

## A wide area measurement based neurocontrol for generation excitation systems

Swakshar Ray<sup>a</sup>, Ganesh K. Venayagamoorthy<sup>b,\*</sup>

<sup>a</sup> Quanta Technology, Raleigh, NC 27607, USA

<sup>b</sup> Real-Time Power and Intelligent Systems Laboratory, Department of Electrical and Computer Engineering, Missouri University of Science and Technology, Rolla, MO 65409-0249, USA

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### ABSTRACT

Power system is a highly interconnected nonlinear system that needs optimal and accurate control for continuous operation. Large power transfer through long transmission line between different electrical areas, stressed system and adverse interaction between local controllers, may give rise to slow frequency inter-area oscillations. The inter-area modes may not be visible from local measurements and hence it is useful to use remote measurement based centralized supplementary control. Wide area control systems (WACSS) using wide-area or global signals can provide remote auxiliary control to local controllers such as automatic voltage regulators, power system stabilizers, etc. to damp out inter-area oscillations. This paper presents a design and real time implementation of a nonlinear neural network based optimal wide area controller using adaptive critic design (ACD). The real time implementation of a power system model is carried out on a real time digital simulator (RTDS). The performance of the WACS as a power system stability agent is studied using a two-area power system under different operating conditions and contingencies. The WACS shows improvement in the damping of inter-area mode with the use of supplementary excitation control. In addition, results show that the designed controller can provide robust performance under small communication delay in remote signal transmission.

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### 1. Introduction

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 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 (Flexible AC Transmission Systems) devices (special power electronic switch based controlled devices which can regulate power flow in transmission line or voltages at the buses), etc. The PSSs are designed to have fixed parameters derived from a linearized model around a certain operating point. Final settings are made using field tests at a couple of operating points. The inherent nonlinearity in the system becomes a major source of model uncertainty. The model uncertainty includes the inaccuracies in modeling the transformers, the transmission lines and the loads.

Although local optimization is realized by these agents (PSSs, AVRs), 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 system (WACS) is proposed (Ni and Heydt, 2002; Taylor et al., 2005). The WACS coordinates the actions of the distributed agents by using SCADA (supervisory control and data acquisition), PMU (phasor measurement unit) or other wide-area dynamic information (Taylor et al., 2005; Kamwa and Grondin, 2002). The WACS 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 to enhance the system dynamic performance (Taylor et al., 2005; Abould-Ela et al., 1996). A WACS is typically composed of two parts, first part that identifies the system or a model which is referred to as a wide area monitor (WAM) in this paper; and the second part is the controller, which is referred to as a wide area controller (WAC).

The major motivation to have a wide area monitoring and control scheme is for the following benefits:

- transmission capacity enhancement can be achieved by online monitoring of the system stability limits and capabilities;
- power system reinforcement based on feedback obtained during analysis of system dynamics;

\* Corresponding author. Tel.: +1573 3416641; fax: +1573 3414532.

E-mail address: [gkumar@ieee.org](mailto:gkumar@ieee.org) (G.K. Venayagamoorthy).

- introduction of a coordinated approach for the execution of stabilizing actions in case of severe network disturbances;
- triggering of additional functions by a WACS;
- better understanding of the dynamic behavior of the system.

In classical modeling of a power system, the parameters of different devices are very important to know beforehand. Also, the linear models are only accurate for the operating point at which they are derived. Any excursion from nominal point of operation would make the model inaccurate. Though online update of linear model is possible, it is computationally intensive and designing a controller at each operating point is a difficult task to do online. Here comes the advantages of using neural network due to its inherent approximation capability.

Neural networks are able to identify and control multiple-input-multiple-output time varying systems as turbogenerators (Jung-Wook et al., 2005; Venayagoorthy and Harley, 2002) 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. Adaptive critic designs (ACDs) have been reported in literature to provide nonlinear optimal control for complex processes and systems (Venayagoorthy and Harley, 2002; Werbos, 1992; Jung-Wook et al., 2005; Govindhasamy et al., 2005).

This paper presents the design of an optimal WACS based on adaptive critics and neural networks for a power system. The controller shows robustness for different operating conditions and small communication delays. The WACS is implemented on the M67 digital signal processor (DSP) which is interfaced to the real time digital simulator (RTDS) that simulates the power system. The rest of the paper is organized as follows. Section 2 describes the multimachine power system studied. Section 3 describes the WACS proposed in this work. Section 4 explains the implementation platform for the WACS—the RTDS and the M67 DSP. Section 5 presents the implementation results. Finally, the conclusion is given in Section 6.

**2. Multimachine power system**

In spite of being a small test system, the two-area power system of Fig. 1 mimics certain behavior of typical systems in actual operation and is a useful system in the study of inter-area

oscillations like those seen in large interconnected power systems (Klein et al., 1991; Kundur, 1994). The two-area system shown in Fig. 1 consists of two fully symmetrical areas linked together by two transmission lines. There are 11 electrical buses in the system and each generator low voltage bus is connected to the 230kV transmission system through a step up transformer. Each area is equipped with two identical synchronous generators rated 20kV/900MVA. All the generators are equipped with identical speed governors and turbines, and exciters and AVRs (Fig. 2). Though there are four generators (G1, G2, G3 and G4) in the system only G1 and G3 are equipped with PSSs. This is because each area has one low frequency oscillatory mode and it can be damped using the excitation control of one generator in each area. Switch  $S_1$  is used to add either the PRBS or WACS supervisory signal to the input of the AVR. Switch  $S_2$  is used to connect or disconnect PSS. During the training of the WACS,  $S_1$  is connected to PRBS signal while during normal operation  $S_1$  is connected to the WACS signal. Load is represented as constant impedances and split between the areas in such a way that area 1 is transferring about 413 MW to area 2. Three electromechanical modes of oscillation are present in this system; two inter-plant modes at 1.1 and 1.2 Hz, one in each area, and one inter-area mode at 0.63 Hz, in which the generating units in one area oscillate against those in the other area. The parameters of the system are given in the Appendix. The two-area power system is simulated

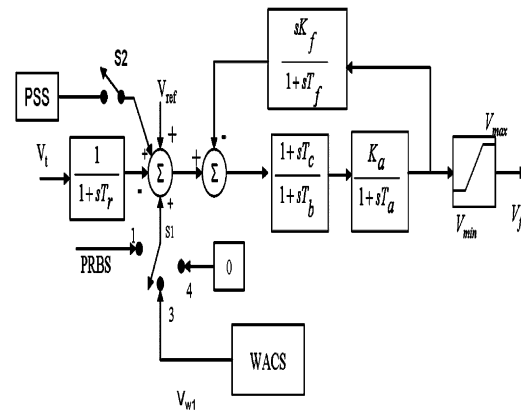


Fig. 2. AVR-exciter model for the generators with supplementary signal from WACS.

