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An application of backtracking search algorithm in designing power system stabilizers for large multi-machine system

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ABSTRACT

This paper deals with the backtracking search algorithm (BSA) optimization technique to solve the design problems of multi-machine power system stabilizers (PSSs) in large power system. Power system stability problem is formulated by an optimization problem using the LTI state space model of the power system. To conduct a comprehensive analysis, two test systems (2-AREA and 5-AREA) are considered to explain the variation of design performance with increase in system size. Additionally, two metaheuristic algorithms, namely bacterial foraging optimization algorithm (BFOA) and particle swarm optimization (PSO) are accounted to evaluate the overall design assessment. The obtained results show that BSA is superior to find consistent solution than BFOA and PSO regardless of system size. The damping performance that achieved from both test systems are sufficient to achieve fast system stability. System stability in linearized model is ensured in terms of eigenvalue shifting towards stability regions. On the other hand, damping performance in the non-linear model is evaluated in terms of overshoot and setting times. The obtained damping in both test systems are stable for BSA based design. However, BFOA and PSO based design perform worst in case of large power system. It is also found that the performance of BSA is not affected for large numbers of parameter optimization compared to PSO, and BFOA optimization techniques. This unique feature encourages recommending the developed backtracking search algorithm for PSS design of large multi-machine power system.

1. Introduction

Stability of modern power system is very important for its secure and reliable operation and it is achieved through proper design of power system stabilizers (PSS). However, instability [1] may arise through growing of power system oscillations and its consecutive events originated from various changes in the system. The changes may be in terms of generator tripping, load addition (suspension or change) and miscellaneous type of faults. Those changes eventually may lead to growing the oscillations of active power generated by synchronous generators [2]. In multi-machine system scenario, two types of power oscillations are observable [3]. The oscillations among the nearby generators of same area are called the local modes of oscillations. Another type of oscillations are the inter-area modes of power oscillations that may tempt other generators of different regions to oscillate along with affected generators [3]. In case of interconnected systems, power oscillations especially inter-area oscillations can be very dangerous, causing the entire system collapse by affecting and tripping generators one by one. The purpose of PSS installation is to damp those oscillations effectively in order to restore system stability [2,3]. For many decades, PSSs have been used as one of the most cost effective damping controller. Unfortunately, PSS can provide effective damping over only local mode of oscillations i.e. which achieves partial system stability [2,4]. As an alternate option to damp inter-area oscillations, addition of FACTS based damping controller is recommended in order to ensure full system stability [3,5]. Obviously, that increase system's total cost and may cause to originate other types of problem in the power system. However, research showed that inter-area oscillating modes can be managed to damp successfully by robust tuning of PSS parameters [6]. Therefore, the robust design of PSS parameters is the main challenges to strengthen entire system stability.

To design PSSs, the analysis of system stability is conducted in linearized model of power system [3,5]. Moreover, the tuning of PSS parameters towards robust design is ensured by various optimization techniques. Over the last few decades, various optimization approaches have been taken into consideration for robust PSS design [5–14].

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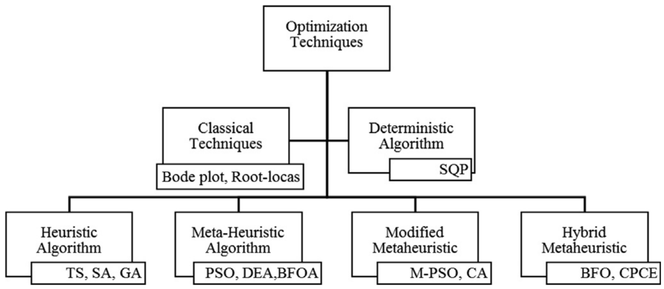

Fig. 1. Classification of different optimization techniques used for power system stabilizer design.

Previously proposed optimization techniques can be classified as shown in Fig. 1.

The application of frequency domain based classical optimization technique such as body plot, root locus and deterministic technique such as sequential quadratic programming have been found for PSS design in [8,15] and [5] respectively. Due to the difficulties and limitations of those techniques to solve non-linear and non-differentiable optimization problem, the application of heuristic techniques got popular in this field. Various heuristic algorithms such as tabu search (TS) [9], simulated annealing (SA) [16], and genetic algorithm (GA) [17] are most widely used algorithms in last decades. However, some deficiencies have been identified in heuristic algorithms such as local minima stagnation, premature convergence, difficulties of control parameter selection [18]. Later on, some higher version of heuristic algorithm known as metaheuristic techniques have been developed and applied to design multi-machine PSSs. The most popular metaheuristic algorithms, for example, particle swarm optimization (PSO) in [10,11], differential evolution algorithm (DEA) in [12], bacterial foraging optimization algorithm (BFOA) in [7] are reported to tune PSSs in multi-machine system. However, previously recommended most of the algorithm's performance deteriorates when a huge number of parameters to be optimized for large multi-machine power system. Moreover, PSS parameter optimization is a complex multimodal optimization problem and it is very difficult to optimize. In order to overcome these type of limitations, the modified version in [13,19] and hybrid version of optimization algorithm in [14,20,21] are recommended for PSS design. Although the modification or combination of different algorithms together may achieve partial success, but the overall computation burden and complexity increase.

Backtracking search algorithm (BSA), a relatively new metaheuristic search algorithm, is claimed to solve complex optimization problem mitigating the major limitations of other algorithms. It is important to testify the scope of BSA in real world optimization problem. This research comes forward to investigate the applicability of BSA for robust PSSs design in large power system. In order to conduct this research, the stability problem of a multi-machine power system is formulated to an optimization problem using the LTI state space linearized model. After that, the BSA is employed to solve the formulated optimization problem which corresponds mainly the relocation of system eigenvalues in a complex s-plane. Later on, the optimized parameters of PSSs obtained from linearized model are used for non-linear model of the power system to conduct a detailed analyses in time domain approach. The complete analyses are compared with other two algorithms, namely BFOA and PSO. Furthermore, comparative study is conducted on two different benchmark power systems to scrutinize the design performance variation with system size. The assessments of the BSA are based on the statistical analysis of solutions, stability analyses of the linear and non-linear models. The statistical analysis is conducted in terms of solution quality and consistency. The stability analysis of the linear model is used to compare the performance of eigenvalue shifting in the complex s-plane. On the other hand, the stability analysis of the non-linear model

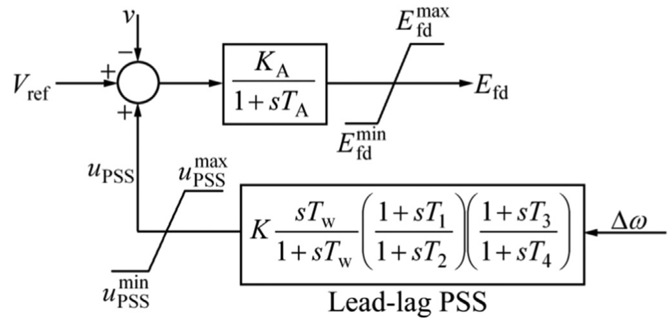

Fig. 2. Power system stabilizer with static exciter model.

is used to evaluate the oscillation damping in terms of settling times and overshoots.

