Power System Stabilizer Driven by an Adaptive Fuzzy Set for Better Dynamic Performance

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This paper presents a novel application of a fuzzy logic controller (FLC) driven by an adaptive fuzzy set (AFS) for a power system stabilizer (PSS). The proposed FLC, driven by AFS, is compared with a classical FLC, driven by a fixed fuzzy set (FFS). Both FLC algorithms use the speed error and its rate of change as input vectors. A single generator equipped with FLC-PSS and connected to an infinite bus bar through double transmission lines is considered. Both FLCs, using AFS and FFS, are simulated and tested when the system is subjected to different step changes in the reference value. The simulation results of the proposed FLC, using the adaptive fuzzy set, give a better dynamic response of the overall system by improving the damping coefficient and decreasing the rise time and settling time compared with classical FLC using FFS. The proposed FLC using AFS also reduces the computational time of the FLC as the number of rules is reduced.

Keywords: fuzzy controller: static and adapted fuzzy sets and power system stabilizer.

1 Introduction

The design of a power system stabilizer is an important issue from the viewpoint of power system stability, since it damps out local plant modes and inter area modes of oscillation without compromising the stability of other modes. A conventional power system stabilizer (CPSS) comprises of a wash out circuit and a cascade of two phase lead networks. To design such a PSS, many strategies [1–6] have been proposed that included techniques such as root locus, Bode plots, eigenvalue assignment, multivariable frequency domain techniques, optimal control design, etc. New techniques [7–10] based on expert systems, neural networks and rule based fuzzy logic for PSS design is also emerging.

The fuzzy logic controller has emerged as a very active and fruitful research area. The adaptive fuzzy controllers provide a means for continuously adapting the fuzzy set to match the desired performance criteria. Its typical application area is for controlling time varying and/or nonlinear plants. Fuzzy controllers may be either static or dynamic. The static fuzzy rules are usually based on operator experience, as fuzzy logic can easily encode linguistic information [11]. This is the main advantage of the fuzzy logic controller over neural networks. In the adaptive case, the linguistic information captured from operator experience can be used to initialize the fuzzy set. This helps to reduce the number of iterations in the training [12].

In this paper, three fuzzy controllers are proposed for PSS. The first uses seven fixed fuzzy sets for the input and output variables. The second uses five fixed fuzzy sets for the input and output variables. The third controller is proposed as an adaptation scheme, based on the back propagation (BP) algorithm [12], which dynamically varies the fuzzy sets to achieve better dynamic performance. The performance of PSS with both static and adaptive fuzzy logic controllers is compared through the simulation results, when the system is subjected to various disturbances.

2 System under study and a mathematical model of it

The system under study consists of a single synchronous generator (S.G) connected to the infinite bus via double short transmission lines, as shown in Fig. 1. A Matlab program has been developed for the system under study. The synchronous generator is equipped with an automatic voltage regulator (AVR). The equations of the system are derived in the d and q-axis in [13, 14]. The magnetic circuit is assumed to be linear. The differential equations that describe the system under study are as follows:

$$\Delta\omega' = \frac{\Delta T_m - D \times \Delta\omega - K_1 \times \Delta\delta - K_2 \times \Delta e'_q}{M} \tag{1}$$

$$\Delta\delta' = \omega_b \times \Delta\omega \tag{2}$$

$$\Delta\Delta e'_q = \frac{\Delta E_{FD} - K_4 \times \Delta\delta}{T'_{do}} - \frac{\Delta e'_q}{T'_{do} \times K_3} \tag{3}$$

$$\Delta E'_{FD} = \frac{K_A \times \Delta V_t - K_A \times K_5 \times \Delta\delta - K_A \times K_6 \times \Delta e'_q}{T_A} + \\ -\frac{\Delta E_{FD} + K_A \times U_{pss}}{T_A} \tag{4}$$

