Robust PSS Design Using Chaotic Optimization Algorithm for a Multimachine Power System

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Abstract- **In this paper, a multiobjective design of the multi-machine power system stabilizers (PSSs) using Chaotic Optimization Algorithm (COA) is proposed. COA, which have the features of easy implementation, short execution time and robust mechanisms of escaping from local optimum, is a promising tool for engineering applications. The PSSs parameters tuning problem is converted to an optimization problem which is solved by a chaotic optimization algorithm based on Lozi map. The robustness of the proposed COA based PSSs (COAPSS) is verified on a multimachine power system under different operating conditions. The results of the proposed COAPSS are demonstrated through eigenvalue analysis and nonlinear time domain simulation.**

I. Introduction

Stability of power systems is one of the most important aspects in electric system operation. This arises from the fact that the power system must maintain frequency and voltage levels, under any disturbance, like a sudden increase in the load, loss of one generator or switching out of a transmission line, during a fault [1]. Since the development of interconnection of large electric power systems, there have been spontaneous system oscillations at very low frequencies in the order of 0.2 to 3.0 Hz. Once started, they would continue for a long period of time. In some cases, they continue to grow, causing system separation if inadequate damping is available. To enhance system damping, the generators are equipped with the power system stabilizers (PSSs) that provide supplementary feedback stabilizing signals in the excitation systems [2].

Despite the potential of the modern control techniques with different structures, power system utilities still prefer the Conventional lead-lag Power System Stabilizer (CPSS) structure [3]. The reasons behind that might be the ease of online tuning and the lack of assurance of the stability related to some adaptive or variable structure techniques. In addition, Gibbard [4] demonstrated that the CPSS provide satisfactory damping performance over a wide range of system loading conditions. The robustness nature of the CPSS is due to the fact that the torque-reference voltage transfer function remains approximately invariant over a wide range of operating conditions. Despite the potential of the modern control techniques with different structures, power system utilities still prefer the Conventional lead-lag Power System Stabilizer (CPSS) structure [5-6]. The reasons behind that might be the ease of online tuning and the lack of assurance of the stability related to some adaptive or variable structure techniques. Moreover, it is shown that the appropriate selection of the CPSS parameters results in satisfactory performance during system upsets. Unfortunately, the problem of the PSS 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. Recently, global optimization techniques like Genetic Algorithms (GA), evolutionary programming, and rule based bacteria foraging [2, 5-6] have been applied for the PSS parameter optimization. These evolutionary algorithms are heuristic population-based search procedures that incorporate random variation and selection operators. A particle swarm optimization for the design of PSS parameters at different operating conditions is presented in [7]. However, the performance of the simple PSO greatly depends on its parameters, and it often suffers the problem of being trapped in the local optima so as to be premature convergence. In order to overcome these drawbacks, a Chaotic Optimization Algorithm based PSS (COAPSS) is proposed in this study. Chaotic optimization algorithms, which have the features of easy implementation, short execution time and robust mechanisms of escaping from the local optimum, is a promising tool for the engineering applications. It is a kind of characteristic of the nonlinear systems which is a bounded unstable dynamic behavior, which exhibits sensitive dependence on the initial conditions and include infinite unstable periodic motions. The COA is based on ergodicity, stochastic properties and 'regularity' of the chaos. It is not like some stochastic optimization algorithms that escape from the local minima by accepting some bad solutions according to a certain probability but COA searches on the regularity of chaotic motion to escape from the local minima.

A new approach for the optimal design of PSS parameter is investigated in this paper. The problem of a robust PSS design is formulated as a multiobjective optimization problem and COA is used to solve it. The effectiveness of the proposed COAPSS is tested on a multimachine power system under different operating conditions and results are demonstrated through eigenvalue analysis and nonlinear time simulation. Results evaluation show that the proposed method achieves good robust performance for damping power system low frequency oscillations under different operating conditions.

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II. CHAOTIC OPTIMIZATION ALGORITHM

Chaos often exists in the nonlinear systems. It is a kind of highly unstable motion of the deterministic systems in finite phase space. An essential feature of the chaotic systems is that small changes in the parameters or the starting values for the data lead to the vastly different future behaviors, such as stable fixed points, periodic oscillations, bifurcations, and ergodicity. This sensitive dependence on the initial conditions is generally exhibited by systems containing multiple elements with nonlinear interactions, particularly when the system is forced and dissipative [10]. Due to the non-repetition of the chaos, it can carry out overall searches at higher speeds than stochastic ergodic searches that depend on the probabilities.

