International Journal of Computational Intelligence in Control, 8(1), 2016

Excitation Control for Damping Inter-Area Oscillations through Recurrent Neural Networks

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Abstract: *In order to effectively restrain inter-area oscillations in power systems, a local measurement based neural excitation controller is proposed to generate global stable signal. This is to replace the global measurement based power system stabilizer (GPSS). The proposed neural controller is constructed by two recurrent neural networks: a recurrent neural identifier (RNID) and a recurrent neural controller (RNCT). Non-measurable global dynamics in large-scale multi-machine power systems is estimated by the RNID and is provided to RNCT in order to generate global stable signals for a higher hierarchy of supplementary excitation control. Simulation results based on Kundur's 2-area 4-machine power system model proved the effectiveness of the proposed local signal based neural identifier and controller in damping inter-area oscillations.*

Keywords: *Excitation control, inter-area oscillation, recurrent neural networks, local signal*

I. INTRODUCTION

Poorly damped low-frequency oscillation is a main cause for instability in power systems. According to [5], power system low-frequency oscillations are classified into two modes: *local modes* with frequency between 0.7~3Hz representing oscillations between one generator and the rest of power grid or oscillations among several adjacent synchronous power generators; and *inter-area modes* with frequency between 0.2~0.7Hz representing swings among different power grids interconnected through tie-lines. For damping low frequency oscillations, synchronous generator excitation control has been proven to be an effective approach. Power system stabilizer is proposed in [2] using local measurements as inputs to generate supplementary stable signal to damp out local mode power system oscillations. However, inter-area mode oscillations among weakly connected power areas are difficult to be damped out only by local-signal based PSS for its lacking of controllability and observability of the global dynamics in power systems.

Consequently with the advanced techniques of remote communication, the global signal based PSS (GPSS) is proposed by introducing remote measurements as inputs. Since the late 90's, researches on remote signal based PSS have been conducted in order to damp out inter-area oscillations more effectively. By extracting electrical power exchanges and bus voltages from remote transmission lines, [6] propose a residue location method for designing remote signals based PSS to improve both damping and

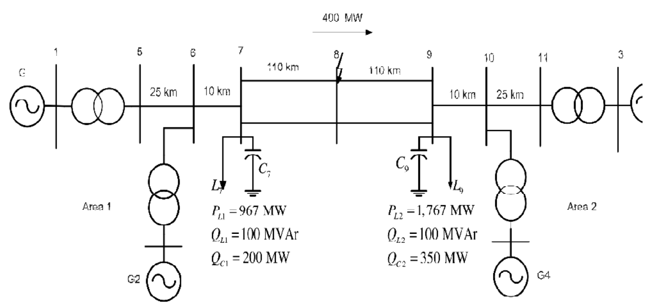


Figure 1: Kundur's 2-area 4-machine Power System Model

synchronizing torques for inter-area oscillation in multiple machine power systems. In [4], a decentralized/hierarchical approach for designing wide-area measurement based stabilizing control on Hydro-Quebec's transmission system is proposed. In that approach, frequency differences between inter-oscillated power grids are obtained from phasor measurement units (PMU) and are used as inputs to global PSS. However, the measurement of remote signal requires additional communication system which lowers the reliability of the control system as well as the time delay and loss of data during communication transmission periods.

According to their universal approximation capability, feedforward and recurrent neural networks are widely used in fields of pattern recognition, classification, system identification and control. Based on the multilayer feed-forward and recurrent neural networks, [8] investigates several types of neural network based system identification and control approaches including parallel mode system identification, series-parallel modes for system identification, direct and indirect adaptive nonlinear control. Besides, static and dynamic back propagation methods are also discussed in [1] for the purpose of offline training of neural identifiers and controllers. In [7], different types of neural network control strategies are surveyed including model predictive control, model reference control and NARMA-L2 control. As a result, neural networks are also widely used in power engineering for identifying power system dynamics and approximating nonlinear controller as substitutions to traditional linear controllers which are designed based on linearized models. For single machine infinite bus system, [3] proposes a method for designing excitation and speed governor controller through neural network based identifier and feedback linearization approach. Reference [1] discusses fuzzy based functional neural networks for excitation control designs; [12] presents excitation control design approach by combining inverse system method and neural networks. In order to enhance the excitation controller performance in time-varying power system with changing network parameters and operation points, [9] presents a continually

