Local Search-based Non-dominated Sorting Genetic Algorithm for Optimal Design of Multimachine Power System Stabilizers

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Abstract-This study presents a metaheuristic method for the optimum design of multimachine Power System Stabilizers (PSSs). In the proposed method, referred to as Local Search-based Non-dominated Sorting Genetic Algorithm (LSNSGA), a local search mechanism is incorporated at the end of the second version of the non-dominated sorting genetic algorithm in order to improve its convergence rate and avoid the convergence to local optima. The parameters of PSSs are tuned using LSNSGA over a wide range of operating conditions, in order to provide the best damping of critical electromechanical oscillations. Eigenvalue-based objective functions are employed in the PSS design process. Simulation results based on eigenvalue analysis and nonlinear time-domain simulation proved that the proposed controller provided competitive results compared to other metaheuristic techniques.

Keywords-power system stabilizer; non-dominated sorting genetic algorithm; local search; eigenvalue analysis; nonlinear time domain simulation

I. INTRODUCTION

The complexity of electricity networks due to several economic, ecological, and technical exigencies has obliged electric companies to operate at full network capacity in order to achieve a balance between the increased consumption and the production, under severe conditions increasingly close to the stability limits. Under these drastic conditions and operating limits, the occurrence of any contingencies or disturbances such as short-circuits, sudden variations in loads, and line outage, can lead to a critical situation often starting with poorly damped Electromechanical Oscillations (EMOs) followed by loss of synchronism and system instability [1]. For instance, these low frequency oscillations may limit the transfer capacity of the power system and continue to grow up resulting in the separation of the system if no adequate response is quickly taken. To overcome the problem of EMOs and improve the system damping, additional stabilizing signals are usually added to the excitation system via the voltage regulator [2]. The Conventional Power System Stabilizer (CPSS) has long been employed to damp out EMOs. Generally, CPSSs are based on lead-lag compensators with fixed parameters determined at the nominal operating condition. However, power systems are strongly nonlinear with configurations and load changing over time, which implies that these fixed parameters of the stabilizers are no longer adapted to the new operating conditions [3]. Therefore, the fundamental problem is not only to determine the optimal parameters of these stabilizers, but also to make them adapt to the modification of the operating points and system configurations. Within this context, diverse research works have been directed towards the design of Power System Stabilizers (PSSs) with optimal performance for a wide range of system parameters, configurations, and operating conditions [4-8]. From the literature review, it was found that several ideas and methods have been suggested for the optimal setting of PSS parameters. The most used PSS design methods are summarized in [9-10] and are divided into three main categories which are adaptive control [11-12], linear approximation [13], and nonlinear models [14]. In [12], Model Reference Adaptive System-based PSS (MRAS-PSS) design has been addressed. The performance of the MRAS-PSS has been assessed through Nonlinear Time Domain Simulation (NTDS). Despite the fact that the adaptive control-based PSS may mitigate the shortcomings of CPSS, it appears complex in nature and costly.

Several numerical techniques have been suggested for the enhancement of small signal stability of interconnected multimachine power systems, such as linear programming and

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gradient methods [15]. Unfortunately, these classical methods require initialization of the problem solutions and they are iterative. Thus, they may fail to converge to the global optima. To avoid the limitations of classical techniques, nonconventional optimization techniques have been used for solving several complex problems. In particular, these techniques have demonstrated high performance when applied to power system problems, such as the problem of the enhancement of power system stability. For instance, a Genetic Algorithm (GA)-based method for the optimal setting of lead-lag PSSs parameters was suggested in [16]. In [4], the same regulators have been optimally designed using Simulated Annealing (SA) where the objective function has been optimized in order to shift all electromechanical modes to the left side in the s-plane. An artificial bee colony-based method has been suggested in [6] for dynamic stability enhancement and its performance was compared with other techniques. In [17], a time domain response based function has been minimized using Particle Swarm Optimization (PSO) in order to tune the parameters of PSS regulators. These regulators are employed for damping inter-area oscillations and local modes. In [18], the whale optimization algorithm was used for tuning the PSS regulators in order to suppress power system oscillations and maintain system stability after the occurrence of faults. The authors have considered an eigenvalue-based objective function in the design process. Other metaheuristic techniques have also been employed for the enhancement of power system stability, such as the Bacteria Foraging Optimization Algorithm (BFOA) [19] and Fuzzy Gravitational Search Algorithm (FGSA) [20]. Unfortunately, these random-based methods have been criticized for their low convergence rate and the fact that they can be trapped in local minima when complex multimodal problems are considered [21]. Within this context, a modified version of the Non-dominated Sorting Genetic Algorithm (NSGAII) for the optimal design of PSS regulators is presented in this study. The main contributions of this work are:

