International Journal of Applied Engineering Research
ISSN 0973-4562 Volume 10, Number 10 (2015) pp. 26209-26220

http://www.ripublication.com

Weighted Differential Evolution Approach Based Optimization For Power Flow Problem

M. Letaief, H. Yahia, N. Liouane
Engineering School of Monastir-Tunisia

Abstract

This paper addresses an application of improved DE Algorithm to solve the optimal power flow (OPF) problem. The proposed approach contributes to speeding up the convergence by better choosing the differentiation direction and the search region for the constrained global optimization problem. As basis for the examination a real practical Engineering problem is employed that consists of optimizing the power flow. The objective is to minimize the total fuel cost of generation while taking power system losses, limits on generator real and reactive power outputs and bus voltages constraints into consideration. Simulations were carried out on IEEE-14 and IEEE-30 bus system. The Weighted DE approach results are compared with the results reported in the literature. The results show the effectiveness and robustness of the proposed approach.

Keywords: Fuel cost, Evolutionary algorithms, Optimal power flow, Weighted differential evolution

Nomenclature

P_G	Generator active power output
Q_G	generator reactive power output
P_D	active power load demand
Q_D	reactive power load demand
P_l	active power loss in transmission lines
Q_l	reactive power loss in transmission lines
V_G	voltage magnitude at generation bus
V_L	voltage magnitude at load bus
V	voltage magnitude at bus
δ	voltage angle
G_C	conductance
B_S	susceptance
Sl	total transmission line loading

Q_C	output shunt *VAR* compensators
T	tap regulating transformers
NT	number of tap regulating transformers
NC	number of shunt *VAR* compensators
NPV	number of voltage controlled buses
NPQ	number of *PQ* buses
NTL	number of transmission lines
F_C	total fuel cost function
a_i, b_i, c_i	cost coefficients of i^{th} generation
λ	penalty factor
D	decision parameters
NP	population size
CR	crossover rate
F	mutation factor
G	number of generations

Introduction

The Optimal Power Flow (OPF) problem has been and continues to receive a lot of interest in electric network system planning, operation and control over the years [1-5]. The OPF problem optimizes single and/or multi objective functions while satisfying power flow constraints as well as the constraints imposed on control and state variables. The solution of OPF problem must satisfy the network security constraints [6].

Conventional mathematical programming techniques, such as nonlinear programming, successive linear programming, interior point methods, quadratic programming, and Newton-based techniques have been applied to solve the OPF problem [7-12]. Although these methods have demonstrated efficacy in handling optimization problems, they may fail to find the global optimum in many difficult problems and frequently get trapped in local optimum. Solutions qualities of classical algorithms are quite sensitive to the starting points and convexity. Moreover, the main difficulties of the OPF are due to non-convex and discontinuous cost characteristics, mixed integer variables, a large number of constraints. To overcome these problems, global optimization based on evolutionary algorithms becomes an attractive tool for solving engineering optimization problems such as OPF. Evolutionary algorithms have proven to be effective in solving nonlinear, non-differentiable and multi-modal optimization problems in the power systems area. These methods search from a population of points instead of a single point as in conventional search and optimization techniques [13]. Moreover they do not require a suitable initial guess. Differential Evolution (DE) method is one among them. DE is a powerful population-based evolutionary algorithm for global optimization, which was originally proposed by Storn and Price [14]. In this paper, an enhanced DE based method has been proposed for solving the complex OPF problem [15]. The remainder of this paper is organized as follows. The mathematical problem formulation of OPF is described in more detail in Sections II, followed by the DE based approach in Section III and IV. Sections V and

VI depict the implementation method and simulation results respectively. Finally, the conclusions drawn are given in Section VII.

