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Adaptive Neural Network Identifiers for Effective Control of Turbogenerators in a Multimachine Power System

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Abstract: This paper provides a novel method for nonlinear identification of multiple turbogenerators in a five-machine 12-bus power system using Continually Online Trained (COT) Artificial Neural Networks (ANNs). Each turbogenerator in the power system is equipped with an adaptive ANN identifier, which is able to identify/model its particular turbogenerator and rest of the network to which it is connected from moment to moment, based on only local measurements. Each adaptive ANN identifier can be used in the design of a nonlinear controller for each turbogenerator in a multimachine power system. Simulation results for the adaptive ANN identifiers are presented.

Keywords: Adaptive Identification, Multimachine Power System, Artificial Neural Networks, Control.

I. INTRODUCTION

The increasing complexity of modern power systems highlights the need for advanced system identification techniques for effective control of multimachine power system. Synchronous turbogenerators supply most of the electrical energy produced by mankind and are largely responsible for maintaining the stability and security of the electrical network. The effective control of these machines is, therefore, important. However, turbogenerators are highly non-linear, time varying, fast acting. Multiple Input Multiple Output (MIMO) machines with a wide range of operating conditions and dynamic characteristics that depend on the entire power system to which each of these is connected [1,2]. Conventional automatic voltage regulators and turbine governors are designed to optimally control each of these turbogenerators around one operating point, at other operating points each turbogenerator's performance is degraded. Adaptive controllers for turbogenerators can be designed using linear models and traditional techniques of identification, analysis, and synthesis to achieve the desired performance. Often restrictive assumptions are made [3] about the likely disturbances. However, due to the nonlinear time varying nature of a turbogenerator, it cannot be accurately modelled as a linear device.

Moreover, when different turbogenerators with conventional controllers are connected, low frequency oscillations may result. Power System Stabilizers (PSSs) are used to damp such oscillations, but the particular position and transfer function of a PSS is not a simple decision and is usually also based on some linearized system model.

In recent years, renewed interest has been shown in the area of power systems control using nonlinear control theory, particularly to improve system transient stability [4-8]. 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. Using nonlinear controllers, power system transient stability can be improved significantly. 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 [9]. However, the use of Artificial Neural Networks offers a possibility to overcome this problem.

Artificial Neural Networks (ANNs) are able to identify/model such time varying single turbogenerator systems [10, 11] and, with continually online training these models can track the dynamics of the turbogenerator system thus yielding adaptive identification. COT ANN controllers have been successfully implemented on single turbogenerators using ANN identifiers [12]. ANN identification of turbogenerators in a multimachine power system has been successfully investigated on a two identical machine system [13].

This paper explains how the COT ANN can be used to identify turbogenerators in a multi-machine power system, where there are always changes in the operating points of the generators, and changes in the network configuration. Simulation results are presented to show successful identification of multiple turbogenerators in a complex environment. The identification of the turbine and exciter dynamics is excluded.

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) [14]. Each machine is represented by a seventh order model. There are three coils on the d-axis and

two on the q-axis and the stator transient terms are not neglected. A five-machine 12-bus system is chosen, in order to illustrate the various concepts involved in the identification process. Machines G1 and G5 are larger machines (300 MVA) compared to machines G2 and G4 (200 MVA). Machine G5 is the infinite bus. The machine parameters are given in Appendix A [15]. Although it is possible to identify/model generators with exciters and turbines using ANNs [10,11,13], in this paper, machines without exciter, turbine, automatic voltage regulator and governor are identified using an ANN.

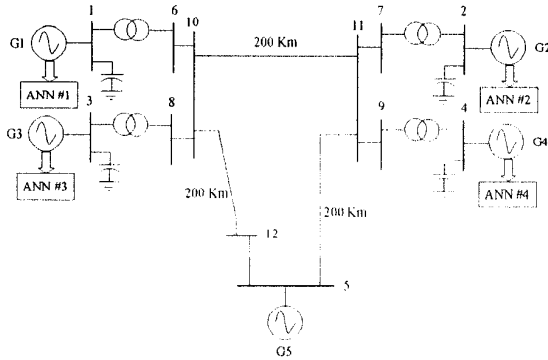


Fig. 1 Multi-machine power system with ANN Identifiers

III. ADAPTIVE NEURAL NETWORK IDENTIFIERS

Fig. 1 shows that four generators are each equipped with an ANN identifier (ANNI). The ANN identifiers are trained online and are therefore called *Adaptive Neural Network Identifiers*.

