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An Adaptive Evolutionary Algorithm Combining Evolution Strategy and Genetic Algorithm (Application of Fuzzy Power System Stabilizer)

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1. Introduction

The research of power system stabilizer (PSS) for improving the stability of power system has been conducted from the late 1960's. Conventionally lead-lag controller has been widely used as PSS. Root locus and Bode plot to determine the coefficient of lead-lag controller (Yu, 1983; Larsen and Swann, 1981; Kanniah et al., 1984), pole-placement and eigenvalue control (Chow & Sanchez-Gasca, 1989; Ostojic & Kovacevic, 1990) and a linear optimal controller theory (Fleming & Jun Sun, 1990; Mao et al., 1990) have been used. These methods, using a model linearized in the specific operating point, show a good control performance in the specific operating point. But these approaches are difficult to obtain a good control performance in case of operating conditions such as change of load or three phase fault, etc. Therefore, several methods based on adaptive control theory (Chen et al., 1993; Park & Kim, 1996) have been proposed to give an adaptive capability to PSS for nonlinear characteristic of power system. These methods can improve the dynamic characteristic of power system, but these approaches cannot be applied for the real time control because of long execution time.

Recently the research for intelligence control method such as fuzzy logic controller (FLC) and neural network for PSS has greatly improved the dynamic characteristic of power system (Hassan et al., 1991; Hassan & Malik, 1993). 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 without the knowledge of the system. Recently, evolutionary computations (EC) that is a kind of a probabilistic optimal algorithm is employed to adjust the membership functions and fuzzy rules of FLC.

The EC is based on the natural genetics and evolutionary theory. The results of this approach show a good performance (Abido and Abdel-Magid, 1998, 1999).

EC is based on the principles of genetics and natural selection. There are three broadly similar avenues of investigation in EC: genetic algorithm (GA), evolution strategy (ES), and evolutionary programming (EP) (J Fogel, 1995). GA simulates the crossover and mutation of natural systems, having a global search capability (Goldberg, 1989), whereas ES simulates the evolution of an asexually reproducing organism. ES can find a global minimum, and by combining another EC it also could be efficient local search technique (Gong et al., 1996).

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The performance of EC is influenced by parameters such as size of population, fitness, probability of crossover, and mutation, etc. If these parameters are not adequately selected, execution time will be longer and premature convergence to local minimum can occur. To solve problems above, several approaches have been proposed. To enhance the performance of GA, the population size, the probability of crossover, mutation and operation method should be adaptively modified in each generation (Arabas et al., 1994; Schlierkamp-Voosen & Muhlenbein, 1996). To enhance the performances of ES and EP, the mutation parameters should be adapted while running ES and EP (Goldberg, 1989; Fogel et al., 1991).

In conventional ES, parameter values and operator probabilities for the GA and ES are adapted to find a solution efficiently. In this paper, however, we propose adaptive evolutionary algorithm (AEA). The ratio of population to which GA and ES will apply is adaptively modified in reproducing according to the fitness. We use ES to optimize locally, while the GA optimizes globally. The resulting hybrid scheme produces improved and reliable results by using the “global” nature of the GA as well as the “local” improvement capability of the ES.

AEA was applied to search the optimal parameters of the membership functions and the suitable gains of the inputs and outputs for fuzzy power system stabilizer (FPSS). The effectiveness of FPSS is demonstrated by computer simulation for single-machine infinite bus system (SIBS) and multi-machine power system (MPS). To show the superiority of FPSS, its performances are compared with those of conventional power system stabilizer (CPSS). The proposed FPSS shows the better control performances than the CPSS in three-phase fault under a heavy load, which is system condition in tuning FPSS. To show the robustness of the proposed FPSS, it is applied to the system with disturbances such as change of the mechanical torque and three-phase fault under nominal and heavy load conditions.

2. Adaptive evolutionary algorithm

2.1 Motivation

GA, one of the probabilistic optimization methods, is robust and is 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 (Renders & Flasse, 1996). ES, which simulates the evolution of asexually reproducing organisms, has efficient local search capability. To solve complex problem, however, it better to a hybrid EC (Gong et al., 1996).

In this paper, to reach the global optimum accurately and reliably in a short execution time, we designed an AEA by using GA and ES together. In AEA, GA operators and ES operators are applied simultaneously to the individuals of the present generation to create the next generation. Individual with higher fitness value has the higher probability of contributing one or more chromosomes to the next generation. This mechanism gives greater rewards to either GA or ES operation depending on what produces superior offspring.

2.2 Adaptive evolutionary algorithm

In AEA, the number of individuals created by GA and ES operations is changed adaptively. An individual is represented as a real-valued chromosome that makes it possible to hybridize GA and ES operations.

ES forms a class of optimization technique motivated by the reproduction of biological system and the population of individuals evolves toward the better solutions by means of

the mutation and selection operation. In this paper, we adopted a (μ, λ) -ES. That is, only the λ offspring generated by mutation competes for survival and the μ parents are completely replaced in each generation. Also, self-adaptive mutation step sizes are used in ES.

For AEA to self-adapt its use of GA and ES operators, each individual has an operator code for determining which operator to use. Suppose a '0' refers to GA, and a '1' to ES. At each generation, if it is more beneficial to use the GA, '0's should appear at the end of individuals. If it is more beneficial to use the ES, '1's should appear. After reproduction by roulette wheel selection according to the fitness, GA operations (crossover and mutation) are performed on the individuals that have the operator code of '0' and the ES operation (mutation) is performed on the individuals that have an operator code of '1'. Elitism is also used. The best individual in the population reproduces both the GA population and ES population in the next generation. The major procedures of AEA are as follows:

- 1) Initialization: The initial population is randomly generated. Operator code is randomly initialized for each individual. According to the operator code, GA operations are performed on the individuals with operator code '0', while ES operations are applied where the operator code is '1'.
- 2) Evaluation and Reproduction: Using the selection operator, individual chromosomes are selected in proportional to their fitness, which is evaluated by the defined objective function. After reproduction, GA operations are performed on the individuals having an operator code of '0' and the ES operations are performed on the individuals having an operator code '1'. At each generation, the percentages of '1's and '0's in the operator code indicate the performance of GA and ES operators.
- 3) Preservation of Minimum Number of Individuals: At each generation, AEA may fall into a situation where the percentage of the offspring by one operation is nearly 100% and the offspring by other operation dies off. Therefore, it is necessary for AEA to preserve certain amount of individuals for each EC operation. In this paper, we randomly changed the operator code of the individuals with a higher percentage until the numbers of individuals for each EC operation become higher than a certain amount of individuals to be preserved. The predetermined minimum number of individuals to be preserved is set to 20% of the population size.
- 4) Genetic Algorithm and Evolution Strategy: The real-valued coding is used to represent a solution (Michalewicz, 1992; Mitsuo Gen and Cheng, 1997). Modified simple crossover and uniform mutation are used as genetic operators. The modified simple crossover operator is a way to generate offsprings population, selecting two strings randomly in parent population, as shown in Fig. 1. If crossover occurs in k -th variable, selecting randomly two strings in t -th generation, offsprings of $t+1$ -th generation are shown in Fig. 1.

In uniform mutation, we selected a random k -th gene in an individual. If an individual and the k -th component of the individual is the selected gene, the resulting individual is as shown in Fig. 2.

Only the λ offspring generated by mutation operation competes for survival and the μ parents are completely replaced in each generation. Mutation is then performed independently on each vector element by adding a normally distributed Gaussian random variable with mean zero and standard deviation (σ), as shown in Eq. (1). After adapting the mutation operator for ES population, if the improved ratio of individual number is lesser

3. Design of fuzzy power system stabilizer using AEA

Conventionally, we have used the knowledge of experts and trial and error methods to tune FLC's for a good control performance, but recently many other ways using EC are proposed to modify fuzzy rule and shape of fuzzy membership function (Abido and Abdel-Magid, 1998, 1999). Scaling factors of input/output and parameters of membership function of FPSS are optimized by means of AEA using GA and ES adaptively, as described in chapter 2.