- Two eigenvalue-based objective functions are optimized simultaneously in order to provide optimum PSS design. The first one is related to the real part of the electromechanical modes whilst the second one corresponds to the damping ratios of the same modes. The optimization of these two objective functions aims to shift all electromechanical modes as much as possible in the left side of the s-plane. In order to make the proposed controller more robust, the PSS parameters are optimized over a wide range of operating conditions.
- The aforementioned objective functions are minimized simultaneously using an improved version of the NSGAII. To do this, a local search procedure is embedded at the end of all iterations of the NSGAII in order to increase its convergence rate and avoid the convergence to local optima. Decision variables of the problem are the PSS parameters and the problem constraints are the bounds of these parameters.
- The simulation results based on eigenvalue analysis and nonlinear time domain simulation demonstrated that the proposed controller provided results competitive with the other metaheuristic techniques implemented recently for the resolution of the PSS design problem, such as NSGAII, SA [4] and Fuzzy Gravitational Search Algorithm (FGSA) [20].

II. PROBLEM FORMULATION OF PSS DESIGN

A. Power Network Model

For stability studies, power network is mostly modeled by a set of nonlinear Differential-Algebraic Equations (DAE) as given in (1)-(3):

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

$$0 = g(X, Y) \quad (2)$$

$$W = h(X, Y, U) \quad (3)$$

The state variables vector and the algebraic variables vector are represented by X and Y respectively. U and W express the input variables vector and the output variables set respectively. The equations of network power flow are represented by a nonlinear algebraic set defined with the symbol g. The dynamics of the system and controller are expressed by the first-order nonlinear differential equations described by the function f. The output variables are described by function h.

In this study, the state vector is $X = [\delta \ \omega \ E_q' \ E_{fd} \ ]^T$. where δ is the rotor angle, and ω is the rotor speed. E_q' is the internal voltage and E_{fd} is the field voltage. The bus voltage magnitudes and phase angles constitute the vector Y. The PSS output signals constitute the control vector U. The PSS design is based on a linearized incremental model of the power system. At an equilibrium point of the power system, the state equations of the system can easily be written if Y is removed and it is assumed that the power flow Jacobian is non-singular, as follows.

$$\Delta\dot{X} = AX + BU \quad (4)$$

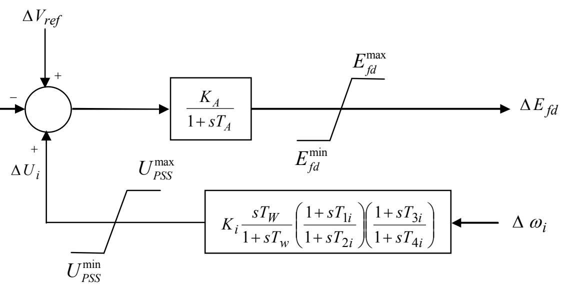


Fig. 1. IEEE type-ST1 excitation system with PSS.

It is worth noting that if the power network is with n machines and m PSSs, the state matrix A is a $4n \times 4n$ matrix and the control matrix B is a $4n \times m$ matrix.

