Hindawi Publishing Corporation
Conference Papers in Engineering
Volume 2013, Article ID 635808, 6 pages
http://dx.doi.org/10.1155/2013/635808

Conference Paper

Performance Assessment of Fuzzy Logic Power System Stabilizer on North Benghazi Power Plant

T. Hussein and A. Shamekh

University of Benghazi, Benghazi, Libya

Correspondence should be addressed to T. Hussein; elmenfy@yahoo.com

Received 27 February 2013; Accepted 12 May 2013

Academic Editors: M. Elmusrati, A. Gaouda, and H. Koivo

This Conference Paper is based on a presentation given by T. Hussein at "International Conference on Electrical and Computer Engineering" held from 26 March 2013 to 28 March 2013 in Benghazi, Libya.

Fuzzy logic design has been implemented online to tune the power system stabilizer gain (K_{PSS}). To assess the performance of the proposed technique, Benghazi North Power Plant (BNPP), at eastern Libyan network, has been utilized as a power system stabilizer (PSS) benchmark. The design considers different operating conditions and large disturbance. A selection of fuzzy rules is derived by means of system output power to tune K_{PSS}, whereas Particle Swarm Optimization technique (PSO) is exploited to calculate the PSS parameters offline according to real-time measurements of the considered plant. Several simulation scenarios have been conducted to show the effectiveness of the proposed PSS in damping of local and interarea modes of oscillation of one-machine infinite-bus system. The study also contains comparison between the proposed technique and conventional PSS (CPSS).

1. Introduction

Power systems are normally designed so that they can operate and survive large disturbances like storms, lightning strikes, equipment failures, and unpredictable fault locations. This usually means that even though some power system equipment will be separated or isolated as a result of automatic protection and control actions, power supply to customers will not be disrupted or, at least, that any such disruptions will be localized.

The phenomenon of electromechanical oscillations between interconnected synchronous generators in power systems is intensively discussed in the literature. Power system oscillations associated with a single generator are classified as local modes of oscillations. Local modes have typically frequencies in the range from 0.7 to 2.0 Hz [1]. Small signal instability occurs when a system perturbation, even a small one, excites a natural oscillatory mode of the power system. These oscillations are slow, usually under 1 Hz. The main method used today to guard against small signal instability is the offline tuning of power system stabilizers (PSS). These PSSs are local controllers on the generators. Thus local controllers are used to mitigate system oscillation modes. However, this procedure, in some circumstances, is recognized to have significant disadvantages [2].

The most commonly used PSS, referred to as conventional PSS (CPSS), is a fixed parameter analog-type device with lead-lag compensation, wash out, and amplifier gains, which are limited and may lose effective damping robustness for overall operation [3, 4].

New controllers need to be developed that can exploit system-wide inputs (not necessarily more inputs per controller but input signals from further away). Such remote signal inputs will obviously require communication channels which could be dedicated or could use a more flexible communication mesh network. Another control concept is to adaptively change the PSS set points according to the power system operating conditions.

Adaptive control can change the controller parameters online based on the changes in system operating conditions. An adaptive controller responds to changes in system operating conditions by determining a new set of control parameters. A number of examples of development and successful implementation of adaptive PSSs (APSSs) based on artificial intelligent (AI) techniques are described in [2].

A self-learning fuzzy logic controller working as AI power system stabilizer is introduced in [5]. The inputs and outputs of the generator are measured; however, there is no need to determine the states of the synchronous generator. An adaptive neuro-fuzzy inference system- (ANFIS-)based PSS is developed [6], which uses the postdisturbance value of the electrical power and speed deviation (obtained online) as inputs. The ANFIS PSS utilizes a zero-order Sugeno-type fuzzy logic controller whose membership functions and consequences are also tuned online by the back-propagation method.