The ANNI is developed using the series-parallel Nonlinear Auto Regressive Moving Average (NARMA) model [16].

This model output \hat{y} (Fig. 2) at time $k+1$ depends on both past n values of output and m past values of input. The ANNI output equation takes the form given by eq. (1).

$$\hat{y}(k+1) = f \left[\begin{matrix} y(k), y(k-1), \dots, y(k-n+1) \\ u(k), u(k-1), \dots, u(k-m+1) \end{matrix} \right] \quad (1)$$

where $y(k)$ and $u(k)$ represent the output and input of the plant at time k respectively. This model has been chosen in preference to other system identification models [16], because online learning is desired to identify the dynamics of the turbogenerator, and therefore avoids a feedback loop in the model, which in turn allows static backpropagation to be used to adjust the ANN weights. This reduces the computational overhead substantially for online training.

The ANN identifiers (ANNI) in Fig. 1 are feedforward multilayer perceptron networks, and each has three layers consisting of an input layer with twelve neurons, a single hidden layer with sigmoidal activation functions consisting of fourteen neurons, and an output layer with two neurons.

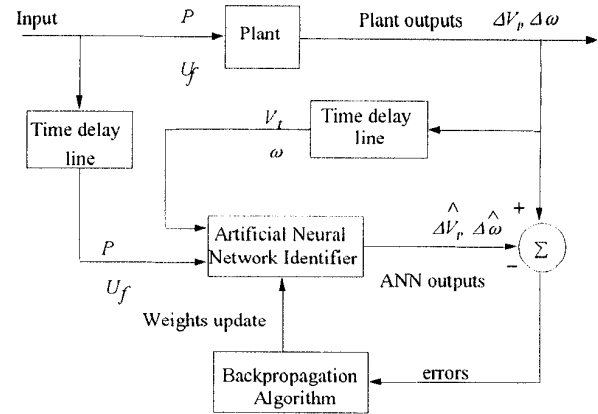


Fig. 2 Plant/adaptive ANN identifier

The ANNI's inputs, outputs and output errors are shown in Fig. 2. The plant described in Fig. 2 represents a generator and the network to which it is connected. A sampling frequency of 100 Hz is chosen, which is sufficiently fast for the ANNI to reconstruct the speed and terminal voltage signals from the sampled input signals.

The inputs to the ANNI shown in Fig. 3 are the *deviation* of the *actual* power ΔP to its turbine, the *deviation* of the *actual* field voltage ΔU_f to its exciter, the *deviation* of the *actual* speed $\Delta \omega$, and the *deviation* of the *actual* RMS terminal voltage ΔV_t 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 ANNI inputs, the ANNI outputs are the *estimated* speed deviation $\hat{\Delta \omega}$ and the *estimated* terminal voltage deviation $\hat{\Delta V_t}$, of its particular generator.

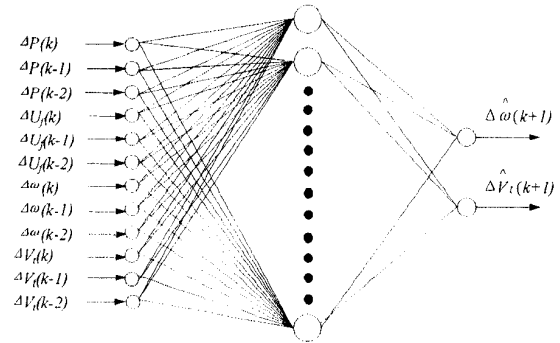


Fig. 3. ANNI input and output signals

The number of neurons in the hidden layer of the ANNI is determined heuristically. The ANNI weights are set to random values $[-0.1, 0.1]$ and backpropagation is used to update the weights of the ANNI. The differences between the respective deviations in *actual* outputs of the plant (ΔV_t , $\Delta \omega$) and the *estimated* outputs of ANNI ($\hat{\Delta V_t}$, $\hat{\Delta \omega}$) form the error signals for updating the weights in the ANNI (Fig. 2).

A reasonable learning rate is determined by training this neural network and setting the learning rate parameter so that a compromise is achieved between the training time and the accuracy of the network.

IV. SIMULATION RESULTS

A constant field voltage U_f and a turbine power signal P are applied to each of the generators at a particular steady state operating point. Then the ANNI is trained by adding pseudorandom binary signals ΔU_f and ΔP (generated in MATLAB during the simulation) to U_f and P respectively. These random signals excite the full range of the dynamic response of the generators.

