The International Journal Of Engineering And Science (IJES)
|| Volume || 3 || Issue || 10 || Pages || 15-25|| 2014 ||
ISSN (e): 2319 – 1813 ISSN (p): 2319 – 1805

Differential Evolution Algorithm for Optimal Power Flow and Economic Load Dispatch with Valve Point Effects

Ngo Cao Cuong
HUTECH High Technology Research Instituite, Viet nam

ABSTRACT
In this paper, we present a Differential Evolution (DE) method and apply it to two problems of optimal power flow (OPF) and the economic load dispatch (ELD) with Valve-Point effects in Power Systems. In the first case, the standard IEEE 30-bus network is tested and its solution is compared to the ones solved by Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Ant Colony Optimization (ACO) methods. For the second one, the NPSO is tested on 13-unit, 40-unit system and validated by comparing results with classical evolutionary programming (CEP), improved fast evolutionary programming (IFEP), improved particle swarm optimization (IPSO) and efficient particle swarm optimization (EPSO) methods. The numerical results are illustrated in many Figures and Tables. It has shown that the proposed method is better than the others in terms of total fuel costs, total loss and computational times.

KEYWORDS: *Index Terms-Differential Evolution, Optimal Power Flow, Economic Load Dispatch.*

Date of Submission: 26 September 2014 — Date of Publication: 10 October 2014

I. INTRODUCTION

Optimal Power Flow (OPF) and Economic Load Dispatch (ELD) problems are the important fundamental issues in power system operation. In essence, they are the optimization problems and their main objective is to reduce the total generation cost of units, while satisfying constraints. Previous efforts on solving OPF and ELD problems have employed various mathematical programming methods and optimization techniques.Recently, differential evolution (DE) algorithm has been proposed and introduced [1, 2]. The algorithm is inspired by biological and sociological motivations and can take care of optimality on rough, discontinuous and multi-modal surfaces. The DE has three main advantages: it can find near optimal solution regardless the initial parameter values, its convergence is fast and it uses few number of control parameters. In addition, DE is simple in coding and easy to use. It can handle integer and discrete optimization [1, 2].

In this paper, the DE is proposed for solving optimal power flow (OPF) problem. The proposed method has been tested on the standard IEEE 30-bus test systems [17]. The obtain results from the proposed method are compared to those ones from PSO [16], GA [17], ACO [19] methods. Besides, DE method is also proposed for solving ELD problem with valve point effects. This method has tested on 13-unit and 40-unit network. The obtained results are compared to those from Classical Evolutionary Programming (CEP) [4], Improved Fast Evolutionary Programming (IFEP) [4], Improved Particle Swarm Optimization (IPSO) [6] and Efficient Particle Swarm Optimization (EPSO) [5] methods.

II. OPTIMAL POWER FLOW PROBLEM

The OPF problem can be described as an optimization (minimization) process with nonlinear objective function and nonlinear constraints. The general OPF problem can be expressed as

Minimize $F(x)$ (1)

subject to $g(x) = 0$ (2)

$h(x) \leq 0$ (3)

where $F(x)$ the objective function, $g(x)$ represents the equality constraints, $h(x)$ represents the inequality constraints and is x is the vector of the control variables, that is those which can be varied by a control center operator (generated active and reactive powers, generation bus voltage magnitudes, transformers taps, etc.).

The essence of the optimal power flow problem resides in reducing the objective function and simultaneously satisfying the load flow equations (equality constraints) without violating the inequality constraints.

The fuel cost function is given by

$$F(x) = \sum_{i=1}^{N_G} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) \quad (4)$$

Where, N_G is the number of generation including the slack bus. P_G is the generated active power at bus i. a_i, b_i and c_i are the unit costs curve for i^{th} generator.

While minimizing the cost function, it is necessary to make sure that the generation still supplies the load demands plus losses in transmission lines. Usually the power flow equations are used as equality constraints [5].

$$\begin{bmatrix} \Delta P_i \\ \Delta Q_i \end{bmatrix} = \begin{bmatrix} P_i(V,\theta) - (P_{G_i} - P_{D_i}) \\ Q_i(V,\theta) - (Q_{G_i} - Q_{D_i}) \end{bmatrix} = 0 \quad (5)$$

Where active and reactive power injection at bus i are defined in the following equation

$$P_i(V,\theta) = \sum_{j=1}^{N_B} V_i V_j \left(G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij} \right) \quad (6)$$

$$Q_i(V,\theta) = \sum_{j=1}^{N_B} V_i V_j \left(G_{ij} \sin\theta_{ij} + \cos B_{ij}\theta_{ij} \right) \quad (7)$$

