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Optimal Rule-Base in Multi-Machine Fuzzy PSS Using Genetic Algorithm

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Abstract: This paper presents a Genetic Algorithms (GA) based rule generation method for Fuzzy Power System Stabilizer (FPSS) to enhance damping of the power system low frequency oscillations. This proposed controller is more efficient because it cope with oscillations and different operating points. There is no doubt that fuzzy controller is tuned on line from the knowledge base and fuzzy interference. Therefore, in this paper for achieving the acceptable level of robust performance exact tuning of fuzzy rule base are very important. For this purpose, the rules of Fuzzy PID controller will be tuned by GA which can reduce fuzzy effort and taking large parametric uncertainties in to account. Also this newly proposed technique make a flexible controller in different operating points. This controller will be applied on 3 machine 9 buses standard power system with different operating conditions in present of disturbance and nonlinearity. The efficacy of proposed controller is compared with robust PSS that tune using Particle Swarm Optimization (RPSSPSO) through FD and ITAE performance indices. According to results, this is cleared that the proposed method of tuning the fuzzy controller's rules is an attractive alternative to conventional fixed gain stabilizer design as it retains the simplicity of the conventional PSS and still guarantees a robust acceptable performance over a wide range of operating and system condition.

Key words: Rule-Base, Fuzzy PID, GA, FPSS, Multi-machine System.

INTRODUCTION

In early sixties, most of the generators were getting interconnected and the automatic voltage regulators (AVRs) were more efficient. With bulk power transfer on long and weak transmission lines and application of high gain, fast acting AVRs, small oscillations of even lower frequencies were observed. The stability of the system, in principle, can be enhanced substantially by application of some form of close-loop feedback control. Over the years a considerable amount of effort has been extended in laboratory research and on-site studies for designing such controllers. The problem, when first encountered, was solved by fitting the generators with a feedback controller which sensed the rotor slip or change in terminal power of the generator and fed it back at the AVR reference input with proper phase lead and magnitude so as to generate an additional damping torque on the rotor (Basler and Schaefer, 2008). Damping power oscillations using supplementary controls through turbine, governor loop had limited success. With the advent fast valving technique, there is some renewed interest in this type of control (Padiyar, 2006). This device came to be known as a Power System Stabilizer (PSS). PSSs are auxiliary control devices on synchronous generators, used in conjunction with their excitation systems to provide control signals toward enhancing the system damping and extending power transfer limits.

Over the years, a number of techniques have been developed for designing PSSs. Conventionally lead-lag controller has been widely used as PSS. Actually these methods show a suitable control performance in the particular operating point, however responding of system in case of operating condition such as change of load or three-phase fault, etc are difficult. Furthermore to solve above problem, several methods which take root in adaptive control theory have been proposed for nonlinear characteristic of power system (Hwang *et al*., 2008). Finally, these methods can improve the dynamic characteristic of power system; however these approaches cannot be applied for the real time control because of long execution time (El-Zonkoly *et al*., 2008).

Limitation of fixed parameter of conventional PSS has lead to advanced control schemes such as H_∞ optimization techniques (Hardiansyah, *et al*., 2006), PSO (Al-Awami *et al*., 2007), GA (Davis, 1987) and fuzzy logic based controls (Hwang *et al*., 2008). In the design of fuzzy logic controllers, unlike most conventional methods, a mathematical model is not required to describe the system under study.

H_∞ optimization techniques (Hardiansyah *et al*., 2006; Xi *et al*., 2002) have been applied to robust PSS design problem. However, the additive and/or multiplicative uncertainty representation cannot treat situations where a nominal stable system becomes unstable after being perturbed. On the other hand, the order of the H_∞ based stabilizer is as high as that of the plant. This gives rise to complex structure of such stabilizers and reduces their applicability.

Particle swarm optimization (PSO) is one of the modern heuristic algorithms. It was developed through simulation of a simplified social system, and has been found to be robust in solving continuous nonlinear

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optimization problems (El-Zonkoly, 2006). The PSO technique can generate a high quality solution within shorter calculation time and stable convergence characteristic than other stochastic methods (Shayeghi *et al*., 2010). Generally, PSO is characterized as a simple concept, easy to implement, and computationally efficient. Unlike the other heuristic techniques, PSO has a flexible and well-balanced mechanism to enhance the global and local exploration abilities. However this is possible to occur that PSO converges junior. This is obvious that the conventional controllers which are optimized by PSO have a suitable reaction in wide range systems. However these optimizations of PSSs are in a particular work point, whereas this is not appropriate for various operating points.

