# Comparative Analysis of Power System Stabilizer under small scale stability considerations using conventional, Neural Network and Fuzzy Logic Based Controllers

***Thesis submitted in partial fulfillment of the requirements for the award of degree of***

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By:


**Manpreet Joshi**

**(80641012)**


Under the supervision of:

**Ms. SUMAN BHULLAR**

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**ELECTRICAL & INSTRUMENTATION ENGINEERING DEPARTMENT**

THAPAR UNIVERSITY

PATIALA – 147004

# Certificate

I hereby certify that the work which is being presented in the thesis entitled, **"Comparative Analysis of power system stabilizer under small scale stability considerations using conventional, Neural Network and Fuzzy Logic Based Controllers "**, in partial fulfillment of the requirements for the award of degree of Master of Engineering in ***Power Systems & Electric Drives*** submitted in Electrical & Instrumentation Engineering Department of Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of Ms. Suman Bhullar.

The matter presented in this thesis has not been submitted for the award of any other degree of this or any other university.

Manpreet Joshi
***(Manpreet Joshi)***

This is to certify that the above statement made by the candidate is correct and true to the best of my knowledge.

Bhullar
1/7/08
**(Ms. Suman Bhullar)**

Electrical & Instrumentation Engg. Department
Thapar University
Patiala

**Countersigned by**

S. Ghosh
(S. GHOSH)
**Professor & Head**
Electrical & Instrumentation Engg. Department
Thapar University
Patiala

R K Sharma
(R.K.SHARMA)
**Dean(Academic Affaris)**
Thapar University,
Patiala.

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Manpreet Joshi
80641012

# ABSTRACT

The low frequency oscillations, which are typically are of the frequency range of 0.2 to 3.0 Hz, are excited by the disturbances in the system or, in some cases, might even build up spontaneously. These oscillations may cause a loss of synchronism and an eventual breakdown of the entire system. Power system stabilizers (PSS) are used to generate supplementary control signals for the excitation system in order to damp the low frequency power system oscillations. The traditional solution to this problem is application of conventional power system stabilizer (CPSS). The constantly changing nature of power system makes the design of CPSS a difficult task. To overcome the drawbacks of conventional PSS (CPSS), numerous techniques have been proposed in the literature. Based on the analysis of existing techniques, this thesis uses an Artificial Intelligent techniques based Power System Stabilizer design. These AI techniques have features of simple structure, adaptivity and fast response. The model is evaluated on a single machine infinite bus power system, then the performance of CPSS, neural network based PSS and Fuzzy Based PSS is compared. The AI based PSS designs give better performance than the conventional PSS.

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# CHAPTER 1

# INTRODUCTION

## 1.1 Power System Stability

Power system stability may be broadly defined as that property of a power system that enables it to remain in a state of operating equilibrium under normal operating conditions and to regain an acceptable state of equilibrium after being subjected to a disturbance.

From this general definition, two categories of stability are derived: small-signal and transient stability. Small-signal stability is the ability of the system to return to a normal operating state following a small disturbance. Investigations involving this stability concept usually involve the analysis of the linearized state space equations that define the power system dynamics. Transient stability is the ability of the system to return to a normal operating state following a severe disturbance, such as a single or multi-phase short-circuit or a generator loss. Under these conditions, the linearized power system model does not usually apply and the nonlinear equations must be used directly for the analysis. A third term, dynamic stability, has been used to describe a separate class of stability. However, this term has represented different concepts for different authors, and there has also been a difference between groups of analysts in North America and Europe. For these reasons, several international engineering organizations have recommended that this term not be considered when discussing the stability problem. [29, 33, 35]

### 1.1.1Types of oscillations:

The disturbances occurring in power system include electro mechanical oscillations of electrical generators. These oscillations are also called power swings and these must be effectively damped to maintain the system stability. Electromechanical oscillations can be classified in four main categories: [29, 35]

1. Local Oscillations: - Between a unit and rest of generating station and between the latter and rest of power system. Their frequency typically ranges from 0.2Hz to 2.5 Hz.

2. Interplant Oscillations: - Between two electrically close generating plants. Frequency can vary from 1 Hz to 2 Hz

3. Inter area Oscillations: - Between two major groups of generating plants. Frequencies are typically in the range of 0.2Hz to 0.8 Hz, generally called low frequency oscillations.

4. Global Oscillations: - Characterized by a common in phase oscillations of all generators as found on an isolated system. The frequency of such global mode is typically under 0.2 Hz.

### 1.1.2 Low frequency oscillations

Low frequency oscillations (LFOs) are generator rotor angle oscillations having a frequency between 0.1-3.0 Hz, and are defined by how they are created or where they are located in the power system. The use of high-gain generator exciters, poorly tuned generation excitation, HVDC converters may create LFOs with negative damping; this is a small-signal stability problem. The mitigation of these oscillations is commonly performed with “supplementary stabilizing signals” and the networks used to generate these signals have come to be known as “Power System Stabilizer” networks. LFOs include local plant modes, control modes, torsional modes induced by the interaction between the mechanical and electrical modes of a turbine-generator system, and inter-area modes, which may be caused by either high-gain exciters or heavy power transfers across weak tie-lines. Of special interest here, inter-area oscillations are on the order of 0.1-0.7 Hz. [26]

### 1.1.3 Analysis of Low Frequency Oscillations

LFOs can be created by small disturbances in the system, such as changes in the load, and are normally analyzed through the small-signal stability (linear response) of the power system. These small disturbances lead to a steady increase or decrease in generator rotor angle caused by the lack of synchronizing torque, or to rotor oscillations of increasing amplitude due to a lack of sufficient damping torque. The most typical instability is the lack of a sufficient damping torque on the rotor’s low frequency oscillations

### 1.1.4 Control Techniques

The control method investigated in this thesis will focus on the use of a power system stabilizer (PSS) in conjunction with the automatic voltage regulators (AVRs) of the generators in the test system. Damping of the LFOs contributes to the enhancement of the stability limits of the system, signifying greater power transfer through the system. The application of PSSs with local input signals for this particular control problem has been previously investigated. [4, 11-13] Often a PSS that is expected to damp oscillations over a broad range of frequencies is not able to sufficiently damp every oscillatory mode that might be excited in the system.

Other methods of controlling LFOs are the introduction of passive or active control elements other than PSSs into the power system. These devices include static VAR compensator (SVC) installations in the system, FACTS devices such as thyristor-controlled series capacitors (TCSCs), unified power controllers (UPCs). However, the analysis of these options will not be performed in this thesis.

## 1.2 Problem Statement

As mentioned earlier, some of the earliest power system stability problems included spontaneous power system oscillations at low frequencies. These low frequency oscillations (LFOs) are related to the small signal stability of a power system and are detrimental to the goals of maximum power transfer and power system security. Once the solution of using damper windings on the generator rotors and turbines to control these oscillations was found to be satisfactory, the stability problem was thereby disregarded for some time. However, as power systems began to be operated closer to their stability limits, the weakness of a synchronizing torque among the generators was recognized as a major cause of system instability. Automatic voltage regulators (AVRs) helped to improve the steady-state stability of the power systems. But With the creation of large, interconnected power systems, another concern was the transfer of large amounts of power across extremely long transmission lines. The addition of a supplementary controller into the control loop, such as the introduction of conventional power system stabilizers (CPSSs) to the AVRs on the generators, provides the means to reduce the inhibiting effects of low frequency oscillations

The conventional power system stabilizers work well at the particular network configuration and steady state conditions for which they were designed. Once conditions change the performance degrades. This can be overcome by a non-linear PSS design based on artificial intelligent techniques such as fuzzy logic, neural networks and Genetic Algorithms.

## 1.3 Solution Methodology

To overcome the drawbacks of conventional PSS (CPSS), numerous techniques have been proposed in the literature. In this thesis work, the conventional PSS's effect on the system damping is then compared with a FLPSS, a neural controller while applied to a single machine infinite bus power system. For the conventional design state space representation method is used here.

## 1.4 Literature Survey

Here is review of some literature that is relevant to carry out this thesis work.

E.V Larsen and D.A. Swann have presented in their 3 part paper titled 'Applying Power system Stabilizer –I, II and III' the history of power system stabilizer and its role in a power system. They recommended that the objective of the most appropriate stabilizer tuning criterion is to provide an adequate amount of damping to local mode of oscillations and inter area modes of oscillations. The studies and field test conducted by the authors indicate that a fast acting excitation system offers best opportunity for increased damping than the use of auxiliary signal into voltage regulators. [12]

Wlfred Watson and Gerald Manchur in paper 'Experience with Supplementary Damping Signals for Generator Static Excitation Systems' has suggested that the use of high speed excitation for generator static excitation systems results in decreased damping, which has a detrimental impact on steady state stability, i.e. it may be lost even at normal full load operation.[41]

F.P. De Mello and C. Concordia in their paper 'Concepts of synchronous machine stability as affected by excitation control' have explored the phenomenon of stability of synchronous machines under small perturbations by examining the case of single machine connected to an infinite bus through external reactance.[10]

Prabha Kundur has discussed in his publication 'Power System Stability and Controls', the stability criterion with respect to synchronous equilibrium. The mathematical model presented for small scale stability state is a set of linear time in variant differential equations. [34]

P.M. Anderson and A.A. Fouad, had mentioned in their publication 'Power System Control and Stability Volume-I', the stability under the condition of small load changes has been called steady state stability. Trends in design of power system components have resulted in lower stability and led to increased reliance on the use of excitation control to improve stability. [32]

IEEE Committee Report (1981), the working group of IEEE on computer modeling of excitation systems, in their report has discussed excitation system models suitable for use in large scale stability studies. [14]

Based on the analysis of existing techniques, Wenxin Liu, Ganesh K. Venayagamoorthy, Donald C. Wunsch, in their paper 'Adaptive Neural Network Based Power System Stabilizer Design' presents an indirect adaptive neural network based power system stabilizer design. The proposed consists of a neuro-controller, which is used to generate a supplementary control signal to the excitation system, and a neuro-identifier, which is used to model the dynamics of the power system and to adapt the neurocontroller parameters. [42]

In their invaluable paper titled 'Identification and Control of Dynamical Systems using Neural Networks' Kumpati s. Narendra and kannan parthasarathy demonstrates that neural networks can be used effectively for the identification and control of nonlinear dynamical systems. The emphasis of the paper is on models for both identification and control. Static and dynamic back-propagation methods for the adjustment of parameters are discussed. In the models that are introduced, multilayer and recurrent networks are interconnected in novel configurations and hence there is a real need to study them in a unified fashion. [20]

An experience of dynamic instability was analyzed in the paper 'analytical investigation of dynamic Instability occurring at power station' presented by J. E. Van Ness , F. M. Brasch, G. L. Landgren and S. T. Naumann The oscillations occurred on a large turbine generator that was operating radially on a long transmission line. The method of analysis was to determine stability by the calculation of the eigen values of the system. Analysis of generator operating levels, excitation system parameters, and the size of the external system model were conducted. [18]

F.P. de Mello, P.J. Nolan, T.F. Laskowski, and J.M. Undrill in their paper ‘coordinated application of stabilizers in multi machine power system’ addresses the problem of the most effective selection of generating units to be equipped with excitation system stabilizers in multi machine systems which exhibit dynamic instability and poor damping of several inter-machine modes of oscillation. Practical means have been developed using eigen value analysis techniques to guide the selection process. [11]

Wah-Chun Chan, Yuan-Yih Hsu, In their work ‘An optimal variable structure stabilizer for power system stabilization’ presents a technique for designing an optimal variable structure stabilizer for improving the dynamic stability of power systems by increasing the damping torque of the synchronous machine in the system. The proposed variable structure stabilizer is optimal in the sense of minimizing a quadratic performance index in the sliding mode operation. [40]

Boonserm Changaroon, Suresh Chandra Srivastava and Dhadbanjan Thukaram in their paper ‘A Neural Network Based Power System Stabilizer Suitable for On-Line Training—A Practical Case Study for EGAT System’ presented the development of a neural network based power system stabilizer (PSS) designed to enhance the damping characteristics of a practical power system network. The proposed PSS consists of a neuro-identifier and a neuro-controlIer which has been developed based on Functional Link Network (FLN) model. A recursive on-line training algorithm has been utilized to train the two neural networks. [7]

A. M. Sharaf, T. T. Lie and H. B. Gooi in their paper ‘Neural Network Based Power System Stabilizers’ discussed the two ANN-PSS designs are driven by the speed error and its rate of change. Other supplementary Stabilizing signals such as voltage deviation, excursion error, and PSS output rate of change are utilized to ensure the best matching between the ANN-PSS design and the optimized conventional analog PSS bench-mark model. [5]

In the paper ‘Fuzzy and Neural Controllers for a Pneumatic Actuator’ the authors, Tiberiu Vesselenyi, Simona Dzitac, Ioan Dzitac, Misu-Jan Manolescu present some modelling applications, which uses fuzzy and neural controllers, developed on a pneumatic actuator containing a force and a position sensor, which can be used for robotic grinding operations. Following the simulation one of the algorithms was tested on an experimental setup. The paper also presents the development of a NARMA-L2 neural controller for a pneumatic actuator using position feedback. [38]

R.Kayalvizhi, S.P.Natarajan and P.Padmaloshani, the authors paper ‘Development of Neuro Controller for Negative Output Self-Lift Luo Converter’ deals with the application of neuro control theory. Due to the time-varying and switching nature of the power electronic converters, their dynamic behaviour becomes highly non-linear. Conventional controllers are incapable of providing good dynamic performance and hence neural network can be utilized as a feedforward controller for controlling power electronic converters. The neuro controller presented in this work is off-line trained using quasi-Newton backpropagation algorithm. [36]

In his work ‘Fuzzy logic and neural controller’ the author Insop Song has designed Fuzzy Logic Controller (FLC) and Artificial Neural Network Controller (ANNC) to control a flexible robotic arm. Both FLC and ANNC are well-known and industry-proven for their effectiveness and good performance; they can be said as universal function approximators FLC can be applied to systems that are non-linear and difficult to model using mathematical tools. ANNC can model, identify, an unknown system and can be trained using a sample data set. This project's target plant was a flexible manipulator. [15]

In the paper ‘Nonlinear System Control Using Neural Networks’ Jaroslava Zilkova, Jaroslav Timko, Peter Girovsky has focused especially on presenting possibilities of applying off-line trained artificial neural networks at creating the system inverse models that are used at designing control algorithm for non-linear dynamic system. The ability of cascade feedforward neural networks to model arbitrary non-linear functions and their inverses is exploited. This paper presents a quasi-inverse neural model, which works as a speed controller of an induction motor. [16]

In the paper ‘A self-tuning power system stabilizer based on artificial neural network’ Ravi Segala, Avdhesh Sharma and M.L. Kothari presents a systematic approach for designing a self-tuning power system stabilizer (PSS) based on artificial neural network (ANN). An ANN is used for self-tuning the parameters of PSS in real-time. The nodes in the output layer provide the optimum PSS parameters. A new approach for the selection of number of neurons in the hidden layer has been proposed. [35]

Michael J. Basler Richard C. Schaefer in their paper titled ‘Understanding power system stability’ discusses power system instability and the importance of fast fault clearing performance to aid in reliable production of power. Explanation is provided regarding small signal stability, high impedance transmission lines, line loading, and high gain, fast acting excitation systems. [28]

N.Nallathambi and P.N.Neelakantan in their paper, ‘Fuzzy logic based power system stabilizer’ presents a study of fuzzy logic power system stabilizer for stability enhancement of a two-area four machine system. In order to accomplish the stability enhancement, speed deviation and active power deviation of the rotor synchronous generator were taken as the inputs to the fuzzy logic controller. These variables take significant effects on damping the generator shaft mechanical oscillations. The stabilizing signals were computed using fuzzy membership function depending on these variables. [30]

In the paper “Plant identification and control using a neural controller based on reference model’ by Cosme Rafael, Marcano-Gamero, Neural Control theory is applied to identify and control a plant conformed by two subsystems of second order which alternate their operation on a constant time base. Firstly, a neural network is trained to learn the plant behaviour. Once trained, this network is integrated to the rest of the system in order to jointly operate with another neural network which will serve as a controller. [8]

M. F. Othman, M. Mahfouf and D.A. Linkens, in the paper ‘Designing Power System Stabilizer For Multimachine Power System Using Neuro-Fuzzy Algorithm’ describes a design procedure for a fuzzy logic based power system stabilizer (FLPSS) and adaptive neuro-fuzzy inference system (ANFIS) and investigates their robustness for a multi-machine power system. Speed deviation of a machine and its derivative are chosen as the input signals to the FLPSS. [23]

Dauda Olurotimi Araromi, Tinuade Jolaade Afolabi, Duncan Aloko, ‘Neural Network Control of CSTR for Reversible Reaction Using Reverence Model Approach’, In this work, non-linear control of CSTR for reversible reaction is carried out using Neural Network as design tool. The Model Reverence approach in used to design ANN controller. This paper represents a preliminary effort to design a simplified neutral network control scheme for a class of non-linear process. [9]

## 1.5 Objectives of the work

The thesis work emphasis on the small scale stability analysis of power system. A Single Machine Infinite Bus system is used here for study. The objectives are divided into the following:

- To design a conventional PSS for the test sstem and to analyze the stability of the system using Eigen value analysis of the state matrix.
- To apply a neural controller and fuzzy logic based controller for the performance analysis of the same system.
- And then a gap analysis is performed by applying a conventional power system stabilizer, neuro- controller and a fuzzy logic based controller.

All the work is done using MATLAB 7.3 software, available with www. mathworks.com

## 1.6 Organization of Thesis Work

**Chapter-1** presents the introduction to Power System stability, Low frequency oscillations, State Space representation, and literature survey, objectives of the research, scope of the research and organization of the research.

**Chapter-2** presents the modeling of power system and formation of state space matrix of the SMIB system.

**Chapter-3** presents the design and analysis of neural network based controller and a fuzzy logic based power system stabilizer.

**Chapter-4** Results

**Chapter-5** Summery and Future scope of the work

**References** present the list of previous papers published by researchers in power system stability analysis, conventional and adaptive controller designs that have been surveyed by the author and also the books in this area.