The inequality constraints of the OPF reflect the limits on physical devices in power systems as well as the limits created to ensure system security. The most usual types of inequality constraints are upper bus voltage limits at generations and load buses, lower bus voltage limits at load buses, reactive power limits at generation buses, maximum active power limits corresponding to lower limits at some generators, maximum line loading limits and limits on tap setting. The inequality constraints on the problem variables considered include

Generation constraint: Generator voltages, real power outputs and reactive power outputs are restricted by their upper and lower bounds as follows

$$P_{Gi,\min} \le P_{Gi} \le P_{Gi,\max} \quad \text{for } i = 1, 2, \ldots, N_G \quad (8)$$

$$Q_{Gi,\min} \le Q_{Gi} \le Q_{Gi,\max} \quad \text{for } i = 1, 2, \ldots, N_G \quad (9)$$

$$V_{Gi,\min} \le V_{Gi} \le V_{Gi,\max} \quad \text{for } i = 1, 2, \ldots, N_G \quad (10)$$

Shunt VAR constraint: Shunt VAR compensations are restricted by their upper and lower bounds as follows

$$Q_{Ci,\min} \le Q_{Ci} \le Q_{Ci,\max} \quad \text{for } i = 1, 2, \ldots, N_C \quad (11)$$

where N_C is the number of shunt compensator.

Transformer constraint: Transformer tap settings are restricted by their upper and lower bounds as follows

$$T_{i,\min} \le T_i \le T_{i,\max} \quad \text{for } i = 1, 2, \ldots, N_T \quad (12)$$

where N_T is the number of transformer tap.

Security constraint: Voltages at load bus are restricted by their upper and lower bounds as follows

$$V_{Li,\min} \le V_{Li} \le V_{Li,\max} \quad \text{for } i = 1, 2, \ldots, N_L \quad (13)$$

where N_L is the number of load bus.

III. ECONOMIC LOAD DISPATCH PROBLEM

The same as OPF, the economic load dispatch problem can be also described as the optimization (minimization) process with the following objective function

$$C = \sum_{i=1}^{N} F_i(P_i) \quad (14)$$

where $F_i(P_i)$ is the fuel cost function of the i^{th} unit and P_i is the power generated by the i^{th} unit.

Subject to power balance constraints

$$\sum_{i=1}^{N} P_i = P_D + P_{Loss} \qquad (15)$$

where P_D is the system load demand and P_{Loss} is the transmission loss. One approach to estimate losses is by modeling them as a function of outputs of the system generator using Kron's loss formula of (16).

$$P_L = \sum_{i=1}^{N_G} \sum_{j=1}^{N_G} P_{G_i} B_{ij} P_{G_i} + \sum_{j=1}^{N_G} P_{G_i} B_{i0} + B_{00} \qquad (16)$$

where B_{ij}, B_{i0}, B_{00} are known as the losses or *B*-coefficients.

and generating capacity constrains

$$P_{i,\min} \le P_i \le P_{i,\max} \quad \text{for } i = 1, 2, \ldots\ldots, N \qquad (17)$$

where $P_{i,min}$ and $P_{i,max}$ are the minimum and maximum power outputs of the i^{th} unit.

The smooth quadratic fuel cost function without valve point loadings of the generating units are given by (4), where the valve-point effects are ignored. The generating units with multi-valve steam turbines exhibit a greater variation in the fuel-cost functions. Since the valve point results in the ripples, a cost function contains higher order nonlinearity. Therefore, the equation (4) should be replaced by (18) for considering the valve-point effects.

The sinusoidal functions are thus added to the quadratic cost functions as follows [6]

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 + \left| e_i \times \sin(f_i \times (P_{i,\min} - P_i)) \right| \qquad (18)$$

where a_i, b_i, c_i are the fuel cost coefficients of the i^{th} unit and e_i and f_i are the fuel cost coefficients of the i^{th} unit with valve point effects.

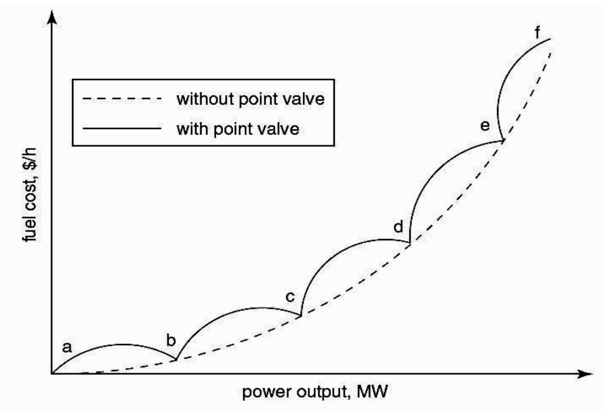

Fig.1: Example cost function with 6 valves [5]

IV. DIFFERENTIAL EVOLUTION

A. Overview of the DE

In 1995, Storn and Price proposed a new floating point encoded evolutionary algorithm for global optimization and named it differential evolution (DE) algorithm owing to a special kind of differential operator, which they invoked to create new off-spring from parent chromosomes instead of classical crossover or mutation [1].

