Improved General Relativity Search Algorithm (IGRSA) for Designing Power System Stabilizers

Behzad Ehsanmaleki[1†] and **Hamid Radmanesh**[2], Non-members

ABSTRACT

This paper proposes a novel optimization algorithm for designing power system stabilizers (PSSs). The prospect of attaining higher stability motivated the authors to creat a new optimization algorithm for this study. A novel algorithm named the Improved General Relativity Search Algorithm (IGRSA) was also developed by cloud theory to improve the performance of GRSA. The supremacy of the proposed approach is tested by comparing it with an introduced objective function in a medium multi-machine power system. The nonlinear simulation results and eigenvalues analysis has demonstrated that the proposed approach in this study is highly effective in enhancing the dynamic stability of the power system.

Keywords: Power System, Power System Stabilizer, Variable Slope Damping Scale, Dynamic Stability

1. INTRODUCTION

In most power plants, PSS is taken into account as an efficient equipment to solve oscillations and stability problems in our process [1-3] .Effective application of stabilizers is mainly related to the effectiveness of objective function, especially when several PSSs are considered simultaneously in system design. There are lots of objective functions that are offered to provide a better condition for PSS design. [4-6].

Moreover, this study regarded damping controllers with a combinational input signal of both local and remote measurements to increment the system stability. The active selection of PSSs parameters can be achieved by solving an optimization problem based on an objective function with a powerful optimization algorithm. As our paper introduces a new algorithm, the main focus of the paper's literature review is MHAs. Although other methods, such as mathematical optimizations, can be considered in the literature review, a deep review may not be carried out, and the sentences will be superficial. In this paper, we do not review algorithms other than MHAs. Meta-Heuristic Algorithms (MHAs) are self-organized and decentralized algorithms for solving complex problems using team intelligence. They often have many parameters that have a significant influence on their efficiency. Thus, we can consider the development of a meta-heuristic algorithm as a configuration problem: the goal is to choose the best building blocks to combine as well as the best parameter setting. They can be classified into the following four groups:

- Physically-based techniques like Gravitational Search Algorithm (GSA) [7] and Black Hole Algorithm (BHA) [8].
- Evolution-based techniques such as Genetic Algorithm (GA) [9] and Bacterial Foraging Algorithm (BFA) [10].
- Social and Swarm-based techniques such as Particle Swarm Optimization (PSO) [11].
- Gray Wolf Optimization (GWO) [12].

Among a large number of published articles in the kinds of literature within the field of MHAs and their practical applications, physically based optimization algorithms have drawn increased attention in the past decade. Some physically based MHAs can be found in [13-17].

Several attempts have been made in the application of MHAs in PSS design; the most recent notable efforts are as follows: The algorithms of tabu search (TS), GA, PSO, and combinatorial discrete and continuous action reinforcement learning automata (CDCARLA) were used by Abido and Abdel-Magid [18-21] to proper estimation of the PSSs parameters for a multi-machine power system. Wang *et al.* [22], [23] developed a gradual self-tuning hybrid differential evolution algorithm (GSTHDEA) and improved ant direction hybrid differential evolution (IADHDE) for the optimal design of PSSs in a multi-machine environment. Ali *et al.* [24] illustrated a hybrid approach involving PSO and BFO algorithms named bacterial swarm optimization (BSO) for searching the parameters of the PSSs. Bacterial foraging optimization (BFO) algorithm is a novel swarm intelligence optimization algorithm based on the foraging behavior of E. Coli. Shakarami *et al.* [25] applied a population-based GWO algorithm for designing wide area PSSs (WAPSSs) considering time delay. The wide area PSS consists of two stages; the input of one stage is a local signal and the input of the other is a global signal. To select the most effective stabilizing signals and the location of controllers, Geometric measure of controllability and observability is used. Beiranvand *et al.* [26] proposed GRSA inspired by general relativity theory and applied it to design PSSs. Ali [27] proposed the BAT

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[1]The author is with Shahid Rajaee Teacher Training University.

[2]The author is with Shahid Sattari Aeronautical University.

[†]Corresponding author: b.ehsanmaleki@sru.ac.ir

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search algorithm based upon the echolocation behavior of bats for rapid and efficient adjustment and set of PSS parameters.

The second part of this paper addresses the improvement of the GRSA using cloud theory, a physically based optimization algorithm. The cloud theory is a fuzzy statistical model where qualitative linguistic variables are statistically related to quantitative fuzzy variables. In the cloud theory, the uncertain relationships between a qualitative concept and its quantitative value are described by a cloud and its drops [28]. The ratio of kinetic energy to the rest mass energy can be replaced by using the cloud theory in the step length calculation stage of GRSA. Diversity in the random clouds could avoid stagnation in the evolution of MHA agents. Stagnation can be measured by calculating the standard deviations. A slight standard deviation at the last iterations usually shows stagnation phenomena which can lead to trapping the MHA in a local minimum. This paper uses cloud theory to improve the GRSA by avoiding possible stagnation in a local minimum. Moreover, concerning the assessment of GRSA with some optimization algorithms such as PSO and GA in [26], improved GRSA just compared with GRSA. In addition, this study regarded damping controllers with a combinational input signal of both local and remote measurements to increment the system stability. The GRSA and IGRSA regarding the determined objective function were applied in PSSs designing, and its positive effects have been observed. Regarding the above illustrations, the novelties of the paper can be summarized as follows: An improved optimization algorithm is proposed, and cloud theory enhances the GRSA to avoid possible stagnation in a local minimum.

