Decentralized Online Neuro-Identification of Turbogenerators in a Multi-machine Power System

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Abstract: This paper proposes a new and a novel technique based on Artificial Neural Networks (ANNs) for nonlinear modeling of turbogenerators in a multi-machine power system. Only local measurements are required by each ANN in this new method, and hence it is called *decentralized neuro-identification*. Each turbogenerator in the power system is equipped with an ANN which is able to identify (or model) its particular turbogenerator from moment to moment. This information can then be used by a second ANN at each generator to enable effective control of the nonlinear non-stationary process under all operating conditions. Simulation results are presented in this paper to show the potential of this new technique for designing future nonlinear ANN controllers.

Keywords: Artificial Neural Networks, Online Identification, Multi-machine Power System, Intelligent Identification.

I. INTRODUCTION

The increasing complexity of modern power systems highlights the need for advanced and intelligent system identification techniques for effective control of multi-machine 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 machines with a wide range of operating conditions and dynamic characteristics that depend on the entire power system to which each of these turbogenerators is connected [1,2]. Conventional automatic voltage regulators and turbine governors are designed to control, in some optimal fashion, each of these turbogenerators in the power system around one operating point. At other operating points each turbogenerator's performance is degraded. When a system configuration or operating condition changes, including a fault, the behavior of the power system may change significantly from that expected, due to the degradation of the conventional controller performance. Conventional controllers do not guarantee the system stability under such circumstances.

Moreover, when different turbogenerators with conventional controllers are connected together, low frequency 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.

Nevertheless, adaptive controllers for turbogenerators can be designed using linear models and traditional techniques of identification, analysis, and synthesis to achieve the desired performance. However, due to the nonlinear time varying nature of a turbogenerator, it cannot be accurately modelled as a linear device. Moreover, restrictive assumptions are often made [3] about the disturbance that the system is likely to be subjected to.

In recent years, renewed interest has been done in the area of power systems control using the recent developed 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 to linearize 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 are of more complicated structure and difficult to implement in practice 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 a 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) have already been used to identify a time varying nonlinear **single** turbogenerator system connected to the infinite bus [10, 11]. With the use of Continually Online Training (COT) these models can track the changing dynamics and configuration of the turbogenerator system, in other words yielding adaptive identification. Furthermore, these ANN models have already been used in the design of a nonlinear adaptive ANN controller for a single-machine-infinite-bus system [12, 13]. Such a controller is therefore informed at all times of the model of the changing system, adapts its own transfer function accordingly, and gives an excellent non-degraded response under all conditions.

The next natural evolutionary step in this process is to extend the single-machine-infinite-bus studies [10, 11] to a multi-machine power system that contains more than only one generator, each equipped with its neuro-identifier. This paper therefore explains how COT artificial neural networks can be used to identify each of the turbogenerators in a two-machine three-bus system from moment to moment to enable effective control at all operating points.

Simulation studies are presented to demonstrate the principles, feasibility and potential of this new technique, and to show that such COT ANNs are capable of robust identification of each of the turbogenerators.

II. MULTI-MACHINE POWER SYSTEM

The multi-machine power system whose schematic diagram is shown in Fig. 1 is modeled in the MATLAB/SIMULINK environment using the power system blockset. A two-machine system is chosen in order to illustrate the various concepts involved in the identification process. The three line impedances are equal and each represents a relatively short 10 km line.

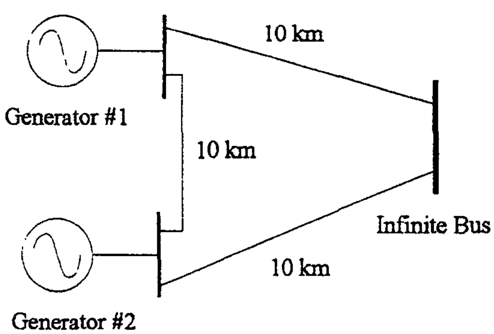

Fig. 1 Multi-machine Power System

III. ARTIFICIAL NEURAL NETWORK IDENTIFIER

The ANN Identifier (ANNI) in Fig. 2 is a feedforward multilayer perceptron network and 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. The plant block in Fig. 2 is modeled using fourteen differential equations that represent the generator, turbine and excitation system (depicted in Fig. 3).