Similar to GAs, DE algorithm is a population based algorithm that uses crossover, mutation and selection operators. The main differences between the genetic algorithm and DE algorithm are the selection process and the mutation scheme that makes DE self adaptive. In DE, all solutions have the same chance of being selected as parents. DE employs a greedy selection process that is the best new solution and its parent wins the competition providing significant advantage of converging performance over genetic algorithms.

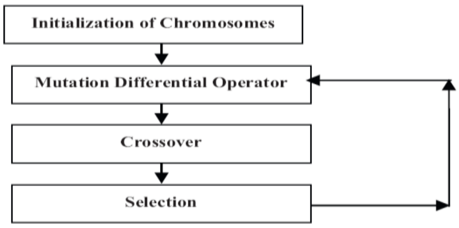

Fig.2: DE cycle of stages

B. Differential Evolution Algorithm

DE algorithm is a population based algorithm using three operators; crossover, mutation and selection. Several optimization parameters must also be tuned. These parameters have joined together under the common name control parameters. In fact, there are only three real control parameters in the algorithm, which are differentiation (or mutation) constant F, crossover constant CR, and size of population NP. The rest of the parameters are dimension of problem D that scales the difficulty of the optimization task; maximum number of generations (or iterations) GEN, which may serve as a stopping condition; and low and high boundary constraints of variables that limit the feasible area [1, 2].The proper setting of NP is largely dependent on the size of the problem. Storn and Price [1] remarked that for real-world engineering problems with D control variables, NP=20D will probably be more than adequate, NP as small as 5D is often possible, although optimal solutions using NP<2D should not be expected. In [24], Storn and Price set the size of population less than the recommended NP=10D in many of their test tasks. In [25], it is recommended using of NP≥4D. In [26], NP=5D is a good choice for a first try, and then increase or decrease it by discretion. So, as a rough principle, several tries before solving the problem may be sufficient to choose the suitable number of the individuals.

The DE algorithm works through a simple cycle of stages, presented in Fig. 2.

These stages can be cleared as follow:

1. Initialization

At the very beginning of a DE run, problem independent variables are initialized in their feasible numerical range. Therefore, if the jth variable of the given problem has its lower and upper bound as x_j^L and x_j^u , respectively, then the jth component of the ith population members may be initialized as

$$x_{i,j}(0) = x_j^L + rand(0,1).(x_j^u - x_j^L) \qquad (19)$$

where rand(0,1) is a uniformly distributed random number between 0 and 1.

2. Mutation

In each generation to change each population member $X_i(t)$, a donor vector $v_i(t)$ is created. It is the method of creating this donor vector, which demarcates between the various DE schemes. However, in this paper, one such specific mutation strategy known as DE/rand/1 is discussed.

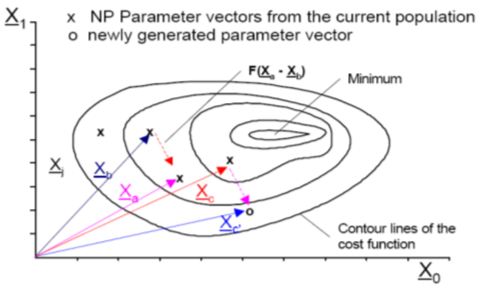

Fig.3: Mutation operator

To create a donor vector $v_i(t)$ for each ith member, three parameter vectors x_{r1}, x_{r2} and x_{r3} are chosen randomly from the current population and not coinciding with the current x_i. Next, a scalar number F scales the difference of any two of the three vectors and the scaled difference is added to the third one whence the donor vector $v_i(t)$ is obtained. The usual choice for F is a number between 0.4 and 1.0. So, the process for the jth component of each vector can be expressed as,

$$v_{i,j}(t+1) = x_{r1,j}(t) + F.(x_{r2,j}(t) - x_{r3,j}(t)) \qquad (20)$$

3. Crossover

To increase the diversity of the population, crossover operator is carried out in which the donor vector exchanges its components with those of the current member $X_i(t)$.

