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# Neural Network Based Decentralized Controls of Large Scale Power Systems

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**Abstract**—This paper presents a suite of neural network (NN) based decentralized controller designs for large scale power systems' generators, one is for the excitation control and the other is for the steam valve control. Though the control inputs are calculated using local signals, the transient and overall system stability can be guaranteed. NNs are used to approximate the unknown and/or imprecise dynamics of the local power system dynamics and the inter-connection terms, thus the requirements for exact system parameters are relaxed. Simulation studies with a three-machine power system demonstrate the effectiveness of the proposed controller designs.

## I. INTRODUCTION

POWER systems are large scale, distributed and highly nonlinear systems with fast transients. One difficulty in controller design is the coordination of the control activities for the subsystem controllers. Due to technical and economic reasons, the concept of centralized control is not applicable. A decentralized control strategy achieves subsystem design separately, requiring local information measurement only or with a minimum amount of information from other subsystems.

The traditional decentralized control strategies of power systems were based on linearized system models at some operating points. The selection of base operating points and tuning of parameters are quite empirical. Furthermore, the controllers' performance cannot be guaranteed under certain unforeseen large disturbances.

Since the differential geometric method was introduced to nonlinear control systems design, various stabilizing control results [1, 2] are reported based on nonlinear multimachine power system models. However, a problem observed with the differential geometric based nonlinear controller designs is the need for the exact knowledge of the system dynamics. Imprecise knowledge of the system dynamics will greatly degrade the performance of controller designs. Since it is not possible to know the system dynamics accurately and to enhance robustness of systems, numerous results on the decentralized nonlinear robust control of power systems, such as [3~5] is introduced. In all these papers, the stability and robustness of the control system were demonstrated using Lyapunov analysis.

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Neural networks have been proven to be an excellent tool for function approximation. NN have been widely used in the indirect and direct types of nonlinear controller designs. Recently, NN were applied to the design of decentralized controllers, such as [6]. In these papers, NNs are used to approximate the unknown nonlinear dynamics of the subsystems and to compensate the unknown nonlinear interactions. Though only local information/measurement are used to design the controllers for subsystems, stability of the overall system and coordination of subsystem controllers can be guaranteed. However, most NN based decentralized control designs are only applicable to nonlinear systems in Brunovsky Canonical Form. To overcome this limitation and to extend the design to a broader class of nonlinear systems, a decentralized NN controller design for the control of a class of more general large-scale nonlinear systems was proposed in [7]. The first or higher order polynomial bound assumption of earlier works on the unknown interconnection terms can be treated here as special cases.

In this paper, the controller design in [7] is extended and introduced to the decentralized excitation and steam valve controls of large-scale power systems. It is shown that the transient stability can be enhanced by both excitation and steam valve control loops. The excitation control is in the form of feedback linearization and the steam valve control is in the form of backstepping. Since the steam valve control model does not satisfy the matching condition, the steam valve control design is more complex than that of excitation control. If more detailed excitation system model is considered, the excitation controller can be designed in the same way as steam valve control. The controller designs in this paper can also be used to enhance the decentralized control of power systems described with differential algebraic equations (DAE) in [8].

## II. DYNAMIC MODELS OF LARGE SCALE POWER SYSTEMS

Following model is used to represent a large scale power system with  $n$  interconnected generators

$$\begin{cases} \dot{\delta}_i = \omega_i \\ \dot{\omega}_i = -\frac{D_i}{2H_i}\omega_i + \frac{\omega_0}{2H_i}(P_{mi} - P_{ei}) \\ E'_{qi} = \frac{1}{T_{d0i}}(E_{fi} - E_{qi}) \\ \dot{P}_{mi} = -\frac{1}{T_{mi}}P_{mi} + \frac{K_{mi}}{T_{mi}}X_{ei} \\ \dot{X}_{ei} = -\frac{K_{ei}}{T_{ei}R_i}\omega_i - \frac{1}{T_{ei}}X_{ei} + \frac{1}{T_{ei}}P_{ci} \end{cases} \quad (1)$$