Multiobjective design that implements hierarchical genetic algorithm (HGA) and parallel Micro-Genetic Algorithm (Micro-GA) is presented in [7]. The method translates the tuning problem into a multi-input multi-output (MIMO) control system problem, where multiple power system stabilizers (PSSs) in multimachine power systems are tuned simultaneously. A rule-based FPSS is designed, whereas the parameters are tuned by another fuzzy logic system; this makes it adaptable to changes in operating conditions [8, 9]. The algorithm is then used to stabilize a synchronous machine, which is part of a multimachine power system.

Power system stabilizer (PSS) in BNPP has been considered for investigation because it has significant impact on dynamic stability of the Libyan power system network. In 1995, a fast static excitation system (PID-system) UNITROL D with supplementary feedback lead-lag PSS was installed by ABB in BNPP. This suggests that the PSS parameters should be retuned regularly in order to cope with the power system growth as well as to handle effectively the new power system structures. This paper recommends the design of fuzzy logic algorithm to tune K_{PSS} of the conventional lead-lag power system stabilizer online, whereas the stabilizer parameters were initially obtained offline using PSO which is explained in Section 4.

2. Fuzzy Logic Control (FLC)

FLC is a kind of a state variable controller governed by a family of rule and a fuzzy inference mechanism. The FLC algorithm can be implemented using heuristic strategies defined by linguistically describe statements [8]. The fuzzy logic controllers are mainly used for power system excitations. In conventional controller designs, a plant needs to be mathematically modeled and from the control law is derived based on the analysis of the mathematical model. The main advantage of fuzzy logic control design lies in the nonlinearity nature of fuzzy control rules that can manage a wide range of operating conditions. The main components in FLC, as shown in Figure 1, are the fuzzifier, rule base, the inference engine mapping, and defuzzifier

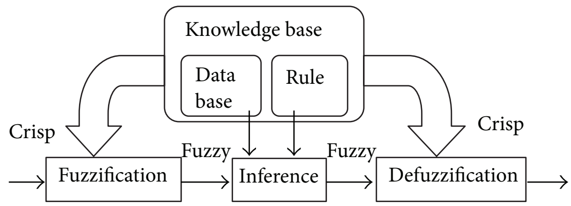

Figure 1: The basic structure of the fuzzy controller.

The inference engine maps the input values into fuzzy values using normalized membership functions and input gains. The fuzzy-logic inference engine deduces the proper control action based on the available rule base. The fuzzy control action is then translated to the proper crisp value through the defuzzifier using normalized membership functions and the output gain. In this work, the output control signal from FLC is employed to optimize the gain of the PSS. The suggested design is introduced as supervisory fuzzy logic PSS (SFPSS). It is worth to note that the trapezoidal membership functions, as shown in Figure 2, are used in control law design.

3. The Proposed Power System Stabilizer (SFPSS)

Essentially, the PSS mechanism can be described as a supplementary control signal that is added to a generator excitation control unit or automatic voltage regulator (AVR). This can improve the overall power system dynamic stability, and particularly to address the control of electromechanical oscillations. Thus, the PSS uses feedback signals such as shaft speed, terminal frequency, active power, and acceleration power to change the summing element of the AVR. This is a very effective method of enhancing small-signal stability performance on a power system grid. Equation (1) describes the block diagram of CPSS at BNPP

$$G_{\mathrm{PSS}}(s) = \left(K_{\mathrm{pss}}\right)\left[\frac{sT_w}{1+sT_w}\right]\left[\frac{1+sT_1}{1+sT_2}\right]\left[\frac{1+sT_3}{1+sT_4}\right]. \quad (1)$$

In (1), T_1 to T_4 denote PSS time constants, whereas T_w represents the time constant of the washout stage filter. As illustrated in Figure 3, the proposed fuzzy logic power system stabilizer consists of a conventional lead-lag stabilizer and a fuzzy logic-based parameter tuner that adjusts the PSS gain (K_{PSS}) according to real-time operating points and knowledge from a rule base prepared offline. $\Delta\omega$ and P_e represent the rotor speed deviation and electrical power, respectively. The implemented rules in the fuzzy logic design are as follows.

Rule 1. If operating point is positive, then K_{PSS} is positive.

Rule 2. If operating point is zero, then K_{PSS} is zero.

