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Power System Stabilizer Tuning based on Fuzzy-Genetic approach

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Abstract

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 PSS (CPSS) has some problems. In order to overcome the drawbacks of CPSS, numerous techniques have been proposed in literatures. In this paper a new Fuzzy type PSS is considered for damping electric power system oscillations. In this Fuzzy approach, the upper and lower bounds of the Fuzzy membership functions are obtained using Genetic Algorithms (GA) optimization method. The proposed Fuzzy-Genetics PSS (FGPSS) is evaluated against the Conventional Power System Stabilizer (CPSS) at a single machine infinite bus power system considering system parametric uncertainties. The simulation results clearly indicate the effectiveness and validity of the proposed method.

Keywords: Electric Power System Stabilizer, Low Frequency Oscillations, Genetic Algorithms Optimization, Fuzzy Logic

INTRODUCTION

Large electric power systems are complex nonlinear systems and often exhibit low frequency electromechanical oscillations due to insufficient damping caused by adverse operating [1]. 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 [1]. 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 [1]. 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 electric 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 [1]. In order to improve the performance of CPSSs, numerous techniques have been proposed for designing them, such as intelligent optimization methods [2-6], Fuzzy logic [7-8] and many other techniques [9-10]. Also the application of robust control methods for designing PSS has been reported in [11-14]. This paper deals with a design method for the stability enhancement of a single machine infinite bus power system using a new Fuzzy type PSS whose membership functions boundaries are tuned by genetic algorithms optimization method. In order to show effectiveness of the new Fuzzy-Genetic PSS (FGPSS), this method is compared with the CPSS. Simulation results show that the proposed method guarantees robust performance under a wide range of operating conditions.

Apart from this introductory section, this paper is structured as follows. The system under study is presented in section 2. Section 3 describes about the system modeling and system analysis is presented in section 4. The power system stabilizers are briefly explained in section 5. Section 6 is devoted to explaining the proposed methods. The design methodology is developed in section 7 and eventually the simulation results are presented in section 8.

System under study

Fig. 1 shows a single machine infinite bus power system [15]. The static excitation system has been considered as model type *IEEE – ST1A*.

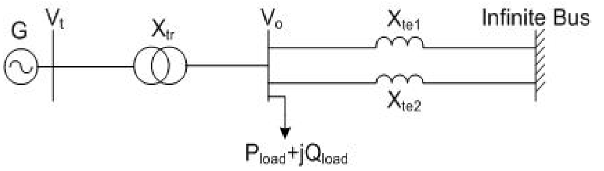

Fig. 1. A single machine infinite bus power system

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 [15]. The nonlinear dynamic model of the system is given as (1).

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

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 (2) [15].

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

Fig. 2 shows the block diagram model of the system. This model is known as Heffron-Phillips model [15]. 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.

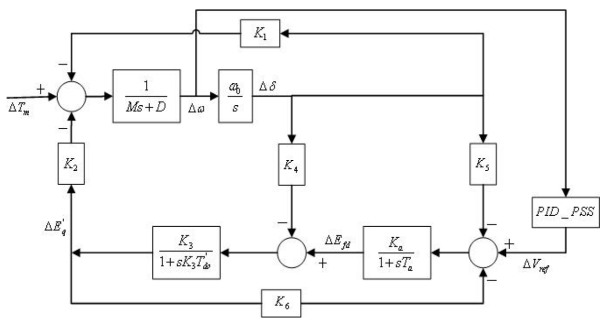

Fig. 2. Heffron-Phillips model of the electric power system

Dynamic model of the system in the state-space form

The dynamic model of the system in the state-space form is obtained as (3) [15].

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

Analysis

In the nominal operating condition, the eigen values of the system are obtained using analysis of the state-space model of the system presented in (3) and these eigen values are listed in Table 1. It is clearly seen that the system has two unstable poles at the right half plane and therefore the system is unstable and needs the Power System Stabilizer (PSS) for stability.

