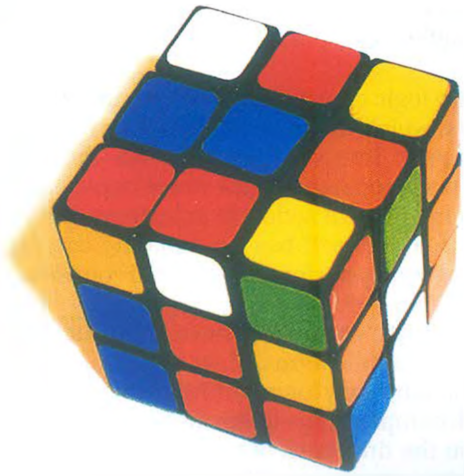
Design of Robust Fuzzy Logic based Damping Controller Using Genetic Algorithm



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ABSTRACT

This paper presents a design procedure for a fuzzy logic based damping controller for the power system. In the proposed fuzzy expert system, speed deviation ($\Delta\omega$) and its derivative ($\Delta\dot{\omega}$) are selected as fuzzy inputs. The parameters of the fuzzy logic damping controller (FLDC) are tuned through Genetic algorithm (GA). To demonstrate the robustness of the FLDC, Simulation studies on single machine infinite bus (SMIB) system subjected to small perturbation and three-phase fault are carried out. Simulation studies show the superiority and robustness of GA based fuzzy logic power system damping controller over the conventionally tuned controller over a wide variation in loading conditions

Keywords- Power system controller, Fuzzy logic controller, Fuzzy logic power system damping controller, Genetic Algorithm, Genetic based power system stabilizer

INTRODUCTION

Modern power systems are usually complex nonlinear systems, which are often subjected to low frequency oscillations. The conventional lead-lag power system stabilizers (PSS) are widely used by power system utilities [5]. Conventional fixed structure power system stabilizer design is based on linearized model around a nominal operating condition. The performance of conventional power system stabilizer (CPSS) becomes sub-optimal as the operating condition changes [1-3].

Recently, several approaches based on modern control theory have been applied to the PSS design problem. The variable structure PSS, self-tuning PSS, artificial neural network based PSS, have been proposed to provide optimum damping to system oscillations under wide variation of system parameters and operating conditions [6-9]. However, realization of self-tuning PSS is difficult, as it requires parameter identification, state observation and feedback gain computation, which is time consuming task. Alternate control schemes such as rule-based and the fuzzy logic control [10-11] have been proposed to design power system stabilizer. Fuzzy logic control appears to possess many advantages such as less computational time and robustness. Fuzzy logic controllers (FLC) are suitable for systems that are structurally difficult to model due to naturally existing non-linearities and other model complexities.

Fuzzy logic controllers can be simply expressed by a set of rules, which describe the behavior of the controller using linguistic terms. Depending on the system state, the controller operates in the range between no control action and full control action in an extremely nonlinear manner. The FLC in itself has no dynamic component i.e. it can immediately perform the desired control action [18].

Fuzzy logic controllers have been successfully applied in control applications, they are subjective and heuristic. Although, fuzzy logic control introduces a good tool to deal with complex, non-linear and ill-defined systems, it suffers from the drawback of tuning of parameters of fuzzy logic power system stabilizer (FLPSS). The generation of membership functions (MFs) and the tuning of scaling factors for FLC are done either iteratively by trial and error or by human expert.

Therefore, the tuning of the fuzzy logic power system stabilizer (FLPSS) parameters is a time consuming task. It necessitates the need for an effective method for tuning the parameters of FLPSS.

Genetic algorithms (GA) are the search technique based on the mechanics of natural selection and survival-of-the-fittest [12]. The advantage of the GA technique is that it is independent of the complexity of the performance index considered. Recently, the application of GAs to tune the parameters of PSS has been reported [13-15].

