01 Jan 2001

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Ganesh K. Venayagamoorthy
Missouri University of Science and Technology

Donald C. Wunsch
Missouri University of Science and Technology, dwunsch@mst.edu

Ronald G. Harley

Recommended Citation

G. K. Venayagamoorthy et al., "A Nonlinear Voltage Controller with Derivative Adaptive Critics for Multimachine Power Systems," *Proceedings of the 22nd IEEE Power Engineering Society International Conference on Power Industry Computer Applications, 2001. PICA 2001*, Institute of Electrical and Electronics Engineers (IEEE), Jan 2001.
The definitive version is available at https://doi.org/10.1109/PICA.2001.932372

A NONLINEAR VOLTAGE CONTROLLER WITH DERIVATIVE ADAPTIVE CRITICS FOR MULTIMACHINE POWER SYSTEMS

[*†]G.K.Venayagamoorthy *Member, IEEE*
Department of Electronic Engineering,
ML Sultan Technikon, POBox 1334 Durban 4000
South Africa
gkumar@ieee.org

[*]R.G.Harley *Fellow, IEEE*
School of Electrical and Computer Engineering
Georgia Institute of Technology Atlanta GA 30332-0250 USA
ron.harley@ee.gatech.edu

D.C.Wunsch *Senior Member, IEEE*
[†]Applied Computational Intelligence Laboratory
Dept. of Electrical and Computer Engineering
University of Missouri-Rolla
MO 65409-0249 USA
dwunsch@ece.umr.edu

[*]Electrical Engineering Department University of Natal Durban 4041 South Africa

Abstract – Based on derivative adaptive critics, a novel nonlinear optimal voltage/excitation control for multimachine power system is presented. The feedback variables are completely based on local measurements. Simulations on a three-machine system demonstrate that the nonlinear controller is much more effective than conventional PID controller equipped with a power system stabilizer for improving dynamic performance and stability under small and large disturbances.

Keywords: Power System Stability, Voltage Regulation, Nonlinear Optimal Control, Adaptive Critic, Artificial Neural Networks.

I. INTRODUCTION

Power systems containing turbogenerators are large-scale nonlinear systems. The traditional excitation controllers for the generators are designed by linear control theory based on a single-machine infinite bus (SMIB) power system model. These SMIB power system models are linearized at specific operating points and then excitation controllers are designed, based on the linearized models. The drawback of this approach is that once the operating point or the system configuration changes, the performance of the controller degrades. Conservative designs are therefore used, particularly in multimachine systems, to attempt satisfactory control over the entire operating range of the power system.

In recent years, renewed interest has been shown in power systems control using nonlinear control theory, particularly to improve system transient stability [1-5]. Instead of using an approximate linear model, as in the design of the conventional power system stabilizer, nonlinear models are used and nonlinear feedback linearization techniques are employed on the power system models, thereby alleviating the operating point dependent nature of the linear designs. Nonlinear controllers significantly improve the power system's transient stability. However, nonlinear controllers have a more complicated structure and are difficult to implement relative to linear controllers. In addition, feedback linearization methods require exact system parameters to cancel the inherent system nonlinearities, and this contributes further to the complexity of stability analysis. The design of decentralized linear controllers to enhance the stability of interconnected nonlinear power systems within the whole operating region is still a challenging task [6]. However, the use of Artificial Neural Networks offers a possibility to overcome this problem.

Multilayer Perceptron type artificial neural networks (ANNs) are able to identify/ model time varying single turbogenerator systems [7, 8] and, with continually online training, these models can track the dynamics of the turbogenerator system, thus yielding adaptive identification. ANN controllers have been successfully implemented on single turbogenerators using ANN identifiers and indirect feedback [9-12]. Moreover, ANN identification of turbogenerators in a multi-machine power system has also been reported [13, 14].

Clearly, nonlinear controllers are needed for nonlinear systems. In this paper a multimachine power systems is modeled using an artificial neural network and used in the development of a nonlinear voltage controller (NVC) based on derivative adaptive critics, to replace the traditional automatic voltage regulator (AVR) and a conventional power system stabilizer (PSS). With derivative adaptive critics, optimal ANN controllers can be designed by using pre-recorded data from the power system operation, and offline training, before allowing the ANN to control the power plant. With adaptive critics, the computational load of online training is therefore avoided. The method presented in this paper can therefore be used in the development of a NVC to be retrofitted to existing plant.

