J Electr Eng Technol Vol. 8, No. 1: 53-63, 2013
http://dx.doi.org/10.5370/JEET.2013.8.1.053

ISSN(Print) 1975-0102
ISSN(Online) 2093-7423

A Study on Multi-objective Optimal Power Flow under Contingency using Differential Evolution

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Abstract – To guide the decision making of the expert engineer specialized in power system o peration and control; the practical OPF solution should take in consideration the critical situati on due to severe loading conditions and fault in power system. Differential Evolution (DE) is one of the best Evolutionary Algorithms (EA) to solve real valued optimization problems. This paper presents simple Differential Evolution (DE) Optimization algorithm to solving multi obje ctive optimal power flow (OPF) in the power system with shunt FACTS devices considering v oltage deviation, power losses, and power flow branch. The proposed approach is examined an d tested on the standard IEEE-30Bus power system test with different objective functions at cr itical situations. In addition, the non smooth cost function due to the effect of valve point has been considered within the second practical network test (13 generating units). The simulation results are compared with those by the other recent techniques. From the different case studies, it is observed that the results demonstrate the potential of the proposed approach and show cl early its effectiveness to solve practical OPF under contingent operation states.

Keywords: Differential evolution, Multi objective function, Optimal power flow, Valve point effect, FACTS, SVC, Contingency.

1. Introduction

The optimal power flow (OPF) problem is one of the important tools in operation and control of large modern power systems based FACTS technology and Renewable energy. The main objective of a practical OPF strategy is to determine the optimal operating state of a power system by optimizing a particular objective while satisfying certain specified physical and security constraints. In its most general formulation, the optimal power flow (OPF) is a nonlinear, non-convex, large-scale, static optimization problem with both continuous and discrete control variables. It becomes even more complex when more than one objective function is considered with various types of practical generators constraints (prohibited zones, valve point effects and ramp rate limits), this type of problem well known as multi objective OPF problem. Over the last several years many mathematical optimization techniques have been applied to solve the OPF problem such as; linear programming (LP), nonlinear programming (NLP), quadratic programming (QP), and interior point methods [2-5]. All these techniques rely on the initial condition and convexity to find the global optimum; the methods based on these assumptions do not guarantee to find the global optimum solution when considering the practical generators constraints (Prohibited zones, valve point effects and ramp rate limits), authors in [1] provide a valuable introduction and surveys the classical optimization techniques. To overcome the drawbacks of the mathematical methods related to the initial condition and to the form of the objective function, a new category of global optimization techniques is developed, this category based on stochastic and heuristic aspect includes; Genetic algorithm (GA) [6, 7], Tabu search (TS) [8], Simulated annealing (SA) [9], Evolutionary programming (EP) [10], Particle swarm optimization (PSO) [11], Differential evolution (DE) [12], Harmony search (HS) [13], Artificial bee colony (ABC) [14], Biogeography based optimization method (BBO) [15, 16], A modified Artificial bee (MABCA) [17], Shuffled frog leaping algorithm (SFL) [18], and Gravitational search algorithm (GSA) [19]. All these methods applied with success to solving various problems related to power system operation and control. Authors in [20] provide a significant and valuable introduction and surveys the non-deterministic and hybrid optimization methods.

Differential Evolution (DE) is a population-based, direct stochastic search algorithm and one of the most prominent new generation EAs, proposed by Storn and Price [21], for optimization problems over a continuous domain. The main advantages of DE are: simple to program, few control parameters, high convergence characteristics. DE has been applied to several engineering problems in different areas. In power system area, DE has received great attention to solving the multi objective optimal power flow considering the integration of multi FACTS devices in a practical electrical network. This paper presents a differential evolution (DE) algorithm adapted for the solution of the multi objective optimal power flow under contingent operation states considering multi shunt FACTS devices.

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Received: July 6, 2011; Accepted: July 31, 2012

2. Mathematical Formulation of Multi Objective Optimal Power Flow Problem

The OPF problem is considered as a general minimization problem with constraints, the aim of OPF is to minimize the one or more objective function while satisfying all the constraints. Fig. 1 shows the strategy of the multi objective OPF. In multi objective OPF we have two or more conflicting objective functions to be optimized simultaneously. As a consequence, there is no unique solution to multi objective optimization problem, but we aim to find all the trade-off solutions available, called pareto-optimal set. The multi objective OPF problem can be formulated as:

$$\text{Minimize } J_i(x,u),\ i=1,.....,\ N_{obj} \tag{1}$$
$$\text{Subject to: } g(x,u)=0 \tag{2}$$
$$h(x,u)\le 0 \tag{3}$$
$$x_{\min} \le x \le x_{\max} \tag{4}$$
$$u_{\min} \le u \le u_{\max} \tag{5}$$

Where J_i is the ith objective function, N_{obj} is the number of objectives, g and h are respectively the set of equality and inequality constraints. The vector of state and control variables are denoted by x and u respectively. In general, the state vector includes bus voltage angles δ, load bus voltage magnitudes V_L, slack bus real power generation $P_{g,slack}$ and generator reactive power Q_g.

$$x=\left[\delta, V_L, P_{g,slack}, Q_g\right]^T \tag{6}$$

The control variable vector consists of real power generation P_g, generator terminal voltage V_g, shunt capacitors/reactors B_{sh}, shunt dynamic compensators (SVC) B_{svc} and transformers tap ratio t.

