01 Oct 2006

Real-Time Implementation of a Dual Function Neuron Based Wide Area SVC Damping Controller

Sandhya R. Jetti

Ganesh K. Venayagamoorthy
Missouri University of Science and Technology

Real-Time Implementation of a Dual Function Neuron based Wide Area SVC Damping Controller

Sandhya R. Jetti, *Student Member, IEEE*, and Ganesh K. Venayagamoorthy, *Senior Member, IEEE*
Real-Time Power and Intelligent Systems Laboratory
Department of Electrical and Computer Engineering
University of Missouri-Rolla
Rolla, MO 65409-0249 USA
sj7v3@umr.edu and gkumar@ieee.org

***Abstract*— The use of wide area measurements for power system stabilization is recently given a lot of attention by researchers and the power industry to avoid cascading failures and blackouts such as the August 2003. This paper presents the design of a nonlinear external damping controller based on wide area measurements as inputs to a Dual Function Neuron (DFN). This DFN controller is specifically designed to enhance the damping characteristics of a power system considering the nonlinearity in the system. The major advantage of the DFN controller is that it is simple in structure with less development time and hardware requirements for real-time implementation. The DFN controller is implemented on a digital signal processor and its performance is evaluated on the IEEE 12 bus FACTS benchmark power system implemented on a real time platform – Real Time Digital Simulator (RTDS). Experimental results show that the DFN controller provides better damping than a conventional linear controller.**

Keywords - damping controller; DSP; dual function neuron; power system; real time digital simulator; SVC; wide area measurements

I. Introduction

Large power systems like the North American Power grid have many interconnections and bulk power transmissions over long distances. Due to this, the existing transmission lines are overloaded and have become vulnerable to various faults. The Flexible AC Transmission System (FACTS) devices, based on power electronics, offer an opportunity to enhance controllability, stability and power transfer capability of AC transmission systems. Static Var Compensator (SVC), a shunt FACTS device has been widely used in power systems. SVC has been used for voltage regulation and to increase transient stability in order to increase power transfer. Thus, allowing the transmission line to be compatible with the prevailing load demand [1]. A suitable supplementary external control signal to the SVC voltage control loop can provide damping and improve the overall power system stability [2], [3].

A power system containing generators and FACTS devices is a highly nonlinear system. Some conventional methods have been used to design supplementary damping controllers, including the classical pole placement method [4], damping torque analysis [5], linear quadratic Gaussian (LQG) [6], adaptive control [7], etc. Almost all of these methods are based on a nominal operating point that is selected from a wide range of operating conditions. In [8] and [9], Particle Swarm optimization (PSO) is applied to tune the parameters of SVC external damping controller but based on some linearised mathematical models of power systems. In [10] a neural network based controller has been designed for SVC but based on locally measured signals.

Most of the methods used for designing SVC external damping controllers are based on linear control techniques where the system equations are linearized around a nominal operating point. As the operating conditions change, its performance degrades. Nonlinear controllers using neural networks can provide suitable and desired control over a wide range of operating conditions. However, they require long development time and large number of neurons to deal with complex problems. Their hardware implementations require high speed processors and a lot of memory. To overcome these drawbacks, a Dual Function Neuron (DFN) that requires much smaller training data and time has been reported in [11]. The DFN has a simple structure and its hardware implementation is less expensive.

The use of wide area measurements provides better understanding of the dynamic behavior of the entire power system. External controllers can be designed using wide area signals based models to provide additional damping to power system oscillations. This paper presents the design of two types of external SVC damping controllers using wide area measurements. The first type of controller is a linear external damping controller and the second type of controller is a nonlinear external damping controller based on a DFN. The DFN controller design is based on a system identifier called the Wide Area Monitor (WAM) in this paper. The external controllers are specifically designed to enhance the damping in a power system under a wide range of operating conditions. In addition, the linear and nonlinear external controllers are implemented on a DSP and evaluated on the IEEE 12 bus FACTS benchmark power system which is implemented on the Real-Time Digital Simulator (RTDS).

The paper is organized as follows. Section II describes the FACTS benchmark power system with the SVC used in

This work is supported by the National Science Foundation, USA under the CAREER grant ECS # 0348221 and the University of Missouri-Rolla Intelligent Systems Center.