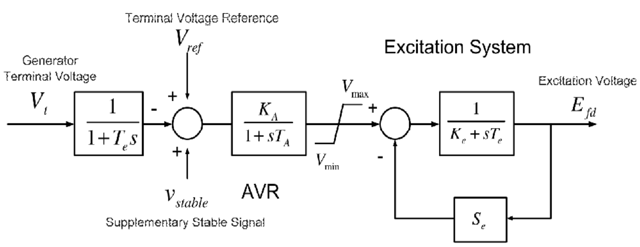


Figure 2: Block Diagram of Automatic Voltage Regulator (AVR) and DC Excitation System

online-trained neural controller by using multilayer perception neural networks as both system identifier and excitation controller. Both identifier and controllers are trained on-line to approximate system dynamics and achieve adaptive control from time to time. Reference [10] presents optimal and adaptive excitation control methods based on different kinds of adaptive critic designs including heuristic dynamic programming, dual heuristic programming and different types of neural networks including multilayer perception and radial basis neural networks.

As a natural consequence, problems rise up on how to combine remote signal based power system control and neural identification and control strategies by taking advantages of both sides. Furthermore, how to use neural network to damp out power system inter-area oscillations only based on local measurements is an attractive and promising topic. In [11], the authors present an adaptive-critic based optimal wide area control strategy for generator excitation systems by combining neural networks, approximated dynamic programming and global signal based excitation control together. Although this approach achieves nonlinear design and online-adaptation of wide area excitation control scheme, the controller still requires remote signals as control inputs.

As a dynamic system itself, the recurrent neural network holds the capability of predicting system dynamics without receiving some non-measurable system states. Therefore, there exists the possibility to approximate global dynamics merely based on local measurements in power systems through the approach of recurrent neural networks. In this paper, we propose a novel approach to design recurrent neural network based controller for generating global stable excitation signal based on local measurements. Our basic idea is to use the compensation capability of recurrent neural networks to estimate power system global dynamics only from local measurement inputs, and then to extract estimated global dynamic signals from system identifier to generate global stable signal through neural controller. Therefore, the local signal based system identifier and controller is capable of replacing the remote signal based GPSS. Our design consists of two parts: a recurrent neural identifier (RNID) and a recurrent neural controller (RNCT). Based on local measurements, the RNID uses a three-layer recurrent neural network to estimate rotor speed and terminal voltage. The RNCT is another three-layer recurrent neural network which uses both local measurements from generator and hidden neurons of RNID as inputs to provide approximated global stable signal.

The performance of the proposed recurrent neural identifier and neural controller is verified in Kundur's two-area four-machine power system. The RNID and RNCT are trained offline at first in batch forms before applied as online identifier and controller. Simulation results show that the local signal based RNID and RNCT can be a satisfactory substitution of GPSS to damp out inter-area oscillations efficiently.

II. POWER SYSTEM MODEL AND EXCITATION CONTROL STRATEGIES

Fig. 1 shows Kundur's 2-area 4-machine power system model consisting of two symmetrical areas interconnected by a 220km two-looped weak tie-line. G1-G4 are synchronous generators with rating of 900MVA and 20kV which consist two power areas –Area1 and Area2 respectively. The transmission system nominal voltage is 230kV. The local loads of two areas and the active power transmitted on tie-line are shown in Fig. 1. The parameters of generators, transformers, transmission lines, speed governor, and excitation controllers can be referred from [5].

The low frequency oscillation modes in Fig. 1 include two local modes and one inter-area mode. The two local oscillation modes are the swing between G1 and G2, and the swing between G3 and G4, respectively. The inter-area mode is the oscillation between Area1 and Area2 connected by transmission tie line. Fig. 2 shows the block diagram of

DC excitation system with automatic voltage regulator (AVR).

In Fig. 2, the signal v_{stable} represents the stable signal provided by supplementary control strategies which can be local signal based power system stabilizer PSS or global signal based power system stabilizer GPSS. The block diagram of PSS and GPSS are shown in Fig. 3 and Fig. 4, respectively.

The gain, washout and compensator blocks constitute the power system stabilizer's framework. In the case of GPSS, remote signals such as tie-line power exchanges $\Delta P_{exchange}$ or frequency differences $\Delta\omega_i - \Delta\omega_j$ between different areas can be introduced as inputs, as shown in Fig. 4.

