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Comparative analysis of population based algorithms and hypothesis test in PSS design for multi machine power system

Akash Saxena[1,*],Vikas gupta[2]

This paper addresses the Power System Stabilizers (PSSs) tuning problem for multi machine system. Often power system is subjected to many disturbances; impact of disturbances on the dynamics of power system is always an unabated dilemma for the researchers; this work analyzes a small signal stability problem for 16 generator 68 bus system. PSSs are cost effective damping controller, which gives sufficient damping when properly tuned. A recently developed swarm based algorithm Cuckoo Search , based on random walk of the species is applied on a conventional objective function to find the optimal parameters for stabilizer. A decisive evaluation is done on the basis of solution quality and convergence speed. A hypothesis based on solution quality is created to compare the solution quality of the CSA with respect to Genetic algorithm (GA), Particle Swarm optimization (PSO) and Gravitational search algorithm(GSA). The solutions obtained from the speed deviation curves prove the efficacy of the proposed algorithm. Efficacy of the proposed method is judged under different fault locations, different permutations of loading conditions and system configurations.

Keywords: Power system stabilizer (PSS); Automatic voltage regulator (AVR); Small signal stability; Cuckoo search algorithm.

1. Introduction

To deal with both oscillatory and nonoscillatory instability, two tradeoffs Automatic Voltage Regulators (AVRs) and PSSs are employed to ensure the system overall stability. High AVR gain and fast response have a detrimental effect on system's oscillatory stability. However, they are required for enhancing transient stability; likewise PSSs are also having a detrimental effect on transient stability and device act as catalyst to improve damping of the system. Because of these virtues, devices are dynamically interlinked with one other. Thus, finding suitable locations and optimal parameters of PSSs in multi machine power system are the fulcrum of this thesis. In the past two decades, the employment of auxiliary excitation control signals for improving the small signal stability of power systems has acknowledged much attention [1]–[7].

Nowadays, the conventional power system stabilizer (CPSS) is widely used by power system utilities. Recently, several approaches based on modern control theory have been applied to PSS design problem. These include optimal, adaptive, variable structure, and intelligent control [8]–[15]. Despite the potential of modern control techniques with different structures, power system utilities still prefer the CPSS structure [8], [11].

The reasons behind that might be the ease of on-line tuning and the lack of assurance of the stability related to some adaptive or variable structure techniques. A PSS design problem is the amalgamation of two sub-modules: The suitable site identification of PSS [16]-[18] and PSS parameter estimation,

[*] Corresponding author: Akash Saxena, Department of Electrical Engineering, MNIT, Jaipur, Rajasthan, India. 302017, E-mail: 2008ree102@mnit.ac.in

[1] Research Scholar, Departement of Electrical Engineering, MNIT, Jaipur.

[2] Associate Professor, Departement of Electrical Engineering, MNIT, Jaipur.

Surprisingly the approach for both the modules is based on some initial operating conditions and system configurations. The more pragmatic aspects of the design synthesis are based upon configuration of the system with an unabated dilemma to address to the issue of whether the design will be suitable for other operating conditions or not. However, the endeavour is to find a robust design that is based on a unique methodology, which inculcates almost all the operating conditions. However, the same is not as yet been evolved.

As the PSS parameters are not explicitly included in the objective function, usually the researcher is left with the choice of interpolation of the parameters with the objective function of the PSS; however, gradient based analysis is also a replica of the numerical one with a similar role. The usefulness of gradient information lies in the capability to measure the relative effect of each PSS parameter contributing the system dynamics. The major contribution of last decade is based on the development of robust design methodology ignoring the complexity of practical power systems; more realistic model with less computation time is required for effective robust control over a wide range of operating conditions. Evolutionary algorithms are proved as torchbearers in the field of computational intelligence [22]-[25]. History is witness that man always derives inspiration from the nature in the form of devices such as air machine (Wright brothers), Gravitational law (Newton)), Algorithms and conjectures. The fast computation with best solution quality is the aspiration of any optimization process. The algorithms developed with the inspiration of nature have many virtues to find the global optimum solution; some of them are based on exploration other on exploitation. The paper touches different dimensions in order to find the global optimum solution with evolutionary technique. Conventional excitation system with PSS and AVRs is shown in Fig.1. Organisation of paper chronologically unfolds the problem associated with critical swing modes in section II mathematical modelling of power system is discussed with the detail of conventional objective function used for optimization. Section III contains the details of proposed methodology and section IV and V shows the results and critical analysis based on hypothesis t test.

