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Ganesh K. Venayagamoorthy
Missouri University of Science and Technology

Radha P. Kalyani

Mariesa Crow
Missouri University of Science and Technology, crow@mst.edu

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Neuroidentification of System Parameters for the Shunt & Series Branch Control of UPFC

R. P. Kalyani, *Student Member, IEEE*, G. K. Venayagamoorthy, *Senior Member, IEEE*, M. Crow, *Senior Member, IEEE*

***Abstract*— The crucial factor affecting the modern power systems today is load flow control. The Unified Power Flow Controller (UPFC) forms an affective means for controlling the power flow. The UPFC consists of shunt and series inverters which are conventionally controlled using linear controllers. This paper presents the design of neuroidentifiers that identify the system parameters that determine the UPFC controller outputs one-time step ahead thus, making the pathway for the design of adaptive neurocontrollers. Two neuroidentifiers are used for identifying the nonlinear dynamics of power system and UPFC, one neuroidentifier for the shunt inverter and the other for the series inverter. Simulation results carried out in the PSCAD/EMTDC environment are presented to show the successful neuroidentification of system parameters are possible.**

***Index Terms*— Power System, Unified Power Flow Controller (UPFC), Neuroidentification, Adaptive control.**

I. INTRODUCTION

With the ever-increasing complexities in power systems across the globe and the growing need to provide stable, secure, controlled, economic, and high-quality electric power –especially in today's deregulated environment – it is envisaged that Flexible AC Transmission System (FACTS) controllers are going to play a critical role in power systems [1]. FACTS enhance the stability of the power system both with its fast control characteristics and with its continuous compensating capability. The two main objectives of FACTS technology are to control power flow and increase the transmission capacity over an existing transmission corridor [2].

Gyugyi proposed the Unified Power Flow Controller which is a new type generation of FACTS devices in 1991 [3]. It is a device, which can control simultaneously all three parameters of power transmission line (impedance, voltage and phase angle). This device combines together the features of two other FACTS devices: the Static Synchronous Compensator (STATCOM) and the Static Synchronous Series Compensator (SSSC). Practically, these two devices are two Voltage Source Inverters (VSIs), one connected in shunt with the transmission line through a shunt transformer and the other in series with the transmission line through a series transformer. These are connected to each other by a common DC link, which is a typical storage capacitor.

The authors are with the Department of Electrical and Computer Engineering, University of Missouri, Rolla, MO, 65401 USA.(e-mail: rpk5f9@umr.edu, gkumar@ieee.org and crow@umr.edu respectively)

The shunt inverter is used for voltage regulation at the point of connection, injecting reactive power into the line and to balance the real power exchanged between the series inverter and the transmission line. Thereby, the UPFC can fulfill functions of reactive shunt compensation, active and reactive series compensation and phase shifting. Besides, the UPFC allows a secondary but important function such as stability control to suppress power system oscillations improving the transient stability of power system [2].

The ability to learn and store information about system nonlinearities allows neural networks to be used for modeling and designing intelligent controllers for power systems [4, 5]. Thus, offering alternatives for conventional control. Neural networks are suitable for multi variable applications as they can easily identify the interactions between the system's inputs and outputs. The application of neural networks in power systems arises due its inherently good property of pattern recognition and rapid computational performance. A radial basis function neural network controller for UPFC based on direct adaptive control has been reported to improve the transient stability performance of a power system [6]. It is known that indirect adaptive control using a model of a plant can overcome the drawbacks of direct adaptive control such as the high loop gains in the system.

This paper presents the use of neural networks (called *neuroidentifiers*) to identify/model the dynamics of a unified power flow controller (UPFC) and the power system in a single machine power system setup. Eventually these neuroidentifiers will be used in the future design of neurocontrollers based on the indirect adaptive control [4, 5] to replace existing conventional PI controllers in the shunt and series branches of a UPFC. The advantage of neurocontrollers over conventional controllers is that they are able to adapt to changes in the operating points and system conditions automatically unlike the conventional controllers whose performances degrade for such changes.