This paper has organized as follows: Section 2 introduces the power system model and PSSs structure and some reviews explaining new and customary existing objective functions in the literature. It also proposes a novel objective function. Section 3 reviews both GRSA and improved GRSA methods. Section 4 presents simulation results and a comparison, which investigates the efficacy of the proposed methods under various system operating conditions. Some conclusions are explained in section 5.

2. PROBLEM STATEMENT

The problem statement is defined in three parts as follows:

2.1 Power system model and PSSs structure

The closed-loop power system nonlinear modeling can be constructed with a set of nonlinear differential-algebraic equations in the following form:

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

Regardless of the damping controller's structure, the linearized incremental model of the interconnected power system around an equilibrium point is generally

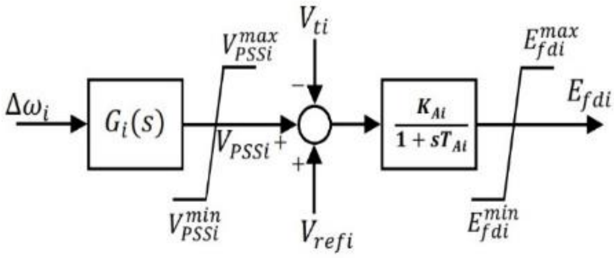

***Fig. 1**: Overall Interconnection of i^{th} PSS with IEEE-type-ST1 Excitation System.*

shown as follows:

$$\Delta\dot{X} = A\Delta X + B\Delta U \tag{2}$$

This paper implements a commonly utilized conventional lead-lag PSS and the IEEE-type-ST1 excitation system similar to Fig. 1 [2]. The considered PSS structure and i^{th} angular speed deviation are denoted as follows:

$$G_i(s) = K_i \frac{T_w s}{\left(1+sT_w\right)} \frac{\left(1+sT_{1i}\right)\left(1+sT_{3i}\right)}{\left(1+sT_{2i}\right)\left(1+sT_{4i}\right)} \tag{3}$$
$$\Delta\omega_i = (\gamma_L \Delta\omega_{Li} + \gamma_R \sum_k \Delta\omega_{Rk})$$

2.2 Overview of utilized Objective Function

Up to now, there have been several attempts with the presentation of the different objective functions to achieve higher small signal stability. A schematic of this convergence region in four well-known objective functions is depicted as a shaded area in Fig. 2. The final objective function is constructed by applying a damping scale function in the form of Eq. (4) [12]. Thus, this damping scale objective function can be written as below (Eq. (5)):

$$\chi \equiv \frac{-\left(\sigma-\sigma_0\right)}{\sqrt{\left(\sigma-\sigma_0\right)^2+\omega^2}} \times 100\% \tag{4}$$

$$Min\, F_1 = \sum_{y=1}^{n_y} (\chi_0 - \min_{1\le q\le n_q} \chi_q)_y \tag{5}$$

In the related convergence region in Fig. 2(d), all damping factors and damping scales are lower and higher than σ_0 and χ_0, respectively. Also, the slope of the straight line of the fan-shaped region is as follows [12]:

$$Slope_{\chi_0} = \pm\sqrt{\frac{1}{\chi_0^2}-1} = \pm\frac{1}{\left|\frac{\zeta_0}{\sqrt{1-\zeta_0^2}} - \frac{\sigma_0}{\omega}\right|} \tag{6}$$

As depicted in Fig. 2(d), the objective function F_1 has no problem with the cases related to the high-frequency or low-frequency lightly damped modes and overcame

