Optimal Dynamic Neurocontrol of a Gate-Controlled Series Capacitor in a Multi-machine Power System

Swakshar Ray, *Student Member, IEEE,* Ganesh K. Venayagamoorthy, *Senior Member, IEEE,* Edson H. Watanabe, *Senior Member, IEEE,* Fabio D. de Jesus

Abstract-- This paper presents the design of an optimal dynamic neurocontroller for a new type of FACTS device - the Gate Controlled Series Capacitor (GCSC) incorporated in a multi-machine power system. The optimal neurocontroller is developed based on the Heuristic Dynamic Programming (HDP) approach. In addition, a dynamic identifier/model and controller structure using the recurrent neural network trained with Backpropagation Through Time (BPTT) is employed. Simulation results are presented to show the effectiveness of the dynamic neurocontroller and its performance is compared with that of the conventional PI controller under small and large disturbances.

Index Terms- **GCSC, Dynamic Neurocontroller, Multimachine Power System, FACTS, Heuristic Dynamic Programming, BPTT**

I. INTRODUCTION

NOWADAYS, it is becoming increasingly difficult to build new electric power transmission lines due to restrictions imposed by financial and environmental issues. As the power consumption is increasing, the existing transmission lines have to be operated more efficiently and close to their stability limits in the future. The Flexible AC Transmission Systems (FACTS) devices have made it possible to control the real and/or the reactive power flow in a transmission line dynamically which not only satisfy the market requirements but also improve the transient performance of the power system. Most commonly used FACTS devices are the series transmission devices which includes the Thyristor Controlled Series Capacitor (TCSC) and the Static Synchronous Series Compensator (SSSC). Recently, a new series FACTS device, the Gate Controlled Series Capacitor (GCSC) has been proposed [1-3] which has advantages over TCSC with regard to the size of the capacitor being smaller and that no line reactor is required. The SSSC is a more complete device in terms of flexibility than the GCSC, however, its cost and complexity is much higher compared to GCSC.

The series line reactance is one of the main factors which govern the maximum power flow through a transmission line. The conventional technique for real power control is to use fixed capacitors in series with the transmission line, thus reducing effective inductive reactance of the line. This method can increase the real power flow in the line and can achieve stability limit close to its thermal limits. But fixed capacitors do not provide options for controlling the power flow according to the requirements which may vary over time. Thus, the advantage of deploying series FACTS devices (TCSC and GCSC) for such conditions. With thyristor or GTO controlled series capacitors, the effective capacitive reactance of the compensator can be varied providing dynamic control of real power flow in a line over certain range of operation. In addition, it may provide damping to the system during transients.

For highly nonlinear systems such as the power system, the performances of the linear controllers degrade as the operating conditions of the system changes [4]. To overcome this problem, researchers have proposed different neural network based nonlinear control strategy for the dynamic systems [5-7]. Direct and indirect adaptive control with MLP and RBF neural networks has been discussed in [5-6] for such systems which relies on continuous online training of the identifier and controller network. Recurrent neural networks (RNNs) are dynamic networks which are robust and fast in learning highly nonlinear system characteristics compared to the MLP feedforward neural networks [8-10]. Backpropagation through time with a truncation depth of h (*BPTT(h)*) has been proven an effective learning algorithm for RNN [8]. In recent past, intelligent control of generator excitation and turbine systems, and FACTS devices have been proven successful mostly with deviation controllers [5, 7, 11].

The GCSC is a relatively inexpensive new series FACTS device which has the potential to be widely applied to the power system in the near future. Thus, the nonlinear optimal control will eventually become necessary to maximize the benefits of a GCSC when integrated into electric power grid. While model based indirect adaptive neurocontrol has been shown effective for controlling nonlinear systems, it is computationally intensive for practical purposes due to continually online training and it is difficult to guarantee

The support from the National Science Foundation under the grants - CAREER ECS # 0348221 and INT # 0305429 is gratefully acknowledged by the authors.

S. Ray and G. K. Venayagamoorthy are with the Real-Time Power and Intelligent Systems (RTPIS) Laboratory, Department of Electrical and Computer Engineering, University of Missouri Rolla, MO 65409, USA (e-mail: sr8r8@umr.edu & gkumar@ieee.org)

E. H. Watanabe and F. D. de Jesus are with the Department of Electrical Engineering, Federal University of Rio de Janeiro, Brazil (e-mail:watanabe@coe.ufrj.br & fabio@coe.ufrj.br)

stability of such controllers unconditionally. Alternative approaches for neurocontroller designs based on Approximate Dynamic Programming (ADP) have been proven effective in providing stable robust control without the need for online training [11-13].