$$u=\left[P_g, V_g, t, B_{sh}, B_{svc}\right]^T \tag{7}$$

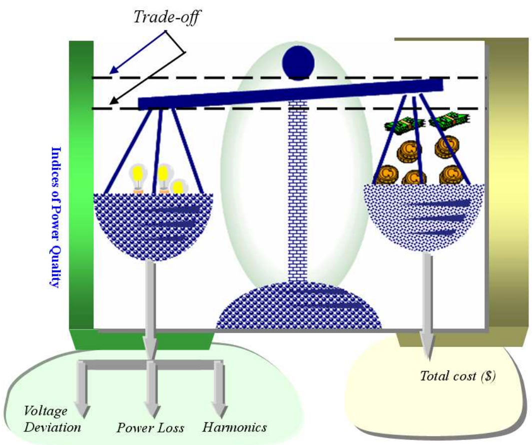

Fig. 1. Multi objective optimal power flow (OPF) strategy.

In this article two type of objective function based fuel cost are considered.

2.1 Smooth cost function using quadratic form

For optimal active power dispatch, the objective function f is the total generation cost expressed in a simple form as follows:

$$\text{Min } f=\sum_{i=1}^{NG}\left(a_i+b_iP_{gi}+c_iP_{gi}^2\right) \tag{8}$$

Where; NG is the number of thermal units, P_{gi} is the active power generation at unit i and a_i, b_i and c_i are the cost coefficients of the ith generator.

- ***Non-smooth Cost Function with Valve-Point Loading Effects***

The valve-point loading effect is taken in consideration by adding a sine component to the cost of the generating units. Typically, the fuel cost function of the generating units with valve-point loadings is represented as follows [22]:

$$f=\sum_{i=1}^{NG}\left(a_i+b_iP_{gi}+c_iP_{gi}^2\right)+\left|d_i\sin\left(e_i\left(P_{gi}^{\min}-P_{gi}\right)\right)\right| \tag{9}$$

d_i and e_i are the cost coefficients of the unit with valve-point loading effects. The input-output performance curve for a typical thermal unit can be represented as shown in Fig. 2.

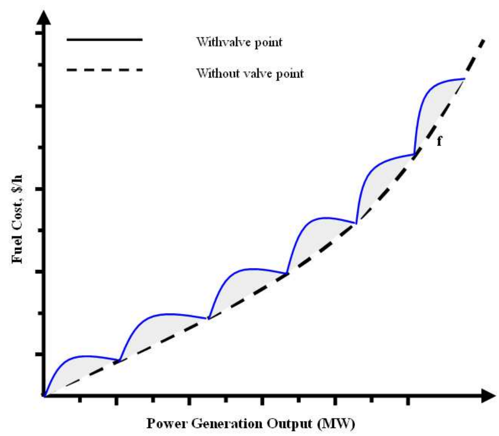

Fig. 2. Input-Output curve under valve-point loading effects.

2.2 Minimization of power loss

The objective function here is to minimize the active power loss (P_{loss}) in the transmission lines that can be expressed through the following equation:

$$J_1 = P_{loss} = \sum_{k=1}^{N_l} g_k \left[\left(t_k V_i \right)^2 + V_j^2 - 2 t_k V_i V_j \cos \delta_{ij} \right] \quad (10)$$

Where, N_l is the number of transmission lines; g_k is the conductance of branch k between buses i and j; t_k the tap ration of transformer k; V_i is the voltage magnitude at bus i; δ_{ij} the voltage angle difference between buses i and j.

2.3 Minimization of voltage deviation

One of the important indices of power system security is the bus voltage magnitude. The voltage magnitude deviation from the desired value at each load bus must be as small as possible. The deviation of voltage is given as follows:

$$J_2 = \Delta V = \sum_{k=1}^{N_{PQ}} \left| V_k - V_k^{des} \right| \quad (11)$$

where, N_{PQ} is the number of load buses and V_k^{des} is the desired or target value of the voltage magnitude at load bus k.

2.4 Minimization of fuel cost and voltage deviation

In this case in order to minimize the fuel cost and improve the voltage profile, the following multi objective function is proposed and expressed as follow:

$$J_3 = \sum_{i=1}^{NG} f_i + \sum_{i \in NL} \omega_{vi} \cdot \left| V_i - V_{ref} \right| \quad (12)$$

Where V_{ref} is the reference (desired) voltage of the buses, which are taken as 1 p.u; ω_{vi} is a weight factor of the *ith* unit. As well known voltage deviation largely depends on system loads, ω_{vi} is given by the following equation:

$$\omega_{vi} = f \cdot \frac{Pd_i}{PD} \quad (13)$$

Where; PD is the total active power demand, Pd_i is the active power demand of the *ith* bus.

2.5 Minimization of fuel cost and total overloading

Security OPF solution should take in consideration the critical situation due to severe loading conditions and fault (contingency situation) in power system, so it is important to maintain the power flow in all lines within the admissible values (thermal limits).

