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UPFC Siting and Sizing in Power Network Using Two Different Evolutionary Algorithms

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Abstract

In emerging electric power systems, increased transactions often lead to the situations where the system no longer remains in secure operating region. The flexible Ac transmission system (FACTS) controllers can play an important role in the power system security enhancement. However, due to high capital investment, it is necessary to locate these controllers optimally in the power system. FACTS devices such as UPFC can regulate the active and reactive power control as well as being adaptive to voltage-magnitude control simultaneously because of their flexibility and fast control characteristics. Placement and sizing these devices in suitable location can lead to control in line flow and maintain bus voltages in desired level and so improve voltage stability margins. Moreover, this adjustment can improve voltage profile system along with reducing the power system losses. This paper proposes a systematic method by which optimal location and sizing of Unified Power Flow Controller (UPFC) to be installed using two different evolutionary algorithm. FACTS DEVICES model is incorporated into a Newton-Raphson algorithm to perform load flow analysis. Optimizing its location becomes a concern when coming to the practical implementation stage. Proposed algorithm is tested on IEEE 24 bus power system for optimal allocation as well as sizing of UPFC device and results are presented.

Keywords: Voltage Profile, Power line losses, Optimal Sitting and Sizing, UPFC, PSO, SFLA.
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1. Introduction

Modern power systems are prone to widespread failures. With the increase in power demand, operation and planning of large interconnected power system are becoming more and more complex, so power system will become less secure. Operating environment, conventional planning and operating methods can leave power system exposed to instabilities. Voltage instability is one of the phenomena which have result in a major blackout. Moreover, with the fast development of restructuring, the problem of voltage stability has become a major concern in deregulated power systems. To maintain security of such systems, it is desirable to plan suitable measures to improve power system security and increase voltage stability margins. FACTS devices can regulate the active and reactive power control as well as adaptive to voltage-magnitude control simultaneously because of their flexibility and fast control characteristics. Placement of these devices in suitable location can lead to control in line flow and maintain bus voltages in desired level and so improve voltage stability margins. FACTS devices can regulate the active and reactive-power control as well as adaptive to voltage magnitude control simultaneously by their fast control characteristics and their continuous compensating capability and so reduce flow of heavily loaded lines and maintain voltages in desired level[1].Besides, FACTS devices can improve both transient and small signal stability margins. Controlling the power flows in the network, under normal and abnormal conditions of the network, can help to reduce flows in heavily loaded lines, reduce system power loss, and so improve the stability and performance of the system without generation rescheduling or topological changes in the network [1]. Because of the considerable costs of the FACTS devices, it is so mementos to find out the optimal location for placement of these devices to improve voltage stability margins and enhance network security [2-7].

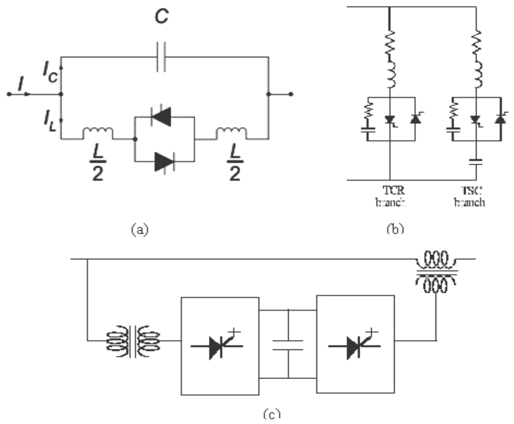

Fig. 1. Considered FACTS Devices (a) TCSC (b) SVC (c) UPFC

Effect of FACTS devices on power system security, reliability and load ability has been studied according to proper control objectives [5-15]. Some of papers have been tried to find suitable location for FACTS devices to improve power system security and load ability [14-17]. Optimal allocation of these devices in deregulated power systems has been presented in [18-19].

