2007

Bio inspired techniques for simultaneous design of multiple optimal power system stabilizers

Tridib Kumar Das

BIO INSPIRED TECHNIQUES FOR SIMULTANEOUS DESIGN OF MULTIPLE OPTIMAL POWER SYSTEM STABILIZERS

by

TRIDIB KUMAR DAS

A THESIS

Presented to the Faculty of the Graduate School of the

UNIVERSITY OF MISSOURI-ROLLA

In Partial Fulfillment of the Requirements for the Degree

MASTER OF SCIENCE IN ELECTRICAL ENGINEERING

2007

Approved by

Ganesh Kumar Venayagamoorthy, Advisor

Keith A. Corzine

Donald C. Wunsch II

PUBLICATION THESIS OPTION

This thesis consists of the following three articles that are accepted or submitted for publication as follows:

Pages 1-31 and Appendices from pages 114-123 are submitted to the IEEE TRANSACTIONS ON POWER SYSTEMS.

Pages 32-73 and Appendices from pages 124-133 are submitted to the IEEE TRANSACTIONS ON EVOLUTIONARY COMPUTATION.

Pages 74-113 and Appendices from pages 134-136 are submitted to IEEE TRANSACTIONS ON INDUSTRY APPLICATIONS

ABSTRACT

Bio-inspired techniques are fields of study that are inspired from topics of connectionism, social behavior and emergence. Researchers have ventured into the intricacies involved with the techniques and devised algorithms based on their study. Such techniques are the focus of this thesis. The two bio-inspired techniques used for simultaneous design of power system stabilizers (PSSs) in this study are –Particle Swarm Optimization (PSO) and Bacteria Foraging Algorithm (BFA). The work in this thesis is presented in three papers as follows:

Paper 1 – This paper introduces an improved PSO called Small Population based PSO (SPPSO) with less number of particles and unique regeneration concept. The efficacy of the algorithm is evaluated for the simultaneous design of power system stabilizers (PSSs) on the two-area and 16 machine power systems.

Paper 2 – The second paper presents a new algorithm-Bacterial Foraging Algorithm (BFA) for simultaneous tuning of multiple PSSs on a 16 machine power system. The variants of the BFA like the run length and the swarming are explored for better performance for two different design techniques and the results are compared.

Paper 3 – The third paper compares SPPSO and BFA towards simultaneous tuning of multiple PSSs on two-area and Nigerian power system. This paper presents both algorithms as a first step towards online optimization and proposes to implement these algorithms in real power systems in near future.

ACKNOWLEDGMENTS

I extend my sincere appreciation to all the people who made this thesis possible. First and foremost, I would like to thank my advisor Dr. Ganesh Kumar Venayagamoorthy, for his encouragement, guidance, co-operation and constant support throughout my graduate studies. He directed me in the right direction to tackle the problems I faced during my research.

In addition, I would also like to extend my gratitude to my thesis committee Dr. Keith A. Corzine and Dr. Donald C. Wunsch II for their insightful suggestions and comments which helped me shape my Masters research in a more realistic way.

I thank the Real-Time Power and Intelligent Systems (RTPIS) Laboratory for providing me with the right platform and environment to carry out my research.

I would also like to thank my family and my friends Mani Hunjan and Swakshar Ray for their constant support and encouragement. Words cannot describe the extent of gratitude I owe to my mother, Sabita Das, without whose selfless support and undying belief no work presented in this thesis would have begun. I will forever be grateful to my father, Pranab Kumar Das for always believing in me and inspiring me.

TABLE OF CONTENTS

Page

PUBLICATION THESIS OPTION ... iii

ABSTRACT ... iv

ACKNOWLEDGMENTS ... v

LIST OF ILLUSTRATIONS ... x

LIST OF TABLES ... xiv

PAPER

1. COMPUTATIONALLY EFFICIENT SPPSO ALGORITHM FOR DESIGN OF POWER SYSTEM STABILIZERS ... 1

Abstract ... 1

I. INTRODUCTION ... 2

II. OPTIMAL PSS DESIGN ... 4

III. PSO AND SPPSO ALGORITHMS ... 7

IV. STUDY SYSTEM ... 11

A. System 1 ... 11

B. System 2 ... 12

1) Case 1- Tuning All PSSs ... 13

2) Case 2-Tuning Selected PSSs ... 13

V. PERFORMANCE COMPARISON ... 14

A. Eigenvalue Analysis ... 14

1) System 1 ... 14

2) System 2 (Case 1) ... 15

B. Computational Complexities ... 15

1) System 1 ... 15

2) System 2 ... 16

VI. TRANSIENT SIMULATION RESULTS ... 18

A. System 1 ... 19

1) Contingency 1 ... 19

2) Contingency 2 ... 19

B. System 2 (Case 1)..........21

1) Contingency 1.......... 22

2) Contingency 2.......... 22

C. Performance Measure of the PSSs in System 1 and 2..........24

1) System 1.......... 24

2) System 2 (Case 1).......... 25

D. Comparison of Tuning of All PSSs (Case 1) and Selected PSSs (Case 2) on System 2..........25

VII. CONCLUSION.......... 29

VIII. REFERENCES.......... 29

2. BACTERIAL FORAGING ALGORITHM AND ITS VARIANTS FOR THE DESIGN OF POWER SYSTEM STABILIZERS.......... 32

Abstract.......... 32

I. INTRODUCTION.......... 33

II. BACTERIAL FORAGING ALGORITHM.......... 35

A. Chemotaxis..........36

B. Swarming..........36

C. Reproduction..........37

D. Elimination and Dispersal..........38

III. VARIANTS OF BFA.......... 40

A. Swarming..........40

B. Fuzzy Adaptive Runlength..........41

C. Optimized Fuzzy Adaptive Runlength..........42

IV. OPTIMAL PSS DESIGN.......... 43

V. CASE STUDY.......... 46

A. Case Study 1.......... 46

1) Approach A: Tuning All PSSs.......... 47

2) Case B: Tuning Selected PSSs.......... 48

B. Approach Study 2.......... 48

VI. PERFORMANCE COMPARISON.......... 50

A. Computational Complexities.......... 50

1) Approach A: Tuning All PSSs.......... 51

2) Approach B: Tuning Selected PSSs ... 53
B. Eigenvalue Analysis ... 54
1) Approach A: Tuning All PSSs ... 55
2) Approach B: Tuning Selected PSSs ... 56
VII. TRANSIENT SIMULATION RESULTS ... 56
A. Time Domain Simulations ... 56
1) Approach A: Tuning All PSSs ... 57
a) Swarming ... 57
b) Fuzzy Adaptive Runlength ... 57
c) PSO Optimized Fuzzy Adaptive Runlength ... 60
2) Approach B: Tuning Selected PSSs ... 62
a) Swarming ... 62
b) Fuzzy Adaptive Runlength ... 63
c) PSO Optimized Fuzzy Adaptive Runlength ... 64
B. Transient Energy Analysis of the Damping Performance ... 66
1) Approach A: Tuning All PSSs ... 67
2) Approach B: Tuning Selected PSSs ... 68
C. Comparison of two PSSs Case Studies ... 68
VIII. CONCLUSION ... 71
IX. REFERENCES ... 71
3. BIO-INSPIRED ALGORITHMS FOR THE DESIGN OF MULTIPLE OPTIMAL POWER SYSTEM STABILIZERS: SPPSO AND BFA ... 74
Abstract ... 74
I. INTRODUCTION ... 75
II. TWO MULTI-MACHINE POWER SYSTEMS ... 77
A. Two Area Multi-Machine Power System ... 78
B. Nigerian Power System ... 79
III. BIO-INSPIRED ALGORITHMS WITH SMALL POPULATION ... 80
A. Small Population Based Particle Swarm Optimization (SPPSO) Algorithm ... 80
B. Bacterial Foraging Algorithm ... 84
1) Chemotaxis ... 84

2) Swarming 85
3) Reproduction 86
4) Elimination and Dispersal 86
IV. OPTIMAL PSS DESIGN 87
V. SIMULATION RESULTS 88
A. Two Area Multi-Machine Power System 89
1) Single Fault: Temporary Transmission Line Outage 90
2) Single Fault: Three Phase Short Circuit 91
3) Combined Fault: Short Circuit followed by a Transmission Line Outage 93
B. Nigerian Power System 94
1) Single Fault: Temporary Transmission Line Outage 95
2) Single Fault: Three Phase Short Circuit 96
3) Combined Fault: Short Circuit followed by Line Outage 98
VI. DISCUSSIONS ON SPPSO AND BFA PSS DESIGNS 99
A. Computational Complexities 99
B. Transient Energy Analysis of the Damping Performance... 105
C. Eigenvalue Analysis... 108
VII. CONCLUSION 111
VIII. REFERENCES 111
APPENDICES
A. APPENDIX FOR PAPER 1 114
B. APPENDIX FOR PAPER 2 124
C. APPENDIX FOR PAPER 3 134
VITA 137

LIST OF ILLUSTRATIONS

Figure Page

PAPER 1

1. Block diagram of power system stabilizer (PSS) 5

2. Regions of eigenvalues location for different objective functions 6

3. Flowchart explaining the methods involved in the optimal PSS design........ 7

4. Movement of a PSO/SPPSO particle in two dimensions from one instant k to another instant *k+1* 9

5. Flowchart for PSO and SPPSO algorithms........ 10

6. Average fitness of the best particle over 20 trials (System 1) 16

7. Average fitness of the best particle over 20 trials (System 2) 18

8. Speed response of G1 and G3 for a 150 ms 3-Φ short circuit at bus 8 for operating condition I 20

9. Speed response of G2 and G3 for a 150 ms 3-Φ short circuit at bus 8 for operating condition II........ 20

10. Speed response of G2 and G3 for a permanent line outage between buses 7 and 8 for operating condition IV 21

11. Speed differences of (G10-G14) and (G3-G13) in rad/sec for a 150 ms 3- Φ short circuit fault at bus 50 for operating condition I 22

12. Speed differences of (G15-G14) and (G15-G16) in rad/sec for a 150 ms 3- Φ short circuit fault at bus 50 for operating condition II 23

13. Speed differences of (G15-G16) and (G15-G14) in rad/sec for a 150 ms 3-Φ short circuit fault at bus 1 followed by opening of the line between buses 1 and 2 for operating condition III 23

14. Speed differences of (G10-G16) and (G14-G15) in rad/sec for a 150 ms 3- Φ short circuit fault at bus 50 for operating condition I 26

15. Speed differences of (G10-G14) and (G1-G10) in rad/sec for a 150 ms 3- Φ short circuit fault at bus 50 for operating condition II 27

15. Speed differences of (G10-G14) and (G1-G10) in rad/sec for a 150 ms 3- Φ short circuit fault at bus 50 for operating condition II 27

16. Speed differences of (G15-G16) and (G10-G15) in rad/sec for a 150 ms 3-Φ short circuit fault at bus 1 followed by opening of the line between buses 1 and 2 for operating condition III 27

PAPER 2

1. Flowchart for BFA 39

2. Membership function used for input [12] 41

3. Block diagram of a power system stabilizer (PSS) 43

4. Region of eigenvalues locations for different objective functions 45

5. Flowchart explaining the methods involved in the optimal PSS design 46

6. 16 machine power system 48

7. PSO optimized membership function for Case A 50

8. PSO optimized membership function for Case B 50

9. Average fitness of the best bacterium over 20 trials (Tuning All PSSs) 53

10. Average fitness of the best bacterium over 20 trials (Tuning Selected PSSs) 54

11. Speed differences of (G2-G12) and (G15-G16) in rad/sec for a 150ms 3-Φ short circuit fault at bus 1 for operating condition II 58

12. Speed differences of (G1-G10) and (G15-G16) in rad/sec for a 150ms 3-Φ short circuit fault at bus 9 followed by immediate opening of the line between buses 8 and 9 for operating condition III 59

13. Speed differences of (G2-G12) and (G10-G15) in rad/sec for a 150ms 3-Φ short circuit fault at bus 1 for operating condition I 59

14. Speed differences of (G2-G10) and (G15-G16) in rad/sec for a 150ms 3-Φ short circuit fault at bus 9 followed by immediate opening of the line between buses 8 and 9 for operating condition III 60

15. Speed differences of (G3-G13) and (G10-G15) in rad/sec for a 150ms 3-Φ short circuit fault at bus 1 for operating condition II 61

16. Speed differences of (G1-G10) and (G15-G10) in rad/sec for a 150ms 3-Φ short circuit fault at bus 9 followed by immediate opening of the line between buses 8 and 9 for operating condition II 61

17. Speed differences of (G3-G13) and (G14-G15) in rad/sec for a 150ms 3-Φ short circuit fault at bus 1 for operating condition I 62

18. Speed differences of (G15-G16) and (G12-G16) in rad/sec for a150ms 3-Φ short circuit fault at bus 9 followed by immediate opening of the line between buses 8 and 9 for operating condition III 63

19. Speed differences of (G15-G16) and (G14-G16) in rad/sec for a 150ms 3-Φ short circuit fault at bus 1 for operating condition I 64

20. Speed differences of (G14-G15) and (G2-G13) in rad/sec for a 150ms 3-Φ short circuit fault at bus 9 followed by immediate opening of the line between buses 8 and 9 for operating condition III 65

21. Speed differences of (G2-G12) and (G12-G15) in rad/sec for a 150ms 3-Φ short circuit fault at bus 1 for operating condition II 65

22. Speed differences of (G14-G12) and (G2-G13) in rad/sec for a 150ms 3-Φ short circuit fault at bus 9 followed by immediate opening of the line between buses 8 and 9 for operating condition III 66

23. Speed differences of (G15-G16) and (G14-G16) in rad/sec for a 150ms 3-Φ short circuit fault at bus 1 for operating condition III 70

24. Speed differences of (G15-G16) and (G14-G15) in rad/sec for a 150ms 3-Φ short circuit fault at bus 9 followed by immediate opening of the line between buses 8 and 9 for operating condition III 70

PAPER 3

1. Two area multi-machine power system 78

2. Block diagram of a power system stabilizer 78

3. The Nigeran, 330 kV, 25 bus grid power system. 79

4. Movement of a PSO particle in two dimensions from one instant k to another instant k+1 82

5. Speed response of generator G2 for a 200ms line outage between bused 8 and 9 90

6. Speed response of generator G3 for a 200ms line outage between bused 8 and 9 91

7. Speed response of generator G1 for a 3 phase 200ms short circuit applied at bus 8.... 92

8. Speed response of generator G4 for a 3 phase 200ms short circuit applied at bus 8.... 92

9. Speed response of generator G1 for a 3 phase 100 ms short circuit applied at bus 8 followed by immediate 100 ms line outage between buses 8 and 9. 93

10. Speed response of generator G3 for a 3 phase 100 ms short circuit applied at bus 8 followed by immediate 100 ms line outage between buses 8 and 9................. 94

11. Speed response of Shiroro (hydro area) for a 200ms line outage between buses 9 and 11.. 96

12. Speed response of Egbin (thermal area) for a 200ms line outage between buses 9 and 11.. 96

13. Speed response of Shiroro (hydro area) for a 3 phase 200ms short circuit applied at the tie line between the thermal and hydro power stations 97

14. Speed response of Delta (thermal area) for a 3 phase 200ms short circuit applied at the tie line between the thermal and hydro power stations 97

15. Speed response of Shiroro (hydro area) for a 3 phase 100ms short circuit applied at bus 25 followed by immediate 100ms line outage of the tie lines between buses 9 and 11(Fig. 3) 98

16. Speed response of Egbin (thermal area) for a 3 phase 100ms short circuit applied at bus 25 followed by immediate 100ms line outage of the tie lines between buses 9 and 11 (Fig. 3) 99

17. Average fitness of the best particle in PSO, SPPSO and the best bacterium in BFA for the study on the two-area multi-machine power system 101

18. Average fitness of the best particle in PSO, SPPSO and the best bacterium in BFA for the study on the Nigerian power system 102

LIST OF TABLES

Table Page

PAPER 1

I. Operating Conditions ... 13

II. Comparison of Computational Complexities of PSO and SPPSO on Systems 1 and 2 ... 17

III. Computational Complexities of the Two PSS Case Studies on System 2 ... 28

PAPER 2

I. Summary of Operating Conditions ... 49

II. Comparison of General Computational Complexity of BFA ... 51

III. Comparison of Computational Complexities of Variants of BFA for Case A ... 52

IV. Comparison of Computational Complexities of Variants of BFA for Case B ... 55

PAPER 3

I. Parameters Limits Used in the Optimization ... 88

II. Factors Affecting the Performance of SPPSO and BFA Algorithms ... 100

III. Comparison of General Computational Complexity of PSO, SPPSO and BFA ... 104

IV. Comparison of Computational Complexities of PSO, SPPSO and BFA for PSS Design for Two Area Power System ... 104

V. Computation Time for PSO, SPPSO and BFA for Two Area Power System ... 105

VI. Normalized P.I for Two Area Multi-Machine Power System. ... 107

VII. Normalized P.I for the Nigerian Power System. ... 107

VIII.Eigenvalues, Frequencies and Damping Ratios of Generating Units in Area 1 in Two Area Multi-Machine Power System ... 109

IX. Eigenvalues, Frequencies and Damping Ratios of Generating Units in Area 2 in Two Area Multi-Machine Power System ... 109

X. Eigenvalues, Frequencies and Damping Ratios of Hydro Generating Units in Nigerian Power System.......... 110

XI. Eigenvalues, Frequencies and Damping Ratios of Thermal Generating Units in Nigerian Power System.......... 110

PAPER 1

COMPUTATIONALLY EFFICIENT SPPSO ALGORITHM FOR DESIGN OF POWER SYSTEM STABILIZERS

Tridib K. Das, *Student Member, IEEE* and
Ganesh K. Venayagamoorthy, *Senior Member, IEEE*

Abstract—**The disturbances occurring in power systems induce electromechanical oscillations. These oscillations need to be damped in order to maintain power system stability. Power System Stabilizers (PSSs) can damp these oscillations by providing auxiliary feedback signals to excitations of generators. This paper presents Particle Swarm Optimization (PSO) with a small population called Small Population based PSO (SPPSO) as a novel technique for optimizing/tuning the parameters of several PSSs in two different power systems. The small population reduces the computational cost and thus can be considered as a first step towards online optimization. A regeneration concept is introduced in SPPSO to have the advantages of PSO. The cost function used in this study takes into account the eigenvalues of the electromechanical modes of the generators. The efficacies of PSO and SPPSO based PSSs designs are compared with conventional PSS design on two power systems in terms of the closed loop system eigenvalues, the transient energies experienced for different operating conditions and the computational complexities of the algorithms. This paper also presents additional results that show improved damping when only critical PSSs are selected for tuning.**

Index Terms – **damping ratio, eigenvalue, particle swarm optimization, participation factors, power system stabilizer, optimization, small population and transient stability.**

I. INTRODUCTION

The demand for electric power has been increasing with time and therefore, to satisfy the power demand, power systems are becoming more interconnected and thus becoming more and more complex. With this type of environment and higher loading of transmission lines, the power system is forced to operate closer to its stability limits. This results in electromechanical oscillations which can threaten the system stability by curtailing the electric power transfers. To maintain system stability, generators are equipped with Power System Stabilizers (PSSs) which modulate the generator output by adding an auxiliary signal to the voltage reference set point. The PSS is endowed with the task of providing phase shift in the frequency range of power system oscillations; typically between the ranges of 0.2Hz-2Hz. It accomplishes this by the presence of lead-lag compensators that shift the electromechanical modes to the left hand side of the s-plane.

Researchers have proposed several modern approaches for PSS design [1]-[3]. However, utilities still prefer the conventional lead-lag compensator structure [4], [5]. This is because of the ease of tuning the parameters during commissioning. Conventional PSS (CPSS), the first in the sequential design process, could not provide effective damping for different operating conditions. To have the PSS provide good damping over a wide range of operating conditions, its parameters need to be fine-tuned in response to all modes of oscillation present in the system. Traditional optimization techniques [6]-[9] have been proposed as solutions; having the above mentioned drawbacks. However, when the cost function is epistatic and the parameters to be optimized are large in number, these techniques exhibit premature convergence and thus cannot guarantee an optimum solution.

Particle Swarm Optimization (PSO) is a popular, evolutionary like algorithm which has been shown to have great potential for single and multi-objective optimization [10], [11]. Optimization of PSS parameters using PSO has been reported in literature [12]. Evolutionary PSO (EPSO) has also been proposed as an optimization technique towards PSS tuning [13]. PSO and EPSO employ larger number of particles to explore the search space and thus present a high burden on computational resources and time. These techniques cannot be conceptualized for online optimization where the state of the system changes over time. To make the PSO feasible for online optimization, the first thing to be done is to reduce the number of individuals employed thus reducing the number of fitness evaluations.

A Small Population based PSO (SPPSO) is presented in this paper as a feasible online implementation tool and is illustrated using Power System Toolbox (PST) [14]. A unique regeneration concept is introduced in SPPSO to overcome the drawback of having a small population. SPPSO is implemented for simultaneous tuning of PSS parameters on a two area (4 generators) and the New England-New York (16 generators) power system. These studies involve tuning parameters of all PSSs and selective critical PSSs. The critical PSSs are selected based on the generator participation factors in the inter-area modes. The latter one provides better damping to the power system oscillations. The cost function used in all these studies is the eigenvalues of the electromechanical modes of the generators.

The rest of the paper is organized as follows: Section II describes the formulation of the cost function used in determining the PSSs parameters by the optimization techniques; Section III elaborates PSO and SPPSO algorithms; Section IV describes the two power systems used in this study; Section V compares the performance of the optimized PSSs; Section VI presents some transient simulation results and finally, the conclusion and future work is given in Section VII.

II. OPTIMAL PSS DESIGN

The generators in the power systems under study have PSS1As [15], as shown in Fig. 1, connected to them. The PSSs provide additional input signals (V_{pss}) to the voltage regulators/excitation systems to damp out the power system oscillations. Some commonly used input signals are rotor speed deviation ($\Delta\omega$), accelerating power and frequency. It consists of an amplifier block of gain constant, K, a block having washout time constant, Tw, and two lag-lead compensators with time constants T1 to T4. The gain K and the four time constants T1 to T4 are the five PSS parameters that need to be optimally selected for each generator to provide effective damping to power system oscillations under a wide range of operating conditions and disturbances.

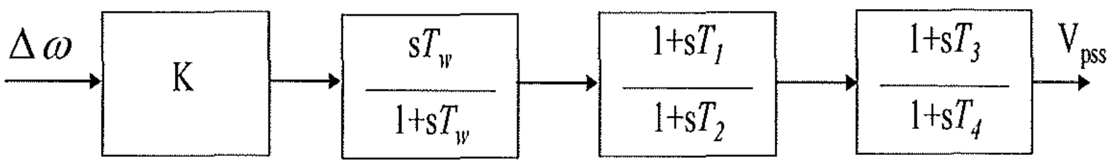

Fig. 1. Block diagram of power system stabilizer (PSS).

The objective in the optimal PSS design is to maximize damping; in other words minimize the overshoots and settling time in system oscillations. An eigenvalue based objective function reflecting damping factor of each of the electromechanical eigenvalues at number of different operating conditions is formulated. The optimization algorithm minimizes the cost function given by:

$$M = aM_1 + (1-a)M_2 \tag{1}$$

where

$$M_1 = \sum_{j=1}^{NP} \sum_{\sigma_{i,j} \geq \sigma_0} \left(\sigma_{i,j} - \sigma_0\right)^2 \tag{2}$$

$$M_2 = \sum_{j=1}^{NP} \sum_{\varsigma_{i,j} \leq \varsigma_0} \left(\varsigma_{i,j} - \varsigma_0\right)^2 \tag{3}$$

a is the weighing factor which is 0.1 for this study. Several values of a have been tried but with 0.1provides the best results. This is because with this value of a, M_1 does not dominate M_2 and vice-versa in magnitude ratio. NP is the number of operating points considered in the design. $\sigma_{i,j}$ is the real part of the i^{th} eigenvalue under j^{th} operating condition considered. The value of σ_o determines the relative stability in terms of damping factor margin provided for constraining the placement of eigenvalues during the process of optimization. The closed loop eigenvalues are placed in the region to the left of the line as shown in Fig. 2 (a). If M_2 is to be taken as the objective function then it limits the maximum overshoot of the eigenvalues as shown in Fig. 2 (b). In case of M_2, ζ_0 is the minimum to be achieved for all electromechanical modes of oscillations. When the cost function is as given by (1), it takes into account both damping and overshoot and the eigenvalues are restricted by design to the D-shaped area as shown in Fig. 2 (c).

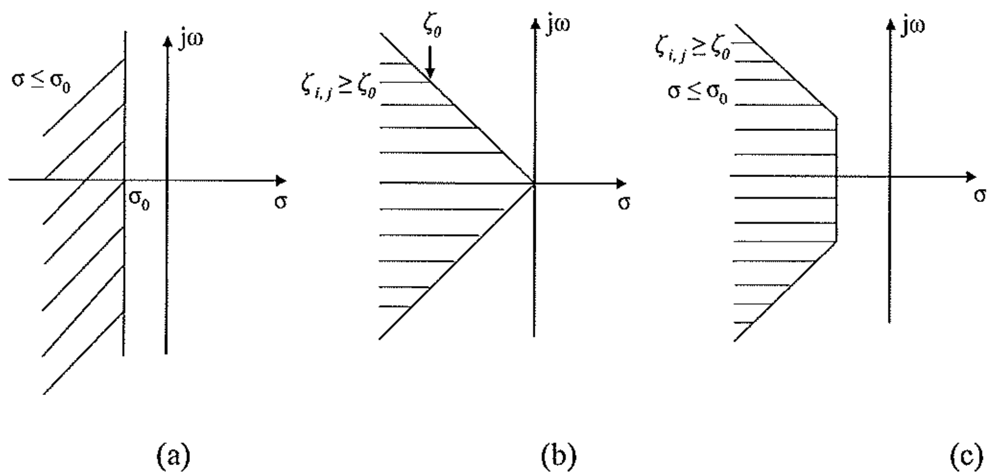

Fig. 2. Regions of eigenvalues location for different objective functions.
(a) Region where $\sigma_{i,j} \leq \sigma_0$ (b) Region where $\zeta_{i,j} \geq \zeta_0$
(c) Region where $\sigma_{i,j} \leq \sigma_0$ *and* $\zeta_{i,j} \geq \zeta_0$

A flowchart as shown in Fig. 3 explains the steps involved in the optimal PSS design. The PSSs parameters to be optimized should be restricted to certain limits. The maximum and the minimum values of these parameters are chosen so that the system may not lose its stability during optimization when the PSSs parameters attain any of these limits.

$$K_{min} \leq K \leq K_{max}, \qquad T_{1min} \leq T_1 \leq T_{1max}, \qquad T_{2min} \leq T_2 \leq T_{2max},$$

$$T_{3min} \leq T_3 \leq T_{3max}, \qquad T_{4min} \leq T_4 \leq T_{4max}.$$

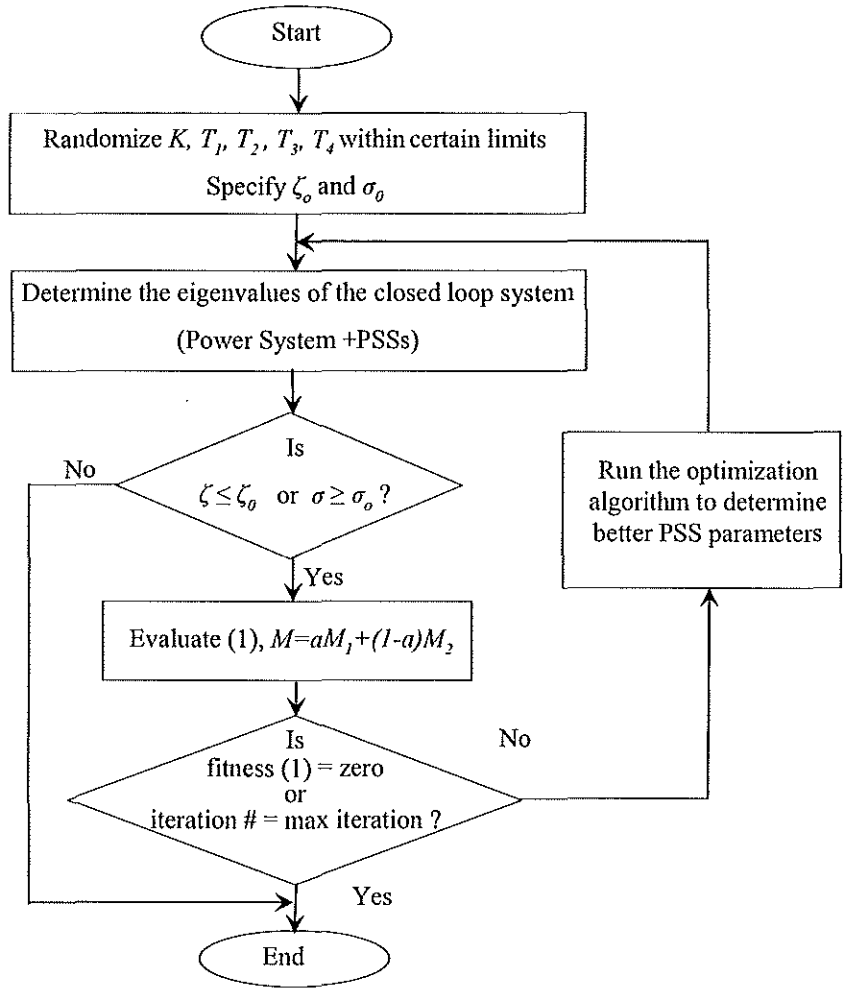

Fig. 3. Flowchart explaining the methods involved in the optimal PSS design.

III. PSO AND SPPSO ALGORITHMS

Particle swarm optimization is a form of evolutionary computation technique (a search method based on natural systems) developed by Kennedy and Eberhart [11]-[12]. PSO like GA is a population (swarm) based optimization tool. However, unlike in GA, individuals are not eliminated from the population from one generation to the next. One major difference between particle swarm and traditional evolutionary computation methods is that particles' velocities are adjusted, while evolutionary individuals' positions are acted upon; it is as if the "fate" is altered rather than the "state" of the particle swarm individuals [16].

The system initially has a population of random solutions. Each potential solution, called *particle*, is given a random velocity and is flown through the problem space. The particles have memory and each particle keeps track of previous best position and corresponding fitness. The previous best value is called the *pbest* of the particle and represented as p_{id}. Thus, p_{id} is related only to a particular particle i. The best value of all the particles' *pbest*s in the swarm is called the *gbest* and is represented as p_{gd}. The basic concept of PSO technique lies in accelerating each particle towards its p_{id} and the p_{gd} locations at each time step. The amount of acceleration with respect to both p_{id} and p_{gd} locations is given random weighting.

Fig. 4 illustrates briefly the concept of PSO, where $x(k)$ is current position, $x(k+1)$ is modified position, $v_{ini}(k)$ is initial velocity, $v_{mod}(k)$ is modified velocity, $v_{pid}(k)$ is velocity considering p_{id} and $v_{pgd}(k)$ is velocity considering p_{gd} at k^{th} iteration in a unit interval.

The velocity and the position of the particles are computed according to (4) and (5) respectively. v_{id} and x_{id} represent the velocity and position of i^{th} particle in d^{th} dimension respectively and, $rand_1$ and $rand_2$ are two uniform random functions.

$$\begin{aligned} v_{id}(k+1) = {} & w \times v_{id}(k) + c_1 \times rand_1 \times (p_{id}(k) - x_{id}(k)) \\ & + c_2 \times rand_2 \times (p_{gd}(k) - x_{id}(k)) \end{aligned} \tag{4}$$

$$x_{id}(k+1) = v_{id}(k+1) + x_{id}(k) \tag{5}$$

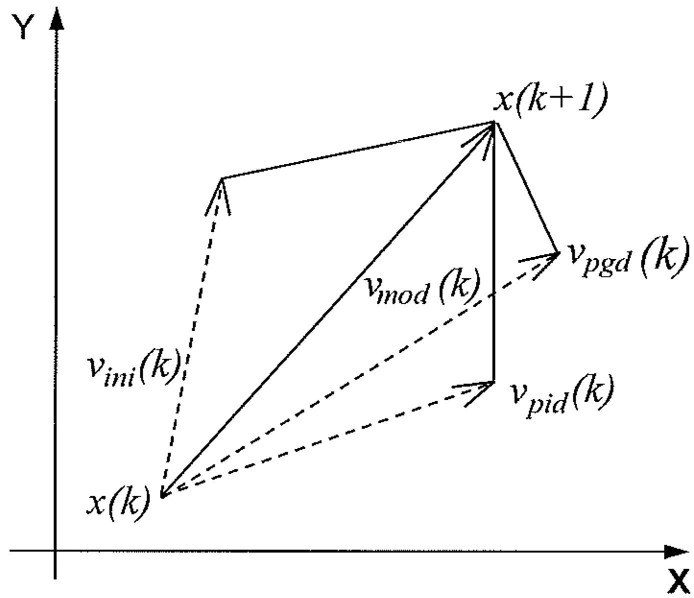

Fig. 4. Movement of a PSO/SPPSO particle in two dimensions from one instant *k* to another instant *k+1*.

The PSO parameters in (4) are as follows: w is called the inertia weight, which controls the exploration and exploitation of the search space; and c_1 and c_2 are the cognition and social acceleration constants.

The modifications proposed to the standard PSO in this paper mainly include two ideas. The first idea is the use of a small population of particles, five or less; calling this algorithm the small population based particle swarm optimization. The second idea is a regeneration concept where new particles are randomly created after every N iteration to replace all but the *gbest* particle in the swarm. In the addition to keeping the *gbest's* particle parameters, the population *pbest* attributes are also transition from one set of population to the next every N iterations. The concept of PSO with regeneration is incorporated to make the convergence faster like it would with a large population of PSO. Randomizing the positions and velocities of the particles helps the particles escape local minima and find the global optimum. The involvement of small population of particles reduces the number of fitness evaluations makes each evaluation less computational intensive than standard PSO algorithm. A flowchart explaining the steps in PSO and SPPSO is shown in Fig. 5.

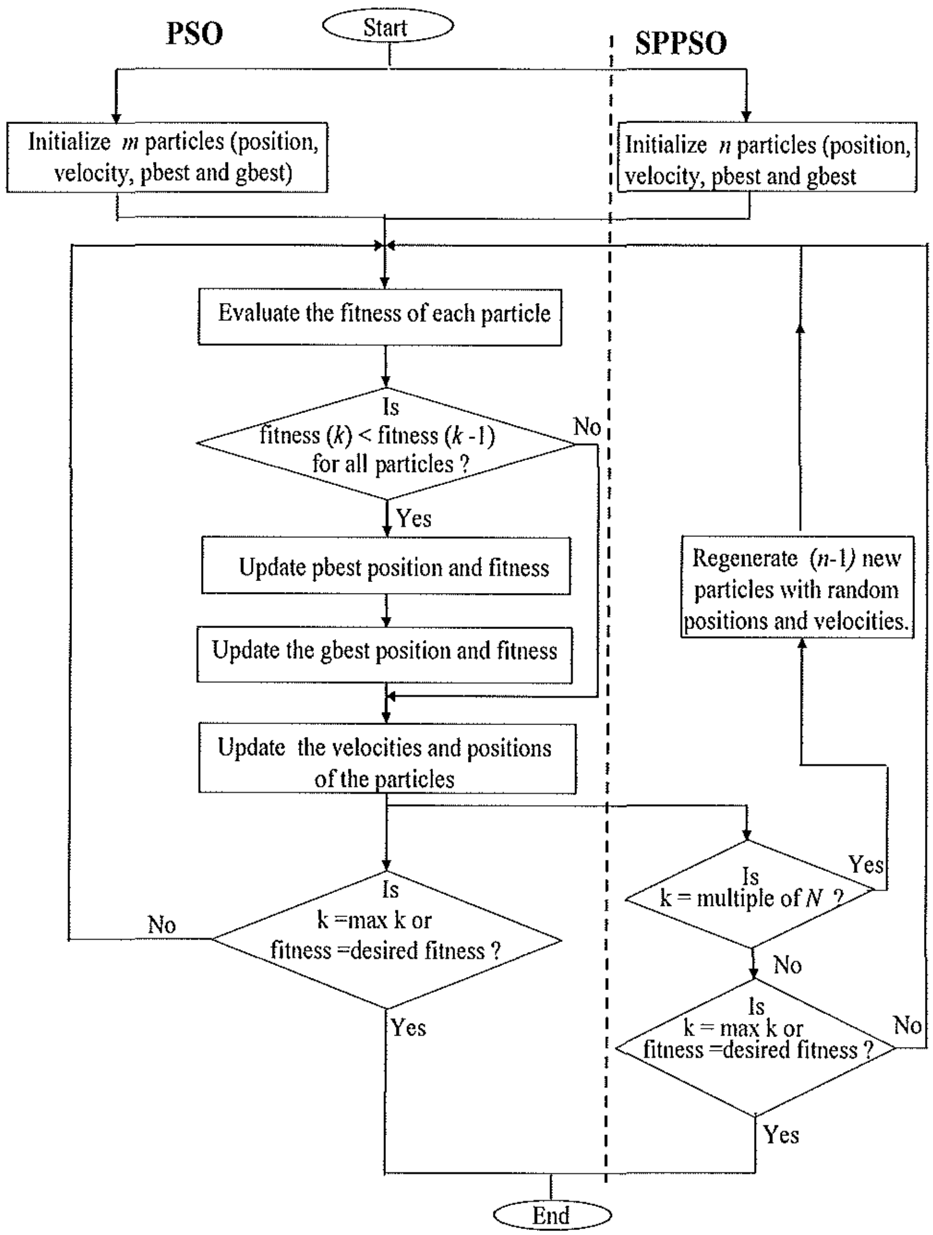

Fig. 5. Flowchart for PSO and SPPSO algorithms.

