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Real-Coded Genetic Algorithm Based Design and Analysis of an Auto-Tuning Fuzzy Logic PSS

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Abstract - One important issue in power systems is dynamic instability due to loosing balance relation between electrical generation and a varying load demand that justifies the necessity of stabilization. Moreover, Power System Stabilizer (PSS) must have capability of producing appropriate stabilizing signals over a wide range of operating conditions and disturbances. To overcome these drawbacks, this paper proposes a new method for robust design of PSS by using an auto-tuning fuzzy control in combination with Real-Coded Genetic Algorithm (RCGA). This method includes two fuzzy controllers; internal fuzzy controller and supervisor fuzzy controller. The supervisor controller tunes the internal one by on-line applying of nonlinear scaling factors to inputs and outputs. The RCGA-based method is used for off-line training of this supervisor controller. The proposed PSS is tested in three operational conditions; nominal load, heavy load, and in the case of fault occurrence in transmission line. The simulation results are provided to compare the proposed PSS with conventional fuzzy PSS and conventional PSS. By evaluating the simulation results, it is shown that the performance and robustness of proposed PSS in different operating conditions is more acceptable

Keywords: Auto-Tuning Fuzzy Controller, Dynamic Stability, Power System Stabilizer, Real Coded Genetic Algorithm

1. Introduction

Power systems are usually encountered different disturbances, which cause low-frequency oscillations in the system. If the damping torque is insufficient, these oscillations grow and consequently the dynamic instability of the system is occurred. In the two last decays, in order to improve the dynamic stability, using of supplementary stabilizing signals in addition to the excitation systems, have been significantly considered[1-20]. Today, conventional PSS with excitation system is widely used in power plants. The tuning of these controllers are usually accomplished based on a linearized model around a single operating condition. Because of approximation in modeling and wide range of operating conditions, and variation of the system topology due to error occurrence, conventional PSS does not provide satisfactory results over a wide range of operating conditions. In recent years, different methodologies based on non-linear control techniques [9], adaptive control [5], [10-13], and artificial intelligence-based approaches [4-8], [11], [13-20] have been proposed to design PSS. Moreover, recent developments in design and manufacturing of excitation systems make the applications of the above-mentioned techniques not only possible but also easy.

In adaptive techniques, on-line system identification is needed which makes these techniques difficult and time consuming and even sometimes impossible. The artificial intelligence-based approaches include fuzzy logic [4,5,8,11, 13,14,16,17], neural networks [5,13,15], and intelligent search algorithm such as genetic algorithm [5-7], [20], Tabo search algorithm[19], and Partial Swarm Optimization algorithm[18]. Fuzzy logic-based PSSs have great potential in increasing the damping of generator oscillations. The main advantage of fuzzy controllers is no requirement to perfect model of the system. When fuzzy logic-based PSS is added to auto-tuning abilities, it exhibits great capabilities and this is the main idea of this paper.

In this paper, an auto-tuning fuzzy logic-based PSS is presented. The proposed PSS includes two fuzzy controllers; internal fuzzy controller and supervisor fuzzy controller. The supervisor controller, tunes the internal one by on-line applying of scaling factors to inputs and outputs. This supervisor controller is trained by using genetic algorithm, however, since the length of the chromosome is large in GA method, in this paper this fuzzy controller is tuned off-line by using RCGA. In this case, the speed of computations in the parameters tuning will be high.

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2. Problem Formulation

2.1 System Modeling

In single machine infinite bus system, the synchronous machine (generator) is connected to an infinite bus through a transformer and two parallel transmission lines. In generator bus, a local load is also supplied. The generator is equipped with an Automatic Voltage Regulator (AVR) in order to keep the voltage level within desired limit. Figure (1) shows the single line schematic of the system. Of course, in this figure, also controller systems injected to the AVR is presented, where they are discussed in the next sections.

In this paper, for the analysis and design of control system, the Heffron-Phillips linearized model is used whose block diagram is shown in figure (2). The proposed PSS is evaluated in three operational conditions; nominal load, heavy load, and in the case of fault occurrence in the transmission line.

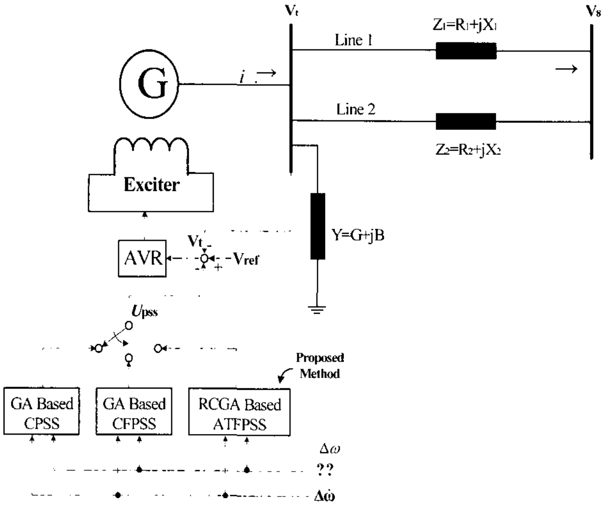


Fig. 1. Schematic of the single machine power system connected to an infinite bus

