Fuzzy Neural Design of Power Systems Stabilizers

التصميم العصبي المضبّب لمثبتات أنظمة القدرة

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Abstract

This paper presents a new approach of designing the Power Systems Stabilizer (PSS) that is based on fuzzy neural system. Adaptive Network based Fuzzy Inference System (ANFIS) is utilized in constructing the Fuzzy Neural Power Systems Stabilizer (FNPSS). The employment of ANFIS enables the system avoiding defects caused when using fuzzy logic and neural networks individually in designing an efficient PSS. Single Machine Infinite Bus (SMIB) power system has been taken as a case study to evaluate the suggested strategy performance. Simulation results have been conducted to confirm the approach validity.

الخلاصة

يستعرض هذا البحث طريقة جديدة لتصميم مثبتات أنظمة القدرة (PSS) و التي تعتمد على أنظمة الأعصاب المضببّة. فقد تم أستخدام الدوائر المتكيفة و التي تعتمد على أنظمة الأستنتاج المضببّ (ANFIS) للحصول على مثبت أنظمة القدرة العصبية المضببّة. أن أستخدام (ANFIS) يمكّن النظام تجنب العيوب الناجمة عن أستخدام المنطق المضببّ و الشبكات العصبية بصورة منفردة في تصميم مثبت كفوء لأنظمة القدرة. و قد تم أخذ نظام القدرة ذو الماكنة المنفردة و الخط اللا متناهي كحالة دراسية لتقييم أداء الستراتيجية المقترحة. كما و قد تم الحصول على نتائج محاكاة لتأكيد فاعلية الطريقة.

Keywords: Power system stabilizer, fuzzy logic, neural networks, ANFIS.

I. Nomenclature

c	Center of the membership functions.
E	The mean square error between the desired and actual speeds.
X_d	*d*- axis synchronous reactance (PU).
$X_d^{'}$	*d*-axis transient reactance (PU).
$X_d^{''}$	*d*-axis sub transient reactance (PU).
X_q	*q*- axis synchronous reactance (PU).
$X_q^{'}$	*q*-axis sub transient reactance (PU).

X_l	Leakage reactance (PU).
$T_{do}^{'}$	*d*-axis transient open circuit time (sec).
$T_{do}^{''}$	*d*-axis sub transient open circuit time (sec).
$T_q^{''}$	*q*-axis short circuit time constant (sec).
R_s	Stator resistance (PU).
P_{REF}	The mechanical power reference (PU).
P	The active power at the generator terminal (PU).
P_{SV}	The feedback the feedback through governor (PU).
T_M	The turbine output torque (PU).
V_{inf}	The infinite voltage (PU).
V_{TREF}	The terminal voltage reference (PU).
V_T	The terminal voltage (PU).
V_A	The voltage regulator output (PU).
V_F	The field voltage (PU).
V_E	The excitation system stabilizing signal (PU).
V_{PSS}	The PSS output signal (PU).
Q	The reactive power at the generator terminal (PU).
$\Delta\omega$	The speed deviation (PU).
e	The speed deviation (PU).
Δe	The change in speed deviation (PU).
$\mu(x)$	The membership function.
σ	The width of membership functions.
α	The firing level of fuzzy rules.
β	The normalized firing level.

II. Introduction

Power System Stabilizers (PSS's) is an important issue from the power system stability point of view since it damps out generators oscillations. They are used to generate supplementary control signals for the excitation in order to damp the low frequency oscillations [1]. Conventional Power System Stabilizers (CPSS) are now widely used in the existing power systems and they enhanced the power systems stability. Depending on a linearized model of the power system around a nominal operating point, CPSS parameters can be determined where they can provide good performance [2, 3].

The advent of fuzzy logic by Zadeh [4] opened a new horizon in the control literature. It was firstly considered as a means of representing and manipulating data that was not precise, but rather fuzzy. It was specially designed to mathematically represent uncertainty and vagueness, and to provide formalized tools for dealing with imprecision intrinsic with many problems. After the introduction of fuzzy set theory by Zadeh, many application fields employed fuzzy logic such as automatic control. Fuzzy control is mainly based on fuzzy inference mechanisms. Mamdani’s fuzzy inference method is the most commonly seen fuzzy methodology [5]. Mamdani’s control system was built using fuzzy set theory. It was proposed in 1975 by Mamdani as an effort to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators. Mamdani’s effort was based on Zadeh’s (1973) paper on fuzzy algorithms for complex systems and decision processes.