Clerk [17] has proposed the use of constriction factor for faster and guaranteed convergence of the PSO algorithm. For implementing PSO with constriction factor, (4) is multiplied by K [18].

where
$$K = \frac{2}{2 - \varphi - \sqrt{\phi^2 - 4\varphi}} \tag{6}$$

$$\varphi = c_1 + c_2 \ , \ \varphi > 4$$

The constriction functionality in PSO can be realized by using (4) with w=0.729, and c_1=c_2=1.494, and is referred to as CPSO and CSPPSO in rest of this paper.

IV. STUDY STSTEM

The design of multiple optimal PSSs simultaneously using PSO and SPPSO is studied on two different power systems described below.

A. System 1

The system 1 is the two area power system [19] which consists of two fully symmetrical areas linked together by two transmission lines. Each area is equipped with two identical synchronous generators rated 20 kV/900 MVA. All the generators are equipped with identical speed governors and turbines, exciters and Automatic Voltage Regulators (AVRs), and PSSs. The loads in the two areas are such that Area 1 is exporting an appreciable amount of power to Area 2. This power network is specifically designed to study low frequency electromechanical oscillations in large interconnected power systems. Three electro-mechanical modes of oscillation are present in this system, two inter-plant modes, one in each area, and one inter-area low frequency mode.

The two-area power system being symmetrical, 5 parameters in total are to be tuned by the optimizing algorithm for the different operating conditions as given in Table I. The optimal parameters are given in Table A.1.

B. System 2

System 2 is a 16 machine, 68 bus, five area power system. It is reduced order model of the New England and New York interconnected power systems of the 1970s [20]. The generators, G1-G9 are representation of the New England Test System (NETS) and generators, G10-G13 represent the New York Power System (NYPS). The last three machines G14-G16 are the representation of the three interconnected areas in the NYPS. All the generators have exciters and governors connected to them. The system experiences four inter-area modes of oscillations (0.39Hz, 0.5 Hz, 0.64 Hz and 0.78 Hz). First three of these are the critical modes. Mode 4 is a higher frequency mode which settles down faster than the other three modes. This last mode settles within the allowed settling time for the system, hence three inter-area modes are the modes to be damped. The system is such that Area 2 imports power from Area 5. The data used for the 16 machine system is taken from [20]. Two cases for PSSs parameters tuning for this system is carried out as described below.

1) Case 1 – Tuning All PSSs:

The parameters of all 16 PSSs in the system are determined by the PSO and SPPSO algorithms; in total therefore 80 optimal parameters are determined for the operating conditions in Table I. These parameters are given in Table A.2.

2) Case 2 – Tuning Selected PSSs:

The critical generators for PSS tuning are identified based on their participation factors in the inter-area modes. The participation factors are high for generators G9 and G13-G16 for the 0.39Hz mode, G14 and G16 for the 0.5 Hz mode, G13 for the 0.64 Hz mode and G14 and G15 for the 0.78 Hz mode. Hence, PSSs to be tuned are connected to these five critical generators (G9 and G13-G16) and thus, 25 parameters are optimized. The remaining 11 generators have the conventional designed PSSs [20] connected to them. These PSSs [20] have K=10.0, T_1=0.08, T_2=0.015, T_3= 0.08 and T_4= 0.015 respectively. The PSO and SPPSO techniques optimize the cost function for the operating conditions given in Table I. The 25 optimal PSS parameters are given in Table A.3.

Table I
Operating Conditions

System	Operating Condition	Power Transfer in (MW)
1	I	246
	II	398
	III	446
	IV	476
2	I	2471
	II	2794
	III	3153

V. PERFORMANCE COMPARISON

This section compares the performance of the optimized PSSs with each other, and with CPSS and PSS [20] on system 1 and system 2 respectively under different operating conditions, given in Table I. The number of particles used in PSO and SPPSO are 20 and 5 respectively. The PSSs performances are compared in terms of closed loop system eigenvalues and computational complexities as described below.

A. Eigenvalue Analysis

The following subsections present the closed loop system eigenvalues and the damping ratios of the two power systems with tuned PSSs.

1) System 1:

The values of ζ_0 and σ_0 used in the optimal PSS design are 0.4 and -1.0 respectively. The frequency ranges used for optimization in this system are 0.4 Hz-1.2 Hz to account for the inter-area modes and 2.85 Hz-3Hz to damp the high frequency oscillations observed in the speed responses of generators. Table A.4 shows the damping ratios and eigenvalues of the systems averaged over 20 CPSO and CPPSO trials for the four operating conditions given in Table I. The PSO and SPPSO with constriction factors give better damping, hence the parameters used further in this study are the PSSs optimized by PSO and SPPSO with constriction factors (CPSO and CSPPSO). The CSPPSO optimized PSSs have real parts of the closed loop system eigenvalues more left to the line σ_0 = -1 than CPSO optimized PSSs and Kundur's PSSs [19]. The damping provided by the CSPPSO optimized PSSs are comparable to the damping provided by CPSO optimized PSSs for any of the operating conditions.

2) System 2 (Case 1):

The cost function used for optimization in this system takes into consideration ζ_0= 0.2 and. σ_0 = -1.0. This being a large system, the value of ζ_0 is taken to be 0.2. The optimization is carried out in the frequency range of 0.3 Hz-0.9 Hz and 2.9 Hz-3.2 Hz so that the four inter-area modes lying in this range are damped properly. The average damping and eigenvalues averaged over 20 trials are given in Table A.5 for operating condition I and II. Similar results are seen for operating condition III but are not shown to limit the length of the paper.

CSPPSO tuned PSSs gives the best damping. Effectiveness of the CPSO and CSPPSO optimized PSSs can be seen in the Tables A.4 and A.5 as the generators do not exhibit local modes of oscillations. The damping ratios within the braces show the minimum and the maximum damping for a given operating condition.

B. Computational Complexities

The computational complexities involved with CPSO and CSPPSO based PSSs design is examined for systems 1 and 2 below.

1) System 1:

Table II shows the computational complexities of the algorithms towards the optimal PSSs design. The average number of iterations to attain 0 fitness over 20 trials with CPSO and CSPPSO are 13.25 and 22.8 respectively. The number of fitness evaluations in CPSO is more than two times the number of fitness evaluations in CSPPSO. The number of additions and multiplications in CSPPSO is reduced by 60% compared to CPSO. To attain the same fitness, CSPPSO requires lesser number of fitness evaluations than CPSO (Fig. 6).

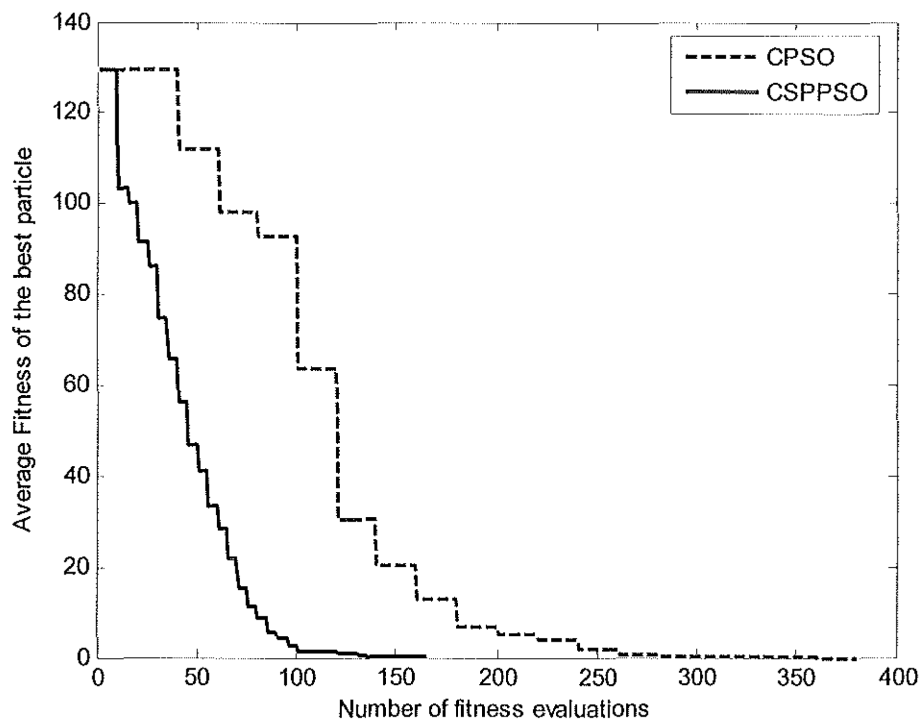

Fig. 6. Average fitness of the best particle over 20 trials (System 1).

2) System 2:

The average number of iterations required to reach 0 fitness over 20 trials for CPSO and CSPPSO are 3.9 and 4.65 respectively. Hence, the computational complexities involved with the algorithms can be quantified as per Table II. The number of fitness evaluations in CPSO is more than five times the number of fitness evaluations in CSPPSO. The number of additions and multiplications in CPSO in comparison to

CSPPSO are increased by 235% for system 2. The average fitness of the best particle over 20 trials is shown in Fig. 7. CSPPSO takes fewer fitness evaluations to reach the desired fitness than that of CPSO.

The lesser number of fitness evaluations makes CSPPSO computationally less intensive. For online optimization where time plays a vital role, CSPPSO is suitable algorithm compared to CPSO which requires more calculations and time to attain a desired fitness.

Table II
Comparison of Computational Complexities of PSO and SPPSO on Systems 1 and 2
(d = number of dimensions)

Algorithms	Number of Fitness Evaluations	Number of Additions	Number of Multiplications
PSO – m particles	$m \times$ *number of iterations*	$5 \times m \times d \times$ *number of iterations*	$5 \times m \times d$ *number of iterations*
CPSO-*20* particles (system 1)	265	6625	6625
CPSO-*20* particles (system 2)	78	31200	31200
CSPPSO – n particles	$n \times$ *number of iterations*	$5 \times n \times d \times$ *number of iterations*	$5 \times n \times d \times$ *number of iterations*
CSPPSO – 5 particles (system 1)	114	2850	2850
CSPPSO – 5 particles (system 2)	23.25	9300	9300

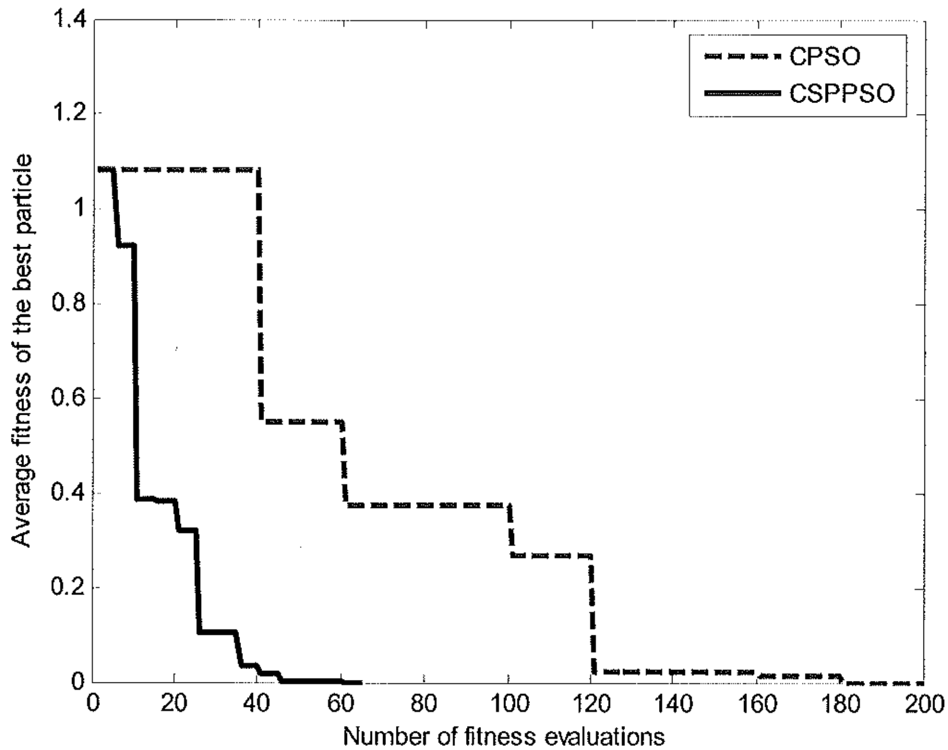

Fig. 7. Average fitness of the best particle over 20 trials (System 2).

VI. TRANSIENT SIMULATION RESULTS

The challenging task of tuning multiple PSSs simultaneously using swarm algorithms in PST is reported in this paper. The responses of the system with CPSO and CSPPSO optimized PSSs are compared with Kundur's PSSs [19] in system 1 and PSSs [20] in system 2 respectively.

A. System 1

The system is subjected to two contingencies for each of the operating conditions given in Table I and the responses are studied for the PSSs parameters given in Table A.1.

1) Contingency 1:

A 150ms duration 3-Φ short circuit is applied at bus 8 of system 1. The speed responses of generators in the two areas for operating conditions I and IV are shown in Figs. 8 and 9. Responses of all the generators on this system for different operating conditions are not shown to limit the length of the paper. The speed oscillations of the generators are better damped with CPSO and CSPPSO optimized PSSs than with Kundur's PSSs [19]. Responses of the CPSO and CSPPSO optimized PSSs are similar. The robustness of CPSO and CSPPSO optimized PSSs can be clearly seen from the damping provided to the generators in both areas of system 1 for these operating conditions.

2) Contingency 2:

The system is subjected to a permanent line outage of a tie line between buses 7 and 8. Fig. 10 shows the speed oscillations of G1 and G3 under operating condition IV. The CPSO and CSPPSO optimized PSSs provide better damping to the oscillations than Kundur's PSS.

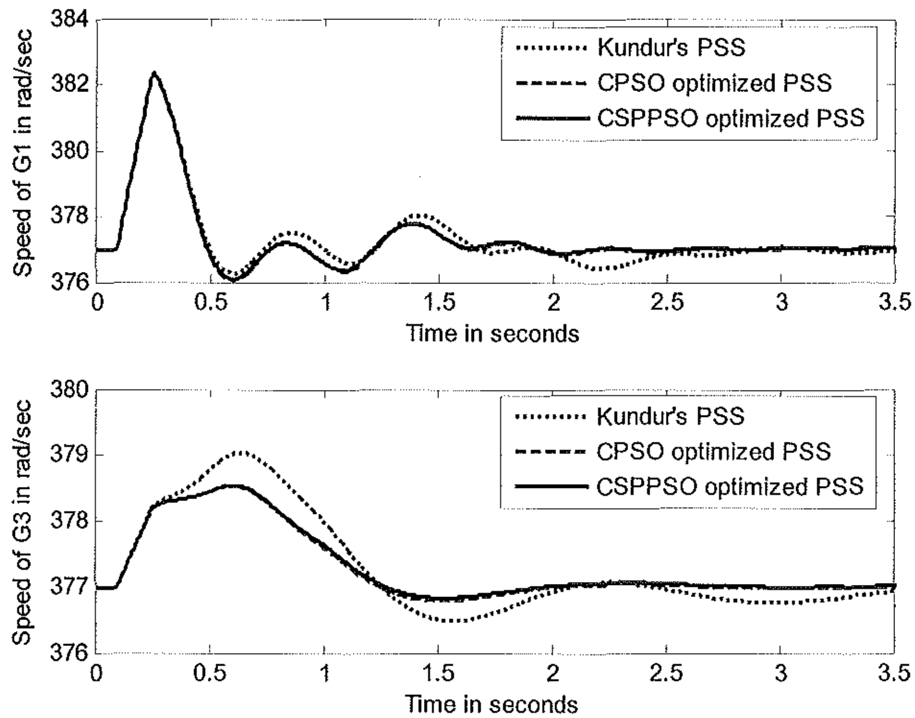

Fig. 8. Speed response of G1 and G3 for a 150ms 3-Φ short circuit at bus 8 for operating condition I.

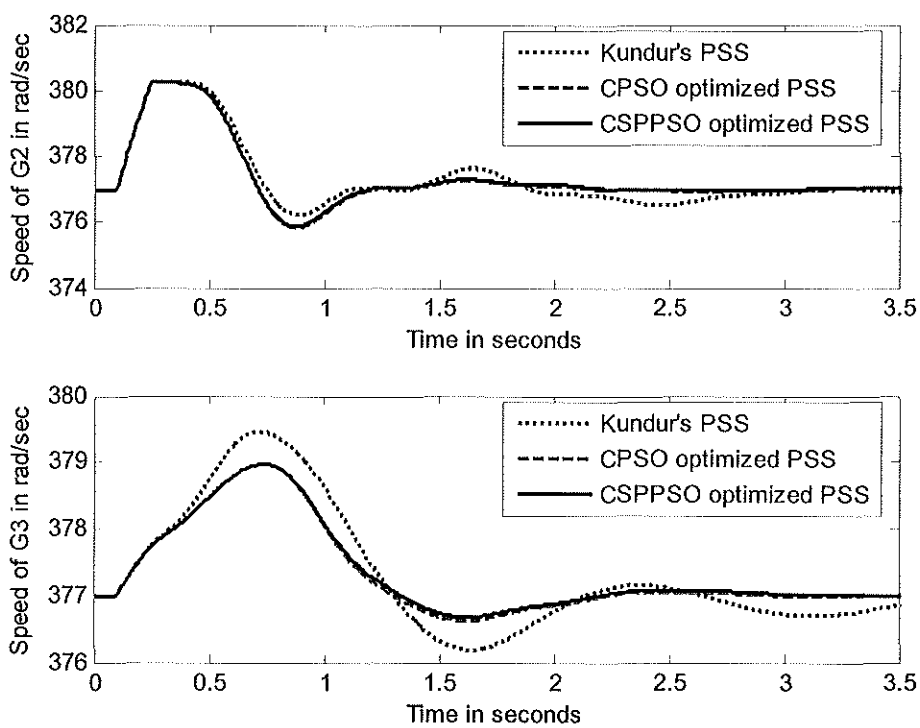

Fig. 9. Speed response of G2 and G3 for a 150ms 3-Φ short circuit at bus 8 for operating condition II.

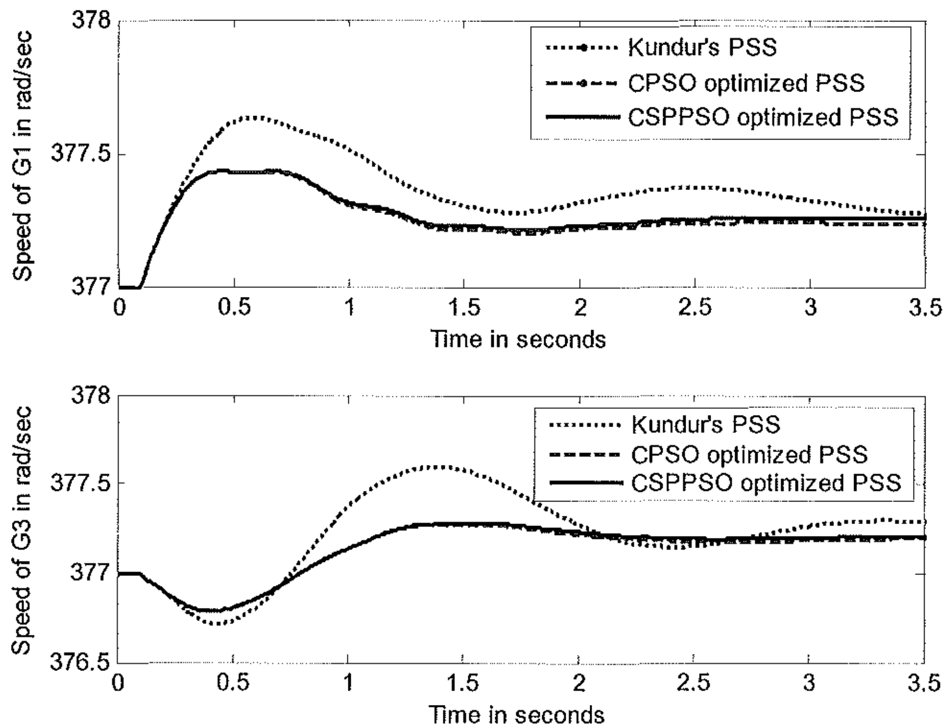

Fig. 10. Speed response of G2 and G3 for a permanent line outage between buses 7 and 8 for operating condition IV.

B. System 2 (Case 1)

The system is subjected to two contingencies for three different conditions as mentioned in Table I and the responses are studied for the PSSs parameters given in Table A.2. The speed differences between generators of different areas are studied to observe the efficacies of the PSS design techniques. The results show that the CSPPSO designed PSSs provide better damping to the speed oscillations than the CPSO designed one. Both CPSO and CSPPSO optimized PSSs exhibit better performance than PSSs [20]. The responses of the generators for contingencies 1 and 2 for operating conditions are as shown below.

1) Contingency 1:

A 150 ms 3-Φ short circuit is applied at bus 50 with an auto recloser. Figs. 11 and 12 shows the speed responses of (G10-G14) and (G3-G13) for operating condition I and (G15-G14), (G15-G16) for operating condition II. The responses exhibit the superiority of CPSO and CSPPSO optimized PSSs over PSSs [20] towards damping power system oscillations.

2) Contingency 2:

The system is subjected to 150 ms 3-Φ short circuit at bus 1 and then the fault is removed by taking out the transmission line between buses 1 and 2 thus changing the system topology. The speed responses of (G15-G16) and (G15-G14) for operating condition III as shown in Fig. 13 corroborate superiority of CPSO and CSPPSO optimized PSSs over PSSs [20] in damping system oscillations.

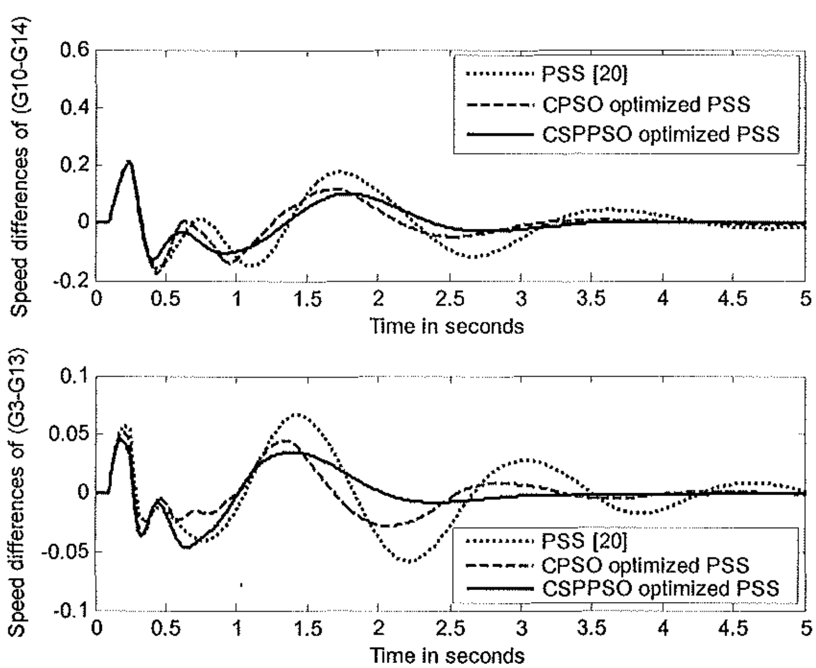

Fig. 11. Speed differences of (G10-G14) and (G3-G13) in rad/sec for a 150 ms 3-Φ short circuit fault at bus 50 for operating condition I.

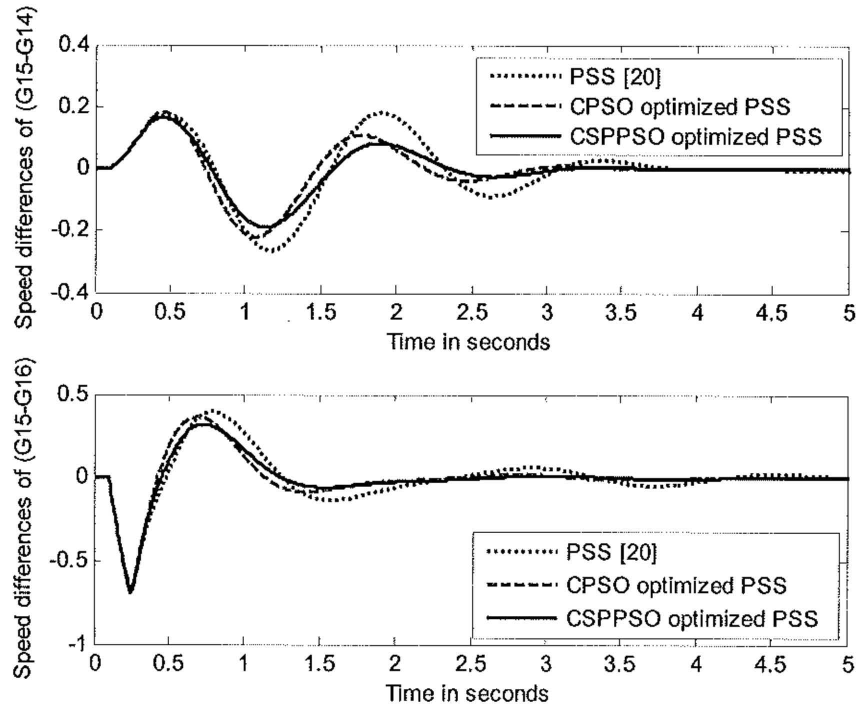

Fig. 12. Speed differences of (G15-G14) and (G15-G16) in rad/sec for a 150 ms 3-Φ short circuit fault at bus 50 for operating condition II.

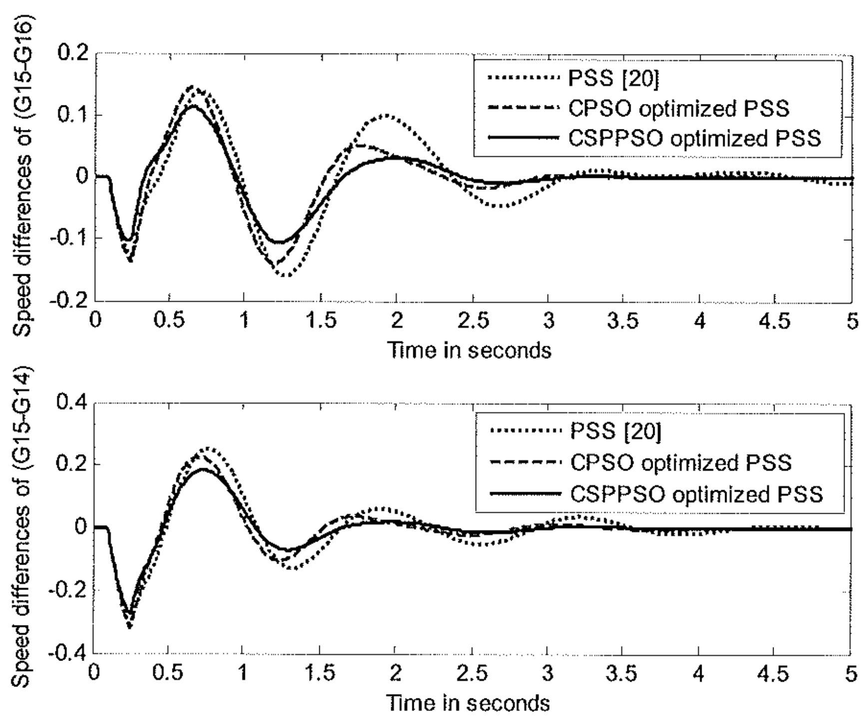

Fig. 13. Speed differences of (G15-G16) and (G15-G14) in rad/sec for a 150 ms 3-Φ short circuit fault at bus 1 followed by opening of the line between buses 1 and 2 for operating condition III.

C. Performance Measure of the PSSs in System 1 and 2

A brief comparison of the CPSO and CSPPSO optimized PSSs designs with CPSS [19] and PSS [20] design for the two-area and the NETS-NYPS power system respectively based on their performance indices are shown in this section. The transient energy of each of the generator for the first 3 seconds of the fault has been calculated using equation (7)

$$TE_{Gen_i} = \frac{1}{2} H_{Gen_i} \int_{t_{flt}}^{t_{flt}+3} \Delta\omega_i^2 \, dt \qquad (7)$$

where i is the generator number and t_{flt} is the time the fault is triggered. The performance index (P.I), given in (8), is a measure of how the system performs under the given conditions with the different set of PSS parameters. The higher the performance indices, better the controller damping performance.

$$\textit{Performance Index (P.I)} = 1/\,TE \qquad (8)$$

1) System 1:

Table A.6 presents the normalized performance indices of Areas 1 and 2 for the system subjected to contingencies 1 and 2 for different operating conditions mentioned in Table I. The normalized performance index is obtained by dividing the P.Is by the P.I of Kundur's in that row. The PSSs parameters used for obtaining these results are the best parameters for four operating conditions averaged over 20 trials. The performance indices as seen in Table A.6 are best in case of system having CPSO and CSPPSO optimized PSSs. The overall performance of the system under different operating conditions improves drastically for the system having CPSO and CSPPSO optimized PSSs.

2) System 2 (Case 1):

The performance indices are evaluated in the same manner as described in (7) and (8). Table A.7 shows the performance indices of the system subjected to contingencies 1 and 2 under different operating conditions. The value of the PSSs parameters used in this study is taken from Table A.2. The overall performance of the system having CPSO and CSPPSO optimized PSSs is better than the system having PSSs [20]. The swarm optimized PSSs parameters give better damping to the system oscillations after a disturbance.

D. Comparison of Tuning of All PSSs (Case 1) and Selected PSSs (Case 2) on System 2

Comparison of tuning of all and selected PSSs towards damping of electromechanical modes for two above mentioned contingencies are shown from Figs. 14-16. The speed responses clearly depict the superiority of Case 2 (tuning selected PSSs) over Case 1 (tuning all PSSs). Speed oscillations get damped faster in the former than the latter.

The study cases are further compared with respect to the oscillatory modes in system 2 for different operating conditions. The damping shown in Table A.8 is the average damping of the electromechanical modes obtained over 20 trials. It is observed that the damping of the system in Case 2 is better than Case 1 for operating conditions given in Table I. This corroborates the superiority of tuning selected PSSs (Case 2) over tuning all 16 PSSs (Case 1). The five critical generators are mainly responsible for the inter-area modes; hence optimizing PSSs parameters at these locations provide improved damping. The tuning of selected PSSs based on the generators participation factors are computationally intensive than tuning of all PSSs as seen from Table III. The PSSs are entrusted with the task of optimizing the electromechanical modes, such that all of them within the desired frequency range have their $\zeta \geqslant \zeta_0$. This process takes longer time in Case 2 than in Case 1. This is because the degree of freedom for the particles in case 2 (25 parameters) is lower compared to Case 1 (80 parameters).

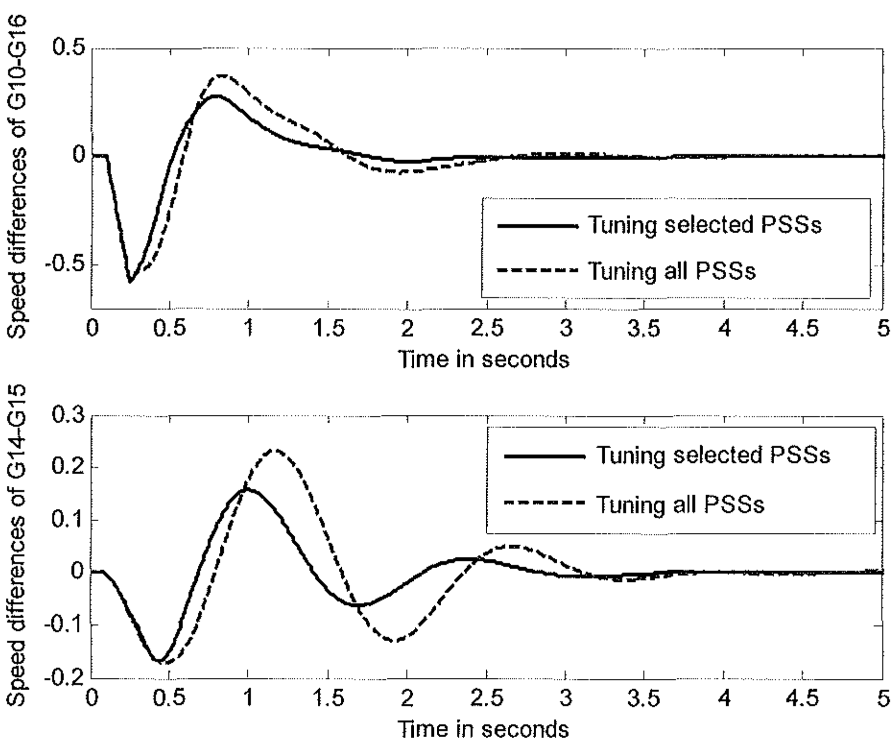

Fig. 14. Speed differences of (G10-G16) and (G14-G15) in rad/sec for a 150ms 3-Φ short circuit fault at bus 50 for operating condition I.

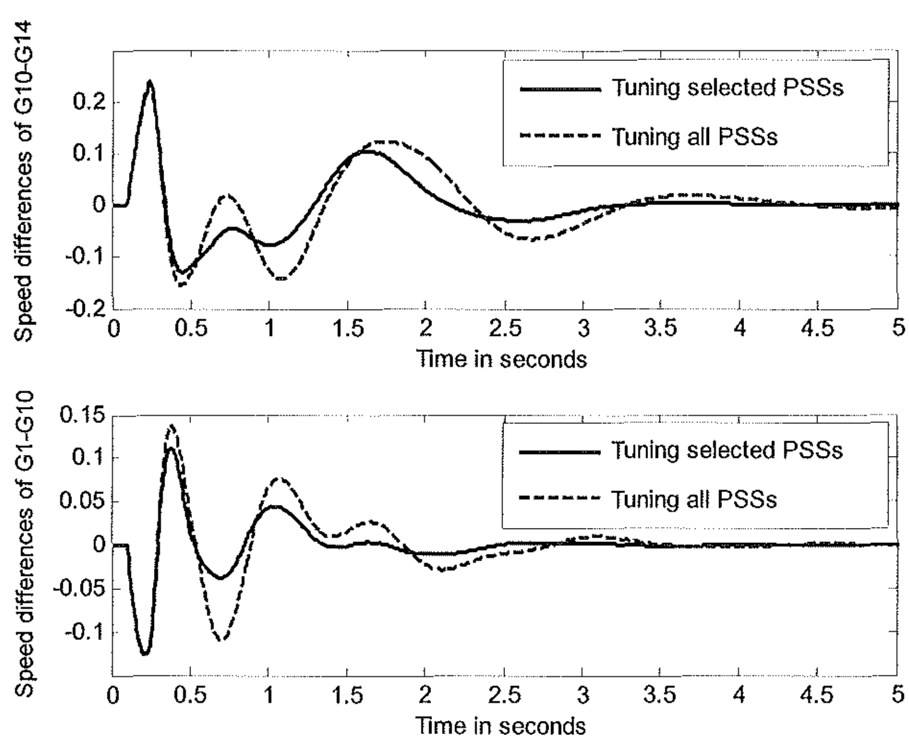

Fig. 15. Speed differences of (G10-G14) and (G1-G10) in rad/sec for a 150ms 3-Φ short circuit fault at bus 50 for operating condition II.