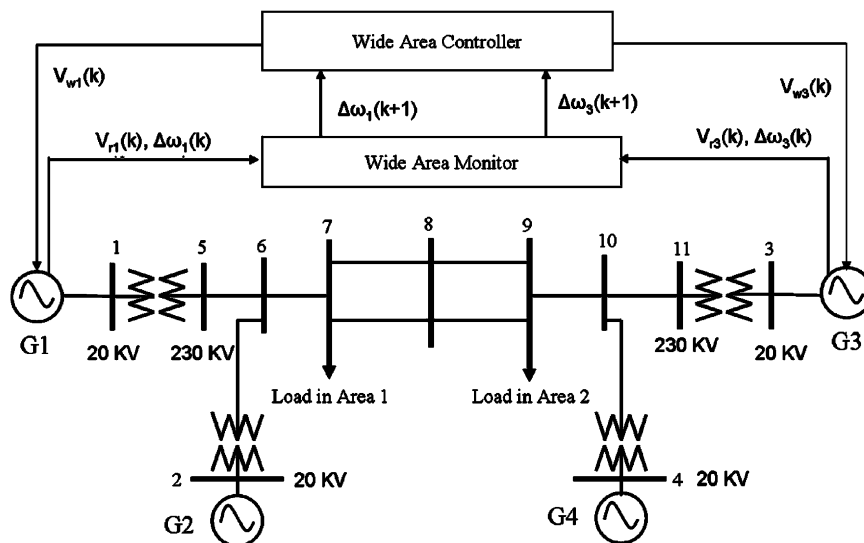


Fig. 1. Two-area power system with WACS consisting of a WAC and a WAM.

on the real-time digital power system simulator (Forsyth et al., 2004). The RTDS simulator platform is explained in Section 4.

### 3. Wide area control system

The WACS is based on ACDs. ACDs are neural network based designs capable of optimization over time under conditions of noise and uncertainty. Families of ACD were proposed as new optimization techniques, based on combined concepts of reinforcement learning and approximate dynamic programming (Werbos, 1992). The adaptive critic method determines optimal control laws for a system by successively adapting two neural networks, namely, an action neural network (which dispenses the control signals) and a critic network (which learns the desired performance index for some function associated with the performance index). These two neural networks approximate the Hamilton–Jacobi–Bellman equation associated with optimal control theory. The adaptation process starts with a non-optimal, arbitrarily chosen control by the action network; the critic network then guides the action network toward the optimal solution at each successive adaptation. During the adaptations, neither of the networks needs any ‘information’ of an optimal trajectory, only the desired cost needs to be known. Furthermore, this method determines optimal control policy for the entire range of initial conditions and needs no continuous online external training, unlike other neurocontrollers (Venayagamoorthy et al., 2002).

In this work, the heuristic dynamic programming (HDP) ACD approach illustrated in Venayagamoorthy et al. (2002) is adopted for the design of a WACS. The WACS provides auxiliary damping to generators G1 and G3 in areas 1 and 2, respectively, as illustrated in Fig. 1. The WACS consists of three neural networks: the critic neural network, the action network (WAC) and the model neural network (WAM). All the neural network inputs are scaled to be within  $-1$  to  $+1$  for effective utilization of the sigmoid function. Multi-Layer Perceptron (MLP) networks are global approximators and its easy to implement. Hence, all the neural networks used in this work are MLP feedforward network. More complex forms of neural networks may be used for complex and large systems where multiple modes and their dynamics need to be approximated. It has been seen that two time delayed values (referred in the figures as ‘TDL’) are sufficient to approximate the modal dynamics for the system. The system has only one inter-area mode. The WACS is designed to mitigate only the oscillation in the inter-area modes and two delayed values for each measurement provide sufficient accuracy in detecting the inter-area dynamics. The training of the neural network uses error minimization using backpropagation algorithm. In the following subsections, individual modules and the backpropagation training algorithm are explained.

#### 3.1. Backpropagation

The WACS is initially trained with pseudorandom binary signals (PRBS) added to the excitation control inputs of the respective generators. The PRBS excites all possible system dynamics. The training of individual neural networks with backpropagation algorithm is given in Eqs. (1)–(8):

$$\bar{d}(k) = \frac{1}{1 + e^{-W_1(k) * \bar{X}(k)}} \quad (1)$$

$d$  is the output of the hidden layer,  $\bar{X}$  is the vector of inputs to the neural network input layer.  $\bar{X}$  comprises the set of measurement

signals and their delayed values.  $W_1$  is the input weight matrix:

$$\bar{y}(k) = W_2(k) * \bar{d}(k) \quad (2)$$

$\bar{y}$  is the output of the neural network and  $W_2$  is the output weight matrix. The weight adjustments are done using steepest descent based backpropagation algorithm as shown below:

$$\bar{E}(k) = \bar{y}_d(k) - \bar{y}(k) \quad (3)$$

$\bar{E}$  is the error vector at each sampling instance.  $\bar{y}_d$  is the desired or actual measurement at time  $t$ :

$$\bar{E}_d(k) = W_2^T(k) * \bar{E}(k) \quad (4)$$

$$\bar{E}_a(k) = \text{diag}(\bar{d})(k) * \text{diag}(1 - \bar{d})(k) * \bar{E}_d(k) \quad (5)$$

$$\frac{\partial \bar{E}(k)}{\partial \bar{X}(k)} = W_1^T(k) * \bar{E}_a(k) \quad (6)$$

$$W_1(k+1) = W_1(k) + \alpha * \bar{E}_a(k) * \bar{X}^T(k) \quad (7)$$

$$W_2(k+1) = W_2(k) + \alpha * \bar{E}(k) * \bar{d}^T(k) \quad (8)$$

$\bar{E}_d$  is the backpropagated error vector at the hidden layer while  $\bar{E}_a$  is the backpropagated error vector at the input layer. The weight adjustments are done at each sampling time.

