A Neural Network Based Wide Area Monitor for a Power System

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Abstract-- **With the deregulation of power industry, many tie lines between control areas are driven to operate near their maximum capacity, especially those serving heavy load centers. Wide area controllers (WACs) using wide-area or global signals can provide remote auxiliary control signals to local controllers such as automatic voltage regulators, power system stabilizers, etc to damp out inter-area oscillations. The power system is highly nonlinear system with fast changing dynamics. In order to have an efficient WAC, an online system monitor/predictor is required to provide inter-area information to the WAC from time to time. This paper presents the design of an online Wide Area Monitor (WAM) using a neural network called the Wide Area Neuroidentifier (WANI). The WANI is used to predict ahead the speed deviations of generators in the different areas using phasor measurement unit (PMU). Results are presented to show the effectiveness of the wide area monitor for different disturbances.**

Index--**Wide Area Monitor (WAM), Wide Area Control (WAC), Wide Area Neuroidentifier (WANI), Two-Area Power System, Neural Networks**

I. INTRODUCTION

A power system consists of components such as generators, lines, transformers, loads, switches and compensators. The general configuration of a modern power system is that power sources and loads are widely dispersed. Generators and loads may be hundreds of miles away. The number of bulk power exchanges over long distances has increased as a consequence of the deregulation of the electric power industry. Usually, distributed control agents are employed to provide reactive control at several places on the power network through power system stabilizers (PSSs), automatic voltage regulators (AVRs), FACTS devices, etc. Although local optimization is realized by these agents, the lack of coordination among the local agents may cause serious problems, such as inter-area oscillations. In order to minimize the problems encountered in a distributed power network control, a centralized wide area control (WAC) scheme is proposed [1].

The WAC coordinates the actions of the distributed agents by for example using SCADA (Supervisory Control And Data Acquisition), PMU (Phasor Measurement Unit) or other available information [2]-[4]. The WAC receives information/data of different areas in the power system and based on some predefined objective functions, sends appropriate control/feedback signals to the distributed agents in the power network. The WAC schematic diagram is shown in Fig. 1.

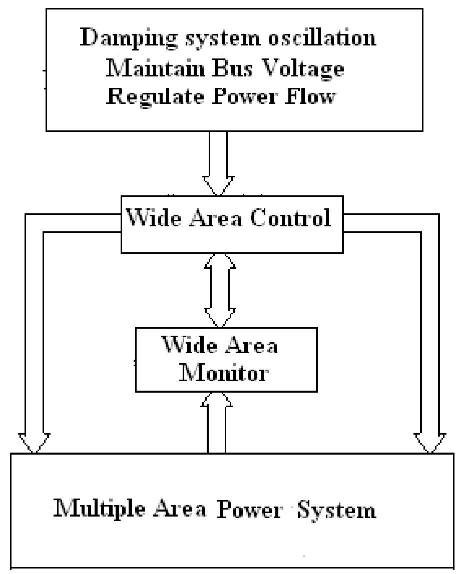

Fig. 1. WAC schematic diagram.

The increasing complexity and highly nonlinear nature of the power system today requires online wide area monitoring (WAM) techniques for the effective control of power network with an adaptive WAC [5], [6]. The major motivation to have a wide area monitoring and control scheme is for the following benefits:

- Transmission capacity enhancement can be achieved by on-line monitoring of the system stability limits and capabilities.
- Power system reinforcement based on feedback obtained during analysis of system dynamics.
- Introduction of a coordinated approach for the execution of stabilizing actions in case of severe network disturbances.
- Triggering of additional functions by a WAC.
- Better understanding of the dynamic behavior of the system.

Neural networks are able to identify/model multiple-input-multiple-output time varying systems as turbogenerators [7] and, with continually online training these models can track the dynamics of these systems thus yielding adaptive identification for changes in operating points and conditions.