A three-machine power system example is simulated with a NVC on one machine. The simulation results show that both voltage regulation and system stability enhancement can be achieved with this proposed controller, regardless of the system operating conditions and types of disturbances.

II. MULTIMACHINE POWER SYSTEM

The multi-machine power system in Fig. 1 is modeled in the MATLAB/SIMULINK environment using the Power System Blockset (PSB) [15]. Each machine is represented by a seventh order model. There are three coils on the d-axis and two coils on the q-axis and the stator transient terms are not neglected. A three machine five-bus system is chosen, to illustrate the effectiveness of an adaptive critic based controller. Machines G1 and G2 are 200 MVA generators. Machine G3 is the infinite bus. The machine parameters [15] are given in Appendix A. Each generator is equipped with an IEEE standard DC exciter [16] shown in Fig. 2. The generators and their excitation systems (without the regulator) are identified/modeled using ANNs [13, 14]. Generator G1 is equipped with a PSS shown in Fig. 3 [17]. The excitation system and PSS parameters are given in Appendix B.

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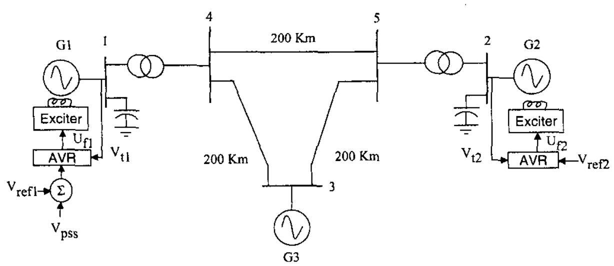


Fig. 1 Multi-machine power system with conventional controllers

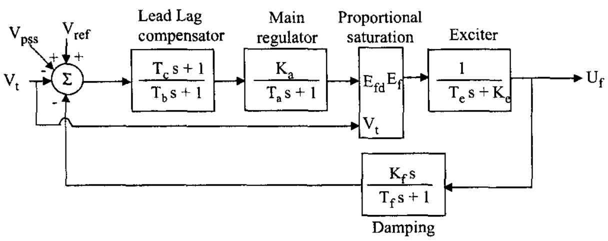


Fig. 2 Block diagram of the excitation system

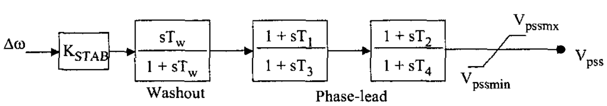


Fig. 3 Block diagram of the PSS

III. DERIVATIVE ADAPTIVE CRITICS' BASED VOLTAGE CONTROLLER

Adaptive Critic Designs (ACDs) are neural network designs capable of optimization over time under conditions of noise and uncertainty. A family of ACDs was proposed by Werbos [18] as a new optimization technique combining concepts of reinforcement learning and approximate dynamic programming. For a given series of control actions, that must be taken in sequence, and not knowing the quality of these actions until the end of the sequence, it is impossible to design an optimal controller using traditional supervised learning.

Dynamic programming prescribes a search which tracks backward from the final step, rejecting all suboptimal paths from any given point to the finish, but retains all other possible trajectories in memory until the starting point is reached. However, many paths which may be unimportant, are nevertheless also retained until the search is complete. The result is that the procedure is too computationally demanding for most real problems. In supervised learning, an ANN training algorithm utilizes a desired output and, comparing it to the actual output, generates an error term to allow learning. For an MLP type ANN the backpropagation algorithm is typically used to get the necessary derivatives of the error term with respect to the training parameters and/or the inputs of the network. However, backpropagation can be linked to reinforcement learning via a network called the ***Critic*** network, which has certain desirable attributes.

Critic based methods remove the learning process one step from the control network (traditionally called the "***Action*** network" or "***actor***" in ACD literature), so the desired trajectory or control action information is not necessary. The critic network learns to approximate the cost-to-go or strategic utility function, and uses the output of an action network as one of its inputs directly or indirectly. When the critic network learns, backpropagation of error signals is possible along its input pathway from the action network. To the backpropagation algorithm, this input pathway looks like just another synaptic connection that needs weight adjustment. Thus, no desired signal is needed. All that is required is a desired cost function J given in eq. (1).

$$J(t) = \sum_{k=0}^{\infty} \gamma^k U(t+k) \tag{1}$$

where γ is a discount factor for finite horizon problems ($0 < \gamma < 1$), and $U(.)$ is the utility function or local cost.