B. Excitation System with PSS Structure

The PSS gives a control effect, by acting via the exciter, to the power system under consideration. This study considers the IEEE type-ST1 excitation system with PSS [6] as shown in Figure 1. V_t is the generator terminal voltage and V_{ref} is the reference terminal voltage. T_A is the amplifier time constant, K_A is the amplifier gain constant, U_i is the output that is the supplementary stabilizing signal, and $\Delta\omega_i$ is the input signal of the i^{th} PSS that is the normalized speed deviation. The PSS's transfer function is shown in the following expression:

$$U_i(s) = K_i \frac{sT_W}{1+sT_W}\left[\frac{(1+sT_1)(1+sT_3)}{1(+sT_2)(1+sT_4)}\right] \quad (5)$$

In (5), the washout block with time constant T_{Wi} is utilized as a high-pass filter, allowing signals in the range of 0.2-2Hz associated with rotor oscillation to pass unchanged, and is generally between 1 and 20s [4]. Compensating for the phase lag between the PSS output and the control operation, which is the electrical torque, is conducted by the two first-order lead-lag transfer functions. Thus, the representation of PSS comprises of two lead-lag blocks, a gain K_i, and a washout bloc with time constant T_{Wi}.

C. Damping Controller Design

The system closed-loop eigenvalues are measured after linearizing the power system around the operating point. Using only the unstable or lightly damped electromechanical forms that need to be moved, the objective functions can be formulated. The issue of the parameter tuning of the PSS controllers that stabilize the system is transformed into a multiobjective minimization problem in this study. One of the considered two eigenvalue-based objective functions stated in [6] aims to transfer the closed-loop eigenvalues to the left side of the line expressed by $\sigma_{ij} = \sigma_0$, as shown in Figure 2(a). J_1 in (12) represents this function and the second objective function is defined by J_2. In fact, and as presented in Figure 2(b), minimizing J_2 equals to raising the damping ratios of all electromechanical modes and place the closed-loop eigenvalues in a D-shape sector corresponding to $\xi_{ij} \geq \xi_0$.

$$\begin{cases} \text{if } max\{\sigma_{ij}\} \leq \sigma_0 \text{ and } min\{\xi_{ij}\} \geq \xi_0, \\ \quad J_1 = max\{\sigma_{ij}\} \\ \quad J_2 = -min\{\xi_{ij}\} \\ \text{else} \\ \quad J_1 = J_{1max} \\ \quad J_2 = J_{2max} \end{cases} \quad (6)$$

where the real part and damping ratio of the i^{th} electromechanical modes corresponding to the j^{th} operating point are expressed by σ_{ij} and ξ_{ij} respectively. The fitness functions J_1 and J_2 are equal to their upper limits J_{1max} and J_{2max} if one or more electromechanical modes are outside the D-shape sector shown in Figure 2(c). It is worth noting that functions J_1 and J_2 have to be minimized subject to the following inequality constraints that describe the bounds of the adjustable parameters of the regulators:

$$K_i^{\min} \leq K_i \leq K_i^{\max} \quad (7)$$

$$T_{1i}^{\min} \leq T_{1i} \leq T_{1i}^{\max} \quad (8)$$

$$T_{2i}^{\min} \leq T_{2i} \leq T_{2i}^{\max} \quad (9)$$

$$T_{3i}^{\min} \leq T_{3i} \leq T_{3i}^{\max} \quad (10)$$

$$T_{4i}^{\min} \leq T_{4i} \leq T_{4i}^{\max} \quad (11)$$

The washout time constant T_w is fixed to 5s in this paper, and typical ranges of the decision variables are [0.01–1.5] for T_{1i} to T_{4i} and [0.1–50] for K_i.