Fig. 3 shows the architecture for tuning scaling factors of input/output and membership function shape of FPSS using AEA. As shown in Fig. 3, the rotor speed deviation of generator and the change rate for rotor speed deviation are used as inputs of FPSS. The control signals of the FPSS are used for enhancing power system damping by supplementary control signals of generators.

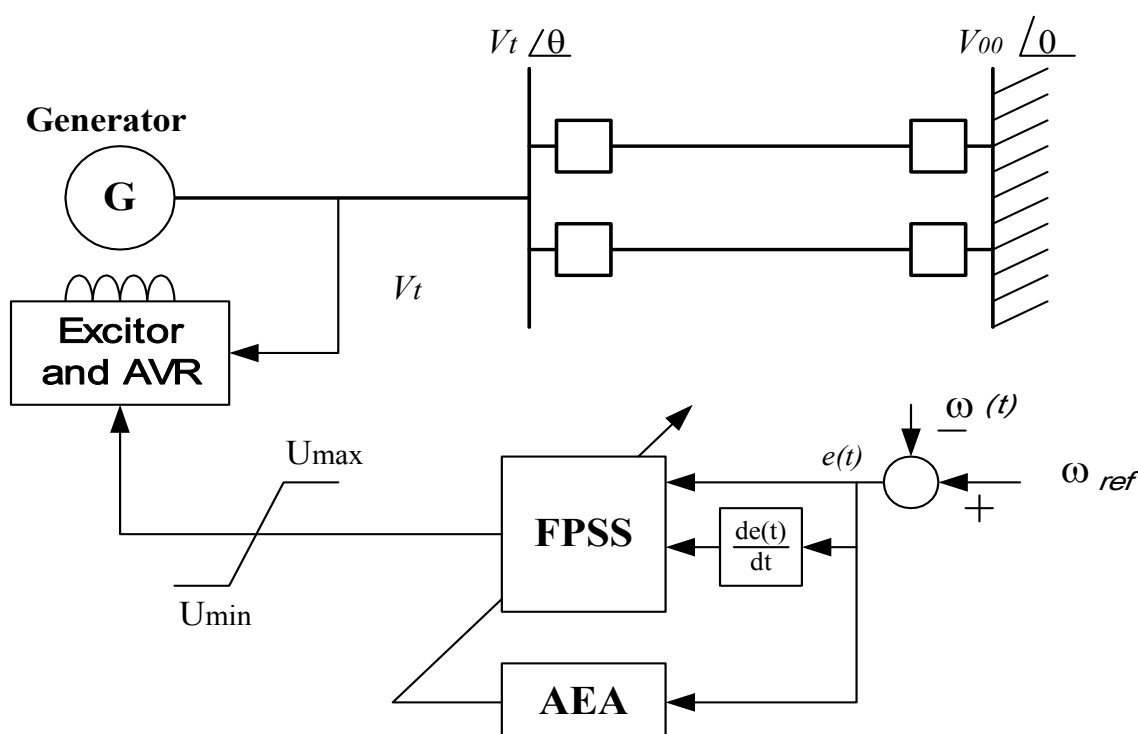


Fig. 3. Configuration for tuning of FPSS using AEA.

The FPSS parameters used in this paper are given below.

- Number of input/output variables : 2/1
- Number of input/output membership functions : 7/7
- Fuzzy inference method : max-min method
- Defuzzification method : center of gravity

Because deviation and change-of-deviation are used as input variables of the FPSS, proportional-derivative (PD)-like FPSS is used. Rule base for the PD-like FPSS from the two-dimensional phase plane of the system in terms of deviation (e) and change-of-deviation (de) is shown in Table 1. As shown in Table 1, the phase plane is divided into two semi-planes by means of switching-line. Within the semi-planes, positive and negative control signals are produced, respectively. The magnitude of the control signals depends on the distance of the state vector from the switching line.

When AEA is tuning the membership functions, fuzzy rules are used for PD-type, as shown in Table 1, where, linguistic variable NB means “Negative Big”, NM means “Negative Medium”, NS means “Negative Small”, etc. Fig. 4 shows triangular membership function used in this paper. Because we use 7 fuzzy variables (PB, PM, ... ,NM, NB) respectively, for input/output of FPSS, the total membership functions will be 21, so 63 variables that include the center and width of all the membership function will be adjusted, but it takes a long calculation time to tune 63 variables using AEA, and suffers from undesirable converging characteristic. In this paper, we fixed center of ZE to 0 and positive and negative membership functions are constructed symmetrical for the 0. So the number of parameters of FPSS will be reduced to 21, which means 3 centers and 4 widths for each variable as shown in Fig. 4.

<div>de</div> <div>e</div>	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NB	NM	NM	NS	ZE
NM	NB	NB	NM	NM	NS	ZE	PS
NS	NB	NM	NM	NS	ZE	PS	PM
ZE	NM	NM	NS	ZE	PS	PM	PM
PS	NM	NS	ZE	PS	PM	PM	PB
PM	NS	ZE	PS	PM	PM	PB	PB
PB	ZE	PS	PM	PM	PB	PB	PB

Table 1. Fuzzy rules of proportional-differential type

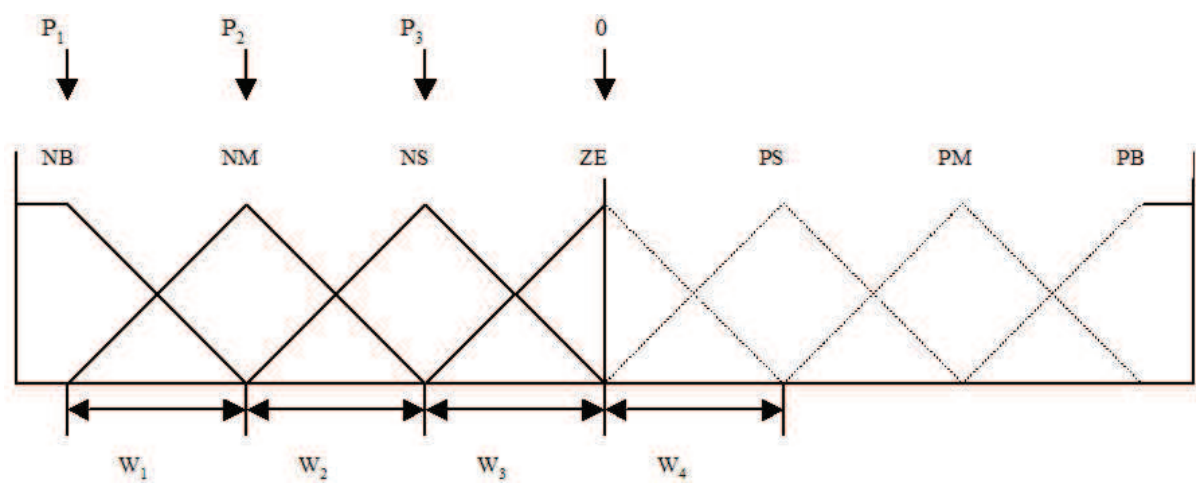
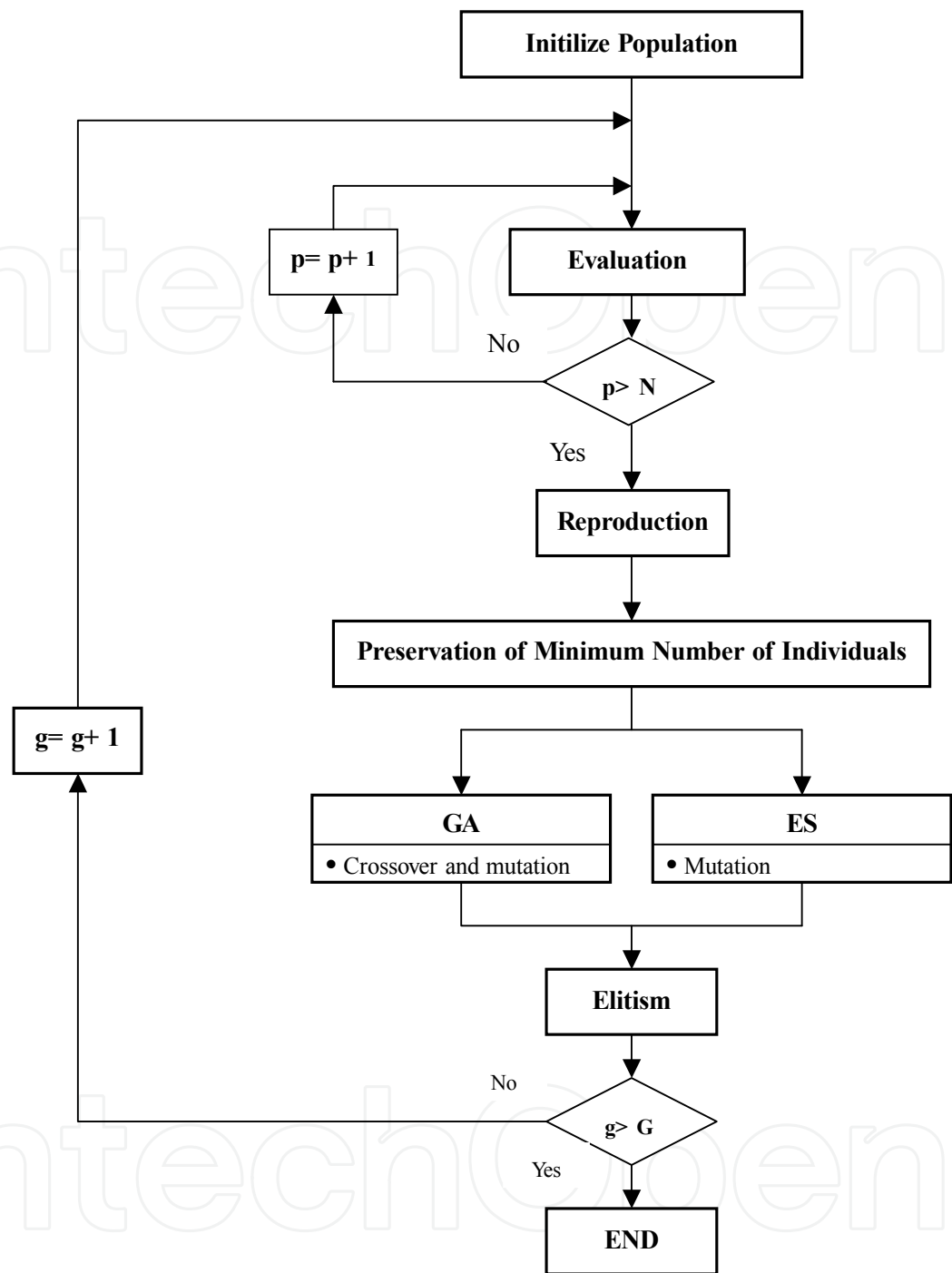


