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Identification of SVC Dynamics Using Wide Area Signals in a Power System

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Abstract— This paper presents the design of a Wide Area Monitor (WAM) using remote area signals, such as speed deviations of generators in a power network, for identifying online the dynamics of a Static Var Compensator (SVC). The design of the WAM is studied on the 12 bus FACTS benchmark system recently introduced. A predict-correct method is used to enhance the performance of the WAM during online operation. Simulation results are presented to show that WAM can correctly identify the dynamics of SVC in a power system for small and large disturbances. Such WAMs can be applied in the design of adaptive SVC controllers for damping interarea oscillations in power networks.

Index Terms— Benchmark FACTS Power System, Neural Networks, SVC, Remote Signals, System Identification, Wide Area Monitor.

I. INTRODUCTION

SEVERAL power system networks have experienced angular instability in the form of low frequency oscillations, mainly due to insufficient damping in the system. Two modes of low frequency oscillations are observed in the power networks. One is the local mode of oscillations associated with one or more generators in an area oscillating against the rest of the system. The other is the interarea mode of oscillations involving a group of generators on the other side. To damp out these oscillations, many supplementary stabilizing controls have been designed such as Power System Stabilizers (PSS) [1], Static VAR Compensators (SVC) [2]-[7] and other Flexible AC Transmission Systems (FACTS devices). SVCs have been employed in power systems to regulate the system voltage and to improve power system stability [2-7]. SVCs have many advantages over traditional reactive power system compensators. They are controlled by high voltage gate turnoff thyristors and diodes based on the electronic power converter principles and can continuously adjust the output of the SVC to feed inductive or capacitive reactive power to the power system. It is proven that a suitable supplementary control signal to the SVC voltage control loop through a controller can provide damping and improve overall power system stability [4-7].

Various control techniques have been used to develop SVC controllers. But the power system is nonlinear with fast changing dynamics. Therefore it is important to identify the dynamics of the network in order to provide correct and accurate control signals to the various generators and power system devices including the SVC. Neural networks are able to identify/model multiple-input multiple-output time varying systems 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. Neural Network based wide area monitor is potentially very promising for identifying highly nonlinear multimachine power system from moment to moment even when the power system configuration changes [8]. The major motivation to have a wide area monitoring scheme is for the following benefits:

- Transmission capacity enhancement can be achieved by on-line monitoring of the system stability limits and capabilities.
- Better understanding of the dynamic behavior of the system.
- In design of adaptive controllers to provide wide area and local control signals to power system elements such as generators, PSSs and FACTS devices.

The main contributions and features of this paper are as follows:

- The design of a wide area monitor for online identification of SVC dynamics on the FACTS benchmark power system [9]. Such WAMs can be applied in the design of adaptive SVC controllers, in the framework of [10]. But the combination of the WAM using remote speed signals and an adaptive SVC controller not only regulates the SVC bus voltage but also has the capability to provide damping to generators in the power network. Such controllers will assist with the global dynamic optimization of the power system and the design of such controllers is a topic of a follow-on paper. But, the design of the WAM is the first step and is discussed in this paper.
- The accuracy of the estimated output of WAM is enhanced with a predict-correct scheme for online operation. This is an advantage when unforeseen disturbances occur which are not included in the training of the WAM or when online WAM training is not desirable/feasible.
- The FACTS benchmark power system stability during

large disturbances has been enhanced by adding turbine-governors to the generators and their parameters are given in the appendix.

The paper is organized as follows. Section II describes the FACTS benchmark power system with the SVC used in this study. Section III describes the identification of the dynamics of SVC using wide area signals and presents some WAM results. Finally, the conclusions are given in Section IV.