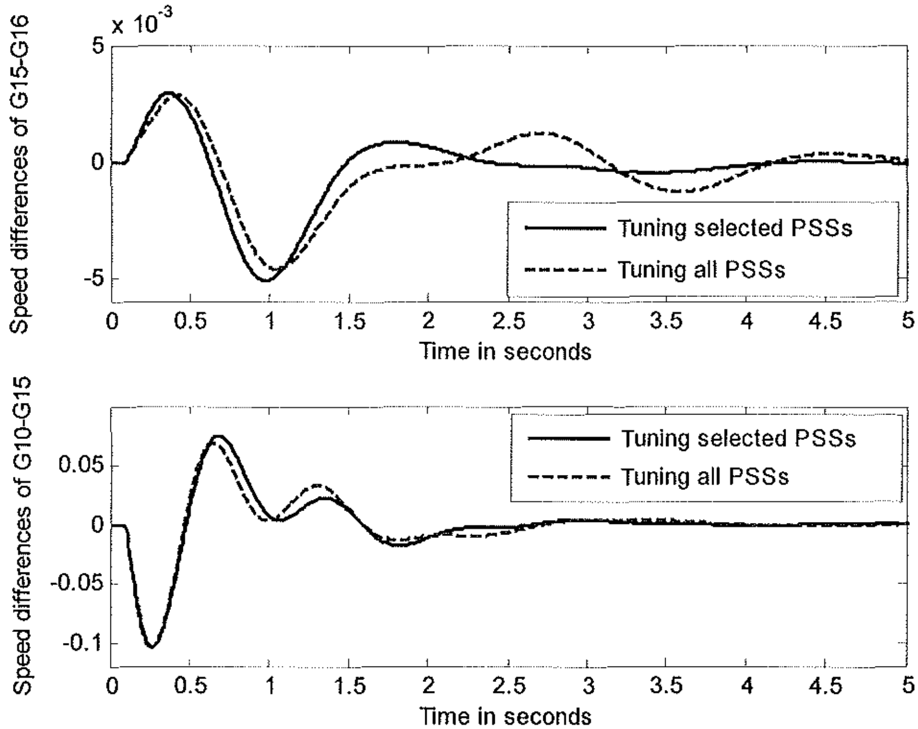

Fig. 16. Speed differences of (G15-G16) and (G10-G15) in rad/sec for a 150ms 3-Φ short circuit fault at bus 1 followed by opening of the line between buses 1 and 2 for operating condition III.

As seen from Table III, the computations involved with the tuning of PSSs in Case 2 involving optimization of 5 parameters of the selected PSSs (25 parameters) is more than the computations involved with tuning of parameters of 16 PSSs (Case 1). Table III also shows the average time required for evaluating the fitness function in each of the proposed design techniques over 10 trials. The processor used in this study is of 1.63GHz and Pentium III processor. It clearly can be seen that the time required to optimize 16 PSSs parameters is comparatively at least three times less than the time required for optimizing the 5 selected PSSs parameters. But, better damping performance can be achieved at the expense of computation overhead.

Table III
Computational Complexities of the Two PSS Case Studies on System 2

Algorithms	Number of Fitness Evaluations	Number of Additions	Number of Multipli-cations	Average computation time (seconds)
SPPSO – 25 parameters	104.5	13062.5	13062.5	1662.91
SPPSO- 80 parameters	23.25	9300	9300	512.193

VII. CONCLUSION

The successful implementation of swarm intelligence techniques for simultaneous design of multiple optimal PSSs has been presented in this paper. The constriction factor based particle swarm optimization and small population based PSO (CPSO and CPPSO) algorithms give robust damping performance for various operating conditions and disturbances as illustrated on the two power systems. The CSPPSO with a small population and the regeneration concept is seen to have faster convergence with few fitness evaluations compared to CPSO. The SPPSO/CSPPSO algorithms are promising techniques for optimizing parameters of a large number of PSSs (example 100) simultaneously on real world power systems. In addition, the selected PSSs tuning can provide improved damping to the inter-area modes in large interconnected systems.

The paper has demonstrated these algorithms as an optimization tool in the PST environment. This is a first step towards online optimization/tuning of PSSs and future work can involve developing these algorithms for real-time dynamic optimization. The potential of these algorithms have been demonstrated for optimal PSS design but can be extended to the design of external damping controllers for FACTS devices.

VIII. REFERENCES

[1] Q. Wenzheng, V, Vittal and M. Khammash, "Decentralized power system stabilizer design using linear parameter varying approach", *IEEE Transactions on Power Systems,* vol. 19, pp. 1951-1960, 2004.

[2] Z. Jiang, "Design of power system stabilizers using synergetic control theory", *IEEE Power Engineering General Meeting,* pp. 1-8, 2007.

[3] Y. Ruhua, H, J. Eghbali and M. H. Neherir, "An online adaptive neuro-fuzzy power system stabilizer for multi-machine systems", *IEEE Transactions on Power* Systems, vol. 17, pp. 1123-1131, 2002.

[4] E. Larsen and D. Swann, "Applying power system stabilizers," *IEEE Transactions on. Power Apparatus and Sys*tems, vol. PAS–100, pp. 3017–3046, 1981.

[5] G. T. Tse and S. K. Tso, "Refinement of conventional PSS design in multimachine system by modal analysis," *IEEE Transactions on Power Systems*, vol. 8, pp. 598–605, 1993.

[6] Y.Y. Hong and W. C. Wu, "A New Approach Using Optimization for Tuning Parameters of Power System Stabilizers," *IEEE Transactions. on Energy Conversion*, vol. 14, No. 3 , pp. 780 - 786, 1999.

[7] M. A. Abido, "Robust design of multi-machine power system stabilizers using simulated annealing," *IEEE Tranactions. on Energy Conversion*, vol. 15, No. 3, pp. 297 –304, 2000.

[8] M. A. Abido and Y. L. Abdel-Magid, "Robust design of multi-machine power system stabilizers using tabu search algorithm," *Proceedings of the IEE Generation Transmission and Distribution*, vol. 147. No. 6, pp. 387-394, 2000.

[9] Y. L. Abdel-Magid and M. A. Abido, "Optimal multiobjective design of robust power system stabilizers using genetic algorithms," *IEEE Transaction on Power Systems*, vol. 18, No. 3, pp. 1125-1132, 2003.

[10] J. Kennedy and R. Eberhart , "Particle swarm optimization", *Proceedings of the IEEE International Conference on Neural Networks*, Perth Australia, Piscataway, NJ, IV: 1942-1948.

[11] Y. del Valle, G. K. Venayagamoorthy, S Mohagegi, J. C. Hernandez and R. G. Harley, "Particle swarm optimization basic concepts, variants and applications in power system", *IEEE Transactions on Evolutionary Computation,* pp.1-25, 2007.

[12] M. A. Abido, "Optimal design of power system stabilizers using particle swarm optimization," *IEEE Transactions on Energy Conversion,* vol. 17, pp. 406-413, Sept. 2002.

[13] V. Miranda, "Evolutionary algorithms with particle swarm movements," *Tutorial at the 13th International Conference on Intelligent System Applications to Power Systems*, Arlington, Nov. 2005.

[14] J. Chow/Cherry Tree Scientific Software, Power System Toolbox Version 2.0, Ontario, K0K-1S0, Canada.

[15] *IEEE Recommended Practice for Excitation System Models for Power System Stability Studies,* 1992. IEEE Standard 421.5.

[16] J. Kennedy, R. C. Eberhart and Y. Shi, *Swarm Intelligence*, Morgan Kaufmann Publishers, 2001.

[17] M. Clerc and J. Kennedy, "The particle swarm-explosion, stability, and convergence in a multidimensional complex space", *IEEE Transactions on Evolutionary Computation*, vol. 6, pp. 58-73, 2002.

[18] R. C. Eberhart and Y. Shi, "Comparing inertia weights and constriction factors in particle swarm optimization", *Proceedings of the IEEE Congress. on Evolutionary Comp*utation, vol. 1, pp. 84-88, 16-19 July, 2000.

[19] P. Kundur, *Power System Stability and Control*, McGraw-Hill, New York: pp. 814, 1974.

[20] G. Rogers, *Power System Oscillations*, Norwell, M.A. Kluwer, 2000.

PAPER 2

BACTERIAL FORAGING ALGORITHM AND ITS VARIANTS FOR DESIGN OF MULTIPLE POWER SYSTEM STABILIZERS

Tridib K. Das, *Student Member, IEEE* and
Ganesh K. Venayagamoorthy, *Senior Member, IEEE*

Abstract—**Electromechanical oscillations are a major concern for power systems since they affect the power flow and stability. Damping these oscillations under a wide range of operating conditions is a challenge to the power system engineers. Power System Stabilizers (PSSs) are effective damping devices which provide auxiliary control signals to the excitations of generators. However, the proper selection of the PSSs parameters to accommodate variations in the power system dynamics is crucial. This paper presents Bacterial Foraging Algorithm (BFA) as a technique for simultaneous design of multiple optimal PSSs and is illustrated on the New England-New York power system. The classical BFA based search can get trapped in local optima and thus fail to provide an optimal solution in a complex environment. This paper investigates three BFA variants for improving the global search capability with regard to the simultaneous tuning of multiple PSSs. The objective function used in this study is the eigenvalues of the electromechanical modes in the system. The three BFA variants are evaluated for damping system oscillations under different contingencies and operating conditions. The variants are compared with respect to their computational complexities, closed loop system eigenvalues and transient energies. In addition, this paper also presents a strategy**

for providing improved damping to the power system oscillations by selecting a few critical generators for their PSS tuning.

Index Terms—**bacterial foraging, fuzzy scheme, multi-machine power systems, optimization, particle swarm optimization, power system stabilizers.**

I. INTRODUCTION

The output power of generators is affected by the presence of low frequency oscillations. Power oscillations come into existence when the transmission lines are operated close to their stability limits. A Power System Stabilizer (PSS) in conjunction with Automatic Voltage Regulators (AVRs) can damp these inter-area oscillations by responding to changes in the generator output power and controls the excitation to reduce the power swings rapidly. For large power systems comprising of many machines, the PSS design is a tedious exercise due to the involvement of large number of controller parameters and system dynamics.

Designing and tuning optimal PSSs to satisfy different system requirements has been an active research area for many years [1]-[10]. The widely used Conventional PSSs (CPSSs) are designed using the theory of phase compensation in frequency domain and are used as lead-lag compensators [8]. The power system being a non-linear system, fixed parameter PSS damping performance degrades with varying operating conditions. To have a fixed parameter CPSS provide good damping over a wide range of operating conditions, its parameters need to be fine tuned to satisfy the system requirements to various modes of oscillations. Most of the techniques [6], [7], [9], [10] proposed to eliminate the drawbacks of the CPSS suffered from complexity, computational overburden and memory requirements. Some of them cannot guarantee robustness as they are capable of using limited number of parameters and optimization functions. Genetic algorithm [6] and simulated annealing [10] are subjected to revisiting of the suboptimal solutions and premature convergence during the optimization.

This paper presents an evolutionary technique called Bacterial Foraging Algorithm (BFA) for the simultaneous design of multiple optimal PSSs on part of a real world power system. This algorithm was proposed in [11] and further enhancements to it are reported in [12]-[14] for applications in power systems. This paper investigates the effect of BFA processes, namely, swarming and the runlength of chemotactic step, on the performance and complexity of simultaneous PSS tuning. Further, the optimization of the fuzzy membership function parameters [12] using Particle Swarm Optimization (PSO) to expedite the BFA search process using an adaptive fuzzy runlength is introduced. The performance of the BFA optimized PSSs for different operating conditions is demonstrated on a New England-New York (16 generator-68 bus) power system [15] simulated in the Power System Toolbox (PST) environment [16]. In addition, the possibilities of tuning selected critical PSSs of generators that participate in inter-area modes are investigated and performance and computational complexities are reported in comparison to tuning all PSSs in the power system. In all these studies, the objective function to be optimized by BFA and its variants is based on the closed loop system eigenvalues.

The rest of the paper is organized as follows: Section II explains the bacterial foraging algorithm used; Section III elaborates the variants of BFA used in this study; Section IV describes the formulation of the cost function used in determining the PSSs parameters by BFA; Section V describes the power system used in this study; Section VI compares the performance of the optimized PSSs; Section VII presents transient simulation results; finally, the conclusions and future work are given in Section VIII.

II. BACTERIAL FORAGING ALGORITHM

Animals with poor foraging strategies (methods for locating, handling and ingesting food) are eliminated by the process of natural selection. This process in turn favors the propagation of genes of those animals that have been successful in their foraging strategies. Species who have better food searching ability are capable of enjoying reproductive success and the ones with poor search ability are either eliminated or reshaped. The BFA mimics the foraging behavior of the *E. coli* bacterium present in our intestines. The foraging consists of four processes: Chemotaxis, Swarming, Reproduction and Elimination-Dispersal [11], and these are briefly explained below. More information on the BFA is given in [11].

A. Chemotaxis:

This stage mimics the bacteria's ability to climb to regions of nutrient concentration, avoiding noxious substances, and searching for way out of neutral media.

The bacterium usually takes a tumble followed by a tumble or a swim to carry out this search. For N_c number of chemotactic steps the direction of movement after a tumble is given by:

$$\theta^{i}(j+1,k,l) = \theta(j,k,l) + C(i) \times \phi(j) \tag{1}$$

where *C(i)* is the step size taken in direction of the tumble by the i^{th} bacterium, *j* is the index for the chemotactic step taken, *k* is the index for the number of reproduction step, *l* is the index for the number of elimination and dispersal event and $\phi(j)$ is the unit length random direction taken at each step.

If the cost at $\theta^{i}(j+1,k,l)$ is better than the cost at $\theta^{i}(j,k,l)$ then the bacterium takes another step of size *C(i)* in that direction (swimming). This process is continued until the number of steps taken is not greater than N_s. This is done to prevent the bacteria trapped in local minima. There should be a tradeoff between the values of N_s to be chosen. It could be half of the value of N_c.

B. Swarming:

The bacteria in times of stresses release attractants to signal other bacteria to swarm together. It however also releases a repellant to signal others to be at a minimum distance from it. Thus all of them have a cell to cell attraction via attractant and cell to cell repulsion via repellant. The equation given below represents the swarming behavior in the bacteria foraging.

$$
\begin{aligned}
J_{cc}(\theta, P(j,k,l)) &= \sum_{i=1}^{S} J_{cc}{}^{i}(\theta, \theta^{i}(j,k,l)) \\
&= \sum_{i=1}^{S} [-d_{attract} \ \exp(-w_{attract} \sum_{m=1}^{p} (\theta_m - \theta_m{}^{i})^2)] \\
&+ \sum_{i=1}^{S} [h_{repellant} \ \exp(-w_{repellant} \sum_{m=1}^{p} (\theta_m - \theta_m{}^{i})^2)]
\end{aligned}
\tag{2}
$$

where, $d_{attract}$ = depth of the attractant effect, $w_{attract}$ = measure of the width of the attractant, $h_{repellant}$ = $d_{attract}$ = height of the repellant effect, $w_{repellant}$ = measure of the width of the repellant, p = number of parameters that need to be optimized, S = number of bacteria.

The total cost function to be optimized by the BFA can be represented by:

$$
J(i, j, k, l) + J_{cc}(\theta, P) \tag{3}
$$

where $J(i, j, k, l)$ is the cost function for the optimization process. The value of $d_{attract}$ and $h_{repellant}$ should be same so that after certain number of iterations after the bacteria converge there should not be any contribution from the swarming part ($J_{cc}=0$). The value of $w_{attract}$ and $w_{repellant}$ should be such that when the bacteria move farther from each other the penalty added to the cost function by J_{cc} should be large.

C. Reproduction:

After all the N_c chemotactic steps have been covered, a reproduction step takes place. S_r (S_r=S/2) bacteria having a lower survival value (less healthy) die and the remaining S_r are allowed to split into two thus maintaining a constant population size.

D. Elimination and Dispersal:

Environment changes for the bacteria all the time. Bacteria are either destroyed or moved to different parts of the intestine resulting in positive and negative influences on their lives. This process is incorporated in the BFA. For each elimination and dispersal event each bacterium is eliminated with a probability of p_{ed}. A low value of N_{ed} (number of elimination and dispersal events) dictates that the algorithm will not rely on random elimination and dispersal events to try to find favorable regions. A high value increases computational complexity but allows bacteria to find favorable regions. The p_{ed} should not be large either or else it would lead to an exhaustive search.

The flowchart describing the BFA algorithm is shown in Fig. 1. BFA due to the above unique processes can find favorable regions during search [11]. Hence, it is applied as an optimization tool for simultaneous design of multiple PSSs in this paper.

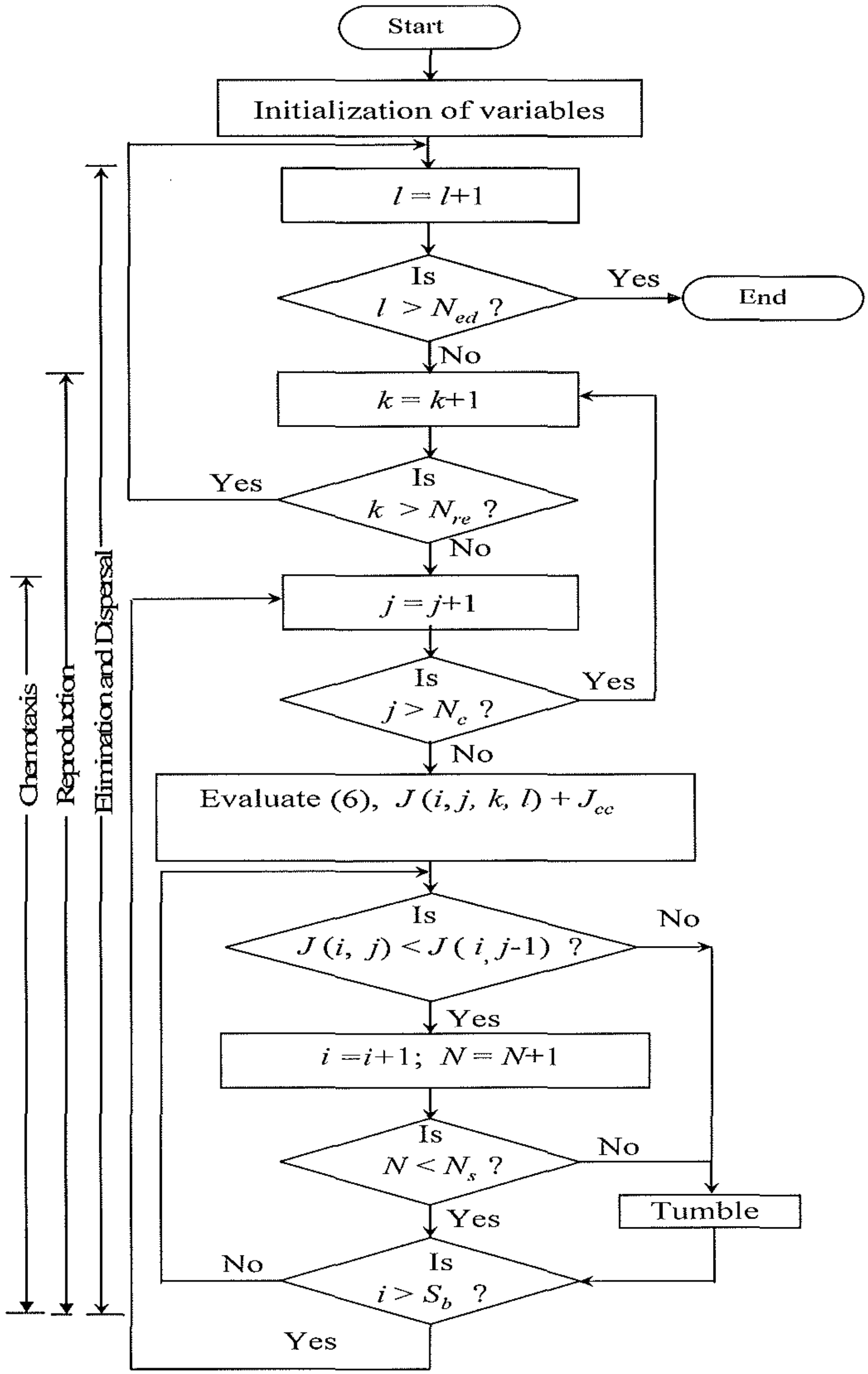

Fig. 1. Flowchart for BFA.

III. VARIANTS OF BFA

Swarming and runlength are the two main factors which affect the performance of BFA. The entire study on the effects of these factors on BFA's performance is categorized into six cases as follows:

- *Case 1*: BFA with fixed runlength with swarming
- *Case 2*: BFA with fixed runlength without swarming.
- *Case 3*: Fuzzy adaptive BFA with swarming
- *Case 4*: Fuzzy adaptive BFA without swarming.
- *Case 5*: PSO optimized fuzzy adaptive BFA with swarming.
- *Case 6*: PSO optimized fuzzy adaptive BFA without swarming.

The following sub-sections describe swarming, fuzzy adaptive runlength and optimized fuzzy adaptive runlength. In all of these studies, the healthiest bacteria is decided by taking the minimum value of each of the bacteria with the chemotactic stages instead of sum of fitness of all chemotactic steps [14].

A. Swarming

Swarming in the BFA, (2), makes it computationally intensive. To evaluate this, the BFA search is carried out with and without swarming between the bacteria. The total cost function to be optimized by BFA is given by (3) and for BFA without swarming, J_{cc}=0.

B. Fuzzy Adaptive Runlength

Classical BFA can potentially get trapped in local optima due to the fixed runlength of the chemotaxis step. To provide BFA with a global optimization capability, the runlength can be made adaptive by using fuzzy concepts [12]. Fig. 2 shows a typical input membership function for a fuzzy inference system. This fuzzy inference is made up of four rules as follows:

R_1: If min (J) is very small (VS), $u_1 = a_1$ min (J).

R_2: If min (J) is small (S), $u_2 = a_2$ min (J).

R_3: If min (J) is medium (M), $u_3 = a_3$ min (J).

R_4: If min (J) is large (L), $u_4 = a_4$ min (J).

where u (u_1, u_2, u_3, u_4) are the outputs of fuzzy inference system. The constants a_1, a_2, a_3, and a_4 in the rules and the fuzzy membership ranges t_1-t_6, in Fig. 2, are usually determined on a trial and error basis.

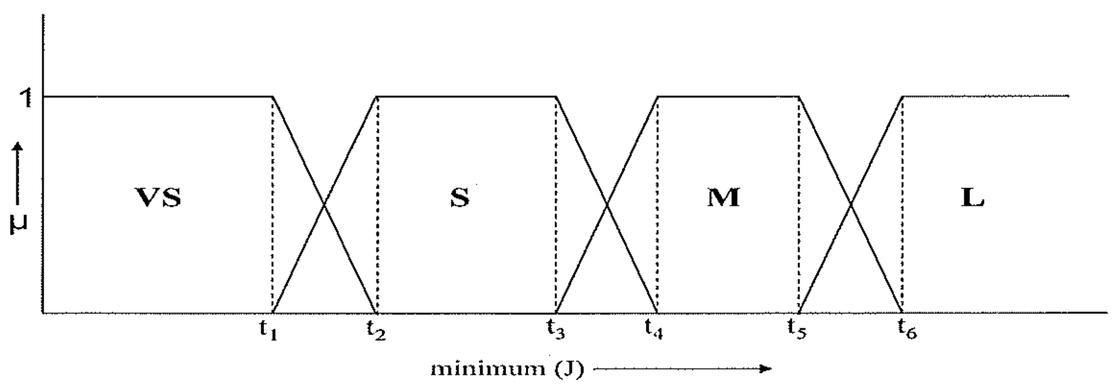

Fig. 2. Membership function used for input [12].

The firing of a particular rule is determined by passing the minimum value of the fitness function (J), given in (3). The chemotactic step as given in (1) is modified and replaced as

$$\theta^{i}(j+1,k,l) = \theta(j,k,l) + u \times C(i) \times \phi(j) \qquad (4)$$

C. Optimized Fuzzy Adaptive Runlength

Instead of determining the vales of a_1-a_4 and t_1-t_6 on a trial and error basis, particle swarm optimization [17], [18] is proposed as a technique for optimizing the parameters of the membership function and rule set. PSO is an evolutionary like technique developed by Kennedy and Eberhart. The two basic equations involved in PSO are

$$\begin{aligned} v_{id} &= w \times v_{id} + c_1 \times rand_1 \times (p_{id} - x_{id}) \\ &\quad + c_2 \times rand_2 \times (p_{gd} - x_{id}) \end{aligned} \qquad (5)$$

$$x_{id} = v_{id} + x_{id} \qquad (6)$$

where v_{id} is the velocity of the d^{th} dimension of the i^{th} particle with which it flies through the search space, x_{id} is the new position of the d^{th} dimension of the i^{th} particle, w is the inertia weight and c_1 *and* c_2 are the cognitive and social acceleration constants which changes the velocity of a particle towards particle's best (p_{id}) and best of all particle's best (p_{gd}) respectively.

IV. OPTIMAL PSS DESIGN

The generators in power systems under study have PSS1As [19] as shown in Fig. 3 connected to them. The PSSs provide additional input signals (Vpss) to the voltage regulators/excitation systems to damp out the power oscillations. Some commonly used input signals are rotor speed deviation (Δω), accelerating power and frequency. It consists of an amplifier block of gain constant, K, a block having washout time constant, Tw, and two lag-lead compensators with time constants T1 to T4. The gain K and the four time constants T1 to T4 are the five PSS parameters that need to be optimally selected for each generator to provide effective damping to power system oscillations under a wide range of operating conditions and disturbances.

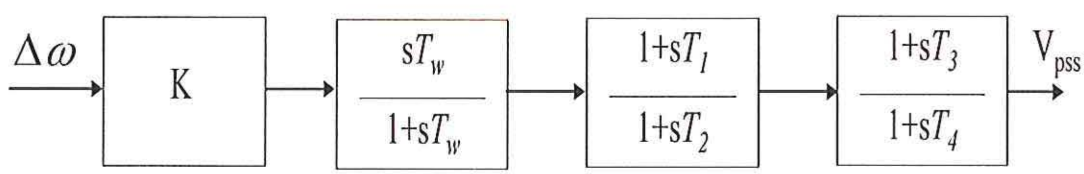

Fig. 3. Block diagram of power system stabilizer (PSS).

The objective in the optimal PSS design is to maximize damping; in other words minimize the overshoots and settling time in system oscillations. An eigenvalue based objective function reflecting damping factor of each of the electromechanical closed loop system eigenvalues at number of different operating conditions is formulated. The optimization algorithm minimizes the cost function given by:

$$M = aM_1 + (1-a)M_2 \tag{7}$$

where

$$M_1 = \sum_{j=1}^{NP} \sum_{\sigma_{i,j} \geq \sigma_0} \left(\sigma_{i,j} - \sigma_0\right)^2 \tag{8}$$

$$M_2 = \sum_{j=1}^{NP} \sum_{\varsigma_{i,j} \leq \varsigma_0} \left(\varsigma_{i,j} - \varsigma_0\right)^2 \tag{9}$$

a is the weighing factor which is 0.1 for this study. Several Number values of a have been tried but 0.1 provides the best results. This is because with this value of a, M_1 does not dominate M_2 and vice-versa in magnitude ratio. NP is the number of operating points considered in the design. $\sigma_{i,j}$ is the real part of the i^{th} eigenvalue under j^{th} operating condition considered. The value of σ_o determines the relative stability in terms of damping factor margin provided for constraining the placement of closed loop system eigenvalues during the process of optimization. The closed loop eigenvalues are placed in the region to the left of the line as shown in Fig. 4 (a). If M_2 is to be taken as the objective function then it limits the maximum overshoot of the eigenvalues as shown in Fig. 4 (b). In the case of M_2, ζ_0 is the minimum damping required for all electromechanical modes of oscillations. When the cost function is as given by (7), it takes into account both damping and overshoot and the eigenvalues are restricted by design to the D-shaped area as shown in Fig. 4 (c).

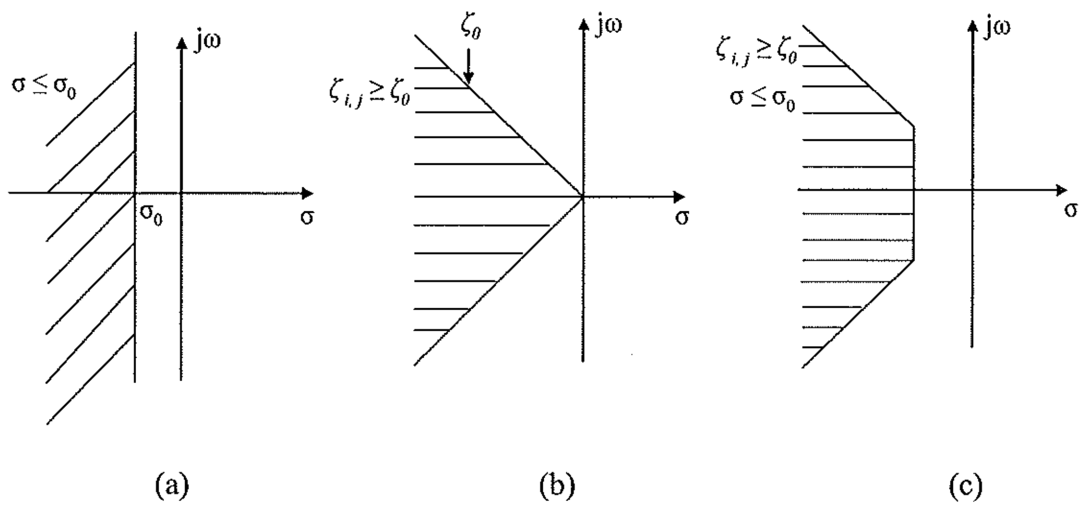

Fig. 4. Regions of eigenvalues location for different objective functions.
(a) Region where $\sigma_{i,j} \leq \sigma_0$ (b) Region where $\zeta_{i,j} \geq \zeta_0$
(c) Region where $\sigma_{i,j} \leq \sigma_0$ *and* $\zeta_{i,j} \geq \zeta_0$

The parameters should be restricted to certain limits. The maximum and the minimum values of these parameters are chosen so that the system may not lose its stability when the PSSs parameters attain any of these limits.

$$K_{min} \leq K \leq K_{max}, \qquad T_{1min} \leq T_1 \leq T_{1max}, \qquad T_{2min} \leq T_2 \leq T_{2max},$$

$$T_{3min} \leq T_3 \leq T_{3max}, \; T_{4min} \leq T_4 \leq T_{4max}.$$

A flowchart shown in Fig. 5 explains the steps involved in the optimal PSS design.

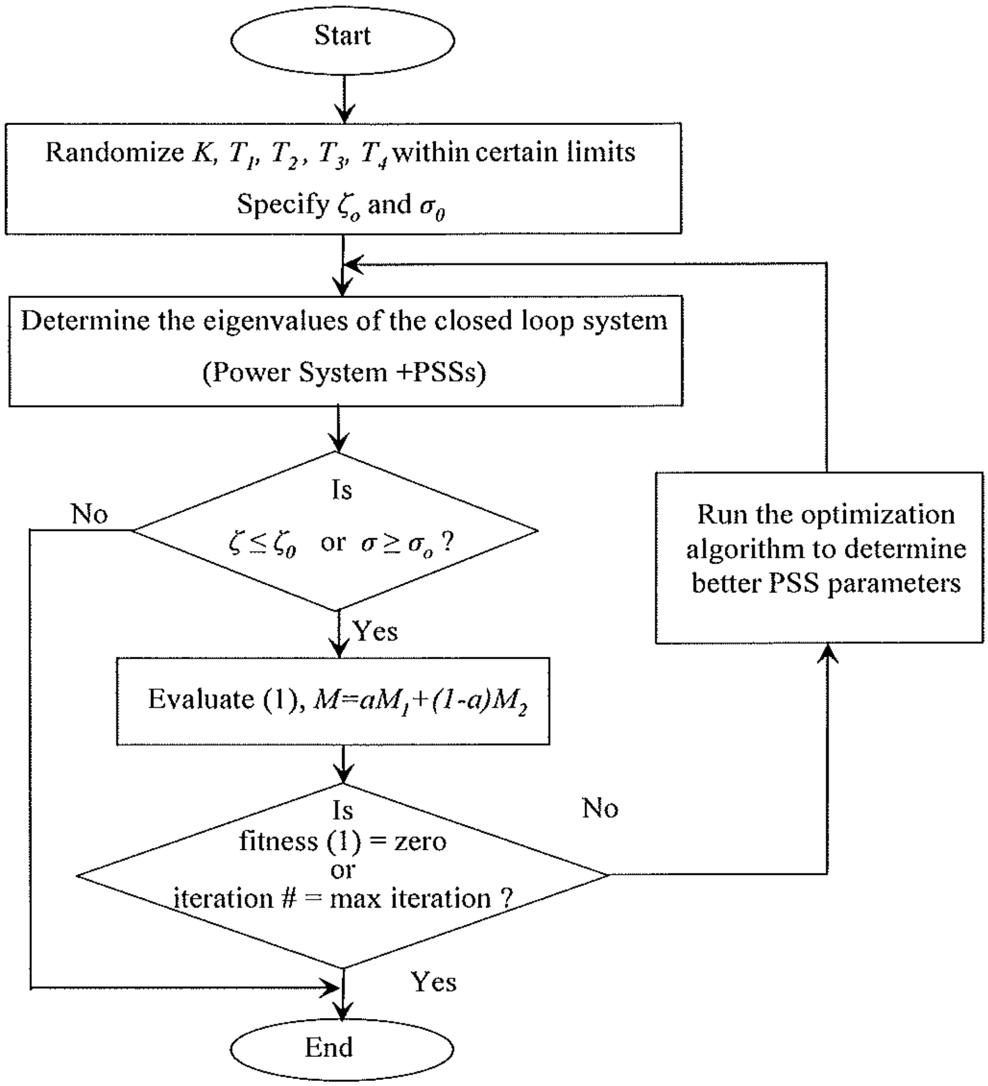

Fig. 5. Flowchart explaining the methods involved in the optimal PSS design.

V. CASE STUDY

A 16 machine-68 bus, five area power system as shown in Fig. 6 is considered for study. It is reduced order model of the New England and New York interconnected power systems of the 1970s [15]. The generators, G1-G9 are representation of the New England Test System (NETS) and generators, G10-G13 represent the New York Power System (NYPS). The last three machines G14-G16 are the representation of the three interconnected areas in the NYPS. All the generators have exciters and governors connected to them. The system experiences four inter-area modes of oscillations (0.39Hz, 0.5 Hz, 0.64 Hz and 0.78 Hz). First three of these are the critical modes. Mode 4 is a higher frequency mode which settles down faster than the other three modes. This last mode settles within the allowed settling time for the system, hence three inter-area modes are the modes to be damped. The system is such that Area 2 imports power from Area 5. The data used for the 16 machine system is taken from [15]. Two design approaches are carried out for the PSS tuning on the 16 machine power system as described below.

A. PSS Design Approaches

Two cases for PSSs parameters tuning for this system is carried out as described below:

1) Approach A: Tuning All PSSs

The parameters of all 16 PSSs in the system are determined by the BFA; in total therefore 80 optimal parameters are determined for the operating conditions in Table I. These parameters are given in Table A.1.

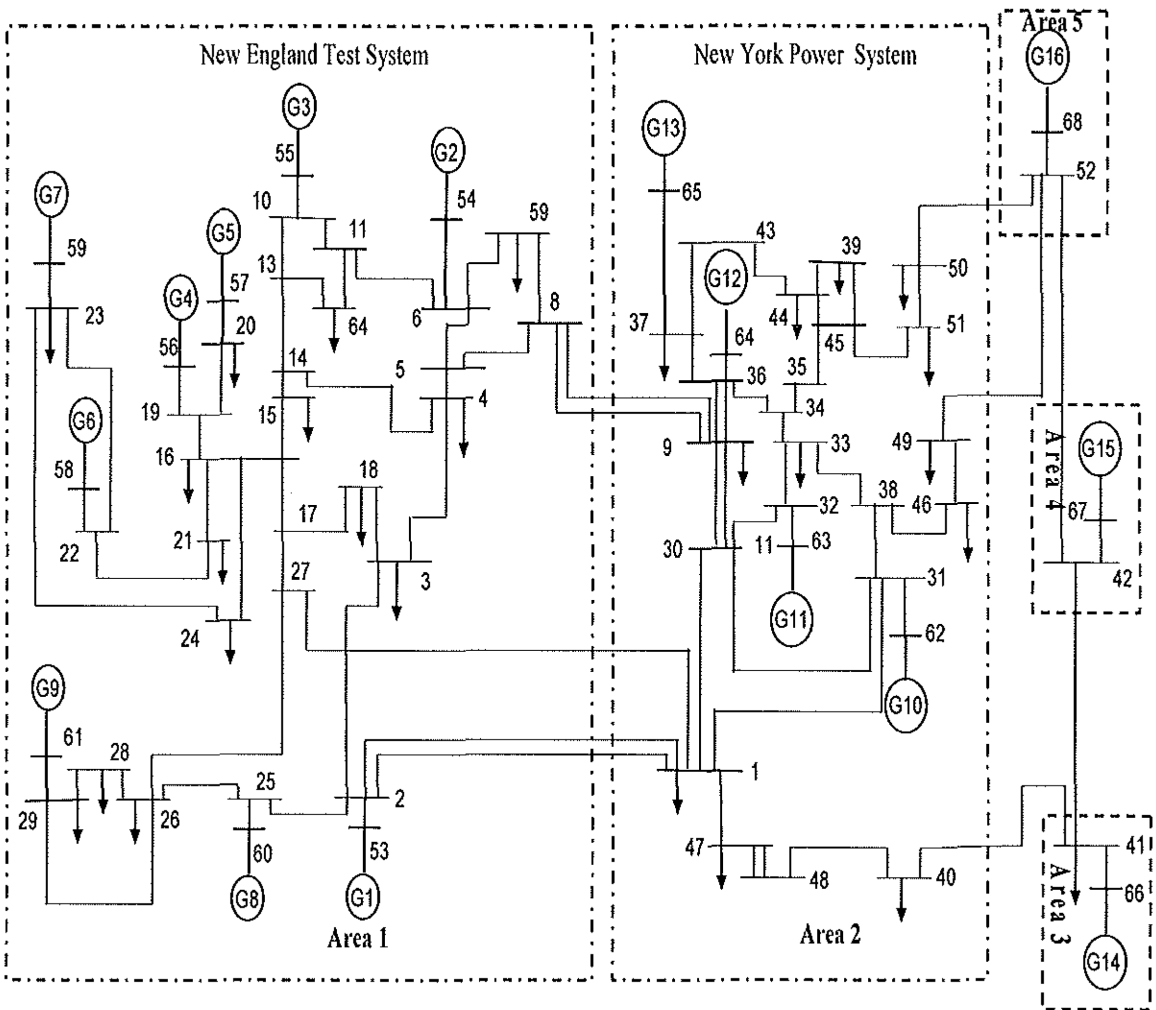

Fig. 6. 16 machine power system.