Lakshmi et al. [17] have proposed a novel approach to design a genetic based fuzzy logic power system stabilizer (GFPSS) for multimachine power system. Abido et al. [16] have proposed an approach to integrate the use of GA and fuzzy logic systems in order to combine their strengths and overcome each other's weakness [16]. The performance of FLPSS can be improved by incorporating a genetic-based learning mechanism.

Although a lot of research work have been reported on fuzzy logic PSS, to the best of author's knowledge, no attempt seems to have been made to answer the following pertinent question:

What is the minimum number of fuzzy MFs which would provide adequate performance of the system with GA based PSS?

In view of the above, the main thrust of the research work presented in this paper is to design a FLPSS using GA which improves dynamic stability of the system considering minimum number of MFs without deteriorating system dynamic performance.

The main objectives of the work presented in this paper are:

1. To present an algorithm for the design of fuzzy logic power system stabilizer using Genetic Algorithm.
2. To analyze the system dynamic performance with the proposed GA based fuzzy logic power system stabilizer (GFLPSS) under different disturbances and hence to compare it with the CPSS.
3. To investigate the effect of variation of number of linguistic variables (i.e., Number of MFs) on the performance of the Genetic algorithm based fuzzy logic power system stabilizer (GFLPSS).
4. To study the system dynamic performance with the GFLPSS under the wide variations in loading conditions.

SYSTEM MODEL

A machine infinite bus system with synchronous generator provided with IEEE Type-ST1 fast exciter model has been used. The non-linear model of the system is described by set of equations given in Appendix I. The nominal system parameters and data are given in Appendix II.

SELECTION OF SUITABLE CONFIGURATION OF FLPSS

The schematic diagram of a synchronous generator excitation control along with FLPSS is shown in Fig.1.
The fuzzy logic PSS design methodology comprises the following steps.
- Identification of input signals
- Determination of Number of MFs
- Shape of Membership Functions

Number of Membership Functions:

The quality of control action which can be achieved using fuzzy logic controllers depend upon the number of membership functions. As the number of membership functions increases, the quality of control improves but at the same time the computational memory and computational time increases [18]. Investigations will be carried out in the proposed work to determine the optimum number of membership functions for a particular shape.

Shape of Membership Functions: The performance of FLPSS depends upon the shape of the membership functions. The most commonly used membership functions are Gaussian, Triangular and Trapezoidal. The performance of the FLPSS designed using GA has been analyzed with Gaussian shape of MFs in the following sections.

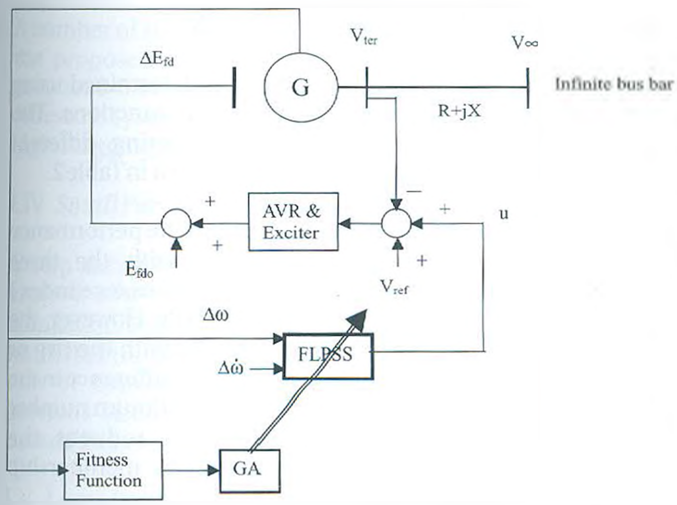

Fig. 1. Block Diagram of FLPSS in a power system

A simple configuration is chosen for the FLPSS as shown in Fig.2. For the present investigations, generator speed deviation ($\Delta\omega$) and its derivative ($\Delta\dot{\omega}$) are chosen as inputs.

