

Full Length Research Paper

Comparison of robust and intelligent based power system stabilizers

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Accepted 7 December, 2010

Power System Stabilizers (PSS) are used to generate supplementary damping control signals for the excitation system in order to damp the low frequency oscillations (LFO) of the electric power system. The PSS is usually designed based on classical control approaches but this Conventional Power System Stabilizers (CPSS) has some problems. To overcome the drawbacks of CPSS, numerous techniques have been proposed in literatures. Intelligent based methods such as Fuzzy logic and genetic algorithms and also robust control methods such as quantitative feedback theory (QFT) have already been used for designing PSS. In this paper the goal is to study comparison of different methods used for designing PSS. For this purpose the Conventional PSS (CPSS), fuzzy based PSS (FPSS), genetic algorithms based PSS (GA-PSS) and also QFT based PSS (QFT-PSS) are considered for comparison purposes. A single machine infinite bus power system with system parametric uncertainties is considered as a case study and the proposed methods are evaluated against one another at this test system. The simulation results clearly indicate the effectiveness and validity of the proposed methods.

Key words: Electric power system stabilizer, low frequency oscillations, genetic algorithms optimization, fuzzy logic, quantitative feedback theory.

INTRODUCTION

Large electric power systems are complex nonlinear systems and often exhibit low frequency electromechanical oscillations due to insufficient damping caused by adverse operating. These oscillations with small magnitude and low frequency often persist for long periods of time and in some cases they even present limitations on power transfer capability (Liu et al., 2005). In analyzing and controlling the power system's stability, two distinct types of system oscillations are recognized. One is associated with generators at a generating station swinging with respect to the rest of the power system. Such oscillations are referred to as "intra-area mode" oscillations. The second type is associated with swinging of many machines in an area of the system against machines in other areas. This is referred to as "inter-area mode" oscillations.

Power System Stabilizers (PSS) are used to generate supplementary control signals for the excitation system in order to damp both types of oscillations (Liu et al., 2005). The widely used conventional Power System Stabilizers (CPSS) are designed using the theory of phase compensation in the frequency domain and are introduced as a lead-lag compensator. The parameters of CPSS are determined based on the linearized model of the power system. Providing good damping over a wide operating range, the CPSS parameters should be fine tuned in response to both types of oscillations. Since power systems are highly nonlinear systems, with configurations and parameters which alter through time, the CPSS design based on the linearized model of the power system cannot guarantee its performance in a practical operating environment. Therefore, an adaptive PSS which considers the nonlinear nature of the plant and adapts to the changes in the environment is required for the power system (Liu et al., 2005).

In order to improve the performance of CPSSs, numerous techniques have been proposed for designing

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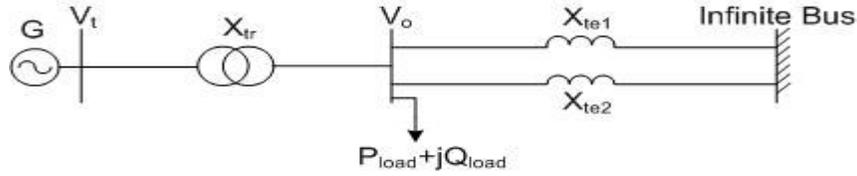


Figure 1. A single machine infinite bus power system.

them, such as intelligent optimization methods (Linda and Nair, 2010; Yassami et al., 2010; Sumathi et al., 2007; Jiang et al., 2008; Sudha et al., 2009) and Fuzzy logic method (Hwanga et al., 2008; Dubey, 2007). Also, many other different techniques have been reported by Chatterjee et al. (2009) and Nambu and Ohsawa (1996) and the application of robust control methods for designing PSS has been presented by Gupta et al. (2005), Mocwane and Folly (2007), Sil et al. (2009) and Bouhamida et al. (2005). Although different methods have been reported for designing PSS but comparison of these different algorithms for obtaining the best method has not already been reported by researchers.

