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Optimal Control Parameters for a UPFC in a Multimachine Using PSO

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***Abstract*-- The crucial factor affecting the modern power systems today is load flow control. The Unified Power Flow Controller (UPFC) is an effective means for controlling the power flow and can provide damping capability during transient conditions. The UPFC is controlled conventionally using PI controllers. The optimal design of the PI controllers for a UPFC is a challenging task and time consuming using the conventional techniques. This paper presents an approach using Particle Swarm Optimization (PSO) for the design of optimal conventional controllers for a UPFC in a multimachine power system. Simulation results are presented to show the effectiveness of the proposed PSO based approach for the design of optimal conventional controllers for a UPFC in a multimachine power system.**

***Index Terms*-- Multimachine Power System, Unified Power Flow Controller (UPFC), PI controllers, Particle Swarm Optimization**

I. INTRODUCTION

WITH the ever-increasing complexities in power systems across the globe and the growing need to provide stable, secure, controlled, economic, and high-quality electric power –especially in today's deregulated environment – it is envisaged that Flexible AC Transmission System (FACTS) controllers are going to play a critical role in power systems [1]. FACTS devices enhance the stability of the power system both with its fast control characteristics and with its continuous compensating capability. The two main objectives of FACTS technology are to control power flow and increase the transmission capacity over an existing transmission corridor [2].

Gyugyi proposed the Unified Power Flow Controller (UPFC) which is a new generation of FACTS devices in 1991 [3]. It is a device, which can control simultaneously all three parameters of power transmission line (impedance, voltage and phase angle). This device combines together the features of two other FACTS devices: the Static Synchronous Compensator (STATCOM) and the Static Synchronous Series Compensator (SSSC). Practically, these two devices are two Voltage Source Inverters (VSI's) connected respectively in shunt with the transmission line through a shunt transformer and in series with the transmission line through a series transformer. These are connected to each other by a common DC link, which is a typical storage capacitor.

The shunt inverter is used for voltage regulation at the point of connection, injecting reactive power flow into the line and to balance the real power flow exchanged between the series inverter and the transmission line. Thus, the UPFC can fulfill functions of reactive shunt compensation, active and reactive series compensation and phase shifting. Besides, the UPFC provides a secondary but important function damping control to suppress power system oscillations, thus, improving the transient stability of power system [2].

Despite the various modern controller design techniques for power systems reported in literature [4-7], the power utilities still prefer the conventional PI controllers. This is probably because of the simplicity and ease of tuning the controllers and the lack of confidence in the stability related to some adaptive control, variable structure control, and intelligent control. The design of optimal controllers for the UPFC is a multimodal problem (i.e., there exists more than one local optimum). Hence, local optimization techniques are not suitable for optimal UPFC controller design. Heuristic search based algorithms such as genetic algorithms (GAs), simulated annealing (SA), tabu search algorithm have been applied for PSS design [8-10]. When the parameters being optimized are highly correlated, these heuristic search algorithms do not perform well [11].

A new technique based on swarm intelligence called the particle swarm optimization that emerges and allies itself to evolutionary algorithms has proven to have great potential for single and multi-objective optimization [12-13]. Swarm algorithms differ from evolutionary algorithms importantly in both metaphorical explanation and how it works. What is new with the swarm algorithm is that the individuals persist over time influencing one another's search of the problem space.

In this paper, particle swarm optimization is used to find the optimal parameters of the UPFC shunt and series VSIs' conventional PI controls in a multimachine power system. The paper is organized as follows: Section II describes the multimachine power system; Section III describes the UPFC and its controls; Section IV describes particle swarm optimization algorithm; Section V describes the how the PSO is used to determine the optimal parameters of the UPFC shunt and series controls; and finally section VI presents some simulation results with the optimal parameters obtained using the PSO algorithm.