Genetic algorithm (GA) is a strong optimization technique which is independent on the complexity of problems and the prior knowledge is not available. These works investigated the use of genetic algorithms for simultaneously stabilization of multi-machine power system over a large scale of scenarios via power system stabilizers with fixed parameters. Although GA is one of the probabilistic optimization methods and robust and able to solve complex and global optimization problem. But GA can suffer from the long computation time before providing an accurate solution because it uses prior knowledge minimally and does not exploit local information (Cupertino *et al*., 2003).

Recently the research for control method based on fuzzy logic controllers (FLC) as PSS has greatly improved the dynamic characteristics of power system (Shayeghi *et al*., 2008). Fuzzy rules and membership functions shape should be adjusted to obtain the best control performance in FLC. Conventionally the adjustment is done by the experience of experts or trial and error methods. Therefore it is difficult to determine the suitable membership functions and rule base without the knowledge of the system. These problems make the design process more difficult (Houn *et al*., 2002).

In this paper to overcome those backwashes a fuzzy PID controller which is automatically optimized by GA is proposed to damp the low frequency oscillations. The motivation for using this hybrid technique is to reduce fuzzy effort and take large parametric uncertainties in to account. Also this newly proposed technique make a flexible controller in different operating points. The proposed controller is tested on 3 machine 9 buses standard power system in different operating conditions. The effectiveness of proposed controller is compared with robust PSS tuned by Particle Swarm Optimization (RPSSPSO) through FD and ITAE performance indices. Actually, this is cleared that the proposed controller is an attractive alternative to conventional fixed gain stabilizer design as it retains the simplicity of the conventional PSS and still guarantees a robust acceptable performance over a wide range of operating and system condition (Wang, 1996).

Power system Description:

The synchronous machine is the most important part in power systems. This part of power system includes electromechanical system which is made of two parts as: electrical and mechanical. The model of power system in this paper is simulated by deferential equations that are presented below for power system in this paper (Padiyar, 2002). Descriptions of these parameters are presented in APPENDIX A.

$$\dot{\delta}_i = \omega_b(\omega_i - 1) \tag{1}$$

$$\dot{\omega}_i = \frac{1}{M_i}(P_{mi} - P_{ei} - D_i(\omega_i - 1)) \tag{2}$$

$$\dot{E}'_{qi} = \frac{1}{T'_{doi}}(E_{fdi} - (x_{di} - x'_{di})i_{di} - E'_{qi}) \tag{3}$$

$$\dot{E}_{fdi} = \frac{1}{T_{Ai}}(K_{Ai}(v_{refi} - v_i + u_i) - E_{fdi}) \tag{4}$$

$$T_{ei} = E'_{qi}i_{qi} - (x_{qi} - x'_{di})\,i_{di}\,i_{qi} \tag{5}$$

GA Based Fuzzy PSS Design Scheme:

Fuzzy logic controller:

Nowadays fuzzy theory is used in almost all sectors of industry and science. One of them is power system control. Fuzzy logic control (FLC) is one of the most successful areas in the application of fuzzy theory and is excellent alternatives to the conventional control methodology when the processes are too complex for the analysis by conventional mathematical techniques (Houn *et al*., 2002; Barreiros *et al*., 2005). Because of the complexity and multi-variable conditions of the power system, conventional control methods may not give satisfactory solutions. Conventionally, we have used the knowledge of experts and trial and error methods to tune FLCs for a good control performance, but recently many other ways using Evolutionary computation are proposed to modify fuzzy rule and shape of fuzzy membership function. The structure of fuzzy controller in the power systems is shown in Fig. 1.

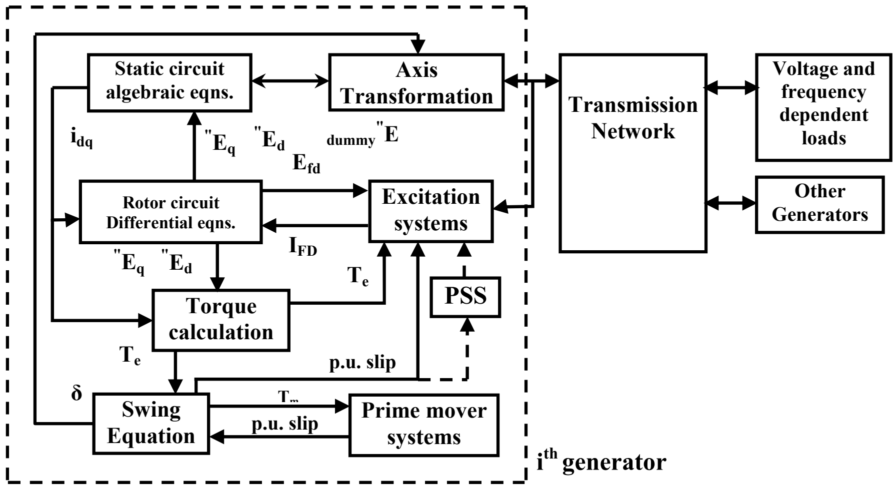

Fig. 1: Structure of PSS in power systems

Also, their robustness and reliability make fuzzy controllers useful for solving a wide range of control problems in power systems. In general, the application of the fuzzy logic to PID control design for the PSS design can be classified in two major categories according to the way of their construction (Caner *et al*., 2008):