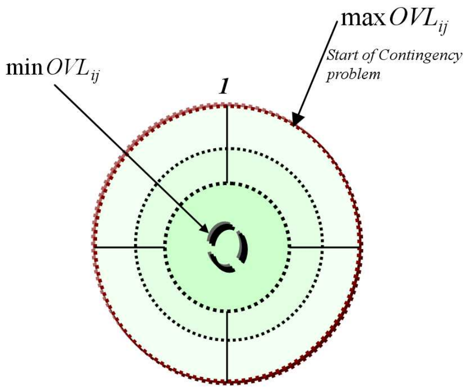

Fig. 3. Contingency evaluation using branch loading indice.

The proposed objective function is formulated as follows:

$$J_4 = \sum_{i=1}^{NG} f_i + \omega_{br} . TOVL \quad (14)$$

$$TOVL = \left(\frac{1}{Nbr} . \sum_{k=1}^{Nbr} OVL_{ij} \right) \quad (15)$$

$$OVL_{ij} = \frac{P_{ij}}{P_{ij}^{\max}} \quad (16)$$

Where, $TOVL$ is the total normalized overloading index, OVL_{ij} is the overloading at branch i-j, Nbr is the number of branch ω_{br} is a weighting factor expressed as follows.

$$\omega_{br} = \frac{f}{PD + P_{loss}} \quad (17)$$

2.6 Equality constraints

The equality constraints $g(x)$ are the real and reactive power balance equations, expressed as follows:

$$P_{gi} - P_{di} - V_i \sum_{j=1}^{Nb} V_j \left(g_{ij} \cos \delta_{ij} + b_{ij} \sin \delta_{ij} \right) = 0 \quad (18)$$

and;

$$Q_{gi} - Q_{di} - V_i \sum_{j=1}^{Nb} V_j \left(g_{ij} \sin \delta_{ij} - b_{ij} \cos \delta_{ij} \right) = 0 \quad (19)$$

Where Nb is the number of buses, P_{gi} , Q_{gi} are the active and the reactive power generation at bus i; P_{di} , Q_{di} are the real and the reactive power demands at bus i ; V_i , V_j , the voltage magnitude at bus i , j respectively; δ_{ij} is the voltage angle difference between buses *i* and *j*, g_{ij} and b_{ij} are the real and imaginary part of the admittance.

2.7 Inequality constraints

The inequality constraints $h(x,u)$ reflect the security limits that can be expressed as follows:

●Upper and lower limits on the active power generations:

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max} \quad (20)$$

●Upper and lower limits on the reactive power generations:

$$Q_{gi}^{\min} \le Q_{gi} \le Q_{gi}^{\max} \quad (21)$$

●Upper and lower limits on the tap ratio (t).

$$t_{ij}^{\min} \le t_{ij} \le t_{ij}^{\max} \quad (22)$$

●Upper and lower limits on the shifting (α) of variable transformers:

$$\alpha_{ij}^{\min} \le \alpha_{ij} \le \alpha_{ij}^{\max} \quad (23)$$

●Upper limit on the power flow (S_{ij}) of branch i-j.

$$S_{ij} \le S_{ij}^{\max} \quad (24)$$

●Upper and lower limits in the bus voltage magnitude:

$$V_i^{\min} \le V_i \le V_i^{\max} \quad (25)$$

●Upper and lower limits in the Shunt FACTS parameters

$$X^{\min} \le X_{FACTS} \le X^{\max} \quad (26)$$

3. Overview of Differential Evolution Technique

Differential evolution (DE) developed by Price and Storn [21] is a simple population based stochastic heuristic aspect. DE has proven to be promising candidate to solve real valued optimization problem. The key idea behind differential evolution approach is a new mechanism introduced for generating trial parameter vectors. In each step DE mutates vectors by adding weighted, random vector differentials to them. If the fitness function of the trial vector is better than that of the target, the target vector is replaced by trial vector in the next generation [24].

3.1 Differential evolution mechanism search

Based on the mechanism search of DE method shown in Fig.4, a brief description of different steps of the standard DE algorithm is given below [21]:

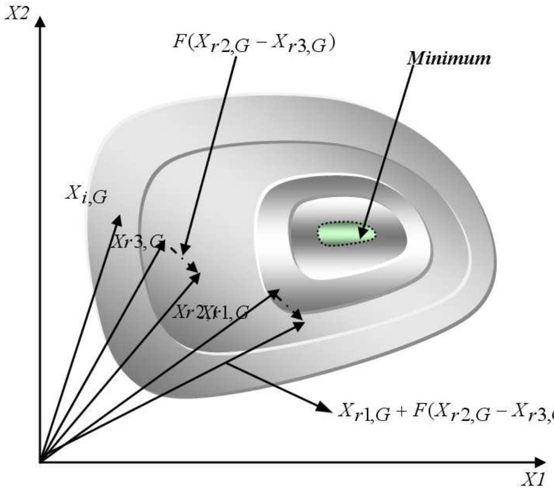

Fig. 4. Mechanism search of DE method

Step 1: Initialization

The population is initialized by randomly generating individuals within the specified constraints:

$$X_i^{(G)} = x_{ij}^{(L)} + rand[0,1] * \left(x_{ij}^{(U)} - x_{ij}^{(L)}\right) \quad (27)$$

Where:

$rand[0,1]$: denotes a uniformly distributed random value within [0, 1].

$x_{ij}^{(L)}$ and $x_{ij}^{(U)}$ are lower and upper boundaries of the parameters x_{ij} respectively for $j = 1, 2, ..., n$.