The pseudorandom signals in Figs. 4 and 5 show $\pm 5\%$ deviations in the steady state values of U and P of generator G1 at operating points given in Appendix B.1. Similar training signals are applied simultaneously to the other generators (G2, G3, G4).

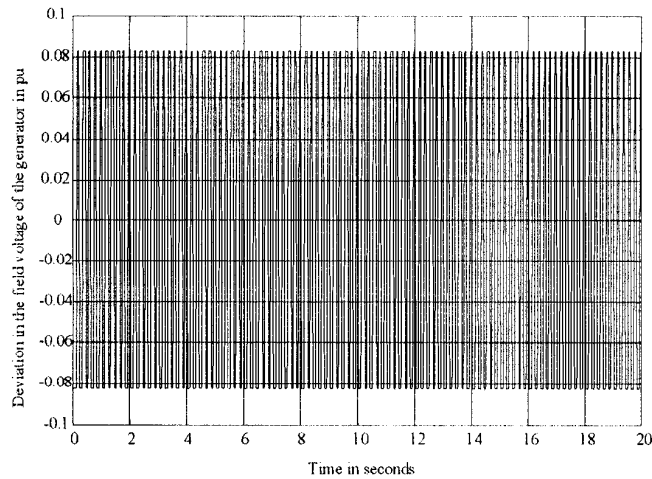


Fig. 4 Training signal ΔU_f applied to the generator G1

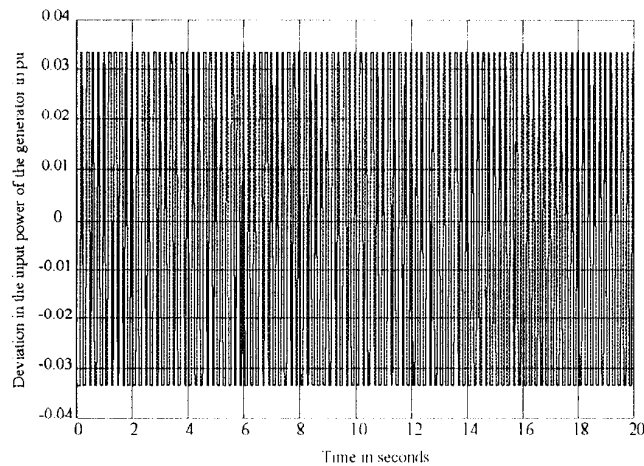


Fig. 5 Training signal ΔP applied to generator G1

A learning gain of 0.3 is used for the backpropagation algorithm. The ANNI is only required to generalize one time step (10 ms) ahead, so no momentum term is used. The training errors are insignificant after only a few seconds of training.

Figs. 6 and 7 show the speed deviation and terminal voltage deviation respectively of generator G1 and ANNI #1 during the first few seconds of training. Figs. 8 and 9 present these results during the fourth and fifth second of training. They show that the ANNI #1 is able to track the outputs of generator G1 within the first two seconds of training. The outputs of the generators and the ANNIs are shown by solid and dashed lines respectively in all diagrams.

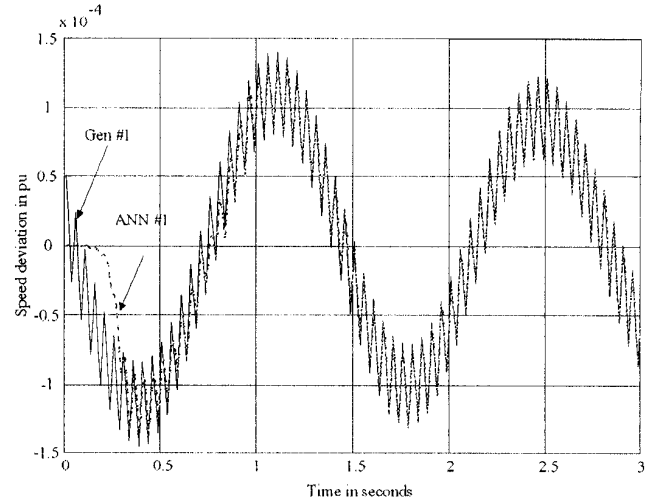


Fig. 6 Speed deviation of the generator G1 ($\Delta\omega$) and the ANNI #1 ($\Delta\hat{\omega}$)