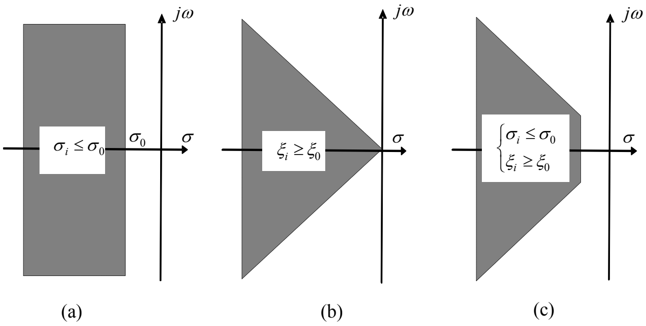


Fig. 2. Electromechanical modes location for different objective functions.

III. DESCRIPTION OF THE PROPOSED OPTIMIZATION TECHNIQUE

Due to its high computational complexity and absence of elitism, the first version of NSGA has been criticized frequently in the literature. To overcome these drawbacks, authors in [22] proposed a new version of NSGA, called NSGAII. The NSGAII algorithm comprises mainly of two parts, which are the non-dominated sorting of solutions and the preservation of the population diversity. In NSGAII, offspring population Q_t is combined with its parent population P_t at each iteration *t*. The combined population is sorted based on non-dominated sorting mechanism into fronts. Then, solutions of one front are sorted using their crowding distances.

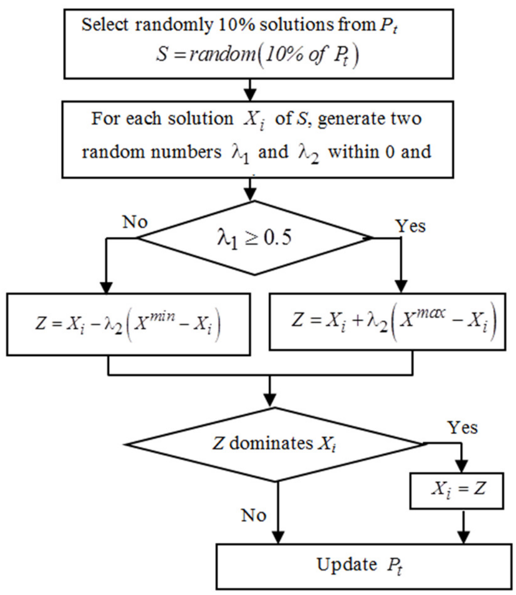


Fig. 3. Flowchart of the local search algorithm.

Despite the tmodifications applied in the NSGAII, it suffers from its low convergence rate due to its random parameters. In addition, NSGAII may fail to converge to the global optima. In order to overcome these limitations, in this study, a local search mechanism is included at the end of NSGAII iterations. This mechanism explores the less-crowded zone in the current archive in order to obtain more non-dominated solutions nearby. The flowchart of the local search algorithm applied for an iteration k is shown in Figure 3.

IV. SIMULATION AND DISCUSSION

In this section, the robustness and effectiveness of the LSNSGA technique, proposed for the determination of the optimal PSS parameters, is evaluated on the 3-machine 9-bus WSCC (Western System Coordinating Council). As shown in Figure 4, this system comprises of 9 buses and 3 generators. All system data are extracted from [6].

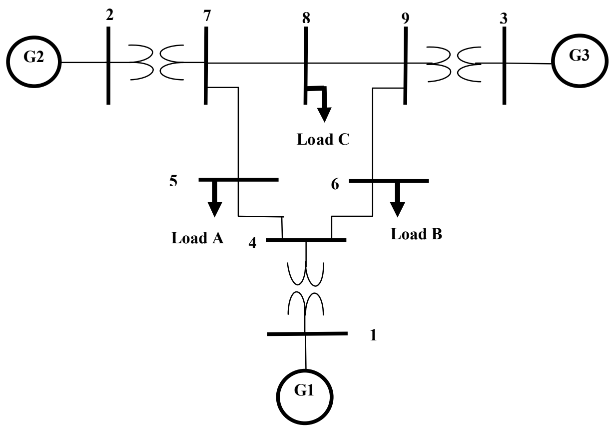


Fig. 4. Single line diagram of the WSCC system.

