollination, both Rule 2 and Rule 3 can be represented as:

$$x_i^{t+1} = x_i^t + \varepsilon\left(x_j^t - x_k^t\right) \tag{12}$$

where x_j^t and x_k^t are pollen from different flowers of the same plant species. This essentially mimics the flower constancy in a limited neighborhood. Mathematically, if x_j^t and x_k^t comes from the same species or selected from the same population, this equivalently becomes a local random walk if we draw ε from a uniform distribution in [0, 1].Pollination may also occur in a flower from the neighboring flower than by the far away flowers. In order to copy this, a switch probability (Rule 4) is used through a proximity probability p to switch between global pollination and local pollination. A preliminary parametric showed that p=0.8 might work better for most applications.

IV. NUMERICAL RESULTS AND DISCUSSIONS

The performance of the FPA based method is tested on IEEE-30 bus system considering three different cost functions. The algorithm is coded in MATLAB 7.6 environment. A Core2Duo processor based PC is used for the simulations.

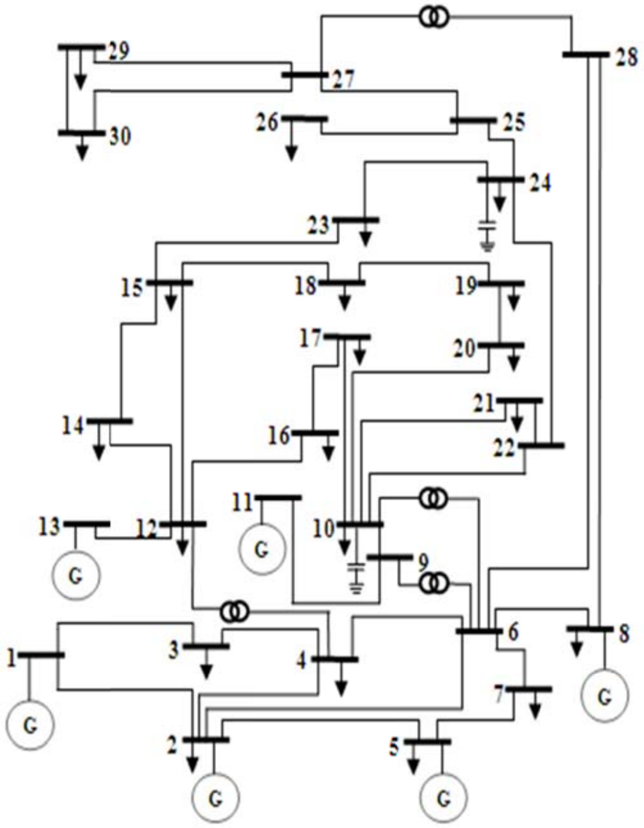

Figure 1. Single line diagram of the IEEE 30 Bus system

The base load condition is taken for the simulation and the system bus and line data are taken from [13]. The system parameters are shown in table 1. Bus 1 is the slack bus and the line data and bus data are on 100 MVA basis. The algorithm is run for 100 iterations with 30 as the population size and proximity probability as 0.8.

TABLE 1. PARAMETERS OF THE IEEE-30 BUS SYSTEM

SI.No.	Parameter	30-bus system
1	Buses	30
2	Branches	41
3	Generator Buses	6
4	Shunt capacitors	2
5	Tap-Changing transformers	4

Total fuel cost is calculated by using the cost function. Three different types of cost functions here. The first one is quadratic cost curve that takes a smooth cost curve by neglecting the effects of valve points. Valve point effect is considered and non-smooth curve is followed in the second case. Minimization of fuel cost results in non optimized emissions from thermal power plants. Total emission is taken as a constraint in ELD and this is the third case.

4.1 *CASE 1. SMOOTH COST CURVE*

In this case the basic and simple form of cost function is taken. The cost co-efficients are shown in table A-1. FPA algorithm is run for the minimum fuel cost. The real power generations corresponding to minimum fuel cost are shown in table 2.

The fuel cost obtained is 802.3491USD/hr. It is seen from the table 2, that the cost suggested by FPA is lower than the cost reported in the recent literatures [14]-[15]. The loss reduction is slightly more than the loss level achieved in [15] but lower than what is given in [14].