Takagi and Sugeno [6] found the most powerful inference mechanism (1985), called Sugeno or Sugeno-Takagi inference mechanism. Sugeno inference mechanism differs from Mamdani’s inference in that linear or constant systems instead of fuzzy sets are formed in the consequences of the fuzzy rules.

On the other hand, neural networks have been utilized in controlling many complex plants [7], and it solved many problems in control. However, both of the fuzzy logic and neural networks have defects; fuzzy logic has the capability of controlling complex plants without the need for the exact mathematical model of the plant, however the parameters of the fuzzy logic are fixed and the plant output may not be optimal. Neural networks has the ability to adapt its parameters in order to have an optimal output, however the exact mathematical model is needed in this case.

Fuzzy neural systems have been recently utilized in order to have an integrated system that overcome defects of both systems, say fuzzy logic and neural networks, and successfully used in control [8, 9]. This effort resulted in a system capable of controlling the complex plants without needing its exact mathematical model; say fuzzy system, in which parameters are adjusted in order to have an optimal output, say neural system.

In the literature of PSS design, both of fuzzy logic and neural networks have been utilized for the sake of designing an efficient PSS [10, 11]. However, both of the schemes are suffering from the defects that are caused due individual systems utilization. This paper suggests a newly developed PSS design that is based on Fuzzy Neural Systems (FNS) to overcome defects caused by individual fuzzy logic and neural networks. The paper is organized as follows; section II describes the system model of the Single Machine Infinite Bus (SMIB) power system. The suggested PSS is presented in section III. Section IV gives simulation results to validate the approach, and section V summarizes the concluded remarks.

III. Power System Model

The Single Machine Infinite Bus power system (SMIB) used to evaluate the FNPSS is shown in Fig.1. The SMIB consists of a synchronous generator, a turbine, a governor, an excitation system, and a transmission line connected to an infinite bus.

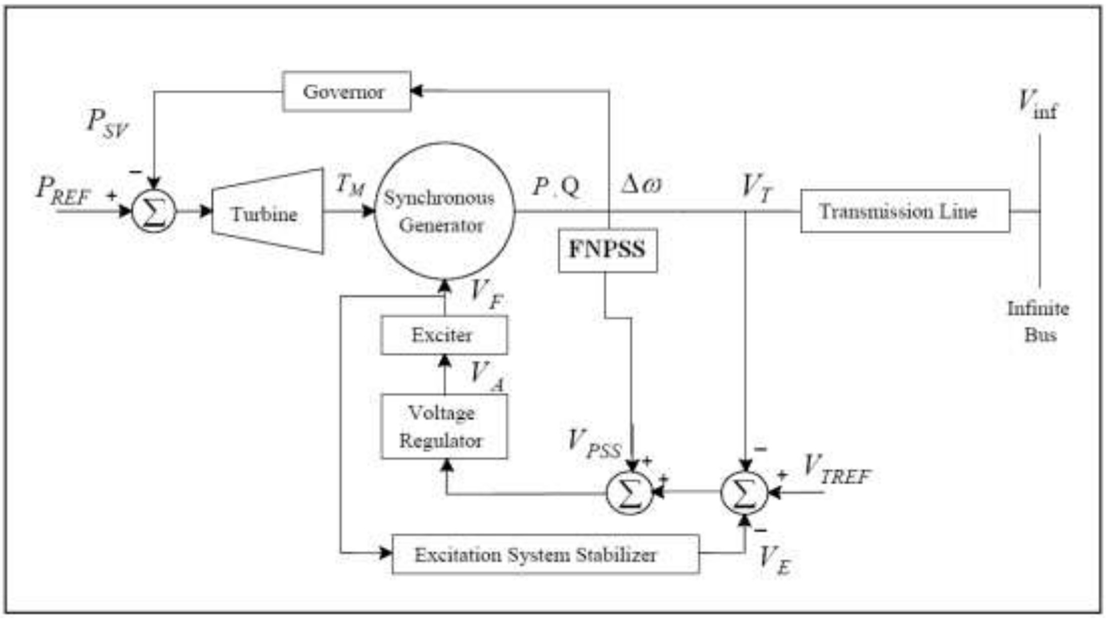

Fig. 1. System model configuration

The synchronous generator can be described by a seventh order d-q axis set of equations with the machine current, speed, and rotor angle as the state variables [12]. The turbine is used to drive the generator and the governor is used to control the speed and the real power. Fig. 2 illustrates the block diagram of a turbine and a conventional governor.

