Research Journal of Applied Sciences, Engineering and Technology 4(3): 214-221, 2012
ISSN: 2040-7467

Submitted: October 07, 2011 Accepted: November 15 , 2011 Published: February 01, 2012

Optimal Design of STATCOM Based OFD Controller using Quantum Particle Swarm Optimization

A. Safari and E. Mazloumi
Young Researchers Club, Ahar Branch, Islamic Azad University, Ahar, Iran

Abstract: This study present the optimal design of OFD (OFD) controller for static synchronous compensator (STATCOM) connected to a power system, in order to increase the damping of low frequency electromechanical oscillations. The design process is converted to an optimization problem with the time domain-based objective function which is solved by a Quantum-behaved Particle Swarm Optimization (QPSO) technique that has fewer parameters and stronger search capability than the Classical Particle Swarm Optimization (CPSO), as well as is easy to implement. To guarantee the robust performance of the OFD controller, the design process takes into account a wide range of operating conditions and system configurations. The simulation results demonstrate the effectiveness of proposed controller in comparison with designed Classical PSO (CPSO) based STATCOM controller.

Key words: CPSO, low frequency oscillations, OFD controller, QPSO, STATCOM

INTRODUCTION

Electromechanical oscillations in power systems are a problem that has been challenging engineers for years. These oscillations may be very poorly damped in some cases, resulting in mechanical fatigue at the machines and unacceptable power variations the across the important transmission lines. For this reason, the applications of the controllers to provide better damping for these oscillations are of utmost importance (Ramos *et al*., 2005).

In recent years, with the rapid development of power electronics, Flexible AC Transmission System (FACTS) devices have been proposed and implemented in high voltage transmission networks. The FACTS devices can be used normally steady-state control of a power system and enhance system stability through improved damping of power swings (Klein *et al*., 1995). However, a supplementary controller may be designed for the FACTS devices to increase the damping of electromechanical oscillatory modes, while meeting the primary goal of the device on power system. The FACTS controllers enhance both dynamic and static performance of power system and thus improvement in overall stability (Noroozian and Andersson, 1993).

The STATCOM is based on the principle that a voltage-source inverter generates a controllable AC voltage source behind a transformer-leakage reactance so that the voltage difference across the reactance produces reactive power exchange between the STATCOM and the transmission network (Hingorani and Gyugyi, 1999; Wang, 2003). It is reported that STATCOM can offer a number of performance advantages for reactive power control applications over the conventional approaches, such as Static Var Compensators (SVC), because of its greater reactive current output capability at depressed voltage, faster response, better control stability, lower harmonics and smaller size, etc.

Several trials have been reported in the literature to dynamic models of STATCOM in order to design suitable controllers for AC, DC voltage and damping controls. (Wang, 2003) presents the establishment of the linearized Phillips-Heffron model of a power system installed with a STATCOM. The author has not presented a systematic approach for designing the damping controllers. Further, no effort seems to have been made to identify the most suitable STATCOM control parameter, in order to arrive at a damping controller. Fuzzy-logic-based controllers have been used for controlling a STATCOM (Moris *et al*., 2003). The performance of such controllers can further be improved by adaptively updating their parameters. Also, although using the robust control methods (Rahim and Kandlawala, 2004; Armansyah *et al*., 2002), the uncertainties are directly introduced to the synthesis, but due to the large model order of power systems the order resulting controller will be very large in general, which is not feasible because of the computational economical difficulties in implementing. An approach based on a zero set concept to the problem of the STATCOM state feedback controller design is presented in (Spitsa *et al*., 2010). This method allows one to calculate a complete set of the admissible state feedback gains that place closed-loop poles into a pre-specified region in the complex plane.

In this study, for the simplicity of practical implementation of the controllers, output feedback control with feedback signals available at the location of the each

Corresponding Author: A. Safari, Young Researchers Club, Ahar Branch, Islamic Azad University, Ahar, Iran

controlled device is most favorable (Lee, 2005; Chen *et al*., 1998; Jalilzadeh *et al*., 2009). The problem can be stated as follows: given a system, find an output feedback gains so that the closed-loop system is stable. The output feedback problem is important in its own right, because these controllers are less expensive to be implemented and more reliable in practice (Huang and Nguang, 2007). The aim of this paper is to tune of output feedback gains for the STATCOM based controllers using the quantum PSO technique. The QPSO algorithm (Coelho, 2008) is depicted only with the position vector without velocity vector, which is a simpler algorithm and the results show that QPSO performs better than classical PSO and is a promising algorithm due to its global convergence guaranteed characteristic (Sun *et al*., 2008; Sun *et al*., 2005; Jalilzadeh *et al*., 2009).