TABLE 2. OPTIMAL REAL POWER SETTINGS, FUEL COST AND LOSS (CASE 1)

Unit power output (MW)	Method		
	IEP [14]	SADE-ALM [15]	FPA
P_1	176.2358	176.1522	176.927
P_2	49.0093	48.8391	49
P_5	21.5023	21.5144	22
P_8	21.8115	22.1299	20
P_{11}	12.3387	12.2435	13
P_{13}	12.0129	12.0000	12
Total P_G	292.9105	292.8791	292.927
P_{loss}	9.5105	9.4791	9.527
Total cost ($/h)	802.465	802.404	802.3491

The strength of an optimization technique greatly lies in its reliable convergence. The convergence efficiency of FPA in handling quadratic cost function is proved in figure 2. The algorithm takes only 48 iterations to converge to the improved results.

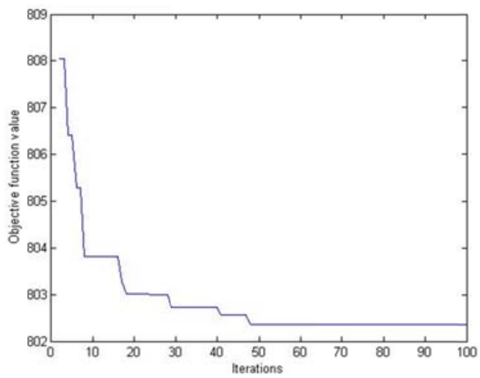

Figure 2. Convergence behavior of FPA (case 1)

4.2 *CASE 2. NON SMOOTH COST CURVE*

Steam turbines have multi stages and steam is injected through a number of valves. Due to the use of multiple valves the cost curve is not smooth. Fuel cost calculated using the quadratic cost curve will have erroneous results. An additional term with sine function is added to the quadratic cost function to take into account the effect of valve points. The corresponding cost coefficients are given in table A-2.

The total fuel cost is minimized to 925.1562 from 944.031. The difference is high and saving in cost is sound. The total system loss is also minimized by a large amount i.e. from12.0096 MW to 10.199 MW and this is an additional benefit. Reduction in loss can be alternatively taken as reduced generation or generation cost. The optimal real power setting corresponding to minimum fuel cost is given in table 3. Performance of FPA is compared with that of IEP and SADE-ALM algorithms.

TABLE 3. OPTIMAL REAL POWER SETTINGS, FUEL COST AND LOSS (CASE 2)

UNIT POWER OUTPUT (MW)	METHOD		
	IEP [14]	SADE-ALM [15]	FPA
P_1	149.7331	193.2903	199.599
P_2	52.0571	52.5735	20
P_5	23.2008	17.5438	24
P_8	33.4150	10.0000	23
P_{11}	16.5523	10.0000	13
P_{13}	16.0875	12.0000	14
Total P_G	291.0458	295.4096	279.599
P_{loss}	7.6458	12.0096	10.199
Total cost ($/h)	953.573	944.031	925.1562

As the valve point effect is considered in this case, the cost function has multiple local optima. However, the algorithm succeeded in retaining the best results and takes only 20 iterations to get converged.

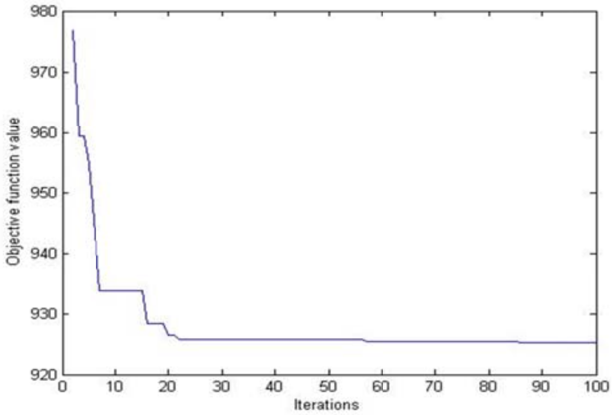

Figure 3. Convergence behavior of FPA (case 2)

4.3 CASE 3. EMISSION CURVE

When only economic consideration is given for ELD problems, the toxic emission from fossil fuel fired plants are not controlled. This will further worsen the environmental pollution. To protect the environment from pollution, the level of emission should be limited. In this case emission is taken as a constraint.