2. Power System Model

In the test system each generator is modelled as a two axis model which has 6 states in state space model, IEEE type 1 model of 3 state variables is used. PSS used in this work is traditional lead lag structure of 3 states.

$$\dot{x} = f(x, r, t) \qquad (1)$$

Where x is the vector of all state variables and r is the notation for input variables. In small signal stability analysis an operating equilibrium can be found by linearizing the state equations around the operating points. The linearize equation of the same is represented by the set of equation below:

$$\begin{Bmatrix} \Delta \dot{x} = A\Delta x + B\Delta v \\ \Delta u = C\Delta x + D\Delta v \end{Bmatrix} \qquad (2)$$

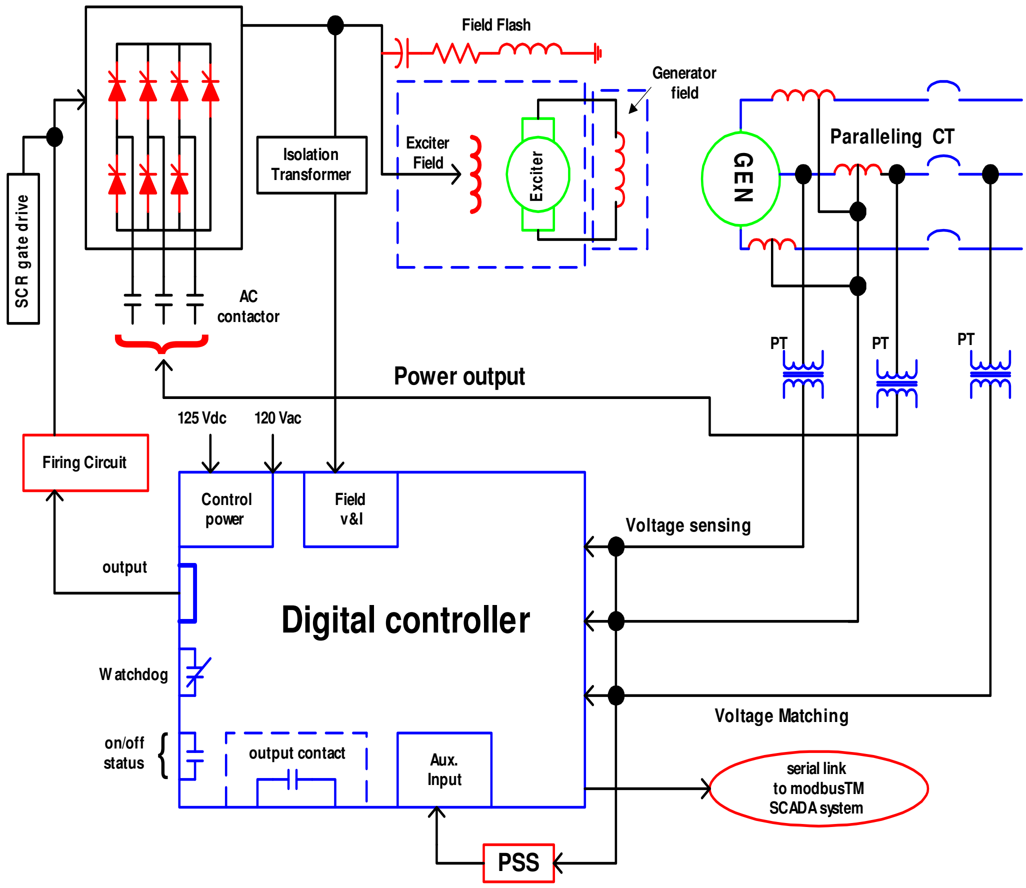

Fig.1 Conventional Excitation System equipped with PSS and AVR

Where v is the vector of network bus voltages and u is the current vector of injection into the network. For Kth PSS the transfer function can be written as per equation (3):