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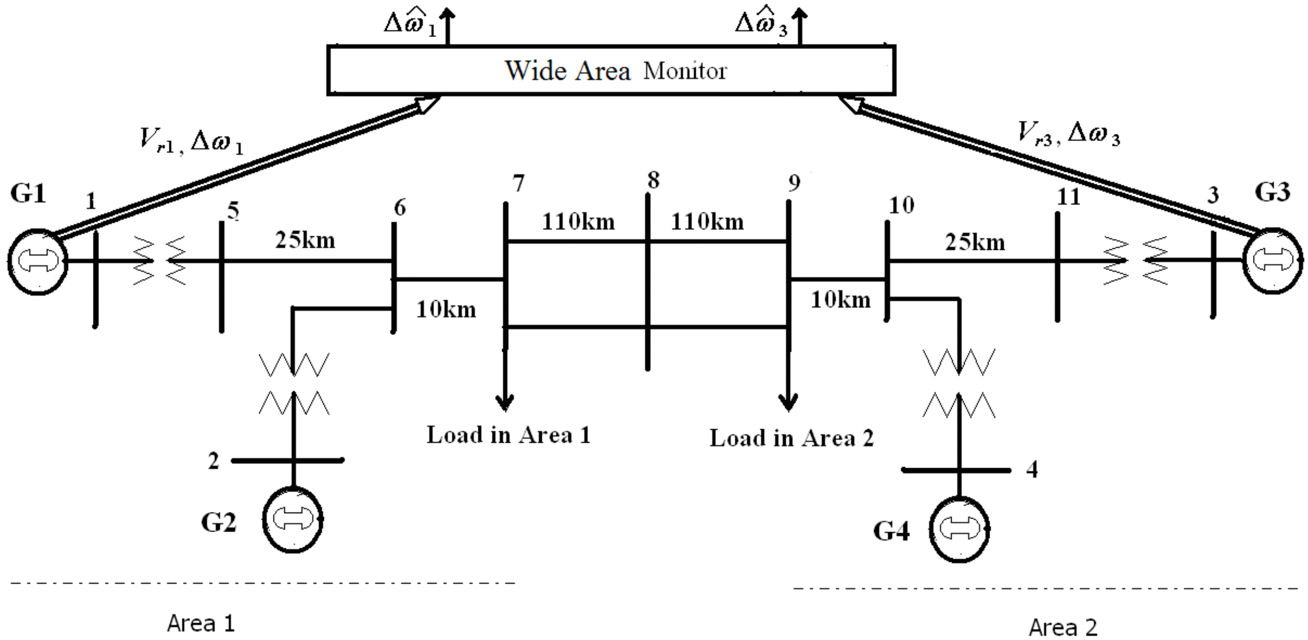

Fig. 2. Two-area power system with a wide area monitor/neuroidentifier.

Online trained neural network identifiers have been successfully implemented for neural network based control of turbogenerators [8], [9].

This paper presents the design of a wide area monitor based on a neural network for a two-area power system [10]. The wide area monitor predicts the speed deviations of generators in the two areas. Section II describes the two area power system. Section III describes the wide area neural network based monitor. Section IV presents the simulation results during learning and testing phase of the WAM. Finally, the conclusions and future work are given in Section V.

II. TWO-AREA POWER SYSTEM

The two area power system is shown in Fig. 2 consists of two fully symmetrical areas linked together by two transmission lines. Each area is equipped with two identical synchronous generators rated 20 kV/900 MVA. All the generators are equipped with identical speed governors and turbines (Fig. 3), exciters and AVRs (Fig. 4), and PSSs (Fig. 5). The loads in the two areas are such that area 1 is exporting 413MW to area 2. This power network is specifically designed to study low frequency electromechanical oscillations in large interconnected power systems. Despite the small size of this power network, it mimics very closely the behavior of typical systems in actual operation [11]. It is specifically designed to study low frequency electromechanical oscillations in large interconnected power systems. Three electro-mechanical modes of oscillation are present in this system [12]; two inter-plant modes, one in each area, and one inter-area low frequency mode. To ultimately design a WAC to provide inter-area oscillation damping, the speed deviations of generator G1 in Area 1 and G3 in Area 2 are measured to provide feedback control signals to the PSSs on G1 and G3. Their measurements in a predicted power system can be carried out using PMUs. In order to achieve this WAC design, a Wide area monitor (WAM) is required and its design is described in the next section. The study is carried out in the PSCAD/EMTDC environment [13].