**Appendix-A** shows the single machine infinite bus system data available in [35]

**Appendix-B** Glossary

**Appendix-C** Nomenclature

# CHAPTER 2

# POWER SYSTEM MODELLING

## 2.1 State Space Representation

Since the problem of LFOs can be analyzed from a small-signal stability standpoint, the power system is described by a set of state equations that are linearized. For this particular study, a search is performed for unstable or poorly-damped inter-area modes of oscillation. A PSS controller is constructed to stabilize and damp these modes together with any local rotor-angle oscillatory modes. However, torsional modes will not be accounted for in the analysis. To this end, a model that is representative of the entire power system, yet which allows the identification of the modes of interest, must be employed. Specifically, the generator and excitation system state equations are linearized and their time derivatives are put into matrix form.[32,34]

### 2.1.1 State Space Model

The state space model presented here follows the definitions established in [34], [29] The notation is borrowed from [34]. To model the behaviour of dynamic systems, quite often a set of n first order nonlinear ordinary differential equations are used. This set commonly has the form

$$\dot{x}_i = f_i\left(x_i, x_2, .....x_n;\quad u_1, u_2, ...u_r; t\right) \qquad \text{i=1,2,....,n} \qquad (2.1)$$

Where *n* is the order of the system and *r* is the number of inputs. If the derivatives of the state variables are not explicit functions of time, (1.1) may then be reduced to:

$$\dot{x} = f(x, u) \qquad (2.2)$$

Where *n* is the order of the system, *r* is the number of inputs and x, u and f denote column vectors of the form

$$x = \begin{bmatrix} x_1 \\ x_2 \\ . \\ . \\ x_n \end{bmatrix} \qquad \text{u}=\begin{bmatrix} \text{u}_1 \\ \text{u}_2 \\ . \\ . \\ \text{u}_\text{r} \end{bmatrix} \qquad \text{f}=\begin{bmatrix} f_1 \\ f_2 \\ . \\ . \\ f_n \end{bmatrix} \qquad (2.3)$$

The state vector x contains the state variables of the power system , the vector u contains the system inputs and $\dot{}$ compasses the derivatives of the state variables with respect to time. The equation relating the outputs to the inputs and state variables can be written as

$$y = g(x, u) \qquad (2.4)$$

The state concept may be illustrated by expressing the swing equation of a generator in per-unit torque as follows:

$$\frac{2H}{\omega_o}\frac{d^2\delta}{dt^2} = T_m - T_e - K_D\Delta\omega_r \qquad (2.5)$$

Where H is the inertia constant at the synchronous speed $\omega_o$ ($\omega_o$ in electrical radians/second), t is time in seconds, δ is the rotor angle in electrical radians, Tm and Te are the per-unit mechanical and electrical torque, respectively, $K_D$ is the damping coefficient on the rotor and $\Delta\omega_r$ is the per-unit speed deviation. Now, expressing (2.5) as two first-order differential equations yields

$$\frac{d\Delta\omega_r}{dt} = \frac{1}{2H}\left(T_m - T_e - K_D\Delta\omega_r\right) \qquad (2.6)$$

$$\frac{d\delta}{dt} = \omega_o\Delta\omega_r \qquad (2.7)$$

If the classical generator model is used and assumed to be connected to an infinite bus through a reactance $X_T$, the dependence of Te on δ can then be written as

$Te=K_T*\sin\delta$ (2.8)

With $K_T = E_{GT}E_B/X_T$, where $E_{GT}$ is the generator terminal voltage and $E_B$ the infinite bus voltage. It is seen that the derivatives of the state variables $\Delta\omega_r$ and δ depend on the latter along with the mechanical torque output Tm. In matrix form, (2.6) and (2.7) reduce to (2.2).

### 2.1.2. Linearization

For the general state space system, the linearization of (2.2) and (2.4) about the operating point $x_o$ and $u_o$ yields the linearized state space system given by

$$\Delta\dot{x} = A\Delta x + B\Delta u \qquad (2.9)$$

$$\Delta y = C\Delta x + D\Delta u \qquad (2.10)$$

Here, Δx is the n state vector increment, Δy is the m output vector increment, Δu is the r input vector increment, A is the n×n state matrix, B is the n×r input matrix, C is te m×n output matrix and D is the m×r feed-forward matrix. Specifically, $\Delta x = x - x_o$, $\Delta y = y - y_o$, and $\Delta u = u - u_o$.

As an example (2.6) and (2.7) are linearired about the operating point ($\delta_o$,$\omega_o$), yielding

$$\frac{d\Delta\omega_r}{dt} = \frac{1}{2H}\left(\Delta T_m - K_S\Delta\delta - K_D\Delta\omega_r\right) \qquad (2.11)$$

$$\frac{d\delta}{dt} = \omega_o\Delta\omega_r \qquad (2.12)$$

Where $K_S$ is the synchronizing torque coefficient.[4]

## 2.2 Eigenvalue and stability

First, the eigenvalues $\lambda_i$ are calculated for the **A**-matrix, which are the non-trivial solutions of the equation

$$\mathbf{A} \quad = \lambda\Phi \qquad (2.13)$$

Where Φ is an *nx1* vector, Rearranging (2.13) to solve for λ yields

$$\det(A-\lambda I)=0 \qquad (2.14)$$

The *n* solutions of (2.14) are the *eigenvalues* ($\lambda_1$, $\lambda_2$,…….$\lambda_n$) of the *nxn* matrix **A**. These eigenvalues may be real or complex, and are of the form σ±jω. If **A** is real, the complex eigenvalues always occur in conjugate pairs.

- A real Eigen value corresponds to a non-oscillatory mode. A negative real eigenvalue represents a decaying mode. The larger its magnitude, faster the decay will be. A positive real Eigen value represents aperiodic instability.
- Complex eigenvalues occur in conjugate pairs, and each pair corresponds to an oscillatory mode.

The real component of the eigenvalues gives the damping, and the imaginary component gives the frequency of oscillation. A negative real part represents a damped oscillation whereas a positive real part represents oscillation of increasing amplitude. Thus, for a complex pair of eigenvalues:

$$\lambda = \sigma \pm j\omega$$

The frequency of oscillation in Hz is given by

$$f = \frac{\omega}{2\pi}$$

This represents the actual or damped frequency. The damping ratio is given by

$$\zeta = \frac{-\sigma}{\sqrt{\sigma^2 + \omega^2}}$$

The damping ratio $\zeta$ determines the rate of decay of the amplitude of the oscillation. The time constant of amplitude decay is $1/|\sigma|$.

### 2.2.1 Mode Shape and Participation Factor

#### a.) Model matrices and eigenvectors

Given any eigenvalue $\lambda_i$, the n-column vector $\Phi_i$ which satisfies

$A\Phi_i=\lambda_i\Phi_i$ (i)

is called the right eigenvector of **A** associated with the eigenvalue $\lambda_i$. Quite similarly, the n-row vector $\Psi_i$ which satisfies

$\Psi_i A=\lambda_i\Psi_i$ (ii)

is called the left eigenvector associated with the eigenvalue $\lambda_i$. For convenience, it is assumed here that the eigenvectors are normalized so that

$\Psi_i\Phi_i=1$ (iii)

To continue the eigen analysis of the matrix A, the following model matrices are introduced:

$\Phi= [\Phi_1\ \Phi_2\ ........\Phi_n]$ (iv)

$\Psi= [\Psi_1^T\ \Psi_1^T........\Psi_n^T]^T$ (v)

The relationships (i) and (iii) can be written in a compact form as

$A\Phi=\Phi\Lambda$ (vi)

$\Psi\Phi=1$, yielding $\Psi=\Phi^{-1}$ (vii)

Once the oscillatory modes have been identified and the modal matrices constructed, an analysis is performed to find the specific rotor-angle modes. These modes provide the largest contribution to the low frequency oscillations.

#### b) Mode Shape

In the previous section, we discussed the system response in terms of the state vectors $\Delta x$ and z, which are related to each other as follows:

$\Delta x = \Phi z(t) = \left[\Phi_1\ \ \Phi_2\ .....\Phi_n\right] z(t)$ (a) And

$z(t) = \Psi\Delta x(t) = \left[\Psi_1^T\ \ \Psi_2^T\ \ ......\Psi_n^T\ \right]^T \Delta x(t)$ (b)

The variables $\Delta x_1, \Delta x_2, ......\Delta x_n$ are the original state variables chosen to represent the dynamic performance of the system. The variables $z_1, z_2, .......z_n$ are transformed state variables such that each variable is associated with only one mode. In other words, the transformed variables z is directly related to the modes. From Equation (a) we see that right eigenvector gives the mode shape, i.e., the relative activity of the state variables when a particular mode is excited. As seen from Equation (b), the left eigenvector $\psi_i$ identifies which combination of the original state variables displays only the ith mode. [34]

### c) Participation factor

One problem is using right and left eigenvectors individually the relationship between the states and the modes is that the elements of the eigenvectors are dependent on units and scaling associated with the state variables. As a solution to this problem, a matrix called the participation matrix (P), which combines the right and left eigenvectors as follows is proposed in reference [2] as a measure of the association between the state variables and the modes.

$$P = [p_1 \quad \mathrm{p}_2 \quad .... \quad \mathrm{p}_\mathrm{k}]$$

With

$$p_i = \begin{bmatrix} p_{1i} \\ p_{2i} \\ . \\ . \\ p_{ki} \end{bmatrix} \begin{bmatrix} \Phi_{1i}\Psi_{i1} \\ \Phi_{2i}\Psi_{i2} \\ . \\ . \\ \Phi_{ki}\Psi_{ik} \end{bmatrix}$$

Where

$\Phi_{ki}$ =the element on the kth row and the ith column of the modal matrix $\Phi$

= kth entry of the right eigenvector $\Phi_i$

$\Psi_{ik}$ = the element on the ith row and the kth column of the modal matrix $\Psi_i$

= kth entry of the right eigenvector $\psi_i$.

The element $p_{ki} = \Phi_{ki}\Psi_{ik}$ is termed the participation factor. It is a measure of relative participation of the kth state variable in the ith mode, and vice versa.

Since $\Phi_{ki}$ measures the activity of $x_k$ in the ith mode and $\Psi_{ik}$ weighs the contribution of this activity to the mode, the product $p_{ki}$ measures the net participation.

## 2.3 Excitation System

From the power system viewpoint, the excitation system should contribute to effective control of voltage and enhancement of system stability. It should be capable of responding rapidly to a disturbance so as to enhance transient stability, and of modulating the generator field so as to enhance small-scale stability. In this dissertation, excitation control has been assumed for the purpose of analysis. Fundamentally, simplest excitation system consists of an exciter only. The duty of an exciter is to provide necessary field current in rotor windings of alternator. When the excitation system also performs the task of maintaining the terminal voltage of alternator constant, under varying load conditions, it incorporates voltage regulator also. [1, 10, 14, 35]

Figure 2.1 shows the functional block diagram of a typical control system for a large synchronous generator. The following is a brief introduction of the various sub systems identified in the Figure.[34]

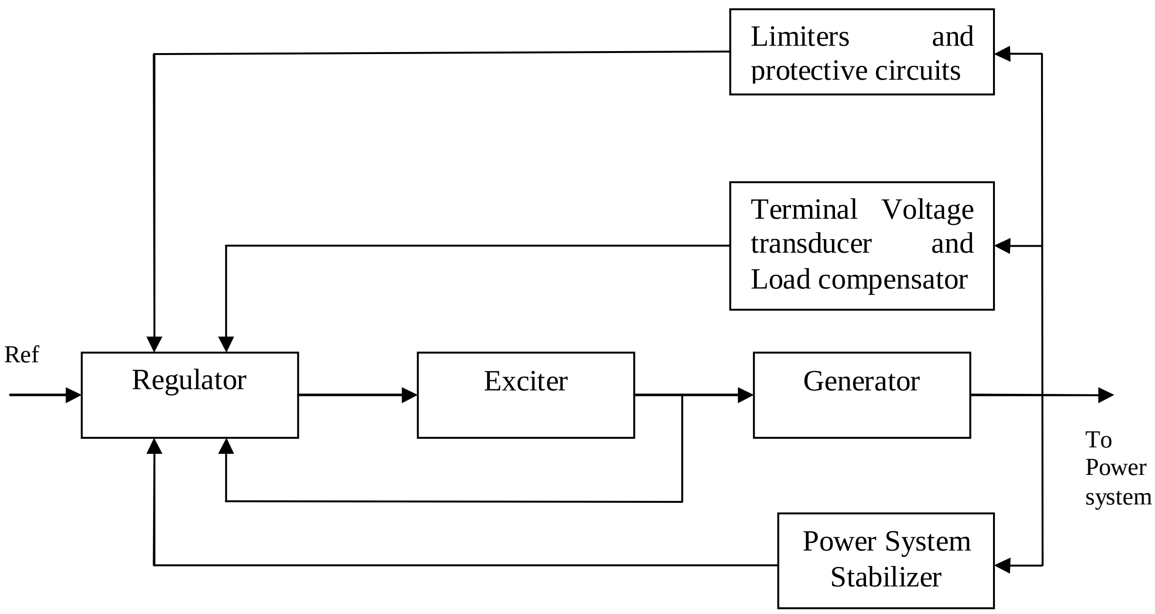



Figure2.1. Block diagram of a synchronous generator excitation system

1. Exciter: Provides dc power to the synchronous machine field winding, constituting the power angle of the excitation system.

2. Regulator: processes and amplifies input control signal to a level and form appropriate for control of the exciter

3. Terminal voltage transducer and load compensator: senses generator terminal voltage, rectifies and filters it to dc quantity, and compares it with a reference which represents the desired terminal voltage. In addition load compensation can be provided

4. Power system stabilizer: provides an additional input signal to the regulator to damp power system oscillation. Some commonly used input signals are rotor speed deviation, accelerating power and frequency deviation.

5. Limiter and protective circuits: these include a wide array of control and protective functions which ensure that the capability limits of exciter and generator are not exceeded. Common functions are field-current limiter, maximum excitation limiter, under excitation limiter etc.

Different types of excitation system are as below: -

a) DC Excitation System: - The system which utilize a direct current generator with a commutator as the source of excitation system power.

b) AC Excitation System: - The system which uses an alternator and either stationary or rotating rectifiers to produce direct current needed for generator field.

c) ST Excitation System: -The system in which excitation power is supplied through transformer and rectifiers.

Static Excitation System offers the ultimate response, which is virtually negligible, and ceiling voltage which are limited only by generator rotor design considerations. With the help of fast transient forcing of excitation and the boost of internal machine flux, the electrical output of the machine may be increased during the first swing compared to the results obtainable with a slow exciter.. The static excitation system utilizes transformers to transform voltage to an appropriate level. Rectifiers, either controlled or non-controlled, provide the necessary direct current for generator field.[1]

### 2.3.1 Power System Stabilizer

Beginning in late 1950's and early 1960's most of the new generating units added to electric utility system were equipped with continuously acting Voltage Regulator. As these units became a large percentage of generating units, it become apparent that voltage regulator i.e. VR action has a detrimental impact upon stability, perhaps more properly steady state stability of power system. Oscillations of small magnitude and low frequency often persisted for long periods of time and in some cases presented limitations on power transfer capability. Power system stabilizers (PSS) were developed to aid in damping these oscillations via modulations of excitation system of generators. The action of a PSS is to extend the angular stability limits of a power system by providing supplemental damping to the oscillation of synchronous machine rotors through the generator excitation. These oscillations of concern typically occur in 0.2 to 2.5 Hz and insufficient damping of these oscillations may limit the ability to transmit power. To provide damping, these stabilizers must produce a component of electrical torque on the rotor which is in phase with speed variations

This supplementary control is very beneficial during line outages and large power transfers. However, power system instabilities can arise in certain circumstances due to negative damping effects of the PSS on the rotor. The reason for this is that PSSs are tuned around a steady-state operating point; their damping effect is only valid for small excursions around this operating point. During severe disturbances, a PSS may actually cause the generator under its control to lose synchronism in an attempt to control its excitation field. [10,34,40]

The function of PSS is to sense shaft speed or frequency deviations, to condition the signal thus obtained and then feed it into the VR as supplementary input. It includes a reset stage, two lead-lag stages and a limiter. The circuit diagram of a typical power system stabilizer is shown here

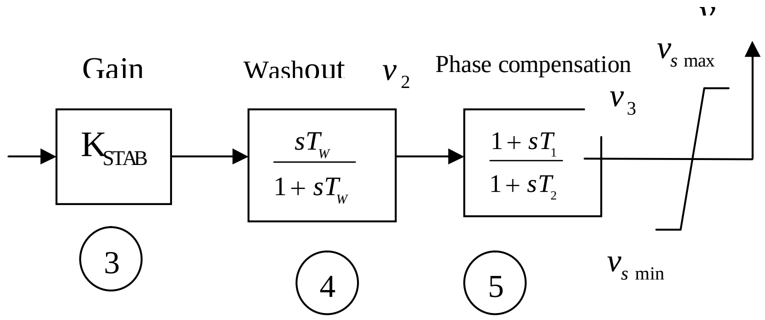



Figure. 2.2: Power System Stabilizer

| | | |
|---|---|---|
| $T_1$ | - | PSS Lead compensating time constant |
| $T_2$ | - | PSS Lag compensating time constant |
| $T_W$ | - | PSS Washout time constant |
| $K_{STAB}$ | - | PSS gain |
| $V_s$ | - | Stabilized output signal |

A “lead-lag” PSS structure is shown in Figure 2.2. The output signal of any PSS is a voltage signal here it is $V_s$.This particular controller structure contains a washout block, $sT_W/(1+sT_W)$, used to reduce the over-response of the damping during severe events. Since the PSS must produce a component of electrical torque in phase with the speed deviation, phase lead blocks circuits are used to compensate for the lag (hence, “lead-lag’) between the PSS output and the control action, the electrical torque. The number of lead-lag blocks needed depends on the particular system and the tuning of the PSS. The PSS gain $K_{STAB}$ is an important factor as the damping provided by the PSS increases in proportion to an increase in the gain up to a certain critical gain value, after which the damping begins to decrease. All of the variables of the PSS must be determined for each type of generator separately because of the dependence on the machine parameters. The power system dynamics also influence the PSS values. The determination of these values is performed by many different types of tuning methodologies. [12,19, 34]

The implementation details differ depending upon the stabilizer input signal employed.

#### 2.3.1.1 Input Signals

The input signal for the PSSs in the system is also a point of debate. The signals that have been identified as valuable include deviations in the rotor speed ($\Delta\omega$), the frequency ($\Delta f$), the electrical power ($\Delta Pe$) and the accelerating power ($\Delta Pa$). Since the main action of the PSS is to control the rotor oscillations, the input signal of rotor speed has been the most frequently advocated in the literature. Controllers based on speed deviation would ideally use a differential-type of regulation and a high gain. Since this is impractical in reality, the previously mentioned lead-lag structure is commonly used. However, one of the limitations of the speed input PSS is that it may excite torsional oscillatory modes.