II. SINGLE MACHINE INFINITE BUS POWER SYSTEM

For identifying the dynamics of a UPFC and the power system, a single machine infinite-bus power system is setup as shown in Fig. 1 in PSCAD/EMTDC environment. This power system comprises of a synchronous generator of rating 590MVA, with exciter-automatic voltage regulator (AVR) and turbine-governor combinations connected to an infinite bus through two sections of transmission lines and the UPFC is placed between the two sections of the transmission lines as shown in Fig. 1.

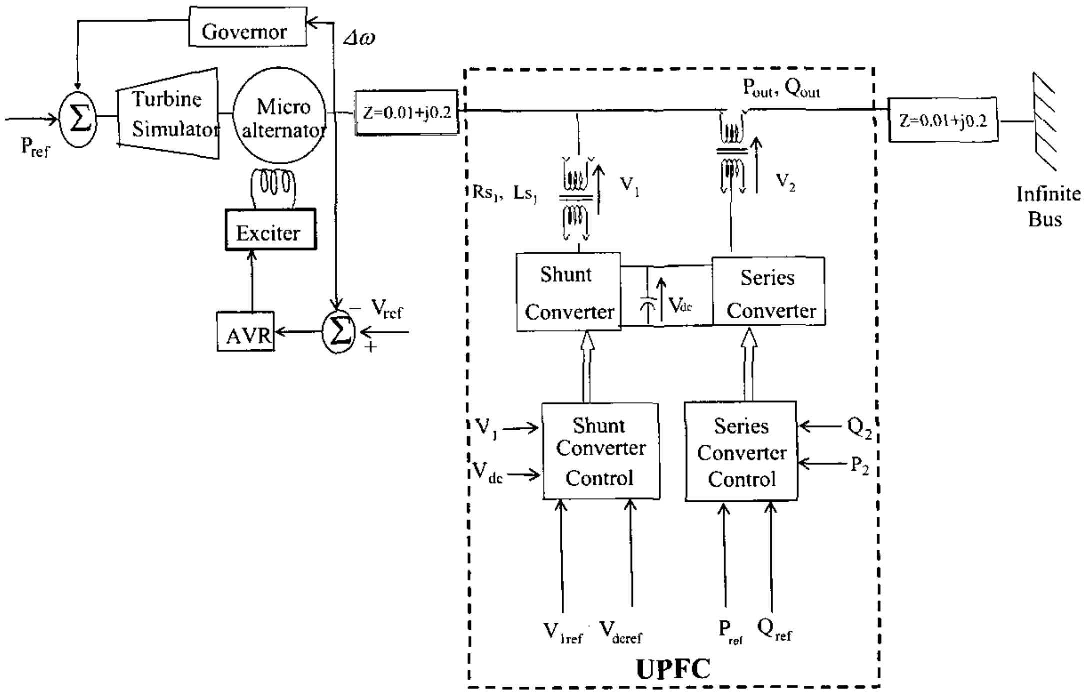

Fig.1 Single machine infinite bus system.

III. UNIFIED POWER FLOW CONTROLLER

UPFC is a generalized synchronous voltage sources (SVS) represented at fundamental frequency by a voltage phasor with a controllable magnitude V $(0 \leq V \leq V_{max})$ and an angle $\alpha (0 \leq \alpha \leq 2\pi)$, in series with the transmission line. The two voltage-sourced inverters in a UPFC are connected back-to-back and have a common DC link provided by a DC storage capacitor. This arrangement functions as an ideal ac-to-ac power inverter in which the real power can freely flow in either direction between the ac terminals of the two inverters, and each inverter can independently generate (or absorb) reactive power at its own ac output terminal.