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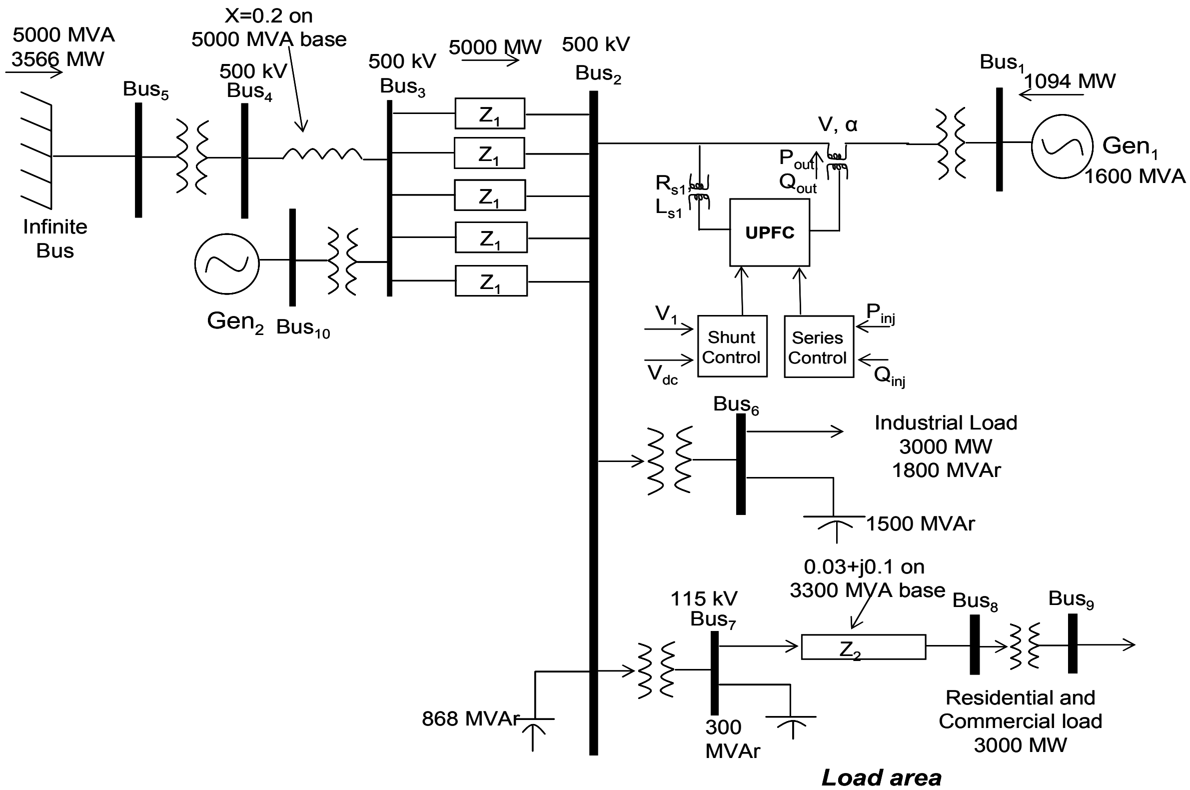

Fig. 1. Multimachine power system with a UPFC installed between buses 1 and 2.

II. Multi Machine Power System

For studying the control of a UPFC in a multimachine power system, the setup shown in Fig.1 is simulated in the PSCAD/EMTDC environment. The power system consists of two synchronous generators Gen_1 and Gen_2 of ratings 1600MVA and 2200MVA respectively along with exciters and governors; and two loads, one of value P (real power) =3000 MW, Q (reactive power) = 1800 MVAR and the other of value P = 3000 MW, Q = 300 MVAR. The third generator is the infinite bus. The parameters of the system in Fig. 1 are given in [14].

III. Unified Power Flow Controller

Unified power flow controller is a generalized synchronous voltage source, represented at the fundamental frequency by voltage phasor V with controllable magnitude V ($0 \le V \le Vmax$) and angle α ($0 \le \alpha \le 2\pi$), in series with the transmission line. The UPFC consists of two voltage-sourced inverters. These back-to-back inverters are operated from a common DC link provided by a DC storage capacitor. This arrangement functions as an ideal ac-to-ac power inverter in which the real power can freely flow in either direction between the ac terminals of the two inverters, and each inverter can independently generate (or absorb) reactive power at its own ac output terminal.