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 [9]. 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 [9]:

- 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 [11] respectively. The hydro and steam turbine models are the non-elastic water column without surge tank and generic turbine PSCAD models [11] respectively. Parameters of governors and turbines are given in the Appendix.
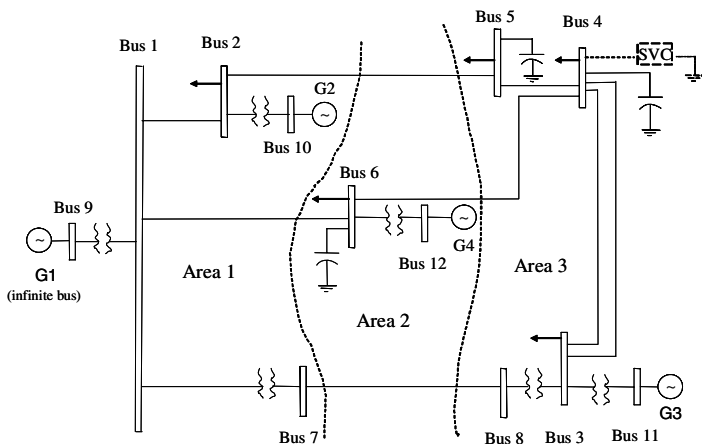

Fig. 1. 12 Bus FACTS benchmark power system with a fixed capacitor/SVC option at bus 4.

Figs. 2 and 3 show the generator speeds for a 200 ms three phase short circuit disturbance applied at bus 3 with and without the governors on the benchmark system. These figures show that the system with the governors damps out the speed oscillations faster.

The primary purpose of SVC application is to maintain bus voltage at or near a constant level, avoiding under voltages especially in heavy load areas. Thus, a SVC is installed at bus 4 in Fig. 1 instead of a fixed capacitor. The main inputs to the SVC controller are the reference voltage (V_{ref}) and the voltage at point of common coupling (V_{pcc}) i.e., bus 4 voltage. Fig. 4 shows the block diagram of the conventional PI control for SVC. In addition, the SVC improves transient stability by dynamically supporting the voltage at key points and the steady state stability by damping out swing oscillations [2]-[7]. Fig. 5 compares the bus 4 voltage for a 5% increase in the load on the system with a fixed capacitor and with SVC installed at bus 4. It can clearly be seen that with a fixed capacitor the voltage is dropped from its actual value whereas with SVC the voltage is maintained constant. It can also be seen that there are lesser oscillations with SVC.
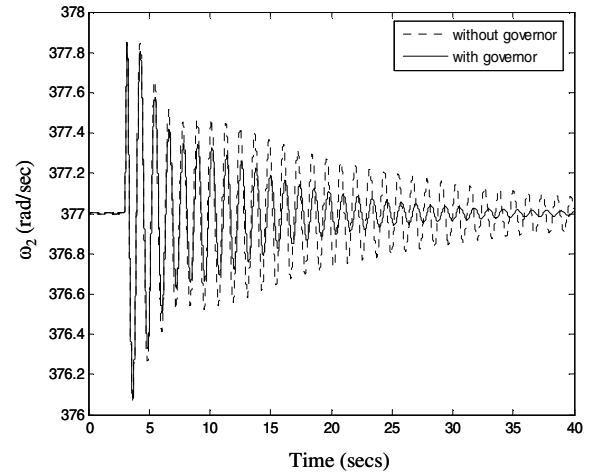

Fig. 2. Speed response of generator G2 with and without governor on the system in Fig. 1 for a 200 ms three phase short circuit at bus 3.
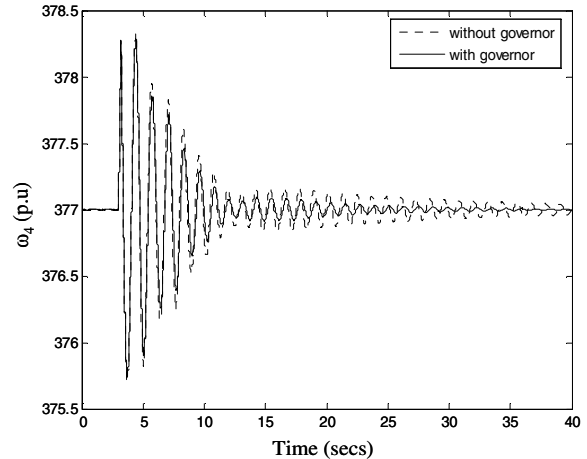