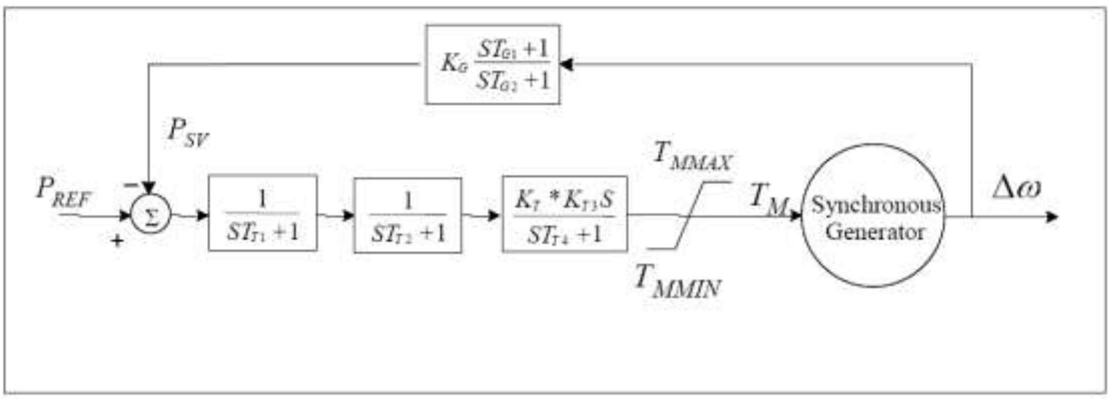

Fig. 2. Block diagram of the turbine and the governor

The excitation system for the generator is modeled according to IEEE Standard 421.5 [11], so that the excitation system block diagram is shown in Fig. 3.

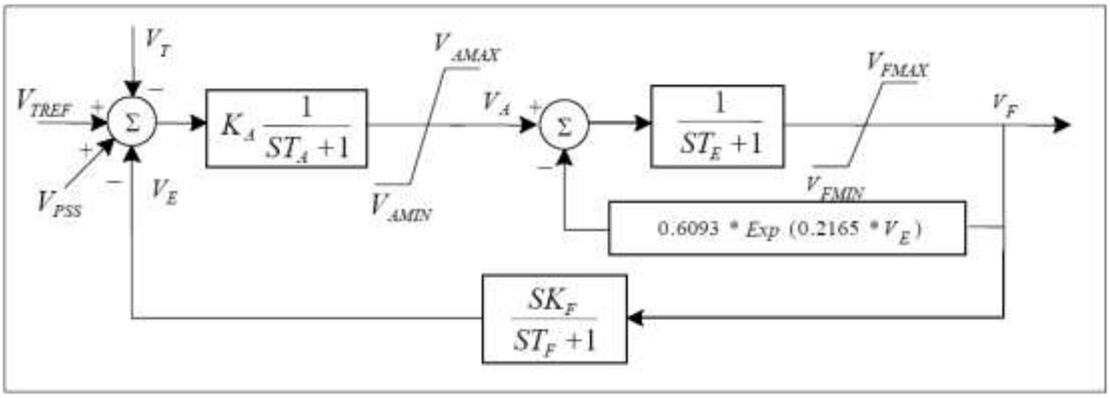

Fig. 3. Block diagram of the excitation system

A Conventional PSS (CPSS) consists of two phase-lead compensation blocks, a signal block, and a gain block. The input signal is the speed deviation $\Delta\omega$. The block diagram of the CPSS is shown in Fig. 4.