#### 3.2. Critic network

The critic network in the HDP based design approximates the cost-to-go function  $J$ , of Bellman’s equation of dynamic programming, shown in (9). The objective of the critic and action network is to minimize (10) and (11), respectively. The critic network is a three layer feedforward neural network with six inputs, a single hidden layer with 10 sigmoidal neurons and two outputs. The two outputs of the critic network represent the cost-to-go functions for generators G1 in area 1 and G3 in area 2. Each area is given a separate cost-to-go function. The critic network training procedure is as explained in Venayagamoorthy et al. (2002) and Werbos (1992). This utility function  $U$  in (9)–(11) is key to form the user-defined optimal cost-to-go function  $J$ , and is selected to give the best trade-off between performance and the control effort. In damping system oscillations, the critic network basically evaluates the area under the oscillating signal beforehand. Thereby, it can modulate the control signal such that oscillations damps out optimally. The critic neural network in Figs. 3 and 5 is a three layer feedforward network with seven input linear neurons, 10 sigmoidal neurons in the hidden layer and one output linear neuron. The critic inputs are the neuroidentifier or model outputs and their two delayed values. During training, two critic networks with identical weights are used to calculate error in (11) as shown in Fig. 3:

$$J_k = \sum_{k=0}^{\infty} \gamma^k U(t+k) \quad (9)$$

where  $U(t)$  is the utility function and  $\gamma$  is the discount factor (between 0 and 1):

$$e_c(k) = \gamma J_{k+1}(\hat{Y}_M(k+1)) + U_k(Y(k)) - J_k(\hat{Y}_M(k)) \quad (10)$$

$$e_A(k) = \frac{\partial J(k)}{\partial A(k)} = \left[ \frac{\partial J(k)}{\partial u_{G1}}, \frac{\partial J(k)}{\partial u_{G3}} \right] \quad (11)$$

#### 3.3. Model network

The HDP design is a model dependent ACD and requires the model of the two-area power system. This dynamic model,

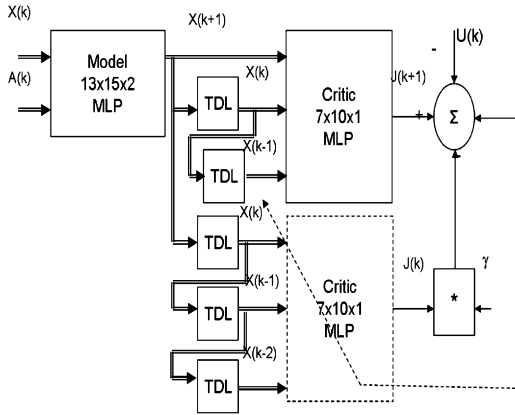


Fig. 3. Critic training.

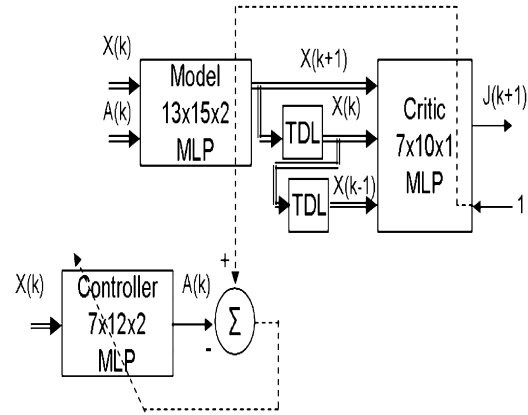


Fig. 5. Wide area controller training.

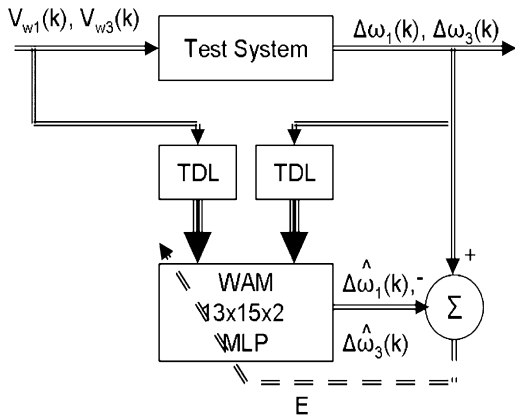


Fig. 4. Wide area monitor training.

referred to as WAM, is a three layer feedforward neural network with 13 inputs, a single hidden layer with 15 sigmoidal neurons and two outputs. The WAM estimates the speed deviations of G1 and G3 (Fig. 4) based on the past speed deviations and inputs to the respective excitation systems. The model network provides an estimated one-step ahead model of the reduced order nonlinear system. The WAM is composed of similar structure as critic and controller. The training of the WAM neural network is carried out using backpropagation algorithm as given in the previous subsection and can also be found in different literatures (Werbos, 1990; Venayagamoorthy and Harley, 2002). An accurate estimation of the model is required to calculate future cost-to-go function by the critic network. Hence, for HDP design, accuracy of model network is one of the important factor in the optimal controller design.

3.4. Action network or controller

The WAC is a three layer feedforward neural network with six inputs, a single hidden layer with 12 sigmoidal neurons and two outputs (Fig. 5). The inputs to the action network are the actual speed deviations of G1 and G3, and each of these inputs is together with two previously delayed values, form the six model network inputs. The two outputs of the WAC,  $V_{\omega 1}$  and  $V_{\omega 3}$ , are voltage additions to G1 and G3's AVR inputs, respectively. The training procedure of the WAC is similar to that in Venayagamoorthy and Harley (2002).

4. Real time implementation platform

Due to the complexity and expensive nature of the power system, it is very difficult to test new control schemes on the practical power system. The proposed WACS is implemented on a DSP and its performance is tested on the two-area power system which is simulated on a real-time power system simulation platform, the RTDS (Fig. 6). The RTDS is a fully digital power system simulator capable of continuous real time operation. It performs electromagnetic transient power system simulations with a typical time step of 50 ms utilizing a combination of custom software and hardware (Forsyth et al., 2004). It is an ideal tool for the design, development and testing of power system protection and control schemes. With a large capacity for both digital and analogue signal exchange (through numerous dedicated, high speed I/O ports) physical protection and control devices can be connected to the simulator to interact with the simulated power system.

The real time simulator RSCAD software consists of two parts, namely the graphical user interface and the underlying solution algorithms for network equations and component models. RSCAD has two modules—the draft and the runtime. The draft module is used for circuit assembly and parameter entry. The runtime module is used to control the operation of the RTDS simulator. Through the runtime, the user can perform real time operation such as the starting and stopping of simulation cases, initiating system disturbances, online monitoring of system quantities, etc. Report ready plots can also be printed directly from runtime.

The WACS consisting of the WAM and WAC is implemented on the Innovative Integration M67 DSP card (based on the TMS3206701 processor), operating at 160 MHz, hosted on a Pentium III 433 MHz personal computer. The M67 DSP card is equipped with two A4D4 modules (Inn, 2001). Each A4D4 module is equipped with four analog-to-digital (A/D) converters and four digital-to-analog (D/A) converters. The DSP (WACS) and RTDS (power system) interface and laboratory is shown in Fig. 6. For the WACS development, a sampling frequency of 40 Hz (period of 25 ms) is used.