Fig. 3. Speed response of generator G4 with and without governors on the system in Fig. 1 for a 200 ms three phase short circuit at bus 3.
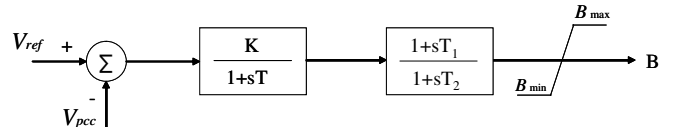

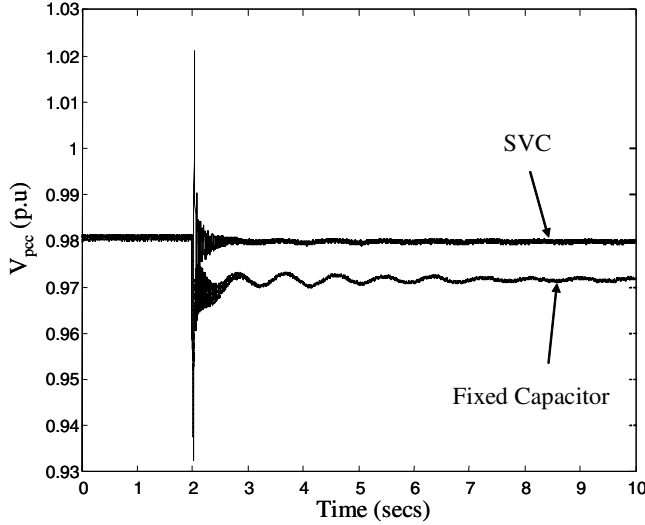Fig. 4. Block diagram of the SVC control.

Fig. 5. Comparison of bus 4 voltage response for a 5% increase in the load at bus 4 at *t = 2* seconds with a fixed capacitor and a SVC.

III. WIDE AREA MONITOR AND RESULTS

The WAM structure is a feedforward neural network and has three layers consisting of a linear input layer with twelve linear neurons, a single hidden layer with 20 sigmoidal activation functions and a linear output layer with one output. The inputs to the WAM consists of the voltage deviations at the point of common coupling (bus 4), wide area signals such as the speed deviations of generators in area 2 and area 3, and deviation in the susceptance value of the SVC. These four inputs are delayed by a sample period of 5 ms and together with eight previously delayed values and a bias form thirteen inputs altogether as shown in Fig. 6. The output of the WAM is the deviation of the bus 4 voltage at time *t* and is given by the following equation:

$$\Delta \hat{V}_{pcc}(t) = f(V, \Phi(u)) \tag{1}$$

where $u = g(W, X)$ and W are the weights in the input layer and X are the inputs; V is the output layer weights and $\Phi(.)$ is a sigmoidal function.
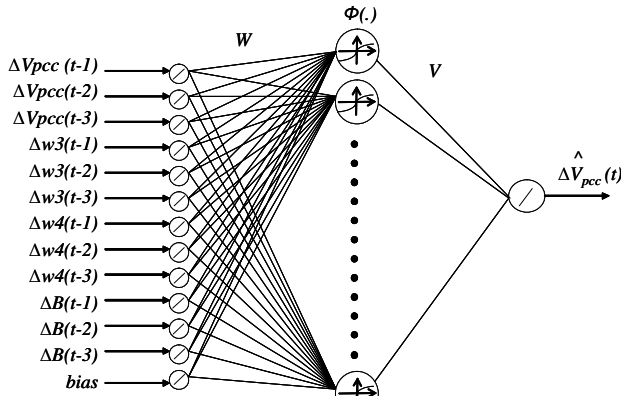

Fig. 6. WAM neural network structure showing the inputs and output.

The WAM neural network weights are set to small random values and the conventional backpropagation algorithm is used to update the weights. The difference between the actual voltage deviation at PCC, ΔV_{pcc} and the estimated output of WAM, $\Delta \hat{V}_{pcc}$ form the error signal for updating the weights. A reasonable learning rate is determined for training by setting the learning rate to achieve a compromise between training time and accuracy of the WAM A learning rate of 0.02 is used for the backpropagation algorithm. The WAM is only required to generalize one time step (5 ms) ahead, thus, no momentum term is used.