2. Problem formulation

2.1. Power system stabilizer

A PSS is the only damping scheme used along with synchronous generator to detect and suppress power system oscillations shown in Fig. 1. The basic block of PSS is the two stages lead lag controller with a gain and a washout block [3]. The input of PSS is usually the speed deviation of rotor [3,5]. From the synchronous machine theory, the output of a generator can be controlled by either changing rotor speed or excitation voltage [2]. Therefore, the working principle of PSS is to detect oscillations to its input and provide required supplementary signal to generator's excitation system to control the active power generation by the generator. The proper selection of the time and gain constants within their boundary limits in Eq. (1) is the main design problem for overall power system stability [2,3,22]. Hence, the value of these quantities are optimized to protect system from instability by providing fast and required damping as shown in Fig. 2.

$$\begin{aligned} &K_{\min} \le K \le K_{\max} \\ &T_{1,\min} \le T_1 \le T_{1,\max} \\ &T_{2,\min} \le T_2 \le T_{2,\max} \\ &T_{3,\min} \le T_3 \le T_{3,\max} \\ &T_{4,\min} \le T_4 \le T_{4,\max} \end{aligned} \tag{1}$$

2.2. System modelling

A power system can be defined by a set of non-linear differential equations as like Eq. (2) [3,5].

$$\begin{aligned} \dot{x} &= f(x, u) \\ y &= g(x, u) \end{aligned} \tag{2}$$

In order to conduct the stability analysis, the entire system is represented in LTI model. The formulation of LTI model is performed in time domain state-space approaches [3]. In order to simplify the entire system modelling burden, the power system toolbox (version 3) from Graham Roger's book is used [3]. The final LTI state -space model is represented as follow -

$$\begin{aligned} \dot{x} &= Ax + Bu \\ y &= Cx + Du \end{aligned} \tag{3}$$

2.3. Stability analysis

The eigenvalues of the state matrix A are calculated as

$$\lambda_i = eig(A) \tag{4}$$

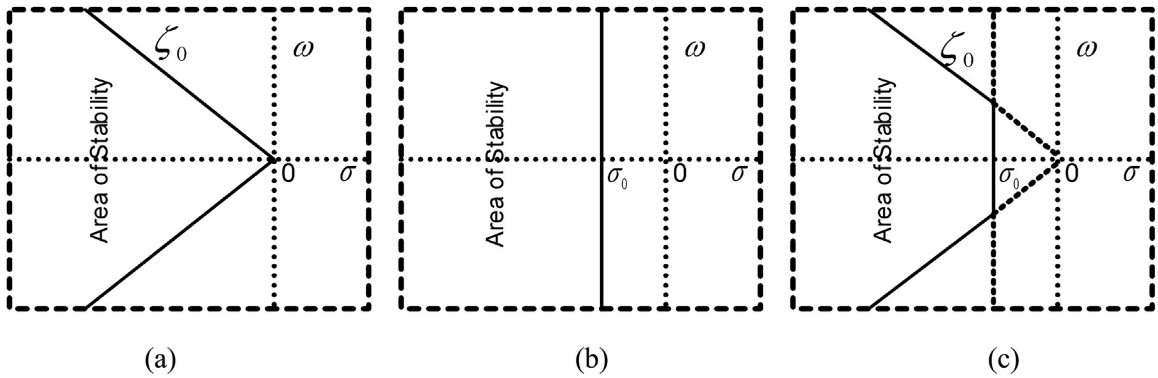

Fig. 3. Formulation of multi-objective D-shaped cost function for stability analysis in s-plane. a) Stability defined by expected damping ratio; b) Stability defined by expected damping factor; c) Combination of expected damping ratio and factor.

According to the theory of advanced control system, system stability can be determined easily based on the location of eigenvalues in s-place (complex plane) [2,3]. System is unstable if any eigenvalue is located in right side of s-plane. Therefore, all eigenvalues are required to move to the left hand side. Additionally two quantities of each eigenvalues contribute to ensure fast and sufficient damping [2,3]. The quantities are the damping ratio and damping factor. They are defined as:

$$\sigma_i = real\,(\lambda_i) \tag{5}$$

$$\zeta_i = -\frac{\sigma_i}{\sqrt{\sigma_i^2 + \omega_i^2}} \tag{6}$$

where, i=1, 2, 3…n and n is the total number of eigenvalues in the power system.

2.4. Cost function

Although many formulation approaches have been developed and used before to design damping controller, the D-shaped objective function in Eq. (7) is proven very significant for the analysis of power system stability [23]. Fig. 3 depicts the detail formulation of D-shaped objective function. The alternative term of objective function is the cost function. The value of this cost function is supposed to minimize and eventually the eigenvalues are shifted towards the area of stability.

$$f = \sum_{j=1}^{np} \sum_{\sigma_{ij} \ge \sigma_0} (\sigma_0 - \sigma_{ij})^2 + a \sum_{j=1}^{np} \sum_{\zeta_{ij} \le \zeta_0} (\zeta_0 - \zeta_{ij})^2 \tag{7}$$

3. Multi-machine benchmark power system

This research is conducted in two benchmark power systems [3]: i) 2-AREA 4-Machine power system shown in Fig. 4, ii) 5-AREA 16-Machine power system shown in Fig. 5. The purpose of using two test system is to investigate the deviation in system damping with increase of system size using different design algorithms.

3.1. 2-AREA 4 machine system

This is the widely used and recommended benchmark test system to study power system oscillations [2,3]. In this test system, both the local and inter-area modes of oscillations can be investigated properly. This system is comprised with 4 identical generators equipped with identical type of turbine governor, static excitation system. Each generator has a PSS to provide damping over growing oscillations. G1 and G2 are in area 1 while G3 and G4 are in area 2. Area 1 connected with area 2 through double circuit tie lines. System after subjected to a fault, G1 oscillates against G2 and G3 oscillates against G4 for local mode of oscillations. Moreover, generators G1 and G2 in area 1 oscillates against generators G3 and G4 in area 2 for inter-area mode of oscillations.

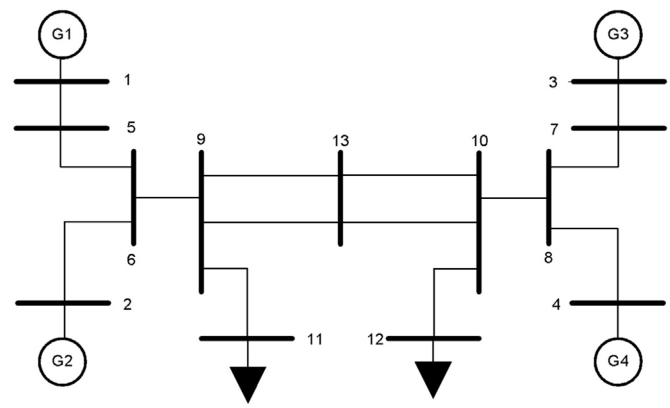

Fig. 4. Single line diagram of 2-AREA 4 machine benchmark power system.