Rule 3. If operating point is negative, then K_{PSS} is negative.

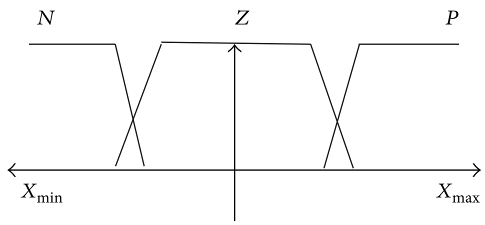

Figure 2: Fuzzy variables, three membership functions.

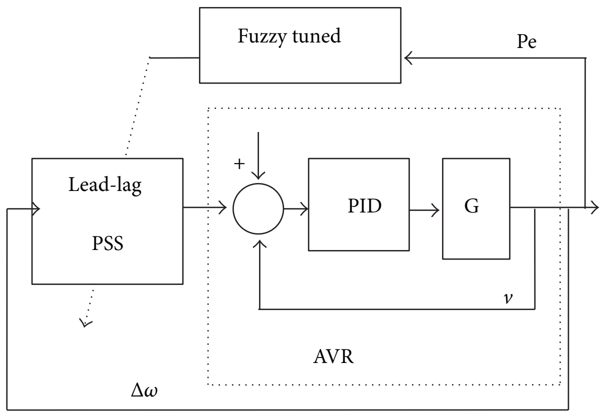

Figure 3: SFPSS block diagram.

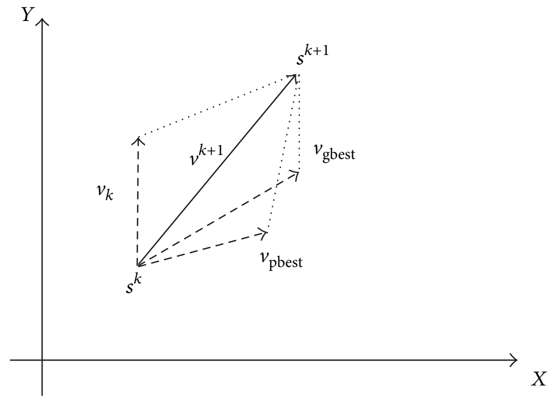

Figure 4: Concept of modification of a searching point. s^k: current searching point, s^{k+1}: modified searching point, v^k: current velocity, v^{k+1}: modified velocity, v_{pbest}: velocity based on pbest, and v_{gbest}: velocity based on gbest.

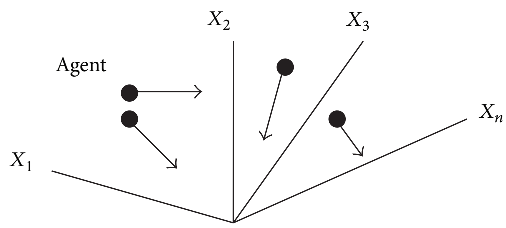

Figure 5: Searching concept with agent in a solution space by PSO.

The designed SFPSS is implemented and tested, by means of computer simulation on a single machine-infinite bus system, where the applied parameters and operating conditions are taken from nominal measurements of BNPP. To confirm the superiority of the proposed technique, three loading conditions are considered. The system parameters and the time constants of the PSS are listed in the appendix.

4. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is one of the optimization techniques that have emerged from the evolutionary computation algorithms [10, 11].

The features of PSO are as follows.

(i) The method is based on searching for swarms such as fish schooling and bird flocking.

(ii) It can be easily implemented and has stable convergence, and the computation time is relatively short.