A power/speed ($\Delta Pe$-$\Delta\omega$) PSS design was proposed as a solution to the torsional interaction problem suffered by the speed-input PSS. The power signal used is the generator electrical power, which has high torsional attenuation. Due to this, the gain of the PSS may be increased without the resultant loss of stability, which leads to greater oscillation damping. A frequency-input controller had been investigated as well. However, it had been found that frequency is highly sensitive to the strength of the transmission system that is, more sensitive when the system is weaker - which may offset the controller action on the electrical torque of the machine. Other limitations include the presence of sudden phase shifts following rapid transients and large signal noise induced by industrial loads. On the other hand, the frequency signal is more sensitive to inter-area oscillations than the speed signal and may to better oscillation attenuation.[33,41]

In this thesis work a speed signal is used as input signal.

#### 2.3.1.2 Control and Tuning

The conflicting requirements of local and inter-area mode damping and stability under both small signal and transient conditions have led to many different approaches for the control and tuning of PSSs. Methods investigated for the control and tuning include state-space/frequency domain techniques, residue compensation, phase compensation/root locus of a lead-lag controller, desensitization of a robust controller, pole-placement for a PID-type controller, sparsity techniques for a lead-lag controller and a strict linearization technique for a linear quadratic controller . The diversity of the approaches can be accounted for by the difficulty of satisfying the conflicting design goals, and each method having its own advantages and disadvantages. This is the crux of the problem of low frequency oscillation damping by the application of power system stabilizers.

#### 2.3.1.3 Conventional Stabilizers

The earlier stabilizer designs were based on concepts derived from classical control theory. Many such designs have been physically realized and widely used in actual systems. These controllers feedback suitably phase compensated signals derived from the power, speed and frequency of the operating generator either alone or in various combination as input signals so as to generate an additional rotor torque to damp out the low frequency oscillations. The gain and the required phase lead/lag of the stabilizers are `tuned' by using appropriate mathematical models, supplemented by a good understanding of the system operation. The principles of operation of this controller are based on the concepts of damping and synchronizing torques within the generator. A comprehensive analysis of these torques has been dealt with by demello and Concordia in their landmark paper in 1969 [10]. These controllers have been known to work quite well in the field and are extremely simple to implement. However, the tuning of these compensators continues to be a formidable task especially in large multi machine systems with multiple oscillatory modes. Larsen and Swann, in their three part paper, [12] describe in detail the general tuning procedure for this type of stabilizers.

#### 2.3.1.4 Limitations of Conventional Controllers

The main drawback of the above controllers is their lack of robustness. Power systems continually undergo changes in the load and generation patterns and in the transmission network. This results in an accompanying change in small signal dynamics of the system. The fixed parameter controllers, tuned for a particular operating condition, usually give good performance at that operating condition. Their performance, at other operating conditions, may at best be satisfactory, and may even become inadequate when extreme situations arise. So as the operating conditions and system configuration are constantly changing in actual power system the performance of the fixed parameter stabilizers cannot be always guaranteed.

## 2.4 Power System Model

The single machine infinite bus power system (SMIB) model used to evaluate the effect of PSS is shown in figure 2.3. The SMIB consists of a synchronous generator, an excitation system or exciter, a voltage transducer and a transmission line connected to an infinite bus. The model is built in MATLAB/SIMULINK environment [10, 44]. In fig 1 $V_{REF}$ is the reference voltage Δω is the speed deviation, $V_S$ is the PSS output signal, In the figure switch S1 is used to carry out tests on the power system with PSS1, PSS2, PSS3 and without PSS (with switch S1 in position 1, 2 , 3 and 4 respectively). [34]

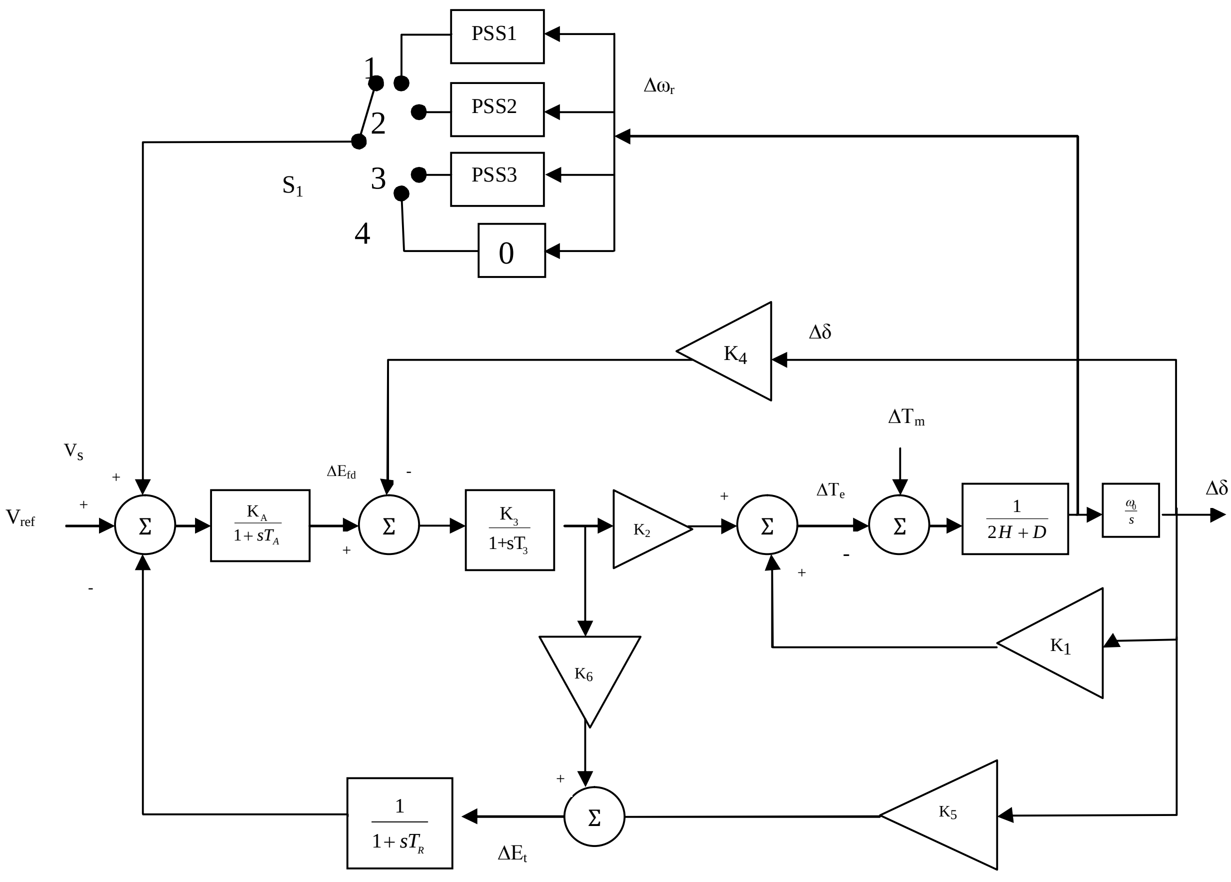



Figure-2.3 Power System Model

PSS1- conventional power system stabilizer

PSS2-adaptive neural network based controller

PSS3-fuzzy logic based controller

0-no controller

## 2.5 Mathematical Formulation of Problem

In this section governing equations of a system consisting of synchronous generator connected to infinite bus through a double circuit transmission line have been developed. A bus bar which maintains constant voltage and constant frequency irrespective of load variations on it is called infinite bus.[34]

lmodel of the system considered is shown in figure 2.4

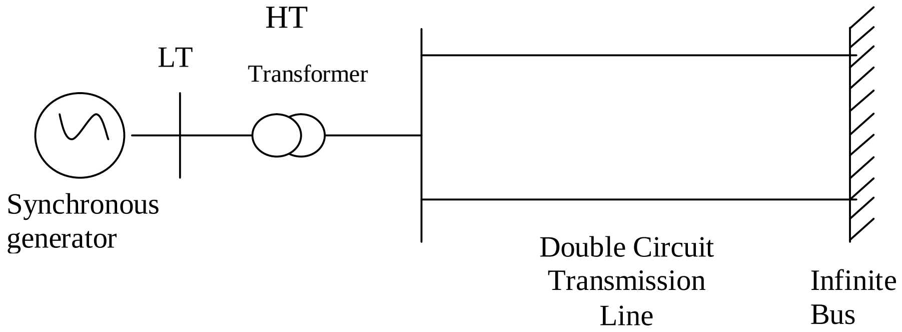



Figure-2.4 Single machine infinite bus system

**2.5.2 Synchronous machine representation:**

The following is a summary of the synchronous machine equations as a set of first order differential equations, with time t in seconds, rotor angle in electrical radians and all other quantities in per unit.

The system modeling is referred from [34],

Now for initial values computations

$$I_t = \frac{\sqrt{P_t^2 + Q_t^2}}{E_t}$$

$$\phi = \cos^{-1}\left(\frac{P_t}{E_t I_t}\right)$$

$$\delta_i = \tan^{-1}\left(\frac{L_{qs} I_t \cos\phi - R_a I_t \sin\phi}{E_t + R_a I_t \cos\phi + L_{qs} I_t sin\phi}\right)$$

With $\delta_i$ known, the d-q components of stator voltage and current are given by

$$e_{do} = E_t \sin\delta_i$$

$$e_{qo} = E_t \cos\delta_i$$

$$i_{do} = I_t \sin\left(\delta_i + \phi\right)$$

$$i_{qo} = I_t \cos\left(\delta_i + \phi\right)$$

$$E_{Bdo} = e_{do} - R_E i_{do} + X_E i_{qo}$$

$$E_{Bqo} = e_{qo} - R_E i_{qo} - X_E i_{do}$$

$$\delta_o = \tan^{-1}\left(\frac{E_{Bdo}}{E_{Bqo}}\right)$$

$$E_B = \sqrt{E_{Bdo}^2 + E_{Bqo}^2}$$

$$e_{fd} = R_{fd} i_{fd}$$

$$E_{fdo} = L_{adu} i_{fdo}$$

$$\psi_{ado} = L_{ads}\left(-i_{do} + i_{fdo}\right)$$

$$\psi_{aqo} = -L_{aqs} i_{qo}$$

$$\psi_{fd} = \left(L_{ad} + L_{fd}\right) i_{fd} - L_{ad} i_d$$

$$\psi_{1d} = L_{ad}\left(i_{fd} - i_d\right)$$

$$\psi_{1q} = \psi_{2q} = -L_{aq} i_q$$

$$T_e = P_t + R_a I_t^2$$

$$L_d^{'} = L_l + \frac{L_{ad} L_{fd}}{L_{ad} + L_{fd}}$$

$$L_d^{''} = L_l + \frac{L_{ad} L_{fd} L_{1d}}{L_{ad} L_{fd} + L_{ad} L_{1d} + L_{fd} L_{1d}}$$

$$R_{fd} = \frac{L_{ad} + L_{fd}}{T'_{do}} \text{ pu}$$

$$R_{1d} = \frac{1}{T''_{do}}\left(L_{1d} + \frac{L_{ad}L_{fd}}{L_{ad} + L_{fd}}\right) \text{ pu}$$

$$R_{1q} = \frac{L_{aq} + L_{1q}}{T'_{qo}}$$

$$R_{2q} = \frac{1}{T''_{qo}}\left(L_{2q} + \frac{L_{aq}L_{1q}}{L_{aq} + L_{1q}}\right)$$

$$L'_{q} = L_{l} + \frac{L_{aq}L_{1q}}{L_{aq} + L_{1q}}$$

$$L''_{q} = L_{l} + \frac{L_{aq}L_{1q}L_{2q}}{L_{aq}L_{1q} + L_{aq}L_{2q} + L_{1q}L_{2q}}$$

$$I_{fd} = L_{adu} i_{fd}$$

$$E_{fd} = \left( L_{adu} / R_{fd} \right) e_{fd}$$

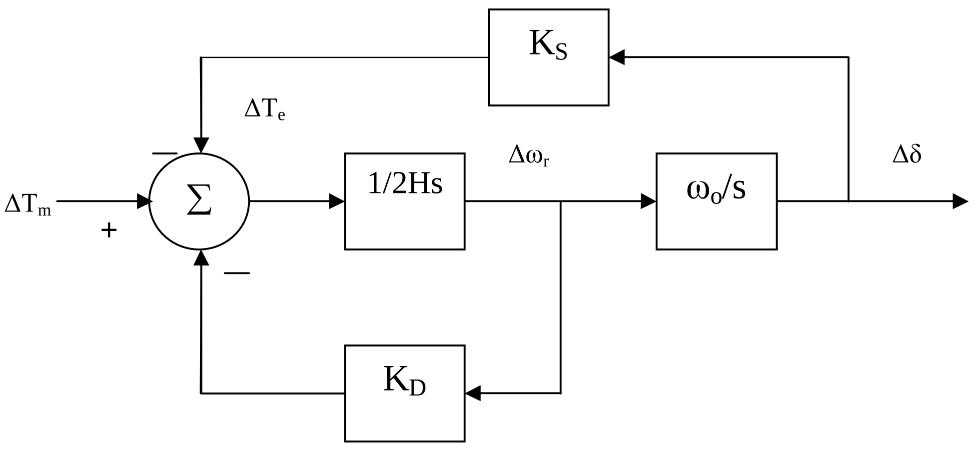



Figure-2.5 Block diagram of a single-machine infinite bus system with classical generator model

Equations of motion

$$p\Delta\omega_r = \frac{1}{2H}(T_m - T_e - K_D\Delta\omega_r) \qquad (2.15)$$

$$p\delta = \omega_0 \Delta\omega_r \qquad (2.16)$$

Where

$\omega_0 = 2\pi f_0$

$\Delta\omega_r$ =pu rotor speed deviation

P= derivative operator d/dt

### 2.5.2.1 Initial values of generator variables:

As noted earlier, the transient stability analysis involves algebraic equations with known initial values. Prefault power flow analysis provides the initial values of network variables, including the active and reactive power outputs and voltages at the generator terminals.

### 2.5.2.2 Classical generator model and infinite bus

For a machine represented by the classical model, $X_{RI} = X_{IR} = X_d^{'}$ and E" is replaced by E'. The rotor angle $\delta$ is the angle by which E' leads R-axis. The magnitude of E' is constant throughout the solution. The R and I components of E' change with $\delta$, as determined by the solution of the swing equation. For a node associated with an infinite bus, both the magnitude and angle of the node voltage remain constant.

### 2.5.2.3 Rotor circuit equations

With rotor currents expressed in terms of rotor and mutual flux linkages, the rotor circuit dynamic equations are:

$$p\psi_{fd} = \omega_0 \left[ e_{fd} + \frac{(\psi_{ad} - \psi_{fd})R_{fd}}{L_{fd}} \right] \qquad (2.17) \quad \text{Here } e_{fd} = \frac{R_{fd}}{L_{adu}} E_{fd}$$

$$p\psi_{1d} = \omega_0 \left( \frac{\psi_{ad} - \psi_{1d}}{L_{1d}} \right) R_{1d} \qquad (2.17.1)$$

$$p\psi_{1q} = \omega_0 \left( \frac{\psi_{aq} - \psi_{1q}}{L_{1q}} \right) R_{1q} \qquad (2.17.2)$$

$$p\psi_{2q} = \omega_0 \left( \frac{\psi_{aq} - \psi_{2q}}{L_{2q}} \right) R_{2q} \qquad (2.17.3)$$

The d- and q-axis mutual flux linkages are given by

$$\psi_{ad} = -L_{ads} i_d + L_{ads} i_{fd} + L_{ads} i_{1d}$$

$$= L''_{ads} \left( -i_d + \frac{\psi_{fd}}{L_{fd}} + \frac{\psi_{1d}}{L_{1d}} \right) \qquad (2.18)$$

$$\psi_{aq} = L''_{aqs} \left( -i_q + \frac{\psi_{1q}}{L_{1q}} + \frac{\psi_{2q}}{L_{2q}} \right) \qquad (2.19)$$

Where

$$L''_{ads} = \frac{1}{\frac{1}{L_{ads}} + \frac{1}{L_{fd}} + \frac{1}{L_{1d}}}$$

$$L''_{aqs} = \frac{1}{\frac{1}{L_{aqs}} + \frac{1}{L_{1q}} + \frac{1}{L_{2q}}}$$

Here $L_{ads}$ and $L_{ags}$ are saturated values of the d- and q-axis mutual inductances given by:

$$L_{ads} = K_{sd} L_{adu}$$

$$L_{aqs} = K_{sq} L_{aqu}$$

And $K_{sd}$ and $K_{sq}$ are computed as function of the air gap flux linkage $\psi_{at}$.

$$e_d = -R_a i_d - \psi_q = -R_a i_d + (L_l i_q - \psi_{aq}) \text{........}(i)$$

$$e_q = -R_a i_q + \psi_d = -R_a i_q + (L_l i_d - \psi_{ad}) \text{........}(ii)$$

*resolving* $E_t$ into d-q components gives

$$e_d = R_E i_d - X_E i_q + E_{Bd} \qquad \text{(iii)}$$

$$e_q = R_E i_q + X_E i_d + E_{Bq} \qquad \text{(iv)}$$

$$E_{Bd} = E_B \sin\delta \qquad \text{(v)}$$

$$E_{Bq} = E_B \cos\delta \qquad \text{(vi)}$$

Using equations i-vi and equations 2.18 & 2.19, we get $i_d$ & $i_q$ as follows

$$i_d = \frac{X_{Tq} E_{qg} - R_T E_{dg}}{F} \qquad (2.20)$$

$$i_q = \frac{R_T E_{qg} + X_{Tq} E_{dg}}{F} \qquad (2.21)$$

Here

$$E_{dg} = \varpi L''_{aqs} \left( \frac{\psi_{1q}}{L_{1q}} + \frac{\psi_{2q}}{L_{2q}} \right) + E_B \sin\delta$$

$$E_{qg} = \varpi L''_{ads} \left( \frac{\psi_{fd}}{L_{fd}} + \frac{\psi_{1d}}{L_{1d}} \right) - E_B \cos\delta$$

$$X_{Td} = X_E + L''_{ads} + L_l$$

$$X_{Tq} = X_E + L''_{aqs} + L_l$$

$$R_T = R_a + R_E$$

$$F = R_T^{\,2} + X_{Td} X_{Tq}$$

Expressing equations (2.20) &(2.21) in incremental values

$$\Delta i_d = m_1 \Delta\delta + m_2 \Delta\psi_{fd} + m_3 \Delta\psi_{1d} + m_4 \Delta\psi_{1q} + m_5 \Delta\psi_{2q}$$

$$(2.23)$$

$$\Delta i_q = n_1 \Delta\delta + n_2 \Delta\psi_{fd} + n_3 \Delta\psi_{1d} + n_4 \Delta\psi_{1q} + n_5 \Delta\psi_{2q}$$