The series inverter provides the main function of the UPFC by injecting a voltage with magnitude V_2, which is controllable and a phase angle α in series with the line via an insertion transformer. This injected voltage acts essentially as a synchronous ac voltage source. The transmission line current flows through this voltage source resulting in a reactive and active power exchange between itself and the ac system. The inverter generates the reactive power exchanged at the ac terminal internally. The active power exchanged at the ac terminal is converted into dc power, which appears at the DC link as a positive or negative real power. The basic function of shunt inverter is to generate or absorb the real power demanded by series inverter at the common DC link. This power demand by the series inverter at the DC link is converted back to ac by the shunt inverter and fed to the transmission line bus via a shunt-connected transformer. In addition to this the shunt inverter can also generate or absorb controllable reactive power if desired and thereby provides independent shunt reactive compensation for the line [3]. The three main control parameters of UPFC are voltage magnitude, voltage angle and shunt reactive current. Control of real and reactive power can be achieved by injecting series voltage with an appropriate magnitude and angle. Following sections of the paper discuss briefly the control structures of shunt and series branches. The transient stability model for the shunt and series branch of a UPFC in the dq reference frame are given in [7].

A. Shunt Branch Control

Control of the shunt inverter is achieved by varying the shunt inverter voltage active and reactive components E_{pd} and E_{pq} accordingly. The reactive power flow and shunt input voltage can be regulated by active voltage component E_{pd} and the DC-link capacitor voltage V_{dc} support can be achieved by regulating E_{pq}. Figure 2 shows a block diagram of a conventional shunt inverter and DC voltage control system.

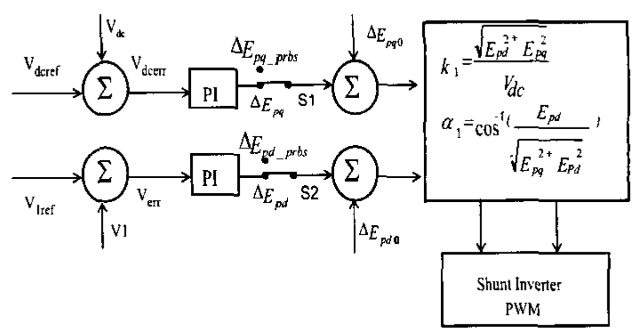

Fig. 2 Shunt Branch Control.

The outputs of the control system are the modulation index k_1 and phase shift α_1. Switches S1 and S2 are used to switch in training signals for the shunt neuroidentifier described in Section IV.

B. Series Branch Control

For the series inverter control, the PQ decoupled control is considered using active and reactive power objectives in this paper. Neglecting inverter losses, the injected active power and reactive power as well as output powers are given below and further simplified forms are given in [7].

$$P_2 = \frac{V_2(E_q - E_q\cos\delta + E_d\sin\delta)}{X} \quad (1a)$$

$$Q_2 = \frac{V_2E_d\cos\delta + V_2E_q\sin\delta - V_2E_d + E_d^{\,2} + E_q^{\,2}}{X} \quad (1b)$$

$$P_{out} = \frac{V_2^{\,2}\sin\delta + V_2E_q}{X} \quad (2a)$$

$$Q_{out} = \frac{2V_2E_d\cos\delta + 2V_2E_q\sin\delta + E_d^{\,2} + E_q^{\,2}}{2X} \quad (2b)$$

where

$$V_2 = \sqrt{E_d^{\,2} + E_q^{\,2}}$$
$$E_q = V_2\sin(\theta_2)$$
$$E_d = V_2\cos(\theta_2)$$

Equation (2a) shows that P_{out} is mainly affected by E_q whereas (2b) shows that Q_{out} affected by both E_q and E_d. In incremental form, the line active and reactive power can be expressed in terms of ΔE_d and ΔE_q.

$$\Delta\, P_{out} = \frac{V_2}{X}\Delta E_q \quad (3a)$$

$$\Delta Q_{out} = \frac{1}{X}(\Delta E_dV_2\cos\delta + \Delta E_qV_2\sin\delta + \Delta E_dE_{d0} + \Delta E_qE_{q0}) \quad (3b)$$

$$\Delta\, Q_{out} = \frac{1}{X}(\Delta E_dV_2 + \Delta E_dE_{d0} + \Delta E_qE_{q0}) \quad (4)$$