In this study, the problem of robust OFD controller design is formulated as an optimization problem and QPSO technique is used to solve it. The proposed design process for controller with the output feedback scheme is applied to a single-machine infinite-bus power system. Since only local and available states ($\Delta\omega$, ΔP_e and ΔV_t) are used as the inputs of each controller, the optimal design of controller can be accomplished. The effectiveness of the proposed controller is demonstrated through nonlinear time-domain simulation studies and some performance indices.

REVIEW OF CLASSICAL PSO AND QUANTUM PSO

Classical PSO: The proposal of PSO algorithm was propounded by several scientists who developed bio-inspired computational simulations of the movement of organisms such as flocks of birds and schools of fish (Kennedy, 1997). Such simulations were heavily based on manipulating the distances between particles, i.e., the simultaneity of the behavior of the swarm was seen as an effort to keep an optimal distance between them. This optimization technique can be used to solve many of the kinds of problems as Genetic Algorithm (GA), and does not suffer from some of GA difficulties. It has also been found to be robust in solving problem featuring non-linearing, non-differentiability and high-dimensionality (Jalilzadeh *et al*., 2009).

The PSO begins with a population of random solutions ‘‘particles’’ in a D-dimension space. The *i*th particle is represented by $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$. Each particle keeps track of its coordinates in hyperspace, which are associated with the fittest solution it has achieved so far. The value of the fitness for particle *i* (pbest) is also stored as $P_i = (p_{i1}, p_{i2}, \ldots, p_{iD})$. The global version of the PSO keeps track of the overall best value (gbest), and its location, obtained thus far by any particle in the population. PSO consists of, at each step, changing the velocity of each particle toward its pbest and gbest

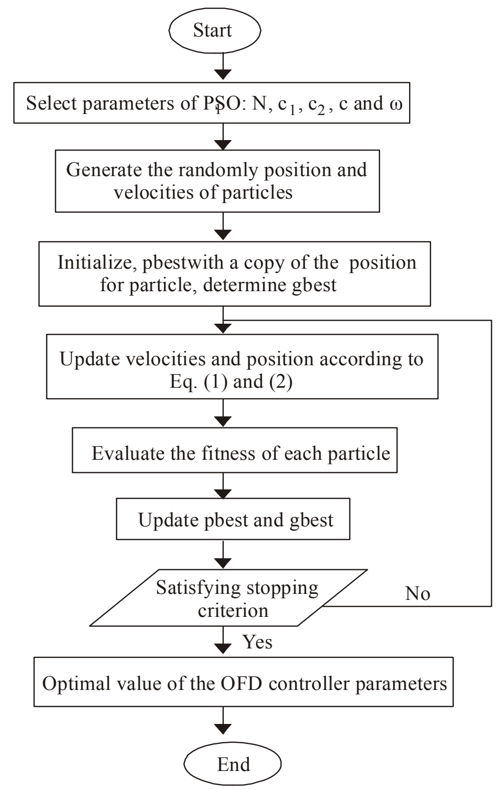

Fig. 1: Flowchart of the proposed PSO technique

according to (1). The velocity of particle *i* is represented as $V_i = (v_{i1}, v_{i2}, \ldots v_{iD})$. Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward pbest and gbest. The position of the *i*th particle is then updated according to (2) (Jalilzadeh *et al*., 2009; Poli *et al*., 2007):

$$v_{id} = w \times v_{id} + c_1 \times rand() \times (Pi_d - x_{id}) + c_2 \times rand() \times (P_{gd} - x_{id}) \quad (1)$$

$$x_{id} = x_{id} + cv_{id} \quad (2)$$

where, P_{id} and P_{gd} are *pbest* and *gbest*. The positive constants c_1 and c_2 are the cognitive and social components that are the acceleration constants responsible for varying the particle velocity towards *pbest* and *gbest*, respectively. Variables r_1 and r_2 are two random functions based on uniform probability distribution functions in the range [0, 1]. The use of variable *w* is responsible for dynamically adjusting the velocity of the particles, so it is responsible for balancing between local and global searches, hence requiring less iteration for the algorithm to converge (Poli *et al*., 2007). Figure 1 shows the flowchart of the PSO algorithm.