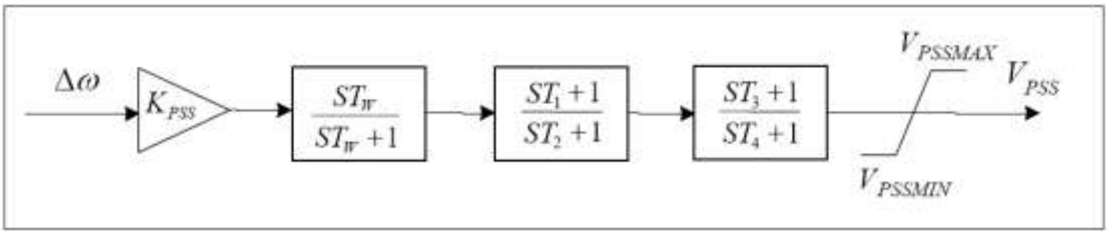

Fig. 4. Block diagram of the conventional power system stabilizer

IV. Fuzzy Neural Power System Stabilizer (FNPSS) Design

Fuzzy Neural systems are considered as one of the most power techniques in artificial intelligence. High mapping (resulted from fuzzy system) and adaptability (resulted from neural system) enables fuzzy neural systems to be more efficient for complex plants control and modeling (See [13] for more information on fuzzy neural systems). This efficiency of fuzzy neural system was the central driving force behind the selection of this technique for construction a PSS using fuzzy neural system which is called Fuzzy Neural PSS (FNPSS).

The inputs of the FNPSS are the speed deviation (e) and change in speed deviation (Δe). The output of the FNPSS is u.

Where:

$$e(k) = \omega(k) - \omega(k-1) \tag{1}$$

And

$$\Delta e(k) = e(k) - e(k-1) \tag{2}$$

The overall output, V_{PSS}, is directly proportional to the fuzzy neural system output u:

$$V_{PSS} = K_{PSS} . u \tag{3}$$

K_{PSS} is a constant

a. The Controller Linguistic Terms

Five linguistic terms (membership functions) are assigned for each one of the inputs and output. These terms are Negative Big (NB), Negative Small (NS), Zero (ZE), Positive Small (PS), and Positive Big (PB). Due to the fact that Sugeno inference mechanism is better integrated with neural networks [8] than that of Mamdani, then Sugeno inference would be utilized to construct the fuzzy neural network.

The linguistic terms of the inputs *e(k)* and *Δe(k)* are fuzzy sets, whereas that of the output *u(k)* are single spikes. The inputs membership functions are Gauss-shaped functions. Fig. 5 shows the chosen initial membership functions of each input.

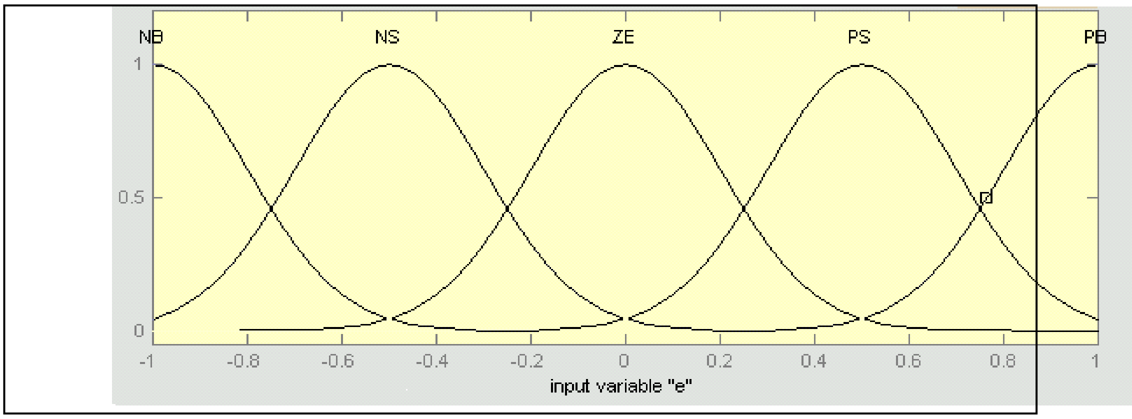

Fig. 5.The membership functions of input linguistic terms.

The memberships functions of the output are single spikes are shown in figure 6.

