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POWER SYSTEM STABILIZATION USING SWARM TUNED FUZZY CONTROLLER

Khaled A. El-Metwally[1,2]

Department of Electrical Engineering,
[1]Cairo University, Giza, Egypt
[2]Sultan Qaboos University, Muscat, Oman
Email: kmetwally@squ.edu.om

Abstract**:** This paper proposes a swarm optimized fuzzy logic based power system stabilizer (SFLPSS). The fuzzy logic stabilizer membership functions parameters, inputs and outputs gains and fuzzy rules are tuned and optimized using particle swarm optimization (PSO) technique. Optimization parameters were subject to realistic constraint. The optimization is done using a seventh order nonlinear model of a single synchronous machine connected to infinite bus bar. A Guided simulation technique using stability limits check is used to accelerate the PSO algorithm search for optimized parameters. Optimization results in reduction of fuzzy rules. Transient tests of the optimized controller performance showed better performance over conventional controllers. *Copyright © 2008 IFAC*

Keywords: Intelligent control of power systems, Artificial intelligence, Neural fuzzy modeling and control

1. INTRODUCTION

Transient stability of power systems is a classical dynamic problem. Power generators are conventionally equipped with automatic voltage regulators (AVRs) to improve their dynamic limits and control their terminal voltages. Unfortunately, AVRs introduce negative damping torques which adversely affect stability (DeMello, et. al. 1969). Following disturbances, such as short circuits and operating point variations, power systems may exhibit unacceptable oscillations or loose synchronism. Power system stabilizers are normally incorporated to suppress these oscillations and damp them quickly (Yu, 1983). Conventional power system stabilizers (CPSS) are normally tuned at a certain operating point. If the system drifts from the original operating point, the performance of a CPSS degrades significantly and an expert control engineer has to retune the CPSS.

To overcome fixed parameters controller limitations, the application of adaptive control of the machine excitation to enhance the transient stability has been given much attention in literature (Malik, 1986; Wang, 1994; Shen, 2003). The implementation of an adaptive power system stabilizer faces some technical difficulties. For example, the estimator, which is the heart of any adaptive controller, will not produce reliable estimates unless the measurements are persistently exciting. Furthermore, the performance of adaptive controllers during the learning phase is usually unacceptable (Wang, 1994).

Fuzzy-logic control has emerged as a promising design technique of power system stabilizers (El-Metwally, 1995; Hosseinzadeh, 1999; Saleh, 2000). Fuzzy logic provides a convenient method for constructing nonlinear controllers via the use of heuristic knowledge. However, the design of a FLPSS requires the selection of the size of the rule base and the shape and parameters of the membership functions. Many researchers focused their efforts to enhance its' performance using different tuning and adaptation methods. These methods include self organizing fuzzy controller (Rojas, 2000 and Tung, 2002) and adaptive fuzzy tuning methods (Elshafei, 2005) and genetic algorithm (Leung, 2004 and Chou, 2006).

This paper proposes a new particle swarm optimized fuzzy logic power system stabilizer (SFLPSS) and overcomes the drawbacks of the regular heuristic tuning of fuzzy controllers. The proposed stabilizer is based on the optimization of input membership shapes, controller gains as well as fuzzy controller rules.

After a power system model description given in Section 2, Section 3 describes briefly the basis of the FLPSS. Section 4 discusses the theoretical background of the particle swarm optimization. Section 5 Optimizes the FLPSS using the guided

PSO. Section 6 compares the Optimized SFLPSS with the conventional CPSS under small and large disturbances. The conclusions are given in section 7.

2. POWER SYSTEM MODEL

A power system model represented by a synchronous machine connected to a constant voltage bus through a double circuit transmission line is considered as a case study. The system consists of a seventh order nonlinear model of a synchronous generator, a governor, a turbine and an automatic voltage regulator. Model details are given in Appendix A.1,A.2 (El-Metwally, 1995). A schematic diagram of the power system is shown in Fig. 1.

For the sake of comparison, the system was configured to switch between different control techniques. The main objective is to show the improvement of the SFLPSS over the standard FLPSS.