1. A typical PSS is constructed as a set of heuristic control rules, and the control signal is directly deduced from the knowledge base.

2. The gains of the conventional PID controller are tuned on-line in terms of the knowledge based and fuzzy inference, and then, the conventional PID controller generates the control signal. Fig. 2 shows the block diagram of the classical fuzzy type controller to PSS design for each generator.

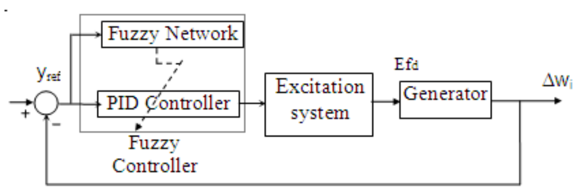

Fig. 2: Block diagram of fuzzy controller

In the design of fuzzy logic controller, there are five parts of the fuzzy inference process:

1- Fuzzification of the input variables.
2- Application of the fuzzy operator (AND or OR) in the anteceden.
3- Implication from the antecedent to the consequent.
4- Aggregation of the consequents across the rules.
5- Defuzzification.

The structure of the classical FPID controller includes two-level. The first level is fuzzy network and the second level is the PID controller. The controller block is formed by the fuzzification of ($\Delta\omega_i$), the interface mechanism and the defuzzification. Therefore Ui is a control signal that applies to the excitation system in each generator. By taking $\Delta\omega_i$ as the system output, the control vector for the a conventional PID controller is given by:

$$u_i = K_{Pi\,i}\Delta\omega_i(t) + K_{Ii}\int_0^t \Delta\omega_i(t)dt + K_{di}\Delta\dot{\omega}_i(t) \tag{6}$$

The parameters, K_{Ii}, K_{di} and K_{pi} are determined by a set of fuzzy rules of the form:
If $\Delta\omega_i$ is A_i and $\Delta(\Delta\omega_i)$ is B_i then K_{di} is C_i and K_{pi} is D_i and K_{Ii} is E_i, $i=1,2,\cdots,n$.
Where, A_i, B_i, C_i, D_i and E_i are fuzzy sets on the corresponding supporting sets.

In the proposed rule base optimization problem, the membership function sets for the K_{Pi}, K_{Ii} and K_{di} are defined as triangular partitions with five segments from 0 to 1 as shown in Fig. 3. Zero (ZO) is the center membership function. The remaining parts of the partition are Negative Big (NB), Negative Small (NS), Positive Small (PS) and Positive Big (PB). The membership function sets for $\Delta\omega_i$, $\Delta(\Delta\omega_i)$ is the same as Membership Function (MF) sets as shown in Fig. 3.

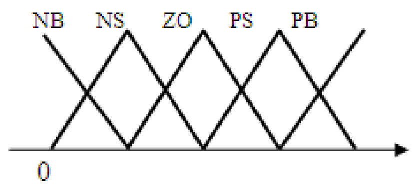

Fig. 3: The MF sets for K_{Pi}, K_{Ii} and K_{di}..

Therefore fuzzy gains are obtained with these equations:

$$K^{'}p(t)=\frac{\sum_{l=1}^{49} y_{p}^{-l}\mu_{A}^{l}(e(t))\mu_{B}^{l}(e^{\cdot}(t))}{\sum_{l=1}^{49}\mu_{A}^{l}(e(t))\mu_{B}^{l}(e^{\cdot}(t))} \tag{7}$$

$$K^{'}d(t)=\frac{\sum_{l=1}^{49} y_{d}^{-l}\mu_{A}^{l}(e(t))\mu_{B}^{l}(e^{\cdot}(t))}{\sum_{l=1}^{49}\mu_{A}^{l}(e(t))\mu_{B}^{l}(e^{\cdot}(t))} \tag{8}$$

$$\alpha(t)=\frac{\sum_{l=1}^{49} y_{\alpha}^{-l}\mu_{A}^{l}(e(t))\mu_{B}^{l}(e^{\cdot}(t))}{\sum_{l=1}^{49}\mu_{A}^{l}(e(t))\mu_{B}^{l}(e^{\cdot}(t))} \tag{9}$$

Whereas: y_{p}^{-l}, y_{d}^{-l}, y_{α}^{-l} are the proportionate stations with fuzzy bundles.