The Lozi's piecewise liner model is a simplification of the He´non map and it admits strange attractors. This chaotic map involves also non-differentiable functions which makes difficult the modeling of the associate time series. The Lozi map is given by [8]:

$$y_1(k) = 1 - a \times |y_1(k-1)| + y(k-1) \quad (1)$$

$$y(k) = b \times y_1(k-1) \quad (2)$$

$$z(k) = (y(k) - \alpha)/\beta - \alpha \quad (3)$$

Where, k is the iteration number. In this study, the values of y are normalized in the range [0,1] to each decision variable in n-dimensional space of optimization problem. Thus, y ε [-0.6418, 0.6716] and $[\alpha, \beta]$=(-0.6418, 0.6716). The parameters used in this work are a = 1.7 and b = 0.5 [11]. Many unconstrained optimization problems with continuous variables can be formulated as the following functional optimization problem.

Find X to minimize $f(X)$, X= [x_1, x_2, …, x_n]

Where, f is the objective function, and X is the decision solution vector consisting of n variables, x_i, bounded by lower (L_i) and upper limits (U_i). The chaotic search procedure based on the Lozi map can be illustrated as follows [8]:

Step 1: Initialization of variables and initial conditions: Set k=1, $y_1(0)$, y(0), for the Lozi map and Set the initial best objective function $\bar{f}$.

Step 2: Algorithm of chaotic global search:

Begin
While $k \le M_g$ *do*
$x_i(k) = L_i + z_i(k) \times (U_i - L_i)$
If $f(X(k)) < \bar{f}$ *Then*
$\bar{X} = X(k)$
$\bar{f} = f(X(k))$
End if
$k = k + 1;$
End while
End

Step 3: Algorithm of chaotic local search:

Begin
While $k \le (M_g + M_L)$ *do*
For $i = 1$ *to* n
If $r < 0.5$ *Then*
$x_i(k) = \bar{x}_i + \lambda \times z_i(k) \times |U_i - \bar{X}_i|$
Else
$x_i(k) = \bar{x}_i - \lambda \times z_i(k) \times |\bar{X}_i - L_i|$
End if
End for
If $f(X(k)) < \bar{f}$ *Then*
$\bar{X} = X(k)$
$\bar{f} = f(X(k))$
End if
$k = k + 1;$
End while
End

The M_g and M_L are maximum number of iterations of chaotic Global search and maximum number of iterations of chaotic Local search, respectively. In this paper, λ is the step size in chaotic local search and linearly is decreased from 0.1 to 0.01. Also, $\bar{f}$ and $\bar{X}$ are the best objective function and the best solution from current run of chaotic search, respectively.

III. PROBLEM STATEMENT

A. Power system model

The complex nonlinear model related to an n–machine interconnected power system, can be described by a set of differential-algebraic equations. For a given operating condition, the multi-machine power system is linearized around the operating point. In this study, the two-axis model [12] given in Appendix is used for the time domain simulations.

B. PSS structure

The operating function of a PSS is to produce a proper torque on the rotor of the machine involved in such a way that the phase lag between the exciter input and the machine electrical torque is compensated. The transfer function of the ith PSS is [12]:

$$U_i = K_i \frac{sT_w}{1 + sT_w} \left[\frac{(1 + sT_{1i})(1 + sT_{3i})}{(1 + sT_{2i})(1 + sT_{4i})} \right] \Delta \omega_i(s) \quad (4)$$

Where, $\Delta\omega_i$ is the deviation in speed from the synchronous speed. This type of stabilizer consists of a washout filter, a dynamic compensator. The output signal is fed as a supplementary input signal, U_i to the regulator of the excitation system. The value of the time constant T_w is usually not critical and it can range from 0.5 to 20 s. In this study, it is fixed to 10 sec. The dynamic compensator is made up to two lead-lag stages and an additional gain.

C. PSS design using COA

For our optimization problem, an eigenvalue based multi objective function reflecting the combination of damping factor and damping ratio is considered as follows [6]:

$$J = \sum_{j=1}^{NP} \sum_{\sigma_i \ge \sigma_0} (\sigma_0 - \sigma_i)^2 + a \times \sum_{j=1}^{NP} \sum_{\zeta_i \le \zeta_0} (\zeta_0 - \zeta_i)^2 \quad (5)$$

