Co-Ordinated Tuning Of AVR-PSS Using Differential Evolution Algorithm

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Abstract— **Automatic Voltage Regulator (AVR) regulates the generator terminal voltage by controlling the amount of current supplied to the generator field winding by the exciter. Power system stabilizer (PSS) is installed with AVR to damp the low frequency oscillations in power system by providing a supplementary signal to the excitation system. Optimal tuning of AVR controller and PSS parameters is necessary for the satisfactory operation of the power system. When applying tuning method to obtain the optimal controller parameters individually, AVR improves the voltage regulation of the system and PSS improves the damping of the system. Simultaneous tuning of AVR and PSS is necessary to obtain better both voltage regulation and oscillation damping in the system. This paper deals with the optimal tuning of AVR controller and PSS parameters in the synchronous machine. The problem of obtaining the optimal controller parameters is formulated as an optimization problem and Differential Evolution (DE) algorithm is applied to solve the optimization problem. DE is a population based search algorithm for global optimization over continuous spaces. The suitability of the proposed approach has been demonstrated through computer simulation in a Single Machine Infinite Bus (SMIB) system and compared with Genetic Algorithm (GA) based approach. The proposed approach is found to have stable convergence characteristics and resulted in good voltage regulation and damping characteristics.**

Keywords- Automatic Voltage Regulator, Power System Stabilizer, Genetic Algorithm, Differential Evolution, Single Machine Infinite Bus system.

I. Introduction

Synchronous generator is equipped automatic voltage regulator and excitation system to automatically control the terminal voltage of the machine. A high-gain fast-response AVR improves the voltage regulation and and improves the ability of the power system to maintain synchronism when subjected to large disturbances. The traditional method of assessing transient stability is through large-signal time-domain simulation. The high-gain fast-response AVR action can lead to reduced damping of electromechanical modes of oscillation. The standard way of eliminating this loss of system damping is either to use transient gain reduction on the AVR or to attach a PSS to appropriate machines [1]. In [2], the author has mentioned that a high-gain AVR has a detrimental effect on oscillation stability and PSS can reduce transient stability by overriding the voltage signal to the exciter. In order to avoid these issues, the actions of the AVR and PSS devices are dynamically interlinked. At a basic level, there is a tradeoff between synchronizing torque provided by the AVR and damping torque provided by the PSS [1].

A PSS is directly connected to the AVR of synchronous generators and the main aim of PSS-AVR excitation control configuration is to provide damping and voltage regulation. Several techniques have been proposed to properly design and tune PSS–AVR schemes [3, 4], using low-order two-axis models [5] of synchronous machines. Recently, evolutionary computation techniques such as Genetic Algorithm [6] and Particle Swarm Optimization (PSO) [7] have been applied to obtain the optimal controller parameters. El-Zonkoly [8] has proposed an Optimal tuning of lead-lag and fuzzy logic based power system stabilizers using PSO method. PSO is a population based optimization algorithm which is inspired by social behavior patterns of organisms such as bird flocking and fish schooling. But Genetic Algorithm suffers from computational burden and memory. Also, the premature convergence of GA degrades its performance and reduces its search capability. This work proposes a Differential Evolution (DE) for optimal tuning of AVR-PSS parameters. DE is an evolutionary algorithm that uses rather greatly selection and less stochastic approach to solve optimization problems than other evolutionary algorithms. The main features of DE are its simple structure, convergence property, quality of solution and robustness. The effectiveness of the proposed approach has been demonstrated through computer simulation in a Single Machine Infinite Bus (SMIB) system and compared with optimal tuning using Genetic Algorithm (GA) based approach.