In many cases, the performance of FPID controller depends on a designed knowledge base in which fuzzy control rules are defined (Barreiros *et al*., 2005; Caner *et al*., 2008). In the traditional method, the rule base is determined by experience and control knowledge of human expert. However, it is a trial and error process and takes much time and cost. In order for a fuzzy controller to perform well, the fuzzy rule base must be carefully designed. Thus, to reduce fuzzy system effort cost the automatic design method for FPID control, which can generate an optimal rule tables without human experts, is desirable. Fig.4. shows the structure of the proposed GA-F PSS to improve power system stability.

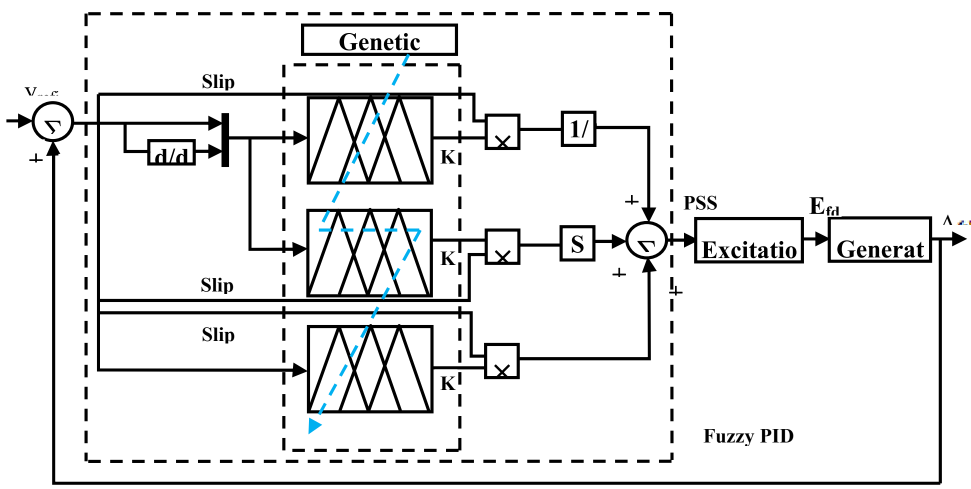

Fig. 4: Structure of the proposed GA-F PSS

Hybrid GA-Fuzzy to Design the Controller:

GAs are search algorithms based on the mechanism of natural selection and natural genetics that operate without knowledge of the task domain and utilize only the fitness of the evaluated individuals. In general, reproduction, crossover and mutation are the three basic operators of the GA's. They can be considered as a general-purpose optimization method and have been successfully applied to search and optimization (Shayeghi *et al*., 2007). During evolution, GAs requires only information the quality of the fitness value produced by each parameter set. This differs from many optimization methods requiring derivative information or complete knowledge of the problem structure and parameter. Hence, the GA is more suitable to deal with the problem of lacking experience or knowledge than other searching methods in particular, when the phenomena being analyzed are describable in terms of the rules for action and learning processes (Mitchell, 2002). In this paper, GA-based Fuzzy (GAF) controller is proposed for the PSS design, which combines the advantage of the GAs and fuzzy control techniques to achieve good robust performance. The motivation of using the proposed GAF PSS is to reduce the fuzzy system effort and determine the optimal controller scheme such that the relative stability is guaranteed and the time domain specifications concurrently secured. The flow chart of GA is shown in Fig. 5.

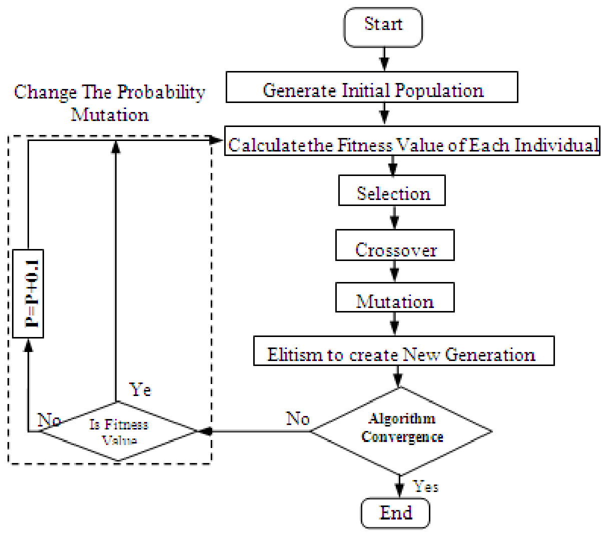

Fig. 5: Modified GA approaches to find optimal rule base sets.