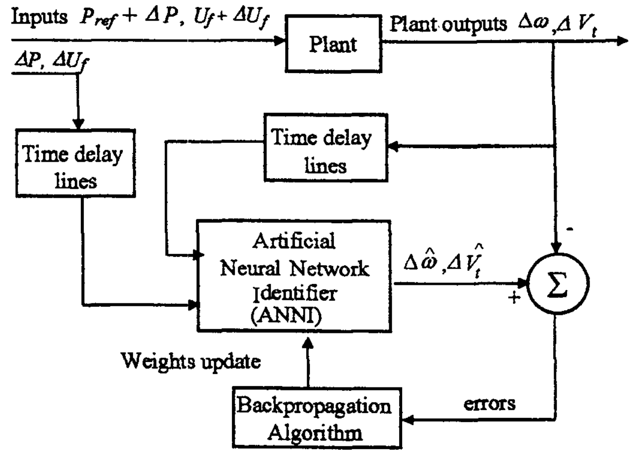

Fig.2. Plant-adaptive ANN identifier configuration

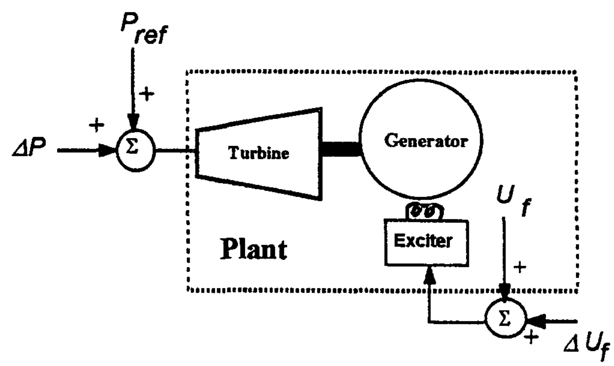

Fig. 3 The Plant

The inputs to the ANNI shown in Fig. 4 are the *deviation* in the *actual* power ΔP to the turbine, the *deviation* in the *actual* field voltage ΔU_f to the exciter, the *deviation* in the *actual* speed $\Delta\omega$, and the *deviation* in the *actual* RMS terminal voltage ΔV_t of the generator. These four ANN inputs are also delayed by the sample period of 20 ms and, together with ten previously delayed values, form twelve inputs altogether to the ANNI. For this set of ANNI inputs, the ANNI outputs are the *estimated* speed deviation $\Delta\hat{\omega}$ and the *estimated* terminal voltage deviation $\Delta\hat{V}_t$.

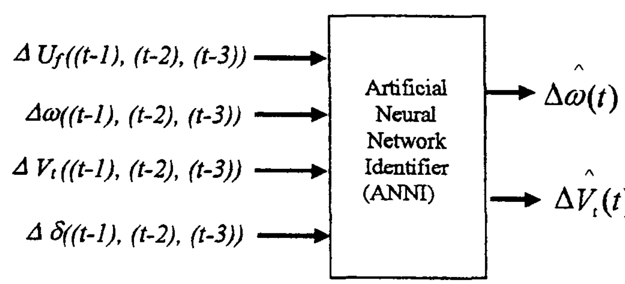

Fig.4. ANNI input and output signals

A sampling frequency of 50 Hz is chosen which is sufficiently fast for the ANNI to reconstruct the speed and terminal voltage signals from the sampled input signals. This is because the natural oscillation frequency of the turbogenerator's speed deviation is about 3 Hz and the response of the turbogenerator to the terminal voltage changes is even slower and is about 0.3 Hz.