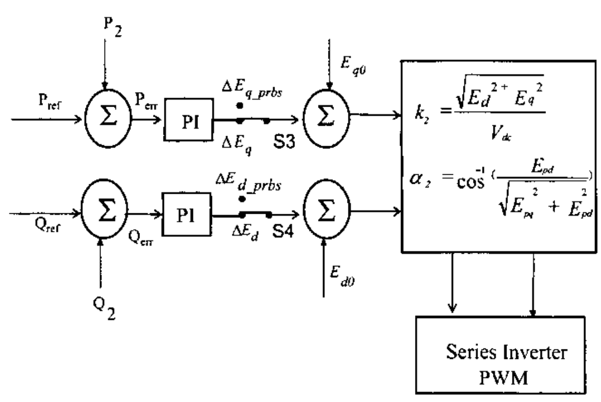

Fig. 3 Series Branch Control.

The block diagram of PQ decoupled series inverter controller is shown in Fig. 3. The outputs of the control system are the modulation index k_2 and phase shift α_2. Switches S3 and S4 are used to switch in training signals for the series neuroidentifier described in Section IV.

IV. Design of Neuro-Identifiers

The identification/modeling of the UPFC and the power system dynamics in Fig. 1 is carried out using two separate neuroidentifiers, one for the shunt inverter and the other for the series inverter. These neuroidentifiers are trained online to dynamically identify the system parameters that determine UPFC controller outputs which are the inputs to PI controllers in Figs. 2 and 3. These are V_{dcerr} V_{err}, P_{err}, and Q_{err} for the shunt and series branches respectively. The neuroidentifier structure is the series-parallel Nonlinear Auto Regressive Moving Average (NARMA) model [4]. The outputs of neuroidentifiers $\hat{y}$ at time (k+1) depends on both past n values of output y and m past values of inputs u. The neuroidentifier output equation takes the form given by eq. (5).

$$\hat{y}(k+1) = f\begin{bmatrix} y(k), y(k-1), \ldots\ldots, y(k-n+1) \\ u(k), u(k-1), \ldots\ldots\ldots, u(k-m+1) \end{bmatrix} \quad (5)$$

The NARMA model is used in preference to other system models because online training is desired to correctly identify the dynamics of the UPFC and the power system therefore avoiding a feedback loop in the model, which allows static back propagation to be used to adjust the neural network weights. This reduces the computational overhead substantially for online training and ensures neural network convergence [4].

A. Shunt Neuroidentifier

The Shunt neuroidentifier (SHNI) is a three layer feedforward neural network with twelve inputs, a single hidden layer with fourteen neurons and two outputs that identifies the dynamics of the shunt inverter and the SMIB power system. There are four different types of inputs. The first two types of inputs to the neuroidentifier are the differences between the following signals: the measured line voltage and its reference value V_{err} , and, the measured DC link voltage and its reference V_{dcerr}. The other two types of inputs are the training signals generated using pseudorandom random signals (PRBS) ΔE_{pd_prbs} and ΔE_{pq_prbs} in proportion to the real and reactive components of shunt inverter voltage E_{pd} and E_{pq} respectively. These PRBS signals are only fed to the shunt inverter and SHNI during the training phase with the aid of switches S1 and S2 (Fig. 2). All the four types of inputs are time delayed by one sample period and together with their eight previously delayed values form the twelve inputs to the SHNI. The outputs of the SHNI, the line voltage difference $\hat{V}_{err}$ and DC link voltage difference $\hat{V}_{dcerr}$ are estimated one step ahead time. Figure 4 shows the shunt neuroidentifier input and output signals.

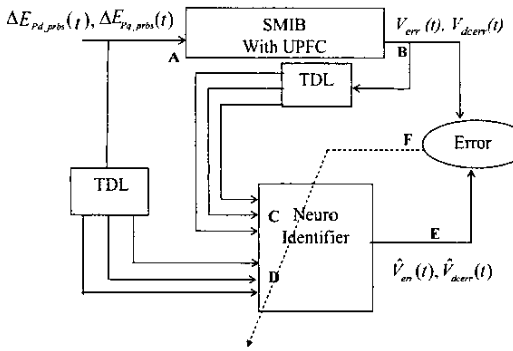

Fig. 4 Neuroidentifier for Shunt branch.

