Performance of unified power-flow controller by proposed Simulated Annealing methods enhance the voltage stability

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Abstract- *The OPF challenge could be defined as the best possible allotment of energy structure controls to gratify the precise purpose of fuel expenditure, energy loss, as well as bus voltage divergence. For controlling the power flow and enhancing system stability, the research includes FACTS device of UPFC. UPFC provides control of power system parameters, such as terminal voltage, line impedance, and phase angle, thereby providing necessary real and reactive power flow control. DC link voltage controller in UPFC plays a vital role in control of terminal voltage and power. PI and Simulated Annealing (SA) methods are used as DC link voltage controller and analyzed. Performance of UPFC by proposed SA method is compared with PI in the aspects of DC link voltage, real and reactive power, and THD.*

Keywords- Unified power-flow controller, Simulated Annealing, voltage divergence, DC link voltage

1. INTRODUCTION

The OPF methods are generally grouped as Conventional and Intelligent. The conventional techniques comprise the eminent techniques like Newton method, Gradient method, Quadratic Programming method, Interior point method and Linear Programming method [1].

OPF aims to optimize a certain objective, subject to the network power flow equations and system and equipment operating limits. The optimal condition is attained by adjusting the available controls to minimize an objective function subject to specified operating and security requirements.

The existing and proposed techniques for the solution of OPF problem is covered in present study. They involve OPF problem formulation, constraints, objective function, applications and in-depth reporting of different popular OPF methods [2].

Intelligent techniques comprise the newly developed and popular methods like Particle swarm optimization, Genetic Algorithm. In this research for an analysis of optimal power flow evolutionary and metaheuristic algorithms are considered. In the evolutionary algorithms PSO and GA are chosen for its multi-parent effect over single-point techniques such as simulated annealing and tabu search. Among the various metaheuristic algorithms Bat algorithm has shown superiority over many other metaheuristics over a wide range of applications [3]. Therefore in this thesis PSO, GA and BAT algorithm are proposed for an analysis of optimal power flow.

For optimum power flow, the solution methodologies problem is extensively covered in this chapter. Reactive power are normally used for the control variables such as adjust on-load tap changing ratio, reactive power compensation capacitor capacity and generator terminal voltage to reduce active power losses.

2. METHODOLOGY

2.1 Particle Swarm Optimization

"Particle Swarm Optimization (PSO) is a population-based stochastic optimization technique inspired by social behavior of fish schooling or bird flocking [4], [5]. In PSO, the search for an optimal solution is carried out using a population of particles, each of which corresponds to a candidate solution to the optimization problem. By following current optimal particles by flying around a multidimensional space, particles change their position until a comparatively unchanged position has been attained or until computational margins are surpassed. Each particle corrects its trajectory on the way to its own prior best position and towards the global best position achieved till then. PSO is easy to execute and offers quick convergence for several optimization problems and has gained a lot of concentration in power system applications recently."

By means of a population of random solutions the system is initialized and searches for optima by updating generations. In PSO, particles called the potential solutions fly through the problem space by following the current optimum particles. Each particle creates its verdict using its own knowledge together with its neighbor"s experience. The main difference between the PSO compared to GA is that PSO does not have genetic operators such as crossover and mutation [6]. Particles update themselves with the internal velocity; they also have a memory important to the algorithm. Flow chart of PSO is shown in Fig. 1.