The number of neurons in the hidden layer of the ANNI is determined heuristically. The ANNI weights are set to small random values [-0.1, 0.1] and the conventional backpropagation algorithm is used to update the weights of the ANNI. The differences between the respective *actual* outputs of the plant and the *estimated* outputs of ANNI form the error signals for the updating the weights in the ANNI. 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

The multi-machine power system with the ANN identifiers described in the section above is shown in Fig. 5. The ANNI #1 is located on generator #1 and ANNI#2 is located on generator #2. ANNI#1 identifies the dynamics of generator #1 and, its turbine governor and excitation system, and other factors that influence the operation of generator #1 as result of generator #2 and the infinite bus. ANNI#2 identifies the dynamics of generator #2 and, its turbine governor and excitation system, and other factors that influence the operation of generator #2 as result of generator #1 and the infinite bus.

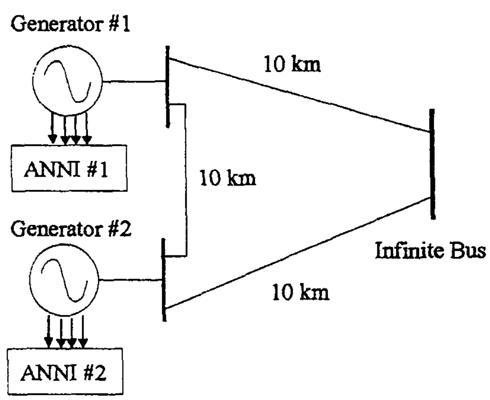

Fig. 5 Multi-machine Power System with ANN Identifiers

A significant finding of this paper is that the two ANNIs cannot be trained simultaneously. Simultaneous training means that ANNI#1 is trying to learn (identify) its generator as well as the rest of the system which contains ANNI#2, which is changing all the time as it is trying to learn (identify) its generator as well as ANNI#1 (which is changing all the time), and so on and so on. Such simultaneous training does not converge. The solution is to train ANNI#1 for a period of time say T1, while during that time, the training of ANNI#2 stops. Thereafter, ANNI#2 trains for a period T2 while ANNI#1 stops training, and so on. Once the training of both ANN identifiers have converged, their model information can be used by adaptive ANN controllers for each generator.

In this particular simulation, the online training of ANNI#1 is first carried out for 10 seconds (while the weights of ANNI#2 are held fixed), and then the weights of the ANNI#1 are fixed while the ANNI#2 undergoes online training for next 10 seconds, and so on. This process is repeated several times till both ANNIs have sufficiently learned the dynamics of generators in the power system, and their training errors have converged to acceptably small values.

In order to train the ANNIs, ± 10% deviations in the input turbine power reference (for a particular operating point given by $P_1 = 0.42$ pu and $Q_1 - 0.26$ pu for generator #1) and ± 15% in the exciter input voltage reference (for the same operating point given by P_1 and Q_1 for generator #1) is applied simultaneously at generator #1. And a ± 12% deviations in the input turbine power reference (for the operating point given by $P_2 = 0.25$ pu and $Q_2 = 0.16$ pu for generator #2) and ± 13% in the exciter input voltage reference (for the same operating point given by P_2 and Q_2 for generator #2) is applied simultaneously at generator #2. These signals are shown in Figs. 6, 7, 8 and 9.

The two generators are chosen to operate at different operating points since this is will have more impact on the ANNIs' identifier learning the dynamics better of the power system when disturbed. Different percentage deviations (from 10% to 15%) are chosen for the training signals for the two generators for the same reason. Smaller percentage deviations in range of 1% to 3% are also found sufficient to cause disturbances in the power system to order to train the ANNIs.