where: Δ defines a small change in the next symbol or variable, ω is the mechanical angular speed, T_m is the mechanical torque. δ defines the power angle and ω_b is the base angular speed. e'_q is the voltage behind the transient reactance in the d-axis. The equations which describe the constants K_1 to K_6 and variable E_{FD} are given in [13, 14]. T'_{do} is the field winding open circuit time constant (sec), V_t is the terminal voltage. K_A and T_A are the exciter gain and time constant. The values of K_A and T_A are given in Appendix 1, U_{pss} is the output of the power system stabilizer. All the system parameters and constants are given in Appendix 1. The mathematical equations of the AVR together with the exciter and the governor are given as follows:
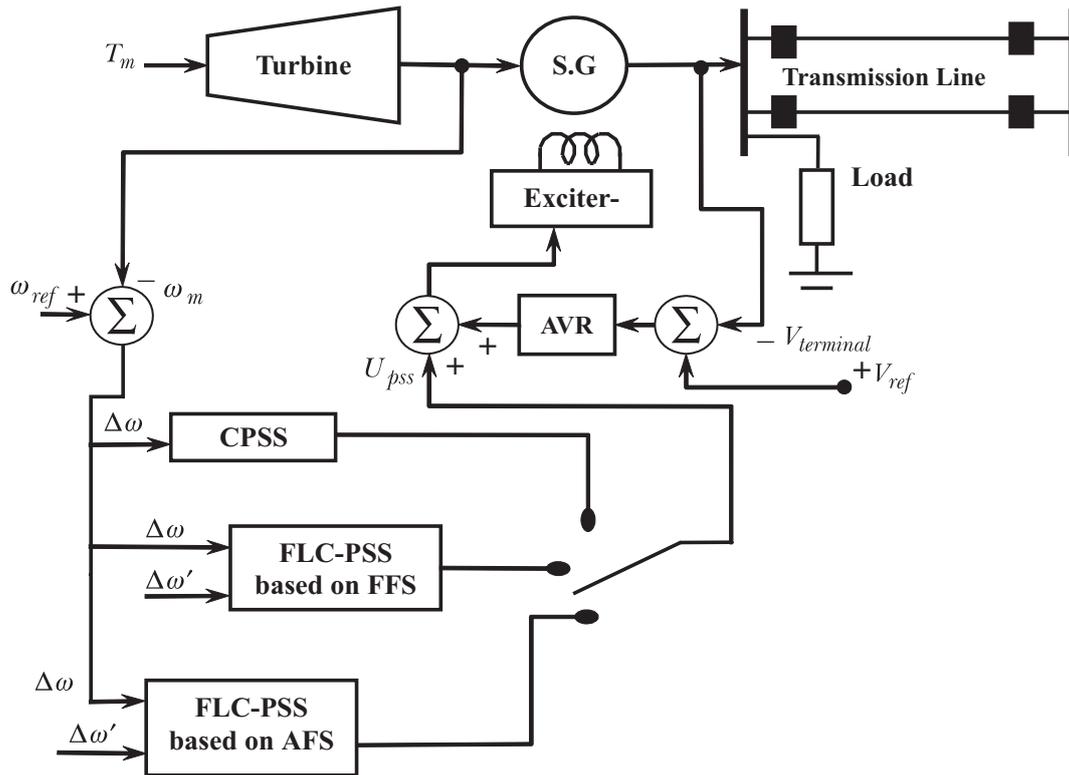
Fig. 1: The synchronous generator, equipped with FLC-PSS based on FFS or AFS or CPSS
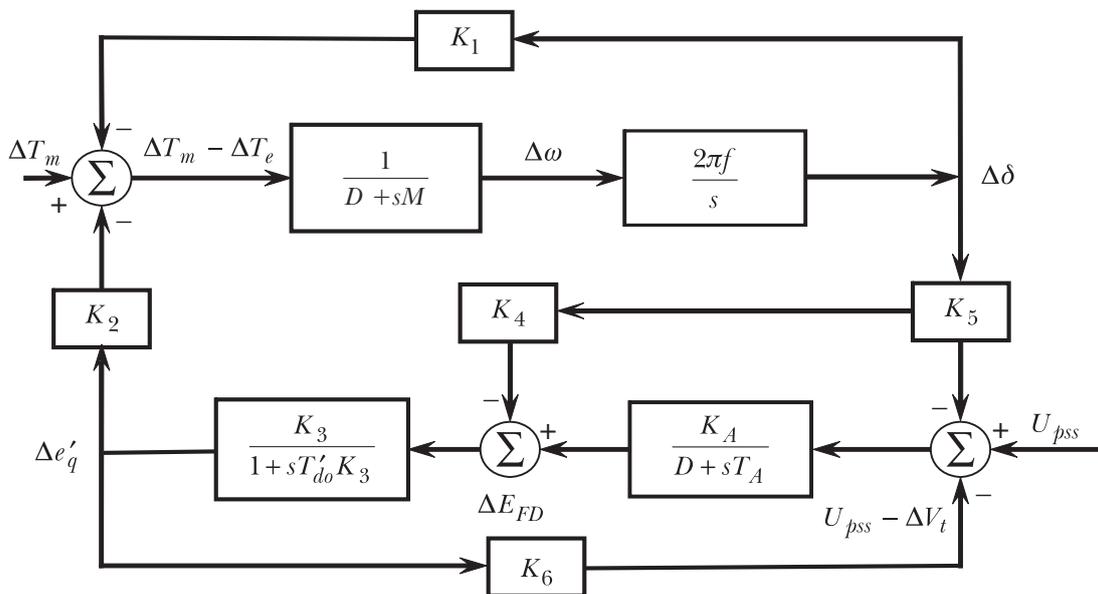
Fig. 2: Transfer function block diagram

$$E_{FD} = \left(\frac{K_A}{1 + sT_A} \right)(V_{ref} - V_t + U_{pss}), \qquad (5)$$

$$g = \left(\left(a + \frac{b}{1 + sT_g} \right) \times \dot{\delta} \right), \qquad (6)$$

where V_{ref} is the reference terminal voltage, a, and b are constants, T_g is the governor time constant. Their values are given in Appendix 1. The complete system model, in block diagram presentation, is shown in Fig. 2.

All the system parameters and the constants of AVR, exciter, governor, and conventional PSS are given in Appendix 1.