Before proceeding with the GA approach, there are two preliminaries to be finished.

1) Definition of suitable coding: one of the most attractive problems in the GA's is coding the solution space. According to Fig. 4, each rule Table has 20 rules. Also, the fuzzy set {NB, NZ, Z, PS, PB} can be represented with an integer set {1, 2, 3, 4, 5}. Thus, the order of parameters is coded into the chromosome (individual). A chromosome represents a candidate solution of the problem. In this method, a solution candidate is expressed by binary coding. Consequently, number of rules and fuzzy set for the K_{Pi}, K_{Ii} and K_{di} in each generation are expressed in term of string consisting of 0 and 1 as shown in Fig.6.

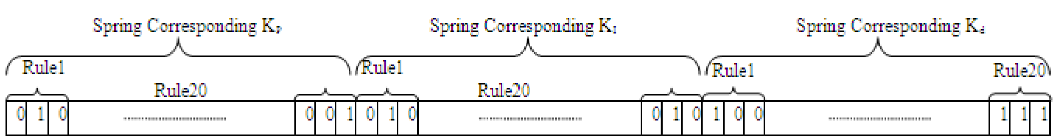

Fig. 6: String encoding the proposed fuzzy control rule Table.

2) Choice of fitness functions: the second preliminary to be finished is choosing the problem-dependent fitness function. In the present study, evaluation of the Integral of the Time multiplied Absolute value of the Error (ITAE) based function is an alternative of the conventional maximization of fitness function, which defined as follows:

$$f(ITAE) = \frac{1}{1 + MSE(ITAE)} \tag{10}$$

where,

$$MSE(ITAE) = (\sqrt{\sum_{i=1}^{m} ITAE_i})/m,$$

$$ITAE_i = 100\int_0^{10} t\ (|\Delta\omega_i|)dt$$

After deciding these two preliminaries, we should choose the genetic operators. This algorithm consists of elitism selection and three kinds of genetic operators which are selection, crossover, mutation to create new generation.

1) *Selection:* selection chooses the individuals in the population as parent individuals to create offspring for the next generation, whose purpose is to emphasize the fitter individuals in the population in hopes that their offspring will in turn have even higher fitness. In this work, the roulette wheel selection is adopted.

2) *Crossover:* Instead of the single-point crossover, we adopt the two-point crossover. For example, the parent individuals h_1 and h_2 given to be crossover at the points k and l with the crossover probability P_c. Results in the new offspring h'_1 and h'_2 are expressed as:

$$h'_1 = \begin{cases} h_{2i} & k < i < l \\ h_{1i} & otherwise \end{cases}$$
$$h'_2 = \begin{cases} h_{1i} & k < i < l \\ h_{2i} & otherwise \end{cases} \tag{11}$$

3) *Mutation:* A position of each gene with probability P_m which is a possible candidate for the mutation is selected randomly and then value of gene, 0 or 1, changed to, 1 or 0, respectively.

4) *Elitism:* Elitism guarantees that the best string individual survives until the last generation. Among parents and their children that are generated by crossover and mutation individuals, they have the best fitness function only survive to the next generation. Size of the individuals in the next generation is the same as the initial population size.

The genetic algorithms are powerful search techniques to optimization, but some well-known disadvantage in GA are poor convergence of the classical GA near the global optimum and convergence to the suboptimum. In order to overcome these drawbacks, the following procedure is being used in the proposed modified GA:

- In each iteration, probability of the mutation (P_m) is changed according to Fig.8 if the fitness function value does not improve in comparison with the previous generation. This method guarantees algorithm convergence to the near optimum solution.

The proposed controller is connected to machines G1 to G3 in the test system. Here, the modified GA evolution procedure is applied to produce rule Tables of the proposed GA-PSOF PSS to guarantee relative stability and concurrently secure the time domain specifications. In this work, these parameters are listed in Table 1. The plot of obtained fitness function value is shown in Fig. 7. The Results of fuzzy rule base sets are listed in Tables 2-4.