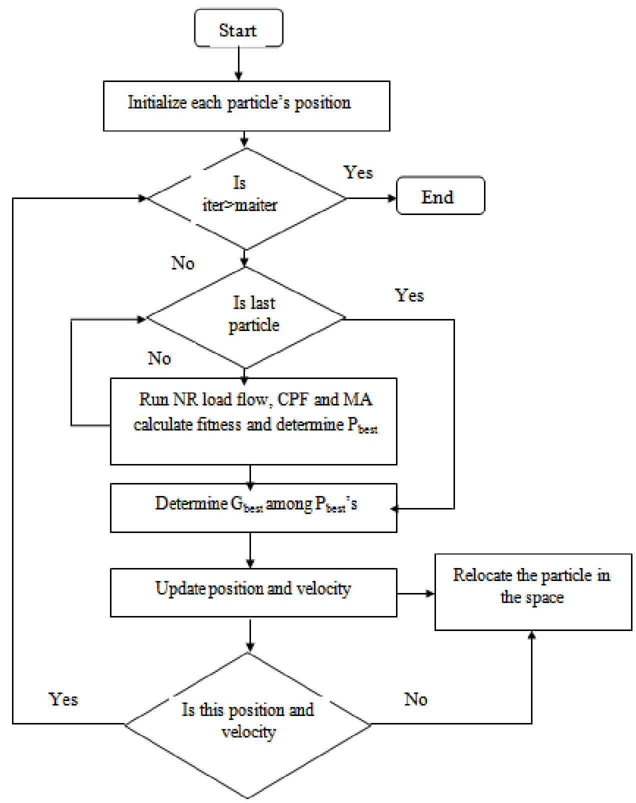

Fig 1. Flow Chart of proposed PSO algorithm

2.1.1 Solution Algorithm

The depiction of basic components necessary for the execution of Solution Algorithm is given below.

Particle, X(t): It is a candidate solution characterized by an m - dimensional vector, where m is the number of optimized parameters. At time t, the jth particle Xj(t) can be depicted as Xj(t) = [xj,1(t),………xj, m (t)], where xs are the optimised parameters and xj, k(t) is the position of the j_{th} particle with respect to the k_{th} dimension, i.e. the value of the k_{th} optimized parameter in the j_{th} candidate solution.

Population, pop (t): It is a set of n particles at time t, i.e. pop (t)= [Xi(t),…. Xn(t)T.

Swarm: It is an actually unsystematic population of moving particles that tend to group together, whereas every particle looks to be moving in a random direction.

Particle velocity, V(t): The moving particles velocity is represented by an m dimensional vector. At time t, the jth particle velocity Vj(t) can be described as Vj(t) = [vj,1(t),……..……vj, m (t)], where vj,k(t) is the velocity component of the jth particle with respect to kth dimension.

Inertia weight, w (t): On the present velocity it is a control parameter, to control the impact of the previous velocities. Therefore it manipulates the trade-off, between the local and global exploration abilities of the particles, large inertia weight to improve the global exploration, is suggested at the initial stages while for final stages, the inertia weight is condensed for better local exploration [7].

Individual best *X (*t*):** In the period of the search process, the particle contrasts its fitness value at the current position, to the best fitness value it has ever achieved at any time up to the current time. The best position that is related to the best fitness encountered up to now is stated as the individual best, X^* (t). In this fashion, the best position X^* (t).for every particle in the swarm, can be resolved and updated in the period of the search. For example, in a minimization problem with objective function J, the individual best of the jth particle $X^*(t)$. For straightforwardness, it is understood that $Jj^* = J(X^*j(t))$. For the jth particle, individual best can be expressed as $X^*j(t) = [xj,\ 1(t)$ ………… $x^*j,\ m(t)]$.

Global best *X* (*t*):** Amid every individual best position (i.e. the best of all) attained so far it is the best position.

Topping criteria: The situation under which the search process will conclude. In the current case, the search will conclude if one of the subsequent conditions is met.

a). The number of iterations since, the final change of the best solution is greater than a pre specified number.

or

b). The number of iterations reaches the maximum permissible number. With the explanation of basic elements as above, the Solution algorithm is created as shown below.

To create a consistent search in the starting stages and extremely local search in afterward stages, an annealing method is followed. A decrement function for lessening the inertia weight given as $w(t)=\alpha w(t-1)$, where α is a decrement constant smaller than but near to 1, is considered here [8].

Possibility checks, for the imposition of the method of the particle positions, after the position updating to avert the particles from flying outside the feasible search space.