3.2. 5-AREA 16 machine system

This is gigantic benchmark power system consisting of 16 generators and 68 bus shown in Fig. 5. There are 5 areas in the system by means of modal analysis [3]. Generators 15 is in area 1, Generator 14 in area 2, Generator 16 in area 3, Generators 1–9 are located in area 4 and Generator 10–13 are in area 5. Area 4 is connected with area 5 through 3 tie lines. Area 3 is connected to area 5 through 2 tie lines. One tie line is between area 2 and area 3.

4. Backtracking search algorithm

BSA is a nature inspired optimization algorithm developed recently by Pinar Civicioglu [24]. Its simplified and unique structure make it a choice to solve real world multimodal optimization problems. Unlike other search algorithms, BSA is highly capable to handle large dimensional problem more accurately. It has only one control parameter and the sensitivity to control parameter selection is almost absent. It is a population based algorithm. It uses large number of population to move towards optimum solution. The unique concepts of this algorithm are the historical population and map matrix. The path for optimum solution is defined by the historical population for each movement. In order to overcome the local minima traps, BSA use the historical population to explore new solution field as well as exploit better solution within a solution field. The historical population works like the memory of search population and help to find optimum direction to obtain solution. On the other hand, map matrix reveals the required adjustment to move search direction in order to ensure precise movement in exploitation search. Therefore, optimum solution is guaranteed based on search exploration and exploitation simultaneously. The working principle of BSA is composed of five main steps described below [24]:

Step 1: *Initialization*

The primary population and historical population of BSA are generated based on uniform distribution ($\cup$) within the boundary constraints. If the optimization problem dimension and population size are D and N respectively for the optimization, then each individual of main population (Pop_i) and historical population (His_i) are initialized as follow:

$$\text{Primary population,} \quad Pop_{n,d} \sim \cup\,(low_d,\ up_d) \tag{8}$$

$$\text{Historical population,} \quad His_{n,d} \sim \cup\,(low_d,\ up_d) \tag{9}$$

$$\text{Fitness value,} \quad y_{pop} = f\,(Pop) \tag{10}$$

where $n \in \{1, 2, 3, \ldots, N\}$ and $d \in \{1, 2, 3, \ldots, D\}$. The search space for PSS parameters (following Eq. (1)) are defined by two row vectors low_d and up_d.

Step 2: *Selection-I*

$$if \quad a < b \quad then \quad His{:} = Pop | a,\ b \sim \cup\ (0,\ 1) \tag{11}$$

$$His{:} \quad = permuting\,(His) \tag{12}$$

Step 3: *Mutation*

The initial value of trial population is known as the mutant.

$$\text{Initial trial population,} \quad Mut = Pop + R.\,(His - Pop) \tag{13}$$

$$\text{Standard Brownian–walk,} \quad R = 3{\cdot}randn \tag{14}$$

where, *randn* is the build-in function for generating normal distribution number (0–1).

Step 4: *Crossover*

This part generate the final form of trial population that complies within the optimization boundary constraints. The crossover of BSA is consisted of two sections:

Step 4 (a): *Part-1*

This process control the number of elements of individuals to be muted by generating binary *map* matrix having same size of *Pop*. It decides which individuals to be manipulated and which will be unchanged through mutation process. The formulation of *map* matrix is based on Eqs. (15) and (16).

$$\text{Map matrix initialization,} \quad map_{(1:N,1:D)} = 1 \tag{15}$$

$$\text{Map matrix formulation,} \quad \begin{array}{l} \text{if } a < b \,|\, a,b \sim U(0,1) \quad \text{then} \\ \quad \text{for } n \text{ from } 1 \text{ to } N \text{ do} \\ \quad\quad map_{n,u_{(1:\lceil mixrate.rand.D \rceil)}} = 0 \,|\, u = permuting(\langle 1,2,3,\ldots,D \rangle) \\ \quad \text{end} \\ \text{else} \\ \quad \text{for } n \text{ from } 1 \text{ to } N \text{ do, } map_{n,randi(D)} = 0, \ \textbf{end} \\ \text{end} \end{array} \tag{16}$$

$$\text{Final trial population,} \quad Trial_{n,d}{:} = \begin{cases} Pop_{n,d} & if \quad map_{n,d} = 1 \\ Mut_{n,d} & if \quad map_{n,d} = 0 \end{cases} \tag{17}$$

Step 4 (b): *Part-2*

Boundary condition checking.

$$Trial_{n,d} = low_d + rand{\cdot}(up_d - low_d), \\ \text{if}(Trial_{n,d} < low_d) \text{ or } (Trial_{n,d} > up_d) \tag{18}$$

Step 5: *Selection-II*

In this section, the trial population from Eq. (18) are used to evaluate the cost function again and corresponding fitness values are determined using Eq. (7). The calculated fitness values are then compared with the fitness values (y_{pop}) of main population (*Pop*) to query any fruitful discovery as shown in Eqs. (19) and (20).

$$\text{Trail population Fitness values} \quad y_{trial} = f\,(Trial) \tag{19}$$

$$Pop_n = Trial_n,\ if\ y_{n,Trial} > y_{n,Pop} \tag{20}$$

To know more about BSA in details, interested readers are referred to its original paper [24]. The following section will depict the major steps to explain the application of this algorithm.

5. BSA implementation for multi-machine PSS design

The entire design for multi-machine PSS using BSA is categorized into three major sections. The use of power system toolbox (version 3) simplifies the overall process. For simplicity and understanding, the overall design procedures are depicted in Fig. 6. The major work functionalities are summarized as follow:

Section 1:

This section is associated with the core steps of BSA technique.

- Part 1: Firstly the BSA is specified with its population size, dimension size, number of generation and control parameter etc.
- Part 2: The boundary limits for search space are defined here using two row vectors (*low*, *up*). These two vectors correspond PSS parameters limits.
- Part 3: In this part, Step 1 from BSA are performed. The following Sections 2 and 3 are incorporated along with this part also.
- Part 4: Steps 2–5 from BSA are followed in this part.
- Part 5: Optimized results are obtained when number of executions meet the maximum generation.

Section 2:

This section deals with determination and selection of eigenvalues from state matrix. The purpose of this section is to sort out the things for calculating cost function value using the given population.

