Simultaneous Coordinated Tuning of PSSs Using Artificial Fish-Swarm Algorithm

LIMIN YANG, Z CHEN,W DU, JIANBO XIN, H F WANG and R DUNN
The Hohai University, Nanjing, China
The Southeast University, Nanjing, China, The Jiangxi Electrical Power Company, China.
The Queen's University of Belfast, Belfast, UK, The University of Bath, Bath, UK

Abstract: -Artificial Fish-Swarm Algorithm (AFSA) is a novel method to search global optimum, which is typical application of behaviorism in artificial intelligence. This paper presents the use of AFSA as a new method for simultaneous coordinated turning of power system stabilizers (PSSs) to enhance small-signal stability in multi-machine system. Using the linearized system model and the parameter-constrained optimization algorithm, the parameters of PSSs are tuned simultaneously. The performance of the proposed PSSs under different loading conditions is investigated. The eigenvalue analysis and the nonlinear simulation results show the effectiveness and robustness of the proposed PSSs to damp out the local as well as the inter-area modes of oscillations over a wide range of loading conditions. The method is applied for coordinated tuning of 15 PSSs in a practical system.

Keywords:- rtificial Fish-Swarm Algorithm (AFSA); PSSs design; Small-signal stability; Coordinated tuning

1 Introduction

With the interconnection of large electric power systems, low frequency oscillations have become the main problem for power system small signal stability. They restrict the steady-state power transfer limits, which therefore affects operation-al system economics and security. Considerable effort has been placed on the application of Power System Stabilizers (PSSs) to damp low frequency oscillations and thereby improve the small signal stability of power systems [1]. To date, PSSs have proved to be very effective and economical tools and therefore have been widely used by utilities.

With the wide application of PSSs, there exists the possibility of adverse interactions, especially in multi-machine, multi-modal power systems [2]. In recent years, the coordination and design of PSSs in order to improve the dynamic performance of a multi-machine system has received great attention [3]–[8]. Some early works in the PSS parameter design, such as the sequential design, the decentralized modal control, the pole-placement, have been reported in the literature. A gradient procedure for optimization of PSS parameters is presented in [3]. The optimization process requires computations of sensitivity factors and eigenvectors at each iteration. This gives rise to heavy computational burden and slow convergence. In addition, the search process is susceptible to be trapped in local minima, and the solution obtained will not be optimal. Unfortunately, the problem of the PSSs design is a multimodal optimization problem (i.e., there exists more than one local optimum). Hence, local optimization techniques, which are well elaborated upon, are not suitable for such a problem. Moreover, there is no local criterion to decide whether a local solution is also the global solution [4].

Therefore, conventional optimization methods that make use of derivatives and gradients are, in general, not able to locate or identify the global optimum, but for real-world applications, one is often content with a "good" solution, even if it is not the best. Consequently, heuristic methods are widely used for global optimization problems. In this paper, Artificial Fish-Swarm Algorithm (AFSA), as a promising heuristic algorithm, is proposed for a PSS design problem. Reference [4] [5] demonstrates that the conventional PSS can provide satisfactory damping performance over a wide range of system loading conditions. For the robust design of PSSs, several operating conditions and system configurations are simultaneously considered to construct an eigenvalue-based objective function and then the PSS parameter design problem is solved by genetic algorithm (GA) [4][5], simulated annealing (SA) [6], evolutionary programming [7] or particle swarm [8] optimization approaches. These optimization approaches are able to converge to a satisfactory design solution.

In this paper, a novel approach to PSSs design by an eigenvalue shift technique using the AFSA [9] is proposed. The problem of PSSs design is formulated as an optimization problem, and the AFSA is employed to solve this optimization problem with the aim of getting optimal settings of the PSS parameters. The proposed design approach has been applied to a 473-buses practical power system. The eigenvalue analysis and the nonlinear simulation results have been carried out to assess the effectiveness of the proposed PSSs under different loading conditions.

