



PID type multiple stabilizers design using elitist gravitational search algorithm

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ABSTRACT

This paper proposed the Proportional Integral Derivative (PID) type multiple stabilizers to damp inter-area and intra-area low frequency oscillations in power system utility. To improve power system stability, optimal tuning of the PID type stabilizer gains and non-smooth nonlinear parameters is importance and a challenging task to accommodate variations in the power system dynamics, mainly when multiple PSSs are applied. Because, it is a computationally expensive combinational and nonlinear optimization problem. In this paper, Elitist Gravitational Search Algorithm (EGSA) is proposed to optimize multiple PID type PSSs gains tuning problem, simultaneously in order to reduce stabilizer design effort and find the best possible solution. The EGSA is a novel meta-heuristic stochastic optimization algorithm and simulates the masses cooperate using a direct form of communication through gravitational force to find the best possible solution within a reasonable computation time. It provides both global and local search by changing the velocities over time to determine distance and direction of agents (masses) for significant increasing the probability of finding the optimal solution and efficiently avoiding local optimum to a large extent. To optimize of multiple PSSs gains a nonlinear time domain-based objective function under various operating conditions is considered. It is solved using EGSA technique that has strong and robust search capability than the other heuristic optimization algorithm, as well as is being easy to implement. The effectiveness of the proposed EGSA based stabilizers is investigated on a two-area four machine power system through the nonlinear time domain simulation and some performance indices under different operation condition and system configurations. The performance of the proposed stabilizer is compared with those of standard Particle Swarm Optimization (PSO) and PSO with time variant acceleration coefficients based designed PSSs to illustrate its robustness and damping quality. The results analysis reveals that the EGSA based tuned PID type PSS is effective and achieves good low frequency oscillations damping capability. Moreover, it is superior that of the PSO method in terms of accuracy, convergence and computational effort.

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Introduction

Noted that the power system demand grows rapidly and the expansions in transmission and generation are restricted with the limited availability of the resources and the strict environmental constraints. Hence, today's power systems are much more loaded than before. This causes the power systems to operate near their stability limits [1]. Conversely, by the development of interconnection of large electric power systems, there have been spontaneous system oscillations at very low frequencies in order of 0.2 to 3.0 Hz. Once started, they would continue for a long period of time. In some times, they continue to grow and caused that the system was separated if adequate damping is not available. Furthermore, low-frequency oscillations presented a limitation on the power-transfer capability of the system. To e system damping, the generators are equipped with power system stabilizers (PSSs) that provide supplementary feedback stabilizing signals in the excitation systems to improve the system damping and extending power transfer limits, thus maintaining reliable operation of the power system [2].

Valuable research contributions from time to time for PSS design like the application of adaptive control [3, 4], robust control techniques [5-7], neural networks [8, 9] and fuzzy logic theory [10-12] have been reported in the the literature. In spite

of the satisfactory results achieved by adaptive stabilizers, the control strategies are required on line system model identification and therefore they are complicated. The advantages of robust control techniques are including system uncertainties and physical understudying of the system in the synthesis procedure [5, 7]. However, the importance and difficulties in the selection of weighting functions have been represented. Moreover, the order of the robust control based stabilizer is high which gives rise to complex structure of such stabilizers and reduces their applicability. It should be noted that, although the performance of the power system is improved by the ANN based stabilizer [8, 9], but the main problem of these techniques are the long training time and selecting the number of layers and number of neurons in each layers. Unlike other classical control methods, fuzzy logic based PSSs are model-free stabilizers; i.e. they do not require an exact mathematical model of the controlled system [10, 12]. On the other hand, robustness and speed are the most important properties than the other classical methodes. However, it should be pointed out that the fuzzy controllers require two or three dimensional rule base. This problem makes the design process more difficult.

The conventional lead-lag compensators have been widely used as the power system stabilizers. However, the PSS parameter tuning problem is a complex exercise. These stabilizers have previously tuned both single and multiple operation points of the power system using various methods. Many random heuristic methods, such as like, genetic algorithms [13], chaotic optimization algorithm [14], rule based bacteria foraging [15], honey bee mating optimization [16] and particle swarm optimization [17] have been reported for achieving high efficiency and search global optimal solution in the problem space. However, in these studies non-smooth parameters of the stabilizer such as saturation limits has not been optimized, Also, it should be noted that the performance of the above methods greatly depends on its control parameters adjustments, and it often suffers the problem of being trapped in the local optima so as to be premature convergence.

Despite the potential of the modern control techniques with different structure, PID type controller is still widely used for industrial applications such as power systems control [18-20]. This is because it performs well for a wide class of process. Also, they give robust performance for a wide range of operating conditions and easy to implement. On the other hand, Shayeghi et. al [20] presented a comprehensive analysis of the effects of the different PID controller parameters on the overall dynamic performance of the PSS problem. It is shown that the appropriate selection of PID controller parameters results in satisfactory performance during system upsets. Thus, the optimal tuning of a PID gains is required to get the desired level of robust performance. Since optimal setting of PID controller gains with non-smooth saturation limits is a *multimodal* optimization problem (i.e., there exists more than one local optimum) and more complex due to nonlinearity, complexity and time-variability of the real world power systems operation. Hence, local optimization techniques, which are well elaborated upon, are not suitable for such a problem.