- Part 1: The input (i.e. the PSS parameters) of this section is the BSA population. The part is associated with organization of PSS para-

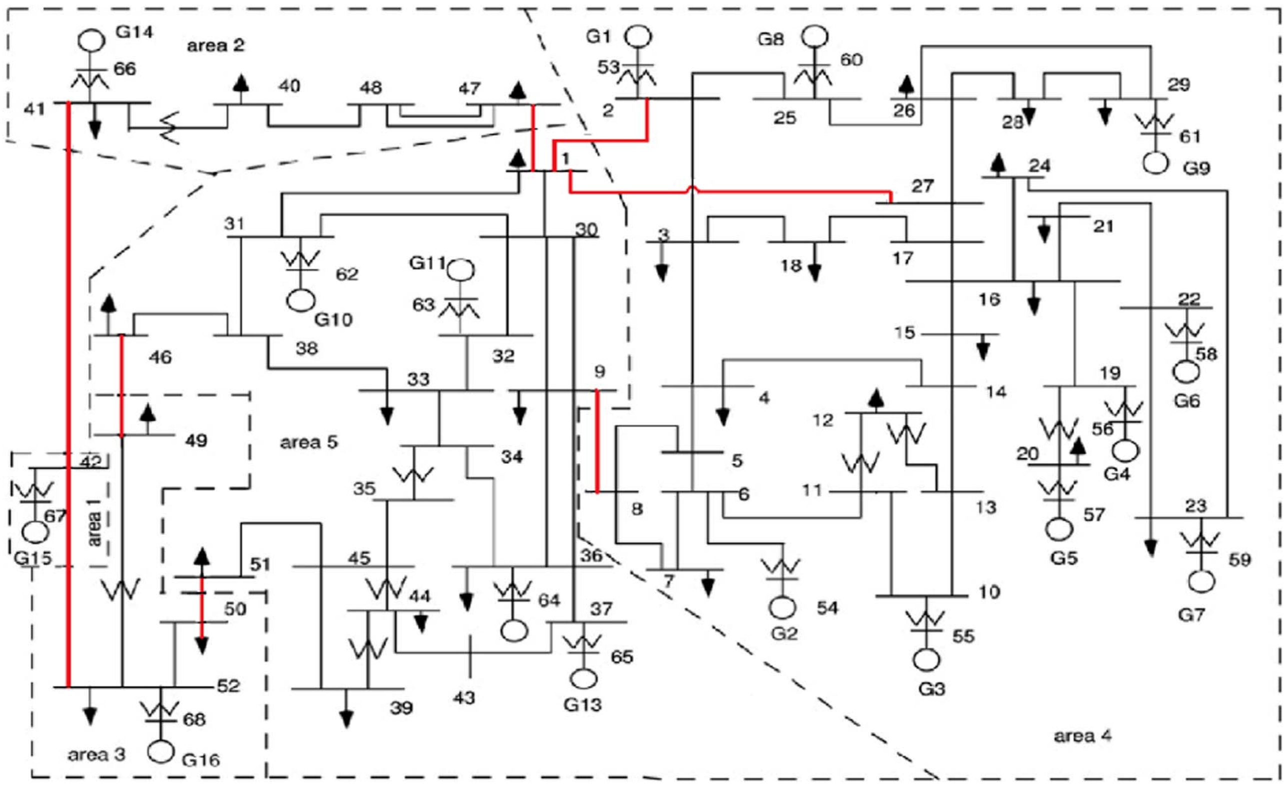

Fig. 5. Single line diagram of 5-AREA 16 machine benchmark power system.

meters according to the data format of power system toolbox.

- Part 2: The organized PSS data along with test power system data are processed to get the system state matrix (A) of linear power system using power system toolbox.
- Part 3: The eigenvalues (λ_i) are determined from the system state matrix (A).
- Part 4: Damping factor (σ_i) and damping ratio (ζ_i) are calculated for each eigenvalue using Eqs. (5) and (6).
- Part 5: The eigenvalues having negative damping factor ($\sigma < 0$) and very high damping ratio ($\zeta > 0.95$) are considered to be zero eigenvalues and those have no influence over system oscillation at all. Non-zero eigenvalues located outside of D-shaped stability region are considered to calculate the cost function value using Eq. (7).

Section 3:

This section deal with the toolbox used for power system linearized model.

- Part 1: Import the data file for test power system
- Part 2: Run load flow analysis
- Part 3: Determined reduced Y matrix
- Part 4: Initialize the state variables ($state_i$), its rate of change ($dstate_i$) and system state matix (A) for time step t=1.
- Part 5: At time step t=2, sequentially state variables are perturbed and estimate the value of $dstate_i$. System state matix (A) is recalculated for each perturbation of state variable.
- Part 6: The formation of final state matrix (A) is done in this part.

6. Results and discussion

The power system data are taken from the power system toolbox (version 3) [3]. For each PSS, the constants K, T_1–T_4 are required to optimize. The value of T_w is set to 10 [23]. The search boundaries for time constants are 0.01–2 s while for gain constants are 0.01–100 [23]. Therefore, the number of PSS optimizing parameters are 4 and total number of parameters to be optimized are 20 and 80 for 2-AREA system and 5-AREA system respectively. The weight factor used in cost function formulation is selected as 10 following previous researches [3,23]. The expected damping ratio and damping factor are selected to 0.15 and −1.0 respectively. The simulation for two systems are conducted individually and all the data are recorded for further analysis. Total simulation times in non-linear model are 10 s for 2-AREA system and 15 s for 5-AREA system respectively. Fault has been applied within this time. PSS parameters are optimized by BSA optimization along with other standard version of PSO and BFOA. The simulation settings for each algorithms (and test systems) are stated in Appendix A section. In the analysis, PSS designed by BSA, BFOA and PSO are denoted as BSA-PSS, BFOA-PSS and PSO-PSS respectively.

The solution consistency achieved by optimization algorithms is very important to investigate their performance. Therefore, simulations for linearized model have been conducted 25 times for each algorithms. The solutions (cost values) from 25 times simulations for 2-AREA system are plotted as box and whisker plots using MATLAB® shown in Fig. 7. According to the box plot, it is observed that the solution attained by BSA is much consistent spread in narrower region (0.2756–0.1069) compared with BFOA (0.6525–0.3539) and PSO (1.2042–0.5691). This characterizes BSA as a good algorithm for a consistent solution than others.

The best solution achieved by each algorithms are enlisted in Table 1 for both multi-machine systems. The optimized PSS parameters from the best solutions are listed in Table 2 and Table 3 for 2-AREA and 5-AREA Systems respectively. System stability analysis in linear and non-linear models are conducted using the optimized parameters from the best solutions. Stability analysis in linear model is concentrated for 2-AREA system by plotting eigenvalues in s-plane. While 5-AREA System is accounted to focus the stability study using non-linear model.