Two types of crossover schemes can be used with DE technique. These are exponential crossover and binomial crossover. Although the exponential crossover was proposed in the original work of Storn and Price [1], the binomial variant was much more used in recent applications [25]. In exponential type, the crossover is performed on the D variables in one loop as far as it is within the CR bound. The first time a randomly picked number between 0 and 1 goes beyond the CR value, no crossover is performed and the remaining variables are left intact. In binomial type, the crossover is performed on all D variables as far as a randomly picked number between 0 and 1 is within the CR value. So for high values of CR, the exponential and binomial crossovers yield similar results. Moreover, in the case of exponential crossover one has to be aware of the fact that there is a small range of CR values (typically [0.9, 1]) to which the DE is sensitive. This could explain the rule of thumb derived for the original variant of DE. On the other hand, for the same value of CR, the exponential variant needs a larger value for the scaling parameter F in order to avoid premature convergence [26].

In this paper, binomial crossover scheme is used which is performed on all D variables and can be expressed as

$$u_{i,j}(t) = \begin{cases} v_{i,j}(t) & if \quad rand(0,1) < CR \\ x_{i,j}(t) & else \end{cases} \qquad (21)$$

$u_{i,j}(t)$ represents the child that will compete with the parent $x_{i,j}(t)$.

4. Selection

To keep the population size constant over subsequent generations, the selection process is carried out to determine which one of the child and the parent will survive in the next generation, i.e., at time t=t+1. DE actually involves the Survival of the fittest principle in its selection process. The selection process can be expressed as,

$$X_i(t+1) = \begin{cases} U_i(t) & if \quad f(U_i(t)) \le f(X_i(t)) \\ X_i(t) & \text{if} \quad f(X_i(t)) < f(U_i(t)) \end{cases} \qquad (22)$$

where, f () is the function to be minimized. From Eq. (10) we noticed that:

• If $u_i(t)$ yields a better value of the fitness function, it replaces its target $X_i(t)$ in the next generation.

• Otherwise, $X_i(t)$ is retained in the population.

Hence, the population either gets better in terms of the fitness function or remains constant but never deteriorates.

C. Differential Evolution Implementation

The proposed DE-based approach has been developed and implemented using the MATLAB software. Several runs have been done with different values of DE key parameters such as differentiation (or mutation) constant F, crossover constant CR, size of population NP, and maximum number of generations GEN which is used here as a stopping criteria to find the optimal DE key parameters. In this paper, the following values of DE key parameters are selected for the optimization of power losses and voltage stability enhancement:

F = 0.2; CR = 0.6; NP = 150; GEN = 300

and DE key parameters for the optimization of voltage deviations are selected as:

F = 0.2; CR = 0.6; NP = 50; GEN = 300

The first step in the algorithm is creating an initial population. All the independent variables which include generator voltages, transformer tap settings and shunt VAR compensations have to be generated according to Eq. (19), where each independent parameter of each individual in the population is assigned a value inside its given feasible region. This creates parent vectors of independent variables for the first generation.

After, finding the independent variables, dependent variables will be found from a load flow solution. These ependent variables include generators reactive power, voltages at load buses and transmission line loadings. It should be mentioned that, the real power settings of the generators are taken from [4].

V. NUMERICAL RESULTS

A. Case of DE problem

To verify the feasibility of the proposed DE method, the standard IEEE 30-bus system [17] has been used to test the OPF problem. The system line and bus data are given in [20]. The system has six generators at buses 1, 2, 5, 8, 11, 13 and four transformers with off-nominal tap ratio in lines 6-9, 6-10, 4-12, and 28-27. The cost coefficients in (4) are given in TABLE.I.. The obtained results of the DE are compared with those of other methods as in TABLE.II.

TABLE I.
GENERATOR COST COEFFICIENTS OF IEEE 30-BUS SYSTEM

Bus	*a*	*b*	*c*
1	0	2.00	0.00375
2	0	1.75	0.01750
5	0	1.00	0.06250
8	0	3.25	0.00834
11	0	3.00	0.02500
13	0	3.00	0.02500