B. Series Neuroidentifier

The Series neuroidentifier (SENI) is a three layer feedforward neural network with twelve inputs, a single hidden layer with fourteen neurons and two outputs that identifies the dynamics of the series inverter and the SMIB power system. There are four different types of inputs. The first two types of inputs to the neuroidentifier are the differences between the following signals: the measured real power and its reference value P_{err} , and, the measured reactive power and its reference Q_{err}. The other two types of inputs are the training signals generated using pseudorandom random signals (PRBS) ΔE_{d_prbs} and ΔE_{q_prbs}. These PRBS signals are only fed to the series inverter and SENI during the training phase with the aid of switches S3 and S4 (Fig. 3). All the four types of inputs are time delayed by one sample period and together with their eight previously delayed values form the twelve inputs to the SENI. The outputs of the SENI, real power difference $\hat{P}_{err}$ and reactive power difference $\hat{Q}_{err}$ are the estimated one step ahead time. Figure 5 shows the series neuroidentifier input and output signals.

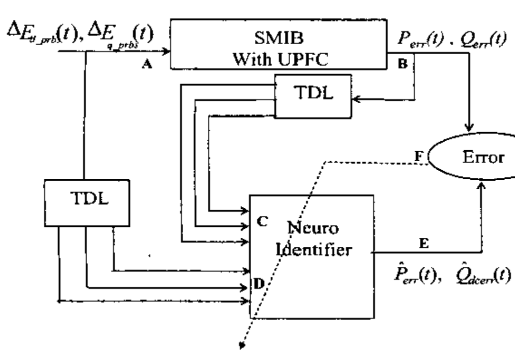

Fig. 5 Neuroidentifier for Series Branch.

C. Training Procedure for the SHNI and SENI

In order for the neuroidentifiers to capture all the possible dynamics of the UPFC and the power system, it is necessary to have a high sampling frequency. The back propagation algorithm is used for updating the input and output weights W in the SHNI and SENI on the error $e(t)$ which is given by the eq. (6) [5].

$$e(t) = \left\{ \left[\Delta V_t(t) - \Delta \hat{V}(t) \right], \left[\Delta \omega(t) - \Delta \hat{\omega}(t) \right] \right\} \tag{6}$$

The training is carried out to minimize eq. (6). The neuroidentifier weights update equation is given by eq. (8).

$$E(t) = \frac{1}{2} \Sigma e^2(t) \tag{7}$$

$$\Delta W = -e(t) \frac{\partial e(t)}{\partial W} \tag{8}$$

The flowchart for the neuroidentifier training appears in Fig. 6.

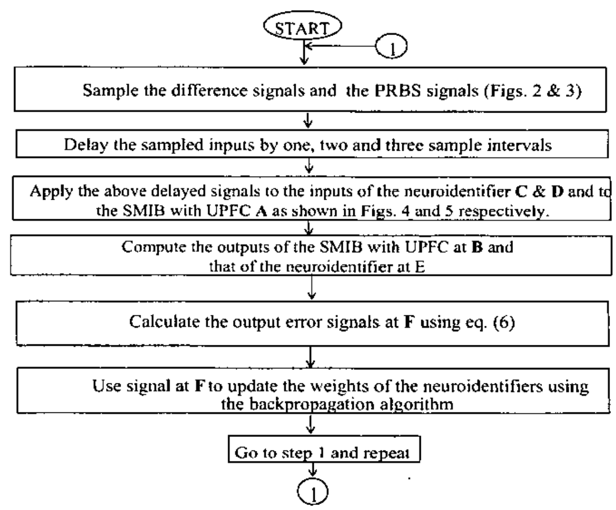

Fig. 6 Flowchart for identification of shunt branch.