3 Fuzzy logic controller

Fuzzy control systems are rule-based systems. A set of fuzzy rules represents the FLC mechanism to adjust the effect of certain system stimuli. The aim of fuzzy control systems is normally to replace a skilled human operator with a fuzzy rules-based system. Also the FLC provides an algorithm which can convert the linguistic control strategy, based on
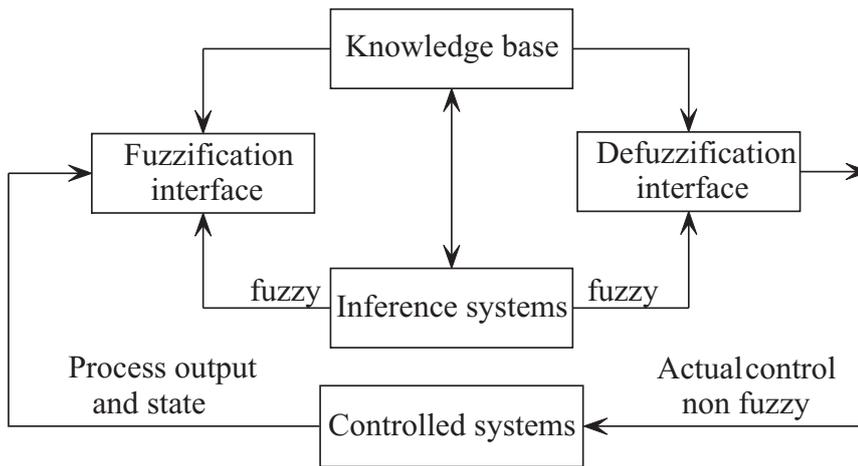
Fig. 3: Generic structure of fuzzy logic controller

expert knowledge, to automatic control strategies. Fig. 3 depicts the basic configuration of the FLC. It consists of a fuzzification interface, a knowledge base, decision making logic, and a defuzzification interface [11].
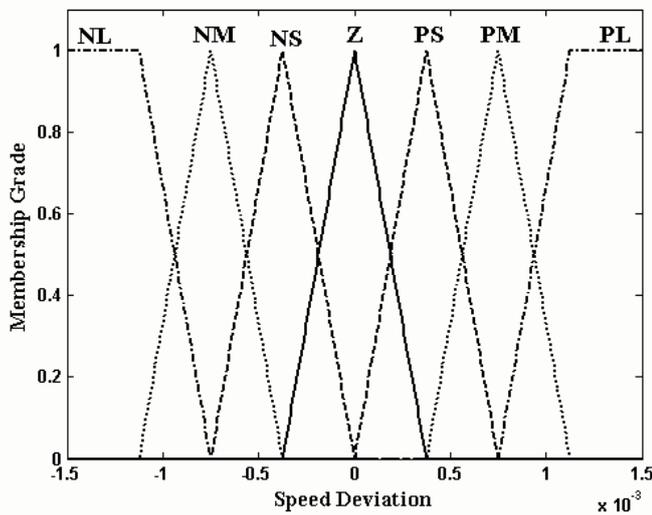
3.1 Global input variables

The fuzzy input vector consists of two variables; first, the generator speed deviation $\Delta\omega$ and, second, the acceleration $\Delta\omega'$. We designed two fuzzy controllers; the first is the fuzzy controller with seven linguistic variables, using fixed fuzzy sets for each one of the input variables, as shown in Fig. 4 and Fig. 5, respectively. The fuzzy set for the output variable is shown in Fig. 6. In these figures, linguistic variables have been used such as PL (Positive Large), PM (Positive Medium), PS (Positive Small), Z (Zero), NS (Negative Small), NM (Negative Medium), NL (Negative Large). They have been used for the output fuzzy set, adding linguistic U to the related ones, as indicated in Table 1.

The second fuzzy controller, based on five linguistic variables, is used for each input variable, as shown in Fig. 7 and Fig. 8. respectively. The fuzzy set for the output variables is shown in Fig. 9. The fuzzy sets shown in Figs. 7, 8, 9 are used for both FLC-PSS with a fixed and adaptive fuzzy set. The solid line, in these figures, represents FFS, while the dotted lines depict these fuzzy sets after applying the adaptation techniques via the back propagation algorithm [12]. The