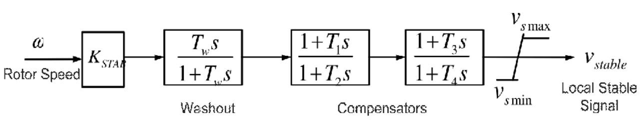


Figure 3: Local Signal Based Power System Stabilizer (PSS)

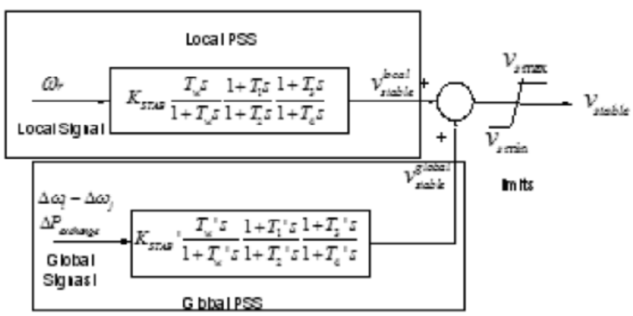


Figure 4: Remote/global Signal based Power System Stabilizer (GPSS)

The residue compensation method can be applied for tuning parameters of local signal based PSS as well as global signal based GPSS [6]. Suppose G_j is the open-loop transfer function for a certain input /output of the j^{th} generator:

$$G_j = y_j / u_j. \tag{1}$$

R_{ij} is the residue associated with the i^{th} low-frequency oscillation mode λ_i and j^{th} transfer function G_j:

$$R_{ij} = \lim_{s\to\lambda_i}(s-\lambda_i)G_j(s) \tag{2}$$

In order to add the damping of current oscillation mode λ_i by shifting it to $\lambda_i' = \lambda_i + \Delta\lambda_i$, the transfer function parameters of global signal based PSS can be tuned to satisfy Equation (3):

$$\Delta\lambda_i = R_{ij} G^{stable}_{global}(\lambda_i).. \tag{3}$$

III. PROPOSED NEURAL IDENTIFIER AND CONTROLLER ARCHITECTURE

Fig. 5 shows the overall framework of excitation control strategies applied on Kundur's 4-machine 2-area power system. In this paper, all generators from G1 to G4 are equipped with AVR. G1 and G2 are equipped with local PSS in order to restrain the poorly damped local oscillation mode between G1 and G2. In order to restrain poorly damped inter-area oscillation between area1 and area2, two options can be adopted as the additional hierarchy of supplementary excitation strategies*:*

1. Remote/global signals of area speed difference ($\Delta\omega_1 + \Delta\omega_2 - \Delta\omega_3 - \Delta\omega_4$) based GPSS on G2, or
2. Local signals including shaft speed, terminal voltage, excitation voltage and accelerating power (ω_2, V_{t2}, E_{fd2}, P_{a2}) based recurrent neural identifier (RNID) and controller (RNCT) on G2;

Fig. 6 shows the architecture of the proposed recurrent neural identifier and controller. Both RNID and RNCT are two layered recurrent neural networks. The hidden neuron of RNID is introduced as partial inputs to RNCT to provide estimated global signals.

With sampling time T_s, 5 time delays of local measurements ω_2, V_{t2}, E_{fd2}, P_{a2} are used as inputs of RNID. 4 time delays of ω_2, V_{t2} with their immediate values and the hidden neuron of RNID are used as inputs of RNCT in order to generate approximated global stable signal $\hat{v}^{global}_{stable}$. Both RNID and RNCT are trained offline in batch forms shown in equations (4)-(12). The training error to be minimized in RNID is:

$$E_i = \sum_t \frac{1}{2}\begin{bmatrix}\Delta\hat{\omega}_2(t)-\Delta\omega_2(t) & \Delta\hat{V}_{t2}(t)-\Delta V_{t2}(t)\end{bmatrix} S \begin{bmatrix}\Delta\hat{\omega}_2(t)-\Delta\omega_2(t)\\ \Delta\hat{V}_{t2}(t)-\Delta V_{t2}(t)\end{bmatrix} \tag{4}$$

$\Delta\hat{\omega}_2, \Delta\hat{V}_{t2}$: estimated speed deviation and terminal voltage of G2 obtained from RNID;

$\Delta\omega_2$, ΔV_{t2}: actual speed deviation and terminal voltage of G2;

S: Weight matrix, in this case $S = \text{diag}(100,1)$;

The training error to be minimized in RNCT is:

$$E_c = \sum_t (\hat{v}^{global}_{stable}(t) - v^{global}_{stable}(t))^2/2\ , \tag{5}$$

$\hat{v}^{global}_{stable}$: approximated global signal generated by RNCT;

v^{global}_{stable} : global stable signal generated by GPSS;