The series inverter provides the main function of the UPFC by injecting a voltage V with controllable magnitude V and phase angle α in series with the line via an insertion transformer. This injected voltage acts essentially as a synchronous ac voltage source. The transmission line current flows through this voltage source resulting in reactive and active power exchange between it and ac system. The inverter generates the reactive power exchanged at the ac terminal internally. The active power exchanged at the ac terminal is converted into dc power, which appears at the DC link as a positive or negative real power demand.

The basic function of shunt inverter is to supply or absorb the real power demanded by series inverter at the common DC link to support the real power exchange resulting from series voltage injection. This DC link demand of series inverter is converted back to ac by shunt inverter and coupled to the transmission line bus via a shunt-connected transformer. In addition to this the shunt inverter can also generate or absorb controllable reactive power, if it is desired and thereby provides independent shunt reactive compensation for the line. The three main control parameters of UPFC are magnitude (V), angle (α) and shunt reactive current control of real and reactive power can be achieved by injecting series voltage with appropriate magnitude and angle. This injected voltage is transformed into dq reference frame, which is split into E_d and E_q. These coordinates can be used to control the power flow.

The controllers for UPFC shunt and series branch VSIs are described below.

A. Shunt Branch Control

Control of the shunt inverter is achieved by varying the shunt inverter voltage active and reactive components E_{pd} and E_{pq} appropriately. The shunt control consists of regulating the bus voltage at the point of contact of shunt VSI and the capacitor dc voltage. The shunt controller structure is shown in Fig. 2. The difference between the bus voltage V_1 and its reference value V_{1ref} is fed to a PI controller to obtain E_{pd} and the difference between the capacitor voltage V_{dc} and its reference value V_{dcref} is fed to another PI controller to obtain E_{pq}. E_{pd} and E_{pq} are then used to generate the modulation index k_1 and phase angle α_1 for the shunt inverter.

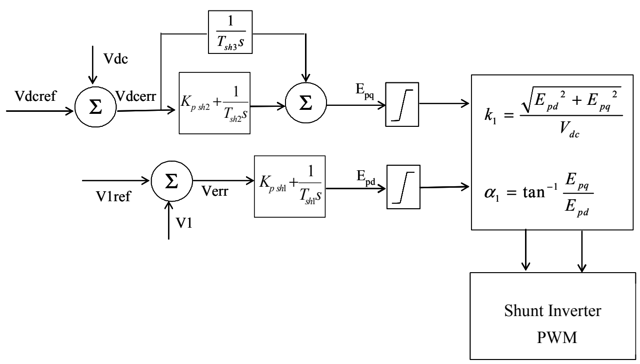

Fig. 2. UPFC shunt branch control – PI controllers for the bus voltage and capacitor dc voltage regulation.

B. Series Branch Control

The three-phase line currents at the secondary side of the insertion transformer (series VSI voltage injection onto the line) is decomposed into its direct component, i_d, and its quadrature component, i_q. These actual signals (i_d and i_q) and the reference d-q current signals (i_d* and i_q*) are compared respectively, as shown in Fig. 3. The error signals I_{derr} and I_{qerr} are then passed through the PI-regulator to get the output signals E_d and E_q which are then passed through a limiter and are used in the calculation of modulation index k_2 and α_2.

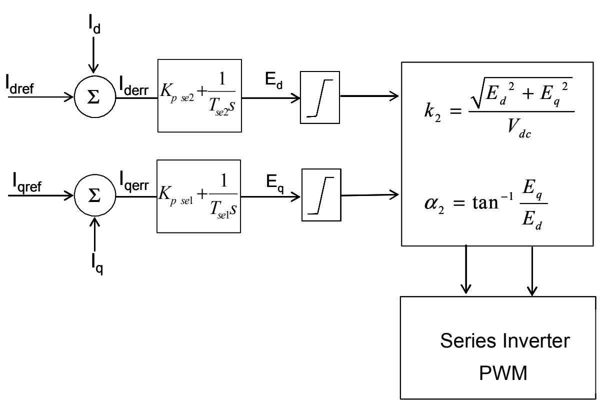

Fig.3. UPFC series branch control – PI controllers for active and reactive power control.