II. Modelling of SMIB System with AVR and PSS

The general system configuration of synchronous machine connected to infinite bus system through transmission network can be represented as shown in Figure 1. The generator excitation system maintains generator voltage and controls the reactive power using an AVR. The role of AVR is to hold the terminal voltage magnitude of a synchronous generator at a specified level. However, these fast acting exciters with high gains can contribute to oscillatory instability in the power system. PSS can be added to the excitation systems to improve the oscillatory instability. The basic function of PSS is to extend the stability limit by modulating generator excitation to provide the positive damping torque to power swing modes. The power system stabilizer (PSS) generates a supplementary signal, which is added to control loop of the generating unit to produce a positive damping. A typical PSS consists of phase compensation stage, a signal washout stage and gain block. To provide damping, PSS must provide a component of electrical torque on the rotor in phase with speed deviations. PSS input signal includes generator speed, frequency and power. For any input signal, the transfer function of PSS must compensate for gain and phase characteristics of the excitation system.

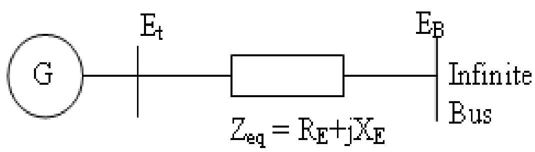


Figure 1. Single Machine Infinite Bus System

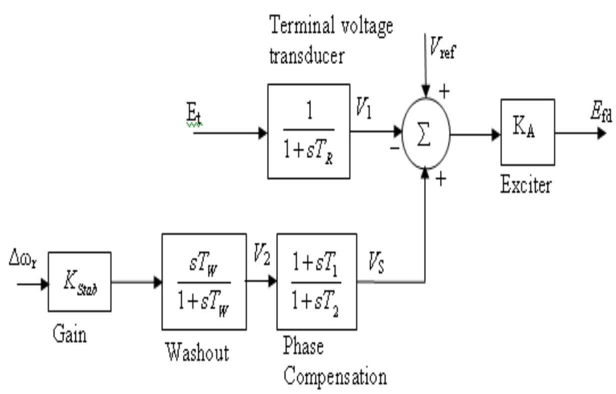


Figure 2. Excitation System with AVR and PSS

Figure 2 shows the thyristor excitation system including AVR and PSS. Figure 3 shows the block diagram representation of the SMIB system to include the excitation system and AVR with PSS. In this representation, dynamic characteristics of the system are expressed in terms of K constants which are given in the Appendix.

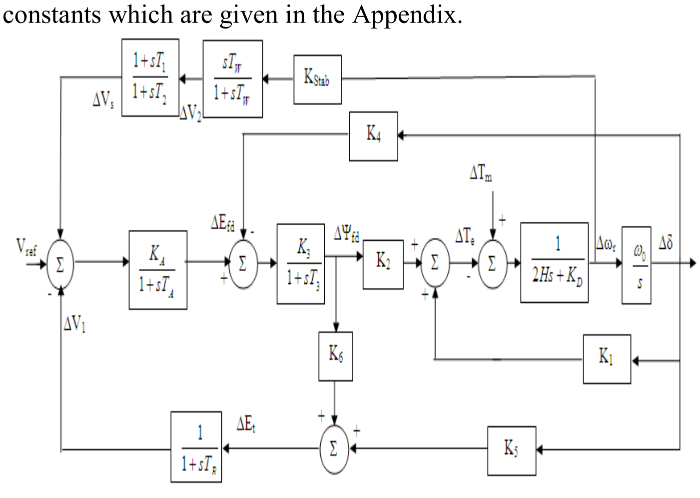


Figure 3. Block diagram representation with Exciter and AVR with PSS

The input control signal to the excitation system is the generator terminal voltage E_t. E_t is not a state variable which is to be expressed in terms of the state variables $\Delta\omega_r, \Delta\delta, \Delta\psi_{fd}$, Δv_1, Δv_2 and Δv_s. The state space representation of the system including excitation system and AVR with PSS is given by,

