

Neuro-fuzzy and nondominated sorting genetic algorithm based power system stabilizer design



Tawfik Guesmi *

College of Engineering, University of Hail, Hail, Saudi Arabia

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ABSTRACT

This study suggests a new method for online enhancement of multimachine system stability. Two steps centered on adjusting power system stabilizers (PSSs) are examined. Firstly, the PSS parameters are tuned off-line using an elitist optimization technique based on genetic algorithms symbolized by NSGAI over a large set of operating conditions. NSGAI was employed to move all electromechanical modes in a pre-specified area in the s-plan. Then, a flexible fuzzy logic-based neural network is proposed to adjust the parameters of the PSSs at any operating condition that can be outside the off-line set by exploiting the off-line results. The suggested controllers are tested by using multi-machine system over some scenarios of serious faults and system configurations. Simulations results show the efficiency and sturdiness of the suggested stabilizers in enhancing the overall system dynamics in real-time at any loading condition selected arbitrarily.

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1. Introduction

In the past few years, power system problems associated with low frequency oscillations (LFO) have been widely revealed and examined. For economic and effectiveness reasons, power system stabilizers (PSSs) have been mostly applied along with excitation generator systems to improve both damping of LFO and stability of the power network during severe interferences. They are employed to develop damping torque for the rotor oscillations across the excitation systems. In most research works, the traditional PSS (CPSS) was commonly provided as a lead-lag filter (Li et al., 2009; Abido, 2000; Sebaa and Boudour, 2009). An extensive research to study the impact of the CPSS parameters on the temporary and powerful activities of power system is provided in (Kundur et al., 1989).

A quite a bit of research references have been released on the area of developing and applying of CPSSs controllers as sufficient damping resources (Ostojic, 1991; Sambariya et al., 2016). The design methods of PSSs such as phase compensation and root locus (Ostojic, 1991), eigenvalue sensitivity analysis (Tse et al., 2001) and poles placement (Abido, 2000) are very suggestive. In (Ataei et al.,

2012; Werner et al., 2003), the PSS adjustment issue is transformed into LMI problem; its solving determines the stabilizer parameters (Ataei et al., 2012). A new LMI based strategy with rank condition has been described in (Kim et al., 2010) to the design of effective PSS. Yet, a one machine test system is investigated in simulation section.

Unfortunately, some of the aforementioned techniques are sequential methods that only consider the damping improvement of one crucial electromechanical mode at a time. Moreover, they are repetitive techniques and require an initialization step. In addition, they can cause the convergence of the search process into local optima. The restrictions of traditional optimization methods were prevented by suggesting some soft computing algorithms. In Hassana et al. (2014), Sebaa and Boudour (2009), genetic algorithms were applied for effective PSS tuning. Two functions in accordance with the eigenvalue analysis have been developed for shifting all closed-loop electromechanical modes in a pre-specified zone in the s-plan. The multi-objective problem (MOP) is transformed into a mono-objective problem by assessing the goals with distinct weights. Accordingly, there is a loss of diversification in the Pareto solutions. In Sambariya et al. (2016), the authors provided a bat-based fuzzy algorithm for an effective PSS design where time-domain objective functions were employed. Other transformative calculations criteria and evolutionary computation algorithm, called bacteria foraging algorithm (BFA) along with maximum neuro-fuzzy

* Corresponding Author.

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plan were developed in [Beno et al. \(2011\)](#) and [Mishra et al. \(2007\)](#) to design intelligent adaptive flexible PSSs for the improvement of both the transient and dynamic stability of multi-machine systems. Nonetheless, The BFA depends on unique search guidelines which may lead to delay in attaining the global solution.

The above design procedures have been done either at single operating point or at several loading conditions at once. Unfortunately, the controllers cannot ensure the system stability with good performance, when loads and/or configuration of the system are changed. Thus, to solve such problem we have to update the controllers' parameters at each loading conditions, which does not guarantee the online decision. Recently, artificial intelligence based PSSs have been well-advised for online enhancement of stability ([Fraile-Ardanuy and Zufria, 2007](#); [Lakshmi and Khan, 1998](#); [Mitra et al., 2007](#); [Abd-Elazim and Ali, 2013](#)). A new neural network based technique for online CPSS setting has been provided in [Segal et al. \(2000\)](#). The stabilizer performance is investigated by varying terminal voltage, power generation and equivalent impedance of one generator system. In [Fraile-Ardanuy and Zufria \(2007\)](#), genetic algorithms (GA) are combined with adaptive network based fuzzy inference systems (ANFIS) for online CPSS tuning. Unluckily, the above online designs are tested only by using a single generator system that cannot ensure the stability of a multimachine system. A fuzzy logic based procedure for online PSS design (FLPSS) was provided and analyzed in [Lakshmi and Khan \(1998\)](#) where speed deviations and their derivatives of machines were chosen as input signals. In [Mitra et al. \(2007\)](#), the FLPSS was used with new input signals, namely, deviation of the real power flow in some lines in combination with the speed deviation. This technique gives better results compared to the FLPSS with angular speed and acceleration input signals.