1-4244-0365-0/06/$20.00 (c) 2006 IEEE

this study. Section III describes the linear external damping controller. Section IV describes the DFN structure, and the design of nonlinear external damping DFN controller and its implementation on the RTDS. Finally, the conclusions are given in Section VI.

II. FACTS Benchmark Power System With SVC

The 12 bus FACTS benchmark system shown in Fig. 1 consists of six 230 kV buses, two 345 kV buses and four 22 kV buses [12]. There are three areas in this system consisting of hydrogenerators G2 and G4, in Areas 1 and 2 respectively, and a thermal generator G3 in Area 3 as shown in Fig.1. This power system is specifically designed to study the applications of FACTS technology. Load flow and dynamic stability studies on the test system revealed that it can use FACTS technology for transmission improvements in the following ways [12]:

- By installing an SVC in Area 3 to alleviate voltage problems at the load center.
- Improvement of dynamic stability with damping controllers on SVC and other FACTS devices.

To avoid system instability during large disturbances, the authors have added governor-turbine models to the hydrogenerators in Areas 1 and 2, and to the thermal generator in Area 3. The hydro governor and steam governor models are the mechanical-hydraulic control and approximate mechanical-hydraulic control PSCAD models [13] respectively. The hydro and steam turbine models are the non-elastic water column without surge tank and generic turbine PSCAD models [13] respectively. Parameters of governors and turbines are given in [14].

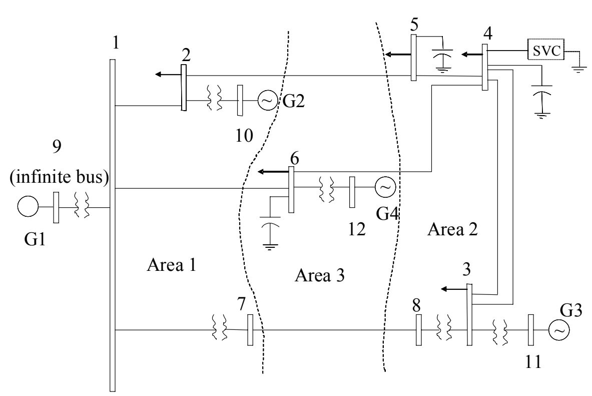

Figure 1. 12 Bus FACTS benchmark power system with SVC at bus 4.

III. Linear External Damping Controller

A conventional linear external damping controller as shown in Fig. 2 has been designed and implemented on the RTDS. The inputs to the controller are speeds of generators G3 and G4 which are wide are measurements and its output is ΔV_{ref} which adds to the SVC internal controller reference, V_{ref}. SVC internal controller in this case is a Proportional-Integral (PI). The parameters of this controller are determined to provide best performance around a nominal operating region. Hence, a nonlinear external controller is required for optimal performance at various operating regions

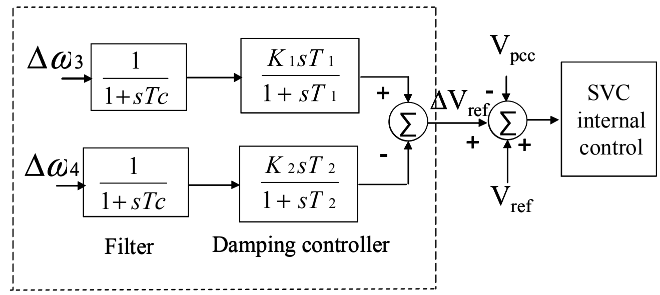

Figure 2. Linear external damping controller for SVC.

IV. Nonlinear External Damping Controller

The design of the nonlinear damping controller is based on the indirect adaptive control scheme as shown in Fig. 3, consisting of a DFN power system dynamics identifier, the WAM and a DFN controller. The following subsection describes the DFN structure, WAM, DFN nonlinear controller and the particle swarm optimization algorithm used in training DFNs.

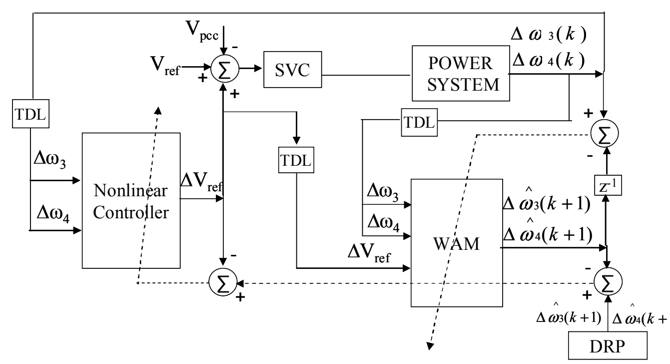

Figure. 3. Block diagram of indirect adaptive control scheme for the development of nonlinear external controller.