Fig. 4. Symmetrical membership functions

The flowchart for the design of FPSS using the proposed AEA is shown in Fig. 5. The procedure for the design of FPSS using AEA is as follows:



where, P : Number of population
G : Specified generation

Fig. 5. Flowchart for the design of FPSS using AEA

Step1) Initialize population

Strings are randomly generated between upper bounds and lower bounds of the membership function parameters and scaling factors of FPSS. The operator code is randomly set to decide if each string is individual of GA or ES. The configuration of population is described in Fig. 6. Also scaling factors of the FPSS are tuned by the AEA.

S_1	P_{11}	...	P_{19}	W_{11}	...	W_{112}	SF_{11}	SF_{12}	SF_{13}	*
S_2	P_{21}	...	P_{29}	W_{21}	...	W_{212}	SF_{21}	SF_{22}	SF_{23}	*
⋮										
S_n	P_{n1}	...	P_{n9}	W_{n1}	...	W_{n12}	SF_{n1}	SF_{n2}	SF_{n3}	*

where, n : population size

P_{ij} : Center of the membership functions

W_{ij} : Width of the membership functions

SF_{ij} : Scaling factors

* : Operator code

Fig. 6. String architecture for tuning membership functions and scaling factors.

Step 2) Evaluation

Each string generated in Step 1 is evaluated using the fitness function in Eq. (3). As shown in Eq. (3), the absolute deviation between the rotor speed and the reference rotor speed of generator is used. The flowchart for evaluation part is shown in Fig. 7.

$$Fitness = \frac{1}{1 + \int_{t=0}^T |\omega_{ref} - \omega(t)|} \quad (3)$$

where, ω_{ref} : Reference rotor speed of generator

$\omega(t)$: Rotor speed of generator

T : No. of data acquired during specified time

Step 3) Reproduction

We used roulette wheel to reproduce in proportion to fitness. After reproduction, the individual operator code of '0' is inserted in the population of GA, the individual operator code of '1' is inserted in the population of ES.

Step 4) Preservation of Minimum Number of Individuals

Among GA and ES, depending on which is stronger, we guarantee minimum number of individuals to offsprings being disappearing by the remaining iterations.

Step 5) GA and ES operation

The individual with operator code of '0' applied crossover and mutation in GA operators and generates offsprings. The individual with operator code of '1' apply mutation in ES operator and generates offsprings.

Step 6) Elitism

We use elitism reproducing the best individual of fitness to GA and ES population by each one.

Step 7) Convergence criterion

We iterate Step 2 – Step 6 until being satisfied of the specified generation.

4. Simulation studies

4.1 Simulation cases of single-machine infinite bus system

We performed nonlinear simulation for SIBS in Fig. 8 to demonstrate the performance of the proposed FPSS. A machine has been represented by third order one-axis nonlinear model, as