To use even the benefits of evolutionary algorithms, fuzzy logic systems and neural networks, a technique for real-time adjustment of the PSSs parameters using the improved version of non-dominated sorting GA (NSGAI) ([Deb et al., 2002](#); [Guesmi et al., 2006](#)) and ANFIS is suggested in this paper. The proposed online design will be done in two steps. The first stage aims to find the optimum PSS parameters using NSGAI for a lot of different operating conditions. Two objective functions will be minimized so as to shift as could as possible all undamped and lightly damped electromechanical modes in a pre-specified zone called D-shape area. In this research, the system will be linearized about each steady state condition.

Nevertheless, the next step relies on the ANFIS training phase according to the data base supplied by the previous step. Input and output data are respectively, operating conditions and optimum controller parameters. Optimum solution will be extracted from the Pareto front using the fuzzy based technique presented in [Abido \(2006\)](#). The

suggested design approach ANFIS-PSS has been applied on a multi-machine power system under different scenarios of severe fault disturbances and loading. Eigenvalue analysis along with simulation results based on nonlinear simulation confirm that the suggested ANFIS-PSSs work effectively for any random operating condition and boosts on real-time the entire system performance.

The main contributions of this work are summarized as follows:

- A new NSGAI and ANFIS based PSS design for online enhancement of multimachine system stability was proposed. The aforementioned objective functions were minimized simultaneously and independently.
- Unlike previous works ([Kashki et al., 2013](#); [Khodabakhshian and Hemmati, 2013](#)), the purpose of this study is not only to place all electromechanical modes in the D-shape area but also it aims to move them as much as possible to the left side.

The rest of this paper lies in six sections. In section two, a mathematical modeling of a multimachine system including PSSs is described. Section three investigates the mathematical formulation of the design of PSS controllers. NSGAI algorithm and the ANFIS principles are described respectively in sections four and five. Section six is consecrated to the establishment of the suggested controllers. A conclusion of this work is drawn in section seven.

2. System modeling

2.1. Power system model

For stability studies, power system is often modeled by nonlinear differential and algebraic equations (DAE) as follows ([Fereidouni et al., 2013](#)) (Eqs. 1-3).

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

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

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

Where, X is the state vector defined by $X = [\delta \ \omega \ E'_q \ E'_{fd}]^T$, Y is the vector of algebraic variables composed of phase angles and magnitudes of voltages at all buses of the studied system and W is the vector of output variables.

The PSS output signals constitute the input vector defined by U . f is a vector function comprising the first order nonlinear differential equations that represent system and controller dynamics and g describes the power flow equations in the network. h is a vector function containing all equations that represent output variables.

A linear incremental model is incorporated in the PSS design method. By exploiting a methodology provided in [Abd-Elazim and Ali \(2013\)](#), power

system with n machines and m PSSs is linearized at a steady state point as given below (Eq. 4).

$$\begin{bmatrix} \Delta \dot{X} \\ 0 \\ \Delta W \end{bmatrix} = \begin{bmatrix} f_x & f_y & f_u \\ g_x & g_y & g_u \\ h_x & h_y & h_u \end{bmatrix} \quad (4)$$

where

$$f_x = \nabla_x^T f, f_y = \nabla_y^T f, f_u = \nabla_u^T f, g_x = \nabla_x^T g, g_y = \nabla_y^T g, g_u = \nabla_u^T g, h_x = \nabla_x^T h, h_y = \nabla_y^T h \text{ and } h_u = \nabla_u^T h$$

Removing ΔY and assuming that power flow Jacobian g_y is non-singular, the system can be readily modelled by the following state equation (Eq. 5).

$$\dot{X} = AX + BU \quad (5)$$

where, A is $4n \times 4n$ matrix and B matrix is $4n \times m$ matrix that are described as follows:

$$A = f_x - f_y g_y^{-1} g_x \text{ and } B = f_u - f_y g_y^{-1} g_u$$

the output variables are written as follows (Eq. 6).

$$\Delta W = C\Delta X + D\Delta U \quad (6)$$

where $C = h_x - h_y g_y^{-1} g_x$ and $D = h_u - h_y g_y^{-1} g_u$.

2.2. PSS with excitation system

The PSS provides control effect through the exciter to the system under research. A lead-lag PSS portrayed in Fig. 1 is examined in this document (Abido, 2000).

The input signal of the i -th PSS is the normalized speed deviation, $\Delta\omega_i$. While the output is the supplementary stabilizing signal, U_i . As shown in the block diagram of Fig. 1, the PSS can be modelled by the transfer function given in Eq. 7.

$$U_i(s) = K_i \frac{sT_{Wi} [(1+sT_{1i})(1+sT_{3i})]}{sT_{Wi} [(1+sT_{2i})(1+sT_{4i})]} \quad (7)$$