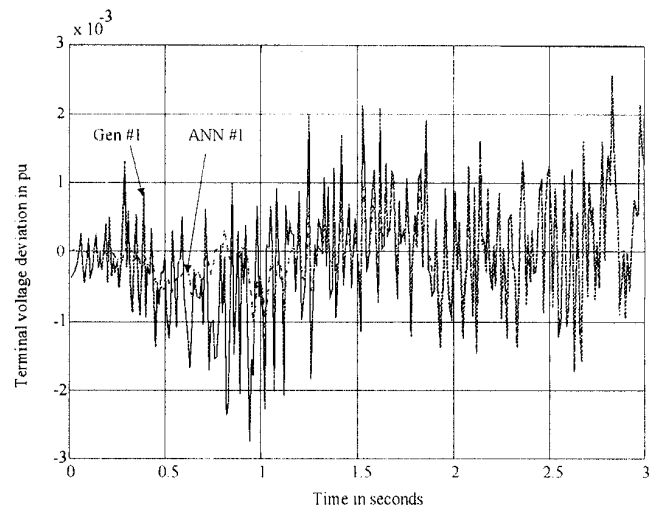


Fig. 7 Terminal voltage deviation of the generator G1 (ΔV_t) and the ANNI #1 ($\Delta \hat{V}_t$)

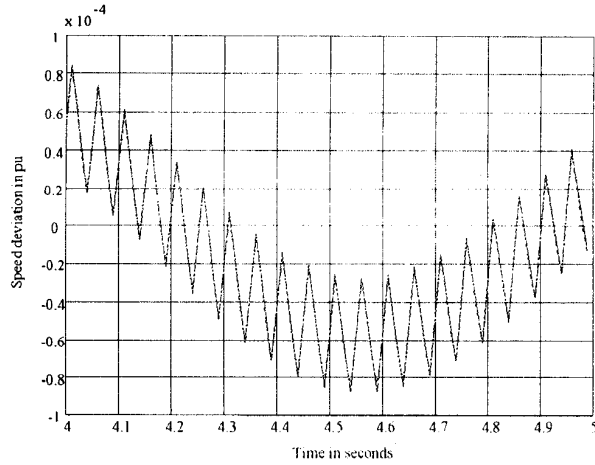


Fig. 8 Speed deviation of the generator G1 ($\Delta\omega$) and the ANNI #1 ($\hat{\Delta\omega}$)

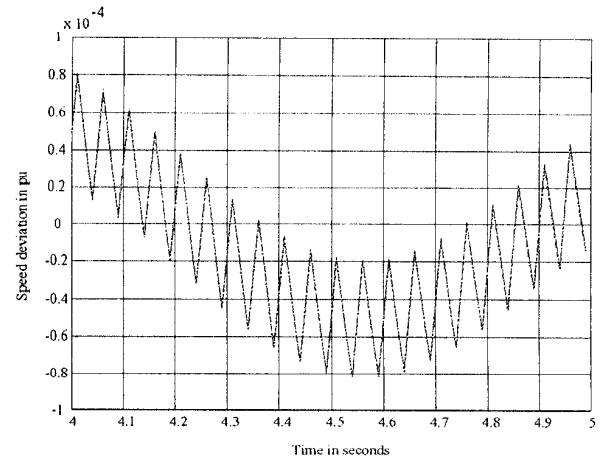


Fig. 10 Speed deviation of the generator G2 ($\Delta\omega$) and the ANNI #2 ($\hat{\Delta\omega}$)

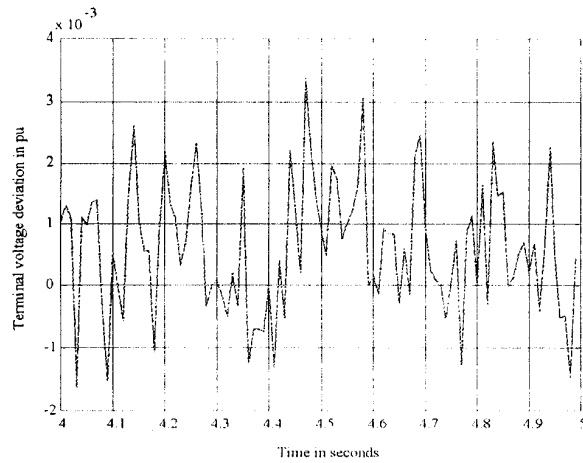


Fig. 9 Terminal voltage deviation of the generator G1 (ΔV_t) and the ANNI #1 ($\hat{\Delta V_t}$)