$$V_k = K_{stab}\frac{sT_{wk}}{(1+sT_{wk})}\frac{(1+sT_{1K})}{(1+sT_{2K})}\frac{(1+sT_{3K})}{(1+sT_{4K})} \qquad (3)$$

Where K_{stab} is gain constant and T_{1K}-T_{4k} is the time constants, T_{wk} is washout time constant for K^{th} PSS.

3. Problem formulation and Algorithm Details

3.1. Objective function

When a power system is subjected to a disturbance the duration of the oscillatory period is determined by the Eigenvalues at the most right side on the s-plane. Objective function in this work formulated with the real part of the Eigenvalues. Suppose the maximum real part of the eigen value is α_j and α_0 is the expected value of eigen, which is a negative no..The base case of 16 generator 68 bus system is considered as the non conforming loads on all load buses i.e. the system is stressed due the presence of 50 % constant impedance and 50 % constant current loads. Table I shows that some modes are poorly damped and others are unstable due to presence of the real positive part of the Eigenvalues. The objective function for obtaining parameters for PSS can be expressed as follows:

$$J = \min(\alpha_0 - \alpha_j)^2 \qquad (4)$$

All damping factors will be shifted to the rectangular shape which is not more than α_0 .

3.2. *Cuckoo Search Algorithm*

CSA is introduced by yang and Deb in 2009 [24]. The CS was inspired by compel brood parasitism of cuckoo species by laying their eggs in the nests of host birds. Some cuckoos have evolved in such a way that female scrounging cuckoos can reproduce or rather imitate the colors and patterns of the eggs of a few chosen host species. This reduces the probability of the eggs being abandoned. Yang and dev also suggested in their research that levy flights is useful for improve solution quality besides on random walk method. A Lévy flight is a random walk in which the step-lengths are distributed according to a heavy-tailed probability distribution. Each egg in a nest represents a solution .the objective it to employ good quality solution in the nest and replace those which are not so good solution. The algorithm based on three idealized rule:

- Each Cuckoo laid one egg only, and dumps the egg in *a randomly chosen nest.*
- *The best nest (with quality solutions) will carry over the next generation.*
- *The number of available nest is fixed and a host can identify an alien egg with probability* P_a *[0, 1].*

Pseudo code of algorithm is presented here.

Begin
Objective function f(x), $x = (x_1, \ldots, x_d)^T$
Generate initial population of
n host nests xi (i = 1,2, …, n)
while *(t <Max Generation) or (stop criterion)*
Get a cuckoo randomly by L´evy flights
Evaluate its quality / fitness F_i
Choose a nest among n (say, j) randomly
if $(F_i > F_j)$,
Replace j by the new solution;
end
A fraction (p_a) *of worse nests*
are abandoned and new ones are built;
Keep the best solutions
(or nests with quality solutions);
Rank the solutions and find the current best
end while
Post process results and visualization
end

Figure 2. Pseudo code of the cuckoo search

Based on the foresaid rules while generating new solutions

$$x_i^{t+1} = x_i^{t} + \alpha \oplus Lev'y(\lambda) \qquad (5)$$

Where α > 0 is the step size, in this work it is taken as constant value 1. Random walk is a markov chain whose next location is depends on the current location (the first term in above equation) and the probability of the transition.
Primary observations about algorithm develop a sense of resemblance with hill climbing in combination with some large scale randomization. However the algorithm is a population based algorithm similar to GA and PSO but randomization of the patterns is done in a more efficient way as the step length is heavy tailed. Thirdly the parameters to be tuned is less than GA and PSO, For these reasons the Cuckoo search found to be very generic and used for wide no of optimization problems.