As shown in Equation (6), the steepest gradient offline-training approach is the most basic method for training multilayer neural networks. We use it to illustrate the way how to train RNID and RNCT:

$$\begin{aligned} W^{ID}(k+1) &= W^{ID}(k) - \beta_i \partial E_i(k)/\partial W^{ID}(k) \\ W^{CT}(k+1) &= W^{CT}(k) - \beta_c \partial E_c(k)/\partial W^{CT}(k) \end{aligned} \tag{6}$$

β_i, β_c: learning rates of RNID and RNCT; *k*: iteration index in training

Equation (6) will be carried out iteratively until the stopping criteria are satisfied. The partial derivatives $\partial E_i / \partial W^{ID}$ and $\partial E_c / \partial W^{CT}$ in Equation (6) can be calculated as:

$$\frac{\partial E_i}{\partial W^{ID}} = \sum_t \left[\frac{\partial \Delta\hat{\omega}_2}{\partial W^{ID}} \quad \frac{\partial \Delta\hat{V}_{t2}}{\partial W^{ID}} \right] S \begin{bmatrix} \Delta\hat{\omega}_2(t) - \Delta\omega_2(t) \\ \Delta\hat{V}_{t2}(t) - \Delta V_{t2} \end{bmatrix} \tag{7}$$

$$\frac{\partial E_c}{\partial W^{CT}} = \sum_t (\hat{v}^{global}_{stable} - v^{global}_{stable}) \frac{\partial \hat{v}^{global}_{stable}}{\partial W^{CT}} \tag{8}$$

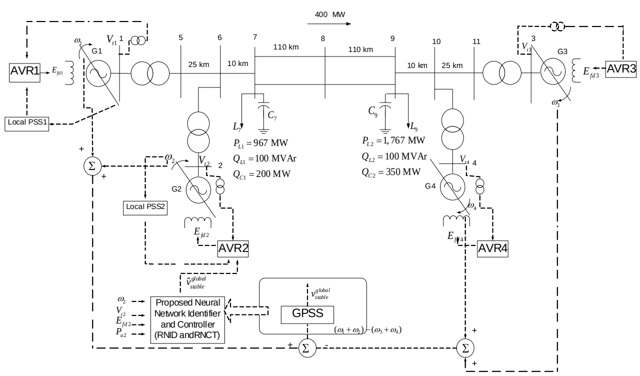


Figure 5: Overall Architecture of Excitation Controls on Kundur's two Area Power System

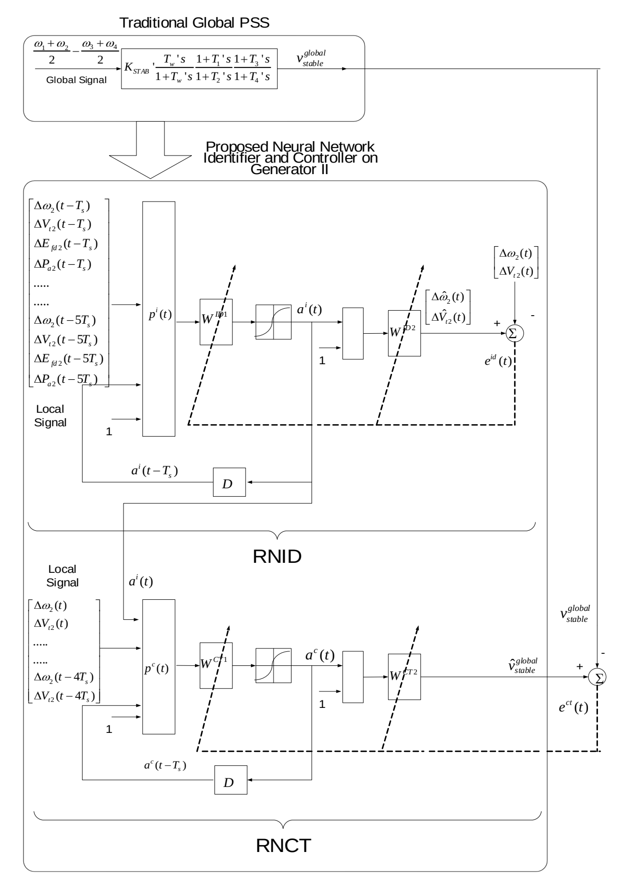
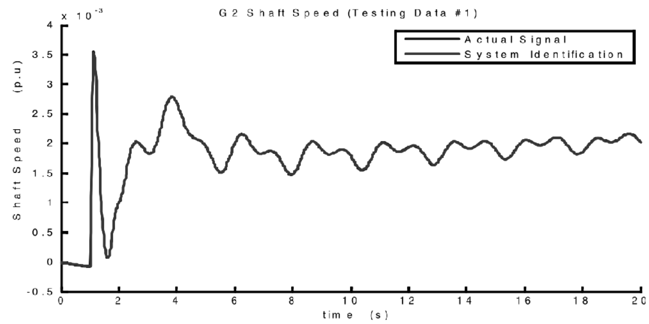