The primary contributions of this paper are:

- The design of a dynamic neuroidentifier for the newly invented GCSC FACTS device incorporated in a multi-machine power system;
- The design of a dynamic neurocontroller for the GCSC FACTS device using the approximate dynamic programming based HDP approach;
- Comparison of the performance of the optimal dynamic neurocontroller with the conventional PI controller for a number of operating conditions.

The rest of the paper is organized as follows: Section II describes the structure of a simple GCSC with its advantages. Section III describes the design of the optimal dynamic neurocontroller based on the HDP approach. Section IV describes the three machine 11 bus power system used in this study. Section V presents some simulation training and test results for the neuroidentifier and the neurocontroller, and comparisons with the conventional PI controller for a number of operating conditions. Finally, the conclusions and future work are given in Section VI.

II. Gate-Controlled Series Capacitor

The Gate Controlled Series Capacitor is composed of two anti-parallel GTOs and a capacitor bank in series with the transmission line as shown by the single line diagram in Fig. 1. If the GTOs are turned on all the time then the capacitor is by-passed and it does not provide any compensation. However, if the GTO's are turned off once per cycle at a determined blocking angle of α, the capacitor in series with the transmission line turns on and off alternately and a voltage V_c appears across the capacitor. The GCSC has a great advantage over TCSC as the blocking angle α can be varied dynamically thus varying the fundamental components of V_c, in contrast to the TCSC firing angle which is discontinuous due to the zone in which a parallel resonance occurs between the Thyristor Controlled Reactor (TCR) and the capacitor [2].

In the GCSC, a blocking angle of 90 degrees means that the capacitor is fully inserted and a blocking angle of 180 degrees means that the capacitor is fully by-passed making effective capacitive reactance zero. The reactance dynamic control range for GCSC can be varied from 0 to X_{max} unlike TCSC where it can only vary between X_{min} to X_{max}, where $X_{min} > 0$. Also, GCSC does not need an extra reactor unlike the TCSC; this reduces the cost of the device. For these reasons, the GCSC might be a better solution in most situations than other controlled series compensators for future deployments.

Different multi-modular structure of the GCSC has been discussed in [3]. For simplicity, only the single module structure of GCSC is considered in this paper.

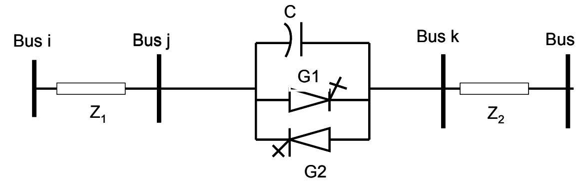


Fig. 1 Schematic diagram of a GCSC inserted between buses j and k in a transmission line.

The GCSC could be used in applications where fixed capacitive compensation, TCSC or SSSC is used today, mainly to control power flow and provide damping of power and generator speed oscillations. The GCSC can operate in an open loop mode controlling the capacitive reactance added in series with the transmission line. It can also operate in a closed loop mode where it controls the real power flow in the transmission line or maintain a constant compensation voltage.

The general control structure of the GCSC FACTS device is shown in Fig. 2. The conventional control is PI based using the power deviation ΔP_l (the difference between the line power reference, P_{lref} and actual line power, P_l) as the input to the controller (shown in Fig. 2 with the switch S open). The output of the PI controller is an angle (α_c). This angle is limited between 0 to 90 degrees and subtracted from 180 degrees to obtain the blocking angle α which is applied to the GCSC. In this paper, a neurocontroller is developed to provide the blocking angle (α), replacing the PI controller and the design is described in the next section.

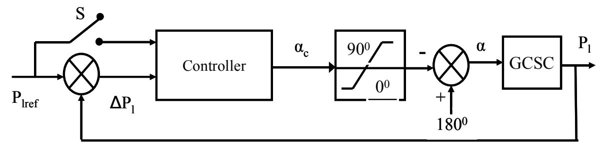


Fig. 2 A general control block diagram of the GCSC.

