Optimal Placement of Compensating Devices in Distribution System by Using PSO Algorithm

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Abstract: ***In a power system, power flows from generating centers to load centers. This process requires investigation, such as bus voltage profile, flow of active power (MW) and reactive power (MVar) in transmission lines, the effect of rearranging circuits and installation of regulating devices etc., for different loading conditions. As modern power system has become more large and complex, due to great electric power demands imposed upon high voltage transmission networks, these investigations should be done with some sort of simulation of the system. FACTS have made the power systems operation more flexible and secure. They have the ability to control, in a fast and effective manner. Amongst the several FACTS controllers, the Unified Power Flow Controller (UPFC) is most effective to improve the voltage profile and reduce the power loss. In other words it can provide functional capabilities of controlling both the active and reactive power independently. Power flow studies and optimization techniques are essential tools for the safe and economic operation of large electrical systems. There are several techniques to find the location of FACTS devices. But in this thesis the optimal placement of UPFC is found using fuzzy approach as the fuzzy can be easily analyzed. The rating value of UPFC is obtained by PSO method which iteratively optimizes global best solution for different loading conditions. The proposed method is tested on the node having maximum loss reduction and poor voltage profile improvement for the various load conditions, like 85%, normal and 110% overloading cases. The overall improvement of the system performance using UPFC is demonstrated on IEEE 14-bus and IEEE 30-bus test systems and the results are discussed.***

Keywords: PSO algorithm, UPFC, IEEE-14 bus system, IEEE-30 bus system

1. Introduction

An electric power system consists of three principle divisions, the generating stations, the transmission systems, and the distribution systems. Electric power is produced by generators, consumed by loads, and transmitted from generators to loads by the transmission system. In the present day scenario, the growing demand and tight restrictions on construction of new transmission lines has resulted in unscheduled power flows and higher transmission losses. This has made the transmission systems increasingly stressed, more difficult to operate and vulnerable to security threats. In addition, existing traditional transmission facilities, in most cases, are not designed to handle the control requirements of complex, highly interconnected power systems. This overall situation requires the review of traditional transmission methods and practices and the creation of new concepts, which would allow the use of existing generation and transmission lines up to their full capabilities without reduction in system stability and security. Another reason that is forcing the review of traditional transmission methods is the tendency of modern power systems to follow the changes in today's global economy that are leading to deregulation of electrical power markets in order to transfer desired power and stimulate competition between utilities. The basic structure of a power system is shown in Figure.1.1.

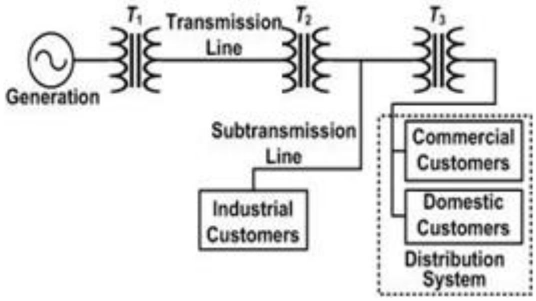


Figure: Typical Electrical Power System

Power System Constraints:

As stated in the introduction, transmission systems are being pushed closer to their stability and thermal limits while the focus on the quality of power delivered is greater than ever. The limitations of the transmission system can take many forms and many involve power transfer between areas or within a single area or region and may include one or more of the following characteristics:

- Steady-state power transfer limit
- Voltage stability limit
- Dynamic voltage limit
- Transient stability limit
- Power system oscillation damping limit
- Inadvertent loop flow limit
- Thermal limit
- Short-circuit current limit
- Others

These constraints affect the quality of power delivered. However, these constraints can be suppressed by enhancing the power system control. One of the best methods for reducing these constraints is FACTS devices. With the rapid development of power electronics, Flexible AC Transmission Systems (FACTS) devices have been proposed and implemented in power systems. FACTS devices can be utilized to control power flow and enhance system stability. Particularly with the deregulation of the electricity market, there is an increasing interest in using FACTS devices in the operation and control of power systems. A better utilization of the existing power systems to increase their capacities and controllability by installing FACTS devices becomes imperative. FACTS devices are cost effective alternatives to new transmission line construction. Reactive power compensation is provided to minimize power transmission losses, to maintain power transmission capability and to maintain the supply voltage. Shunt compensation is a method to control the impedance of a transmission line.