III. WIDE AREA MONITOR

The wide area monitor also called the Wide Area Neuroidentifier (WANI) in this paper, for the two-area power system is based on a feedforward multilayer perceptron neural network. It has three layers consisting of an input layer with twelve linear neurons, a single hidden layer with fifteen sigmoidal neurons, and an output layer with two linear neurons. The WANI's inputs and outputs are shown in Fig. 6. The inputs to WANI are inputs to AVRs (V_{r1}, V_{r3}) and speed deviations ($\Delta\omega_1, \Delta\omega_3$) of generator G1 and G3 in areas 1 and 2 respectively. These signals are given to the WANI every 10 ms, which is possible with the PMU technology.

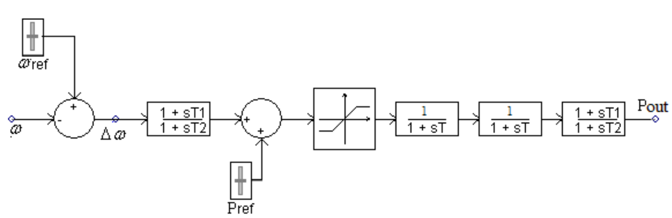

Fig. 3. Speed governor and turbine on generator G1, G2, G3 and G4.

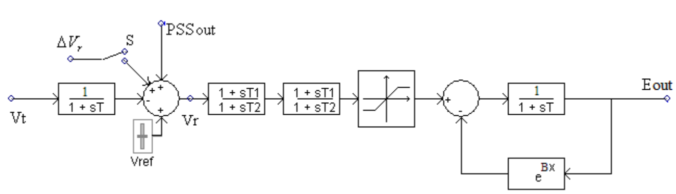

Fig. 4. Exciter and AVR on generator G1, G2, G3 and G4.

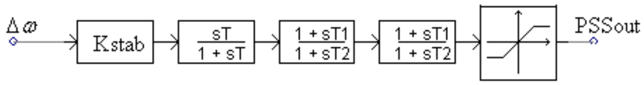

Fig. 5. PSS on generator G1, G2, G3 and G4.

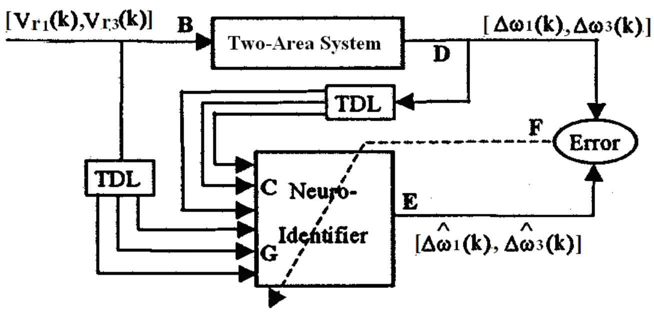

Fig. 6. Wide area monitor/neuroidentifier for a two-area power system.

The four inputs mentioned above are also delayed by the sample period of 10 ms and, together with eight previously delayed values, form twelve inputs altogether. The outputs of the WANI are the estimated speed deviation $\Delta\hat{\omega}_1$ and $\Delta\hat{\omega}_3$ of G1 and G3 respectively at the next time step.

The number of neurons in the hidden layer of the WANI is determined heuristically. The differences between the actual speed deviations of the generators and the estimated outputs of WANI form the error signals for updating the weights as shown in Fig. 6. The initial weights of the WANI are set to random values [-0.1, 0.1], and the backpropagation algorithm is used to update the weights.

The WANI undergoes two phases of training namely *forced training* and *natural training*. Forced trained is carried with forced perturbations applied to generators' excitation. These perturbations are small pseudorandom binary signals (PRBS), usually ±10% of the respective AVR. The PRBS are used to excite all possible dynamics of the power network [7]-[9]. Natural training is carried out with a smaller neural network learning rate under natural disturbances. Natural disturbances include change in loads in the two areas, transmission line outage and short circuits faults.

IV. SIMULATION RESULTS

Two sets of results are presented. The first set is for forced training and the second set for natural training.