where  $i=1, \dots, n$ ,  $\delta_i$  is the power angle in rad,  $\omega_i$  is the relative speed in rad/s,  $D_i$  is the per unit damping constant,  $H_i$  is the inertia constant in second,  $P_{mi}$  is the mechanical input power in p.u.,  $P_{ei}$  is the electrical power in p.u.,  $E_{qi}$  is the q-axis internal transient electric potential in p.u.,  $E_{fi}$  is the EMF in the quadrature axis in p.u.,  $E_{fi}$  is the equivalent EMF in the excitation coil in p.u.,  $P_{mi}$  is the mechanical input power in p.u.,  $X_{ei}$  is the steam valve opening in p.u.,  $K_{mi}$  is the gain of the turbine,  $K_{ei}$  is the gain of the speed governor,  $T_{mi}$  is the time constant turbine in second,  $T_{ei}$  is the time constant of the speed governor in second,  $R_i$  is the regulation constant in p.u., and  $P_{ci}$  is the power control input in p.u..

The following equations are necessary to calculate  $E_{qi}$  and  $P_{ei}$  from the algebraic power network equations.

$$E_{qi} = E'_{qi} + (x_{di} - x'_{di})I_{di}$$

$$\begin{cases} P_{ei} = E'_{qi} \sum_{j=1}^n E'_{qj} B_{ij} \sin(\delta_i - \delta_j) \\ Q_{ei} = -E'_{qi} \sum_{j=1}^n E'_{qj} B_{ij} \cos(\delta_i - \delta_j) \end{cases} \begin{cases} I_{di} = -\sum_{j=1}^n E'_{qj} B_{ij} \cos(\delta_i - \delta_j) \\ I_{qi} = \sum_{j=1}^n E'_{qj} B_{ij} \sin(\delta_i - \delta_j) \end{cases} \quad (2)$$

where  $Q_{ei}$  is the reactive power in p.u.,  $I_{di}$  is the direct axis current in p.u.,  $I_{qi}$  is the quadrature axis current in p.u., and  $B_{ij}$  is the  $i$ th row and  $j$ th column element of nodal susceptance matrix at the internal nodes after eliminating all physical buses in p.u. [5].

#### A. Model for excitation controller design

Since the time constants of the turbine control loop are much larger than that of the excitation control loop, mechanical power input to the generator is assumed to be constant, which is  $P_{mi} = P_{mi0}$ . For simplification, electrical power deviation  $\Delta P_{ei}$ , defined as  $\Delta P_{ei} = P_{ei} - P_{mi0}$ , is introduced as a new state variable. After transformation, the model becomes

$$\begin{cases} \dot{\delta}_i = \omega_i \\ \dot{\omega}_i = -\frac{D_i}{2H_i} \omega_i - \frac{\omega_0}{2H_i} \Delta P_{ei} \\ \Delta \dot{P}_{ei} = -\frac{1}{T'_{doi}} \Delta P_{ei} + \frac{1}{T'_{doi}} v_{fi} + \gamma_i(\delta, \omega) \end{cases} \quad (3)$$

where  $v_{fi}$  is the control signal for the transformed system model,  $\gamma_i(\delta, \omega)$  is called the interconnection term because it is function of state variables other than the  $i$ th subsystem.  $v_{fi}$  and  $\gamma_i(\delta, \omega)$  are defined according to (4) and (5) respectively. The process resulting the following equations can be found in [1].

$$\gamma_i(\delta, \omega) = E'_{qi} \sum_{j=1}^n \dot{E}'_{qj} B_{ij} \sin(\delta_i - \delta_j) - E'_{qi} \sum_{j=1}^n E'_{qj} B_{ij} \cos(\delta_i - \delta_j) \omega_j \quad (4)$$

$$v_{fi} = I_{qi} E_{fi} - (x_{di} - x'_{di}) I_{qi} I_{di} - P_{mi} - T'_{doi} Q_{ei} \omega_i \quad (5)$$

If  $v_{fi}$  is designed as the control signal for the transformed model, then the actual control signal  $E_{fi}$  can be calculated according to (5) from locally measurable variables.