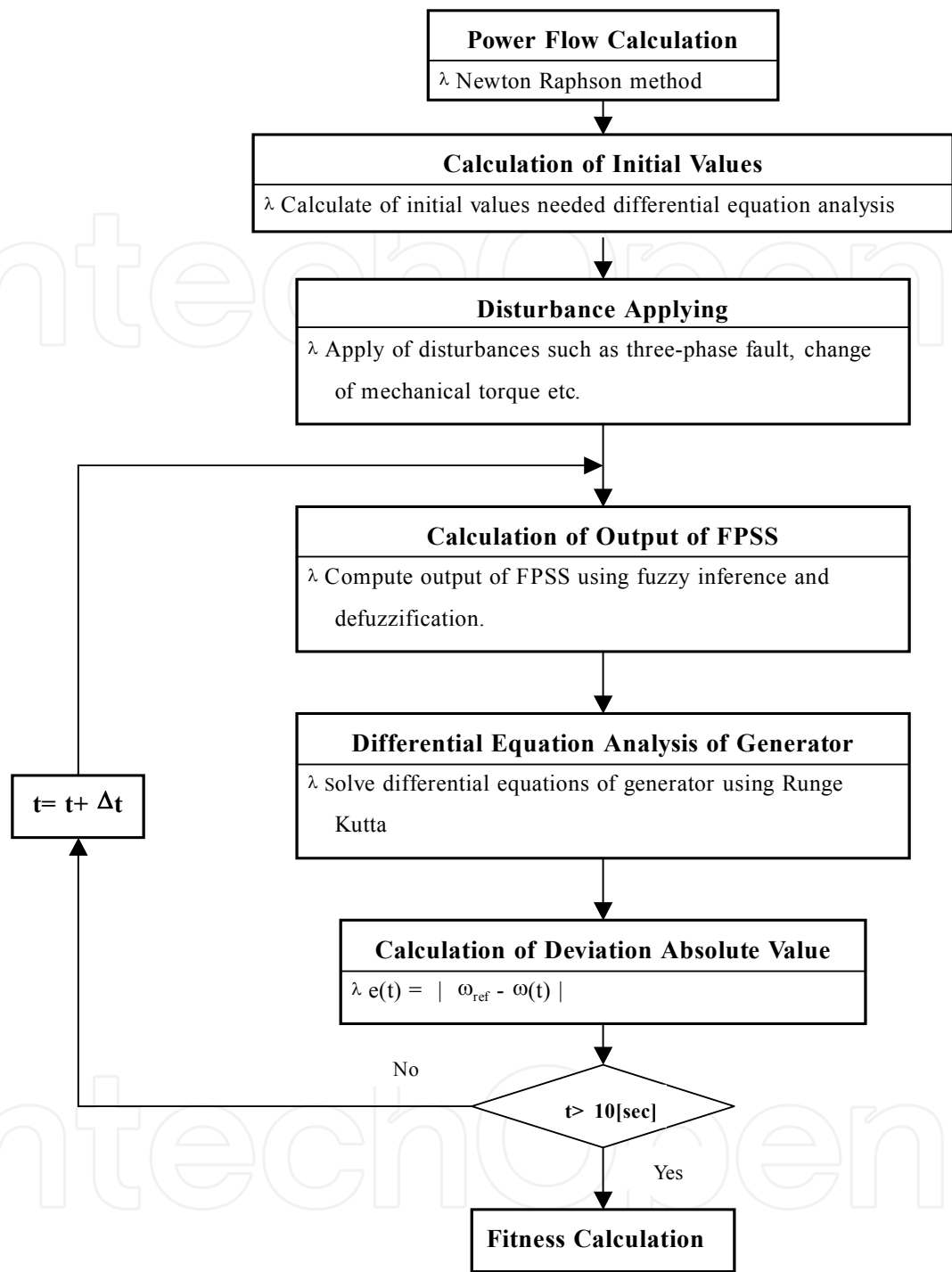


Fig. 7 Flowchart for evaluation part

shown in appendix. Details of the system data are given in Yu, 1983. Table 2 shows the simulation coefficients of AEA used in nonlinear simulation. The execution time in PC 586 (300 MHz) takes about 30 minutes to tune the parameters of FPSS under the condition in Table 2. Fig. 9 shows membership functions shape of FPSS tuned by AEA, where scaling constant of deviation is 0.24, scaling constant of deviation rate is 3.50 and scaling constant of

output part is 2.75. We reviewed the performance of FPSS proposed in this paper and compared it with CPSS (Yu, 1983). In CPSS, time constants (T_1 , T_2) were designed based on phase compensation as in Eq. (4), where washout filter (T_w) is 3 sec, stabilization gain (K_{pss}) is 7.09, and T_1 , T_2 are 0.1 sec, 0.065 sec respectively.

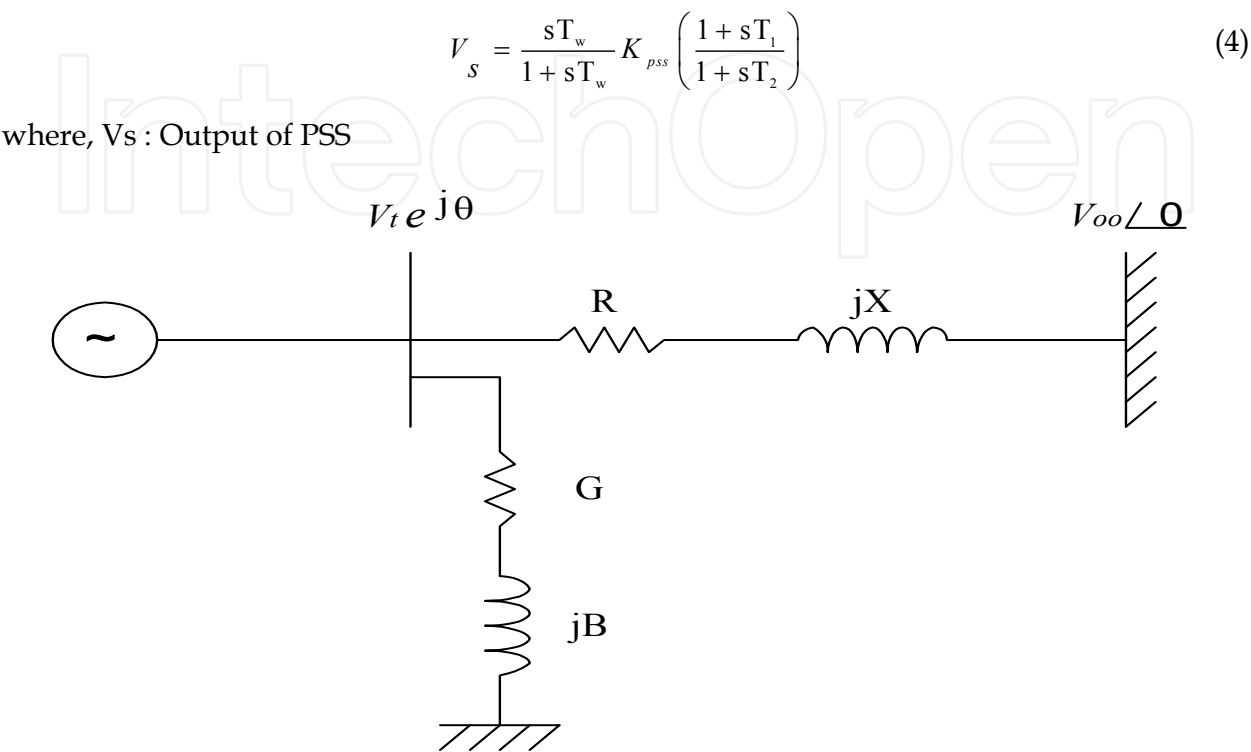


Fig. 8. Single-machine infinite system used in performance evaluation

Methods	AEA	
	SIBS	MPS
Size of population	50	100
Crossover probability	0.95	0.95
Mutation probability	0.005	0.005
δ	0.5	0.5
C_d	0.95	0.95
C_I	1.05	1.05
Number of Generation	100	200