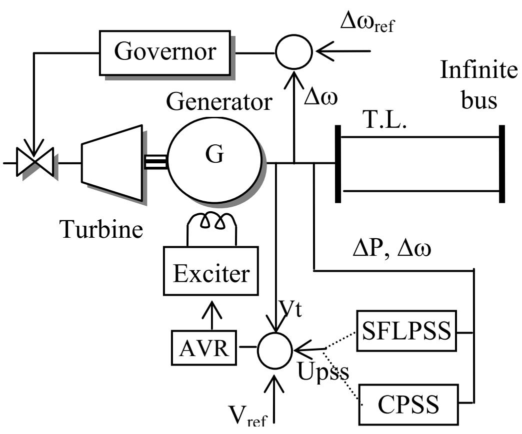


Figure 1 Schematic of the power system model.

3. FUZZY LOGIC POWER SYSTEMS STABILIZER

The T-S fuzzy-logic configuration is adapted to implement the FLPSS. The T-S fuzzy controller is composed of three parts: the fuzzifier, the inference engine and the defuzzifier (Elshafei, 2005); see Fig. 2. The fuzzifier consists of two inputs uses five normalized membership functions for each input in addition to the input gain. The five memberships represent the fuzzy sets variation from negative big to positive big (NB, NS, Z, PS, PB) as shown in Fig.3. In the current FLPSS, the speed deviation, Δω, and active power deviation, ΔPe, of the synchronous machine are chosen as the inputs. The input gains are named $K_{\Delta\omega}$, $K_{\Delta p}$.

The second part is the inference engine which is responsible of generating the fuzzy decision based on defined fuzzy rules. The rules used in implementation are given in Table 1. The last part is the defuzzifier which consists of fuzzy 25 singletons covering the input space. Control signal from the FLPSS, Upss, is injected to the summing point of the machine AVR; see Fig.1.

In standard fuzzy logic controllers, of the above mentioned structure is simply implemented as a feed-forward neural network for purposes of simulation or hardware implementation.

Table 1 Initialization of Fuzzy Logic PSS rules

Speed Deviation	Accelerating Real Power				
	NB	**NS**	**Z**	**PS**	**PB**
NB	-1	-1	-1	-0.5	0
NS	-1	-0.5	-0.5	0	0.5
Z	-1	-0.5	0	0.5	1
PS	-0.5	0	0.5	0.5	1
PB	0	0.5	1	1	1

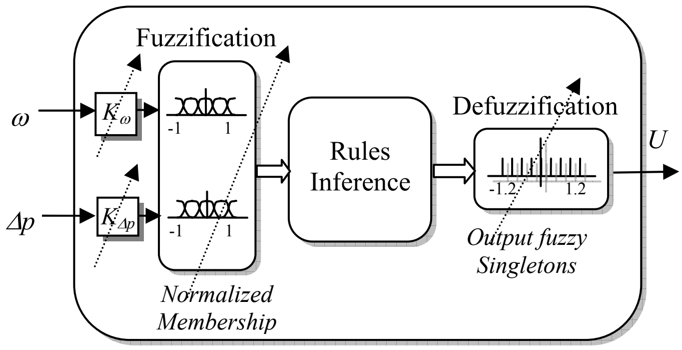


Figure 2. The basic structure of the T-S fuzzy controller

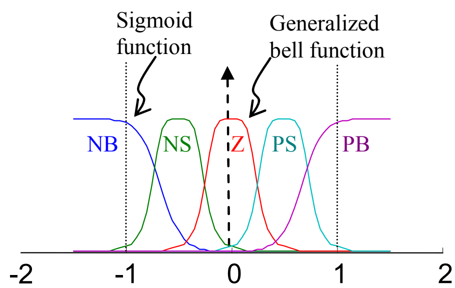


Figure 3 Five membership functions for each input

4. PARTICLE SWARM OPTIMIZATION

The particle swarm optimization (PSO) method is a probabilistic optimization algorithm originally proposed by J. Kennedy as a simulation of social behavior in (Kennedy, 1995). The algorithm starts with a population of potential solutions (particles) to the problem under consideration and uses them to probe the search space. A particle, i, is defined as a moving point of position coordinate $X_i=(x_{i1},x_{i2},....x_{iD})^T$ in a D-dimension hyperspace. For each particle, each individual of the population has an adaptable velocity (position change)