The linearized state equations of the single machine connected to an infinite bus are given as:

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \\ \dot{x}_4 \end{bmatrix} = \begin{bmatrix} \frac{D}{M} & \frac{K_1}{M} & \frac{K_2}{M} & 0 \\ 2\pi f & 0 & 0 & 0 \\ 0 & \frac{K_4}{T'_{do}} & \frac{1}{T'_{do}K_3} & \frac{1}{T'_{do}} \\ 0 & \frac{K_A K_5}{T_A} & \frac{K_A K_6}{T_A} & -\frac{1}{T_A} \end{bmatrix} \cdot \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ \frac{K_A}{T_A} \end{bmatrix} \cdot u(t) \qquad (1)$$

$$Y = \begin{bmatrix} 0 & 1 & 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} \qquad (2)$$

where $x_1 = \Delta\omega$, $x_2 = \Delta\delta$, $x_3 = \Delta E'_q$, and $x_4 = \Delta E_{fd}$.

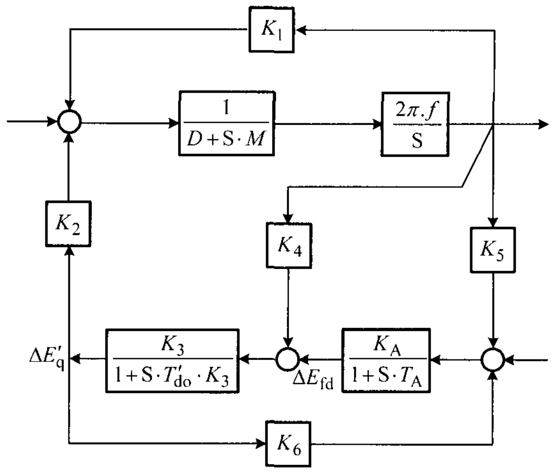


Fig. 2. The block diagram of the Heffron-Phillips model of single machine infinite bus system

2.2. Conventional PSS (CPSS) Design

The control objective of PSS is to suppress the generator electromechanical oscillations and enhance the overall stability of power system by using a supplementary stabilizing signal in the excitation system. This stabilizer should be designed so that the delayed phase is deleted and by high bandwidth feedback makes it possible that system responds quickly to the stabilizing corrections. This conventional PSS is a double stage Lead-Lag compensator with time constants T_1 to T_4 and gain K_p as following:

$$K(s) = K_P \cdot \left(\frac{T_W \cdot S}{1+T_W \cdot S}\right) \cdot \left(\frac{1+T_1 \cdot S}{1+T_2 \cdot S}\right) \cdot \left(\frac{1+T_3 \cdot S}{1+T_4 \cdot S}\right) \qquad (3)$$

where T_w is the washout time constant needed to prevent steady state offset of the voltage and is selected equal to 10 seconds. The value ranges of other parameters are usually as follows:

$T_1 \geq 0$, $T_2 \geq 0.01$, $T_3 \leq 1$, $T_4 \leq 0.5$, and $0 < K_p < 20$.

In this PSS, usually $\Delta\omega$ is sampled and suitable signal for reference voltage (U_{PSS}) in Heffron-Phillips model is obtained.

3. Fuzzy Logic Power System Stabilizer (FLPSS)

Power systems usually operate under highly uncertain and stress conditions. Moreover, load variations cause the generator dynamic characteristics also vary so different operating conditions are obtained. Therefore, power system controllers should be designed to maintain the robust stability of the system. On the other hand, a CPSS is designed for a linear model representing the generator at a certain operating point and it often does not provide satisfactory results over a wide range of operating conditions. To overcome these drawbacks, fuzzy logic controller (FLC) is an effective tool, which has non-linear structure. In fuzzy controller design, there is no need to perfect model of the system, which is a significant advantage.

In what follows, we will describe how the FLPSS has been synthesized. The design process of fuzzy logic controller may be split into five steps: 1) the selection of control variables, 2) the membership function definition or "the fuzzification", 3) the rule creation or "the knowledge base", 4) the fuzzy interface engine, and 5) the defuzzification strategy or "the defuzzifier". These steps are shown in figure (3).