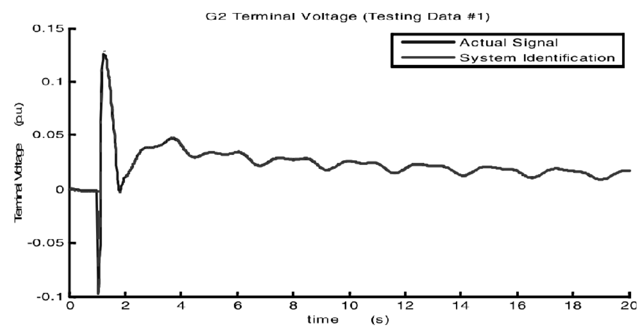
Figure 6: Proposed Neural Network Identifier and Controller

For recurrent neural networks, the training process requires back propagation through time method. Equations (9)-(12) show the backpropatation-through-time training procedure for all layers of RNID and RNCT.

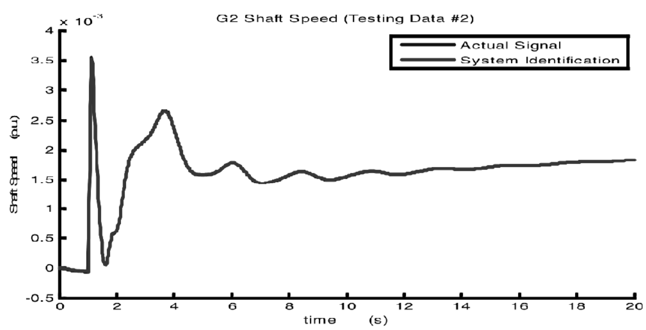
For the 2nd layer of RNID:



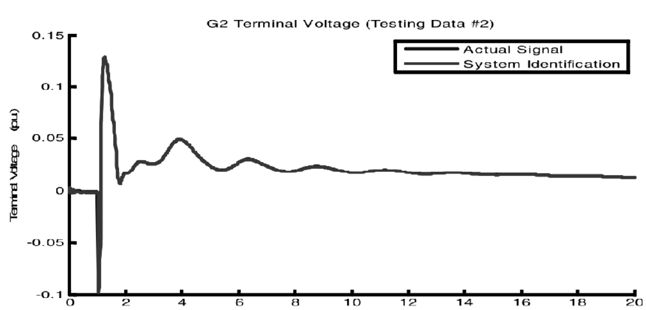
(a) Testing Data # 1 $\Delta\omega_2 / \Delta\hat{\omega}_2$



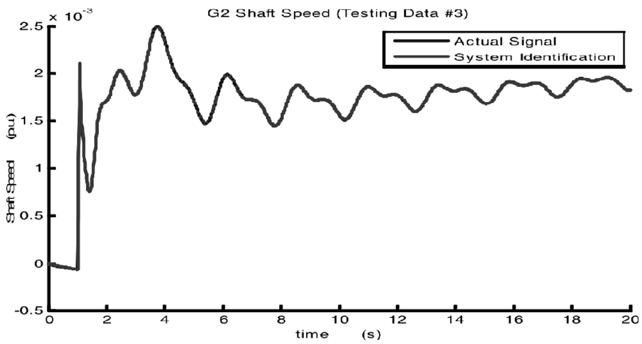
(b) Testing Data # 1 $\Delta V_{t2} / \Delta\hat{V}_{t2}$



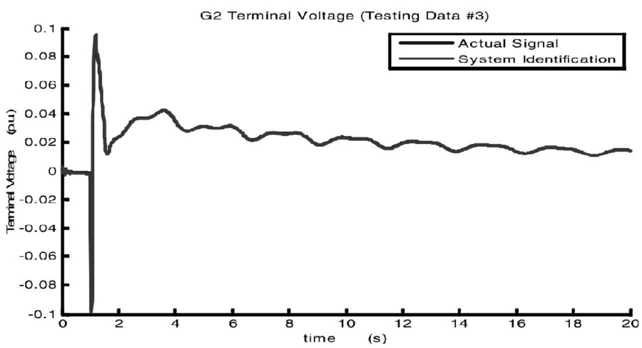
(c) Testing Data # 2 $\Delta\omega_2 / \Delta\hat{\omega}_2$