$V_i=(v_{i1},v_{i2},\ldots,v_{iD})^T$, according to which it moves in the search space. Each individual particle performance is evaluated by the objective function. The best particle position of the current population, the local best, P_{lb}, and the best particle position of all previous iterations, the global best, P_{gb}, are stored and used for adaptation of the new particle speed and position(Parsopoulos, 2002 and Clerc, 2002). The adaptation of the particles speeds and position is given by the following two equations:

$$v_{id}^{n+1} = w\cdot v_{id}^{n} + \alpha(P_{lb}^{n} - x_{id}^{n}) + \beta(P_{gb}^{n} - x_{id}^{n}) \quad (1)$$

$$x_{id}^{n+1} = x_{id}^{n} + v_{id}^{n+1} \quad (2)$$

Where, n is the iteration number, i is current particle, d is the current dimension index, α,β are bounded positive uniform distribution random numbers to control particle global minimum approaching mechanism. The speed of the particle is bounded to $\pm V_{max}$ to prevent search explosion. An important source of the swarm's search capability is the interactions among particles as they react to one another's findings. The algorithm in pseudo code is given as follows:

Initialize population
Do
For *i = 1* to Population Size
  if $f(X) < f(P_{lb})$ then $P_{lb} = X$
  $P_{gb} = \min(P_{lb})$
  For *d = 1* to Dimension
    $v_{id}^{n+1} = v_{id}^{n} + \alpha(P_{lb}^{n} - x_{id}^{n}) + \beta(P_{gb}^{n} - x_{id}^{n})$
    $v_{id}^{n+1} = sign(v_{id}^{n+1})\cdot\min(abs(v_{id}^{n+1}), v_{\max})$
    $x_{id}^{n+1} = x_{id}^{n} + v_{id}^{n+1}$
  Next *d*
Next *i*
Until termination criterion is met

5. CONSTRAINED SFLPSS GUIDED WITH STABILITY LIMITS CHECK

The particle swarm optimization algorithm is used to optimize six input parameters of the fuzzy controller; the three controller gains ($k_{\Delta\omega}$, $k_{\Delta p}$, k_v) and three parameters to adjust the input memberships. In addition it optimizes the 25 output fuzzy singletons as well. This sums up to a total of 30 optimzed parameters. The generalized bell function and the sigmoid functions given in (3) and (4) are used to describe the input membership functions as in Fig. 3. The use of the sigmoid functions in the upper and lower boundary of the variable (-1,1) is important in order to ensure open sets. These open sets are necessary to provide the correct fuzzy decision in case of input lies outside the minimum and maximum range.

$$gbell(x;\ a,\ b\ ,c) = \frac{1}{1+\left|\frac{x-c}{a}\right|^{2b}} \quad (3)$$

$$sigmoid(x;\ c,\ \tau) = \frac{1}{1+e^{-\tau(x-c)}} \quad (4)$$

All membership centroids (c–parameter) are fixed and symmetrically distributed over the normalized range (-1, 1) while the parameters *a, b, τ,* are used as optimization parameters. Figure 4 shows the effect of the selected parameters variations on the shape of the generalized bell and the sigmoid functions.