IV. Particle Swarm Optimization

Particle swarm optimization is a form of evolutionary computation technique (a search method based on natural systems) developed by Kennedy and Eberhart [15-17]. PSO like a genetic algorithm (GA) is a population (swarm) based optimization tool. However, unlike in GA, particles/individuals are not eliminated from the population from one generation to the next. One major difference between particle swarm and traditional evolutionary computation methods is that particles' velocities are adjusted, while evolutionary individuals' positions are acted upon; it is as if the "fate" is altered rather than the "state" of the particle swarm individuals [17].

The system initially has a population of random solutions. Each potential solution, called *particle*, is given a random velocity and is flown through the problem space. The particles have memory and each particle keeps track of previous best position and corresponding fitness. The previous best value is called as p_{best}. Thus, p_{best} is related only to a particular particle. It also has another value called g_{best}, which is the best value of all the particles p_{best} in the swarm. The basic concept of PSO technique lies in accelerating each particle towards its p_{best} and the g_{best} locations at each time step. Acceleration has random weights for both p_{best} and g_{best} locations.

Fig. 4 illustrates briefly the concept of PSO, where P^k is current position, P^{k+1} is modified position, V_{ini} is initial velocity, V_{mod} is modified velocity, V_{pbest} is velocity considering p_{best} and V_{gbest} is velocity considering g_{best}.

(i) Initialize a population (array) of particles with random positions and velocities of *d* dimensions in the problem space.
(ii) For each particle, evaluate the desired optimization fitness function in *d* variables.
(iii) Compare particle's fitness evaluation with particle's p_{best}. If current value is better than p_{best}, then set p_{best} value equal to the current value and the p_{best} location equal to the current location in *d*-dimensional space.

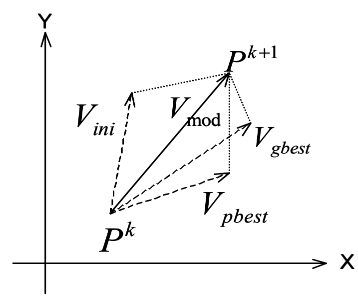

Fig. 4 Concept of changing a particle's position in PSO [18].

(iv) Compare fitness evaluation with the population's overall previous best. It the current value is better than g_{best}, then reset g_{best} to the current particle's array index and value.
(v) Change the velocity and position of the particle according to (1) and (2) respectively. V_{id} and X_{id} represent the velocity and position of i^{th} particle with *d* dimensions respectively and, $rand_1$ and $rand_2$ are two uniform random functions.

$$V_{id} = w \times V_{id} + c_1 \times rand_1 \times (P_{bestid} - X_{id}) + c_2 \times rand_2 \times (G_{bestid} - X_{id}) \quad (1)$$

$$X_{id} = X_{id} + V_{id} \quad (2)$$

(vi) Repeat step (ii) until a criterion is met, usually a sufficiently good fitness or a maximum number of iterations/epochs.

PSO has many parameters and these are described as follows: *w* called the inertia weight controls the exploration and exploitation of the search space because it dynamically adjusts velocity. Local minima are avoided by small local neighborhood, but faster convergence is obtained by larger global neighborhood and in general, global neighborhood is preferred. Synchronous updates are more costly than the asynchronous updates.

V_{max} is the maximum allowable velocity for the particles i.e. in case the velocity of the particle exceeds V_{max} then it is reduced to V_{max}. Thus, resolution and fitness of search depends on V_{max}. If V_{max} is too high, then particles will move beyond good solution and if V_{max} is too low, then particles will be trapped in local minima. c_1 *and* c_2 termed as cognition and social components respectively are the acceleration constants which changes the velocity of a particle towards p_{best} and g_{best} (generally somewhere between p_{best} and g_{best}). Velocity determines the tension in the system. A swarm of particles can be used locally or globally in a search space. In the local version of the PSO, the g_{best} is replaced by the l_{best} and the entire procedure is same.

V. Design of Optimal Controller Parameters Using PSO

In the UPFC, there are two proportional gains (K_{sh1} and K_{sh2}) and three integral time constants (T_{sh1}, T_{sh2} and T_{sh3}) in the shunt VSI controls; and there are two proportional gains (K_{se1} and K_{se2}) and two integral time constants (T_{se1} and $Tse2$) in the series VSI controls. The challenge is to determine all these four gains and five time constants for the UPFC to provide optimal damping during transient conditions such as three phase faults. In order to do this for the power system in Fig. 1, the speed deviation of generators Gen_1 and Gen_2 are used as the measure of performance of the shunt and series VSI controls.