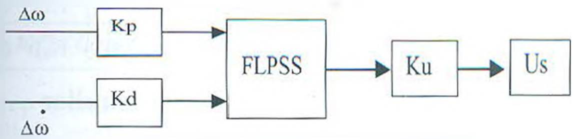

Fig.2. Block diagram of FLPSS

In practice, only shaft speed is easily available. The acceleration is derived by measuring at two successive instants i.e.

$$\Delta\dot{\omega}(kT) = \frac{[\Delta\omega(kT) - \Delta\omega(k-1)T]}{T}$$

where, T is the sampling period and K is the sampling count. In the present study, T = 10 ms is considered. The inputs are normalized by using normalization factors K_p and K_d.

DESIGN OF FUZZY LOGIC PSS

In the proposed approach, the parameters of fuzzy logic power system stabilizer are optimized using GA. The GA based design comprises of the following two steps:

1. Evaluation of performance index for each of the string in the current population. The tuning parameters must be decoded from each string in the population and the system is simulated to obtain the performance index.

2. GA operators are applied to get next generation of the strings.

The above two steps are repeated from generation to generation until the population and an optimal parameter set have been obtained.

The dynamic performance of the system with FLPSS highly depends upon the normalization and de-normalization factors. In the proposed genetic based fuzzy logic power system stabilizer (GFLPSS), these normalization and de-normalization factors K_p, K_d, K_u and one parameter of the fuzzy inference system(FIS) structure have been tuned using GA.

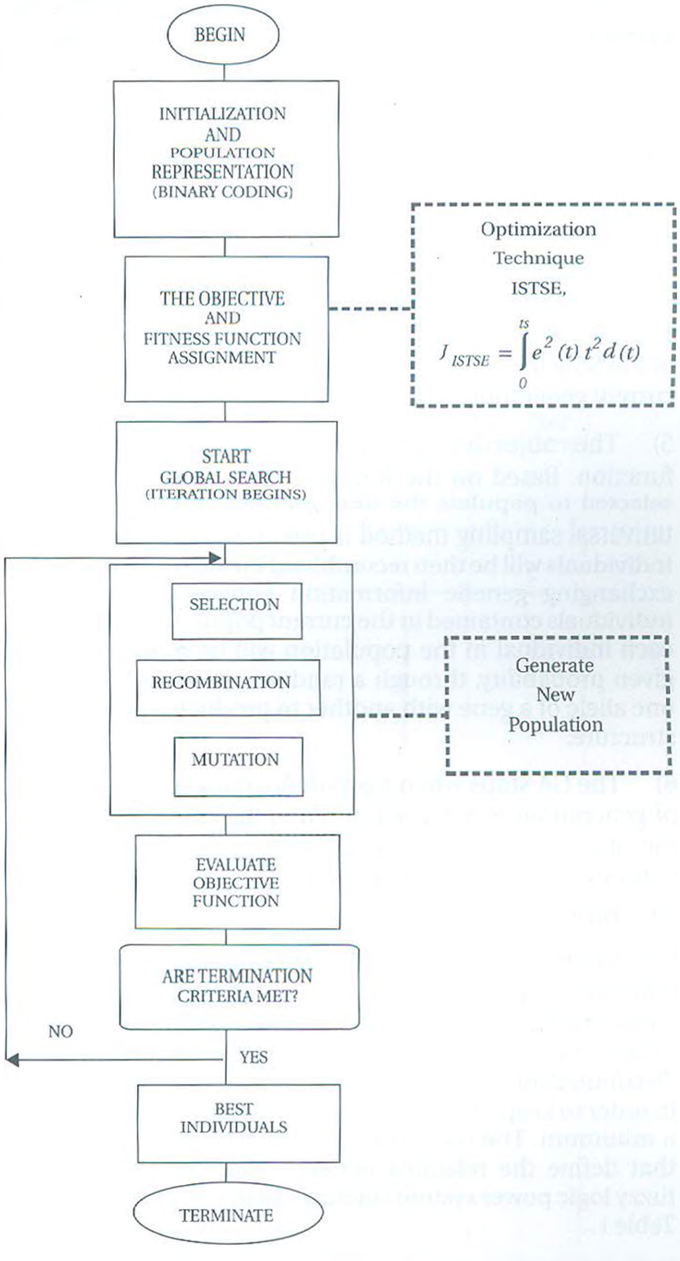

Fig. 3. GA Flow Chart

DESIGN ALGORITHM

The step-by-step design procedure for tuning of FLPSS parameters for Gaussian shape of MFs using GA for a nominal operating condition is as follows:

1) The lower and upper bounds for the parameters to be optimized using GA have been selected. Gaussian Membership Functions - Parameter Set (K_p, K_d, K_u, σ)

$$0 \le K_p \le 200$$
$$0 \le K_d \le 50$$
$$0 \le K_u \le 1$$
$$0.1 \le \sigma \le 1$$

2) An initial population of individuals is generated using a random generator uniformly distributing the numbers in the desired range.

3) A objective function J considered for the optimization of the parameters is as follows:

$$J = \int_0^\infty t^2 e^2(t)\,dt$$

where, e(t) is ($\Delta\omega$t), speed deviation of the generator following 5% step increase in mechanical input torque i.e., $\Delta T_m = 0.05$ p.u.

4) If the value of J is minimum, then the optimum value of FLPSS parameters are set at the values obtained in the current generation otherwise go to step 5.

5) The objective function is mapped into fitness function. Based on the fitness, some individuals will be selected to populate the next generation. The stochastic universal sampling method is used for selection. Selected individuals will be then recombined through a crossover by exchanging genetic information between pairs of the individuals contained in the current population. After that, each individual in the population will be mutated with a given probability, through a random process of replacing one allele of a gene with another to produce a new genetic structure.

6) The GA stops when a pre-defined maximum number of generations is achieved or when the value returned by the objective function, being below a threshold, remain constant for a number of iterations.

I.I. Rule Base

Five labels are chosen for the linguistic variables used to represent the inputs and output. The labels are NB (Negative Big), NS (Negative Small), ZO (Zero), PS (Positive Small), PB (Positive Big). Symmetrical and uniformly distributed membership functions have been used for MFs, in order to keep the number of parameters to be optimized a minimum. The rule table giving a complete set of rules that define the relations between inputs and output of fuzzy logic power system stabilizer in this study is shown in Table 1.

The rule table is then transformed into a fuzzy relation matrix. The stabilizer output is determined using the min-max composition rules

$\Delta\omega$ \ $\Delta\omega$	NB	NS	ZO	PS	PB
NB	NB	NB	NB	NS	ZO
NS	NB	NS	NS	ZO	PS
ZO	NB	NS	ZO	PS	PB
PS	NS	ZO	PS	PS	PB
PB	ZO	PS	PB	PB	PB

I.II Optimum Parameters of GFLPSS

The optimum parameters of FLPSS are determined using GA for Gaussian shape of membership functions. The optimized parameters of FLPSS considering different numbers of membership functions are shown in Table 2.

It is clear from the results of the Table 2 that the performance of the FLPSS is somewhat degraded with the three membership functions as the value of performance index J is high as compare to other number of MFs. However, the performance of the FLPSS is just identical with the five or seven number of MFs .as there is hardly any difference in the value of performance index J_{min}. Thus the optimum number of membership function is five, as it reduces the computational time as compare to seven membership functions..

Table 2
TUNED PARAMETERS OF GFLPSS

NumMF	Kp	Kd	Ku	Sigma	Jmin*
3	200.00	50.000	1.0000	0.5523	8.96*e-5
5	194.061	46.122	0.9752	0.4317	1.27* e-7
7	192.437	48.491	0.3541	0.1904	1.26* e-7

I.III Comparison with Conventional Controller

The dynamic performance of the proposed GA based FLPSS is compared with the conventional lead-lag controller whose output is given by:

$$U_C = \frac{sT_W K_C(1+sT_1)(1+sT_3)}{(1+sT_W)(1+sT_2)(1+sT_4)}\Delta\omega \qquad (3)$$

where,
K_c - PSS gain
T_1, T_3 - Lead-time constants
T_2, T_4 - Lag time constants
T_w - Washout time constant
In this study T_w is chosen equal to 10 sec and $T_1 = T_3$, $T_2 = T_4$.
The optimized values of K_c, T_1, T_2 are obtained using phase compensation technique [4].
The optimum values of CPSS parameters are as follows:
$K_c = 7.5563$, $T_1 = 0.3320$ s, $T_2 = 0.0727$ s.