Since the gravitational search algorithm have not yet been applied to solve the multiple PSS design problem, we present a new approach for the optimal tuning of the PSS parameters, simultaneously by using the elitist gravitational search algorithm in this paper. The Elitist GSA (EGSA) algorithm is a typical swarm-based approach to optimization, in which the search algorithm is inspired by the law of gravity and mass interactions. Unlike the other heuristic techniques such as PSO, it performs both global search and local search in each iteration process for significant probability increasing of the optimal solution finding and efficiently avoiding local optimum to a large extent. In the EGSA, the particles, called agents, are a collection of masses which interact with each other based on the Newtonian gravity and the laws of motion. The agents share information using the gravitational force to guide the search toward the best location in the search space. In GSA, in moving all agents to a new position, the direction and distance of agents are updated by their velocities. By changing the velocities over time, the agents are likely to move toward the global optima. Thus, GSA incorporates a flexible and well-balanced mechanism to adapt to the global and local exploration and exploitation abilities within a short computation time due to the velocity updating schemes used and the global search ability mechanism employed [21]. Also, it has fewer control parameters and a higher success rate since it does exploration and exploitation processes together efficiently. This newly developed optimization algorithm is

simple, robust and capable to solve multi-variable, multi-modal and difficult combinatorial optimization problems.

In this study, in order to reduce PSS design problem effort and improve computational efficiency, the GSA optimizer is proposed for the simultaneous optimal tuning of PID type multiple stabilizers to achieve desired level of low frequency oscillations damping and improve dynamic stability of the multimachine power system. The tuning problem of the stabilizer gains and saturation limits are automatically optimized according to a time domain based objective function by EGSA method. Multiple operation conditions are considered in synthesis process to guarantee the relative stability and concurrently secure the time domain specifications. The efficiency and performance of the proposed stabilizers is tested on a multi-machine power system under different operating conditions in comparison with the PSO with Time Variant Acceleration Coefficients (PSO-TVAC) [22] and standard PSO based tuned PID type PSSs through nonlinear time domain simulation and some performance indices. The results analysis confirms the robust performance of the proposed method for damping low frequency oscillations than the PSO and PSO-TVAC methods. Thus, the proposed EGSA method provides a useful promising scheme to choose desirable PID type PSS from a set of optimally tuned PSSs for the system operator, PSS manufacturer and customers.

Problem Formulation

A two-area four-machine power system, shown in Fig. 1, is considered for the multiple PSS design. Each area consists of two generator units. The rating of each generator is 900 MVA and 20 kV. Each of the units is connected through transformers to the 230 kV transmission line. There is a power transfer of 400 MW from Area 1 to Area 2. The detailed line data, bus data and the dynamic characteristics for the machines, exciters, and loads are given in [3]. The loads are modeled as constant impedances. For the power system stability analysis a sufficient mathematical models considering a set of nonlinear differential-algebraic equations by assembling the models for each generator, load and other devices such as controls in the system is required. The two-axis model (fourth order) [2] given in Appendix is used for the time domain simulations study for each machine. The loads are modeled as constant impedances. A first order model of a static type automatic voltage regulator was used.

A. PSS structure

The operating function of a PID type 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 structure of the PID type stabilizer to modulate the excitation voltage is shown in Fig. 2. The structure consists of a signal washout block, a PID controller as opposed to the traditional lead-lag controller and a saturation limiter.

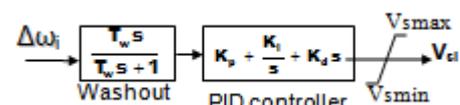


Fig. 2. Structure of the PID type stabilizer

$\Delta\omega_i$ is the speed deviation of the i th generator and V_{si} is the output signal fed as a supplementary input signal to the regulator of the excitation system. The washout filter, which really is a high pass filter, is regarded as to reset the steady-state offset in the output of the stabilizer. The value of the time constant T_w is usually not critical and it can range from 1 to 20 s. It should be noted that the PSS output must be limited to V_s^{max} and V_s^{min} for

avoiding actuator system damaging. All stabilizer parameters were regarded as adjustable. Stabilizer performance robustness is satisfied by considering several operating conditions and the system configurations, simultaneously. Thus, the optimized parameters of PID type stabilizer are:

- K_{Pi} , K_{Ii} and K_{Di} Gains of PID
- T_{Wi} Time constant of washout filter
- V_s^{max} and V_s^{min} PSS output saturations

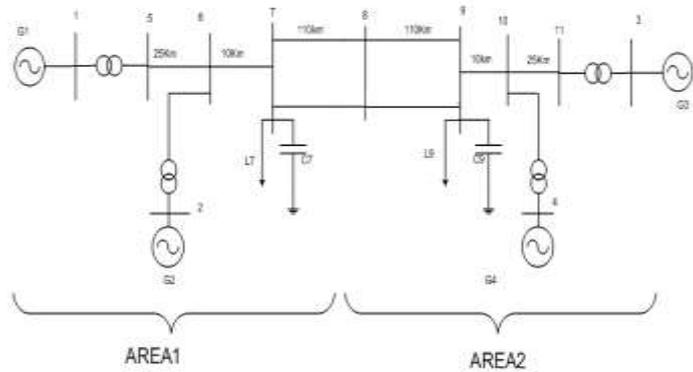


Fig. 1. Two-area multi-machine power system

Elitist Gravitational Search Algorithm

Heuristic algorithms are stochastic global optimization methods which mimic biological or physical processes. One of the newest heuristic algorithms that have been inspired by the physical laws is Gravitational Search Algorithm (GSA) which was first introduced by Rashedi et al [21]. It is a new member of swarm intelligence based on the metaphor of gravitational interaction between masses to solve multi-variable, multi-modal and difficult combinatorial optimization problems. This algorithm describes the mass interactions behavior, learning and information sharing characteristics of masses. It is a very simple, robust and population based stochastic optimization algorithm [24].

This algorithm provides an iterative approach that simulates mass interactions, and moves through a multi-dimensional search space under the influence of gravitation. In GSA, the swarms, called agents, are a collection of masses which interact with each other by the Newtonian laws of gravity and the laws of motion. The swarms share information using a direct form of communication, through gravitational force to guide the search toward the best position in the search space process. The high performance and the global search ability of GSA in solving various nonlinear functions infers from the results of experiments undertaken previously [21, 25].