4. Case study

The 5 area, 16 machine, 68 bus system (R. Graham) Fig 5 shows the one-line diagram of the test system, the load model of the system is set to be nonconforming 50%constant impedance and 50 % constant current loads on all load buses. Nonlinear simulation of the test is done on Matlab by using Power System Toolbox [20].

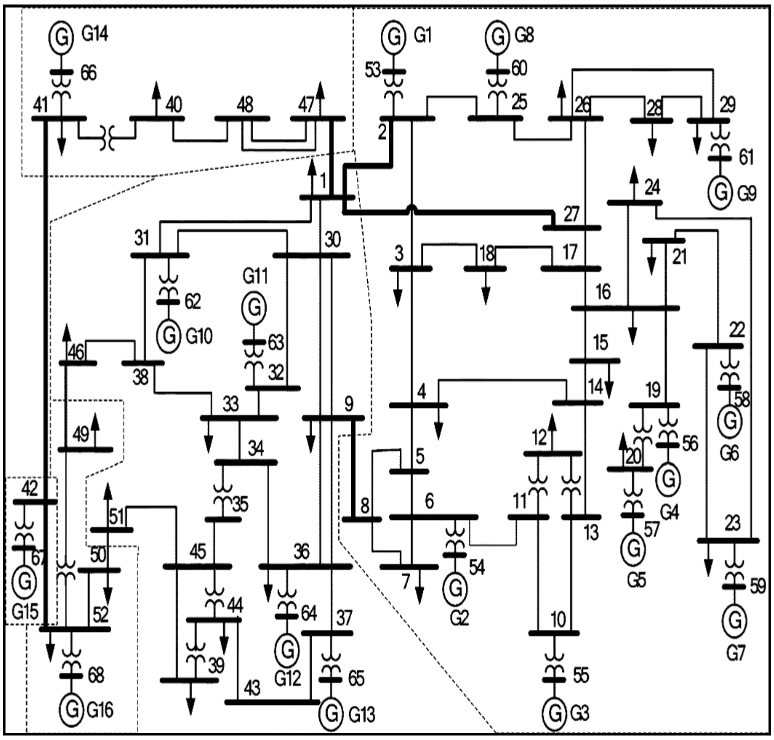

Figure 3. Five Areas, 16 generators 68 bus Power System

Following contingencies conditions are taken to compare the performance of different algorithms.

(a)A 6 cycle three phase fault disturbance at the end of bus 9 at t=0.1 sec Line 8-9.

(b) Reduction in generation limits on G5 and a three phase at t=0.1, 6 cycle disturbance at line 43-44.