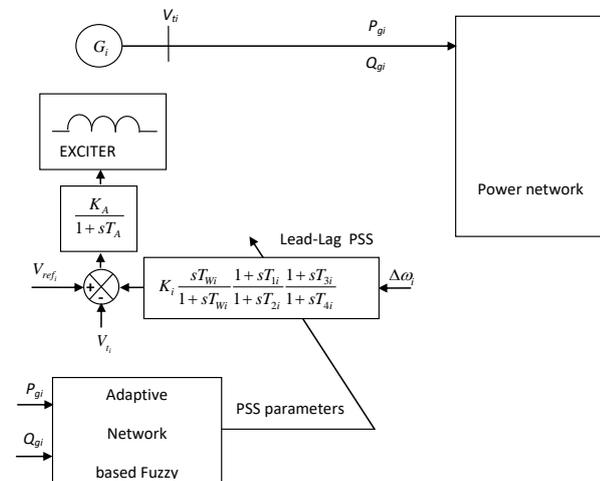


Fig. 1: Power network with ANFIS-PSS controllers

In the past equation, the washout block is used as a high-pass filter eventually continuous with time constant T_{Wi} sufficient to allow the signals in range 0.2-2 Hz associated with rotor oscillation to successfully pass without modification. In general, it is in the variety of 1-20s (Kundur et al., 1989). The two first order lead-lag filters are applied to compensate the phase lag between the output of the PSS and the control action that is the electric torque.

3. Design strategy

The closed-loop modes are analyzed after linearizing the system around the operating point. Then, objective functions will be formulated using only the lightly damped or unstable electromechanical modes that need to be shifted. In this document, the issue of PSS parameters tuning that consolidates the stability of the system is transformed into a bi-objective minimization issue. The first objective function indicated by J_1 in Eq. 8 aims to move all electromechanical mode into the left-side of the vertical line described by $\sigma_{ij} = \sigma_0$, Fig. 2a. However, the second one is described by J_2 . It is obvious that minimize J_2 matches to maximize the minimum of damping ratios of all electromechanical modes and place all electromechanical modes in a wedge-shape sector defined by $\xi_{ij} \geq \xi_0$, Fig. 2b. As consequence, the maximum overshoot is limited. Compared with over previous works (Kashki et al., 2013; Khodabakhshian and Hemmati, 2013), the purpose of this formulation is not only to shift the electromechanical modes into the D-shape zone (Fig. 2c) but also it aims to move them as much as possible to the left side.

$$\left\{ \begin{array}{l} \text{if } \sigma_{ij} \leq \sigma_0 \text{ and } \xi_{ij} \geq \xi_0, \\ J_1 = \max(\sigma_{ij}) \\ J_2 = -\min(\sigma_{ij}) \\ \text{else,} \\ J_1 = J_{1max} \\ J_2 = J_{2max} \end{array} \right. \quad (8)$$

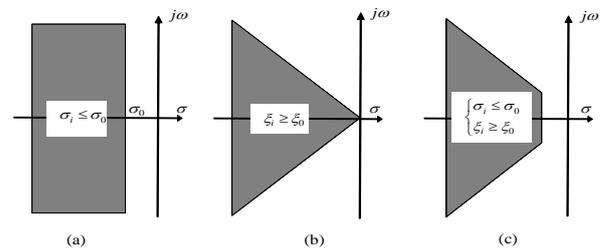


Fig. 2: Location of electromechanical modes

Objective functions J_1 and J_2 will be minimized with respect to the bounds of the PSSs parameters given by inequalities 9-13.

$$K_i^{min} \leq K_i \leq K_i^{max} \quad (9)$$

$$T_{1i}^{min} \leq T_{1i} \leq T_{1i}^{max} \quad (10)$$

$$T_{2i}^{min} \leq T_{2i} \leq T_{2i}^{max} \quad (11)$$

$$T_{3i}^{min} \leq T_{3i} \leq T_{3i}^{max} \quad (12)$$

$$T_{4i}^{min} \leq T_{4i} \leq T_{4i}^{max} \quad (13)$$

Other constraints can be included in system constraints, which are the electromechanical mode frequency limits (Eq. 14).

$$\omega_{min} \leq \omega \leq \omega_{max} \quad (14)$$

The time constant T_{Wi} of the washout will be fixed to 5s. Typical ranges of the decision variables are [1-20] for K_i and [0.01-1.5] for T_{4i} . ω_{max} and ω_{min} are 2 and 0.2 Hz, respectively.

4. Presentation of NSGAI approach

As mentioned, NSGAI is employed in the optimization step. Starting by a population P_t with N_p individuals, NSGAI generates new population Q_t called offspring population. These two populations will be combined in one population R_t . Then, R_t is classified into different non-domination levels R_t^j . Thus, R_t^1 is the Pareto front. Generally speaking, all solutions of R_t^j dominate all solutions of R_t^{j+1} . On the other hand, all solutions having the same non-domination level will be sorted in accordance with their crowding distances. Finally, solutions of R_t^1 are priority to be inserted into the next population P_{t+1} followed by solutions from R_t^2 and so on until P_{t+1} is filled. If the size of P_{t+1} is greater than N_p , excess elements that are from the last front will be removed according to their crowding distances in ascending order. The basic flowchart of NSGAI is shown in Fig. 3.