Table 1: GA Set Parameters

Number of generation	100
Population size	20
Crossover rate	0.97
Mutation rate	0.08

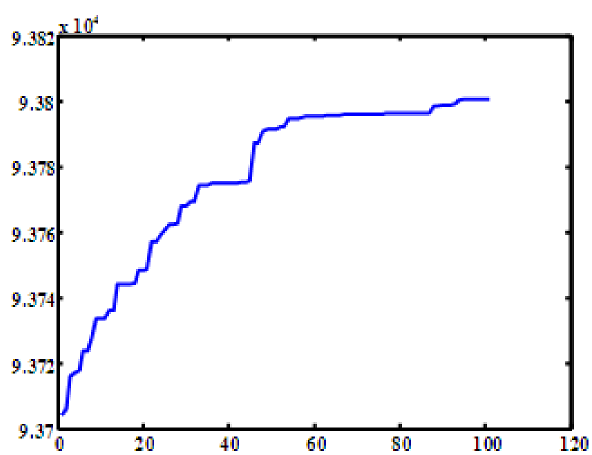

Fig. 7: Optimal trend of fitness function evaluation

Table. 2: Optimal vales gain of K_I

	NB	NS	PS	PB
NB	NB	NB	NM	NS
NS	NB	NB	PM	PM
Z	PM	PB	NB	NB
PS	NB	NB	PB	NB
PB	NS	PM	PM	ZO

Table. 3: Optimal values gain of K_{Pi}

	NB	NS	PS	PB
NB	PM	PM	PB	PS
NS	PM	NS	PB	NM
Z	PS	PB	PB	PB
PS	PB	PB	PM	NM
PB	PS	NS	PB	NB

Table. 4: Optimal values gain of K_{di}

	NB	NS	PS	PB
NB	PM	PM	PB	PS
NS	PM	NS	PB	NM
Z	PS	PB	PB	PB
PS	PB	PB	PM	NM
PB	PS	NS	PB	NB

Case study 1:

In this study, the three-machine nine-bus power system shown in Fig.8 is considered. Details of the system data and load condition are given in Ref. (Shayeghi *et al*., 2010). Furthermore operating of system is tasted in three different conditions as nominal, lightly and heavily loading conditions.

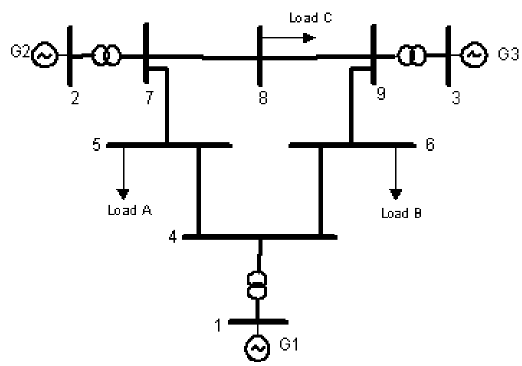

Fig. 8: Three-machine nine-bus power system.

Nonlinear time-domain simulation:

To demonstrate the effectiveness and robustness of the proposed GA based fuzzy PSS, simulation studies are carried out under fault disturbances for the one scenario. The performance of the proposed PSSs is compared to those of the PSSs tuned using the particle swarm optimization (PSO) method (Shayeghi *et al*., 2010) for different operating conditions.

Scenario 1:

In this scenario, performance of the proposed controller under transient conditions is verified by applying a 6-cycle three-phase fault at t=1 sec, on bus 7 at the end of line 5-7. The fault is cleared by permanent tripping the faulted line. Speed deviations of the generators G_1 to G_3 under light load condition are shown in Fig.9. It can be seen that the overshoot, undershoot, settling time and speed deviations of all machines are greatly reduced by applying the proposed GA-F PSSs.