2) Approach B: Tuning Selected PSSs

The critical generators for PSS tuning are identified based on their participation factors in the inter-area modes. The participation factors are high for generators G9 and G13-G16 for 0.39Hz mode, G14 and G16 for 0.5 Hz mode, G13 for 0.64 Hz mode and G14 and G15 for 0.78 Hz mode. Hence, PSSs to be tuned are connected to these five critical generators (G9 and G13-G16) and thus, 25 parameters are optimized. The remaining 11 generators have the unoptimized PSS [15] connected to them. The parameters of PSS [15] are K= 10.0, T_1 =0.08s, T_2 =0.015s, T_3= 0.08s, T_4 =0.015s respectively. BFA optimizes the cost function for the operating conditions given in Table I. The 25 optimal PSS parameters are given in Table A.2.

Table I
Summary of Operating Conditions

Condition	Power Transfer from Area 2 to Area 5 (MW)
I	2471
II	2794
III	3153

A. PSO Optimized Fuzzy Inference System

The PSO optimized BFA membership parameters are as shown in Figs. 7 and 8 for design approaches A and B respectively. PSO is implemented in optimizing 10 parameters of the membership function.

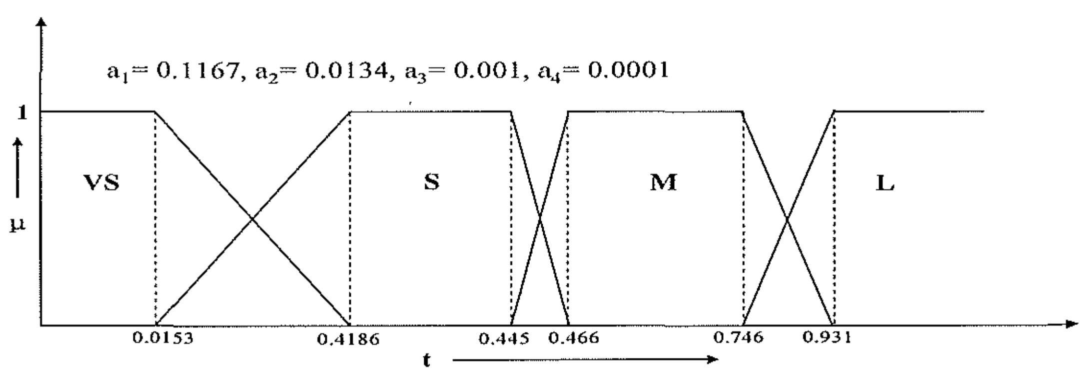

Fig. 7. PSO optimized membership function for Case A.

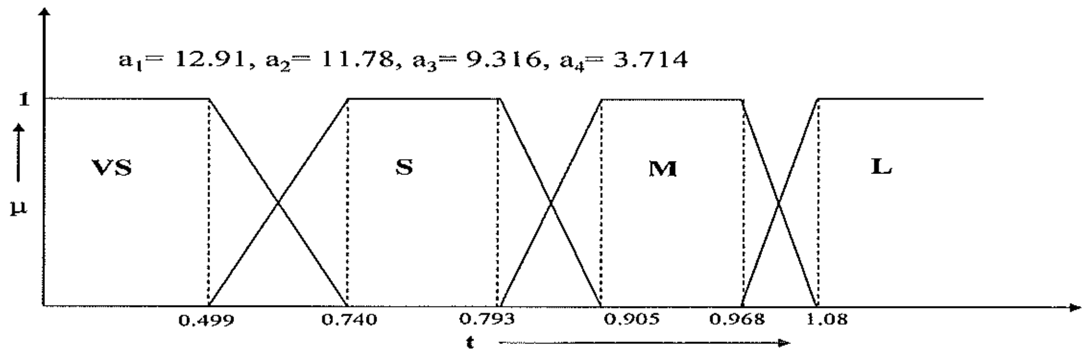

Fig. 8. PSO optimized membership function for Case B.

The trial and error parameters for the tuning of all PSSs (Approach A) and tuning of selected PSSs (Approach B) respectively are

- Approach A: t_1=0.01, t_2=1.1×t_1, t_3=0.1, t_4=1.1×t_2, t_5=1, t_6=1.1×t_5

a_1=1.0, a_2=0.1, a_3=0.01, a_4=0.001.

Approach B: t_1=0.001, t_2=1.1×t_1, t_3=0.01, t_4=1.1×t_2, t_5=0.1, t_6=1.1×t_5, a_1=130.0, a_2=35, a_3=10, a_4=11.

The PSO optimized BFA membership parameters as seen from Figs. 7 and 8 clearly depict the fact that the parameters need not to be in any multiples of other, like assumed in the trial and error parameters above. The parameters in Figs. 7 and 8 are the best PSO gbest parameters obtained over 10 trials which took least number of iterations to converge to zero fitness (given by (3)) over 20 BFA trials.

VI. PERFORMANCE COMPARISON

This section evaluates the performance of the proposed PSSs for the six cases of BFA on the 16 machine power system with respect to the computational complexities and closed loop system eigenvalues as described below.

A. Computational Complexities

In BFA, for every reproduction and elimination-dispersal cycle, a fitness evaluation is carried out after all the chemotactic steps are covered; hence $S \times N_c$ evaluations are performed. Table II gives a comparison perspective in general on the computational complexities for the six case studies.

Table II
Comparison of General Computational Complexity of BFA
(S = Number of bacteria, N_c = Number of Chemotactic Loops, N_{re} = Number of Reproduction Loops, N_{ed} = Number of Elimination and Dispersal Loops, p = Number of parameters to be optimized by BFA)

Variants	Number of Fitness Evaluations	Number of Additions	Number of Multiplications
Case 1	$S \times N_c \times N_{re} \times N_{ed}$	$(5p-1) \times S \times N_c \times N_{re} \times N_{ed}$	$(4+2p) \times S \times N_c \times N_{re} \times N_{ed}$
Case 2	$S \times N_c \times N_{re} \times N_{ed}$	$p \times S \times N_c \times N_{re} \times N_{ed}$	$2p \times S \times N_c \times N_{re} \times N_{ed}$
Case 3	$S \times N_c \times N_{re} \times N_{ed}$	$(5p-1) \times S \times N_c \times N_{re} \times N_{ed}$	$(4+3p) \times S \times N_c \times N_{re} \times N_{ed}$
Case 4	$S \times N_c \times N_{re} \times N_{ed}$	$p \times S \times N_c \times N_{re} \times N_{ed}$	$3p \times S \times N_c \times N_{re} \times N_{ed}$
Case 5	$S \times N_c \times N_{re} \times N_{ed}$	$(5p-1) \times S \times N_c \times N_{re} \times N_{ed}$	$(4+3p) \times S \times N_c \times N_{re} \times N_{ed}$
Case 6	$S \times N_c \times N_{re} \times N_{ed}$	$p \times S \times N_c \times N_{re} \times N_{ed}$	$3p \times S \times N_c \times N_{re} \times N_{ed}$

1) Approach A: Tuning All PSSs

The average number of iterations over 20 trials required to converge to fitness of zero are 11.35, 13.3, 8.3, 9.15, 7.1 and 7.94 for Cases 1, 2, 3, 4, 5 and 6 respectively. Inclusion of swarming in the BFA increases the number of additions and multiplications as can be seen from Table II. The number of additions is higher in Case 1 compared to Case 2; Case 3 compared to Case 4 and Case 5 compared to Case 6. The number of multiplications involved with Cases 2, 4 and 6 is more than that with Cases 1, 2 and 3 respectively because the average iterations required in both cases are very close to each other. Adaptive runlength improves the convergence speed of BFA. BFA in Case 5 exhibits the least number of fitness evaluations. This means that PSO optimized fuzzy inference system based BFA with swarming achieves faster convergence.

Table III
Comparison of Computational Complexities of BFA Variants for Approach A

Variants	Number of Fitness Evaluations	Number of Additions	Number of Multiplications
Case 1	181.60	1507.28	21779.2
Case 2	212.80	17024.0	34048.0
Case 3	132.80	52987.2	32403.2
Case 4	146.40	11712.0	35136.0
Case 5	113.60	45326.4	27718.4
Case 6	127.04	10163.2	30489.6

Fig. 9 shows that the average number of fitness evaluations required in Cases 1-6 to converge to zero fitness over 20 trials. The number of fitness evaluations is the least in Case 5. This result corroborates the fact that PSO is capable of optimizing parameters of the fuzzy inference system which expedites the search process.

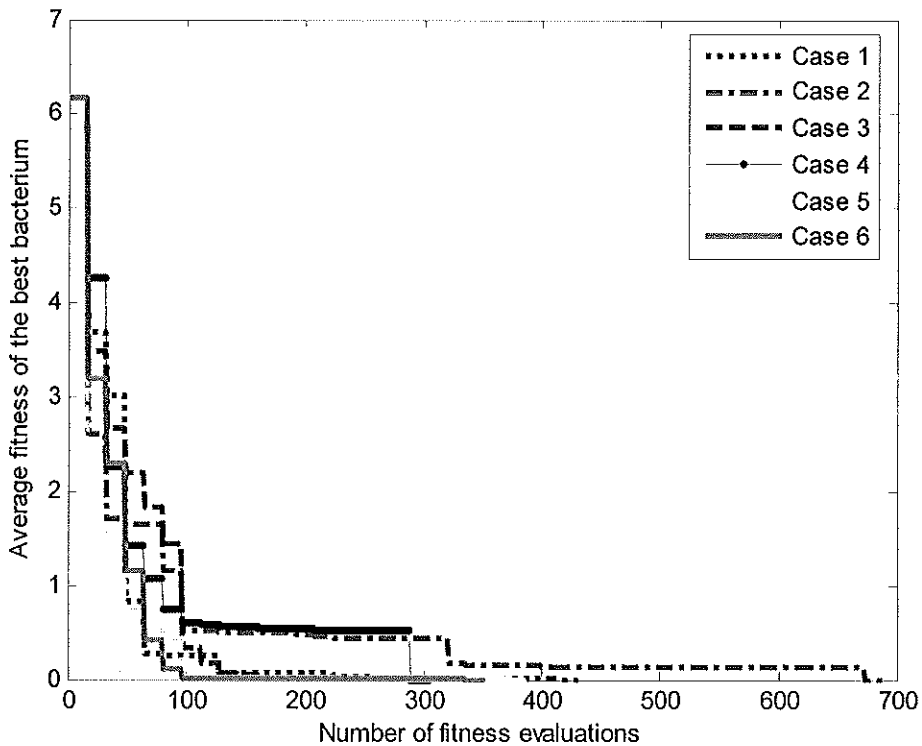

Fig. 9. Average fitness of the best bacterium over 20 trials (Approach A).

2) Appoach B: Tuning Selected PSSs

Table IV shows the computational complexities involved with each of the BFA variants for optimizing selected 5 PSSs parameters of the 16 machine power system. Inclusion of swarming in BFA (Cases 1, 3 and 5) increases the computation in comparison to BFA without swarming (Cases 2, 4 and 6). The number of additions of Case 1 increases by 324% and number of fitness evaluations decreases by 11.64% than Case 2. The number of multiplications increases by making the runlength adaptive. Multiplications in Case 3 are 8.43% higher than multiplications in Case 1. The number of fitness evaluations, additions and multiplications is higher in Cases 1, 3 and 5 than in

Cases 2, 4 and 6 respectively. The average number of iterations required to reach zero fitness are 20.04, 24.05, 15.75, 18.6, 14.8 and 17.25 for Cases 1, 2, 3, 4, 5 and 6 respectively.

The fitness of the best bacterium over 20 trials for Cases 1-6 is shown in Fig. 10. The least number of fitness evaluations are seen in Case 5

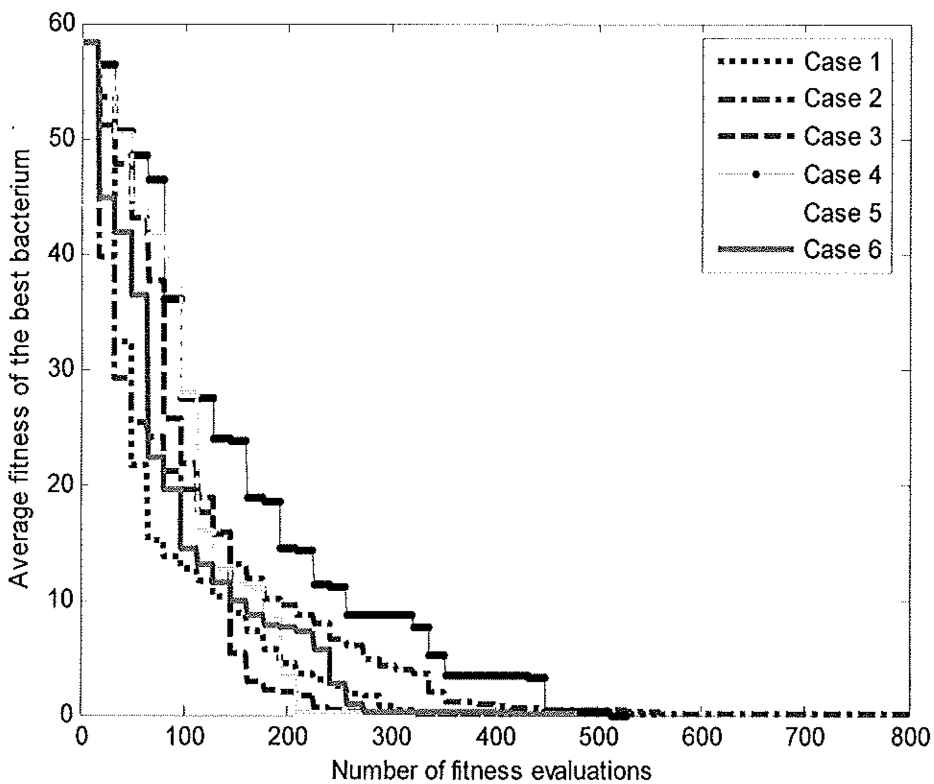

Fig. 10. Average fitness of the best bacterium over 20 trials (Approach B).

Table IV
Comparison of Computational Complexities of BFA Variants for Approach B

Variants	Number of Fitness Evaluations	Number of Additions	Number of Multiplications
Case 1	320.64	39759.36	17314.56
Case 2	384.8	9620	19240
Case 3	252	31248	19908
Case 4	297.6	6300	18900
Case 5	236.8	29363.2	18707.2
Case 6	276	6896	20700

B. Eigenvalue Analysis

The system is linearized about different operating points as mentioned in Table I. The oscillation modes of interest to be damped are in ranges of 0.3Hz-1.0 Hz and 2.9-3.2 Hz in the 16 machine power system [15]. The closed loop system eigenvalues obtained with approaches A and B are discussed below.

1) Approach A: Tuning All PSSs

Table A.3 shows the closed loop system eigenvalues with the 16 BFA optimized PSSs for the operating condition I. BFA optimized PSSs provide better damping to the electromechanical oscillations than the conventional designed PSS [15] for the same operating condition. The damping provided in BFA Cases 3 and 5 is better than with other cases. This corroborates the superiority of the swarming, adaptive runlength and PSO optimized fuzzy BFA. It is observed that all the BFA cases achieve a damping greater than the minimum 20% specified in the design. The damping is more in Case 1 than in Case 2; Case 3 than in Case 1; Case 5 than Case 6 and Case 3 than Case 4.

2) Appraoch B: Tuning Selected PSSs

The damping provided by the BFA optimized PSSs are better than the damping provided by conventionally designed PSS [15]. BFA with swarming is better than BFA without swarming. Improved damping can be exhibited by BFA optimized PSSs with adaptive runlength and swarming. PSO optimized fuzzy inference system based BFA brings about improvement to damping than the BFA with trial and error parameters. Table A.4 corroborates the above mentioned facts..

VII. TRANSIENT SIMULATION REULTS

This section shows the transient responses of the system with two proposed PSS design approaches under three operating conditions for two different contingencies as below.

A. Time Domain Simulations

The challenging task of tuning multiple PSSs using the different BFA variants in PST environment is reported in this paper.

Contingency 1: A 3-Φ short circuit of 150 ms is applied at bus 1 with an autorecloser. *Contingency 2*: The system is subjected to 150 ms 3-Φ short circuit at bus 9 and then the fault is removed by taking out a transmission line between buses 8 and 9, thus changing the topology of system.

The speed differences of different generators under the two contingencies for the two proposed PSS design approaches are as below.

1) Approach A: Tuning All PSSs

The responses of the generators for PSSs tuned with the different BFA variants (parameters are given in Table A.1) are discussed below:

a) Swarming

S Swarming improves the performance and the speed of convergence of BFA. Bacteria in this case gather information from the swarm and search for food. This section compares the responses of the generators with and without swarming. Swarming expedites the search process. The difference in speed of the generators for two contingencies gets damped faster in Case 1 than in Case 2. Both the responses are better than the response with conventionally designed PSS [15]. The responses of the generators are shown in Figs. 11-12.

b) Fuzzy Adaptive Run Length

Making the runlength adaptive using a fuzzy inference system improves the performance of the BFA as shown in Figs. 13 and 14. PSSs in Cases 1-6 provide better damping to the system oscillations than PSS [15]. Case 3 is better in damping the oscillations than Case 1.

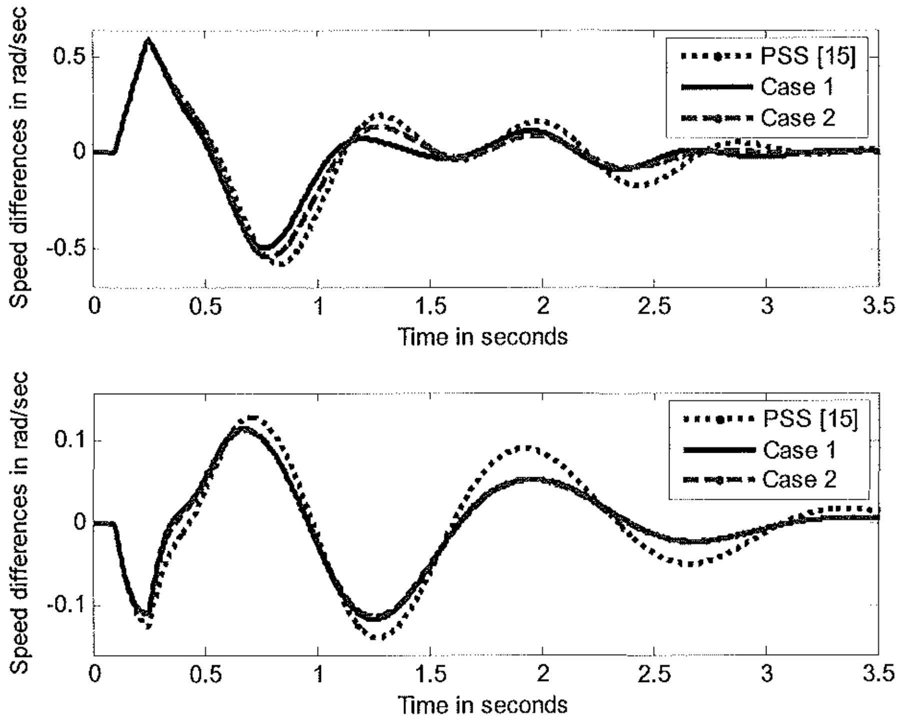

Fig. 11. Speed differences of (G2-G12) and (G15-G16) in rad/sec for a 150ms 3-Φ short circuit fault at bus 1 for operating condition II.

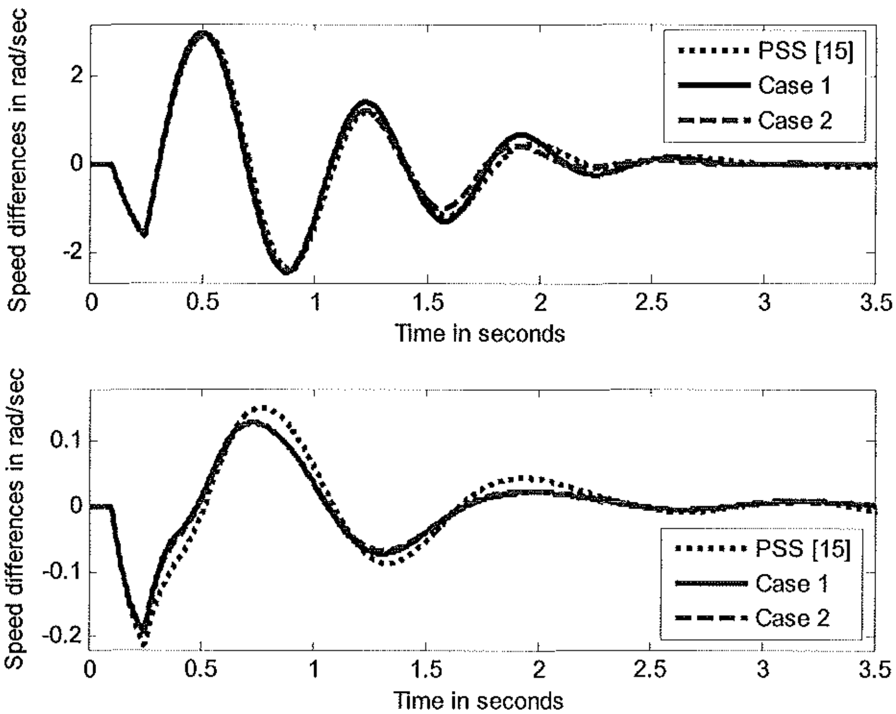

Fig. 12. Speed differences of (G1-G10) and (G15-G16) in rad/sec for a 150ms 3-Φ short circuit fault at bus 9 followed by immediate opening of the line between buses 8 and 9 for operating condition III.

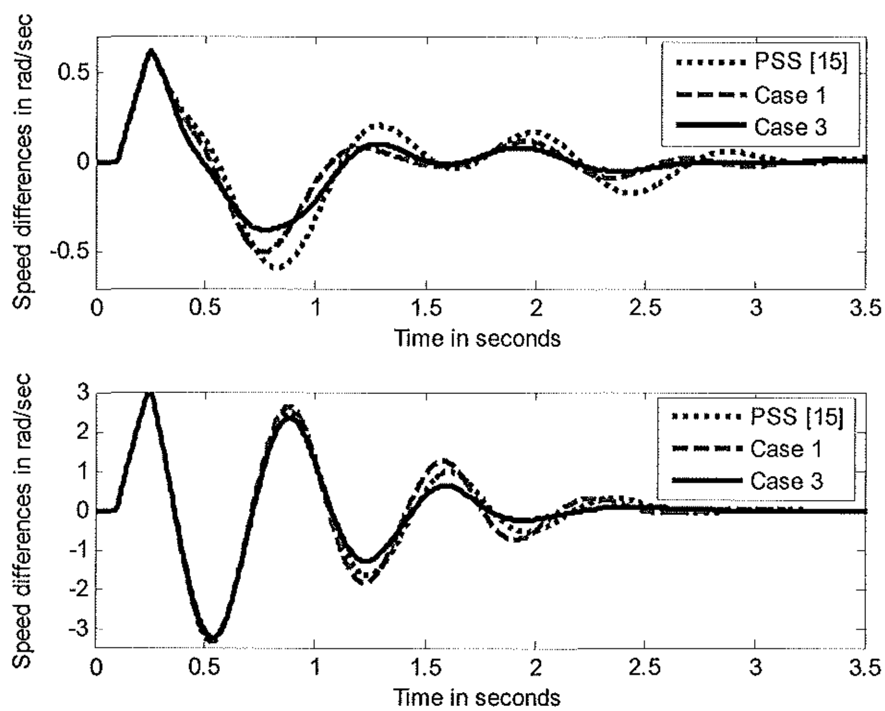

Fig. 13. Speed differences of (G2-G12) and (G10-G15) in rad/sec for a 150ms 3-Φ short circuit fault at bus 1 for operating condition I.

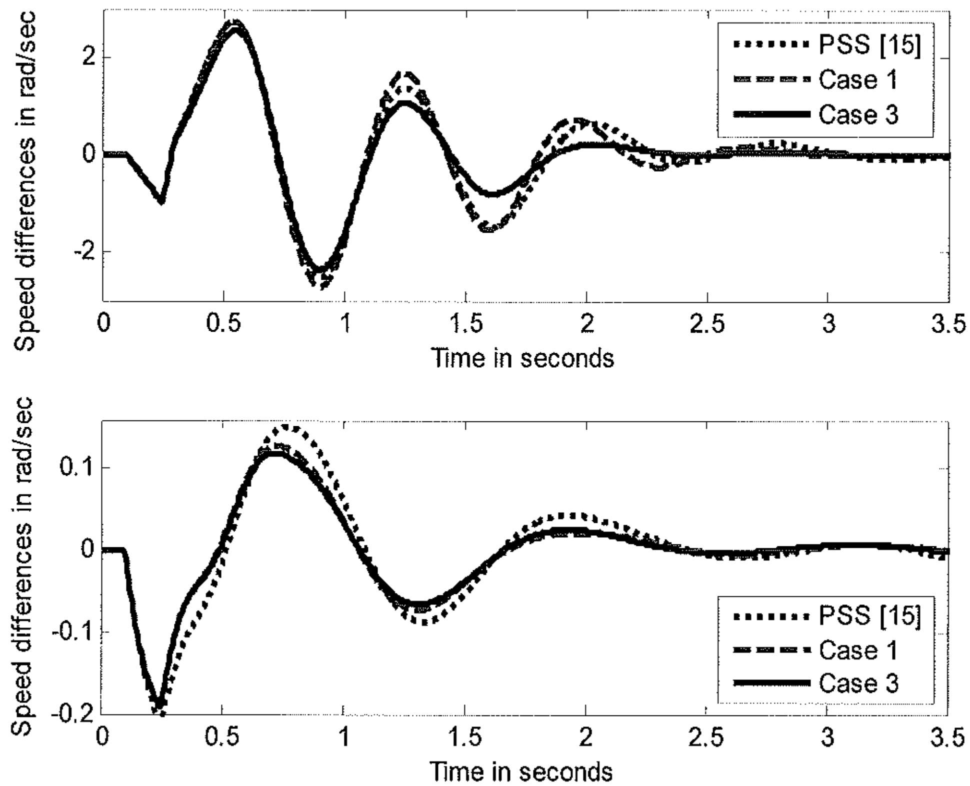

Fig. 14. Speed differences of (G2-G10) and (G15-G16) in rad/sec for a 150ms 3-Φ short circuit fault at bus 9 followed by immediate opening of the line between buses 8 and 9 for operating condition III.

c) PSO Optimized Fuzzy Adaptive Runlength

PSO optimized fuzzy inference system based BFA PSS design (Cases 5 and 6) provides better damping than the BFA PSS design with trial and error parameters (Cases 3 and 4). The responses of the generators are shown in Figs. 15 and 16.

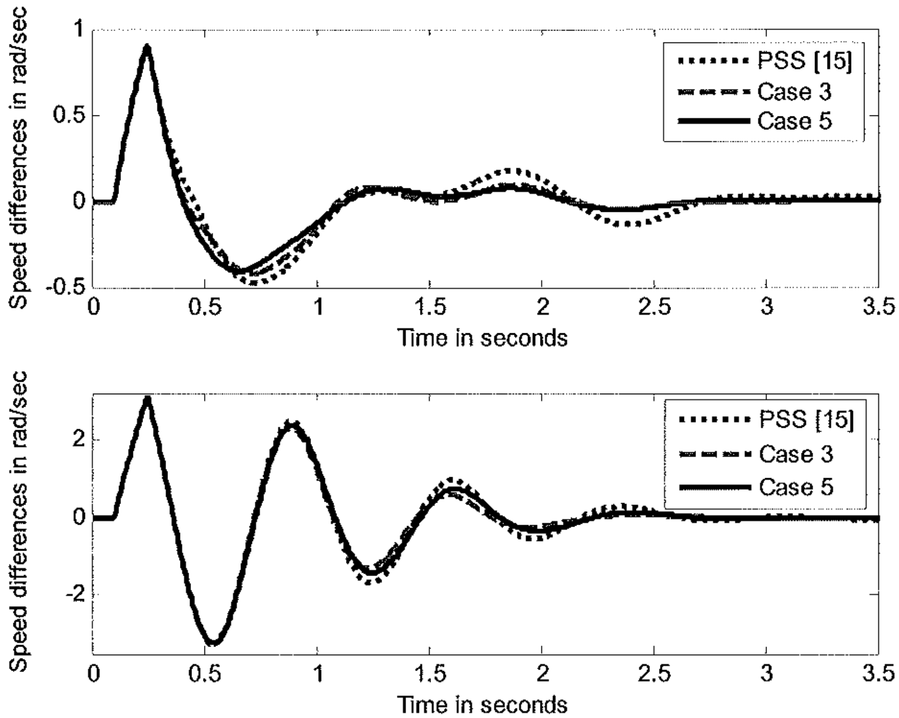

Fig. 15. Speed differences of (G3-G13) and (G10-G15) in rad/sec for a 150ms 3-Φ short circuit fault at bus 1 for operating condition II.

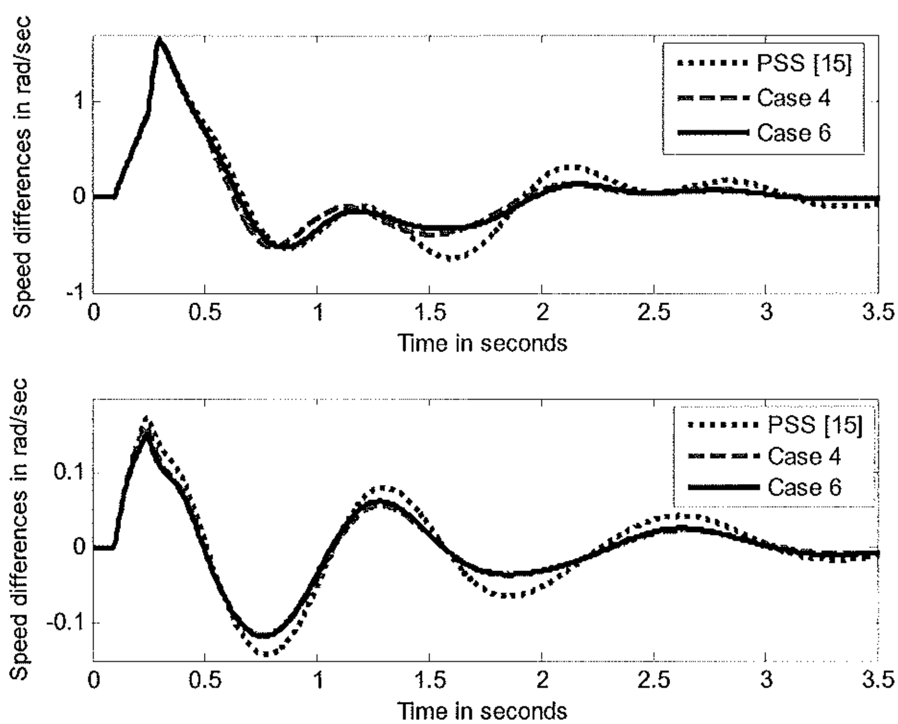

Fig. 16. Speed differences of (G1-G10) and (G15-G10) in rad/sec for a 150ms 3-Φ short circuit fault at bus 9 followed by immediate opening of the line between buses 8 and 9 for operating condition II.

2) Approach B: Tuning Selected PSSs

The responses of the generators for PSSs tuned with the different BFA variants (parameters are given in Table A.2) are discussed below.

a) Swarming

BFA optimized PSSs in Case 1 damps out the oscillations of the generators faster than the PSSs in Case 2. The responses of the speed differences of the generators are shown in Figs. 17 and 18. The responses depict that swarming improves the performance of the system.

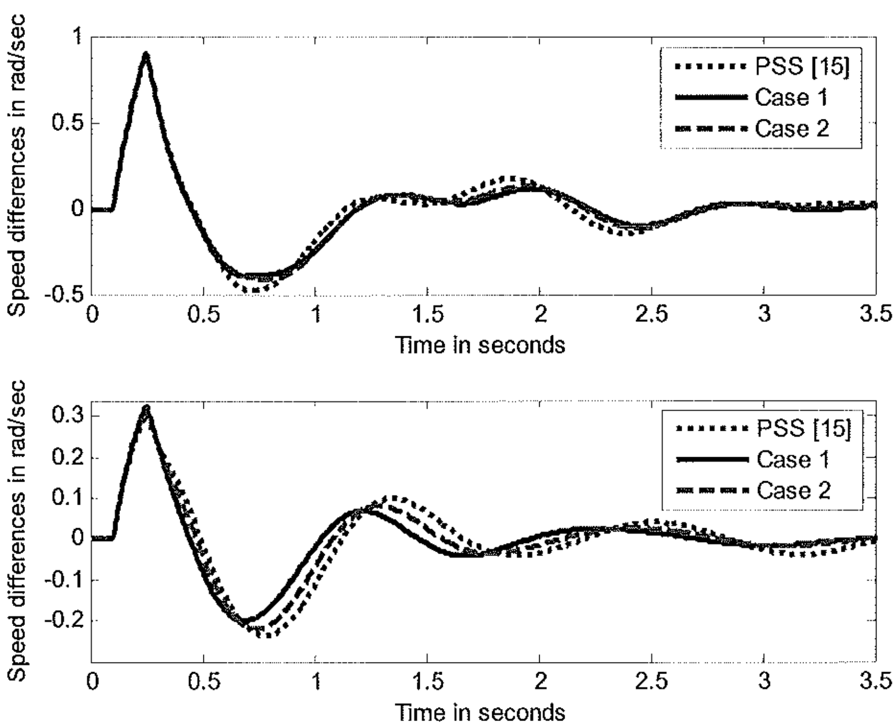

Fig. 17. Speed differences of (G3-G13) and (G14-G15) in rad/sec for an 150 ms 3-Φ short circuit fault at bus 1 for operating condition I .