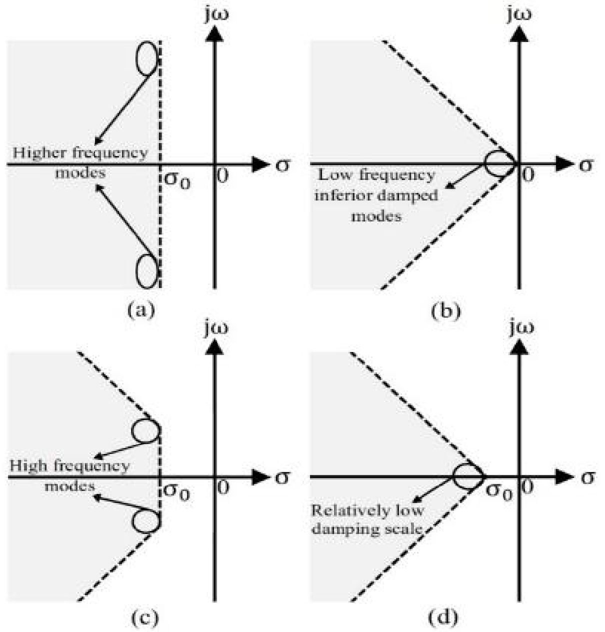

Fig. 2: *Convergence Regions of Four Objective Functions. (a) Rectangular Region of Damping Factor [5]. (b) Fan-shaped Region with Tip at the Origin of Damping Ratio [7]. (c) D-shaped Region of Damping Factor and Damping Ratio [18]. (d) Fan-shaped Region with Tip at σ_0 and the Damping Ratio ζ_0 of Damping Scale [23].*

the disadvantage of prior works. If σ_0 is zero, $Slope_{\chi_0}$ will be similar to $Slope_{\zeta_0}$ in its value; in other cases, as long as σ_0 pursues negative values, the magnitude of $Slope_{\chi_0}$ is smaller than that of $Slope_{\zeta_0}$ [12].

3. OVERVIEW OF GRSA AND PROPOSE OF IGRS ALGORITHM

3.1 Overview of GRSA

General Relativity Search Algorithm (GRSA) is a novel MHA inspired by General Relativity Theory [26], which is depicted by the flowchart (Fig. 3). In GRSA, a tensor of agents is considered in a space free from all external non-gravitational fields and propels toward a position with the least action. In GRSA, step length and step direction for updating the agents are computed separately using particle velocity and geodesics. GRSA shows good performance in solving optimization problems.

GRSA starts with randomly generated initial agents in the problem geometry and dimension. Each agent (particle) is a feasible solution to the problem represented as a tensor. Based on general relativity theory, a particle follows a geodesic path based on its energy-momentum and surrounding gravitational fields in the curved space-time. It moves toward the best position, where it has minimum action. The objective function of the optimization problem is computed for all particles and considered as their actions. Step length and step direction for updating the position of a particle are determined by its velocity and geodesic tangent, respectively. Particles with large gravitational fields have a significant effect on forming geodesics for other particles, while the evolutions of these particles are mainly dependent on their energy momentum and geodesic tangent. GRSA evolves to find the optimization problem solution through iterative calculation of step length and step direction for each particle position.

The step length and step direction in GRSA are calculated using existing relativistic equations for energy-momentum, curved space-time geometry, and geodesic tangent vectors. Finally, Einstein's field equation applies the effect of the gravitational field of particles on space-time, and a new position of particles is obtained. Fig. 5 illustrates the simplified flowchart of GRSA, and details of this optimization method are given in [26].

3.2 Proposed improved GRSA

In this optimization algorithm, like in GRSA, a random tensor of solution agents forms a search space. This search space is uniformly divided into some search subspaces. After that, step length and step direction can be calculated as subsections for the subspaces.

3.2.1 Step length computation

Initially, to calculate the ratio of kinetic energy to the rest masses energy, a forward normal cloud at time t (iteration t) for i^{th} agent, which details of *FNC* are given in [28], is generated as:

$$\left[X_i(t), \mu_i(t)\right] = FNC(Ex, He, En, Dn) \tag{7}$$

$$En = \frac{\left|f_g - f_{rand}\right|}{\left|f_{ave}\right| + \varepsilon} \tag{8}$$

$$He = \frac{\left|f_g - f_{ave}\right|}{\left|f_{ave}\right| + \varepsilon} \tag{9}$$

Then the energy conversion ratio is defined as:

$$\xi_i(t) = X_{i,rand} \ \ if \ \ X_{i,rand} < 0 \ \ and \ \ X_{i,rand} \in X_{decile} \tag{10}$$

where $X_{i,rand}$ such that its certainty degree belongs to a decile of μ where t/t_{max} value belongs to. For example, if $t/t_{max} = 0.43$, a drop will be selected in a set by the certainty degree in the range of [0.4 0.5]. This selection process by a moving window which its certainty degree enhances with iterations, is demonstrated in Fig. 4. Thereafter, speed and step length for the agent is given as:

$$\gamma_i(t) = 1 + \xi_i(t)(1 - K_g) \tag{11}$$

$$V_{ij}(t) = K_{V,\,ij}(t)\sqrt{\frac{1}{\gamma_{ij}^2(t)} - 1} \tag{12}$$

$$K_{V,ij}(t) = \left|T_j^{Best,s}(t) - T_j^{rand,s}(t)\right| \tag{13}$$

$$\lambda_{ij}(t) = \omega_t V_{ij}(t),\ i \in \{1, 2, \ldots, l\},\ j \in \{1, 2, \ldots, d\} \tag{14}$$