Table 2. Coefficients for simulation using AEA

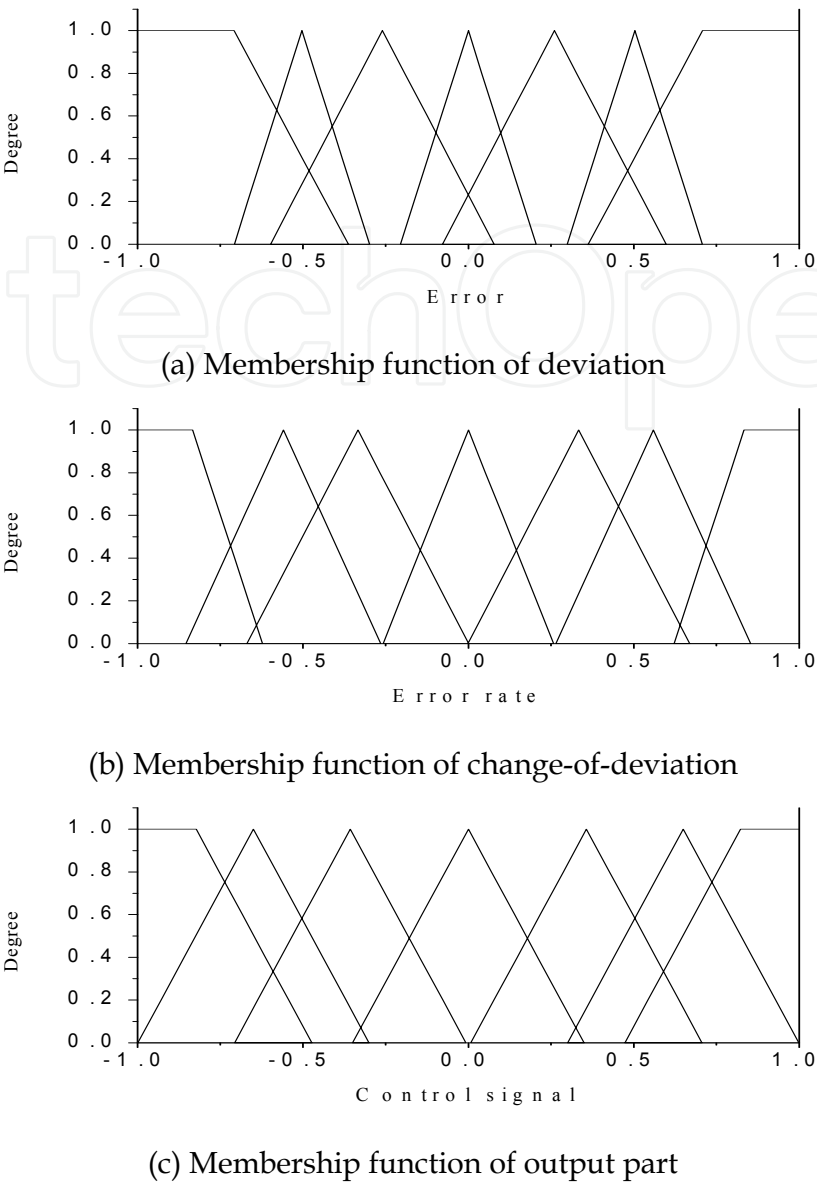


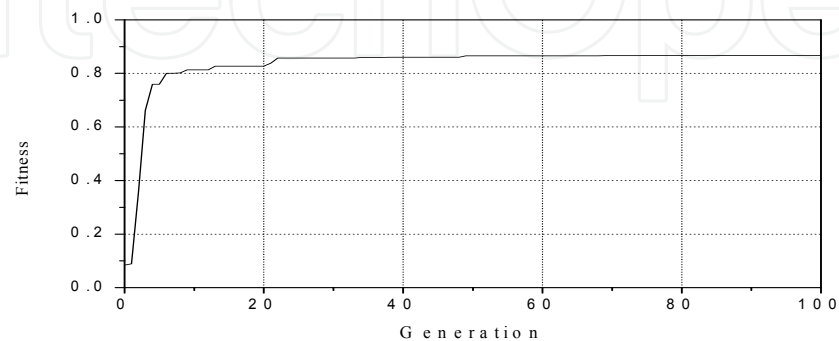
Fig. 9. Tuned membership function of FPSS

Fig. 10 (a) shows the fitness values by AEA in each generation. Fig. 10 (b) shows the number of individuals for GA and ES in the AEA. As shown in Fig. 10, the number of individuals of GA is higher than that of individuals of ES in early generation. But, from generation to generation, the number of individuals of ES goes higher than that of individuals of GA. The AEA produces the improved reliability by exploiting the “global” nature of the GA initially as well as the “local” improvement capabilities of the ES from generation to generation.

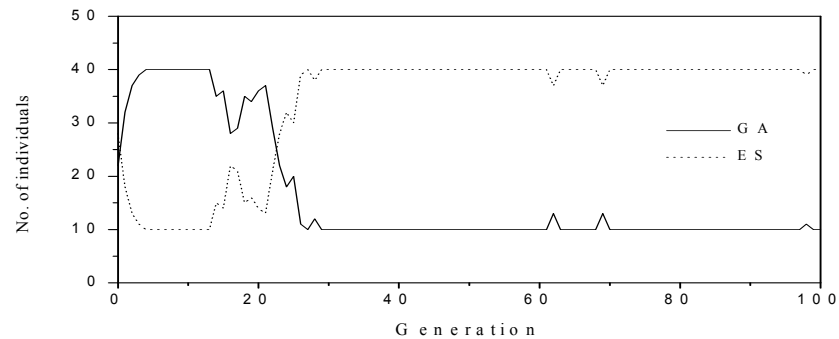
Analysis conditions used for comparing control performance of CPSS with FPSS optimized by AEA are summarized in Table 3. Table 3 is classified into four cases according to the power system simulation cases used in designing FPSS and in evaluating the robustness of FPSS. As shown in Table 3, Case-1 is used to design FPSS and tune scaling constant of input/output variable and membership functions of FPSS by AEA. We used Case-2 and Case-4 in evaluating the robustness of FPSS.

1) Heavy load condition

Fig. 11 shows generator angular velocity and the phase angle both without PSS and with CPSS and FPSS under Case-1 in Table 3. As shown Fig. 11, the FPSS shows the better control performance than CPSS in terms of settling time and damping effect. To evaluate the robustness of FPSS, Fig. 12 shows generator response characteristic in case that PSS is not applied. In this case, CPSS and proposed FPSS are applied under Case-2 of Table 3. As shown in Fig. 12, FPSS shows the better control performance than CPSS in terms of settling time and damping effect.



(a) fitness



(b) Number of individuals of GA and ES in AEA

Fig. 10. Fitness and number of individuals of GA and ES in each generation

Simulation cases	Operating conditions	Disturbance	Fault time [msec]
Case-1	Heavy load $P_e = 1.3$ [pu] $Q_e = 0.015$ [pu]	A	40
Case-2		B	-
Case-3	Nominal load $P_e = 1.0$ [pu] $Q_e = 0.015$ [pu]	A	40
Case-4		B	-

A: Three phase fault

B: Mechanical torque was changed as 0.1 [pu]

Table 3. Simulation cases used in evaluation of controller performance

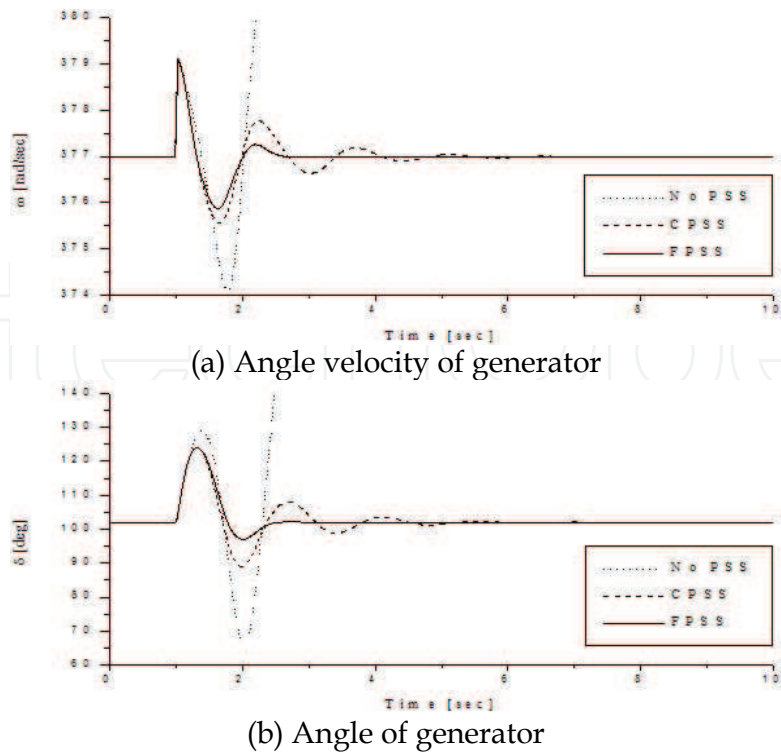


Fig. 11. Responses of generator when three-phase fault was occurred in heavy load

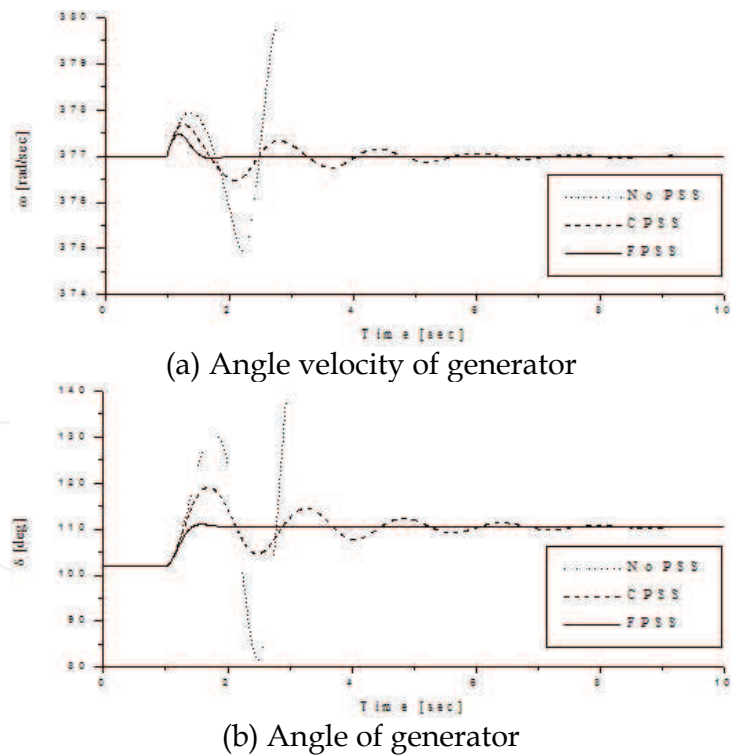


Fig. 12. Responses of generator when mechanical torque was changed into 0.1[pu] in heavy load

2) Nominal load condition

To evaluate the robustness of FPSS, Fig. 13-14 show generator response characteristic in case that PSS is not applied, and CPSS and proposed FPSS are applied under Case-3 and 4 of

Table 3. As shown in Fig. 13-14, the FPSS shows the better control performance than CPSS in terms of settling time and damping effect.

