

Application of NSGAII Approach to Optimal Location of UPFC Devices in Electrical Power Systems

I. Marouani, T. Guesmi, H. Hadj Abdallah and A. Ouali

Sfax National Engineering School, Electrical Department. BP W, 3038 Sfax-Tunisia

Abstract: Heuristic approaches are traditionally applied to find the optimal location of flexible AC transmission system (FACTS) in a small power system. This paper shows the application of an elitist multi-objective evolutionary algorithm (MOEA) based on non-dominated sorting genetic algorithm II (NSGAII) for optimal placement of unified power flow controller (UPFC) in order to solve a Multi Objective Problem (MOP). This non linear MOP involves the simultaneous optimization of three objective functions, real power loss in transmission lines, voltage deviation at load buses and the generation cost of the active power, while satisfying several equality and inequality constraints. The MOP constraints are the load flow equations and the security limits. A 14 bus system is used as an example to illustrate the technique of optimization. Results show that the NSGA II is able to find the best solution with statistical significance and a high degree of convergence. A detailed description of this approach, results and conclusions are also presented.

Key words: Modeling • Power flow • Optimization • FACTS • UPFC and NSGAII

INTRODUCTION

Industrialization and the population growth are the first factors for which electric energy consumption increases regularly. This phenomenon is accompanied by a deep restructuration of the electric energy sector. The fast development of solid-state has made flexible AC transmission system (FACTS) devices a promising concept for future power systems.

FACTS controllers are based on power electronic devices. They are capable to control various electrical parameters of transmission systems. The UPFC is the universal and the most versatile FACTS devices, which consists of series and parallel connected converters. It can provide simultaneous and independent control of voltage magnitude and active and reactive power flow. In this paper, a UPFC has been considered as additional control parameters in the optimal reactive power dispatch (ORPD).

The ORPD problem consists to minimize total system transmission loss, improve voltage profile and reduce the generation cost. In previous work, several methods are used to solve this multi-objective optimization problem (MOP). Reference [1-3] proposes a nonlinear programming algorithm. In [4-5], a linear programming algorithm was introduced.

Actually, new algorithms including FACTS devices are proposed to solve the ORPD problem. However, these researches consider the problem as mono-objective and it was solved using several methods, such as, particle swarm optimization (PSO) technique [6, 7], iterative techniques [8, 9], differential evolution [10, 11] and (GA) [12].

This paper presents an approach to find optimum location and parameters of a UPFC in a power system, with minimum transmission losses and voltage deviation at load buses. This approach is based on an elitist multi-objective evolutionary algorithm (MOEA) which is called NSGAII [13].

The power losses and the voltage deviation are provided by the load flow program which is formulated by the equality and inequality constraints.

In the literature, many power flow algorithms are proposed. The majority of these methods are based on Newton-Raphson algorithm because of its quadratic convergence properties [14, 15]. An existing Newton-Raphson load flow algorithm is modified to include FACTS devices is presented in [15]. In this paper, this algorithm is extended in order to include the UPFC devices into the power system.

The proposed algorithm is tested on the IEEE-14 bus test system and using MATLAB software package.

Implemented Power System Model

Symbolic Representation of a Power System: The block diagram given in Figure. 1 shows a symbolic representation of a power system that includes several generators, several loads and multi type FACTS devices.

Power Flow in Line Transmission: Power flow through the transmission line k-m namely P_{km} is depended on line reactance X , bus voltage magnitudes V_k, V_m and phase angle between sending and receiving buses $\delta_k - \delta_m$. It is expressed by:

$$P_{km} = \frac{V_k V_m}{X} \sin(\delta_k - \delta_m) \quad (1)$$

The synchronous voltage source approach to transmission line compensation and control is illustrated symbolically in Figure. 2. As shown, the shunt connected Static Synchronous Compensator (STATCOM) can control the transmission line voltage, the series connected Static Synchronous Series Compensator (SSSC) the effective line impedance and the Unified Power Flow Controller (UPFC) all of the variables (voltage, impedance and angle) [16], selectively or concurrently.

The UPFC is a FACTS device which is capable of providing active and reactive load flow control between its terminals. It may also provide reactive power compensation to the bus at which it is connected.

Mathematical Model of Power Systems with UPFC

Devices: The objective of this section is to give a power flow model for a power system with a UPFC device. Modified Newton-Raphson algorithm as described in [15] is used to solve the power flow equations.

Power Flow Analysis without UPFC: Consider a power system with N buses. For each bus i , the injected real and reactive powers can be described as:

$$P_i = \sum_{j=1}^N V_i V_j Y_{ij} \cos(\delta_i - \delta_j - \theta_{ij}) \quad (2)$$

$$Q_i = \sum_{j=1}^N V_i V_j Y_{ij} \sin(\delta_i - \delta_j - \theta_{ij}) \quad (3)$$

Where:

V_i and δ_i are respectively modulus and argument of the complex voltage at bus i .

Y_{ij} and θ_{ij} are respectively modulus and argument of the ij -th element of the nodal admittance matrix Y.