(d) Testing Data # 2 $\Delta V_{t2} / \Delta\hat{V}_{t2}$

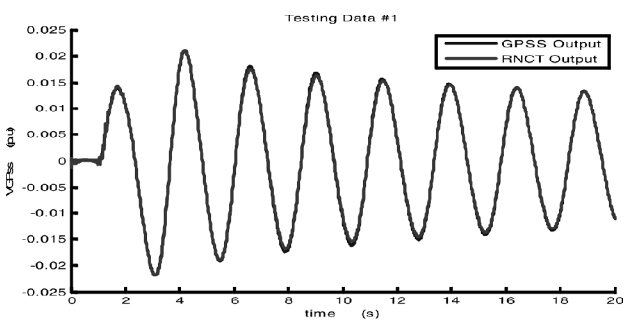


(e) Testing Data # 3 $\Delta\omega_2 / \Delta\hat{\omega}_2$

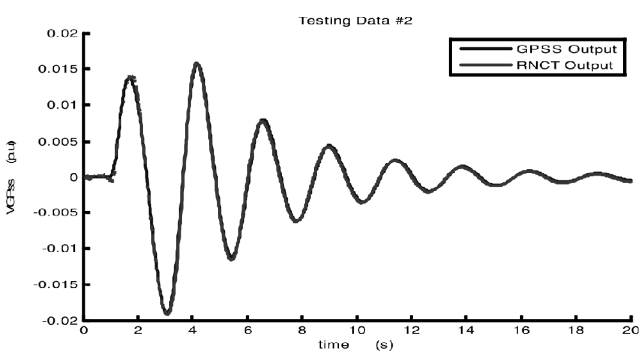


(f) Testing Data # 3 $\Delta V_{t2} / \Delta\hat{V}_{t2}$

Figure 7: Offline Testing Results of RNID based on 3 Sets of Testing Data



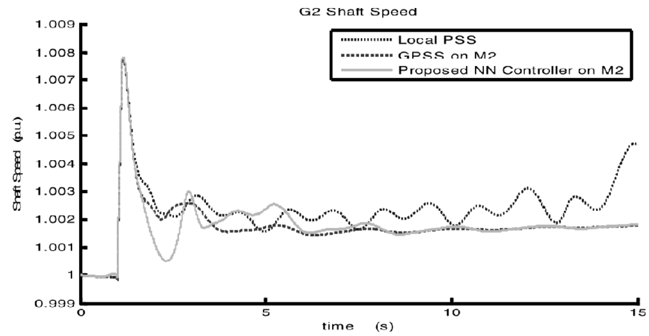
(a) Testing Data # 1 $\Delta v_{stable}^{global} / \Delta\hat{v}_{stable}^{global}$



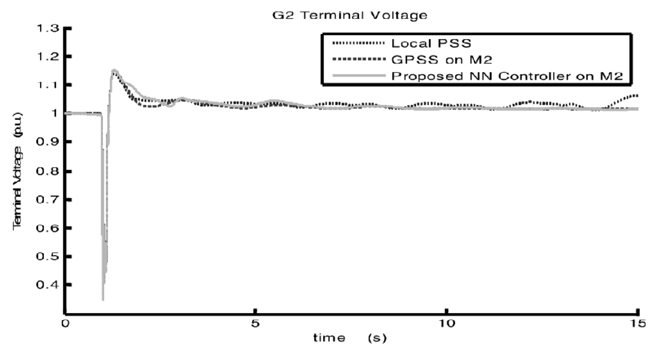
(b) Testing Data # 2 $\Delta v_{stable}^{global} / \Delta\hat{v}_{stable}^{global}$

Figure 8: Offline Testing Results of RNCT based on 2 Sets of Testing Data

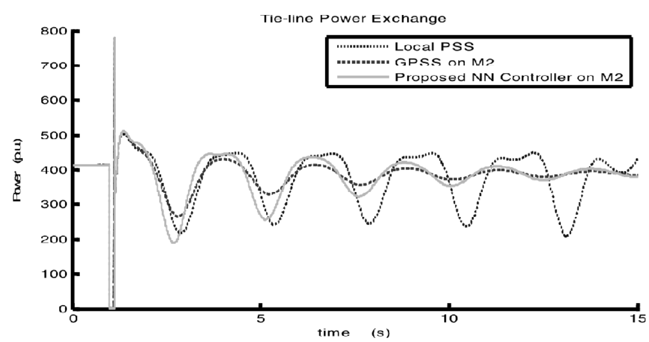
Caste 1: Disturbance 1: three-phase short circuit fault occured at t = 1. 0s on Bus #7 with 0.2s Duration