Fig. 4: Input fuzzy sets for speed deviation
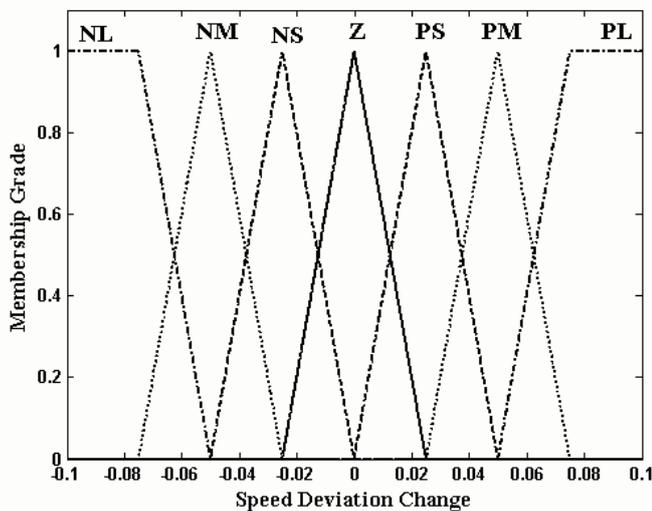
Fig. 5: Input fuzzy sets for speed deviation change
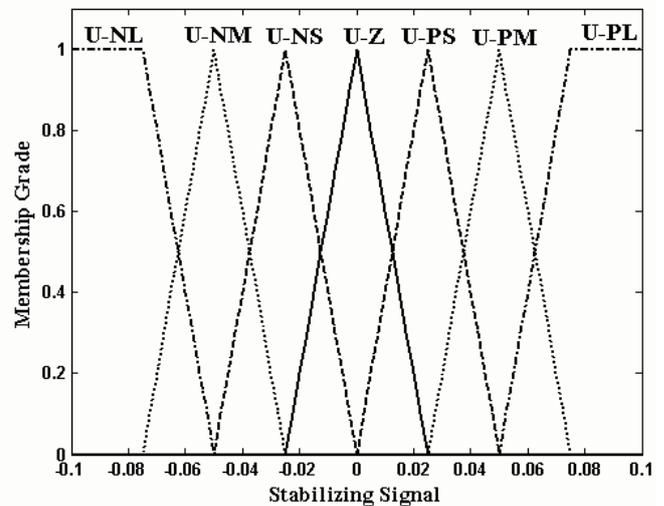
Fig. 6: Output fuzzy sets
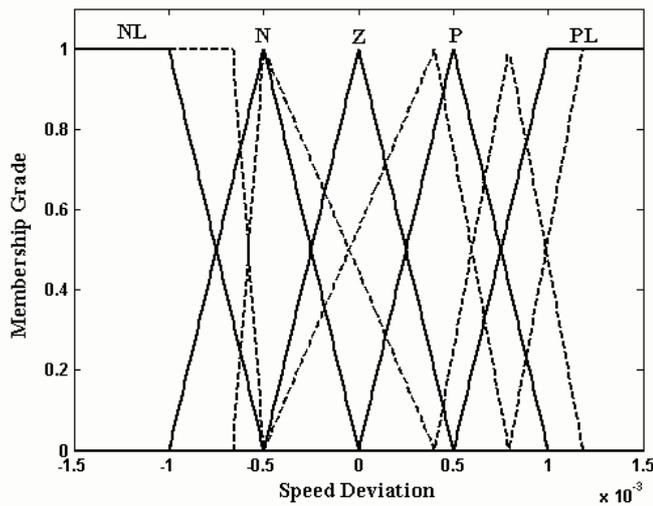
Fig. 7: Solid lines: represent the FFS or *MFs* before adaptation. Dashed lines: represent the AFS or Normalized *MFs* after adaptation.
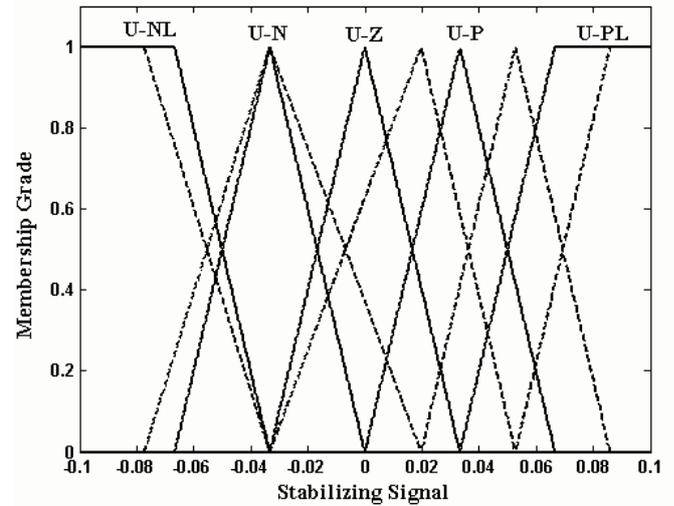
Fig. 9: Solid lines: represent the FFS or *MFs* before adaptation. Dashed lines: represent the AFS or Normalized *MFs* after adaptation.
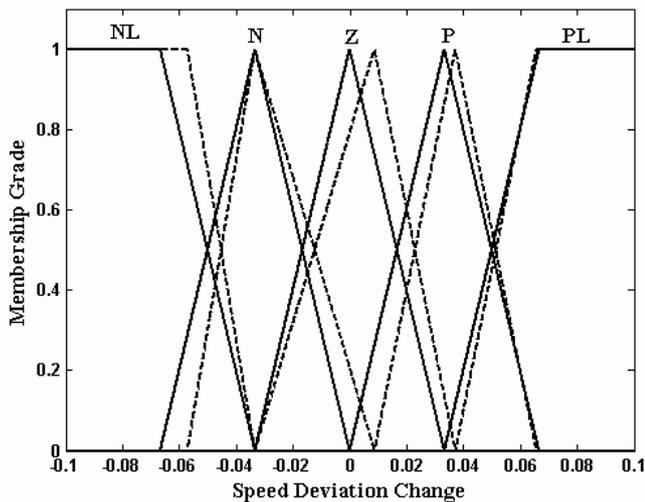
Fig. 8: Solid lines: represent the FFS or *MFs* before adaptation. Dashed lines: represent the AFS or Normalized *MFs* after adaptation.

adaptation technique is used to modify the membership function (*MF*) of each fuzzy set. In these figures, *MFs* of the linguistic variables have been used, such as PL (Positive Large), P (Positive), Z (Zero), N (Negative), NL (Negative Large). These linguistic variables have been used for the output fuzzy set, adding linguistic U to the related ones, as indicated in Table 2.