Two sets of results are presented. The first set uses the so-called *forced training*, which shows how well the WAM is able to track as long as the training continues while the system is forcefully perturbed by applying Pseudorandom Binary Signals (PRBS) in the excitation system of the generators G3 and G4, i.e. in the voltage references, ΔV_{ref3} and ΔV_{ref4} and in the susceptance output of the SVC control, ΔB (Fig. 4) . The second set of results uses natural operation signals, this is called the *natural training*, where ΔV_{ref3} and ΔV_{ref4}, and ΔB are both set to zero. Disturbances like load changes will cause the WAM to adapt and learn the dynamics..

A. Forced Training

A constant excitation voltage references V_{ref3} and V_{ref4}, and a susceptance B_{ref} are applied to the generators G3 and G4, and SVC respectively at a particular steady state operating point. Then the WAM is trained by adding pseudo-random binary signals (PRBS) ΔV_{ref3} and ΔV_{ref4} and ΔB to V_{ref} of generators G3 and G4 and susceptance B respectively. These PRBS signals excite the full range of the dynamic response of the power system [10]. Fig. 7 shows the block diagram of the WAM during forced training.
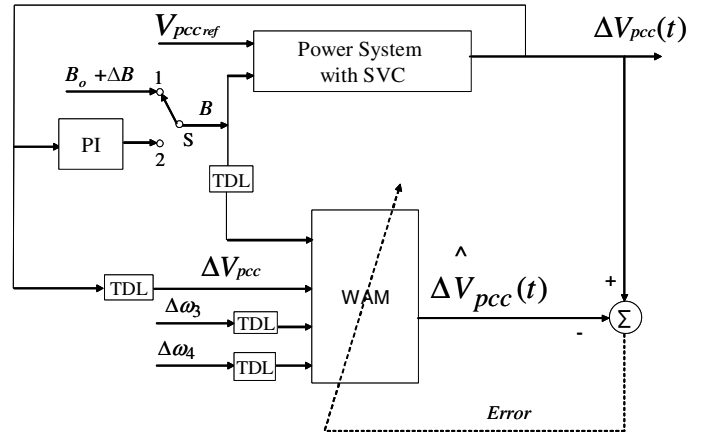

Fig. 7. Block diagram of forced training of the WAM.

The PRBS in Figs. 8 and 9 shows ±10% deviations in the steady state values of V_{ref4} and *B*. PRBS applied to V_{ref} are of frequencies 5, 3 and 2 Hz and that applied to *B* are of frequencies 2, 1.5 and 0.5 Hz. Fig. 10 shows the corresponding estimated output of the WAM and the actual voltage deviation at bus 4 during forced training.
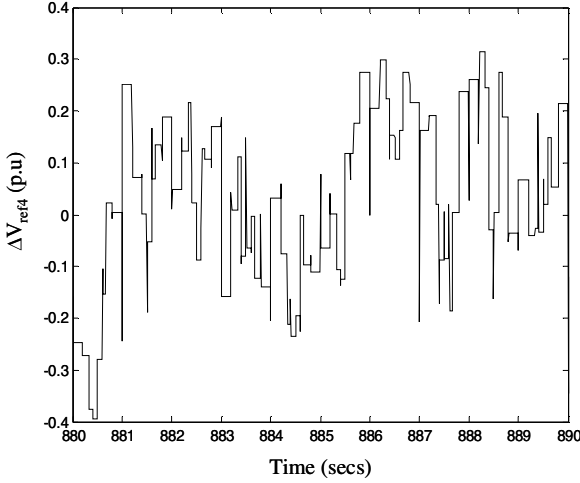
Fig. 8. PRBS signal applied to the excitation system of generator G4, ΔV_{ref4}.
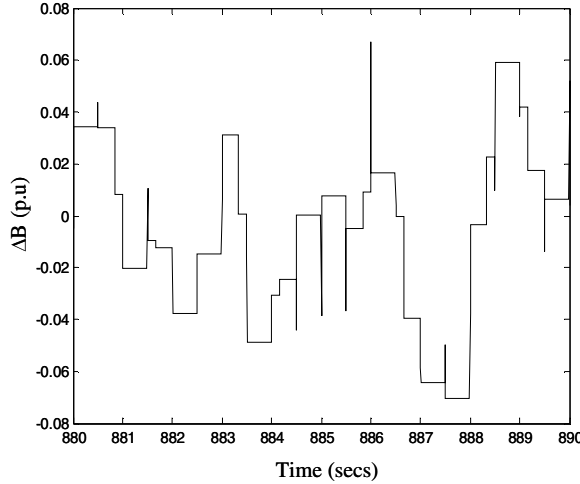