$$\begin{bmatrix} \Delta\dot{\omega} \\ \Delta\dot{\delta} \\ \Delta\dot{\psi}_{fd} \\ \Delta\dot{v}_1 \\ \Delta\dot{v}_2 \\ \Delta\dot{vs} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & 0 & 0 & 0 \\ a_{21} & 0 & 0 & 0 & 0 & 0 \\ 0 & a_{32} & a_{33} & a_{34} & 0 & a_{36} \\ 0 & a_{42} & a_{43} & a_{44} & 0 & 0 \\ a_{51} & a_{52} & a_{53} & 0 & a_{55} & 0 \\ a_{61} & a_{62} & a_{63} & 0 & a_{65} & a_{66} \end{bmatrix} \begin{bmatrix} \Delta\omega_r \\ \Delta\delta \\ \Delta\psi_{fd} \\ \Delta v_1 \\ \Delta v_2 \\ \Delta v_s \end{bmatrix} \quad (1)$$

where, $a_{11} = -\frac{K_D}{2H}$ $\quad a_{12} = -\frac{K_1}{2H}$ $\quad a_{13} = -\frac{K_2}{2H}$

$$a_{21} = \omega_0 = 2\pi f_0 \qquad a_{32} = -\frac{\omega_0 R_{fd}}{L_{fd}} m_1 L_{ads}'$$

$$a_{33} = -\frac{\omega_0 R_{fd}}{L_{fd}}\left[1 - \frac{L_{ads}'}{L_{fd}} + m_2 L_{ads}'\right] \quad a_{34} = -\frac{\omega_0 R_{fd}}{L_{adu}} K_A$$

$$a_{36} = \frac{\omega_0 R_{fd}}{L_{adu}} K_A \qquad a_{42} = \frac{K_5}{T_R} \quad a_{43} = \frac{K_6}{T_R}$$

$$a_{44} = -\frac{1}{T_R} \qquad a_{51} = K_{Stab} a_{11} \quad a_{52} = K_{Stab} a_{12}$$

$$a_{53} = K_{Stab} a_{13} \; a_{55} = -\frac{1}{T_W} \; a_{61} = \frac{T_1}{T_2} a_{51} \; a_{62} = \frac{T_1}{T_2} a_{52}$$

$$a_{63} = \frac{T_1}{T_2} a_{53} \quad a_{65} = \frac{T_1}{T_2} a_{55} + \frac{1}{T_2} \quad a_{66} = -\frac{1}{T_2}$$

The expression for the K constants used in the above equation are given in the Appendix.

III. Problem Formulation

Stability problems, such as low frequency oscillations, have become increasingly common in large interconnected power systems. The Eigen value and Modal Analysis provides an extension of analytical methods to examine these oscillations. Eigen value analysis uses the standard linear, state space form of system equations and provides an appropriate tool for evaluating system conditions for the study of small signal stability of power system. Eigen value analysis investigates the dynamic behavior of the power system under different characteristic frequencies ("modes"). In a power system, it is required that all modes be stable. Moreover, it is desired that all electromechanical oscillations be damped out as quickly as possible. The results of an Eigen value analysis are given as frequency and relative damping for each oscillatory mode. In this paper, the Eigen values are calculated based on state variables from state matrix A in the equation (1).

The co-ordinated tuning of AVR gains and Power System Stabilizer parameters is necessary to improve the damping performance of power systems with fast transient response. The task of simultaneous tuning of controller parameters is formulated as an optimization problem with the objective function given by

$$\text{Min} \quad DI = \sum_{i=1}^{n} (1 - \zeta_i) \tag{2}$$

where, ζ is Damping ratio, DI is Damping index and n is total number of dominant Eigen values. The above optimization problem is subjected to the following constraints:

$$\begin{aligned} &K_A^{\min} \le K_A \le K_A^{\max} \\ &K_{Stab}^{\min} \le K_{Stab} \le K_{Stab}^{\max} \\ &T_A^{\min} \le T_A \le T_A^{\max} \\ &T_1^{\min} \le T_1 \le T_2^{\max} \\ &T_2^{\min} \le T_2 \le T_2^{\max} \\ &T_W^{\min} \le T_W \le T_W^{\max} \end{aligned} \tag{3}$$

Differential Evolution algorithm is applied to the above optimization problem to search for the optimum value of the controller parameters. The detail of the proposed method is given in the next section.