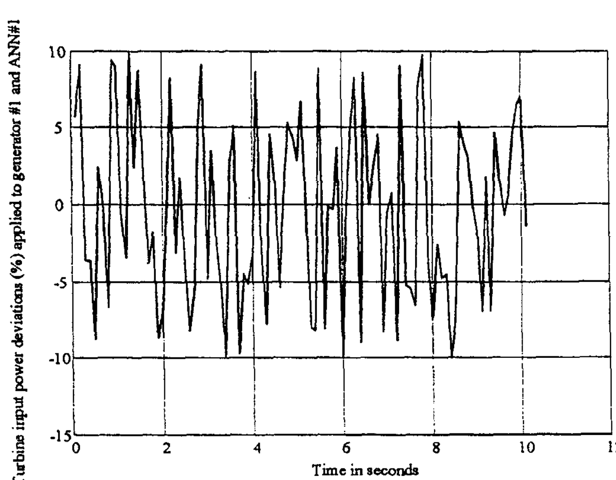

Fig. 6 ± 10% Deviations in the turbine input power of generator #1

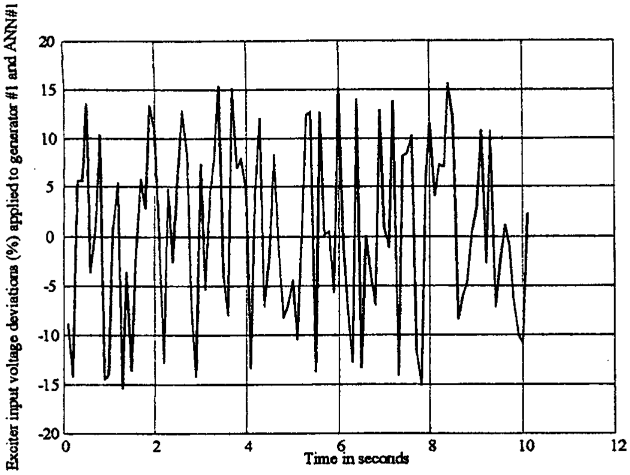

Fig. 7 ± 15% Deviations in the exciter input voltage of generator #1

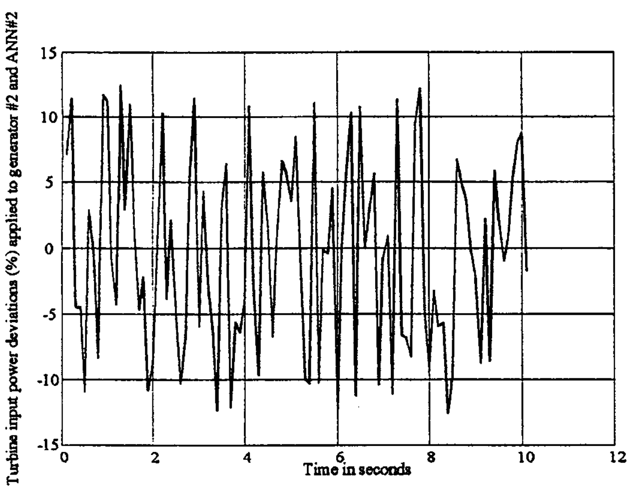

Fig. 8 ± 12% Deviations in the turbine input power of generator #2

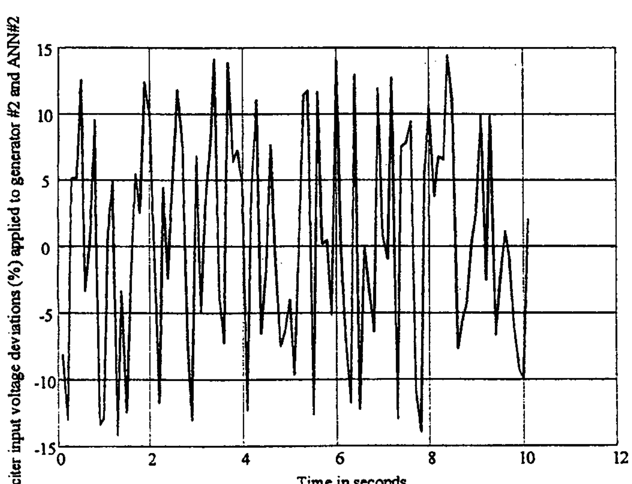

Fig. 9 ± 13% Deviations in the exciter input voltage of generator #2

The terminal voltage deviation and speed deviation of both the generator #1 and the ANN identifier #1 during the first training phase are shown in Figs. 10 and 11 respectively. The terminal voltage deviation and speed deviation of both the generator #2 and the ANN identifier #2 during the first training phase are similar to Figs. 10 and 11.