2 Problem statement

2.1Power System Model

Tuning of power system damping controllers typically uses a small-signal model represented by a set of equations (1) which is defined by the linearization of the differential algebraic equations (DAE) around an operating condition:

$$\begin{bmatrix} d\Delta\boldsymbol{x}/dt \\ \boldsymbol{0} \end{bmatrix} = \begin{bmatrix} \tilde{\boldsymbol{A}} & \tilde{\boldsymbol{B}} \\ \tilde{\boldsymbol{C}} & \tilde{\boldsymbol{D}} \end{bmatrix} \begin{bmatrix} \Delta\boldsymbol{x} \\ \Delta\boldsymbol{y} \end{bmatrix} \quad (1)$$

where $\Delta\boldsymbol{x}$ is the vector of the state variables, such as the machines speed, machines angles, and fluxes; and $\Delta\boldsymbol{y}$ the vector of the algebraic variables, such as bus voltages and phases; The state matrix $\boldsymbol{A}$ is simply obtained by eliminating the algebraic variables $\Delta\mathbf{y}$:

$$\boldsymbol{A} = \tilde{\boldsymbol{A}} - \tilde{\boldsymbol{B}}\tilde{\boldsymbol{D}}^{-1}\tilde{\boldsymbol{C}} \quad (2)$$

From (2), the eigenvalues $\lambda_i = \delta_i \pm j\omega_i$ of the total system can be evaluated. A good measure of damping is the damping ratio. It is defined is

$$\zeta = \frac{-\delta}{\sqrt{\alpha^2 + \omega^2}} \quad (3)$$

2.2 PSS structure

A widely used acceleration power ΔP -based conventional PSS is considered throughout the study. The transfer function of the *i-th* PSS is

$$U_{si} = K_i \frac{sT_{wi}}{1+sT_{wi}} \frac{1+sT_{1i}}{1+sT_{2i}} \frac{1+sT_{3i}}{1+sT_{4i}} \Delta P_{ei} \quad (4)$$

The first term in (4) is a washout term with a time lag T_w . The second term is a lead compensation to improve the phase lag through the system. The time constants T_{wi} are usually prespecified.The remaining parameters, namely, K_i , T_{1i} , T_{2i} , T_{3i} and T_{4i} are assumed to be adjustable parameters.

It is noted that eigenvalues of matrix $\boldsymbol{A}$ (2) are functions of the five parameters of each PSS. The optimization problem, namely, simultaneous coordinated tuning of these PSS parameters, is solved using AFSA. For a given operating point, the multi-machine power system is linearized around the operating point, the eigenvalues of the closed-loop system are computed, and the objective function is evaluated using only the unstable and lightly damped eigenvalues that need to be shifted.

C. Objective Function

The tuning criterion function is defined to be the sum of the spectrum damping ratios for all operating conditions in *m*. The constraint set comprises the parameter bounds plus the performance requirement for a minimum specified damping ratio. Therefore, the design problem can he formulated as the following optimization problem:

$$\max F = \sum_{k=1}^{m} \left(\sum_{j=1}^{n} \zeta_j\right)_k \quad (5)$$

Subject to

$$K_{i(\min)} \le K_i \le K_{i(\max)}$$
$$T_{1i(\min)} \le T_{1i} \le T_{1i(\max)}$$
$$T_{2i(\min)} \le T_{2i} \le T_{2i(\max)}$$
$$T_{3i(\min)} \le T_{3i} \le T_{3i(\max)}$$
$$T_{4i(\min)} \le T_{4i} \le T_{4i(\max)}$$

where *m* is the number of operating points considered in the design process, and *n* is the number of unstable or lightly damped electromechanical modes which are needed to consider.

The problem defines in (5) is a complex optimization problem with an implicit objective function, which depends on the evaluation of the eigenvalues of a large matrix. The problem is very difficult to solve using conventional methods.