Step 2: Mutation

The role of mutation operation (or differential operation) is to avoid search stagnation by introducing new parameters into the population according to the following equation:

$$v_i^{(G+1)} = x_{r3}^{(G)} + f_m * \left(x_{r2}^{(G)} - x_{r1}^{(G)}\right) \quad (28)$$

Three vectors $x_{r3}^{(G)}$, $x_{r2}^{(G)}$ and $x_{r1}^{(G)}$ are randomly selected from the population and $r_1 \ne r_2 \ne r_3$, then the vector difference between them is established. $f_m \succ 0$ is a real parameter, called scaling factor, and it is usually taken from the range [0, 2], many schemes of creation of a candidature are possible, details on different schemes can be found in [20-24].

Step 3: Crossover

The crossover operator creates the trial vectors, which are used in the selection process. A trial vector is a combination of a mutant vector and a parent vector which is formed based on probability distributions. For each mutate vector, $v_i^{(G+1)}$, an index $rnbr(i) \in \{1, 2, ..., n\}$ is randomly chosen using a uniform distribution, and a trail vector, $u_i^{(G+1)} = \left[u_{i1}^{(G+1)}, u_{i2}^{(G+1)}, \ldots, u_{i2}^{(G+1)}\right]^T$ is generated according to the following equation:

$$u_{ij}^{(G+1)} = \begin{cases} v_{ij}^{(G+1)} \; if\left(rand\left[0,1\right] \le CR\right) or \left(j = rnbr\left(i\right)\right) \\ x_{ij}^{(G)} \; otherwise \end{cases} \quad (29)$$

Step 4: Selection

The selection operator chooses the vectors that are going to compose the population in the next generation. These vectors are selected from the current population and the trial population. Each individual of the trial population is compared with its counterpart in the current population based on the following condition.

$$x_i^{(G+1)} = \begin{cases} u_i^{(G+1)} \; if\left(f\left(u_i^{(G+1)}\right) \prec f\left(x_i^{(G)}\right)\right) \\ x_i^{(G)} \; otherwise \end{cases} \quad (30)$$

Where f is the fitness function.

4. Shunt Facts Modelling

4.1 Static VAR compensator (SVC)

The Static VAr Compensator (SVC) [23] is a shunt connected VAr generator or absorber whose output is adjusted dynamically to exchange capacitive or inductive current so as to maintain bus voltage at a desired value. It includes separate equipment for leading and lagging VArs. The basic steady state model shown in Fig. 5 is used in this study to incorporate the SVC on the power flow problem. This model is based on representing the SVC Controller as variable susceptance or firing angle control.

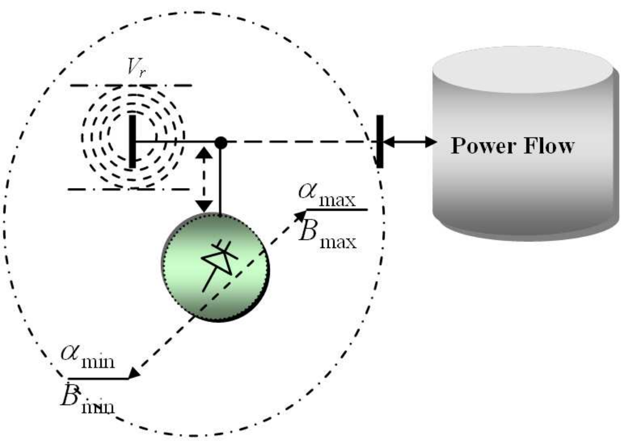

Fig. 5. SVC Steady-state circuit representation based power flow.

$$I_{SVC} = jB_{SVC}V \quad (31)$$

$$\left.\begin{aligned} B_{SVC} &= B_C - B_{TCR} = \frac{1}{X_C X_L}\left\{X_L - \frac{X_C}{\pi}\left[2\left(\pi - \alpha\right) + \sin\left(2\alpha\right)\right]\right\}, \\ X_L &= \omega L, X_C = \frac{1}{\omega C}, \end{aligned}\right\} \quad (32)$$

Where, $B_{SVC}, \alpha, X_L, X_C, V$ are the shunt susceptance, firing angle, inductive reactance, capacitive reactance of the SVC controller, and the bus voltage magnitude to which the SVC is connected, respectively.

The exchange reactive power Q_i^{SVC} with the bus i can be expressed as,

$$Q_i^{SVC} = B_i^{SVC}.V_i^2 \quad (33)$$

5. Numerical Results and Analysis

The proposed algorithm is developed in the Matlab programming language (6.5 version) using Microsoft Windows XP. All the programs were run on 2.6 GHz Pentium IV processor with 500MB of random access memory. The proposed approach has been tested on two test network; IEEE 30-Bus with smooth cost function considering all security constraints under contingency situations, and to the 13 generating units considering valve point effects.