A. Dual Function Neuron

A common neuron model consists of a sigmoidal threshold function and ordinary summation or product as aggregation functions whereas a DFN has fuzzy compensatory operators [15] as aggregation operators. For a network with a single output, the size of a conventional neural network like the Multilayer Perceptron (MLP) is given as $(n \times m \times 1)$ whereas the size of a DFN is given as $(n \times 2 \times 1)$ where n and m are the number of input and hidden neurons respectively. Comparing the number of weights in both the cases, for a single output, MLP has large number of weights compared to a DFN. Due to the less number of weights and fuzzy aggregation operators, a DFN has shorter training time and can maintain its fault tolerant capabilities for any complex problem. The structure of a DFN is shown in Fig. 4.

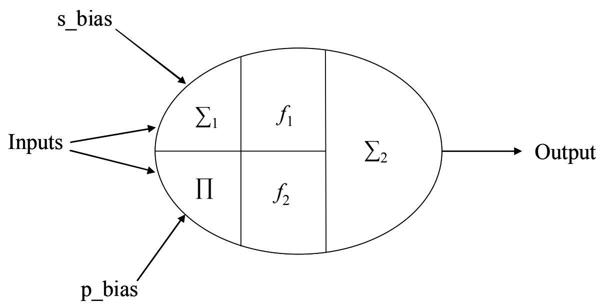

Figure 4. Dual function neuron model.

B. Wide Area Monitor (WAM)

As a first step towards designing the controller, a wide area monitor has been designed using a DFN. WAM provides model/dynamics of the system at every instant of time to the controller so that it can generate accurate control signals. As shown in Fig. 5, the inputs to the WAM are time delayed, *(k-1), (k-2), (k-3)* values of the speed deviations of generators G3 and G4, and the voltage reference ΔV_{ref}. The output of the WAM is the estimated speed deviations of generators G3 and G4 at time instant *k*. This WAM is realized using two separate DFNs. Figs. 6 and 7 show the DFN based WAM for estimating generator G3 and G4 speed deviations respectively. The sigmoidal function (f_1) is used with the $\sum_1$ summation aggregation function while the Gaussian function (f_2) is used with the $\prod$ product aggregation function. Thus, there is flexibility at both the aggregation and the threshold level in the DFN and so it is better equipped to model the nonlinearities involved in the power system than just a single functional neuron or network.

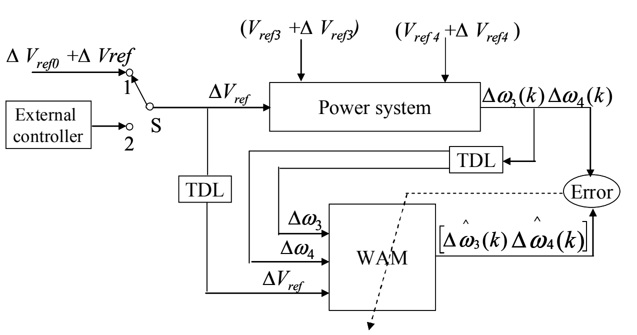

Figure 5. Block diagram of training of WAM with PRBS signals applied.

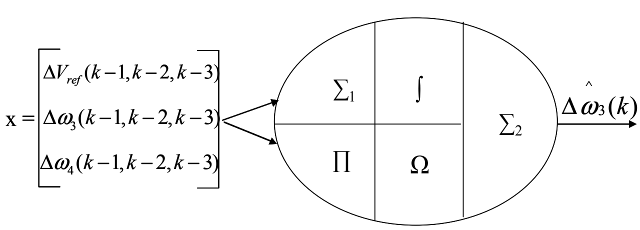

Figure 6. DFN structure of WAM estimating speed deviation of G3.

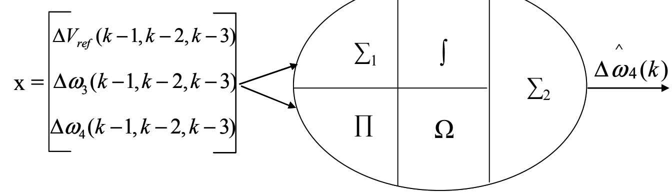

Figure 7. DFN structure of WAM estimating speed deviation of G4.