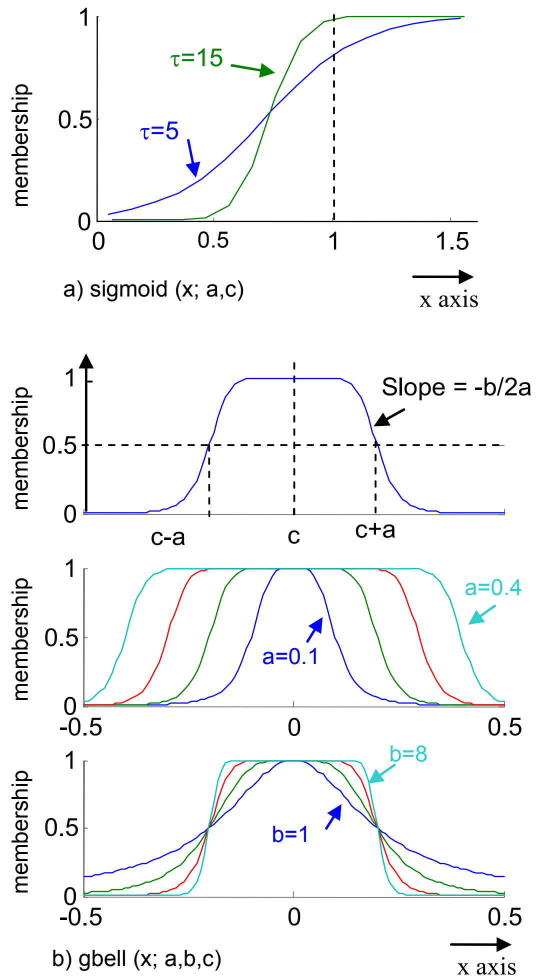


Figure 4 Sigmoid and generalized bell functions

Realistic constrains applied to bound the PSO search space were; $a\in[0.15,0.4]$, $b\in[1,10]$, $\tau\in[5,15]$, and $u_{ci}\in[-1,1]$. $k_u\in[-1.2,1.2]$. Parameters $k_{\Delta\omega}$, $k_{\Delta p}$ were left unconstrained.

The particle swarm optimization tuning of the fuzzy power system stabilizer parameters was done using nonlinear simulation with guided stability limit checks (Al-Hinai, 2007). The developed technique facilitates using the PSO in nonlinear simulation environments. It provides more robust controller design since it considers disturbances based on nonlinear simulations rather than linearization around selected operating conditions. Moreover, the role of guided stability limits is to provide faster PSO searching by ignoring the undesired solutions that exceeds specified conversions limits thus allowing the selection of only stable runs to affect the performance objective function. Figure 5 illustrates the stability limits set to early detect the divergent simulations and saving simulation time. The objective function used for the PSO was set as the sum square error of the system speed deviation as:

$$J = \sum_{i=1}^{N} (\Delta\omega)^2 \qquad (5)$$

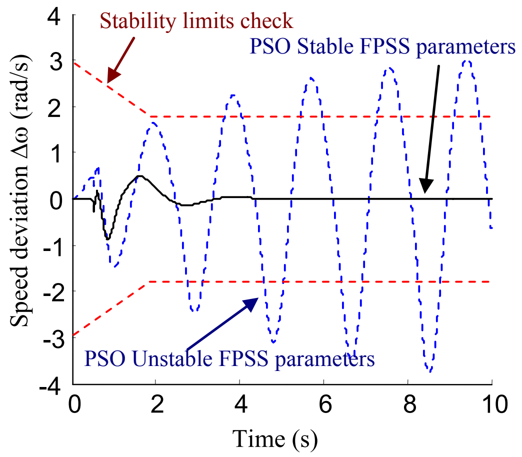


Figure 5 Guided PSO using Stability limits check

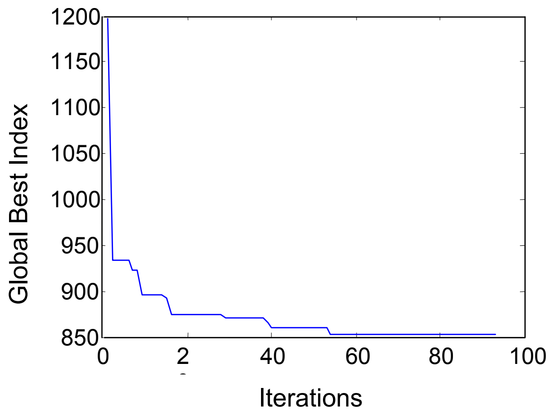


Figure 6 Objective function index conversion

The optimization was started with 40 birds, α=2.2, β=2.1 and a Vmax=5. The particles inertia weight factor w was set to 0.5+rand(.)/2 to provide better conversion as adapted in (Bergh, 2004). The global index optimization index conversion is shown in Fig. 6 while the initial and final rules contours variations are shown in Fig 7. It worth mentioning that this optimization is done for only 2-inputs with 5 membership functions each, i.e. only 25 rules. This is close to 50% less the comenly used number of rules in literature which is 49 (El-Metwally, 1995).