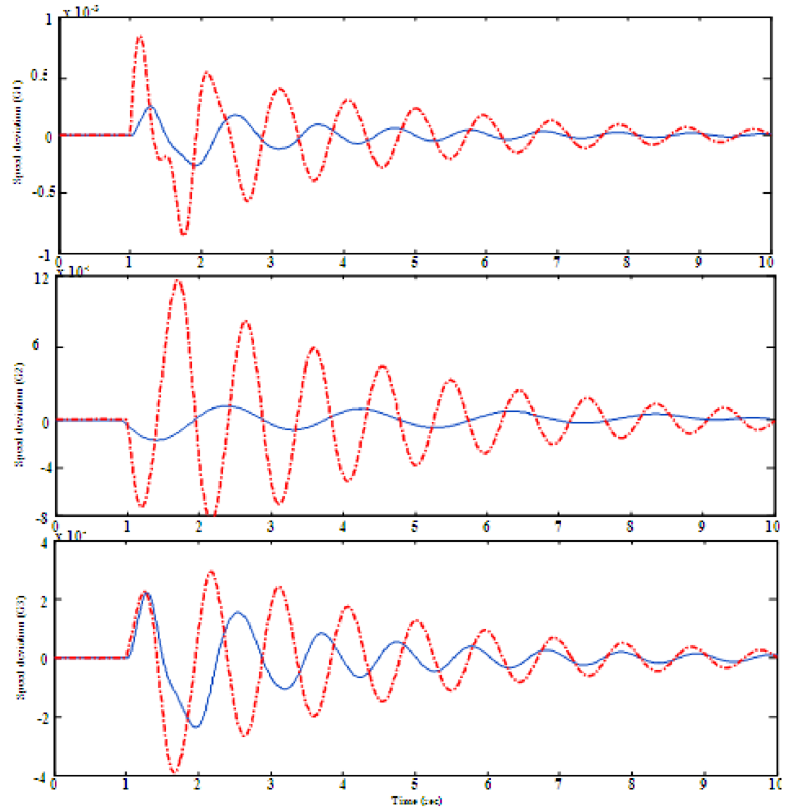

Fig. 9: System response under scenario 1 with light loading condition: Solid (GA-FPSS), Dashed (RPSSPSO).

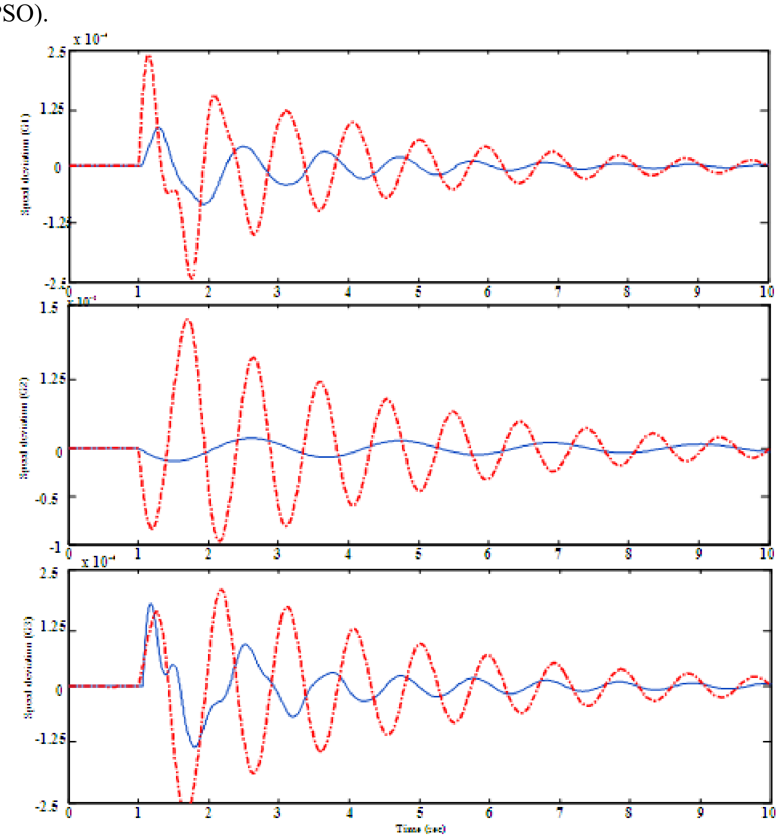

Fig. 10: System response under scenario 2 with heavy loading condition: Solid (GA-FPSS), Dashed (RPSSPSO).

Scenario 2:

It is very important to test the PSS under the loading power factor operating condition. A 0.2 p.u. step increase in mechanical torque was applied at t=1.0. Figs 10, show the result of simulation that are tested in heavy load condition.

Scenario 3:

In this scenario a 0.2 p.u. step increase in mechanical torque was applied at t=0.5 and after a few seconds a 6-cycle three-phase fault at *t*=5 sec, on bus 7 at the end of line 5-7 for system will be applied. The results of simulation in nominal load condition are shown in Figs. 11.