Constant excitation voltage references V_{ref3} and V_{ref4} are applied to the generators G3 and G4 at a particular steady state operating point respectively. WAM is trained by adding pseudo-random binary signals (PRBS), ΔV_{ref3} and ΔV_{ref4}, to generators G3 and G4 respectively, and ΔV_{ref} at summation junction of SVC voltage reference, V_{ref}. As shown in Fig. 5, switch S is placed in position 1 during training with PRBS signals applied. These PRBS signals excite the full range of the dynamic response of the power system [16]. The PRBS signals provide ±10% deviations in the steady state values of V_{ref3}, V_{ref4}, and ΔV_{ref}. The PRBS signals applied to generator excitations are sum of signals of frequencies 5 Hz, 3 Hz and 2 Hz and the PRBS to the SVC voltage reference are sum of signals of frequencies 0.5 Hz, 0.3 Hz and 0.2 Hz. WAM is trained offline using Particle Swam Optimization (PSO) technique described below.

C. Nonlinear DFN Controller

Once the WAM is trained, the next step is to design the nonlinear controller. The inputs to the DFN based nonlinear controller are speed deviations of generators G3 and G4 and the output is the control signal to the SVC, deviation in voltage reference, ΔV_{ref}. The DFN nonlinear controller structure is shown in Fig. 8.

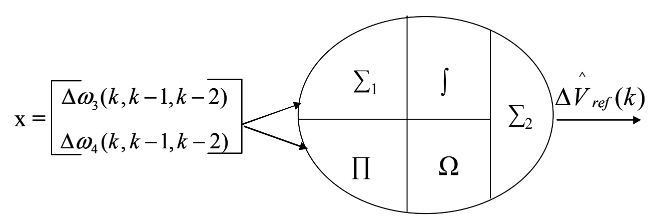

Figure. 8. DFN structure for nonlinear controller.

For training the DFN controller, the WAM is used to predict the speed deviations of generators G3 and G4 at time instant *(k+1)*. A Desired Response Predictor (DRP) is used to predict speeds at time instant *(k+1)* [16]. The difference between these signals and outputs of WAM are backpropagated through WAM to obtain derivates with respect to ΔV_{ref}. This backpropagated signal is the target for the nonlinear controller. The controller training is shown in Fig. 3. The system is subjected to various small and large disturbances like transmission line outages and short circuit faults for training the DFN controller.

The DRP equations in the DFN controller design in Fig. 3 is given by

$$\hat{\Delta\omega}_3(k+1) = 0.4\times\Delta\omega_3(k) + 0.4\times\Delta\omega_3(k-1) + 0.16\times\Delta\omega_3(k-2) \quad (1)$$

and $$\hat{\Delta\omega}_4(k+1) = 0.4\times\Delta\omega_4(k) + 0.4\times\Delta\omega_4(k-1) + 0.16\times\Delta\omega_4(k-2) \quad (2)$$

D. DFN Training Using PSO

PSO is a type of evolutionary computing technique [17]. The PSO algorithm is a population-based search algorithm, based on the simulation of the social behavior of birds within a flock. A swarm consists of a set of particles, where each particle represents a potential solution with parameters in d dimensions. Dimension d is determined based on the number of weights in the DFN. The changes to the position of a particle (i^{th} particle) and its operation in a swarm are influenced by the experience and the knowledge of its neighbors. The PSO is governed by two equations given in (3) and (4). Selection of the PSO parameters plays an important role in the optimization of any problem. Following parameters are used for the PSO algorithm in this paper.

- Maximum velocity, V_{max} 2
- Maximum search space range (-100,100)
- Inertia weight, w 0.8
- Acceleration constants, c_1 c_2 2, 2
- Size of swarm 25

The velocity of the i^{th} particle in the d^{th} dimension is given by:

$$v_{id}(k+1) = w\times v_{id}(k) + c_1\times rand_1\times(p_{id}(k) - x_{id}(k)) + c_2\times rand_2\times(p_{gd}(k) - x_{id}(k)) \quad (3)$$

The position vector of the i^{th} particle in the d^{th} dimension is changed in (4).

$$x_{id}(k+1) = x_{id}(k) + v_{id}(k+1) \quad (4)$$

V. Real-Time Implementation and Results

A. Real Time Digital Simulator (RTDS)

Due to the complexity and expensive nature of the power system, it is very difficult to test new control methods and algorithms on the real world power system. 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 microseconds utilizing a combination of custom software and hardware. The proprietary operating system used by the RTDS guarantees “hard real time” during all simulations [18]. It is an ideal tool for the design, development and testing of power system protection and control designs.