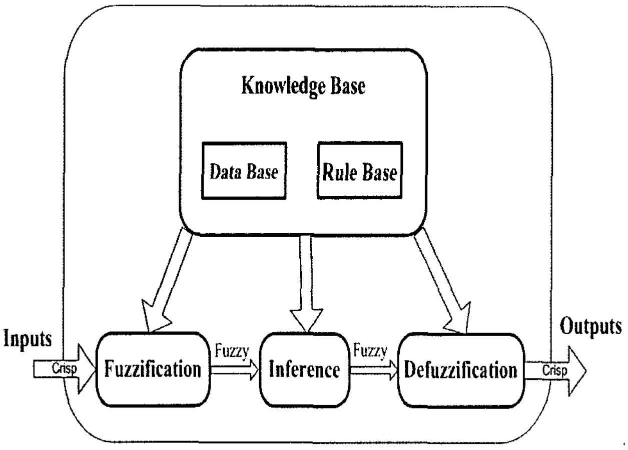


Fig. 3. The basic structure of the fuzzy controller

Also, in figure (4) it is shown how to use fuzzy controller in a PSS structure. In the proposed method, two variables $\Delta\omega$ and $\Delta\dot{\omega}$ are used as input signals in PSS. The coefficients K_{in1} and K_{in2} in input stage, keep the input signals within allowable limit. These coefficients are called scaling factors which transform the real value scale to required value in decision limit. The output signal (U_{PSS}) is injected to the summary point of the AVR as the supplementary signal.

Each of FLPSS input and output fuzzy variables $Y = (\Delta\omega, \Delta\dot{\omega}, U_{PSS})$ membership functions have been chosen identical because of the normalization achieved on the physical variables. The normalization is important because it allows the controller to associate equitable weight to each of the rules and therefore, to calculate correctly the stabilizing signal.

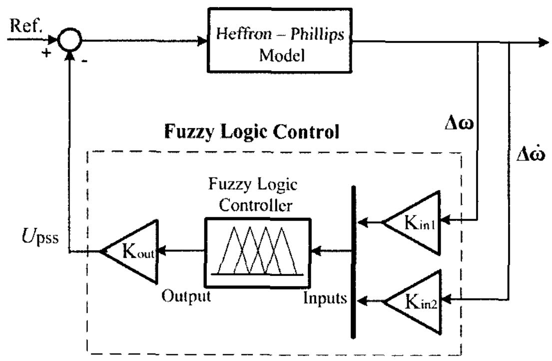


Fig. 4. Schematic Structure of FLPSS

Each of the input and output fuzzy variables, y_i is assigned seven linguistic fuzzy subsets varying from Negative Big (NB) to Positive Big (PB). Each subset is associated with a triangular membership function to form a set of seven normalized and symmetrical triangular membership functions for fuzzy variables (see figure (5)).

The y_{max} and y_{min} represent maximum and minimum variation of the input and output signals. These values are selected based on simulation data. The range of each fuzzy variable is normalized between -4 to 4 by introducing a scaling factor to represent the actual signal.

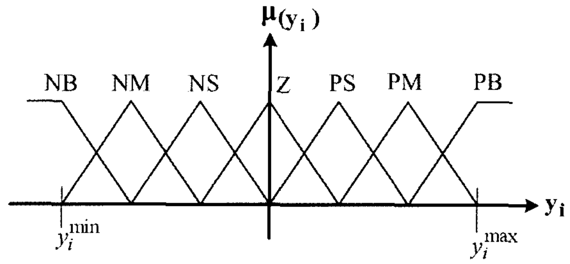


Fig. 5. Fuzzy variable, y_i, seven membership functions

The output signal was obtained by using the following principles:

- f the speed deviation is important, but tends to decrease, then the control must be moderated. In other words, when the machine decelerates, even though the speed is important, the system is capable, by itself, to return to steady state.
- f the speed deviation is weak, but tends to increase, the control must be significant. In this case, it means that, if the machine accelerates, the control must permit to reverse the situation.

The interface mechanism of the FLC is represented by a 7×7 decision table. The set of decision rules relating all possible combinations of inputs to outputs is based on previous experience in the field. This set is made up of 49 rules expressed using the same linguistic variables as those of the inputs and is stored in the form of a decision table shown in table (1).

Table 1. FLPSS decision table

$\Delta\omega$ \ $\Delta\dot{\omega}$	NB	NM	NS	Z	PS	PM	PB
NB	NB	NB	NB	NB	NM	NS	Z
NM	NB	NB	NM	NM	NS	Z	PS
NS	NB	NM	NM	NS	Z	PS	PM
Z	NM	NM	NS	Z	PS	PM	PM
PS	NM	NS	Z	PS	PM	PM	PB
PM	NS	Z	PS	PM	PM	PB	PB
PB	Z	PS	PM	PB	PB	PB	PB

4. Auto-Tuning Fuzzy logic PSS (ATFPSS)

An important disadvantage of fuzzy controller is that there is no systematic scheme for parameters adjustment. Although different types of fuzzifications, defuzzifications, and reasoning algorithms are available which provide possible selection of various membership functions within allowable limits and also choice of scaling factors provide various options for designer, however, this makes the optimum selection problem more difficult.