III. HDP Optimal Neurocontroller Design

The neurocontroller design implemented in this paper is based on the Heuristic Dynamic Programming (HDP) approach of Adaptive Critic Designs (ACDs) [14]. ACDs are neural network designs for optimization over time using combined concepts of reinforcement learning and dynamic programming [5]. ACDs use two neural networks, the Critic and Action networks to solve the Hamilton-Jacobi-Bellman equation of optimal control. The critic network approximates the cost-to-go function J of Bellman's equation of dynamic programming, given in (1).

$$J(t) = \sum_{k=1}^{\infty} \gamma^k U(t+k) \tag{1}$$

Where γ is a discount factor between 0 and 1, and $U(t)$ is a utility function or a local performance index. The action neural network also referred to as the Actor in the ACD literature and this network provides optimal control to minimize or maximize the cost-to-go function J. It is referred to as the neurocontroller in this paper providing the optimal control signal to the GCSC. Several other ACD approaches such as the Dual-Heuristic programming (DHP) and the Global Dual-Heuristic Programming (GDHP) exist [14]. The HDP, DHP and GDHP are all model dependent designs. Model independent designs called the action dependent HDP, DHP and GDHP (ADHDP, ADDHP and ADGDHP respectively) also exist [14]. The HDP approach illustrated in Fig. 3 is used for the neurocontroller design in this paper and is explained below including the development of a model using a neural network (the neuroidentifier) [15].

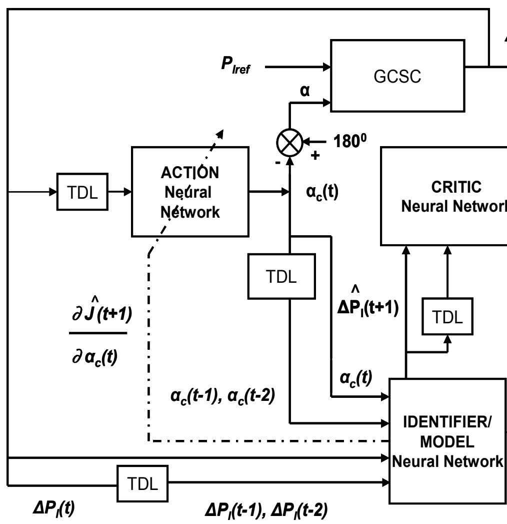


Fig. 3 HDP design of optimal neurocontroller.

A. Neuroidentifier

The power system is nonlinear with frequent changes in operating regions due to load changes, disturbances and set point changes. The transactions on power market and commitments also require the need to change line power flows. Thus, the settings of the series reactive compensators are required to change dynamically. During these changes of operating conditions, a system identifier can be used to predict the changes one or few steps ahead.

For HDP neurocontroller designs, a neural network based one step ahead predictions has been found sufficient in providing accurate feedback for the action network weight updates [12]. In this paper, a Recurrent Neural Network (RNN) is used to provide a dynamic neuroidentifier structure. The RNN tracks the power deviations over time. RNNs are known to provide better and faster tracking of dynamical systems than the feedforward neural networks [11]. The RNN neuroidentifier consists of 2 input linear neurons, a context layer with 11 linear neurons, a hidden layer with 10 sigmoidal neurons and an output layer with 1 linear neuron. The context layer inputs are the outputs of the hidden and the output layer delayed by one time step. The weights of the RNN are updated with the backpropagation through time algorithm with truncation of *5* (*BPTT(5)*). The BPTT algorithm is briefly described below in Section III C.

B. HDP Critic Neural Network

As mentioned above the critic network approximates the cost-to-go function J in (1). The critic network is trained forward in time, which is of great importance for real-time optimal control operation. The ability to foresee future cost and take preventive action ahead of time is important in optimal controller designs.

In the training of the critic network, the objective is to minimize (2) given below.

$$\sum_{t=0}^{\infty} E^2(t) \tag{2}$$

Where
$$E(t) = \gamma \hat{J}(Y(t+1)) + U(Y(t) - \hat{J}(Y(t)) \tag{3}$$

Here, $\hat{J}$ is the estimated cost-to-go $J(t)$ by the critic network at time t. The weight updates for the critic network using the standard backpropagation is given by (4).

$$\Delta W_C = \eta_C . E(t) . \frac{\partial \hat{J}(Y(t))}{\partial W_C} \tag{4}$$

Where η_c and W_c are the learning rate and the weights of the critic neural network respectively. A detailed explanation for the derivation of the utility function is given in [7, 16]. The utility function U in (1) and (3) plays an important role to form the user-required optimal cost-to-go function J, and is selected to give the best trade-off between performance and the cost of control.