Where, $\sigma_{i,j}$ and $\zeta_{i,j}$ are the real part and the damping ratio of the ith eigenvalue of the jth operating point. The value of α is chosen at 10. The NP is the total number of operating points for which the optimization is carried out. By optimizing J, all the closed loop system poles should lie within a D-shaped sector are shown in Fig. 1 in the negative half plane of the $j\omega$ axis for which $\sigma_i < -1$, $\zeta_i > 0.2$. The design problem can be formulated as the following constrained optimization problem, where the constraints are the PSS parameter bounds:

$$
\begin{aligned}
&\textit{Minimize } J \textit{ subject to} \\
&K_i^{\min} \le K_i \le K_i^{\max} \\
&T_{1i}^{\min} \le T_{1i} \le T_{1i}^{\max} \\
&T_{2i}^{\min} \le T_{2i} \le T_{2i}^{\max} \\
&T_{3i}^{\min} \le T_{3i} \le T_{3i}^{\max} \\
&T_{4i}^{\min} \le T_{4i} \le T_{4i}^{\max}
\end{aligned} \tag{6}
$$

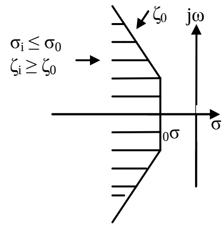

Figure1: Region of eigenvalue location for *J* objective function.

IV. CASE STUDY

In this study, the three-machine nine-bus power system shown in Fig. 2 is considered as a test system. Details of the system data are given in Ref. [13]. The generator and system loading levels at these cases are given in Tables 1 and 2.

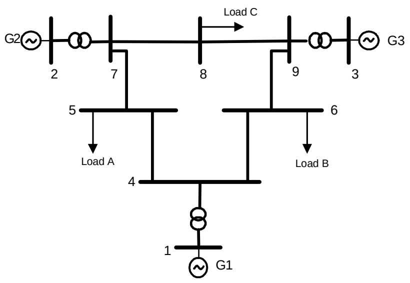

Figure 2: Three-machine nine-bus power system.

A. COA-based PSS Design and Eigenvalues Analysis

In this paper, PSS according to the participation factor as given in Ref. [5] is connected to G_2 and G_3 machines in the test system. In the proposed method, we must tune the PSSs parameters, optimally to improve the overall system dynamic stability, in a robust way under different operating conditions and disturbances. The optimization of the PSS parameters is carried out by evaluating the multiobjective function as given in (5) which is considered a multiple of the operating conditions. The operating conditions considered are:

i) Nominal case of the system
ii) Heavy loading of the system
iii) Light loading of the system

In order to acquire better performance, maximum number of iterations of chaotic global and local search are chosen as 1000 and 400, respectively. Also, λ is the step size in chaotic local search and linearly decreases from 0.1 to 0.01. Results of the PSSs parameter set values are given in Table 3. In order to facilitate comparison with CPSS, for design and tuning of the CPSS for this multi-machine power system, the method in [3] were used. The CPSS parameters for G_2 and G_3 are given in Table 4. The electromechical modes and the damping ratios obtained for all operating conditions, both with and without PSS in the system are given in Table 5.

Table I
Generator operating conditions (in pu)

Gen	Nominal		Heavy		Light	
	P	Q	P	Q	P	Q
G_1	0.72	0.27	2.21	1.09	0.36	0.16
G_2	1.63	0.07	1.92	0.56	0.80	-0.11
G_3	0.85	-0.11	1.28	0.36	0.45	-0.20

Table II
Loading conditions (in pu)

Load	Nominal		Heavy		Light	
	P	Q	P	Q	P	Q
A	1.25	0.5	2.0	0.80	0.65	0.55
B	0.90	0.30	1.80	0.60	0.45	0.35
C	1.0	0.35	1.50	0.60	0.50	0.25

Table III
Optimal PSSs parameters using COA

Gen	K	T_1	T_2	T_3	T_4
G_2	21.23	0.4521	0.1570	0.1633	0.0538
G_3	37.74	0.2135	0.0311	0.1249	0.0964

Table IV
CPSS parameters

Gen	K	T_1	T_2	T_3	T_4
G_2	15.26	0.2371	0.0477	0.1811	0.1776
G_3	20.56	0.5751	0.2703	0.3755	0.1412

When PSS is not installed, it can be seen that some of the modes are poorly damped and in some cases, are unstable (highlighted in Table 5). Moreover, it is also clear that the system damping with the proposed COA based tuned PSSs is significantly improved.

B. Nonlinear Time-Domain Simulation

To assess the effectiveness and robustness of the proposed controller, the performance of the proposed controller under transient conditions is verified by applying a 6-cycle three-phase fault at t=1 sec, at bus 7 at the end of line 5-7 is considered [12]. The fault is cleared by permanent tripping of the faulted line. The speed deviation of the generator G_2 under the nominal, light and heavy loading conditions are shown in Fig 3. It can be seen that the COA based PSSs tuned using the multiobjective function achieves good robust performance and provides superior damping in comparison with the classic method.