In this paper, by considering seven regions of membership functions, the number of rules is equal to 49. This makes the membership functions more accurate and causes to define the rule base more precisely. One other important point is suitable determination of the scaling factors; K_{in1} , K_{in2} and K_{out} . If these factors are determined suitably, then the probable errors in other different parts of fuzzy controller can be neglected. For this purpose, an Auto-Tuning Fuzzy logic controller for PSS (ATFPSS) is used as follows.

The proposed ATFPSS is a hierarchical controller, which includes two fuzzy controllers. The internal controller is the main controller whose structure was described completely in previous section. The second controller, which is supervisor controller, tunes the scaling factors on-line. The schematic structure of the proposed stabilizer is shown in figure (6).

As it is shown in this figure, in the supervisor fuzzy controller two set of signals are used; local input signals and supplementary signals. The local input signals are the inputs of the main controller, i.e., the generator speed deviation $\Delta\omega$ and its derivative $\Delta\dot{\omega}$. Also, the supplementary signal in this supervisor fuzzy controller is virtual time signal. This signal is obtained in the system starting with disturbance occurrence and is continued by a unit ramp function in the considered time, which is 5 seconds in our case study. Of course, these signals can be supplementary signals, which are not taken from local system and can be received from other points of the system or from protection relays. Moreover, the output signals of the supervisor controller are the scaling factors K_{in1} , K_{in2} and K_{out} which are determined on-line in order to apply to internal (or main) controller. Therefore, the supervisor controller has three inputs and three outputs.

The permitted range for the local input signals $\Delta\omega$ and $\Delta\dot{\omega}$ are [-4, +4] and [-1, +1] respectively, and for the supplementary input signal t is selected as [0, +5]. Also, the permitted limit for each output signal of supervisor controller is considered as [0, +10].

In the supervisor fuzzy controller, to make the computations easier and quick, triangular membership functions are used in the input-output space. For the first input allowable limit $\Delta\omega$, because of its importance, five triangular membership functions with uniform distribution and 50% overlap and for the second input allowable limit $\Delta\dot{\omega}$, three triangular membership functions are used. For the allowable limit of the supplementary input t also, four triangular membership functions with 50% overlap is considered. Therefore, input space is three-dimensional space and divided into 60 subspaces. The fuzzy rules of the supervisor fuzzy controller for the first output K_{in1} is presented in table (2). For two other outputs K_{in2} and K_{out} can also be presented in the same table, however, for the second and third outputs, the membership functions have the index 2,i and 3,i respectively. Of course, the distribution routine of these membership functions are not definite for which in the next section a novel technique is presented.

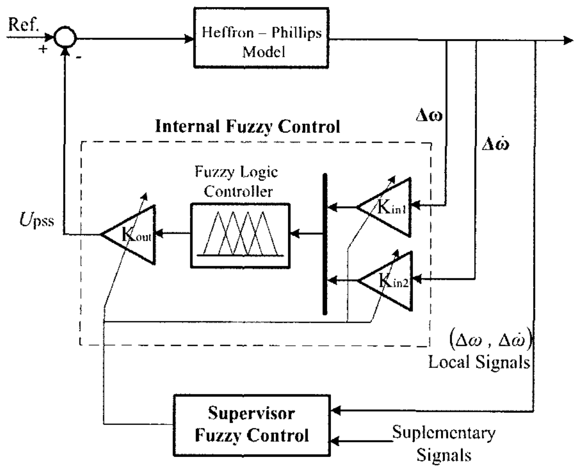
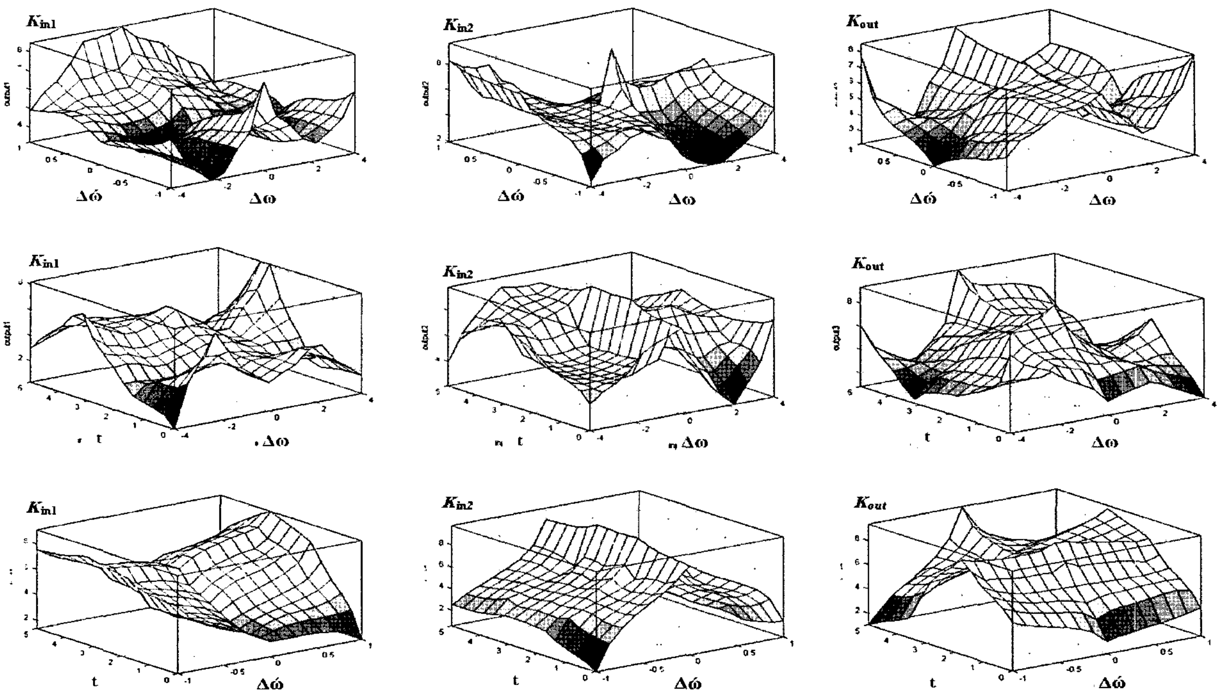