2. Particle Swarm Optimization

Introduction

Kennedy and Eberhart first established a solution to the complex non-linear optimization problem by imitating the behavior of bird flocks. They generated the concept of function-optimization by means of a particle swarm. Consider the global optimum of an *n*-dimensional function defined by

$$f(x_1, x_2, x_3\ldots\ldots\ldots x_n) = f(X).$$

where x_i is the search variable, which represents the set of free variables of the given function. The aim is to find a value x^* such that the function $f(x^*)$ is either a maximum or a minimum in the search space.

The Particle Swarm Optimization (PSO) algorithm is a multi-agent parallel search technique which maintains a swarm of particles and each particle represents a potential solution in the swarm. All particles fly through a multidimensional search space where each particle is adjusting its position according to its own experience and that of neighbors. Suppose x_i^t denote the position vector of particle i in the multidimensional search space (i.e. R^n) at time step, then the position of each particle is updated in the search space by

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad \text{with } x_i^0 \sim U(x_{min}, x_{max})$$

Where, v_i^t is the velocity vector of particle that drives the optimization process and reflects both the own experience knowledge and the social experience knowledge from the all particles; $U(x_{min}, x_{max})$ is the uniform distribution where x_{min} *and* x_{max} are its minimum and maximum values respectively.

Therefore, in a PSO method, all particles are initiated randomly and evaluated to compute fitness together with finding the personal best (best value of each particle) and global best (best value of particle in the entire swarm). After that a loop starts to find an optimum solution. In the loop, first the particles' velocity is updated by the personal and global bests, and then each particle's position is updated by the current velocity. The loop is ended with a stopping criterion predetermined in advance.

The global best PSO (or g_{best} PSO) is a method where the position of each particle is influenced by the best-fit particle in the entire swarm. It uses a star social network topology where the social information obtained from all particles in the entire swarm.

In this method each individual particle has a current position in search space x_i, a current velocity v_i and a personal best position in search space $p_{best,\,i}$. The personal best position $p_{best,\,i}$ corresponds to the position in search space where particle had the smallest value as determined by the objective function f, considering a minimization problem. In addition, the position yielding the highest value amongst all the personal best $p_{best,\,i}$ is called the global best position which is denoted by g_{best}.

Considering minimization problems, then the personal best position $p_{best,\,i}$ at the next time step, t + 1, is calculated as

$$P_{best,i}^{t} = \begin{cases} P_{best,i}^{t} & if\ f(x_i^{t+1}) > P_{best,i}^{t} \\ x_i^{t+1} & if\ f(x_i^{t+1}) \le P_{best,i}^{t} \end{cases}$$

Where f :R^n-→R is the fitness function. The global best position g_{best} at time step is calculated as

$$G_{best} = \min\{P_{best,i}^{t}\}, \text{where } i \in [1, \ldots, n]$$

Therefore it is important to note that the personal best $p_{best,\,i}$ is the best position that the individual particle has visited since the first time step. On the other hand, the global best position g_{best} is the best position discovered by any of the particles in the entire swarm.

Velocity Updates

PSO is initialized with a group of random particles and the searches for optima by updating generations. In every iteration each particle is updated by following "two best" values. The first one is the best solution (fitness value) it has achieved so far. This is called P_{best}. Another value that is tracked by the particle swarm optimizer is the best value obtained so far by any particle in the population. This best value is the global best called G_{best}. After finding the best values the particles updated its velocity and position with the following equation.