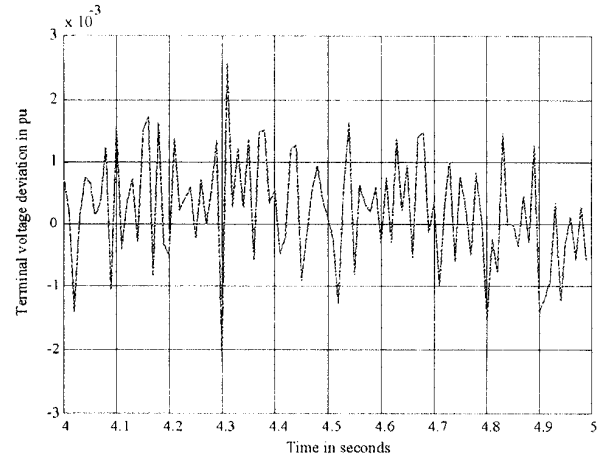


Fig. 11 Terminal voltage deviation of the generator G2 (ΔV_t) and the ANNI #2 ($\hat{\Delta V_t}$)

Figs. 10 and 11 show the speed deviation and terminal voltage deviation, respectively, of generator G2 and ANNI #2 during the fourth and fifth second of training. Once again, ANNI #2 is able to track the outputs of generator G2 within the first two seconds of its training. Similar results have been found for generators G3 and G4. All results show that the errors between the ANNs' outputs and generators' outputs are insignificant after a few seconds of online training.

Figs. 8 to 11 prove that the ANNs have learned the dynamics of the generators, and the network to which they are connected, with sufficient accuracy.

After five seconds of training (Figs. 6 to 11 at operating points given in Appendix B.1), the operating points are changed (Appendix B.2) and the training continues. However, the training signals are now reduced to only $\pm 2\%$ deviations in the field voltage U_f and input power P , and the results for generator G3 and ANNI #3 appear in Figs. 12 and 13, and those for generator G4 and ANNI #4 in Figs. 14 and 15. The results for generators G1 and G2 have been found to be similar to those of generators G3 and G4. Moreover, despite the changes in the operating points, the ANNs are able to track the output changes of the generators immediately.

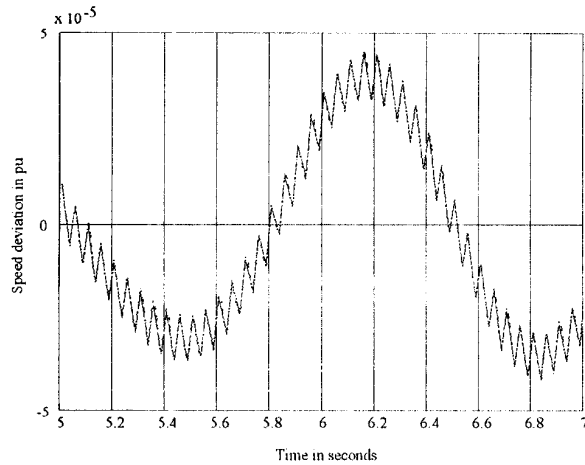


Fig. 12 Speed deviation of the generator G3 ($\Delta\omega$) and the ANNI #3 ($\hat{\Delta\omega}$)

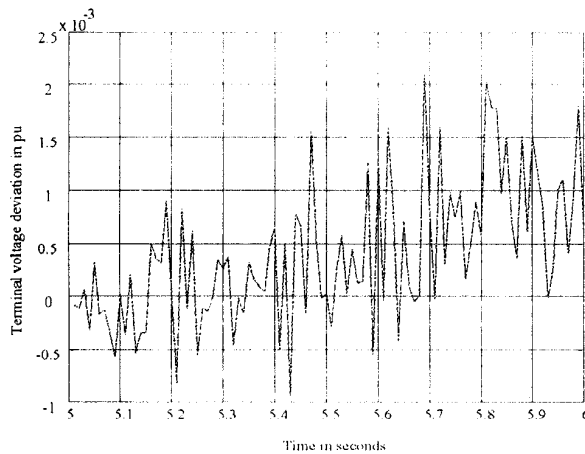


Fig. 13 Terminal voltage deviation of the generator G3 (ΔV_t) and the ANNI #3 ($\hat{\Delta V_t}$)