Where $m_1 = \frac{E_B}{F} \left( X_{Tq} \sin\delta_o - R_T \cos\delta_o \right)$

$$m_2 = \frac{X_{Tq}}{F}\frac{L_{ads}^{''}}{L_{fd}}$$

$$m_3 = \frac{X_{Tq}}{F}\frac{L_{ads}^{''}}{L_{1d}} \qquad (2.23.1)$$

$$m_4 = -\frac{R_T}{F}\frac{L_{aqs}^{''}}{L_{1q}}$$

$$m_5 = -\frac{R_T}{F}\frac{L_{aqs}^{''}}{L_{2q}}$$

$$n_1 = \frac{E_B}{F}\left(R_T \sin\delta_o + X_{Td}\cos\delta_o\right)$$

$$n_2 = \frac{R_T}{F}\frac{L_{ads}^{''}}{L_{fd}}$$

$$n_3 = \frac{R_T}{F}\frac{L_{ads}^{''}}{L_{1d}} \qquad (2.23.2)$$

$$n_4 = -\frac{X_{Td}}{F}\frac{L_{aqs}^{''}}{L_{1q}}$$

$$n_5 = -\frac{X_{Td}}{F}\frac{L_{aqs}^{''}}{L_{2q}}$$

$$\Delta\psi_{ad} = L_{ads}^{''}\left(-\Delta i_d + \frac{\Delta\psi_{fd}}{L_{fd}} + \frac{\Delta\psi_{1d}}{L_{1d}}\right)$$

$$= \left(\text{-m}_1 L_{ads}^{''}\right)\Delta\delta + L_{ads}^{''}\left(\frac{1}{L_{fd}} - m_2\right)\Delta\psi_{fd} + L_{ads}^{''}\left(\frac{1}{L_{1d}} - m_3\right)\Delta\psi_{1d} + \left(\text{-m}_4 L_{ads}^{''}\right)\Delta\psi_{1q} + \left(\text{-m}_5 L_{ads}^{''}\right)\Delta\psi_{2q} \qquad (2.24)$$

$$\Delta\psi_{aq} = L_{aqs}^{''}\left(-\Delta i_q + \frac{\Delta\psi_{1q}}{L_{1q}} + \frac{\Delta\psi_{2q}}{L_{2q}}\right)$$

$$= \left(\text{-n}_1 L_{aqs}^{''}\right)\Delta\delta + \left(\text{-n}_2 L_{aqs}^{''}\right)\Delta\psi_{fd} + \left(\text{-n}_3 L_{aqs}^{''}\right)\Delta\psi_{1d} + L_{aqs}^{''}\left(\frac{1}{L_{1q}} - n_4\right)\Delta\psi_{1q} + L_{aqs}^{''}\left(\frac{1}{L_{2q}} - n_5\right)\Delta\psi_{2q} \qquad (2.24.1)$$

The air gap torque required for the solution of the swing equation is

$$T_e = \psi_d i_q - \psi_q i_d$$

$$= \psi_{ad} i_q - \psi_{aq} i_d \qquad (2.25)$$

Linearized form of equation (2.25)

$$\Delta T_e = \psi_{ado}\Delta i_q + i_{qo}\Delta\psi_{ad} - \psi_{aqo}\Delta i_d - i_{do}\Delta\psi_{aq} \qquad (2.26)$$

Substituting the values of $\Psi_{ad}$,$\Psi_{aq}$,$\Delta i_d$,$\Delta i_q$ from equations (2.18) ,(2.19) and (2.23) in eq (2.26), we get

$$\Delta T_e = K_1\Delta\delta + K_2\Delta\psi_{fd} + K_{21}\Delta\psi_{1d} + K_{22}\Delta\psi_{1q} + K_{23}\Delta\psi_{2q} \qquad (2.27)$$

Where

$$K_1 = n_1\left(\psi_{ado} + L''_{aqs}i_{do}\right) - m_1\left(\psi_{aqo} + L''_{ads}i_{qo}\right)$$

$$K_2 = n_2\left(\psi_{ado} + L''_{aqs}i_{do}\right) - m_2\left(\psi_{aqo} + L''_{ads}i_{qo}\right) + \frac{L''_{ads}}{L_{fd}}i_{qo}$$

$$K_{21} = n_3\left(\psi_{ado} + L''_{aqs}i_{do}\right) - m_3\left(\psi_{aqo} + L''_{ads}i_{qo}\right) + \frac{L''_{ads}}{L_{1d}}i_{qo} \qquad (2.28)$$

$$K_{22} = n_4\left(\psi_{ado} + L''_{aqs}i_{do}\right) - m_4\left(\psi_{aqo} + L''_{ads}i_{qo}\right) - \frac{L''_{aqs}}{L_{1q}}i_{do}$$

$$K_{23} = n_5\left(\psi_{ado} + L''_{aqs}i_{do}\right) - m_5\left(\psi_{aqo} + L''_{ads}i_{qo}\right) - \frac{L''_{aqs}}{L_{2q}}i_{do}$$

From equations (2.15) & (2.28)

$$p\Delta\omega_r = \frac{1}{2H}(\Delta T_m - \Delta T_e - K_D\Delta\omega_r)$$

$$= \frac{1}{2H}(\Delta T_m - K_1\Delta\delta - K_2\Delta\psi_{fd} - K_{21}\Delta\psi_{1d} - K_{22}\Delta\psi_{1q} - K_{23}\Delta\psi_{2q} - K_D\Delta\omega_r) \qquad (2.29)$$

$$= a_{11}\Delta\omega_r + a_{12}\Delta\delta + a_{13}\Delta\psi_{fd} + a_{14}\Delta\psi_{1d} + a_{15}\Delta\psi_{1q} + a_{16}\Delta\psi_{2q} + b_{11}\Delta T_m$$

Where

$$a_{11} = -\frac{K_D}{2H} \qquad a_{12} = -\frac{K_1}{2H}$$
$$a_{13} = -\frac{K_2}{2H} \qquad a_{14} = -\frac{K_{21}}{2H} \qquad (2.30)$$
$$a_{15} = -\frac{K_{22}}{2H} \qquad a_{16} = -\frac{K_{23}}{2H}$$
$$b_{11} = \frac{1}{2H}$$

From equation (2.16), in terms of incremental values

$$p\Delta\delta = a_{21}\Delta\omega_r$$
$$where\ a_{21} = \omega_o = 2\pi f_o \qquad (2.31)$$

From equations (2.17), & (2.23)

$$p\Delta\psi_{fd} = a_{31}\Delta\omega_r + a_{32}\Delta\delta + a_{33}\Delta\psi_{fd} + a_{34}\Delta\psi_{1d} + a_{35}\Delta\psi_{1q} + a_{36}\Delta\psi_{2q} + b_{32}\Delta E_{fd}$$

(2.32)

*where*

$$a_{31} = 0$$

$$a_{32} = -\frac{\omega_0 R_{fd}}{L_{fd}} \mathrm{m}_1 L''_{ads} \qquad a_{33} = -\frac{\omega_0 R_{fd}}{L_{fd}} \left( 1 - \frac{L''_{ads}}{L_{fd}} + \mathrm{m}_2 L''_{ads} \right) \quad (2.33)$$

$$a_{34} = -\frac{\omega_0 R_{fd}}{L_{fd}} \left( \mathrm{m}_3 L''_{ads} - \frac{L''_{ads}}{L_{fd}} \right) \qquad a_{35} = -\frac{\omega_0 R_{fd}}{L_{fd}} \mathrm{m}_4 L''_{ads}$$

$$a_{36} = -\frac{\omega_0 R_{fd}}{L_{fd}} \mathrm{m}_5 L''_{ads} \qquad \mathrm{b}_{32} = \frac{R_{fd}\omega_0}{L_{adu}}$$

$$p\Delta\psi_{1d} = -\omega_o R_{1d} \Delta i_{id}$$

$$= a_{41}\Delta\omega_r + a_{42}\Delta\delta + a_{43}\Delta\psi_{fd} + a_{44}\Delta\psi_{1d} + a_{45}\Delta\psi_{1q} + a_{46}\Delta\psi_{2q} \quad (2.34)$$

*where*

$$a_{41} = 0 \qquad a_{42} = -\frac{\omega_0 R_{1d}}{L_{1d}} \mathrm{m}_1 L''_{ads}$$

$$a_{43} = -\frac{\omega_0 R_{1d}}{L_{1d}} \left( \mathrm{m}_2 L''_{ads} - \frac{L''_{ads}}{L_{fd}} \right) \qquad a_{44} = -\frac{\omega_0 R_{1d}}{L_{1d}} \left( 1 - \frac{L''_{ads}}{L_{fd}} + \mathrm{m}_3 L''_{ads} \right) \quad (2.35)$$

$$a_{45} = -\frac{\omega_0 R_{1d}}{L_{1d}} \mathrm{m}_4 L''_{ads} \qquad a_{46} = -\frac{\omega_0 R_{1d}}{L_{1d}} \mathrm{m}_5 L''_{ads}$$

Similarly

$$p\Delta\psi_{1q} = -\omega_o R_{1q} \Delta i_{1q}$$

$$= a_{51}\Delta\omega_r + a_{52}\Delta\delta + a_{53}\Delta\psi_{fd} + a_{54}\Delta\psi_{1d} + a_{55}\Delta\psi_{1q} + a_{56}\Delta\psi_{2q} \quad (2.36)$$

*where*

$$a_{51} = 0 \qquad a_{52} = -\frac{\omega_0 R_{1q}}{L_{1q}} n_1 L''_{aqs}$$

$$a_{53} = -\frac{\omega_0 R_{1q}}{L_{1q}} n_2 L''_{aqs} \qquad a_{54} = -\frac{\omega_0 R_{1q}}{L_{1q}} n_3 L''_{aqs} \quad (2.37)$$

$$a_{55} = -\frac{\omega_0 R_{1q}}{L_{1q}} \left( 1 - \frac{L''_{aqs}}{L_{1q}} + n_4 L''_{aqs} \right) \qquad a_{56} = -\frac{\omega_0 R_{1q}}{L_{1q}} \left( n_5 L''_{aqs} - \frac{L''_{aqs}}{L_{2q}} \right)$$

$$p\Delta\psi_{2q} = -\omega_o R_{2q} \Delta i_{2q}$$

$$= a_{61}\Delta\omega_r + a_{62}\Delta\delta + a_{63}\Delta\psi_{fd} + a_{64}\Delta\psi_{1d} + a_{65}\Delta\psi_{1q} + a_{66}\Delta\psi_{2q} \quad (2.38)$$

*where*

$$a_{61} = 0 \qquad a_{62} = -\frac{\omega_0 R_{2q}}{L_{2q}} n_1 L''_{aqs}$$

$$a_{63} = -\frac{\omega_0 R_{2q}}{L_{2q}} n_2 L''_{aqs} \qquad a_{64} = -\frac{\omega_0 R_{2q}}{L_{2q}} n_3 L''_{aqs} \tag{2.39}$$

$$a_{65} = -\frac{\omega_0 R_{2q}}{L_{2q}} \left( n_4 L''_{aqs} - \frac{L''_{aqs}}{L_{2q}} \right) \qquad a_{66} = -\frac{\omega_0 R_{2q}}{L_{2q}} \left( 1 - \frac{L''_{aqs}}{L_{2q}} + n_5 L''_{aqs} \right)$$

### 2.5.2.4 Effects of excitation system

The input control signal to the excitation system is normally the generator terminal voltage $E_t$. Considering the standard generator model, $E_t$ is not a state variable. Therefore, $E_t$ has to be expressed in terms of the state variables $\Delta\omega_r$, $\Delta\delta$ and $\Delta\psi_{fd}$.

If AVR action is to be represented, we need the expression for $\Delta E_t$, which is calculated as follows:

$E_t$ can be expressed as

$$E_t = e_d + je_q$$

*hence* $E_t^2 = e_d^2 + e_q^2$

*applying a* small perturbation,

$$\left(E_{to} + \Delta E_t\right)^2 = \left(e_{do} + \Delta e_d\right)^2 + \left(e_{qo} + \Delta e_q\right)^2$$

*by* neglecting second order terms

$$E_{to}\Delta E_t = e_{do}\Delta e_d + e_{qo}\Delta e_q$$

$$\therefore \Delta E_t = \frac{e_{do}}{E_{to}}\Delta e_d + \frac{e_{qo}}{E_{to}}\Delta e_q \tag{2.40}$$

The stator voltage equations are

$$\Delta e_d = -R_a \Delta i_d + L_l \Delta i_q - \Delta\psi_{aq}$$

$$\Delta e_q = -R_a \Delta i_q - L_l \Delta i_d + \Delta\psi_{ad} \tag{2.41}$$

By using equation 2.22, 2.23& 2.23.1, $\Delta E_t$ can be expressed as

$$\Delta E_t = K_5 \Delta\delta + K_6 \Delta\psi_{fd} + K_{61}\Delta\psi_{1d} + K_{62}\Delta\psi_{1q} + k_{63}\Delta\psi_{2q} \tag{2.42}$$

Where the values of $K_5$, $K_6$, $K_{61}$, $K_{62}$, $K_{63}$ are obtained as follows:

$$K_5 = \frac{e_{do}}{E_{to}}\left(-m_1 R_a + n_1 L_l + n_1 L''_{aqs}\right) + \frac{e_{qo}}{E_{to}}\left(-n_1 R_a - m_1 L_l + m_1 L''_{ads}\right)$$

$$K_6 = \frac{e_{do}}{E_{to}}\left(-m_2 R_a + n_2 L_l + n_2 L''_{aqs}\right) + \frac{e_{qo}}{E_{to}}\left(-n_2 R_a - m_2 L_l + L''_{ads}\left(\frac{1}{L_{fd}} - m_2\right)\right)$$

$$K_{61} = \frac{e_{do}}{E_{to}}\left(-m_3 R_a + n_3 L_l + n_3 L''_{aqs}\right) + \frac{e_{qo}}{E_{to}}\left(-n_3 R_a - m_3 L_l + L''_{ads}\left(\frac{1}{L_{1d}} - m_3\right)\right)$$

$$K_{62} = \frac{e_{do}}{E_{to}}\left(-m_4 R_a + n_4 L_l - L''_{aqs}\left(\frac{1}{L_{1q}} - n_4\right)\right) + \frac{e_{qo}}{E_{to}}\left(-n_4 R_a - m_4 L_l - m_4 L''_{ads}\right)$$

$$K_{62} = \frac{e_{do}}{E_{to}}\left(-m_5 R_a + n_5 L_l - L''_{aqs}\left(\frac{1}{L_{2q}} - n_5\right)\right) + \frac{e_{qo}}{E_{to}}\left(-n_5 R_a - m_5 L_l - m_5 L''_{ads}\right) \qquad (2.43)$$

### 2.5.2.5 Excitation System Representation

Here illustrated the method of incorporating Models for different types of excitation systems into a small scale stability program by considering the excitation system model shown in figure. It represents a bus-fed thyristor excitation system with an automatic voltage regulator (AVR) and a power system stabilizer (PSS). A high exciter gain ($K_A$) without transient gain reduction or derivative feedback is used.

#### 2.5.2.5.1 Excitation system model

The model shown in figure is representative of thyristor excitation system classified as type ST1A. The model shown in figure 2.6, is the simplified model, it includes only those elements which are necessary for the representation of a specific system. A high exciter gain, without transient gain reduction or derivative feedback is used. Parameter $T_R$ represents the terminal voltage transducer time constant.