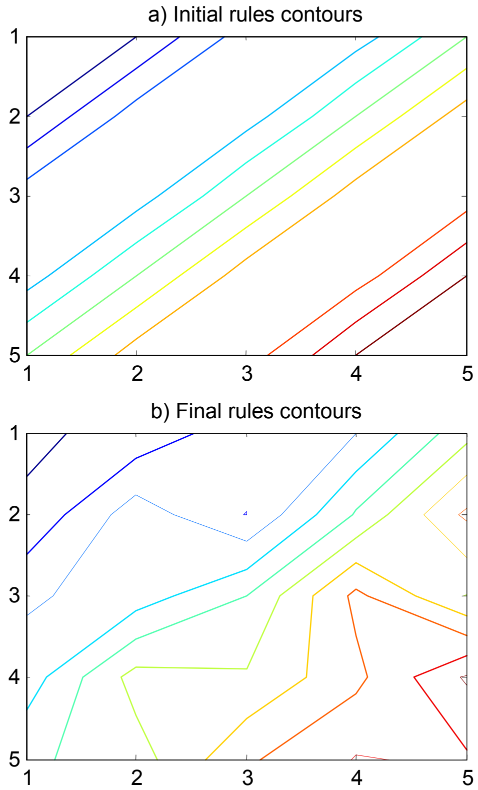


Figure 7 a) Initial and b) Final rules contours

6. SIMULATION RESULTS

The SFLPSS was tested for a sever 3 phase to ground test disturbances while working on a full load at 0.95 pu. active power and 0.9 power factor lagging and compared with the conventional stabilizer CPSS (CPSS Malik, 1986). Figure 8 shows the response of the system speed deviation with SFLPSS, CPSS and No PSS cases. Both controllers have the same overshoot however the SFLPSS reaches the steady state faster than the conventional CPSSS. This result shows the ability of the optimize controller to stabilize the power system under sever disturbance.

The response of the controller was also tested at light loading conditions with a 0.3 pu. active power and 0.8 pf lagging with a disturbance of 0.2 pu. input torque at 0.5 second and the disturbance was released at 5 sec. This type of disturbance is enough to force the system to work near the saturation limits at these conditions. The proposed controller also showed a a better overshoot reduction and faster response compared wit the performance of conventional one as shown in Fig.9.

A final test was done on the machine at leading power factor case (0.3 pu. active power & 0.8 leading pf) with a similar 0.2 pu. input torque disturbance. The speed deviation in Fig.10 shows better behavior of the SFLPSS in overshoot reduction and in settling time.

7. CONCLUSIONS

The paper proposes an optimized tuning of the fuzzy logic power system stabilizers parameters and rules. Both fuzzy inputs membership functions and the fuzzy rules were tuned and optimized using particle swarm optimization technique. The optimization is done using realistic parameters constrains. The PSO algorithm is guided with simulation stability limits check to speed up search and reject unstable responses. The optimization was done for 31 parameters representing the fuzzy controller input/output gains and the membership functions shapes and 25 rules singleton. This tuning enables the use of only 25 rules FLPSS instead of 49 rules previously reported in literature. Simulation results showed better performance in both overshoot reduction and settling time of the SFLPSS over conventional CPSS at different loading conditions and different system disturbances.