Mathematical Problem Formulation of OPF

The optimal power flow problem is a nonlinear optimization problem. The essential goal of the OPF is to minimize the settings of control variables in terms of a certain objective function subjected to various equality and inequality constraints. The optimal power flow problem requires the solution of nonlinear equations, describing optimal and secure operation of power systems. The general optimal power flow problem can be mathematically expressed as a constrained optimization problem as follows:

Minimize $F(x,u)$

(1)

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

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

where

F is the objective function to be minimized,

x is the vector of dependent variables including, generator active power output at slack bus P_{G1}, load bus voltage V_L, generator reactive power output Q_G, and transmission line loading S_l.

In this manner x can be expressed as:

$$x^T = \left[P_{G1}, V_{L1} \ldots V_{LNPQ}, Q_{G1} \ldots Q_{GNPV}, S_{l1} \ldots S_{lNTL}\right] \quad (4)$$

In a similar way, the vector of control variables u can be expressed as:

$$u^T = \left[P_{G2} \ldots P_{GNG}, V_{G1} \ldots V_{GNG}, Q_{C1} \ldots Q_{CNC}, T_1 \ldots T_{NT}\right]$$

(5)

In this paper, minimization of fuel cost is considered as an objective function to examine the performance of the proposed approach. The total fuel cost function for a number of thermal generating units can be expressed by a quadratic function as:

$$F_c = \sum_{i=1}^{NG} \left(a_i P_{Gi}^2 + b_i P_{Gi} + C_i\right) \quad \$/h \quad (6)$$

g is the equality constraints of OPF problem which represent power balance constraints. The total power generation must cover the total load demand and the power loss in transmission lines as:

$$\sum_{i=1}^{NG} P_{Gi} - P_D - P_l = 0$$

(7)

$$\sum_{i=1}^{NG} Q_{Gi} - Q_D - Q_l = 0 \tag{8}$$

using load flow equations, g can be rewritten as:

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j \left[G_{Cij} \cos(\delta_i - \delta_j) + B_{Sij} \sin(\delta_i - \delta_j) \right] = 0 \tag{9}$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j \left[G_{Cij} \sin(\delta_i - \delta_j) + B_{Sij} \cos(\delta_i - \delta_j) \right] = 0 \tag{10}$$

h is inequality constraints that includes:

1. Generator capacity limits: for stable operation, voltage magnitude, active and reactive power outputs are restricted by their upper and lower limits as:

$$\begin{aligned} &V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max}, \mathrm{i} = 1, 2, \ldots, \mathrm{NPV} \\ &P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}, \mathrm{i} = 1, 2, \ldots, \mathrm{NPV} \\ &Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max}, \mathrm{i} = 1, 2, \ldots, \mathrm{NPV} \end{aligned} \tag{11}$$

2. Transformer constraints: transformer tap settings are restricted by the minimum and maximum limits as:

$$T_i^{\min} \le T_i \le T_i^{\max} \ \mathrm{i} = 1, 2, \ldots, \mathrm{NT} \tag{12}$$

3. Shunt VAR compensator constraints: shunt VAR compensators are restricted by their lower and upper limits as:

$$Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max} \ \mathrm{i} = 1, 2, \ldots, \mathrm{NC} \tag{13}$$

4. Security constraints: these contain the voltage magnitude constraints at load buses and transmission line loading limits. these constraints can be written as:

$$V_{Li}^{\min} \le V_{Li} \le V_{Li}^{\max} \ \mathrm{i} = 1, 2, \ldots, \mathrm{NPQ} \tag{14}$$

$$\sqrt{P_{li}^2 + Q_{li}^2} \le S_{li}^{\max} \ \mathrm{i} = 1, 2, \ldots, \mathrm{NTL} \tag{15}$$

The inequality constraints of dependent variables contain load bus voltage magnitude, real power generation output at slack bus, reactive power generation output and line loading. A common way for handling the inequality constraints is the use of a penalty function added to the objective function. Here, a penalty factor multiplied with the square of the disregard value of dependent variable is added to the objective function and any unfeasible solution obtained is declined. Mathematically, penalty function can be expressed as [11]:

$$J\,\text{mod} = \sum_{i=1}^{NPV} F_i(P_{Gi}) + \lambda_P (P_{G1} - P_{G1}^{\lim})^2 + \lambda_V \sum_{i=1}^{NPO} (V_{Li} - V_{Li}^{\lim})^2 + \lambda_Q \sum_{i=1}^{NPV} (Q_{Gi} - Q_{Gi}^{\lim})^2 + \lambda_S \sum_{i=1}^{NTL} (S_{li} - S_{li}^{\lim})^2 \tag{16}$$