According to the research results for the bird flocking, birds find the foods by flocking not by each individual. Each particle keeps track of its coordinates in the space, which are associated with the best solution. This value is called pbest. Another best value that is tracked by the global version of the particle swarm optimizer is the overall best value, and its location obtained so far by any particle in the group is called gbest. The PSO concept is, at each time step, changing the velocity of each particle toward its pbest and gbest location. The modified velocity of each agent can be calculated using the current velocity and the distance from pbest and gbest as shown below:

$$v_i^{k+1} = w_i v_i^k + c_1 \text{rand} \times \left(\text{pbest} - s_i^k\right) + c_2 \text{rand} \times \left(\text{gbest} - s_i^k\right), \tag{2}$$

where v_i^k is current velocity of particle i at iteration k, v_i^{k+1} is modified velocity of particle i, rand is random number between 0 and 1, s_i^k is current position of particle i at iteration k, pbest is pbest of particle i, gbest is gbest of particle i, w_i is weight function for velocity of agent i, and c_i is weight coefficient.

Using the above equation, a certain velocity that gradually gets close to pbest and gbest can be calculated. The current position (searching point in the solution space) can be modified by the following equation:

$$s_i^{k+1} = s_i^k + v_i^{k+1}. \tag{3}$$

Figure 4 shows the concepts of modification of a searching point by PSO.

Figure 5 shows a searching concept with agent in a solution space.

The Algorithm of PSO. The proposed algorithm of PSO for searching the optimal values of the PSS parameters is as follows.

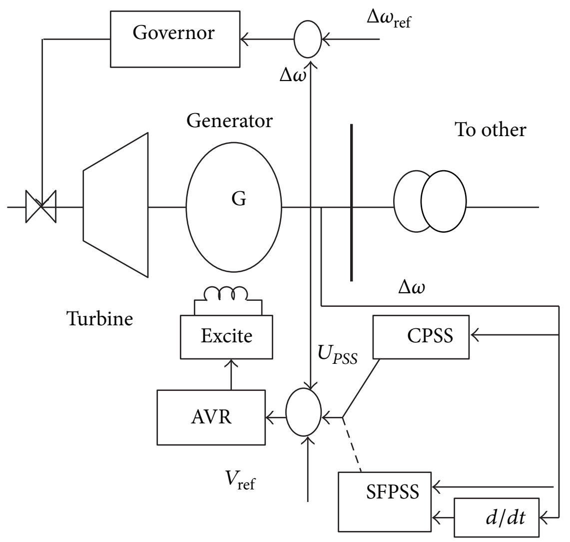

Figure 6: Schematic diagram of power system model.

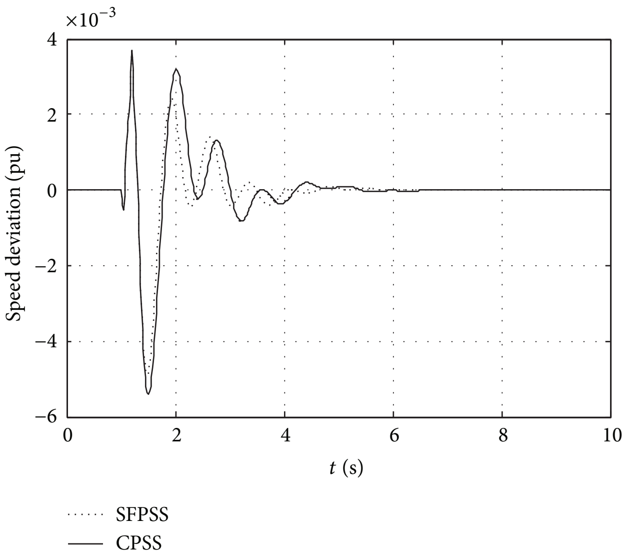

Figure 7: Speed deviation (operating condition I).

(1) Initialize the swarm with random positions and velocities.

(2) Calculate the fitness function of each particle by

$$0.5 \times \text{sum}(\omega - \omega_d)^2 \times t, \tag{4}$$

where ω is actual speed and ω_d is desired speed.

(3) Determine the pbest and the gbest positions.

(4) Update the velocity of particle using (2).

(5) Update the position of particle using (3).

(6) If the evaluation value of each particle is better than the previous pbest, the value is set to pbest. If the best pbest is better than gbest, the value is set to gbest.