5.1 Educational simulator based matlab: GLOBOPF package

The proposed simulator called global OPF (GLOBOPF) has been developed under the basic graphic user interface (GUI) from MATLAB program. In this first version (1.01) the user can choose the method for optimization (GA, PSO, DE, Fuzzy-GA, FPSO,), edit, modify and save the related

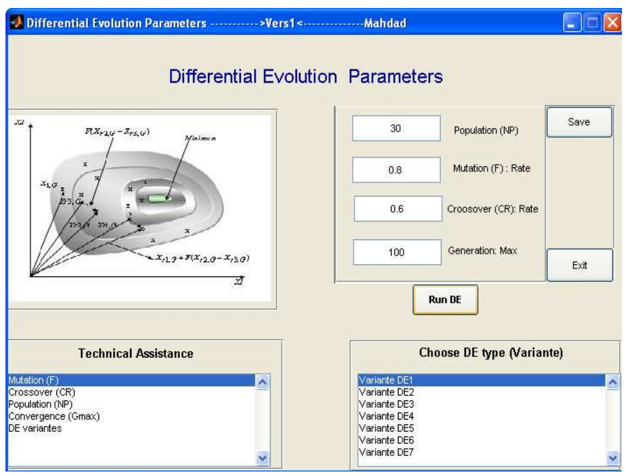

Fig. 6. Frame of the DE parameters adjustment based GLOBOPF Package.

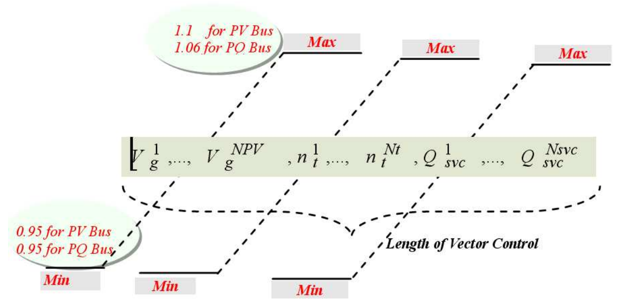

Fig. 7. Vector control structure based DE for optimal power flow.

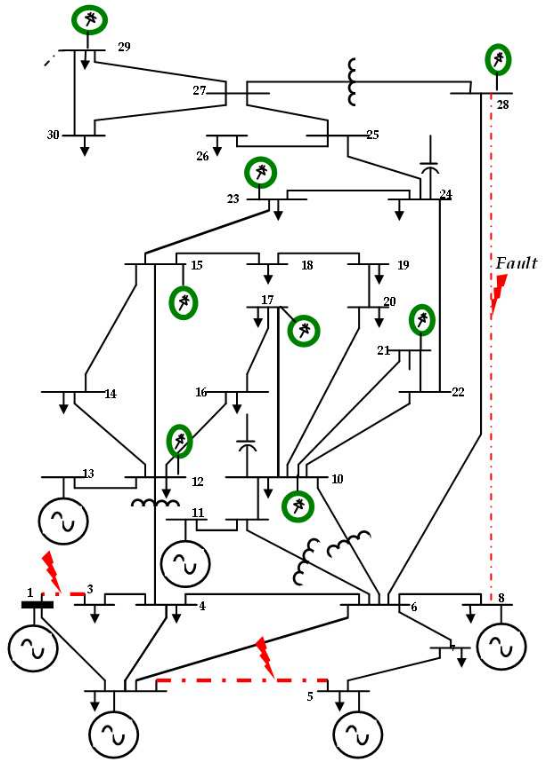

Fig. 8. Single line diagram for the modified IEEE 30-Bus test system considering Shunt FACTS devices.

parameters. It is important to note that adjusting parameters of these optimization methods is an important task to achieve better results. Fig. 6 shows the basic frame of the DE parameters.

5.2 DE parameters:

Initially, several runs are done with different values of DE parameters such as: mutation constant fm, crossover constant CR, size population NP, and maximum number of generations $G\max$ which is used in this study as convergence criteria. The following values are selected based on the size of the power system test and the loading condition (at normal or under contingency).

$fm = 0.4 - 0.95$; $CR = 0.5 - 0.8$; $NP = 10 - 30$; $G\max = 250$

5.3 Test system 1: Smooth cost function considering all security constraints under contingency situation

The first test system has 6 generating units; 41 branch system, the system data taken from [22]. It has a total of 24 control variables described as follows: five units active power outputs, six generator-bus voltage magnitudes, four transformer-tap settings, nine bus shunt FACTS controllers (SVC). Fig. 7 shows the structure of the vector control to be optimized. The single line diagram of the modified IEEE 30-Bus electrical network is shown in Fig. 8.

5.4 Case 1: Single objective function:

In this case, the problem is solved as single objective optimization, three objective functions are treated, fuel cost, power transmission losses and voltage deviation. Table 1 shows the control settings and objective function values for base case (without any optimization function) and with single objective functions considering multi shunt FACTS devices.

Table 1 Control variables optimized using single objective function:

		Proposed Approach Case 1: Single objective function			
Control Variable	Base case	OF*=Cost/with and without SVC		OF=Ploss	OF=VD
P_{G1}	99.578	177.780		57.450	101.040
P_{G2}	80.00	48.6100		79.500	79.9400
P_{G5}	50.00	20.7800		48.500	50.0000
P_{G8}	20.00	20.9752		34.500	35.0000
P_{G11}	20.00	12.0000		28.500	10.5100
P_{G13}	20.00	12.0000		38.500	12.5000
V_{G1}	1.0	1.09890		1.0560	1.04060
V_{G2}	1.0	1.07990		1.0543	1.03190
V_{G5}	1.0	1.05190		1.0366	1.03190
V_{G8}	1.0	1.06090		1.0447	0.99370
V_{G11}	1.0	1.09390		1.1000	1.00530
V_{G13}	1.0	1.08690		1.0656	1.02510
$T_{6\text{-}9}$	1.0	1.07110		1.0765	1.0490
$T_{6\text{-}10}$	1.0	0.91810		0.9226	0.9000
$T_{4\text{-}12}$	1.0	1.00990		1.0148	0.9890
$T_{28\text{-}27}$	1.0	0.98950		0.9943	0.9690
Q_{svc} (10)	0	0	3.7500	0.0500	4.6250
Q_{svc} (12)	0	0	3.7500	0.0500	4.6250
Q_{svc} (15)	0	0	2.2500	0.0300	2.7750
Q_{svc} (17)	0	0	3.7500	0.0500	4.6250
Q_{svc} (20)	0	0	3.6000	0.0480	4.4400
Q_{svc} (21)	0	0	4.6125	0.0515	5.6888
Q_{svc} (23)	0	0	2.8800	0.0384	3.5520
Q_{svc} (24)	0	0	3.4350	0.0458	4.2365
Q_{svc} (29)	0	0	3.7500	0.0250	4.6250
FC ($/h)	902.5583	**800.1072**	**799.3070**	952.9361	898.0054
Loss(MW)	6.089	8.987	8.741	**3.547**	5.587
DV (p.u)	1.1767	0.9064	1.3175	0.4103	**0.1516**

* OF: Objective function

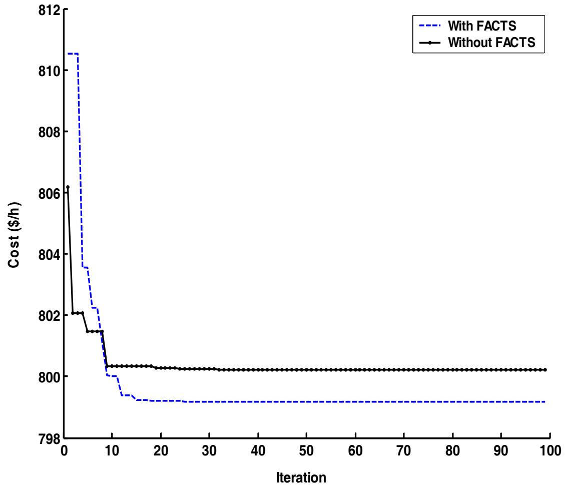

Fig. 9. Convergence characteristic: Case1: Minimize fuel cost with and without shunt FACTS.

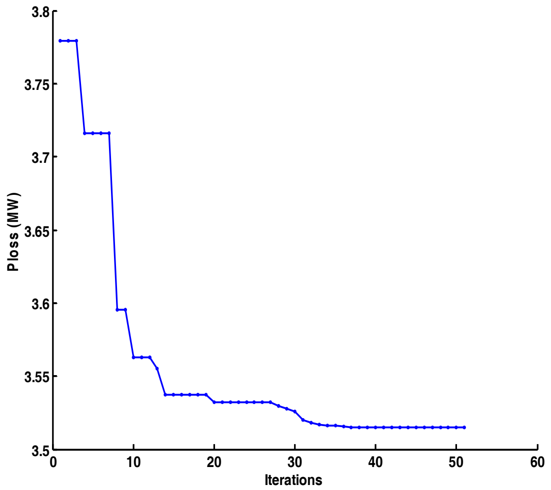

Fig. 10. Convergence characteristic: Case1: Minimize power loss considering multi shunt FACTS.

Fig. 9 shows the convergence of the best total fuel cost with and without shunt FACTS devices; Fig. 10 shows the convergence characteristic of the best power loss considering multi shunt FACTS controllers. The proposed approach can reach to the optimum solution at a reduced number of iteration, less than 25 iterations for fuel cost minimization and less than 40 iterations for power loss minimization. All reported results for the DE in this paper are feasible solutions satisfying the OPF security constraints (generator reactive power limits, power flow in branches and voltage limits).

5.5 Case 2: Multi objective function

- ***Minimization of fuel cost and voltage deviation***

In this case (case 2.1), fuel cost optimized in coordination with voltage deviation, this case is very important, it allows to the expert to take an efficient compromise decision.

Table 2. Control variables optimized using multi objective function: Case 2.1: Fuel cost and voltage deviation.

		Case 2: Multi objective function Cost & voltage deviation	
Control Variables	Base case	OF*=Cost+VD	
		Without SVC Controllers	With SVC Controllers
P_{G1}	99.578	179.130	
P_{G2}	80.00	47.7460	
P_{G5}	50.00	21.0368	
P_{G8}	20.00	21.6138	
P_{G11}	20.00	11.9414	
P_{G13}	20.00	11.7360	
V_{G1}	1.0	1.0420	
V_{G2}	1.0	1.0299	
V_{G5}	1.0	1.0041	
V_{G8}	1.0	1.0129	
V_{G11}	1.0	1.0880	
V_{G13}	1.0	1.0545	
$T_{6\text{-}9}$	1.0	1.0775	
$T_{6\text{-}10}$	1.0	0.9235	
$T_{4\text{-}12}$	1.0	1.0159	
$T_{28\text{-}27}$	1.0	0.9953	
Q_{svc} (10)	0	0	3.7500
Q_{svc} (12)	0	0	3.7500
Q_{svc} (15)	0	0	2.2500
Q_{svc} (17)	0	0	3.7500
Q_{svc} (20)	0	0	3.6000
Q_{svc} (21)	0	0	3.8625
Q_{svc} (23)	0	0	2.8800
Q_{svc} (24)	0	0	3.4350
Q_{svc} (29)	0	0	1.8750
FC ($/h)	902.5583	**803.5845**	**802.9156**
Loss (MW)	6.089	10.0077	9.8040
DV (p.u)	1.1767	**0.5603**	**0.2592**