Our decentralized controller design requires the bound of the interconnection term to be expressed as a sum of functions of subsystem signals. Same assumption as [4] is adopted here, that is “ $E_{fi}$  may rise by up to  $k$  times of the  $E_{qi}$ , with  $k > 1$ ”.

It is necessary to note that we are not assuming the exact value of  $k$  to be known. We are assuming the ratio between  $E_{fi}$  and  $E_{qi}$  is known instead. During the controller design, the impact of  $k$  will be approximated by NNs.

According to [5],  $\gamma_i(\delta, \omega)$  is bounded according to

$$|\gamma_i(\delta, \omega)| \leq \sum_{j=1}^n (\gamma_{i1j} |\sin \delta_j| + \gamma_{i2j} |\omega_j|) \leq \sum_{j=1}^n (\gamma_{i1j} |\delta_j| + \gamma_{i2j} |\omega_j|) \quad (6)$$

where  $\gamma_{i1j}$  and  $\gamma_{i2j}$  are unknown constants decided by system parameters.

The model can be further simplified into (7) by introducing a new state vector  $x_i = [x_{i1} \ x_{i2} \ x_{i3}]^T = [\delta_i - \delta_{i0} \ \omega_i \ \dot{\omega}_i]^T$ .

$$\begin{cases} \dot{x}_{i1} = x_{i2} \\ \dot{x}_{i2} = x_{i3} \\ \dot{x}_{i3} = f_i(\cdot) + u_i + \Delta_i(x) \end{cases} \quad (7)$$

where  $f_i(\cdot) = k_{i1}x_{i2} + k_{i2}x_{i3}$  with  $k_{i1-3}$  defined as  $k_{i1} = -D_i/(2H_i T_{doi})$ ,  $k_{i2} = -D_i/(2H_i) - 1/T_{doi}$ ,  $k_{i3} = -\omega_0/(2H_i T_{doi})$  correspondingly,  $\Delta_i(x) = -\omega_0/(2H_i) \gamma_i(x)$ , and the newly introduced control signal  $u_i$  is defined as  $u_i = -\omega_0/(2H_i T_{doi}) v_{fi}$ .

After transformation, the bound of the interconnection terms can be expressed as (8).

$$|\Delta_i(x)| \leq \sum_{j=1}^n \delta_{ij} (|x_{j1}|, |x_{j2}|) \quad (8)$$

#### B. Model for the steam valve controller design

The following set of equations is used in our decentralized steam valve controller design.

$$\begin{cases} \dot{\delta}_i = \omega_i \\ \dot{\omega}_i = -\frac{D_i}{2H_i} \omega_i + \frac{\omega_0}{2H_i} (P_{mi} - P_{ei}) \\ \dot{P}_{mi} = -\frac{1}{T_{mi}} P_{mi} + \frac{K_{mi}}{T_{mi}} X_{ei} \\ \dot{X}_{ei} = -\frac{K_{ei}}{T_{ei} R_i \omega_0} \omega_i - \frac{1}{T_{ei}} X_{ei} + \frac{1}{T_{ei}} P_{ci} \end{cases} \quad (9)$$

For this steam valve control model,  $P_{ei}$  is the interconnection term. According to [5],  $P_{ei}$  is bounded by (10).

$$|P_{ei}| \leq \sum_{j=1}^n g_{ij} |\sin \delta_j| \leq \sum_{j=1}^n g_{ij} |\delta_j| \quad (10)$$

where  $g_{ij}$  are unknown constants decided by generation capacities.