Fig. 9. PRBS signal applied in the SVC control signal, ΔB during forced training.

Fig. 10. Actual and WAM estimated voltage deviations at the SVC bus with PRBS signals applied to the SVC control signal and excitations of generators G3 and G4 during the forced training phase.

After the training is completed, the weights of WAM are frozen and tested to verify if the WAM is able to track the

dynamics of SVC with PRBS applied to the excitation voltage references of G3 and G4, and SVC control output. Fig. 11 shows that the WAM is able to track the voltage deviations at the point of common coupling. The forced training of the WAM with PRBS signals of Figs. 8 and 9 is now terminated and from here the natural training starts with weights obtained from the PRBS training.
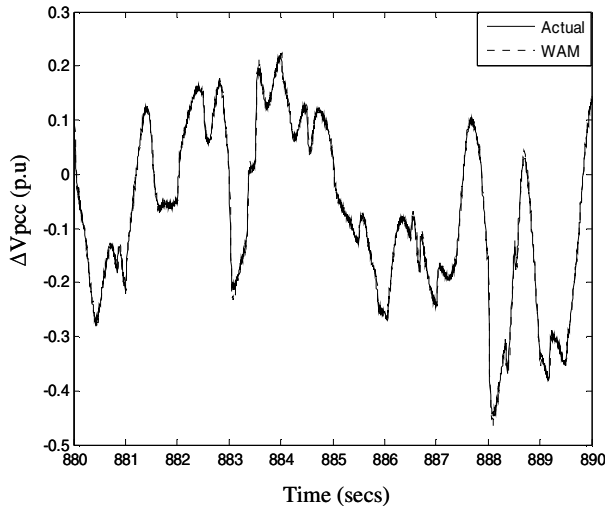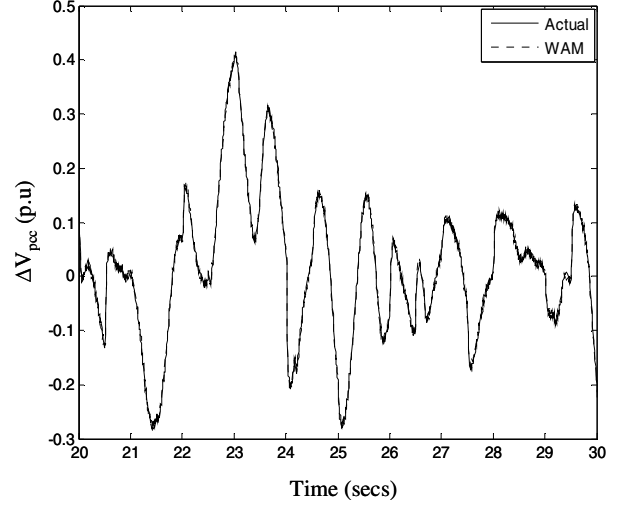

Fig. 11. Actual and WAM estimated voltage deviations at the SVC bus with PRBS signals applied to the SVC control signal and excitations of generators G3 and G4 during the testing phase.

B. Natural Training

During natural training switch S in Fig. 7 is placed in position 2. The WAM is trained using natural disturbances such as load changes and short circuit faults. After the training is completed, the WAM weights are frozen and three different tests are carried out in order to evaluate the performances of the WAM for changes in the power system network configuration. The first test is a short circuit at bus 3. The second test is carried out to simulate the effects of a loss of one of the parallel transmission lines between buses 3 and 4. The third test is carried with a change in load of ±5% at bus 4.