PSO, simulation of bird flocking in two-dimension space can be explained as follows. The position of each agent is represented by XY-axis position and the velocity is expressed by V_x (the velocity of X-axis) and V_y (the velocity of Y-axis) which is shown in figure 4.5. Modification of the agent position is realized by the position and velocity information. PSO procedures based on the above concept can be described as follows. Namely, bird flocking optimizes a certain objective function. Each agent knows its best value so far (p_{best}) and its XY position. Moreover, each agent knows the best value in the group (g_{best}) among p_{best}. Each agent tries to modify its position using the current velocity and the distance from p_{best} and g_{best}. The modification can be represented by the concept of velocity. Velocity of each agent can be modified by the following equation,

$$Vi^{k+1}=V_i^{k} + C_1\times rand_1\times(p_{besti} - S_i^k) + C_2\times rand_2\times(g_{besti} - S_i^k)$$
$$S_i^{k+1} = S_i^k + Vi^{k+1}$$

Where,

Vi^{k+1}	= Velocity of particle i at iteration k+1
V_i^k	= Velocity of particle i at iteration k
S_i^{k+1}	= Position of particle i at iteration k+1
S_i^k	= Position of particle i at iteration k
C_1	= Constant weighting factor related to p_{best}
C_2	= Constant weighting factor related to g_{best}
$Rand_1$	= Random number between 0 and 1
$Rand_2$	= Random number between 0 and 1
P_{best}	= p_{best} position of particle i
G_{best}	= g_{best} position of the swarm

Equations (4.7) and (4.8) describe the velocity and position update, respectively. The equation (4.7) calculates a new velocity for each particle based on the particle's previous velocity.

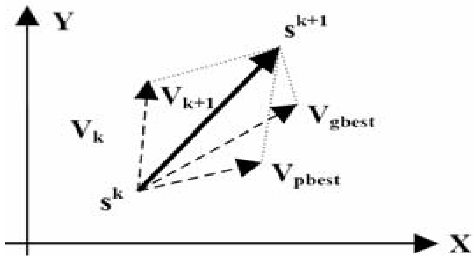


Figure: Concept of modification of a searching point

S^k = Current position
S^{k+1} = Modified position
V_{orig} = Current velocity
V_{mod} = Modified velocity
V_{pbest} = Velocity based on P_{best}
V_{gbest} = Velocity based on G_{best}

PSO Parameters

The performance of the PSO is greatly affected by its parameter values. Therefore, a way to find a suitable set of parameters has to be chosen. In this case, the selection of the PSO parameters follows the strategy of considering different values for each particular parameter and evaluating its effect on the PSO performance. The optimal values for the PSO parameters are shown in Table .

Number of Particles

There is a trade-off between the number of particles and the number of iterations of the swarm and each particle fitness value has to be evaluated using a power flow solution a teach iteration, thus the number of particles should not be large because computational effort could increase dramatically. Swarms of 5 and 20 particles are chosen as an appropriate population sizes.

Inertia Weight

The inertia weight is linearly decreased. The purpose is to improve the speed of convergence of the results by reducing the inertia weight from an initial value of 0.9 to 0.1 in even steps over the maximum number of iterations as shown in equation below,

$$Wk = 0.9\text{-}0.8\left(\frac{\text{iter}-1}{\text{max iter}-1}\right)$$

Where,
Wk is the inertia weight at iteration k.
iter is the iteration number (k).
Maxiter is the maximum number of iterations.

Acceleration Constants

A set of three values for the individual acceleration constants are evaluated to study the effect of giving more importance to the individual's best or the swarm's best: C1 = {1.5, 2, 2.5}. The value for the social acceleration constant is defined as: C2 = 4.5 – C1.

Number of Iterations

Different numbers of iterations {10, 25, 50, 100} are considered in order to evaluate the effect of this parameter on the PSO performance.

Values for Maximum Velocity

In this case, for each particle component, values for the maximum velocity have to be selected based on previous results, a value of 7 is considered as the maximum velocity for the location line number.

Table: Optimal Values for PSO Parameters

Parameter	Optimal values
Number of particles	25
Inertia weight	Linearly decreases
Individual acceleration constant	2.5
Social acceleration constant	2
Number of iterations	100
Velocity bounds	(0.1-0.9)
Rand1, Rand2	(0.3, 0.2)

PSO Algorithm

Step 1: Initially [nop x *n*] number of particles are generated randomly within the limits, where nop is the population size and *n* is the number of UPFC devices. Each row represents one possible solution to the optimal UPFC-sizing problem.

Step 2: Similarly [nop x n] number of initial velocities is generated randomly between the limits. Iteration count is set to one.