The Critic and the Action networks, can be connected together directly (Action-dependent designs) or through an identification model of a plant (Model-dependent designs). There are three classes of implementations of ACDs called Heuristic Dynamic Programming (HDP), Dual Heuristic Programming (DHP), and Globalized Dual Heuristic Dynamic Programming (GDHP), listed in order of increasing complexity and power [19]. This paper presents the DHP model dependent design, and compares its performance against the results obtained using a conventional PID controller with power system stabilizer.

The critic network is trained forward in time, which is of great importance for real-time operation. DHP has a critic network which estimates the derivatives of J with respect to a vector of observables of the plant, ΔY. The critic network learns minimization of the following error measure over time:

$$\| E \| = \sum_t E^T(t) E(t) \tag{2}$$

where

$$E(t) = \frac{\partial J[\Delta Y(t)]}{\partial \Delta Y(t)} - \gamma \frac{\partial J[\Delta Y(t+1)]}{\partial \Delta Y(t)} - \frac{\partial U(t)}{\partial \Delta Y(t)} \tag{3}$$

where $\partial(.)/\partial \Delta Y(t))$ is a vector containing partial derivatives of the scalar (.) with respect to the components of the vector ΔY. The critic network's training is more complicated than in HDP [10] since there is a need to take into account all relevant pathways of backpropagation as shown in Fig. 4, where the paths of derivatives and adaptation of the critic are depicted by dashed lines.

In DHP, application of the chain rule for derivatives yields

$$\frac{\partial J(t+1)}{\partial \Delta Y_j(t)} = \sum_{i=1}^{n} \lambda_i(t+1) \frac{\partial \Delta Y_i(t+1)}{\partial \Delta Y_j(t)}$$
$$\sum_{k=1}^{m} \sum_{i=1}^{n} \lambda_i(t+1) \frac{\partial \Delta Y_i(t+1)}{\partial A_k(t)} \frac{\partial A_k(t)}{\partial \Delta Y_i(t)} \quad (4)$$

where $\lambda_i(t+1) = \partial J(t+1)/\partial \Delta Y_i(t+1))$, and n, m are the numbers of outputs of the model and the action networks, respectively.

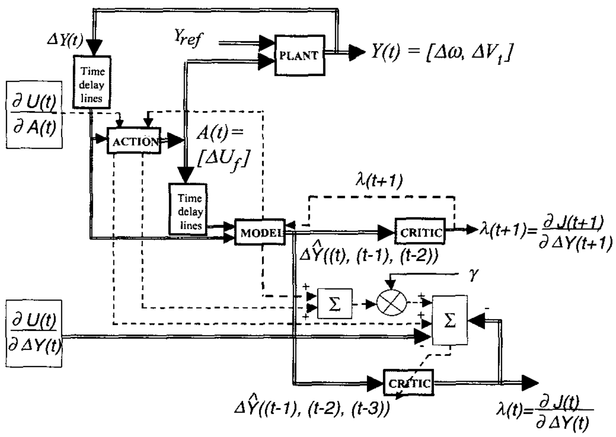


Fig. 4 DHP critic network adaptation

By exploiting eq. (4), each of n components of the vector $E(t)$ from eq. (3) is determined by

$$E_j(t) = \frac{\partial J(t)}{\partial \Delta Y_j(t)} - \gamma \frac{\partial J(t+1)}{\partial \Delta Y_j(t)} - \frac{\partial U(t)}{\partial \Delta Y_j(t)} - \sum_{k=1}^{m} \frac{\partial U(t)}{\partial A_k(t)} \frac{\partial A_k(t)}{\partial \Delta Y_j(t)} \quad (5)$$

The action network is adapted in Fig. 5 by propagating $\lambda(t+1)$ back through the model to the action.