3 Artificial fish swarm algorithm

3.1 Overview

AFSA is a stochastic and effective global optimization algorithm which mainly simulates fish schooling the behaviour of prey, swarm and follow [9]. AFSA possess similar attractive features of genetic algorithm (GA) such as independence from gradient information of the objective function, the ability to solve complex nonlinear high dimensional problems. Furthermore, they can achieve faster convergence speed and require few parameters to be adjusted. Whereas the AFSA does not possess the crossover and mutation processes used in GA, so it could be performed more easily. AFSA is also an optimizer based on population. The system is initialized firstly in a set of randomly generated potential solutions, and then performs the search for the optimum one iteratively.

3.2 AFSA Algorithm

Information about good solutions spreads through the swarm, and thus the AF tend to move to good areas in the search space. The general principles for the AFSA are stated as follows. Suppose that the searching space is *D*-dimensional and *N* fish form the colony. The *i-th* AF represents a *D*-dimensional vector $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$ (*i =1, 2, . . . , N*, here *N* is the swarm size) that is used to evaluate the quality of the AF. The state of each AF is a potential result. Therefore we could calculate the AF's fitness by putting its state into a designated objective function. When the fitness is higher, the corresponding X_i is "better". Given a fitness function $f(X)$ where X is a vector of D real-valued random variables; the AFS object initializes firstly a swarm of fish, each fish is randomly positioned in the D-dimensional real number space, and is a candidate solution to the fitness function; and then performs the search for the optimum one iteratively. During the search process each AF successively adjusts its state toward the good areas according to the behavior of prey, swarm and follow, and finally gains the global optimum. The behavior description of the AF is as follows:

1) Prey Behavior: Suppose that an AF's current state is X_i. We randomly select a new state X_j in its visual field according to the following equation:

$$X_j = X_i + Rand() \times Visual . \quad (6)$$

where $Rand()$ is a random function in the range [0,1] , and $Visual$ represents the visual distance of AF. If $f(X_i) < f(X_j)$, that is, satisfy the onward condition, then AF's state at the next iteration is calculated following equation:

$$X_i^{(t+1)} = X_i^{(t)} + Rand() \times Step \times (X_j - X_i^{(t)}) / \| X_j - X_i^{(t)} \| \quad (7)$$

where $X_i^{(t+1)}$ represents the AF's next state with the current state $X_i^{(t)}$; $d_{i,j} = \| X_j - X_i \|$ represents the Euclidean relative distance between X_i and X_j; and $Step$ represents the distance that AF can move for each step. In the opposite case , if $f(X_i) \geq f(X_j)$, then afresh select a new state X_j according to (6), and judge whether it satisfy the onward condition or not; After trying several times, if still did not find to satisfy the onward condition, then random move one step according to the following equation:

$$X_i^{(t+1)} = X_i^{(t)} + Rand() \times Step . \quad (8)$$

2) Swarm Behavior: An AF with the current state X_i seeks the companion's number in its current neighborhood where satisfy $d_{i,j} < Visual$; and calculate their centre position X_{centre}. If $nf \times f(X_i) < \delta \times f(X_{centre})$, that is, satisfy the onward condition, then the AF's state at the next iteration is calculated as follows:

$$X_i^{(t+1)} = X_i^{(t)} + Rand() \times Step \times (X_{centre} - X_i^{(t)}) / \| X_{centre} - X_i^{(t)} \| . \quad (8)$$

where nf represents the companion's number in the AF current neighborhood; and δ is a positive constant of greater than 1, called the crowded degree factor. Otherwise the AF carries out the prey behavior.

3) Follow Behavior: An AF with the current state X_i seeks the companion X_{max} that the optimization function value is maximum among all ones in its current neighborhood ($d_{i,j} < Visual$). If $nf \times f(X_i) < \delta \times f(X_{max})$, that is, satisfy the onward condition, then the AF's state at the next iteration is calculated as follows:

$$X_i^{(t+1)} = X_i^{(t)} + Rand() \times Step \times (X_{min} - X_i^{(t)}) / \| X_{min} - X_i^{(t)} \| \quad (9)$$

Otherwise the AF carries out the prey behavior.

Each artificial fish evaluates its current environment based on the behavior description of the AF, thus choose a fit behavior to move toward superior state quickly. Finally, the most AF can gather in the global optimum surroundings generally.