5. Implementation results

The implementation results of WACS consisting of the WAM and the WAC are given below.

5.1. Wide area monitor

The training of the WAM consists of two phases of training namely: the forced training and natural training

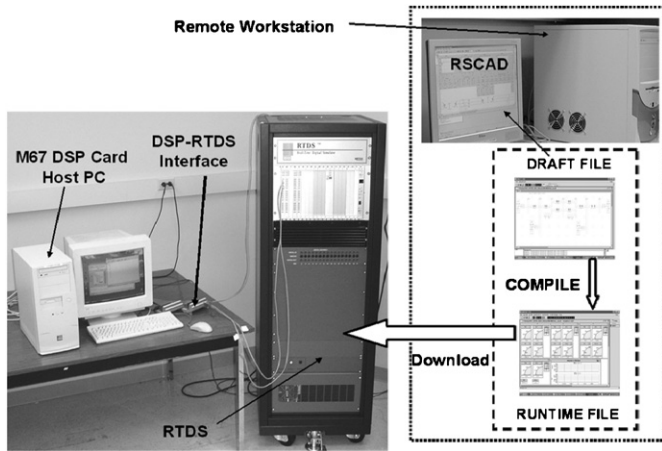


Fig. 6. Laboratory hardware setup with the RTDS.

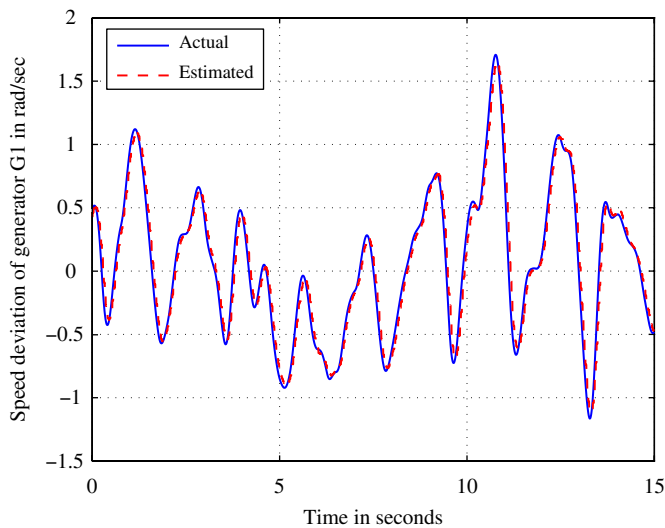


Fig. 7. Neuroidentifier estimates of speed deviation of generator G1 for forced PRBS disturbances.

(Venayagamoorthy and Harley, 2002; Venayagamoorthy et al., 2002; Jung-Wook et al., 2003). Forced training refers to training of the WAM with PRBS applied to the excitation systems of the generators. Natural training refers to training of the WAM under natural disturbances such as transmission line outage, load changes and faults. Typical testing results of the WAM for forced PRBS signals are shown in Figs. 7 and 8. The estimated speed deviation by the WAM (shown by the red line) is compared with the actual generator speed deviations (blue line). These results show that the WAM has successfully learnt the dynamics of the two-area power system. Similarly, good estimation results are observed for other natural disturbances at various operating points.

## 5.2. Wide area controller

Like the WAM, the training of the WAC consists of forced training and natural training (Venayagamoorthy and Harley, 2002; Venayagamoorthy et al., 2002; Jung-Wook et al., 2003). During the forced training, PRBS signals are applied to the excitation systems of generators G1 and G3 and the derived target control signal is used to train the controller. For the WAC

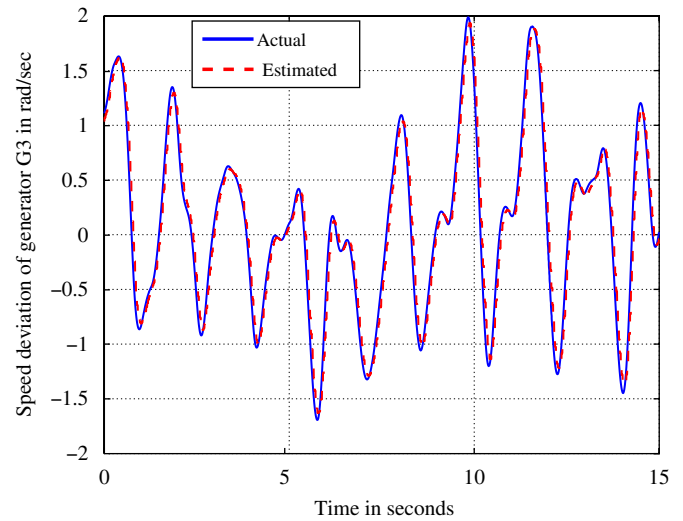


Fig. 8. Neuroidentifier estimates of speed deviation of generator G3 for forced PRBS disturbances.

Table 1  
Nominal and other operating conditions.

Operating conditions	Power transfer (MW)	Area 1 load (MW)	Area 2 load (MW)
Nominal (First)	490	967	1767
Second	246	1120	1180
Third	446	920	1380

training, the critic network is trained with the utility functions given in (12), (13) and (14) for generators G1 and G3, respectively.

$$u_{G1} = [4\Delta\omega_1(t) + 4\Delta\omega_1(t-1) + 0.16\Delta\omega_1(t-2)] \quad (12)$$

$$u_{G3} = [4\Delta\omega_3(t) + 4\Delta\omega_3(t-1) + 0.16\Delta\omega_3(t-2)] \quad (13)$$

$$U = u_{G1}^2 + u_{G3}^2 \quad (14)$$

Once the forced WAC training results are satisfactory, the WAC neural network weights are frozen. The neural network model can be updated continuously to track any major changes in the system operating points and topologies. But, the controller can be updated only at certain intervals if the system changes significantly. This procedure can iterated off-line without disturbing the actual system. To verify the robust performance of the controller, the power system is subjected to different types of disturbances under different operating conditions as given in Table 1. Figs. 9 and 10 show the speed deviations of generators G1 and G3 of the two-area power system with no PSS (uncompensated—blue line), with PSS on G1 and G3 (red line), and, with WAC and PSS on G1 and G3 (black line) due to a 10 cycle 3 –  $\Phi$  short circuit at bus 8. It is clear from these figures that the PSS can stabilize the system. The WACS provides slightly better damping than the PSSs on G1 and G3. The combination of PSSs on G1 and G3, and the wide area control signals for generators G1 and G3 (black line) provides significant improvement in damping of the power system oscillations.