The critic neural network in Fig. 3 is a three layer feedforward network with 3 input linear neurons, 10 sigmoidal neurons in the hidden layer and one output linear neuron. The critic inputs are the neuroidentifier output and its two delayed values. The critic's output is the cost-to-go function $\hat{J}(t)$.

C. Action Neural Network / Dynamic Neurocontroller

The action network inputs are the power deviation ΔP_l and reference line power P_{lref} as shown in Fig. 2 (with the switch S now closed). A recurrent neural network is used to implement a dynamic controller. The RNN consists of 2 input layer linear neurons, 10 hidden layer sigmoidal neurons, 1 output layer linear neuron and 10 context layer linear neurons as illustrated in Fig. 4.

The change in the action network weights ΔW_A are calculated by backpropagating a '1' through the trained critic network and then backpropagating the derivative $\partial J/\partial A$ through the trained neuroidentifier to obtain $\partial J/\partial A$ as shown in Fig. 3. The error in the action network output is given by (5) where $\hat{Y}_M$ the output of the neuroidentifier/model in Fig. 3 (TDL is the time delay).

$$e = \frac{\partial \hat{J}}{\partial A} = \left(\frac{\partial \hat{J}}{\partial \hat{Y}_M} \right) \left(\frac{\partial \hat{Y}_M}{\partial A} \right) \tag{5}$$

The weights of the RNN are updated with the backpropagation through time algorithm with truncation of h

(*BPTT(h))*. Here truncation depth *h* is the number of samples handled or number of internal iterations performed before the weights are updated. The BPTT training algorithm calculates at each step the output error with respect to the input signal X. These errors are backpropagated through the RNN to get finally $\partial e(t)/\partial X(t-h)$(Fig. 5). The weights of the RNN are updated using the standard backpropagation after *h* internal iterations and the change in the action network's weights ΔW_A with a truncation depth for the BPTT of 5 is given by (6).

$$\Delta W_A = \eta_A \cdot \frac{\partial e(t)}{\partial X(t-h)} = \eta_A \cdot \left(\frac{\partial \hat{J}(t)}{\partial A(t-5)} \right) \tag{6}$$

Here η_A and W_A are the learning rate and the weights of the action neural network respectively.

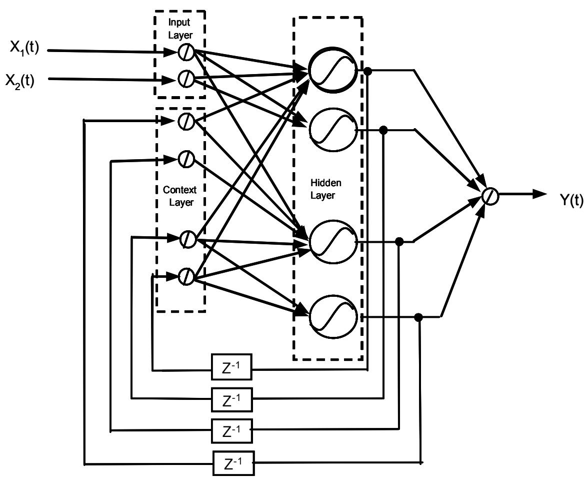


Fig. 4 A recurrent neural network structure.

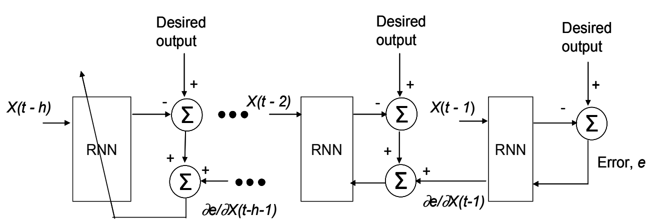


Fig. 5 Backpropagation through time (BPTT) training structure.