Fig 12 shows the block diagram of the system during natural operation. A *Predict-Correct* scheme is used during natural testing of the WAM.

C. Predict-Correct Scheme

In order to further enhance the accuracy of the voltage deviations prediction by the trained WAM, error feedback is used to compensate for the low frequency offset in the predictions [12]. This technique uses past plant outputs and the corresponding model predictions to generate a correction to the current WAM estimate, $\hat{V}_{pcc}(t)*$. The scheme is usually implemented as follows:

$$\hat{C}(t)* = \hat{C}(t) + \frac{1}{N}\sum_{j=1}^{N} [C(t-j) - \hat{C}(t-j)] \quad (2)$$

For the WAM, predict correct scheme of first order is used

which is given as follows:

$$\Delta \hat{V}_{pcc}(t)^* = \Delta V_{pcc}(t) + [\Delta V_{pcc}(t-1) - \Delta \hat{V}_{pcc}(t-1)] \quad (3)$$
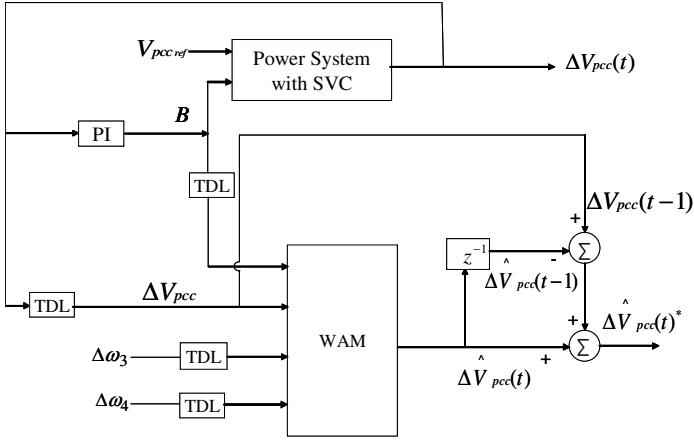

Fig. 12. Block diagram for during testing of the WAM for natural disturbances with the predict-correct scheme.

Fig. 13 shows the voltage at the SVC bus (bus 4) during 100 ms three phase short circuit fault applied at bus 3. Actual bus voltage is shown by a solid line and the estimated output of the WAM with and without the correction method is shown by the dashed and dotted lines respectively. It is clearly seen that for large disturbances the WAM with the correction method estimates the bus voltage deviations better.
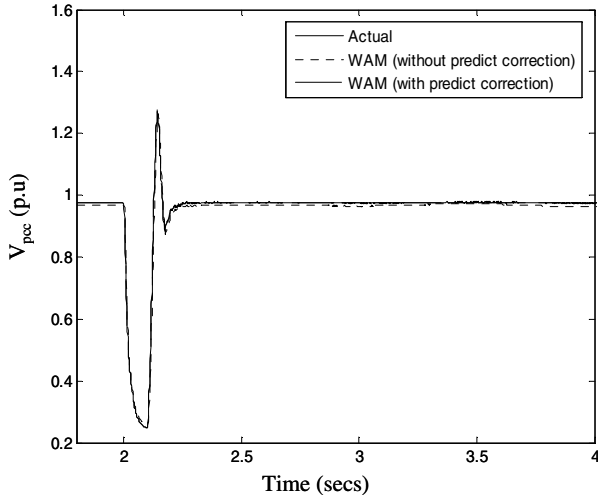

Fig.13. Actual and WAM estimated voltage deviations with and without predict correction method at the SVC bus for a 100 ms three short circuit fault applied at bus 3.