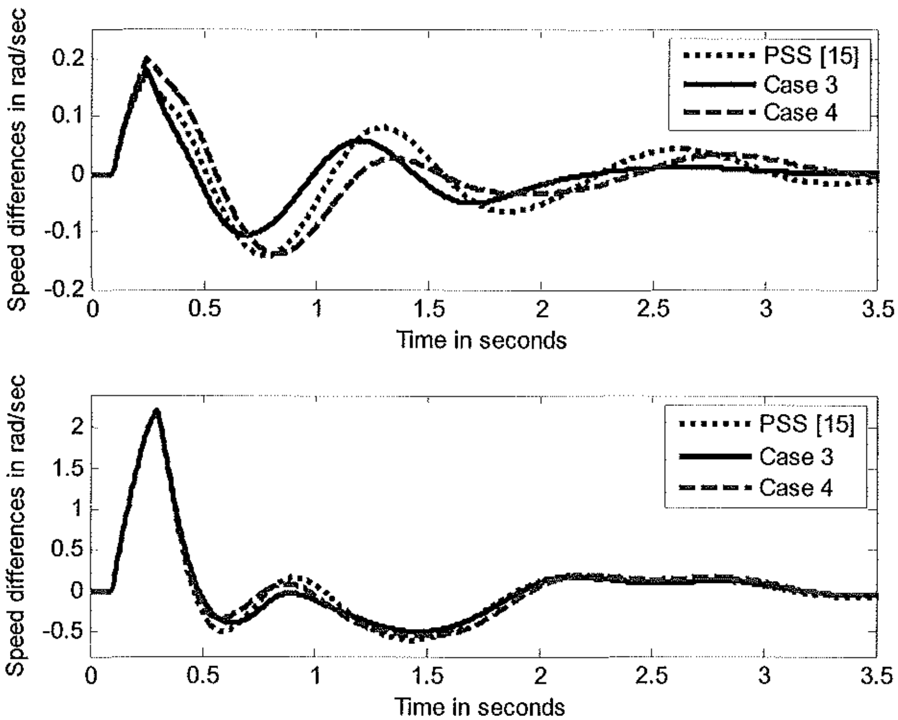

Fig. 18. Speed differences of (G15-G16) and (G12-G16) in rad/sec for a 150 ms 3-Φ short circuit fault at bus 9 followed by immediate opening of the line between buses 8 and 9 for operating condition III.

b) Fuzzy Adaptive Runlength

Adaptive the runlength using a fuzzy inference system improves the performance of the BFA as shown in Figs. 19 and 20. PSSs in Cases 1-6 provide better damping to the system oscillations than the conventionally designed PSS [15]. Case 3 is better in damping the oscillations than Case 1.

c) PSO Optimized Adaptive Fuzzy Runlength

Optimization of the fuzzy inference system parameters gives better capability to BFA to perform better than that unoptimized case and than the conventional PSS design. The responses of the generators are shown in Figs. 21 and 22..

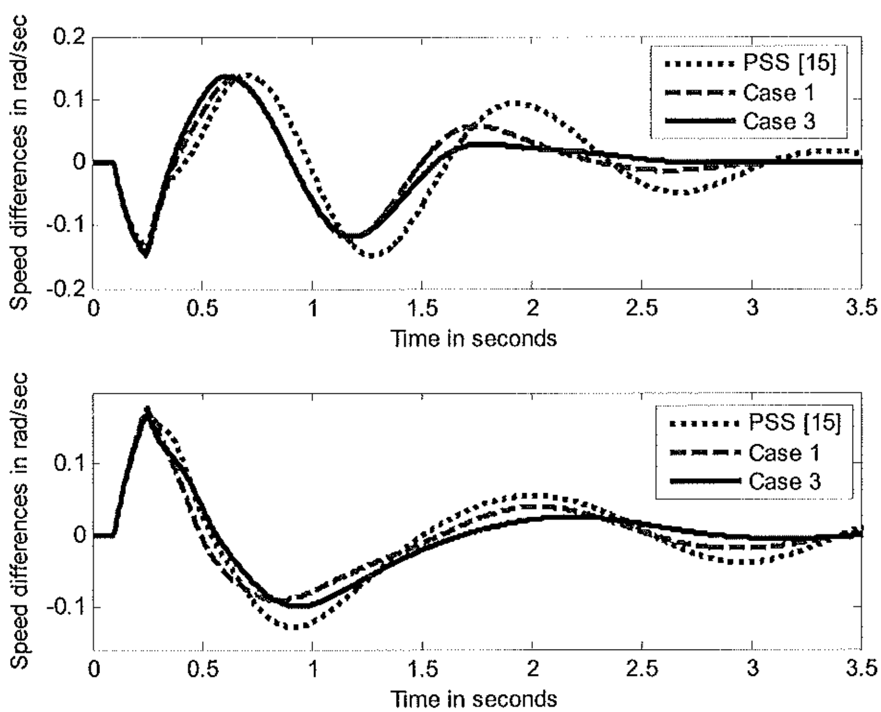

Fig. 19. Speed differences of (G15-G16) and (G14-G16) in rad/sec for an 150 ms 3-Φ short circuit fault at bus 1 for operating condition I .

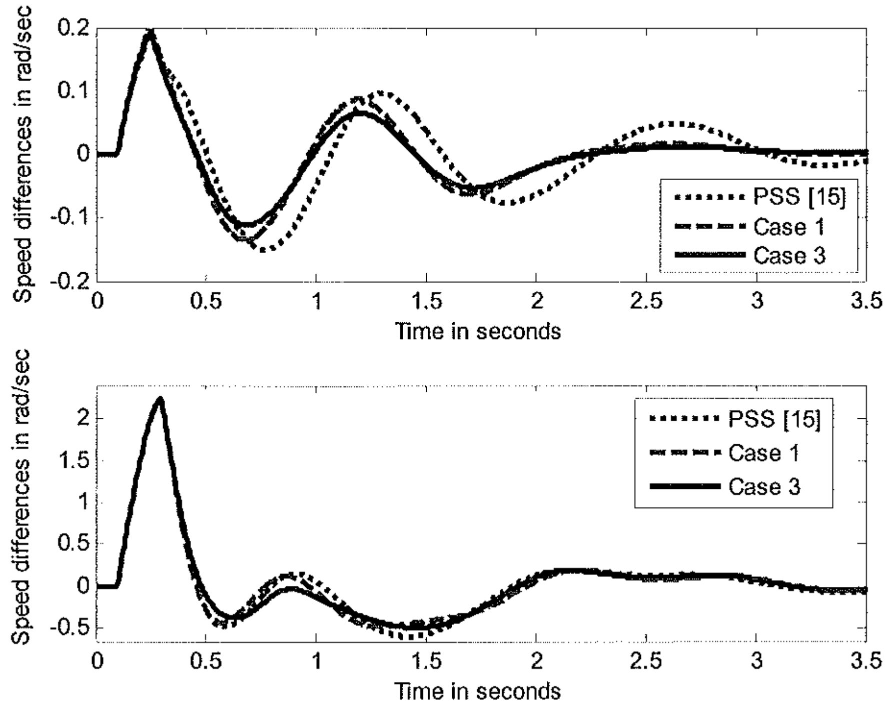

Fig. 20. Speed differences of (G14-G15) and (G2-G13) in rad/sec for a 150 ms 3-Φ short circuit fault at bus 9 followed by immediate opening of the line between buses 8 and 9 for operating condition III.

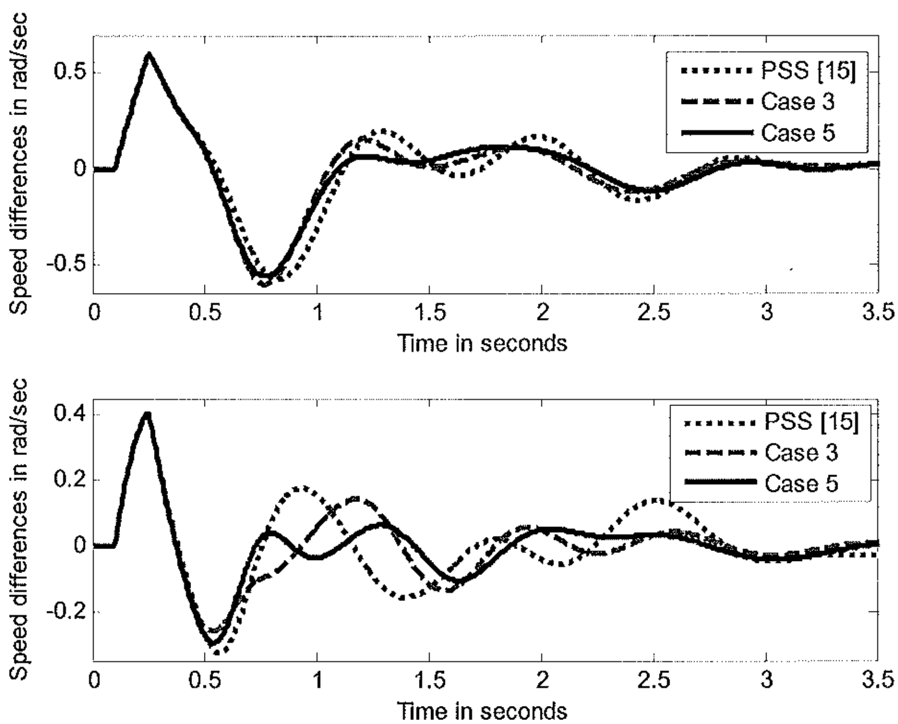

Fig. 21. Speed differences of (G2-G12) and (G12-G15) in rad/sec for an 150 ms 3-Φ short circuit fault at bus 1 for operating condition II.

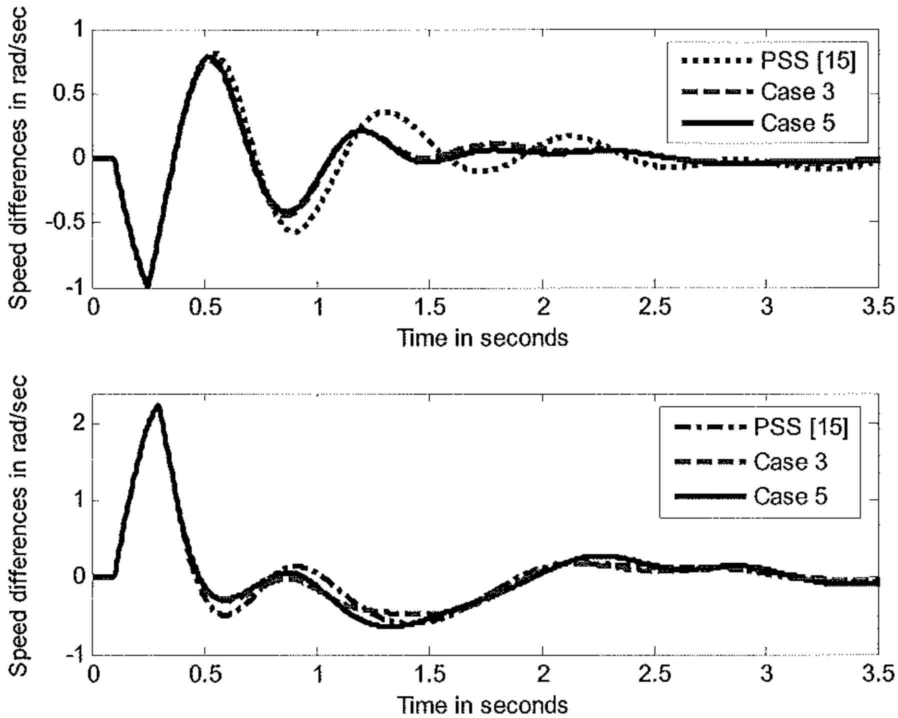

Fig. 22. Speed differences of (G14-G12) and (G2-G13) in rad/sec for a 150 ms 3-Φ short circuit fault at bus 9 followed by immediate opening of the line between buses 8 and 9 for operating condition III.

Similar responses can be seen for contingencies 1 and 2 for the three operating conditions given in Table I. The responses are not shown to limit the length of the paper. The responses in the above figures clearly show that the BFA optimized PSSs independent of the type of variants used in optimization performs better than the conventionally designed PSS [15] for any disturbance and operating conditions.

B. Transient Energy Analysis of the Damping Performance

This section compares the BFA variants in PSS tuning in terms of the transient energies. The transient energy of each of the generator for the first 3 seconds of the fault has been calculated using (10) and the total transient energy (TE) of all the generators in a given area is given by (11).

$$TE_{Gen_i} = \frac{1}{2} H_{Gen_i} \int_{t_{flt}}^{t_{flt}+3} \Delta\omega_i^2\, dt \tag{10}$$

where i is the generator number, t_{flt} is the time at which the fault is triggered.

$$TE = \sum_{i=1}^{N} TE_{Gen_i} \tag{11}$$

where N is the number of generators present in a given area of a system. The performance index (P.I), given in (12), is a measure of how the system has performed under the given conditions with the different set of PSS parameters. The higher the performance index the better the controller damping performance.

$$Performance\ Index\ (P.I) = 1/\ TE \tag{12}$$

The P.Is in each case in each area is normalized. The P.Is are normalized by dividing each P.Is with the P.Is of PSS [15] of the corresponding row. The transient energies of the system are analyzed for two PSS design approaches below:

1) Approach A: Tuning All PSSs

Table A.5 shows the P.Is for each area for each of the variants used in this study. In each of the cases of study, the P.I of the system is better than the P.I of the system having conventionally designed PSS [15]. The overall improvement in P.I provided by BFA optimized PSSs (Case 1) over conventionally designed PSS [15] is 48%, 6%, 76%, 59% and 55% for Areas 1-5 respectively for operating condition I. Similarly making the run length adaptive in Case 3 improves the P.I over Case 1 by 7.92% for Area 3. Optimizing the BFA parameters by PSO further improves the P.I of Case 5 over Case 3 by 6.08% and 45.28% for Area 1 and Area 2 respectively. Improvement in damping can be seen in the system having PSO optimized fuzzy inference system based BFA for Cases 1, 3 and 5 compared to PSSs in Cases 2, 4 and 6 respectively. These results suggest that swarming is important for better performance of BFA. Interaction amongst the bacteria makes the search process faster. The performance can be further improved by making the runlength adaptive in which the bacteria takes a small step when it is closer to the nutrient and a larger step when it is farther away from it. Performance can further be improved by optimizing the fuzzy inference system parameters by PSO. These inferences can be drawn from the Tables A.5.

2) Approach B: Tuning Selected PSSs

The P.Is of the areas is compared by subjecting the system two different contingencies as mentioned previously. BFA optimized PSSs provide better damping to the system oscillations than the conventionally designed PSS [15]. Overall P.Is of Areas 1 and 4 in Case 1 improves by 3.84% and 2.17% respectively than the P.Is in Case 2 for operating condition I. Overall P.Is of Areas 1, 3, 4 and 5 in Case 3 improves by 6.9%, 76.8%, 43.4% and 27.6% respectively for the same areas in Case 1. This can be seen from the Table A.6.

C. Comparison of PSSs Approaches A and B

This section compares two different PSSs design approaches proposed in this paper. The two studies are compared in terms of eigenvalues and transient energy analysis for different operating conditions as given in Table I.

The improvement in the speed responses of the generators employing 5 PSSs over 16 PSSs can be seen in Figs. 23 and 24 for the two contingencies. Tuning selected PSSs (25 parameters) gives better damping to the oscillations than tuning all PSSs (80 parameters).

Tables A.3 and A.4 shows the eigenvalues of the system under two PSSs design approaches. Selected 5 PSSs tuning is better than tuning all 16 PSSs in providing damping to the oscillations. Tables III and IV shows the computations involved with the two PSS design approaches. The number of fitness evaluations in Approach B is higher than Approach A. With 11 conventionally designed PSS on the 16 machine power system, Approach B has a lesser degree of freedom compared to Approach A.

Approach B performs better than Approach A for most of the cases. In Approach B, the critical generators are selected based on their participation factors in the electromechanical oscillations. Thus, the BFA is able to find parameters of PSSs connected to these critical generators and thus improved damping

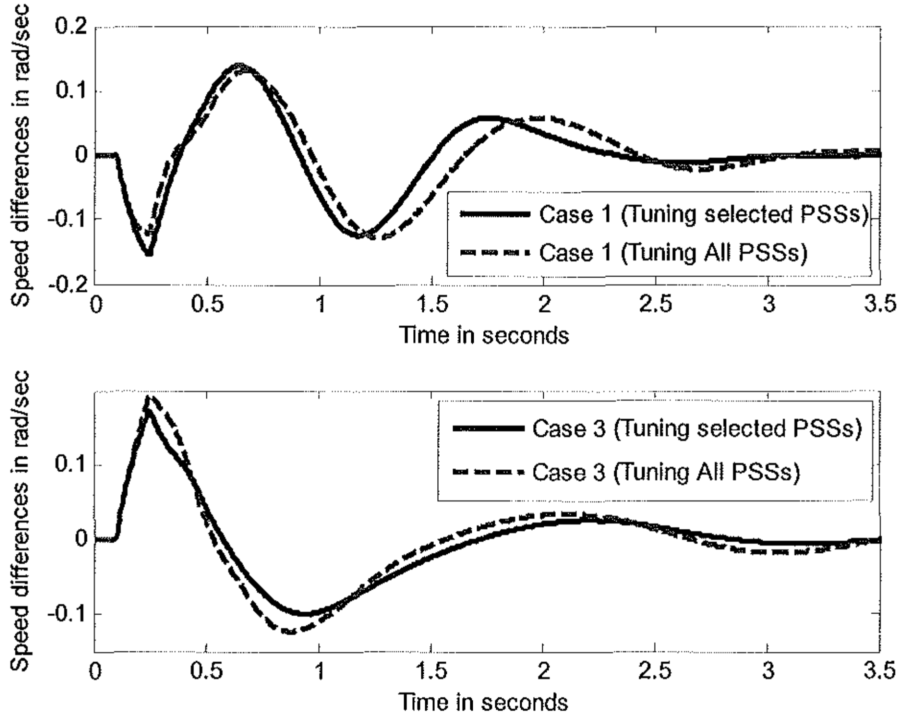

Fig 23. Speed differences of (G15-G16) and (G14-G16) in rad/sec for a 150 ms 3-Φ short circuit fault at bus 1 for operating condition III.

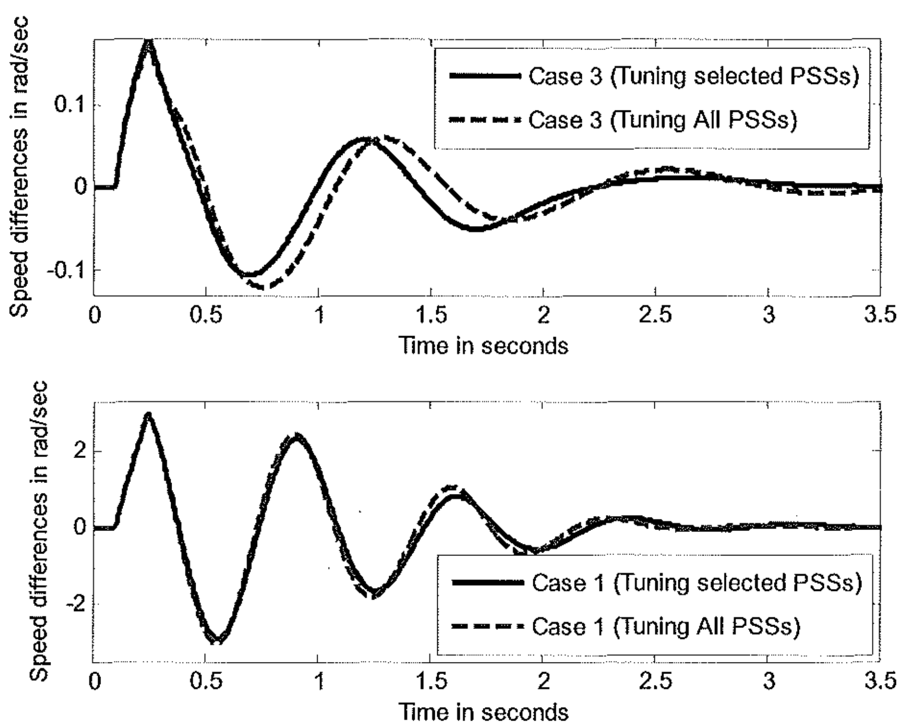

Fig. 24. Speed differences of (G15–G16) and (G14-G15) in rad/sec for a 150 ms 3-Φ short circuit fault at bus 9 followed by immediate opening of the line between buses 8 and 9 for operating condition III.

VIII. CONCLUSION

This paper has demonstrated BFA as a useful optimization tool in the PST environment. The robustness of the optimization technique can be seen from the damping provided to all the generators when subjected to disturbances. This study of the effects of the different BFA variants is quite helpful in optimizing the BFA search performance. Inclusion of swarming and adaptive runlength improves its performance. PSO optimized fuzzy inference system based BFA provides better damping than the unoptimized BFA PSSs. Damping, closed loop system eigenvalues and transient energies are the few areas which corroborated BFA to be an efficient optimization technique.

For larger systems employing multiple generators (example 100), PSSs to be tuned can be identified based on the participation factors of the generators in the electro-mechanical modes. This would bring about improved damping and thus better transient response. Future work can involve developing BFA for the design of external controllers to FACTS devices

IX. REFERENCES

[1] G. Radman and Y. Smaili, "Performance evaluation of PID power system stabilizer for synchronous generator", *Southeastern, IEEE Conf. Proc.,* 11-13 April, 1988, pp.597-601.

[2] Y. Ruhua, H, J. Eghbali and M. H. Neherir, "An online adaptive neuro-fuzzy power system stabilizer for multimachine systems", *IEEE Trans. on Power* Syst., vol. 17, pp. 1123-1131, 2002.

[3] Q. Wenzheng, V. Vittal and M. Khammash, "Decentralized power system stabilizer design using linear parameter varying approach", IEEE Trans. on Power Syst., vol. 19, pp.1951-1960, 2004.

[4] J. M. Arredono, "Results of a study on location and tuning of power system stabilizers," Int.. Journal on Electric Power Energy System, vol. 19, pp. 563-567, 1997.

[5] V. A. Maslennikov and S. M. Ustinov, "The optimization method for coordinated tuning of power system regulators," in Proc. on 12th Power System Computer Conf., PSCC, Dresden, Germany, 1996, pp. 70-75.

[6] Y. L. Abdel-Magid and M. A Abido "Optimal multiobjective design of robust power system stabilizers using genetic algorithms", IEEE Trans. om Power Syst., vol. 18, pp.1125-1132, 2003.

[7] M. A. Abido, "A novel approach to conventional power system stabilizer design using tabu search," Int. Journal Electric Power Energy System, vol. 21, pp. 443-454, June 1999.

[8] Kundur, P, "Power System Stability and Control," Electric Power Research Institute, Power System Engineering Series, McGraw-Hill, Inc.,New York, 1994.

[9] M. A. Abido and Y. L. Magid, "Optimal design of power system stabilizers using evolutionary programming", IEEE Trans. on Energy Conv., vol. 17, pp. 1123-1131, 2002.

[10] M. A. Abido, "Robust design of multi-machine power system stabilizers using simulated annealing," IEEE Trans. on Energy Conversion, vol. 15, pp.297-304, Sept. 2000.

[11] K. M. Passino, "Biomimicry of bacterial foraging for distributed optimization and control," IEEE Control System Magazine, vol. 22, Issue 3, pp. 52-67, June 2002.

[12] S. Mishra, "A hybrid fuzzy least square bacterial foraging strategy for harmonic estimation", IEEE Trans. on Evolutionary Computation, vol. 9. Issue 1, pp. 61-73, Feb. 2005.

[13] S. Mishra, "Hybrid least square adaptive bacterial foraging strategy for harmonic estimation", IEEE Proc. on Generation Transmission and Distribution, vol. 152, Issue 3, pp. 379-389, May 2005.

[14] M. Tripathy, S. Mishra and G. K. Venayagamoorthy, "Bacteria Foraging: A New Tool for Simultaneous Robust Design of UPFC Controllers", Vancouver Canada, Int.Joint Conf. on Neural Networks, July 2006, pp. 2274-2280.

[15] G. Rogers, "Power System Oscillations" Norwell, M. A. Kluwer, 2000.

[16] J. Chow/Cherry Tree Scientific Software, Power System Toolbox Version 2.0, Ontario, K0K-1S0, Canada.

[17] J. Kennedy and R. Eberhart, "Particle Swarm Optimization ," IEEE International Conf. on Neural Networks, Perth, Australia. vol. 4, pp. 1942-1948, Dec 1995.

[18] J. Kennedy, R. C. Eberhart and Y. Shi, Swarm Intelligence, Morgan Kaufmann Publishers, 2001.

[19] IEEE Recommended Practice for Excitation System Models for Power System Stability Studies, 1992. IEEE Standard 421.5.

PAPER 3

BIO-INSPIRED ALGORITHMS FOR THE DESIGN OF MULTIPLE OPTIMAL POWER SYSTEM STABILIZERS: SPPSO AND BFA

Tridib K. Das, *Student Member, IEEE*,
Ganesh K. Venayagamoorthy, *Senior Member, IEEE* and
Usman O. Aliyu, *Member, IEEE*

Abstract— Damping intra-area and inter-area oscillations are critical to optimal power flow and stability in a power system. Power System Stabilizers (PSSs) are effective damping devices as they provide auxiliary control signals to excitation systems of generators. The proper selection of PSS parameters to accommodate variations in the power system dynamics is important and is a challenging task especially when several PSSs are involved. Two classical bio-inspired algorithms, Small Population based Particle Swarm Optimization (SPPSO) and Bacterial Foraging Algorithm (BFA), are presented in this paper for the simultaneous design of multiple optimal PSSs in two power systems. A classical PSO with a small population of particles is called SPPSO in this paper. The SPPSO uses the regeneration concept, introduced in this paper, to attain the same performance as a PSO algorithm with a large population. Both algorithms use time domain information to obtain the objective function for the determination of the optimal parameters of the PSSs. The effectiveness of the two algorithms are evaluated and compared for damping the system oscillations during small and large disturbances and their robustness is illustrated using the transient energy analysis. In addition, the computational complexities of the two algorithms are also presented.

Index Terms—**Bacterial foraging, computational complexity, multi-machine power systems, Nigerian power system, particle swarm optimization, power system stabilizers, regeneration stability, small population and transient energy analysis.**

I. INTRODUCTION

In power systems, reliability and transfer capability are often limited by stability constraints like transient stability, oscillatory stability and voltage stability. Maintaining system stability presents new challenges as power systems are operating today under more stressed conditions and uncertainty than in the past. If stability problems are accurately identified and properly mitigated, significant economic gains can be realized. Power System Stabilizers (PSSs) are used as supplementary control devices to provide extra damping and improve the dynamic performance of the power system. PSSs are very effective controllers in enhancing the damping of low-frequency oscillations; since they can increase damping torque for inter -area modes by introducing additional signals into the excitation controllers of the generators. These oscillations come into existence when generators fall out of step from each other. Depending on their location in the system, some generators participate in a single mode of oscillation, while others participate in more than one mode.

Researchers have been putting lots of efforts in the design of optimal PSSs to satisfy different system requirements. Several PSS design techniques have been reported [1]-[3]. These algorithms employ large number of particles or individuals in the optimization. The involvement of large number of particles takes a significant amount of computation time. This may pose a serious problem for systems which desire faster convergence. To avoid burden on time and resources, the need for developing small population based algorithms like the Micro-Genetic Algorithm (μ-GA) [4] comes into mind. μ-GA with its small population size and re-initialization process is capable of improving the exploitation characteristics of the GA without affecting its exploration characteristics. The involvement of fewer numbers of particles can be considered as first step towards online optimization, where fast plugging of updated parameters is desired. However, studies have revealed that GA has a degraded performance if the function to be optimized is epistatic (where parameters to be optimized are highly co-related) [5]. The GA algorithm also has the demerit of premature convergence. This paper therefore, explores the efficacies of two new small population based algorithms for the tuning of PSS parameters.

Two bio-inspired algorithms, a Small Population based Particle Swarm Optimization (SPPSO) and Bacterial Foraging Algorithm (BFA), for the simultaneous design of multiple optimal PSSs is presented. SPPSO is capable of exploration and exploitation like PSO. The involvement of a number of stages in BFA greatly reduces the possibility of getting trapped in the local minima during the search process. This approach is a sincere effort by the authors towards determining efficacies of small population based algorithms as a first step towards online optimization. These algorithms are selected in an effort to overcome computational overburden. The objective function formulated for the optimization takes into consideration time domain information from the PSCAD/EMTDC models [6], making it suitable for future online optimization. The effectiveness of SPPSO and BFA as optimization algorithms for simultaneous multiple optimal PSSs design are evaluated on a two- area benchmark system [7] and the Nigerian power system [8]. The robustness of the optimally tuned PSSs is further compared using the transient energy analysis.

The rest of the paper is organized as follows: Section II presents the power systems considered in this study. Section III describes the bio-inspired algorithms used. Section IV explains the design of an optimal PSS. Section V presents some simulation results. Section VI presents some analysis and discussions on SPPSO and BFA. Finally, the conclusions and future work are given in Section VII.

II. TWO MULTI-MACHINE POWER SYSTEMS

In this study, two different power systems are considered. The first one is an 11 bus and 4 machine system and the second one is a 25 bus and 7 machine system.

A. Two Area Multi-Machine Power System

The two area power system used in this study is simulated in the PSCAD/EMTDC environment which allows detailed representation of the power system dynamics. The small two area power system shown in Fig. 1, consists of two fully symmetrically areas linked together by two transmission lines. Each area is equipped with two identical synchronous generators rated 20kV/900 MVA. All generators are equipped with identical speed governors and turbines, exciters and Automatic Voltage Regulators (AVRs) and PSSs. The loads in the two areas are such that Area 1 is exporting about 413 MW to Area 2. This power network is specifically designed to study low frequency electromechanical oscillations in two interconnected power systems [7].

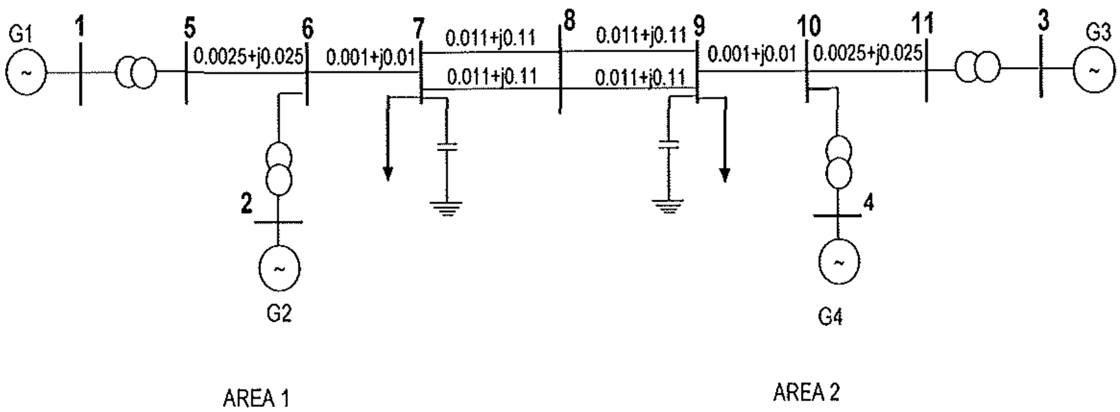

Fig. 1. Two area multi-machine power system.

The PSSs provide additional input signal (V_{pss}) to the voltage regulators/excitation systems to damp out the power oscillations. Some commonly used input signals are rotor speed deviation ($\Delta\omega_r$), accelerating power and frequency. A typical PSS block diagram is shown in Fig. 2. It consists of an amplifier block of gain constant K, a block having a washout time constant T_w and two lead-lag compensators with time constants T_1 to T_4. The gain and the four lead-lag compensator time constants are to be selected for optimal performance over a wide range of operating conditions.

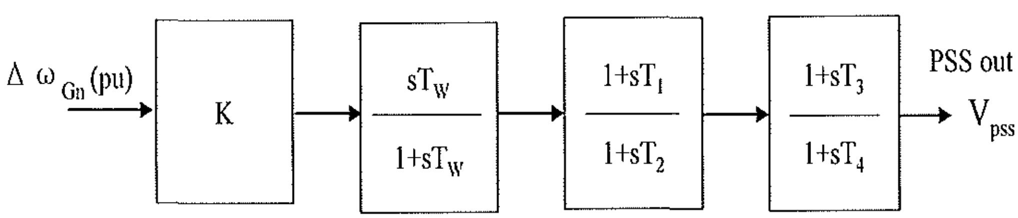

Fig. 2. Block diagram of a power system stabilizer.

B. Nigerian Power System

The Nigerian 330kV, 25 bus grid power system is shown in Fig. 3 above. It consists of 7 generating units in two distinct areas (4 thermal units and 3 hydro units), 7 generator step-up transformers equipped with tap changers, and compensation reactors of different discrete values located at 8 different nodes. This system has two inter-area modes (hydro and thermal) and several intra-area modes (hydro and thermal) [8]. There is a damping of 3.8 % for 1.223 Hz mode experienced by the hydro generating units and damping of 3.4 % for 1.225 Hz mode experienced by the thermal generating units. This makes the system potentially unstable when experiencing large disturbances. Thus, the need for design of optimal PSSs for the hydro and thermal areas. Hence, two PSSs of the form in Fig. 2 are added to the excitations of generators at Shiroro and Egbin power stations (Fig. 3).

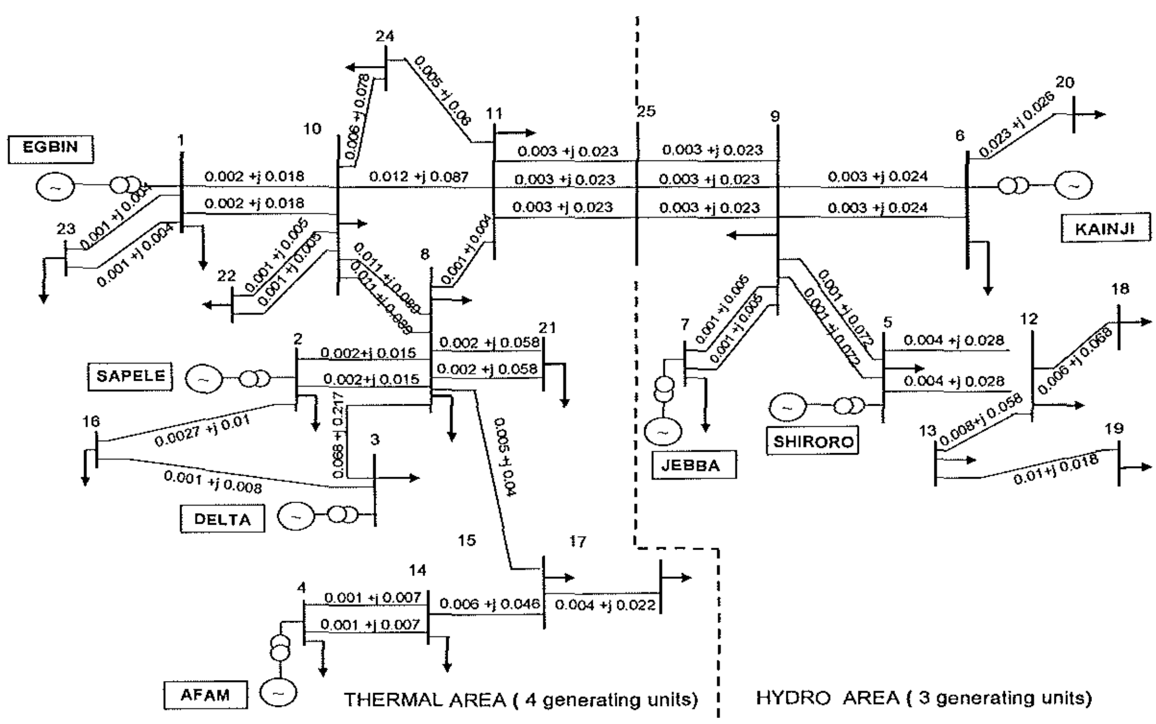

Fig. 3. The Nigerian 330kV, 25 bus grid power system.

III. BIO-INSPIRED ALORITHMS WITH SMALL POPULATION

The beauty of particle swarm optimization lies in its ability to explore and exploit the search space by varying its parameters (inertia weight and acceleration constants). Bacterial foraging algorithm due to its unique operators (elimination and dispersal events) can find favorable regions during search. These unique features of the algorithms overcome the premature convergence problem and enhance the search capability. Hence, they are suitable algorithms for simultaneous design of multiple optimal PSSs. Improvements over the classical PSO and BFA algorithms have been reported in the literature [9]-[12]. Improvements to the classical PSO are reported by modifying the PSO parameters using adaptive critics [9] or by introducing a mutation operator [10]. Similarly, improvements to the classical BFA are reported by varying the run step length using fuzzy [11] or adaptive [12] techniques. The authors in this paper however compare the classical BFA [13] and PSO [14] with algorithms employing a small population. The comparison is made in terms of their computational complexities and speed for the design of multiple optimal PSSs. The two classical bio-inspired algorithms used in this paper are described below.

A. Small Population Based Particle Swarm Optimization (SPPSO) Algorithm

The SPPSO algorithm is derived from the PSO algorithm. PSO is a form of evolutionary computation technique (a search method based on natural systems) developed by Kennedy and Eberhart [9], [10]. PSO like GA is a population (swarm) based optimization tool. However, unlike in GA, individuals are not eliminated from the population from one generation to the next. One major difference between particle swarm and traditional evolutionary computation methods is that particles' velocities are adjusted, while evolutionary individuals' positions are acted upon; it is as if the "fate" is altered rather than the "state" of the particle swarm individuals [11].

Each potential solution, called *particle*, is given a random velocity and is flown through the problem space. The particles have memory and each particle keeps track of previous best position and corresponding fitness. The previous best value is called the p_{best} of the particle and represented as p_{id}. Thus, p_{id} is related only to a particular particle i. The best value of all the particles' p_{best} in the swarm is called the g_{best} and is represented as p_{gd}. The basic concept of PSO technique lies in accelerating each particle towards its p_{id} and the p_{gd} locations at each time step. The amount of acceleration with respect to both p_{id} and p_{gd} locations is given random weighting.