For economic reasons, only machines 2 and 3 are equipped with PSSs. In order to increase the robustness of the proposed LSNSGA-based controller (LSNSGA-PSS), 4 different operating conditions were used. These conditions are shown in Table I. All experiments are implemented on Matlab environment using a machine with 8GB RAM, Intel core i7 1.8GHz, and Windows 7. Maximum number of iterations and population size are selected to be 100 and 200 respectively. The mutation and crossover probabilities are 0.2 and 0.9.

TABLE I. SYSTEM OPERATING CONDITIONS (IN PU)

		Base case		Case 1		Case 2		Case 3	
		P	***Q***	***P***	***Q***	***P***	***Q***	***P***	***Q***
Gen	G1	0.72	0.27	2.21	1.09	0.36	0.16	0.33	1.12
	G2	1.63	0.07	1.92	0.56	0.8	-0.11	2.00	0.57
	G3	0.85	-0.11	1.28	0.36	0.45	-0.20	1.50	0.38
Load	A	1.25	0.50	2.00	0.80	0.65	0.55	1.50	0.90
	B	0.90	0.30	1.80	0.60	0.45	0.35	1.20	0.80
	C	1.00	0.35	1.50	0.60	0.50	0.25	1.00	0.50

A. Implementation of the LSNSGA for Optimum PSS Design

To investigate the performance of the proposed method, the results obtained using LSNSGA-PSS are compared with those of other metaheuristic techniques such as NSGAII, SA [4], and FGSA [20]. The convergence characteristic of the proposed optimization technique for the optimum tuning of PSS parameters is illustrated in Figure 5. Optimum PSSs parameters for the proposed method and for the SA and FSGA techniques are given in Table II. System eigenvalues and damping ratios corresponding to the optimal PSS parameters, obtained using these techniques are given in Table III.

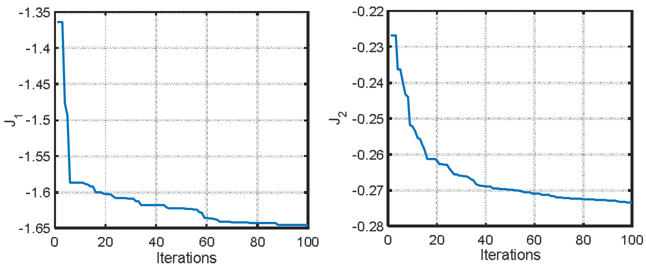


Fig. 5. Convergence characteristics of the LSNSGA.

TABLE II. OPTIMAL PSS PARAMETERS

Method	Gen	*K*	T_1	T_2	T_3	T_4
LSNSGAII-PSS based on J_1	G2	2.4238	0.8075	0.1611	1.0973	0.7417
	G3	9.9970	0.9867	1.2183	0.2652	0.4252
LSNSGAII-PSS based on J_2	G2	2.4529	0.8034	0.1642	1.1028	0.7448
	G3	9.9996	0.9840	1.2069	0.2252	0.4313
NSGAII-PSS	G2	2.4530	0.8035	0.1642	1.1027	0.7447
	G3	9.9995	0.9834	1.2069	0.2267	0.4327
SA-PSS	G2	11.008	0.216	0.05	0.104	0.05
	G3	0.319	0.410	0.05	0.233	0.05
FGSA-PSS	G2	30.911	0.222	0.012	0.34	0.054
	G3	30.931	0.229	0.015	0.24	0.034

From Table III, it is obvious that the system is poorly damped when no controller is used for the base case, case 1, and case 2 and it is unstable for case 3. In addition, it can be seen that the proposed controller provides better damping of all electromechanical modes than the other controllers. It is worth noting that all electromechanical controllers obtained using LNSGA-PSS are shifted in D-shape zone defined by $\sigma_0 = -1$ and $\xi_0 = 20\%$.