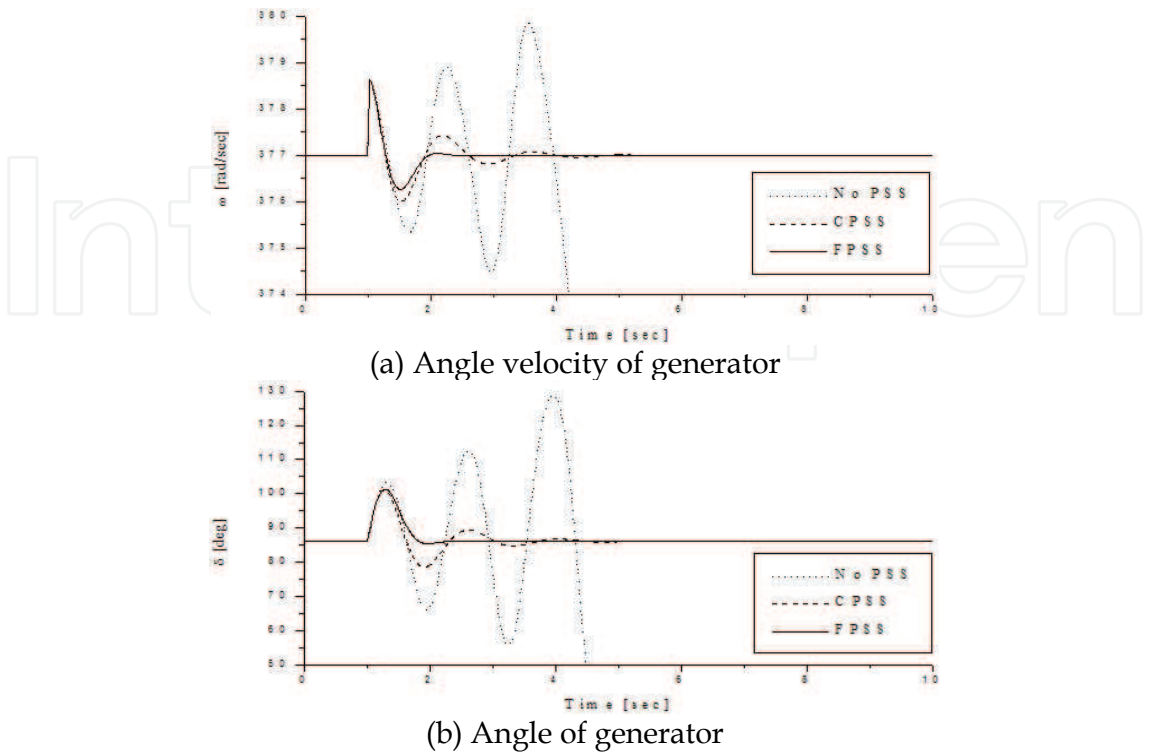


Fig. 13. Responses of generator when three-phase fault was occurred in nominal load

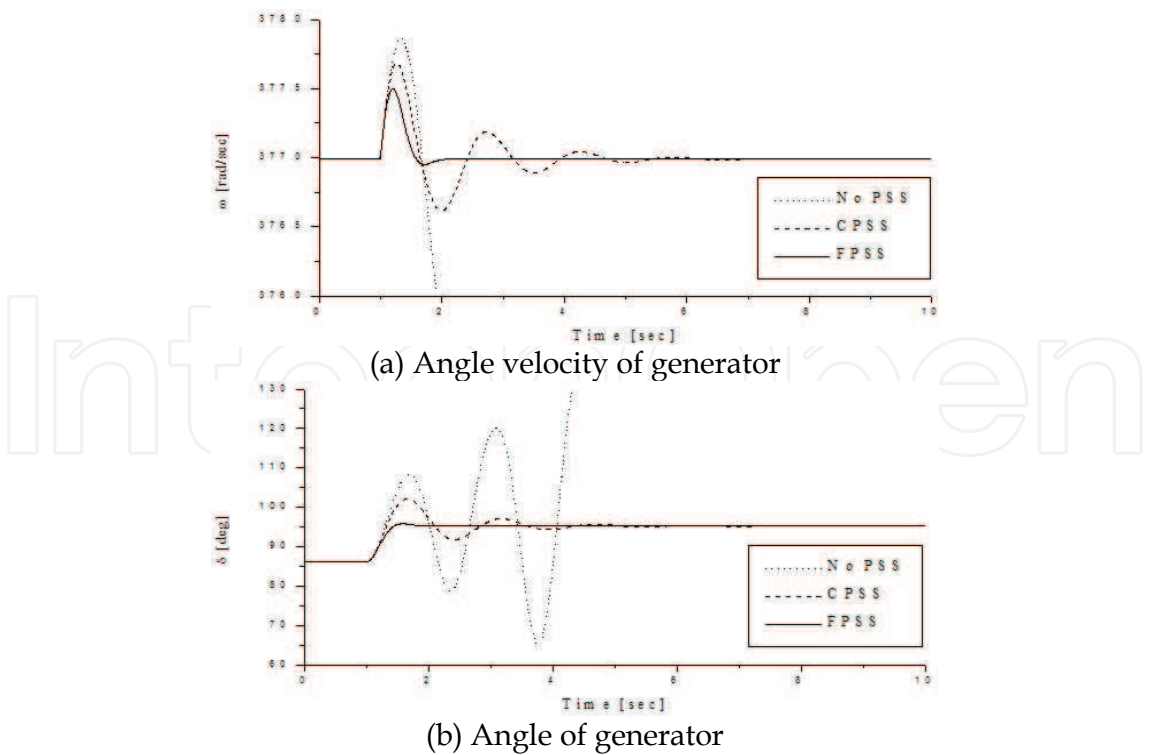


Fig. 14. Responses of generator when mechanical torque was changed into 0.1[pu] in nominal load

3) Dynamic stability margin

To evaluate the dynamic stability margin (He & Malik, 1997) of CPSS and FPSS, a simulation study is conducted with the initial operating condition of light, nominal and heavy load as given in Table 3. The mechanical torque is increased gradually. The dynamic stability margin is described by the maximum active power in which the system losses synchronism. Table 4 shows the dynamic stability margin. In Table 4, we can find FPSS increases the dynamic stability of generator.