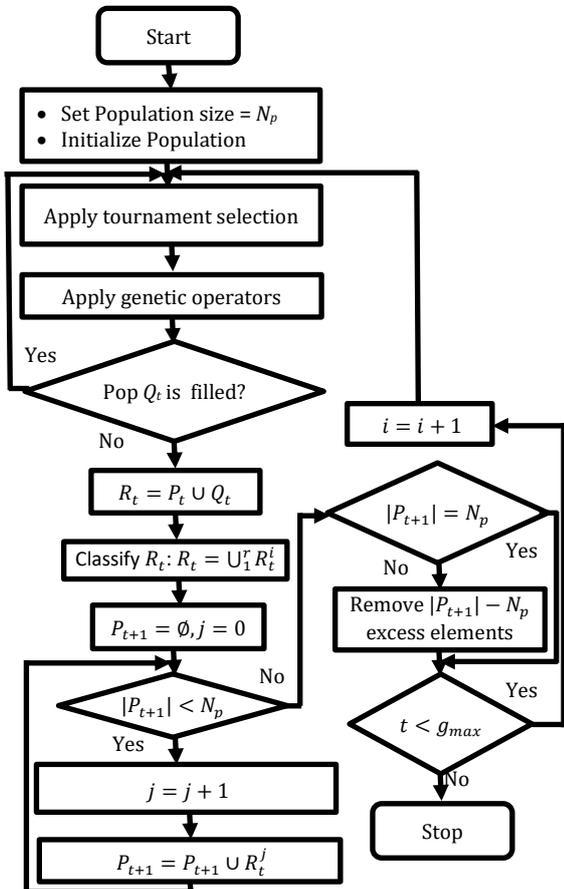


Fig. 3: Basic flowchart of NSGAI

5. ANFIS technique

ANFIS firstly proposed by Jang (1993) was used for online adjustment of PSSs parameters. The choice of the number of membership functions (MF) is a tricky step that influences the convergence of ANFIS method. Several works have been proposed to choose this parameter such as trial and error method and clustering based techniques (Fraile-Ardanuy and Zufria, 2007). In this study, density measure based clustering approach is used in training phase. For a set $X = \{X_1, X_2, \dots, X_n\}$ with n data points, the density measure based clustering technique is summarized in Fig. 4. Where, r_a and r_b are positive constants that are set to 0.5 and 0.8 respectively.

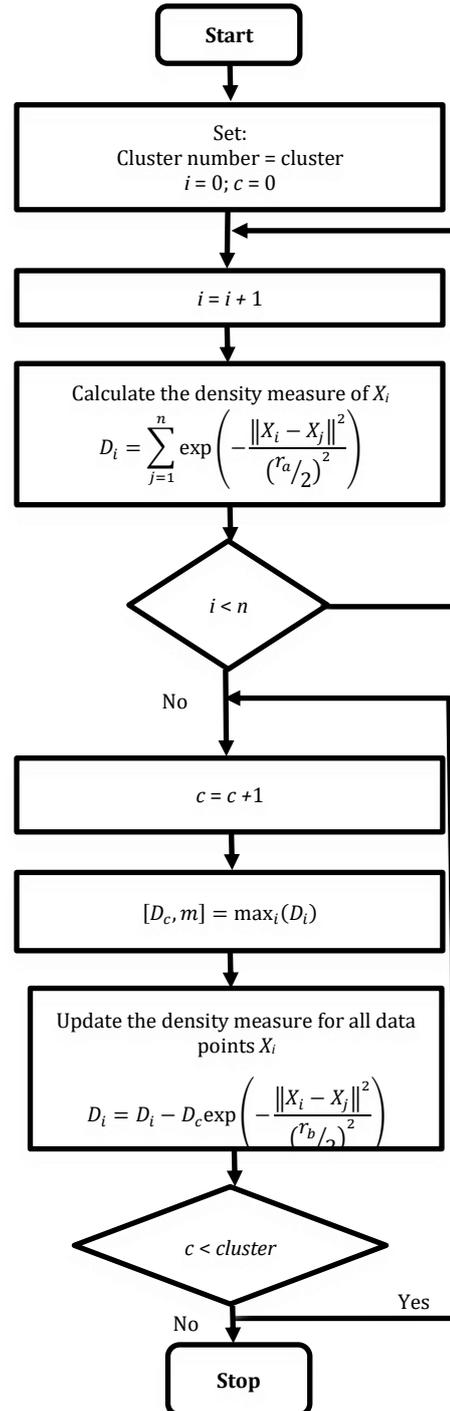


Fig. 4: Proposed clustering technique

Fig. 5 illustrates an example of cluster points and cluster centers for two input variables that can be loading factors relative to active and reactive powers P and Q . It is clear that the number of clusters is 8 for 1000 data points chosen randomly between 0.2 and 1.6.