Fig. 6. Schematic structure of the proposed Auto-Tuning Fuzzy Controller



(a) (b) (c)

Fig. 7. Control Surface of supervisor fuzzy controller for; a) The first scaling factor (K_{in1}); b) The second scaling factor (K_{in2}); c) The Third scaling factor (K_{out})

Table 2. The Fuzzy rules for the first output in the supervisor fuzzy controller

Time ↓	$\Delta\omega$ → / $\Delta\dot{\omega}$ ↓	NB	NM	Z	PM	PB
VS	N	$MF_{1,1}$	$MF_{1,2}$	$MF_{1,3}$	$MF_{1,4}$	$MF_{1,5}$
	Z	$MF_{1,6}$	$MF_{1,7}$	$MF_{1,8}$	$MF_{1,9}$	$MF_{1,10}$
	P	$MF_{1,11}$	$MF_{1,12}$	$MF_{1,13}$	$MF_{1,14}$	$MF_{1,15}$
S	N	$MF_{1,16}$	$MF_{1,17}$	$MF_{1,18}$	$MF_{1,19}$	$MF_{1,20}$
	Z	$MF_{1,21}$	$MF_{1,22}$	$MF_{1,23}$	$MF_{1,24}$	$MF_{1,25}$
	P	$MF_{1,26}$	$MF_{1,27}$	$MF_{1,28}$	$MF_{1,29}$	$MF_{1,30}$
M	N	$MF_{1,31}$	$MF_{1,32}$	$MF_{1,33}$	$MF_{1,34}$	$MF_{1,35}$
	Z	$MF_{1,36}$	$MF_{1,37}$	$MF_{1,38}$	$MF_{1,39}$	$MF_{1,40}$
	P	$MF_{1,41}$	$MF_{1,42}$	$MF_{1,43}$	$MF_{1,44}$	$MF_{1,45}$
B	N	$MF_{1,46}$	$MF_{1,47}$	$MF_{1,48}$	$MF_{1,49}$	$MF_{1,50}$
	Z	$MF_{1,51}$	$MF_{1,52}$	$MF_{1,53}$	$MF_{1,54}$	$MF_{1,55}$
	P	$MF_{1,56}$	$MF_{1,57}$	$MF_{1,58}$	$MF_{1,59}$	$MF_{1,60}$

In figure (7), the surface control of interface mechanism of the supervisor fuzzy control is presented for all outputs. These surfaces are achieved by RCGA based optimization where discussed in the next section. In this figure, the first, second and third inputs are the generator speed deviation ($\Delta\omega$), its derivative ($\Delta\dot{\omega}$) and virtual time signal respectively. Also, the outputs are scaling factors of K_{in1}, K_{in2} and K_{out} which are presented in figures (7.a), (7.b) and (7.c) respectively.

5. Application of RCGA in ATFPSS

As it was explained in the previous section, in the supervisor fuzzy controller which tunes the scaling factors K_{in1} , K_{in2} and K_{out} on-line, all the parameters of the membership functions related to inputs, outputs and rules (presented in table (2)) are not definite. Since these parameters can be determined off-line, using of RCGA in their determination is very effective. In this paper, RCGA instead of the conventional Standard GA (SGA) is used, because the SGA encodes the optimization parameters into binary code string. Real-valued encodings have been confirmed to have better performance than either binary or gray encoding for constraint optimization problems [21]. So, in the RCGA, a gene is the optimization parameter itself where it is selected from Alphabet set. The chromosome takes the form:

$$chromosome = [a_1 \; a_2 \cdots a_N] \quad (4)$$

where $a_1, ..., a_N$ are all real values of membership function parameters related to inputs, outputs, and fuzzy rules in supervisor controller.