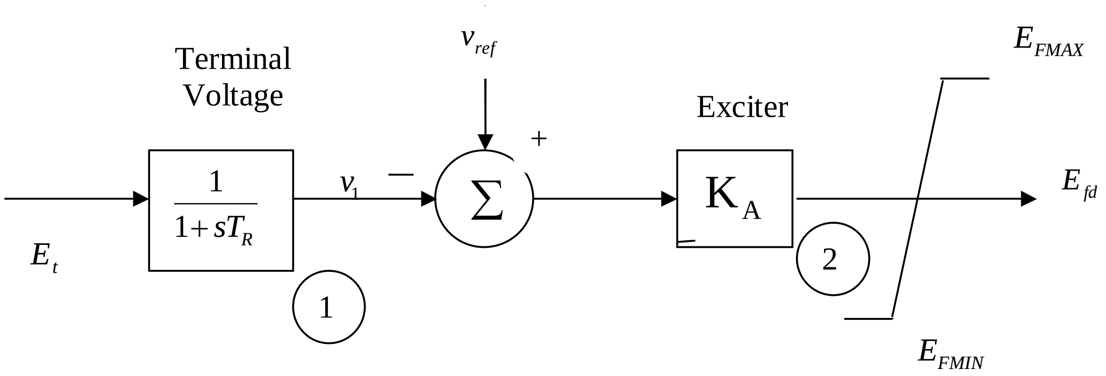



Figure-2.6 Thyristor excitation system with AVR

For a bus-fed (potential source) thyristor exciter, the voltages vary with the generator terminal voltage ($E_t$) and exciter output current ($I_{fd}$):

$$E_{F\max} = V_{R\max} E_t - K_c I_{fd}$$

$$E_{F\min} = V_{R\min} E_t$$

From block 1 of figure, we may write

$$pv_1 = \frac{1}{T_R}(E_t - v_1)$$

Using perturbed values

$$p\Delta v_1 = \frac{1}{T_R}(\Delta E_t - \Delta v_1)$$

*Substituting* for $\Delta E_t$ from equation (2.39), we get

$$p\Delta v_1 = \frac{1}{T_R}(K_5 \Delta\delta + K_6 \Delta\psi_{fd} + K_{61}\Delta\psi_{1d} + K_{62}\Delta\psi_{1q} + k_{63}\Delta\psi_{2q} - \Delta v_1) \qquad (2.44)$$

from block 2 of figure

$$\Delta E_{fd} = K_A (v_{ref} - v_1)$$

*or*

$$\Delta E_{fd} = K_A(-\Delta v_1) \qquad (2.45)$$

The field circuit dynamic equation developed in equation 2.31, with the effect of excitation system included, becomes

$$p\Delta\psi_{fd} = a_{31}\Delta\omega_r + a_{32}\Delta\delta + a_{33}\Delta\psi_{fd} + a_{34}\Delta\psi_{1d} + a_{35}\Delta\psi_{1q} + a_{36}\Delta\psi_{2q} + a_{37}\Delta v_1 \qquad (2.46)$$

*here* $a_{37} = -b_{32}K_A = -\dfrac{\omega_o R_{fd}}{L_{adu}}K_A$ (2.47)

the expressions for $a_{31}, a_{32}, a_{33}, a_{34}, a_{35}, a_{36}$ will remain unchanged since we have a

first-order model for the exciter, the order of the overall system equation will be

incresed by 1, the new state variable added is $\Delta v_1$ from equation (2.46)

$$p\Delta v_1 = a_{71}\Delta\omega_r + a_{72}\Delta\delta + a_{73}\Delta\psi_{fd} + a_{74}\Delta\psi_{1d} + a_{75}\Delta\psi_{1q} + a_{76}\Delta\psi_{2q} + a_{77}\Delta v_1 \qquad (2.48)$$

where

$a_{71} = 0$

$a_{72} = \dfrac{K_5}{T_R}$ ; $a_{73} = \dfrac{K_6}{T_R}$ ; $a_{74} = \dfrac{K_{61}}{T_R}$ ; $a_{75} = \dfrac{K_{62}}{T_R}$

$a_{76} = \dfrac{K_{63}}{T_R}$ ; $a_{77} = -\dfrac{1}{T_R}$

### 2.5.2.6. Effect of power system stabilizer on the system state matrix

Since the purpose of a PSS is to introduce a damping torque component, a logical signal to use for controlling generator excitation is speed deviation $\Delta\omega_r$. If the exciter's transfer function $G_{ex}(s)$ and the generator excitation function between $\Delta E_{fd}$ and $\Delta T_e$ were pure gains, a direct feedback of $\Delta\omega_r$ would result in a damping torque component. However, in practice both the generator and the exciter exhibit frequency dependent gain and phase characteristics. Therefore, the PSS transfer function, $G_{PSS}(s)$, should have appropriate phase compensation circuits to compensate for the phase lag between the exciter input and the electrical torque. In the ideal case, with the phase characteristics of $G_{PSS}(s)$ being an exact inverse of the exciter and generator phase characteristics to be compensated, the PSS would result in a pure damping torque at all frequencies.[10,11, 12,34]

If the phase-lead network provides more compensation than the phase lag between $\Delta T_e$ and $\Delta v_s$, the PSS introduces, in addition to a damping component of torque, a negative synchronising torque component. Whereas with under compensation a positive synchronising torque component is introduced. Usually, the PSS is required to contribute to the damping of rotor oscillations over a range of frequencies, rather than a single frequency.

Here illustrated the basic structure, modelling and performance of PSS by considering a thyristor excitation system, Figure 2.7 shows block diagram of the excitation system, including the AVR and PSS. As we are concerned with transient performance, stabilizer output limits and exciter output limit are also shown. The limits are non wind up limits.

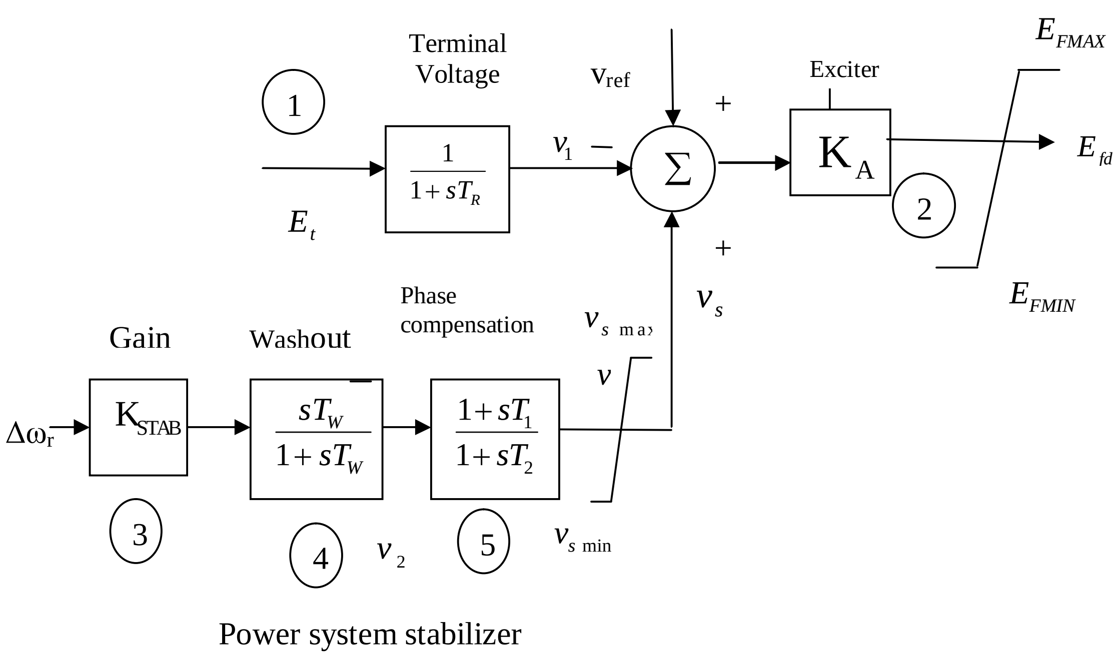



Figure-2.7 Thyristor excitation system with AVR and PSS

The PSS representation in figure 2.7consists of three blocks: a phase compensation block, a signal washout block and a gain block.

The phase compensation block 5 provides the appropriate phase-lead characteristics to compensate for the phase lag between the exciter input and the generator electrical torque. The figure shows a single first order block, in practice, two or more first order blocks may be used to achieve the desired phase compensation. In some cases, second order blocks with complex roots have been used. Generally some under compensation is desirable so that the PSS, in addition to significantly increasing the damping torque, results in a slight increase of the synchronising torque.

The signal washout block 4 serves as a high- pass filter, with the time constant $T_W$ high enough to allow signals associated with oscillations in $\omega_r$ to pass unchanged. Without it, steady changes in speed would modify the terminal voltage. It allows the PSS to respond only to changes in speed. It critically ranges from 1 to 20 secs. The main consideration is that it should be long enough to pass stabilizing signals at the frequencies of interest unchanged, but not so long that it leads to undesirable generator voltage excursions during system- islanding conditions.

The stabilizer gain (block 3) $K_{STAB}$ determines the amount of damping introduced by the PSS. Ideally, the gain should be set at a value corresponding to maximum damping. However, it is often limited by other considerations.

### 2.5.2.7 System state matrix including PSS

From block 4 of figure, using perturbed values, we have

$$p\Delta v_2 = K_{STAB} p\Delta\omega_r - \frac{1}{T_W}\Delta v_2$$

Substituting for $p\Delta\omega_r$ from equation (2.28) we get

$$p\Delta v_2 = K_{STAB}\left(a_{11}\Delta\omega_r + a_{12}\Delta\delta + a_{13}\Delta\psi_{fd} + a_{14}\Delta\psi_{1d} + a_{15}\Delta\psi_{1q} + a_{16}\Delta\psi_{2q} + b_{11}\Delta T_m\right) - \frac{1}{T_W}\Delta v_2$$

$$= a_{81}\Delta\omega_r + a_{82}\Delta\delta + a_{83}\Delta\psi_{fd} + a_{84}\Delta\psi_{1d} + a_{85}\Delta\psi_{1q} + a_{86}\Delta\psi_{2q} + a_{88}\Delta v_2 + K_{STAB} b_{11}\Delta T_m$$

(2.49)

$a_{81} = K_{STAB} a_{11}$ $\qquad$ $a_{85} = K_{STAB} a_{15}$

$a_{82} = K_{STAB} a_{12}$ $\qquad$ $a_{86} = K_{STAB} a_{16}$

$a_{83} = K_{STAB} a_{13}$ $\qquad$ $a_{87} = 0$

$a_{84} = K_{STAB} a_{14}$ $\qquad$ $a_{88} = -\frac{1}{T_W}$

$a_{89} = 0$ $\qquad$ $b_{81} = \frac{K_{STAB}}{2H}$

Now from block 5,

$$\frac{v_3}{v_2} = \frac{1+sT_1}{1+sT_2}$$

$$\Delta v_s = \Delta v_3 = \Delta v_2 \left( \frac{1+pT_1}{1+pT_2} \right)$$

$$p\Delta v_s = \frac{T_1}{T_2} p\Delta v_2 + \frac{1}{T_2}\Delta v_2 - \frac{1}{T_2}\Delta v_s$$

Now substituting value of $p\Delta v_2$ from equation (2.49)

$$p\Delta v_s = \frac{T_1}{T_2}\left( a_{81}\Delta\omega_r + a_{82}\Delta\delta + a_{83}\Delta\psi_{fd} + a_{84}\Delta\psi_{1d} + a_{85}\Delta\psi_{1q} + a_{86}\Delta\psi_{2q} + a_{88}\Delta v_2 \right)$$

$$+ \mathrm{K_{STAB}} b_{11}\Delta T_m + \frac{1}{T_2}\Delta v_2 - \frac{1}{T_2}\Delta v_s$$

$$p\Delta v_s = a_{91}\Delta\omega_r + a_{92}\Delta\delta + a_{93}\Delta\psi_{fd} + a_{94}\Delta\psi_{1d} + a_{95}\Delta\psi_{1q} + a_{96}\Delta\psi_{2q} + a_{98}\Delta v_2$$

$$+ a_{99}\Delta v_s + \mathrm{b}_{91}\Delta T_M \qquad (2.50)$$

where

$$a_{91} = \frac{T_1}{T_2} a_{81} \qquad a_{92} = \frac{T_1}{T_2} a_{82}$$

$$a_{93} = \frac{T_1}{T_2} a_{83} \qquad a_{94} = \frac{T_1}{T_2} a_{84}$$

$$a_{95} = \frac{T_1}{T_2} a_{85} \qquad a_{96} = \frac{T_1}{T_2} a_{86}$$

$$a_{97} = 0 \qquad a_{98} = \frac{T_1}{T_2} a_{88} + \frac{1}{T_2}$$

$$a_{99} = -\frac{1}{T_2} \qquad \mathrm{b}_{91} = \frac{T_1}{T_2} b_{81}$$

Now $v_s = v_3$

With

$$v_{s\max} \geq v_s \geq v_{s\min}$$

From block 2, the exciter output voltage is

$$E_{fd} = K_A \left[ V_{ref} - v_1 + v_s \right]$$

With

$$E_{F\max} \geq E_{fd} \geq E_{F\min}$$

Both limits considered here are windup limits.

$$\Delta E_{fd} = K_A \left[ \Delta v_s - \Delta v_1 \right]$$

the field circuit equation, with PSS included, becomes

$$p\Delta \psi_{fd} = a_{31}\Delta\omega_r + a_{32}\Delta\delta + a_{33}\Delta\psi_{fd} + a_{34}\Delta\psi_{1d} + a_{35}\Delta\psi_{1q} + a_{36}\Delta\psi_{2q} + a_{37}\Delta v_1 + a_{39}\Delta v_1$$

$$here \quad a_{39} = -b_{32}K_A = -\frac{\omega_o R_{fd}}{L_{adu}} K_A \quad and\ a_{37} = 0 \quad with\ \Delta T_m = 0$$

The complete state space model, including the PSS, has the following form (with constant input torque & with constant field voltage, i.e $\Delta E_{fd}$ =0, $\Delta T_m$=0)

$$\begin{bmatrix} \Delta\dot{\omega}_r \\ \Delta\dot{\delta} \\ \Delta\dot{\psi}_{fd} \\ \Delta\dot{\psi}_{1d} \\ \Delta\dot{\psi}_{1q} \\ \Delta\dot{\psi}_{2q} \\ \Delta\dot{v}_1 \\ \Delta\dot{v}_2 \\ \Delta\dot{v}_s \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} & a_{15} & a_{16} & 0 & 0 & 0 \\ a_{21} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & a_{32} & a_{33} & a_{34} & a_{35} & a_{36} & a_{37} & 0 & a_{39} \\ 0 & a_{42} & a_{43} & a_{44} & a_{45} & a_{46} & 0 & 0 & 0 \\ 0 & a_{52} & a_{53} & a_{54} & a_{55} & a_{56} & 0 & 0 & 0 \\ 0 & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} & 0 & 0 & 0 \\ 0 & a_{72} & a_{73} & a_{74} & a_{75} & a_{76} & a_{77} & 0 & 0 \\ a_{81} & a_{82} & a_{83} & a_{84} & a_{85} & a_{86} & 0 & a_{88} & 0 \\ a_{91} & a_{92} & a_{93} & a_{94} & a_{95} & a_{96} & 0 & a_{98} & a_{99} \end{bmatrix} \begin{bmatrix} \Delta\omega_r \\ \Delta\delta \\ \Delta\psi_{fd} \\ \Delta\psi_{1d} \\ \Delta\psi_{1q} \\ \Delta\psi_{2q} \\ \Delta v_1 \\ \Delta v_2 \\ \Delta v_s \end{bmatrix} + \begin{bmatrix} b_{11} & 0 \\ 0 & 0 \\ 0 & b_{32} \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ b_{81} & 0 \\ b_{91} & 0 \end{bmatrix} \begin{bmatrix} \Delta T_M \\ \Delta E_{fd} \end{bmatrix}$$

The generator field voltage $e_{fd}$ in the reciprocal per unit system is related to exciter output voltage $E_{fd}$ as follows:

$$e_{fd} = \frac{R_{fd}}{L_{adu}} E_{fd}$$

Which is of the form Δ ˙ = Δ + Δ , here A and B are the State matrix of the System considered. ΔX is the state vector and ΔU is the input vector. Then the eigen value analysis is performed on the system using MATLAB and results are checked. Also the system response, root locus and zero-pole plots are plotted using a step input for the system with stabilizer and without stabilizer.

## 2.6 Algorithm for stability analysis of the system having synchronous generator equipped with type ST1 static excitation system without stabilizer:

The various steps in this algorithm for computations in this case are given below**:**

1. Read synchronous generator and exciter parameters.
2. Select all time constants of the block diagram shown in Fig. 2.3
3. Calculate initial valves of $I_{po}$, $I_{qo}$, $E_{qo}$, $E_o$, ,$\delta$, $i_{qo}$, $i_{do}$, $e_{qo}$, $e_{do}$ from the equations given in 2.5.2.
4. Compute also the values of $K_1$ to $K_6$ from their corresponding equations.
5. Compute eigen values of the system matrix [A] with the help of M-file (program) developed by using the mathematical formulation described in equations 2.15 to 2.50.
6. Calculate the matrix A, B, C and D
7. Compute the transfer function of the system.
8. Plot the step response of the system. for plotting the deviation in output speed ( $\Delta\omega$) verses time in seconds.
9. Use all these computed values of the K constants for the simulation of system using MATLAB/ SIMULINK blockset.

On the similar steps the values of A, B, C, D matrices of the test system when equipped with a stabilizer are computed. Then the step responses of the systems are compared. Results are shown in chapter 4.

# CHAPTER-3

# NEURAL NETWORK AND FUZZY LOGIC BASED CONTROLLERS

## 3.1 Artificial Neural Network

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANN's, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANN's as well [6,16].

The basic building block of all biological brains is a nerve cell, or a neuron as shown in the Fig. 3.1. Each neuron acts as a simplified numerical processing unit. In essence, the brain is a bundle of many billions of these biological processing units, all heavily interconnected and operating in parallel. In the brain, each neuron takes several input values from other neurons, applies a transfer function and sends its output on to the next layer of these neurons. These neurons in turn send their output to the other layers of neurons in a cascading fashion. The following figure shows the structure of a neural cell or neuron.

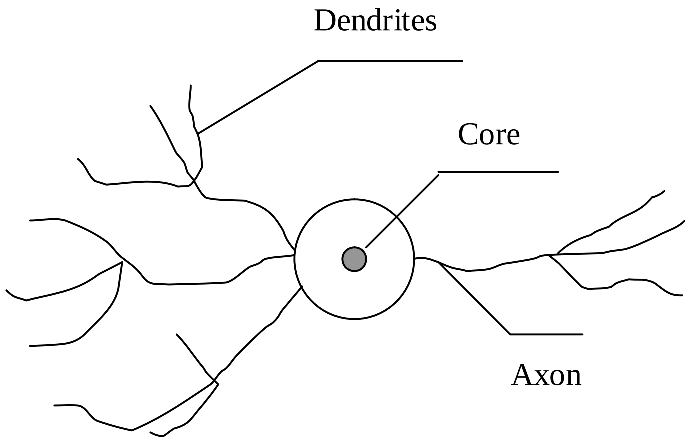



Figure.3.1 Structure of a neural cell in the Human Brain

As the figure Indicates, a neuron consists of a core, dendrites for incoming information and an axon with dendrites for outgoing information that is passed to connected neurons. Information is transported between neurons in form of electrical simulations along the dendrites. Incoming information's that reach the neuron's dendrites is added up and then delivered along the neuron's axon to the dendrites at its end, where the information is passed to other neurons if the stimulation has exceeded a certain threshold. In this case neuron is said to be activated. If the incoming stimulation is had been too low, the information will not be transported any further. In this case, the neuron is said to be inhibited.[37]

In a similar manner, ANN's are usually formed from many hundreds or thousands of simple processing units, connected in parallel and feeding forward in several layers. In a biological neural network, the memory is believed to be stored in the strength of interconnections between the layers of neurons. Using neural network terminology, the strength or influence of an interconnection is known as its weight. ANN borrows from this theory and utilizes variable interconnections weights between layers of simulated neurons.

ANN's were proposed early in 1960's, but they received little attention until mid 80's. Prior to that time, it was not generally possible to train networks having more than two layers. These early two layers networks were usually limited to expressing linear relationships between binary input and output characters. Unfortunately, the real world is analog and doesn't lend itself to a simple binary model. The real breakthrough in ANN research came with the discovery of the back propagation method.

Because of fast and inexpensive personal computers availability, the interest in ANN's has blossomed. The basic motive of the development of the neural network was to make the computers to do the things, which a human being cannot do. Therefore, ANN is an attempt to simulate a human brain.

Hence, the ANN architecture can be easily compared with the human brain. The following section follows a brief review about the literature of the neural networks and its structures.