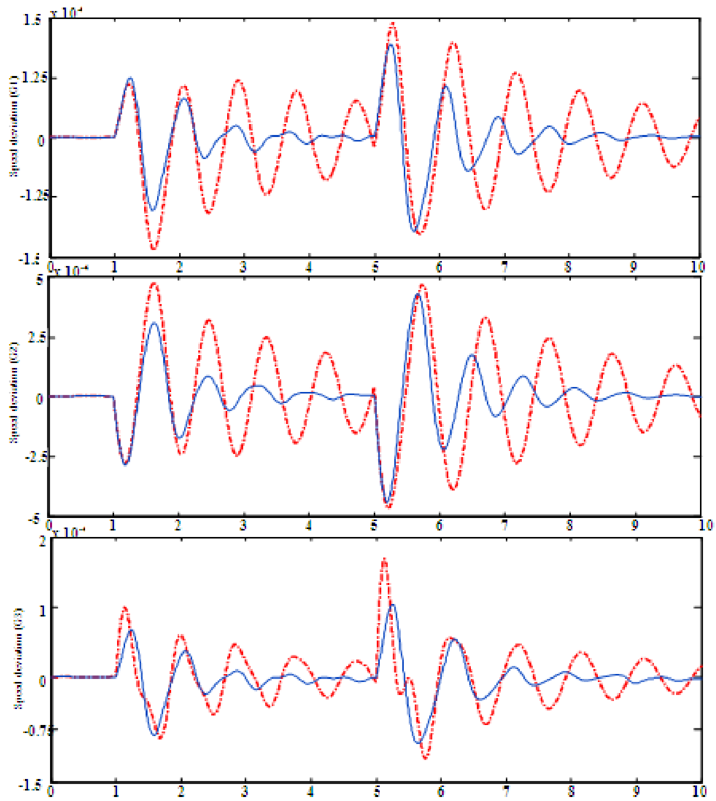

Fig. 11: System response under scenario 3 with nominal loading condition: Solid (GA-FPSS), Dashed (RPSSPSO).

To demonstrate performance robustness of the proposed method, two performance indices: the Integral of the Time multiplied Absolute value of the Error (ITAE) and Figure of Demerit (FD) based on the system performance characteristics are defined as:

$$ITAE_i = 100\int_0^{10} t(|\Delta\omega_i|)dt \qquad (12)$$

$$FD = (OS \times 10^{-4})^2 + (US \times 10^{-4})^2 + T_s^{\,2} \qquad (13)$$

where Overshoot (OS), Undershoot (US) and settling time of rotor angle deviation of one machine is considered for evaluation of the FD. It is worth mentioning that the lower the value of these indices is, the better the system response in terms of time-domain characteristics. Numerical results of performance robustness for all cases are listed in Table 5-6. It can be seen that the values of these system performance characteristics with the proposed controller are much smaller compared to that RPSSPSO. This demonstrates that the overshoot, undershoot settling time and speed deviations of all machines are greatly reduced by applying the proposed GA based fuzzy PSSs.

Table 5: Value of ITAE in different techniques

Method	Scenario 1 Nominal	Light	Heavy	Scenario 2 Nominal	Light	Heavy	Scenario 3 Nominal	Light	Heavy
TSPSS	36.03	36	37.4	37.1	36.7	38.5	40.1	38.5	43
GA-FPSS	0.73	0.70	0.79	0.76	0.73	0.84	0.81	0.79	0.88

Table 6: Value of FD in different techniques

Method	Scenario 1 Nominal	Light	Heavy	Scenario 2 Nominal	Light	Heavy	Scenario 3 Nominal	Light	Heavy
TSPSS	84	81	90	86	82	95	91	90	103
GA-FPSS	1.68	1.62	1.74	1.7	1.68	1.81	1.9	1.87	1.98

Conclusions:

In this paper, a new robust GA based fuzzy PSS is proposed to enhance relative stability and secure operation of the multi machine power systems. This control strategy was chosen because of increasing the complexity and changing the structure of the power systems. This newly developed control strategy combines advantage of the fuzzy control system and GA techniques for achieving the desired level of robust performance under different operating conditions and load disturbances. It should be noted that the construction of the optimal rule base sets for the proposed fuzzy PSS is very important to achieve the best performance. Thus, to reduce the fuzzy system effort and cost saving, a modified GA has been used to produce fuzzy rule Tables. The salient feature of the proposed method is that it does not require an accurate model of the system. All PSSs are designed simultaneously, by taking into consideration the interaction among them. Moreover, they have simply and decentralized nature since only local measurements are employed as the stabilizer inputs. This makes the proposed FPSS easy to implement which ideally useful for the real world power systems. The proposed GA based fuzzy PSS was tested on a three-machine power system power system to demonstrate its robust performance under different operating conditions. The nonlinear time simulation results confirm that the proposed FPSS can work effectively over a wide range of loading conditions and is superior to the classical PSSs tuned based on the PSO.

Appendix A:

Machine models description:

δ	Rotor angle
ω	Rotor speed
P_m	Mechanical input power
P_e	Electrical output power
E'_q	Internal voltage behind x'_d
E_{fd}	Equivalent excitation voltage
T_e	Electic torque
T'_{do}	Time constant of excitation circuit
K_A	Regulator gain
T_A	Regulator time constant
v_{ref}	Reference voltage
v	Terminal voltage

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