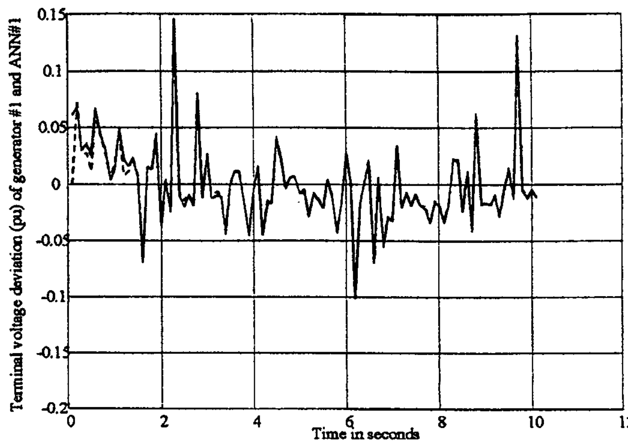

Fig. 10 The terminal voltage deviation of generator #1 and ANN #1

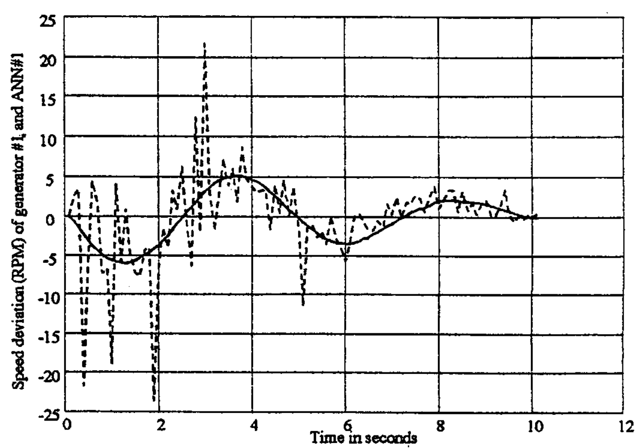

Fig. 11 The speed deviation of generator #1 and ANN #1

The terminal voltage deviation and speed deviation of the generators and the ANN identifiers after a period of 50 s of online training are shown in Figs. 12, 13, 14 and 15.