2. Particle Swarm Optimization

Kennelly inspired by social behaviour of bird flocking or fish schooling. PSO is a population based search method which it moves from a set of points with likely improved iterations. PSO uses a population of solution called particles, which fly through the search space with directed velocity vectors to find a better solution [8]. Each particle keeps track of its co-ordinates in the problem space which are associated with the best solution (fitness) it has achieved so far. This fitness value is stored. This value is called the pbest (personal best). Another “best” value that is tracked by the particle swarm optimizer is the best value obtained so far by any particle in the immediate neighbourhood of the particle. This location is called lbest (local best). When a particle takes all the population as its topological neighbours, the best value is called the gbest (global best). PSO concept consists of at each time step changing the velocity (accelerating) of each particle toward its pbest and ibest location. Acceleration is weighted pbest a random term with separate random numbers being generated for acceleration toward pbest and ibest locations. The velocity of the particle is given by [5]:

$$V_i^{(u+1)} = w \times V_i^{(u)} + C_1 \times rand() \times \left(pbest_i - P_i^{(u)}\right) + C_2 \times rand() \times (gbest_i - P_i^{(u)}) \quad (1)$$

And the position is given by:

$$P_i^{(u+1)} = P_i^{(u)} + V_i^{(u+1)} \quad (2)$$

The term rand()× $(pbest_i - P_i^{(u)})$ is called particle memory influence. The term rand()× $\left(gbest_i - P_i^{(u)}\right)$ is called swarm influence. $V_i^{(u)}$ which is the velocity of ith particle at iteration “u” must lie in the range

$$V_{min} \leq V(u)_i \leq V_{max} \quad (3)$$

The parameter V_{max} determines the resolution, or fitness, with wich regions are to be searched between the present position and the target position. If V_{max} is too high, particles may fly past good solutions. If V_{min} is too small, particle may not explore sufficiently beyond local solutions. V_{max} is often set at 10-20% of the dynamic range on each dimention. The constants C_1 and C_2 pull each particle towards pbest and gbest positions. Low value allow particles to roam far from the other hand, high value result in abrupt movement towards, or past, target regions. The acceleration constant C_1 and C_2 are often set to be 2.0. Suitable selection of inertia weight “w” provides a balance between global and local explorations thus requiring less iteration on average to find a sufficiently optional solution. The inertia weight W is set according to the following equation:

$$W = W_{msx} - \left[\frac{W_{max} - W_{min}}{ITER_{mx}}\right] \times ITER \quad (4)$$

Where W is the inertia weighting factor, W_{max} is maximum value of weighting factor, W_{min} is minimum value of weighting factor, $ITER_{max}$ is maximum number of iterations and ITER is current number of iteration [5, 7].

A) *Proposed algorithm steps:*

The sequential steps to find the optimum solution follow:

Step1: The power of each unit, velocity of particle, is randomly generated which must be in the maximum and minimum limit. These initial individuals must be feasible candidate solutions that satisfy the partial operation constraints.

Step2: each set of solution in the space should satisfy:

$$\sum_{i=1}^{N} P_g = P_D + P_L \quad (5)$$

$$P_L = P_{gg} \times Bu \times Pgg' + B0 \times Pgg' + B00u \quad (6)$$

Step3: The voltage profile and loss function of each individual Pgi, is calculated in the population using the evaluation function F. Here F is:

$$F = a \times (P_{gi}^2) + b \times P_{gi} + c \quad (7)$$

Where a,b and c are constants. The presented value is set as the pbest value.
Step4: Each pbest values are compared with the other pbest values in the population. The best evaluation value among the bpest is denoted as gbest.
Step5: The member velocity V of each individual Pg is updated according to the velocity update equation.
Step6: The velocity component constraint occurring in the limits from the following conditions are checked:

$$Vd_{min} = -0.5 \times P_{min}$$
$$Vd_{max} = +0.5 \times P_{max} \quad (8)$$

Step7: The position of each individual Pg is modified according to the position update equation:

$$Pgid(u+1) = Pgid(u) + Vid(u+1) \quad (9)$$

Step8: The cost function of each new is calculated if the evaluation value if each individual is better than previous pbest, the current value is set to be pbest. If the best pbest is better than gbest, the value is set to be gbest [5].
*Step*9: if the number of iterations reaches the maximum, then go to step 10. Otherwise go to step 2.
Step10: The individual that generates the latest gbest is the optimal generation power of each unit with the minimum total generation cost.