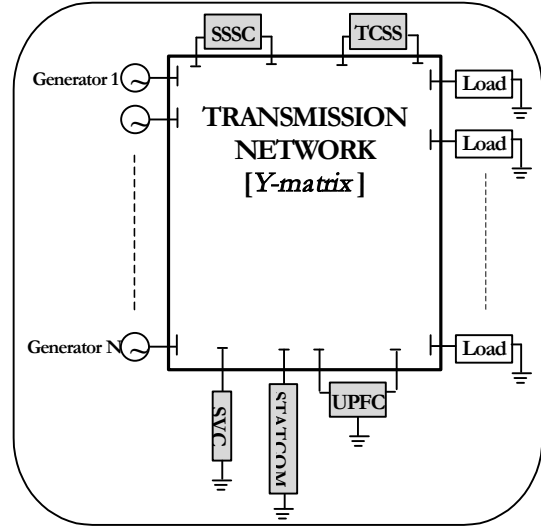


Fig. 1: Symbolic representation of a power system

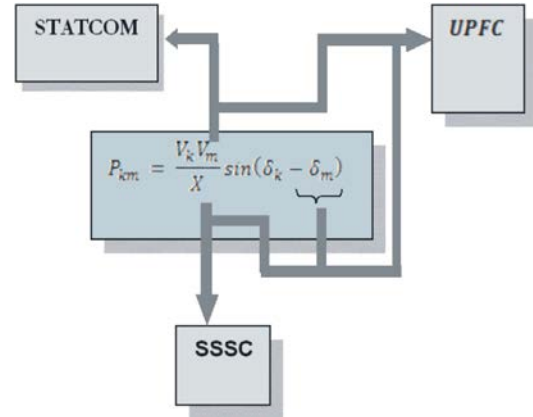


Fig. 2: The family of synchronous voltage source based power flow controllers

The power flow equations are solved using the Newton-Raphson method where the nonlinear system is represented by the linearized Jacobian equation given by the following equation:

$$\begin{bmatrix} J^1 & J^2 \\ J^3 & J^4 \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta V \end{bmatrix} = \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} \quad (4)$$

The ij -th elements of the sub-jacobian matrices J^1, J^2, J^3 and J^4 are respectively

$$J^1(i, j) = \frac{\partial P_i}{\partial \delta_j}, J^2(i, j) = \frac{\partial P_i}{\partial V_j}, J^3(i, j) = \frac{\partial Q_i}{\partial \delta_j} \text{ and } J^4(i, j) = \frac{\partial Q_i}{\partial V_j}$$

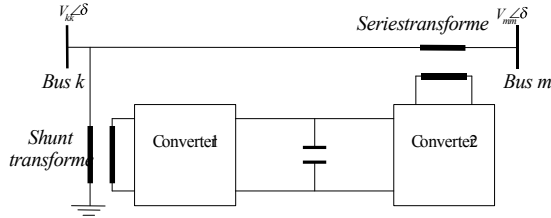


Fig. 3: Simplified diagram of UPFC

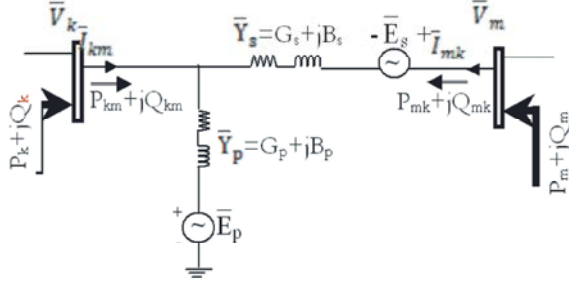


Fig. 4: Equivalent circuit of UPFC

Power Flow Analysis with UPFC: Basically, the UPFC is composed of series and shunt voltage source inverters. These two inverters share a common DC-link storage capacitor [17]. They are connected to the power system through two coupling transformers. The series inverter injects a controllable AC voltage system in series with the transmission line to control the real and reactive power flows. The shunt inverter supplies or absorbs the real power demand (negative or positive value) by the series inverter at the DC-link. Also, it can provide independent shunt reactive compensation and generate or absorb controllable reactive power [17, 18].

Where

$$P_{km} = V_k^2 Y_p \cos \theta_p + V_k^2 Y_s \cos \theta_s - V_k E_p Y_p \cos(\delta_k - \delta_p - \theta_p) + V_k E_s Y_s \cos(\delta_k - \delta_s - \theta_s) - V_m V_k Y_s \cos(\delta_k - \delta_m - \theta_s) \quad (9)$$

$$Q_{km} = -V_k^2 Y_p \sin \theta_p - V_k^2 Y_s \sin \theta_s - V_k E_p Y_p \sin(\delta_k - \delta_p - \theta_p) + V_k E_s Y_s \sin(\delta_k - \delta_s - \theta_s) - V_m V_k Y_s \sin(\delta_k - \delta_m - \theta_s) \quad (10)$$

$$P_{mk} = -V_m^2 Y_s \cos \theta_s - V_m E_s Y_s \cos(\delta_m - \delta_s - \theta_s) - V_m V_k Y_s \cos(\delta_m - \delta_k - \theta_s) \quad (11)$$

$$Q_{mk} = -V_m^2 Y_s \sin \theta_s - V_m E_s Y_s \sin(\delta_m - \delta_s - \theta_s) - V_m V_k Y_s \sin(\delta_m - \delta_k - \theta_s) \quad (12)$$

The schematic diagram of UPFC is shown in Figure 3.

The series voltage source is modelled as an ideal series voltage E_s in series with impedance. The shunt voltage source inverter is equivalent to an adjustable voltage source E_p in series with impedance. E_s and E_p are controllable in magnitude and phase. Figure 3 represents the equivalent circuit of UPFC installed between buses k and m [19].

Y_s is the admittance of the line $k-m$ including the series component of the UPFC. Y_p is the admittance of the parallel component.

From the Figure 4, the injected real and reactive powers for all buses of the system with UPFC remain same as those of the system without UPFC except for buses k and m , where they have the following expressions [15-20]:

$$P_k = P_{km} + \sum_{j=1}^N V_k V_j Y_{kj} \cos(\delta_k - \delta_j - \theta_{kj}) \quad (5)$$

$$Q_k = Q_{km} + \sum_{j=1}^N V_k V_j Y_{kj} \sin(\delta_k - \delta_j - \theta_{kj}) \quad (6)$$

$$P_m = P_{mk} + \sum_{j=1}^N V_m V_j Y_{mj} \cos(\delta_m - \delta_j - \theta_{mj}) \quad (7)$$

$$Q_m = Q_{mk} + \sum_{j=1}^N V_m V_j Y_{mj} \sin(\delta_m - \delta_j - \theta_{mj}) \quad (8)$$

E_p and δ_p are magnitude and phase of the shunt voltage source. E_s and δ_s are magnitude and phase of the series voltage source.