V. SIMULATION RESULTS

The SHNI and SENI training are carried out for the generator operating point of P=0.6 p.u and Q =0.15 p.u. The training is carried out in three phases namely (a) the first phase focuses on the identification of the shunt branch of UPFC (b) the second phase on identification of series branch of UPFC and (c) the third phase concentrates on the identification of both the shunt and series branches of the UPFC in Fig. 1. In all the phases, the neuroidentifiers also identify the dynamics of the power system. A sampling frequency of 50 kHz is used to get inputs to the neuroidentifiers.

A. Phase 1 – Shunt branch identification:

Figure 4 shows the neuroidentifier inputs and outputs for the shunt branch identification. Training signals are applied to the shunt inverter with the aid of the switches S1 and S2 (Fig. 2) for a period of time until sufficient identification is achieved by the SHNI. Figures 7 and 8 depict the two PRBSs which are applied to the shunt inverter.

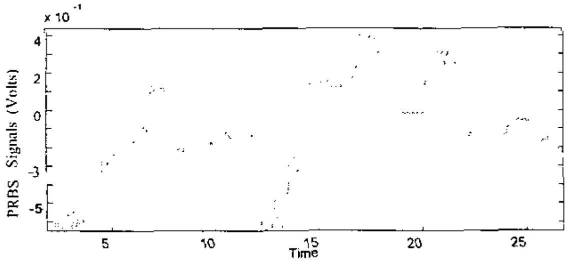

Fig. 7. PRBS training signal E_{pd_prbs} applied to the shunt branch of UPFC with the aid of switch S1 in Fig. 2.

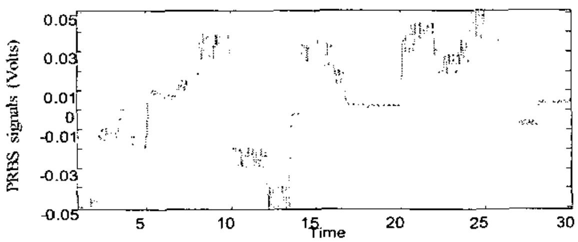

Fig. 8. PRBS training signal E_{pq_prbs} applied to the shunt branch of UPFC with the aid of switch S2 in Fig. 2.

These PRBS are applied only to the shunt branch of UPFC. The SHNI is trained with a learning rate of 0.09. Figures 9 and 10 show the actual difference in the measured DC link voltage and its reference value V_{dcerr} and the corresponding estimated difference value by the neuroidentifier $\hat{V}_{dcerr}$ to these PRBS training signals. Figure 10 shows the response over a smaller time scale compared to Fig. 9. Figure 11 shows the actual difference in the measured line voltage and its reference value and the corresponding estimated difference value V_{err} by the neuroidentifier $\hat{V}_{err}$ to these PRBS training signals. It is clear from Figs. 10 and 11 that SHNI is able to estimate the V_{dcerr} and V_{err} accurately enough after 90 seconds.

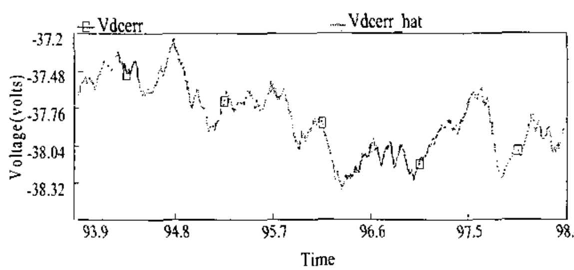

Fig. 9 Actual signal V_{dcerr} and estimated signal $\hat{V}_{dcerr}$ for shunt branch..

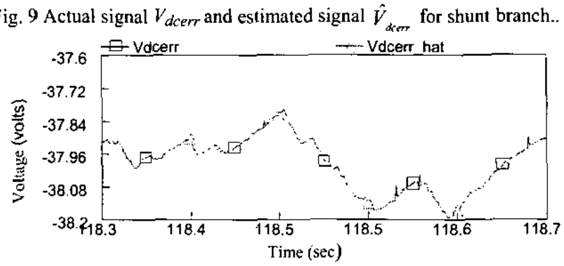

Fig. 10 Actual signal $Vdcerr$ and identified signal $\hat{V}_{dcerr}$ for shunt branch.

