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Gravitational Search Algorithm based Optimal Design of Multi Objective Power System Stabilizers

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Abstract

This paper proposes a new optimization algorithm which is based on the law of gravity and mass interactions called Gravitational Search Algorithm (GSA) for optimal design of power system stabilizers (PSS). The parameters of the proposed GSA based PSS (GSAPSS) are formulated as amulti objective optimization problem and optimized in order to damp all the unstable electromechanical modes of the system and to shift them to the left in S-plane. The performance of the proposed GSAPSS is tested on the WSCC 3-machine, 9-bus power system under different operating conditions and system configurations. The test results are compared with conventional PSS (CPSS) and Genetic Algorithm based PSS (GAPSS) to validate the efficacy and superiority of the proposed approach.

Keywords:

Electromechanical oscillations;
GravitationalSearch Algorithm;
Optimization;
Power system stabilizer;

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1. Introduction

Damping of low frequency electromechanical oscillations is considered to be one of the most interesting and challenging tasks in power industry for the secure operation of the power system. These oscillations are often observed when large power systems are connected with weak tie-lines and also due to fast acting exciters with high gain Automatic voltage regulators (AVR) [1]. Over the past three decades, Power System Stabilizer (PSS), which acts as a supplementary modulation controller in the excitation systems has been the conventional means to curb with this problem.

The PSS feedback signals generate an additional rotor torque to damp out the low frequency oscillations. The Gain and the required stage lead/lag of the PSS stabilizer are tuned by utilizing proper numerical models, supplemented by a decent comprehension of the system operation. The controller principle is based on damping and synchronous torques within the generator. A thorough examination of these torques have been managed by deMello and Concordia in their paper in 1969 [1]. These controllers have been known to work great in the field and are to a great degree easy to actualize. The tuning of these compensators keeps on being a considerable assignment particularly in extensive multi-machine system with multiple oscillatory modes. Larsen and Swann, in their three section paper [2], describe in detail the general tuning procedure which employs Gradient procedure for optimization of PSS parameters.

The fundamental disadvantage of the above controllers is their inherent lack of robustness. Power systems constantly experience changes in the load and generation patterns in the transmission network. These outcomes result in a change in small signal dynamics of the system. The settled parameter controllers, tuned for a specific working condition, generally give a fair performance at that operating condition. Their execution, at other working conditions, may, best case scenario be agreeable, and may even wind up noticeably lacking when extreme circumstances emerge. In addition to that, conventional optimization methods that make use of derivatives and gradients are not able to locate or identify the global optimum.

To limit the effects of these problems, different techniques of sequential design of PSS are presented [3, 4] to damp out one of the electromechanical modes at a time. However, the stabilizers intended to damp one mode can deliver adverse impacts in different modes. Thus, the need for simultaneous optimization of PSS parameters was observed and was first implemented by Hsu and Chen in 1987 and Yu and Li in 1990 [5, 6]. Unfortunately, these techniques presented in [4, 5] requires heavy computational burden for determining the parameters of PSS.

From the most recent decades, interests have been centered on the advancement of the PSS parameters to give satisfactory execution to every operating condition. Hence, many optimization techniques such as Simulated Annealing (SA) [7], Genetic Algorithms (GA) [8], Particle swarm optimization (PSO) [9] et.al, have been used to find the optimum set of parameters to effectively tune the PSS. The results obtained were observed to be promising and confirm the potential of these algorithms for optimal PSS design. However, every such technique is found to have its own pros and cons. Simulated Annealing algorithm has demonstrated to be an effectual means in escaping from local minima, but, its repeatedly annealing schedule is observed to be very slow especially if the objective function is extensive to compute. GA, a population-based search algorithm, which works with a population of strings that represent different potential solutions, has the ability to arrive at the global solution point swiftly, as it can handle the search space from different directions simultaneously. Crossover and mutation operators between chromosomes, makes the GA far less sensitive of being trapped in local optima. However, GA has shown degraded performance when dealing with highly epistatic (i.e., the parameters of objective function are highly correlated) problems [10]. Also, it pains from premature convergence which can highly affect the effectiveness of the optimal solution. PSO, a stochastic, population based algorithm, modeled with swarm intelligence is very simple to implement with much less parameters to train. However, PSO cannot work out the problems of scattering and optimization [11]. Moreover, the algorithm suffers from slow convergence in refined search stage which may lead it to possible entrapment in local minima. Several other meta-heuristic algorithms such as, Bacterial foraging algorithm [12], Artificial bee colony algorithm [13], Harmony search algorithm [14] et.al, were also proposed for optimal design of PSS to overcome the disadvantages of the above described approaches.