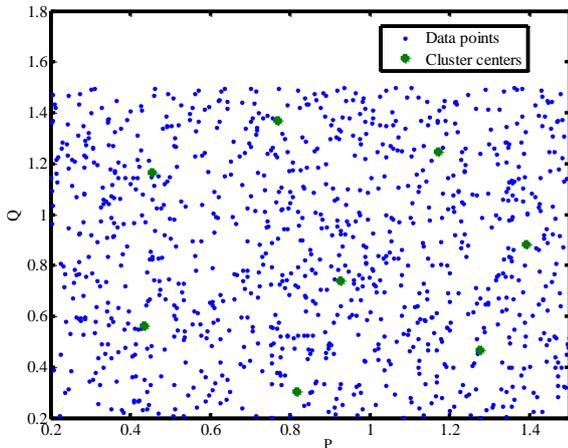


Fig. 5: Data points and cluster centers

6. Implementation of the proposed controllers

To illustrate the sturdiness and efficiency of the recommended ANFIS-based controllers (ANFIS-PSS), the 3-machine 9-bus WSCC (western system coordinating council) portrayed in Fig. 6 is regarded. All data of the studied system are presented in detail in Pai (1989). The system operating condition for the base case is depicted in Table 1. For this system, the assumption is that all machines except G1 are equipped with PSS. The pre-specified D-shape zone is defined by $\sigma_0 = -2$ and $\xi_0 = 20\%$.

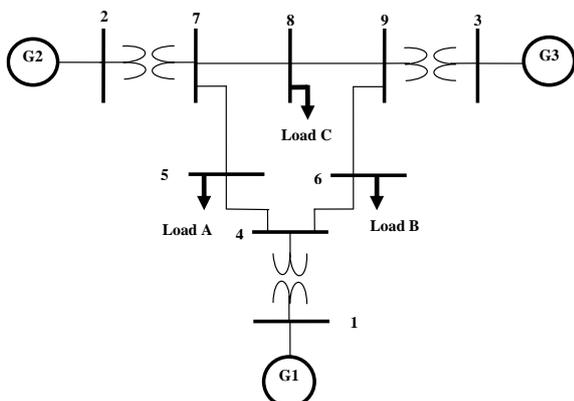


Fig. 6: WSCC system

Table 1: Operating condition for the base case

		P [pu]	Q [pu]
Gen	G1	0.72	0.27
	G2	1.63	0.07
	G3	0.85	-0.11
Load	A	1.25	0.50
	B	0.90	0.30
	C	1.00	0.35

6.1. Off-line data collection

In this stage, NSGAI algorithm was executed for preparing the input-output set. A large range of

operating points described in Eqs. 23 and 24 are used. Where, P_{Loi} and Q_{Loi} correspond to the nominal case load of bus number i . Variables λ_p and λ_q are loading factors that will be varied individually, from 0.2 to 1.5. In this manner, the load power variation ranges will be covered (Eqs. 15 and 16).

$$P_{Li} = \lambda_p P_{Loi} \tag{15}$$

$$Q_{Li} = \lambda_q Q_{Loi} \tag{16}$$

The set of training data is chosen to be with 1936 input-output pairs constituted by loading factors as input data and PSS parameters as output data.

To justify the use of NSGAI, a comparison with existing evolutionary algorithms such as NSGA is evident. For fair evaluation, NSGAI and NSGA programs have been written with the same number of generations (100), probability of crossover (0.9) and same probability of mutation (0.1).

The execution of the two methods is accomplished by generating the Pareto fronts depicted in Fig. 7, the variation of the fitness functions versus generation number (Fig. 8) and the optimized PSSs parameters illustrated by Table 2. Obtained results for the base case show that NSGAI has better diversity characteristics with minimum values of fitness functions J_1 and J_2 .

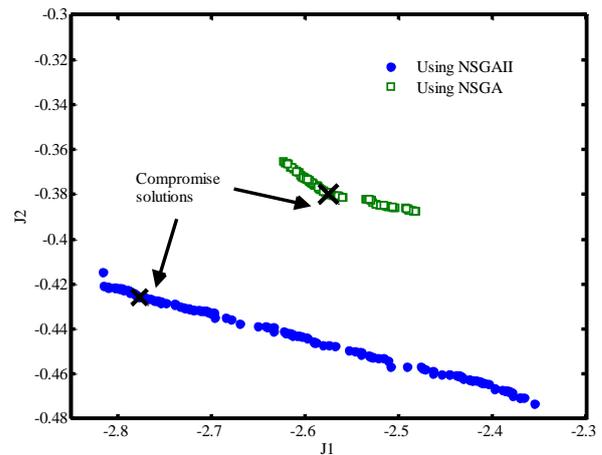


Fig. 7: Pareto solutions for the base case

Table 2: Optimal setting parameters

Method	Gen.	K	$T1$	$T2$	$T3$	$T4$
NSGA	G2	3.2940	0.0629	0.4234	1.4972	0.1046
	G3	6.2904	0.2348	0.2235	0.2912	0.0210
NSGAI	G2	6.0874	0.9426	0.3129	0.2530	0.1352
	G3	2.4439	1.4712	0.4607	0.1886	0.2000

Electromechanical modes along with damping ratios at the base case without and with PSSs controllers are summarized in Table 3. It is evident also, that the stabilizer NSGAI-PSSs outperforms the NSGA-PSSs and they provide the best damping. Moreover, there isn't any doubt that these modes are badly damped, when PSSs are not installed.