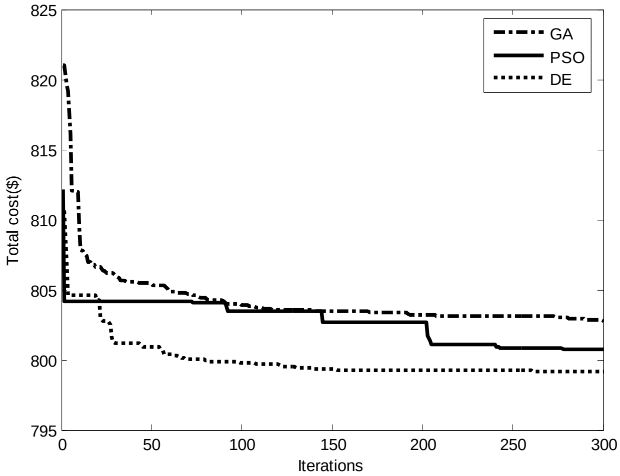

Fig.4: Convergence nature of GA, PSO and DE in IEEE 30-bus system

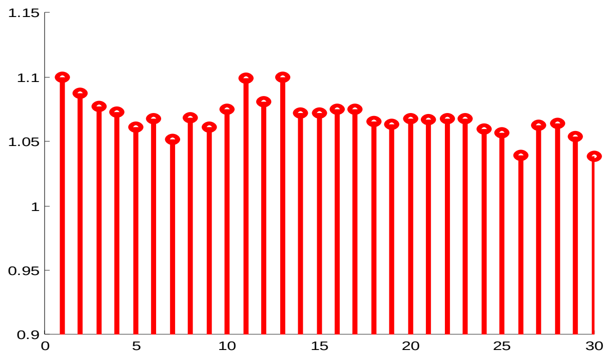

Fig. 5: System voltage profile of IEEE 30-bus system

The obtained results for the IEEE 30-bus system using the DE are given in Table II and the results are compared with those from PSO [16], GA [17] and ACO [19]. From the compared results in TABLE.II, It shows that the DE has succeeded in finding a global optimal solution. As visualized from the Fig.4 and Table III, it gives that the proposed DE method of optimization is more efficient when compared with other optimization methods. The optimum active power is in their secure values and is far from the min and max limits. It is also clear from the optimum solution that the DE easily prevent the violation of all the active constraints. The security constraints are also checked for voltage magnitudes in Fig.5. The voltage magnitudes are between their minimum and maximum values. No load bus was at the lower limit of the voltage magnitudes.

TABLE II.

COMPARISON OF RESULTS OF IEEE-30 BUS SYSTEM

Variable	Optimization Methods			
	PSO	GA	ACO	**DE**
P_1	176.96	179.367	177.863	177.1567
P_2	48.98	44.24	43.8366	48.6905
P_5	21.30	24.61	20.8930	21.3013
P_8	21.19	19.90	23.1231	20.9714
P_{11}	11.97	10.71	14.0255	11.9314
P_{13}	12.00	14.09	13.1199	12.0078
Q_1	-	-3.156	-	-11.3708
Q_2	-	42.543	-	32.6600
Q_5	-	26.292	-	30.9043
Q_8	-	22.768	-	34.1242
Q_{11}	-	29.923	-	18.0076
Q_{13}	-	32.346	-	9.1585
Q_{c10}	3.35	-	-	4.9759
Q_{c12}	2.20	-	-	4.9773
Q_{c15}	1.98	-	-	4.8419
Q_{c17}	3.15	-	-	4.2934
Q_{c20}	4.54	-	-	3.8339
Q_{c21}	3.81	-	-	4.9725
Q_{c23}	3.98	-	-	3.2182
Q_{c24}	5.00	-	-	4.9978
Q_{c29}	2.51	-	-	3.0210
n_{11}	1.0702	-	-	1.0657
n_{12}	0.9557	-	-	0.9211
n_{15}	0.9724	-	-	1.0012
n_{36}	0.9728	-	-	0.9728
V_1	1.0855	-	-	1.100
P_{Loss}	-	9.5177	9.4616	8.66
Cost ($/h)	**800.41**	**803.699**	**803.123**	**799.194**
Time (s)	**-**	**315**	**20**	**14.213**

B. Case of Economic Load Dispatch problem

1. *Case of thirteen-unit system*

Consider a thirteen generators case. The cost coefficients of these generators are given in [7]. The demanded load PD of this problem is 1800MW.

TABLE III.

COMPARISON OF RESULTS OF 13-UNIT SYSTEM CONSIDERING VALVE-POINT EFFECTS

Method	CPU time (sec.)	Mean cost ($/h)	Maximum cost ($/h)	Minimum cost ($/h)
CEP	293.41	18190.32	18404.04	18048.21
IFEP	156.81	18127.06	18267.42	17994.07
FEP	166.43	18200.79	18453.82	18018.00
MFEP	315.98	18192.00	18416.89	18028.09
APPSO	–	18014.61	18291.92	17978.89
DPSO	–	18084.99	18310.43	17976.31
EP-SQP	–	18106.93	–	17991.03
PSO-SQP	–	18029.99	–	17969.93
DE	**4.45**	**17968.97**	**17969.02**	**17968.94**

TABLE IV.