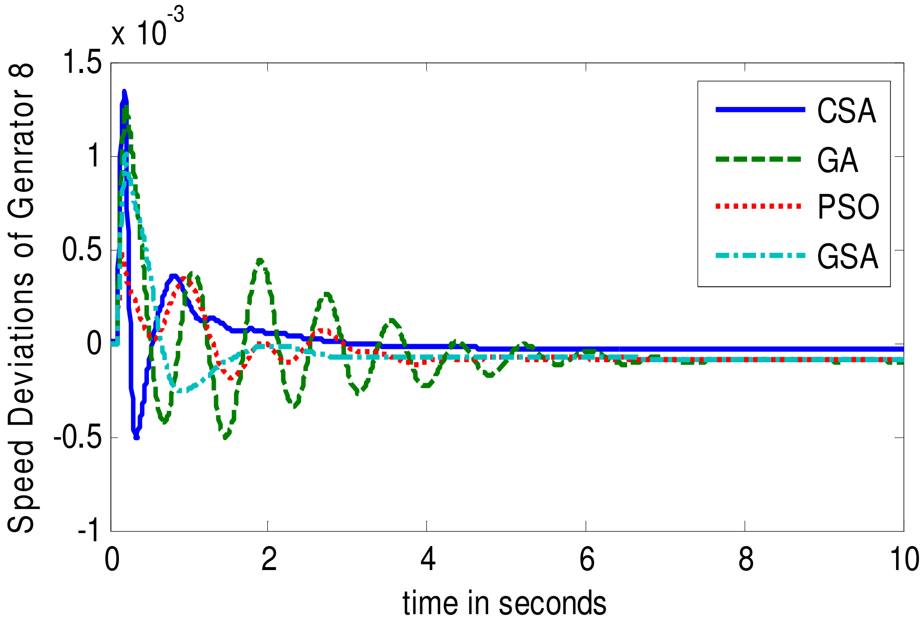

Figure 4. Speed deviation curve for generator 8(Case a)

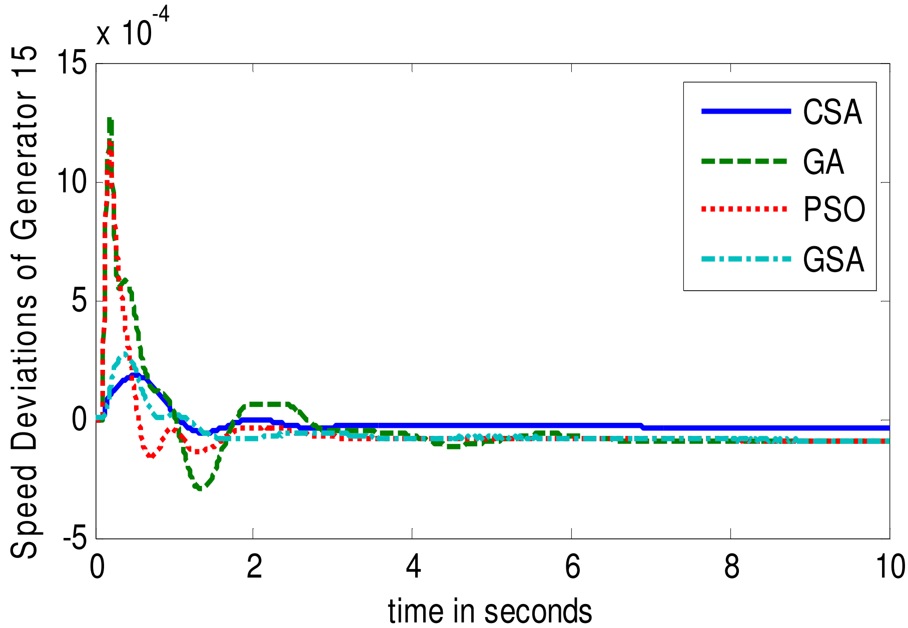

Figure 5 Speed deviation curve for generator 15 (Case b)