Finally, the modified power flow equations can be solved with the Newton-Raphson method by using equation (13).

	δ_k	δ_m	δ_p	δ_s	E_s	E_p	V_m		
$P_k \rightarrow$	●1 ●2 J_{P_s}	●36 ●37 J_{P_s}	●38 ●39 J_{P_s}	●40 ●41 J_{P_s}	●5 ●6 J_{P_p}	●7 ●8 J_{P_p}		$\Delta\delta$	ΔP
$P_m \rightarrow$	●3 ●4								
$P_{Ep} \rightarrow$	●15 ●16	●17 ●18	●19 ●20	●21 ●22				$\Delta\delta_p$	ΔP_s
$P_{km} \rightarrow$	●22 ●23	●24 ●25	●26 ●27	●28 ●29				$\Delta\delta_s$	ΔP_{km}
$Q_{km} \rightarrow$	●29 ●30	●31 ●32	●33 ●34	●35 ●36				ΔE_s	ΔQ_{km}
$Q_k \rightarrow$	●8 ●9 J_{P_s}	●41 ●42 J_{P_s}	●43 ●44 J_{P_s}	●45 ●46 J_{P_s}	●12 ●13 J_{P_p}	●14 ●15 J_{P_p}		ΔE_p	ΔQ
$Q_m \rightarrow$	●10 ●11							ΔV	

(13)

Problem Formulation as a Multi- Objective Optimization

Problem: In this paper, the ORPD problem including UPFC is defined to search the optimal location and design of the UPFC in order to minimize the real power losses and voltage deviation under several constraints.

Real Power Losses: The real power losses can be presented by the following equation [19-20]:

$$F_1 = \sum_{i=1}^N \sum_{j=1}^N Y_{ij} V_i V_j \cos(\delta_i - \delta_j - \theta_{ij}) \quad (14)$$

Voltage Deviation: This objective consists to minimize the deviation in voltage magnitude at load buses. It can be expressed as [21]:

$$F_2 = \sum_{i=1}^{NL} (V_i - V_i^{ref})^2 \quad (15)$$

Where:

N_L : Number of load buses;
 V_i^{ref} : prespecified reference value of the voltage magnitude at the i-th load bus.

In this paper, $V_i^{ref} = 1pu$.

Generation Cost Function: The generation cost function $F_3(P_G)$ en \$/h is represented by a quadratic function at the following form [22]:

$$F_3(P_G) = \sum_{i=1}^{N_g} a_i + b_i P_{Gi} + c_i P_{Gi}^2 \quad (16)$$

The coefficients a_i , b_i and c_i are appropriate to every production unit, N_g the number of generators and P_{Gi} the real power output of an i th generator, it can be simulated as

$$P_{Gi} = \lambda K_{Gi} P_{Gi0} \quad (17)$$

Where:

P_{Gi0} : Active power generation of generator i in base case.
 λ : Loading parameter.
 K_{Gi} : Factor of contribution of each generator i to satisfy the request of the load.

Problem Constraints: The equality constraints are the load flow equations given by (18) and (19).

$$P_{Gi} - P_{Di} = P_i \quad (18)$$

$$Q_{Gi} - Q_{Di} = Q_i \quad (19)$$

Where:

P_{Gi} and Q_{Gi} are generated real and reactive powers at bus i , respectively.
 P_{Di} and Q_{Di} are real and reactive power loads at bus i , respectively.

For the system with UPFC, when the losses are neglected, the active power P_{Ep} provided by the shunt connected voltage source is equal to injected active power P_{Es} via the series connected voltage source. So, other equality constraint is considered:

$$\begin{aligned} P_{Ep} - P_{Es} &= -G_p E_p^2 - G_s E_s^2 + E_p V_k Y_p \cos(\delta_p - \delta_k - \theta_p) \\ &- E_s V_k Y_s \cos(\delta_s - \delta_k - \theta_s) + E_s V_m Y_s \cos(\delta_s - \delta_m - \theta_s) = 0 \end{aligned} \quad (20)$$

The inequality constraints are:

Security Limits: Two inequality constraints are considered. The first constraint includes voltage limits at load buses as shown in (21)

$$V_{Li}^{\min} \leq V_{Li} \leq V_{Li}^{\max}, i = 1, \dots, N_L \quad (21)$$

Where $V_{Li}^{\min}$ and $V_{Li}^{\max}$ are respectively lower and upper limits voltage at load buses.

The second is represented by the line flow limits. It considers that the real power flow P_{li} in each transmission line i among the N_{line} lines of the power system must be lower than its maximum value $P_{li}^{\max}$. Mathematically, it can be written as:

$$P_{li} \leq P_{li}^{\max}, \quad i = 1, \dots, N_{line} \quad (22)$$

Operating Limits of the UPFC: Voltage magnitude and phase of shunt and series voltage sources of UPFC must lie within their lower and upper limits.

$$E_p^{\min} \leq E_p \leq E_p^{\max} \quad (23)$$

$$E_s^{\min} \leq E_s \leq E_s^{\max} \quad (24)$$

$$0 \leq \delta_s \leq 2\pi \quad (25)$$

$$0 \leq \delta_p \leq 2\pi \quad (26)$$

Problem Solution Using MOEA: In a MOP, there may not exist one solution that is best with respect to all objectives. Usually, the aim is to determine the trade-off surface, which is a set of non-dominated solution points, known as Pareto optimal solutions. Every individual in this set is an acceptable solution.

For any two X_1 and X_2 , we can have one of two possibilities: one dominates the other or none dominates the other. In a minimization problem, we say that the solution X_1 dominates X_2 , if the following two conditions are satisfied [21-23]:

$$\begin{cases} \forall i \in \{1, 2, \dots, N_{obj}\}, f_i(X_1) \leq f_i(X_2) \\ \exists j \in \{1, 2, \dots, N_{obj}\}, f_j(X_1) < f_j(X_2) \end{cases} \quad (27)$$

Where:

N_{obj} : Number of objective functions.

f_i : i th objective function.