Quantum PSO: In classical PSO technique, a particle is depicted by its position vector x_i and velocity vector v_i, which determine the trajectory of the particle. The dynamic behavior of the particle is widely divergent form that of that the particle in CPSO systems in that the exact values of x_i and v_i cannot be determined simultaneously. In quantum world, the term trajectory is meaningless, because x_i and v_i of a particle cannot be determined simultaneously according to uncertainty principle. Therefore, if individual particles in a PSO system have quantum behavior, the PSO algorithm is bound to work in a different fashion (Coelho, 2008). In the quantum model of a PSO called here QPSO, the state of a particle is depicted by wave function $\Psi(x, t)$ instead of position and velocity. Employing the Monte Carlo method, the particles move according to the following iterative equation (Sun *et al*., 2005):

$$\begin{aligned} x(t+1) &= p + \beta.|Mbest - x(t)|.In(1/u) \; if \; k \geq 0.5 \\ x(t+1) &= p + \beta.|Mbest - x(t)|.In(1/u) \; if \; k \leq 0.5 \end{aligned} \quad (3)$$

where u and k are values generated according to a uniform probability distribution in range [0, 1], the parameter β is called Contraction-Expansion (CE) Coefficient, which can be tuned to control the convergence speed of the particle. In the QPSO, the parameter β must be set as β<1.782 to guarantee convergence of the particle (Sun *et al*., 2008). Thus the Eq. (3) is the fundamental iterative equation of the particle's position for the QPSO. Moreover, unlike the PSO, the QPSO needs no velocity vectors for particles at all, and also has fewer parameters to control (only one parameter β except population size and maximum iteration number), making it easier to implement. Where, Mbest called Mean best position is defined as the mean of the pbest positions of all particles. That is given as follows:

$$Mbest = \frac{1}{N}\sum_{d=1}^{N} p_{id}(t) \quad (4)$$

Trajectory analyses in (Sun *et al*., 2005) demonstrated the fact that convergence of the PSO algorithm may be achieved if each particle converges to its local attractor, *p* defined at the coordinates:

$$p = (c_1 p_{id} + c_2 P_{gd}) / (c_1 + c_2) \quad (5)$$

The procedure for implementing the QPSO is given by the following steps (Coelho, 2008):

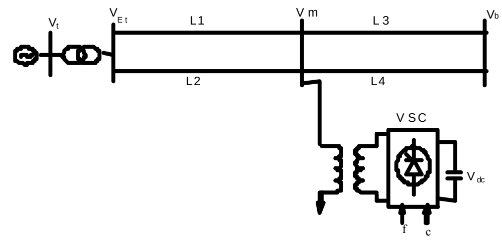

Fig. 2: SMIB power system equipped with STATCOM

Step 1: **Initialization of swarm positions:** Initialize a population (array) of particles with random positions in the n-dimensional problem space using a uniform probability distribution function.

Step 2: **Evaluation of particle's fitness:** Evaluate the fitness value of each particle.

Step 3: **Comparison to pbest (personal best):** Compare each particle's fitness with the particle's pbest. If the current value is better than pbest, then set the pbest value equal to the current value and the pbest location equal to the current location in n-dimensional space.

Step 4: **Comparison to gbest (global best):** Compare the fitness with the population's overall previous best. If the current value is better than gbest, then reset gbest to the current particle's array index and value.

Step 5: **Updating of global point:** Calculate the Mbest using Eq. (4).

Step 6: **Updating of particles' position:** Change the position of the particles according to Eq. (3), where c_1 and c_2 are two random numbers generated using a uniform probability distribution in the range [0, 1].

Step 7: **Repeating the evolutionary cycle:** Loop to Step 2 until a stop criterion is met, usually a sufficiently good fitness or a maximum number of iterations (generations).

TEST SYSTEM WITH STATCOM

A Single Machine Infinite Bus power (SMIB) system installed with a STATCOM, as shown in Fig. 2, are considered. The system data is listed in the Appendix.

The system consists of a Step Down Transformer (SDT) with a leakage reactance XSDT, a three phase GTO-based voltage source converter, and a dc capacitor (Wang, 2003).