In this paper the authors are willing to study and comparison of different algorithms for designing PSS. For this comparison purpose, the conventional PSS (CPSS), Fuzzy based PSS (FPSS), genetic algorithms based PSS (GA-PSS) and also QFT based PSS (QFT-PSS) are considered. To show effectiveness of the proposed methods, these methods are compared with one another. Simulation results show that the proposed methods guarantees robust performance under a wide range of operating conditions.

System under study

Figure 1 shows a single machine infinite bus power system. The static excitation system has been considered as model type IEEE – ST1A (Kundur, 1993).

Dynamic model of the system

Nonlinear dynamic model

A nonlinear dynamic model of the system is derived by disregarding the resistances and the transients of generator, transformers and transmission lines (Kundur, 1993). The nonlinear dynamic model of the system is given as (equation 1).

Linear dynamic model of the system

A linear dynamic model of the system is obtained by

linearizing the nonlinear dynamic model around the nominal operating condition. The linearized model of the system is obtained as (equation 2) (Kundur, 1993).

$$\begin{cases} \dot{\omega} = \frac{(P_m - P_e - D\Delta\omega)}{M} \\ \dot{\delta} = \omega_0(\omega - 1) \\ \dot{E}'_q = \frac{(-E_q + E_{fd})}{T'_{do}} \\ \dot{E}_{fd} = \frac{-E_{fd} + K_a(V_{ref} - V_t)}{T_a} \end{cases} \quad (1)$$

$$\begin{cases} \Delta \dot{\delta} = \omega_0 \Delta \omega \\ \Delta \dot{\omega} = \frac{-\Delta P_e - D \Delta \omega}{M} \\ \Delta \dot{E}'_q = (-\Delta E_q + \Delta E_{fd})/T'_{do} \\ \Delta \dot{E}_{fd} = -\left(\frac{1}{T_A}\right)\Delta E_{fd} - \left(\frac{K_A}{T_A}\right)\Delta V \end{cases} \quad (2)$$

Figure 2 shows the block diagram model of the system. This model is known as Heffron-Phillips model (Kundur, 1993). The model has some constants denoted by K_i . These constants are functions of the system parameters and the nominal operating condition. The nominal operating condition parameters are given in the appendix.

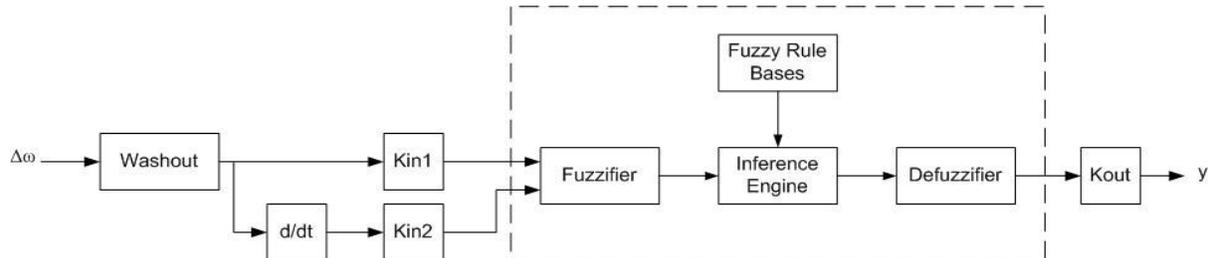
Dynamic model of the system in the state-space form

The dynamic model of the system in the state-space form is obtained as (equation 3) (Kundur, 1993).