In this paper, a new population-based search algorithm, Gravitational search algorithm (GSA), which is based on the metaphor of gravitational interaction between the masses, is proposed for optimal tuning of PSS parameters. To investigate the potential of the proposed approach in shifting the unstable and poorly damped electromechanical modes to the left in S-plane under wide varied operating conditions, an eigenvalue based objective function reflecting the combination of damping factor and damping ratio is formulated. Finally, the Eigen value analysis and contingency analysis have been carried out to access the effectiveness of the proposed GSAPSS under different loading conditions. Finally the supremacy in the performance of the proposed GSAPSS over CPSS and GAPSS is acknowledged.

2. Problem formation

2.1 System Modelling:

The power system is modeled by a set of non-linear differential equations as

$$\dot{X} = f(X,U) \qquad (1)$$

Here, X is the vector of state variables and U is the vector of input variables to the PSS. The generators in the power system are represented by a fourth-order model [15] and the non-linear differential equations representing any i^{th} generator are given here below

$$\dot{\delta}_i = \omega_i - \omega_s \qquad (2)$$

$$\dot{\omega}_i = \frac{\omega_s}{2H}\left(P_{m_i} - P_{e_i}\right) \qquad (3)$$

$$\dot{E}'_{q_i} = \frac{1}{T_{do_i}}\left(-E'_{q_i} - I_{d_i}\left(X_{d_i} - X'_{d_i}\right) + E_{fd_i}\right) \qquad (4)$$

$$\dot{E}'_{d_i} = \frac{1}{T_{qo_i}}\left(-E'_{d_i} + I_{q_i}\left(X_{q_i} - X'_{q_i}\right)\right) \qquad (5)$$

$$\dot{E}'_{fd_i} = \frac{1}{T_{a_i}}\left(-E'_{fd_i} + K_{a_i}\left(V_{ref_i} - V_{t_i}\right)\right) \qquad (6)$$

Therefore, the state equation of the power system with n machines and n PSSs is given by

$$\Delta\dot{X} = A\Delta X + BU \qquad (7)$$

Where, A is $5n \times 5n$ matrix and equals to $\frac{\partial f}{\partial x}$ and B is $5n \times n$ matrix and equals to $\frac{\partial f}{\partial U}$

2.2 PSS Structure:

A widely used conventional PSS structure is considered throughout the study and shown in Fig 1.

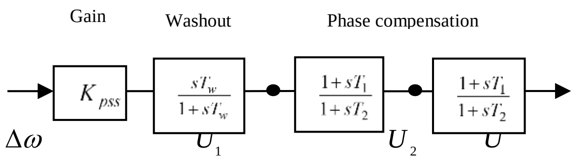

Fig.1. Structure of Power System Stabilizer

It consists of three units: Phase compensation unit, washout filter and gain unit. Accelerating power (Δp) or Rotor speed deviation $(\Delta\omega)$ is usually chosen as the input signal to the PSS. In this study $(\Delta\omega)$ is chosen as the input to PSS. The washout term with a time lag T_W, usually is selected between 1 to 20 seconds [15]. The phase compensation unit with time constants, T_1, T_2, T_3 and T_4 is to improve the phase lag through the system. The state space equations for the PSS can be written as

$$U_1 = \frac{1}{T_w}\left(K_{pss} \cdot \Delta\omega - U_1\right) \qquad (8)$$

$$U_2 = \frac{1}{T_2}\left(K_{pss} \cdot \frac{(T_2 - T_1)}{T_2} \cdot \Delta\omega - \frac{(T_2 - T_1)}{T_2} U_1 - U_2\right) \qquad (9)$$

$$U = \frac{1}{T_4}\begin{pmatrix} K_{pss}\cdot\frac{T_1}{T_2}\frac{(T_4-T_3)}{T_4}\cdot\Delta\omega - \frac{T_1}{T_2}\frac{(T_4-T_3)}{T_4}U_1 \\ +\frac{(T_4-T_3)}{T_4}U_2 - U \end{pmatrix} \quad (10)$$