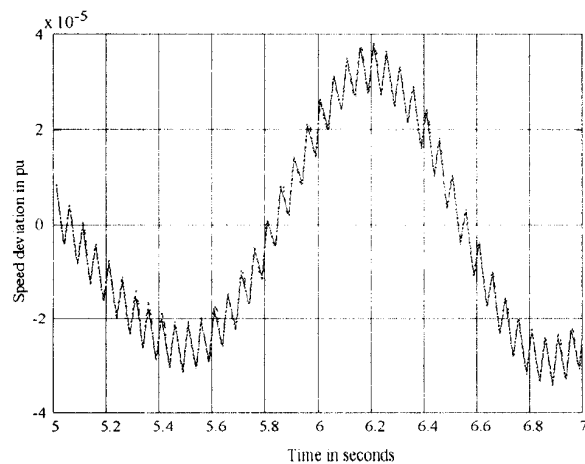


Fig. 14 Speed deviation of the generator G4 ($\Delta\omega$) and the ANNI #4 ($\hat{\Delta\omega}$)

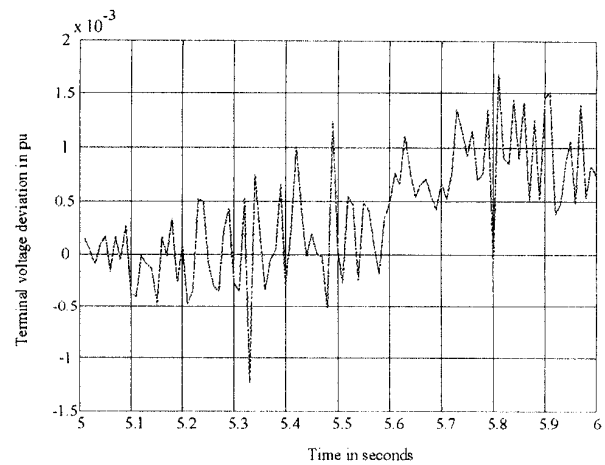


Fig. 15 Terminal voltage deviation of the generator G4 (ΔV_t) and the ANNI #4 ($\hat{\Delta V_t}$)

V. CONCLUSIONS

A multiple number of multi-layer feedforward neural networks have been successfully applied to identify/model multiple turbogenerators in a power system. Simulation results indicate that the proposed scheme is potentially very promising for identifying highly nonlinear MIMO turbogenerators in the input-output representation form. Furthermore, it is important to emphasize that *no off-line training is necessary*. Such neural network models may first be used in a multi-machine power system plant simulator and eventually find a place in the control room, providing plant operators and power system control engineers with enhanced understanding of the operation of the turbogenerators. However, further laboratory testing is still needed to evaluate critically the goodness and confidence levels of these models under development for multimachine power systems.

VI. ACKNOWLEDGEMENTS

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APPENDIX A

Parameters of the generators (G1, G2, G3 & G4)

	G1	G2	G3	G4
$X_d(pu)$	1.80	1.80	1.80	1.80
$X_q(pu)$	0.30	0.30	0.30	0.30
$X_d'(pu)$	0.25	0.25	0.25	0.25
$X_q'(pu)$	1.70	1.70	1.70	1.70
$X_q''(pu)$	0.25	0.25	0.25	0.25
$X_i(pu)$	0.20	0.20	0.20	0.20
$R_{stator}(pu)$	0.0025	0.0025	0.0025	0.0025
$H(s)$	6.5	6.175	6.5	6.175
Capacity (MVA)	300	200	300	200
L-L Volts	13800	13800	13800	13800
Freq. (Hz)	60	60	60	60

APPENDIX B

B.1 First set of operating points

	G1	G2	G3	G4
$P_e(pu)$	0.6668	0.6511	0.6668	0.6511
$Q(pu)$	0.0726	0.0444	0.0726	0.0444
$V_i(pu)$	1.1893	1.1893	1.1893	1.1893

B.2 Second set of operating points

	G1	G2	G3	G4
$P_e(pu)$	0.6668	0.6511	0.3336	0.2502
$Q(pu)$	0.0002	-0.0310	-0.0125	-0.0449
$V_i(pu)$	1.1884	1.1877	1.1691	1.1519

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. From 1994 to 1995, he worked as a Computer Engineer at Square One Comnet, Maseru, Lesotho. 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. 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 an 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.