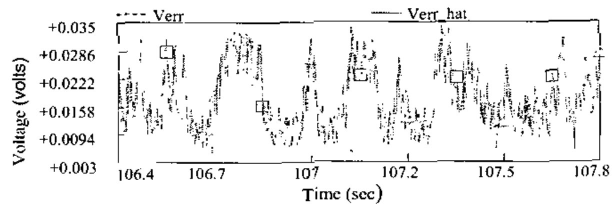

Fig. 11 Actual signal $Verr$ and identified signal $\hat{V}_{err}$ for shunt branch.

B. Phase 2 - Series Branch Identification

Figure 5 shows the neuroidentifier inputs and outputs for the series branch identification. Training signals are applied to the series inverter with the aid of the switches S3 and S4 (Fig. 3) for a period of time until sufficient identification is achieved by the SENI. Figures 12 and 13 depict the two PRBSs which are applied to the series inverter.

These PRBS are applied only to the series branch of UPFC. The SENI is trained with a learning rate of 0.09. Figures 14 and 15 show the actual difference in the measured reactive power and its reference value Q_{err} and the corresponding estimated difference value by the neuroidentifier $\hat{Q}_{err}$ to these PRBS training signals. Figure 15 shows the response over a smaller time scale compared to Fig. 14. Figure 16 shows the actual difference in the measured real power and its reference value and the corresponding estimated difference value P_{err} by the neuroidentifier $\hat{P}_{err}$ to these PRBS training signals. It is clear from Figs. 15 and 16 that SENI is able to estimate the P_{err} and Q_{err} accurately enough after 50 seconds. It is observed that series inverter dynamics are identified faster by neuroidentifier compared to the shunt inverter dynamics.

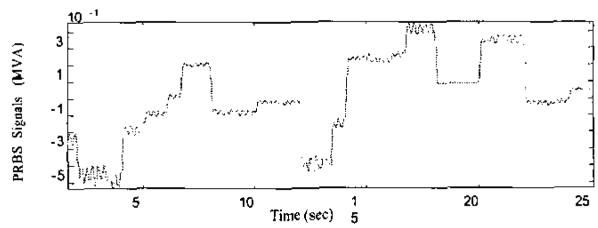

Fig. 13. PRBS training signal E_{p_prbs} applied to the series branch of UPFC with the aid of switch S3 in Fig. 3.

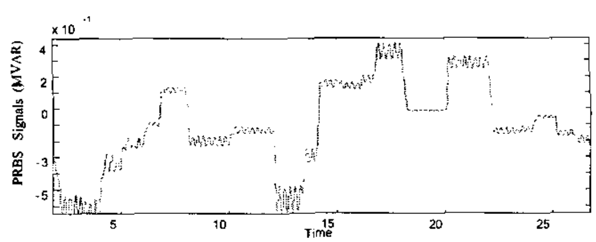

Fig. 13. PRBS training signal E_{q_prbs} applied to the series branch of UPFC with the aid of switch S4 in Fig. 3.

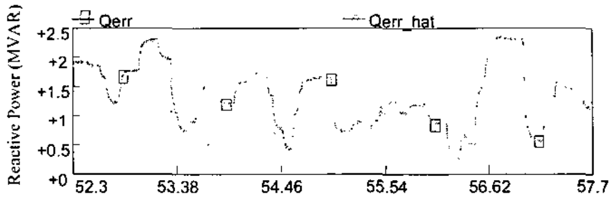

Fig. 14 Actual signal Q_{err} and identified signal $\hat{Q}_{err}$ for series branch.

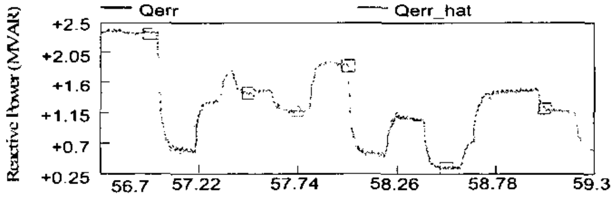

Fig. 15 Actual signal Q_{err} and identified signal $\hat{Q}_{err}$ for series branch.