IV. Overview of Differential Evolution Algorithm

Differential Evolution [9] is a population-based stochastic search algorithm that works in the general framework of evolutionary algorithms. The optimization variables are represented as floating point numbers in the DE population. It starts to explore the search space by randomly choosing the initial candidate solutions within the boundary. Differential evolution creates new off springs by generating a noisy replica of each individual of the population. The individual that performs better from the parent vector (target) and replica (trial vector) advances to the next generation. This optimization process is carried out with three basic operations namely, mutation, crossover and selection. The details of these operators are given below.

A. Mutation

After the population is initialized, the mutation operator is in charge of introducing new parameters into the population. To achieve this, the mutation operator creates mutant vectors by perturbing a randomly selected vector (X_a) with the difference of two other randomly selected vectors (X_b and X_c). All of these vectors must be different from each other, requiring the population to be of at least four individuals to satisfy this condition. To control the perturbation and improve convergence, the difference vector is scaled by a user defined constant in the range between 0 and 1.2.

$$X_{n,i} = X_{a,i} + F\left(X_{b,i} - X_{c,i}\right) \tag{4}$$

where, F is scaling constant

B. Crossover

The crossover operator creates the trial vectors which are used in the selection process. A trial vector is a combination of mutant vector and a parent vector based on different distributions like uniform distribution, binomial distribution, exponential distribution is generated in the range [0,1] and compared against a user defined constant referred to as the crossover constant. If the value of the random number is less or equal to the value of the crossover constant, the parameter will come from the mutant vector, otherwise the parameter comes from the parent vector.

The crossover operation maintains diversity in the population preventing local minima convergence. The crossover constant must be in the range from 0 to 1. If the value of crossover constant is one then the trial vector will be composed of entirely mutant vector parameters. If the value of crossover constant is zero then the trial vector will be composed of entirely parent vector. Trial vector gets at least one parameter from the mutant vector even if the crossover constant is set to zero.

$$X''_{i,j}(G) = \begin{cases} X'_{i,j}(G) & \text{if } \eta_j \le C_r \text{ or } j = q \\ X_{i,j}(G) & \text{otherwise} \end{cases} \tag{5}$$

Where, q is randomly chosen index,

C_r is Crossover constant,

$X_{i,j}(G)$ is parent vector

$X'_{i,j}(G)$ is mutant vector

$X''_{i,j}(G)$ is trial vector

C. Selection

The selection operator chooses the vectors that are going to compose the population in the next generation. This operator compares the fitness of the trial vector and fitness of the corresponding target vector and selects the one that performs better.

$$X_i^{(G+1)} = \begin{cases} X''_i(G) & \text{if } f\left(X''_i(G)\right) \le f(X_i(G)) \\ X_i(G) & \text{otherwise} \end{cases} \tag{6}$$

The selection process is repeated for each pair of target and trial vector until the population for the next generation is complete.

V. DE Implementation of AVR-PSS Tuning

When applying DE to optimize the controller gains, two main issues need to be addressed:

(a) Representation of the decision variables and

(b) Formation of the Fitness function

A. Variable Representation

Each individual in the genetic population represents a candidate solution. For tuning of AVR with PSS controller, the elements of the solution consist of AVR exciter gain (K_A), Stabilizer gain (K_{Stab}), AVR exciter time constant (T_A), time constant of Lead compensator (T_1), time constant of Lag compensator(T_2) and washout time constant (T_W). These variables are represented as floating point numbers in the DE population. With this representation, an individual in the DE population for computing optimal controller parameters will look like the following:

$$\underbrace{198.345}_{K_A} \quad \underbrace{48.452}_{K_{Stab}} \quad \underbrace{0.0132}_{T_A} \quad \underbrace{3.247}_{T_1} \quad \underbrace{0.0501}_{T_2} \quad \underbrace{0.0122}_{T_W}$$