In GSA, the effectiveness of the swarms is measured by their masses. All the swarms are likely to move toward the global optima attract each other by the gravity force, while this force causes a global movement of all swarms toward the swarms with heavier masses. The heavy masses correspond to best solutions of the problem. In other words, each mass place represents a solution, and the algorithm is navigated by properly adjusting the gravitational and inertia masses. By lapse of time, the masses will be attracted by the heaviest mass which it represents an optimum solution in the search space. Thus, in GSA, all swarms move to a new place by updating their direction and distance determined by their velocities. Consequently, the swarms are likely to move toward the global optima by changing the velocities over the time. This algorithm is an iterative process similar to the other swarm intelligence based approaches. It starts with N agents (masses) in a d-dimension space, where N and d denote the size of population

and the number of optimization parameters, respectively. The i th agent is represented by:

$$X_i = (x_i^1, \dots, x_i^d, \dots, x_i^n) \text{ for } i = 1, 2, \dots, N \quad (1)$$

Where, x_i^d is the position of agent i in dimension d and n is the search space dimension.

After evaluating the current population cost (fitness), the mass of each swarm is determined as follows:

$$M_i(k) = \frac{q_i(k)}{\sum_{j=1}^N q_j(k)} \quad (2)$$

$$q_i(k) = \frac{f_i(k) - f_{worst}(k)}{f_{best}(k) - f_{worst}(k)}$$

Where, $f_i(k)$ represent the fitness value of the swarm i at iteration k . $f_{best}(k)$ and $f_{worst}(k)$ is the best and worst fitness of all swarms, respectively and defined as follows:

$$f_{best}(k) = \min_{j=1, \dots, N} f_j(k) \quad (3)$$

$$f_{worst}(k) = \max_{j=1, \dots, N} f_j(k)$$

To calculate the acceleration of a swarm, total forces from a set of heavier masses applied on it should be regarded as based on a combination of the law of gravity as follows:

$$F_i^d(k) = \sum_{j=T_{best}, j \neq i} r_j G(k) \frac{M_i(k) M_j(k)}{R_{ij}(k) + \epsilon} (x_j^d(k) - x_i^d(k)) \quad (4)$$

where r_j is a random number in the range $[0,1]$, $G(k)$, M_i and M_j is the gravitational constant, M_i and M_j are masses of swarms i and j at iteration k , respectively; ϵ is a small value and $R_{ij}(k)$ is the Euclidean distance between two swarms i and j and calculated as follows:

$$R_{ij}(k) = \|X_i(k), X_j(k)\|_2 \quad (5)$$

T_{best} is the set of first T swarms with the best fitness value and biggest mass, which is a function of iteration (time), initialized to T_0 at the beginning and decreased with iteration. It is used to improve the performance of GSA by controlling exploration and exploitation at search process. This strategy is known as *elitist* selection [26]. Here, T_0 is set to N (total number of swarms) and is decreased linearly to one. Thus, the algorithm uses the exploration at beginning and by lapse of iterations, exploration fades out and exploitation fades in. Using the law of motion, the acceleration of the i th swarm at iteration k and in direction d is given by:

$$a_i^d(k) = \frac{F_i^d(k)}{M_i(k)} = \sum_{j=T_{best}, j \neq i} r_j G(k) \frac{M_j(k)}{R_{ij}(k) + \epsilon} (x_j^d(k) - x_i^d(k)) \quad (6)$$

$$d = 1, 2, \dots, n; \quad i = 1, 2, \dots, N$$

In the next step, the velocity of a swarm is computed as a fraction of its current velocity added to its acceleration as follows:

$$v_i^d(k+1) = r_i \times v_i^d(k) + a_i^d(k) \quad (7)$$

Then, swarm position is updated in each search strategy according to Eq. (9).

$$x_i^d(k+1) = x_i^d(k) + v_i^d(k+1) \quad (8)$$

Where, x_i^d , v_i^d and a_i^d are the position, velocity acceleration of swarm i in dimension d , respectively. r_i is a uniform random variable in the range $[0,1]$. This random number is applied to give a randomized characteristic to the search process.

It should be noted that the gravitational constant $G(t)$ is an important control parameter in determining the performance of GSA and adjusting its accuracy. Thus, it is generally reduced with iteration k as follows:

$$G(k) = G_0 \exp(\alpha \times k / K_{max}) \quad (9)$$

Where, G_0 is the initial value, α is a constant and K_{max} is the maximum iteration number.

It is obvious that from the above clarification the control parameters used in the GSA algorithm are the number of population size N , the value of initial gravitational constant G_0 , α and the maximum iteration number (generation). Figure 3 shows the implementation flowchart of the summarized GSA method steps.

The main features of the GSA algorithm are physical metaphor, robustness, easy implementation and high quality solutions. Also, it has fewer control parameters and conducts both global search and local search in each iteration process, and as a result the probability of finding the optimal parameters is significantly increased. Thus, it has a flexible and well-balanced mechanism to enhance the global and local exploration abilities unlike the other heuristic techniques.