### 3.1.1 Properties of neural networks

The use of neural networks offers the following useful properties and capabilities:

1. Nonlinearity. A neural network, made up of an interconnection of nonlinear neurons, is itself nonlinear. Moreover, the nonlinearity is of a special kind in the sense that it is distributed throughout the network. Most real systems, including power systems are nonlinear, so this property is very desirable for its applications in power systems.

2. Input-Output Mapping. A popular paradigm of learning called learning with a teacher or supervised learning involves modification of the synaptic weights of a neural network by applying a set of labeled training samples or task examples. Each example consists of a unique input signal and a corresponding desired response. The network learns from the examples by constructing an input-output mapping for the problem. In power system voltage security analysis, the traditional approaches which are widely used can be used to generate those training samples.

3. Adaptivity. Neural networks have a built-in capability to adapt their synaptic weights to changes in the surrounding environment. In particular, a neural network trained to operate in a specific environment can be easily retrained to deal with minor changes in the operating environmental conditions. Moreover, when it is operating in a non stationary environment, a neural network can be designed to change its synaptic weights in real time.

4. Fault tolerance. A neural network has the potential to be inherently fault tolerant in the sense that its performance degrades gracefully under missing or erroneous data. The reason is that the information is distributed in the network, the errors must be extensive before catastrophic failure occurs.[6]

### 3.1.2 The model of a Neural Network

The basic functional outline before mentioned has many complexity and exceptions, but then the most ANN models only these simple characteristics. They typically consist of many hundreds of simple processing units, which are wires together in a complex communication network. Each node or unit is simplified model of a simple neuron which fires, if it receives a sufficiently strong input signal from other node. [6]

These nodes can be grouped it to different layers. A layer of processing elements makes independent decision or computation on data and passes the result to another layer. The next layer in turn makes its independent computation and passes the result to another layer. Each processing element makes the computation based

upon sum weights of its inputs. The first layer is the input layer and the last layer is called output layer. The layers that are placed in between are called hidden layers.
Fig. shows general idea how an artificial neural network works:

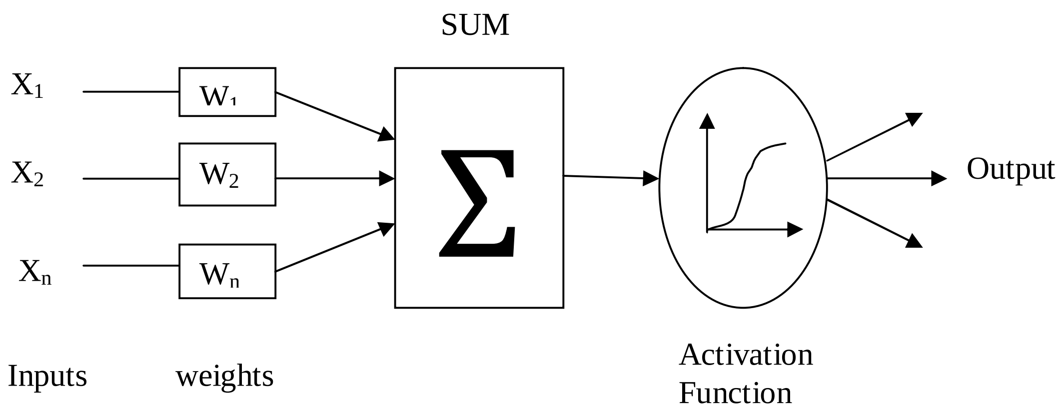



Figure 3.2 Artificial Neural Network

Here a set of input labeled $X_1$, $X_2$….Xn is applied to the artificial neuron. These inputs collectively referred to as the vector 'X', corresponds to the signals into the synapse of a biological neuron. Each signal is multiplied by an associated weight $W_1$, $W_2$…..Wn before it is applied to the summation block. Each weight corresponds to the strength of a single biological synaptic connection. The set of weight is referred collectively as the vector 'W'. The summation block refers to the biological cell body, adds all the weighted inputs algebraically, producing an output that we call SUM. This may be compactly stated in vector notation as

$$SUM = X*W$$

Or $$SUM = X_1*W_1 + X_2*W_2 + \ldots\ldots + Xn*Wn.$$

This SUM output is then multiplied by the activation function to get desired output.

## 3.2 Neuro Controller

The basic objective of a controller is to provide the desired output for any system. Since neural networks [24, 35] have learning and self-organizing abilities allowing them to adapt changes in data, the input-output data necessary for the off-line training of the neural network have been obtained in the present work using reference and plant models.

Trials have been carried to obtain maximum accuracy with minimum number of neurons per layer. The feed forward neural network controller developed consists of three layers, with one neuron in the input layer, 20 neurons in the hidden layer and one neuron in the output layer. The activation function used for the hidden layer is bipolar sigmoid while the activation function of the output layer is linear.

Backpropagation algorithm [7,9] is used for training of the created network. This algorithm is the most popular supervised learning rule for multi-layer feedforward networks. Quasi-Newton method applied for updating weights is a one-dimensional minimization related numerical interpolation method which has a fast convergence property known as quadratic convergence and hence it exhibits super linear convergence near target. With backpropagation algorithm, the input data is repeatedly presented to the neural network. With each presentation the output of the neural network is compared to the desired output and an error is computed. This error is then fed back to the neural network and used to adjust the weights such that the error decreases with each iteration and the neural model gets closer and closer to producing the desired output. This process is known as "training".[36, 43]

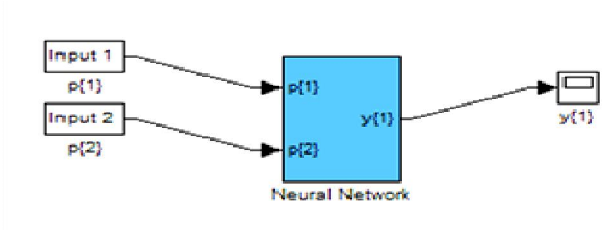



Figure 3.3 Simulink block of neuro controller

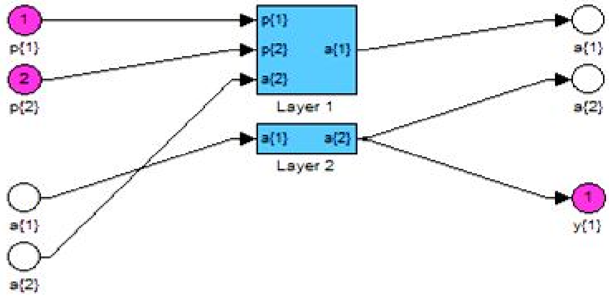



Figure3.4 Simulink block of neural network used as a neuro-controller

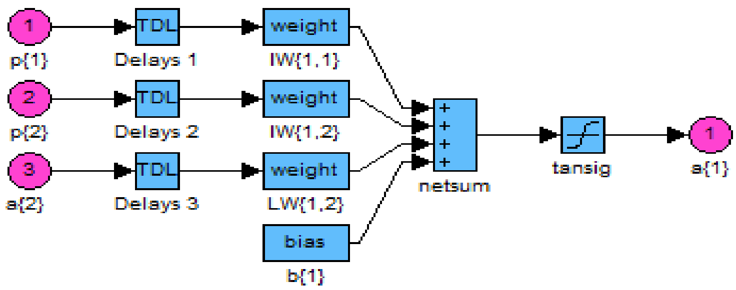



Figure 3.5 Simulink block of input and hidden layer of neuro controller

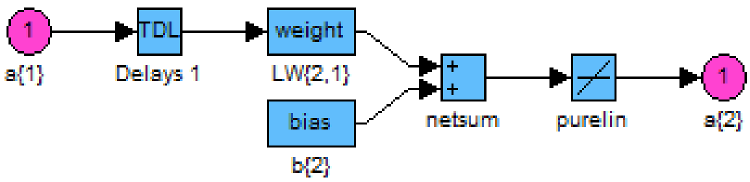



Figure 3.6 Simulink block of output layer of neuro controller

### 3.2.1 Neuro- Identifier

The neuro-identifier is also a multi-layer feedforward network trained with back propagation algorithm. All the inputs and outputs signals of the neuro-identifier are normalized to the range of [-1, 1]. [20,42,]

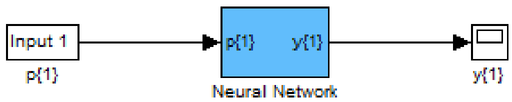



Figure 3.7 Simulink block of Neural Plant identifier

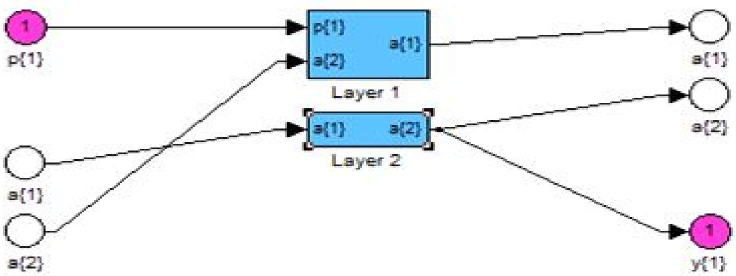



Figure 3.8 Simulink block of the neural network used as a plant identifier

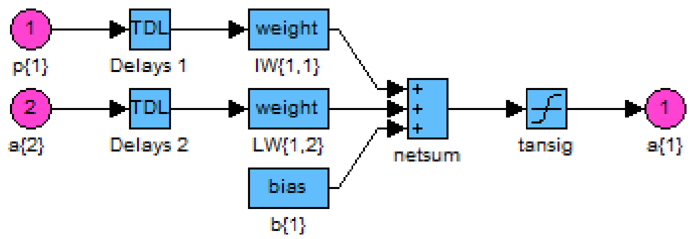



Figure 3.9 Simulink block for the input and hidden layer of the plant identifier

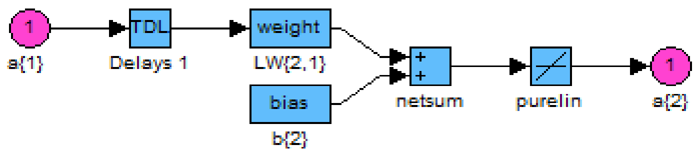



Figure 3.10 Simulink block for the ouput layer of the neuro identifier

For backpropagation training algorithm, the derivative of the activation function is needed. Therefore the activation function selected must be differentiable. The logistic or sigmoid function satisfies this requirement and it is the commonly used soft-limiting activation function. It is also quite common to use linear output nodes to make learning easier and using linear activation in the output layer does not compress the range of output. MSE is the performance criteria used in this work that evaluates the network according to the mean of square of error between target and computed output. [23, 30]

### 3.2.2 Model Reference Control

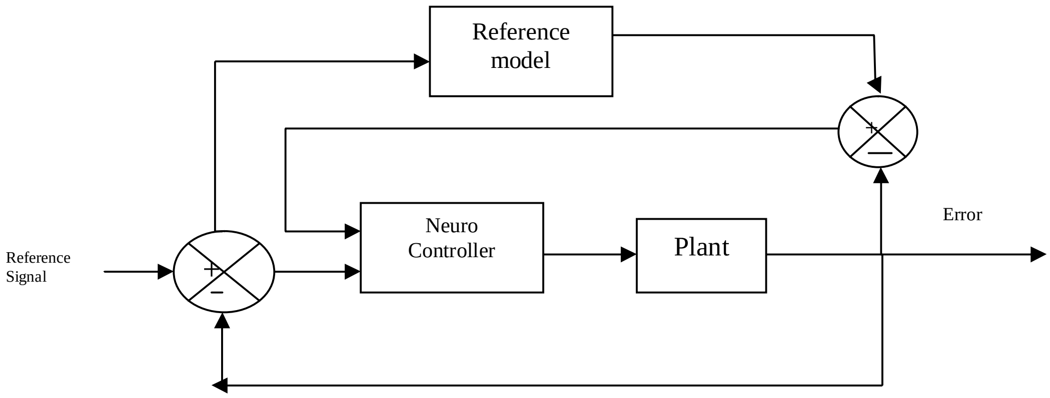



Figure 3.11 Model Reference Control

An illustration of model reference control is presented in figure 3.3 In the figure the network has two inputs, one of the inputs is difference between plant output and model reference output and second input is difference between model output and reference signal. Both plant model and reference model are used to train the network. The resulting ANN model will serve as controller for the system. Fig.3.3 explains the model reference control system. ANN controller uses these to adjust its weights until the output of the plant looks similar to model reference output trajectory. [9, 13]
ANN controller will have two input, error signal from reference model output, and plant output, the second error signal comes from difference between reference signal and plant output. The procedures involved in training the network are generation and validation of training data sets; preprocessing of data set and training and validation of network. To have good representation of the model, two data sets were generated from the system to train the network, one data set for validation and another one testing. Uniform random input signals, which span the upper and lower limit of operating range, were used to excite the system. This was done to enable network learn the nonlinear nature of the system, [22, 26]. Here the MATLAB/ SIMULINK software is used.

## 3.3 Fuzzy Logic based Power System Stabilizer

Here a fuzzy logic power system stabilizer is developed, using speed and speed deviation. As inputs and provide an auxiliary signal for the excitation system of a synchronous motor.

### 3.3.1 Fuzzy logic system

Fuzzy logic is a superset of conventional Boolean logic that has been extended to handle the concept of partial truth-truth-values between “completely true” and “completely false”.

**Fuzzy subsets**

In classical set theory, a subset U of asset S can be defined as a mapping from the elements of S to the elements the subset [0, 1],

$U: S \rightarrow \{0, 1\}$

The mapping may be represented as a set of ordered pairs, with exactly one ordered pair present for each element of S. The first element of the ordered pair is an element of the set S, and the second element is an element of the set (0, l). The value zero is used to represent non-membership and the value one is used to represent complete membership. The truth or falsity of the statement 'X is in U' is determined by finding the ordered pair whose first element is X. The statement is true if the second element of the ordered pair is 1, and the statement is false if it is 0.

Fuzzy logic has the advantage of modeling complex, nonlinear problems linguistically rather than mathematically and using natural language processing (computing with words). The use of fuzzy logic requires, however, the knowledge of a human expert to create an algorithm that mimics his/her expertise and thinking. Also, studying the stability of a fuzzy system is a demanding task.

A typical fuzzy system consists of a rule base, membership functions and an inference procedure [3].

### 3.3.2 Fuzzy logic controller

In the design of an FLC system it is assumed that:

- A solution exists.
- The input and output variables can be measured.
- An adequate solution is acceptable.
- A linguistic model can be created based on the knowledge of a human expert.

Basic block diagram of fuzzy logic controller is as shown under.[21,38,30]

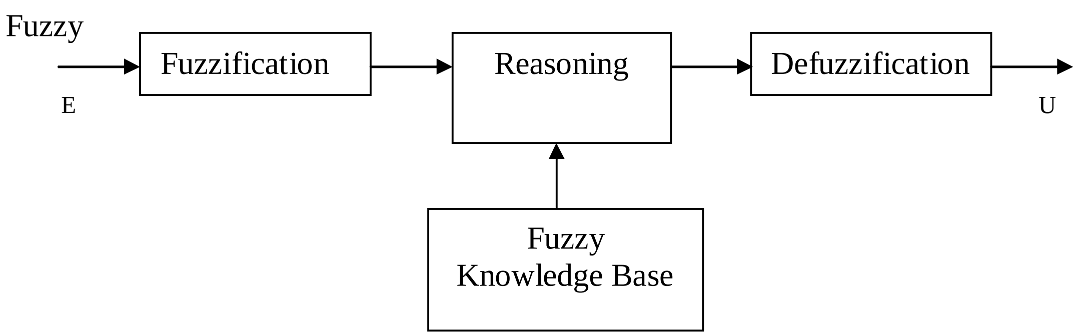



Figure3.12 Basic structure of a fuzzy logic controller

The main building units of an FLC are a fuzzification unit, a fuzzy logic reasoning unit, a knowledge base, and a defuzzification unit. Defuzzification is the process of converting inferred fuzzy control actions into a crisp control action. Sometimes, In the case of highly complex systems, fuzzy logic could be the only solution.

The functions of the above modules are described below.

*(i) Fuzzification*

(a) Measure the values of input variables

(b) Performs a scale mapping that transforms the range of values of input variables into corresponding universe of discourse.

(c) Performs the function of fuzzification that converts input into suitable linguistic values.

*(ii) Knowledge Base:*

It consists of data base and linguistic control rule base.

(a) The database provides necessary definitions, which are used to define linguistic control rules and fuzzy data, manipulation in an, FLC.

(b) The rule base characterizes the control goals and control policy of the domain experts by means of set of linguistic control rules.

*(iii) Decision Making Logic:*

It has the capability of simulating human decision making based on fuzzy concepts and of inferring fuzzy control actions employing fuzzy implication and the rules of inference in fuzzy logic.

*(iv) Defuzzification:*

(a) A scale mapping which converts the range of values of input variables into corresponding universe of discourse.