$$\begin{bmatrix} \Delta \dot{\delta} \\ \Delta \dot{\omega} \\ \Delta \dot{E}'_q \\ \Delta \dot{E}_{fd} \end{bmatrix} = \begin{bmatrix} 0 & \omega_0 & 0 & 0 \\ -\frac{K_1}{M} & 0 & -\frac{K_2}{M} & 0 \\ \frac{K_4}{T'_{do}} & 0 & -\frac{K_3}{T'_{do}} & \frac{1}{T'_{do}} \\ \frac{K_A K_5}{T_A} & 0 & -\frac{K_A K_6}{T_A} & -\frac{1}{T_A} \end{bmatrix} \times \begin{bmatrix} \Delta \delta \\ \Delta \omega \\ \Delta E'_q \\ \Delta E_{fd} \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ \frac{1}{M} & 0 \\ 0 & 0 \\ 0 & \frac{K_A}{T_A} \end{bmatrix} \times \begin{bmatrix} \Delta T_m \\ \Delta V_{ref} \end{bmatrix} \quad (3)$$

Table 2. Optimal parameters of GA-PSS using genetic algorithms.

GA-PSS Parameters	K_P	K_I	K_D
Optimal value	63.396	9.9974	11.9952

**Figure 3.** Fuzzy supplementary controller.**Table 3.** The linguistic variables for $\Delta\omega$.

Big positive (BP)	Medium positive (MP)	Small positive (SP)	Zero (ZE)
Big negative (BN)	Medium negative (MN)	Small negative (SN)	

$$\text{PID - PSS} = K_p + \frac{K_I}{S} + K_D S \quad (4)$$

The parameter ΔE_{ref} is modulated to the output of GA-PSS and speed deviation $\Delta\omega$ is considered as input to GA-PSS. The optimum values of K_P , K_I and K_D which minimize an array of different performance indexes are accurately computed using a genetic algorithms. In this study the performance index is considered as (equation 5). In fact, the performance index is the Integral of the Time multiplied Absolute value of the Error (ITAE).

$$\text{ITAE} = \int_0^t t |\Delta\omega| dt \quad (5)$$

The parameter "t" in performance index is the simulation time. It is clear to understand that the controller with lower performance index is better than the other controllers. To compute the optimum parameter values, a 0.1 step change in reference mechanical torque (ΔT_m) is assumed and the performance index is minimized using Genetic Algorithms. The following genetic algorithm parameters have been used in present research:

- i) Number of Chromosomes: 3; Population size: 48
- ii) Crossover rate: 0.5; Mutation rate: 0.1

The optimum values of the parameters K_P , K_I and K_D are obtained using continuous type Genetic Algorithms and summarized in the Table 2.

Fuzzy logic based PSS

In this section Fuzzy logic method is considered for designing PSS. Fuzzy method has three major sections as membership functions, rule bases and defuzzification. In the classical Fuzzy methods, the

boundaries of membership functions are adjusted based on expert person experiences that may be with trial and error and does not guarantee performance of the system. To solve this problem, in this paper the boundaries of the membership functions are tuned by an optimal search for achieving the best boundaries. Therefore the boundaries of input and output membership functions are considered as uncertain and then the optimal boundaries are obtained by genetic algorithms (Cordon et al., 2001). Here the proposed Fuzzy controller block diagram is given in Figure 3.

In fact, it is a nonlinear PI-type Fuzzy logic controller with two inputs and one output. In this paper ΔV_{ref} is modulated in order to output of Fuzzy PSS (FPSS) and the speed deviation $\Delta\omega$ and its rate $d(\Delta\omega)/dt$ are considered as the inputs to the FPSS. The inputs are filtered by washout block to eliminate the DC components. Also there are three parameters denoted by K_{in1} , K_{in2} and K_{out} which are defined over an uncertain range and then obtained by Genetic Algorithms optimization method. Therefore the boundaries of inputs and output signals are tuned on an optimal value.

Though the Fuzzy controller accepts these inputs, it has to convert them into Fuzzified inputs before the rules can be evaluated. To accomplish this, one of the most important and critical blocks in the whole Fuzzy controllers should be built and it is The Knowledge Base. It consists of two more blocks namely the data base and the rule base (Rajase and Vijay, 2007).