The goal of a multi-objective optimization algorithm is not only to guide the search towards the Pareto optimal front, but, also to maintain population diversity in the set of the non-dominated solutions.

In the rest of this section, we will present the elitist MOEA NSGAIL. So, we must be start with a presentation of the NSGA approach.

NSGA Approach: The basic idea behind NSGA is the ranking process executed before the selection operation. The ranking procedure consists to find the non-dominated solutions in the current population P . These solutions represent the first front F_1 . Afterwards, this first front is eliminated from the population and the rest is processed in the same way to identify non-dominated solutions for the second front F_2 . This process continues until the population is properly ranked. So, can write [24]:

$$P = \bigcup_{j=1}^r F_j \quad (28)$$

Where, r is the number of fronts.

The same fitness value f_k is assigned to all of individuals of the same front F_k . This fitness value decreases while passing from the front F_k to the F_{k+1} . To maintain diversity in the population, a sharing method is used. Let consider d_{ij} the variable distance (Euclidean norm) between two solutions $\underline{X}_i$ and $\underline{X}_j$.

$$d_{ij} = \sqrt{\sum_{k=1}^S \left(\frac{X_k^{(i)} - X_k^{(j)}}{X_k^{\max} - X_k^{\min}} \right)^2} \quad (29)$$

Where S is the number of variables in the MOP. The parameters $X_k^{\max}$ and $X_k^{\min}$ respectively the upper and lower bounds of variable X_k .

$$\underline{X}_i = (X_1^{(i)}, X_2^{(i)}, \dots, X_S^{(i)}) \quad (30)$$

The sharing procedure is as follows :

Step 1: Fix the niche radius σ_{share} and a small positive number ε .

Step 2: Initiate $f_{min} = N_{pop} + \varepsilon$ and the counter of front $j = 1$.

Step 3: From the r non-dominated fronts F_j which constitute P .

$$P = \bigcup_{j=1}^r F_j \quad (31)$$

Step 4: For each individual $\underline{X}_q \in F_j$:

- Associate the dummy fitness $f_j^{(q)} = f_{\min} - \varepsilon$;
- Calculate the niche count n_{cq} as given in [] ;
- Calculate the shared fitness $f_j^{(q)} = \frac{f_j^{(q)}}{n_{cq}}$.

Step 5: $F_{\min} = \min(F_j^{(q)}; q \in P_j)$ and $j = j + 1$.

Step 6: If $j \leq r$, then, return to step 4. Else, the process is finished.

The MOEAs using non-dominated sorting and sharing have been criticized mainly for their $O(MN^3)$ computational complexity (M is the number of objectives and N is the population size). Also, these algorithms are not elitist approaches and they need to specify the sharing parameter. To avoid these difficulties, we present in the following an elitist MOEA which is called Non-dominated Sorting Genetic Algorithm II (NSGAI) [24-25].

NSGAI Approach: In this approach, the sharing function approach is replaced with a crowded comparison.

Initially, an offspring population Q_i is created from the parent population P_i at the t^{th} generation. After, a combined population R_i is formed.

$$R_i = P_i \cup Q_i \quad (32)$$

R_i is sorted into different no domination levels F_i as shown in the NSGA approach. So, we can write :

$$R_i = \bigcup_{j=1}^r F_j, \text{ where, } r \text{ is number fronts.}$$

Finally, one iteration of the NSGAI procedure is as follows :

Step 1: Create the offspring population Q_i from the current population P_i .

Step 2: Combine the two population Q_i and P_i to form R_i .

Step 3: Find the all non-dominated fronts F_i and R_i .

Step : Initiate the new population $P_{t+1} = \emptyset$ and the counter of front for inclusion $i = 1$.

Step 5: While $|P_{t+1}| + |F_i| \leq N_{pop}$, do:

$$\begin{aligned} P_{t+1} &\leftarrow P_{t+1} \cup F_i \\ i &\leftarrow i + 1 \end{aligned} \quad (33)$$

Step 6: Sort the last front F_i using the crowding distance in descending order and choose the first $(N_{pop} - |P_{t+1}|)$ elements of F_i .

Step 7: Use selection, crossover and mutation operators to create the new offspring population Q_{t+1} of size N_{obj} .

To estimate the density of solution surrounding a particular solution $\underline{X}_i$ in a non-dominated set F , we calculate the crowding distance as follows:

Step 1: Let's suppose $q = |F|$. For each solution $\underline{X}_i$ in F , set $d_i = 0$.

Initiate $m = 1$.

Step 2: Sort F in the descending order according to the objective function of rank m .

Let's consider $I^m = \text{sort}_{[f_m]}(F)$ the vector of indices, i.e. I_i^m is the index of the solution $\underline{X}_i$ in the sorted list according to the objective function of rank m .

Step 3: For each solution $\underline{X}_i$ which verifies $2 \leq I_i^m \leq (q-1)$, update the value of d_i as follows:

$$d_i \leftarrow d_i + \frac{f_{I_i^m+1}^m - f_{I_i^m-1}^m}{f_{I_i^m}^{\max} - f_{I_i^m}^{\min}} \quad (34)$$

Then, the boundary solutions in the sorted list (solutions with smallest and largest function) are assigned an infinite distance value, i.e. if, $I_i^m = 1$ or $I_i^m = q$, $d_i = \infty$.

Step 4: If $m = M$, the procedure is finished. Else, $m = (m + 1)$ and return to step 2.

Implementation of the NSGAI Approach: The optimal configuration of the UPFC devices is encoded by its location and control parameters.

The location is defined by the number n_L of line where it is installed and the number b_{sh} of the bus where the parallel component is connected. E_p , E_s , δ_p and δ_s are considered as the control parameters.