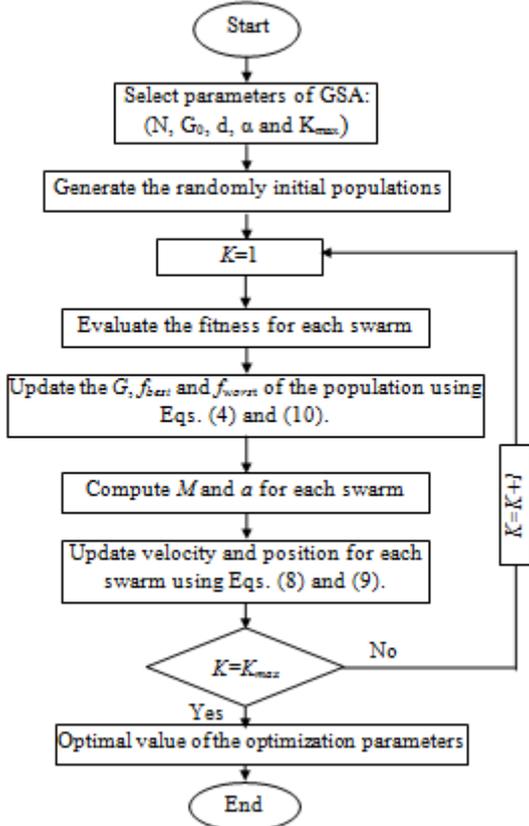


Fig. 3. Flowchart general principal of the GSA

Multiple PSS Design

This section describes how the GSA method is applied to optimal tuning of the PSS parameters for the two-area multi-machine power system as shown in Fig. 1. Now like any other optimization problem, a cost or fitness function needs to be formulated for the optimal PSS design. To optimize PSS parameters, selection of a proper cost function is very important. Because, different fitness functions promote different bio-inspired algorithms behaviors. The goal of optimal stabilizer design task is to maximize low frequency oscillation damping; i.e.: minimize the settling time and overshoots in system dynamics response. A cost function which minimizes the time domain based system response characteristics is used in this study to achieve the PSS design task. It can be defined as follows:

$$J_i = \sum_{j=2}^4 \int_0^{t_{im}} t^2 (\Delta\omega_j^2 + \gamma\Delta\omega_{34}^2) dt + \lambda \max(OS_{11}^2, OS_{12}^2, OS_{13}^2, OS_{34}^2) \quad (10)$$

$$F = \sum_{i=1}^{NP} J_i \quad (11)$$

Where, λ and γ are considered 0.007 and 0.34, respectively. NP is the total number of operating points considered for optimization process. The main feature of this cost function is that it needs the minimal dynamic plant information.

The design problem can be formulated as the following constrained optimization problem, where the constraints are the PSS parameters bounds:

$$\begin{aligned} & \text{Minimize } F \text{ Subject to} \\ & T_{wi}^{\min} \leq T_{wi} \leq T_{wi}^{\max} \\ & K_{Pi}^{\min} \leq K_{Pi} \leq K_{Pi}^{\max} \\ & K_{Li}^{\min} \leq K_{Li} \leq K_{Li}^{\max} \\ & K_{Di}^{\min} \leq K_{Di} \leq K_{Di}^{\max} \\ & V_s^{\min} \leq V_s \leq V_s^{\max} \\ & -V_s^{\min} \leq -V_s \leq -V_s^{\max} \end{aligned} \quad (12)$$

Typical ranges of the optimized PSS parameters are [0.1-20] for T_w and [0.01-50] for PID controller parameters (K_{pi} , K_{li} and K_{Di}) and [0.05-0.5] for V_s^{\max} and $-V_s^{\min}$. to keep the system within the stability margin during the online optimization. The proposed approach employs bi-inspired EGSA, PSO-TVAC (see Ref. [22] for more details) and PSO [20] algorithms to solve this optimization problem and search for the optimal set of PID type PSSs parameters. To evaluate the efficiency and robustness of the proposed optimization technique various operating conditions and the system configurations, simultaneously are considered. The multiple operation conditions are given in Table 1. The proposed EGSA based multiple stabilizers design flowchart is depicted in Fig. 4.

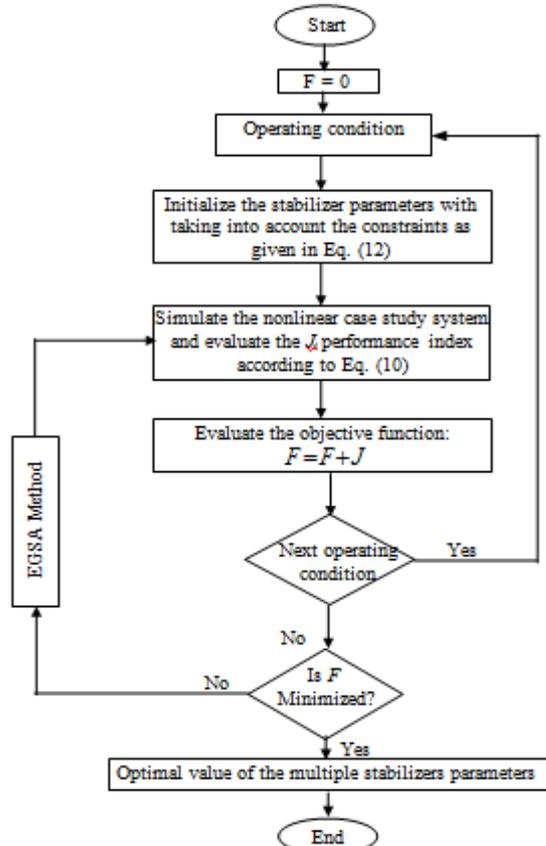


Fig. 4. Flowchart of the proposed EGSA based multiple stabilizers design

The stabilizer parameters optimization is carried out by evaluating the fitness function as given in Eq. (10) for four operating conditions as given in Table 1 by applying a 6-cycle three-phase fault at the middle of one of the transmission line between bus-7 and bus-8. The fault is cleared by permanent tripping of the faulted line. In this study, the EGSA module works offline. For the each PSS, the optimal setting of six parameters is determined by the EGSA, i.e. 24 parameters to be optimized, namely K_{P_i} , K_{I_i} , K_{D_i} , V_s^{\max} and $-V_s^{\min}$ for $i= 1-4$.

In order to make possible comparison with the PSO and PSO-TVAC approaches, the design and tuning of the PSS parameters for this multi-machine power system, PAO and PSO-TVAC methods (For more details see the Refs. [20, 22]) were applied. In order to acquire better performance, the control parameters of the proposed EGSA and PSO algorithms is given in Table 2. Optimized PSSs parameter set values corresponding to the best fitness achieved by each algorithm after 10 trials based on the cost function as given in Eq. (12) are listed in Table 3.