$x^{\lim}$ is the limit value of the dependant variable x and is given as:

$$x^{\lim} = \begin{cases} x^{\max}, & if\ x \rangle x^{\max} \\ x^{\min}, & if\ x \langle x^{\min} \end{cases} \tag{17}$$

DE Optimization Process

The Evolutionary algorithms (EAs) differ from the traditional optimization techniques in that EAs make use of a population of solutions, not a single point solution. Differential evolution (DE) initially proposed in [15] is a popular evolutionary algorithm (EA) gaining significant interests during recent years due to its simplicity, efficiency and robustness. DE shares a number of similar concepts to other EAs. The evident distinction is the mutation step used to generate a new candidate solution. DE is capable of handling non-differentiable, non-linear, non-convex, and multi-modal objective functions.

Differential Evolution Algorithm (DEA) combines simple arithmetical operators with the classical operators of recombination, mutation and selection to evolve from a randomly generated starting population to a final solution. At every generation G during the optimization process, DE algorithm maintains a population P^G of NP vectors of candidate solutions to the problem at hand.

$$P^G = \left\lfloor X_1^G, ..., X_i^G, ..., X_{NP}^G \right\rfloor \tag{18}$$

Each candidate solution X_i is a D-dimensional vector, containing as many integer-valued parameters as the problem decision parameters D.

$$X_i^G = \left\lfloor x_{1,i}^G, ..., x_{j,i}^G, ..., x_{D,i}^G \right\rfloor i = 1, ..., NP,\ j = 1, ..., D \tag{19}$$

There are several DE strategies to be employed for optimization. Through these variants of DE, the strategy used for optimizing the load flow problem is $DE/best/1/bin$. It operates like the classical DE, except that the base vector is selected from the best vector among the population and the other 2 individuals are selected randomly. $DE/best/1/bin$ starts by defining and evaluating the initial population through calculating the fitness value for each individual. After that, until the termination condition is not reached, the necessary individuals are picked, and a new one is produced according to the selected DE scheme. This new individual is evaluated and compared with the old one. Only the one with the best fitness value will be chosen and pass for population of the next generation.

In DE, the search mechanism is based on mutation, which, associated with recombination and selection, directs the search towards potential areas of optimal solution [16]. It is possible to efficiently converge towards the optimal solution by calculating a differential which creates a vector that will point in the general direction of the optimal search region. Many modified strategies have been proposed for the last years [17]. They aim at speeding up the convergence by better choosing the differentiation direction and the search region. Here, we propose a new modified version of basic DE called Weighted Differential Evolution. This strategy consists in using the best individual for base vector and combining it with 2 weighted other randomly chosen individuals for differential vectors. Our approach can be seen as a parallel exploration of the regions which are the most likely to comprise the solution to the optimization problem. In this way, the global minimum is reached in less iteration.

Improved De Algorithm

A major drawback of the conventional DE is that the convergence slows down as the region of global optimum is being approached. This problem is addressed here by making a modification to the basic DE algorithm to make it more efficient. For the preliminary DE based weighted, *DE/best/1/bi*n is the candidate learning strategy. The following is an outline of the proposed Weighted Differential Evolution (W-DE) algorithm.

Step 1: Parameter setup, The user chooses the parameters of population size, the boundary constraints of optimization variables, the mutation factor, the crossover rate, and the stopping criterion of maximum number of generations ($G_{\max}$), like the conventional DE.