B) Shuffle Frog Leaping Algorithm

The OPF problem is a non-linear optimization problem. By considering the increased emission non-linearity degree and local optima numbers of this problem, it is necessary to solve it with a very accurate algorithm to prevent it from being trapped in local optima and to converge it to globally optimum results in proper time. SFLA mimics the metaphor of natural biological evolution that is based on populations of frogs in nature searching for food (Eusuff, Lansey, & Pasha, 2006). The SFLA is a decreased based stochastic search algorithm which is started with an initial frog population whose characteristics represent the decision variables of the optimization problem. An initial population of F frogs is created randomly. For K-dimensional problems (K variables), a frog i is represented as $X_i = (x_{i1}, x_{i2}, \dots, x_{ik})$. Initially, the objective function is calculated for each frog, and afterwards frogs are sorted in a descending manner according to their fitness.

In SFLA, the total population is divided into groups (memeplexes) that search independently. In this process, the first frog goes to the first memeplex, the second frog goes to the second memeplex, frog m goes to the qth memeplex, and frog mþ1 goes to the first memeplex, and so on. In the each memeplex, the frogs with the best and the worst fitness are recognized as Xb and Xw, respectively. Also, the frog with the best fitness in all memeplexes is recognized as Xg. Then, the following process is applied to improve only the frog with the worst fitness (not all frogs) in each iterate. Correspondingly, the location of the frog with the worst fitness is regulated as follows:

$$v_i = rand(0) \times (X_b - X_w) + rand(0) \times (X_g - X_w) \quad (10)$$

$$X_{w(new)} = X_w + v_i \rightarrow -v_{min} \leq v_{i_i} \leq v_{max} \quad (11)$$

where rand(.) is a random number between 0 and 1, and V_{max} is the maximum permitted change in a frog's location. If this process generates a better solution, it replaces the worst frog. Otherwise, the calculations in Equations (21) and (22) are repeated for specific iterations ($Iter_{max1}$). In addition, to provide the opportunity for random generation of improved information, random virtual frogs are generated and substituted in the population if the local search cannot find better solutions respectively in each iterate. After a number of iterations ($Iter_{max1}$), all groups are combined and share their ideas with themselves through a shuffling process. The local search and the shuffling processes continue until the defined convergence criteria are satisfied. The aim of the entire process is to determine global optimal solutions.

Besides the privileges of SFLA, it also has some problems, such as the possibility of being trapped in the local optima or premature convergence to local optima. Therefore, for solving the complicated optimization problem it is necessary to enhance the FLA algorithm's search ability by mutation or hybrid this algorithm by other optimization problems. In this paper a new mutation is proposed in order to support the SLFA drawbacks. This new mode is called the modified shuffle leaping frog algorithm (MSLFA).

3. Mathematical Model of UPFC Device

In this paper steady state model of FACTS devices are developed for power flow studies. So TCSC is modelled simply to just modify the reactance of transmission line. SVC and UPFC are modelled using the power injection models [20-24]. Models integrated into transmission line for TCSC and UPFC and SVC is modelled is incorporated into the bus as shunt element of transmission line. Mathematical models for FACTS devices are implemented by MATLAB programming language. The unified power flow controller (UPFC) is the most versatile among a variety FACTS devices which can be used for power flow control, enhancement of transient stability, damping system oscillations and voltage regulations. Load flow control with unified power flow controller can maintain the reliable system operation in the event of additionally demanded power transients. UPFC has been proved to be an effective means for regulating voltage profile and power flow in modern power systems. It facilitates greater control of power, such that it flows on the prescribed transmission routes and secure loading of transmission lines to levels nearer to their thermal limits is possible. In power systems, FACTS DEVICES are used for the best utilization of the existing transmission lines. UPFC is located in order to maximize the system load ability while observing thermal and voltage constraints. Power transmitted by the network to the consumers is increased keeping the power system in a secure state in terms of branch loading and voltage levels. Two types of UPFC models are reported in papers [22-25]. One is coupled model [22] and other is decoupled model [23-25]. In the first type, UPFC is modeled with series combination of a voltage source and impedance in the transmission line. In decoupled model, UPFC is modeled with two separated buses. First model is more complex compared with the second one because modification of Jacobian matrix in coupled model is inevitable. While decoupled model can be easily implemented in conventional power flow algorithms without modification of Jacobian matrix elements, in this paper, decoupled model used for modeling UPFC in power flow study (Fig 2).