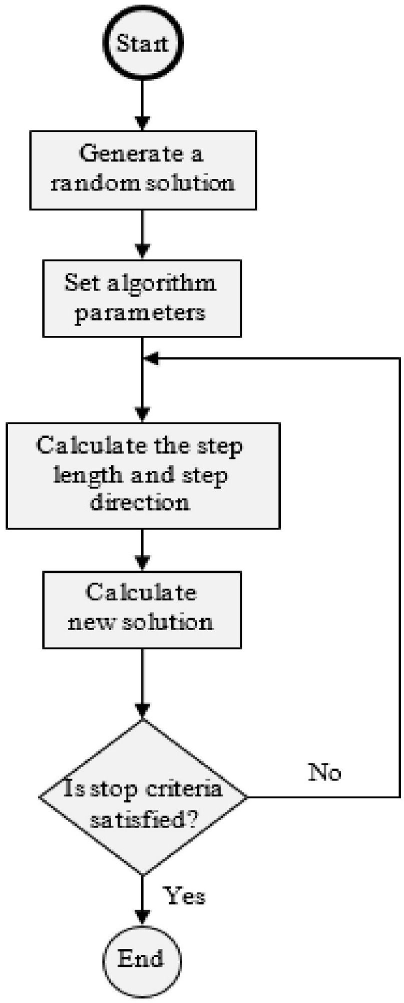

Fig. 3: *GRSA Flowchart.*

In Eq. (14), variable ω_t linearly decreases from 0.9 to 0.1 and provides a smaller step length in the vicinity of the global optimal point by increasing iterations.

3.2.2 Step direction computation

Time-like, space-like and null geodesics are used to obtain step direction for a particle which $K_{f,i}\epsilon\{0,1\}$, as follows:

$$\delta_{ij}(t) = -sign(\delta_{tl,ij}(t) + K_{f,j}\delta_{sl,ij}(t) + (1-K_{f,j})\delta_{null,ij}(t)) \tag{15}$$

where

$$\delta_{tl,i}(t) = sign(T_i(t) - T_i(t-1)) \tag{16}$$

$$\delta_{sl,i}(t) = sign(T_i(t) - TG) \tag{17}$$

$$\delta_{null,i}(t) = sign(T_i(t) - TB_i) \tag{18}$$

From Eq. (20), note that if $K_{f,j}$ becomes one, the corresponding component of time-like geodesic tangent will be in the same direction with space-like geodesic, and else it will be in the same direction with null geodesic. Therefore, the tendency to move toward a particle with larger energy momentum increases along a time-like geodesic.

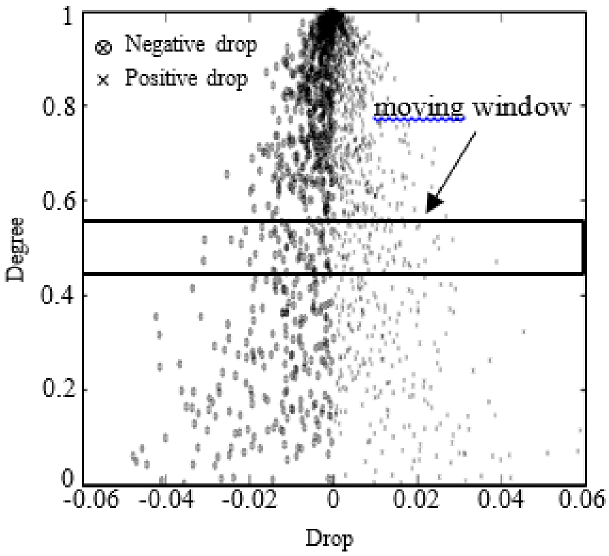

Fig. 4: *Selection of $\xi_i(t)$ from the Negative Drops Inside the Moving Window.*

3.2.3 Updating particles tensor

By computing step length and step direction from Eq. (19) and (20), respectively, the new positions of the particles are as follows:

$$T_{ij}(t+1) = T_{ij}(t) + \lambda_{ij}(t)\delta_{ij}(t) \tag{19}$$

To improve search capabilities, a mutation operation will be performed for particles with the worst positions in the overall search space. In this process, the value of parameter S is chosen, and the mutation operation will be performed with the best position in all subspaces using Einstein's field equation to these positions. The steps for the proposed IGRSA are as follows:

(i) Generate a random initial tensor for a population of particles;
(ii) Divide the initial tensor into some subspaces uniformly;
(iii) Calculate action (cost function) for all particles;
(iv) Assign ξ for each particle using cloud theory;
(v) Calculate the particle's velocity;
(vi) Compute displacement step length for particles;
(vii) Compute displacement step direction for particles;
(viii) Update the position of particles;
(ix) Perform mutation operation for a number of S particles with worst positions using Einstein's equation;
(x) Repeat steps (iii) to (ix) until the stop criterion is satisfied;
(xi) End.