Generally, after building up the fuzzy set for input and output variables it is required to develop the set of rules, the so-called Look-up Table, in which the relation between the input variable, $\Delta\omega$ and $\Delta\omega'$, and the output variable of fuzzy controller is defined. The output of the FLC is used to adjust the U_{pss} value, as shown in Fig. 1. These look-up tables are given in Table 1, when using seven fuzzy sets (7FLC), and Table 2, when using five fuzzy sets (5FLC).

The surface viewer, as shown in Fig. 10, has a special capability that is very helpful in cases with two (or more) inputs and one output. This figure shows the output surface of the FLC of the system versus two inputs.

Table 1: Look-up table defining the relation between the input and output variable in a fuzzy set form for seven fuzzy sets

Speed deviation ($\Delta\omega$)	Speed deviation chang ($\Delta\omega'$)						
	NL	NM	NS	Z	PS	PM	PL
NL	U_NL	U_NL	U_NL	U_NL	U_NM	U_PS	U_Z
NM	U_NL	U_NM	U_NM	U_NM	U_NS	U_Z	U_PS
NS	U_NL	U_NM	U_NS	U_NS	U_Z	U_PS	U_PM
Z	U_NL	U_NM	U_NS	U_Z	U_PS	U_PM	U_PL
PS	U_NM	U_NS	U_Z	U_PS	U_PS	U_PM	U_PL
PM	U_NS	U_Z	U_PS	U_PM	U_PM	U_PL	U_PL
PL	U_Z	U_PS	U_PM	U_PL	U_PL	U_PL	U_PL

Table 2: Look-up table defining the relation between the input and output variable in a fuzzy set form for five fuzzy sets

Speed deviation ($\Delta\omega$)	Speed deviation chang ($\Delta\omega'$ţ)				
	NL	N	Z	P	PL
NL	U–NL	U–NL	U–NL	U–N	U–Z
N	U–NL	U–NL	U–N	U–Z	U–P
Z	U–NL	U–N	U–Z	U–P	U–PL
P	U–N	U–Z	U–P	U–PL	U–PL
PL	U–Z	U–P	U–PL	U–PL	U–PL
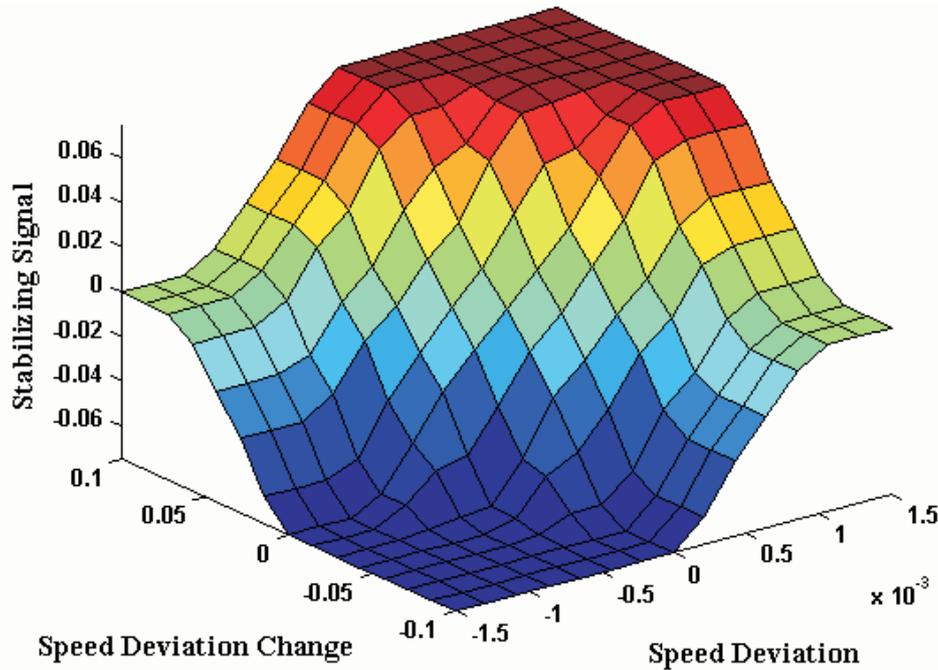
Fig. 10: Rules surface viewer for FLC using a fuzzy set

3.2 The defuzzification method

The Minimum of Maximum value method has been used to calculate the output from the fuzzy rules. This output is usually represented by a polyhedron map, as shown in Fig. 11. The defuzzification stage is executed in two steps. First, the minimum membership is selected from the minimum value of the two input variables (x_1 and x_2) with the related fuzzy set