IV. Multi-Machine Power System

The 11 bus multi-machine power system used in this study is shown in Fig. 6. Bus 1 is the infinite or slack bus. This is a two area power system with five parallel transmission lines between areas 1 and 2 (buses 5 and 10 respectively). Area 1 consists of an infinite bus and generator 2, and area 2 consists of generator 3 and the loads. The GCSC is integrated in this system between area 1 and area 2 to provide control over real power flow from one area to the other. For the operating condition – P_1 = 3562 MW, Q_1 = 1276 MVAR, P_2 =1480 MW, Q_2 = 484 MVAR *and* P_3 = 1084 MW and Q_3 = 272 MVAR with industrial loads of 3000 W and 1800 MVAR and residential loads of 3000 MW and 90 MVAR connected to buses 6 and 9 respectively, area 1 transfers almost 5000 MW of real power to area 2. The power system is simulated in the PSCAD/EMTDC environment.

V. Results and Discussions

The neurocontroller is developed in three steps namely – the neuroidentifier training, critic network training and the action network training. The neuroidentifier training involves two phases, one with forced perturbations applied at a nominal operating point (α = 135 degree) for the GCSC using pseudo-random binary signals (PRBS) in the range of 0.1 to 0.5 Hz and the other phase is training with natural disturbances such as short circuit faults. The power network is sampled at 500 Hz to provide the inputs to the neuroidentifier. Fig. 7 shows the performance of the trained neuroidentifier for step changes in the P_{lref}.

The training procedure detailed in [12] is used for the critic and action training at different operating points and conditions until the weights of the networks do not change significantly. The utility function *U(t)* given in (7) is chosen to provide stable feedback for optimal controller development [16].

$$U(t) = (\Delta P(t) + 5\Delta P(t-1) + 9\Delta P(t-2))^2 \tag{7}$$

The initial weights of the action network are those that can provide stabilizing control at one operating point. These weights can be obtained by learning the existing PI controller or using the indirect adaptive control scheme [12].

Obtaining the initial weights of the action network is known as pre-training the neurocontroller. After pre-training of the neurocontroller, the control of the GCSC is switched to the neurocontroller. PRBS forced training signals is added to the power line reference to train the critic and action network. The critic and action training is interleaved. Once the action network weights have converged for a number of operating conditions and points, the weights are fixed and neurocontroller is tested for different conditions.

Fig. 8 shows the response of the PI and the neurocontroller for a 3-phase 150ms short circuit fault applied at bus 5. It can be seen that the performance of the both controllers is the same for this fault. But for the same fault applied at bus 6, the PI controller performance degrades while HDP based neurocontroller still performs well as shown in Figs. 9 and 10. In the first case, the PI controller was fine tuned to provide good damping and as a result the performance observed in Fig. 8 is the same as that of the neurocontroller and this is not the case in Figs. 9 and 10.

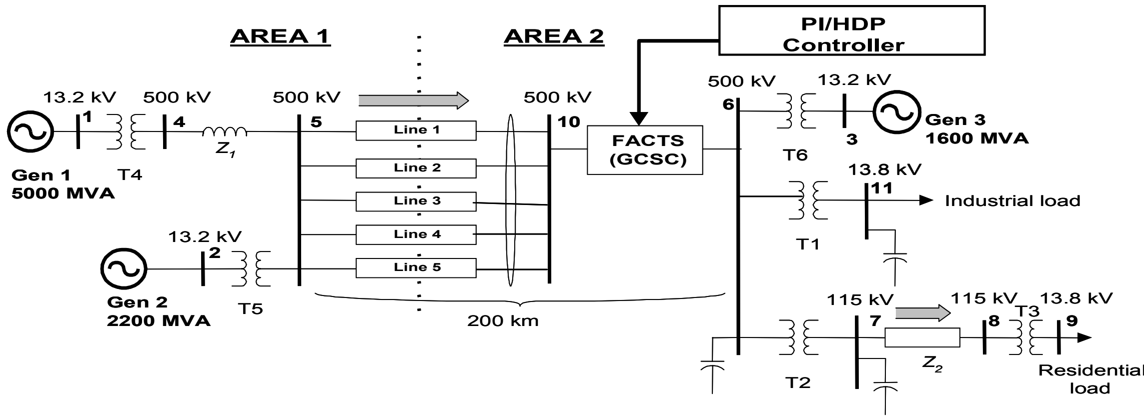


Fig. 6 Three machine 11 bus power system with a GCSC installed between buses 6 and 10.