Figs. 11 and 12 show the speed deviations of G1 and G3 for one of the parallel transmission line outage between buses 7 and 8. It can be observed that the PSS, WAC and the combined WAC and PSS, all stabilize the power system. The WAC and PSSs together

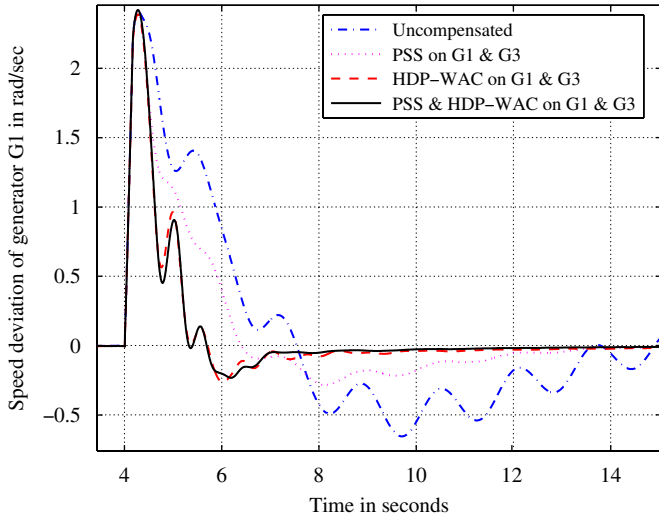


Fig. 9. Speed deviation of generator G1 for different controller combination for a 3 –  $\phi$  short circuit at bus 8 (Fig. 1) for 10 cycles (166.67 ms) under first operating condition.

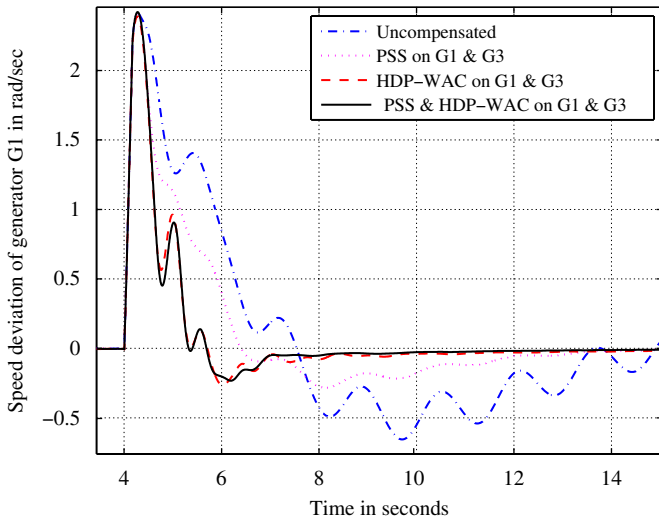


Fig. 10. Speed deviation of generator G3 for different controller combination for a 3 –  $\phi$  short circuit at bus 8 (Fig. 1) for 10 cycles (166.67 ms) under first operating condition.

damp out the oscillations faster. There is a small steady state error in the speed response causing a 0.08% and 0.1% change in the frequency with the WAC and the PSSs, respectively. This is as a result of the speed governors have a 5% droop setting.

Figs. 13 and 14 show the speed deviations of G1 and G3 for load changes in areas 1 and 2. The load in area 1 is decreased from 967-j100 to 870-j90 MVA and the load in area 2 is increased from 1767-j250 to 1863-j260 MVA. It can be observed that the PSS, the WAC and the combined WAC and PSS, all stabilize the power system. The WAC and PSSs together damp out the oscillations faster. The WAC by itself damps out the oscillations quicker than the PSSs. There is a small steady state error in the speed response causing a 0.05% and 0.07% change in the frequency with the WAC and the PSSs, respectively. This is again as a result of the speed governors have a 5% droop setting.

To verify the robustness of the WACS design, the PSS and WACS signals are separately applied to generator G1 excitation. The generator G3 was supplied with both PSS and WACS. Correspond-

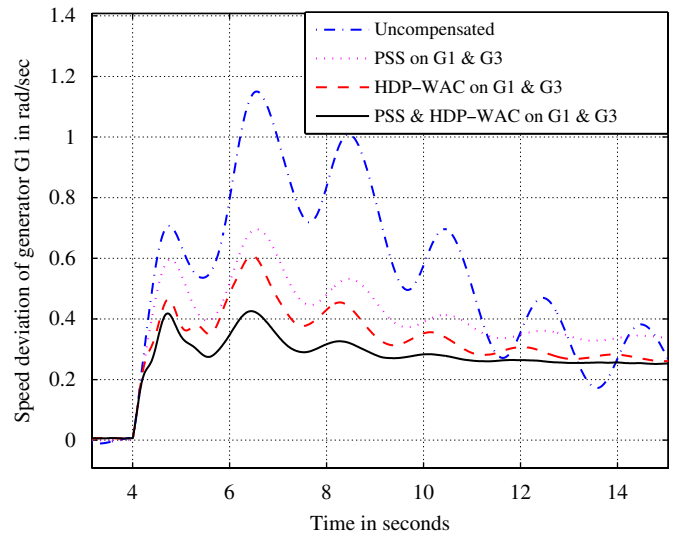


Fig. 11. Speed deviation of generator G1 for different controller combination for one of the parallel transmission line outage between buses 7 and 8 (Fig. 1) under first operating condition.