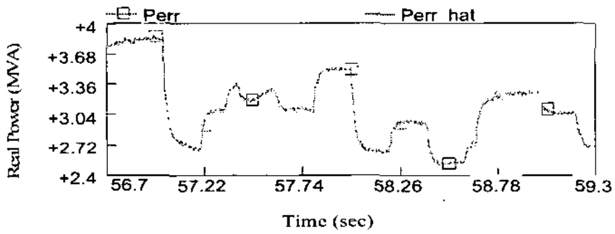

Fig. 16 Actual signal P_{err} and identified signal $\hat{P}_{err}$ for series branch.

C. Phase 3 - Identification of both branches of UPFC

In this phase the series and shunt branches are identified together by applying simultaneously the PRBS training signals to the shunt and series branches of the UPFC. Figures 17 and 18 show the responses for the shunt branch. Figures 19 and 20 show the responses for the series branch. It is once again observed that the SHNI and SENI identify the dynamics of the UPFC and the power system sufficiently well to implement a potential adaptive neurocontrol scheme to improve the transient stability performance of the power system.

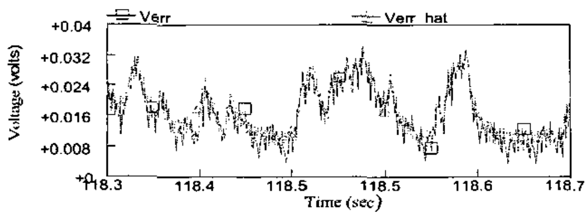

Fig. 17 Actual signal V_{err} and identified signal $\hat{V}_{err}$ for shunt branch.

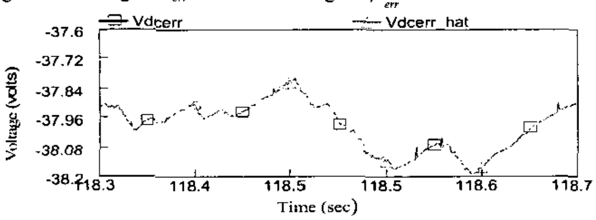

Fig. 18 Actual signal V_{dcerr} and Identified signal $\hat{V}_{dcerr}$ for shunt branch.

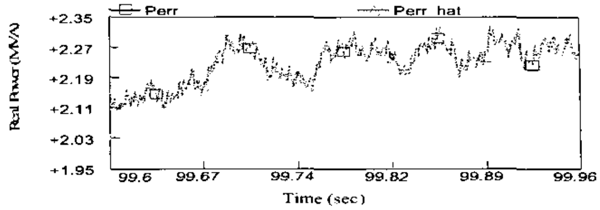

Fig. 19 Actual signal P_{err} and identified signal $\hat{P}_{err}$ for series branch.

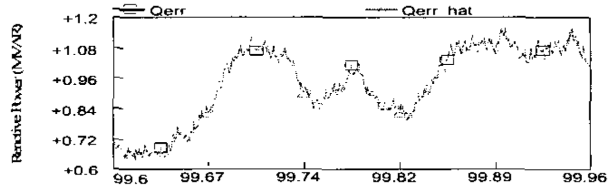

Fig. 20 Actual signal Q_{err} and Identified signal $\hat{Q}_{err}$ for series branch.

VI. CONCLUSION

In this paper, neuroidentifiers trained online to dynamically identify the system parameters that determine UPFC controller outputs has been proposed. These neuroidentifiers aid in the design of neurocontrollers, which are versatile in controlling the UPFC at various operating points. Identification of shunt and series branches of UPFC plays an important role for the successful implementation of indirect adaptive neurocontrol which is envisaged to be the next task to improve the transient stability performance of the power system. Further, these neuroidentifiers learns the dynamics of the shunt and series branches very fast, which is very important for real time implementation. Current work involves extension of this paper to carry out similar neuroidentification on multimachine power systems.

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