The performances of the linear and nonlinear external damping controllers are evaluated on the IEEE 12 bus FACTS benchmark power implemented on the RTDS. The WAM and nonlinear controller are implemented on a DSP which is interfaced to RTDS that runs the power system. With a large capacity for both digital and analogue signal exchange (through numerous dedicated, high speed I/O ports), physical protection and control devices are connected to the simulator to interact with the simulated power system. The nonlinear controller is trained offline and is implemented on the Innovative Integration M67 DSP card is equipped with two A4D4 modules [19]. Each A4D4 module is equipped with four digital-to-analog (D/A) converters and four digital-to-analog (D/A) converters. The DSP and RTDS interface and laboratory hardware setup is shown in Fig. 9. More details on the laboratory setup are given in [20].

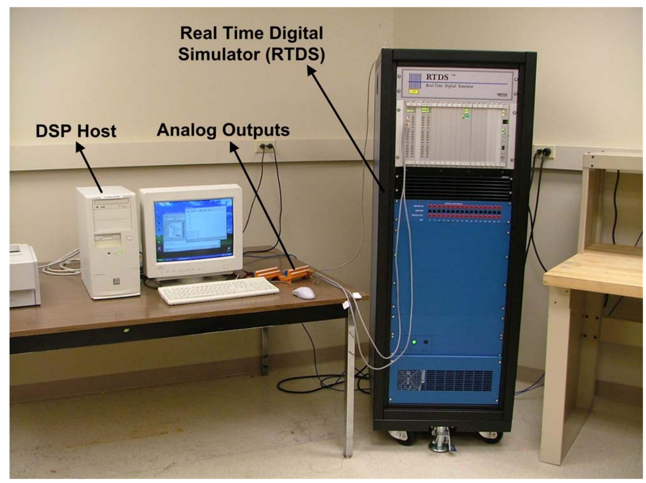

Figure. 9. Laboratory hardware setup with RTDS.

B. Experimental Results

This section presents experimental results obtained with the linear and nonlinear external damping controllers. After the WAM is pre-trained, it is tested under small and large disturbances - PRBS signals and short circuit faults respectively. Fig. 10 shows a typical PRBS signal applied to the excitation system of generator G4 and Fig. 11 shows corresponding speed deviation of generator G4. Fig. 12 shows speed deviation of generator G3 and output of WAM for transmission line outage between buses 4 and 5 in Fig. 1. It can be seen that WAM predicts the speed deviations of generators G3 and G4 accurately.

Several tests are carried out to evaluate the impact of linear and nonlinear external damping controllers on the power system oscillations damping. Typical results are shown in Figs. 13 to 17. Figs. 13 and 14 show the speed deviations of generators G3 and G4 respectively for a 200 ms three phase short circuit applied at bus 7 with and without a linear external damping controller to the SVC (Fig. 1). It can be clearly seen that the damping is improved with the external controller.

Fig. 15 shows the speed deviations of generator G3 for a 200 ms three phase short circuit fault applied halfway between buses 7 and 8. It can be seen that the nonlinear controller damps out the oscillations within the first two seconds of the fault whereas takes over 8 seconds.

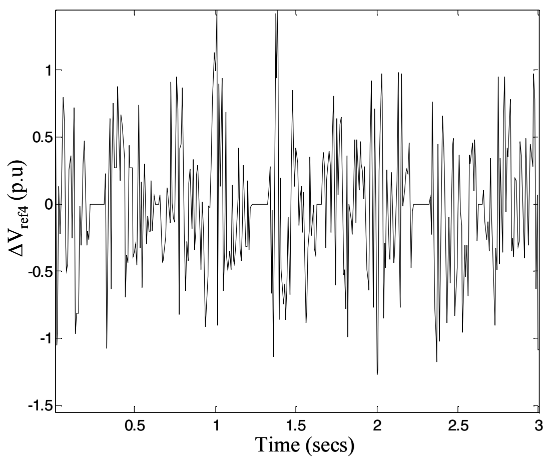

Figure 10. PRBS signal applied to the excitation system of generator G4, ΔV_{ref4}.