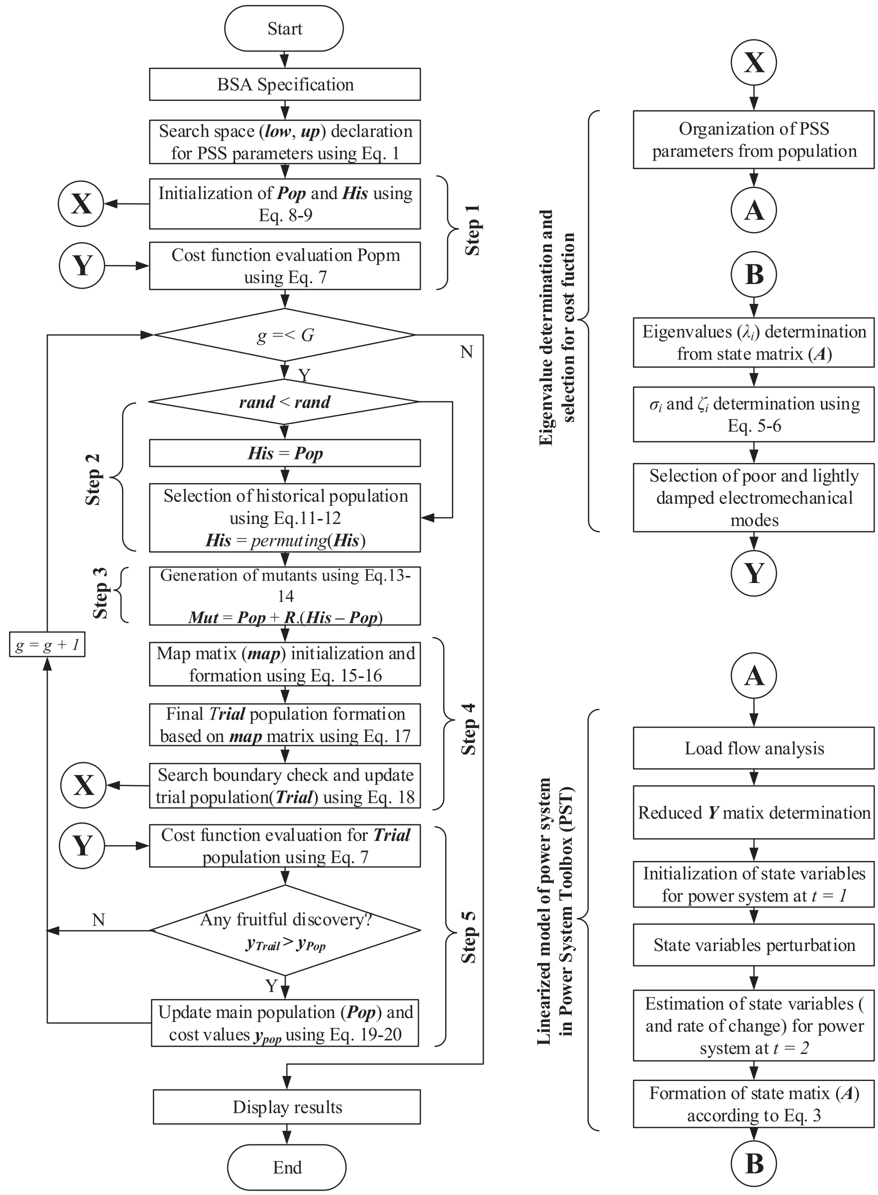

Fig. 6. BSA implementation block diagram for multi-machine PSSs optimization design.

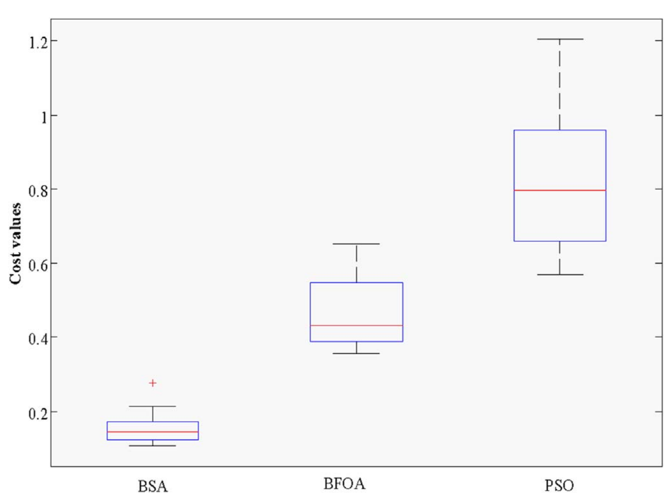

Fig. 7. Solution consistency checking: box and whisker plots drawn from 25 individual simulations for BSA, BFOA and PSO in 2-AREA system.

Table 1
Best solution (cost values) obtained by each algorithms for 2-AREA and 5-AREA systems.

System	Cost function values		
	BSA	BFOA	PSO
2-AREA	0.10685	0.35395	0.56908
5-AREA	4.76445	10.3127	6.4688

6.1. System stability in linear model

The eigenvalues obtained from system state matrix (A) using optimized parameters from Table 2 is plotted in s-plane. In Fig. 8, the depicted brown line represent the D-shaped stability region for electromechanical modes. From Fig. 8, the electromechanical modes for BSA-PSS have been achieved the minimum expected damping ratio while BFOA-PSS and PSO does not obtain for some specific modes. Although, BSA-PSO does not achieve desired minimum damping factor for one electromechanical modes. However, that specific mode has very high damping ratio (> 0.85) and therefore, it does not affect system

Table 2
Best optimized parameters using each optimization algorithms for 2-AREA System.

Objective functions		K	T_1	T_2	T_3	T_4
BSA	*PSS1*	7.7483	0.0341	0.0100	0.4213	0.0100
	PSS2	3.3929	0.5471	0.8452	1.7415	0.2853
	PSS3	9.7805	1.9169	0.5148	0.0391	0.0100
	PSS4	15.1784	2.0000	1.7374	0.0100	0.2618
BFOA	*PSS1*	8.6324	0.9751	0.7540	0.2903	0.1154
	PSS2	5.1218	1.0584	0.9204	1.3847	1.1607
	PSS3	6.8648	0.7150	0.3188	1.6174	0.3783
	PSS4	6.5016	0.2418	0.7024	1.1174	0.9842
PSO	*PSS1*	9.1542	0.7601	0.5087	0.1762	0.9241
	PSS2	16.0642	0.3158	0.9641	1.0557	0.8161
	PSS3	7.5012	0.6102	0.3214	1.5811	0.3183
	PSS4	9.2315	0.6865	0.8562	0.6531	0.7041

Table 3
Best optimized parameters using each optimization algorithms for 5-AREA system.