Step 2: Initialization, set generation G = 0. Initialize a population of *NP* individuals with random values generated according to a uniform probability distribution in the *D* dimensional problem space. These initial values are chosen randomly within user defined bounds.

$$x_{j,i}^{G=0} = x_j^{\min} + rand_j[0,1]\left(x_j^{\max} - x_j^{\min}\right) \tag{20}$$

where $i = 1,..., NP$, and $j = 1,..., D$. $x_{j,i}^{G=0}$ is the initial value (G=0) of the j^{th} parameter of the i^{th} individual vector. $x_j^{\min}$ and $x_j^{\max}$ are the lower and upper bounds of the j^{th} decision parameter, respectively. Corresponding fitness value of each vector is evaluated and stored.

Step 3: Mutation operation, the crucial idea of DE is a novel mutation paradigm, which is executed by adding a weighted difference vector between two selected individuals to the third individual. It was found that this kind of mutation has desired self-adaptation feature based on current population diversity [17]. The mutation strategy of classical DE perturbs the best vector of the current population by single difference of two other randomly selected vectors (X_{r1} and X_{r2}), while W-DE generates new vectors by adding the weighted difference between two vectors to a best vector. For each target vector a mutant vector (V_i^G) is produced using the following formula

$$V_i^G = X_{best}^G + F\left(W_{r1}X_{r1}^G - W_{r2}X_{r2}^G\right) \tag{21}$$

where X_{best}^G is the best performing vector of the current generation. Vector indices $r1$ and $r2$ are randomly chosen, which $r1$ and $r2 \in \{1,...,NP\}$ and $r1 \neq r2 \neq i$. F is typically chosen from within the range $[0,1]$.

The couple (W_{r1}, W_{r2}) represents the calculated weight to be used with (X_{r1}^{G}, X_{r2}^{G}) vectors in goal of the fitness-proportionate selection. We assume here that C_1 and C_2 are the X_{r1} and X_{r2} performances respectively. Hence the weight of X_{r1} is defined in (22) and the weight of X_{r2} in (23).

$$W_{r1} = \frac{C_1}{C_1 + C_2} \tag{22}$$

$$W_{r2} = \frac{C_2}{C_1 + C_2} \tag{23}$$

Step 4: Crossover operation, to increase the potential diversity of the population a crossover operator is used. At the generation *G*, the crossover operation creates trial vectors (U_i) by mixing the parameters of the mutant vectors (V_i) with the target vectors (X_i) according to a selected probability distribution.

$$U_i^G = \begin{cases} V_i^G, & \text{if } rand_j(0,1) \le CR \quad or\ j = Rnbr(i) \\ X_{best}^G, & otherwise \end{cases} \tag{24}$$

The crossover constant CR is a user-defined value, which is usually selected from within the range [0,1]. $rand_j$ is a the trial parameter with randomly chosen index $\in [0,1]$. $Rnbr(i)$ is the trial parameter with randomly chosen index $\in \{1,...,D\}$, which ensures that the trial vector gets at least one parameter from the mutant vector.

Step 5: Selection operation, the selection operator chooses the vectors which are going to compose the population in the next generation. This operator compares the fitness of the trial vector and the corresponding target vector and selects the one that provides the best solution. The fitter of the two vectors is then allowed to advance into the next generation. The selection process may be outlined as:

$$X_i^{G+1} = \begin{cases} U_i^G & if\ f\left(U_i^G\right) \le f\left(X_i^G\right) \\ X_{best}^G & otherwise \end{cases} \tag{25}$$

where f is the function to be minimized.

The selection process is repeated for each pair of target/trail vector until the population for the next generation is complete.

Implementation of Proposed Approach

The main steps of the proposed method for optimal power flow are described by the flowchart given in Fig. 1. Constraints are managed in the first conditional block of the flowchart.