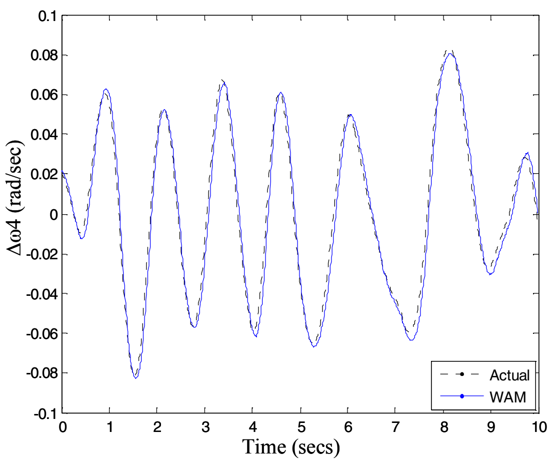

Figure 11. Actual and WAM predictions of speed deviation of generator G4 for PRBS signals applied.

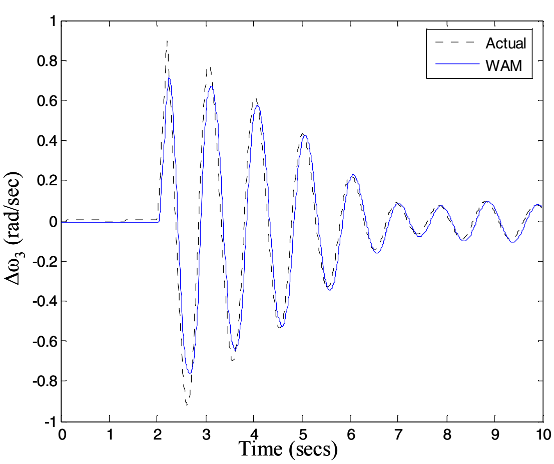

Figure. 12. Actual and WAM predictions of speed deviation of generator G3 for a transmission line outage between buses 4 and 5 in Fig. 1.

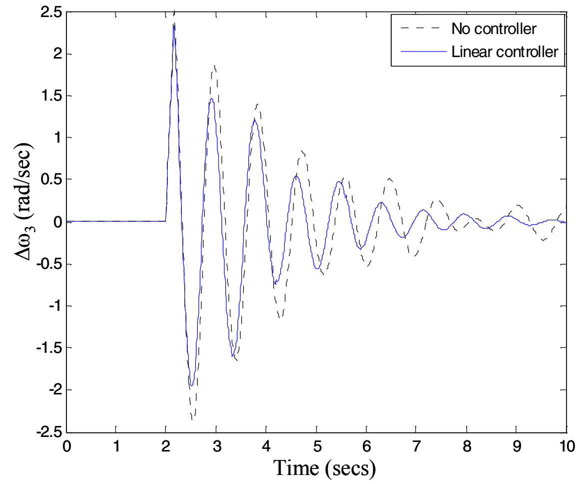

Figure. 13. Speed deviation of generator G3 with and without a linear controller for a three phase short circuit fault of 200ms at bus 7.

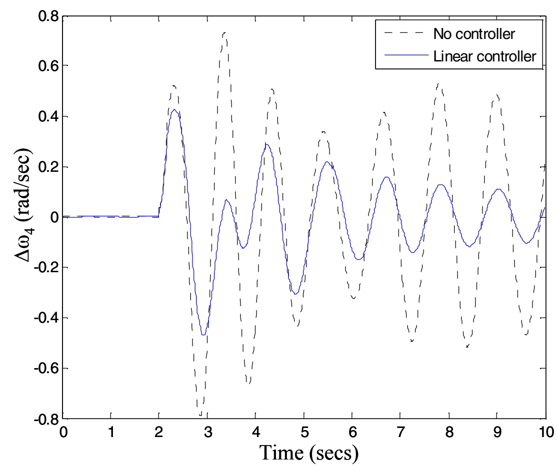

Figure. 14. Speed deviation of generator G4 with and without a linear controller for a three phase short circuit fault of 200ms at bus 7.