The proposed NSGAI has been implemented using real-coded genetic algorithm (RCGA). So, a chromosome X corresponding to a decision variable is represented as a string of real values x_i , i.e. $X = x_1 x_2 \dots x_{lchrom}$. $lchrom$ is the chromosome size and x_i is a real number within its lower limit a_i and upper limit b_i , i.e. $x_i \in [a_i, b_i]$. Thus, for two individuals having as chromosomes respectively X and Y and after generating a random number $\alpha \in [0,1]$, the crossover operator can provide two chromosomes X' and Y' with a probability P_c as follows [25]:

$$\begin{cases} X' = \alpha X + (1 - \alpha)Y \\ Y' = (1 - \alpha)X + \alpha Y \end{cases} \quad (35)$$

In this study, the non-uniform mutation operator has been employed. So, at the t th generation, a parameter x_i of the chromosome X will be transformed to other parameter x'_i with a probability P_m as follows:

$$x'_i = \begin{cases} x_i + \Delta(t, b_i - x_i), & \text{if } \tau = 0 \\ x_i - \Delta(t, x_i - a_i), & \text{if } \tau = 1 \end{cases} \quad (36)$$

$$\Delta(t, y) = y \left(1 - e^{-(1-t/g_{max})^\beta} \right) \quad (37)$$

Where τ is random binary number, r is a random number $\varepsilon \in [0,1]$ and g_{max} is the maximum number of generations. β is a positive constant chosen arbitrarily.

The following figure presents the NSGAI algorithm.

Simulation Results: The proposed algorithm is tested on the IEEE-14 bus test system, G3, G4 and G5 are synchronous compensators in this work.

Presentation of the Studied System: In order to verify the presented model of UPFC, the effectiveness of the approach proposed and illustrate the impacts of UPFC, we study two cases for a test system IEEE 14-bus, with and without UPFC. Data and results of system are based on 100 MVA and bus 1 is the bus of reference. All data of the system are given from Appendix.

Base Case: The convergence characteristic for the power flow program without UPFC is given in Figure 8.

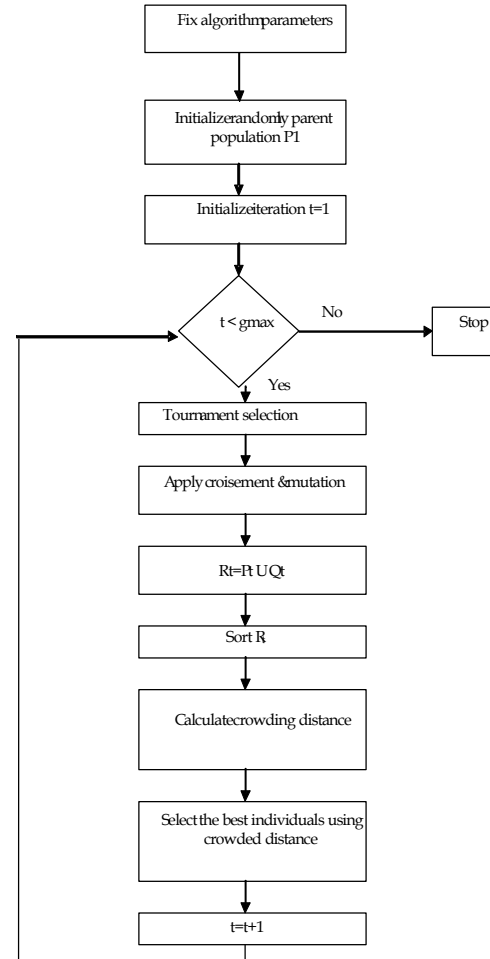


Fig. 5: Flow chart of NSGAI algorithm

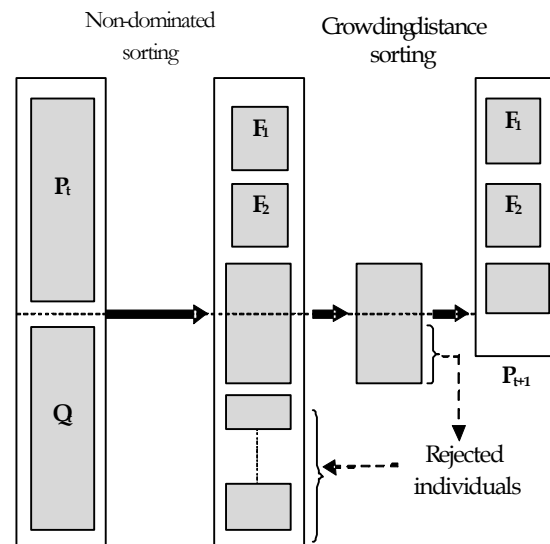


Fig. 6: One iteration of NSGAI

Table 1. Solutions of the power flow program for the system without UPFC

Bus No	V (pu)	θ (Degree)	Bus No	V (pu)	θ (Degree)
1	1.0600	0	2	1.0400	-5.9494
3	1.0100	-11.8544	4	0.9988	-11.0012
5	0.8261	-5.9961	6	1.0200	-15.7206
7	1.0231	-12.5841	8	1.0500	-14.6278
9	1.0090	-13.8579	10	0.8817	-13.9215
11	1.0507	-13.2540	12	1.0528	-11.5281
13	1.0418	-12.9908	14	0.8703	-14.0047

Figure 9 represents the evolution of the active production according to loading parameter. It can see clearly that the active production of two generators G1 and G2 increases from the nominal state of the load ($\lambda=1$ and $P_D = 2.59$ pu) to $\lambda=1.755$. This evolution will be stopping at the maximum loading parameter which corresponds to the voltage collapse point. The generators function almost near to their maximum limit, which corresponds well at a considerable cost.

Table 1 shows the voltage magnitudes and angles given by the power flow program, for the system without UPFC. The corresponding values of generation cost, voltage deviation and real power losses are respectively, 480.10^3 (\$/h), 0.16 (pu) and 0.17 (pu), when the active power requested (P_D) equal to 259 MW.