6.2. Training phase

The second stage of the online PSS design procedure aims to establish a relationship between

input and output data by employing ANFIS. To accelerate the convergence of the learning stage, an ANFIS is applied for each controller parameter. Using the data base provided in the previous stage, the initial MFs with a cluster radius $r_a = 0.5$ are displayed in Fig. 9. On the other hand, the performance of the ANFIS is tested by visualizing two parameters from its output set that are K_1 and K_2 for 44 samples from the checking set, Fig. 10.

Table 3: Electromechanical modes for base case

Method	Base case
Without PSS	$-0.1124 \pm j7.7400, 0.0145$ $-1.3346 \pm j9.1096, 0.1450$
NSGA-PSS (best compromise solution)	$-2.5748 \pm 5.6254i, 0.4162$ $-2.8809 \pm 7.0134i, 0.3800$
NSGAI-PSS (best compromise solution)	$-2.7769 \pm 4.1314i, 0.5578$ $-2.8950 \pm 6.1549i, 0.4256$

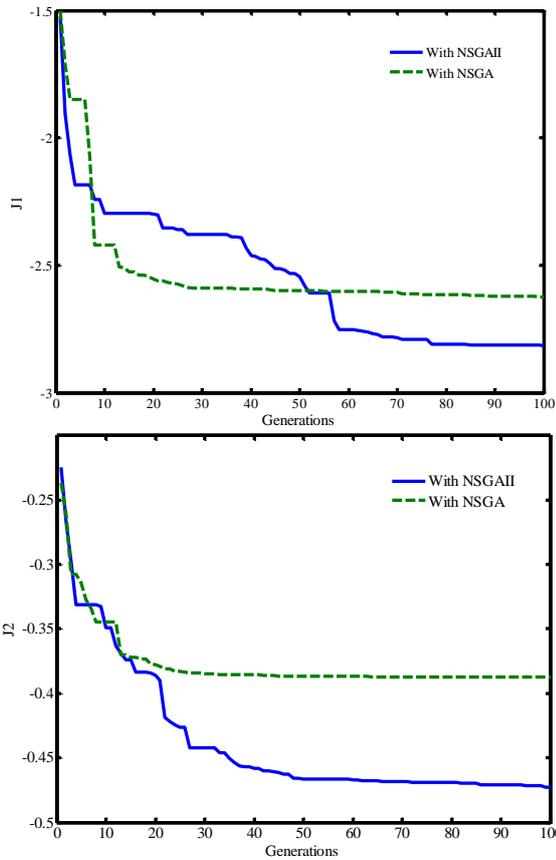


Fig. 8: Convergence of objective functions for the base case

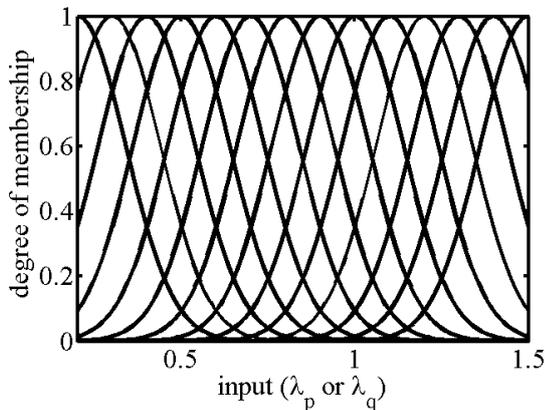


Fig. 9: Initial MF for PSSs parameters

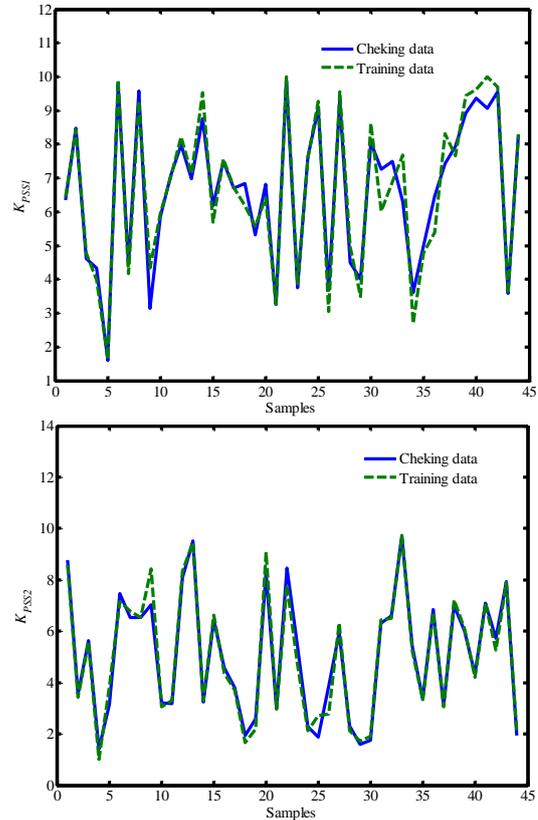


Fig. 10: Prediction data versus checking data

Fig. 11 indicates that all electromechanical modes for two operating conditions chosen arbitrary that are given in Table 4 have been properly shifted to the specified D-shape zone, when the suggested ANFIS-PSS controllers are installed.