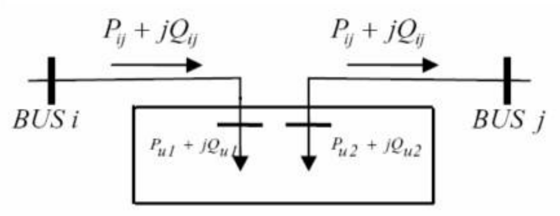

Fig. 2. Decoupled model for UPFC

UPFC controls power flow of the transmission line where is installed. To obtain UPFC model in load flow study, it is represented by four variables: P_{u1}, Q_{u1}, P_{u2}, Q_{u2}. Assuming UPFC to be lossless, real power flow from bus i to bus j can be expressed as:

$$P_{ii} = P_{u1} \tag{12}$$

Although UPFC can control the power flow, but cannot generate the real power. So:

$$P_{ii} = P_{u1} \tag{13}$$

$$P_{u1}+P_{u2} = 0 \tag{14}$$

Each reactive power output of UPFC Q_{u1}, Q_{u2} can be set to an arbitrary value depend on rating of UPFC to maintain bus voltage.

A) Power injection model

A series connected voltage source is located between nodes *m* and *k* in the given power system.

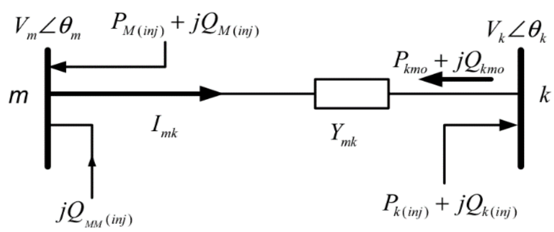

Fig. 3. Injecting Model

$P_{m(inj)}+jQ_{m(inj)}$ are power injected into node m by UPFC, as oppose to $P_{k(inj)}+jQ_{k(inj)}$ which are injected into node K by UPFC. These additional injection powers are used to control the power flow through the line between node m and node K. the new mismatch equation when UPFC is installed in power system are expressed as below:

$$P_{Gi} - P_{Li} = \sum_{j\in i} V_i V_j (G_{ij} cos\theta_{ij} + B_{ij} sin\theta_{ij}) \tag{15}$$

$$Q_{Gi} - Q_{Li} = \sum_{j\in i} V_i V_j (G_{ij} sin\theta_{ij} + B_{ij} cos\theta_{ij}) \tag{16}$$

where n is the total number of busses in the power system P_{Gi} and Q_{Gi} are active and reactive power injected to the bus I by generator. P_{Li} and Q_{Li} are active and reactive power extracted from bus I by load. V_i is magnitude of voltage of bus I, V_j is magnitude of voltage of bus j. $\theta_{ij} = \theta_i - \theta_j$ is the phase angle difference between bus I and j, G_{ij}, B_{ij} denote the element Y_{ij} of admittance matrix of power system.

$$P_{Gm} - P_{Lm} + P_{m(inj)} = \sum_{j\in m} V_m V_j (G_{mj} cos\theta_{mj} + B_{mj} sin\theta_{mj}) \tag{17}$$

$$Q_{Gm} - Q_{Lm} + Q_{m(inj)} = \sum_{j\in m} V_m V_j (G_{mj} sin\theta_{mj} + B_{mj} cos\theta_{mj}) \tag{18}$$

$$P_{GK} - P_{LK} + P_{K(inj)} = \sum_{j\in K} V_K V_j (G_{Kj} cos\theta_{Kj} + B_{Kj} sin\theta_{Kj}) \tag{19}$$

$$Q_{GK} - Q_{LK} + Q_{K(inj)} = \sum_{j\in K} V_K V_j (G_{Kj} sin\theta_{Kj} + B_{Kj} cos\theta_{Kj}) \tag{20}$$

The UPFC injection model can easily be incorporated in a load flow program. If UPFC is located between node m and node k in power system Linearized load flow model can be also presented.