Rule 1: If x_1 is **PS** and x_2 is **PM** then y is **U-PM**
Rule 2: If x_1 is **Z** and x_2 is **PS** then y is **U-PS**
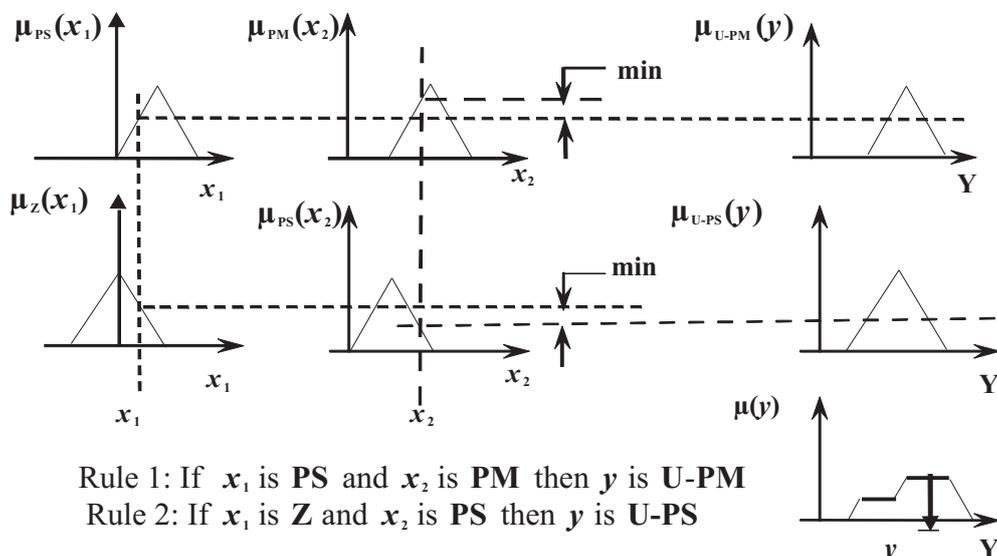
Fig. 11: Schematic diagram of the defuzzification method using the center of area

in that rule. This minimum membership is used to rescale the output rule, and then the maximum is taken to give the final polyhedron map, as shown in Fig. 11. Finally, the centroid or center of area has been used to compute the fuzzy output, which represents the defuzzification stage, as follows:

$$U_{pss} = \frac{\int y\,\mu(y)\,\mathrm{d}y}{\int \mu(y)\,\mathrm{d}y}$$

4 The proposed adaptive fuzzy logic controller

The adaptive fuzzy logic controller (AFLC), using an adaptive fuzzy set, has the same inputs and output as a static FLC. A full rule base (25 rules) is also defined. The rules have the general form:

*If $\Delta\omega$ is **NL** and $\Delta\omega'$ţ is **N** then U_{pss} is U–NL,*

where the membership functions (MF_i) is defined as follows: $MF_j \in \{NL, N, Z, P \text{ and } PL\}$ as in the static fuzzy case. However, the output space has 25 different fuzzy sets. To accommodate the change in operating conditions, the adaptation algorithm changes the parameters of the input and output fuzzy sets.

The algorithm presented in this section is designated to optimize the rule base of the fuzzy controller by shifting and/or modifying the support of the input and output fuzzy sets. In addition, it will not modify the rules or the structure of the fuzzy controller. In general the membership grade of fuzzy sets $\left(\mu_j^{(i)}\right)$ used in this research for input or output variables has a triangular or trapezoidal configuration. These fuzzy sets are defined as follows:

In the case of a triangle MF, the three parameters $\{a, b, c\}$ are defined as follows:

$$\mu_j^{(i)}(x;a,b,c) \overset{def}{=} \begin{cases} 0 & x \le a \\ \dfrac{x - a_j^{(i)}}{b_j^{(i)} - a_j^{(i)}} & a \le x \le b \\ \dfrac{c_j^{(i)} - x}{c_j^{(i)} - b_j^{(i)}} & b \le x \le c \\ 0 & c \le x \end{cases}$$

Where $a_j^{(i)}, b_j^{(i)}, c_j^{(i)} \in \mathbb{R}$ and $a_j^{(i)} \le b_j^{(i)} \le c_j^{(i)}$, where $\mathbb{R}$ is the real number set. This means that $\mu_j^{(i)}\left(a_j^{(i)}\right) = 0$, $\mu_j^{(i)}\left(b_j^{(i)}\right) = 1$ and $\mu_j^{(i)}\left(c_j^{(i)}\right) = 0$, as shown in Fig. 12. The triangular mem-
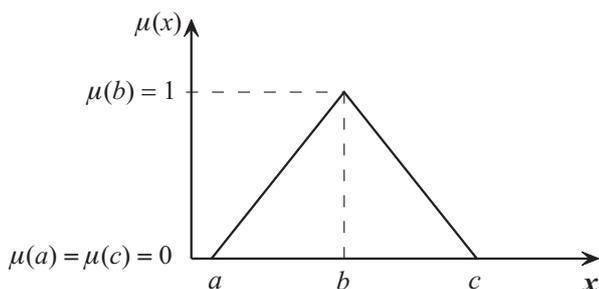
Fig. 12: Triangular membership function (*MF*)

bership functions used symmetric consequents and antecedents to represent the fuzzy set [11].

In the case of a trapezoidal *MF*, the four parameters $\{a, b, c, d\}$ are defined as follows:

$$\mu_j^{(i)}(x;a,b,c,d) \overset{def}{=} \begin{cases} 0 & x \le a \\ \dfrac{x - a_j^{(i)}}{b_j^{(i)} - a_j^{(i)}} & a \le x \le b \\ 1 & b \le x \le c \\ \dfrac{d_j^{(i)} - x}{d_j^{(i)} - c_j^{(i)}} & c \le x \le d \\ 0 & d \le x \end{cases}$$