B. Fitness Function

Evaluation of the individuals in the population is accomplished by calculating the objective function value for the problem using the parameter set. The result of the objective function calculation is used to calculate the fitness value of the individual. Fitter chromosomes have higher probabilities of being selected for the next generation. The fitness function is the reciprocal of the performance criterion given in (2). Hence, the minimization of objective function given by (2) is transformed to a fitness function to be maximized as:

$$Fitness = \frac{k}{Min\,(DI)} \tag{7}$$

where k is a constant. This is used to amplify (1/ F), the value of which is usually small, so that the fitness value of the chromosome will be in a wider range.

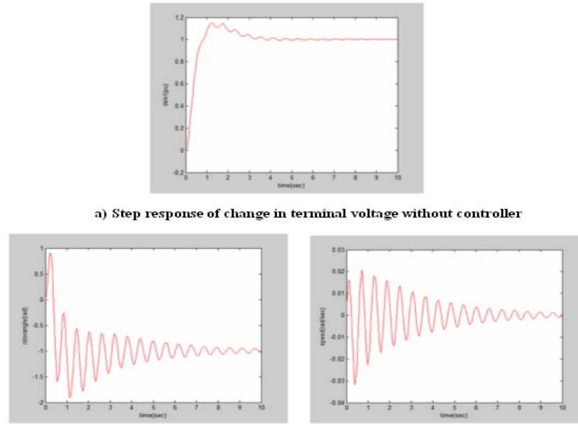
VI. SIMULATION RESULTS

The tuning of AVR-PSS parameters was tested in a typical single-machine infinite-bus system under normal and fault conditions. The software for the Differential Evolution algorithm was written in MATLAB and executed on a PC with 2.4 MHZ and 256 MB RAM. The parameters of the excitation system are given in Table 1.

TABLE 1: PARAMETERS OF THE EXCITATION SYSTEM

K_1 =1.591	K_2 = 1.5	K_3 = 0.333	K_4 = 1.8
K_5 = -0.12	K_6 = 0.3	ω_0 = 314	T_m = 1
T_R = 0.02	T_3 =1.91	H = 3	K_D = 0

The response of the system without controller and PSS is shown in Figure 4. From the figure, it is found that the response of the system has not settled to the desired value and more oscillations are present.



a) Step response of change in terminal voltage without controller

b) Response of Rotor angle deviation without controller

c) Response of Rotor speed deviation without controller

Figure 4. Response of the system without controller and PSS

The proposed method was applied to obtain the controller parameters under normal condition. AVR exciter gain (K_A), Stabilizer gain (K_{Stab}), AVR exciter time constant (T_A), time constant of Lead compensator (T_1), time constant of Lag compensator (T_2) and washout time constant (T_W) are taken as the optimization variables. They are represented as a floating point numbers in the population. The initial population is generated randomly between the variables lower and upper limits. The fitness function given by (7) is used to evaluate the fitness value of each set of controller parameters. The performance of DE for various value of crossover and mutation probabilities in the ranges 0 – 1 and 0 – 1.2 respectively was evaluated. The best results of the DE are obtained with the following control parameters.

Number of generations	: 75
Population size	: 50
Crossover probability	: 0.8
Mutation probability	: 0.3

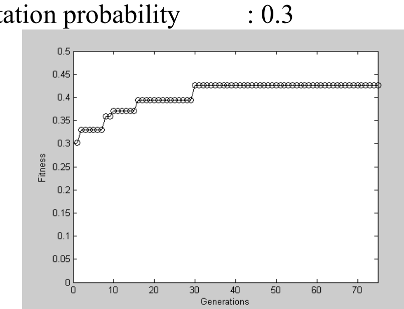


Figure 5. Convergence characteristics of DE

The proposed method took 213 sec to complete the 75 generations. Figure 5 shows the convergence characteristics of DE algorithm. After 30 generations it is found that all the individuals have reached almost the same fitness value. This shows that DE has reached the optimal solution. It can be seen that the fitness value increases rapidly in the first 30 generations of the DE. During this stage, the DE concentrates mainly on finding feasible solutions to the problem. Then the value increases slowly and settles down near the optimum value with most of the individuals in the population reaching that point.