B. Nonlinear Time Domain Simulation

To assess the effectiveness and robustness of the proposed controller, a 6-cycle fault disturbance in the line 5-7, close to bus 5 is applied. The fault is cleared by tripping the line 5–7 with successful reclosure after 1.0s. Nonlinear simulation results obtained using LSNSGA are compared with the results from SA-PSS, FGSA-PSS, and without controller. System responses at the operating conditions specified above are shown in Figures 6 and 7. Figure 6 depicts the speed deviations in per unit and Figure 7 illustrates the internal voltages. From Figures 6 and 7, it can be clearly seen that the suggested LSNSGA-PSS controller improved greatly the system stability and it provided better damping of the electromechanical oscillations than the other techniques, at all operating conditions.

TABLE III. EIGENVALUES AND DAMPING RATIOS OF THE ELECTROMECHANICAL MODES

Method	Base case	Case 1	Case 2	Case 3
Without PSS	-0.1124±j7.7400, 0.0145	-0.0374±j7.8347, 0.0048	-0.2142±j6.3226, 0.0339	+0.0181±j8.0903, -0.0022
	-1.3346±j9.1096, 0.1450	-0.7023±j10.5832, 0.0662	-0.8227±j6.9390, 0.1177	-0.4515±j11.3794, 0.0396
LSNSGAII-PSS based on J_1	-2.6031± j6.2412, 0.3849	-1.7361±j6.3024, 0.2656	-1.6459±j5.2350, 0.2999	-1.9885±j6.4392, 0.2951
	-2.9611±j6.8626, 0.3962	-4.3102±j8.9358, 0.4345	-2.0874±j6.3268, 0.3133	-4.5721±j9.4259, 0.4364
LSNSGAII-PSS based on J_2	-2.6448±j6.1179, 0.3968	-1.7774±j6.3792, 0.2684	-1.6318±j5.2411, 0.2973	-2.0258±j6.5302, 0.2963
	-2.7138±j7.3837, 0.3450	-3.9494±j9.3519, 0.3890	-1.9142±j6.5763, 0.2795	-4.2547±j9.9153, 0.3943
LSNSGAII-PSS (best compromise solution)	-2.5491±j 5.9300, 0.3949	-1.7847±j6.2809, 0.2733	-1.6283±j5.1460, 0.3017	-2.0326±j6.4097, 0.3023
	-2.7394±j7.5113, 0.3426	-3.8660±j9.3531, 0.3820	-1.8925±j6.6077, 0.2753	-4.1434±j9.9371, 0.3849
SA-PSS	-1.6530±j5.1835, 0.3038	-1.3442±j5.6104, 0.2330	-1.3510±j4.5402, 0.2852	-1.4203±j5.6820, 0.2425
	-0.7082±j7.6085, 0.0927	-0.6774±j8.6128, 0.0784	-0.4869±j6.4701, 0.0750	-0.6073±j9.1726, 0.0661
FGSA-PSS	-1.0692±j 1.9971, 0.4719	-0.9256±j2.4987, 0.3473	-1.0438±j1.8555, 0.4903	-0.9196±j2.5427, 0.3401
	-0.2328±j4.1174, 0.0564	-0.1382±j4.5924, 0.0301	-0.3301±j3.6252, 0.0907	-0.1696±j4.4911, 0.0377