Where $a_j^{(i)}, b_j^{(i)}, c_j^{(i)}, d_j^{(i)} \in \mathbb{R}$ and $a_j^{(i)} \le b_j^{(i)} \le c_j^{(i)} \le d_j^{(i)}$. This means that $\mu_j^{(i)}\left(a_j^{(i)}\right) = 0$, $\mu_j^{(i)}\left(b_j^{(i)}\right) = 1$, $\mu_j^{(i)}\left(c_j^{(i)}\right) = 1$ and $\mu_j^{(i)}d\left(c_j^{(i)}\right) = 0$, as shown in Fig. 13. The trapezoidal membership functions used symmetric consequents and antecedents to represent the fuzzy set [11].
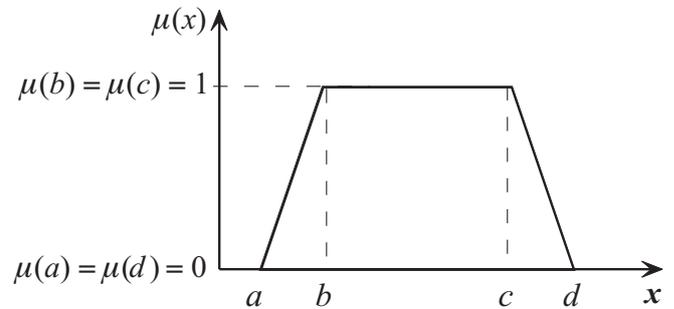
Fig. 13: Trapezoidal membership function (*MF*)

The updated parameters of the membership functions of the fuzzy set for the input and output variables used the on-line back-propagation (BP) algorithm [12]. A simple mathematical form of the on-line updating for the *MF* is given by the following equation:

$$\theta\{k + 1\} = \theta\{k\} + \alpha \times \Delta\theta\{k\}$$

Where α represents the learning rate and θ represents the parameters $a_j^{(i)}, b_j^{(i)}, c_j^{(i)}, d_j^{(i)} \in \mathbb{R}$ of the membership function of the fuzzy sets for the input and output variables. $\Delta\theta\{k\}$ is the change of these parameters based on the performance of the system under study [12]. Figs. 7, 8, and 9 show the simulation results of the normalized *MFs* of the input and output fuzzy sets before and after adaptation. The tuning strategy goal for the AFS is to achieve a fast dynamic response, with no overshoot and negligible steady state error. The complexity of the fuzzy logic controller is reduced due to the lower number of rules and adaptation of the membership function parameters.

5 Simulation results of S.G equipped with FLC-PSS based on FFS and AFS

The system data given in Appendix-1 is used to test the proposed FLC-PSS. The proposed FLC has two input variables, $\Delta\omega$ and $\Delta\omega'$. Different simulation results have been obtained for the system given in Fig. 1. These results are

obtained when the S.G. is subjected to different dynamic disturbances, while the system is normally loaded and 0.65 p.u. active power and 0.45 p.u. reactive power are delivered. These disturbances are applied as a step change in the mechanical power command and the voltage reference command, respectively.

5.1 Mechanical torque disturbance

The first case was studied when the S.G. was subjected to a 10 % step increase in the reference mechanical torque and then the torque returned to the initial condition. Figs. 14a, b show the simulation results for this case with the power angle δ, in radians, and the speed deviation $\Delta\omega$, in rad/sec.

The dynamic responses using a CPSS FLC with static seven and five fuzzy sets for the input and output variables and an adaptive fuzzy logic controller (AFLC) are shown in Figs. 14a and 14b, respectively. The dynamic response when using AFLC is superior to the three other controllers as regards the rising time, settling time and damping coefficient of the overall system. Figs. 9, 10 and 11 show the normalized

a)

b)
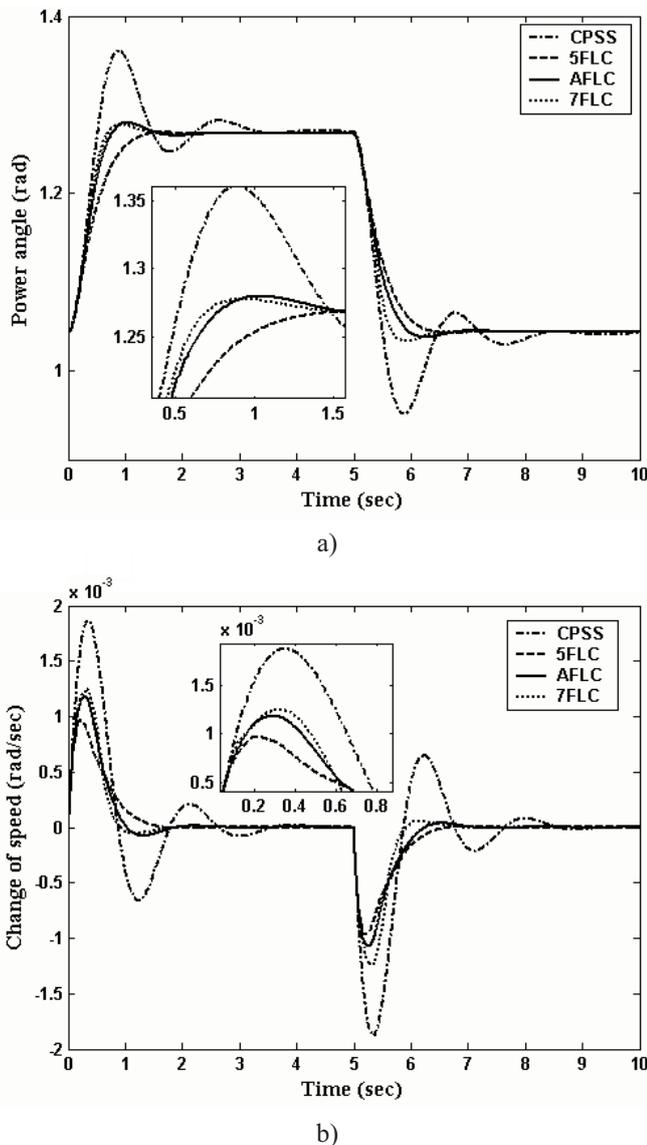
Fig. 14: Dynamic response of the synchronous generator (S.G.) equipped with FLC-PSS, AFLC-PSS and CPSS, (a) Power angle displacement, (b) Speed change

MFs before and after training, using the BP technique for the input and output variables of the fuzzy controller.