Results and Discussion

To evaluate the effectiveness and robustness of the proposed PID type stabilizer, simulation studies are carried out for various fault disturbances and fault clearing sequences for two scenarios through the nonlinear time simulation and some performance indices using the following three designed stabilizers:

- i) PSO optimized PID type stabilizer [20]
- ii) PSO-TVAC optimized PSS [22].
- iii) EGSA optimized PID type stabilizer

The respective optimized PSS parameters for these methods are given in Table 3.

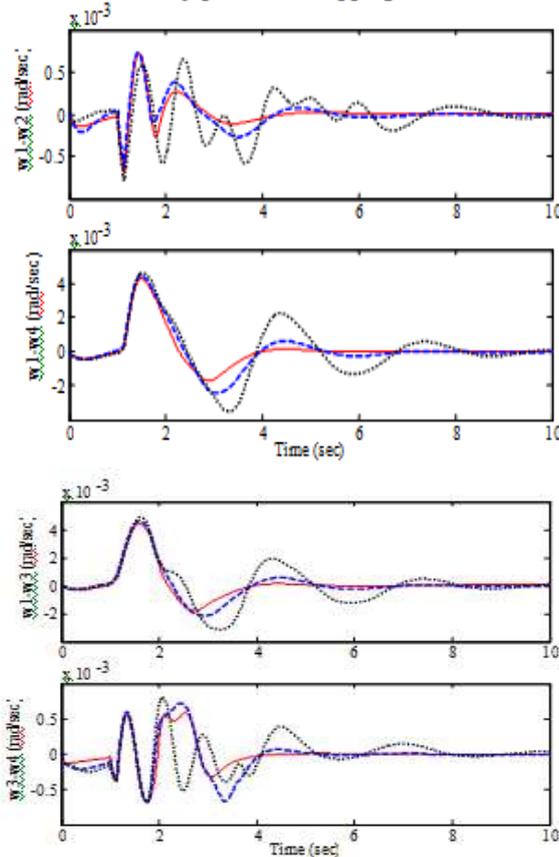


Fig. 5. Inter-area and local mode of oscillations in scenario 1 for case 1; Solid (EGSA), Dashed (PSO-TVAC), Dotted (PSO).

A. Scenario 1

In this scenario, the performance of the proposed stabilizer under transient conditions is verified by applying a 6-cycle three-phase fault at the middle of one of the transmission line between bus-7 and bus-8. The fault is cleared by permanent tripping of the faulted line.

The inter-area and local mode of oscillations is shown in Figs. 5-7, respectively. The performance of the EGSA based optimized multiple PID type stabilizer is quite prominent in and the overshoots and settling time are appreciably enhanced with the proposed PSS that of the PSO-TVAC and PSO methods one.

B. Scenario 2

In this scenario, another severe disturbance is considered for several loading conditions; that is, a 6-cycle, three-phase fault is applied at the same above mentioned location in scenario 1. The fault is cleared without line tripping and the original system is restored upon the clearance of the fault. The system response is shown in Figs. 8-10 for different cases. It can be seen that the proposed GSA based stabilizer has good ability for damping low frequency oscillations and stabilizes the system quickly.

To demonstrate effectiveness of the proposed EGSA based stabilizer, some indices based on the system performance characteristics are described as:

$$IAE = 10^4 \times \int_0^{tsim} (|\Delta\omega_{12}| + |\Delta\omega_{13}| + |\Delta\omega_{14}| + |\Delta\omega_{34}|) dt \tag{13}$$

$$ITAE = 10^4 \times \int_0^{tsim} t \cdot (|\Delta\omega_{12}| + |\Delta\omega_{13}| + |\Delta\omega_{14}| + |\Delta\omega_{34}|) dt \tag{14}$$

$$ISE = 10^4 \times \int_0^{tsim} (\Delta\omega_{12}^2 + \Delta\omega_{13}^2 + \Delta\omega_{14}^2 + \Delta\omega_{34}^2) dt \tag{15}$$

$$FD = (OS \times 4000)^2 + (US \times 1000)^2 + T_s^2 \tag{16}$$

Where, OS , US and T_s are mean overshoot, mean undershoot and mean settling time of four relative speed deviations of $\Delta\omega_{12}$, $\Delta\omega_{13}$, $\Delta\omega_{14}$ and $\Delta\omega_{34}$. It is merit mentioning that the lower the value of these indices is, the better the system response in terms of the time-domain characteristics.

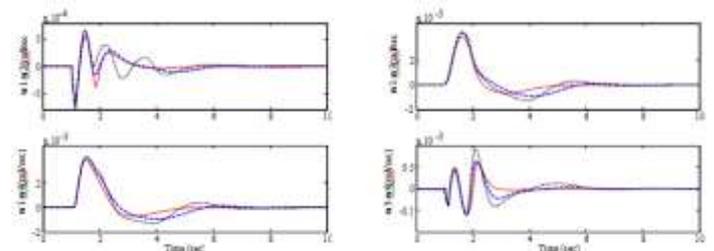


Fig. 6. Inter-area and local mode of oscillations in scenario 1 for case 2; Solid (EGSA), Dashed (PSO-TVAC), Dotted (PSO).

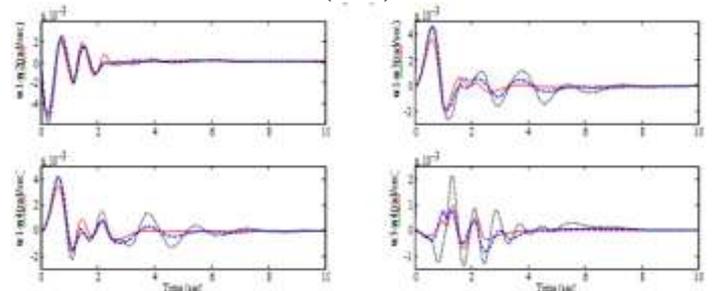


Fig. 7. Inter-area and local mode of oscillations in scenario 1 for case 4; Solid (EGSA), Dashed (PSO-TVAC), Dotted (PSO).