In addition, it is obvious that these modes can be considered close to those achieved when applying the NSGAI based design. The first case correspond to $\lambda_p = 0.4$ and $\lambda_q = 0.7$. However, the second one is defined by $\lambda_p = 0.2$ and $\lambda_q = 1.1$.

6.3. Nonlinear time-domain simulation

The main purpose of this section is to confirm the efficiency of the ANFIS-PSS controllers in improving the system damping characteristics by nonlinear time-domain simulation. Therefore, two scenarios of severe fault disturbances are simulated for the two loading conditions mentioned above.

- i) Scenario 1, 6-cycle fault disturbance at bus 5 at the end of line 5-7. The fault is cleared by tripping the line 5-7 with successful reclosure after 1.0s ;
- ii) Scenario 2, is equivalent to the previous scenario with a step increase of 0.2 p.u. in mechanical power. The fault is removed by tripping the line 5-7 with successful reclosure after 1.0s.

Fig. 12 depicts some results obtained using nonlinear simulation at the previous arbitrary loading conditions. Since all system variables have the same dynamic performances, simply the speed deviations of generators are considered. It is obvious

that NSGAI-PSS controllers are able to give excellent damping features at any operating condition.

Table 4: Operating conditions for cases 1 and 2

		Case 1 $\lambda_p = 0.4,$ $\lambda_q = 0.7$		Case 2 $\lambda_p = 0.4,$ $\lambda_q = 1.1$	
		P	Q	P	Q
Gen	G1	0.2864	0.1890	0.1432	0.2970
	G2	0.6520	0.4690	0.3260	0.7370
	G3	0.3400	-	0.1700	-0.1199
Load	A	0.5000	0.3500	0.2500	0.5500
	B	0.3600	0.2100	0.1800	0.3300
	C	0.4000	0.2450	0.2000	0.3850

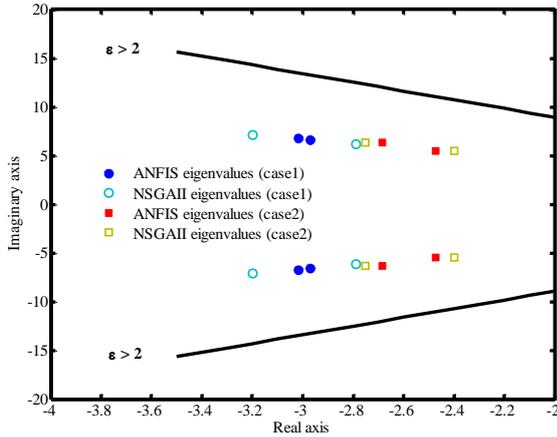


Fig. 11: D-shape sector for cases 1 and 2

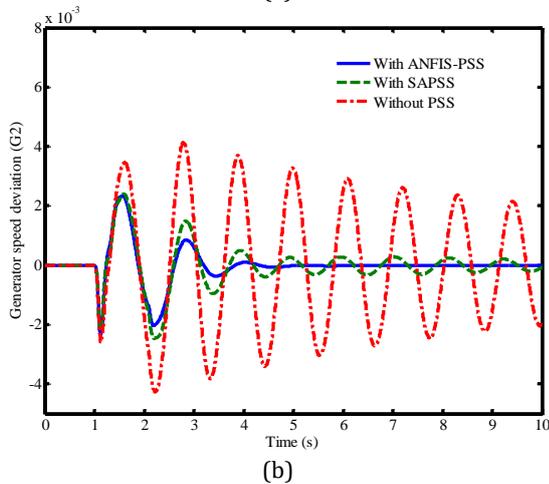
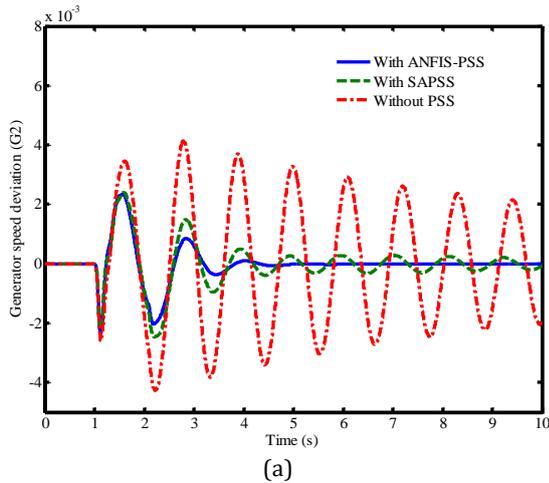


Fig. 12: Speed deviations in pu of G2 and G3 a) Scenario 1 for Case 1 b) Scenario 2 for Case 2

Therefore, both controllers NSGAI-PSSs and ANFIS-PSSs lead to the same results. Nevertheless, Table 5 proves clearly that the recommended ANFIS-based controllers are suitable for on-line stability enhancement due to its reduced CPU time. Results have been obtained using MATLAB R2009a installed on a PC with i7-4510U CPU @ 2.60 GHz, 64 bit.