Thus, the transfer function of the i^{th} PSS connected to the i^{th} generator can be written as

$$G_{PSS_i} = \frac{U_i}{\Delta\omega_i} = K_{PSS_i}\cdot\frac{sT_w}{1+sT_w}\cdot\left(\frac{1+sT_{1i}}{1+sT_{2i}}\right)\cdot\left(\frac{1+sT_{3i}}{1+sT_{4i}}\right) \quad (11)$$

Here the two stages of the phase compensator are considered to be identical. Hence, $T_1 = T_3$ and $T_2 = T_4$. Also the time constant T_w of the washout circuit is taken as 10 sec.

Thus, the overall transfer function of the PSS is given by

$$G_{PSS_i} = K_{PSS_i}\cdot 10\cdot\left(\frac{1+sT_{1i}}{1+sT_{2i}}\right)^2 \quad (12)$$

Here, The stabilizer gain K_{PSS_i} and the time constants T_1 and T_2 remains to be optimized.

2.3 Objective Function:

The optimization problem, which is selection of the PSS parameters (K_{pss}, T_1 and T_2) is done by formulating the objective functions as described in this sub section. The different Eigen value based objective functions which reflects damping factor (σ) and damping ratio (ζ) of each of the electromechanical Eigen values are considered. These two objective functions are joined and reformulated into a single multi-objective function. It is to be particularly noted that the objective functions are evaluated considering only the unstable and lightly damped Eigen values that needs to be shifted into a prescribed relatively stable, highly damped zone.

The parameters of PSS are selected so as to minimize the following objective function

$$J = J_1 + \alpha J_2 \quad (13)$$

Where, $$J_1 = \sum_{j=1}^{NP}\sum_{\sigma_{i,j}\ge\sigma_0}\left[\sigma_0 - \sigma_{i,j}\right]^2 \quad (14)$$

$$J_2 = \sum_{j=1}^{NP}\sum_{\xi_{i,j}\le\xi_0}\left[\xi_0 - \xi_{i,j}\right]^2 \quad (15)$$

Here, α is taken as 10 in respect with [8]. NP is the number of operating points taken in the optimization process, $\sigma_{i,j}$ is the real part of i^{th} Eigen value of the j^{th} operating point. The value of σ_0 determines the relative stability in terms of damping factor for constraining the placement of Eigen values during the optimization process. Similarly, $\xi_{i,j}$ is the damping ratio of the i^{th} Eigen value in the j^{th} operating point and ξ_0 is the desired minimum damping ratio which is to be achieved. Thus, if only J_1 is taken as the objective function, the closed loop Eigen values of the system are placed in the region to the left of the dashed line as shown in Fig 2(a). Whereas with J_2 taken as the objective function, it constrains the maximum overshoot of all the Eigen values of the system as shown in Fig 2(b). But, when optimized with J, The Eigen values are restricted to the D – shaped sector as shown in Fig 2(c).

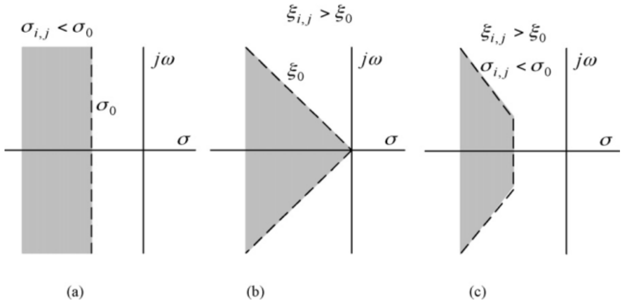

Fig.2. Regions of Eigen value locations for different objective functions

In such a way, the entire design process is formulated as a multi-objective optimization problem with constraints imposed on PSS parameter bounds as,

Minimize J , Subject to

$$\begin{Bmatrix} K_{PSS_i}\min \le K_{PSS_i} \le K_{PSS_i}\max \\ T_{1_i}\min \le T_{1_i} \le T_{1_i}\max \\ T_{2_i}\min \le T_{2_i} \le T_{2_i}\max \end{Bmatrix} \qquad (16)$$

The typical ranges for the optimized parameters are $[1-50]$ for K_{PSS_i} , $[0.5-0.9]$ for T_{1_i} , $[0.1-0.5]$ for T_{2_i} . The proposed approach employs Gravitational search algorithm to solve this optimization problem and search at best for an optimal set or a near optimal set of PSS parameters.