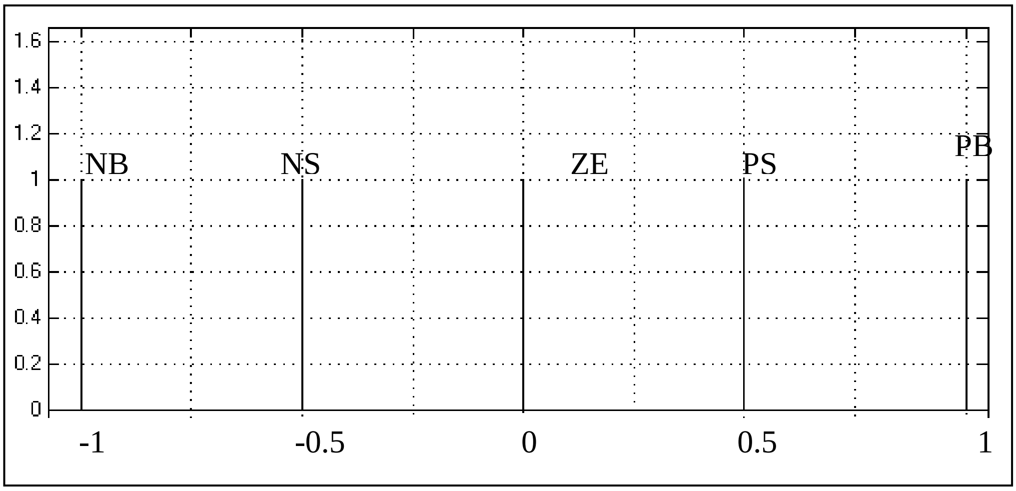

Fig. 6. The membership functions of output linguistic terms.

For both figures (5 and 6), the x-axis is the input variable and the y-axis is the grade of membership to a certain linguistic term.

b. The FNPSS Rules

The FNPSS rules are of the form:

"if *e(k)* is A and *Δe(k)* is B then *u(k)* is C"

Where A and B are fuzzy sets, C is a single spike. The rules of the fuzzy neural controller are summarized in the matrix of table 1 (See [13] for more details on how the rules matrix is generated).

Table 1 Linguistic output control rules matrix.

Δe \ e	NB	NS	ZE	PS	PB
PB	ZE	PS	PS	PB	PB
PS	NS	ZE	PS	PS	PB
ZE	NS	NS	ZE	PS	PS
NS	NB	NS	NS	ZE	PS
NB	NB	NB	NS	NS	ZE

The square of intersection of a row and a column gives the output membership function corresponding to that rule, i.e.

"if *e(k)* is NB and *Δe(k)* is PS then *u(k)* is NS"

c. The FNPSS Structure

The ANFIS is the most suitable fuzzy neural network for controller realization and fuzzy inference parameter adaptation. So, ANFIS is utilized to establish the job of the controller above. Fig. 7 shows the structure of the utilized ANFIS with constant consequent part of rules. ANFIS consists of six layers:

Layer 1

Due to the fact that there are two inputs for the ANFIS, say *e(k)* and *Δe(k)*, two neurons are within layer 1, so:

$$O_1^1(k) = e(k) \tag{4}$$

$$O_2^1(k) = \Delta e(k) \tag{5}$$

Layer 2

Five membership functions are for each input; so five neurons are required for each input. Consequently, ten neurons are within layer 2.