To arrive at the nine optimal parameters using the particle swarm optimization, five PSO particles are selected each providing a stable dynamic and transient UPFC control. The PSO algorithm minimizes the following cost function.

$$Cost = \sum_{t=0}^{20000} \left(\sqrt{\left(\Delta\omega_1(t)\right)^2} + \sqrt{\left(\Delta\omega_2(t)\right)^2} \right) \qquad (3)$$

Where $\Delta\omega_1$ and $\Delta\omega_2$ are the speed deviations of generators Gen_1 and Gen_2 respectively, t represents the simulation time steps in PSCAD. The cost is calculated in the first two seconds of the fault.

VI. Simulation Results

The multimachine power system in Fig. 1 has the operating points for Gen_1: $P_1 = 1094$ MW, $Q_1 = -94$ MVAR and Gen_2: $P_2 = 1500$ MW, $Q_2 = 0$ MVAR. At this operating point, the nine combined parameters of the UPFC shunt and series branch controllers are optimized for transient stability using the PSO algorithm. The five PSO particles initial settings for a given run are shown in Table I. The PSO parameters used in the simulation are $w = 0.8$ and $c_1 = c_2 = 2$. After ten iterations with the PSO algorithm, the optimal parameters (g_{best}) are found and shown in the last row of Table I. The PSO process was carried out over 20 trial runs. Overall, parameters close to the optimal values in Table I are obtained on the various trial runs. This observation is coherent with literature [19].

TABLE I
PSO Particles' Initial Parameters and the Final Optimal Parameters During One of the Trial Runs

Particles	P_{sh1}	T_{sh1}	P_{sh2}	T_{sh2}	T_{sh3}	P_{se1}	T_{se1}	P_{se2}	T_{se2}
1	1.0	0.01	0.8	0.04	0.5	3.5	0.1	4.5	0.1
2	1.0	0.01	0.5	0.04	0.5	3.5	0.1	4.5	0.1
3	1.0	0.01	0.5	0.04	2	3.5	0.1	4.5	0.1
4	1.0	0.01	0.5	0.04	2	1	0.8	4.5	0.1
5	1.0	0.01	0.5	0.04	2	1	0.01	1	0.1
Optimal Parameters	0.1	0.01	1.05	0.01	1.0	2.72	0.59	4.02	0.01

Figs. 5 and 6 compare the speed of Gen_1 and Gen_2 respectively, obtained with the parameters of particle 1 and with that obtained from the optimal parameters determined by PSO for 150 ms three phase short circuit applied at bus 4.

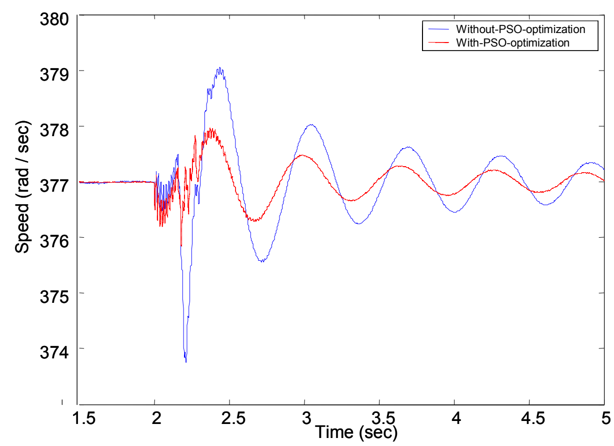

Fig. 5. Speed of generator Gen_1.

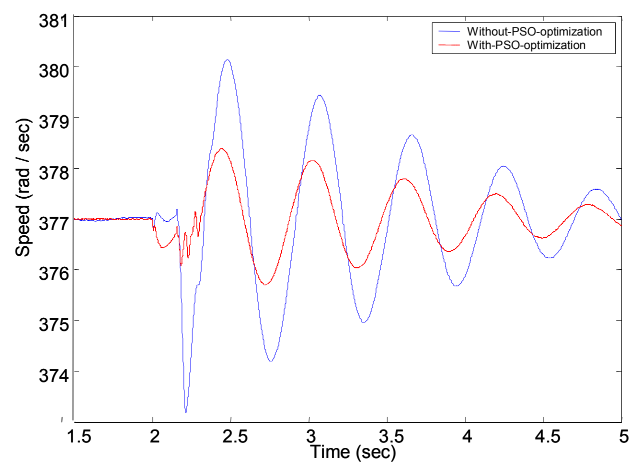

Fig. 6. Speed of generator Gen_2.