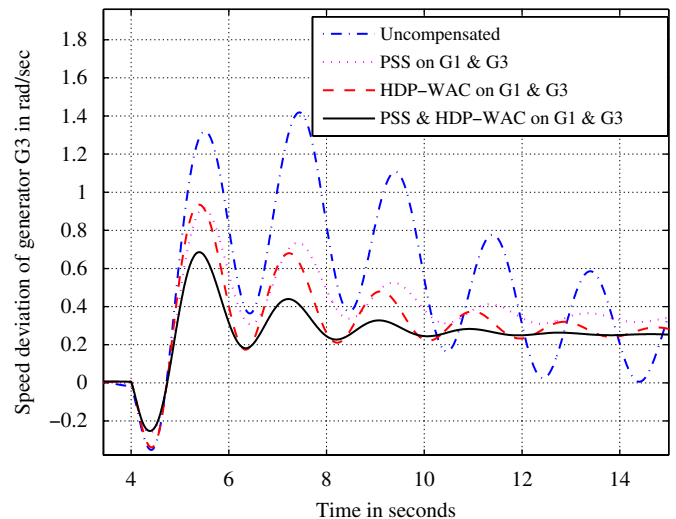
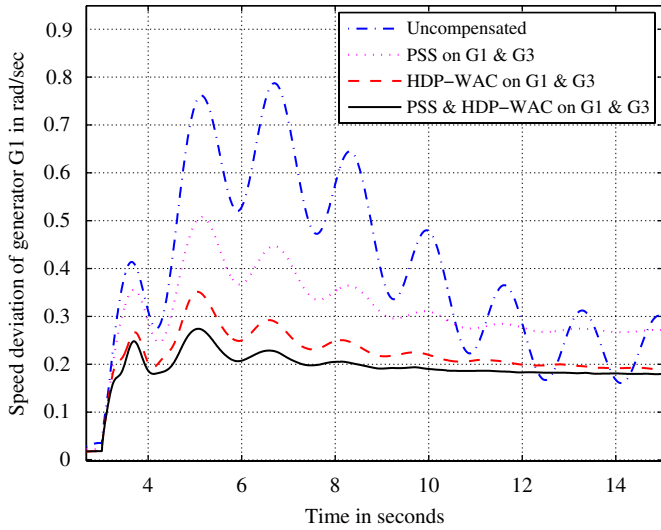


Fig. 12. Speed deviation of generator G1 for different controller combination for one of the parallel transmission line outage between buses 7 and 8 (Fig. 1) under first operating condition.

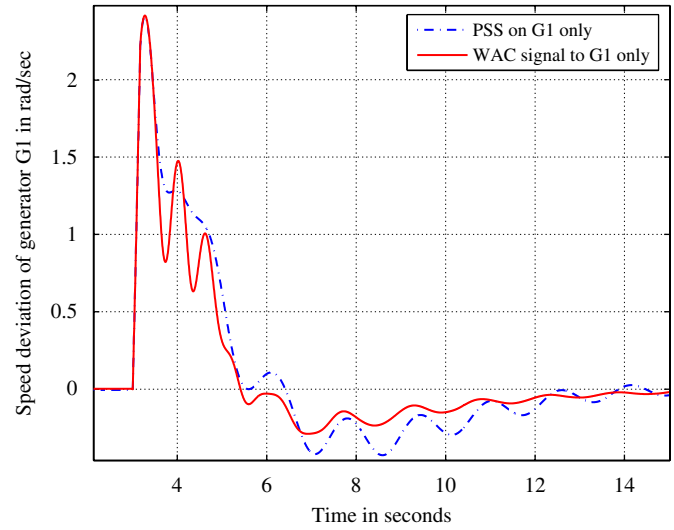
ing speed oscillations for a 3 –  $\phi$  fault at bus 8 is presented in Figs. 15 and 16.

The closed loop system is also tested for two other power transfer operating conditions as given in Table 1. To verify the robustness of such control design for different disturbances, a 3 –  $\phi$  short circuit for 166.67 ms (10 cycles) is applied to buses 8 and 11. The corresponding responses are given in Figs. 17 and 18. The PSS and WACS combined performance shows superior damping of both inter-area and intra-area modes for the second operating condition.

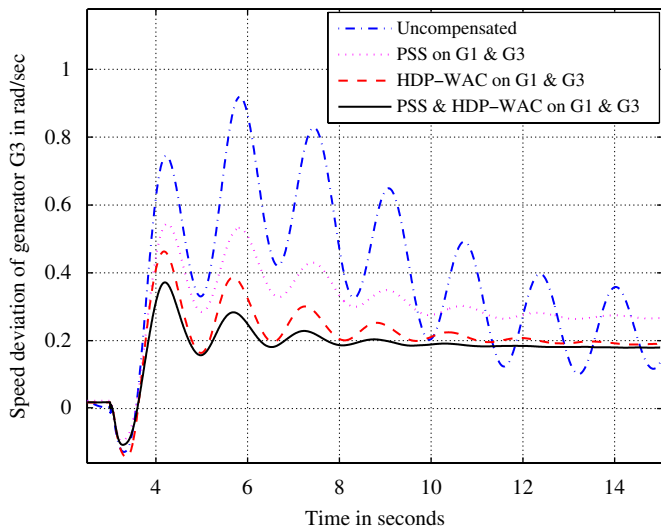
For the third operating condition (Table 1), 10 cycles 3 –  $\phi$  short circuit is applied at buses 8 and 11, respectively. Figs. 19 and 20 show better damping with WACS supplementary control signal. Due to long distance communication of remote signals, even with sophisticated signal transmission technology, there can be small delays (typically, less than 100 ms) in signal transmission. Without a proper control design, this delay may create instability especially for slower modes or slow frequencies of



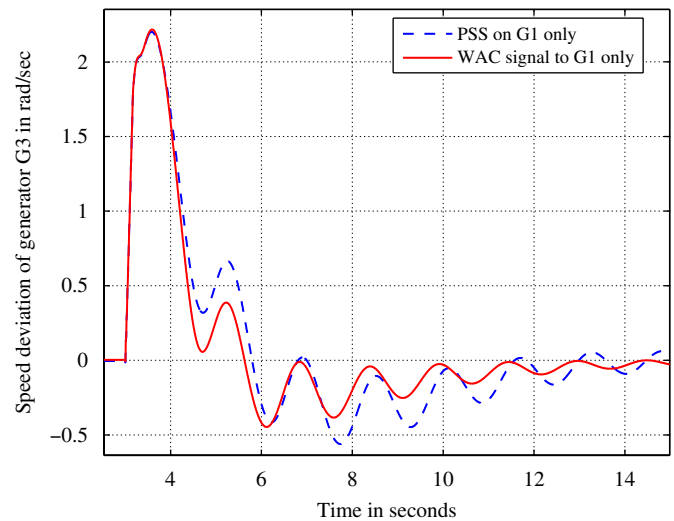
**Fig. 13.** Speed deviation of generator G1 for different controller combination for a load decrease in area 1 and an increase in area 2 (Fig. 1) under first operating condition.



**Fig. 15.** Speed deviation of generator G1 (1) with only one PSS connected to G1, (2) with only one WAC signal connected to G1 under first operating condition.



**Fig. 14.** Speed deviation of generator G3 for different controller combination for a load decrease in area 1 and an increase in area 2 (Fig. 1) under first operating condition.



**Fig. 16.** Speed deviation of generator G3 (1) with only one PSS connected to G1, (2) with only one WAC signal connected to G1 under first operating condition.

oscillation. To verify the robustness of the proposed control design using neural networks and adaptive critic architecture, a  $3 - \Phi$  short circuit is applied at bus 8 (Fig. 1) for 10 cycles and a communication delay of 100 ms is simulated. Fig. 21 shows little degradation in performance due to the communication delay, though the controller is not designed explicitly to compensate for delays.