The control variables, optimal power generation, fuel cost, total power loss and voltage deviation of the overall system are shown in Table 2. The compromise solution found in this case is 802.9156 ($/h) for fuel cost, and 0.2592 p.u for voltage deviation considering multi SVC

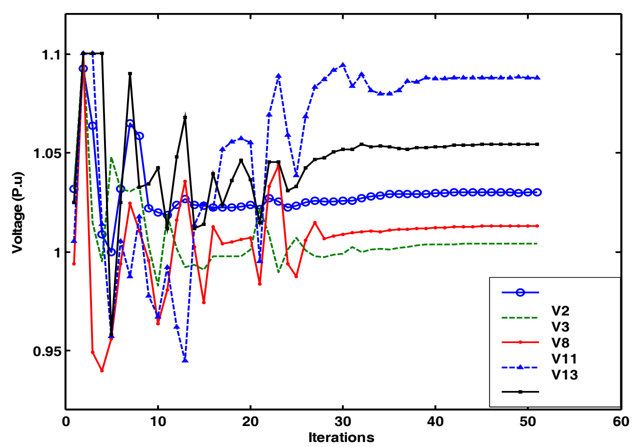

Fig. 11. Convergence characteristic of voltage control.

compensators which are better compared to the optimized results found without considering multi SVC Controllers. Fig. 11 shows the relationship between the voltage vector control of generating units and the iteration. It can be observed from results depicted in Table 2 that the voltage profile is improved, while the total cost increased slightly compared to case 1(fuel cost minimization, 799.3070 (\$/h)). It is important to note that the final solution found for all cases satisfy all security constraints.

● ***Minimization of fuel cost and total overloading***

The main objective of this case (case 2.2) is to enhance the system loadability at critical situation. The total fuel cost optimized in coordination with the total over loading index (TOVL). In this study the system optimized under the following critical situations:

- Faults at three branches 1-3, 2-6, 8-28.
- Load increased at a critical value (λ =1.034 p.u) as follows:

$$\begin{cases} P_d = \lambda P_o \\ Q_d = \lambda Q_o \end{cases} \tag{34}$$

Where, λ is the loading factor, P_o, Q_o are the active and reactive power at the normal condition.

Table 3 shows the new system data adapted in this case, from Table 4, It was found that the OVL indice in line 2-4

Table 3 System Data at critical situation.

Faults: Branches	[1-3], [2-6], [8-28]
Loading Factor: λ (p.u)	1.034
Total power demand (MW)	293.04

Table 4 Control variables optimized: Case 2.2: Fuel cost and total overloading.

Control Variable	Base case	Case 2: Multi objective function Cost & System loading
P_{G1}	116.56	96.7800
P_{G2}	79.62	48.3400
P_{G5}	50.00	50.0000
P_{G8}	20.00	35.0000
P_{G11}	20.00	30.0000
P_{G13}	20.00	40.0000
V_{G1}	1.0	1.0890
V_{G2}	1.0	1.0732
V_{G5}	1.0	1.0890
V_{G8}	1.0	1.0375
V_{G11}	1.0	1.0237
V_{G13}	1.0	1.0009
T_{6-9}	1.0	1.0765
T_{6-10}	1.0	0.9226
T_{4-12}	1.0	1.0148
T_{28-27}	1.0	0.9943
Q_{svc} (10)	Without SVC Controllers: 0	With SVC Controllers: 4.6200
Q_{svc} (12)	0	4.6200
Q_{svc} (15)	0	2.7720
Q_{svc} (17)	0	4.6200
Q_{svc} (20)	0	4.4352
Q_{svc} (21)	0	5.6826
Q_{svc} (23)	0	3.5482
Q_{svc} (24)	0	4.2319
Q_{svc} (29)	0	4.6200
FC (\$/h)	**948.9279**	**956.8886**
Loss (MW)	**13.141**	**7.079**
DV (p.u)	**1.6249**	**0.3198**
TOVL	**0.3792**	**0.3476**
Max OVL_{ij}	**1.4210**	**0.8992**
Critical branch	**2-4**	**2-4**
Total PG	306.180	300.12
Total PD	**293.04**	**293.04**
Q_{Gi} Violation	**Yes**	**No**

Table 5 Control variables optimized using multi objective function: Case 2: Fuel cost and total overloading.