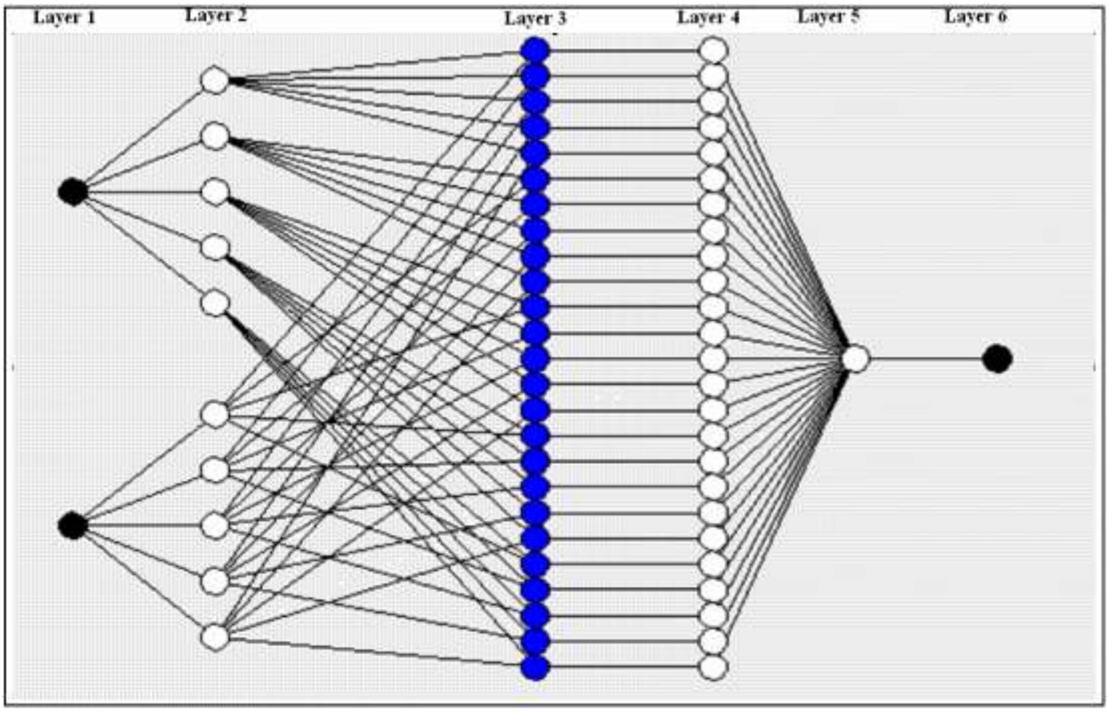

Fig.7. The ANFIS structure.

Since the used membership functions for each linguistic term are Gauss, the activation function for each neuron within layer 2 is:

$$\mu(x) = \exp\left(-\frac{(x-c)^2}{2.\sigma^2}\right) \qquad (6)$$

Where x is the input to that neuron, c is the center; σ is the width of the Gauss membership function.

Layer 3

Twenty-five neurons are required in layer 3; due to the fact that layer 3 neurons realizes the fuzzy *AND* operation of each rule. The utilized t-norm is the min operation:

$$AND(a,b) = \min(a,b) \qquad (7)$$

The result of each neuron within layer 3 would be the firing level for that rule, i.e.

$$\alpha_w = \min(a_p, b_q) \qquad (8)$$

w=1,2…25

p=1,2… 5

q=1,2…5

Layer 4

There are twenty-five rules in the fuzzy inference mechanism. So twenty-five neurons are required for layer 4, one for each rule that represents the normalized firing level for that rule, i.e.

$$\beta_m = \frac{\alpha_m}{\sum_{k=1}^{25} \alpha_k} \qquad (9)$$

m=1,2,…,25

Layer 5

This is a single neuron layer that performs the defuzzification process. The center of area (COA) defuzzification approach is utilized, i.e.

$$y = \sum_{m=1}^{25} \beta_m \cdot Z_m \qquad (10)$$

Or,

$$y = \frac{\sum_{m=1}^{25} \alpha_m \cdot Z_m}{\sum_{r=1}^{25} \alpha_r} \qquad (11)$$

Layer 6

This is also a single neuron layer, which is dedicated to output the result obtained from layer 5. So,

$$u(k) = y \qquad (12)$$

d. Fuzzy Inference Parameters Adjustment:

Gradient descent method is utilized to adjust the parameters of the fuzzy inference for giving an optimal output that is as near as possible to the reference input. So,

$$c_i(t+1) = c_i(t) - \eta_1 \frac{\partial E^k\left(c_i(t), \sigma_j(t), z_m(t)\right)}{\partial c_i(t)} \qquad (13)$$

$$\sigma_j(t+1) = \sigma_j(t) - \eta_2 \frac{\partial E^k\left(c_i(t), \sigma_j(t), z_m(t)\right)}{\partial \sigma_j(t)} \qquad (14)$$

$$z_m(t+1) = z_m(t) - \eta_3 \frac{\partial E\left(c_i(t), \sigma_j(t), z_m(t)\right)}{\partial z_m(t)} \qquad (15)$$

Where: t is the iteration index.