A. Forced training

A constant AVR input voltage V_{ref} and a turbine power signal P_{ref} are applied to each of the generators at a particular steady state operating point. Pseudorandom binary signal (PRBS) ΔV_{r1} and ΔV_{r3} are applied to G1 and G3 respectively to train the WANI, with the switch S in Fig. 4 closed. The PBRS in Figs. 7 and 8 show $\pm$ 10% deviations in the steady state values of V_{ref1} and V_{ref3} of G1 and G3 at an operating point given in the appendix.

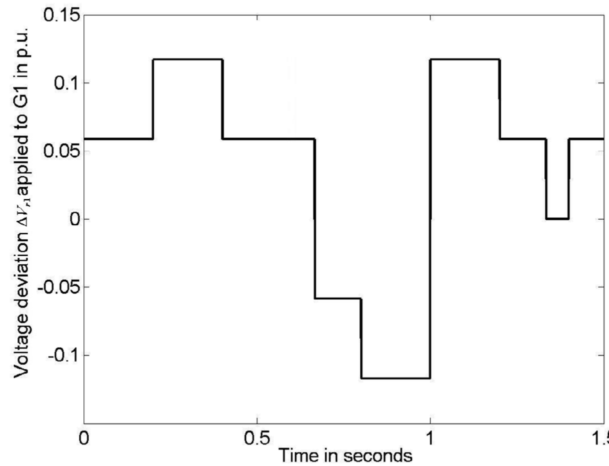

Fig. 7. Forced PRBS training signal ΔV_{r1} applied to G1.

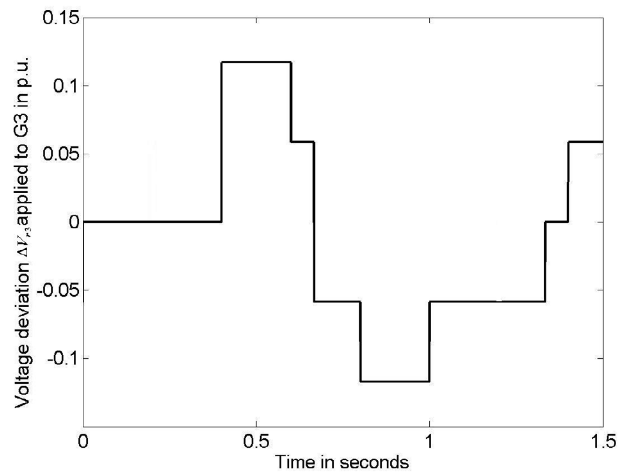

Fig. 8. Forced PRBS training signal ΔV_{r3} applied to G3.

Figs. 9 and 10 show the actual speed deviations and estimated speed deviations by WANI of G1 and G3. It is clear from these figures that the WANI is able to estimate the speed deviations of G1 and G3 sufficiently well indicating that it has learned the power network dynamics.

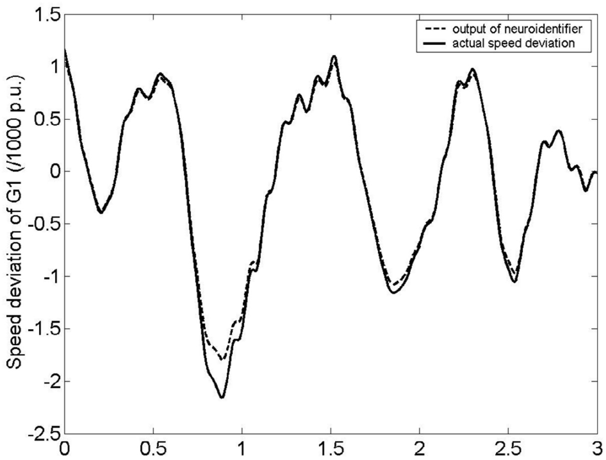

Fig. 9. Speed deviation of G1 and the WANI during forced training.