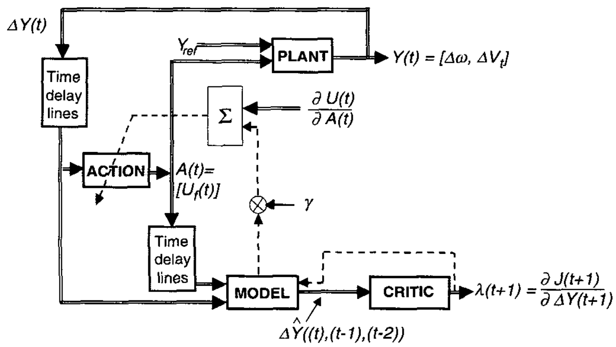


Fig. 5 DHP action network adaptation

The goal of such adaptation can be expressed as:

$$\frac{\partial U(t)}{\partial A(t)} + \gamma \frac{\partial J(t+1)}{\partial A(t)} = 0 \quad \forall t \quad (6)$$

The weights' update expression is:

$$\Delta W_A = -\alpha \left[\frac{\partial U(t)}{\partial A(t)} + \gamma \frac{\partial J(t+1)}{\partial A(t)} \right]^T \frac{\partial A(t)}{\partial W_A} \quad (7)$$

where α is a positive learning rate.

IV. THREE ARTIFICIAL NEURAL NETWORKS - MODEL, CRITIC AND ACTION

A nonlinear neural network based voltage controller (NVC) is designed to replace the AVR on generator G1 and therefore an ANN model of generator G1 and the network to which it is connected is obtained as described in [13,14]. The ANN model in Figs. 4 & 5 is a three layer feedforward network with twelve inputs, a single hidden layer of fourteen neurons and two outputs. The inputs to the ANN are the *deviation* of the *actual* power ΔP_I to its turbine, the *deviation* of the *actual* field voltage ΔU_{fI} to its exciter, the *deviation* of the *actual* speed $\Delta\omega_I$, and the *deviation* of the *actual* RMS terminal voltage ΔV_{tI} of its generator. These four inputs are also delayed by the sample period of 10 ms and, together with eight previously delayed values, form twelve inputs altogether. For this set of inputs, the outputs are the *estimated* speed deviation $\Delta\hat{\omega}_I$ and the *estimated* terminal voltage deviation $\Delta\hat{V}_{tI}$, of generator G1.

The critic network in Figs. 4 & 5 is also a three layer feedforward network with six inputs, thirteen hidden neurons and, two outputs. The inputs to the critic network are the speed *deviation* $\Delta\omega$ and terminal voltage *deviation* ΔV_{tI}. These inputs are time delayed by a sample period of 10 ms, and together with the four previously delayed values, form the six inputs for the critic network. The outputs of the critic are the derivatives of the J function with respect to the output states of generator G1.

The action network in Figs. 4 & 5 is also a three layer feedforward network with six inputs, a single hidden layer with ten neurons and a single output. The inputs are the generator's *actual* speed and *actual* terminal voltage deviations, $\Delta\omega_I$ and ΔV_{tI} respectively. Each of these inputs is time delayed by 10 ms and, together with four previously delayed values, form the six inputs. The output of the action network (NVC), $A(t) = [\Delta U_f]$, the *deviation* in the field voltage, augments the input to the generator's exciter.

V. SIMULATION OF NVC AND RESULTS

The training procedure for the critic and action networks is similar to adaptive critic designs for SMIB [10, 12]. It consists of two training cycles: the critic's and the action's. The critic's adaptation is done initially with a pretrained action network, to ensure that the whole system, consisting of the ACD and the plant, remains stable. The action network is pretrained on a linearized model of the generator. The action is trained further while keeping the critic network parameters fixed. This process of training the critic and the action one after the other is repeated until an acceptable performance is achieved. The

ANN model parameters are assumed to have converged globally during its offline training [14] and, it is not adapted concurrently with the critic and action networks.

A discount factor γ of 0.5 and the utility function given in eq. (8) are used in the Bellman's equation (eq. (1)) for the training of the critic network (eqs. (3)) and the action network (eq. (6)). Once the critic network's and action network's weights have converged, the action network (NVC) is connected to the generator G1 (Fig. 6).

$$U(t) = [4\Delta V(t) + 4\Delta V(t-1) + 16\Delta V(t-2)]^2 + [0.4\Delta\omega(t) + 0.4\Delta\omega(t-1) + 0.16\Delta\omega(t-2)]^2 \quad (8)$$

At two different operating conditions and three different disturbances, the transient performance of the NVC is compared, with that of a conventional controller (AVR) [20], as well as with that of the AVR equipped with a PSS (whose parameters are carefully tuned [17] for the first set of the operating condition given in Appendix C)

3% Step change in V_{t1} at first operating condition
At the *first* operating condition (Appendix C), a 3% step increase occurs in the desired terminal voltage of G1. Figs. 7 and 8 show that the NVC ensures no overshoot on the terminal voltage unlike with the AVR and AVR+PSS, and that the NVC also provides superior speed deviation damping. For this same disturbance, Fig 9 shows the speed deviations of generator G2 (controlled by an AVR only), and it is clear that with a NVC on generator G1, the speed deviation damping of generator G2 is also much improved.