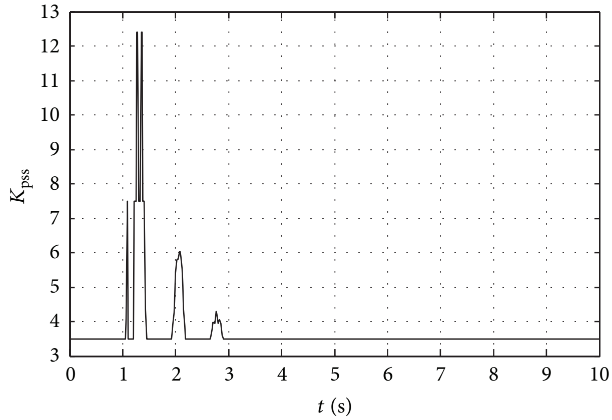

Figure 8: K_{PSS} (operating condition I).

(7) If the iteration number reaches the maximum iteration number, then go to step (8). Otherwise, go to step (2).

(8) Plot pbest, gbest, and compute (4) for the control candidates with optimal values of PSS parameters.

5. Simulation Results

The performance of SFPSS is evaluated by subjecting the system to a large disturbance in a form of a three-phase fault of one transmission line. The fault occurs at 1 sec. and cleared at 1.2 sec. A schematic diagram representation of one generator connected with SFPSS is shown in Figure 6. For comparison purpose, the system is configured to switch between two different control techniques, in order to show the advantages of the proposed SFPSS over CPSS. The suitability of the proposed technique is checked by the performance index (J_p), which is calculated by (5)

$$J_p = \sum \Delta\omega^2. \tag{5}$$

Figures 7, 8, 9, 10, 11, and 12 show the system results with SFPSS and CPSS. As mentioned before, three loading conditions are considered. These are as follows.

Operating conditions I:

(a) active power ($P_e = 0.4$ pu),

(b) reactive power ($Q_e = 0.0016$ pu).

Operating conditions II:

(a) active power ($P_e = 0.6$ pu),

(b) reactive power ($Q_e = 0.004$ pu).

Operating conditions III:

(a) active power ($P_e = 0.85$ pu),

(b) reactive power ($Q_e = 0.008$ pu).

Obviously, the results have shown that SFPSS has better transient response as well as minimum steady state error than

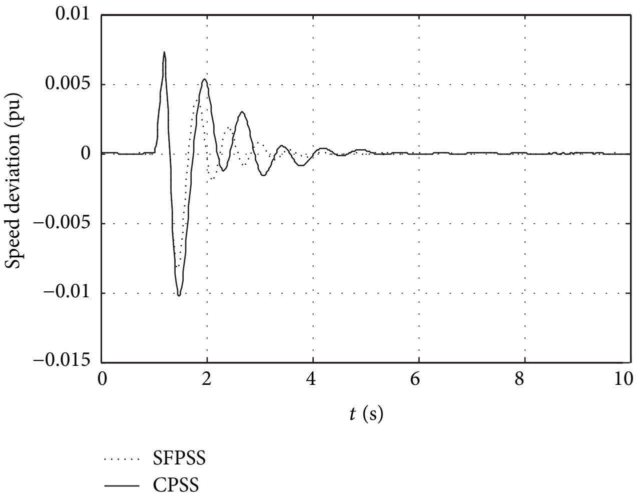

Figure 9: Speed deviation (operating condition II).

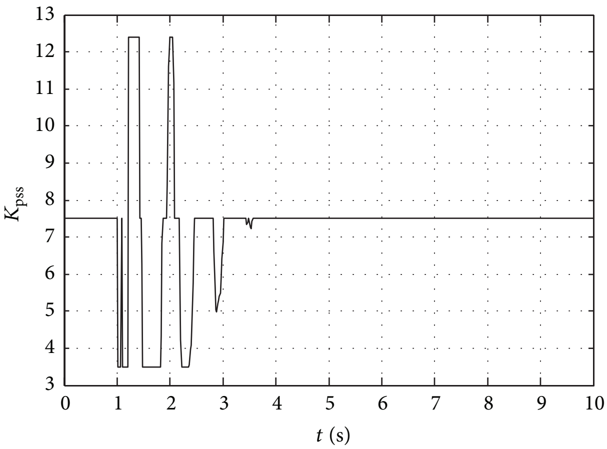

Figure 10: K_{PSS} (operating condition II).