3. Gravitational Search Algorithm

3.1 Overview:

The basic idea which motivates the proposed approach is based on the interaction of masses in the universe in accordance with Newtonian gravity law [16]. The gravitation is the attraction of masses by other masses. The amount of attraction depends on the amount of masses and the distance between them. This gravity law defined by Newton is as follows, “Every particle in the universe attracts every other particle with a force that is directly proportional to the product of the masses of the particles and inversely proportional to the square of the distance between them”. It is formulated by the following equation.

$$F = G\frac{M_1 M_2}{R^2} \qquad (17)$$

In this equation, *F* is the gravitational force (in N), G is the gravitational constant with a value of 6.67259×10^{-11} (in N (m2/kg2)), M_1 and M_2 are the masses of first and second particles, respectively (in kg), and R is the straight-line distance between the two particles (in m).

According to Newton’s second law of motion, when a force (here it is gravitational force), *F*, is applied to a particle, its acceleration, *a*, depends only on the force and its mass, *M* [16] as,

$$a = \frac{F}{M} \qquad (18)$$

Thus, there is an attracting gravity force on every particles of the universe where the effect of bigger and the closer particle is higher. An increase in the distance between two particles means decreasing the gravity force between them.

The proposed algorithm, GSA, is inspired by the above physical phenomenon. The agents are considered as objects and their performance is measured by their masses. All these objects attract each other by the gravity force, and this force causes a global movement of all objects towards the objects with heavier masses. The masses co-operate using the direct form of communication, gravitational force. By lapse of time, we expect that masses be attracted by the heaviest mass. This mass will present an optimum solution in the search space.

To describe GSA, consider a system with N masses (agents) and d dimensions. The solution set X which consists of randomly generated positions of N masses for d dimensions is shown below,

$$X = \begin{bmatrix} X_{11} & X_{12} & . & . & X_{1d} \\ X_{21} & X_{22} & . & . & X_{2d} \\ . & . & . & . & . \\ . & . & . & . & . \\ X_{N1} & X_{N2} & . & . & X_{Nd} \end{bmatrix} \quad (19)$$

Here, N is the total number of agents, d is the number of dimensions in the optimization problem.The position of the i^{th} mass can be defined as

$$X_i = [X_{i1} \quad X_{i2} \quad . \quad . \quad X_{id}] \quad (20)$$

Here, X_{id} is the position of i^{th} mass in the d^{th} dimension. The positions of masses correspond to the solutions of the problems.

The mass of each agent is calculated after computing the fitness of that current agent as:

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \quad (21)$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_i(t)} \quad (22)$$

Where, $M_i(t)$ and $fit_i(t)$ represents mass and fitness value of agent i at t. $worst(t)$, $best(t)$ depends on the optimization problem. i.e., for a minimization problem,

$$best(t) = \min fit_i(t); i \in \{1,...N\} \quad (23)$$

$$worst(t) = \max fit_i(t); i \in \{1,...N\} \quad (24)$$

For a maximization problem,

$$best(t) = \max fit_i(t); i \in \{1,...N\} \quad (25)$$

$$worst(t) = \min fit_i(t); i \in \{1,...N\} \quad (26)$$

Now, the gravitational force acting on mass i from mass j is given as,

$$F_i^d = G(t) * \frac{M_i(t) M_j(t)}{R_{ij}(t) + \varepsilon} \left(X_j^d(t) - X_i^d(t) \right) \quad (27)$$

Here, G is the gravitational constant, initialized at the beginning and will reduce with time in order to control the search accuracy, $R_{ij}(t)$ is the Euclidian distance between two agents i, j as defined in (2), ε is a small constant added to avoid division by zero.