Optimal Case

Mono-Objective Optimization: To optimize the three functions, cost, voltage deviation and active power losses, the real coding genetic algorithm is used. The population size is 200 for generation cost and 300 for voltage deviation and active power losses. Crossover and mutation probabilities were selected as 0.9 and 0.01. The optimization program is characterized by maximum number of generations equal to 100.

Fig. 10, 11 and 12 illustrate the convergence of three objective functions, cost, active power losses and voltage deviation respectively.

Figures 10, 11 and 12 show respectively, the convergence of function cost, active power losses and voltage deviation to 477.103 (\$/h), 0.07 (pu) and 0.09 (pu), where, the active power requested (P_D) equal to 259 MW. These objectives are optimized individually.

Bi-Objectives Optimization

Generation Cost and Power Losses: On problem simulations, the population size and the maximum number of iterations were choosing respectively as 200 and 100. Crossover and mutation probabilities were selected as 0.9 and 0.01.

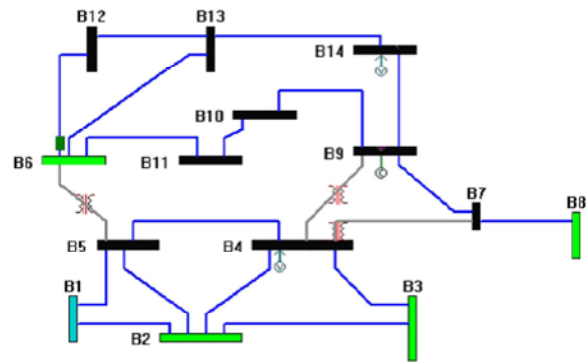


Fig 7: IEEE-14 bus test system

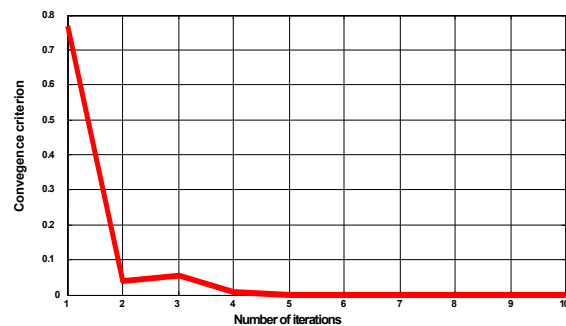


Fig. 8: Convergence criterion of the power flow algorithm

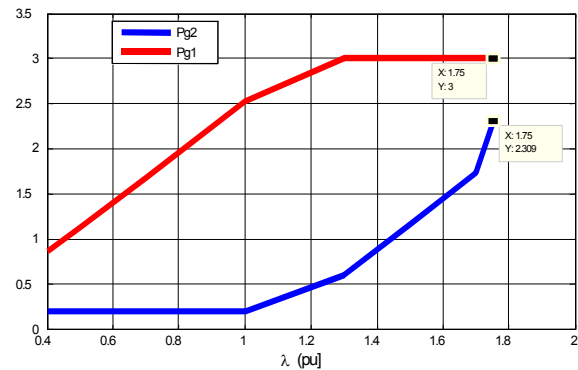


Fig. 9: Evolution of active power generation with loading parameter

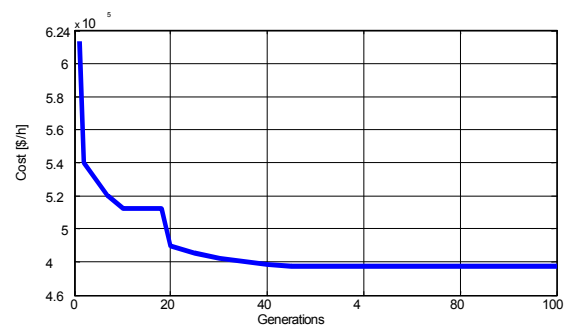


Fig. 10: Convergence of generation cost function

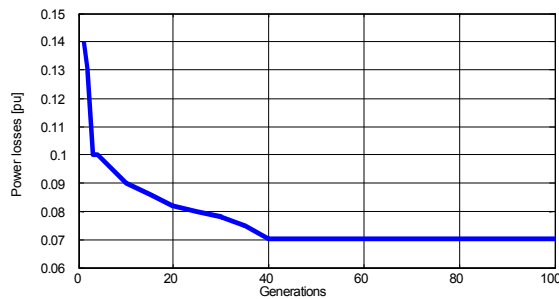


Fig. 11: Convergence of power loss function

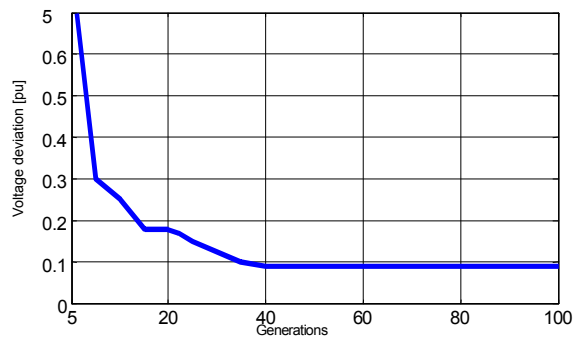


Fig. 12: Convergence of voltage deviation

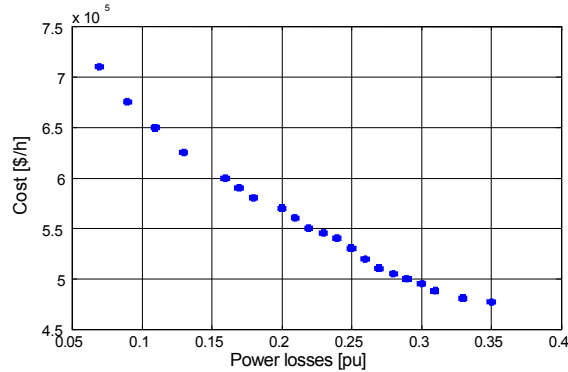


Fig. 13: Pareto-optimal front using NSGAII algorithm of power losses and cost function.