Data base

Data Base consists of the membership function for input variables $\Delta\omega$ and $d(\Delta\omega)/dt$ and output variable described by linguistic variables shown in Tables 3 to 5 (Rajase and Vijay, 2007). The "triangular membership functions" are used as membership functions for the input and output variables. The Figures 4 to 6 illustrate these in detail indicating the range of all the variables. These ranges are defined as default and then tuned via cascade K

Table 4. The linguistic variables for $d(\Delta\omega)/dt$.

Positive (P)	Negative	Zero (ZE)
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Table 5. The linguistic variables for output.

Big positive (BP)	Medium positive (MP)	Small positive (SP)
Big negative (BN)	Medium negative (MN)	Small negative (SN)
Zero (ZE)	Very big positive (VBP)	Very big negative (VBN)

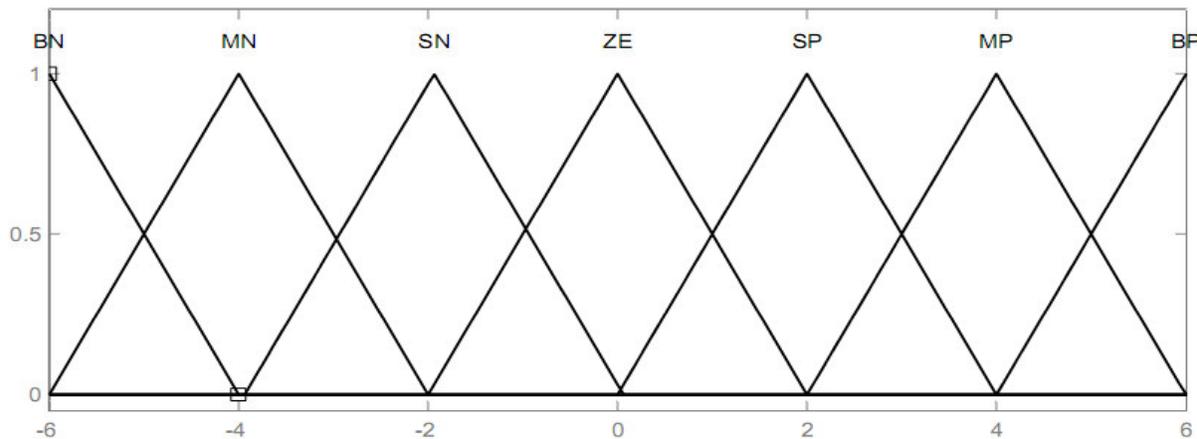


Figure 4. Membership function of input 1 ($\Delta\omega$).

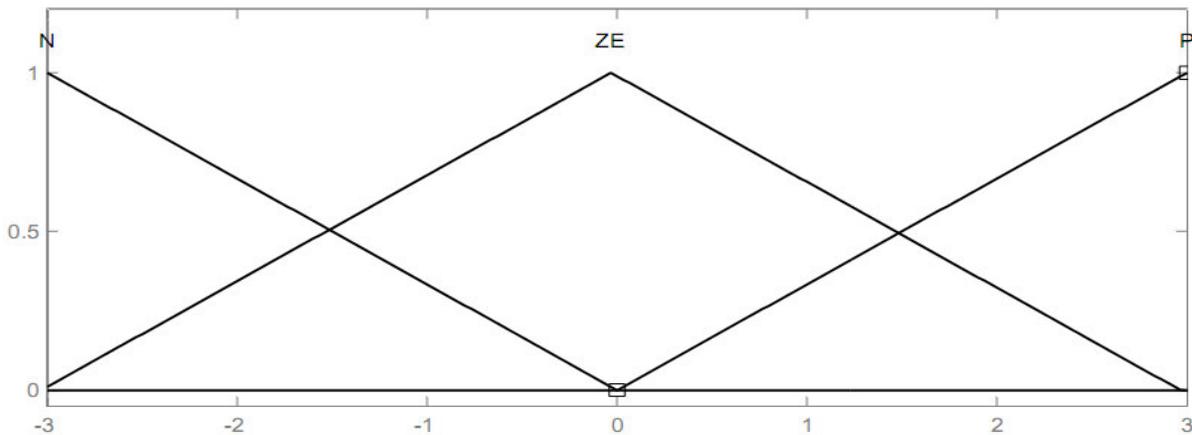


Figure 5. Membership function of input 2 ($d(\Delta\omega)/dt$).