5% Step change in V_{t1} at second operating point
At the *second* operating condition (Appendix C), a 5% step increase occurs in the desired terminal voltage of G1. Figs. 10 and 11 show that the NVC again provides the best damping, which proves that the NVC has learned and adapted itself to the new operating condition. In fact Fig. 11 shows signs of an inter-area mode starting up at about 4.5 seconds, and the NVC is far more successful in damping this, than the other two controllers. The speed deviation damping on generator G2 is also superior when the NVC is added to generator G1 (not shown due to space limitations).

Three phase short circuit
At the *second* operating condition (Appendix C), a 100 ms short circuit occurs halfway between busses 3 and 4 (Fig. 6). Figs. 12 and 13 show that the NVC again has better damping on the terminal voltage as well as the speed deviation of G1

All these results show that at operating conditions different from the one at which the AVR and PSS were tuned, and for large disturbances, their performance has degraded. The NVC on the other hand has given excellent performance under all the conditions tested. Many more tests were done to confirm this.

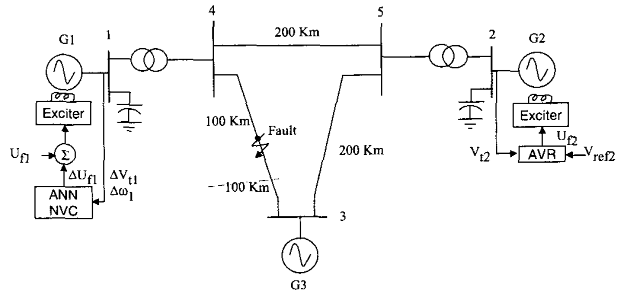


Fig. 6 Multi-machine power system with an ANN NVC on generator G1 and an conventional AVR on generator G2.

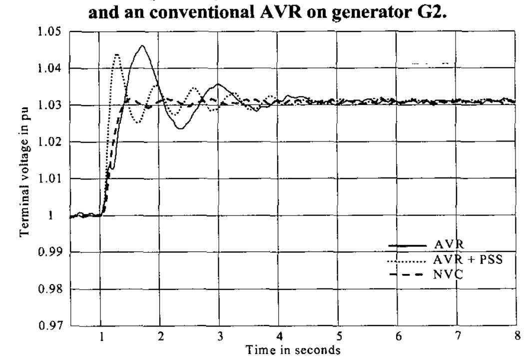


Fig. 7 Terminal voltage of generator G1 for a 3% step change in its desired terminal voltage

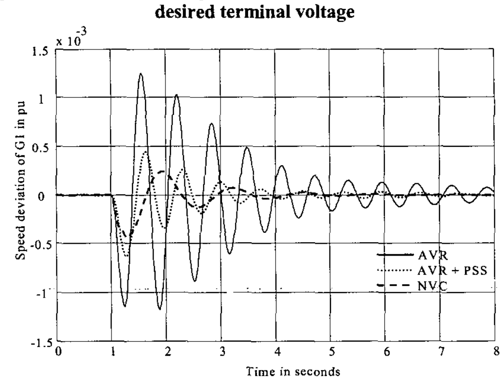


Fig. 8 Speed deviations of generator G1 for a 3% step change in its desired terminal voltage

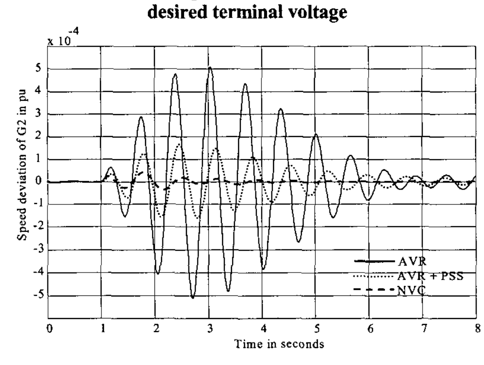


Fig. 9 Speed deviation of generator G2 for a 3% step change in its desired terminal voltage