### 5.3. Impact of such design in modern power system

The results show significant improvement in damping using combination of PSSs on two generators (one at each area) and WACS signals applied in addition to the PSS. The study system is a simple system with only four generators but real world systems have several generators interacting with each other. During disturbances, these generators can initiate inter-area oscillations of small magnitude but for sustained duration. This sustained

oscillations can ultimately destabilize the system and even cause voltage collapse. Though the magnitude of such inter-area oscillations may well be within the utility frequency limits, the duration of such oscillations must be limited within 10–15 s according to most of the utility and reliability council regulations. With the WACS providing additional damping for inter-area oscillations can strengthen the stability and reliability of the interconnected bulk power system. From the simple examples shown in the paper, it is evident that the WACS signals provide significant enhancement in damping the inter-area modes and hence oscillations damp out within 10s, thus providing better reliability in handling contingencies. Another point should be mentioned here, that with the increase of the power demand and minimum investment in the new infrastructures, the existing components need to be utilized close to their stability limits. During such stressed conditions, damping in the system degenerates. Using wide area control as explained in the paper, the stability and reliability can be maintained under the stressed

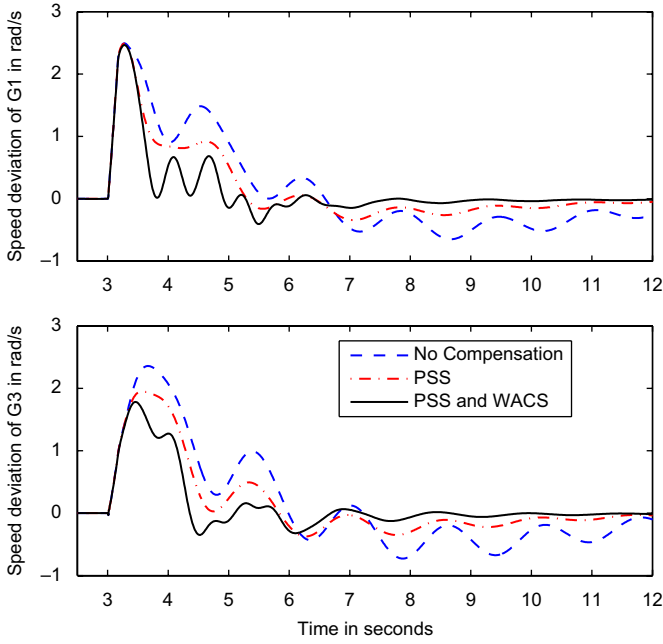


Fig. 17. Speed deviation of generators G1 and G3 for different controller combination for a 3- $\phi$  short circuit at bus 8 (Fig. 1) for 10 cycles (166.67 ms) under second operating condition.

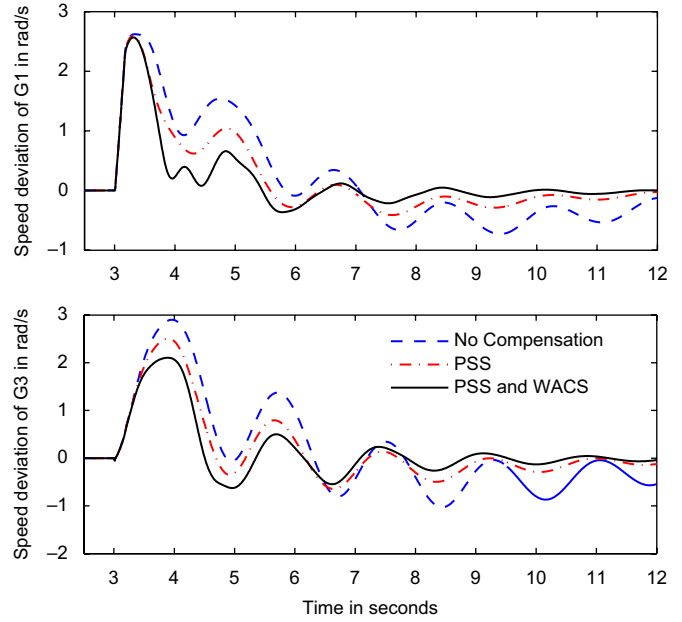


Fig. 19. Speed deviation of generators G1 and G3 for different controller combination for a 3- $\phi$  short circuit at bus 8 (Fig. 1) for 10 cycles (166.67 ms) under third operating condition.

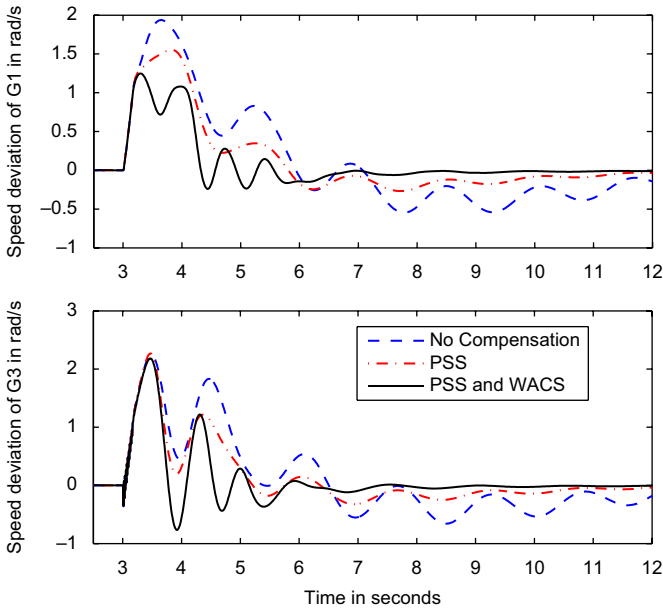


Fig. 18. Speed deviation of generators G1 and G3 for different controller combination for a 3- $\phi$  short circuit at bus 11 (Fig. 1) for 10 cycles (166.67 ms) under second operating condition.