Algorithms		K	T_1	T_2	T_3	T_4
BSA	*PSS1*	7.4796	0.8329	0.8247	0.5677	0.0786
	PSS2	4.1629	0.7910	0.1020	0.6587	1.1224
	PSS3	4.1049	1.0510	0.4939	0.5558	0.6085
	PSS4	5.1507	0.7397	0.0408	0.5298	0.7585
	PSS5	1.3900	1.2361	0.6996	0.5546	0.8911
	PSS6	1.9086	0.9429	0.7705	0.7013	0.9365
	PSS7	10.2108	0.8692	1.0375	0.8644	1.3098
	PSS8	9.3250	0.3292	0.9987	0.5302	0.0200
	PSS9	11.1997	0.4045	1.0404	0.6427	0.0335
	PSS10	6.9675	0.8119	1.6054	1.4964	0.2325
	PSS11	6.9854	0.3095	0.0124	0.4184	1.1249
	PSS12	3.3121	1.1550	0.7626	0.8992	0.0608
	PSS13	11.8973	1.0895	0.5557	0.8760	0.9437
	PSS14	14.7728	0.9819	0.6763	1.7135	0.8104
	PSS15	13.0235	0.8943	0.6299	0.4798	0.7965
	PSS16	12.8661	1.4113	0.5436	0.6029	1.4328
BFOA	*PSS1*	16.5316	0.6521	0.0201	1.9412	1.5652
	PSS2	3.5332	0.4751	0.0735	0.4905	0.3091
	PSS3	13.1333	0.3468	0.1441	0.3233	0.5532
	PSS4	3.0055	0.9648	0.0912	0.7740	1.3309
	PSS5	4.0030	0.8115	1.6095	0.3723	0.9474
	PSS6	0.6793	0.9515	0.6399	0.6646	0.1315
	PSS7	4.0797	0.3238	0.2213	1.6175	1.7123
	PSS8	9.3228	1.5343	0.8599	0.0347	1.6630
	PSS9	9.5229	0.9072	1.7342	1.8482	0.9841
	PSS10	6.7403	1.1404	1.5348	1.2845	0.0358
	PSS11	17.6909	0.2237	1.4312	0.1089	1.0350
	PSS12	2.1094	1.4463	0.8521	1.4056	0.0758
	PSS13	13.5247	1.5165	1.3539	1.4165	1.2115
	PSS14	2.4333	0.5376	0.8575	0.8368	0.5892
	PSS15	17.3905	1.8248	1.4358	1.4164	0.7714
	PSS16	21.8207	1.6825	0.6476	1.2471	1.4104
PSO	*PSS1*	24.6676	0.6798	0.0224	1.9914	1.4499
	PSS2	3.5179	0.4735	0.0735	0.5011	0.3037
	PSS3	13.2826	0.2963	0.0176	0.3066	0.6196
	PSS4	3.4820	1.0126	0.0555	0.7065	1.1751
	PSS5	2.9444	0.9895	1.2069	0.3457	0.9446
	PSS6	0.6991	0.9894	0.2901	0.6593	0.1643
	PSS7	3.9415	0.2748	0.0719	1.6390	1.2445
	PSS8	9.3230	1.6421	1.0587	0.9589	1.6628
	PSS9	8.3219	0.9190	1.5360	1.7655	0.8654
	PSS10	6.6366	1.2352	1.4388	1.2504	0.0125
	PSS11	17.8621	0.2218	1.5133	0.3029	1.0523
	PSS12	1.2670	1.4354	0.8521	1.5852	0.0188
	PSS13	13.5618	1.4635	1.3777	1.5125	1.0893
	PSS14	1.1139	0.2146	0.8439	0.9206	0.7568
	PSS15	15.8296	1.7756	1.4196	1.4049	0.8018
	PSS16	21.7997	0.8181	0.6282	1.2477	1.4392

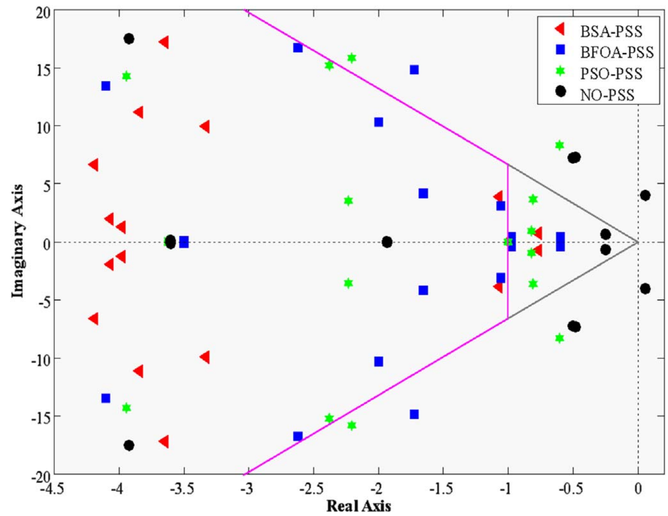

Fig. 8. Comparative progress of electromechanical modes in D-shaped region for best optimization solution in 2-AREA system.

very much. On the other hand, PSO-PSS has modes that are very poor in terms of damping factor and ratio. In comparison, BSA based design perform significantly better to move oscillating modes into D-shaped stable region.

6.2. Stability check in non-linear model

The amount of damping is visualized in non-linear simulation of power system in terms of settling time and overshoot. The setting time represent how fast the system will get return to its stability. On the other hand, system's capability to deal with transient moment is ensured by the value of overshoot. In a practical scenario, the size of power system is relatively large and vast number of PSS parameters are required to optimize. It is a challenge for optimization algorithms to perform consistently with different system size. Therefore, PSSs optimization for two different systems are considered to investigate their design performance which ultimately represent the viable optimization algorithm. System oscillations have been initialized by applying a three-phase fault at Bus 9 (between line 9–13) and at Bus 1 (between line 1–2) for 2-AREA and 5-AREA multi-machine systems respectively. Both systems are affected severely due to three-phase fault.

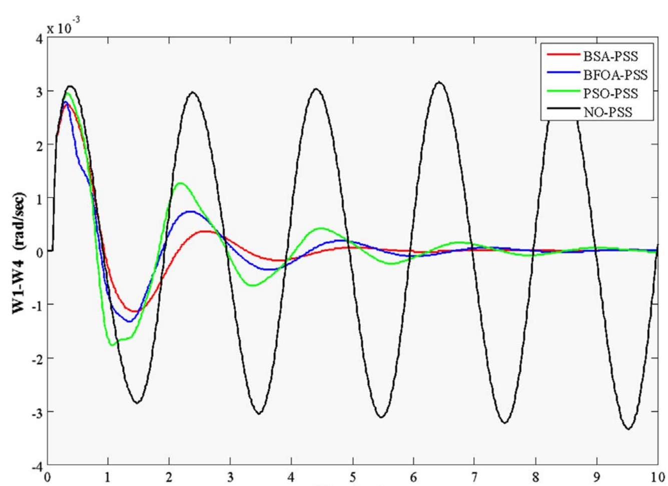

Fig. 9. Inter-area mode between G1 and G4 (W1-W4) for three phase fault at bus 9 of 2-AREA system.