$\eta_{1,2,3}$ are the learning factors.

$E(c_i(t),\sigma_j(t),z_k(t))$ is the mean square error between the desired speed output value (ω_d) and the actual value (ω), i.e.

$$E\left(c_i(t),\sigma_j(t),z_m(t)\right)=\frac{1}{2}\left(\omega_d^k-\omega^k\left(c_i(t),\sigma_j(t),z_m(t)\right)\right)^2 \qquad (16)$$

k is time index.

i is the index of the input membership functions centers (i=1,2…10)

j is the index of the input membership functions widths (j=1,2…10)

m is the index of the rules outputs corresponding to the m^{th} rule.

So, equations (12), (13), and (14) are on-line adjusting the centers, widths, and rules outputs respectively.

V. Simulation Results

Simulation results have been conducted using MATLAB/SIMULINK on a SMIB model of parameters given in the appendix. Fig. 8 shows the change in speed when a three phase to ground fault is taken place on the bus at 0.1 sec, and then the fault is cleared at 0.2 sec. The performance of both the CPSS and FNPSS are illustrated in Fig. 8. It is obvious that the performance of the FNPSS is better than that of the CPSS. In spite of the harmful fault that may cause instability in the system, however, the efficient performance of the FNPSS makes the speed deviation to be as close as possible to zero. This high performance is obtained due to the online adjustment of the fuzzy controller's parameters that makes the cost function, and consequently the speed deviation, as close as possible to zero.

Fig. 9 illustrates the performance of FNPSS under step change in the reference voltage from 1 (P.U.) to 1.1 (P.U.) at time 4 sec. The adaptive nature of the FNPSS makes it possible for the system to have an excellent performance against the reference voltage step change. Moreover, the area of operation of FNPSS is larger than that of CPSS due to the following causes:

1. The adaptive nature of the suggested FNPSS enables the adjustment of its parameters such that an optimal performance is achieved.
2. CPSS are designed on the assumption of a linearized model of the system that makes its performance to be acceptable with operating points that lay only within the region of linearization. FNPSS is designed with system nonlinearity to be taken into account. This feature makes the FNPSS to have excellent performance for different operating conditions.

For the reasons above, excellent performance of FNPSS was obtained against sudden power system changes and fluctuations.