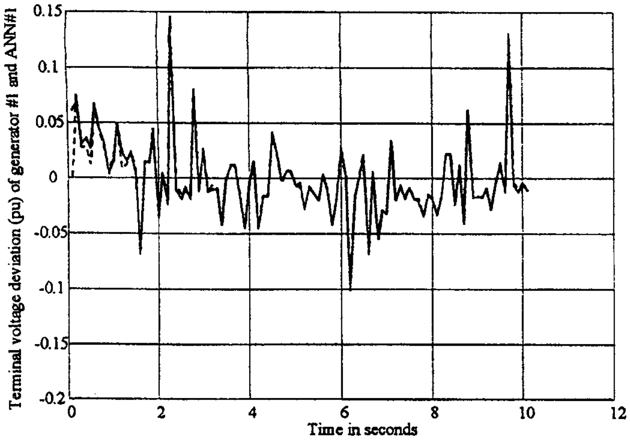

Fig. 12 The terminal voltage deviation of generator #1 and ANN #1

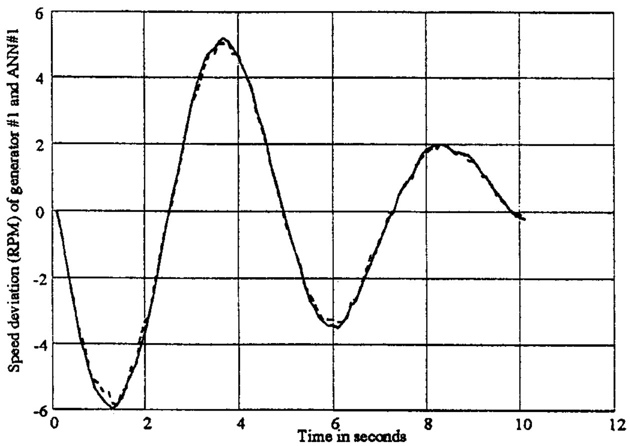

Fig. 13 The speed deviation of generator #1 and ANN #1

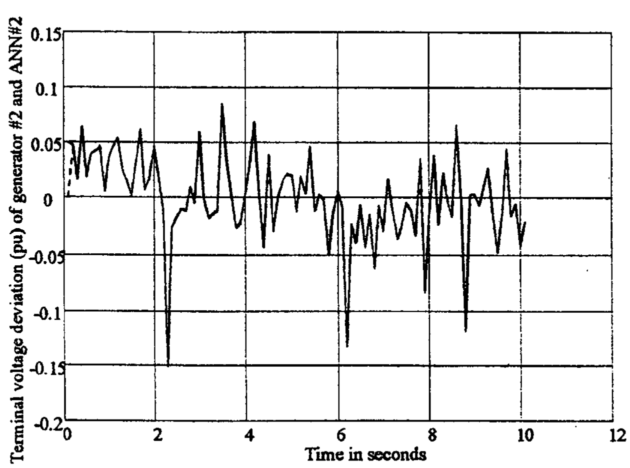

Fig. 14 The terminal voltage deviation of generator #2 and ANN #2

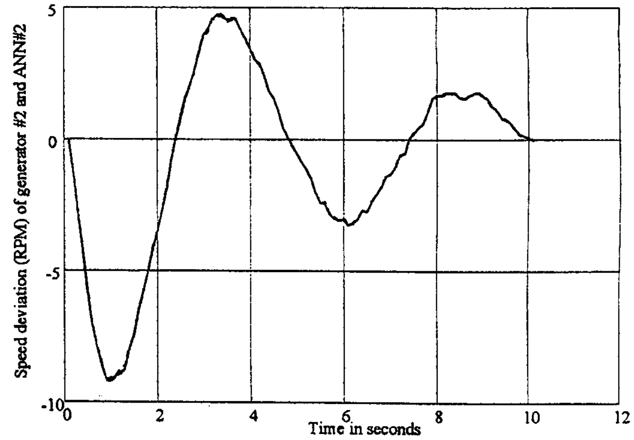

Fig. 15 The speed deviation of generator #2 and ANN #2

The ANNIs have been trained at different operating points on the two generators. Their *estimated* outputs are so close to the *actual* outputs of the generators, that it is impossible to show two sets of curves in the above results. The training process has therefore converged successfully. It is observed from the speed deviation figures that the generators are swinging against each other possibly because the disturbance on each machine is different.

V. CONCLUSIONS

Early conclusions of this study indicate that COT ANN can model/identify turbogenerators' dynamics in a multi-machine power system. The successful identification of turbogenerators' dynamics occurs because ***online training never stops***. The COT ANN identifier can be used in conjunction with a separate ANN controller to allow greater usage of each of the turbogenerators in a multi-machine power system by effective control of the excitation voltage and turbine power of turbogenerators especially during transients and changes in network configurations and operating points.

VI. ACKNOWLEDGMENTS

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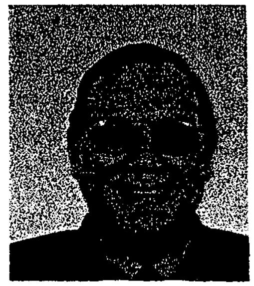
VIII. BIOGRAPHIES

Ganesh K Venayagamoorthy was born in Jaffna, Sri Lanka in 1972. He received a BEng (Honours) degree with a First class in Electrical and Electronic Engineering from the Abubakar Tafawa Balewa University, Nigeria, in March 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 Electronics Engineering at the M L Sultan Technikon, Durban, South Africa lecturing Systems Simulation and Digital Signal Processing. He took up an appointment as a Research Associate for seven months in 1999 at the Texas Tech University, USA. His research interests are in power systems, control systems, signal processing and artificial neural networks. He is a NRF and a Telkom (SA) Centre of Excellence grantholder. He is a Member of IEEE, SAIEE 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, and he is currently located at Georgia Tech in Atlanta. He has co-authored more than 200 papers in refereed journals and international 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 is an elected IEEE Industry Applications Society Distinguished Lecturer for the period 2000-2001. 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 intelligent control algorithms.