Problem formulation: The dynamic model of the STATCOM is required in order to study the effect of the STATCOM for enhancing the small signal stability of the power system. The voltage source converter of

STATCOM generates a controllable AC voltage source $v_o(t) = V_0\sin(wt-\phi)$ behind the leakage reactance. The voltage difference between the STATCOM bus AC voltage, $v_L(t)$ and $v_0(t)$ produces reactive power exchange between the STATCOM and the power system, which can be controlled by adjusting the magnitude V_0 and the phase ϕ. The dynamic relation between the capacitor voltage and current in the STATCOM circuit are expressed as (Rahim and Kandlawala, 2004):

$$\bar{I}_{Lo} = I_{Lod} + jI_{Loq}, \qquad (6)$$

$$V_o = cV_{dc}(\cos\varphi + j\sin\varphi) = cV_{dc}\angle\varphi \qquad (7)$$

$$\dot{V}_{dc} = \frac{I_{dc}}{C_{dc}} = \frac{c}{C_{dc}}(I_{Lod}\cos\varphi + I_{Log}\sin\varphi) \qquad (8)$$

where for the PWM inverter $c = mk$ and k is the ratio between AC and DC voltage depending on the inverter structure, m and c are the modulation ratio and phase defined by the PWM. The C_{dc} is the dc capacitor value and I_{dc} is the capacitor current while i_{Lod} and i_{Loq} are the *d*- and *q*-components of the STATCOM current, respectively. The dynamics of the generator and the excitation system are expressed through a fourth order model is given as (Jalilzadeh *et al*., 2009):

$$\dot{\delta} = \omega_0(\omega - 1) \qquad (9)$$

$$\omega = (P_m - P_e - D\Delta\omega)/M \qquad (10)$$

$$E_q' = (-E_q + E_{fd})/T_{do}' \qquad (11)$$

$$\dot{E}_{fd} = (-E_{fd} + K_a(V_{ref} - V_t))/T_a \qquad (12)$$

The expressions for the d-q axes currents in the transmission line and STATCOM, respectively, are given as follows (Rahim and Kandlawala, 2004):

$$I_{tlq} = \frac{(1 + \frac{X_{LB}}{X_{SDT}})e_q' - \frac{X_{LB}}{X_{SDT}} mV_{dc}\sin\varphi - V_b\cos\varphi}{X_{tL} + X_{LB} + \frac{X_{tL}}{X_{LB}} + (1 + \frac{X_{LB}}{X_{SDT}})x_d'} \qquad (13)$$

$$I_{tlq} = \frac{\frac{X_{LB}}{X_{SDT}} mV_{dc}\cos\varphi + V_b\sin\varphi}{X_{tL} + X_{LB} + \frac{X_{tL}}{X_{LB}} + (1 + \frac{X_{LB}}{X_{SDT}})x_q} \qquad (14)$$

$$I_{Lod} = \frac{e_q' - (x_d' + X_{tL})I_{tLq} - mV_{dc}\sin\varphi}{X_{SDT}} \qquad (15)$$

$$I_{Loq} = \frac{mV_{dc}\cos\varphi - (x_d' + X_{tL})I_{tLq}}{X_{SDT}} \qquad (16)$$

The X_T, x_d' and x_q are the transmission line reactance, d-axis transient reactance, and q-axis reactance, respectively. A linear dynamic model is obtained by linearizing the nonlinear model round an operating condition. The Phillips-Heffron model of the power system with FACTS devices is obtained by linearizing nonlinear equations of the power system around an operating condition. The linearized model of power system as shown in Fig. 2 is given as follows:

$$\Delta\dot{\delta} = \omega_0\Delta\omega, \qquad (17)$$

$$\Delta\dot{\omega} = (-\Delta P_e - D\Delta\omega)/M \qquad (18)$$

$$\Delta\dot{E}_q' = (-\Delta E_q + \Delta E_{fd})/T_{do}' \qquad (19)$$

$$\Delta\dot{E}_{fd} = (K_A(\Delta v_{ref} - \Delta v) - \Delta E_{fd})/T_A \qquad (20)$$

$$\Delta\dot{v}_{dc} = K_7\Delta\delta + K_8\Delta E_q' - K_9\Delta v_{dc} + K_{dc}\Delta c + K_{d\varphi}\Delta\varphi \qquad (21)$$

$$\Delta P_e = K_1\Delta\delta + K_2\Delta E_q' + K_{pdc}\Delta v_{dc} + K_{pc}\Delta c + K_{p\varphi}\Delta\varphi \qquad (22)$$

$$\Delta E_q' = K_4\Delta\delta + K_3\Delta E_q' + K_{qdc}\Delta v_{dc} + K_{qc}\Delta c + K_{q\varphi}\Delta\varphi \qquad (23)$$

$$\Delta V_t = K_5\Delta\delta + K_6\Delta E_q' + K_{Vdc}\Delta v_{dc} + K_{vc}\Delta c + K_{v\varphi}\Delta\varphi, \qquad (24)$$