Fig. 4 illustrates briefly the concept of PSO, where x_i is current position, x_{i+1} is modified position, v_{ini} is initial velocity, v_{mod} is modified velocity, v_{pid} is velocity considering p_{id} and v_{pgd} is velocity considering p_{gd}. The following steps explain the procedure in the classical PSO algorithm.

1) Initialize a population of particles with random positions and velocities in d dimensions of the problem space.
2) For each particle, evaluate the desired optimization fitness function.
3) Compare every particle's fitness evaluation with its p_{best} value, p_{id}. If current value is better than p_{id}, then set p_{id} value equal to the current value and the p_{id} location equal to the current location in d-dimensional space.
4) Compare the updated p_{best} values with the population's previous g_{best} value, p_{gd}. If any of p_{best} values is better than p_{gd}, then update p_{gd} and its parameters.

5) Compute the new velocities and positions of the particles according to (1). v_{id} and x_{id} represent the velocity and position of i^{th} particle in d^{th} dimension respectively and, $rand_1$ and $rand_2$ are two uniform random functions.

$$\begin{aligned} x_{id}(k+1) = x_{id}(k) + w \times v_{id}(k) + c_1 \times rand_1 \times (p_{id}(k) - x_{id}(k)) \\ + c_2 \times rand_2 \times (p_{gd}(k) - x_{id}(k)) \end{aligned} \tag{1}$$

6) Repeat from step 2 until a specified terminal condition is met, usually a sufficiently good fitness or a maximum number of iterations.

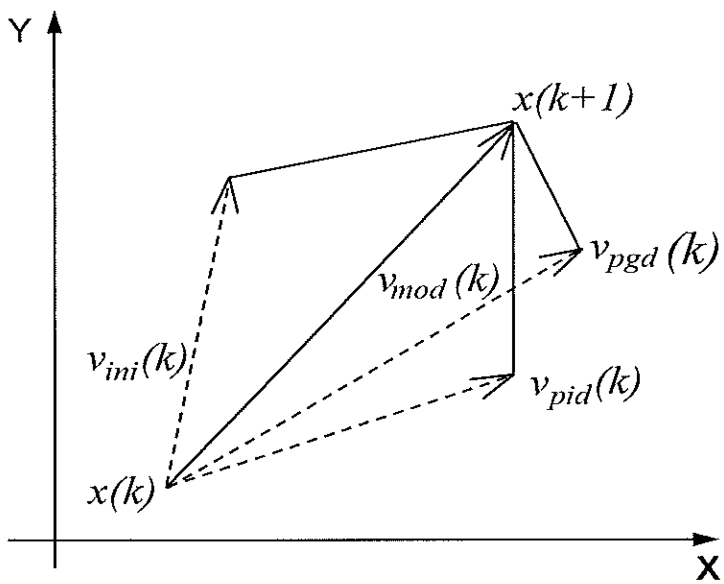

Fig. 4. Movement of a PSO particle in two dimensions from one instant k to another instant $k+1$.

The PSO parameter w in (1) is called the inertia weight, which controls the exploration and exploitation of the search space. Local minima are avoided by small local neighborhood, but faster convergence is obtained by larger global neighborhood and in general, global neighborhood is preferred.

The velocity is restricted to a certain dynamic range. v_{max} is the maximum allowable velocity for the particles i.e. in case the velocity of the particle exceeds v_{max} then it is reduced to v_{max}. Thus, resolution and fitness of search depends on v_{max}. If v_{max} is too high, then particles will move beyond good solution and if v_{max} is too low, then particles will be trapped in local minima. c_1 and c_2 termed as cognition and social components respectively are the acceleration constants which change the velocity of a particle towards p_{id} and p_{gd} (generally somewhere between p_{id} and p_{gd}).

The SPPSO is a classical PSO algorithm but with a small population. The concept of regeneration is introduced by the authors to give particles the ability to keep carrying out the search despite a small population. The particles are regenerated after every N iterations retaining their previous g_{best} (p_{gd}) and p_{best} (p_{id}) fitness values and positions. The selection of the value N is crucial in realizing an efficient SPPSO algorithm. If the value of N is low, the new particles may be regenerated too quickly and in turn disturb the search process. Thus the particles will move erratically in the search space. On the other hand, if the particles are regenerated at a higher value of N the search process will be delayed. Randomizing the positions and velocities of the particles every N iterations aids the particles in avoiding local minima and finding the global minimum. The regeneration concept drastically reduces the number of evaluations required to find the best solution and each evaluation is less computational intensive compared to the classical PSO algorithm.

B. Bacterial Foraging Algorithm (BFA)

Animals with poor foraging strategies (methods for locating, handling and ingesting food) are eliminated by the process of natural selection. This process in turn favors the propagation of genes of those animals that have been successful in their foraging strategies. Species who have better food searching ability are capable of enjoying reproductive success and the ones with poor search ability are either eliminated or reshaped. The BFA mimics the foraging behavior of the E. coli bacterium present in our intestines. This algorithm has been successfully demonstrated as an optimization tool in power system harmonic estimation [11-12]. The foraging process consists of four stages: chemotaxis, swarming, reproduction and elimination [13] and these are briefly explained below. More information on the BFA is given in [13].

1) Chemotaxis:

This stage mimics the bacteria's ability to climb to regions of nutrient concentration, avoiding noxious substances, and searching for way out of neutral media. The bacterium usually takes a tumble followed by a tumble or a swim to carry out this search. For N_c number of chemotactic steps the direction of movement after a tumble is given by:

$$\theta^{i}(j+1,k,l) = \theta(j,k,l) + C(i) \times \phi(j) \tag{2}$$

where C(i) is the step size taken in direction of the tumble by the i^{th} bacterium, j is the index for the chemotactic step taken, k is the index for the number of reproduction step, l is the index for the number of elimination and dispersal event and $\phi(j)$ is the unit length random direction taken at each step. In other published applications [11-12], the number of bacteria is reported to be eight or more in the BFA. In this study, the authors experimented with the step size for a small population of bacteria (five or less) and found that using a linearly decreasing step size resulted in faster convergence for the BFA. Thus, the population of the BFA and SPPSO are comparable.

If the cost at $\theta^{i}(j+1,k,l)$ is better than the cost at $\theta^{i}(j,k,l)$ then the bacterium takes another step of size C(i) in that direction (swimming). This process is continued until the number of steps taken is not greater than N_s (counter for number of swim steps). This is done to prevent the bacteria trapped in local minima. There should be a tradeoff between the values of N_s to be chosen. It could be half of the value of N_c.

2) *Swarming:*

The bacteria in times of stresses release attractants to signal other bacteria to swarm together. It however also releases a repellant to signal others to be at a minimum distance from it. Thus all of them have a cell to cell attraction via attractant and cell to cell repulsion via repellant. The equation given below represents the swarming behavior in the bacteria foraging.

$$\begin{aligned} J_{cc}(\theta, P(j,k,l)) &= \sum_{i=1}^{S} J_{cc}{}^{i}(\theta, \theta^{i}(j,k,l)) \\ &= \sum_{i=1}^{S}[-d_{attract} \exp(-w_{attract} \sum_{m=1}^{p}(\theta_m - \theta_m{}^{i})^2)] \\ &+ \sum_{i=1}^{S}[h_{repellant} \exp(-w_{repellant} \sum_{m=1}^{p}(\theta_m - \theta_m{}^{i})^2)] \end{aligned} \tag{3}$$

where, $d_{attract}$= depth of the attractant effect, $w_{attract}$= measure of the width of the attractant, $h_{repellant}$= $d_{attract}$ = height of the repellant effect, $w_{repellant}$=measure of the width of the repellant, p = number of parameters to be optimized, S = number of bacteria.

The total cost function to be optimized by the BFA can be represented by:

$$J(i, j, k, l) + J_{cc}(\theta, P) \tag{4}$$

where $J(i, j, k, l)$ is the cost function for the optimal PSS design described in Section IV and given by (5). The value of $d_{attract}$ and $h_{repellant}$ should be same so that after certain number of iterations after the bacteria converge there should not be any contribution from the swarming part ($J_{cc}= 0$). The value of $w_{attract}$ and $w_{repellant}$ should be such that when the bacteria move farther from each other the penalty added to the cost function by J_{cc} should be large.

3) Reproduction:

After all the N_c chemotactic steps have been covered, a reproduction step takes place. S_r (S_r=S/2) bacteria having a lower survival value (less healthy) die and the remaining S_r are allowed to split into two thus maintaining a constant population size.

4) Elimination and Dispersal:

Environment changes for the bacteria all the time. Bacteria are either destroyed or moved to different parts of the intestine resulting in positive and negative influences on their lives. This process is incorporated in the BFA. For each elimination and dispersal event each bacterium is eliminated with a probability of p_{ed}. A low value of N_{ed} (number of elimination and dispersal events) dictates that the algorithm will not rely on random elimination and dispersal events to try to find favorable regions. A high value increases computational complexity but allows bacteria to find favorable regions. The p_{ed} should not be large either or else it would lead to an exhaustive search. The number of reproduction and elimination and dispersal events is problem specific. The values used in this study are decided by trial and error.

IV. OPTIMAL PSS DESIGN

This section describes how the bio-inspired algorithms are used to determine the optimal parameters of the PSSs for the power systems in Figs. 1 and 3. For each PSS, the optimal parameters are determined by the SPPSO and BFA, i.e. 20 parameters (4 PSSs) in total for the small two area multi-machine power system and 10 parameters (2 PSSs) for Nigerian power system. Just like any other optimization problem, a cost or an objective function needs to be formulated for the optimal PSS design. The objective in the optimal PSS design is to maximize damping; in other words minimize the overshoots and settling time in system oscillations.

The integrated transient response area of the speed deviation of the generators is used as the cost function to be minimized by the bio-inspired algorithms. This in turn means improved system damping. Since in an interconnected power system there are several generators that experience the impact of a transient, a single objective function is formulated that accounts for the impact seen by all generators and is given by (5)

$$J' = \sum_{n=1}^{N} \sum_{Gn}^{m} J_{Gn} \tag{5}$$

where

$$J_{G_n} = \sum_{j=1}^{NP} \sum_{t=t_0}^{t_2/\Delta t} (\Delta\omega_{Gn}(t)) \times (A \times (t - t_0) \times \Delta t) \tag{6}$$

where NP is the number of operating points for which optimization is carried out, N is the number of faults for which the optimization is carried out, A is a weighing factor, m is the number of generators in the system, $\Delta\omega_{Gn}$ is the speed deviation of the generator Gn, t_0 is the time the fault is cleared, t_0 and t_2 are the start and end times of the simulation respectively considered for the transient area calculation, Δt is the speed signal sampling period, t is the simulation time in seconds. Limits are placed on the PSSs parameters to keep the system within the stability margin during the online optimization. The PSS parameter limits used for the two area multimachine power system (Fig. 1) and the Nigerian power system (Fig. 3) are given in Table I.

Table I
Parameters Limits Used in the Optimization

Two Area Power System	Nigerian Power System
$5 \leq K \leq 30$	$0.05 \leq K \leq 30$
$0.005 \leq T_1 \leq 2$	$0.005 \leq T_1 \leq 2$
$0.001 \leq T_2 \leq 1$	$0.001 \leq T_2 \leq 1$
$0.01 \leq T_3 \leq 10$	$0.01 \leq T_3 \leq 10$
$0.005 \leq T_4 \leq 15$	$0.005 \leq T_4 \leq 15$

The optimization is carried out by subjecting the power systems to a small disturbance and a large disturbance. In this study, first, a temporary 200ms duration transmission line outage is placed (on one of the tie lines) and when the system returns to steady state, a three phase short circuit of 200ms duration is applied at the middle of tie lines. The value of J^t is computed using (5) for a given set of parameters for the PSSs and the bio-inspired algorithms are applied to compute the new set of parameters.

V. SIMULATION RESULTS

The entire simulation is carried out with the power systems simulated in the PSCAD/EMTDC environment and the bio-inspired algorithms implemented in FORTRAN. The challenging task of using the bio-inspired algorithms to tune multiple

PSSs in PSCAD from the time domain information is reported for the first time to the knowledge of the authors. The number of particles used in SPPSO is five and the number of bacteria in BFA is four. The values of parameters used in this study are: $N_c = 4$, $N_{re} = 15$, $N_{ed} = 10$, $N_s = 4$, $d_{att} = 0.01$, $h_{rep} = 0.01$, $w_{att} = 0.4$, $w_{rep} = 0.42$, $w = 0.8$, $c_1 = 2.0$ and $c_2 = 2.0$. The fitness evaluations of the particles and the bacteria are carried out online. The performance of the PSSs optimized by the PSO, SPPSO and BFA algorithms are evaluated on Kundur's two area and the Nigerian power systems for small and large disturbances.

A. Two Area Multi-Machine Power System

Three tests are carried out and the responses are studied for the five cases mentioned below. The respective optimized PSS parameters for these cases are given in Table A.1

- *No PSS:* In this case, the power system is without any PSSs.
- *Conventional PSS (CPSS):* The PSSs parameters in this case are those obtained from [17]. These parameters are the same for all four generators and are as follows: K= 20.00, T_1=0.05s, T_2=0.02s, T_3=3.00s and T_4=5.40s respectively.
- *PSO optimized PSS:* The PSSs parameters in this case are the optimized parameters obtained using the PSO algorithm.
- *SPPSO optimized PSS:* The PSSs parameters in this case are the optimized parameters obtained using the SPPSO algorithm.
- *BFA optimized PSS:* The PSSs parameters in this case are the optimized parameters obtained using the BFA algorithm.

1) Single Fault – Temporary Transmission Line Outage:

A 200ms transmission line outage is applied between buses 8 and 9 in Fig.1. This is a small type of disturbance for a power system where a transmission line between buses 8 and 9 is removed for 200ms. The speed responses of generators G2 and G3 for the above mentioned cases are shown in Figs. 5 and 6 respectively. Similar responses are observed for generators G1 and G4 and are not shown to limit the length of the paper. The addition of PSSs improved the damping in the system oscillations. Response of G2 clearly shows that the response of PSO and SPPSO are comparable. PSO and SPPSO optimized PSSs exhibit better damping than BFA optimized PSSs which in turn exhibits better damping than CPSS. For generator G3, the performances of SPPSO and PSO optimized PSSs are comparable and better than those with BFA optimized PSSs and CPSS.

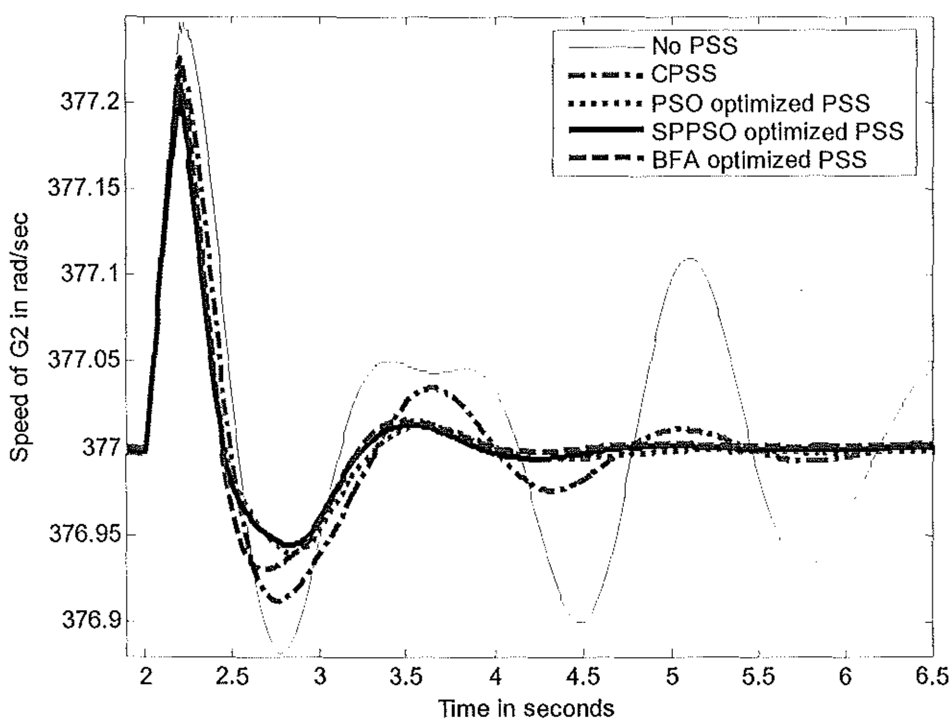

Fig. 5. Speed response of generator G2 for a 200ms line outage between buses 8 and 9.

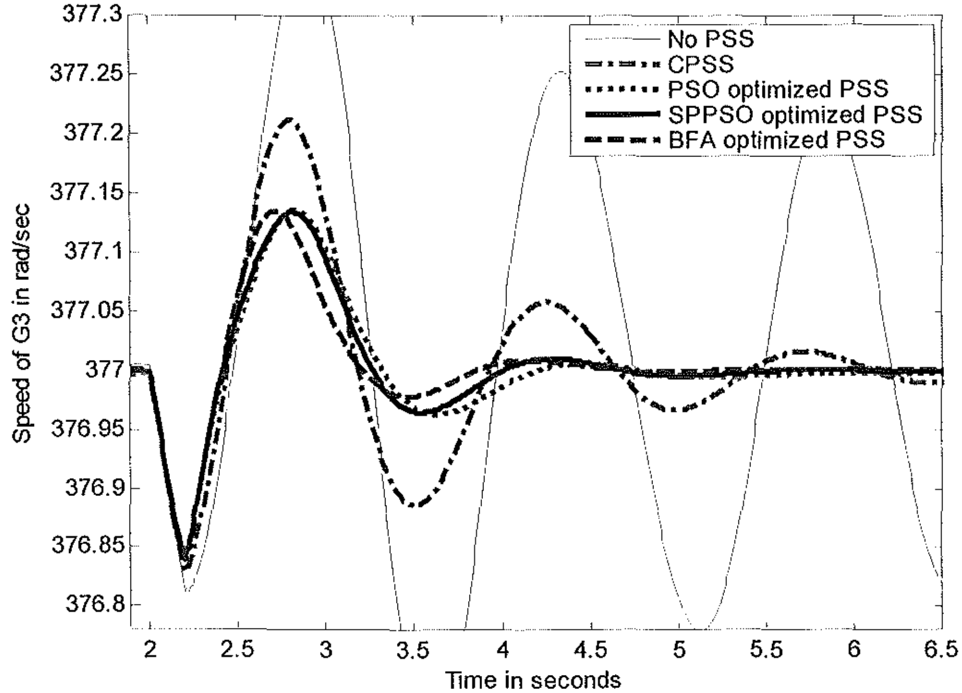

Fig. 6. Speed response of generator G3 for a 200ms line outage between buses 8 and 9.

2) Single Fault – Three Phase Short Circuit:

A three phase short circuit of 200ms duration is applied at bus 8 in Fig.1. This is a severe fault compared to the transmission line outage of 200 ms. The speed responses of generators G1 and G4 for the above mentioned cases are shown in Figs. 7 and 8 respectively. Similar responses are observed for generators G2 and G3. It is clear from these figures once again that the PSSs improve the damping in the system; system having CPSS/ BFA optimized PSSs/SPPSO/PSO optimized PSSs show better damping than the system without PSSs. Damping is best with systems having PSO and SPPSO optimized PSS followed by BFA optimized PSSs and CPSSs. The speed responses for PSO and SPPSO optimized PSS have a settling time of about a second faster than BFA optimized PSSs.

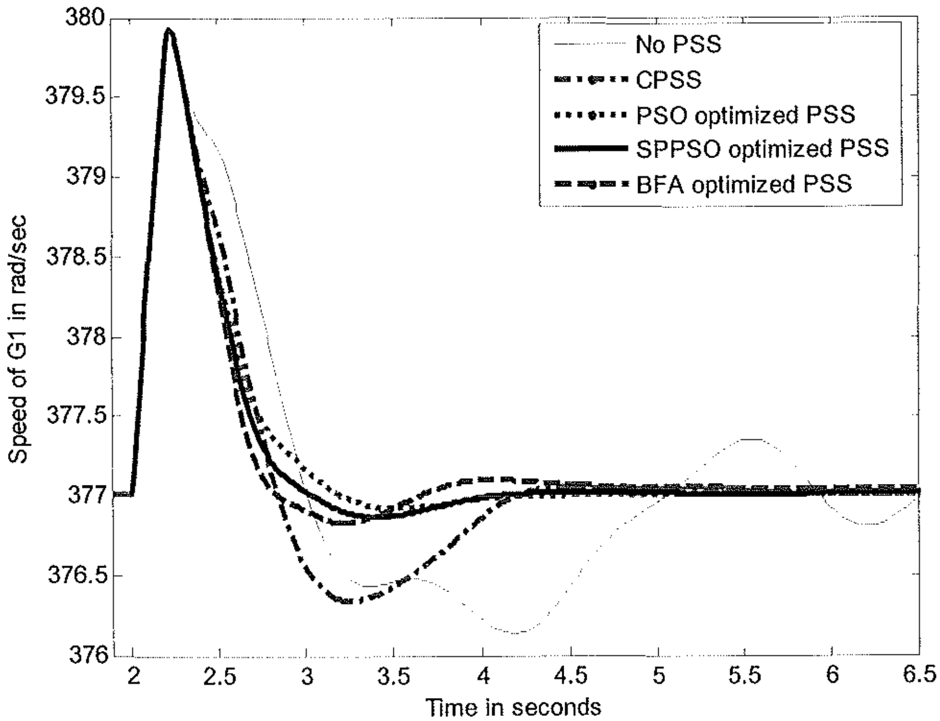

Fig. 7. Speed response of generator G1 for a 3 phase 200ms short circuit applied at bus 8.

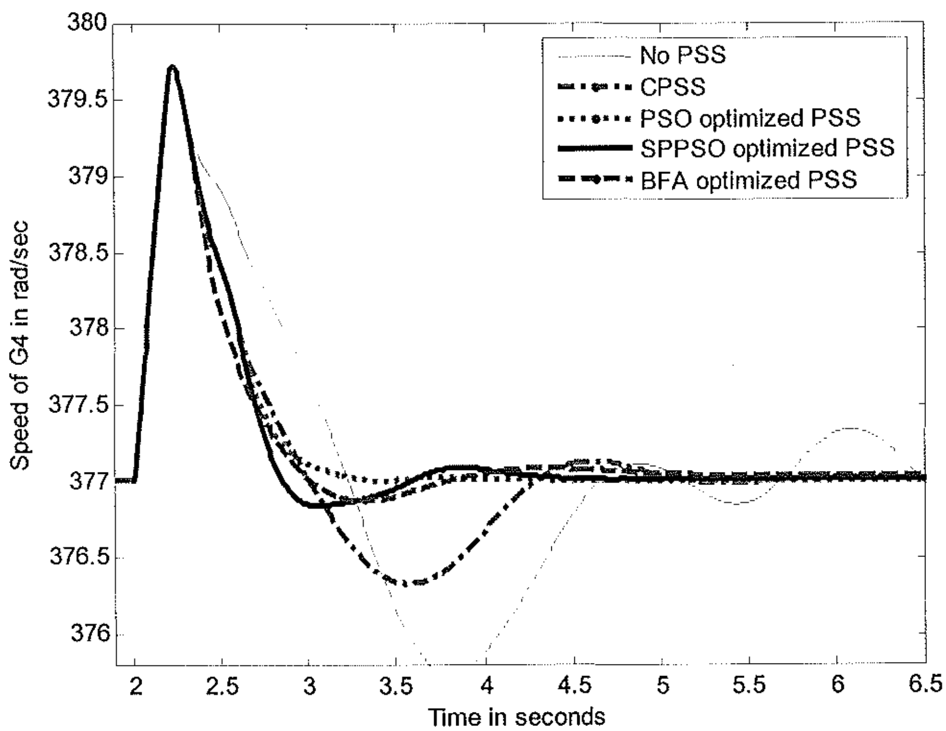

Fig. 8. Speed response of generator G4 for a 3 phase 200ms short circuit applied at bus 8.

3) Combined Fault – Short Circuit Followed by a Transmission Line Outage:

A double cascaded fault is now applied to test the robustness of the different optimized PSSs parameters. A 100ms three phase short circuit at bus 8 is applied followed immediately by a 100ms line outage between buses 8 and 9 immediately in Fig. 1. The speed responses of generators G1 and G3 for the above mentioned cases are shown in Figs. 9 and 10 respectively. Similar responses are observed for generators G2 and G4. The damping of the system improves from system having no PSS to SPPSO optimized PSSs. The system without any PSS have minimum or no damping hence the oscillations are sustained. The system with SPPSO and PSO optimized PSSs is the best. The performance of the system with the SPPSO optimized PSSs is much better than the system having BFA optimized PSSs to provide damping during multiple faults.

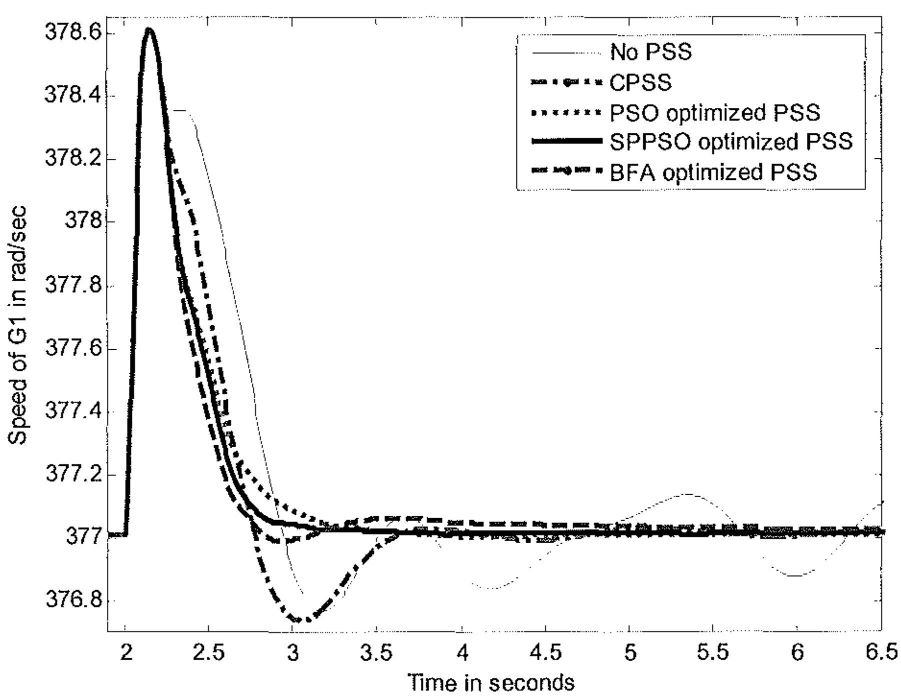

Fig. 9. Speed response of generator G1 for a 3 phase 100ms short circuit applied at bus 8, followed by immediate 100ms line outage between buses 8 and 9.

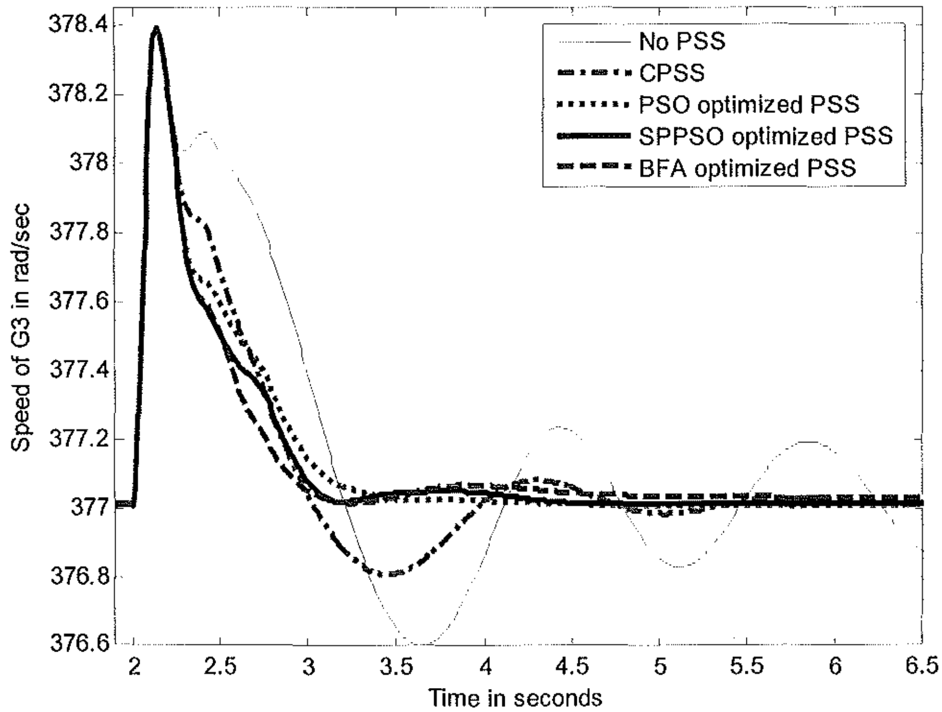

Fig. 10. Speed response of generator G3 for a 3 phase 100ms short circuit applied at bus 8, followed by immediate 100ms line outage between buses 8 and 9.

B. Nigerian Power System

The following three tests are carried out and the responses are studied for three cases mentioned below and the respective optimized PSS parameters for these cases are given in Table A.2.

- *No PSS:* In this case, the power system is without any PSSs.
- *PSO optimized PSS:* The PSSs parameters in this case are the optimized parameters obtained using the PSO algorithm.
- *SPPSO optimized PSS:* The PSSs parameters in this case are the optimized parameters obtained using the SPPSO algorithm.

- *BFA optimized PSS:* The PSSs parameters in this case are the optimized parameters obtained using the BFA algorithm.

1) Single Fault – Temporary Transmission Line Outage:

A temporary 200ms duration transmission line outage is placed on the tie-lines connecting the hydro and thermal areas between buses 9 and 11. The speed responses of the generators in both hydro and thermal areas for the above mentioned cases are shown in Figs. 11 and 12 respectively. The Nigerian power system without PSS for a short duration transmission line outage exhibits minimum damping and maximum overshoot with many oscillatory modes. The overshoot and the settling time are minimized with the SPPSO optimized PSSs. Here, it is clear that even for disturbances not as severe as a three phase short circuit, the SPPSO outperforms the BFA. This is because the PSO and SPPSO optimized PSSs gains are greater than the BFA optimized PSSs gains.

2) Single Fault – Three Phase Short Circuit:

A three phase short circuit of 200ms duration is applied at the middle of the tie line (bus 25) connecting the thermal area to the hydro area in Fig. 3. The speed responses of two generators, one in the thermal area (Delta) and the other in the hydro area (Shiroro) are shown in Figs. 13 and 14 respectively. The PSSs with SPPSO optimized parameters exhibit the best performance followed by PSO optimized parameters further followed by BFA optimized parameters. The settling time is minimized and the system gets damped quickly within 3 to 4 seconds of the disturbance for PSO and SPPSO optimized PSSs parameters.

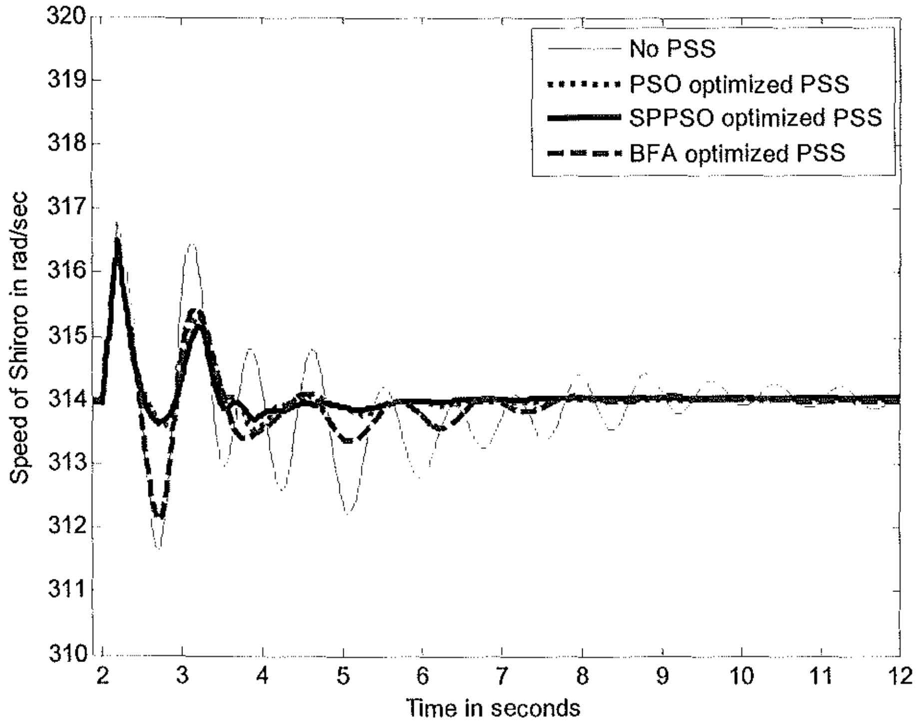

Fig. 11. Speed response of Shiroro (hydro area) for a 200ms line outage between buses 9 and 11.

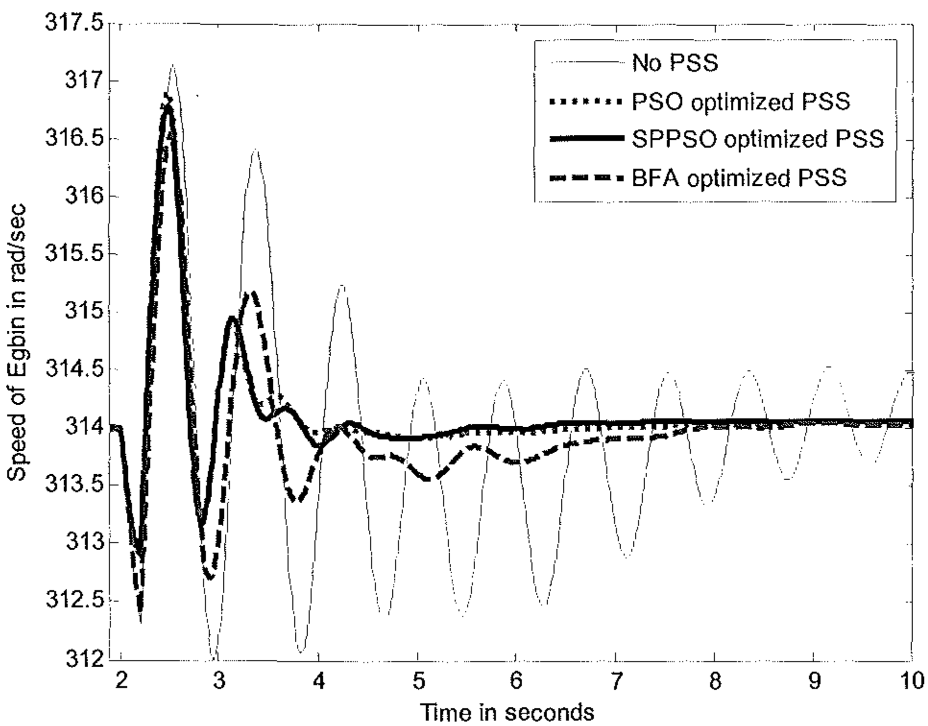

Fig. 12. Speed response of Egbin (thermal area) for a 200ms line outage between buses 9 and 11.

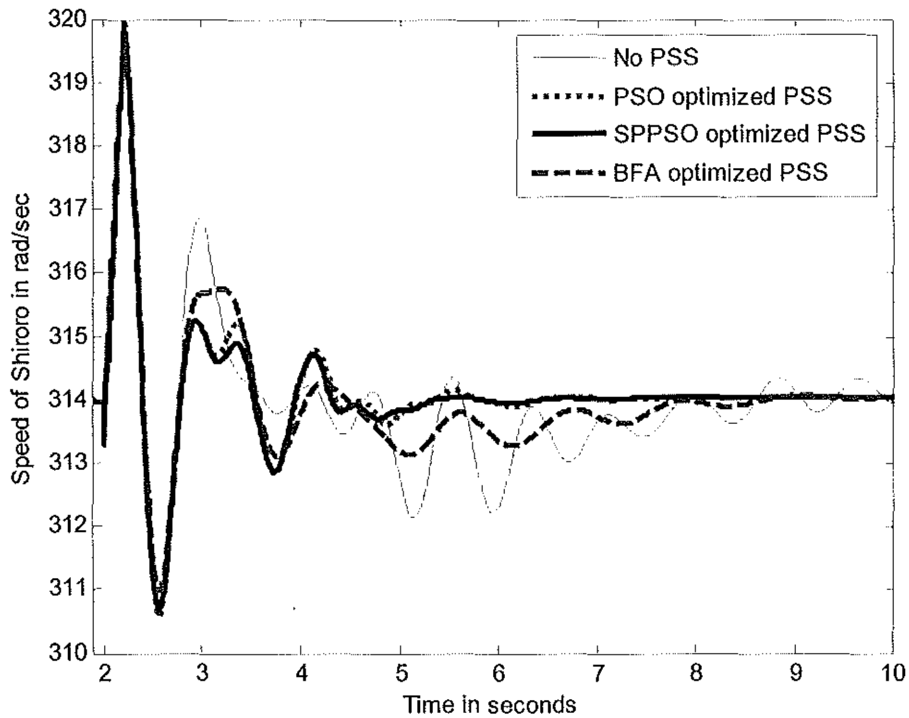

Fig. 13. Speed response of Shiroro (hydro area) for a 3 phase 200ms short circuit applied at the tie line between thermal and hydro power stations.