Table V
Eigenvalues and damping ratios of the electromechanical modes with and without PSSs

	Nominal	Light	Heavy
Without PSSs	**-0.028 ± i7.64**, 0.003 **-0.51 ± i 3.96**, 0.127	**0.068 ± i6.74**, -0.01 **-0.28 ± i4.45**, 0.062	**0.128± i8.31**, -0.015 **-0.014± i4.01**, 0.003
CPSSs	-0.57 ± i6.83, 0.083 -0.44 ± i2.65, 0.164	-0.51 ± i5.64, 0.09 -0.49 ± i3.13, 0.154	-0.15 ± i6.31, 0.023 -0.32 ± i3.31, 0.096
COAPSSs	-1.54 ± i4.44, 0.327 -1.35 ± i2.51, 0.473	-1.64 ± i4.07, 0.373 -1.23 ± i3.12, 0.366	-1.92 ± i4.63, 0.383 -1.01 ± i4.28,0.227

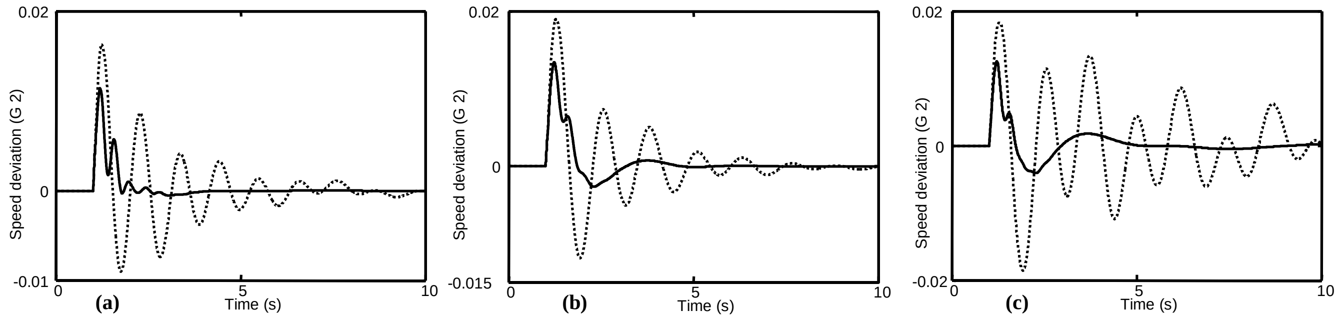

Figure 3: System response under a) Nominal b) Light c) Heavy loadings; Soiled (COAPSS) and Dotted (CPSS).

V. CONCLUSIONS

In a multi-machine environment, the sequential tuning of the PSS (i.e. CPSS) parameters does not guarantee the robustness of the PSS with variable operating condition, location, and severity of the faults. For this reason, in this paper, the PSSs parameters tuning problem is converted to an optimization problem which is solved by a chaotic optimization algorithm based on the Lozi map. Since chaotic mapping enjoys certainty, ergodicity and the stochastic property, the proposed chaotic optimization introduces chaos mapping using Lozi map chaotic sequences which increases its convergence rate and resulting precision that escapes from the local minima. The effectiveness of the proposed method is tested on a multimachine power system for a wide range of loading conditions. Eigenvalues analysis give the satisfactory damping on the system modes, especially the low frequency modes, for systems with the proposed COA based tuned PSSs. Time-domain simulations show that the oscillations of the synchronous machines can be quickly and effectively damped for the power systems with the proposed PSSs over a wide range of loading conditions.

APPENDIX

Machine models

$$\dot{\delta}_i = \omega_b(\omega_i - 1) \quad \text{(A.1)}$$

$$\dot{\omega}_i = \frac{1}{M_i}(P_{mi} - P_{ei} - D_i(\omega_i - 1)) \quad \text{(A.2)}$$

$$\dot{E}'_{qi} = \frac{1}{T'_{doi}}(E_{fdi} - (x_{di} - x'_{di})i_{di} - E'_{qi}) \quad \text{(A.3)}$$

$$\dot{E}_{fdi} = \frac{1}{T_{Ai}}(K_{Ai}(v_{refi} - v_i + u_i) - E_{fdi}) \quad \text{(A.4)}$$

$$T_{ei} = E'_{qi} i_{qi} - (x_{qi} - x'_{di}) i_{di} i_{qi} \quad \text{(A.5)}$$

Where,

δ	Rotor angle
ω	Rotor speed
P_m	Mechanical input power
P_e	Electrical output power
E'_q	Internal voltage behind x'_d
E_{fd}	Equivalent excitation voltage
T_e	Electic torque
T'_{do}	Time constant of excitation circuit
K_A	Regulator gain
T_A	Regulator time constant
v_{ref}	Reference voltage
v	Terminal voltage

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