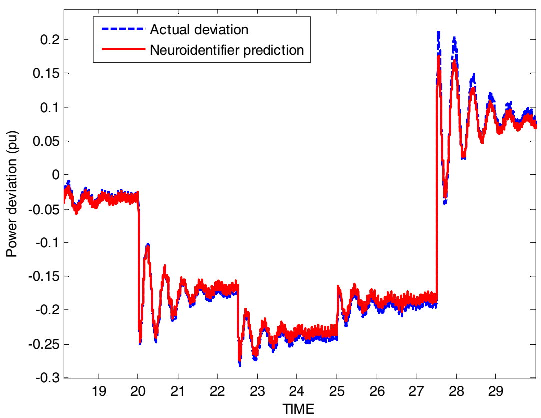


Fig. 7 Performance of the neuroidentifier for step changes in the power line reference P_{lref}.

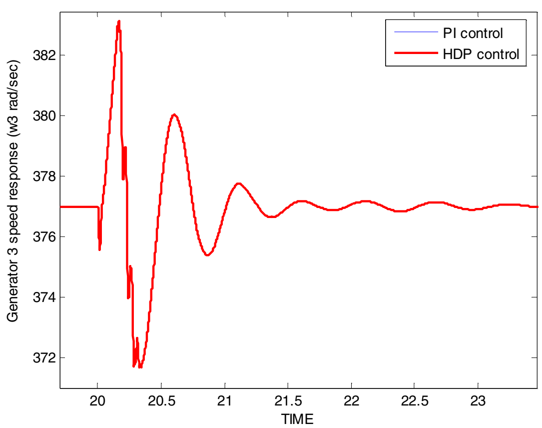


Fig. 8 Generator 3 speed responses during a 150 ms 3-phase short circuit fault at bus 5 (responses of both controllers are almost identical). Identical performance is observed with the PI and HDP controllers.

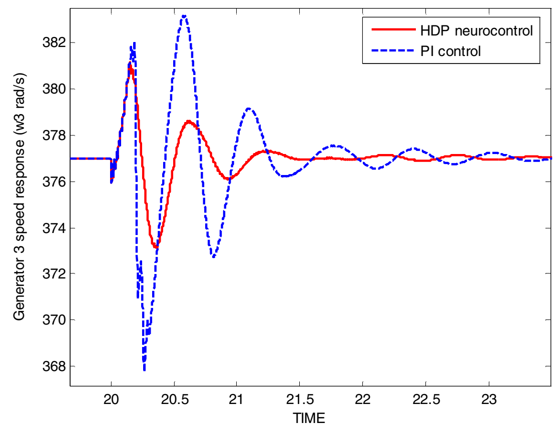


Fig. 9 Responses of generator 3 for a 3-phase short circuit fault at bus 6 for 150 ms with the PI controller and the HDP neurocontroller.

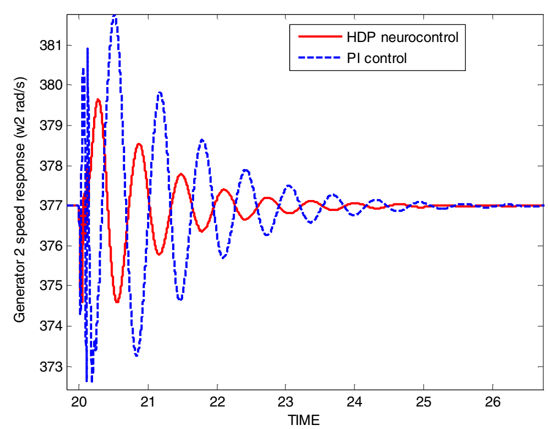


Fig. 10 Responses of generator 2 for a 3-phase short circuit fault at bus 6 for 150 ms with the PI controller and the HDP neurocontroller on the GCSC.

Fig. 11 shows the speed oscillations of generators 3 for outage of one of the five transmission lines connecting the two areas for 500 ms. The HDP neurocontroller tested above provides better damping in the first few cycles however, the settling time is approximately similar. It has been observed that the neurocontroller exhibits a robust performance despite changes in operating conditions unlike the PI controller.