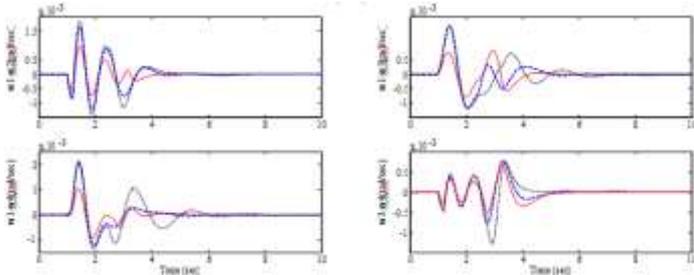


Fig. 8. Inter-area and local mode of oscillations in scenario 2 for case 2; Solid (EGSA), Dashed (PSO-TVAC), Dotted (PSO)

Numerical results of performance robustness for all system loading cases are shown in Figs. 11 and 14 with three stabilizers under scenarios 1 and 2. Evaluation of these figures shows that the using the proposed EGSA based PID type stabilizers the speed deviations of all machines are quickly damped and has small overshoot, undershoot and settling time. Furthermore, it achieves good robust performance against system loading conditions and configuration changes compared to that of PSO-TVAC and PSO based designed stabilizers.

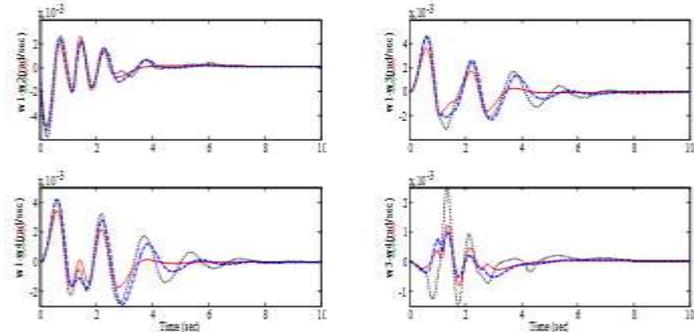


Fig. 9. Inter-area and local mode of oscillations in scenario 2 for case 3; Solid (EGSA), Dashed (PSO-TVAC), Dotted (PSO).

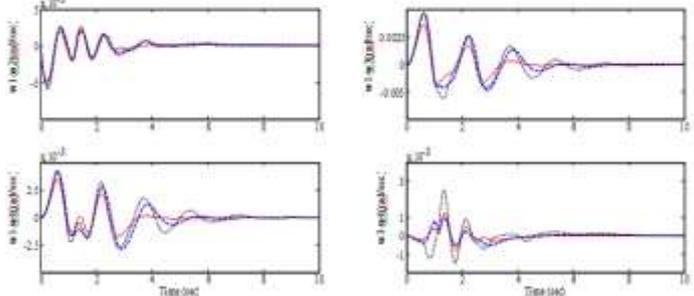
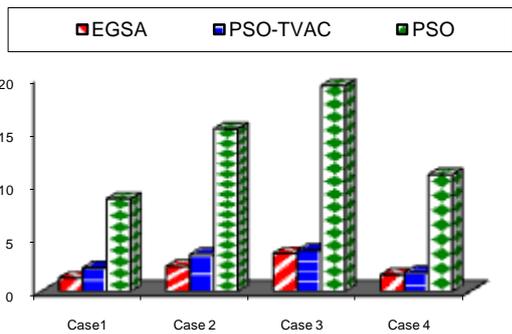
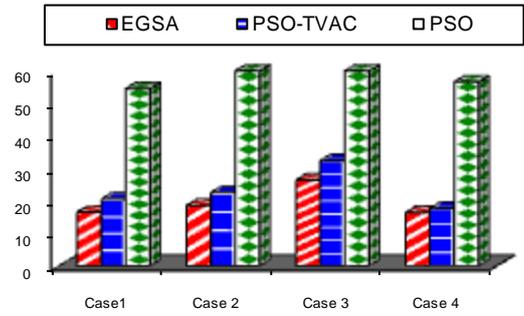


Fig. 10. Inter-area and local mode of oscillations in scenario 2 for case 4; Solid (EGSA), Dashed (PSO-TVAC), Dotted (PSO).

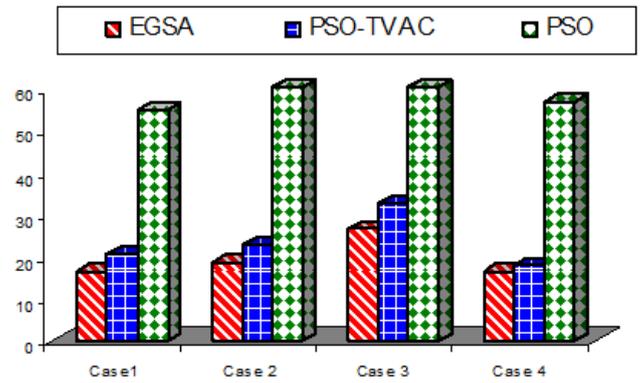


(a)

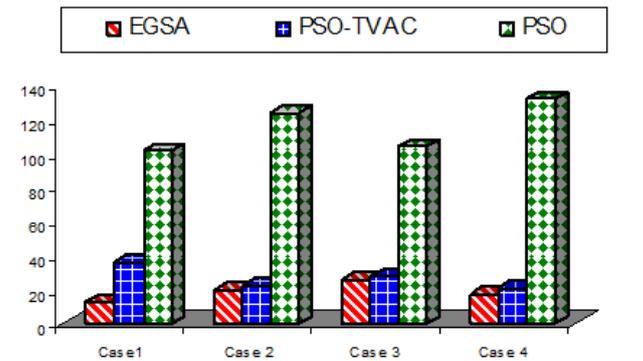


(b)

Fig. 11: Values of performance index in scenario 1 a) IAE and b) ITAE.