Table 1. The eigen values of the closed loop system

-4.2797
-46.366
+0.1009 + j4.758
+0.1009 - j4.758

Power system stabilizer

A Power System Stabilizer (PSS) is provided to improve the damping of power system oscillations. Power system stabilizer provides an electrical damping torque (ΔT_m) in phase with the speed deviation ($\Delta\omega$) in order to improve damping of power system oscillations [15]. As referred before, many different methods have been applied to design power system stabilizers so far. In this paper a new Fuzzy-Genetic PSS (FGPSS) is considered for damping power system oscillations [16]. In the next section, the proposed method is briefly introduced and then designing the FGPSS, based on the proposed method, is presented.

Design methodology

As mentioned before, in this paper a new Fuzzy type PSS in considered for damping power system oscillations. Fuzzy method has three major sections as membership functions, rule bases and defuzzification. In 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. For 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 [16]. Here the proposed Fuzzy controller block diagram is given in Fig. 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 PSS and the speed deviation $\Delta\omega$ and its rate $d(\Delta\omega)/dt$ are considered as the inputs to the PSS. 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 [16].

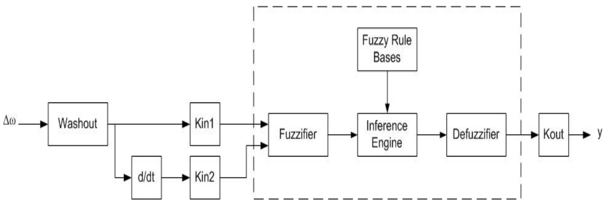

Fig. 3. Fuzzy supplementary controller

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 2-4 [17].

Table 2. The linguistic variables for $\Delta\omega$

Big Positive (BP)	Medium Positive (MP)	Small Positive (SP)
Big Negative (BN)	Medium Negative (MN)	Small Negative (SN)
Zero (ZE)		

Table 3. The linguistic variables for $d(\Delta\omega)/dt$

Positive (P)	Negative	Zero (ZE)

Table 4. 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)

The "triangular membership functions" are used as membership functions for the input and output variables. The Figs. 4-6 illustrate these in detail indicating the range of all the variables. These ranges are defined as default and then tuned via cascade K parameters (K_{in1}, K_{in2} and K_{out}) and adjusted on the optimal values.

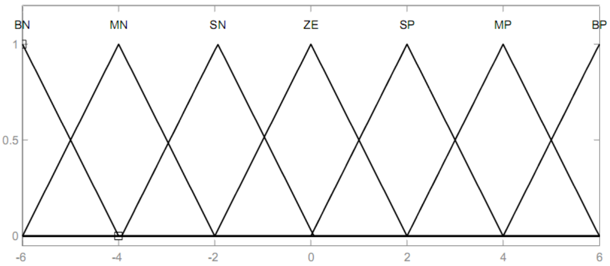

Fig. 4. Membership function of input 1 ($\Delta\omega$)

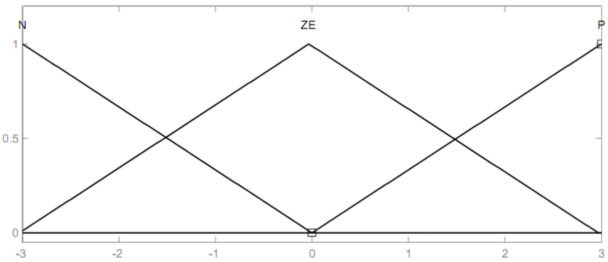

Fig. 5. Membership function of input 2 ($d(\Delta\omega)/dt$)

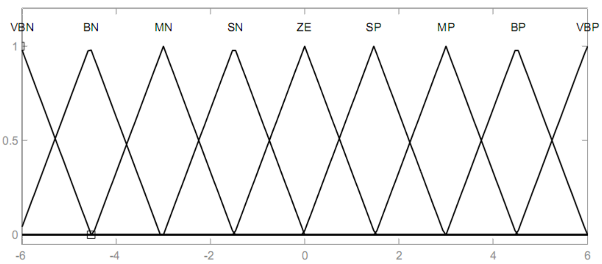

Fig. 6. Membership function of output

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 5.

Table 5. 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

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 [17]. Plotting the inputs versus output based rules base is shown in Fig. 7.