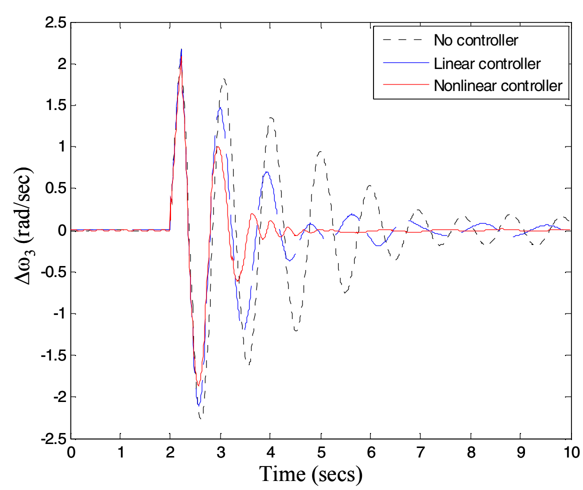

Figure. 15. Speed deviation of generator G3 for a three phase short circuit fault of 200ms halfway between buses 7 and 8.

Figs. 16 and 17 show the speed deviations of generators G3 and G4 respectively for a 200 ms three phase short circuit applied halfway between buses 7 and 8 but now there system has experienced a permanent line outage between buses 4 and 6. This causes a change in the operating condition of the power system. Damping is improved with the external controllers. The nonlinear controller damps the speed oscillations much faster in the case of generator G3 and minimizes the magnitude of oscillations in the case of generator G4.

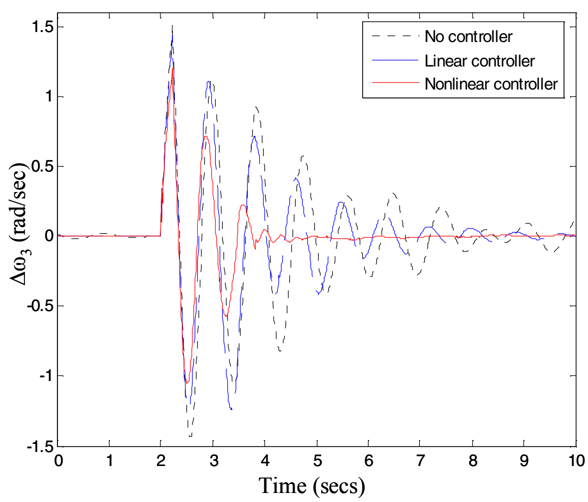

Figure. 16. Speed deviation of generator G3 for line 4-6 outage and a three phase short circuit fault of 200ms halfway between 7 and 8.

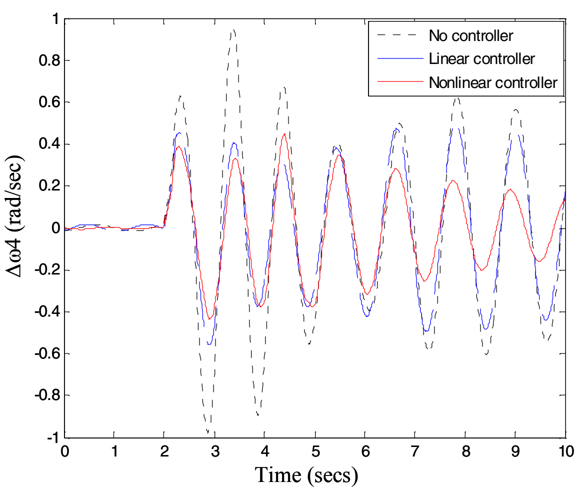

Figure. 17. Speed deviation of generator G4 for line 4-6 outage and a three phase short circuit fault of 200ms halfway between 7 and 8.

VI. CONCLUSIONS

The design and real-time implementation of a dual function neuron based nonlinear external damping controller for a SVC has been presented. A DFN based wide area monitor has been developed to identify the power system dynamics. The performance of a DFN based nonlinear controller has been compared with a conventional linear external damping controller. The inputs to the WAM and external controllers are wide area measurements which provide better information of the system dynamics from moment to moment and thus, a better external feedback control.

The major advantage of the DFN based control architecture is that the DFN has shorter training time and can maintain its fault tolerant capabilities for any complex problem. Hence, combining benefits of DFN and wide area measurements not only helps in designing good controller but also makes it easier to implement in real time. Experimental results show that WAM identifies the system dynamics correctly and the nonlinear DFN controller provides better damping to the system oscillations. Future work involves developing the PSO to be computationally efficient for online adaptation of the parameters of the DFN WAM and nonlinear controller.