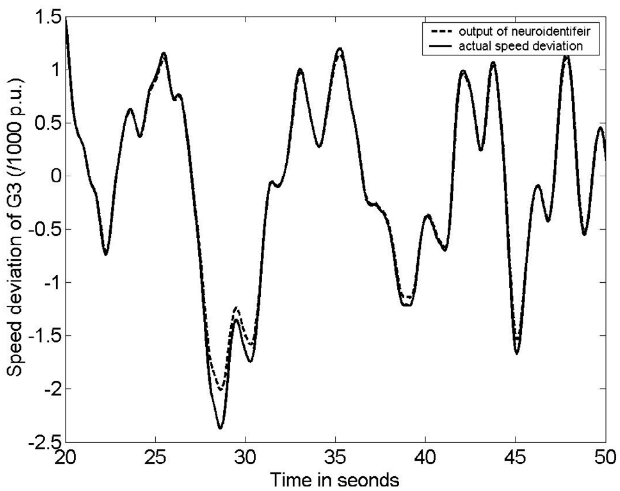

Fig. 10. Speed deviation of G3 and the WANI during forced training.

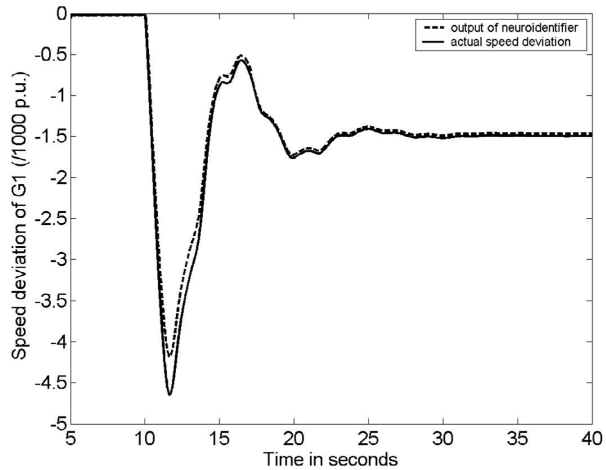

Fig. 11. Speed deviation of G1 and the WANI during load change.

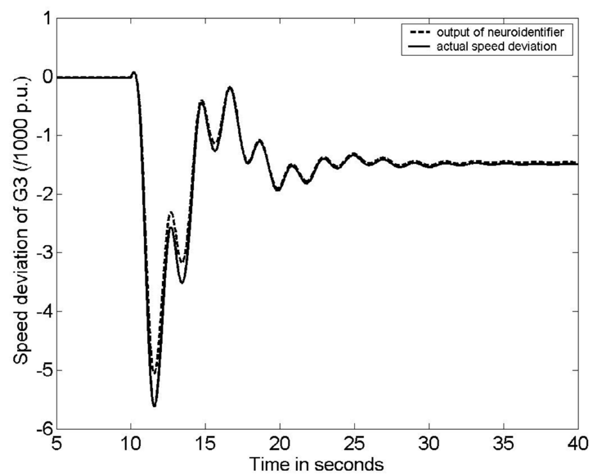

Fig. 12. Speed deviation of G3 and the WANI during load change.

B. Natural training

The natural training continues with weights obtained from the forced training when the switch S in Fig. 4 is opened. As mentioned above, natural disturbances are applied for further training. Thereafter, the weights of the WANI are fixed (training terminated). Three different tests are carried out in order to evaluate the performances of the WANI for changes in the power system configuration and disturbances.

The first test is load changes in the area 1 and area 2. Load in area 1 is decreased by 10% (32.2MW, 3.3MVAR) and simultaneously, the load in area 2 is increased by 10% (58.9MW, 8.3MVAR). The actual speed deviation and the estimated speed deviations by the WANI of G1 and G3 are shown in Figs. 11 and 12 respectively.

The second test is one where there is outage of one of the parallel transmission lines between buses 7 and 9 in Fig. 2. The actual speed deviation and the estimated speed deviations by the WANI of G1 and G3 are shown in Figs. 13 and 14 respectively.

The third test is a five cycles (83 ms) three-phase short circuit fault applied at bus 8 in Fig. 2. The actual speed deviation and the estimated speed deviations by the WANI of G1 and G3 are shown in Figs. 15 and 16 respectively.