SIMULATION RESULTS

Table 3
GA PARAMETERS

Number of individuals (N_{ind})	30
Number of variables (N_{var})	4
Generation gap (G_{gap})	0.90
Probability of crossover (P_c)	0.85
Probability of mutation (P_m)	0.001
Number of maximum generation	80

A number of simulation studies have been performed with the proposed FLPSS. The dynamic performance of the proposed GA based FLPSS is compared with the CPSS for different system loading conditions (Heavy, Nominal, Light, Lagging p.f.), small perturbation and large fault.

I.IV *Small Perturbation Test at Nominal Load*

A step increase in 5% in mechanical input torque was applied while generator-loading condition is (P_1, Q_1). Simulation result are shown in Fig. 4 .It is clear from the result that the performance of the FPSS is much superior to that of conventional PSS. The system returns to its previous steady state much faster with the proposed GA based FPSS.

I.V *Large Disturbance Test*

At nominal loading conditions, A 3-phase fault of 4-cycle duration was applied at the generator terminals at t = 0.25 sec. The examination of result shown in Fig.5 reveal that the proposed FPSS provide better damping to system oscillations as compare to CPSS under the fault.

I. VI *Light Load Test*

A step increase in 5% in mechanical input torque was applied while generator is running at light loading condition i.e. (P_2, Q_2). The examination of result as shown in Fig.6 show that the proposed FPSS provide better damping to system oscillations as compare to CPSS. The system dynamic response is better in terms of peak deviation and settling time with the proposed PSS as compare to CPSS.

I.VII *Heavy Load Test*

A small perturbation 5% increase in mechanical input torque was applied while generator is running at heavy loading condition i.e. (P_3, Q_3). Simulation result as shown in Fig.7 reveal that the dynamic performance of FPSS is much superior to that of the CPSS.

I.VIII *Robust Testing of the Proposed FPSS*

The system dynamic performance with the GA based FPSS is now examined considering different loading conditions for both small and large perturbation as shown in Table 4.

Table 4
SYSTEM LOADING CONDITIONS

Loading conditions	P (p.u.)	Q (p.u.)	Vt (p.u.)
Nominal	P_1=0.9	Q_1=0.2907	V_{t1}=1.0
Leading	P_2=0.6	Q_2= -0.1	V_{t2}=0.95
Heavy	P_3=1.1	Q_3=0.35	V_{t3}=1.0
Lagging	P_4=0.85	Q_4=0.27	V_{t4}=0.95