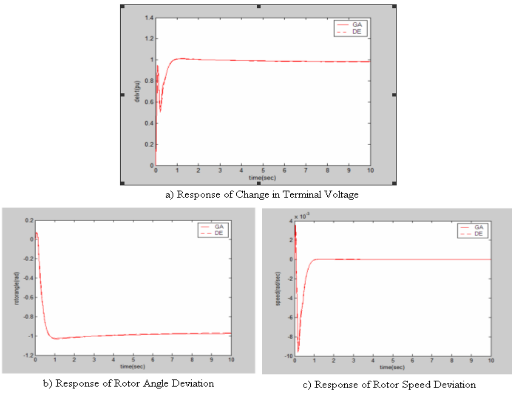


Figure 6. Response of the system with GA and DE based AVR-PSS Under normal condition

TABLE 2: TRANSIENT PARAMETERS OF THE SYSTEM UNDER NORMAL CONDITION

Parameters	GA based AVR-PSS	DE based AVR-PSS
K_A	246.6446	225.8553
T_A	0.0154	0.0128
K_{Stab}	49.9707	49.5398
T_W	4.2569	3.2522
T_1	0.0506	0.05
T_2	0.0105	0.0104
T_s (sec)	0.7422	0.6493
T_r (sec)	0.6872	0.5715
Osh (%)	0.0080	0.0064
ESS	0.0896	0.00123
F	1.3433	1.2750
Time (sec)	273.9690	212.7970

The system response with optimal values of controller parameters is given in Figure 6. The results obtained by DE are given in Table 2. To compare the performance of AVR-PSS tuned by DE with AVR-PSS tuned by GA, simulation was carried out using Genetic Algorithm. The response of the system is also given in Figure 6. The results obtained by GA is also given in Table 2. On comparing the results, it is found that the proposed algorithm has resulted in minimum values of the objective function, overshoot and steady state error. Both GA and DE algorithm has resulted in damping the oscillation with better transient response. But the proposed algorithm took less computation time and memory storage when compared with AVR-PSS tuned by GA.

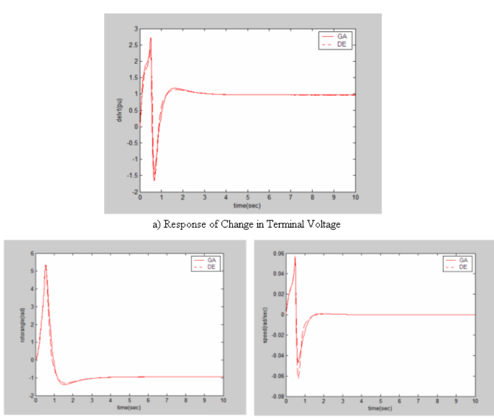


Figure 7 Response of the system with GA and DE based AVR-PSS Under fault condition

TABLE 3: TRANSIENT PARAMETERS OF THE SYSTEM UNDER FAULT CONDITION

Parameters	GA based AVR-PSS	DE based AVR-PSS
K_A	150.7331	148.9166
T_A	0.0122	0.0101
K_{Stab}	49.8534	47.8521
T_W	1.1486	1.0905
T_1	0.0821	0.0501
T_2	0.0095	0.0067
T_s (sec)	2.9439	1.3634
T_r (sec)	0.1204	0.1205
Osh (%)	1.7220	1.8563
ESS	0.0239	0.00952
F	0.1743	0.0588
Time (sec)	119.9850	95.1880

To analyze the performance of the AVR-PSS under the fault condition, a fault is applied at the generator terminal and the response of the system was observed. Figure 7 shows the system response during the above contingency with proposed approach. It can be observed that the controller is able to suppress the oscillations and provide good damping characteristics. The transient parameters of the system are obtained under fault condition are given in Table 3.