C. Application of AFSA to PSS Design

The AFSA algorithm described before has been applied to search for optimal or near optimal settings of the PSS optimized parameters. In our implementation, the search will terminate if the maximum number of iterations reaches.

The upper and lower limits on the design parameters are established based on either engineering judgment or previous controller setups. In this paper, the parameters of AFSA are set as follows: the swarm size N=20, $Visual$=0.3, $Step$=0.005, δ =1.6181, Max iterations is 200.

4 Case study

4.1 A Practical System

The test system used to assess the performance of the proposed method is a province system of Central China. The system is comprised of 473AC buses, 571AC branches, and 40 synchronous machines. The small-signal analysis and stability analysis environment for this system in the year 2006 are established for the study. A detailed model is adopted for generators with consideration of automatic voltage regulators (AVR), as well as PSS when they exist. The speed governors are not represented. In order to study the comprehensive oscillatory features of the system, three typical loading conditions—base load level, peak load level, and weak load level—are studied.

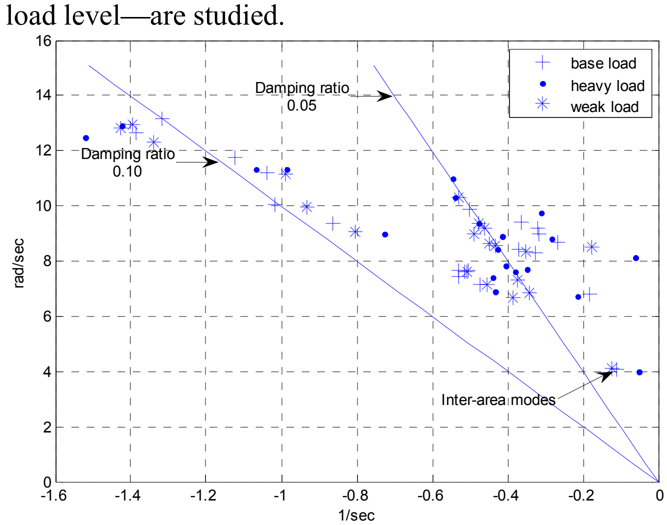

Fig.1 Electromechanical modes without PSSs

Using the subspace inverse iterate method [10], the electromechanical modes with frequency in the range of 0.1–2.0 Hz is scanned and the modes with damping ratio less than 0.10 are picked out. And only these are considered in the optimization. Fig.1 shows the electromechanical modes in s-plant without PSSs for three conditions. As it shown, the damping ratios of some local modes and some inter-area modes are less than 0.05. In practice, electromechanical oscillations with damping ratios less than 0.05 are not satisfactory.

4.2 Selection Sites of PSS

For installation of the power system stabilizers, there are two tasks to be completed: selection of sites and tuning of parameters. In order to suppress the poorly damped oscillatory modes effectively, proper selection of PSS sites is of great importance. Modal approaches for finding the optimal site of PSS include the participation factor, the transfer function residues and eigensolution free method [11]. The eigensolution free method of reduced-order modal control analysis is an effective method which not only completely avoids the numerical difficulty of eigensolution of high-dimensional matrices in the modal analysis but also greatly reduces the computational cost in selecting suitable installing locations of PSS. Therefore, the eigensolution free is adopted here to select the optimal location of PSS for the damping of low frequency oscillation.

The results of eigensolution free method indicate that generators in FengCheng, JingGangShan, JiuJiang2 □ 3 and Wan'An Station have preferable effects on the damping of modes which is shown in Fig.1. The number of generators of the five generation stations is 15. The generators and AVRs of each station are identical, and the generators of each station are connected to a high voltage bus by transformers. So it is assumed here that the parameters of PSS for each station are same. Therefore, the optimization objective is to coordinate 5 ΔP -measurement PSSs that have the structure given in (4).

4.3 PSS Design

In this case, there are 25 parameters to be optimized namely, K_i, T_{1i} , T_{2i}, T_{3i} and T_{4i} ,i = 1, 2,…, 5(i.e. D=25). The time constants T_w are set to be 10. Typical bounds of the optimized parameters K_i, T_{1i} T_{2i} T_{3i} and T_{4i} are list in Table1.