Thus, by the law of motion as stated earlier, the acceleration of agent as in (2) is given by

$$a_i^d(t) = \frac{F_i^d(t)}{M_i^d(t)} \quad (28)$$

Later, the next velocity of an agent $V_i^d(t+1)$ is calculated as a fraction of its current velocity $V_i^d(t)$ added to its acceleration $a_i^d(t)$ as,

$$V_i^d(t+1) = rand * V_i^d(t) + a_i^d(t) \quad (29)$$

Here, $rand$ is a uniform random variable with limits $[0,1]$

Finally, the next position of an agent is calculated as,

$$X_i^d(t+1) = X_i^d(t) + V_i^d(t+1) \quad (30)$$

3.2 Implementation:

Based on the above discussion, the proposed GSA is implemented for tuning the parameters of PSS as a multi objective optimization problem. The implementation of the proposed technique to tune the parameters of PSS was clearly summarized as a flow chart in Fig 4.

The GSA will be terminated when the termination condition is met. This may be usually a sufficiently a good objective function value or a maximum number of iterations.

The maximum number of iterations (n_{max}) criterion is employed in this work and is taken as 100.

The number of agents is taken as 50.

The proposed GSA-based approach was implemented using MATLAB 7.14 and the developed software program was executed on Intel (R) Core i3-2370M CPU @2.40GHz.

4. Results and Analysis.

In this paper, the WSCC 3-machine, 9-bus power system shown in Fig. 3 is considered as the test system. The details of the system data is provided in [17]. It is assumed that all generators are equipped with PSSs. The PSS parameters are optimized at the operating condition designated as *base case* and in order access the effectiveness and robustness of the proposed algorithm in tuning the PSS, two different operating conditions designated as *case 1* and *case 2* in addition to the *base case* are considered. The generator and system loading levels at these cases are given in Tables I and II respectively. Table III, IV and V represent the optimal parameters of CPSS, GAPSS and proposed SAPSS respectively.

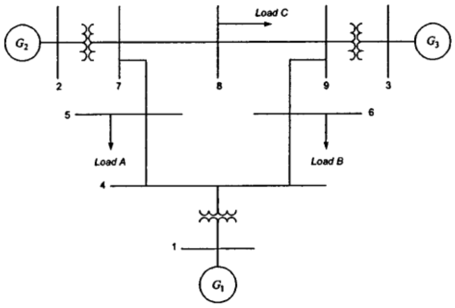

Fig.3. WSCC 3-machine, 9-bus power system

TABLE I
GENERATOR LOADINGS IN PU ON THE GENERATOR OWN BASE

Gen#	Base case		Case-1		Case-2	
1	0.289	0.109	0.892	0.440	0.33	1.120
2	0.849	0.035	1.000	0.294	2.000	0.570
3	0.064	-0.085	1.000	0.280	1.500	0.380

TABLE II
LOADS IN PU ON SYSTEM 100-MVA BASE

Load#	Base case		Case-1		Case-2	
A	1.250	0.500	2.000	0.800	1.500	0.900
B	0.900	0.300	1.800	0.600	1.200	0.800
C	1.000	0.350	1.500	0.600	1.000	0.500

TABLE III
OPTIMAL PARAMETERS OF CPSS

Gen#	Kpss	T1	T2
1	4.332	0.405	0.273
2	2.463	0.371	0.299

3	0.399	0.375	0.296

TABLE IV
OPTIMAL PARAMETERS OF GAPSS

Gen#	Kpss	T1	T2
1	27.1280	0.580	0.496
2	7.5326	0.5766	0.260
3	1.8647	0.8467	0.313

TABLE V
OPTIMAL PARAMETERS OF GSAPSS

Gen#	Kpss	T1	T2
1	11.290	0.5590	0.2260
2	1.8148	0.7372	0.3630
3	1.1395	0.5215	0.1189