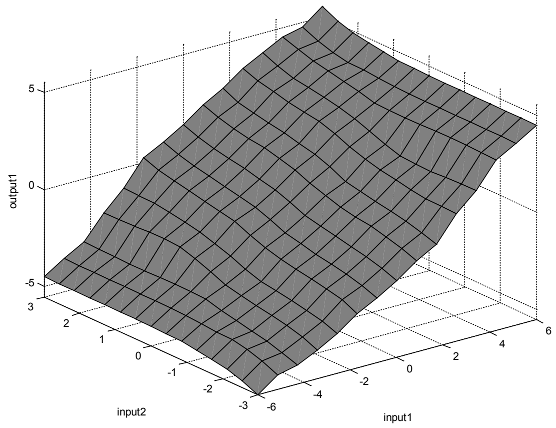

Fig. 7. The output coefficient versus two inputs

Methodologies adopted in fuzzy inference engine

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 and all the weights are equal [17].

Defuzzification method

The Defuzzification method followed in this study is the "Center of Area Method" or "Gravity method". This method is discussed in [17]. As mentioned before, in this paper the boundaries of the membership functions are adjusted by genetic algorithms. In the next section a brief introduction about genetic algorithms is presented.

Genetic Algorithms

Genetic Algorithms (GA) are global search techniques, based on the operations observed in natural selection and genetics [18]. They operate on a population of current approximations-the individuals-initially drawn at random, from which improvement is sought. Individuals are encoded as strings (Chromosomes) constructed over some particular alphabet, e.g., the binary alphabet {0.1}, so that chromosomes values are uniquely mapped onto the decision variable domain. Once the decision variable domain representation of the current population is calculated, individual performance is assumed according to the objective function which characterizes the problem to be solved. It is also possible to use the variable parameters directly to represent the chromosomes in the GA solution. At the reproduction stage, a fitness value is derived from the raw individual performance measure given by the objective function and used to bias the selection process. Highly fit individuals will have increasing opportunities to pass on genetically important material to successive generations. In this way, the genetic algorithms search from many points in the search space at once and yet continually narrow the focus of the search to the areas of the observed best performance. The selected individuals are then modified through the application of genetic operators. In order to obtain the next generation Genetic operators manipulate the characters (genes) that constitute the chromosomes directly, following the assumption that certain genes code, on average, for fitter individuals than other genes. Genetic operators can be divided into three main categories [18]: Reproduction, crossover and mutation.

Reproduction: selects the fittest individuals in the current population to be used in generating the next population.

Cross-over: causes pairs, or larger groups of individuals to exchange genetic information with one another

Mutation: causes individual genetic representations to be changed according to some probabilistic rule.

Fuzzy controller tuning using Genetic Algorithms

In this section the membership functions of the proposed FGPSS 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 FGPSS and speed deviation $\Delta\omega$ and its rate are considered as input to FGPSS. 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 this study the performance index is considered as (4). In fact, the performance index is the Integral of the Time multiplied Absolute value of the Error (*ITAE*).

$$\mathrm{ITAE} = \int_0^t t|\Delta\omega|dt \qquad (4)$$

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 (ΔTm) is assumed and the performance index is minimized using genetic algorithms. The following genetic algorithm parameters have been used in present research.

Number of Chromosomes: 3

Population size: 48

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 6.

Table 6. 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

Simulation results

In this section, the proposed FGPSS is applied to control the under study system (single machine infinite bus power system). To show effectiveness of the proposed optimal FGPSS, A classical lead-lag PSS based on phase compensation technique (CPSS) is considered for comparing purposes.

The detailed step-by-step procedure for computing the parameters of the classical lead-lag PSS (CPSS) using phase compensation technique is presented in [15]. Here, the CPSS has been designed and obtained as (5).

$$\mathrm{CPSS} = \frac{35\,(0.3S + 1)}{(0.1S + 1)} \tag{5}$$

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 (DT_m) at all operating conditions (Nominal, Heavy and Very heavy) and results are shown at Table 7. Following step change at DT_m, the optimal FGPSS has better performance than the CPSS at all operating conditions.