The K_1, $K_2 \ldots K_9$, K_{pu}, K_{qu} and K_{vu} are linearization constants. The state-space model of power system is given by:

$$\dot{x} = Ax + Bu \qquad (25)$$

where, the state vector a, control vector u, A and B are:

$$x = [\Delta\delta \ \ \Delta\omega \ \ \Delta E'_q \ \ \Delta E_{fd} \ \ \Delta v_{dc}]^T U = [\Delta c \ \ \Delta\varphi]^T$$

$$A = \begin{bmatrix} 0 & w_0 & 0 & 0 & 0 \\ -\frac{K_1}{M} & 0 & -\frac{K_2}{M} & 0 & -\frac{K_{pdc}}{M} \\ -\frac{K_4}{T'_{do}} & 0 & -\frac{K_3}{T'_{do}} & -\frac{1}{T'_{do}} & -\frac{K_{pdc}}{T'_{do}} \\ -\frac{K_A K_5}{T_A} & 0 & -\frac{K_A K_6}{T_A} & -\frac{1}{T_A} & -\frac{K_A K_{vdc}}{T_A} \\ K_7 & 0 & K_8 & 0 & K_9 \end{bmatrix} \quad (26)$$

$$B = \begin{bmatrix} 0 & 0 \\ -\frac{K_{pc}}{M} & -\frac{K_{p\varphi}}{M} \\ -\frac{K_{qc}}{T'_{do}} & -\frac{K_{q\varphi}}{T'_{do}} \\ -\frac{K_A K_{vc}}{T_A} & -\frac{K_{v\varphi}}{T_A} \\ K_{dc} & K_{d\varphi} \end{bmatrix}$$

Structure of the OFD controller: A power system can be described by a Linear Time Invariant (LTI) state space model as follows (Lee, 2005):

$$\dot{x} = Ax + Bu \quad (27)$$

$$y = Cx \quad (28)$$

where x, y and u denote the system linearized state, output and input variable vectors, respectively. The A, B and C are constant matrixes with appropriate dimensions which are dependent on the operating point of the system. The eigenvalues of the state matrix A that are called the system modes define the stability of the system when it is affected by a small interruption. As long as all eigenvalues have negative real parts, the power system is stable when it is subjected to a small disturbance. An output feedback controller has the following structures:

$$u = -Gy \quad (29)$$

Substituting (29) into (28) the resulting state equation is:

$$\dot{x} = A_C x \quad (30)$$

where, A_c is the closed-loop state matrix and is given by:

$$A_C = A - BGC \quad (31)$$

Only the local and available state variables $\Delta\omega$, ΔP_e and ΔVt are taken as the input signals of each controller, so the implementation of the designed stabilizers becomes more feasible. By properly choosing the feedback gain G, the eigenvalues of closed-loop matrix A_c are moved to the left-hand side of the complex plane and the desired performance of controller can be achieved.

QPSO based OFD controller: The proposed controller must be able to work well under all the operating conditions where the improvement in damping of the critical modes is necessary. Since the selection of the output feedback gains for mentioned STATCOM based damping controller is a complex optimization problem. Thus, to acquire an optimal combination, this paper employs QPSO (Coelho, 2008) to improve optimization synthesis and find the global optimum value of objective function. For our optimization problem, objective function is time domain-based objective function (Jalilzadeh *et al.*, 2009):

$$J = \sum_{i=1}^{Np} \int_0^{tsim} |\Delta\omega_i|.tdt \quad (32)$$

where, the t_{sim} is the time range of simulation and N_P is the total number of operating points for which the optimization is carried out. It is aimed to minimize this objective function in order to improve the system response in terms of the settling time and overshoots. The design problem can be formulated as the following constrained optimization problem, where the constraints are the controller parameters bounds:

Minimize J subject to:

$$\begin{aligned} G_1^{\min} &\le G_1 \le G_1^{\max} \\ G_2^{\min} &\le G_2 \le G_2^{\max} \\ G_3^{\min} &\le G_3 \le G_3^{\max} \end{aligned} \quad (33)$$

Typical ranges of the optimized parameters are [100-200] for G_1 and [0.01-10] for G_2 and G_3.The optimization of controller parameters is carried out by evaluating the objective function as given in (32), which considers a multiple of operating conditions. The operating conditions are considered as:

- **Base case:** P = 0.80pu, Q = 0.2 pu and X_L=0.4 pu.(Nominal loading)
- **Case 1:** P = 0.2 pu, Q = 0.01 and X_L = 0.4 pu.(Light loading)
- **Case 2:** P = 1.20 pu, Q = 0.4 and X_L = 0.4 pu. (Heavy loading)
- **Case 3:** The 20% increase of line reactance X_L at nominal loading condition

Table 1: Optimal parameters of the OFD controllers

Controller parameters	*C* based controller		*ϕ* based controller	
	QPSO	CPSO	QPSO	CPSO
G_1	161.56	189.25	114.34	105.05
G_2	2.5320	2.9108	1.1988	1.2334
G_3	1.0750	0.8898	1.2550	1.7611

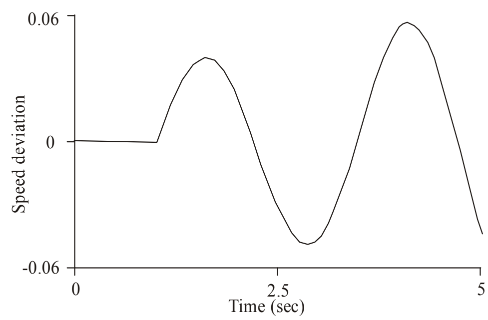

Fig. 3: Response of the system without controller

- **Case 4:** The 20% increase of line reactance X_L at heavy loading condition

In this study, in order to acquire better performance, number of particle, particle size, number of iteration and β is chosen as 30, 3, 50 and 1.5, respectively. It should be noted that QPSO algorithm is run several times and then optimal set of STATCOM controller parameters is selected. The final values of the optimized parameters are given in Table 1.

SIMULATION RESULTS

To assess the effectiveness and robustness of the proposed controllers, the performance of the proposed controller under transient conditions is verified by applying a 6-cycle three-phase fault at t = 1 sec, at the middle of the L_3 transmission line. The fault is cleared by permanent tripping of the faulted line. The response of the system without controller is shown in Fig. 3. When STATCOM is not installed it can be seen that system is unstable. The system response to this disturbance of generator at nominal, light and heavy loading conditions due to designed controller based on the C and ϕ are shown in Fig. 4 and 5. It is also clear that the system damping with the proposed method based tuned STATCOM based controller are significantly improved. The performance of the proposed method is compared to that of the classical method. It can be seen that the QPSO based designed controller achieves good robust performance, provides superior damping in comparison with the CPSO method. This illustrates the potential and effectiveness of the proposed design approach to obtain an optimal set of output feedback controller gains.

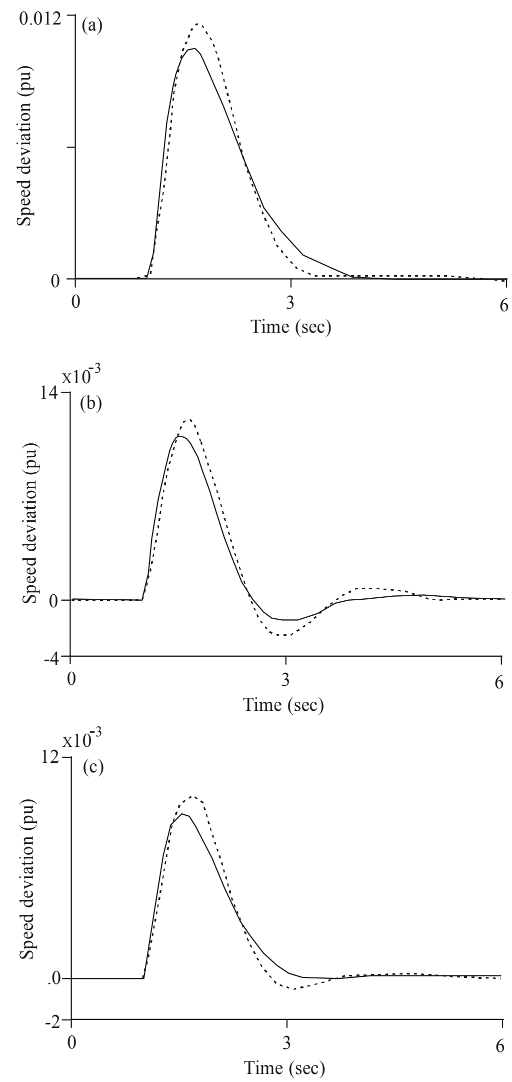

Fig. 4: Dynamic responses for Δω at (a) nominal (b) light and (c) heavy loading; solid (QPSO based ϕ controller) and dashed (CPSO based ϕ controller)