TABLE VI
EIGEN VALUES AND DAMPING RATIOS FOR DIFFERENT CASES

	Without PSS	With CPSS	With GAPSS	With GSAPSS
Base Case	-0.2367 + 8.5507i ; 0.0277 -0.8075 +13.254i ; 0.0608	-0.8017 + 9.0603i; 0.0881 -11.1414 + 9.4032i ;0.7642	-3.9936 +12.6912i ; 0.3002 -4.0591 + 5.7725i ; 0.5752	-3.3177 + 5.9727i ; 0.4856 -7.3577 + 7.2382i ; 0.7129
Case 1	-0.1421 + 8.4615i ; 0.0168 -0.3139 +13.1984i ;0.0238	-0.8024 + 8.9184i ; 0.0896 -11.1601 +10.3813i ;0.7322	-3.3263 + 6.0414i ; 0.4823 -8.6204 + 9.6271i ; 0.6671	-2.6140 + 6.1744i ; 0.3899 -6.3277 + 7.9464i ; 0.6229
Case 2	0.1153 +13.221i ; -0.0087 0.0990+ 8.5483i ; -0.0116	0.0316 +13.7795i ; -0.0023 -0.3549 + 8.9847i ; 0.0395	-3.8036 + 6.3262i ; 0.5153 -6.4053 +10.0518i ; 0.3415	-3.0086 + 6.8735i ; 0.4010 -7.3876 + 9.5720i ; 0.6110

The electromechanical modes and the damping ratios obtained for all the above cases without PSS, with CPSS, with GAPSS and with the proposed GSAPSS are given in Table V. From the Table V, it is very clear that without PSS the system is unstable with very poor damping ratio. When CPSS is installed the system performance is slightly improved for all operating conditions excepting *case 2.* This validated the fact that the CPSS parameters tuned around one operating point cannot guarantee the desired performance for another environment. With GAPSS and GSAPSS, it is proved that the system is quite robust for wide range of operating conditions.

To further investigate the efficacy of the proposed PSSs a contingency case is simulated which is a 6-cycle fault disturbance at bus 7 at the end of line 5–7 with the system operating with case 2. The system responses to the considered faults with CPSS, GAPSS and GSAPSS are given in Fig 4 and 5.

For completeness and clear insight the performance index (PI) which is Integral of Time multiplied Absolute value of Error (ITAE) is evaluated.

$$PI = ITAE = \int_0^n t.\left(|\Delta\omega_1| + |\Delta\omega_2| + ...|\Delta\omega_n|\right) \qquad (31)$$

Here n represents the number of generators. The lower the value of this index is, the better the system response in terms of time-domain characteristics.

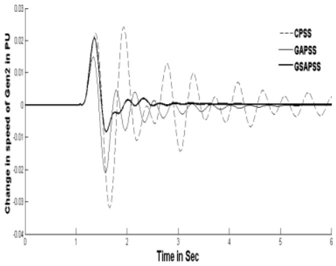

Fig. 4 Comparison of speed deviations of Generator 3

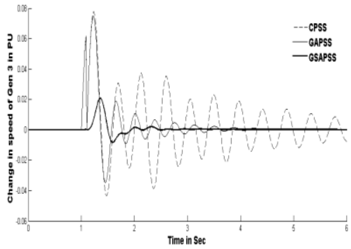

Fig. 5 Comparision of speed deviations of Generator 2

It is observed that the PI of CPSS for the considered contingency is 40.067 whereas the PI for GAPSS and GSAPSS are 7.763 and 5.732 respectively. This demonstrates that the settling time and speed deviations of all generators are greatly reduced by applying the GSAPSS and the efficacy and supremacy in the proposed approach is established.

5. Conclusions

One of the primary requirements of a good tuning method is that the resulting PSS be robust enough to wide variations in system parameters. In this respect, Gravitational Search Algorithm based method to tune PSS (GSAPSS) is developed and presented in this paper. The proposed method for tuning the PSSs is tested on a multi-machine test system under wide varied operating conditions and the results are compared. The conventionally tuned PSS (CPSS) fails to stabilize the system at certain operating conditions. The Genetic Algorithm based tuning of PSS (GAPSS) is proven to be satisfactory whereas the proposed Gravitational Search Algorithm based PSS (GSAPSS) is excellent in providing the necessary damping to the system. The proposed method also provides the option of including any operating point within its tuning domain, thus ensuring system stability over a large domain.

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