The RCGA structure is summarized as follows:

1) **Initial population**: The RCGA operates on a population of N_{pop} chromosomes simultaneously.

The initial population of real number vectors is created randomly. In this paper, the population size (N_{pop}) is selected as the number of genes of each chromosome. Once the initialization is completed, the population enters the main GA loop. In this loop, the stages 2 to 7 are carried out in turn. The GA loop continues until the termination conditions in stage 3 are fulfilled.

2) **Scaling**: The scaling operator, a preprocessor, is usually used to scale the objective function into an appropriate *Fitness Function*. The fitness value for each member of population is determined by relation (5):

$$Fitness(n) = M - \sum_{i=1}^{m} \left(\alpha_i \cdot ITAE_{i,\pm 0.2} + \beta_i \cdot y_{\max}^{i,\pm 0.2}\right) - \sum_{i=1}^{m} \left(\lambda_i \cdot dif_i\right) \quad (5)$$

where m is the number of operating conditions, which for determination of the fitness amount of each population member is evaluated. In this paper, m is considered equal 3. In other words, 3 operational conditions are used; nominal load, heavy load, and fault occurrence in transmission line. Also, *ITAE* is Integral Time-weighted Absolute value of Error, $y_{\max}$ is the maximum of the absolute value of the generator speed deviation $\Delta\omega$, *dif* denotes to the number of sign changes in derivative of the generator speed, α, β and λ are the coefficients which are selected by designer and show in fact, the weighting of other parameters ($y_{\max}$, *dif*, *ITAE*). M is a large positive value. In our case study, these values are selected as $\alpha = \beta = 1000$, $\lambda = 0.08$, and M=100. It should be noted that, ± 0.2 in the relation (5) means that in determining the amount of fitness, both positive and negative disturbances are applied to the system.

3) **Termination criterion**: After the fitness has been calculated, it has to be determined if the termination criterion has been met. This can be done in several ways. The algorithm used here stops when a finite generation number has been reached and the best fit among the population is declared the winner and solution to the problem.

4) **Selection**: The selection (or reproduction) operator selects good chromosomes on the basis of their fitness values and produces a temporary population, namely, the mating pool. This can be achieved by many different schemes, but the most common method is *Roulette Wheel Selection*. This operation generates a measure that reflects the fitness of the previous generation's candidates.

5) **Crossover**: The crossover operator is the main search tool. It mates chromosomes in the mating pool by pairs and generates candidate offspring by crossing over the mated pairs with probability P_{cross}. The probability of parent-chromosome crossover is assumed to be between 0.6 and 1.0. Here, the arithmetical one-point crossover is used and introduced.

6) **Mutation**: After crossover, some of the genes in the candidate offspring are inverted with the probability P_{mut}. This is the mutation operation for the GA. In this paper, the probability of non-uniform mutation (P_{mut}) is assumed to be between 0.01 and 0.1.

7) **Elitism**: The postprocessor is the elisit model. The worst chromosome in the newly generated population is replaced by the best chromosome in the old population if the best number in the newly generated population is worse than that in the old population. It is adopted to ensure the algorithm's convergence. This method of preserving the elite parent is called elitism.

6. Simulation Results

6.1. Initial Data

To demonstrate the effectiveness of the proposed PSS whose parameters are adapted by the Adaptive Fuzzy Logic (and are tuned by RCGA), time domain simulations were performed for the generator under major disturbance conditions over a wide range of loading conditions.

The considered system is a synchronous machine connected to an infinite bus through two parallel transmission lines as shown in figure (1).

In this paper, in order to investigate the performance of the proposed stabilizer, the Heffron-Phillips linearised model as figure (2) is used. The initial values and constants of the related system, which are used in the simulations, are summarized in table (3).

Moreover, since the performance of the proposed stabilizer is investigated for three different operating conditions (nominal load, heavy load, and in the case of fault occurrence in transmission line), the required coefficients for these conditions are given in table (4) [22]. In table (5), the poles and zeroes of the power system are

Table 3. Initial values and constants of the single machine connected to infinite bus

Generator Constants	$M = 9.26, D = 0, T'_{do} = 7.76, X_d = 0.973, X'_d = 0.19, X_q = 0.55$
Exciter Constants	$K_A = 50.0$, $T_A = 0.05$
Line Parameters	$R_1 = 0.051, X_1 = 1.49, R_2 = 0.102, X_2 = 2.99, G = 0.249, B = 0.262$
Initial Values	$P_{e0} = 1.0$ pu , $Q_{e0} = 0.015$ pu , $V_{t0} = 1.05$ pu

presented which as expected, without the supplementary excitation system (i.e. without PSS signal), system is unstable and there is a non-minimum phase zero and also a zero in the origin.