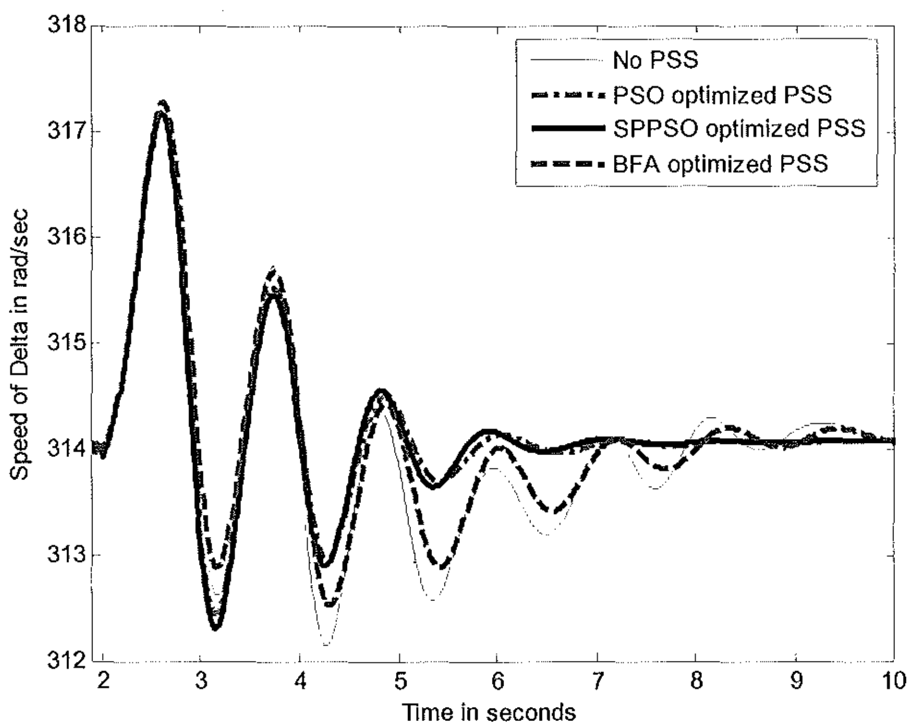

Fig. 14. Speed response of Delta (thermal area) for a 3 phase 200ms short circuit applied at the tie line between thermal and hydro power stations.

3) Combined Fault – Short Circuit Followed by a Transmission Line Outage:

A double cascaded fault is now applied to test the robustness of the different optimized PSSs parameters. A 100ms short circuit is applied at the middle of the tie lines connecting thermal area to the hydro area (bus 25) immediately followed by a 100ms line outage of the tie lines between buses 9 and 11. The speed responses of the generators in hydro and thermal areas for the above mentioned cases are shown in Figs. 15 and 16 respectively. The performance of the system with PSO and SPPSO optimized parameters is the best. The oscillations in the system settle down faster and overshoot minimized for PSS parameters obtained using PSO and SPPSO.

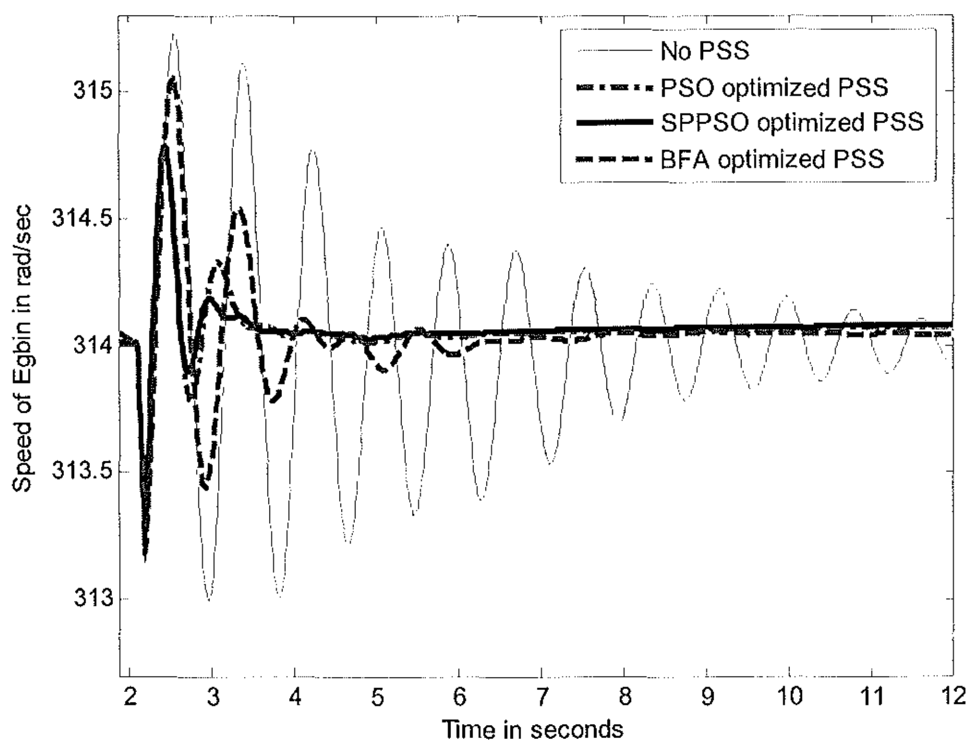

Fig. 15. Speed response of Shiroro (hydro area) for a 3 phase 100ms short circuit applied at bus 25 followed by immediate 100ms line outage of the tie lines between the buses 9 and 11 (Fig. 3).

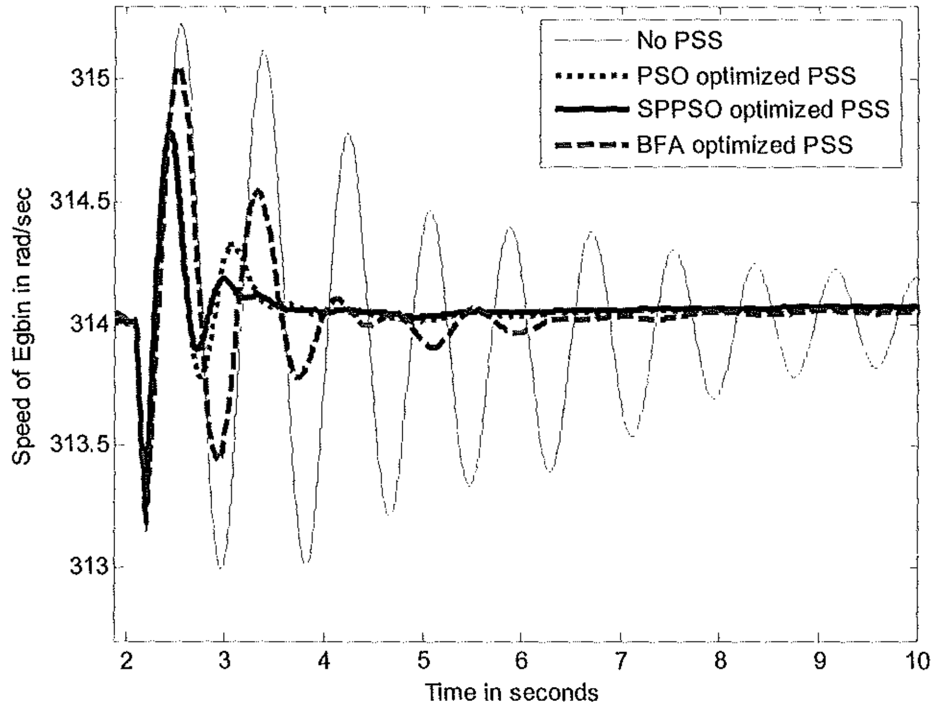

Fig. 16. Speed response of Egbin (thermal area) for a 3 phase 100ms short circuit applied at bus 25 followed by immediate 100ms line outage of the tie lines between the buses 9 and 11 (Fig. 3).

VI. DISCUSSIONS ON SPPSO AND BFA PSS DESIGNS

This section compares the two bio-inspired algorithms for the design of multiple optimal PSS in terms of their computational complexities and performances of the optimized PSSs using the transient energy analysis.

A. Computational Complexities

The number of fitness evaluations involved in BFA is more than those involved in SPPSO for a single iteration. In BFA, for each bacterium, the fitness is evaluated a number of times. The number of stages involved makes the algorithm computationally intensive. In addition, the number of factors involved in BFA is twice as much as in PSO/SPPSO as shown in Table II and this makes BFA more complex. These factors need to be properly chosen for the algorithm to perform optimally. The dependence of the algorithm on so many parameters makes it handicapped in finding out the global optimum. Performance of the BFA can be improved by choosing the parameters effectively [12]. Similarly, PSO performance can also be improved [9]. However, this paper mainly focuses in comparing the classical BFA with the classical PSO. In BFA, for every reproduction and elimination and dispersal stage, a fitness evaluation is carried out after all the chemotactic steps are covered; hence $S \times N_c$ evaluations are performed. This is equivalent to one PSO iteration. In the case of SPPSO/PSO, *m/n* fitness evaluations are carried out for *m/n* particles respectively.

Table II
Factors Affecting the Performance of SPPSO & BFA Algorithms

No. of factors	PSO/ SPPSO	BFA
1	w	$d_{attract}$
2	c_1	$w_{attract}$
3	c_2	$h_{repellant}$
4	v_{max}	$w_{repellant}$
5	v_{min}	N_c
6	$-N$	N_{re}
7	-	N_{ed}
8	-	N_s
9	-	$C(i)$
10	-	P_{ed}

The average fitness over ten trials of best bacterium (BFA) and best particle (PSO and SPPSO) versus the number of iterations during the optimization process is shown in Figs. 17 and 18 for the two multimachine power systems respectively. It can be seen that fitness of best particle in SPPSO and PSO converges faster as compared to fitness of best bacterium in BFA for same number of iterations (150) in both power systems under study. PSO and SPPSO are faster in finding lower fitness values than BFA. For the two-area power system, PSO converges to a lower average fitness than SPPSO. The fitness however is close to the fitness at which SPPSO converges. The x-coordinate is the number of iterations, which if interpreted in terms of fitness evaluations would be high for PSO. If fitness closer to what PSO achieves in 150 iterations can be achieved in fewer computations and less time, then the algorithm could be a considered as a potential online optimization tool. Computational burden is reduced drastically in SPPSO.

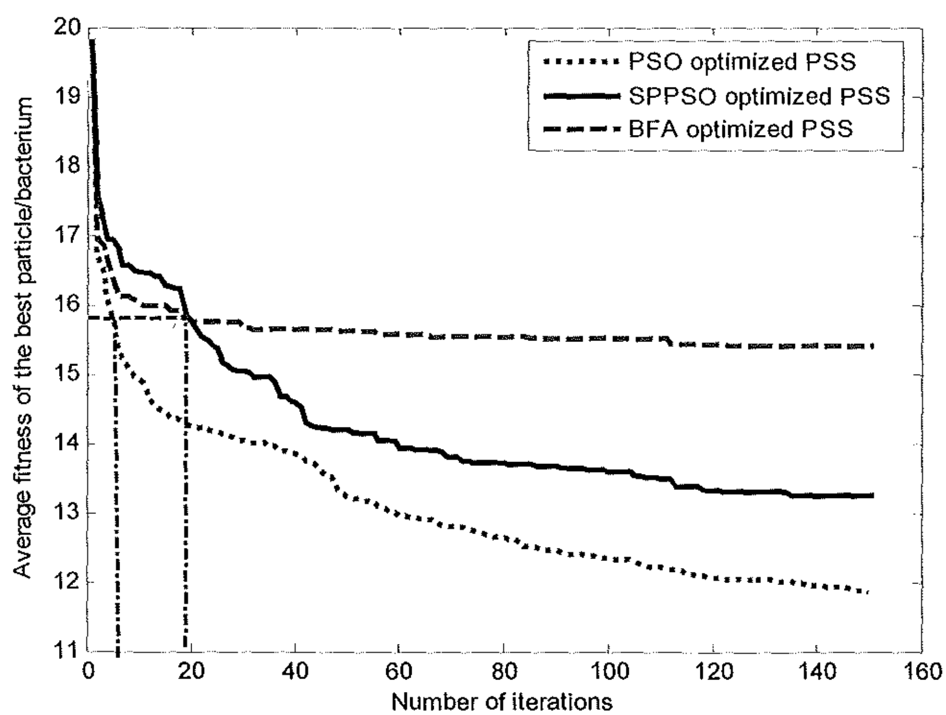

Fig. 17. Average fitness of the best particle in PSO, SPPSO and the best bacterium in BFA for the study on the two-area multi machine power system.

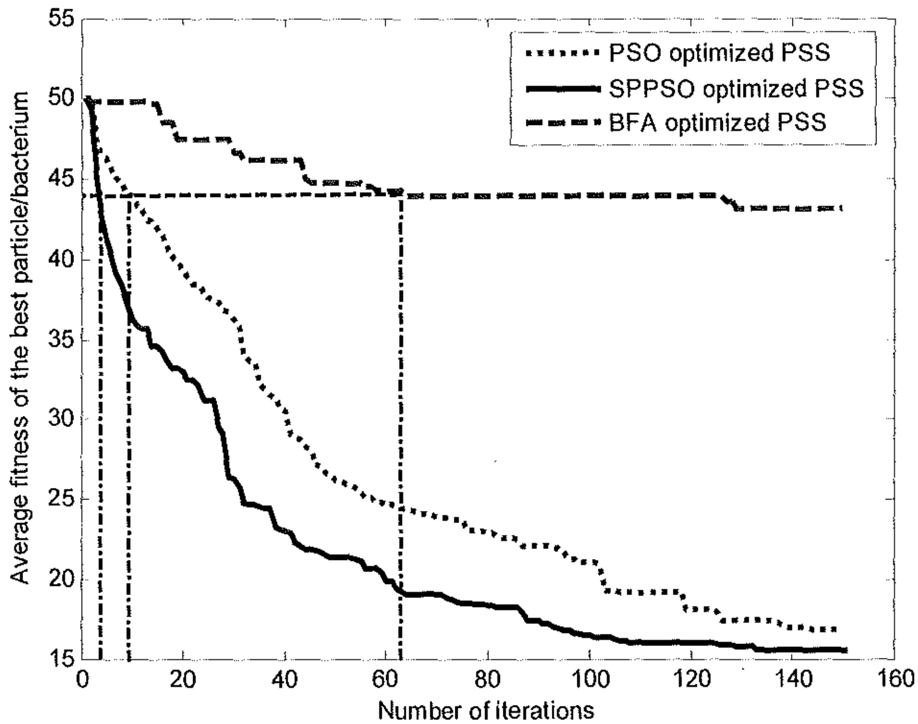

Fig. 18. Average fitness of the best particle in PSO, SPPSO and the best bacterium in BFA for the study on the Nigerian power system.

Table III gives a general comparative analysis on the computational complexities of the PSO, SPPSO and the BFA algorithms. Table IV shows specifically the computational complexities of the algorithms in the optimal PSSs design for the two area multimachine power system in Fig. 1. The number of fitness evaluations in PSO is higher than the number of fitness evaluations in BFA and SPPSO; the number of additions and multiplications in SPPSO is lower in comparison to that of the PSO and BFA. For example, from Fig. 17 for the two area multimachine power system, to attain a fitness of 15.57, PSO takes 5 iterations; SPPSO takes 19 iterations while BFA takes 19 iterations. This translates to PSO carrying out 100 fitness evaluations, 10000 additions and 10000 multiplications while SPPSO carrying out 95 fitness evaluations, 9500 additions and

9500 multiplications while BFA carrying out 304 fitness evaluations, 24016 additions and 13376 multiplications respectively.

Likewise from Fig. 18 for the Nigerian power system, it can be seen that to attain a fitness value of 43.97, PSO, SPPSO and BFA take 9, 4 and 63 iterations respectively. This translates to the PSO carrying out 180 fitness evaluations, 18000 additions and 18000 multiplications ; SPPSO carrying out 20 fitness evaluations, 2000 additions and 2000 multiplications while BFA carrying out 1008 fitness evaluations, 39312 additions and 24192 multiplications. This clearly shows that the SPPSO is much less computationally intensive, at least twice as fast on a small power system (Fig.1) and at least an order faster in the Nigerian power system (Fig. 3) as compared to the BFA algorithm.

SPPSO along with PSO and BFA are allowed to run on a Intel (R) 4, 2.79 GHz processor and time required to finish 150 iterations in PSCAD platform are tabulated in Table V. Table V also includes the computation time involved in optimizing the PSS parameters on Power System Toolbox(PST) platform [18]. It can be clearly seen that the SPPSO takes least amount of time in its row to finish 150 iterations in PSCAD and to reach zero fitness in PST. For the Nigerian power system the time required to finish 150 iterations on the PSCAD platform is 766325 s 37908.35s and 481539.23s, for PSO, SPPSO and BFA respectively. Thus systems employing SPPSO can save considerable amount of time and therefore is feasible for online optimization with high speed processors.

Table III
Comparison of General Computational Complexities of PSO, SPPSO, and BFA

Algorithms	Number of stages involved	Number of Fitness Evaluations	Number of Additions	Number of Multipli-cations
PSO – n particles	1	$n \times iterations$	$5 \times n \times d \times iterations$	$5 \times n \times d \times iterations$
SPPSO – m particles	1	$m \times iterations$	$5 \times m \times d \times iterations$	$5 \times m \times d \times iterations$
BFA – S bacteria	4 (Chemotaxis, Swarming, Reproduction, and Elimination and Dispersal)	$S \times N_c \times N_{re} \times N_{ed}$ (1 PSO $iteration = S \times N_c$)	$(4p-1) \times S \times N_c \times N_{re} \times N_{ed}$	$(4+2p) \times S \times N_c \times N_{re} \times N_{ed}$

Table IV
Comparison of Computational Complexities of PSO, SPPSO and BFA for PSS Design for Two Area Power System ($N_c = 4$, $N_{RE} = 15$, $N_{ED} = 10$)

Algorithms	Number of stages involved	Number of Fitness Evaluations	Number of Additions	Number of Multipli-cations
PSO- 20 particles	1	3000	300000	300000
SPPSO – 5 particles	1	750	75000	75000
BFA – 4 bacteria	4	2400	189600	105600

Table V
Computation Time for PSO, SPPSO and BFA for Two Area Power System

Platform	Time (seconds)		
	PSO	SPPSO	BFA
PSCAD	227557.00	12544.15	48638.93
PST	202.28	102.25	407.04

B. Transient Energy Analysis of the Damping Performance

A brief comparison of the two algorithms based on the transient energy calculations is shown in Tables VI and VII. The transient energy of each generator for the first 5 seconds of the fault has been calculated using (7) and the total transient energy (TE) of all the generators in a given area is given by (8).

$$TE_{Gen_i} = \frac{1}{2} H_{Gen_i} \int_{t_{flt}}^{t_{flt}+5} \Delta\omega_i^{2}\, dt \qquad (7)$$

where i is the generator number, t_{flt} is the time at which the fault is triggered and H_{Geni} is the moment of inertia of the generator i.

$$TE = \sum_{i=1}^{N} TE_{Gen_i} \qquad (8)$$

where N is the number of generators present in a given area of a system. The performance index (P.I), given in (9), is a measure of how the system has performed under the given conditions with the different set of PSS parameters. The higher the performances index the better the controller damping performance.

$$Performance\ Index\ (P.I.) = 1/\,TE \qquad (9)$$

Table VI presents the normalized performance indices of Area 1 and Area 2 for the different disturbances for the two area multi-machine power system. The normalized performance index is obtained by dividing the P.Is by the P.I obtained with no PSS in the system. The results show that the performance indices are best when the PSSs use the SPPSO optimized parameters. The overall performance row indicates that the bio-inspired optimization techniques improve the damping and minimize the overshoot in the oscillations for small and large disturbances. There is 19.17% , 24.65% and 16.43% overall improvement in damping in Area 1 with the PSO, SPPSO and BFA respectively optimized PSS parameters compared to the PSS parameters in [17]. Similarly, the overall improvement in the damping provided in Area 2 is 20.6%, 28.75%, and 33.47% with the PSO, SPPSO and BFA respectively optimized PSS parameters compared to the PSS parameters in [17].

Table VII shows the P.Is of the hydro and the thermal areas under different operating conditions for the Nigerian power system. P.I. is best with SPPSO optimized parameters followed by PSO and then the BFA optimized parameters. This corroborates the superiority of the SPPSO algorithm over the BFA for same operating conditions. There is an overall improvement of 48%, 90% and 99% in damping in Hydro area with the BFA, PSO and SPPSO respectively optimized PSS parameters compared to the case without any PSS in the system. Similarly, an overall improvement in the damping provided in Thermal area is 87%, 248% and 245% with the BFA, PSO and SPPSO respectively optimized PSS parameters compared to the case without any PSS in the system.

Table VI
Normalized P.I. for Two Area Multi-Machine Power System

Disturbance	Areas	No PSS	CPSS	PSO	SPPSO	BFA
Short Circuit	1	1.0	1.56	1.88	1.96	1.96
	2	1.0	1.94	2.40	2.66	2.60
Line Outage	1	1.0	1.40	1.50	1.63	1.63
	2	1.0	3.02	3.64	3.68	4.06
Short Circuit and Line Outage	1	1.0	1.49	1.84	1.92	1.89
	2	1.0	2.05	2.39	2.66	2.68
Overall Performance	1	1.0	1.48	1.74	1.84	1.82
	2	1.0	2.33	2.81	3.00	3.11

Table VII
Normalized P.I for the Nigerian Power System

Disturbance	Areas	No PSS	PSO	SPPSO	BFA
Short Circuit	Hydro	1.0	1.53	1.54	1.32
	Thermal	1.0	4.20	4.07	1.57
Line Outage	Hydro	1.0	2.55	2.75	1.66
	Thermal	1.0	2.38	2.55	2.06
Short Circuit and Line Outage	Hydro	1.0	1.62	1.68	1.47
	Thermal	1.0	3.88	3.75	1.98
Overall Performance	Hydro	1.0	1.90	1.99	1.48
	Thermal	1.0	3.48	3.45	1.87

PSO in each of the transient energy calculations is comparable with SPPSO. However, PSO after certain number of iterations can be trapped in local optima as the velocity of the particle becomes zero when the same particle is both the p_{best} and the g_{best}. When the velocity of the particle is zero, the position of the particle cannot be updated and thus the search will be trapped in a local optimum. SPPSO owing to its regeneration can generate new particles after every N iteration thus eliminating the drawback of zero velocity.

C. Eigenvalue Analysis

Prony Analysis [19-20] is used to determine the eigenvalues of the systems under study. Tables VIII to XI list the complex eigenvalues of all the generators in the two area and the Nigerian power system. The best eigenvalue of each of the generator for each mode is highlighted in all the tables. In summary, the eigenvalues generated by system having bio-inspired optimized PSSs have the highest negative real part in that row and thus improve system stability. SPPSO and BFA optimized PSSs exhibit best results for the inter-area and local modes in the different areas, for the two area power system as shown in Tables VIII and IX. The SPPSO optimized PSSs exhibit the best damping for most of the modes in the different areas in the Nigerian power system as shown in Tables X and XI.

Table VIII
Eigenvalues, Frequencies and Damping Ratios of Generating Units in Area 1 in Two Area Power System

Type of PSSs	Eigenvalues	Frequency (Hz)	Damping Ratio (%)
No PSS	-0.14 ± j4.20	0.67	3.35
	-0.4 ± j6.39	1.02	6.25
	-0.92 ± j7.48	1.20	12.21
CPSS	-0.86 ± j4.24	0.69	19.07
	-1.08 ± j6.31	1.02	17.31
	-2.29 ± j7.31	1.22	30.01
BFA optimized	**-1.76 ± j4.02**	0.72	**40.21**
	-1.82± j5.55	0.93	**31.22**
	-1.82 ± j7.25	1.19	24.35
SPPSO optimized	-1.50 ± j4.13	0.7	34.11
	-1.60 ± j5.55	0.92	27.79
	-2.74 ± j7.55	1.28	**34.13**

Table IX
Eigenvalues, Frequencies and Damping Ratios of Generating Units in Area 2 in Two Area Power System

Type of PSSs	Eigenvalues	Frequency (Hz)	Damping Ratio (%)
No PSS	-0.14 ± j4.20	0.67	3.41
	-0.41 ± j6.52	1.04	6.64
	-0.63 ± j8.52	1.36	7.44
CPSS	-0.82 ± j4.25	0.69	19.10
	-0.95± j6.14	0.99	15.37
	-2.16 ± j7.22	1.20	28.77
BFA optimized	**-1.76± j3.59**	0.67	**42.01**
	-1.11 ± j 6.05	0.98	18.08
	-2.45 ± j 7.78	1.30	**30.08**
SPPSO optimized	-1.70± j4.05	0.70	38.86
	-1.43± j5.53	0.91	**25.07**
	-2.29± j7.51	1.25	29.23

Table X
Eigenvalues, Frequencies and Damping Ratios of Hydro Generating Units in Nigerian Power System

Type of PSSs	Eigenvalues	Frequency (Hz)	Damping Ratio(%)
No PSS	-0.55 ± j 5.51	0.88	10.07
	-0.34 ± j 7.63	1.21	4.44
	-0.60 ± j 9.12	1.45	6.57
BFA optimized	-0.62 ± j 5.46	0.87	11.28
	-0.94 ± j 6.52	1.04	14.36
	-1.38 ± j 8.79	1.41	15.56
SPPSO optimized	**-1.13 ± j 5.04**	0.82	**21.99**
	-1.67 ± j 7.69	1.25	**21.32**
	-2.10 ± j 10.52	1.70	**19.66**

Table XI
Eigenvalues, Frequencies and Damping Ratios of Thermal Generating Units in Nigerian Power System

Algorithms	Eigenvalues	Frequency (Hz)	Damping Ratio(%)
No PSS	-0.47 ± j 5.67	0.90	08.40
	-0.25 ± j 7.62	1.21	03.30
	-0.91 ± j 9.51	1.52	09.54
BFA optimized	-0.60 ± j 5.42	0.86	11.00
	-1.62 ± j 6.56	1.07	**24.02**
	-0.87 ± j 8.34	1.33	10.42
SPPSO optimized	**-1.15 ± j 5.75**	0.93	**19.60**
	-0.83 ± j 6.66	1.06	12.48
	-1.58 ± j 9.76	1.57	**16.04**

VII. CONCLUSION

The successful implementation of the two bio-inspired algorithms for simultaneous design of the multiple optimal PSSs has been presented in this paper. The SPPSO and BFA algorithms give robust damping performance for various operating conditions and disturbances. The SPPSO with the regeneration concept is shown to have faster convergence using lower number of fitness evaluations and algebraic operations. BFA owing to its unique processes can find good optimal solutions. The SPPSO however is found to be superior to the BFA and PSO in terms of computational complexity, transient energy analysis, convergence speed and damping performances.

The paper has presented the SPPSO and the BFA as optimization tools in the PSCAD/EMTDC environment. This is a first step towards online optimization and future work can involve developing these algorithms further for real-time optimization in power systems.

VIII. REFERENCES

[1] Y. L. Abdel-Magid, M. A Abido, S. Al-Baiyat and H. Manatawy, "Simultaneous stabilization of multimachine power system via genetic algorithms," *IEEE Trans. on Power System*, vol. 145, pp. 1428-1439, Nov 1999.

[2] M. A. Abido, "A novel approach to conventional power sysetm stabilizer design using tabu search," *Int. Journal Electric Power Energy System*, vol. 21, pp. 443-454, June 1999.

[3] M. A. Abido, "Robust design of multimachine power system stabilizers using simulated annealing," *IEEE Trans. on Energy Conversion*, vol. 15, pp.297-304, Sept. 2000.

[4] G. A. Bakare, U. O. Aliyu, G. K. Venayagamoorthy and Y. K. Shuaiba, "Genetic algorithms based economic dispatch with applications to coordination of Nigerian thermal power plants", *IEEE Power Engg. Soc. Gen Meeting*, Vol. 1,pp-551-556, June 2005.

[5] D. B. Fogel, "Evolutionary computation toward a New Philosophy of Machine Intelligence", New York: IEEE, 1995.

[6] Manitoba HVDC Research Centre Inc, PSCAD/EMTDC user's guide, version 3.0, 244 Cree Crescent, Winnipeg, Manitoba, Canada R3J 3W1.

[7] P. Kundur, M. Klein, G. J Rogers and M. S. Zywno, "Application of power system stabilizers for enhancement of overall stability", *IEEE Trans on Power System*, vol. 4, pp. 614-626, 1989.

[8] G. K. Venayagamoorthy, U. O. Aliyu, J. H. Chow and J. J. Sanchez-Gasca, "Modal extraction with three different methods for Nigerian power system", *Int. Conf. on Power Syst. Opertion and Planning –VI*, pp. 61-66, May, 2005.

[9] S. Doctor and G. K. Venayagamoorthy, "Improving the performance of particle swarm optimization using adaptive critics designs", *IEEE Proc. Swarm Intelligence Symposium* , pp 393-396, 8-10th June, 2005,

[10] Q. L. Zhang, L. Xang and Q. A. Tran, "A modified particle swarm optimization algorithm", *Proc. on 2005 Int. Conf. on Machine Learning and Cybernetics*, vol. 5, pp. 3030-3035, 18-21 Aug, 2005.

[11] S. Mishra, "A hybrid fuzzy least square bacterial foraging strategy for harmonic estimation", *IEEE Trans. on Evolutionary Computation*, vol. 9. Issue 1, pp. 61-73, Feb. 2005.

[12] S. Mishra, "Hybrid least square adaptive bacterial foraging strategy for harmonic estimation", *IEEE Proc. on Generation Transmission and Distribution*, vol. 152, Issue 3, pp. 379-389, May 2005.

[13] K. M. Passino, "Biomimicry of bacterial foraging for distributed optimization and control," *IEEE Control System Magazine*, vol. 22, Issue 3, pp. 52-67, June 2002.

[14] J. Kennedy and R. Eberhart, " Particle Swarm Optimization ," *IEEE International Conf. on Neural Networks*, Perth, Australia. vol. 4, pp. 1942-1948, Dec 1995.

[15] Y. del Valle Y, G. K. Venayagamoorthy, S. Mohagheghi, J. C. Hernandez and R. G. Harley, "Particle swarm optimization: Basic concepts, variants and applications in power systems", *IEEE Trans. on Evolutionary Computation*, in press.

[16] J. Kennedy, R. C. Eberhart and Y. Shi, Swarm Intelligence, Morgan Kaufmann Publishers, 2001.

[17] P. Kundur, Power System Stability and Control, McGraw Hill, New York: 1974, pp. 814.

[18] J. Chow/Cherry Tree Scientific Software, Power System Toolbox Version 2.0, Ontario, K0K-1S0, Canada

[19] J. F. Hauer, "Application of Prony Analysis to the determination of modal content and equivalent models for measured power system response", *IEEE Trans. on Power Systems*, vol 6, issue 3, pp. 1062-1068, Aug. 1991.

[20] M. A. Johnson, I. P. Zarafonitis and M. Calligaris, "Prony analysis and power system stability-some recent theoretical and applications research", *IEEE Power Engg. Soc. Meeting*, vol.3, pp.1918-1923, Jul. 2000.