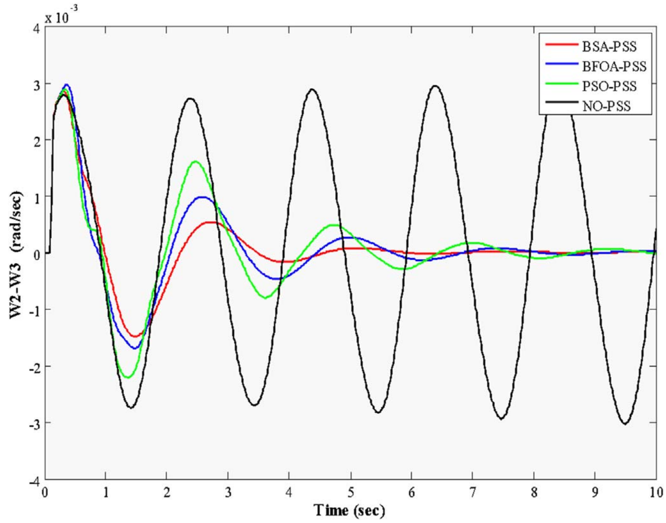

Fig. 10. Inter-area mode between G2 and G3 (W2-W3) for three phase fault at bus 9 of 2-AREA system.

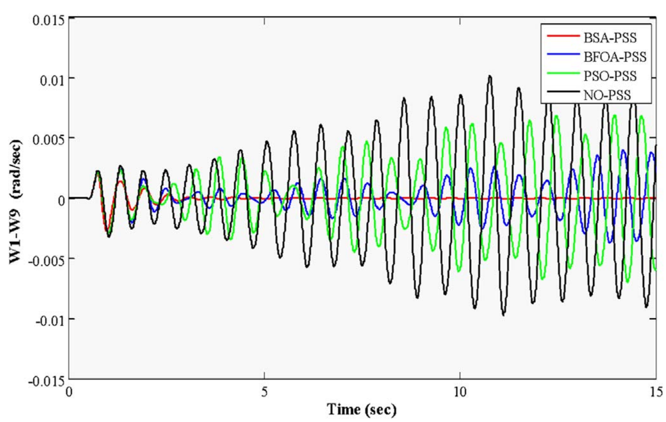

Fig. 11. Local mode in area 4 between G1 and G9 (W1-W9) for three phase fault at bus 1 of 5-AREA system.

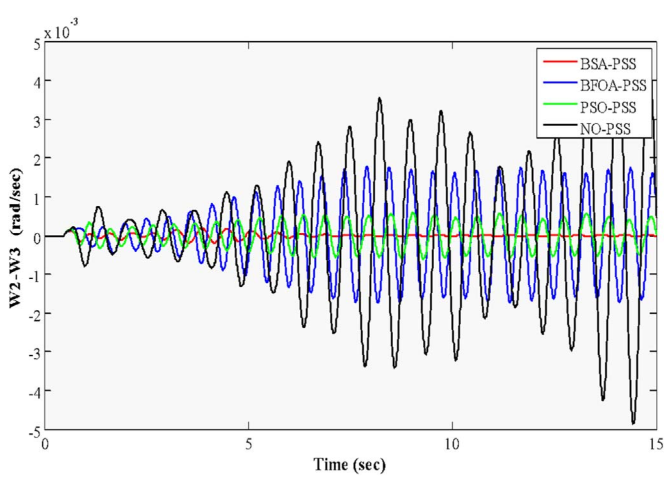

Fig. 12. Local mode in area 4 between G2 and G3 (W2-W3) for three phase fault at bus 1 of 5-AREA system.

6.2.1. 2-AREA system

For this system, the three-phase fault is applied at 100 ms for 100 ms duration and the total simulation time 10 s. Two active inter-area modes of oscillations are considered to investigate the improvement of system damping using different optimization algorithms shown in Figs. 9 and 10. Generator 1 in Area 1 oscillates against

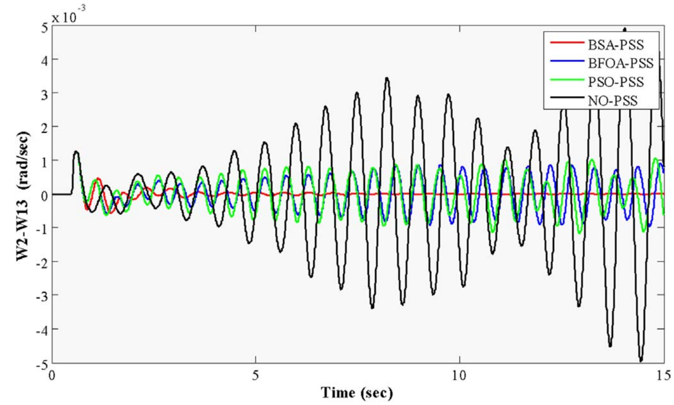

Fig. 13. Inter-Area mode between G2 in Area 4 and G13 in Area 5 (W2-W13) for three phase fault at bus 1 of 5-AREA system.

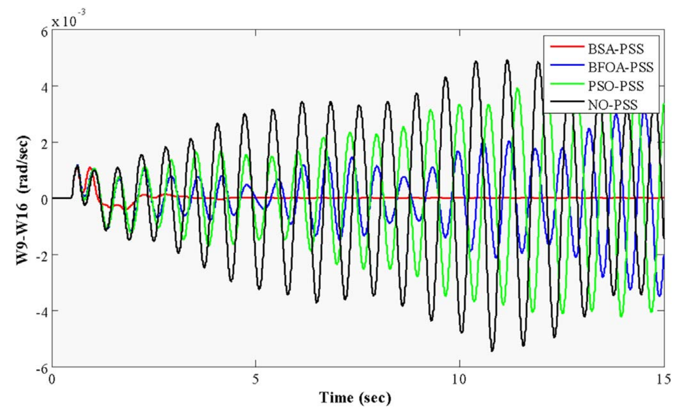

Fig. 14. Inter-Area mode between G9 in Area 4 and G16 in Area 3 (W9-W16) for three phase fault at bus 1 of 5-AREA system.

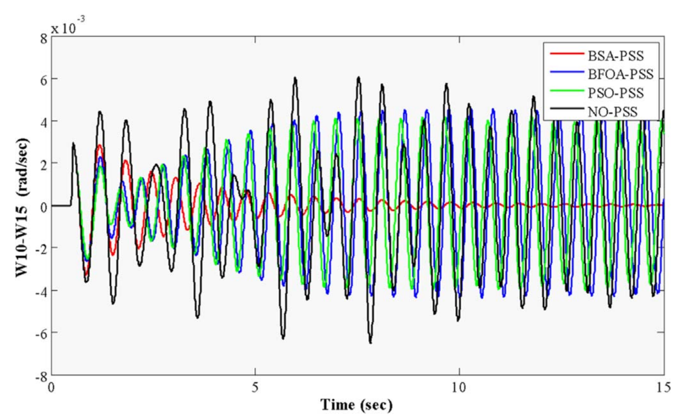

Fig. 15. Inter-Area mode between G10 in Area 5 and G15 in Area 1 (W10-W15) for three phase fault at bus 1 of 5-AREA system.