parameters (K_{in1} , K_{in2} and K_{out}) and adjusted on the optimal values.

Rule base

The other half of the knowledge base is the Rule Base which consists of all the rules formulated by the experts. It also consists of

weights which indicate the relative importance of the rules among themselves and indicates the influence of a particular rule over the net Fuzzified output. The Fuzzy rules which are used in this scheme are shown in Table 6. The next section specifies the method adopted by the Inference Engine especially the way it uses the Knowledge Base consisting of the described Data Base and Rules Base (Rajase and Vijay, 2007).

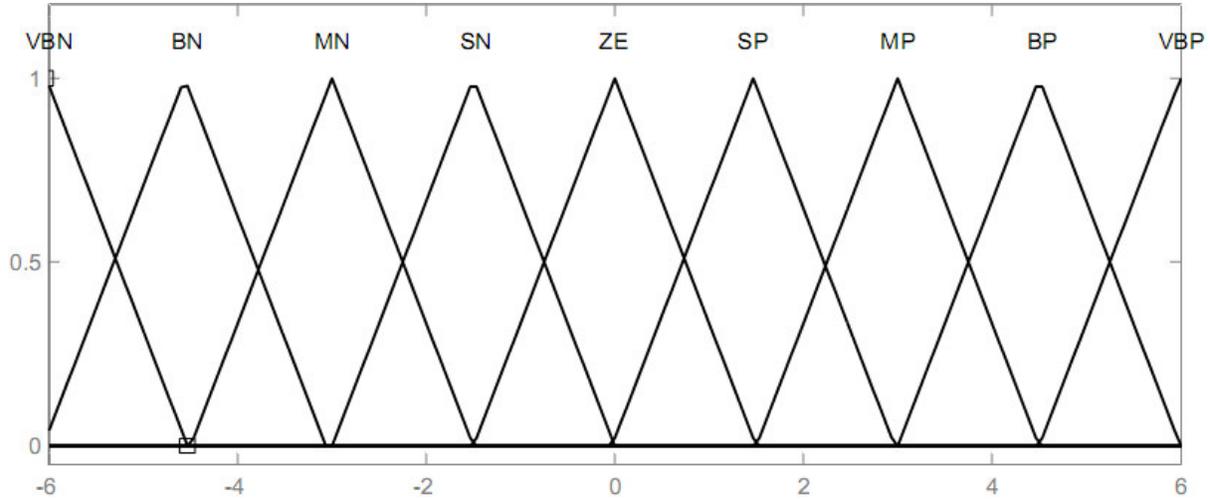


Figure 6. Membership function of output.

Table 6. Fuzzy Rule Bases.

$\Delta\omega$ $d(\Delta\omega)/dt$	BN	MN	SN	ZE	SP	MP	BP
N	VBN	BN	MN	SN	ZE	MP	BP
ZE	BN	MN	SN	ZE	SP	MP	BP
P	BN	MN	ZE	SP	MP	BP	VBP

Fuzzy inference engine methodology

Though many methodologies have been mentioned in evaluating the various expressions like Fuzzy union (OR operation), Fuzzy intersection (AND operation) and etc with varying degree of complexity. Here in Fuzzy scheme the most widely used methods for evaluating such expressions are used. The function used for evaluating OR is “MAX”, which is the maximum of the two operands and similarly the AND is evaluated using “MIN” function which is defined as the minimum of the two operands. It should be note that in the present research paper, the equal importance is assigned to all the rules in the Rules Base (Rajase and Vijay, 2007).