5.2 Terminal voltage disturbance

The second case of disturbance is carried out when the S.G. is subjected to a 10 % step increase in the Voltage reference, and then returns to the initial condition. Figs. 15a and 15b show δ, in radians, and $\Delta\omega$, in rad/sec, respectively. The dynamic performance of AFLC-PSS is much better in compared with five FLC-PSS, and the same conclusions have been reached as those obtained with Torque reference disturbances, as regards rising time, percentage overshoot, and oscillations.

a)

b)
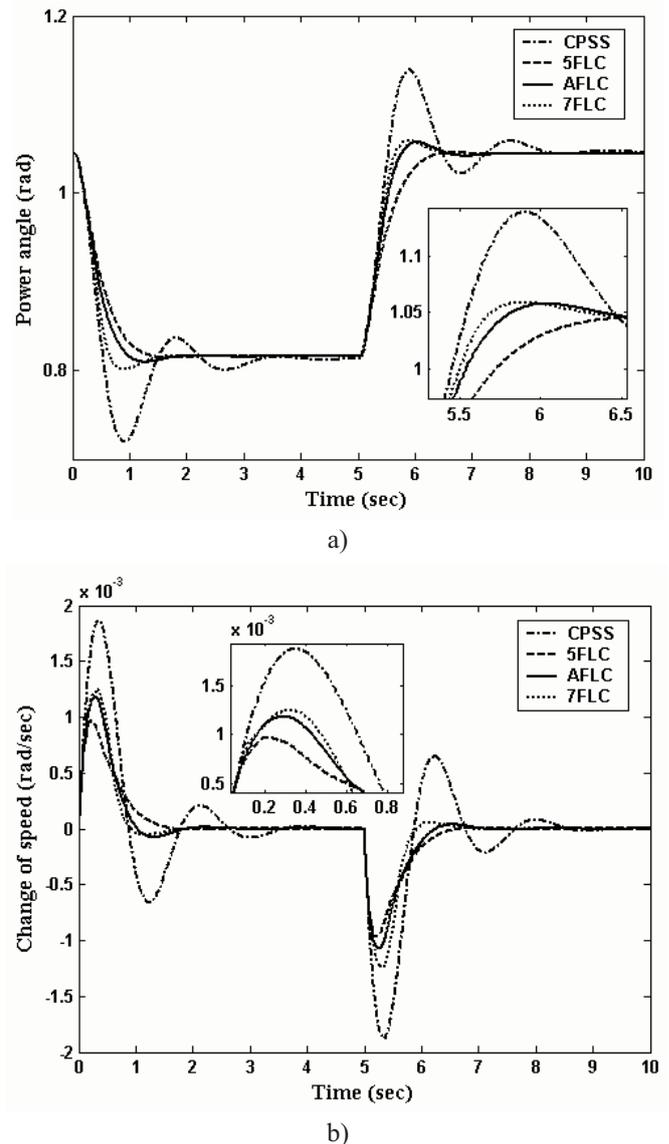
Fig. 15: Dynamic response of the synchronous generator (S.G.) equipped with FLC-PSS, AFLC-PSS and CPSS, a) Power angle displacement, b) Speed change

6 CONCLUSIONS

This paper introduces a novel application FLC-PSS and tests it through a simulation program based on an adaptive fuzzy set. A classical fuzzy logic controller, using a fixed fuzzy set, was simulated and tested. The settling time and the rise

time are decreased when using the adaptive fuzzy controller. A AFLC also improves the damping coefficient of the overall system under study. Simulation results show the superiority of the adaptive fuzzy controller in over other controllers. The simulation results also show the effectiveness of the proposed FL with an adaptive fuzzy set scheme as a promising technique. In addition the proposed technique reduces the computation time of the FLC. The number of rules is reduced from 49 in the case of seven fuzzy sets, to 25 when using AFLC.

Appendix 1

The data of the machine, AVR exciter and governor are given as follows:

All parameters and data are given in per-unit values

$P_e = 0.65$, $Q_e = 0.45$, $V_t = 1$, $X_d = 1.2$,

$X'_d = 0.19$, $X_q = 0.743$, $H = 4.63$, $T'_d = 7.76$, $D = 2$,

Local load data: $G_2 = 0.249$, $B_1 = 0.262$

Line data: $R_{T.L} = 0.034$, $X_{T.L} = 0.997$

AVR data: $K_A = 400$, $T_A = 0.02$

Speed Governor parameters (in p.u.) $a = -0.001238$,
                                       $b = -0.17$,
                                       $T_g = 0.03$.

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