(b) Defuzzification, which yields a non-fuzzy, control action from an inferred fuzzy control action.[39]

**3.3.2.1 Membership function**

The linguistic variables chosen for this controller are speed deviation, change in speed deviation and voltage. In this, the speed deviation and change in speed deviation are the input linguistic variables and voltage is the output linguistic variable. Each of the input and output fuzzy variables 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 membership functions for each fuzzy variable. The membership function for each linguistic variable is given in figures 3.3.2., 3.3.3 and 3.3.4 Membership function plots are given below:

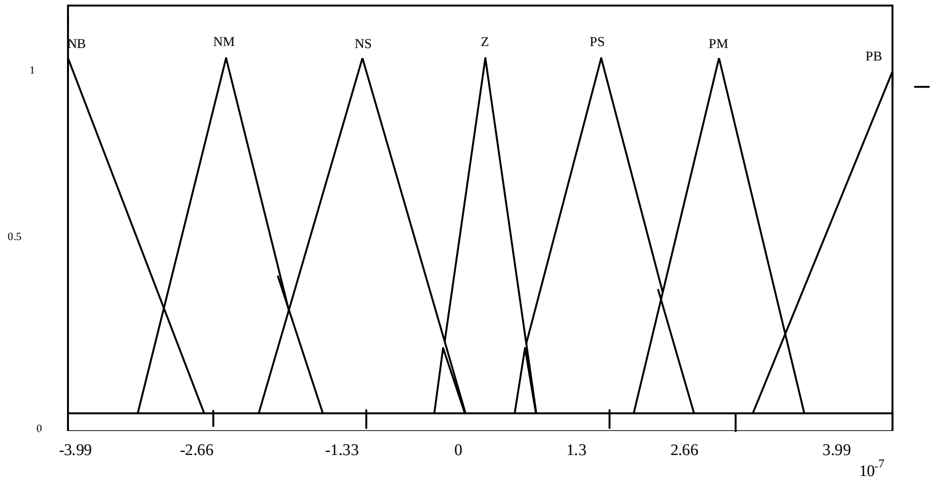



Figure 3.13 Input variable "Speed deviation (error)"

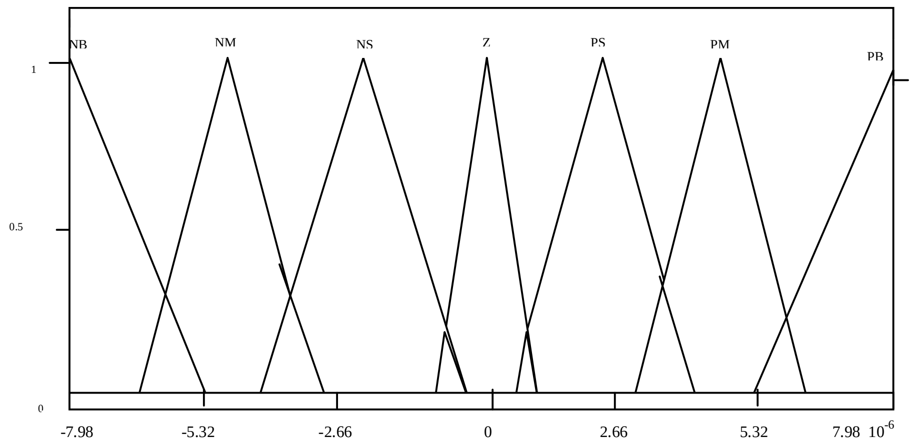



Figure 3.14 Input variable "Acceleration (error change)

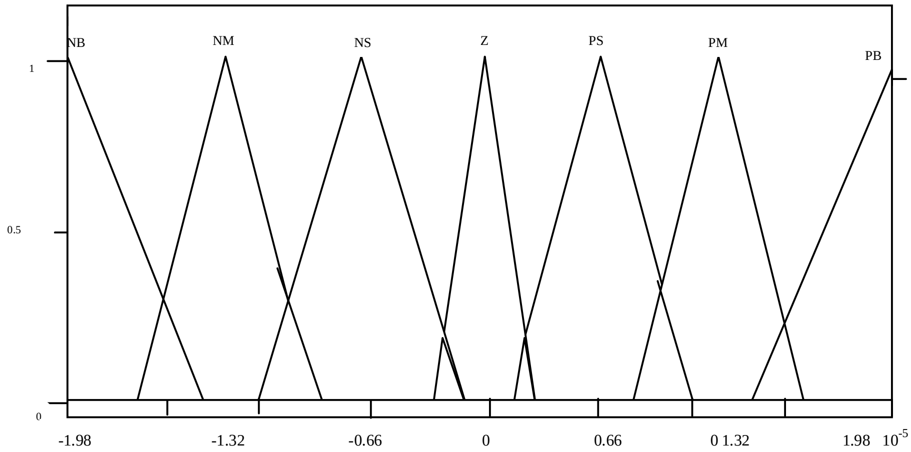


Figure 3.15 Output variable "Upss (Voltage)"

Proper values of gains are selected for both the inputs and for the output of FLC. This helps in good performance of the system

### 3.3.2.2 Fuzzy rule base

The linguistic terms chosen for this controller are seven. They are negative big (NB), negative medium (NM), negative small (NS), zero (Z), positive small (PS), positive medium (PM) and positive big (PB). After assigning the input, output ranges to define fuzzy sets, mapping each of the possible seven input fuzzy values of speed deviation; change in speed deviation i.e acceleration to the seven output fuzzy values is done through a rule base. The rules are framed keeping in mind the nature of the system performance and the common sense. This is prepared by training the controller. [23,27,30]

### 3.3.2.3 Training the Controller

The ranges can be calculated from the generated data for simulation by the conventional controller. For the rule-base, the relationship between the fuzzy controller inputs and its output can be extracted from the following algorithm:

1. Simulate the conventional controller.
2. Save each sample value of ($\Delta\omega$ , change in $\Delta\omega$, and Upss)
3. at each sample time t:

$\Delta\omega$ belongs to the class with max membership among (NB, NM, NS, ZR, PS, PM, PB) (i)

Change in $\Delta\omega$ ($\Delta\dot{\omega}$) belongs to the class with max membership among (NB, NM, NS, ZR, PS, PM, PB) (ii)

This will form the contents of the rule-antecedent (If-part of a rule)

Upss belongs the class with max membership among (NB, NM, NS, ZR, PS, PM, PB) so at sample time t, Upss is $u_1$... (c)

The contents of the rule-consequent (then-part of the rule)

And a total rule can be formed as:

From (a), (b) and (c): the rule “If $\Delta\omega$ is ω_1 and change in $\Delta\omega$ is dω_1 then Upss is u_1”

After generating the rules, the tuning procedures are carried out manually by observation of the control surface relating to the controller.

| **Speed deviation** | **Change in Speed Deviation** | | | | | | |
|---|---|---|---|---|---|---|---|
| | NB | NM | NS | ZR | PS | PM | PB |
| NB | NB | NB | NB | NB | NM | NS | ZR |
| NM | NB | NB | NM | NM | NS | Z | PS |
| NS | NB | NM | NS | NS | Z | PS | PM |
| ZP | NM | NM | NS | Z | Z | PM | PM |
| PS | NM | NS | Z | Z | PS | PM | PB |
| PM | NS | Z | PS | PM | PM | PM | PB |
| PB | ZR | Z | PM | PB | PB | PB | PB |

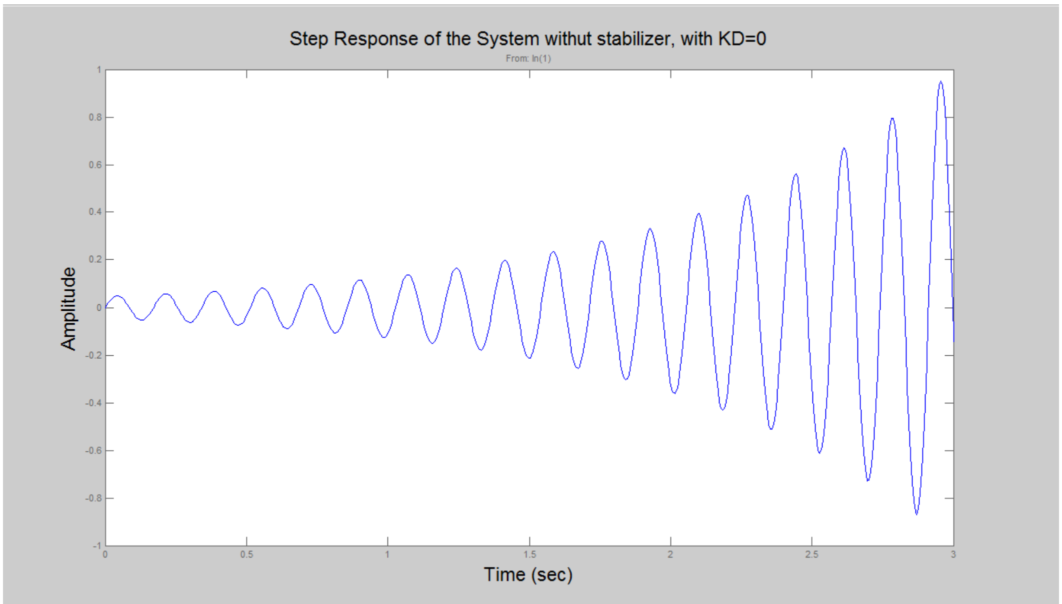
Table3.1 Rule base prepared from the conventional controller

A single machine infinite bus test system model is developed using MATLAB/SIMULINK. The fuzzy logic controller is separately designed in FIS editor and then it is interfaced with the simulink model of the plant.

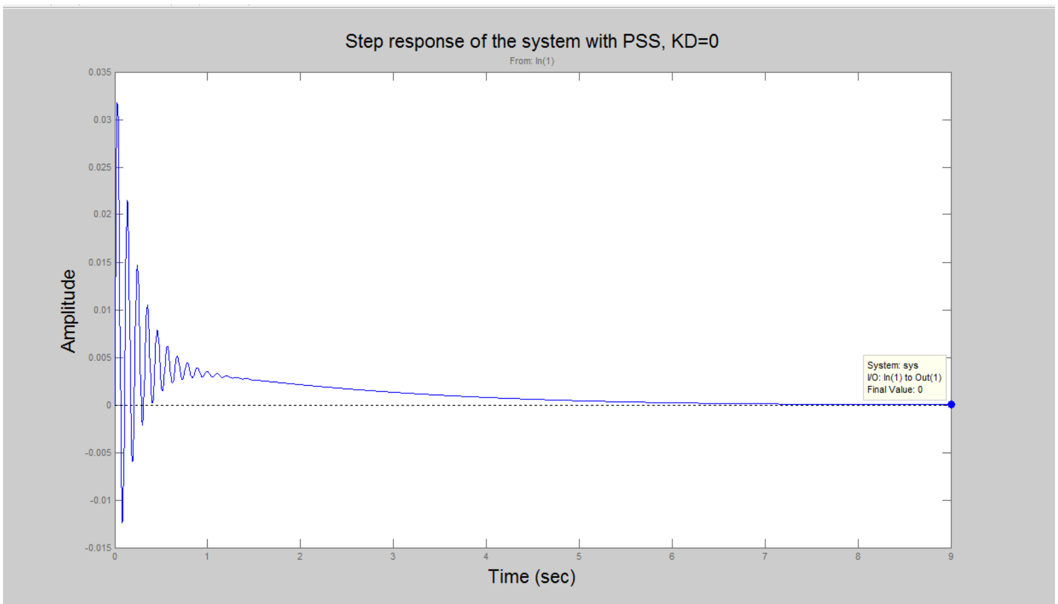
# CHAPTER 4

# RESULTS

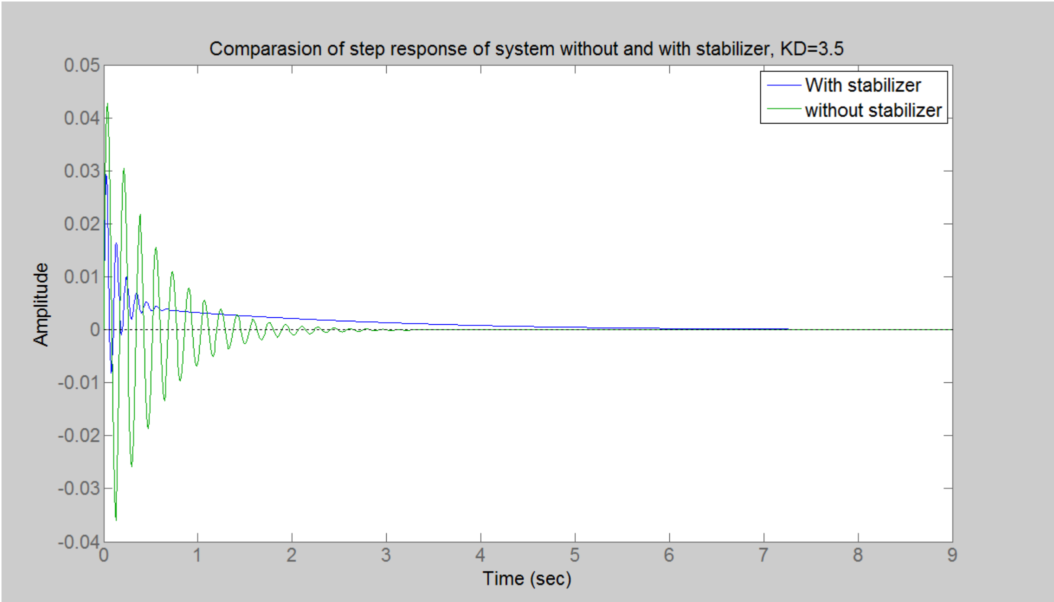
4.1 Step response of the system without PSS, with $K_D$=0




4.1 Step response of the system with PSS, with $K_D$=0



4.3 Comparisons of Step response of the system with stabilizer and without stabilizer




COMPARISON

This section shows the comparison of stabilizers mentioned earlier, all this analysis is done with MATLAB 7.3.

The following figures show the speed response of the test system, when applied to a step input.

Red-CPSS, Blue - Fuzzy Logic Based PSS, Cyan-Neural Network Based Controller, Yellow-Without any Stabilizer

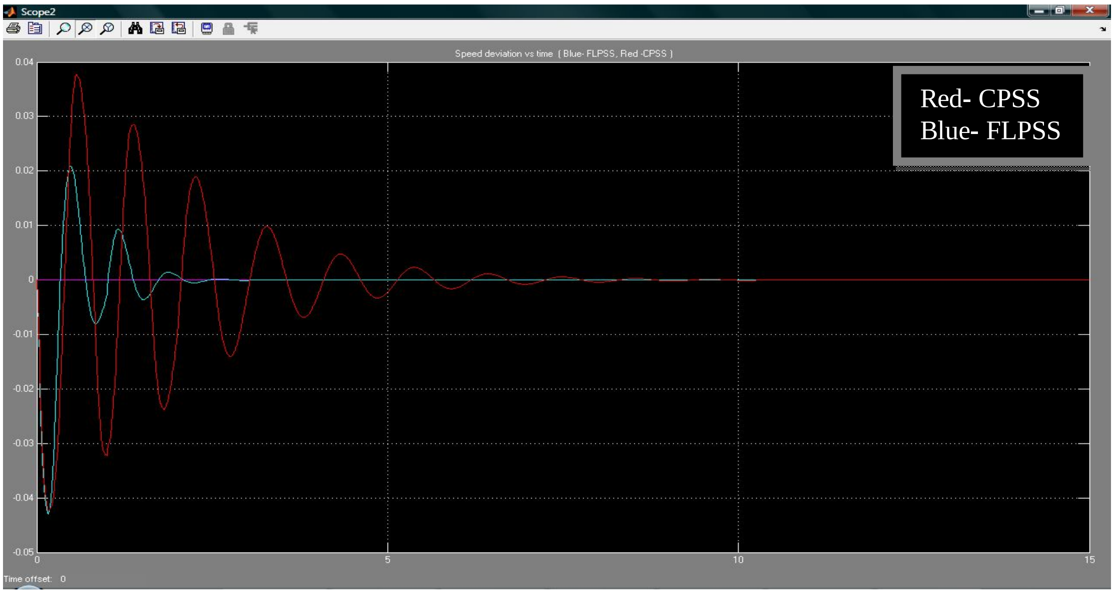



Fig 4.4 System response to a step input (Speed deviation vs. Time)

System response with CPSS and with FLPSS

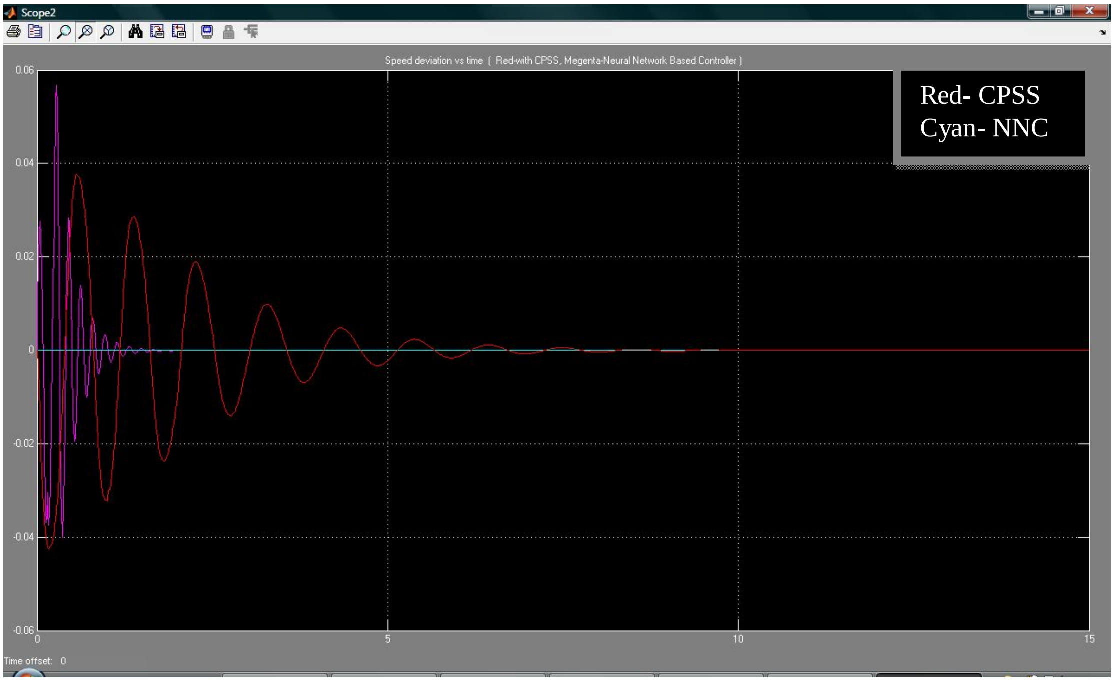



Fig 4.5 System response to a step input (Speed deviation vs. Time)

System response with CPSS and with Neural Network based controller.