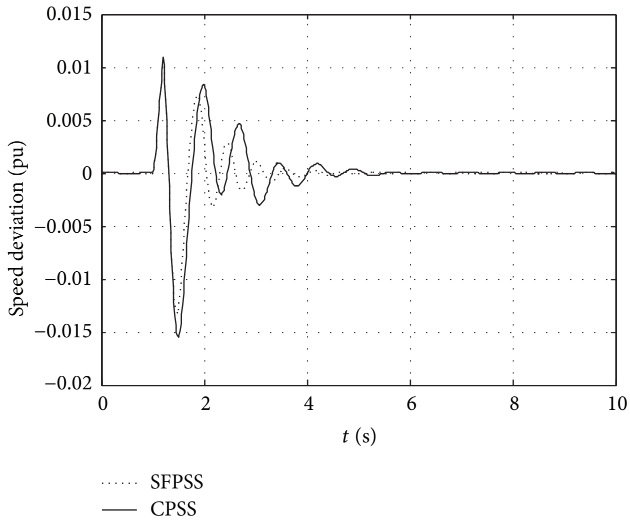

Figure 11: Speed deviation (operating condition III).

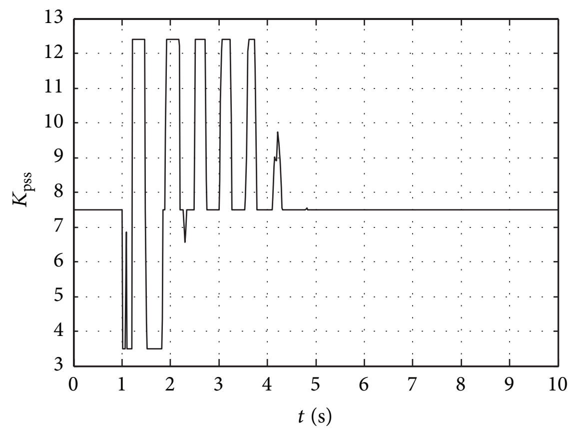

Figure 12: K_{PSS} (operating condition III).

CPSS. The simulation results have also displayed that the SFPSS algorithm can cope with large disturbance at different operating points and has a significant impact in overall power system stability. It is very important to note that K_{PSS} has a mild action, which means that it can be safely exploited. However, in several occasions it hits the saturation limits. In terms of statistics, Table 1 visibly shows that SFPSS is superior compared with CPSS; hence it can significantly minimize J_p index.

6. Conclusion

In this study, fuzzy logic control is applied to tune K_{pss} online. PSO technique is implemented to find the parameters of PSS based on the offline measurements. The suggested design is tested on BNPP benchmark. The article reveals that the developed algorithm is straightforward and systematic to be implemented. The results have shown that the designed stabilizer has the capability to maintain the system to operate at the optimum response in the sense of transient condition, settling time, and steady state error. Furthermore, this improvement can be achieved over a wide range of operating conditions.

Table 1

Technique	Operating conditions I	Operating conditions II	Operating conditions III
J_p (SFPSS)	0.000087	0.00021	0.00056
J_p (CPSS)	0.00037	0.00089	0.0012

Appendix

The generator parameters in per unit on rated 210 MVA and 15.75 kV base are

$$x_d = 2.53\,\text{pu}, \qquad x_q = 2.36\,\text{pu},$$

$$x'_d = 0.248\,\text{pu}, \qquad x'_q = 0.4\,\text{pu},$$

$$
\begin{gathered}
x_d'' = 0.187\,\text{pu}, \qquad x_q'' = 0.2\,\text{pu}, \\
T_{do}' = 10.8\,\text{S}, \qquad R_s = 0.001\,\text{pu}, \\
T_{do}'' = 0.03\,\text{S}, \qquad x_i = 0.17\,\text{pu}, \\
T_{qo}' = 0.99\,\text{S}, \qquad T_{qo}'' = 0.034\,\text{S}, \qquad H = 1.29\,\text{S}, \\
T_1 = 0.15, \qquad T_2 = 0.03, \qquad T_3 = 0.15, \\
T_4 = 0.03, \qquad T_W = 1.65.
\end{gathered}
\tag{A.1}
$$