Step 3: By placing all the '*n'* UPFC devices of each particle at the respective candidate locations and load flow analysis is performed to find the total real power lossPL_{upfc} . The same procedure is repeated for the 'nop' number of particles to find the total real power losses. Fitness value corresponding to each particle is evaluated using the equation for maximum loss reduction.

Fitness function for maximum loss reduction is given by:
Fitness $F_A = P_L - P_{Lupfc}$
Where, PL is Original total real loss, P_{Lupfc} is Present total real loss with UPFC.

Step 4: New velocities for all the particles within the limits are calculated using above equation and the particle positions are updated using above equations.

Step 5: Once the particles are updated, load flow analysis is performed; new-Fitness is calculated using equation . If the new-fitness is greater than P_{best} -fitness then the corresponding particle is moved to the p_{best}-particle.

Step 6: Maximum of P_{best} -fitness gives the g_{best} -fitness and the corresponding particle is stored as g_{best} -particle.

Step 7: From P_{best} --fitness maximum fitness and average fitness values are calculated. Error is calculated using the below equation.
Error = (max. fitness – avg. fitness)
If this error is less than a specified tolerance then go to step 9.

Step 8: The current iteration count is incremented and if iteration count is not reached maximum then go to step 4.

Step 9: g_{best} -fitness gives maximum loss reduction and g_{best} -particle gives the optimal UPFC sizes.

PSO Flow Chart

In conventional PSO algorithm, the search velocity v(n) is always clamped within a range, which is denoted by V_{max}. Given an optimization problem, the proper range of V_{max} for good performance is always limited and hard to be predicted. Hence, a PSO with decreasing V_{max} method (PSO) is developed, in which V_{max} is decreasing over time. By using this method, a large scale of searching is expected at the early steps, so that the population can remain in enough diversity profitable to converge to the global optimum. As the searching process continues, the searching scale is reduced to allow the solution to be found.

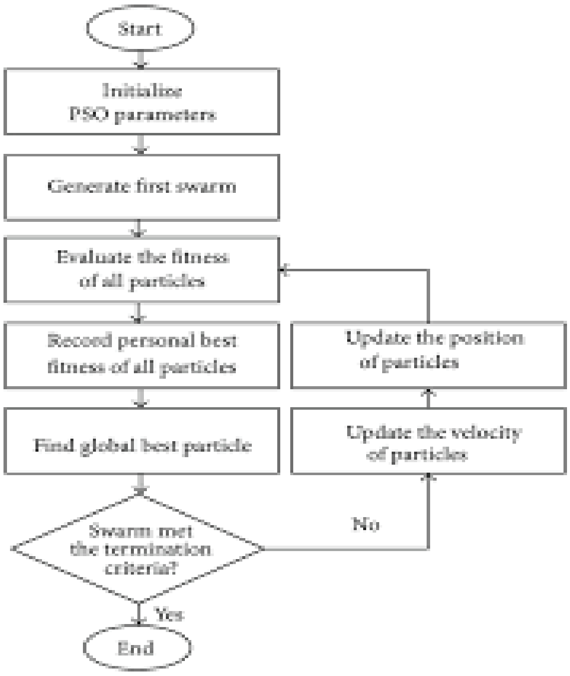


Figure: Flow chart of PSO

3. Results and Discussions

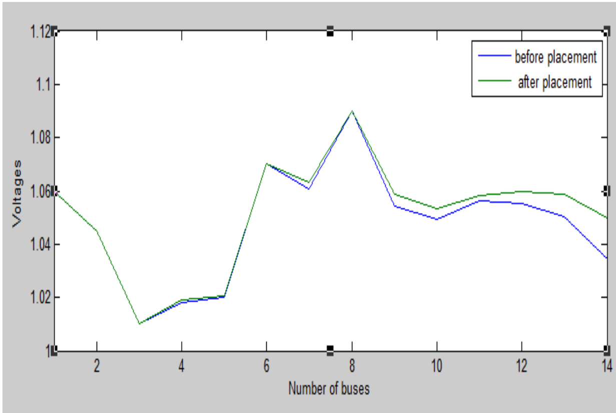
Results for 14 bus system with UPFCs with PSO for various locations.