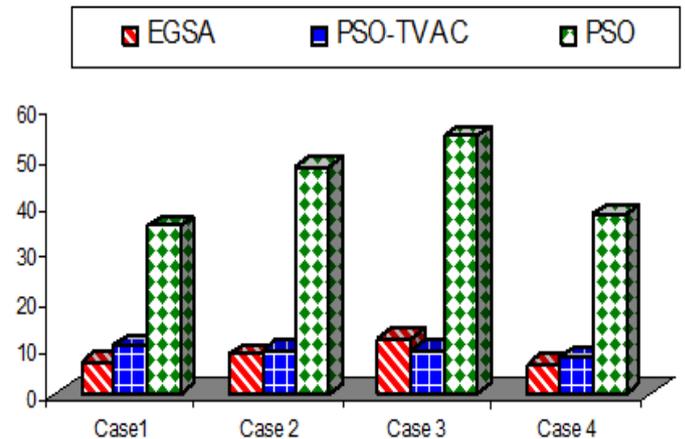


(a)



(b)

Fig. 12. Values of performance index in scenario 1 a) ISE and b) FD.



(a)

Table 1. Four operating condition (pu)

Operating Condition	G ₁		G ₂		G ₃		G ₄	
	P	Q	P	Q	P	Q	P	Q
Case 1 (Base Case)	0.7778	0.1021	0.7777	0.1308	0.7879	0.0913	0.7778	0.0918
Case 2 (20% increase for system load in case 1)	1.084	0.3310	0.7778	0.4492	0.7879	0.1561	0.7778	0.2501
Case 3 (20% decrease for system load in case 1)	0.7778	0.0502	0.2333	0.0371	0.7989	0.0794	0.7778	0.0704
Case 4 (Loss of a line between bus 7 and bus 8)	0.7778	0.1021	0.7777	0.1308	0.7989	0.0903	0.7778	0.0981

Table 2. EGSA and PSO parameters for optimization

PSO-TVAC		PSO		EGSA	
C _{1f}	0.2	C ₁	2.0	Swarm dimension	24
C _{1i}	2.5	C ₂	2.0	Population size	60
C _{2f}	2.5	w	0.9	G ₀	20
C _{2i}	0.2	Population	40	α	100
φ	4.1	Iteration	100	Iteration	100
w _{min}	0.4	-	-	-	-
w _{max}	0.9	-	-	-	-
Population	40	-	-	-	-
Iteration	100	-	-	-	-

Table 3. Optimal PSS parameters

Method	Gen	T _w	K _p	K _i	K _D	V _{max}	V _{min}
EGSA	G ₁	9.452	37.12	1.15	5.23	0.082	-0.084
	G ₂	9.767	36.78	2.00	4.12	0.092	-0.072
	G ₃	8.095	35.99	1.96	3.43	0.087	-0.054
	G ₄	8.897	33.22	1.95	4.13	0.095	-0.093
PSO-TVAC	G ₁	8.675	16.16	1.45	5.12	0.054	-0.087
	G ₂	9.321	18.75	1.32	3.42	0.065	-0.052
	G ₃	8.986	27.49	0.86	4.45	0.086	-0.034
	G ₄	9.547	19.53	0.09	4.83	0.095	-0.045
PSO	G ₁	8.654	18.42	2.34	3.25	0.056	-0.065
	G ₂	9.564	25.49	2.03	4.43	0.038	-0.042
	G ₃	8.817	26.34	1.26	3.21	0.098	-0.046
	G ₄	9.557	16.32	1.25	4.76	0.065	-0.086

Table 4. PSO, PSO-TVAC and EGSA results for 10 trials

Trials	PSO				PSO-TVAC				EGSA			
	Best fitness	Mean fitness	Elapsed time (s)	Iteration	Best fitness	Mean fitness	Elapsed time(s)	Iteration	Best fitness	Mean fitness	Elapsed time(s)	Iteration
1	0.0667	0.318	22412	62	0.0667	0.1021	21321	42	0.0667	0.0988	21092	31
2	0.0876	0.347	22413	73	0.0668	0.1023	21323	44	0.0671	0.0976	21092	23
3	0.0698	0.318	22412	52	0.0673	0.1069	21322	43	0.0667	0.0972	21093	34
4	0.0698	0.317	22412	64	0.0667	0.1028	21321	47	0.0667	0.0984	21091	22
5	0.0987	0.317	22413	65	0.0672	0.1023	21321	41	0.0667	0.0999	21090	35
6	0.0767	0.319	22414	65	0.0667	0.1039	21323	32	0.0672	0.0993	21093	29
7	0.0788	0.317	22412	63	0.0670	0.1021	21325	33	0.0667	0.0981	21094	31
8	0.0756	0.348	22413	71	0.0667	0.1072	21321	35	0.0667	0.0987	21093	34
9	0.0981	0.316	22412	85	0.0696	0.1031	21321	35	0.0699	0.0998	21093	23
10	0.0954	0.319	22414	74	0.0723	0.1022	21320	46	0.0667	0.0956	21093	35
Average	SD=0.0117	0.0120	22412.7	68	SD=0.0017	0.0019	21321.8	40	SD=0.0001	0.0012	21092.4	30

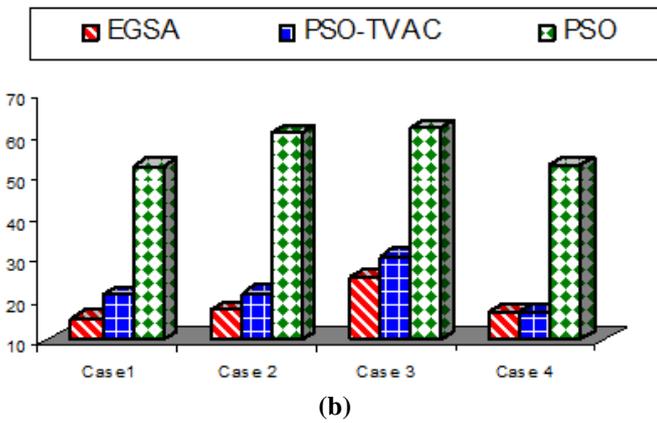


Fig. 13. Values of performance index in scenario 2 a) IAE and b) ITAE.