(a) ω_2



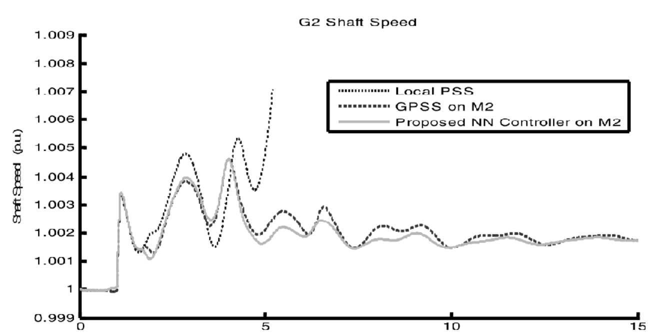
(b) V_{t2}



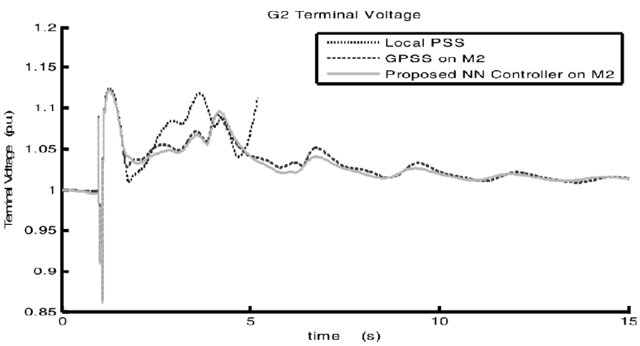
(c) $P_{exchange}$

Figure 9: System Responses with three Phase Short Circuit Fault at Bus #7

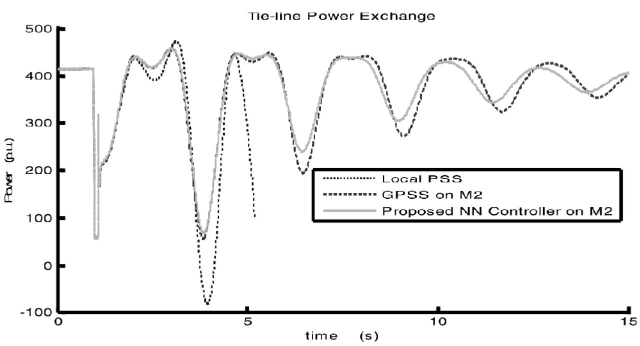
Caste 2: Disturbance 3: Three-phase Short Circuit Fault Occurred at t = 1.0s on Bus #9 with 0.18s Duration



(a) ω_2



(b) V_{t2}



(c) $P_{exchange}$

Figure 10: System Responses with three Phase Short Circuit Fault at Bus #9

$$\begin{bmatrix} \dfrac{\partial \Delta\hat{\omega}_2(t)}{\partial W^{i2}} & \dfrac{\partial \Delta\hat{V}_{t2}(t)}{\partial W^{i2}} \end{bmatrix} = \begin{bmatrix} \dfrac{\partial^e \Delta\hat{\omega}_2}{\partial W^{i2}} & \dfrac{\partial^e \Delta\hat{V}_{t2}(t)}{\partial W^{i2}} \end{bmatrix} \tag{9}$$

where ∂^e means explicitly derivative.

For the 1st layer of RNID:

$$\begin{bmatrix} \dfrac{\partial \Delta\hat{\omega}_2(t)}{\partial W^{i1}} & \dfrac{\partial \Delta\hat{V}_{t2}(t)}{\partial W^{i1}} \end{bmatrix} = \begin{bmatrix} \sum_{n=t}^{1} \dfrac{\partial^e \Delta\hat{\omega}_2(t)}{\partial a^i(n)} \dfrac{\partial a^i(n)}{\partial W^{i1}} & \sum_{n=t}^{1} \dfrac{\partial^e \Delta\hat{V}_{t2}(t)}{\partial a^i(n)} \dfrac{\partial a^i(n)}{\partial W^{i1}} \end{bmatrix} \tag{10}$$