Loading condition	Losses without UPFC (MW)	UPFC Location	PSO	
			Rating of UPFC (p.u)	Losses with UPFC (MW)
100% Normal loading	13. 3938	5	4∠8.484 3∠9.256	13.3196
85% loading	8.0728	5, 4	3∠7.582 3∠8.595	8.0488
110% loading	16.7223	14, 9	4∠8.756 3∠7.782	16.6266

Voltages of 14 bus system for (100%) normal loading.

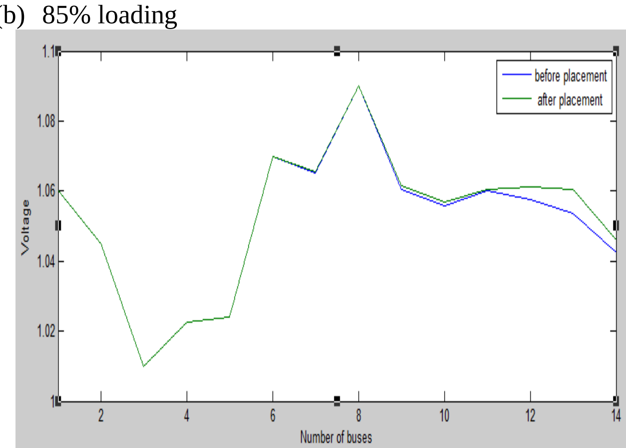
Bus no	Voltages (p.u)	
	Before UPFC	After UPFC
1	1.060000	1.0600
2	1.045000	1.0450
3	1.010000	1.0100
4	1.018275	1.0190
5	1.020034	1.0205
6	1.070000	1.0700
7	1.060813	1.0633
8	1.090000	1.0900
9	1.054083	1.0590
10	1.049452	1.0535
11	1.056123	1.0582
12	1.055048	1.0597
13	1.050109	1.0587
14	1.034347	1.0498

(a) Normal loading.



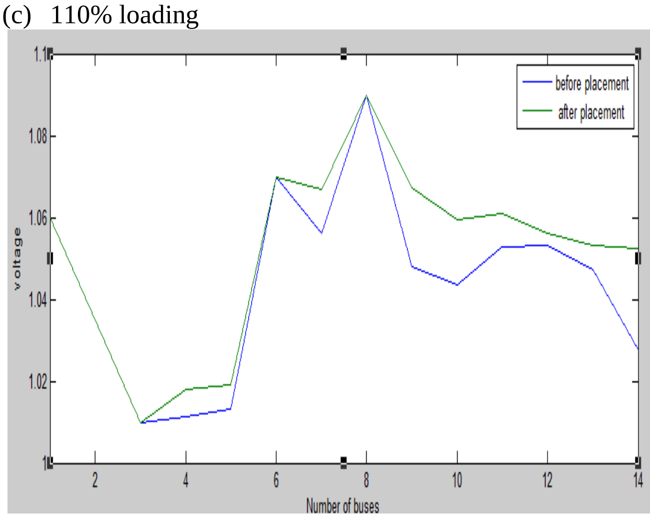
Voltage profile before and after placement of UPFC for normal loading (100%)

(b) 85% loading



Voltage profile before and after placement of UPFC for under loading (85%).

(c) 110% loading



Voltage profile before and after placement of UPFC for heavy loading (110%)

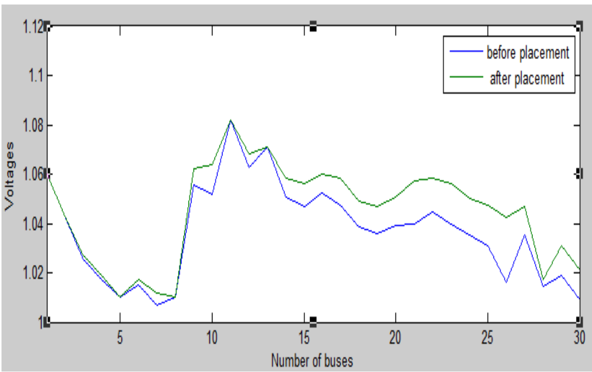
C	Losses without UPFC (MW)	UPFC Location	PSO	
			Rating of UPFC (p.u)	Losses with UPFC (MW)
Normal loading	17.528	21, 24, 30	5∠2.852, 3∠1.298, 1∠0.565	17.3568
85% loading	12.1131	26 21, 7	4∠1.825, 3∠1.296, 1∠0.425	12.0155
110% loading	21.9318	21, 24, 26	5∠2.992, 2∠0.942 1∠0.956	21.7544

Results for 30 bus system with UPFCs with PSO for various locations.