REFERENCES

[1] Narain G. Hingorani and Laszlo Gyugi, Understanding FACTS, concepts and Technology of Flexible AC Transmission Systems, New Jersey, IEEE press.

[2] C.J. Wu and Y.S. Lee, "Damping of synchronous generator by static reactive power compensator with digital controller," in Proc. IEE Generation, Transmission and Distribution, pp.18-24, 1991.

[3] E.N. Lerch, D. Povh and L. Xu, "Advanced SVC Control for Damping Power System Oscillations," IEEE Trans. Power Systems, vol.2 (6), pp.524-535, May 1991.

[4] P. Kundur, Power System Stability and Control, McGraw- Hill, Inc., New York ,1993.

[5] K. R. Padiyar and R. K. Varma, "Damping torque analysis of static var ystem controllers," IEEE Trans. Power Systems, vol. 6, no. 2, pp. 458–465, May 1991.

[6] J. R. Smith, D. A. Pierre, D. A. Rudberg, and A. P. Johnson, "An enhanced LQ adaptive var unit controller for power system damping," IEEE Trans. Power Systems, vol. 4, no. 2, pp. 443–451, May 1989.

[7] J. R. Smith, D. A. Pierre, I. Sadighi, M. H. Nehrir, and J. F. Hauer, "A Supplementary adaptive var unit controller for power system damping," IEEE Trans. Power Systems, vol. 4, no. 3, pp. 1017–1023, Aug. 1989.

[8] T. Okada, T. Watanabe and K. Yasuda, "Parameter Tuning of Fixed Structure Controller for Power System Stability Enhancement", IEE Transmission and Distribution Conference and Exhibition: Asia Pacific., vol.1, pp. 162-167, 2002.

[9] S.M. Bamasak, and M.A. Abido, "Assessment study of shunt FACTS based Controllers Effectiveness on Power System Stability Enhancement", IEE Universities Power Engineering Conference, vol.1, pp. 274-278, 2004.

[10] B. Changaroon, S.C Srivastava, D. Thukaram, S. Chirarattananon, "Neural network based power system damping controller for SVC", IEE Proc. Gene. Trans. and Dist., vol. 146, Issue 4, pp. 370 – 376, 1999.

[11] D. K. Chaturvedi, O. P. Malik, and P. K. Kalra, "Generalised neuron-based adaptive power system stabilizer," IEE Proc. Generation. Transmission & Distribution, vol. 151, pp. 213-218, 2004.

[12] S. Jiang, U.D. Annakkage and A.M. Gole, "A Platform for Validation of FACTS Models," IEEE Trans. Power Delivery, vol. PP, pp.1 – 8, 2005.

[13] Manitoba HVDC Research Centre Inc, PSCAD/EMTDC user's guide, version 4.1, 244 Cree Crescent, Winnipeg, Manitoba, Canada R3J 3W1.

[14] J. Sandhya and G. K. Venayagamoorthy, “Identification of SVC dynamics using wide area signals in a power system”, IEEE PES General Meeting, 2006.

[15] M. Mizumoto “Pictorial representations of fuzzy connectives”, Fuzzy Sets Syst., vol.32, pp. 45–79, 1989.

[16] G. K. Venayagamoorthy and R. G. Harley, “Two separate continually online-trained neurocontrollers for excitation and turbine control of a turbogenerator”, IEEE Transactions on Industry Applications, vol: 38, issue: 3 , May 2002, pp: 887 – 893.

[17] V. G. Gudise, G. K. Venayagamoorthy, “Comparison of particle swarm optimization and backpropagation as training algorithms for neural networks”, IEEE Swarm Intelligence Symposium, Indianapolis, IN, USA, pp.110 – 117, 2003.

[18] P. Forsyth, T. Maguire and R. Kuffel, “Real time digital simulation for control and protection system testing, “IEEE 35th Annual Power Electronics Specialistis Conference., vol. 1, pp. 329-335, 2004.

[19] OMNIBUS User’s Manual, Innovative Integration, California, USA, Feb. 2001.

[20] G.K.Venayagamoorthy, S. Ray, “A neural network based optimal wide area scheme for a power system”, Industry Applications Conference, vol. 1, pp. 700-706, Oct. 2005.