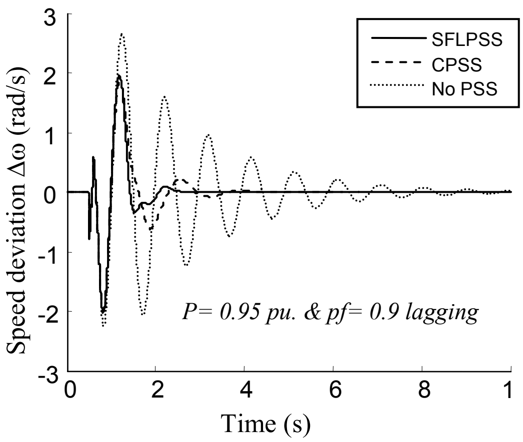


Figure 8 Response to 3-phase to ground disturbance

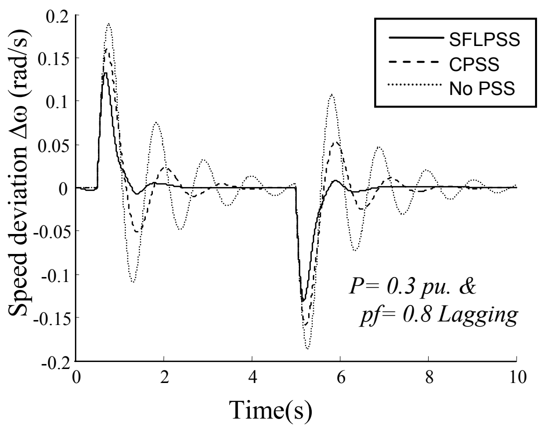


Figure 9 Response to 0.2 pu input torque disturbance

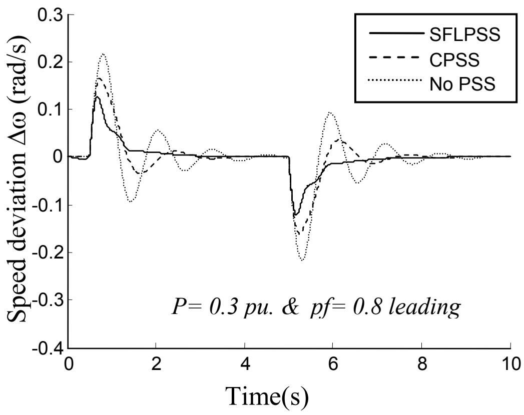


Figure 10 Response to 0.2 pu. input torque disturbance at leading power factor

REFERENCES

Al-Hinai, A. and A. Feliachi, "Impact of Microturbines on Load Following Control in Deregulated Power Distribution Systems," 9th IASTED 2007, Clearwater, Florida, Jan 3 – 5, 2007.

Bergh, F. and A.P. Engelbrecht, "Self-Organizing Hierarchical Particle Swarm Optimizer With Time-Varying Acceleration Coefficients", IEEE Transactions on Evolutionary Computation, Vol. 8, No. 3, June 2004.

Chou, C-H "Genetic algorithm-based optimal fuzzy controller design in the linguistic space" Fuzzy Systems, IEEE Transactions on vol.14(3), June 2006 pp.372 - 385

Clerc, M. and J. Kennedy, "The particle swarm-Explosion, stability, and convergence in a multidimensional complex space", IEEE trans. Evolutionary Computation, vol. 6, 2002, pp. 58-73.

DeMello, F. and C. Concordia "Concepts of synchronous machine stability as affected by excitation control", IEEE transaction PAS, vol. 88, no. 4, 1969, pp. 316-329.

El-Metwally, K.A and O. Malik, "Fuzzy logic power system stabilizer", IEE Proc. Generation, Transmission, and Distribution, vol. 142(3), 1995, pp. 277-281.

Elshafei, A.L. and K.A. El-Metwally, A.A.Shaltout "A Variable-Structure Adaptive Fuzzy-Logic Stabilizer for Single and Multi-Machine Power Systems", Control Engineering Practice Journal, March 2005.

Hosseinzadeh, N. and A. Kalam, "A rule-based fuzzy power system stabilizer tuned by a neural network", Energy Conversion, IEEE Transactions, vol. 14(3), Sept. 1999, pp.773 – 779.