4. SIMULATION RESULTS AND DISCUSSION

The case study is a 10-machine 39-bus system as a medium multi-machine power system, shown in Fig.5. Generally speaking, the PSS optimum parameters will be obtained by applying an objective function (OF, F_1)

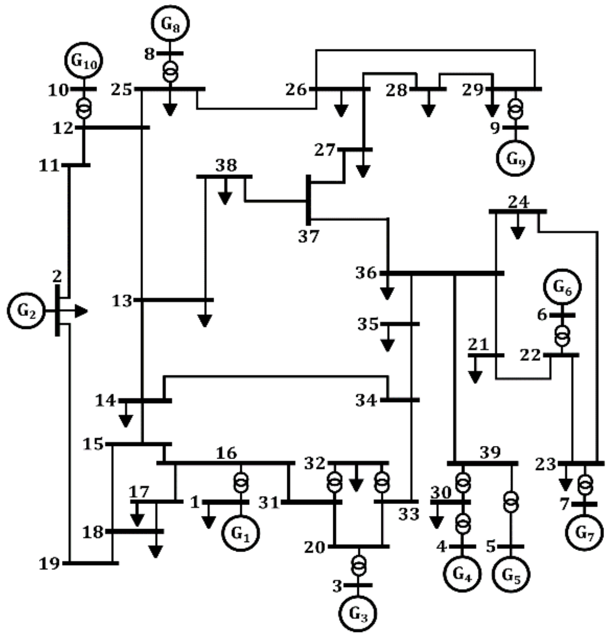

***Fig. 5**: Single line Diagram of 10-machine 39-bus (New England) Test System.*

and considering the following constrained optimization problems.
Minimize (OF, F_1) subject to:

$$K_i^{min} \leq K_i \leq K_i^{max} \tag{20}$$

$$T_{1i}^{min} \leq T_{1i} \leq T_{1i}^{max} \tag{21}$$

$$T_{2i}^{min} \leq T_{2i} \leq T_{2i}^{max} \tag{22}$$

$$T_{3i}^{min} \leq T_{3i} \leq T_{3i}^{max} \tag{23}$$

$$T_{4i}^{min} \leq T_{4i} \leq T_{4i}^{max} \tag{24}$$

The range of optimizing our parameters is [0:001 50] for K_i and [0:01 1.0] for T_{1i}, T_{2i}, T_{3i} *and* T_{4i}. Furthermore, the optimization algorithm of IGRSA has been chosen for this optimization procedure.

4.1 Tested system

The single-line diagram of the IEEE 10 machine (New England) power system (Fig. 5) is considered for simulation, and the detail of system data is taken from [29]. In this study, to achieve the overall dynamic stability of the test system with the presented approaches, all generators, except G2, an equivalent power source of the U.S.-Canadian interconnection system, are equipped with PSSs. To design robust PSSs, two different operating conditions, in addition to our base case, are characterized by the system under both severe loading conditions and critical line outage. Here the ”Robust” term is used in this concept that the designed controllers will be responsive to load changes and keep the system stable.
The three cases are defined as follows:
Base case: normal condition [29].
Case 1: outage of the line between buses 21-22.
Case 2: outage of the line between buses 21-22 and 10% increase in the loads at even buses.

The cases mentioned above are chosen based on the authors’ knowledge obtained from various simulated cases. Base case (normal condition) would be the state of the selected power system with any abnormal change in its structure. In the New England power system, the line between buses 21 and 22 would be susceptible. More specifically, when this line is outaged, maintaining the system stability would become so complicated that PSSs should be optimized effectively. This circumstance has been named Case 1. To make the situation harder, we have increased the load of even buses, named Case 2.

The results of sensitivity analysis, as it is needed for designing PSSs, illustrate the oscillation among given i^{th} and $k^{\ th}$ generators as follows:

Considering ”$\sim$ ”as an oscillation symbol, G_1~G_3 ,G_4~(G_2 & G_6), G_5~G_4 and G_7~G_6. Therefore, all the generators G1, G4, G5, and G7 are selected to be equipped with the WAPSSs. The feedback combination signal of the $i^{\ th}$ generator is $\omega_i - \sum_k \omega_k$.

4.2 Nonlinear Time-Domain Simulation

The nonlinear time-domain simulation of the power system is conducted from [29], which uses a power flow program [30] to calculate the dynamic initial conditions and MATLAB/Simulink to solve the described DAEs of the dynamic model of a power system in [31] using an Ordinary Differential Equation (ODE) solver.

Furthermore, to ascertain the robustness of the designed PSSs in the state of variable operating conditions, the time-domain simulations are derived from studying the system response to the following disturbances:

1. A three-phase short circuit fault at bus 39 at $t = 1$ s. The fault is cleared by tripping the line between buses 36−39 after 100 ms.
2. 0.05 pu increment in V_{ref} of the G_3 excitation system at $t = 1$ s with a duration of 100 ms.
3. 50% load change (decrement) at bus 35 at $t = 1$ s with a duration of 100 ms.