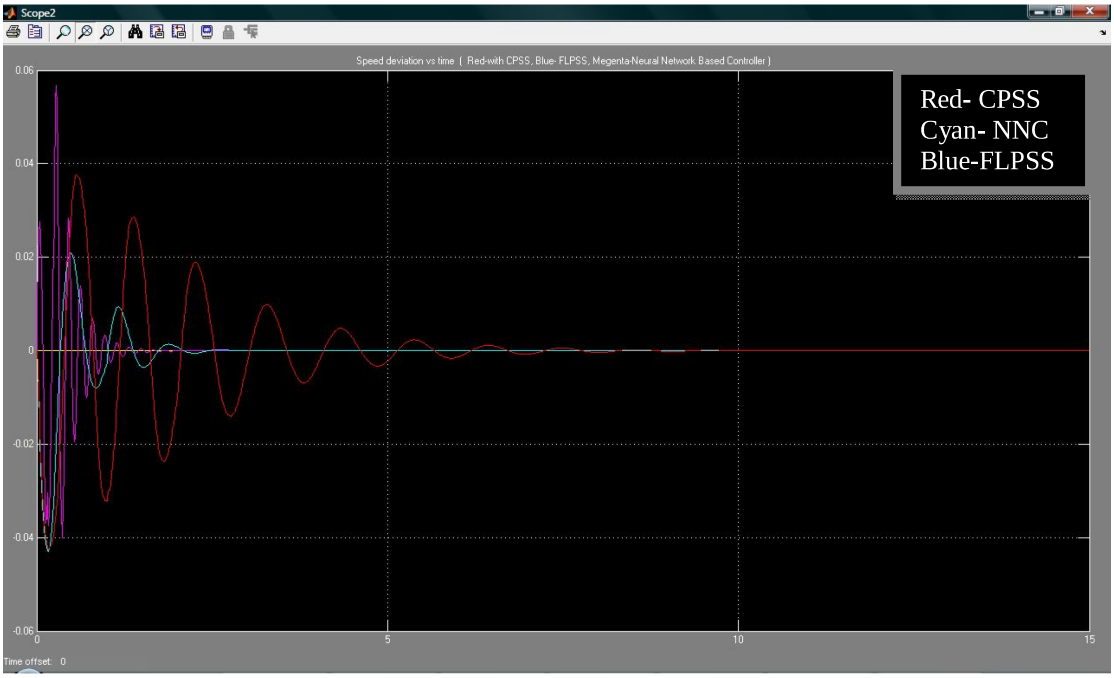



Fig 4.6 System response to a step input (Speed deviation vs. Time)

System response with CPSS, with Neural Network based controller and a FLPSS.

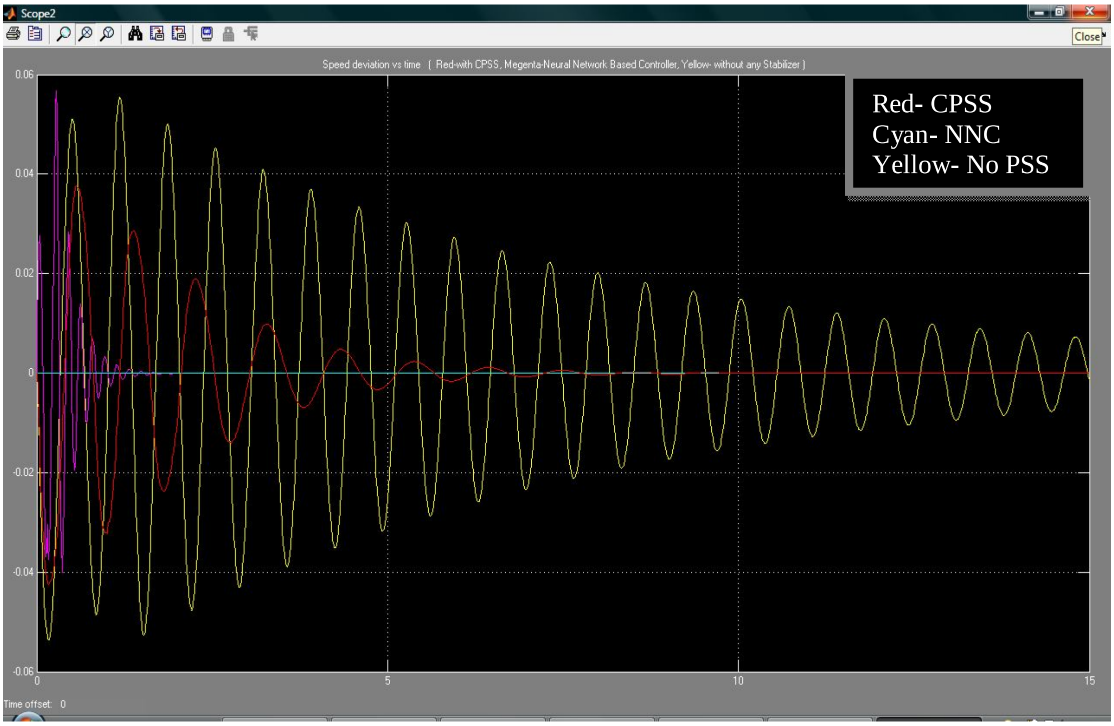



Fig 4.7 System response to a step input (Speed deviation vs. Time)

System response with CPSS, Neural Network based controller and without any Stabilizer.

## Conclusions

From the graphs given above following observations are made regarding the Peak value, settling time and steady state value of the system

| **Controller used** | **Peak Value** | **Settling Time (sec)** | **Steady state time(sec)** |
|---|---|---|---|
| **CPSS** | 0.04 | 7.2 | 9.81 |
| **FPSS** | 0.021 | 2.4 | 3.05 |
| **Neural Network Based Controller** | 1st peak-0.03<br>2nd peak-0.05 | 1.12 | 2.65 |

Table 4.1 Conclusions

## Results from eigen value analysis of the system

### 1. With Conventional Stabilizer

System State Matrices

A =

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 0 | -3.2653 | -1.5986 | -1.5377 | -0.4344 | -2.5203 | 0 | 0 | 0 |
| 376.9911 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | -0.0695 | -0.8346 | 0.5531 | 0.0008 | 0.0049 | -6.8707 | 0 | 6.8707 |
| 0 | -3.1404 | 24.7896 | -37.5092 | 0.0380 | 0.2202 | 0 | 0 | 0 |
| 0 | -0.3959 | -0.0086 | -0.0083 | -2.8768 | 1.9907 | 0 | 0 | 0 |
| 0 | -8.7814 | -0.1908 | -0.1835 | 7.6114 | -27.2669 | 0 | 0 | 0 |
| 0 | 3.9138 | 9.3377 | 8.9821 | -1.7927 | -11.0573 | -50.0000 | 0 | 0 |
| 0 | -31.0201 | -15.1863 | -14.6080 | -4.1267 | -23.9425 | 0 | -0.7143 | 0 |
| 0 | -144.7606 | -70.8693 | -68.1706 | -19.2581 | -111.7316 | 0 | 26.9697 | -30.3030 |

B =

| | |
|---|---|
| 1.7500 | 0 |
| 0 | 0 |
| 0 | 0.1374 |
| 0 | 0 |
| 0 | 0 |
| 0 | 0 |
| 0 | 0 |
| 16.6250 | 0 |
| 77.5833 | 0 |

Transfer function of the system b1/a1=

b1 =
1.0e+007 *
[ 0 0.0000 0.0000 0.0015 0.0385 0.4493 1.8016 2.7054 1.1672 0 ]

a1 =
1.0e+009 *
[ 0.0000 0.0000 0.0000 0.0005 0.0153 0.2948 2.6142 7.0054 5.2521 1.2334 ]

Eigen values=

-4.2855 +41.1615i
-4.2855 -41.1615i
-51.1575
-41.9742
-27.8071
-16.2251
-0.5050 + 0.1196i
-0.5050 - 0.1196i
-2.7598

Right Eigen Vector

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 0.0213 - 0.0124i | 0.0213 + 0.0124i | 0.0023 | -0.0060 | -0.0009 | 0.0199 | -0.0009 + 0.0002i | -0.0009 - 0.0002i | 0.0022 |
| -0.1325 - 0.1814i | -0.1325 + 0.1814i | -0.0167 | 0.0539 | 0.0129 | -0.4616 | 0.6706 | 0.6706 | -0.3031 |
| -0.0114 - 0.1610i | -0.0114 + 0.1610i | -0.1585 | 0.0801 | -0.2204 | 0.2816 | -0.4271 - 0.0139i | -0.4271 + 0.0139i | 0.5423 |
| -0.0487 - 0.0427i | -0.0487 + 0.0427i | 0.2841 | -0.4084 | -0.5570 | 0.3992 | -0.3454 - 0.0081i | -0.3454 + 0.0081i | 0.4130 |
| 0.0014 - 0.0034i | 0.0014 + 0.0034i | 0.0001 | -0.0010 | -0.0367 | -0.0601 | -0.3782 + 0.0269i | -0.3782 - 0.0269i | -0.6255 |
| 0.0420 - 0.0054i | 0.0420 + 0.0054i | -0.0052 | 0.0286 | 0.4589 | 0.3142 | -0.3221 + 0.0093i | -0.3221 - 0.0093i | -0.0930 |
| -0.0460 - 0.0140i | -0.0460 + 0.0140i | -0.9197 | -0.3768 | -0.5416 | 0.0309 | -0.0046 - 0.0071i | -0.0046 + 0.0071i | 0.2061 |
| 0.2048 - 0.1146i | 0.2048 + 0.1146i | 0.0218 | -0.0580 | -0.0092 | 0.1974 | 0.0104 - 0.0157i | 0.0104 + 0.0157i | 0.0284 |
| 0.9271 | 0.9271 | 0.2180 | -0.8232 | 0.3683 | -0.6369 | 0.0100 - 0.0146i | 0.0100 + 0.0146i | 0.0180 |

EVR =

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| -4.2855 +41.1615i | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | -4.2855 -41.1615i | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | -51.1575 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | -41.9742 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | -27.8071 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | -16.2251 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | -0.5050 + 0.1196i | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | -0.5050 - 0.1196i | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -2.7598 |

Left Eigen Vector=

1.0e+002 *

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 0.1329 + 0.0508i | -0.0071 + 0.0139i | -0.0009 + 0.0111i | -0.0056 + 0.0029i | 0.0006 + 0.0036i | -0.0085 + 0.0069i | -0.0008 - 0.0010i | 0.0005 - 0.0009i | 0.0013 + 0.0009i |
| 0.1329 - 0.0508i | -0.0071 - 0.0139i | -0.0009 - 0.0111i | -0.0056 - 0.0029i | 0.0006 - 0.0036i | -0.0085 - 0.0069i | -0.0008 + 0.0010i | 0.0005 + 0.0009i | 0.0013 - 0.0009i |
| -0.0087 + 0.0000i | 0.0012 + 0.0000i | -0.0014 - 0.0000i | 0.0067 - 0.0000i | 0.0002 - 0.0000i | -0.0030 - 0.0000i | -0.0085 - 0.0000i | -0.0003 - 0.0000i | 0.0005 - 0.0000i |
| 0.0832 + 0.0000i | -0.0093 + 0.0000i | 0.0068 + 0.0000i | -0.0137 + 0.0000i | 0.0022 - 0.0000i | -0.0163 + 0.0000i | -0.0058 + 0.0000i | 0.0026 - 0.0000i | -0.0040 + 0.0000i |
| -0.0785 - 0.0000i | 0.0058 - 0.0000i | 0.0008 - 0.0000i | -0.0006 + 0.0000i | -0.0057 + 0.0000i | 0.0185 + 0.0000i | -0.0003 + 0.0000i | -0.0023 + 0.0000i | 0.0023 - 0.0000i |
| 0.1080 + 0.0000i | -0.0046 - 0.0000i | -0.0108 - 0.0000i | 0.0034 - 0.0000i | -0.0044 - 0.0000i | 0.0060 - 0.0000i | 0.0022 + 0.0000i | 0.0092 - 0.0000i | -0.0053 |
| 0.0792 - 2.8224i | 0.0008 + 0.0038i | -0.0056 + 0.0096i | -0.0001 + 0.0001i | -0.0047 + 0.0089i | -0.0011 + 0.0019i | 0.0008 - 0.0013i | -0.0018 + 0.2860i | -0.0013 + 0.0022i |
| 0.0792 + 2.8224i | 0.0008 - 0.0038i | -0.0056 - 0.0096i | -0.0001 - 0.0001i | -0.0047 - 0.0089i | -0.0011 - 0.0019i | 0.0008 + 0.0013i | -0.0018 - 0.2860i | -0.0013 - 0.0022i |
| 0.1424 + 0.0000i | -0.0010 - 0.0000i | 0.0070 - 0.0000i | -0.0002 - 0.0000i | -0.0103 - 0.0000i | -0.0004 - 0.0000i | -0.0010 + 0.0000i | -0.0232 - 0.0000i | 0.0018 - 0.0000i |

| Eigenvalue | Damping | Freq. (rad/s) |
|---|---|---|
| -5.05e-001 + 1.20e-001i | 9.73e-001 | 5.19e-001 |
| -5.05e-001 - 1.20e-001i | 9.73e-001 | 5.19e-001 |
| -2.76e+000 | 1.00e+000 | 2.76e+000 |
| -1.62e+001 | 1.00e+000 | 1.62e+001 |
| -2.78e+001 | 1.04e+000 | 2.78e+001 |
| -4.29e+000 - 4.12e+001i | 1.04e+000 | 4.14e+001 |
| -4.29e+000 - 4.12e+001i | 1.00e+000 | 4.14e+001 |
| -4.20e+001 | 1.00e+000 | 4.20e+001 |
| -5.12e+001 | 1.00e+000 | 5.12e+001 |

## 2. Results For the system, without stabilizer

State Matrix

A1 =

$$\begin{bmatrix} 0 & -3.2653 & -1.5986 & 14.0000 & -0.4344 & -2.5203 \\ 376.9911 & 0 & 0 & 0 & 0 & 0 \\ 0 & -0.0695 & -0.8346 & 0.5531 & 0.0008 & 0.0049 \\ 0 & -3.1404 & 24.7896 & -37.5092 & 0.0380 & 0.2202 \\ 0 & -0.3959 & -0.0086 & -0.0083 & -2.8768 & 1.9907 \\ 0 & -8.7814 & -0.1908 & -0.1835 & 7.6114 & -27.2669 \end{bmatrix}$$

$$B1 = \begin{bmatrix} 1.7500 & 0 \\ 0 & 0 \\ 0 & 0.1374 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

$$\text{Eigen Values} = \begin{bmatrix} 1.0208 + 36.6868i \\ 1.0208 - 36.6868i \\ -42.2146 \\ -25.6652 \\ -1.8516 \\ -0.7977 \end{bmatrix}$$

Tranfer function of the system, without stabilizer (b/a=)

b =
1.0e+005 *
[ 0 0 0 0.0022 0.2437 6.2740 1.3672 ]
a =
1.0e+006 *
[ 0.0000 0.0001 0.0025 0.0954 1.6991 3.9982 2.1556 ]

| Eigenvalue | Damping | Freq. (rad/s) |
|---|---|---|
| -7.98e-001 | 1.00e+000 | 7.98e-001 |
| -1.85e+000 | 1.00e+000 | 1.85e+000 |
| -2.57e+001 | 1.00e+000 | 2.57e+001 |
| 1.02e+000 + 3.67e+001i | -2.79e-002 | 3.67e+001 |
| 1.02e+000 - 3.67e+001i | -2.79e-002 | 3.67e+001 |
| -4.22e+001 | 1.00e+000 | 4.22e+001 |

**Conclusion**

Mathematical results of the system analysis shows that by Using a PSS Damping is increased which leads to the stability enhancement of the system. The system without PSS has positive eigen values which shows the instability of the system.

# CHAPTER 5

# SUMMARY & FUTURE SCOPE OF WORK

**SUMMARY**

In the present work a comparative analysis of various types of power system stabilizers is performed, while applied to a Single machine Infinite bus power System. For the same set of conditions the fuzzy logic power system stabilizer (FLPSS) has increased the damping of the system causing it to settle back to steady state in much less time than the conventional power system stabilizer (CPSS) and it also decreases the peak value. The FLPSS, though rather basic in its control proves that it is indeed a good controller due to its simplicity. A neuro controller is though a little tough to design but gives good performance; the settling time and steady state time are decreased to great extent. The value of the $2^{nd}$ peak is more with neural based controller, but this can also be decreased by training the network differently

**Future Scope of thesis**

Results of this work tell that Adaptive or Artificial intelligence based PSS is a possibility but still further work is needed to confirm their use. Testing using more complex network models must be carried out. Moreover same work can be carried out under transient stability conditions of the power system. Different training technique can be used for training purpose of neural networks.

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# APPENDIX-A

Parameters for the SMIB test system of figure 2.3, except f and H, all the values are in p.u.[34].

| | | | | | | |
|---|---|---|---|---|---|---|
| H=3 | Ld=1.81 | Lq=1.76 | Ldd=0.30 | Lqq=0.65 | Lddd=0.23 | Lqqq=0.23 |
| Ll=0.15 | Ra=0.003 | Tdo=8.0 | Tqo=1.0 | Wo=377 | D1=0 | Tdoo=0.03 |
| Tqoo=0.07 | f=60 | KA=100 | TA=0.05 | TR=0.02 | Efmax=1.0 | Efmin=-1.0 |
| $K_{STAB}$=9.5 | Vsmax=0.2 | Vsmin=-0.2 | Tw=1.41 | T1=0.154 | T2=0.033 | Xe=0.4 |
| Re=0.02 | Po=0.9 | Qo=0.436 | Eto=1.0 | $\delta_o$=28.34 | Eb=0.90081 | |

# GLOSSARY

| | |
|---|---|
| **AVR** | **Automatic Voltage Regulator** |
| **LFO** | **Low Frequency Oscillation** |
| **PSS** | **Power System Stabilizer** |
| **CPSS** | **Conventional Power System Stabilizer** |
| **FLPSS** | **Fuzzy Logic Power System Stabilizer** |
| **SMIB** | **Single Machine Infinite Bus System** |
| **FLC** | **Fuzzy Logic Controller** |

# Nomenclature

| | |
|---|---|
| T'do | d-axis transient time constant (s) |
| T"do | d-axis subtransient time constant (s) |
| T'qo | q-axis transient time constant (s) |
| T"qo | q-axis subtransient time constant (s) |
| H | Inertia constant (s) |
| D | Damping factor (pu) |
| Xd | d-axis synchronous reactance (pu) |
| Xq | d-axis synchronous reactance (pu) |
| X'd | d-axis transient reactance (pu) |
| X'q | d-axis transient reactance (pu) |
| X"d | X"q d- & q-axis subtransient reactance (pu) |
| Vref | Reference input voltage |
| Et | Terminal voltage |
| Eb | infinite bus voltage |
| $E_{FD}$ | equivalent excitation voltage |
| Vs | stabilizer output |
| Tm | Mechanical input torque |
| $K_A$ | voltage regulator gain |
| $T_A$ | voltage regulator time constant |
| $T_R$ | Voltage transducer's time constant |
| $T_w$ | washout time constant |
| $T_1$, $T_2$ | PSS time constants |
| $K_{STAB}$ | PSS gain |
| K1-K6 | Constants of the linearized model |
| $\delta$ | Torqe angle |
| Eq' | q-axis component of voltage behind transient reactance |
| $\omega_r$ | Rated angular speed |
| Xe, Re | Transmission system parameters |