The particle velocity in the k_{th} dimension is limited to some maximum value, v_{kmax}. With this limit, enhancement of local exploration space is achieved and it realistically simulates the incremental changes of human learning. In order to ensure uniform velocity through all dimensions, the maximum velocity in the k_{th} dimension is given as:

$$V_{kmax} = \frac{Xkmax - Xkmin}{N}$$

In PSO algorithm, the population has n particles, and each particle is an m dimensional vector, where m is the number of optimized parameters. Incorporating the above modifications, the computational flow of PSO technique can be described in the following steps.

Step 1 (Initialization)

$$[X_j(0),\ j = 0, 1, 2, \ldots n]$$

Where,

$$X_j(0) = [X_{j,1}(0), \ldots\ldots\ldots X_{j,m}(0)]$$

$X_{j,k}(0)$ is generated by randomly selecting a value with uniform probability over the kth optimized parameter search space $[X_{kmax}, X_{kmin}]$.

Similarly, generate randomly initial velocities of all particles,

$$[V_j(0),\ j = 0, 1, 2, \ldots n]$$

Where,

$$V_j(0) = [V_{j,1}(0), \ldots\ldots\ldots V_{j,m}(0)]$$

- $V_{j,k}(0)$ is generated by randomly selecting a value with uniform probability over the k_{th} dimension $[-X_{kmax}, X_{kmin}]$.
- Each particle in the initial population is evaluated using the objective function *J*.
- For each particle, set $X_0^*(0) = X_j(0)$, $Jj^* = Jj$, j =1, 2, ….., n. Search for the best value of the objective function J_{best}.
- Set the particle associated with J_{best} as the global best $X^{**}(0)$, with an objective function of J^{**}.
- Set the initial value of the inertia weight w(0).

Step 2 (Time updating)

Update the time counter t = t + 1.

Step 3 (Weight updating)

Update the inertia weight $w(t)=\alpha w(t-1)$

Step 4 (Velocity updating)

Using the global best and individual best of each particle, the j^{th} particle velocity in the k_{th} dimension is updated according to the following equation:

Step 5 (Position updating)

Based on the updated velocities, each particle changes its position according to the following equation:

$$X_{j,k}(t) = V_{j,k}(t-1) + X_{j,k}(t-1)$$

If a particle violates its position limits in any dimension, set its position at the proper limit.

Step 6 (Individual best updating)

Each particle is evaluated according to its updated position. If

Step 7 (Global best updating)

Search for the minimum value Jj among Jj^*, where min is the index of the particle with minimum objective function

Step 8 (Stopping criteria)

If one of the stopping criteria is satisfied then stop; else go to step 2.

2.2 Objective Function for PSO

Voltage integrated control and Reactive power are normally used for the control variables such as adjust on-load tap changing ratio, reactive power compensation capacitor capacity and generator terminal voltage to reduce active power losses and increase power factor to ensure the voltage within the specified limit. This analysis adopted smallest active power loss as the control optimization objective function, generator reactive power and nodes voltages as state variables, on-load tap changing ratio and reactive power compensation capacitor capacity and generator terminal voltage as the control variables, mathematical model are as follows:

$$\text{minf} = \sum_{x=1}^{Nn} Plossx$$

2.3 Simulation Analysis of PSO in Optimal Power Flow Control

There are discussing the PSO simulation in optimal power control in various parameter.

2.3.1 Cost Optimization of PSO

PSO: 1/50 iterations, GBest = 7927773.0219071107.

PSO: 10/50 iterations, GBest = 7919868.2389082452.

PSO: 20/50 iterations, GBest = 7915334.1705612.

PSO: 30/50 iterations, GBest = 7898649.0694836471.

PSO: 40/50 iterations, GBest = 7893281.6893112473.

PSO: 50/50 iterations, GBest = 7828249.4674299723.

GBest is the best cost value for the iteration. As it can be seen, the cost keeps on reducing, thereby obtaining cost optimization from PSO. The 50th iteration has the lowest value, therefore giving us the graph in Fig 2 and 3. The dimension of PSO is limited by the best cost attained. In this analysis best value is attained at 50th iteration so the dimension is limited to 53.