Conditions \ Methods		CPSS	FPSS
Light load	Maximum active power [pu]	1.02	1.06
	Maximum generator phase angle [rad]	2.44	2.46
Nominal load	Maximum active power [pu]	1.22	1.27
	Maximum generator phase angle [rad]	2.35	2.45

Table 4. Dynamic stability margin (SIBS)

4.2 Simulation cases of multi-machine power system

To demonstrate the performance of the proposed FPSS, we performed nonlinear simulation for WSCC 3-machine, 9-bus system (Anderson & Found, 1977) as in Fig. 15. Constants of generator and exciter, load admittance, and load condition used in generator dynamic characteristic analysis are shown in Appendix (Abido & Abdel-Magid, 1999). Coefficients for simulation of AEA are shown in Table 2. We compared the proposed FPSS with the conventional power system stabilizer, CPSS, for multi-machine power system. In CPSS, time constants (T_1 , T_2) were designed based on phase compensation as in Eq. (5), where washout filter (T_w) is 1.5 sec, stabilization gain (K_{pss}) is 15, and T_1 , T_2 are 0.29 sec, 0.029 sec respectively.

$$V_s = \frac{sT_w}{1 + sT_w} K_{pss} \left(\frac{1 + sT_1}{1 + sT_2} \right)^2$$

(5)

As shown in Table 5, simulation cases used in comparing control performance of FPSS with CPSS are classified into Case-1 to Case-4. Case-1 was for the power operating condition used in designing FPSS. Case-2 and Case-4 were for evaluating the robustness of FPSS

Simulation cases	Operating conditions	Disturbance	Fault time [msec]
Case-1	Heavy load	A	70
Case-2		B	70
Case-3	Nominal load	A	70
Case-4		B	70

- A: Three phase fault in bus-7
- B: Three phase fault between bus-5 and bus-7

Table 5. Simulation cases used in evaluation of controller performance

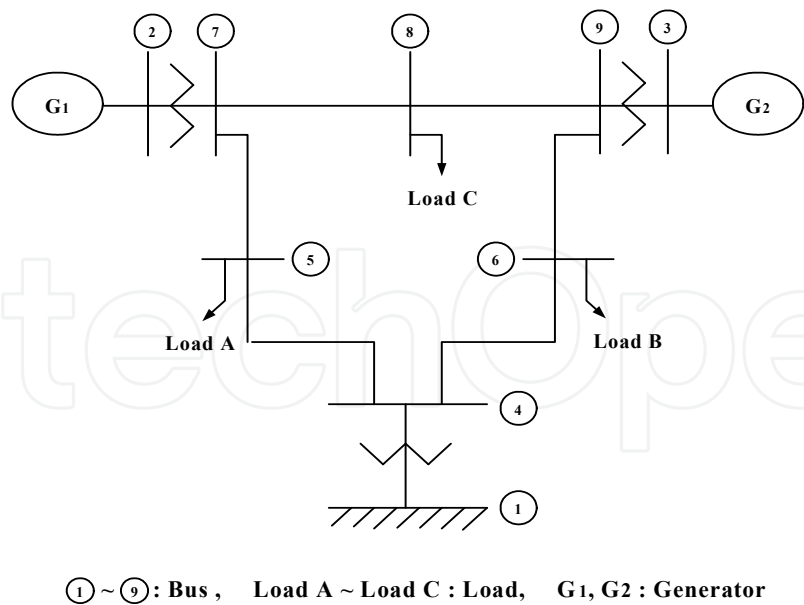


Fig. 15. WSCC 3-machine, 9-bus system

1) Heavy load condition

Fig. 16 shows generator phase angles (G_1 , G_2) both without PSS and with CPSS and FPSS under Case-1 in Table 5. As shown Fig. 16, the FPSS shows the better control performance than CPSS in terms of settling time and damping effect. To evaluate the robustness of FPSS, Fig. 17 shows generator phase angles (G_1 , G_2) both without PSS and with CPSS and FPSS under Case-2 in Table 5. As shown in Fig. 17, FPSS shows the better control performance than CPSS in terms of settling time and damping effect.

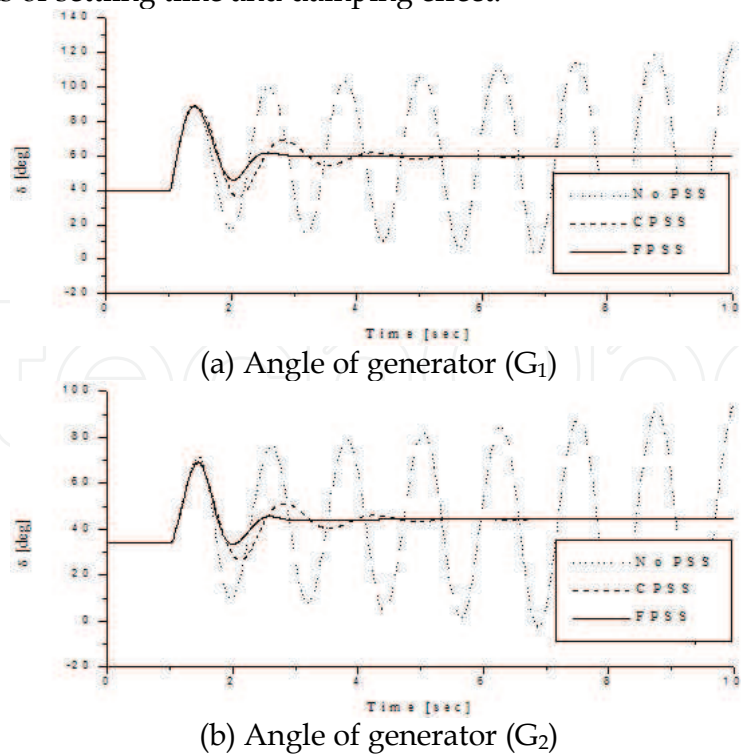


Fig. 16. Responses of generator when three-phase ground fault was occurred at bus-7 under heavy load condition

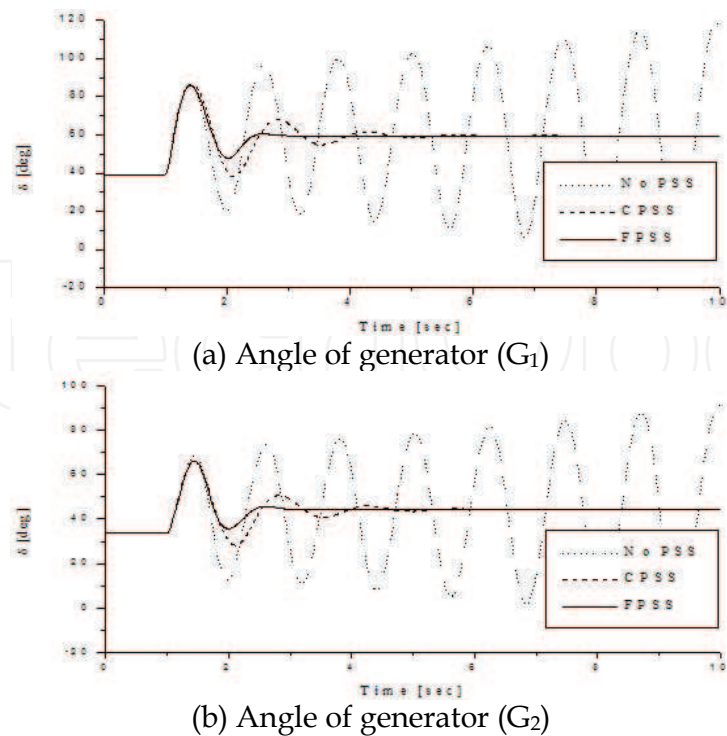


Fig. 17. Responses of generator when three-phase ground fault was occurred at bus-5 and bus-7 under heavy load condition

2) Nominal load condition

To evaluate the robustness of FPSS, Fig. 18-19 shows generator response characteristic in case that PSS is not applied, and CPSS and proposed FPSS are applied under Case-3 and 4 in Table 3. As shown in Fig. 18-19, the FPSS shows the better control performance than CPSS in terms of settling time and damping effect.