Because of space constraints, some studies were only conducted with the appearance of the first disturbance. The first disturbance would be more severe than the others, which has been considered for this study. If the proposed method becomes effective in such a circumstance, it will certainly excel in other conditions. The next study would utilize other disturbances for a bigger power system.

4.3 Evaluation of Optimization Methods

The specific aim, which is focused here, is to clarify the positive effect of the proposed optimization algorithm in all presented operating conditions. The rotor angle of different generators concerning G_1 under the first disturbance has been shown in Fig. 6. Analysis ascertains that the PSSs, which are tuned with IGRSA, can provide more positive damping in the system response in all conditions.

***Table 1**: Performance indices.*

Algorithm	GRSA	IGRSA
BFV	10.5933	1.5103
AV	11.1469	4.2871
STD	4.4651	0.5212

***Table 2**: Results of performance indices with different algorithms.*

Algorithm	Parameter	Disturbance		
		D.1	D.2	D.3
GRSA	PI_1	0.0290	0.9221	0.0117
	PI_2	0.1533	2.1974	0.3226
IGRSA	PI_1	0.0153	0.8661	0.1090
	PI_2	0.1239	1.9819	0.3068

The selection of generators from different parts of the power system was to demonstrate the effectiveness of the proposed algorithm in every situation.

These figures show that the response of the generators undergoes more fluctuations by applying the old optimization algorithm. In contrast, the designed PSSs, considering the proposed optimization algorithm, can effectively reduce the fluctuations to settle down faster and reach new steady state conditions.

4.4 Evaluation of Performance Indices

The optimization performance of each search algorithm is investigated by three indexes. These indexes are the Best Function Value (BFV), Average Value (AV), and Standard Deviation (STD) of function values obtained at the end of 30 successive runs of these optimization algorithms [26]. To give more details, the index of AV is a criteria to determine how the function would be converged, the index of BFV determine the number of iteration for getting global optimum, and the index of STD would determine the robustness of the proposed algorithms in finding near global optimal solutions. The standard deviation is the average amount of variability in your dataset. It tells you, on average, how far each value lies from the mean. A high standard deviation means that values are generally far from the mean, while a low standard deviation indicates that values are clustered close to the mean. Because of space constraints, only the severe condition of case 2 with the first disturbance is reported.

To investigate and complementary study of the system response in different operating conditions, two common performance indices (PI) which are related to the settling time and overshoot of speed response [19] are described as follows:

$$PI_1 = \sum_{i=1}^{n} \int_{t=0}^{t=t_{sim}} \left(t\Delta\omega_i\right)^2 dt \tag{25}$$

$$PI_2 = \sum_{i=1}^{n} \int_{t=0}^{t=t_{sim}} \left(\Delta\omega_i\right)^2 dt \tag{26}$$