Leung, F.H. H.K. Lam, S.H. Ling, P.K. Tam, “Optimal and stable fuzzy controllers for nonlinear systems based on an improved genetic algorithm”, Industrial Electronics, IEEE Transactions, vol. 51(1), 2004, pp:172 - 182

Jiao, X. and Y. Sun, “Non-Linear adaptive control for transient stability enhancement of synchronous generator”, Int. J. Modeling. Identification and Control, vol. 1(3), 2006, pp.171-176.

Kennedy, J. and R. C. Eberhart, “Particle swarm optimization,” in Proc. IEEE Int. Conf. Neural Networks, Perth, Australia, Nov. 1995, pp. 1942–1948.

Malik, O.P. "Adaptive control of synchronous machine excitation", pp.61-79, in "Microprocessor-Based Control Systems", edited by Sinha, N.K., D.Reidel Publishing Company, Boston, USA,1986.

Parsopoulos, K.E. and M.N. Vrahatis, "Recent approaches to global optimization problems through Particle Swarm Optimization," Natural Computing 1: Kluwer Academic Publishers, 2002, pp.235–306.

Rojas, I. H. Pomares, J. Ortega, A. Prieto, “Self-organized fuzzy system generation from training examples”, Fuzzy Systems, IEEE Transactions on, vol. 8(1), Feb. 2000, pp.23 - 36

Shen, T. Mei,S., Lu,Q.,Hu,W. and Tamura. K., “Adaptive nonlinear excitation control with L2 disturbance attenuation for power systems”, Automatica, Vol. 39(1), 2003, pp81-89.

Saleh, R.A. and H.R. Bolton, “Genetic algorithm-aided design of a fuzzy logic stabilizer for a superconducting generator”, Power Systems, IEEE Transactions vol. 15(4), Nov.2000, pp.1329 – 1335.

Tung, W.L. and C. Quek, "GenSoFNN: a generic self-organizing fuzzy neural network", Neural Networks, IEEE Transactions, vol. 13(5), 2002, pp.1075 – 1086.

Wang, Y. D. Hill, R. Middleton, and L. Gao “Transient stabilization of power systems with an adaptive control law”, Automatica, vol. 30(9),1994, pp. 1409-1413.

Yu, Y. "Electric Power Systems Dynamics", Academic Press, 1983.

APPENDIX

A.1 The generating unit is modeled by a seventh ordered model as follows:

$$\dot{\delta} = \omega_0 \cdot \omega$$

$$\dot{\omega} = \frac{1}{2H}(T_m + g + K_d\dot{\delta} - T_e)$$

$$\dot{\lambda}_d = e_d + r_a i_d + \omega_o(\omega+1)\lambda_q$$

$$\dot{\lambda}_q = e_q + r_a i_q + \omega_o(\omega+1)\lambda_d$$

$$\dot{\lambda}_f = e_f - r_f i_f$$

$$\dot{\lambda}_{kd} = -r_{kd} i_{kd}$$

$$\dot{\lambda}_{kq} = -r_{kq} i_{kq}$$

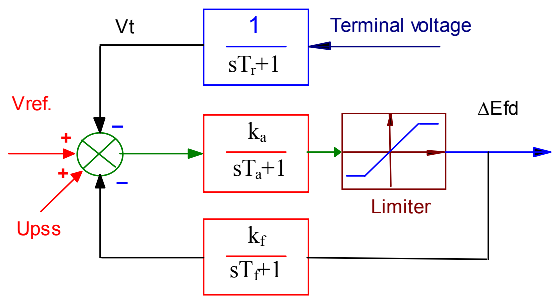
$r_a = 0.007$ $H = 30$ $r_f = .00089$ $r_{kd} = 0.023$

$r_{kq} = 0.023$ $K_d = 0$ $x_d = 1.24$ $x_f = 1.33$

$x_{kd} = 1.15$ $x_{md} = 1.126$ $x_q = 0.743$ $x_{kq} = 0.652$

$x_{mq} = 0.626$ $g = 0.25$

A.2 AVR model



Tr=0.04, ka=20, Ta=0.05, kf=1, Tf=0