The speed response during a 150 ms three phase short circuit applied at bus 4 obtained with the parameters of particle 5 and with that obtained from the optimal parameters

(g_{best}) determined by PSO are shown in Figs. 7 and 8 for generators Gen_1 and Gen_2 respectively. In both cases, the controllers with optimal parameters determined by the PSO give better damping of the speed deviations of the generators. This performance was achieved with the cost function given in (3). The objective function can be modified to include setting time.

The PSO based UPFC controller parameter tuning for large power systems in real-time can be based on snapshots of the transient performance of power system under some disturbance and running the PSO optimization on a fast DSP processor. Every time the operating conditions change, an optimization of PI controllers' parameters may be necessary.

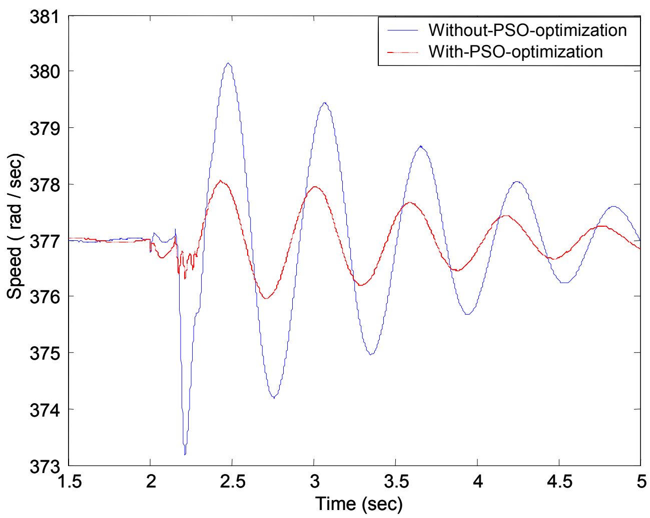

Fig. 7. Speed of generator Gen_1.

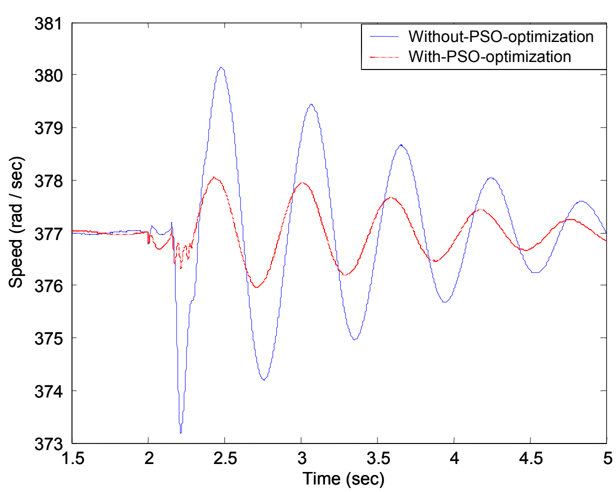

Fig. 8. Speed of generator Gen_2.

VII. Conclusion

This paper has shown based on some preliminary studies that particle swarm optimization can be applied to obtain the optimal parameters for the unified power flow controller shunt and series voltage source inverter PI controls. It is anticipated that the cost function can be modified further to include other constraints such as settling time and/or rise time in addition to area under a curve. This concept can be extended to include in the optimization of the controller parameters other UPFC functions such as to maximize reactive and real power compensation, minimize voltage deviation at the shunt bus for multiple operating points and disturbances. Future work also involves benchmarking the PI controller parameters obtained by PSO with those from other methods.

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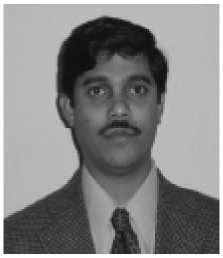
IX. BIOGRAPHIES



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