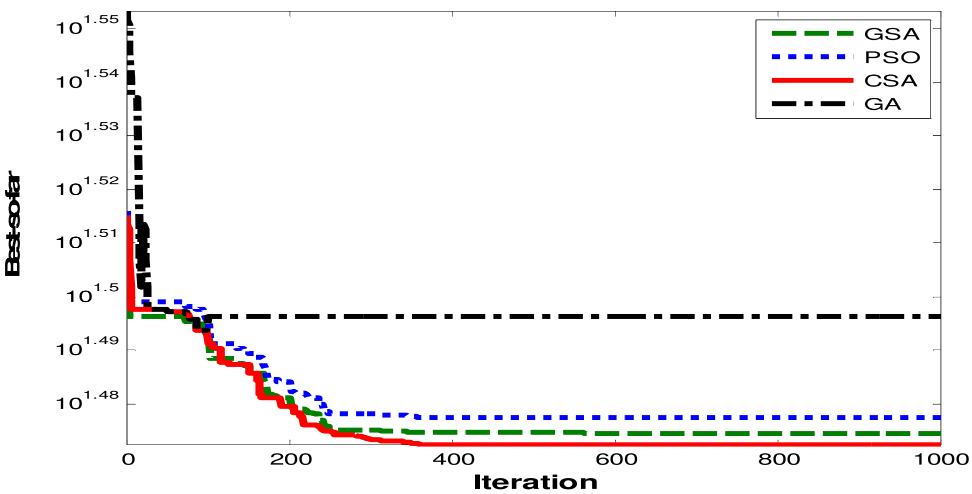

Figure 6 Convergence characteristics of all four algorithms

Table 1: Critical Eigen Values

Swing Modes	Eigenvalues	Damping
31	**0.3745-6.8347i**	**-0.00409**
32	**0.3745-6.8347i**	**-0.00409**
33	**0.01432- 6.904i**	**-0.00207**
34	**0.01432 + 6.904i**	**-0.00207**
35	-0.04981 + 7.346i	0.0067
36	-0.04981 + 7.346i	0.0067
40	-0.01368 - 8.077i	0.00169
41	-0.01368 + 8.077i	0.00169
42	-0.04616 - 8.102i	0.00569
43	-0.04616 + 8.102i	0.00569
55	-0.0388 - 11.655i	0.00333
56	-0.0388 + 11.655i	0.00333

Table 2: Optimal PSS parameters

	GA			***PSO***			***GSA***			***CSA***		
	K_{STAB}	T_1	T_3	K_{STAB}	T_1	T_3	K_{STAB}	T_1	T_3	K_{STAB}	T_1	T_3
Gen. 1	*5.05994*	*0.190592*	*0.02291*	*20.365*	*0.02033*	*0.02291*	*20*	*0.021953*	*0.146875*	*20.2978*	*0.069*	*0.041*
Gen. 2	*2*	*0.2*	*0.04984*	*19.766*	*0.04495*	*0.04984*	*20.00293*	*0.176641*	*0.062173*	*21.62*	*0.032*	*0.048*
Gen. 3	*7.57283*	*0.2*	*0.0368*	*30.01*	*0.04951*	*0.0368*	*20*	*0.03023*	*0.079258*	*14.67*	*0.049*	*0.05*
Gen. 4	*2*	*0.2*	*0.004*	*24.3354*	*0.03088*	*0.004*	*20*	*0.110985*	*0.085365*	*20.01*	*0.046*	*0.058*
Gen. 5	*3.61312*	*0.020005*	*0.05042*	*14.048*	*0.04995*	*0.05042*	*20.625*	*0.077816*	*0.02*	*22.24*	*0.032*	*0.054*
Gen. 6	*14.2881*	*0.131212*	*0.02737*	*26.8593*	*0.05013*	*0.02737*	*20*	*0.0095*	*0.125684*	*20.02*	*0.048*	*0.047*
Gen. 7	*2.09192*	*0.2*	*0.04963*	*13.453*	*0.049*	*0.04963*	*20.15625*	*0.186895*	*0.098253*	*16.94*	*0.041*	*0.054*
Gen. 8	*2*	*0.2*	*0.02212*	*20.476*	*0.04585*	*0.02212*	*20.07813*	*0.033672*	*0.074199*	*19.33*	*0.049*	*0.045*
Gen. 9	*25.5237*	*0.020003*	*0.0236*	*23.57*	*0.04056*	*0.0236*	*20.11719*	*0.073487*	*0.095*	*19.61*	*0.052*	*0.048*
Gen10	*5.05994*	*0.190592*	*0.02291*	*18.365*	*0.02033*	*0.02291*	*20*	*0.021953*	*0.146875*	*28.27*	*0.069*	*0.041*
Gen. 11	*2*	*0.2*	*0.04984*	*19.7*	*0.04495*	*0.04984*	*20.00293*	*0.176641*	*0.062173*	*12.62*	*0.032*	*0.048*
Gen. 12	*7.57283*	*0.2*	*0.0368*	*30.01*	*0.04951*	*0.0368*	*20*	*0.03023*	*0.079258*	*14.67*	*0.049*	*0.05*
Gen. 13	*2*	*0.2*	*0.004*	*24.3354*	*0.03088*	*0.004*	*20*	*0.110985*	*0.085365*	*10.01*	*0.046*	*0.058*
Gen. 14	*3.61312*	*0.020005*	*0.05042*	*14.048*	*0.04995*	*0.05042*	*20.625*	*0.077816*	*0.02*	*12.24*	*0.032*	*0.054*
Gen. 15	*14.2881*	*0.131212*	*0.02737*	*21.79*	*0.05013*	*0.02737*	*20*	*0.0095*	*0.125684*	*20.02*	*0.048*	*0.047*
Gen. 16	*2.09192*	*0.2*	*0.04963*	*16.43*	*0.049*	*0.04963*	*20.15625*	*0.186895*	*0.098253*	*16.94*	*0.041*	*0.054*