The objective function is highly non linear due to the presence of sin term. The proposed algorithm performs well while using this objective function. The best emission level produced by FPA is less than the one reported in the literatures. 0.19422 is the minimum emission that was the recently reported best results. FPA achieves emission level as 0.1886 and it is clear from table 4 that the best cost corresponding to the best emission is also really good.

TABLE 4. BEST NO_x EMISSION

Optimal solution	NSGA[16]	NPGA[17]	SPEA[18]	FPA
P_{G1}	0.4113	0.3923	0.4043	0.42218
P_{G2}	0.4591	0.4400	0.4525	0.4500
P_{G5}	0.5117	0.5565	0.5525	0.4700
P_{G8}	0.3724	0.3695	0.4079	0.4500
P_{G11}	0.5810	0.5599	0.5468	0.5400
P_{G13}	0.5304	0.5163	0.5005	0.5300
Best emission	0.19432	0.19424	0.19422	0.1886
Corresp. cost	647.251	645.984	642.603	639.012

Convergence to the best results is depicted in figure 4. The algorithm converges in 20 iterations showing its reliability. To reach the minimum emission of 0.1886 from the initial value of about 0.24 the moves in a sooth manner without sluggishness.

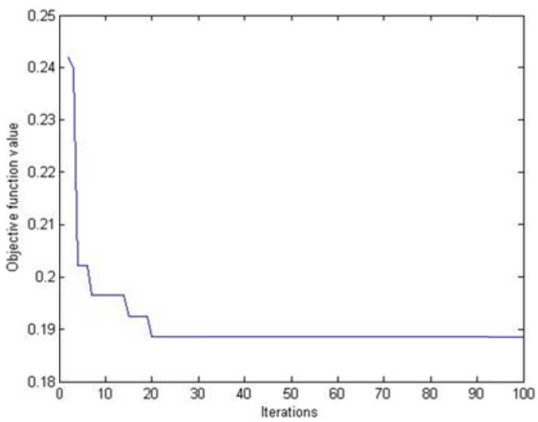

Figure 4.Convergence behavior of FPA (case 3)

V. CONCLUSIONS

In this work, a new bio inspired algorithm is implemented for different ELD problems. The numerical results clearly show that the proposed algorithm gives better results. The FPA optimization algorithm outperforms the other recently reported algorithms. The strength of the algorithm is proved in all the three different types of ELD problems. The three objective functions are entirely different in nature and require algorithms are different strengths and hence it can be said that the algorithm is could be suitable for different power system optimization problems. It is obvious from the convergence quality of FPA algorithm in different objectives, the robustness of the algorithm is proved.The algorithm is easy for implementation and can be coded in any computer language. Power system operation optimization problems can be attacked with this algorithm. Power system operators can use this algorithm for various optimization tasks.

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Appendix

TABLE A.1 : GENERATOR COST COEFFICIENTS IN CASE 1

BUS NO.	Real Power Output Limit(MW)S		Cost Coefficients		
	Min	Max	a	b	c
1	50	200	0.00375	2.00	0
2	20	80	0.01750	1.75	0
5	15	50	0.06250	1.00	0
8	10	35	0.00834	3.25	0
11	10	30	0.02500	3.00	0
13	12	40	0.02500	3.00	0

TABLE A. 2 : GENERATOR COST COEFFICIENTS IN CASE 2

Bus No.	Real Power limit		Cost Coefficients				
	Min	Max	a	b	c	e	f
1	50	200	0.00160	2.00	150	50	0.063
2	20	80	0.01000	2.50	25	40	0.098

TABLE A. 3 NO_x EMISSION COEFFICIENTS FOR CASE 3

Unit i	a_{iN}	b_{iN}	c_{iN}	d_{iN}	e_{iN}
1	4.091e-2	-5.554e-2	6.490e-2	2.0e-4	2.857
2	2.542e-2	-6.047e-2	5.638e-2	5.0e-4	3.333
3	4.258e-2	-5.094e-2	4.586e-2	1.0e-6	8.000
4	5.326e-2	-3.550e-2	3.380e-2	2.0e-3	2.000
5	4.258e-2	-5.094e-2	4.586e-2	1.0e-6	8.000
6	6.131e-2	-5.555e-2	5.151e-2	1.0e-5	6.667