Table 4. The coefficients K_1 to K_6 for the Heffron-Phillips model in different operational conditions

Operation Conditions↓	K_1	K_2	K_3	K_4	K_5	K_6
Nominal Load	0.5441	1.2067	0.6584	0.6981	-0.0955	0.8159
Heavy Load	0.4563	1.4477	0.6584	0.8706	-0.1675	0.7747
Fault in the Line	0.4007	1.1404	0.7095	0.6834	-0.1207	0.8348

Table 5. Poles and zeroes of the power system

Poles	Zeros
0.2951+j4.9596 0.2951-j4.9596 -10.3929+j3.2837 -10.3929-j3.2837	0 3.9694*e7 -3.9694*e7

6.2. Simulation results of the proposed ATFPSS and comparison with CPSS and CFPSS

In this section, in order to investigate the performance of the proposed Auto-tuning Fuzzy logic PSS (ATFPSS), which is tuned by RCGA, a CPSS and a CFPSS (which are tuned by GA) are also designed and simulated.

In order to compare the performance of the above mentioned PSSs, the speed deviation and torque angle deviation of the generator when mechanical torque was changed by 0.2(p.u.) in three operating conditions (nominal load, heavy load, and in the case of fault occurrence in transmission line), are presented. Also, to evaluate the performance of the designed PSSs, three following indices are introduced: i) the maximum speed deviation of the generator ($\Delta\omega_{max}$), ii) Integral Absolute value of Error (IAE), and iii) ITAE.

The speed deviation of the generator for step disturbance in the mechanical torque with amplitude +0.2(p.u.) in the nominal load operating condition for CPSS, CFPSS, and ATFPSS is shown in figure (8.a). Figure (8.b) also shows the torque angle deviation of the generator for the same above conditions. The speed deviation and torque angle deviation of the generator for heavy load operating condition and in the case of fault occurrence in the transmission line are shown in figures (9) and (10) for different PSSs. As it is seen from these figures, the graph of $\Delta\omega$, and $\Delta\delta$ in the case of using RCGA-based ATFPSS is more suitable than other PSSs in the settling time and damping effect points of view. On the other hand, the simulation results shows, the auto-tuning fuzzy logic controller applied to a power system stabilizer (ATFPSS) provided better response than the CPSS and CFPSS.

Also, the introduced indices for evaluating the performance of the different PSSs are presented in table (6) for different operating conditions. It is seen that the performance criteria in the case of ATFPSS in comparison with CPSS and CFPSS have been improved significantly.

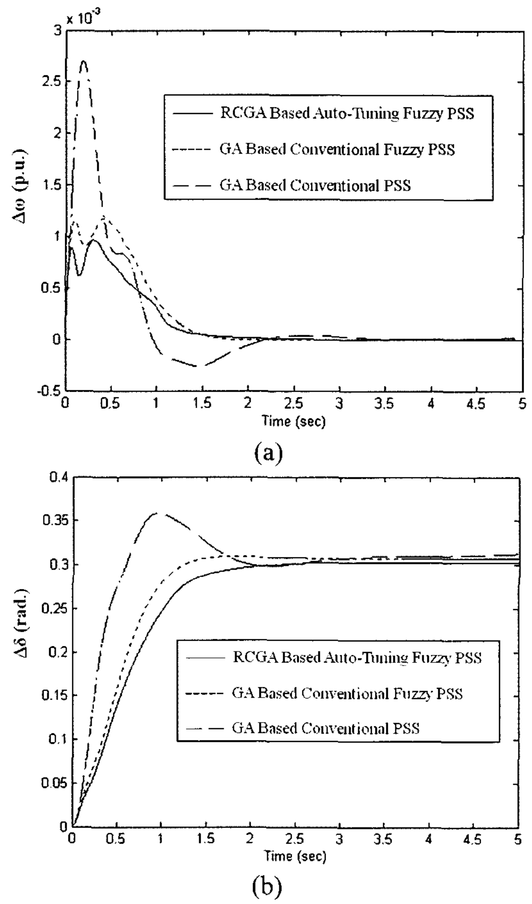
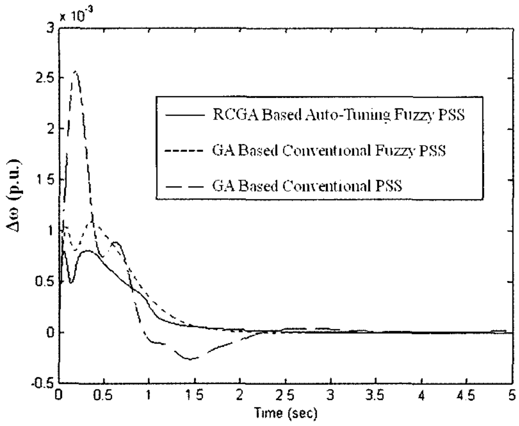