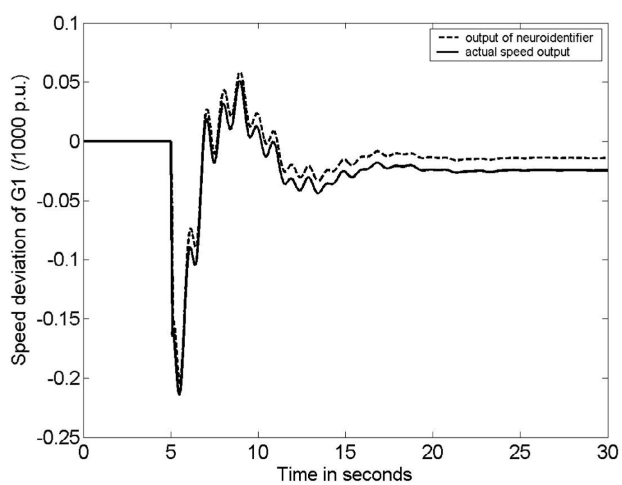

Fig. 13. Speed deviation of G1 and the WANI during transmission line outage between buses 7 and 9 (Fig. 2).

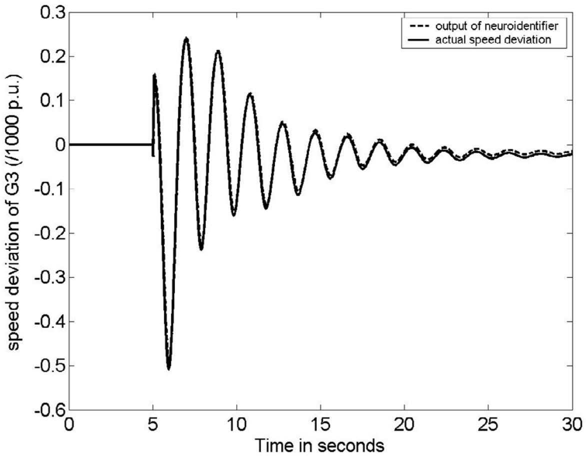

Fig. 14. Speed deviation of G3 and the WANI during transmission line outage between buses 7 and 9 (Fig. 2).

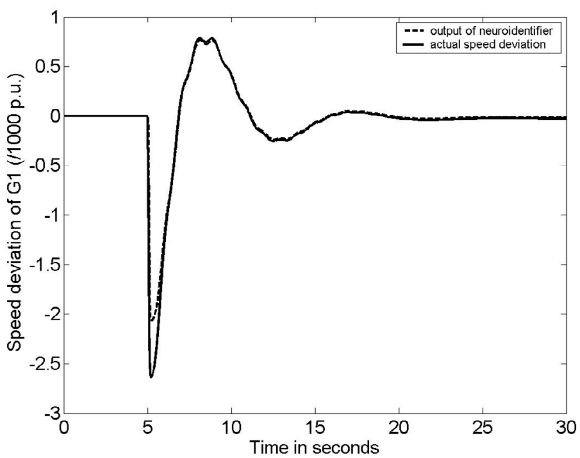

Fig. 15. Speed deviation of G1 and the WANI during short circuit fault.

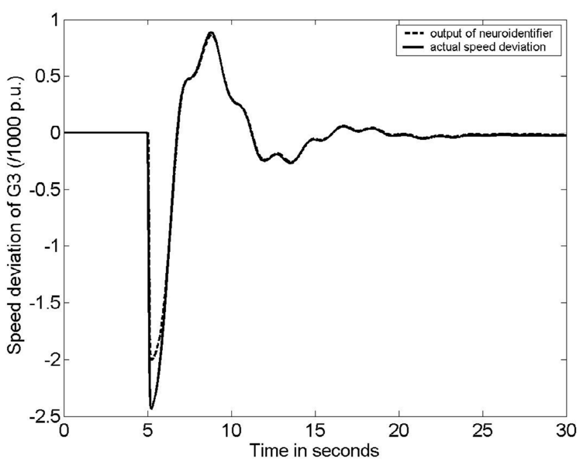

Fig. 16. Speed deviation of G3 and the WANI during short circuit fault.

All the above results of Figs. 9 to 16 show that the WANI is able to estimate the speed deviations of G1 and G3 at the next time step with changes in the two-area power system configuration, implying that the forced and natural training carried with the PRBS is sufficient to excite all the possible dynamics of the system.