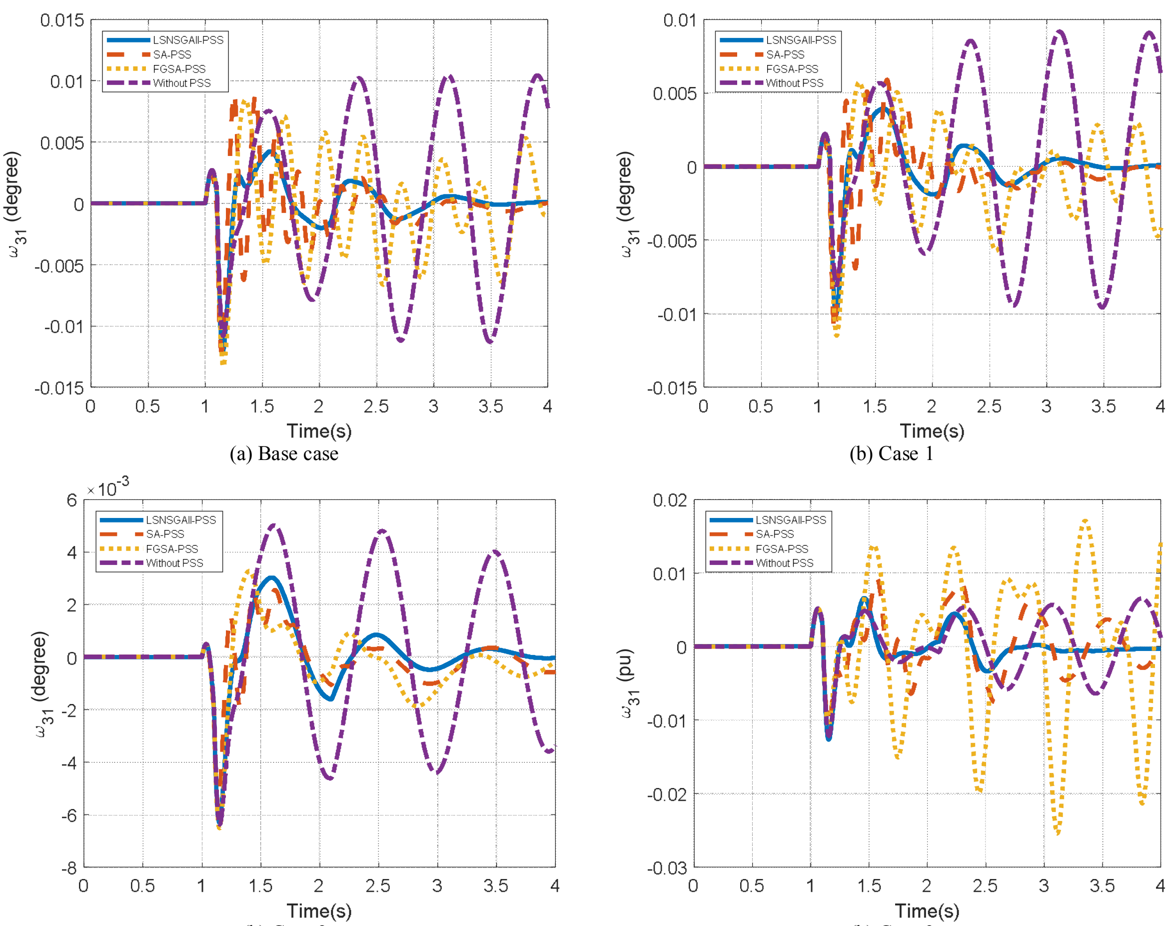
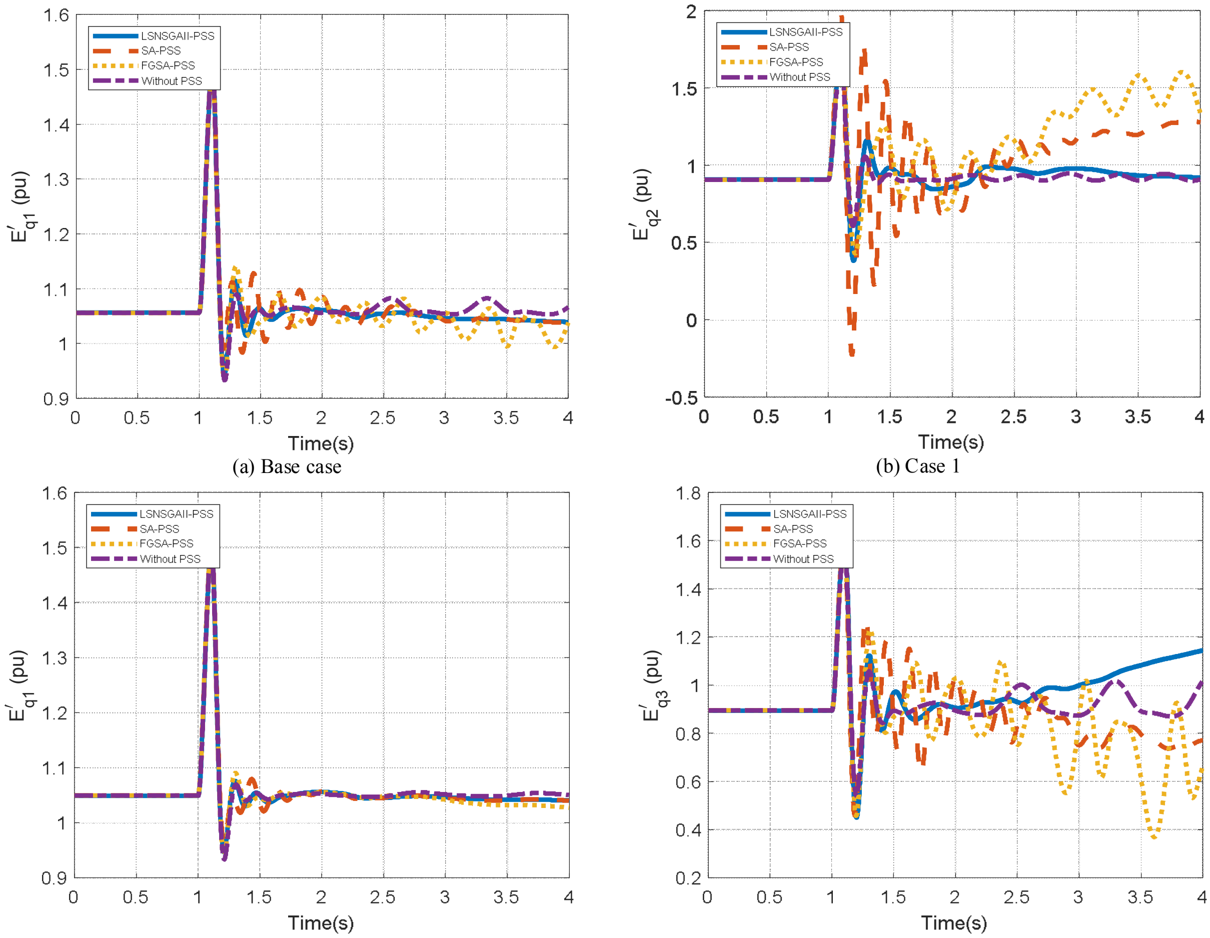


Fig. 6. System responses for speed deviations in pu.



(a) Base case (b) Case 1 (b) Case 2 (b) Case 3

Fig. 7. System responses for internal voltages in pu.

V. CONCLUSION

PSSs represent an effective means for damping electromechanical modes. However, current power networks are becoming strongly nonlinear with configurations and load changing over time. Thus, it is mandatory to adjust the PSS parameters in order to guarantee the optimal damping of system oscillations at any operating condition, system configuration, or disturbance. In order to do this, this study presents an improved version of NSGAII, referred to as LSNSGA, for robust PSS design over a wide range of operating conditions. In the proposed technique, a local search procedure is added to the original NSGAII in order to improve its convergence characteristics. The LSNSGA is used to tune the PSSs parameters in a way that the system stability is optimally improved after the occurrence of fault. In the design process, two eigenvalue-based objective functions are considered. The robustness and performance of the proposed controllers (LSNSGA-PSSs) are tested on a 3-machine 9-bus system. The comparison with other metaheuristic techniques showed that LSNSGA-PSSs controllers provide the best results.

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