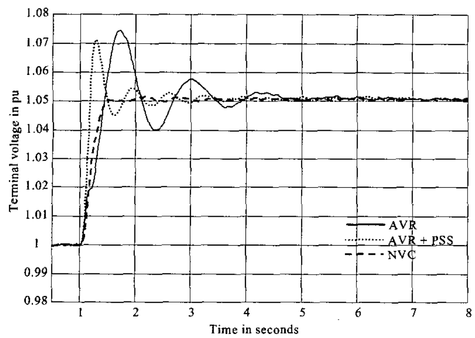


Fig. 10 Terminal voltage of generator G1 for a 5% step change in its desired terminal voltage

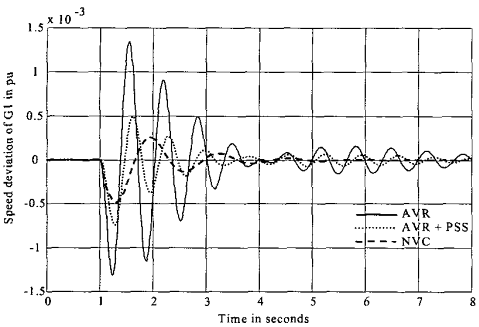


Fig. 11 Speed deviation of generator G1 for a 5% step change in its desired terminal voltage

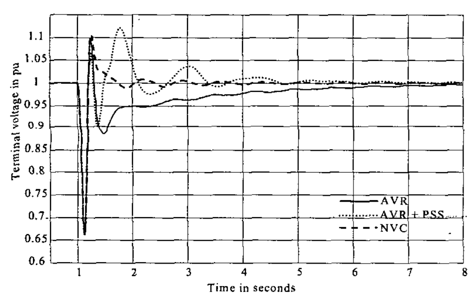


Fig. 12 Terminal voltage of generator G1 for a 100 ms three phase short circuit between bus 3 and 4 (Fig. 6)

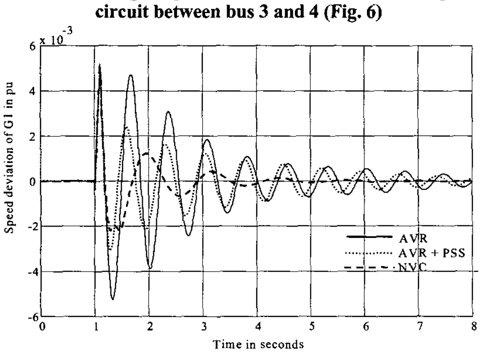


Fig. 13 Speed deviation of generator G1 for a 100 ms three phase short circuit between bus 3 and 4 (Fig. 6)

VI. CONCLUSIONS

A new design method, based on derivative adaptive critics for an intelligent nonlinear voltage controller (NVC) of generators in a multi-machine power system has been presented. All control variables are based on local measurements, thus, the control is decentralized. The results show that the NVC ensures a superior transient response throughout the system, for different disturbances and different operating conditions, compared to a conventional AVR and PSS. Further studies with NVCs on multiple generators on a larger system are currently in progress and preliminary results look encouraging. The success of the NVC is based on using deviation signals, and having a complete nonlinear model of the process.

The use of such intelligent nonlinear controllers will allow power plants to operate closer to their stability limits.

VI. REFERENCES

[1] Q.Lu and Y.Sun, "Nonlinear stabilizing control of multimachine systems," IEEE Trans. Power System, vol. 4, 1989, pp. 236-241.

[2] W.Mielczarski and A.Zajaczkowski, "Nonlinear field voltage control of a synchronous generator using feedback linearization", Automatica, vol. 30, 1994, pp. 1625-1630.

[3] J.W.Chapman, M.D.Ilic, C.A.King, L.Eng and H.Kaufman, "Stabilizing a multimachine power system via decentralized feedback linearizing excitation control", IEEE Trans. Powers System, vol. 8, 1993, pp. 830-839.

[4] Y.Wang, D.J.Hill, L.Gao and R.H.Middleton, "Transient stability enhancement and voltage regulation of power system", IEEE Trans. Power System, vol. 8, 1993, pp. 620-627.

[5] Y.Wang, G.Guo, D.J.Hill and L.Gao, "Nonlinear decentralized control for multimachine power system transient stability enhancement", Proceedings of 1995 Stockholm Power Tech Conference, pp. 435-440.