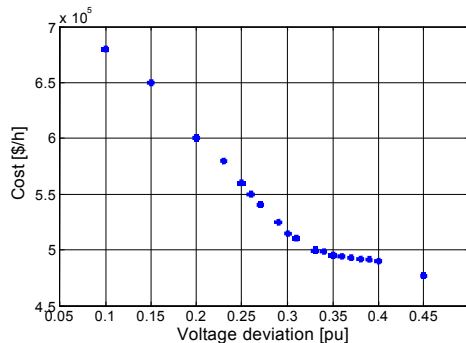


Fig. 14: Pareto-optimal front using NSGAII algorithm of voltage deviation and cost function.

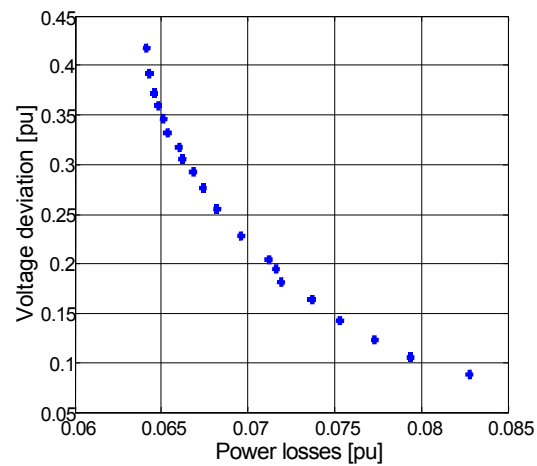


Fig. 15: Pareto-optimal front using NSGAII algorithm of power losses and cost function.

Fig. 13 shows, Pareto-optimal front for generation cost and active power losses.

The generation costs of the non-dominated solutions thus appear to be inversely proportional to their active power losses, as illustrate in Fig. 13.

Generation Cost and Voltage Deviation: On problem simulations, the population size and the maximum number of iterations were choosing respectively as 200 and 100. Crossover and mutation probabilities were selected as 0.7 and 0.01

Fig. 14 shows Pareto-optimal front for generation cost and Voltage deviation.

The generation costs of the non-dominated solutions thus appear to be inversely proportional to their voltage deviation, as illustrate in Fig. 14.

Voltage Deviation and Active Power Losses: On problem simulations, the population size and the maximum number of iterations were choosing respectively as 150 and 100. Crossover and mutation probabilities were selected as 0.8 and 0.01.

Fig.15 shows Pareto-optimal front for voltage deviation and active power losses.

The voltage deviation of the non-dominated solutions thus appear to be inversely proportional to their active power losses, as illustrate in Fig. 15.

Figure 15. shows that UPFC can minimize power losses and voltage deviation, with the properly selected parameters.

Table 1: Solutions of the power flow program for the system without UPFC

Bus No	V (pu)	θ (Degree)	Bus No	V (pu)	θ (Degree)
1	1.0600	0	2	1.0400	-5.9494
3	1.0100	-11.8544	4	0.9988	-11.0012
5	0.8261	-5.9961	6	1.0200	-15.7206
7	1.0231	-12.5841	8	1.0500	-14.6278
9	1.0090	-13.8579	10	0.8817	-13.9215
11	1.0507	-13.2540	12	1.0528	-11.5281
13	1.0418	-12.9908	14	0.8703	-14.0047

Table 2: Best solution for minimum voltage deviation

E_s [p.u.]	δ_s [°]	E_p [p.u.]	δ_p [°]	V_D [p.u.]	Correspondent P_L [p.u.]
0.1068	56.921	1.0588	-13.17	0.0841	0.0832

Table 3: Best solution for minimum power losses

E_s [p.u.]	δ_s [°]	E_p [p.u.]	δ_p [°]	P_L [p.u.]	Correspondent V_D [p.u.]
0.1141	10.017	1.0023	-20.07	0.0643	0.4207

Table 4: The limit values of the three functions

	Minimum cost	Minimum losses	Minimum deviation
Cost (\$/h)	4.8274e+005	6.3752e+005	6.1274e+005
Losses (pu)	0.2007	0.1116	0.1923
Deviation (pu)	0.2943	0.3156	0.1663
E_s [pu]	0.0010	0.1096	0.0032
δ_s [deg.]	55.6170	348.9485	95.8444
E_p [pu]	0.9248	1.0153	0.9000
δ_p [deg.]	4.2112	4.2112	3.4893
$Pg2$ [pu]	1.8491	2.3294	2.6213
$Pg1$ [pu]	2.5191	2.4927	2.7249

Table 5: Effect of UPFC on loading parameter

Case	λ_{max} [pu]	P_{max}	P_{nom}	$Pg1$ (pu)	$Pg2$ (pu)
Without FACTS	1.755	4.5454	2.59	3	2.3090
With FACTS	1.988	5.1489	2.59	2.7249	2.6213

Table 6: Impact of UPFC on generation cost for three years

Generation cost without FACTS (million \$)	Generation cost with FACTS (million \$)	Economic (million \$)
12614.4	12539	61.7

Table 2 shows that the optimal solution for minimum voltage deviation corresponds to maximum power losses. Conversely, in table 3, the optimal solution for minimum power losses corresponds to maximum voltage deviation.

The optimal location of UPFC for the two cases is between buses 12 and 13.

Multi Objectives Optimization: The population size and the maximum number of iterations were selected as 200 and 100. We keep the same crossover and mutation probabilities that those of optimization generation cost and active losses.

The Pareto-optimal front of generation cost, voltage deviation and active losses is illustrated in Fig. 16.