For the 2nd layer of RNCT:

$$\frac{\partial \hat{v}_{stable}^{global}(t)}{\partial W^{a2}} = \frac{\partial^e \hat{v}_{stable}^{global}(t)}{\partial W^{a2}}. \tag{11}$$

For the 1st layer of RNCT:

$$\frac{\partial \hat{v}_{stable}^{global}(t)}{\partial W^{a1}} = \sum_{n=t}^{1} \frac{\partial^e \hat{v}_{stable}^{global}(t)}{\partial a^a(n)} \frac{\partial a^a(n)}{\partial W^{a2}}. \tag{12}$$

Since the convergence rate by using steepest decent method is very slow, a much faster strategy named Levenberg-Marquardt (LM) method is widely used. In the following section, the LM method is used for offline training of RNID and RNCT.

IV. SIMULATION RESULTS

The simulation study is conducted on the 2-area power system shown in Fig. 5. Before online application, RNID and RNCT are firstly trained offline with sample time T_s=0.02s. A batch of training data are obtained by applying random input deviations to supplementary excitation control signal, as well as introducing three-phase fault at bus 8. In case of offline training and testing, the proposed controller is disconnected to excitation system in order to get open-looped outputs. Online application of RNID and RNCT are conducted successively to replace GPSS controller on G2 generator. The online application performance of RNID and RNCT is compared with that of GPSS.

(A) Offline Training and Testing

Both RNID and RNCT are trained by using Levenberg-Marquardt back-propagation through time method based on a batch of training data obtained by different disturbances. After training, 3 sets of testing data are introduced to RNID and 2 sets of testing data are introduced to RNCT. Figs. 7 and 8 show the offline testing results of RNID and RNCT respectively. In Fig. 7, the solid curves represent actual speed and voltage deviation signals, whereas dashed curves represent estimated states obtained from RNID. In Fig. 8, the solid curves represent GPSS output stable signal whereas dashed curves represent RNCT output stable signal.

Figs. 7 and 8 show that based on the accurate approximation capability of RNID for estimating system dynamics, the RNCT is able to approximate the global stable signal generated from GPSS successfully. The online performance of RNID and RNCT are shown in the following.

(B) Online Simulation Results

After offline training, the RNID and RNCT are applied online to generate supplementary global stable signal as the substitution to remote signal based GPSS. Three-phase short circuit faults are introduced to Bus #7 and Bus #9 (see Fig. 5) with the corresponding system responses shown in Figs. 9-10 respectively. In Figs. 9-10, Dotted lines represent system dynamics with only local PSS applied; dashed lines represent system response with GPSS applied; and solid lines represent system dynamics with RNID and RNCT equipped. The responses of G2 rotor speed ω_2, G2 terminal voltage V_{t2} and exchange power from Area1 to Area2 are recorded.

Figs. 9-10 show that the proposed NN controller successfully damps out inter-area oscillations in Kundur's 2-area power system. Especially in Fig. 10, the performance of local signal based RNID and RNCT overwhelms the global signal based GPSS. Simulation results prove that the proposed neural identifier and controller is a practical substitution of the remote signal based GPSS, and is robust for difference fault locations.

V. CONCLUSION AND PERSPECTIVE

A novel recurrent neural identification/control architecture for excitation systems is proposed to damp out inter-area power system oscillations based on local measurements. Two neural networks named RNID and RNCT are used for identifying system dynamics and generating global stable control signals respectively. By the predicted non-measurable global information from RNID, RNCT generates global stable signal for generator excitation system. After offline training in batch forms, online application on Kundur's 2-area power system is successfully conducted which show the effectiveness of the proposed neural controller for damping out inter-area oscillations. Simulation results show that the proposed RNID and RNCT can be a good substitution of the GPSS with robust performances according to different perturbation location in power systems.

Since the power system is a time-varying system with structure and parameter changes during its operations, the future design of our algorithm must take those uncertainties into consideration. The adaptation of the proposed neural identifier and controller with respect to operation changes must be considered in the future. Recent researches have been carried out on on-line tuning of neural controller parameters which provides a good approach for the further development of our proposed algorithm. On the other hand, the neural controller proposed in this paper is far from optimal, how to optimize its control performance is another issue needed to be taken into account. As online adaptive and optimal tuning methods to optimize the neural controller performance over a specified (or infinite) time horizon, model predictive control and adaptive critics will provide a good direction for future improvements of our proposed identifier and controller.

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