Generator 4 in Area 2 and Generator 2 in Area 1 oscillates against Generator 3 in Area 2 due to inter-area oscillations. Oscillation for mode W1-W4 is damped completely at 4.55 s, 7.7 s and 9.85 s using BSA-PSS, BFOA-PSS and PSO-PSS respectively while the overshoot is comparatively much lower for BSA-PSS than BFOA-PSS and PSO-PSS. Moreover, oscillation for mode W2-W3 is also suppressed faster using BSA-PSS than BFOA-PSS and PSO-PSS. Although, the overshoot in case of second mode (Fig. 10) are almost equivalent for BSA-PSS and BFOA-PSS except for PSO-PSS. In brief for 2-AREA system, stability is achieved successfully using PSSs designed by all three optimization algorithms. Moreover, BSA based design performs faster stability

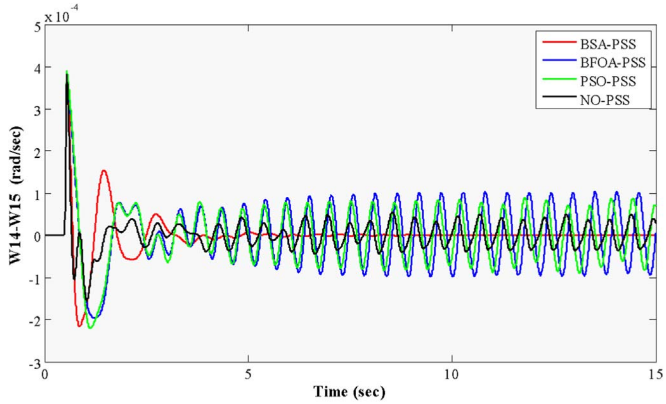

Fig. 16. Inter-Area mode between G14 in Area 2 and G15 in Area 1 (W14-W15) for three phase fault at bus 1 of 5-AREA system.

compared to BFOA and PSO based design.

6.2.2. 5-AREA system

Due to gigantic size of this system, the simulation time is taken 15 s for a better and wider analysis of system damping. The three-phase fault is applied at 500 ms of system simulation and remained for 150 ms. In order to analysis stability in large power system, 5 different modes that include 2 local and 4 inter-area oscillations are considered to study damping using different algorithms based design. In this power system, Area 4 consists of large number of Generators and fault is also applied within this area. Local mode oscillations within Area 4 are shown in Figs. 11 and 12 and inter-area mode oscillations of different areas are shown in Figs. 13–16.

From Figs. 11–16, it is obvious that the system damping is not achieved by BFOA-PSS and PSO-PSS except BSA-PSS. Although oscillations keep growing for two local modes W1-W9 (Fig. 11) and W2-W3 (Fig. 12), the performance of BFOA-PSS and PSO-PSs are totally opposite to each other. In inter-area modes W2-W13 (Fig. 13) W10-15 (Fig. 15), both BFOA-PSS and PSO-PSS achieve negligible positive system damping and perform almost equal which ultimately failed to lead system stability. However, after being affected severely, the stability for all modes is achieved by BSA-PSO completely. In case of inter-area mode W9-W16 between Area 4 and 3 (Fig. 14), BFOA-PSS perform better than PSO-PSS without attaining stability while BSA-PSS achieves. In mode W14-15 (Fig. 16), both BFOA and PSO based design contribute to provide negative damping causing the system oscillation worsen. While BSA based design provide positive damping leading the system gets back stability faster. In summary, the weakness of other algorithms are revealed through this comparative study in different system size in case of PSS design. This means, performance of BFOA-PSS and PSO-PSS depends on modes and may achieve negative damping instead of positive damping.

7. Conclusion

This research has conducted a practical application of BSA technique by designing PSSs in large multi-machine power system. The performance of BSA is compared with BFOA and PSO techniques for PSS design. Extensive analysis has been conducted to investigate the feasibility of BSA that includes analysis in linear and non-linear models of multi-machine power systems. Two different multi-machine (2-AREA and 5-AREA) systems are considered to examine the design performance variation with increase of system size. The comparative study has been carried out in terms of solution consistency, moving eigenvalues into stable regions and improving overall system damping. Solution consistency is evaluated based on boxplots drawn from 25 individual simulations for each algorithm. From the results, it is found that BSA is far superior to find a consistent solution than that of BFOA and PSO. In linear model analysis, only BSA based design successfully achieves expected damping ratio for all electromechanical modes. Additionally, in non-linear analysis, BSA based systems attain sufficient damping that suppresses system oscillations completely. Both multi-machine systems possess positive and fast damping using BSA-PSS. On the other hand, BFOA and PSO based design have achieved relatively poor damping for the 2-AREA system than BSA-PSS. However, in case of the 5-AREA system, stability is not achieved using BFOA-PSS and PSO-PSS. Moreover, system oscillations become worsen from the negative damping using BFOA and PSO based design for the large 5-AREA system. That reveals the weakness of BFOA and PSO algorithms for higher dimensional problem. Therefore, this research recommends BSA as one of the unique optimization algorithm for the PSS design in large power system.

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Appendix A

Linear model optimization Settings:

- 2-AREA system
  1. Design Setting: expected design damping factor (σ_0)=−1, expected design damping ratio (ζ_0)=0.15; problem dimension (D)=20;
  2. Optimization Algorithm Settings:
     1. - BSA Settings: population size (N)=25; generation (G)=500; $mixrate$=1.0;
     2. - BFOA Settings: population size (N)=25; generation (G)=500; chemotactic steps=70; reproduction steps=5; elimination-dispersal steps=5; p_{ed}=0.25; C=0.05; m_{ar}=0.1; w_{at}=0.2; w_{re}=10.
     3. - PSO Settings: population size (N)=25; generation (G)=500; cognitive constant, C_1=2; social constant, C_2=2; w_{min}=0.4; w_{max}=0.9.
- 5-AREA system:
  1. Design Setting: expected design damping factor (σ_0)=−1, expected design damping ratio (ζ_0)=0.15; problem dimension (D)=80;
  2. Optimization Algorithm Settings:
     1. - BSA Settings: population size (N)=25; generation (G)=1500; $mixrate$=1.0;
     2. - BFOA Settings: population size (N)=25; generation (G) =1500; chemotactic steps=70; reproduction steps=5; elimination-dispersal steps=5; p_{ed}=0.25; C=0.05; m_{ar}=0.1; w_{at}=0.2; w_{re}=10.
     3. - PSO Settings: population size (N)=25; generation (G) =1500; cognitive constant, C_1 =2; social constant, C_2=2; w_{min}=0.4; w_{max}=0.9.

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