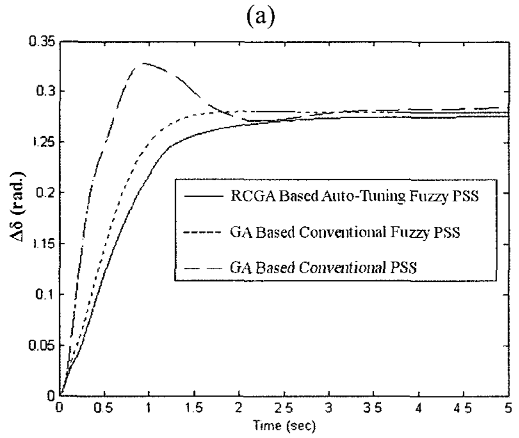
Fig. 8. Responses of generator when mechanical torque was changed by 0.2(p.u.) in nominal load condition a) $\Delta\omega$; b) $\Delta\delta$

Table 6. The performance indices for evaluating different PSSs in three operating conditions

Conditions → / Methods ↓	Nominal Load Condition ↓			Heavy Load Condition ↓			Fault Condition in the Line ↓		
	$\Delta\omega_{max}$	**ITAE**	**IAE**	**$\Delta\omega_{max}$**	**ITAE**	**IAE**	**$\Delta\omega_{max}$**	**ITAE**	**IAE**
CPSS	2.70	0.81	1.37	2.57	0.77	1.26	2.81	1.20	1.76
CFPSS	1.17	0.54	0.99	1.09	0.48	0.89	1.32	0.73	1.21
Proposed Method: ATFPSS	0.96	0.40	0.73	0.80	0.39	0.67	1.07	0.55	0.89

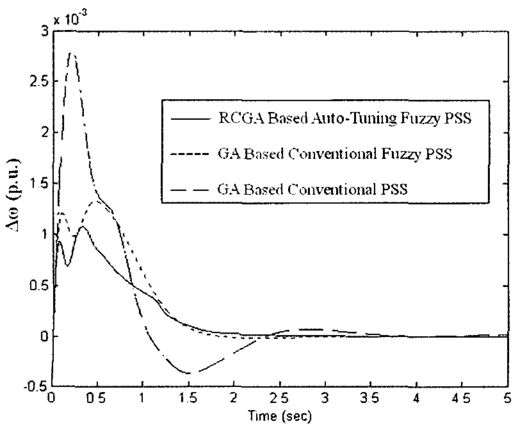


(a)

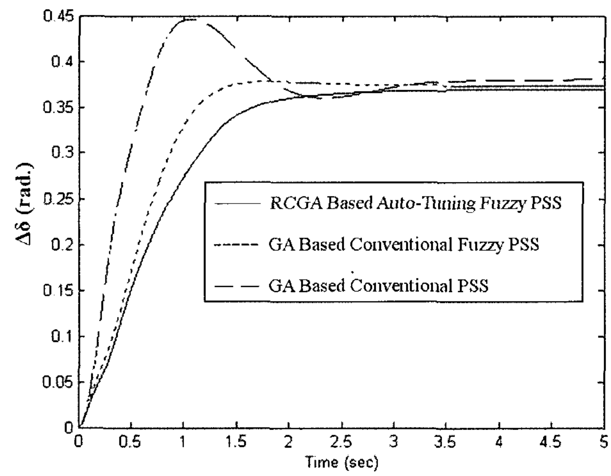


(b)

Fig. 9. Responses of generator when mechanical torque was changed by 0.2(p.u.) in heavy load condition a) $\Delta\omega$; b) $\Delta\delta$



(a)



(b)

Fig. 10. Responses of generator when mechanical torque was changed by 0.2(p.u.) in the line fault occurrence; a) $\Delta\omega$; b) $\Delta\delta$

7. Conclusion

In this paper, a new method for Auto-tuning Fuzzy logic Power System Stabilizers (ATFPSS) by using Real-Coded Genetic Algorithm (RCGA) has been presented. The related structure consists of two fuzzy controllers; internal fuzzy Moreover, RCGA-based method is used for off-line controller and supervisory fuzzy controller. The supervisory controller performs on-line tuning of scaling factors. determination of the membership functions and rules. The alternative options and variety of input signals of this supervisor controller, are its important advantages, which improves the performance and reliability of the PSS in emergency conditions. Finally, to evaluate the effectiveness of the proposed methodology, two other design methods; CPSS and CFPSS, were also simulated. The results for various operating conditions and disturbances show that the proposed stabilizer is able to provide good damping over a wide range and improves the overall system performance.

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