[6] Z.Qiu, J.F.Dorsey, J.Bond and J.D.McCalley, "Application of robust control to sustained oscillations in power systems", IEEE Trans. Circuits System, I, vol. 39, 1992, pp. 470-476.

[7] G.K.Venayagamoorthy and R.G.Harley, "A continually online trained artificial neural network identifier for a turbogenerator", Proceedings of 1999 IEEE International Electric Machines and Drives Conference, 0-7803-5293-9/99, pp. 404 – 406.

[8] G.K.Venayagamoorthy and R.G.Harley, "Implementation of an adaptive neural network identifier for effective control of turbogenerators", Proceedings of 1999 IEEE Budapest Power Tech Conference, BPT99-431-6.

[9] G.K.Venayagamoorthy and R.G.Harley, "Experimental studies with a continually online trained artificial neural network controller for a turbogenerator", Proceedings of the International Joint Conference on Neural Networks, IJCNN 1999, vol. 3, pp. 2158-2163.

[10] G.K.Venayagamoorthy, D.C.Wunsch and R.G.Harley, "Neurocontrol of turbogenerators with adaptive critics designs", Proceedings of the IEEE Africon 99 Conference, vol. 1, pp. 489-494.

[11] G.K.Venayagamoorthy, D.C.Wunsch and R.G.Harley, "Adaptive critic based neurocontroller for turbogenerators with global dual heuristic programming", Proceedings of IEEE PES 2000 Winter Meeting, vol. 1, pp. 291-294.

[12] G.K.Venayagamoorthy, R.G.Harley, and D.C.Wunsch, "Comparison of a heuristic dynamic programming and a dual heuristic programming based adaptive critics neurocontroller for a turbogenerator", Proceedings of the International Joint Conference on Neural Networks, IJCNN 2000, paper no. 660.

[13] G.K.Venayagamoorthy and R.G.Harley, "Decentralized online neuro-identification of turbogenerators in a multi-machine power system", Proceedings of IEEE PES 2000 Summer Meeting, paper no. 2000SM408.

[14] G.K.Venayagamoorthy, R.G.Harley, and D.C.Wunsch, "Adaptive neural network identifiers for effective control of turbogenerators in a multimachine power system", Proceedings of the IEEE PES Winter Meeting 2001, paper no. 2001WM154.

[15] G.Sybille, P.Brunelle, R.Champagne, L.Dessaint and Hoang Lehuy, "Power system blockset version 2.0", Mathworks Inc., 2000.

[16] IEEE, "Recommended practice for excitation system models for power system stability studies", IEEE Std. 421.5-1992, August 1992.

[17] P.Kundur, M.Klein, G.J.Rogers, M.S.Zywno, "Application of power system stabilizers for enhancement of overall system stability", IEEE Trans. on Power Systems, vol. 4, no. 2, May 1989, pp. 614-626.

[18] P.Werbos, Approximate dynamic programming for real-time control and neural modeling, in Handbook of Intelligent Control, White and Sofge, Eds., Van Nostrand Reinhold, ISBN 0-442-30857-4, pp 493 – 525.

[19] D.Prokhorov, D Wunsch, "Adaptive Critic Designs", IEEE Trans. on Neural Networks vol. 8, no.5, pp 997-1007.

[20] W.K.Ho, C.C.Hang, L.S.Cao, "Tuning of PID controllers based on gain and phase margin specifications", Proceedings of the 12th Triennial World Congress on Automatic Control, 1993, pp. 199 –202.

VII. APPENDIX

APPENDIX A

Parameters of the generators (G1 & G2)

	G1	G2		G1	G2
$X_d (pu)$	1.305	1.305	$R_{stator} (pu)$	0.0029	0.002 9
$X_d' (pu)$	0.296	0.296	$H (s)$	3.2	3.2
$X_d'' (pu)$	0.252	0.252	*Capacity (MVA)*	200	200
$X_q (pu)$	0.474	0.474	*L-L Volts*	13800	13800
$X_q'' (pu)$	0.243	0.243	*Freq. (Hz)*	60	60
$X_l (pu)$	0.18	0.18			

APPENDIX B

Parameters of the excitation system (Fig. 2) and PSS (Fig. 3)

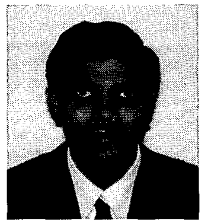
K_a= 50, T_a = 0.001 s, T_b = 0.189 s, T_c = 2.266 s, K_f = 0.001, T_f = 0.1 s, K_e = 1, T_e = 0 s, E_{fmin} = -11.5 pu & E_{fmax} = 11.5 pu.