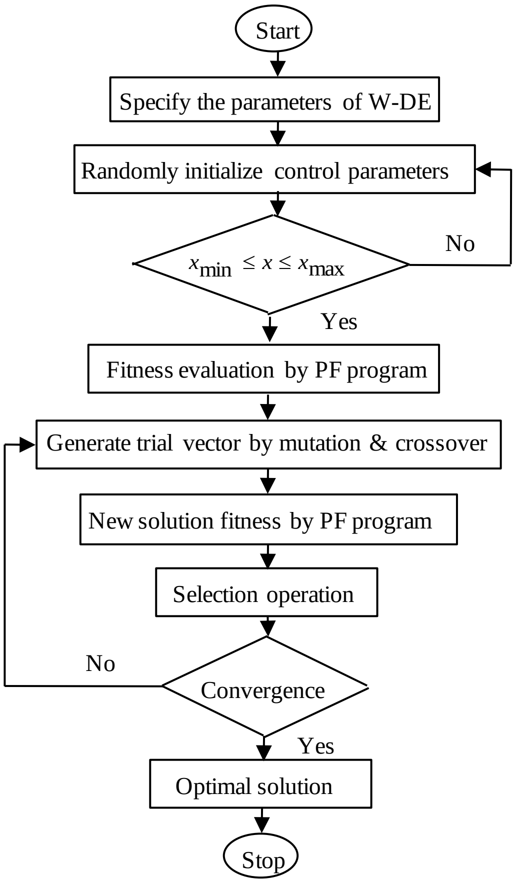

Figure 1: Flowchart of the W-DE/best/1/bin strategy

Simulation Results

In order to illustrate the efficiency and robustness of the proposed W-DE based OPF algorithm, two case studies were performed. In the first case study, we consider the IEEE 14-bus test system, with a quadratic model of generator cost curves. In the second case study, we consider the IEEE 30-bus system, also with a quadratic model of generator cost curves. In each case study, two sets of 15 successful test runs for solving the OPF problem were performed; the first set (DE–OPF) is based on the Basic differential evolution algorithm and the second one is based on the enhanced differential evolution algorithm (WDE-OPF). Each optimization approach (DE–OPF and WDE–OPF) was implemented under the MATLAB computational environment and run on PC with Pentium core duo processor operating @ 2 GHz with 2 GB RAM. The Power flow is run using the program developed in laboratory based Newton-Raphson method.

Case 1. IEEE 14-bus system

In the network test of IEEE 14-Bus system, there are 14 buses, out of which 5 are generator buses. Bus 1 is the slack bus, 2, 3, 6 and 8 are taken as PV generator buses and the rest are PQ load buses. The network has 20 branches, 17 of which are transmission lines and 3 are tap- changing transformers. It is assumed that shunt compensation capacitor is available at bus 9 for voltage control. Totally, there are 14 control variables, which consist of 5 unit active power generators, 5 generator bus voltage magnitudes, 3 tap changing transformers, and 1 shunt VAR compensator. The system data and initial operating conditions of the system are given in [11].

The W-DE parameters for handling the inequality constraints (16) used for the optimal power flow solution are chosen as:

$F = 0.5$, $CR = 0.5$, $NP = 50$, and $G^{\max} = 250$.

Fig. 2 shows the convergence characteristics of total fuel cost minimization obtained by DE, GA and W-DE. The convergence of W-DE is faster while obtaining a better solution in lesser computational time. The minimum costs achieved after successful run of W-DE, DE, and GA algorithms are 839.182, 839.735, and 839.863 respectively.

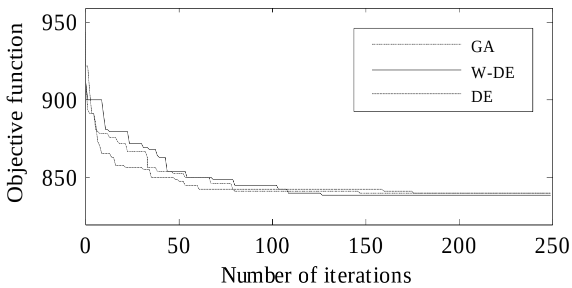

Figure 2: Cost convergence versus generations

Table 1 shows the optimal control variables obtained for the optimal power flow of the IEEE-14 bus system and table 2 shows a comparison between the results of fuel cost obtained from the proposed approach and those reported in the literature. The W-DE approach is useful for obtaining high-quality solution in a very less time and outperforms the other techniques.