OPTIMAL DISPATCH AND THE CORRESPONDING COST IN 13-UNIT SYSTEM

Unit	$P_{i,min}$	$P_{i,max}$	Generation (MW)	Cost ($)
1	0	680	538.5587405	4993.5385438

2	0	360	150.4425834	1547.3385496
3	0	360	224.3995664	2152.8361465
4	60	180	109.8665500	1129.4760320
5	60	180	109.8665500	1129.4760320
6	60	180	109.8665502	1129.4760359
7	60	180	109.8665516	1129.4760597
8	60	180	109.8665500	1129.4760321
9	60	180	109.8665500	1129.4760321
10	40	120	77.3999125	808.6529682
11	40	120	40.0000017	474.5440299
12	55	120	55.0000000	607.5910000
13	55	120	55.0000000	607.5910000
Total Generation & Cost DE			**1800.0000**	**17968.95667**

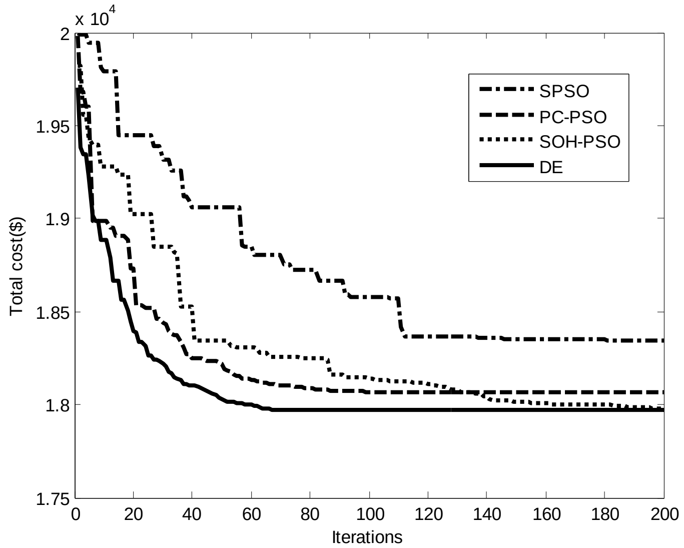

Fig. 6: Convergence nature of SPSO, PC_PSO, SOH_PSO and DE in tested case of 13-unit system considering valve-point effects

TABLE.III shows the minimum, mean, maximum cost achieved by the DE algorithm in 100 runs. Obviously, the minimum costs acquired by the proposed methods are all lower than that obtained by CEP [4], FEP [4], IFEP [4], MFEP [4], APPSO [7], DPSO [7], EP-SQP [21], PSO-SQP [21]. The maximum costs of DE are lower than the minimum costs of other method. The standard deviation of proposed methods is also lower than other method. These results show that the proposed methods are feasible and indeed capable of acquiring better solution. The optimal dispatches of the generators are listed in TABLE IV. Also note that all outputs of generator are within its permissible limits.

2. *Case of forty-unit system*

To verify the feasibility of the proposed DE method, the forty-unit system [7] were tested. The input data and the cost coefficients for 40-generating units are given in [7]. The total demanded load P_D of this problem is 10500 MW. The results obtained from the DE are compared with those as in TABLE.V.

TABLE V.

COMPARISON OF RESULTS OF 40-UNIT SYSTEM CONSIDERING VALVE-POINT EFFECTS

Method	CPU time (sec.)	Mean cost ($/h)	Maximum cost ($/h)	Minimum cost ($/h)
CEP	1955.20	124793.48	126902.89	123488.29
IFEP	1165.70	123382.00	125740.63	122624.35
APPSO	-	123985.15	126259.11	122044.63
DPSO	-	123647.81	125295.98	122159.99
IPSO	-	121699.30	122168.11	121495.70
EPSO	-	NA	NA	124577.27
MPSO	-	NA	NA	122252.26
ESO	-	122524.07	123143.07	122122.16
PSO-LRS	-	122558.46	123461.68	122035.79
NPSO	-	122221.37	122995.09	122221.37
NPSO-LRS	-	122209.32	122981.60	121664.43
SOH_PSO	-	121853.57	122446.30	121501.14

DE	**7.47**	**121467.99**	**121773.89**	**121416.42**

TABLE.V shows the best solution time, maximum cost, mean cost, and minimum cost achieved by the DE algorithms in 100 runs. The DE required the least solution time. The minimum cost achieved by DE was the best. The maximum costs of DE are lower than the minimum costs that obtained by CEP [4], IFEP [4], IPSO [6], APPSO [7], DPSO [7], EPSO [5], MPSO [23], ESO [22], PSO-LRS [24], NPSO [24], NPSO-LRS [24], SPSO [9], PC_PSO [9], SOH_PSO [9]. The standard deviation of proposed methods is also lower than other method.

The generation outputs and the corresponding costs of the best solution are provided in TABLE.VI. The DE has provided better solutions compared with other methods. We have also observed that the solutions obtained by DE always satisfy the equality and inequality constraints.