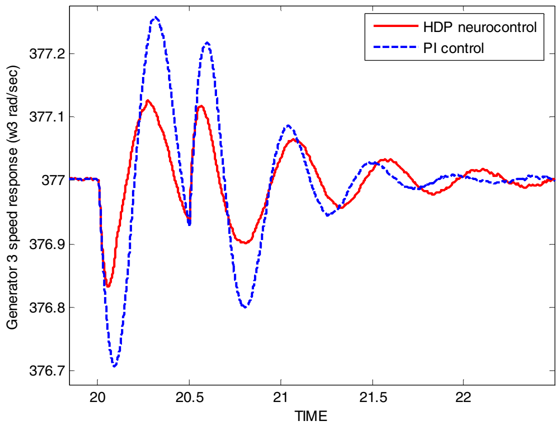


Fig. 11 Responses of generator 3 for a transmission line outage for 500 ms with the PI controller and the HDP neurocontroller on the GCSC.

VI. Conclusions

This paper has presented the design an optimal controller using recurrent neural networks and the heuristic dynamic programming approach for the GCSC series FACTS device. The dynamic neuroidentifier and neurocontroller provides fast tracking and improved control performance. The recurrent neural networks architecture provides dynamic adaptation capability even when the weights are fixed. Simulation results show that the neurocontroller exhibits robust performance for different operating conditions and disturbances.

The simple and cost effective GCSC FACTS device has the potential for its application for power flow control and damping oscillations, replacing existing fixed series capacitor banks and other series compensators. The proposed neurocontroller design provides a basis for further enhancement of the cost effective series FACTS device.

Future work involves investigating the performance of other types of neurocontrol strategies for the GCSC in order to provide better stability to the generator dynamics. Future focus will also investigate the optimal location or locations for a GCSC to incorporate it in a larger power system.

VII. References

[1] L. F. W. de Souza, E. H. Watanabe, M. Aredes, "GTO controlled series capacitor", in *Proc. IEEE Power Engineering Society winter meeting.*, vol. 4, pp. 2520-2525, Jan. 2000.

[2] L. F. W. de Souza, E. H. Watanabe, J. E. R. Alves, L. A. S. Pilotto, "Thyristor and gate controlled series capacitors: comparison of components rating", in *Proc of IEEE Power Engineering Society General Meeting*, vol. 4 , pp: 2547, July 2003.

[3] L. F. W. de Souza, E. H. Watanabe, M. Aredes, "GTO controlled series capacitors: multi-module and multi-pulse arrangements", *IEEE Transactions on Power Delivery*, vol. 15 , no. 2 , pp. 725 – 731, Apr. 2000.

[4] P. M. Anderson, A. A. Fouad, *Power System Control and Stability*, New York, IEEE Press, 1994, ISBN 0-7803-1029.

[5] Jung-Wook Park, R. G. Harley, G. K. Venayagamoorthy, "Adaptive-critic-based optimal neurocontrol for synchronous generators in a power system using MLP/RBF neural networks", *IEEE Transactions on Industry Applications*, vol. 39, no. 5, pp. 1529 – 1540, Sep.-Oct. 2003.

[6] P. K. Dash, S. Mishra, G. Panda, "A radial basis function neural network controller for UPFC", *IEEE Transaction on Power System,* vol. 15, no. 4, pp. 1293-1299, 2000.

[7] G. K. Venayagamoorthy, R. G. Harley, "Two separate continually online-trained neurocontrollers for excitation and turbine control of a turbogenerator", *IEEE Transactions on Industry Applications*, vol. 38, no. 3, pp. 887 -893, May/June 2002.

[8] P. J. Werbos, "Backpropagation through time: What it does and how to do it", *Proceedings of the IEEE*, vol. 78, no. 10, pp. 1550-1560, 1990.

[9] L. A. Feldkamp, G. V. Puskorius, D. V. Prokhorov, "Unified formulation for training recurrent networks with derivative adaptive critics", *International Conference on Neural Networks*, vol. 4, pp. 2268-2272, 1997.

[10] N. E. Barabanov, D. V. Prokhorov, "Global stability analysis of discrete-time recurrent neural networks", *Proceedings of American Control Conference*, vol. 6, pp. 4550-4555, 2001.