For CPSS,

$$K_{PSS} = 20, \tag{A.2}$$

where x_i is leakage reactance, x_d is d-axis synchronous reactance, x_d' is d-axis transient reactance, $x_d^{\approx}$ is d-axis subtransient reactance, x_q is q-axis synchronous reactance, x_q' is q-axis transient reactance, $x_q^{\approx}$ is q-axis subtransient reactance, T_{do}' is d-axis transient open-circuit time constant, T_{do}'' is d-axis subtransient open-circuit time constant, T_{qo}' is q-axis transient open-circuit time constant, $T_{qo}^{\approx}$ is q-axis subtransient open-circuit time constant, R_s is stator resistance, and H is moment of inertia time constant.

Acknowledgment

Special thanks are due to the National Academy for Scientific Research (NASR) in Libya for its financial support.

References

[1] M. Klein, G. J. Rogers, and P. Kundur, "A fundamental study of inter-area oscillations in power systems," *IEEE Transactions on Power Systems*, vol. 6, no. 3, pp. 914–921, 1991.

[2] O. P. Malik, "Artificial intelligence techniques applied to adaptive power system stabilizer design," in *Proceedings of the IEEE Power Engineering Society General Meeting (PES '06)*, June 2006.

[3] M. Nambu and W. Ohsawa, "Development of an advanced power system stabilizer using a strict linearization approach," *IEEE Transactions on Power Systems*, vol. 11, no. 2, pp. 813–818, 1996.

[4] M. Eboul-Ela, A. Salam, J. Macclley, and A. Fouad, "Damping controller design for power system oscillations using global signals," *IEEE Transactions on Power Systems*, vol. 11, no. 2, 1996.

[5] T. Abdelazim and O. P. Malik, "An adaptive power system stabilizer using on-line self-learning fuzzy systems," in *Proceedings of the IEEE Power Engineering Society General Meeting*, pp. 1715–1720, July 2003.

[6] R. You, H. J. Eghbali, and M. H. Nehrir, "An online adaptive neuro-fuzzy power system stabilizer for multimachine systems," *IEEE Transactions on Power Systems*, vol. 18, no. 1, pp. 128–135, 2003.

[7] K. Hongesombut, S. Dechanupa, Y. Mitani, and I. Ngamroo, "Robust power system stabilizer tuned based on multiobjective design using hierarchical and parallel micro genetic algorithm," in *Proceedings of the 15th Power Systems Computation Conference (PSCC '05)*, pp. 22–26, Liege, Belgium, August 2005.

[8] N. Hosseinzadeh, "A self-tuned fuzzy-logic power system stabilizer," in *Proceedings of the 9th Iranian Conference on Electrical Engineering*, Proceeding on Power, pp. 8.1–8.9, Tehran, Iran, May 2001.

[9] T. Hussein, A. L. Elshafei, and A. Bahgat, "Design of a hierarchical fuzzy logic PSS for a multi-machine power system," in *Proceedings of the 15th IEEE Mediterranean Conference on Control and Automation (MED '07)*, pp. 1–6, July 2007, T26-006.

[10] Y. Fukuyama, "A particle swarm optimization for reactive power and voltage control considering voltage stability," in *Proceeding of IEEE International Conference on Intelligent System Application to Power System (SAP '99)*, pp. 1–6, Rio de Janeiro, Brazil, April 1999.

[11] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proceedings of the IEEE International Conference on Neural Networks (ICNN '95)*, vol. 4, pp. 1942–1948, Perth, Australi, December 1995.


The Scientific World Journal
Hindawi Publishing Corporation
http://www.hindawi.com
Volume 2013