To demonstrate performance robustness of the proposed method, two performance indices: the Integral of the Time multiplied Absolute value of the Error (ITAE) and Figure of Demerit (FD) based on the system performance characteristics are defined as (Jalilzadeh *et al*., 2009):

$$ITAE = 10000 \int_0^{tsim} |\Delta\omega|.tdt$$
$$FD = (OS \times 200)^2 + (US \times 1000)^2 + T_s^2 \tag{34}$$

where, speed deviation (Δω), Overshoot (OS), Undershoot (US) and settling time of speed deviation of the machine is considered for evaluation of the ITAE and FD indices. It is worth mentioning that the lower the value

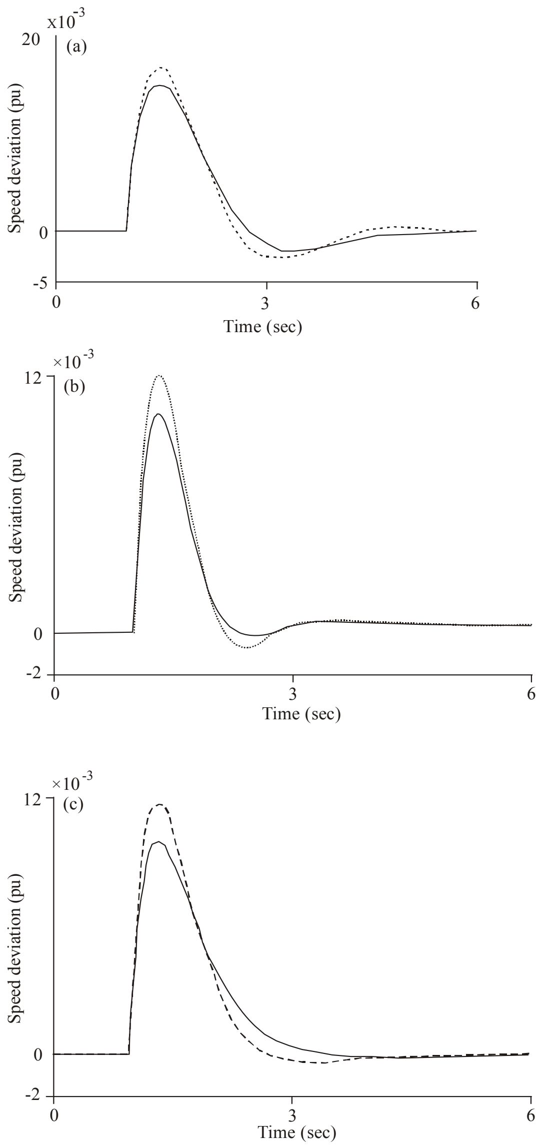

Fig. 5: Dynamic responses for Δω at (a) nominal (b) light and (c) heavy loading; solid (QPSO *based C controller*) and dashed (CPSO *based C controller*)

Table 2: Values of performance index ITAE

Type of algorithm	Nominal		Light		Heavy	
	C	ϕ	C	ϕ	C	ϕ
CPSO	34.000	26.460	18.550	21.87	18.04	17.16
QPSO	33.328	26.050	14.931	20.19	17.68	17.03

of these indices is, the better the system response in terms of time-domain characteristics. Numerical results of performance robustness for nominal, light and heavy loading cases are given in Table 2 and 3. This demonstrates that the overshoot, undershoot, settling time and speed deviations of the machine are greatly reduced

Table 3: Values of performance index FD

Type of algorithm	Nominal		Light		Heavy	
	C	ϕ	C	ϕ	C	ϕ
CPSO	347.5	151.31	130.07	218.79	144.42	102.01
QPSO	310.1	133.37	104.34	183.12	108.05	93.108

by applying the proposed QPSO based tuned output feedback controllers.

CONCLUSION

This study has discussed OFD controller design for STATCOM with multiple operating points. The design problem of the robustly selecting output feedback controller parameters is converted into an optimization problem which is solved by a quantum PSO with the time domain-based objective function. Only the local and available state variables $\Delta\omega$, ΔP_e and ΔV_t are taken as the input signals of each controller, so the implementation of the designed stabilizers becomes more feasible. The effectiveness of the proposed controllers for improving dynamic stability has been demonstrated on a single machine infinite bus. Numerical results have shown that the proposed damping controller can ensure the simultaneous stability and adequate damping for the multiple operating points. The system performance characteristics in terms of ITAE and FD indices reveal that using the proposed QPSO based controllers the overshoot, undershoot, settling time and speed deviation of rotor are greatly reduced at various operating conditions.