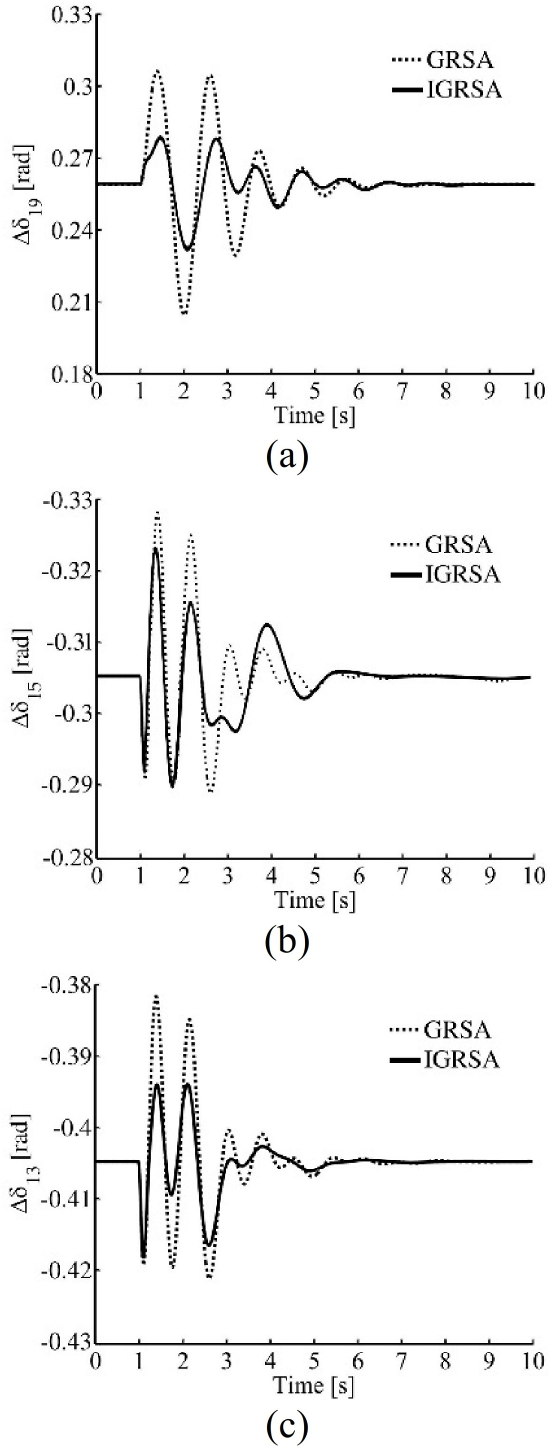

***Fig. 6**: Rotor angle deviation with the first disturbance in different cases. a) Base case b) Case 1 c) Case 2.*

The performance indices of PI_1 and PI_2 for case 2 and considering all disturbances are reported in Table II. Here, it should be mentioned that the lower values of performance indices resulted in better system performance from the dynamic stability point of view. The supremacy of the proposed design technique will be evident from the analytical study of the obtained performance indices in the different disturbances.

5. CONCLUSION

This work aims to introduce a new meta-heuristic optimization method and simultaneously get involved with designing highly effective PSSs. The cloud theory was used to improve GRS algorithm performance, and a technique named IGRSA was presented. Finally, IGRSA was utilized to optimize the objective function. The obtained results through optimization of utilized objective function and use of IGRSA show that this method is the most effective way in PSS designing. Furthermore, small signal analysis and time domain simulations on a multi-machine power system illustrate the effectiveness of the proposed method.

Nomenclature

Symbol	Definition	Unit
A, B	Constant matrices of state-space equations	-
C_r	Crossover probabilities	-
Cte	Constant value prespecified in different conditions	-
d	Dimension of particle position	-
Dn	Dimension of cloud	-
E_{fdi}	Field's voltage of i^{th} excitation system	Volt
En	Entropy or uncertainty measurement of the qualitative concept	-
Ex	Mathematical expectation of cloud drop	-
F_1	Damping scale objective function	-
f_{ave}	Average value of the function	-
f_g	Best solution so far for the optimization algorithm	-
f_{rand}	Random selected objective function value in current subspace	-
FNC	Forward normal cloud generator	-
G_i	Transfer function of i^{th} PSS	-
GM_1	Geometry coefficient	-
GM_2	Geometry coefficient	-
He	Hyper-entropy or uncertainty measurement of entropy	-
H	Search subspace size	-
K_g	Random vector ($1 \times d$ vector) with uniformly random numbers in the range [0 1]	-
$K_{f,j}$	Random vector of j^{th} component	-
K_{Ai}	Gain of i^{th} excitation system	-
k	Subscript index of machine numbers	-
K_i	Optimal value of i^{th} PSS's stabilizer gain	-
$K_{V,ij}(t)$	Distance of best position and a random particle position in search subspace s	-
l	Number of particles	-
M_g	Maximum generation	-
M_p	Mutation probabilities	-
N_p	Population size	-
n	Number of state variable	-
n_k	Number of steps in slope change	-
n_m	Number of test system's machine	-
q	Subscript index of system's eigenvalues	-
r	Step length of damping factor intervals	-
S_s	Search space size	-
S	Number of search subspaces	-
$Slope_{\zeta_0}$	Convergence region's slope in the old objective function	Degree
$Slope_{\chi_0}$	Convergence region's slope in the objective function F_1	Degree
s	Denotation of the complex plane	-
$sign$	Signum function	-
S_s	Search space size	-
T_{Ai}	Time constant of i^{th} excitation system	-
T_{ji}	j^{th} optimal time constant of i^{th} PSS	-
T_w	Washout time constant	-
t	Number of iterations	-
$T_i(t)$	Best particle position obtained in exploration so far	-
$T_{ij}(t)$	Best position of j^{th} component of i^{th} particle	-
$T^{rand,s}$	Random position in search subspace s	-
$T^{Bset,s}$	Best position in search subspace s	-
$T_j^{Best,s}(t)$	j^{th} component of best position in search subspace s	-
TG	Global best particle position obtained in tensor so far	-
TB_i	Best position obtained in the exploration so far	-
$X_i(t)$	Cloud drop of i^{th} agent	-
$X_{i,rand}$	Negative random selected cloud drop of i^{th} agent	-
y	Subscript index of system's operating condition	-
U	Vector of input variable	-
$V_{ij}(t)$	Velocity vector of i^{th} agent of j^{th} dimension	-
V_{PSSi}	Output voltage of i^{th} PSS	Volt
V_{refi}	Reference voltage of i^{th} generator	Volt
V_{ti}	Terminal voltage of i^{th} generator	Volt
X	Vector of state variable	-
γ_L	Weight of local machine feedback signal	-
γ_R	Weight of remote machine feedback signal	-
σ	Damping factor of eigenvalue	-
σ_0	Initial value of damping factor	-
σ_k	Damping factor of k^{th} step	-
ω_{Li}	Angular speed of i^{th} local machine	Rad/s
ω_{Rk}	Angular speed of k^{th} remote machine	Rad/s
ω_i	Angular speed of i^{th} machine	Rad/s
χ_q	Damping scale of q^{th} eigenvalue	-
$\mu_i(t)$	Certainty degree of i^{th} cloud drop	-
$\xi_i(t)$	Energy conversion ratio of i^{th} iteration	-
$\delta_{tl,ij}(t)$	Time-like geodesic direction of j^{th} component of i^{th} particle at t^{th} iteration	-
$\delta_{null,ij}(t)$	Null geodesic direction of j^{th} component of i^{th} particle at t^{th} iteration	-
$\delta_{sl,ij}(t)$	space-like geodesic direction of j^{th} component of i^{th} particle at t^{th} iteration	-
$\delta_{ij}(t)$	Step direction of j^{th} component of i^{th} particle at t^{th} iteration	-
$\lambda_{ij}(t)$	Step length of j^{th} dimension of i^{th} particle at t^{th} iteration	-
$\gamma_i(t)$	Scalar value related to i^{th} particle at t^{th} iteration	-
ζ_0	Initial value of damping ratio	-
ω_t	Weighting factor in step length equation	-
ε	Very small number	-
∂	Symbol of deviation	-
Δ	Symbol of difference	-