5. Hypothesis Test

The objective of this work is to statistically compare the performance of the four heuristic search methods, GSA, PSO, GA with CSA, using a representative set of test problems that are of diverse properties. The *t*-test (hypothesis testing) is used to assess and compare the effectiveness and efficiency of both search algorithms. In hypothesis testing, a null hypothesis, *H* o will be correctly accepted with a significance (or confidence) level (1 −α) and falsely rejected with a type I error probability α . If the null hypothesis is false, it will be correctly rejected with a power of the test (1 − β) and will be falsely accepted with a type II error probability β . The decision options summary is presented in Table 1. *Ha corresponds* to an alternative hypothesis that is complimentary to *H*o.

Table 3. Decision Making through Hypothesis Test

Table	Possible decision outcomes in hypothesis testing	
Action	H_0 is true	H_0 is false
Accept H_0, reject H_a	(1-α) significance level	β
Reject H_0 and Accept Ha	α	1-β
Sum	1	1

An alternate hypothesis is created which obey following procedure; By running all algorithm 20 times and standard deviations of the objective function values has been compared as expected the value of standard deviations are very low for CSA as compared with GA,PSO and GSA. Objective to test:

whether H_a:μ Q sol>99%With a null hypothesis H_o: μ Q sol<99%

where :Q sol= Solution obtained from Any algorithm-Solution obtained from CSA/Solution by CSA

$$t = \frac{\overline{Q_{sol}} - 99\%}{s(\overline{Q_{sol}})}$$

$$\alpha = \beta = 1\% \;\; and \; \mathrm{n} = 10$$

$$\mathrm{t}_{\mathrm{critical}} = 2.821$$

Table 4 Hypothesis T test

System	Calculated value of t ,t(critical)=2.821		
	PSO	GA	GSA
(16 Generator)	-3.13609	0.46482	**15.6675**

From table 4 it is observed that value of t is greater than t critical only for GSA which shows that alternate hypothesis is accepted for GSA and rejected for GA and PSO. The same can observed from convergence characteristics, that premature convergence occurs in GA as compared with PSO. During this analysis various parameters and decision variables for algorithms are shown in appendix I.

5. Conclusion

This paper presents a hypothesis based comparison of four algorithms in the PSS design problems there are total 48 parameters are optimized with the help of GA, PSO, GSA and CSA. The speed deviations curves of generators are plotted and exhibited in the proposed work it can be concluded from here that hypothesis test on GSA is accepted and the responses obtained under different operating condition suggests that CSA has an upped edge over all rest algorithms. Testing of design under hard operating conditions validate efficacy of the proposed design.

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Appendix –I

a) Parameter for GA
   i. Population size=100,
   ii. Maximum no of generations =1000,
   iii. Crossover =8e-1
   iv. Mutation Probability =1e-3.
b) Parameter for PSO
   i. No. of Particle=100,
   ii. Inertia=0.4,
   iii. C_1 & C_2 =2.
c) Parameter for GSA:
   i. α=20;
   ii. G_0=100;
   iii. N=100;
   iv. Maximum Iteration = 1000;
d) Parameter for CSA:
   i. Number of nests (different solutions)=100
   ii. Discovery rate of alien eggs/solutions pa=0.25;

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