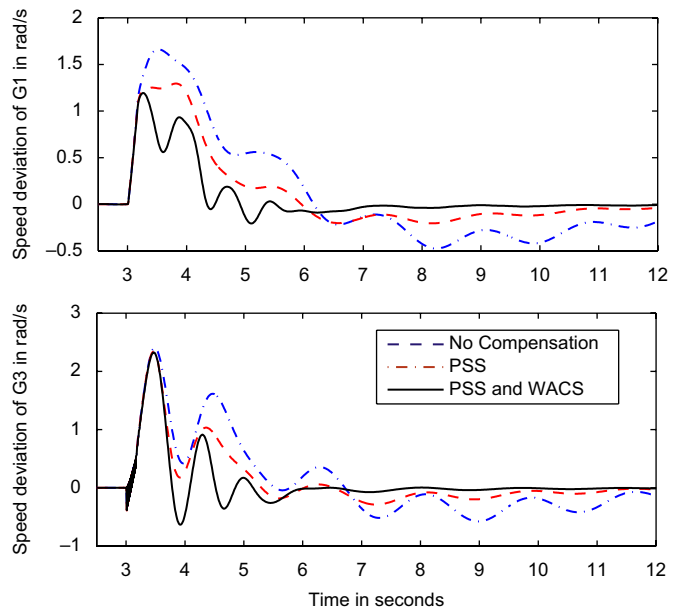


Fig. 20. Speed deviation of generators G1 and G3 for different controller combination for a 3- $\phi$  short circuit at bus 11 (Fig. 1) for 10 cycles (166.67 ms) under third operating condition.

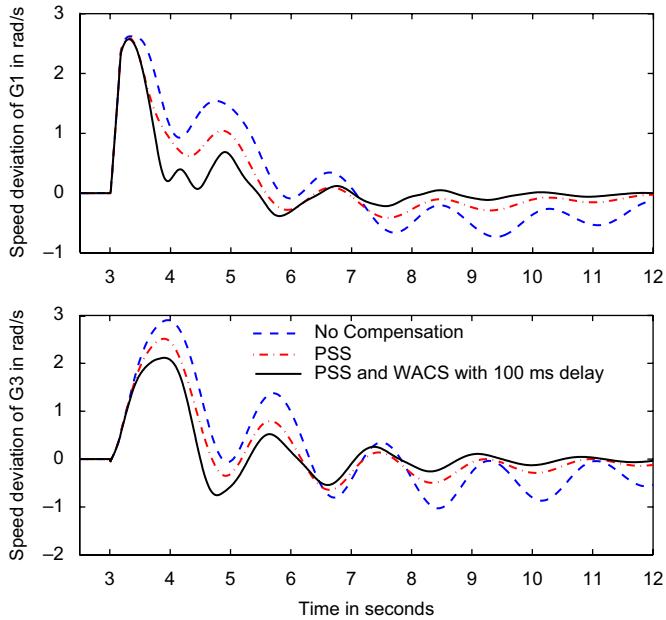
condition by providing additional damping to the system. In worst case scenarios, this might help to prevent a wide spread black-out from happening.

### 6. Conclusion

The paper has presented the design and real time DSP implementation of an optimal WACS for a power system using

ACDs. The power system dynamics is estimated online by a WAM using a feedforward neural network accurately and is in turn used to adapt the weights of another neural network to provide nonlinear optimal control. The design is based on combined concepts of approximate dynamic programming and reinforcement learning.

The WACS together with the PSSs provides superior damping of system oscillations caused by small and large disturbances over a wide range of operating conditions. In addition, the real time



**Fig. 21.** Speed deviation of generator G1 and G3 for different controller combination for a 3- $\phi$  short circuit at bus 8 (Fig. 1) for 10 cycles (166.67 ms) under third operating condition with a communication delay of 100 ms.

implementation of the WACS for the two-area power system simulated on the RTDS has demonstrated the possibility of practical incorporation of such designs for real world power systems.

Future work remains to be investigated is the coordination of multiple WACs for different PSS and FACTS devices and their practical implementation aspects. The vision is to achieve an auxiliary supervisory control network providing an optimal robust performance for multiple power system devices using both local and remote measurements.

## References

- Abou-El-ela, M.E., Sallam, A.A., McCalley, J.D., Fouad, A.A., 1996. Damping controller design for power system oscillations using global signals. *IEEE Transactions on Industrial Electronics* 11, 767–773.
- Forsyth, P., Maguire, T., Kuffel, R., 2004. Real time digital simulation for control and protection system testing. In: *IEEE 35th Annual Power Electronics Specialists Conference*, vol. 1. pp. 329–335.
- Govindhasamy, J.J., McLoone, S.F., Irwin, G.W., 2005. Second-order training of adaptive critics for online process control. *IEEE Transactions on System, Man and Cybernetics—Part B* 35 (2), 381–385.
- Inn, 2001. *OMNIBUS User's Manual*.
- Jung-Wook, P., Harley, R.G., Venayagamoorthy, G.K., 2003. Mlp/rbf neural networks based on-line global model identification of synchronous generator. *IEEE Transactions on Industry Applications* 39 (5), 1529–1540.
- Jung-Wook, P., Harley, R.G., Venayagamoorthy, G.K., 2005. Mlp/rbf neural networks based on-line global model identification of synchronous generator. *IEEE Transactions on Industrial Electronics* 52 (6), 1685–1695.
- Kamwa, I., Grondin, R., 2002. Pmu configuration for system dynamic performance measurement in large, multiarea power systems. *IEEE Transactions on Power Systems* 17 (2), 385–394b.
- Klein, M., Rogers, G.J., Kundur, P., 1991. A fundamental study of inter-area oscillations in power systems. *IEEE Transactions on Power Systems* 6 (3), 914–921.
- Kundur, P., 1994. *Power System Stability and Control*, first ed. McGraw-Hill Inc., New York.
- Ni, H., Heydt, G.T., 2002. Power system stability agents using robust wide area control. *IEEE Transactions on Power Systems* 17 (4), 1123–1131.
- Taylor, C.W., Erickson, D.C., Martin, K.E., Wilson, R.E., Venkatasubramanian, V., 2005. Wacs-wide area stability and voltage control system: R & d and online demonstration. *Proceedings of the IEEE* 93 (5), 892–906.
- Venayagamoorthy, G.K., Harley, R.G., 2002. Two separate continually online-trained neurocontrollers for excitation and turbine control of a turbogenerator. *IEEE Transactions on Industry Applications* 38 (3), 887–893.
- Venayagamoorthy, G.K., Harley, R.G., Wunsch, D.C., 2002. Comparison of heuristic dynamic programming and dual heuristic programming adaptive critics for neurocontrol of a turbogenerator. *IEEE Transactions on Neural Networks* 13 (3), 764–773.
- Werbos, P.J., 1990. Backpropagation through time: What it does and how to do it? In: *Proceedings of IEEE*, vol. 78. pp. 1550–1560.
- Werbos, P.J., 1992. *Handbook of Intelligent Control*, first ed. McGraw-Hill Inc., New York.