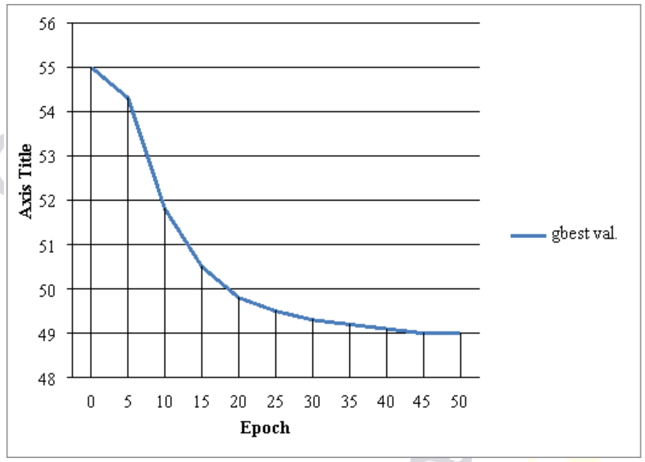

Fig 2. PSO Simulation analysis

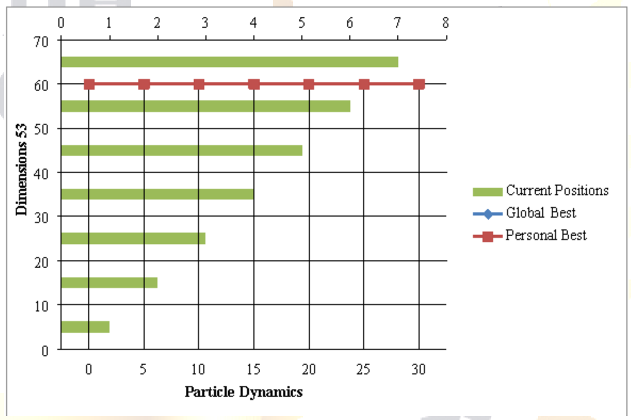

Fig 3. PSO Simulation Analysis

Performance of PSO based OPF is presented in table 1 and 2 in the aspect of power loss and bus voltage.

Table 1. Real Power Loss Before and After Correction

Real Power Loss Before Correction p.u	Real Power Loss After Correction p.u
0.489462	0.4780842

Table 2. Bus Voltage Before and After Correction

S. No.	Real Power Loss Before Correction p.u	Real Power Loss After Correction p.u

1	1.056	1.0601
2	0.9810	1.0255
3	0.95212	1.0256
4	0.96012	0.2564
5	0.931215	1.0800
6	0.95586	1.256
7	0.91222	0.4568
8	0.95888	1.02556
9	0.92356	0.2564
10	0.95444	1.6897
11	1.0256	1.0555
12	1.0555	1.25558
13	1.8551	1.0225

The Optimal Power Flow (OPF) as discussed earlier is defined as a static nonlinear optimization problem to determine all of the adjustable variables.

3. CONCLUSIONS

In conclusion, present study was design based on FACTS device of UPFC for controlling the power flow and enhancing system stability. The voltage controller in shunt control plays a major role in controlling the voltage and the reactive power injected by UPFC. PI and simulated annealing (SA) methods are applied and the performances were compared in UPFC in aspects of Maintained voltage and Harmonics reduction. PI controller lags to maintain voltage around 5% whereas SA eliminates drop in voltage. In aspects of Harmonics reduction, the PI controller reduces harmonics around 85% whereas SA reduces harmonics around 95%. Hence in both aspects such as Maintained voltage and Harmonics reduced SA produces better results in UPFC. Therefore SA based UPFC is suitable for IEEE 30 bus system.

4. SCOPE FOR FURTHER STUDY

In this study, optimal power flow for voltage control using various controllers such as PSO, BAT and GA are discussed. Comparative analysis validates the effectiveness of GA in OPF. Voltage control of power system is extended to utilization of UPFC. Significance of DC link voltage control in UPFC in the aspect of voltage stability is discussed with the new algorithm of SA and compared with PI based UPFC. All above said analysis are studied in IEEE 30 bus system. The application of this system can be extended to higher IEEE bus systems for voltage stability and reactive power control.

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