Branch From	Branch To	Case 2: Multi objective function Cost & TOLV, S_{ij} (MVA)	S_{ij}^{max} (MVA)
1	2	96.8285	130
1	3	0	130
2	4	58.4489	65
3	4	2.7745	130
2	5	66.5025	130
2	6	0	65
4	6	36.9077	90
5	7	32.0072	70
6	7	23.0187	130
6	8	4.7642	32
6	9	17.4720	65
6	10	25.0136	32
9	11	31.5553	65
9	10	34.3879	65
4	12	12.2228	65
12	13	40.4860	65
12	14	8.2531	32
12	15	20.7195	32
12	16	9.8944	32
14	15	2.4023	16
16	17	7.0301	16
15	18	7.1134	16
18	19	4.2498	16
19	20	8.3987	32
10	20	8.8227	32
10	17	5.9690	32
10	21	17.2400	32
10	22	8.2448	32
21	22	2.1101	32
15	23	7.1184	16
22	24	6.3515	16
23	24	3.3664	16
24	25	3.2280	16
25	26	4.4120	16
25	27	6.4977	16
28	27	17.8809	65
27	29	6.6500	16
27	30	7.3192	16
29	30	4.3285	16
8	28	0	32
6	28	17.5809	32
λ (p.u)	1.034, PD=**293.04 MW**		

was 1.4210 p.u at the base case (without optimization) which is more than its stable limit (1 p.u), by adjusting dynamically the reactive power of shunt FACTS controllers installed at specified buses in coordination with the others control variables such as: tap transformers, voltage control of generating units, and active power generation, the congestion at line 2-4 relieved, the OVL at this line reduced to 0.8992 p.u, compared to the based case (1.4210 p.u), the voltage deviation also reduced to 0.3198 p.u compared to the base case (1.6249 p.u). Table 5 shows the optimal repartition of power transit in all lines considering faults in two lines and load increased with 3.4% from the base case, as we can see the power flow in all lines are far from their thermal limits. We can also conclude that optimal adjustment of reactive power of multi SVC Controllers installed at specified buses enhances the power system security at critical situations.

5.6 Test System 2: with valve-point loading effects

This case study consisted of 13 thermal units of generation with the effect of valve point loading, it has more local minima and thus it is difficult to attain the global solution. The security constraints are not taken in consideration. The system data taken from [23]. The load demand of this test system is 1800 MW. The convergence of the best total fuel cost considering valve point effect is shown in Fig. 12.

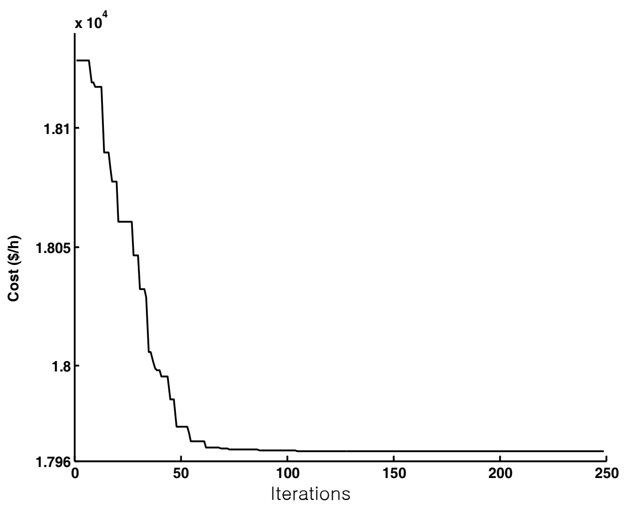

Fig. 12. Convergence characteristic of the 13 generating units with valve point loading effects.

The output power of the generators of the 13 unit test system in the minimum solution of the proposed approach and for the pattern search algorithm are shown in Table 6, the minimum cost achieved by the proposed approach (17963.92097$/h), is less than PS algorithm. Observing the comparison results depicted in Table 7, the proposed approach is shown to be more efficient than other recent metaheuristic optimization methods.

Table 6. Economic Dispatch Results for 13-Generating Units using the Proposed Approach: PD=1800MW

N°	Our approach		PS [24]
	Run1	Run2···	
1	628.2183	628.3155	538.5587
2	149.5496	149.5184	224.6416
3	222.9150	222.9137	149.8468
4	109.8614	109.8651	109.8666
5	109.8656	109.8591	109.8666
6	109.8595	109.8196	109.8666
7	60.0000	60.0000	109.8666
8	109.8663	109.8528	109.8666
9	109.8642	109.8559	109.8666
10	40.0000	40.0000	77.4666
11	40.0000	40.0000	40.2166
12	55.0000	55.0000	55.0347
13	55.0000	55.0000	55.0347
TP (MW)	1800	1800	1800
Cost $//h)	**17964.05149**	**17963.92097**	17969.17

Table 7. Comparison of best results for fuel cost: Case Study: 13 thermal units with valve point effect.

Methods	Minimum Cost($/h)
Particle swarm optimization [25]	18030.72000
Evolutionary programming [25]	17994.07000
Hybrid evolutionary programming with SQP [25]	17991.03000
Genetic algorithm [25]	17975.34370
Hybrid differential evolution [25]	17975.73000
Hybrid particle swarm with SQP [25]	17969.93000
Pattern search method [26]	17969.17000
Best result of this paper	**17963.92097**

6. Conclusion

A simple differential evolution (DE) method integrated in a flexible Package based GUI using Matlab program is proposed and adapted to enhance the solution of the multi objective OPF under contingency situation considering multi shunt FACTS devices. The performance of the proposed strategy in terms of solution quality and convergence characteristics has been tested with IEEE 30-Bus with smooth cost function considering all security constraints under abnormal conditions, and with 13 generating units considering the valve point effects. The simulation results are compared with those by the other recent techniques. It is observed that the proposed approach is capable of finding the near global solution of non-linear and non-differentiable objective functions and obtain a competitive solution at critical situations.

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