Fig. 14 shows the voltage at the SVC bus (bus 4) during a 50 ms line outage between buses 3 and 4. Fig. 15 shows voltage at the SVC bus for a 5% increase in the load at bus 4.
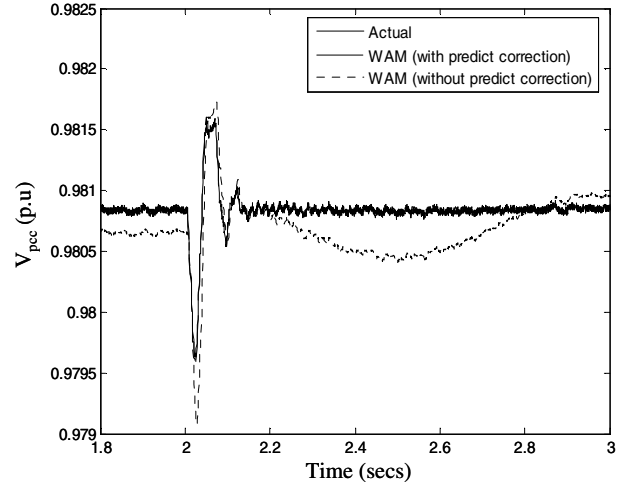

Fig.14. Actual and WAM estimated voltage deviations with and without predict correction method at the SVC bus for a 50ms line outage between buses 3 and 4.
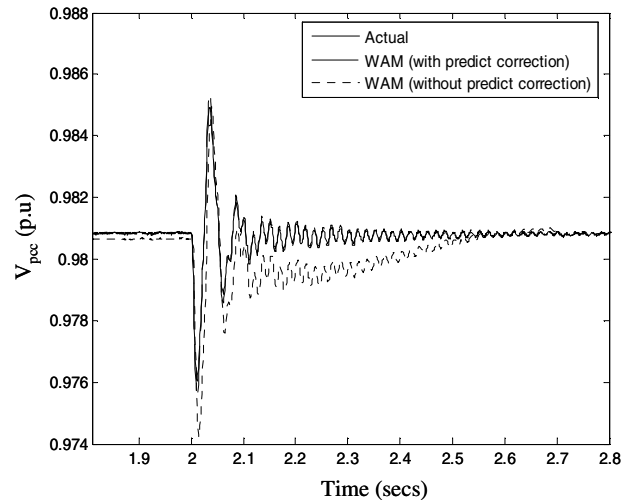

Fig.15. Actual and WAM estimated voltage with and without predict correction method at the SVC bus for a 5% increase in load at the SVC bus.

IV. CONCLUSIONS

This paper presented the design of a Wide Area Monitor (WAM) for a SVC installed on the 12 bus FACTS benchmark power system. The inputs to the WAM are remote speed signals, which provide information for online identification of the dynamic behavior of the entire power system. From the simulation results, it can be seen that the WAM can identify the dynamics of the SVC under small and large disturbances accurately. The predict-correct method further improves the predictions of the WAM. In addition, the paper has shown that adding governors to the proposed FACTS benchmark system improves the transient stability.

With the accurate identification of the dynamics of SVC and the entire power system using the remote signals, a wide area controller or even a local adaptive controller can be designed to control the SVC and provide better damping to the interarea oscillations.

V. Appendix

Hydro Governor Data
    servo gain Q= 5.0 p.u
    permanent droop R_p= 0.04 p.u
    temporary droop R_t = 0.40 p.u
    main servo time constant T_g = 0.2 sec
    pilot valve and servo motor time constant T_p= 0.05 sec
    reset or dashpot time constant T_r = 5.0 sec.

Steam Governor Data
    initial value of control valve flow area CV_o= 0.0 p.u
    inverse of regulation K_g= 20.0 p.u
    gate servo time constant T_{SM}= 0.3 sec
    speed relay lag time constant T_{SR}= 0.1 sec.

Hydro Turbine Data
    turbine gain factor flow A_t = 1.136
    penstock head loss coefficient f_p= 0.02 p.u
    gate position G = 1.0 p.u
    no load water flow q_{NL} = 0.05 p.u
    water starting time T_w = 1.6sec.

Steam Turbine Data
    K_1 = 0.26 p.u K_3 = 0.3 p.u K_5= 0.44 p.u
    K_7 = 0.0 p.u K_2= 0.0 p.u K_4= 0.0 p.u
    K_6 = 0.0 p.u K_8=0.0 p.u
    steam chest time constant T_4 = 0.4sec
    reheater time constant T_5= 8 sec
    reheater/cross-over time constant T_7= 0.3 sec
    $PMECH_{HP} + PMECH_{LP}$= 0.4 p.u.