Table 7. The calculated ITAE

	FGPSS	CPSS
Nominal operating condition	5.5259×10^{-4}	$5.5686\times^{10}$-4
Heavy operating condition	5.1769×10^{-4}	7.2451×10^{-4}
Very heavy operating condition	3.9219×10^{-4}	8.9021×10^{-4}

Also the control effort signal is one of the most important factors to compare responses. The output of the FGPSS is considered as the control effort signal. The control effort signal is computed as (6).

$$\mathrm{Control\_Effort} = \int_0^t t\,|\Delta \mathrm{Vref}|\,dt \tag{6}$$

The control effort has been calculated following a 10% step change in the reference mechanical torque (DT_m) at all operating conditions (Nominal, Heavy and Very heavy) and results are shown at Table 8. It is clear to see that following step change at DT_m, the FGPSS has lower control effort than the other method at all operating conditions. This means that the optimal FGPSS damps power system oscillations by injecting lower control signal.

Table 8. The calculated control effort signal

	FGPSS	CPSS
Nominal operating condition	0.0783	0.0327
Heavy operating condition	0.0813	0.0490
Very heavy operating condition	0.0814	0.0721

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. Fig. 8 shows $\Delta\omega$ at nominal, heavy and very heavy operating conditions following 10% step change in the reference mechanical torque (DT_m). It is clear to seen that the FGPSS has better performance than the other method at all operating conditions.

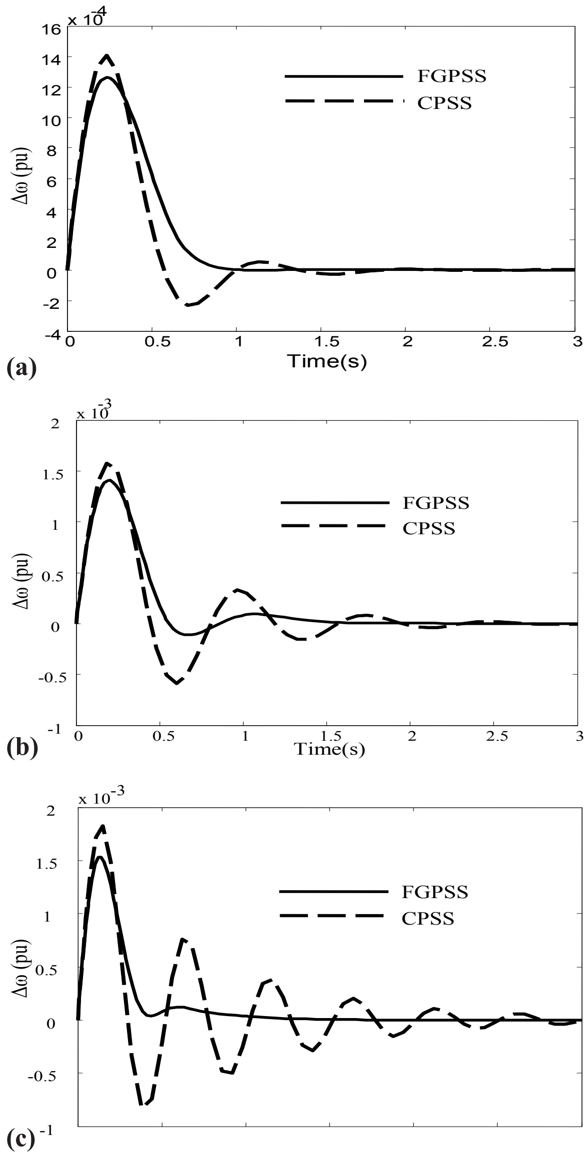

Fig. 8. Dynamic responses Δω following 0.1 step in the reference mechanical torque (ΔTm)
a: Nominal operating condition b: Heavy operating condition c: Very heavy operating condition

CONCLUSIONS

In this paper a new Fuzzy PSS based on genetic algorithms optimization method has been successfully proposed. The final designed FGPSS has characteristics of the both optimal and nonlinear controllers. The proposed method was 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 optimal FGPSS is capable of guaranteeing the robust stability and robust performance of the power system under a wide range of system uncertainties. These results and the suitability of Fuzzy logic to nonlinear problems, open the door to study the effect of nonlinear constraints on the power system damping oscillations problems.

Appendix

The nominal parameters and operating conditions of the system are listed in Table 9.

Table 9. The nominal system parameters

Generator	M = 10 Mj/ MVA	T'_{do} = 7.5 s	X_d = 1.68 p.u.
	X_q = 1.6 p.u.	X´d = 0.3 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.

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