APPENDIX A
APPENDIX FOR PAPER 1

Table A.1
System 1 PSS Parameters

Generator	Kundur's parameters	CPSO optimized parameters	CSPPSO optimized parameters
G1-G4	$K = 20.0$, $T_1 = 0.05$, $T_2 = 0.02$, $T_3 = 3.0$, $T_4 = 5.4$	$K = 26.49$, $T_1 = 0.061$, $T_2 = 0.01$, $T_3 = 5.11$, $T_4 = 5.55$	$K = 21.21$, $T_1 = 0.062$, $T_2 = 0.01$, $T_3 = 3.74$, $T_4 = 3.247$

Table A.2
Parameters of the 16 Tuned PSSs in System 2 (Case 1)

Generator	CPSO optimized parameters	CSPPSO optimized parameters
G1	$K = 14.67$, $T_1 = 0.02$, $T_2 = 0.01$, $T_3 = 0.01$, $T_4 = 0.01$	$K = 10.37$, $T_1 = 0.06$, $T_2 = 0.01$, $T_3 = 0.08$, $T_4 = 0.01$
G2	$K = 14.20$, $T_1 = 0.01$, $T_2 = 0.01$, $T_3 = 0.04$, $T_4 = 0.01$	$K = 18.53$, $T_1 = 0.07$, $T_2 = 0.01$, $T_3 = 0.05$. $T_4 = 0.01$
G3	$K = 16.20$, $T_1 = 0.06$, $T_2 = 0.01$, $T_3 = 0.05$, $T_4 = 0.01$	$K = 19.21$, $T_1 = 0.07$, $T_2 = 0.01$, $T_3 = 0.06$, $T_4 = 0.01$
G4	$K = 13.47$, $T_1 = 0.02$, $T_2 = 0.01$, $T_3 = 0.01$, $T_4 = 0.01$	$K = 10.02$, $T_1 = 0.06$, $T_2 = 0.01$, $T_3 = 0.07.$, $T_4 = 0.01$
G5	$K = 17.76$, $T_1 = 0.06$, $T_2 = 0.01$, $T_3 = 0.01$, $T_4 = 0.01$	$K = 15.49$, $T_1 = 0.07$, $T_2 = 0.01$, $T_3 = 0.05$. $T_4 = 0.01$
G6	$K = 18.32$, $T_1 = 0.05$, $T_2 = 0.01$, $T_3 = 0.06$, $T_4 = 0.01$	$K = 12.16$, $T_1 = 0.06$, $T_2 = 0.01$, $T_3 = 0.08$, $T_4 = 0.01$
G7	$K = 10.97$, $T_1 = 0.01$, $T_2 = 0.01$, $T_3 = 0.01$, $T_4 = 0.01$	$K = 19.66$, $T_1 = 0.06$, $T_2 = 0.01$, $T_3 = 0.07$, $T_4 = 0.01$
G8	$K = 15.30$, $T_1 = 0.05$, $T_2 = 0.01$, $T_3 = 0.063$, $T_4 = 0.01$	$K = 11.11$, $T_1 = 0.08$, $T_2 = 0.01$, $T_3 = 0.08$. $T_4 = 0.01$
G9	$K = 13.56$, $T_1 = 0.01$, $T_2 = 0.01$, $T_3 = 0.04$, $T_4 = 0.01$	$K = 19.36$, $T_1 = 0.06$, $T_2 = 0.01$, $T_3 = 0.06$. $T_4 = 0.01$
G10	$K = 18.62$, $T_1 = 0.06$, $T_2 = 0.01$, $T_3 = 0.05$, $T_4 = 0.01$	$K = 11.21$, $T_1 = 0.07$, $T_2 = 0.01$, $T_3 = 0.05$. $T_4 = 0.01$
G11	$K = 12.46$, $T_1 = 0.04$, $T_2 = 0.01$, $T_3 = 0.04$, $T_4 = 0.01$	$K = 18.21$, $T_1 = 0.08$, $T_2 = 0.01$, $T_3 = 0.07$. $T_4 = 0.01$
G12	$K = 17.27$, $T_1 = 0.07$, $T_2 = 0.01$, $T_3 = 0.02$, $T_4 = 0.01$	$K = 15.96$, $T_1 = 0.08$, $T_2 = 0.01$, $T_3 = 0.06$, $T_4 = 0.01$
G13	$K = 17.06$, $T_1 = 0.01$, $T_2 = 0.01$, $T_3 = 0.01$, $T_4 = 0.01$	$K = 19.46$, $T_1 = 0.07$, $T_2 = 0.01$, $T_3 = 0.06$. $T_4 = 0.01$
G14	$K = 13.54$, $T_1 = 0.07$, $T_2 = 0.01$, $T_3 = 0.07$, $T_4 = 0.01$	$K = 18.20$, $T_1 = 0.05$, $T_2 = 0.01$, $T_3 = 0.07$, $T_4 = 0.01$

Table A.2 (Cont'd)
Parameters of the 16 Tuned PSSs in System 2 (Case 1)

Generator	CPSO optimized parameters	CSPPSO optimized parameters
G15	K = 15.89, T_1 = 0.06, T_2 = 0.01, T_3 = 0.01, T_4= 0.01	K = 18.11, T_1 = 0.07, T_2 = 0.01, T_3 = 0.05.,T_4 = 0.01
G16	K = 18.67, T_1 = 0.04, T_2 = 0.01, T_3 = 0.01, T_4= 0.01	K = 18.86, T_1 = 0.06, T_2 = 0.01, T_3 = 0.08, T_4 = 0.01

Table A.3
Parameters of the 5 Tuned PSSs in System 2 (Case 2)

Generator	CPSO optimized parameters	CSPPSO optimized parameters
G9	K = 19.45, T_1 = 0.93, T_2 = 0.80, T_3 = 0.64, T_4= 0.37	K = 20.91, T_1 = 0.67, T_2 = 0.55, T_3 = 0.97. T_4 = 1.18
G13	K = 18.47, T_1 = 1.22, T_2 = 0.83, T_3 = 0.98, T_4= 0.46	K = 23.38, T_1 = 0.88, T_2 = 0.39, T_3 = 0.91. T_4 = 0.96
G14	K = 19.50, T_1 = 0.74, T_2 = 0.55, T_3 = 0.86, T_4= 0.52	K = 19.81, T_1 = 0.40, T_2 = 0.49, T_3 = 0.97, T_4 = 1.13
G15	K = 19.10, T_1 = 0.98, T_2 = 0.18, T_3 = 0.52,T_4= 0.70	K = 26.47, T_1 = 0.58, T_2 = 0.57, T_3 = 1.27.,T_4 = 0.60
G16	K = 20.43, T_1 = 0.74, T_2 = 0.97, T_3 = 0.94, T_4= 0.49	K = 21.03, T_1 = 1.26, T_2 = 0.99, T_3 = 1.37, T_4 = 0.92

Table A.4
Oscillatory Modes of System 1 for Different Operating Condition

Operating Condition	Parameters	Eigenvalues	Frequency (Hz)	Damping (%) ± std (min, max)
I	Kundur	-0.96 ± j 4.22 -6.28 ± j 7.00 -5.64 ± j 7.26	0.67 1.12 1.15	22.2 66.3 61.3
	PSO	-1.72± j 3.65	0.58	41.56 ± 0.58 (40.87 , 42.76)
	SPPSO	-1.71± j 3.68	0.58	41.54 ±0.48 (40.86, 42.3)
	CPSO	-1.74 ± j 3.64	0.58	41.72 ±0. 74 (40.8, 43.25)
	CSPPSO	-1.74± j 3.61	0.57	42.06±0. 80 (40.81, 43.55)
II	Kundur	-0.95 ± j 4.05 -6.27 ± j 7.12 -5.43 ± j 7.38	0.64 1.13 1.17	22.9 66.8 59.2
	PSO	-1.71± j 3.52	0.56	42.65± 0.60 (41.91, 43.87)
	SPPSO	-1.74 ± j 3.51	0.56	42.80 ±0. 81 (41.85, 44.38)
	CPSO	-1.74± j 3.50	0.55	42.82 ±0.75 (41.87, 44.54)
	CSPPSO	-1.74± j 3.47	0.55	43.10±0. 85 (41.87, 44.74)

Table A.4 (Cont'd)
Oscillatory Modes of System 1 for Different Operating Condition

Operating Condition	Parameters	Eigenvalues	Frequency (Hz)	Damping (%) ± std (min, max)
III	Kundur	-0.92 ± j 4.14 -6.26 ± j 7.13 -5.62 ± j 7.26	0.65 1.13 1.15	21.6 65.9 61.2
	PSO	-1.69± j 3.62	0.57	40.85± 0.54 (40.16, 41.71)
	SPPSO	-1.69 ± j 3.6	0.57	41.05 ±0. 78 (40, 42.56)
	CPSO	-1.7± j 3.6	0.57	41.04 ±0.73 (40.13, 42.7)
	CSPPSO	-1.7 ± j 3.56	0.56	41.3±0. 83 (40.01, 42.88)
IV	Kundur	-0.91 ± j 4.12 -6.25 ± j 7.14 -5.61 ± j 7.26	0.65 1.13 1.15	21.5 65.8 61.1
	PSO	-1.67± j 3.61	0.57	40.78± 0.54 (40.0, 41.97)
	SPPSO	-1.68 ± j 3.58	0.57	40.98 ±0. 78 (40.0, 42.48)
	CPSO	-1.69± j 3.58	0.57	40.95 ±0.73 (40.0, 42.63)
	CSPPSO	-1.68 ± j 3.55	0.56	41.22±0. 83 (40.0, 42.8)

Table A.5
Oscillatory Modes of System 2 With 16 Tuned PSSs (Case 1)

Operating Condition	Parameters	Eigenvalues	Frequency (Hz)	Damping (%) ± std (min, max)
I	PSS [20]	-0.77 ± j 2.59	0.41	28.53
		-0.79 ± j 3.42	0.54	22.7
		-0.82 ± j 4.05	0.64	19.70
		-1.63 ± j 7.12	1.13	22.3
		-2.33 ± j 7.32	1.17	30.0
	PSO Constriction (CPSO)	-1.05 ± j 2.59	0.41	37.05 ± 0.68 (35.12, 37.89)
		-1.07 ± j 3.42	0.57	29.86± 0.92 (28.09, 31.19)
		-1.34 ± j 4.22	0.67	28.02±1.59 (23.74, 31.24)
	SPPSO Constriction (CSPPSO)	-1.01± j 2.48	0.39	37.19± 0.81 (34.29, 38.16)
		-1.04± j 3.30	0.52	30.13±1.22 (27.45, 32.53)
		-1.16± j 3.92	0.62	28.00±1.25 (24.37.29.30)
II	PSS [20]	-0.77 ± j 2.62	0.41	28.21
		-0.80 ± j 3.45	0.54	22.66
		-0.82 ± j 4.08	0.65	19.76
		-1.63 ± j 7.12	1.13	22.38
		-2.35 ± j 7.37	1.17	30.30
	PSO Constriction (CPSO)	-1.05 ± j 2.62	0.41	36.60 ± 0.65 (34.78, 37.43)
		-1.08 ± j 3.45	0.54	29.90± 0.93 (28.15, 31.28)
		-1.35 ± j 4.23	0.67	28.07±1.59 (23.71, 31.20)
	SPPSO Constriction (CSPPSO)	-1.01± j 2.51	0.40	36.75 ±0.78 (33.98, 37.68)
		-1.04± j 3.32	0.52	30.17 ±1.20 (27.57, 32.54)
		-1.16± j 3.93	0.62	28.05 ±1.25 (24.39, 29.39)

Table A.6
Normalized P.I of System 1 for Operating Condition I, II and III

Operating Condition	Disturbances	Areas	Kundur	CPSO	CSPPSO
I	Short Circuit	Area 1	1.0	1.79	1.81
		Area 2	1.0	2.36	2.28
	Line Outage	Area 1	1.0	1.60	1.53
		Area 2	1.0	1.53	1.44
	Overall Performance	Area 1	1.0	1.70	1.67
		Area 2	1.0	1.93	1.86
II	Short Circuit	Area 1	1.0	2.01	1.72
		Area 2	1.0	1.94	1.97
	Line Outage	Area 1	1.0	1.43	1.35
		Area 2	1.0	1.45	1.36
	Overall Performance	Area 1	1.0	1.72	1.54
		Area 2	1.0	1.70	1.66
III	Short Circuit	Area 1	1.0	2.05	2.06
		Area 2	1.0	2.19	2.14
	Line Outage	Area 1	1.0	1.44	1.36
		Area 2	1.0	1.45	1.34
	Overall Performance	Area 1	1.0	1.74	1.71
		Area 2	1.0	1.82	1.74

Table A.7

Normalized P.I of System 2 for Operating Condition I and II

Operating Condition	Disturbances	Areas	PSS [20]	CPSO	CSPPSO
I	Contingency 1	Area 1	1.0	1.52	1.39
		Area 2	1.0	1.52	1.43
		Area 3	1.0	1.28	1.30
		Area 4	1.0	1.02	1.05
		Area 5	1.0	1.58	1.47
	Contingency 2	Area 1	1.0	1.27	1.42
		Area 2	1.0	1.87	1.70
		Area 3	1.0	1.38	1.42
		Area 4	1.0	1.60	1.54
		Area 5	1.0	1.88	1.58
	Overall Performance	Area 1	1.0	1.40	1.40
		Area 2	1.0	1.69	1.56
		Area 3	1.0	1.33	1.36
		Area 4	1.0	1.31	1.30
		Area 5	1.0	1.73	1.53
II	Contingency 1	Area 1	1.0	1.50	1.37
		Area 2	1.0	1.51	1.42
		Area 3	1.0	1.28	1.30
		Area 4	1.0	1.03	1.07
		Area 5	1.0	1.60	1.48
	Contingency 1	Area 1	1.28	1.43	1.28
		Area 2	1.86	1.70	1.86
		Area 3	1.39	1.45	1.39
		Area 4	1.62	1.56	1.62
		Area 5	1.92	1.60	1.92

Table A.7 (Cont'd)
Normalized P.I of System 2 for Operating Condition I and II

Operating Condition	Disturbances	Areas	PSS [20]	CPSO	CSPPSO
	Overall Performance	Area 1	1.0	1.39	1.40
		Area 2	1.0	1.68	1.56
		Area 3	1.0	1.34	1.38
		Area 4	1.0	1.33	1.322
		Area 5	1.0	1.76	1.54

Table A.8
Oscillatory Modes of the Two PSS Tuning Cases on System 2

Operating Condition	Parameters	Eigenvalues	Frequency (Hz)	Damping (%) ± std (min, max)
I	CSPPSO optimized 16 PSSs	-1.01± j 2.48	0.39	37.19± 0.81 (34.29, 38.16)
		-1.04± j 3.30	0.52	30.13±1.22 (27.45, 32.53)
		-1.16± j 3.92	0.62	28.00±1.25 (24.37.29.30)
	CSPPSO optimized 5 PSSs	-1.51± j 2.10	0.33	40.68 ±6.41 (30.75, 58.40)
		-1.64± j 3.23	0.51	32.16 ±4.25 (26.38, 45.35)
		-1.17± j 3.78	0.60	27.07 ±2.44 (23.38, 30.53)
II	CSPPSO optimized 16 PSSs	-1.01± j 2.48	0.39	37.19± 0.81 (34.29, 38.16)
		-1.04± j 3.30	0.52	30.13±1.22 (27.45, 32.53)
		-1.16± j 3.92	0.62	28.00±1.25 (24.37.29.30)

Table A.8 (Cont'd)
Oscillatory Modes of the Two PSS Tuning Cases on System 2

Operating Condition	Parameters	Eigenvalues	Frequency (Hz)	Damping (%) ± std (min, max)
	CSPPSO optimized 5 PSSs	-1.45± j 2.21	0.34	40.30 ±6.41 (30.43, 57.84)
		-1.68± j 3.25	0.51	31.77 ±4.47 (26.06, 45.98)
		-1.86± j 3.25	0 .60	27.67 ±3.11 (23.51, 35.70)
III	CSPPSO optimized 16 PSSs	-1.01± j 2.44	0.38	37.73 ±0.85 (34.66, 38.74)
		-1.03± j 3.28	0.52	30.11 ±1.21 (27.52, 32.54)
		-1.15± j 3.91	0.62	27.95 ±1.24 (24.36, 29.26)
	CSPPSO optimized 5 PSSs	-1.49± j 2.04	0.32	41.17 ±6.41 (31.17, 59.00)
		-1.61± j 3.22	0.51	32.20 ±7.01 (26.77, 44.70)
		-1.16± j 3.78	0.60	26.91 ±2.39 (23.24, 30.30)

APPENDIX B
APPENDIX FOR PAPER 2

Table B.1
Parameters of the PSSs used in Approach A

M/c	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
G1	$K=17.00$ $T_1=0.05$ $T_2=0.01$ $T_3=0.05$ $T_4=0.01$	$K=12.64$ $T_1=0.05$ $T_2=0.01$ $T_3=0.08$ $T_4=0.01$	$K=10.98$ $T_1=0.08$ $T_2=0.01$ $T_3=0.08$ $T_4=0.04$	$K=19.88$ $T_1=0.08$ $T_2=0.03$ $T_3=0.01$ $T_4=0.01$	$K=10.37$ $T_1=0.09$ $T_2=0.01$ $T_3=0.07$ $T_4=0.01$	$K=18.58$ $T_1=0.06$ $T_2=0.01$ $T_3=0.11$ $T_4=0.01$
G2	$K=14.80$ $T_1=0.05$ $T_2=0.01$ $T_3=0.05$ $T_4=0.01$	$K=13.09$ $T_1=0.06$ $T_2=0.01$ $T_3=0.07$ $T_4=0.01$	$K=14.84$ $T_1=0.09$ $T_2=0.01$ $T_3=0.02$ $T_4=0.02$	$K=12.47$ $T_1=0.06$ $T_2=0.01$ $T_3=0.01$ $T_4=0.01$	$K=17.89$ $T_1=0.06$ $T_2=0.01$ $T_3=0.09$ $T_4=0.05$	$K=16.12$ $T_1=0.05$ $T_2=0.02$ $T_3=0.06$ $T_4=0.01$
G3	$K=15.69$ $T_1=0.06$ $T_2=0.02$ $T_3=0.02$ $T_4=0.01$	$K=17.40$ $T_1=0.06$ $T_2=0.01$ $T_3=0.05$ $T_4=0.01$	$K=14.47$ $T_1=0.06$ $T_2=0.02$ $T_3=0.01$ $T_4=0.02$	$K=18.90$ $T_1=0.06$ $T_2=0.02$ $T_3=0.09$ $T_4=0.01$	$K=15.05$ $T_1=0.05$ $T_2=0.01$ $T_3=0.03$ $T_4=0.01$	$K=17.97$ $T_1=0.09$ $T_2=0.04$ $T_3=0.04$ $T_4=0.01$
G4	$K=16.46$ $T1=0.04$ $T_2=0.01$ $T_3=0.09$ $T_4=0.02$	$K=12.37$ $T_1=0.06$ $T_2=0.01$ $T_3=0.08$ $T_4=0.02$	$K=18.20$ $T_1=0.04$ $T_2=0.01$ $T_3=0.03$ $T_4=0.02$	$K=10.31$ $T_1=0.07$ $T_2=0.01$ $T_3=0.06$ $T_4=0.01$	$K=19.20$ $T_1=0.05$ $T_2=0.01$ $T_3=0.07$ $T_4=0.01$	$K=12.18$ $T_1=0.08$ $T_2=0.01$ $T_3=0.06$ $T_4=0.01$
G5	$K=14.84$ $T_1=0.07$ $T_2=0.01$ $T_3=0.08$ $T_4=0.01$	$K=17.07$ $T_1=0.06$ $T_2=0.01$ $T_3=0.05$ $T_4=0.01$	$K=16.99$ $T_1=0.04$ $T_2=0.01$ $T_3=0.01$ $T_4=0.02$	$K=16.79$ $T_1=0.07$ $T_2=0.01$ $T_3=0.06$ $T_4=0.01$	$K=16.37$ $T_1=0.08$ $T_2=0.04$ $T_3=0.03$ $T_4=0.03$	$K=15.30$ $T_1=0.06$ $T_2=0.01$ $T_3=0.06$ $T_4=0.02$
G6	$K=19.16$ $T_1=0.07$ $T_2=0.01$. $T_3=0.05$ $T_4=0.01$	$K=18.85$ $T_1=0.05$ $T_2=0.01$ $T_3=0.05$ $T_4=0.01$	$K=18.56$ $T_1=0.08$ $T_2=0.01$ $T_3=0.01$ $T_4=0.02$	$K=12.15$ $T_1=0.08$ $T_2=0.03$ $T_3=0.05$ $T_4=0.02$	$K=19.64$ $T_1=0.11$ $T_2=0.01$ $T_3=0\ 06$ $T_4=0.02$	$K=15.86$ $T_1=0.03$ $T_2=0.01$ $T_3=0\ 07$ $T_4=0.02$
G7	$K=13.79$ $T_1=0.04$ $T_2=0.01$ $T_3=0.07$ $T_4=0.01$	$K=15.48$ $T_1=0.05$ $T_2=0.01$ $T_3=0.07$ $T_4=0.01$	$K=19.92$ $T_1=0.10$ $T_2=0.01$ $T_3=0.01$ $T_4=0.02$	$K=17.11$ $T_1=0.05$ $T_2=0.01$ $T_3=0.06$ $T_4=0.01$	$K=15.42$ $T_1=0.02$ $T_2=0.01$ $T_3=0.03$ $T_4=0.03$	$K=14.65$ $T_1=0.01$ $T_2=0.02$ $T_3=0.07$ $T_4=0.01$
G8	$K=11.7$ $T_1=0.05$ $T_2=0.01$ $T_3=0.01$ $T_4=0.01$	$K=17.97$ $T_1=0.08$ $T_2=0.01$ $T_3=0.08$ $T_4=0.01$	$K=10.07$ $T_1=0.10$ $T_2=0.01$ $T_3=0.01$ $T_4=0.01$	$K=15.42$ $T_1=0.08$ $T_2=0.04$ $T_3=0.05$ $T_4=0.01$	$K=12.05$ $T_1=0.05$ $T_2=0.02$ $T_3=0.08$ $T_4=0.02$	$K=12.43$ $T_1=0.07$ $T_2=0.01$ $T_3=0.06$ $T_4=0.02$

Table B.1 (Cont'd)
Parameters of the PSSs used in Approach A

M/c	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
G9	K=14.5 T_1=0.06 T_2=0.01 T_3=0.07 T_4=0.01	K=18.28 T_1=0.05 T_2= 0.01 T_3= 0.06 T_4=0.01	K=16.53 T_1=0.06 T_2= 0.01 T_3= 0.01 T_4=0.03	K=13.99 T_1=0.07 T_2= 0.03 T_3= 0.06 T_4=0.02	K=16.27 T_1=0.06 T_2= 0.01 T_3= 0.09 T_4=0.03	K=15.73 T_1=0.02 T_2= 0.01 T_3= 0.06 T_4=0.01
G10	K=13.49 T_1=0.05 T_2=0.01 T_3=0.07 T_4= 0.01	K=17.17 T_1=0.07 T_2= 0.01 T_3= 0.05 T_4= 0.01	K=18.11 T_1=0.06 T_2= 0.01 T_3= 0.01 T_4= 0.01	K=11.28 T_1=0.10 T_2= 0.04 T_3= 0.06 T_4= 0.01	K=12.47 T_1=0.07 T_2= 0.01 T_3= 0.10 T_4= 0.03	K=10.77 T_1=0.09 T_2= 0.02 T_3= 0.08 T_4= 0.03
G11	K=17.89 T_1=0.07 T_2=0.03 T_3=0.07 T_4= 0.01	K=15.93 T_1=0.07 T_2=0.01 T_3= 0.05 T_4= 0.01	K=18.43 T_1=0.06 T_2=0.03 T_3=0.01 T_4= 0.02	K=16.15 T_1=0.05 T_2=0.02 T_3=0.05 T_4= 0.03	K=12.87 T_1=0.10 T_2=0.01 T_3=0.06 T_4= 0.02	K=12.26 T_1=0.08 T_2=0.01 T_3= 0.06 T_4= 0.02
G12	K=19.47 T_1=0.06 T_2=0.02 T_3=0.06 T_4= 0.03	K=17.41 T_1= 0.06 T_2= 0.01 T_3=0.08 T_4= 0.03	K=19.27 T_1= 0.09 T_2= 0.02 T_3= 0.01 T_4= 0.01	K=17.94 T_1= 0.03 T_2= 0.01 T_3=0.06 T_4= 0.01	K=15.08 T_1= 0.08 T_2= 0.01 T_3= 0.03 T_4= 0.04	K=17.89 T_1= 0.06 T_2= 0.01 T_3= 0.09 T_4= 0.01
G13	K=19.86 T_1=0.08 T_2=0.02 T_3=0.076 T_4=0.026	K=16.60 T_1=0.07 T_2=0.01 T_3=0.05 T_4=0.01	K=19.93 T_1=0.09 T_2=0.02 T_3= 0.01 T_4=0.01	K=19.79 T_1=0.09 T_2=0.02 T_3= 0.07 T_4=0.03	K=16.96 T_1=0.08 T_2=0.01 T_3= 0.04 T_4=0.01	K=19.45 T_1=0.04 T_2=0.01 T_3= 0.09 T_4=0.02
G14	K=19.66 T_1=0.08 T_2=0.01 T_3=0.069 T_4= 0.033	K=19.72 T_1=0.07 T_2=0.01 T_3 = 0.08 T_4= 0.01	K=19.34 T_1=0.03 T_2=0.01 T_3 = 0.04 T_4= 0.01	K=19.17 T_1=0.07 T_2=0.02 T_3 = 0.07 T_4= 0.02	K=14.95 T_1=0.07 T_2=0.04 T_3 = 0.07 T_4= 0.03	K=19.31 T_1=0.05 T_2=0.03 T_3 = 0.06 T_4= 0.01
G15	K=17.63 T_1=0.077 T_2= 0.01 T_3=0.04 T_4= 0.01	K=19.28 T_1=0.05 T_2= 0.01 T_3= 0.05 T_4= 0.01	K=19.07 T_1=0.06 T_2= 0.01 T_3= 0.01 T_4= 0.04	K=19.53 T_1=0.08 T_2= 0.02 T_3= 0.04 T_4= 0.01	K=17.38 T_1=0.07 T_2= 0.01 T_3= 0.08 T_4= 0.01	K=13.50 T_1=0.10 T_2= 0.01 T_3= 0.09 T_4= 0.02
G16	K=19.73 T_1=0.071 T_2= 0.01 T_3=0.09 T_4=0.02	K=19.71 T_1=0.07 T_2= 0.01 T_3= 0.06 T_4=0.01	K=18.35 T_1=0.08 T_2= 0.01 T_3= 0.06 T_4=0.03	K=19.70 T_1=0.09 T_2= 0.02 T_3= 0.05 T_4=0.02	K=19.71 T_1=0.01 T_2= 0.01 T_3= 0.04 T_4=0.02	K=18.90 T_1=0.10 T_2= 0.06 T_3= 0.02 T_4=0.02

Table B.2
Parameters of the PSSs used in Approch B

M/c	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
G9	K=13.98 T_1=0.18 T_2= 0.11 T_3= 0.46 T_4=0.23	K=15.80 T_1=0.24 T_2= 0.15 T_3= 0.05 T_4=0.02	K=10.94 T_1=0.67 T_2= 0.80 T_3= 1.23 T_4=0.29	K=10.91 T_1=0.36 T_2=1.92 T_3= 1.74 T_4=0.08	K=14.03 T_1=0.10 T_2= 0.55 T_3= 0.58 T_4=0.17	K=18.35 T_1=2.37 T_2= 0.67 T_3= 0.97 T_4=2.52
G13	K=14.40 T_1=0.43 T_2=0.09 T_3=0.01 T_4=0.16	K=13.91, T_1=0.38 T_2=0.12 T_3=0.02 T_4=0.09	K=15.94 T_1=1.40 T_2=0.80 T_3= 0.50 T_4=1.10	K=16.38 T_1=3.02 T_2=0.48 T_3= 0.69 T_4=2.00	K=20.03 T_1=0.01 T_2=0.41 T_3= 1.10 T_4=0.01	K=13.83 T_1=0.63 T_2=0.23 T_3= 1.36 T_4=1.96
G14	K=16.07 T_1=0.47 T_2=0.11 T_3=0.01 T_4= 0.12	K=19.66 T_1=0.15 T_2=0.29 T_3= 0.08 T_4= 0.03	K=11.75 T_1=2.37 T_2=2.13 T_3 = 2.10 T_4= 0.87	K=13.67 T_1=2.43 T_2=1.25 T_3 = 0.10 T_4= 3.35	K=11.33, T_1=0.42 T_2=0.25 T_3 = 0.53 T_4= 0.40	K=19.70 T_1=1.08 T_2=1.43 T_3 = 1.29 T_4= 0.41
G15	K=20.19 T_1=0.56 T_2= 0.18 T_3= 0.03 T_4= 0.30	K=18.68 T_1=0.29 T_2= 0.15 T_3= 0.05 T_4= 0.16	K=17.76 T_1=0.72 T_2= 0.87 T_3= 1.60 T_4= 0.60	K=16.01 T_1=0.70 T_2= 0.16 T_3= 0.81 T_4= 0.62	K=11.36 T_1=0.54 T_2= 0.75 T_3= 0.08 T_4= 0.90	K=13.04 T_1=0.01 T_2= 1.95 T_3= 1.12 T_4= 2.10
G16	K=13.77 T_1=0.25 T_2=0.08 T_3=0.01 T_4=0.06	K=20.13 T_1=0.57 T_2= 0.12 T_3= 0.17 T_4=0.37	K=13.69 T_1=1.61 T_2= 0.04 T_3= 0.01 T_4=0.61	K=18.06, T_1=0.74 T_2= 0.62, T_3= 1.65 T_4=1.01	K=16.65 T_1=0.02 T_2= 0.19 T_3= 0.94 T_4=0.22	K=20.30 T_1=1.43 T_2= 1.84 T_3= 1.59 T_4=0.33

Table B.3
Oscillatory Modes of the 16 Machine Power System (Approch A) for Operating Condition I.

Parameters	Eigenvalues	Frequency (Hz)	Damping (%) ± std
PSS [15]	-0.77 ± j 2.59	0.41	28.53
	-0.79 ± j 3.42	0.54	22.7
	-0.82 ± j 4.05	0.64	19.70
BFA (Case 1)	-1.05 ± j 2.47	0.39	37.20 ±0.77 (35.75, 38.76)
	-1.06 ± j 3.27	0.52	29.57±1.00 (27.17, 31.11)
	-1.20 ± j 3.89	0.61	28.53±1.44 (25.42, 32.15)
BFA (Case 2)	-1.03 ± j 2.49	0.39	37.07 ±0.85 (34.19, 38.48)
	-1.07 ± j 3.28	0.52	29.81±0.87 (27.87, 31.66)
	-1.22 ± j 3.97	0.63	28.77±0.95 (27.39, 31.01)
BFA (Case 3)	-1.05 ± j 2.47	0.39	37.12 ±0.66 (36.32, 39.25)
	-1.05 ± j 3.31	0.52	29.81±0.89 (27.87, 31.66)
	-1.26 ± j 3.89	0.61	28.83±0.93 (27.39, 31.01)
BFA (Case 4)	-1.02 ± j 2.49	0.39	36.79 ±0.51 (35.96, 37.98)
	-1.06 ± j 3.34	0.53	29.30±1.02 (27.52, 30.99)
	-1.20 ± j 3.91	0.62	28.54±1.04 (26.67, 29.90)

Table B.3 (Cont'd)
Oscillatory Modes of the 16 Machine Power System (Approach A) for Operating Condition I

Parameters	Eigenvalues	Frequency (Hz)	Damping (%) ± std
BFA (Case 5)	-1.03 ± j 2.51	0.40	36.87 ±0.48 (36.08, 37.84)
	-1.08 ± j 3.36	0.53	29.66±1.13 (28.07, 31.48)
	-1.27± j 3.97	0.63	28.53±1.23 (25.73, 30.62)
BFA (Case 6)	-1.01 ± j 2.47	0.39	36.69 ±0.56 (35.39, 37.91)
	-1.01 ± j 3.25	0.51	29.40±1.03 (27.49, 31.50)
	-1.19± j 3.95	0.63	28.04±1.02 (25.26, 28.99)

Table B.4
Oscillatory Modes of the 16 Machine Power System (Approach B) for Operating Condition II.

Parameters	Eigenvalues	Frequency (Hz)	Damping (%)± std
PSS [15]	-0.77 ± j 2.59	0.41	28.53
	-0.79 ± j 3.42	0.54	22.7
	-0.82 ± j 4.05	0.64	19.70
BFA (Case 1)	-1.01 ± j 2.53	0.40	35.85 ±0.64 (34.32, 37.31)
	-1.22 ± j 3.29	0.52	32.25±3.89 (26.93, 38.73)
	-1.05 ± j 3.96	0.63	25.6±1.23 (23.93, 27.92)
BFA (Case 2)	-1.01 ± j 2.49	0.39	35.61 ±0.84 (34.41, 37.55)
	-1.11 ± j 3.28	0.52	30.85±3.01 (27.25, 38.48)
	-1.21 ± j 3.95	0.62	26.21±1.46 (23.42, 29.38)
BFA (Case 3)	-1.06 ± j 2.15	0.34	41.49 ±4.53 (33.83, 54.72)
	-1.75 ± j 3.00	0.47	34.13±6.18 (25.64, 50.34)
	-1.08 ± j 3.72	0.59	26.98±2.71 (23.42, 32.3)
BFA (Case 4)	-1.31 ± j 2.44	0.38	41.69 ±3.90 (36.25, 48.23)
	-1.35 ± j 3.6	0.57	35.95±5.31 (26.22, 47.78)
	-1.03 ± j 3.79	0.59	26.81±1.87 (23.91, 31.28)

Table B.4 (Cont'd)
Oscillatory Modes of the 16 Machine Power System (Approach B) for Operating Condition II.

Parameters	Eigenvalues	Frequency (Hz)	Damping (%)± std
BFA (Case 5)	-1.28 ± j 2.02	0.32	41.96 ±4.76 (36.41, 53.62)
	-1.12± j .2.77	0.44	34.81±6.55 (27.03, 51.21)
	-1.07± j 3.74	0.59	27.11±1.86 (23.60, 30.09)
BFA (Case 6)	-1.05 ± j 2.24	0.35	40.91 ±2.72 (36.96, 46.96)
	-1.21 ± j 2.54	0.40	32.85±4.53 (25.04, 43.41)
	-1.02± j 4.02	0.64	27.04±2.84 (24.12, 35.13)

Table B.5
Overall Normalized P.I. for Approach A.

Disturbance	Variants	Areas	PSS [15]	16 PSSs design Op 1	Op 2	Op 3
Overall Performance	Case 1	Area 1	1.0	1.48	1.48	1.48
		Area 2	1.0	1.06	1.05	1.05
		Area 3	1.0	1.76	1.69	1.70
		Area 4	1.0	1.59	1.56	1.55
		Area 5	1.0	1.55	1.53	1.53
	Case 2	Area 1	1.0	1.46	1.47	1.46
		Area 2	1.0	1.31	1.31	1.31
		Area 3	1.0	1.62	1.62	1.62
		Area 4	1.0	1.52	1.53	1.52
		Area 5	1.0	1.49	1.48	1.49
	Case 3	Area 1	1.0	1.57	1.57	1.57
		Area 2	1.0	1.54	1.55	1.54
		Area 3	1.0	1.64	1.64	1.64
		Area 4	1.0	1.55	1.55	1.55
		Area 5	1.0	1.50	1.50	1.51
	Case 4	Area 1	1.0	1.42	1.42	1.42
		Area 2	1.0	1.12	1.12	1.11
		Area 3	1.0	1.61	1.61	1.61
		Area 4	1.0	1.49	1.50	1.57
		Area 5	1.0	1.49	1.48	1.52
	Case 5	Area 1	1.0	1.55	1.56	1.55
		Area 2	1.0	1.22	1.22	1.22
		Area 3	1.0	1.77	1.61	1.60
		Area 4	1.0	1.52	1.52	1.52
		Area 5	1.0	1.51	1.51	1.51
	Case 6	Area 1	1.0	1.58	1.58	1.58
		Area 2	1.0	0.95	0.95	0.94
		Area 3	1.0	1.67	1.67	1.67
		Area 4	1.0	1.52	1.53	1.52
		Area 5	1.0	1.47	1.47	1.47

Table B.6
Overall Normalized P.I. for Approach B.

Disturbance	Variants	Areas	PSS [15]	5 PSSs design		
				Op 1	Op 2	Op 3
Overall Performance	Case 1	Area 1	1.0	1.08	1.08	1.08
		Area 2	1.0	1.03	1.04	1.03
		Area 3	1.0	1.52	1.53	1.52
		Area 4	1.0	1.38	1.38	1.38
		Area 5	1.0	1.30	1.30	1.31
	Case 2	Area 1	1.0	1.04	1.05	1.04
		Area 2	1.0	1.04	1.05	1.04
		Area 3	1.0	1.49	1.48	1.49
		Area 4	1.0	1.41	1.40	1.43
		Area 5	1.0	1.27	1.30	1.31
	Case 3	Area 1	1.0	1.03	1.07	0.99
		Area 2	1.0	1.10	1.11	1.10
		Area 3	1.0	2.44	2.10	2.14
		Area 4	1.0	1.98	1.76	1.81
		Area 5	1.0	1.66	1.57	1.61
	Case 4	Area 1	1.0	0.98	0.98	0.98
		Area 2	1.0	1.05	1.06	1.05
		Area 3	1.0	1.54	1.55	1.54
		Area 4	1.0	1.53	1.53	1.52
		Area 5	1.0	1.53	1.53	1.55
	Case 5	Area 1	1.0	0.98	0.92	0.91
		Area 2	1.0	1.08	1.09	1.08
		Area 3	1.0	1.81	1.59	1.74
		Area 4	1.0	1.70	1.73	1.67
		Area 5	1.0	1.46	1.46	1.45
	Case 6	Area 1	1.0	1.07	1.08	1.07
		Area 2	1.0	1.07	1.08	1.07
		Area 3	1.0	1.77	1.86	1.78
		Area 4	1.0	1.52	1.54	1.51
		Area 5	1.0	1.26	1.25	1.26

APPENDIX C
APPENDIX FOR PAPER 3

Table C.1
Two Area Power System Optimized PSS Parameters

Generator	PSO optimized parameters	SPPSO optimized parameters	BFA optimized parameters
G1	K = 30.00 T_1 = 1.17 s T_2 = 0.39 s T_3 = 5.77 s T_4 = 15.00 s	K = 23.71 T_1 = 1.28 s T_2 = 0.50 s T_3 = 3.77 s T_4 = 7.03 s	K = 23.84 T_1 = 2.00 s T_2 = 1.00 s T_3 = 6.16 s T_4 = 8.25 s
G2	K =30.00 T_1 = 1.21 s T_2 = 0.34 s T_3 = 4.36 s T_4 =14.66 s	K =22.76 T_1 = 1.54 s T_2 = 0.49 s T_3 = 3.61 s T_4 =8.45 s	K =21.48 T_1 = 2.00 s T_2 = 1.00 s T_3 = 4.93 s T_4 = 8.19 s
G3	K = 17.71 T_1 = 0.83 s T_2 = 0.36 s T_3 = 10.00 s T_4 = 15.00 s	K = 23.88 T_1 = 1.25 s T_2 = 0.75 s T_3 = 5.35 s T_4 = 8.57 s	K = 18.22 T_1 = 2.00 s T_2 = 1.00 s T_3 = 4.87 s T_4 = 7.24 s
G4	K = 29.77 T_1 = 0.90 s T_2 = 0.55 s T_3 = 4.10 s T_4 = 15.00 s	K = 27.31 T_1 = 1.17 s T_2 = 1.00 s T_3 = 2.96 s T_4 = 8.18 s	K = 20.71 T_1 = 2.00 s T_2 = 1.00 s T_3 = 4.74 s T_4 = 8.92 s

Table C.2
Nigerian Power System Optimized PSS Parameters

Generator	PSO optimized parameters	SPPSO optimized parameters	BFA optimized parameters
Egbin	$K = 30.00$ $T_1 = 0.210$ s $T_2 = 0.001$ s $T_3 = 10.00$ s $T_4 = 10.70$ s	$K = 25.830$ $T_1 = 0.380$ s $T_2 = 0.990$ s $T_3 = 0.350$ s $T_4 = 0.005$ s	$K = 1.250$ $T_1 = 0.290$ s $T_2 = 0.030$ s $T_3 = 0.220$ s $T_4 = 0.005$ s
Shiroro	$K = 6.44$ $T_1 = 0.670$ s $T_2 = 0.001$ s $T_3 = 0.010$ s $T_4 = 0.050$ s	$K = 28.210$ $T_1 = 0.690$ s $T_2 = 0.770$ s $T_3 = 0.230$ s $T_4 = 0.005$ s	$K = 1.950$ $T_1 = 0.250$ s $T_2 = 0.050$ s $T_3 = 0.280$ s $T_4 = 0.030$ s

VITA

Tridib Kumar Das, received B.E degree with a first class in Electrical Engineering from the University College of Engineering; Burla, India in August 2002. He was a lecturer in Eastern Academy of Science and Technology, Bhubaneswar, India from Sept'2002- May'2005. He received his Masters degree in Electrical Engineering at the Real-Time Power and Intelligent Systems laboratory in University of Missouri, Rolla in December 2007.