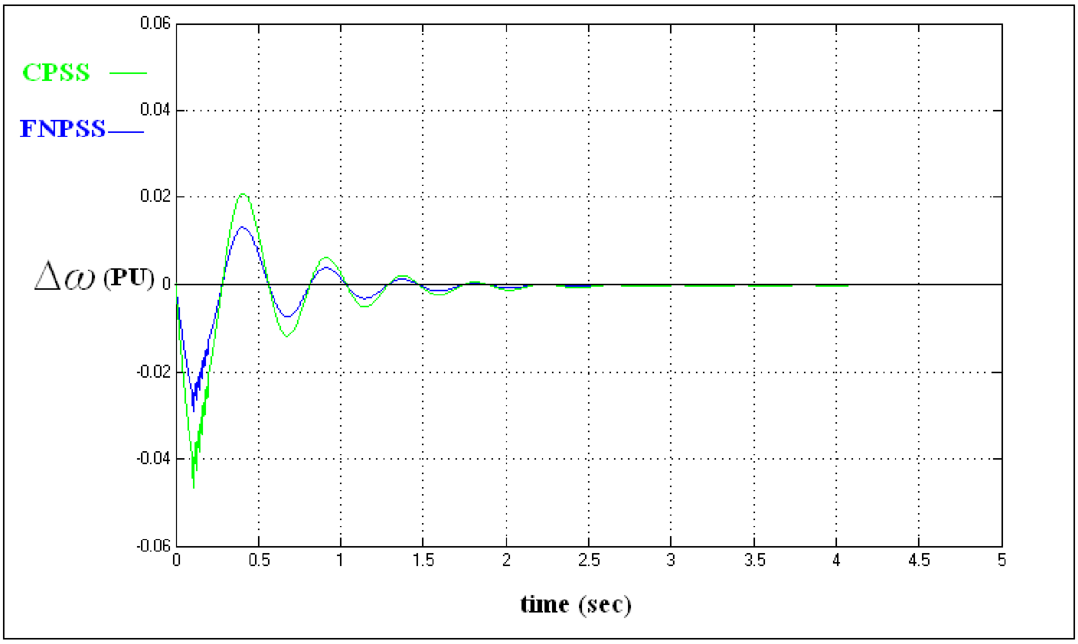

Fig. 8. The speed deviation (PU) for a fault at the bus

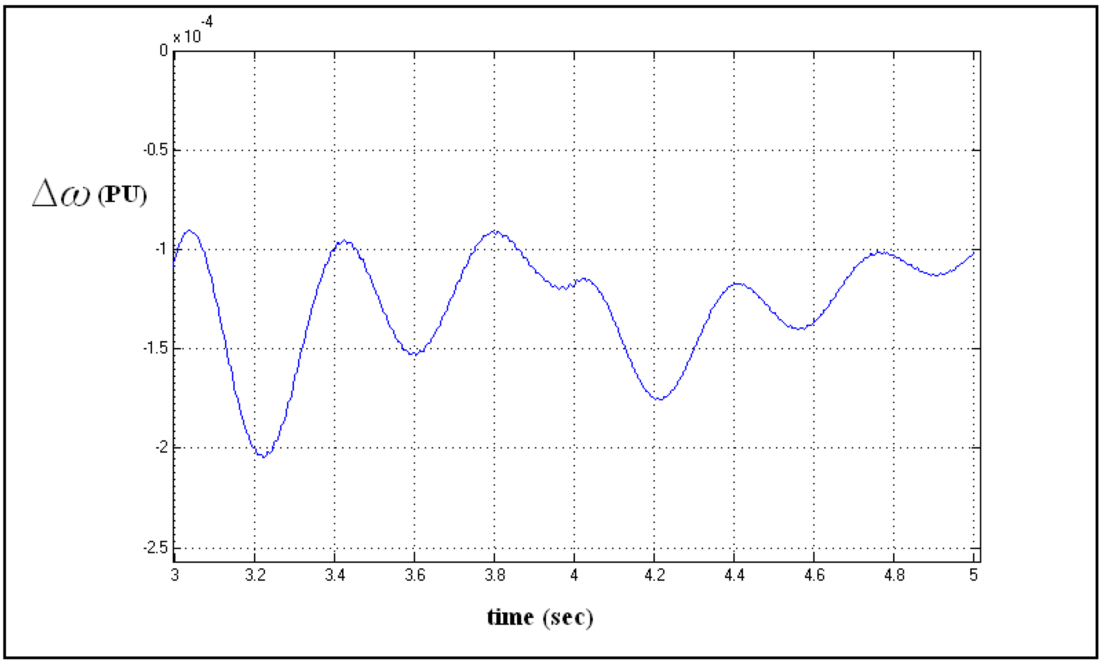

Fig. 9. The speed deviation for a step change in the reference voltage

VI. Conclusion

It has been proven that the performance of the suggested FNPSS for a SMIB system is excellent against harmful system variation like ground faults. This is, mainly, due to the adaptive nature and capability to control complex plants when using fuzzy neural systems. Such adaptive nonlinear PSS yield better and faster damping, especially against large disturbances such as a ground fault. The FNPSS is also having an excellent performance in the case of step reference voltage increment. Gradient descent method has been utilized as the optimization technique in order to tune the fuzzy logic parameters for having an optimal output.

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Appendix

Machine parameters

The machine is a salient pole synchronous generator which is having the parameters:

X_d*=1.305 P.U. (d- axis synchronous reactance)*

$X_d^{'}$*=0.296 P.U. (d-axis transient reactance)*

$X_d^{''}$*= 0.252 P.U. (d-axis sub transient reactance)*

X_q*=0.474 P.U. (q- axis synchronous reactance)*

$X_q^{''}$*=0.243 P.U. (q-axis sub transient reactance)*

X_l*= 0.18 P.U. (leakage reactance)*

$T_{do}^{'}$*=4.49 Sec (d-axis transient open circuit time)*

$T_{do}^{''}$*=0.0681 Sec (d-axis sub transient open circuit time)*

$T_q^{''}$*=0.0513 Sec (q-axis short circuit time constant)*

R_s*=0.003 P.U. (stator resistance)*