TABLE VI.

PTIMAL DISPATCH AND THE CORRESPONDING COST IN 40-UNIT SYSTEM

Unit	$P_{i,min}$	$P_{i,max}$	Generation (MW)	Cost ($)
1	36	114	110.7998	925.0964
2	36	114	110.7998	925.0963
3	60	120	97.3999	1190.5485
4	80	190	179.7330	2143.5503
5	47	97	87.7999	706.5001
6	68	140	142.7998	1604.7428
7	110	300	259.5996	2612.8845
8	135	300	284.5996	2779.8366
9	135	300	284.5996	2798.2302
10	130	300	130.0000	2502.0650
11	94	375	93.9998	1893.3043
12	94	375	93.9944	1908.1362
13	125	500	304.5195	5110.2971
14	125	500	304.5195	5149.6989
15	125	500	394.2793	6436.5862
16	125	500	394.2793	6436.5862
17	220	500	489.2793	5296.7107
18	220	500	489.2793	5288.7651
19	242	550	511.2793	5540.9292
20	242	550	505.0000	5627.7512
21	254	550	523.2793	5071.2897
22	254	550	523.2793	5071.2896
23	254	550	523.2793	5057.2231
24	254	550	523.2793	5057.2230
25	254	550	523.2793	5275.0885
26	254	550	523.2793	5275.0885
27	10	150	11.0000	1164.0309
28	10	150	10.0000	1140.5240
29	10	150	10.0000	1140.5240
30	47	97	95.0000	823.1977
31	60	190	197.9999	1658.9037
32	60	190	197.9999	1658.9037
33	60	190	197.9999	1658.9037
34	90	200	180.0000	1841.2934
35	90	200	164.7998	1539.8703
36	90	200	205.6835	2091.6657
37	25	110	109.9995	1220.1637
38	25	110	108.0000	1207.1644
39	25	110	100.0000	1126.5035
40	242	550	503.2792	5534.6712
Total Generation & Cost DE			**10500.00**	**121417.31**
SPSO			10500.000	122049.6600
PC-PSO			10500.000	121767.8900
SOH-PSO			10500.000	121501.1400

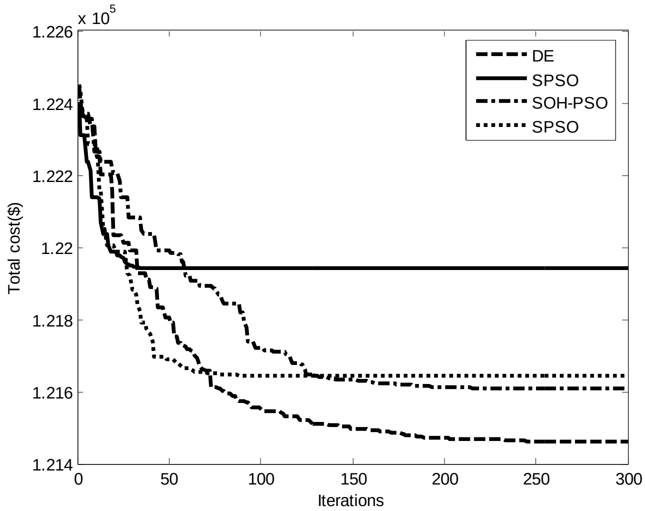

Fig.7. Convergence nature of SPSO, PC_PSO, SOH_PSO and DE in tested case of 40-unit system considering valve-point effects

VI. CONCLUSION

In this paper, the differential evolution method has been presented to solve the OPF and non-smooth ELD problems. From the obtained results of OPF and ELD are tested to IEEE 30-bus, 13-unit and 40-unit networks, we can present the some following conclusions + The differential evolution method has increased the convergence speed of our algorithm. It also means that the iterative numbers are decreased as in Fig.4.

The proposed algorithms have the capability to obtain better solutions than various other methods in terms of total costs and computational times. Therefore, this algorithm is effective and efficient solving the OPF and ELD problems of large-scale power systems with valve point effects and FACTS devices.With the advantages of DE, we can use it for calculating some problems in power systems such as the OPF of AC/DC power systems, the OPF of interconnected systems, the FACTS location optimization, etc. All will be done in next works.

REFERENCES

[1]. R. Storn, K. Price, Differential Evolution, "A Simple and Efficient Adaptive Scheme for Global Optimization over Continuous Spaces," Technical Report TR-95-012, ICSI, 1995.

[2]. S. Das, A. Abraham, A. Konar, "Particle Swarm Optimization and Differential Evolution Algorithms: Technical Analysis, Applications and Hybridization Perspectives," Available at www.softcomputing.net/aciis.pdf.