[11] G. K. Venayagamoorthy, "Dynamic optimization of a multimachine power system with a FACTS device using identification and control ObjectNets", *Conference record of the 39th IAS Annual Meeting*, vol. 4, pp. 2643-2650, 2004.

[12] G. K. Venayagamoorthy, R. G. Harley, D. C. Wunsch, "Comparison of heuristic dynamic programming and dual heuristic programming adaptive critics for neurocontrol of a turbogenerator", *IEEE Transactions on Neural Networks*, vol. 13, no. 3 , pp. 764-773, May 2002.

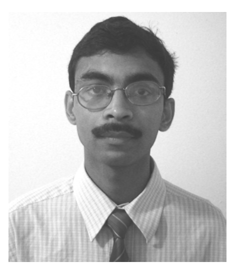
[13] G. K. Venayagamoorthy, R. G. Harley, D. C. Wunsch, "Implementation of adaptive critic based neurocontrollers for turbogenerators in a multimachine power system", *IEEE Transactions on Neural Networks*, vol. 14, no. 5, pp. 1047 – 1064, Sep. 2003.

[14] J. Si, A. Barto, W. Powell, D. C. Wunsch, *Handbook of Learning and Approximate Dynamic Programming*, Wiley, July 2004, ISBN 0-471-66054-X.

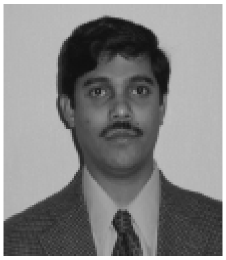
[15] K. S. Narendra, K. Parthasarathy, "Identification and control of dynamical systems using neural networks," *IEEE Transactions on Neural Networks*, vol. 1, pp. 4–27, Mar. 1990.

[16] G. K. Venayagamoorthy, R. G. Harley, D. C. Wunsch, "Dual heuristic programming excitation neurocontrol for generators in a multimachine power system", *IEEE Transactions on Industry Applications*, vol. 39, no. 2, pp. 382 – 394, Mar./Apr. 2003.

VIII. Biographies



Swakshar Ray (S'02) received the B.E. degree with a first class honors in Electrical Engineering from the Jadavpur University, Calcutta, India, and the M.S. degree in Electrical Engineering from Oklahoma State University, Stillwater, USA, in August 2000 and December 2003, respectively. He was a Commissioning Engineer in the Control and Automation Division, Larsen and Toubro India Ltd. from August 2000 to December 2001. Currently he is a PhD candidate in the University of Missouri-Rolla and a member of the Real-Time Power and Intelligent Systems Laboratory. His research interests are in control systems, power systems, computational intelligence and signal processing. Mr. Ray is the recipient of Hughes Scholarship from the Department of Electrical and Computer Engineering, Oklahoma State University, in 2003 and the IEEE Computational Intelligence Society (CIS) W. J. Karplus summer research grant in 2005. He is also a member of the task force on Intelligent Control Systems of IEEE Power Engineering Society.



Ganesh Kumar 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 a Senior Lecturer at the Durban Institute of Technology, South Africa prior to joining the University of Missouri-Rolla (UMR), USA as an Assistant Professor in the Department of Electrical and Computer Engineering in May 2002. He is the Director of the Real-Time Power and Intelligent Systems Laboratory at UMR. His research interests are in computational intelligence, power systems, evolvable hardware and signal processing. Dr. Venayagamoorthy has attracted in excess of $ 1 million in research funding from external sources since joining UMR. He has published over 130 papers in refereed journals and international conferences. Dr. Venayagamoorthy is the 2005 IEEE Industry Application Society (IAS) Outstanding Young Member award recipient, a 2004 NSF CAREER award recipient, the 2004 IEEE St. Louis Section Outstanding Young Engineer, the 2003 International Neural Network Society (INNS) Young Investigator award recipient, a 2001 recipient of the IEEE Computational Intelligence Society (CIS) W. J. Karplus summer research grant and the recipient of five prize papers with the IEEE IAS and IEEE CIS. He is an Associate Editor of the IEEE Transactions on Neural Networks. He is a Senior Member of the South African Institute of Electrical Engineers, a Member of INNS and the American Society for Engineering Education. He is currently the IEEE St. Louis CIS and IAS Chapter Chair, the Chair of the task force on Intelligent Control Systems and the Secretary of the Intelligent Systems subcommittee of IEEE Power Engineering Society.