Defuzzification method

The defuzzification method followed in this study is the “Center of Area Method” or “Gravity method”. This method is discussed in (Rajase and Vijay, 2007). As mentioned before, in this paper the boundaries of the membership functions are adjusted by genetic algorithms. In the next section the FPSS tuning using genetic algorithms is presented.

FPSS tuning using genetic algorithms

In this section the membership functions of the proposed FPSS are tuned by K parameters (K_{in1} , K_{in2} and K_{out}). These K parameters are obtained based on Genetic Algorithms optimization method. The parameter ΔE_{ref} is modulated to output of FPSS and speed deviation $\Delta\omega$ and its rate are considered as input to FPSS. The

optimum values of K_{in1} , K_{in2} and K_{out} which minimize an array of different performance indexes are accurately computed using Genetic algorithms. In order to this study, the performance index is considered as (Equation 5). To compute the optimum parameter values, a 0.1 step change in reference mechanical torque (ΔT_m) is assumed and the performance index is minimized using genetic algorithms. The following genetic algorithm parameters have been used in present research:

- i) Number of Chromosomes: 3; Population size: 48
- ii) Crossover rate: 0.5; Mutation rate: 0.1.

The optimum values of the parameters K_{in1} , K_{in2} and K_{out} are obtained using Genetic Algorithms and summarized in the Table 7. The boundaries of K_{in1} , K_{in2} and K_{out} for optimal search are presented in the appendix.

Conventional PSS and QFT based PSS

The detailed step-by-step procedure for computing the parameters of the classical lead-lag PSS (CPSS) using phase compensation technique has been presented by Kundur (1993). Here, the CPSS has been designed and obtained as (equation 6).

$$CPSS = \frac{35(0.3S + 1)}{(0.1S + 1)} \tag{6}$$

In the CPSS design, the Washout block parameter $T_w = 10$ and Damping ratio = 0.5 have been considered. Also the detailed step-by-step procedure to design the robust PSS based on the quantitative feedback theory (QFT-PSS) has been developed by

Table 7. Obtained parameters K_{in1} , K_{in2} and K_{out} using genetic algorithms.

Parameters	K_{in1}	K_{in2}	K_{out}
Obtained value	72.5	30.7	0.34

Table 8. The calculated ITAE.

Operating condition	CPSS	QFT-PSS	FPSS	GAPSS
Nominal	5.7569×10^{-4}	5.5686×10^{-4}	5.5259×10^{-4}	3.9652×10^{-4}
Heavy	7.2451×10^{-4}	4.4080×10^{-4}	5.1769×10^{-4}	3.4632×10^{-4}
Very heavy	8.9021×10^{-4}	3.4774×10^{-4}	3.9219×10^{-4}	2.8288×10^{-4}

Sedigh and Alizadeh (1994) and Rao and Sen (1999). The QFT-PSS has been designed and obtained as (equation 7). In the design process disturbance rejection bounds are considered for designing PSS and for easy implementation, the order of final controller is reduced by model reduction technique.

$$\text{QFT - PSS} = \frac{30(0.42S + 1)}{(0.045S + 1)} \quad (7)$$

RESULTS AND DISCUSSION

The proposed PSSs are applied to control of system. In order to study the PSS performance under system uncertainties (controller robustness), three operating conditions are considered as follow:

- i. Nominal operating condition
- ii. Heavy operating condition (20% changing parameters from their typical values)
- iii. Very heavy operating condition (50% changing parameters from their typical values).

In order to demonstrate the robustness performance of the proposed method, The ITAE is calculated following a 10% step change in the reference mechanical torque (ΔT_m) at all operating conditions (nominal, heavy and very heavy) and results are shown at Table 8. Following step change at ΔT_m , the optimal GA-PSS has better performance than the other methods at all operating conditions. After GAPSS, the QFT-PSS has lower ITAE than the other methods.