Table 5: CPU time in seconds

NSGA-II algorithm	ANFIS-based approach
227.4479	0.0143

Effectiveness of ANFIS-PSSs controllers is, also, verified and confirmed by two dynamic performance indices based on the generator speed deviation. The minimum values of these indices called ITAE and FD match an excellent damping. ITAE and FD are defined as follows (Eqs. 17 and 18).

$$ITAE = \frac{\sum_{i=1}^{N_g} 1000 \int_0^{t_{sim}} t(|\Delta\omega_i|) dt}{N_g} \quad (17)$$

$$FD = \frac{\sum_{i=1}^{N_g} (500 \times OS_i)^2 + (500 \times US_i) + T_{Si}^2}{N_g} \quad (18)$$

where, T_{Si} , US_i and OS_i are respectively, settling time, undershoot and overshoot of the i -th generator speed deviation $\Delta\omega_i$.

Form Figs. 13 and 14, it is clear that ANFIS-PSSs controllers have the best performance compared to NSGA-PSSs and the simulated annealing based power system stabilizer (SAPSS) proposed in (Abido, 2000).

7. Conclusion

This study attempts at suggesting a comprehensive scheme for online enhancement of power system stability. Firstly, an elitist technique based on GA symbolized by NSGAI is used to gather the training set. Real power and reactive power demands that can be directly measurable was considered as input data. However, optimum parameters of PSSs represent the output data. Then, the acquired data base is employed in the ANFIS training stage to provide the optimal stabilizer parameters at any loading condition.

The effectiveness of the suggested controllers has been tested on a well-known benchmark power system called "western system coordinating council".

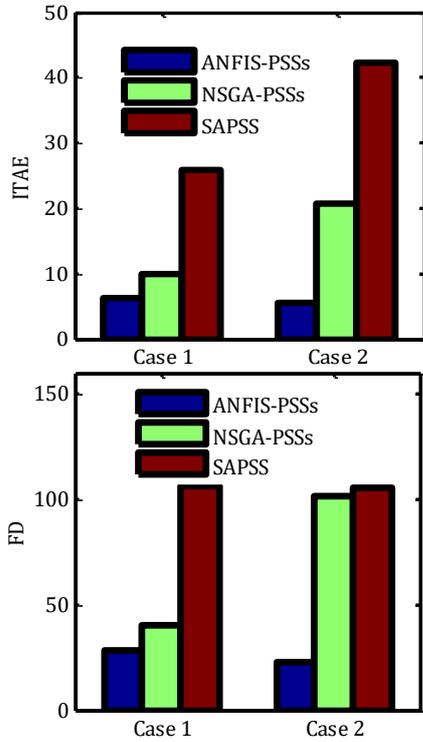


Fig. 13: Performance indices for Scenario 1

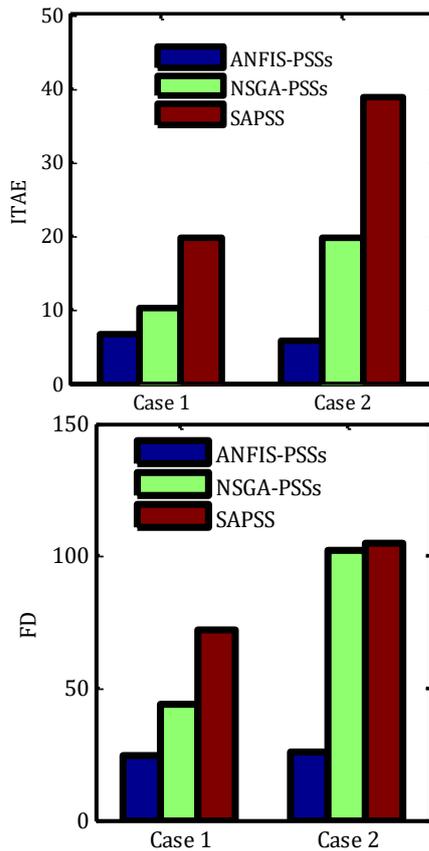


Fig. 14: Performance indices for Scenario 2

Simulation results approve the following outcomes:

- The proposed ANFIS-PSS controllers work effectively at any arbitrary operating condition and enhance the performance of the overall system on real-time.

- Since inputs are measurable variables, the suggested stabilizers can be implemented easily in practice.

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List of symbols

E'_q	Internal voltage
E_{fd}	Field voltage
V_{refi}	Reference voltage of machine G_i
V_{ti}	Terminal voltage of machine G_i
K_A	Amplifier gain of the excitation system
T_A	Amplifier time constant of the excitation system
T_{Wi}	Washout time constant
g_{max}	Maximum number of generation
J_1 and J_2	Fitness functions
J_{1max}	Upper limit of J_1
J_{2max}	Upper limit of J_2
δ	Rotor angle of the machine
ω	Speed deviation of the machine
σ_j	Real part of the i -th electromechanical modes corresponding to the j -th operating point
ξ_{ij}	Damping ratio of the i -th electromechanical modes corresponding to the j -th operating point
σ_0 and ξ_0	Threshold parameters of the pre-specified D -shape sector

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