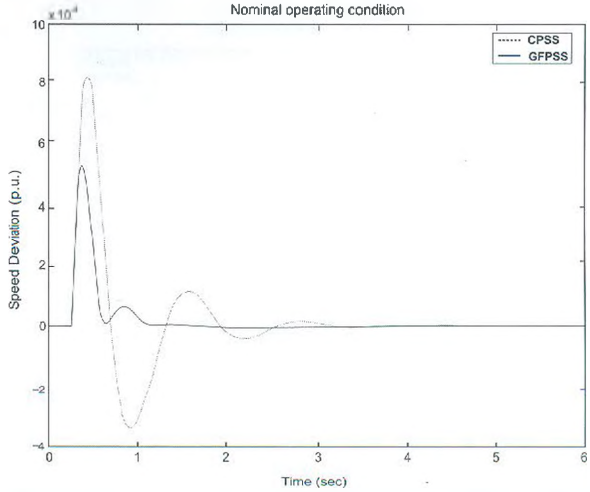

Fig. 4. Dynamic response for Δω for small perturbation at nominal load

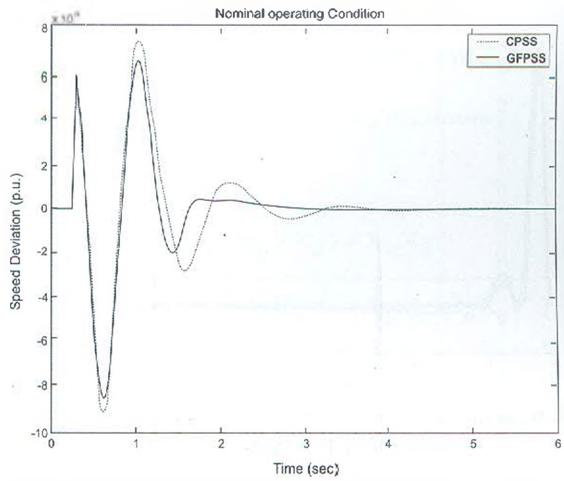

Fig. 5. Dynamic response for Δω for 4-cycle, 3-phase fault at nominal load

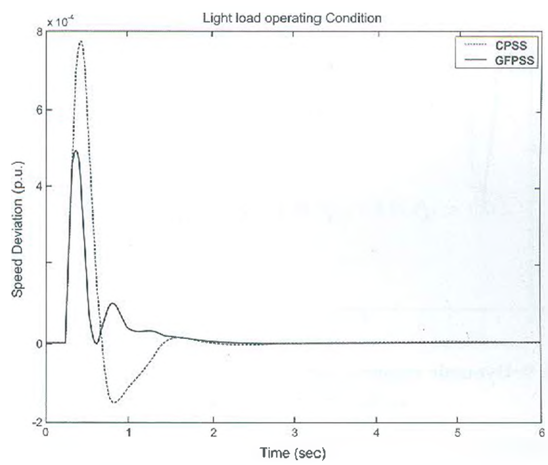

Fig. 6. Dynamic response for Δω for small perturbation at light load

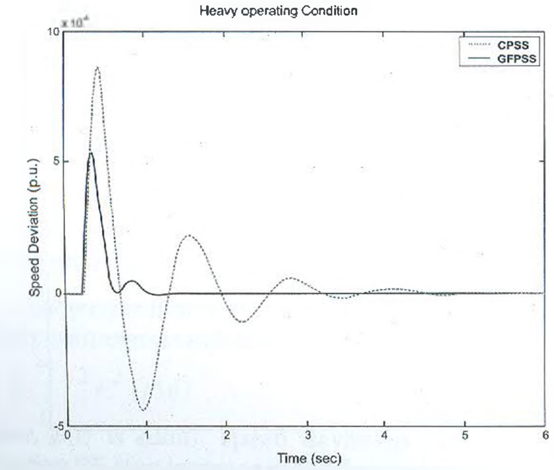

Fig. 7. Dynamic response for Δω for small perturbation at heavy load

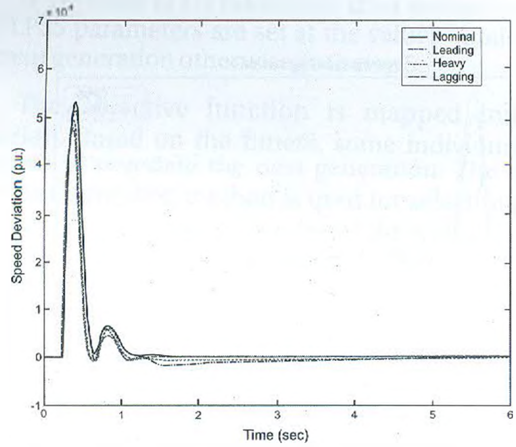

Fig. 8. Dynamic response for Δω for small perturbation under different loadings

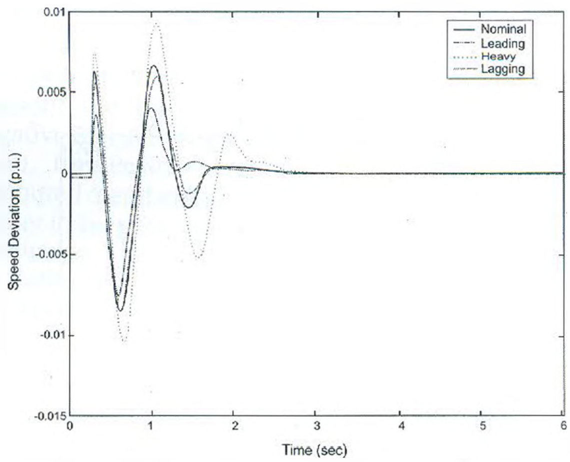

Fig. 9. Dynamic response for Δω for 4-cycle, 3-phase fault at under different loadings

To Demonstrate the robustness of the proposed GPSS, a small perturbation of 5% step increases in the input mechanical torque was applied at various Poading conditions. A3 page fault of 4- cycle duration was applied at generator generator terminals to test the effectiveness of the proposed genetic based FLPSS under large perturbation. The examination of simulation results as shown in fig. 8 and fig. 9 reveal that the propossed GFPSS in quite robust to wide variations in loading conditions considering small perturbations & large perturbations.

CONCLUSIONS

This paper presents a systematic approach for the design of fuzzy logic based power system stabilizer and the parameters of the FPSS are tuned through genetic algorithm. The optimum number of membership functions is five as it reduces the computational burden and provides satisfactory performance under severe conditions. Simulations