Table 1: Optimal Control Variables

Power gen. (MW)	P_{G1}	P_{G2}	P_{G3}	P_{G6}	P_{G8}
	112.175	70.123	28.131	26.420	26.873
Gen. voltages (pu)	V_{G1}	V_{G2}	V_{G3}	V_{G6}	V_{G8}
	1.037	1.029	1.048	1.044	1.036
Trans. tap & shunt VAR	$T_{4\text{-}7}$	$T_{4\text{-}9}$	$T_{5\text{-}6}$		Q_{C9}
	1.041	0.951	0.956		3.847

Table 2: Comparison Of Fuel Cost

Method	Cost ($/h)
EP [18]	839.2810
PSO [18]	839.2236
Proposed W-DE	839.182

Case 2. IEEE 30-bus system

The test System-IEEE 30 bus system [9] consists of 30 buses, out of which 6 are generator buses. Bus 1 is the slack bus, 2, 5, 8, 11 and 13 are taken as PV buses and the remaining 24 are PQ buses. The network has 41 branches, 4 transformers and 2 capacitor banks. The four branches 6–9, 9–10, 4–12, 27–28 are under load tap changing transformers. In DE solution for OPF, the total control variables are 16: six unit active power outputs, six generator bus voltage magnitudes, and four transformers tap settings.

To verify the effectiveness and performance of the proposed method for solving OPF problem using W-DE algorithm, standard IEEE 30-bus system is considered for simulation study. The network, load, generator and cost factors data were taken from [9].

Fig. 3 shows the convergence characteristics of total fuel cost minimization obtained by DE, GA, and W-DE. Solutions achieved by W-DE, DE, and GA approaches are 799.8739, 801.3598, and 801.9724 respectively. W-DE achieves the least total fuel cost.

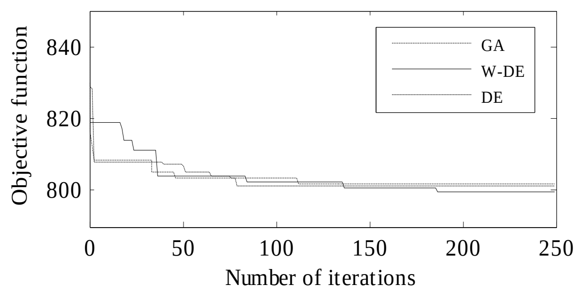

Figure 3: Cost convergence versus generations

Table 3 shows a comparison between the results of fuel cost obtained from the proposed approach and those reported in the literature. The comparison is carried out with the same control variable limits, initial conditions, and other system data. It is clear from the table that the proposed W-DE approach outperforms the EP and the PSO techniques.

Table 3: Comparison of Fuel Cost

Method	*Cost ($/h)*
EP [18]	800.966
PSO [18]	801.0204
Proposed W-DE approach	799.8739

Conclusion

This paper has presented an application of the improved differential evolution technique dedicated to minimizing the total fuel cost on the standard IEEE 14-bus and IEEE 30-bus systems. The W-DE approach was successfully applied to find the optimal settings of the decision variables. The simulation results demonstrate the effectiveness and robustness of the proposed algorithm to solve OPF problem. Moreover, the results of the proposed W-DE algorithm have been compared to those reported in the literature. The comparison confirms the effectiveness and the superiority of the enhanced DE algorithm over the other classical and heuristic techniques in terms of solution quality.

Acknowledgements

Authors would like to thank Professor R. Dhifaoui for all of his interest and helpful discussions on this work.

References

[1] Lin, W., Cheng, F., , and Tsay, M., 2001, “Non-convex Economic Dispatch By Integrated Artificial Intelligence,” IEEE Trans. On Power Systems, 16 (2), pp. 307-311.