APPENDIX

Requirement data and the parameters of implied optimization algorithms that should be established before performing the optimization process are listed in Table.A1 and Table.A2, respectively. The optimal parameters of the proposed PSSs are given in Table.A3.

Table (A1): *Requirement data*

Parameter	Symbol	Unit	Value
Initial value of damping factor	σ_0	-	-0.5
Number of operating conditions	n_y	-	3
Number of steps in slope change	n_k	-	1000
Washout time constant	T_w	Sec	10
Weight of local machine feedback signal	γ_L	-	1
Weight of remote machine feedback signal	γ_R	-	-1

Table (A2): *Strategy parameters of optimization algorithms*

O.A	Strategy parameter	Value
GRSA & IGRSA	*h* (Search subspace size)	10×*d*
	S (Number of search subspaces)	[*d*/3]
	S_s (Search space size)	*S*×*h*
	t_{max} (Maximum number of iterations)	10×*n*
	GM_{max} (Maximum of geometry coefficient)	1
	GM_{min} (Minimum of geometry coefficient)	0
	GM_1 (Geometry coefficient)	0.01
	GM_2 (Geometry coefficient)	0.99

Table (A3): *Optimal parameters of the proposed PSSs*

Gen	Proposed Objective Function With GRSA				
	K	T_1	T_2	T_3	T_4
G_1	16.9523	0.5033	0.1708	0.3986	0.0209
G_3	2.6856	0.3305	0.0206	0.6281	0.2350
G_4	45.0241	0.5252	0.0201	0.4207	0.5239
G_5	4.8984	0.3366	0.0200	0.3934	0.1849
G_6	45.3028	0.6905	0.2952	0.3499	0.0228
G_7	2.895	0.5971	0.0200	0.8119	0.6676
G_8	3.0008	0.4011	0.2050	0.5041	0.0229
G_9	5.5970	0.5146	0.0205	0.1888	0.2132
G_{10}	12.405	0.1861	0.1607	0.4746	0.0244
	Proposed Objective Function With IGRA				
	K	T_1	T_2	T_3	T_4
G_1	9.85593	0.3234	0.0206	0.4374	0.2480
G_3	5.2179	0.4145	0.3323	0.5872	0.0202
G_4	49.1629	0.3935	0.0227	0.7656	0.4550
G_5	36.2130	0.7135	0.2667	0.3764	0.0235
G_6	7.3360	0.3640	0.1800	0.3095	0.0200
G_7	40.3200	0.2357	0.0207	0.2878	0.1561
G_8	6.6582	0.3246	0.0203	0.3063	0.1364
G_9	15.1155	0.4622	0.1928	0.1946	0.0311
G_{10}	11.6817	0.4945	0.1725	0.1900	0.0317

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Behzad Ehsanmaleki was born on May 6, 1991 in Tehran, Iran. He obtained a scholarship from the Ministry of Education, Iran in 2009 to persue the BSc./B.Tech degree in Electrical Engineering. He received BSc./B.Tech and MSc./M.Tech degree in Electrical Engineering from Lorestan University and Shaheed Rajaee Teacher Training University in 2013 and 2016, respectively. His current research interests are Power System Stability and Flexible Alternating Current Transmission System (FACTS) devices.

Hamid Radmanesh (Member, IEEE) received a B.Sc. degree in electrical engineering from the Malek-Ashtar University of Technology, Tehran, Iran, in 2006, a M.Sc. degree in electrical engineering from Shahed University, Tehran, in 2009, and the Ph.D. degree in electrical engineering from the Amirkabir University of Technology (AUT), Tehran, Iran, in 2015. His research interest includes transient in power systems, HVDC transmission systems, and more electric aircraft. He has authored over 100 published technical papers.