4. Simulation and Results

Based on Section 3, the DG placement and sizing with an objective of increasing the voltage stability margin can be for-mulated by increasing the voltage of the system using DG units. The following equation is obtained from [24] and is used to improve the voltage profile of the system:

$$Max(V_{profile}) = \frac{\sum_{n=1}^{N} V_n pr_n}{96}, n = 1,2,\dots,N \tag{21}$$

The highest implies the best location for the installation of the UPFC units in term of improving the voltage profile. A weighting factor is chosen based on the importance and criticality of different loads. In this paper, the weighting factor is designed to be a ratio of the load demand at a specific bus to total demand:

$$k_i = {p_{i,n}}/{p_{TD,n}} \tag{22}$$

This means the bus that has highest load demand will have the highest factor. The rationale behind this design is to improve the voltages in the buses that have high power demand, and consequently improve the voltage stability margin, where is the power demand at bus at state, and is the total power demand of the system at state. Starting with a set of equal weighting factors, modifications can be made and, based on an analysis of the results, the set that will lead to the most acceptable voltage profile on a system-wide basis can be selected. It should be noted that if all the load buses are equally weighted, the value of is given as $k_1 - k_2 - k_n - {1}/{m}$ [24]. This voltage profile expression allows the important load to have a strong impact, because the weighting factor can be based on their important bus. To optimize the steady state performance of the distribution system, candidate integrates UPFC at the optimal location, minimum power loss along with improve the voltage profile as double objective function while satisfying several equality and inequality constrains [14]-[16].

$$PL = \left[\left(\sum_{l=1}^{L} P_{iLoss}\right)^2 + \left(\sum_{l=1}^{L} Q_{iLoss}\right)^2\right]^{1/2} \tag{23}$$

$$V_P = \sum_{i=1}^{N\,Bus} (Bus\ Voltage_i - 1) \tag{24}$$

$$Fitness = W_1 \times V_P + W_2 \times P_L \tag{25}$$

Where V_p is voltage profile violation from the base voltage (1 p.u).

5. Case Studies

As illustrated in Fig. 4, 24bus test system with 10 generators has been considered. PSO and SFLA applied for compression the final results to achieve the optimum placement and sizing of the UPFC.

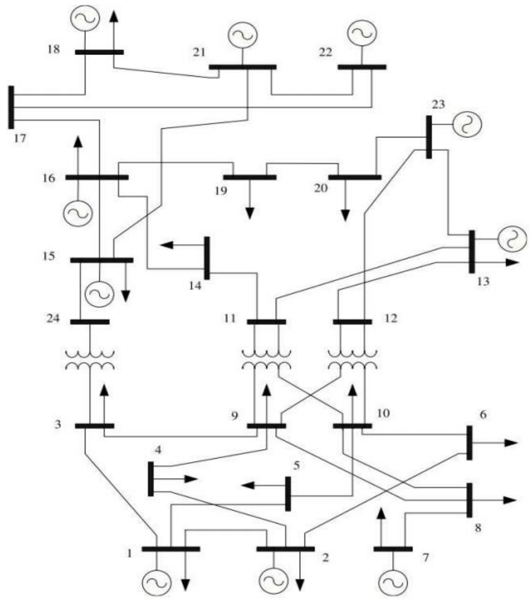

Fig. 4. 24 bus test system [1]

Table 1., shows the compression of buses which are used in order to place the UPFC as well as amount of reactive power which is adjusted by SFLA and PSO. Table 2 and Fig. 5 illustrate UPFC parameters along with enhanced voltage profile before and after UPFC allocation and sizing.