V. CONCLUSIONS

The neural network based wide area monitor has been successfully developed to predict ahead the speed deviations of the two generators in two different areas. Simulation results indicate that the proposed scheme is potentially very promising for identifying highly nonlinear multimachine power system from moment to moment even when the power system configuration changes.

With this wide area monitor/neuroidentifier, it is possible to extend this work to include a neural network based wide area controller that is nonlinear and adaptive. The use of the WANI overcomes the difficulties and limitations of having up-to-date analytic equations of the power network every time the operating points and the configuration changes. Future work involves the design of a WAC with consideration of time delays in the inputs to the WANI and, the real time implementation of the wide area monitor and control scheme.

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VII. APPENDIX

Synchronous Generators (identical):

Xd=1.8 Xq=1.7 Xl=0.2 Xd'=0.3 Xq'=0.55
Xd"=0.25 Xq"=0.25 Ra=0.0025 (all in per-unit)
H=6.5s (for G1 and G2) H=6.175s (for G3 and G4)

Operating Points of the Power System:

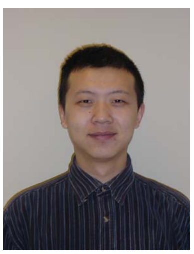
G1: P=700MW, Q=185MVar, Vt=$1.03\angle 20.2°$
G2: P=700MW, Q=235MVar, Vt=$1.01\angle 10.5°$
G3: P=719MW, Q=176MVar, Vt=$1.03\angle -6.8°$
G4: P=700MW, Q=202MVar, Vt=$1.01\angle -17.0°$

Load 1: P_L=967MW, Q_L=100MVar, Qc=200MW
Load 2: P_L=1767MW, Q_L=100MVar, Qc=350MW

Parameters of the Turbine, Exciter, and PSS:

Turbine: ω ref=1 p.u. Pref=0.779 p.u. T1=0.867s T2=2.662s
Exciter: Vref=1.734 p.u. T1=0.05s T2=0.02s T=15s B=1.6
PSS: Kstab=20 T1=0.05s T2=0.02s T=10s

VIII. BIOGRAPHIES



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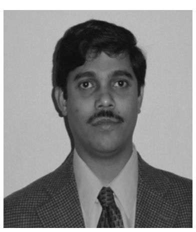

Ganesh K Venayagamoorthy (M'97, SM'02) received the B.Eng. (Honors) degree with a first class honors in Electrical and Electronics Engineering from the Abubakar Tafawa Balewa University, Bauchi, Nigeria, and the MScEng and PhD degrees in Electrical Engineering from the University of Natal, Durban, South Africa, in March 1994, April 1999 and February 2002, respectively. He was appointed as a Lecturer with the Durban Institute of Technology, South Africa during the period March 1996 to April 2001 and thereafter as a Senior Lecturer from May 2001 to April 2002. 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 computational intelligence, power systems, evolving hardware and signal processing. He has authored/co-authored over 100 papers in refereed journals and international conferences. Dr. Venayagamoorthy is a 2004 NSF CAREER award recipient, 2004 IEEE St. Louis Section Young Engineer award recipient, the 2003 International Neural Network Society Young Investigator award recipient, a 2001 recipient of the IEEE Neural Network Society summer research scholarship and the recipient of five prize papers with the IEEE Industry Application Society and IEEE Neural Network Society.

He is a Senior Member of the South African Institute of Electrical Engineers, a Member of International Neural Network Society (INNS) and the American Society of Engineering Education (ASEE). He is an Associate Editor of the IEEE Transactions on Neural Networks. He is currently the IEEE St. Louis Computational Intelligence and Industry Applications Societies' Chapter Chair. He is the Chair of the task force on Intelligent Control Systems and the Secretary of the Intelligent Systems subcommittee of IEEE Power Engineering Society. He was the Technical Program Co-Chair of the International Joint Conference on Neural Networks (IJCNN), Portland, OR, USA, July 20 – 24, 2003 and the International Conference on Intelligent Sensing and Information Processing (ICISIP), Chennai, India, January 4 – 7, 2004. He has organized special sessions and given tutorials/workshops in many international conferences and invited to speak in many countries including Australia, Brazil, Canada, India, Mexico, New Zealand, Nigeria, South Africa, Taiwan and USA.