Table 1 Bounds of the parameters used in the design

Bounds	K_i	T_{1i}	T_{2i}	T_{3i}	T_{4i}
Lower limit	0.10	0.01	0.10	0.10	0.01
Upper limit	20.0	1.00	5.00	1.00	0.10

The AFSA algorithm has been applied to search for settings of these parameters in order to maximize the damping of all lightly damped electromechanical modes of oscillation: for instance, local modes, inter-area modes. The final values of the optimized parameters are given in Table 2. It is worth mentioning that the limits of the PSSs are set to 0.05 pu to avoid unrealistic values.

After the coordinated tuning, the electromechanical modes with the proposed PSSs are shown in Fig.2. It can be seen that the electromechanical modes of the base case with the proposed PSSs have been shifted to the left of line ζ >0.05. It is obvious that the system damping greatly improved and enhanced all cases. Especially, the inter-area modes (0.65Hz mode) of three conditions are also shown in Fig.2. The damping ratios of these modes are improved.

Table 2 Optimal values of PSS parameters

STATION	No. of PSS	K_i	T_{1i}	T_{2i}	T_{3i}	T_{4i}
FengCheng	4	2.0	0.02	0.50	0.90	0.10
JingGangShan	2	2.0	0.02	0.30	0.30	0.06
JiuJiang2	2	3.0	0.90	3.00	0.25	0.05
JiuJiang3	2	2.0	0.04	0.60	0.70	0.03
Wan'An	5	10.0	0.12	2.60	0.10	0.03

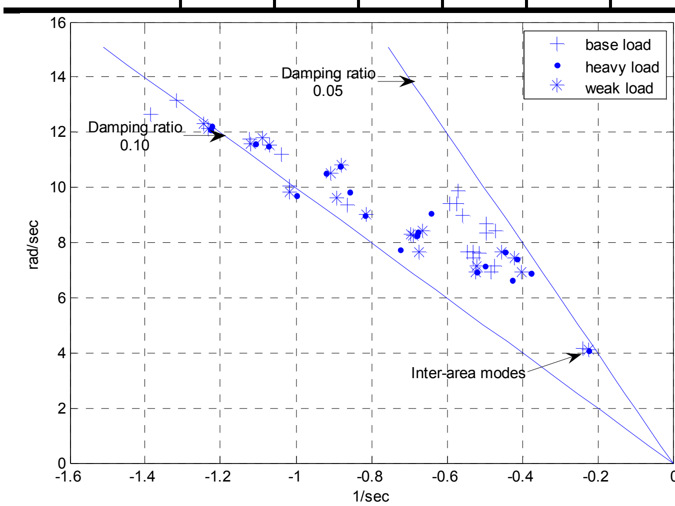

Fig.2 Electromechanical modes with proposed PSSs

4.4 Nonlinear Time-Domain Simulation

To verify the performance of the proposed simultaneous coordinated tuning method, a complete nonlinear-model time simulation was performed under the peak load condition of the test power system. At time equal to 1.0s, a three-phase fault of 60-ms duration was applied on NanChang at the end of line CiHu–NanChang which is a very important 500 kV AC interconnect transmission line. The swing angles of generators in the province relative to her neighboring province obtained in the simulation are shown in Figs. 3 for the peak load condition. It is clear that the system performance with the proposed PSSs is effective and that the oscillations are damped out much faster.