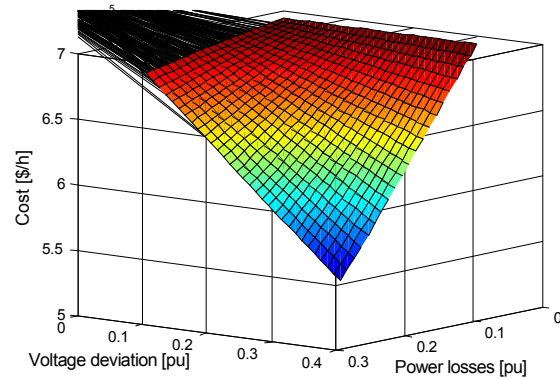


Fig. 16: Pareto-optimal front using SPEA algorithm in case of three objective functions.

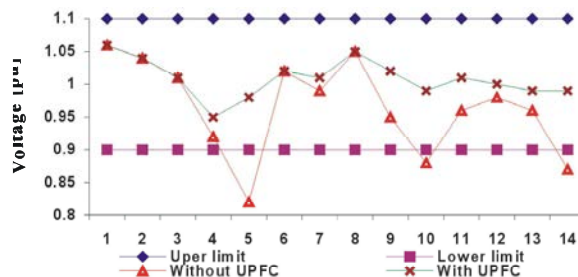


Fig. 17: Voltage profile after and before employing UPFC

The limit values of the three objectives with the properly selected parameters of UPFC are regrouped in Table 4.

The number of functions, variables and constraints reduce the margin variation of some parameters. The optimal place and the arrangement of UPFC are obtained with NSGAI approach by modification of crossover and mutation probabilities. This optimal location is between buses 12 and 13.

Effect of Upfc on Voltage Profile and Generation Cost:

The voltage profile of the system with and without UPFC devices are shown in Fig.17. As shown in the figure, the voltage at bus 5, bus10 and bus 14 were out of acceptable limits (<0.9 pu) and improved significantly with the UPFC devices installed.

Table 5 shows that the use of UPFC increases the loading parameter up to the value $\lambda=1.988$ pu compared to the base case $\lambda=1.755$ pu, without the generators reaching the maximum limits. An improvement of loading parameter of 0.2340 pu (equivalence of 60.6060 MW) is obtained with a minimum cost.

The unit for generation cost is (\$/Hour) and for the investment cost of FACTS devices are (\$). They must be unified into \$/Hour. Normally, the FACTS devices will be in-service for many years [26, 27]. However, only a part of its lifetime is employed to regulate the power flow. In this paper, three years is applied to evaluate the cost function. Therefore the average value of the investment costs are calculated using the following equation:

$$Cost_{Generation/3years} = Cost_{Generation/hour} * 8760 * 3 \quad (38)$$

UPFC capital cost (installing and equipment) equals to 13.7 millions \$ [28]. The reduced generation cost that is returned by using UPFC is given in Table. 6.

CONCLUSION

This paper presents the application of NSGAII technique to find the optimal location of UPFC for minimizing simultaneously generation cost of active power, real power loss in transmission lines and voltage deviation at load buses, under several equality and inequality constraints. Modified Newton-Raphson algorithm including UPFC is used to solve the load flow equations.

The UPFC can provide control of voltage magnitude, voltage phase angle and impedance. Therefore, it can be utilized to effectively increase power transfer capability of the existing power transmission lines, since it reduces considerably the real power losses and the generation cost and also an improvement in the voltage profile.

The simulations results obtained for the IEEE-14 bus network showed the effectiveness of the proposed method. This approach is able to give several possible solutions simultaneously. These solutions are presented by Pareto-optimal front. Also, this method does not impose any limitation on the number of objectives, constraints.

Appendix-1:

Table (A1): Line data for IEEE-14 BUS.

Line	R (Ω)	X(Ω)	Line	R (Ω)	X(Ω)
10-11	8.205	19.207	3-4	6.701	17.103
12-13	22.092	19.988	4-5	1.335	4.211
13-14	17.093	34.802	6-11	9.498	19.89
1-2	1.938	5.917	6-12	12.291	25.581
1-5	5.403	22.304	6-13	6.615	13.027
2-3	4.699	19.797	7-8	0	17.615
2-4	5.811	17.632	7-9	0	11.001
2-5	5.695	17.388	9-10	3.181	8.45

Appendix-2:

Table (A2): Transformer data for IEEE-14 BUS.

Transformer	Shc Volt. %	u, Magnitude HV-Side (pu)	u, Magnitude LV-Side (pu)
Trf 4-9	20.912	0.9079347	0.9030717
Trf 5-6	55.618	0.9195941	0.9354145
Trf 4-7	25.202	0.9079347	0.9267493

Appendix-3:

Table (A3): Load data for IEEE-14 BUS.

Load	Active power MW	Reactive power Mvar	Power Factor
Ld 10	14.157	9.123	0.841
Ld 11	5.505	2.831	0.889
Ld 12	9.595	2.517	0.967
Ld 13	21.235	9.123	0.918
Ld 14	23.438	7.865	0.948
Ld 2	34.134	19.977	0.863
Ld 3	148.177	29.887	0.980
Ld 4	75.189	-6.135	0.997
Ld 5	11.955	2.517	0.978
Ld 6	17.618	11.797	0.831
Ld 9	46.403	26.112	0.871

Appendix-4:

Table (A4): Generation data for IEEE-14 BUS.

Gi	N° Bus	P_{gi}^{min} (pu)	P_{gi}^{max} (pu)	Q_{gi}^{min} (pu)	Q_{gi}^{max} (pu)
G1	1	0.3	3	-0.5	0.5
G2	2	0.2	2.7	-0.8	1
G3	3	0.2	2	-0.8	0.8
G4	6	0.4	2	-0.7	0.7
G5	8	0.2	2.5	-0.8	0.8

Appendix-5:

Table (A5): Generation cost function for IEEE-14 BUS.

	a_i	b_i	c_i
G1	100	69	1.06
G2	100	69	0.4
G3	100	69	0
G4	100	13.8	0
G5	100	18	0

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