Table.1.
PSO and SFLA results for different approaches

	Time	***Fitness***	***V_p***	***Pl_{oss}***
Base Grid	---------	0.7909	0.5818	51.2464
PSO	306.8601	0.7801	0.5536	51.5794
SFLA	62.9842	0.7800	0.5536	51.5776

In order to improve the final results weight factor is changed to 0.6 for power loss and 0.4 for voltage profile. Table 2 shows the new results achieved from changing the weight factor

Table.2.
UPFC parameter adjustment using PSO and SFLA

	Base Grid	***PSO***	***SFLA***
Time (Sec.)	-	226	63.09366
Fit	0.8327	0.8239	0.8239
Vp	0.5818	0.5689	0.5691
P_{loss}	51.2464	50.9316	50.9310
Q_{conv}	-	-17.164	-17.056
Line	-	7	7
r	-	0.0786	0.0778

In compression between PSO and SFLA, PSO has better and more accurate results with less total operational cost and higher in risk level. Higher risk means less reliable and unsafe schedule. In compression between study in this paper and [1], this study has improved the results. On the other hand, as illustrated in Fig. 6, convergence speed in SFLA is much higher than the PSO as for SFLA after almost 500 iteration simulations reach the final result where in PSO it took about 800 iterations to reaching the optimum answer.

6. Conclusion

In this paper a novel approach for optimal placement of UPFC as FACTS devices based on Particle Swarm Optimization Algorithm (PSO) and Shuffle Frog Leaping Algorithm (SFLA) is presented. Simulation of IEEE 24 bus test system for different scenarios along with different weight factors for the placement and sizing of UPFC devices leads to improve in voltage profile margin of power system and reduce losses.

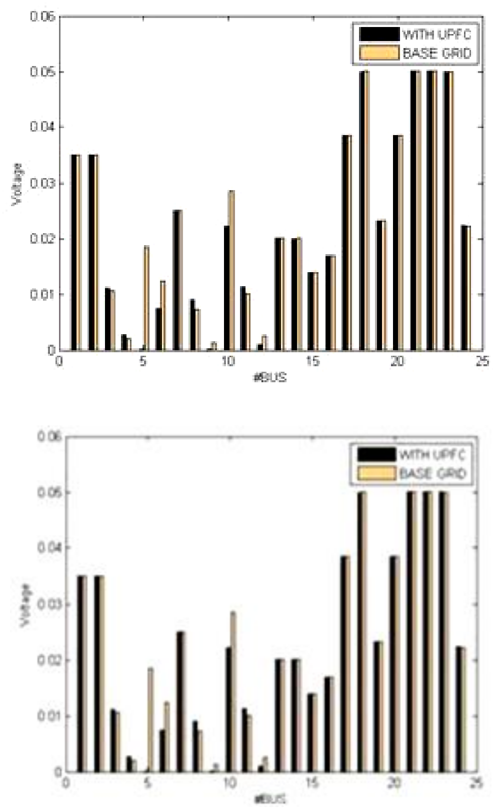

Fig. 5. Voltage profile improvement comparison between base grid and after UPFC placement and sizing (a) results related to PSO algorithm (b) results related to SFLA algorithm

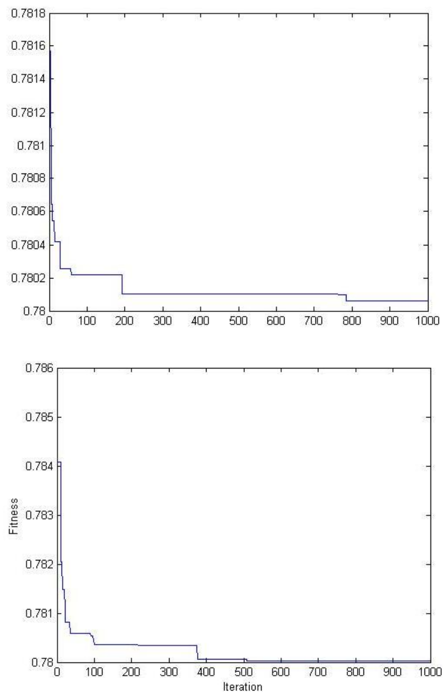

Fig. 6. Comparison of iteration to reaching the optimum result (a) PSO algorithm (b) SFLA algorithm

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