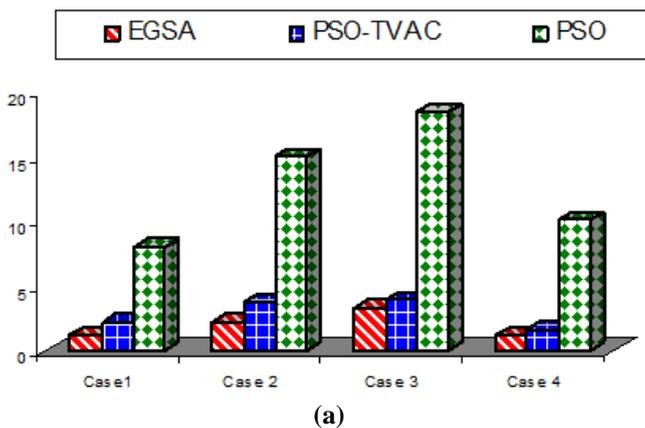


Fig. 14. Values of performance index in scenario 2 a) ISE and b) FD

Computational effort

In order to have a fair comparison in terms of solution quality and computation effectiveness among the three methods (PSO, PSO-TVAC and EGSA), same number of iterations are carried out. To reveal the precisions of these algorithms, a maximum number of iteration cycles are considered as a stopping condition. Each algorithm is run for 10 trials and the best fitness value, Standard Deviation (SD), the least iteration and elapsed time satisfied by each method are considered as criteria of the strength and computational flow of the approach. The results using the PSO, PSO-TVAC and EGSA algorithms based on the fitness function as given in Eq. (12) for optimal setting of the multiple PID type stabilizer parameters are listed in Table 4. Also, the mean fitness functions evaluating process among 10 trials is depicted in Fig. 15 which confirms high-

quality convergence procedure for the EGSA algorithm. It is clear that the best SD and the best fitness value in 7 times are achieved by the EGSA than the other technique. Also, it has fewer iterations and less computational time to reach a predefined threshold in comparison to PSO and PSO-TVAC. In addition, it has less iteration which is about 44% and 75% of PSO and PSO-TVAC algorithms, respectively and less computational time to reach a predefined threshold in comparison to other methods. The best fitness achieved by the ABC is 0.0667 which is the lowest among the three algorithms. Also, the result shows that, using EGSA for optimal setting of PID type stabilizers has faster convergence rate compared to PSO one. Thus, it can be concluded that the proposed EGSA method has stronger capability for finding the superior quality solution and higher computation efficiency than the PSO and PSO-TVAC approaches.

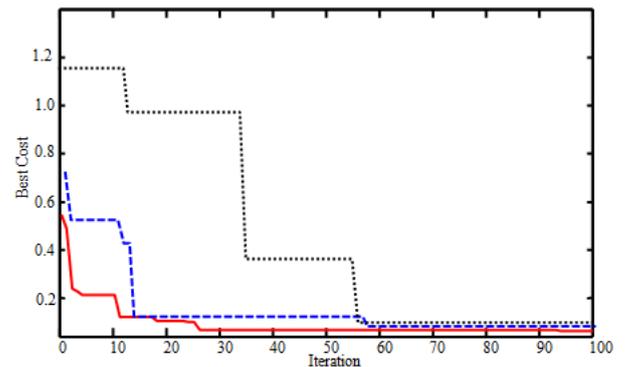


Fig. 15: Fitness convergence; Solid (EGSA), Dashed (PSO-TVAC), Dotted (PSO)

Conclusions

In this paper, a novel elitist GSA algorithm has been successfully applied to optimal setting of multiple PID structured proposed PSSs, simultaneously to improve the relative stability and secure operation of the multi machine power systems. A time domain-based cost function under multiple operation conditions is considered to optimize all stabilizer parameters and it is solved by EGSA. This algorithm incorporates a flexible and well-balanced mechanism to adapt to the global and local exploration and exploitation abilities within a short computation time due to the velocity updating schemes used and the global search ability mechanism employed. Also, it has fewer control parameters and is easy to implement without additional computational complexity. Thus, the convergence precision and speed are remarkably improved and then the high precision and efficacy are confirmed.

The non-linear time domain simulation results show the elitist GSA algorithm provides good potential for efficiently damping low frequency oscillations over a wide range of operation conditions. Furthermore, the system specification analysis using different introduced performance indices illustrated that the proposed EGSA algorithm is superior that of the PSO-TVAC and PSO in terms of accuracy and computational effort. In addition, the comparative performances analysis of the EGSA, PSO-TVAC and PSO optimization techniques to optimize of multiple PID structured proposed stabilizer parameters have been carried out for ten trials run. It is evident that the convergence, high computation efficacy and solution quality for tuning PSS parameters and stabilizing the power system under low frequency oscillations are achieved by the EGSA. Thus, this optimization technique could be a useful promising tool for multiple stabilizers design in the real world

power systems.

Appendix A: Machine models

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

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

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

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

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

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