SVC data
    K_p = 1.5 T_i = 0.01.

VI. References

[1] P. Kundur, M. Klein, G.J. Rogers and M.S. Sywno, "Application of power system stabilizer for enhancement of overall system stability," IEEE Trans. Power Systems, vol. 4 (2), pp. 614-626, 1989.

[2] H.F. Wang and F.J. Swift, "Capability of the static var compensator in damping power system oscillations," in Proc. 1996 IEEE C. Generation, Transmission and Distribution Conf., pp.353-358.

[3] L. Angquist, B. Lundin, J.Samuelsson, "Power oscillation damping using controlled reactive power compensation- a comparison between series and shunt approaches," IEEE Trans. Power Systems, vol.8, Issue 2, pp. 687-700, May 1993.

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

[5] N.G.Hingorani, "FACTS Flexible AC Transmission System," in Proc. 1991 IEE Fifth International Conference on AC and DC Power Transmission, pp.1-7.

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

[7] 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.

[8] G.K. Venayagamoorthy and S. Ray, "A neural network based optimal wide area control scheme for a power system," in Proc. 2005 IEEE Industry Applications Annual Meeting, pp.700 – 706.

[9] 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.

[10] G.K. Venayagamoorthy and R.G. Harley, "A Continually Online Trained Neurocontroller for Excitation and Turbine Control of a Turbogenerator," IEEE Trans. Energy Conversion, vol.16, Issue 3, pp. 261-269, Jun 2001.

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

[12] J.J. Govindhasamy, S.F. McLoone, G.W. Irwin, "Second-Order Training of Adaptive Critics for Online process control," IEEE Trans. Systems, Man and Cybernetics-Part B, vol. 35, pp.381 – 385.

VII. Biographies

Sandhya Rani Jetti (S'05) received the B.Tech degree in Electrical and Electronics Engineering in 2005 from Jawaharlal Nehru Technological University, Hyderabad, India and currently pursuing M.S degree in Electrical Engineering, University of Missouri, Rolla (UMR), USA. Sandhya is currently a Graduate Research Assistant in the Real Time Power and Intelligent Systems (RTPIS) Laboratory at UMR. Her research interests are in the applications of computational intelligence techniques for power system stability and control.

Ganesh Kumar Venayagamoorthy (S'01, M'97, SM'02) received his PhD degree in Electrical Engineering from the University of Natal, Durban, South Africa, in February 2002. He is currently an Assistant Professor of Electrical and Computer and the Director of the Real-Time Power and Intelligent Systems Laboratory at University of Missouri, Rolla. His research interests are in computational intelligence, power systems control and stability, evolvable hardware and signal processing. He has published over 150 papers in refereed journals and international conferences. Dr. Venayagamoorthy is the recipient, of the following awards - 2005 IEEE Industry Application Society (IAS) Outstanding Young Member award, 2005 South African Institute of Electrical Engineers Young Achiever's award, 2004 NSF CAREER award, the 2004 IEEE St. Louis Section Outstanding Young Engineer award, the 2003 International Neural Network Society (INNS) Young Investigator award, 2001 IEEE Computational Intelligence Society (CIS) W. J. Karplus summer research grant and five prize papers with the IEEE IAS and IEEE CIS. He is a Senior Member of the IEEE and the South African Institute of Electrical Engineers, a Member of INNS and the American Society for Engineering Education. He is an Associate Editor of the IEEE Transactions on Neural Networks and was a Guest Editor for the Neural Networks journal. He is currently the IEEE St. Louis IAS Chapter Chair, the Chair and the founder of IEEE St. Louis CIS Chapter, the Chair of the Task Force on Intelligent Control Systems and the Secretary of the Intelligent Systems subcommittee of IEEE Power Engineering Society. Dr. Venayagamoorthy was the Technical Program Co-Chairs of the 2003 International Joint Conference on Neural Networks, Portland, OR, USA and the 2004 International Conference on Intelligent Sensing and Information Processing, Chennai, India. He has served as member of the program committee, organized and chaired panel/special sessions, and presented tutorials at several international conferences and workshops.