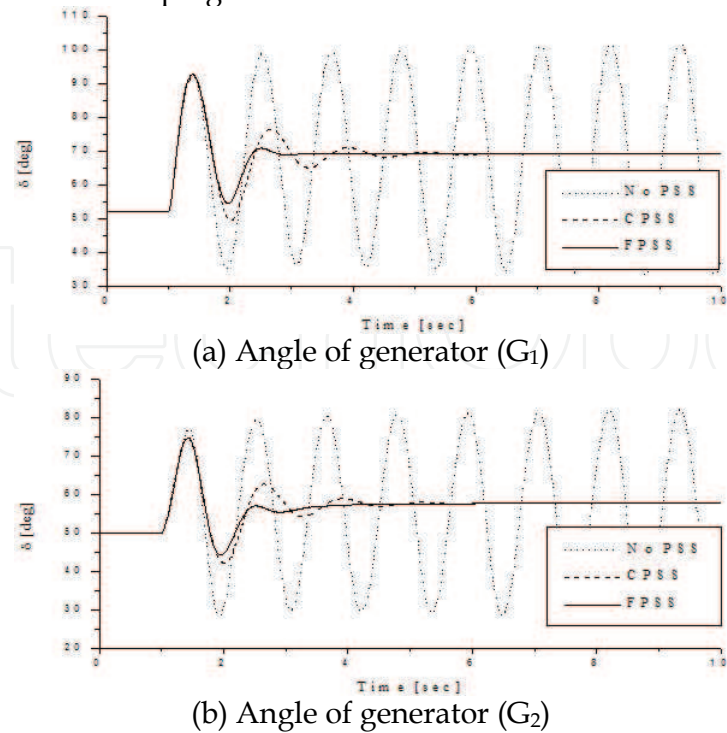


Fig. 18. Responses of generator when three-phase ground fault was occurred at bus-7 under nominal load condition

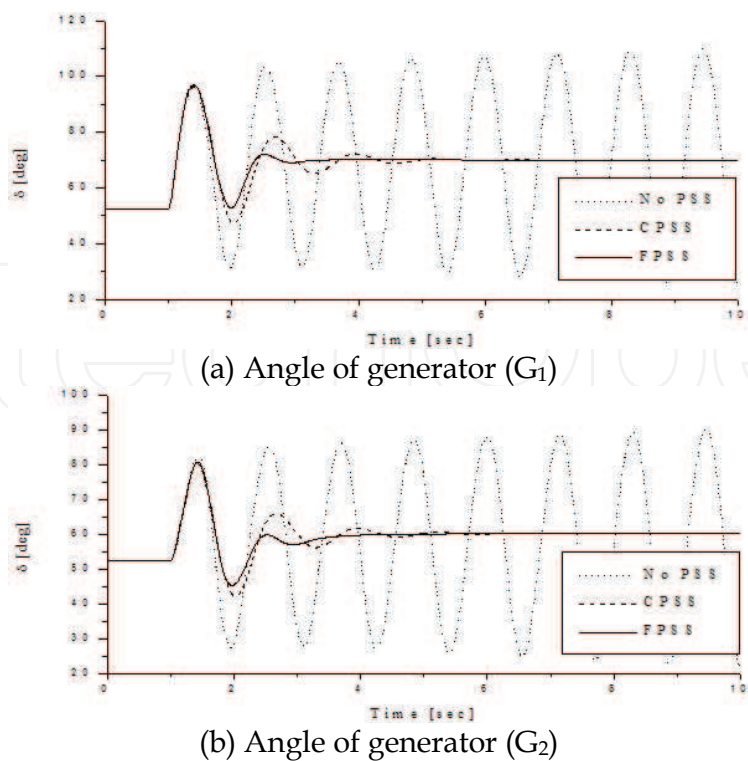


Fig. 19. Responses of generator when three-phase ground fault was occurred at bus-5 and bus-7 under nominal load condition

3) Dynamic stability margin

Table 6 shows the dynamic stability margin (He and Malik, 1997) of CPSS and FPSS when the mechanical torque was increased gradually. In Table 6, we can find FPSS increases the dynamic stability of generator.

Methods Conditions		CPSS		FPSS	
		G ₁	G ₂	G ₁	G ₂
Heavy load	A	3.04	2.44	3.11	2.51
	B	2.25	1.39	2.25	1.46
Nominal load	A	2.84	2.29	2.91	2.36
	B	2.52	1.58	2.52	1.63

A : Maximum active power [pu]
B : Maximum generator phase angle [rad]

Table 6. Dynamic stability margin (MPS)

5. Conclusions

In this paper, we tuned membership functions shape and input/output gain of FPSS using AEA that is algorithm that ratio of population to which GA and ES will adapt is adaptively

modified in reproduction according to the fitness. In the SIBS and MPS, we analyzed simulation results of FPSS and CPSS. The results are as following:

- ① As a result of applying AEA to the design of FPSS, in the early generation, it is shown the number of population of GA is higher than that of population of ES, also the number of population of ES grows as the number of generation increases. This shows that the global search is executed through GA in the early generation and the local search is executed adaptively by means of ES as the number of generation increases.
- ② FPSS showed the better control performance than CPSS in terms of settling time and damping effect when three- phase fault under heavy load that is used in tuning FPSS occurs. To evaluate the robustness of FPSS, we analyzed dynamic characteristic of generator for changeable mechanical torque in heavy load, and change of mechanical torque and three-phase fault in nominal. FPSS showed the better damping effect than CPSS.
- ③ As result of finding dynamic stability margin and successive peak damping ratio, FPSS more increased dynamic stability margin and showed the better result than CPSS in terms of successive peak damping ratio.

6. Acknowledgments

This research was supported by the Program for the Training of Graduate Students in Regional Innovation which was conducted by the Ministry of Commerce Industry and Energy of the Korean Government.

7. Appendix

A. System Model

$$\frac{dE_q'}{dt} = -\frac{1}{T_{do}}[E_q' + (X_d - X_d')I_d - E_{fd}]$$

$$\frac{d\delta}{dt} = \omega - \omega_{ref}$$

$$\frac{d\omega}{dt} = \frac{\omega_{ref}}{2H}[T_m - E_q'I_q - (X_q - X_q')I_dI_q]$$

$$\frac{dE_{ef}}{dt} = \frac{K_a}{T_a}(V_{ref} - V_t + V_s) - \frac{1}{Ta}E_{fd}$$

where,

$$V_t = \sqrt{V_d'^2 + V_q'^2}$$

$$I_d = \frac{1}{\Delta}[\text{Re}(E_d' - V_\infty \sin \delta) + (X_e + X_q')(E_q' - V_\infty \cos \delta)]$$

$$I_q = \frac{1}{\Delta}[\text{Re}(E_q' - V_\infty \cos \delta) - (X_e + X_d')(E_d' - V_\infty \sin \delta)]$$

$$V_d = E_d' + \frac{X_q'}{\Delta} [R_e(E_q' - V_\infty \cos \delta) - (X_e + X_d')(E_d' - V_\infty \sin \delta)]$$
$$V_q = E_q' - \frac{X_d'}{\Delta} [R_e(E_d' - V_\infty \sin \delta) + (X_e + X_q')(E_q' - V_\infty \cos \delta)]$$
$$\Delta = R_e^2 + (X_e + X_d')(X_e + X_q')$$

B. Nomenclature

- δ : Rotor angle of generator
- ω : Rotor speed of generator
- ω_{ref} : Reference rotor speed of generator
- H : Inertia constant of generator
- T_m : Mechanical input of generator
- X_d : d-axis synchronous reactance of generator
- X_d' : d-axis transient reactance of generator
- X_q : q-axis synchronous reactance of generator
- E_q' : q-axis voltage of generator
- E_{fd} : Generator field voltage
- T_{do}' : d-axis transient time constant of generator
- I_d : d-axis current of generator
- I_q : q-axis current of generator
- V_t : Terminal voltage
- V_{ref} : Reference voltage
- V_s : PSS signal
- V_{oo} : Voltage of infinite bus
- K_a : AVR gain
- T_a : Exciter time constant
- R_e : Equivalent resistance of transmission line
- X_e : Equivalent reactance of transmission line

C. Multi-machine Power System

1. Constants of generator and exciter

Parameters Generators	H [sec]	X_d [pu]	X_d' [pu]	X_q [pu]	T_{do}' [pu]	T_{qo}' [pu]
G1	6.4	0.8958	0.1198	0.8645	6.0	0.535
G2	5.4	1.3125	0.1813	1.2578	5.89	0.6

2. Load admittance

Load	Nominal load	Heavy load
Load A	1.261 - j0.504	2.314 - j0.925
Load B	0.878 - j0.293	2.032 - j0.677
Load C	0.969 - j0.339	1.584 - j0.634

3. Loading conditions

Generators		G ₁	G ₂
Loading condition			
Nominal load	P [pu]	1.35	0.80
	Q [pu]	0.02	- 0.12
Heavy load	P [pu]	1.65	1.05
	Q [pu]	0.53	0.35

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