Also the control effort signal is one of the most important factors to compare responses. The output of the PSS (ΔV_{ref}) is considered as the control effort signal. The control effort signal is computed as (equation 8).

$$\text{Control_Effort} = \int_0^t |\Delta V_{ref}| dt \quad (8)$$

The control effort has been calculated following a 10% step change in the reference mechanical torque (ΔT_m) at

all operating conditions (Nominal, Heavy and Very heavy) and results are shown at Table 9. It is clear to see that following step change at ΔT_m , the GA-PSS has lower control effort than the other method at all operating conditions. This means that the optimal GA-PSS damps power system oscillations by injecting lower control signal. Although the control effort and performance index results are enough to compare the methods, but it can be more useful to show responses in figures. Figure 7 shows $\Delta \omega$ at nominal, heavy and very heavy operating conditions following 10% step change in the reference mechanical torque (ΔT_m).

It is clear to see that the GA-PSS has better performance than the other methods at all operating conditions. After GA-PSS the QFT-PSS can be evaluated as second method from view of comparison. QFT-PSS characteristics in the damping power system oscillations are in the range of acceptable. Eventually between two other methods, the FPSS has a very significant performance than CPSS. The CPSS ability in damping power system oscillations goes to unstable and large oscillations with changing system operating conditions and under heavy loads.

Conclusions

In this paper, different robust and intelligent methods such as conventional, genetic algorithms, fuzzy logic and QFT have been successfully proposed to design PSS. The proposed methods were applied to a typical single machine infinite bus power system containing system parametric uncertainties and various loads conditions. The simulation results demonstrated that the designed methods are capable of guaranteeing the robust stability and robust performance of the power system under a wide range of system uncertainties. But in view of comparison, the optimal GA-PSS has better performance rather than the other methods and after it the QFT-PSS can be evaluated as second method.

The new PID type GA-PSS which has the best

Table 9. The calculated control effort signal.

Operating condition	CPSS	QFT-PSS	FPSS	GAPSS
Nominal	0.0327	0.0308	0.0883	0.0321
Heavy	0.0490	0.0334	0.0813	0.0400
Very heavy	0.0721	0.0421	0.0814	0.0359