[3]. Nidul Sinha, R. Chakrabarti and P. K. Chattopadhyay, "Evolutionary Programming Techniques for Economic Load Dispatch," *IEEE Transactions on Evolutionary Computation*, Vol. 7 No.1, pp. 83-94, 2003.

[4]. Dr. K. Thanushkodi, S. Muthu Vijaya Pandian, R.S.Dhivy Apragash, M. Jothikumar, S.sriramnivas and K.Vindoh, "An Efficient Particle Swarm Optimization for Economic Dispatch Problems With Non-smooth cost functions," *WSEAS Transactions on Power Systems*, Issue 4, Volume 3, pp. 257-266, April 2008.

[5]. Jong-Bae Park, *Member, IEEE*, Yun-Won Jeong, Woo-Nam Lee, and Joong-Rin Shin, "An Improved Particle Swarm Optimization for Economic Dispatch Problems with Non-Smooth Cost Functions," *IEEE Power Engineering Society General Meeting*, 2006.

[6]. C. H. Chen, and S. N. Yeh, "Particle Swarm Optimization for Economic Power Dispatch with Valve-Point Effects," *2006 IEEE PES Transmission and Distribution Conference and Exposition Latin America*, Venezuela, 15-18 Aug. 2006.

[7]. K. S. Swarup, "Swarm intelligence approach to the solution of optimal power flow," *Indian Institute of Science*, pp. 439–455, Oct. 2006.

[8]. K. T. Chaturvedi, Manjaree Pandit Member IEEE, and Laxmi Srivastava Member IEEE, "Self-Organizing Hierarchical Particle Swarm Optimization for Nonconvex Economic Dispatch," *IEEE Transactions on Power Systems*, Vol. 23, No. 3, pp. 1079-1087, August 2008.

[9]. Hirotaka Yoshida, Kenichi Kawata, Yoshikazu Fukuyama, Yosuke Nakanishi, "A Particle Swarm Optimization for Reactive Power and Voltage control considering Voltage security assessment," *IEEE Trans. on Power Systems*, Vol.15, No.4, pp.1232-1239, November 2001.

[10]. *G.* Krost, G. K. Venayagamoorthy, L. Grant, "Swarm Intelligence and Evolutionary Approaches for Reactive Power and Voltage Control," *2008 IEEE Swarm Intelligence Symposium*, September 21-23, 2008.

[11]. N. Mo, Z.Y. Zou, K.W. Chan and T.Y.G. Pong, "Transient stability constrained optimal power flow using particle swarm optimisation," *IEEE* Generation, Transmission & Distribution, Volume 1, Issue 3, pp. 476–483, May 2007.

[12]. Bo Zhao, Quanyuan Jiang, Chuangxin Guo, Yijia Cao, "A novel particle swarm optimization approach for optimal reactive power dispatch," *15th PSCC, Liege,* Session 21, 22-26 August 2005.

[13]. Adel Ali Abou El-Ela, Ragab Abdel-Aziz El-Sehiemy "Optimized Generation Costs Using Modified Particle Swarm Optimization Version," *Wseas Transactions on Power Systems*, pp. 225-232, Oct. 20, 2007.

[14]. S. Sutha, and N. Kamaraj, "Optimal Location of Multi Type Facts Devices for Multiple Contingencies Using Particle Swarm Optimization," *International Journal of Electrical Systems Science and Engineering*, Volume 1, Number 1, pp. 16-22.

[15]. M.A. Abido, "Optimal Power Flow Using Particle Swarm Optimization," *Elsevier Science, Electrical Power and Energy Systems*, 24 (2002), pp. 563-571, 2002.

[16]. Tarek Bouktir, Linda Slimani, M. Belkacemi, "A Genetic Algorithm for Solving the Optimal Power Flow Problem," *Leonardo Journal of Sciences*, Issue 4, pp. 44-58, January-June 2004.

[17]. Musrrat Ali, Millie Pant, and V. P. Singh, "An Improved Differential Evolution Algorithm for Real Parameter Optimization Problems," International Journal of Recent Trends in Engineering, Vol. 1, No. 5, May 2009.

[18]. Boumediène Allaoua, Abdellah Laoufi, "Optimal Power Flow Solution Using Ant Manners for Electrical Network," *Advances in Electrical and Computer Engineering*, Volume 9, Number 1, pp. 34-40, 2009.

[19]. Hadi Saadat, Milwaukee School of engineering, "Power System analysis," second edition, *Mc GrawHill*, 2002.

[20]. T.A.A. Victoire, A.E. Jeyakumar, Hybrid PSO-SQP for economic dispatch with valve-point effect, Electric Power Syst. Res. 71 (1), pp. 51–59, 2004.