Appendix: The nominal parameters of the system are listed in Table 4.

Table 4: System parameters

	M = 8 MJ/MVA	$T_{d'o}$ = 5.44 s	X_d = 1pu
Generate	Xq = 0.6 p.u	$X_{d'}$ = 0.3 p.u	D = 0
Excitation system		K_a = 50	T_a = 0.5 s
Transformers		X_r = 0.1 pu	X_{SDT} = 0.1 pu
Transmission line		X_q = 0.4 pu	
DC link Parameter		V_{DC} = 1 pu	C_{DC} = 1pu
STATCOM parameter		C = 0.25	ϕ = 52′
		K_s = 1	T_s = 0.05

REFERENCES

Armansyah, F., N. Yorino and H. Sasaki, 2002. Robust synchronous voltage sources designed controller for power system oscillation damping. Int. J. Elec. Power Energ. Syst., 24: 41-49.

Chen, X.R., N.C. Pahalawaththa, U.D. Annakkage and C.S. Cumble, 1998. Design of decentralized output feedback TCSC damping controllers by using simulated annealing. IEE Proc. Gener. Trans. Dist., 145(5): 553-558.

Coelho, L.S., 2008. A quantum particle swarm optimizer with chaotic mutation operator, Chaos Soliton. Fractals, 37: 1409-1418.

Hingorani, N.G. and L. Gyugyi, 1999. Understanding FACTS: Concepts and Technology of Flexible AC Transmission Systems, Wiley-IEEE Press.

Huang, D. and S.K. Nguang, 2007. Static output controller design for fuzzy systems: An ILMI approach. Inf. Sci., 177: 3005-3015.

Jalilzadeh, S., H. Shayeghi, A. Safari and D. Masoomi, 2009. Output Feedback UPFC Controller Design by Using Quantum Particle Swarm Optimization. IEEE International Conference. ECTI-CON, pp: 28-31.

Kennedy, J., 1997. The particle swarm: Social adaptation of knowledge. Proceeding of the International Conference on Evol. Comput., Pp: 303-308.

Klein, M., L.X. Le, G.J. Rogers, S. Farrokhpay and N.J. Balu, 1995.H_∞ Damping controller design in large power systems. IEEE T. Power Syst., 10: 158-166.

Lee, S., 2005. Optimal decentralized design for output-feedback power system stabilizers. IEE Proc. Gene. T. Dis., 152(4): 494-502.

Moris, S., P.K. Dash and K.P. Basu, 2003. A fuzzy variable structure controller for STATCOM. Elec. Power Syst. Res., 65: 23-34.

Noroozian, M. and G. Andersson, 1993. Power flow control by use of controllable series components. IEEE T. Power Deliv., 8: 1420-1429.

Poli, R., J. Kennedy and T. Blackwell, 2007. Particle swarm optimization: An overview. Swarm Intelligent, 1: 33-57.

Ramos, R.A., A.C.P. Martins and N.G. Bretas, 2005. An improved methodology for the design of power system damping controllers. IEEE T. Power Syst., 20(4): 1938-1945.

Rahim, H.M.A. and M.F. Kandlawala, 2004. Robust STATCOM voltage controller design using loop shaping technique. Elect Power Syst. Res., 68: 61-74.

Spitsa, V., A. Alexandrovitz and E. Zeheb, 2010. Design of a robust state feedback controller for a STATCOM using a zero set concept. IEEE Trans. Power Deliv., 25(1): 456-467.

Sun, J., W. Fang and W. Xu, 2005. Adaptive parameter control for quantum-behaved particle swarm optimization on individual level. Proceeding IEEE international conference. on systems, man and cybernetics, Big Island (USA), pp: 3049-3054.

Sun, J., W. Fang, W. Chen and W. Xu, 2008. Design of two dimensional IIR digital filters using an improved quantum-behaved particle swarm optimization algorithm. Proceeding of American control conference (AACC), pp: 2603-2608.

Wang, H.F., 2003. Phillips-Heffron model of power systems installed with STATCOM and applications. IEE Proc. Gener. Transm. Distrib., 146(5): 521-527.