T_w = 3 s, T_1 = 0.2 s, T_2 = 0.2 s, T_3 = 0.045 s, T_4 = 0.045 s, K_{STAB} = 33.93, Vpssmx = 0.2 pu & Vpssmin = -0.1 pu.

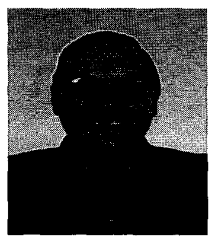
APPENDIX C

	Condition one		Condition two	
	G1	G2	G1	G2
$P_e (pu)$	0.7500	0.3500	0.5000	0.6500
$Q (pu)$	-0.1216	-0.1598	-0.1493	-0.1341
$V_t (pu)$	1	1	1	1

VIII. BIOGRAPHIES



Ganesh K Venayagamoorthy was born in Jaffna, Sri Lanka. He received a BEng (Honours) degree with a First class in Electrical and Electronics Engineering from the Abubakar Tafawa Balewa University, Nigeria, in 1994 and a MScEng degree in Electrical Engineering from the University of Natal, South Africa, in April 1999. Currently he is pursuing a PhD degree in Electrical Engineering at the University of Natal, South Africa. Since 1996, he has been on the Faculty of the Department of Electronic Engineering at the M L Sultan Technikon, Durban, South Africa lecturing Control Systems and Digital Signal Processing. He was a Research Associate at the Texas Tech University, USA in 1999 and at the University of Missouri-Rolla, USA in 2000/2001. His research interests are in power systems, control systems, signal processing and artificial neural networks. He is a Member of IEEE, SAIEE (South Africa) and an Associate Member of IEE.



Ronald G Harley was born in South Africa. He obtained a BScEng degree (cum laude) from the University of Pretoria in 1960, and a MScEng degree (cum laude) from the same University in 1965. He then moved to Imperial College in London and graduated with a PhD in Engineering from London University in 1969. In 1970 he was appointed to the Chair of Electrical Machines and Power Systems at the University of Natal in Durban, South Africa. He is currently at the Georgia Institute of Technology, Atlanta, USA. He has co-authored some 220 papers in refereed journals and international conferences. Altogether 9 papers attracted prizes from journals and conferences. Ron is a Fellow of the SAIEE, a Fellow of the IEE, and a Fellow of the IEEE. He is also a Fellow of the Royal Society in South Africa, a Fellow of the University of Natal, and a Founder Member of the Academy of Science in South Africa formed in 1994. He has been elected as a Distinguished Lecturer by the IEEE Industry Applications Society for the years 2000 and 2001. His research interests are in the dynamic and transient behavior of electric machines and power systems, and controlling them by the use of power electronics and control algorithms.

Donald Wunsch received the Ph.D. EE and the M.S. App. Math from the Univ. of Washington in '91 and '87, the B.S. in App. Math from the Univ. of New Mexico in '84. Since '99, he is the M.K. Finley Missouri Distinguished Prof. of Computer Engineering in the Dept. of ECE, Univ. of Missouri - Rolla, and heads the Applied Computational Intelligence Laboratory. Previously, he was Associate Prof. at Texas Tech. Prior to joining Tech in '93, he was Senior Principal Scientist at Boeing, where he invented the first optical ART1 neural network, and other applied research. He also worked for Intl. Laser Systems and Rockwell Intl., and consulted for Sandia Labs, White Sands, and Accurate Automation Corp. Current research includes adaptive critic designs; neural network optimization, forecasting and control; and fuzzy risk assessment for high-consequence surety. He is an Academician in the Intl. Academy of Technological Cybernetics, and in the Intl. Informatization Academy; and is recipient of the Halliburton Award for excellence, and a NSF CAREER Award. He is a member of the Intl. Neural Network Society, ACM, a life member of the AAAI, and previously served as Associate Editor of the IEEE Trans. on Neural Networks and voting member of the IEEE Neural Network Council. He has well over 100 publications in computational intelligence, and attracted well over $3 million in competitively awarded sponsored research funding since 1994, and over $1 million since coming to UMR.