VII. CONCLUSION

This paper has demonstrated the importance of co-ordinated tuning of AVR controller and Power System Stabilizer in synchronous machines. Differential Evolution Algorithm is applied for obtaining the optimal parameters of AVR gains and PSS controller parameters simultaneously. The response of the system tuned with the proposed approach is found to have minimum overshoot, settling time, rising time and steady state error when compared with individual tuning. Also, the proposed method has resulted in better dynamic performance as well as transient response of the system. Further, the DE algorithm took less time to reach the optimal solution.

VIII. LIST OF SYMBOLS

E_B : Infinite bus voltage in pu

E_t : Generator terminal voltage in pu

ω_0 : Rotor electrical speed in rad/sec

ω_r : Angular speed of the rotor in rad/sec

ψ_{fd} : Field circuit flux linkage

δ_0 : Initial rotor angle in elect. Rad

K_D : Damping torque coefficient in pu torque/pu speed deviation

K_S : Synchronizing torque coefficient in pu torque/rad

H : Inertia constant in MW.s/MVA

R_T : Total system resistance in pu

R_{fd} : Field circuit resistance in pu

L_{fd} : Field circuit reactance in pu

X_{Tq} : Total q-axis reactance of the system in pu

X_{Td} : Total d-axis reactance of the system in pu

L_{adu} : Generator d-axis unsaturated value of mutual inductance in pu

L_{aqu} : Generator q-axis unsaturated value of mutual inductance in pu

L_{ads} : Generator d-axis saturated value of mutual inductance in pu

L_{aqs} : Generator q-axis saturated value of mutual inductance in pu

X_d : Synchronous reactance of the generator in pu

X'_d : Transient reactance of the generator in pu

K_A : Exciter gain

T_W : Time constant of washout block in sec

T_1, T_2: Phase compensator time constants in sec

Osh : Overshoot (%)

Ess : Steady state error

Ts : Settling time in sec

Tr : Rising time in sec

APPENDIX

K constants of the SMIB system including the excitation system and AVR with PSS:

$$K_1 = n_1\left(\psi_{ad0} + L_{aqs} i_{d0}\right) - m_1\left(\psi_{aq0} + L'_{ads} i_{q0}\right) \quad \text{(A.1)}$$

$$K_2 = n_2\left(\psi_{ad0} + L_{aqs} i_{d0}\right) - m_2\left(\psi_{aq0} + L'_{ads} i_{q0}\right) + \frac{L'_{ads}}{L_{fd}} i_{q0} \quad \text{(A.2)}$$

$$K_3 = \frac{L_{ads} + L_{fd}}{L_{adu}} \frac{1}{1 + \frac{X_{Tq}}{D}\left(X_d - X'_d\right)} \quad \text{(A.3)}$$

$$K_4 = L_{adu} \frac{L_{ads}}{L_{ads} + L_{fd}} \frac{E_B}{D}\left(X_{Tq} \sin\delta_0 - R_T \cos\delta_0\right) \quad \text{(A.4)}$$

$$K_5 = \frac{e_{d0}}{E_{t0}}\left[-R_a m_1 + L_l n_1 + L_{aqs} n_1\right] + \frac{e_{q0}}{E_{t0}}\left[-R_a n_1 - L_l m_1 - L'_{ads} m_1\right] \quad \text{(A.5)}$$

$$K_6 = \frac{e_{d0}}{E_{t0}}\left[-R_a m_2 + L_l n_2 + L_{aqs} n_2\right] + \frac{e_{q0}}{E_{t0}}\left[-R_a n_2 - L_l m_2 + L'_{ads}\left(\frac{1}{L_{fd}} - m_2\right)\right] \quad \text{(A.6)}$$

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