[2] Nanda, J., and Badr, R., 2002, “Application of Genetic Algorithm to Economic Load Dispatch with Line Flow Constraints,” Electric power and energy systems, 24 (9), pp. 723-729.

[3] Varadarajan, M., and Swarup, K. S., 2008, “Solving Multi-Objective Optimal Power Flow using Differential Evolution,” lET Gener. Transm. Distrib., 2 (5), pp. Vo1.2, (Issue 5): 720-730.

[4] Balamurugan, R., and Subramanian, S., 2007; “Self Adaptive Differential Evolution Based Power Economic Dispatch of Generators with Valve Point Effects and Multiple Fuel Options,” International Journal Of Computer Science And Engineering, 1 (1); pp. 10-17, 2007.

[5] Bhattacharya, A., and Chattopadhyay, C., 2011; “Application of biogeography-based optimization to solve different optimal power flow problems,” IET Gener. Transm. Distrib., 5 (1), pp. 70-80.

[6] Zhao, B., Guo, C. X., and YJ. Cao, Y. J., 2005, “multiagent-based particle swarm optimization approach for optimal reactive power dispatch,” IEEE Trans. Power Syst., 20 (1), pp. 1070-1078.

[7] Mendoza, J. E., et al., 2007, “Multi-objective location of automatic voltage regulators in a radial distribution network using a micro genetic algorithm,” IEEE Trans. Power Syst., 2 (1), pp. 404–412.

[8] Chang, C. F., et al., 2007, “Robust searching hybrid differential evolution method for optimal reactive power planning in large-scale distribution systems,” Electr. Power Syst. Res., 77 (6), pp. 430–437.

[9] Vlachogiannis, J. G., and Lee, K. Y., 2006, “A comparative study of particle swarm optimization for optimal steady state performance of power systems,” IEEE Trans. Power Syst., Vol. 21 (Issue 4): 1718–1728, 2006.

[10] Wei, L., Fang, L., Chung, C. Y., and Wong, K. P., A hybrid genetic algorithm-interior point method for optimal reactive power flow,” IEEE Trans. Power Syst., 21, pp. 1163–1169.

[11] Yoshida, H., Fukuyama, Y., Kawata, K., and Takayama, K., 2001, “A particle swarm optimization for reactive power and voltage control considering voltage security assessment,” IEEE Trans. Power Syst. 15, (4), pp. 1232-1239.

[12] Lee, K. Y., Bai, X., and Park, Y. M., 1995, “Optimization method for reactive power planning by using a modified simple genetic algorithm,” IEEE Trans. Power Syst., 10, (4), pp. 1843–1850.

[13] Zhang, M., Luo, W., and Wang, X., 2008, “Differential evolution with dynamic stochastic selection for constrained optimization,” International Journal of Information Science,” pp. 3043–3074.

[14] Storn, R., and Price, K., 1997, “Differential Evolution - A simple and Efficient Heuristic for Global Optimization over Continuous Spaces,” Journal of Global Optimization,” 11, pp. 341-359.

[15] Yahia, H., Liouane, N., and Dhifaoui, R., 2010, “Weighted Differential Evolution Based PWM Optimization for Single Phase Voltage Source Inverter,” International Review of Electrical Engineering (IREE), 5, (5), pp. 1956-1962.

[16] W. L. Price, W. L., 1997, “Global Optimization by Controlled Random Search,” Computer Journal”, 20, pp. 367-370.

[17] Yang, R., and Douglas, I., 1998; “Simple Genetic Algorithm with Local Tuning: Efficient Global Optimizing Technique,” Journal of Optimization Theory and Applications, 98, (2), pp. 449-465.

[18] Reddy, M. L., Reddy, M. R., and Reddy, V. C. V., 2012, “Optimal Power Flow Using Particle Swarm Optimization,” International Journal of Engineering Sciences & Emerging Technologies, 4, (1), pp. 116-124.