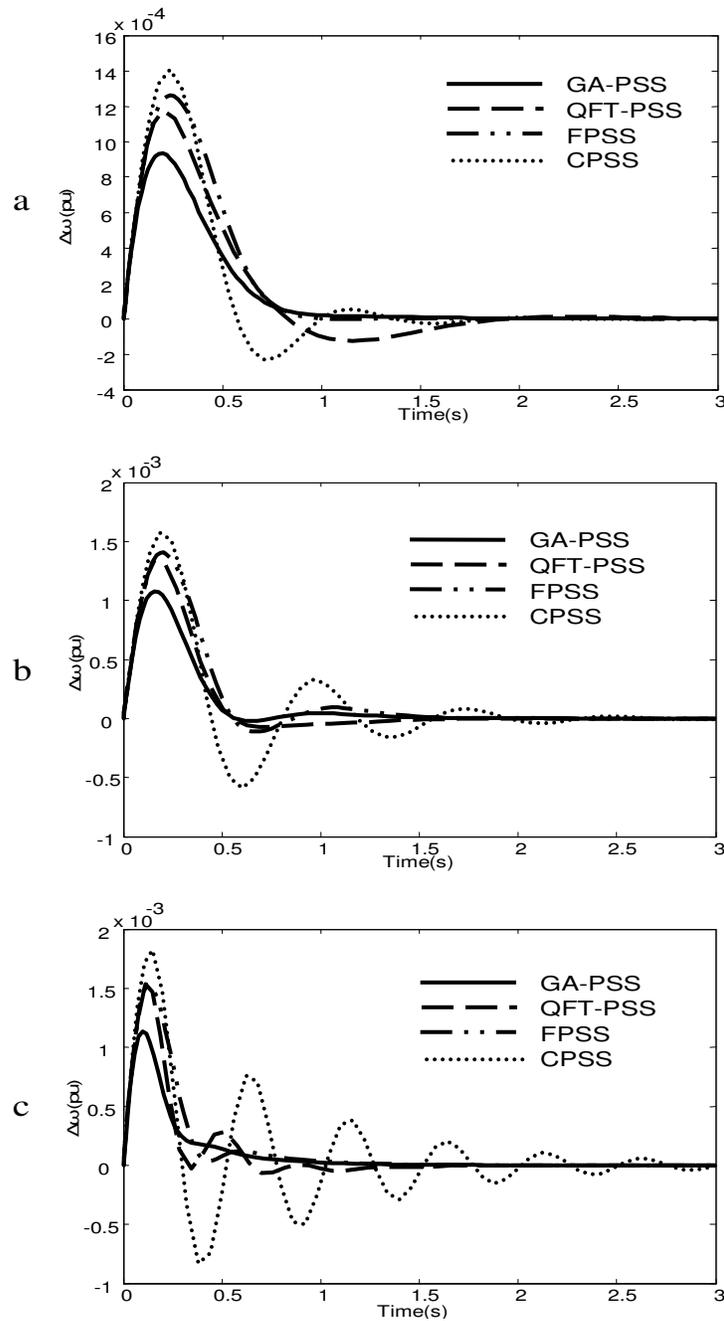


Figure 7. Dynamic responses $\Delta\omega$ following 0.1 step change in the reference mechanical torque (ΔT_m) **a:** Nominal operating condition **b:** Heavy operating condition **c:** Very heavy operating condition.

performance can be considered as a new methodology for designing PSS. This method leads to two useful aspects, in first it is easy to implementation for the sake of its PID configuration and also it obtains the robust performance and robust stability under system uncertainties. These results open the door to study the effect of nonlinear constraints on the power system damping oscillations problems.

Nomenclature: ω , Synchronous speed; δ , synchronous angle; P_m , input mechanical power; P_e , output electrical power; M , Inertia; E_q , q axis voltage, E_{fd} , field voltage; E_q , transient voltage of q axis; T_{do} , transient time constant of q axis; K_a , excitation system gain; T_a , excitation system time constant; V_t , Terminals voltage; V_{ref} , reference voltage of excitation system; T_m , mechanical torque; **PSS**, power system stabilizer; **CPSS**, conventional power system stabilizer; **FPSS**, fuzzy Power system stabilizer; **GA-PSS**, genetic algorithms power system stabilizer; **QFT-PSS**, quantitative feedback theory power system stabilizer; **PID**, proportional – Integral – differential; **ITAE**, integral of the time multiplied absolute value of the error.

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APPENDIX

The nominal operating condition parameters of the system are listed in Table 1. The boundaries of K_{in1} , K_{in2} and K_{out} , for optimal search are listed in Table 2.

Table 1. The nominal system parameters.

Generator	M = 10 Mj/MVA $X_q = 1.6$ p.u.	$T'_{do} = 7.5$ s $X'd = 0.3$ p.u.	$X_d = 1.68$ p.u. D = 0
Excitation system		$K_a = 50$	$T_a = 0.02$ s
Transformer		$X_{tr} = 0.1$ p.u.	
Transmission lines	$X_{te1} = 0.5$ p.u.	$X_{te2} = 0.9$ p.u.	
Operating condition	$V_t = 1.05$ p.u.	$P = 1$ p.u.	$Q = 0.2$ p.u.

Table 2. The boundaries of K_{in1} , K_{in2} and K_{out} .

Parameters	$0.1 \leq K_{in1} \leq 1000$	$0.1 \leq K_{in2} \leq 1000$	$0.1 \leq K_{out} \leq 0.5$
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