of the response of the proposed FPSS to small perturbation, large perturbation, and different loading conditions have demonstrated the effectiveness of the FPSS. Investigations reveal that the dynamic performance of the system with FPSS is quite robust over a wide range of operating conditions for both small and large perturbation and it is superior to than that of conventionally tuned PSS.

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Appendix I

System Non-linear Dynamic Model

$$\dot{\omega} = (T_m - T_e)/2H$$

$$\dot{\delta} = \dot{u}_0(\dot{u} - 1)$$

$$\dot{E}'_q = (E_{fd} - (E'_q + (x_d - x'_d)i_d)/T'_{do}$$

$$\dot{E}_{fd} = (K_A(V_{ref} - V_t + U_s) - E_{fd})/T_a$$

where,

$$T_e = V_{td}I_d + V_{tq}I_q$$

$$V_t = \sqrt{V_{td}^2 + V_{tq}^2}$$

$$V_{td} = X_q I_q$$

$$V_{tq} = E'_q - X'_d I_d$$

$$I_d = [(X_e + X_q)(E'_q - E_B \text{cosäo} - E_B R_E \text{sinäina}_e^2$$

$$I_q = [R_e(E'_q - E_B \text{cosäo} + (X_e + X'_d)E_B \text{sinäina}_e^2$$

$$E'_q = V_{tq} + X'_d I_d$$

$$Z_e^2 = R_e^2 + X_e^2 + X_e(X_q + X'_d) + X_q X'_d$$

$$E_B = \sqrt{[(V_{to} - I_d R_e + I_q X_e)^2 + (I_q R_e + I_d X_e)^2]}$$

Appendix II

Nominal System Parameters

Generator :

$M = 2H = 7.0; X_d = 1.81; X_q = 1.76; X'_d = 0.3$

$L_{adu} = 1.65; L_{aqu} = 1.60; L_l = 0.16;$

$R_a = 0.03; R_{fd} = 0.0006; L_{fd} = 0.153;$

$A_{sat} = 0.031; B_{sat} = 6.93; \Psi_{T1} = 0.8;$

Excitation System :

$K_{AVR} = 400; T_A = 0.05; T_B = 1.0; T_C = 8.0; T_R = 0.02;$

PSS :

$T_w = 1.4;$

Transmission Line

$X_e = 0.65; R_e = 0.0;$

Operating Condition

$P = 0.9; V_t = 1.0; E_B = 1.0; f = 60Hz$