Voltages of 30 bus system for (100%) normal loading.

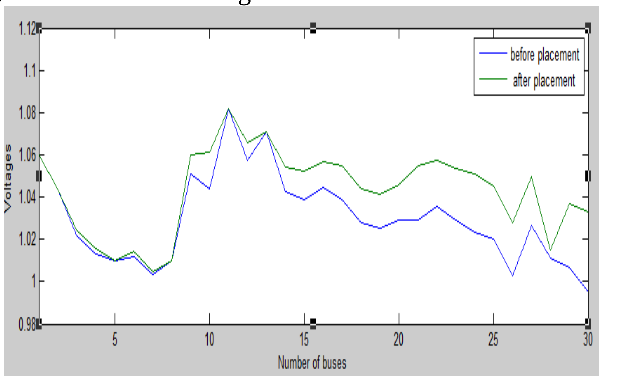
Bus no	Voltages (p.u)	
	Before UPFC	After UPFC
1	1.060000	1.0600
2	1.043000	1.0430
3	1.021675	1.0237
4	1.012920	1.0154
5	1.010000	1.0100
6	1.012084	1.0146
7	1.003468	1.0050
8	1.010000	1.0100
9	1.050724	1.0600
10	1.043758	1.0615
11	1.082000	1.0820
12	1.057605	1.0655
13	1.071000	1.0710
14	1.042879	1.0541
15	1.038445	1.0525
16	1.044520	1.0566
17	1.038654	1.0548
18	1.028158	1.0437
19	1.025210	1.0416
20	1.029062	1.0458
21	1.029261	1.0549
22	1.035288	1.0572
23	1.029134	1.0537
24	1.023652	1.0507
25	1.020157	1.0450
26	1.002530	1.0278
27	1.026518	1.0497
28	1.010864	1.0151
29	1.006749	1.0369
30	0.995315	1.0329

(a) 85% loading.



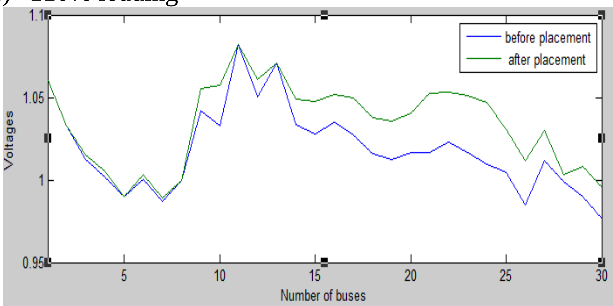
Voltage profile before and after placement of UPFC for under loading (85%)

(b) 100% normal loading.



Voltage profile before and after placement of UPFC for normal loading (100%)

(c) 110% loading



4. Conclusions

In this thesis, the power loss reduction and voltage profile improvement in the transmission network is done with the help of UPFC device which has been incorporated with the help of two techniques namely fuzzy approach and particle swarm optimization. The optimal locations of UPFC are obtained using fuzzy approach and optimal ratings for the respective locations are obtained using PSO algorithm.

The proposed method is tested on IEEE-14 bus system where power loss reduction before and after placement of UPFC for different loading conditions are considered. The total active power loss for normal loading condition is reduced from 13.3938 MW to13.3196 MW, under loading condition loss is reduced from 8.0728MW to 8.0488 MW and over loading condition from 16.7223 MW to 16.6266 MW with simultaneous improvement of the voltages at buses.

The proposed method is tested on IEEE-30 bus system where power loss reduction before and after placement of UPFC for different loading condition are considered. The total active power loss for normal loading condition is reduced from 17.528 MW to 17.3568 MW, under loading condition loss is reduced from 12.1131MW to 12.0155 MW and over loading condition from 21.9318 MW to 21.7544 MW with simultaneous improvement of the voltages at buses.

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