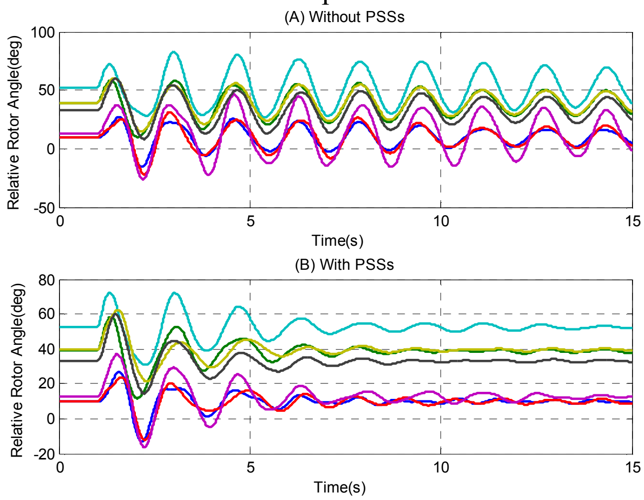

Fig.3 Swing angles without and with the PSSs for the three-phase fault under the peak load condition

5 Conclusions

Artificial Fish Swarm Algorithm, a new population-based evolutionary computation technique inspired by the natural social behavior of fish schooling and swarm intelligence, is an efficient and effective global optimization algorithm. In this paper, the AFSA is proposed for simultaneous coordinated turning of conventional lead-lag PSS parameters. The proposed method has been applied to a practical multi-machine power system with different loading conditions. In the process of optimization, all PSSs are designed simultaneously, taking into consideration the interaction among them. Since eigenvector calculations and sensitivity analysis are not required to evaluate the proposed objective function, heavy computations of the design process are avoided.

The eigenvalue analysis reveals the effectiveness of the proposed PSSs to damp out local as well as inter-area modes of oscillations. And the nonlinear time simulation results confirm that the proposed PSSs can work effectively over a wide range of loading conditions and system configurations.The results of this work showed that in a multi-machine system, fixed-structure PSSs can be tuned to provide satisfactory damping performance over a prespecified set of operating conditions. The AFSA-based tuning process has shown robustness in achieving PSSs satisfying the design criteria in a large-scale realistic power system.

References:

[1] P. Kundur, *Power System Stability and Control*. McGraw-Hill, 1993.

[2] Graham Rogers, *Power System Oscillation.* Kluwer Academic Publishers, 2000

[3] V. A. Maslennikov and S. M. Ustinov, "The optimization method for coordinated tuning of power system regulators," in *Proc. 12th Power Syst. Comput. Conf.* , Dresden, Germany, 1996, pp. 70–75.

[4] Y. L. Abdel-Magid, M. A. Abido, S. A. Al-Baiyat, and A. H. Mantawy, "Simultaneous stabilization of multimachine power systems via genetic algorithms" *IEEE Trans. on Power Systems,* Vol. 14, 1428-1439.

[5] Y. L. Abdel-Magid and M. A. Abido, "Optimal multiobjective design of robust power system stabilizers using genetic algorithms" *IEEE Trans. on Power Systems,* Vol. 18, No. 3, August 2003, pp. 1125-1132

[6] M. A. Abido, "Robust design of multimachine power system stabilizers using simulated annealing," *IEEE Trans. on Energy Conversion,* Vol. 15, No. 3, September 2000, pp. 297-304.

[7] M. A. Abido and Y. L. Abdel-Magid, "Optimal Design of Power System Stabilizers Using Evolutionary Programming," *IEEE Trans. on Energy Conversion,* Vol. 17, No. 4, December 2002, pp. 429-436

[8] M. A. Abido, "Optimal design of power system stabilizers using particle swarm optimization," *IEEE Trans. on Energy Conversion,* Vol. 17, No. 3, September 2002, pp. 406-413.

[9] Li Xiao-lei, Shao Zhi-jiang, Qian Ji-xin. An optimizing method based on autonomous animate: fish-swarm algorithm[J]. *System Engineering Theory and Practice*, 2002, 11: 32-38.

[10] Wang Xifan, Modern Power *System Analysis,* Science Press 2003

[11] Wang, H.F., Swift, F.J., and Li, M.: 'Indices for selecting the best location of PSSs or FACTS-based stabilisers in multimachine power systems: a comparative study', *IEE Proc., Gener. Transm. Distrib.*, 1997, 144, (2), pp. 155–159

[12] P Zhang, Coonick A H. Coordinated synthesis of PS5 parameters in multi-machine power systems applied to using the method of inequalities [J]. *IEEE Transactions on Power Systems,* 2000, 15(2): 811-816