Define  $\Delta P_{mi} = P_{mi} - P_{mi0}$ ,  $\Delta X_{ei} = X_{ei} - X_{ei0}$ , where  $P_{mi0}$  and  $X_{ei0}$  are the stable values of  $P_{mi}$ ,  $X_{ei}$  respectively for some initial operating point, then (9) can be transformed into (11).

$$\begin{cases} \dot{\delta}_i = \omega_i \\ \dot{\omega}_i = k_{i4} \omega_i + k_{i5} \Delta P_{mi} + k_{i6} - k_{i5} P_{ei} \\ \Delta \dot{P}_{mi} = k_{i7} \Delta P_{mi} + k_{i8} \Delta X_{ei} \\ \Delta \dot{X}_{ei} = k_{i9} \omega_i - k_{i10} \Delta X_{ei} + k_{i10} P_{ci} \end{cases} \quad (11)$$

where,  $k_{i4} = -D_i/(2H_i)$ ,  $k_{i5} = \omega_0/(2H_i)$ ,  $k_{i6} = k_{i5}/P_{mi0}$ ,  $k_{i7} = -1/T_{mi}$ ,  $k_{i8} = K_{mi}/T_{mi}$ ,  $k_{i9} = -K_{ei}/(T_{ei} R_i \omega_0)$ ,  $k_{i10} = 1/T_{ei}$ .

For simplification, define  $x_i = [x_{i1}, x_{i2}]^T = [\delta_i, \omega_i]^T$  and  $\xi_i = [\xi_{i1}, \xi_{i2}]^T = [k_{i5} \Delta P_{mi}, k_{i5} k_{i8} \Delta X_{ei}]^T$ , then the system dynamics can be transformed into (12).

$$\begin{cases} \dot{x}_{i1} = x_{i2} \\ \dot{x}_{i2} = f_{i0}(x_{i2}) + \xi_{i1} + \Delta_i(x) \\ \dot{\xi}_{i1} = f_{i1}(\xi_{i1}) + \xi_{i2} \\ \dot{\xi}_{i2} = f_{i2}(x_{i2}, \xi_{i2}) + u_i \end{cases} \quad (12)$$

where,  $f_{i0}(x_{i2})=k_{i4}x_{i2}+k_{i6}$ ,  $f_{i1}(\xi_{i1})=k_{i7}\xi_{i1}$ ,  $f_{i2}(x_{i2}, \xi_{i2})=k_{i5}k_{i8}k_{i9}x_{i2}-k_{i10}\xi_{i2}$ , and the bound of the interconnection term  $\Delta_i(x)$  is given by (13).

$$|\Delta_i(x)| \leq \sum_{j=1}^n \delta_j |x_{j1}| \quad (13)$$

### III. DECENTRALIZED CONTROLLER DESIGNS

The decentralized excitation and steam valve controls are designed separately according to their corresponding transformed models.

#### A. NN based decentralized excitation controller design

First consider the  $i$ th subsystem. Define the filter error  $r_i$  as

$$r_i = [\Lambda_i^T \quad 1]^T x_i \quad (14)$$

where  $x_i=[x_{i1}, x_{i2}, x_{i3}]^T$ ,  $\Lambda_i=[\lambda_{i1}, \lambda_{i2}]^T$  is an appropriately chosen coefficient vector such that  $x_i \rightarrow 0$  as  $r_i \rightarrow 0$  (i.e.  $s^2 + \lambda_{i2}s + \lambda_{i1} = 0$  is Hurwitz).

Taking the derivative of  $r_i$  to get

$$\dot{r}_i = [0 \quad \Lambda_i^T] \dot{x}_i + f_i(\cdot) + u_i + \Delta_i(x) + d_i \quad (15)$$

For subsystem without interconnection term  $\Delta_i(x)$ , the control signal  $u_i$  can be chosen as:

$$u_i = -K_i r_i - [0 \quad \Lambda_i^T] \dot{x}_i - f_i(\cdot) \quad (16)$$

where  $K_i > 0$  is the design parameter.

To counteract the effects of interconnection terms, NNs are used here. According to the NN approximation theory, it can be concluded that there is a NN such that

$$W_i^T \Phi_i(X_i) + \varepsilon_i = \sum_{j=1}^n \delta_{ji}(|x_{j1}|, |x_{j2}|) \quad (17)$$

where  $X_i = [|x_{i1}|, |x_{i2}|, 1]^T$  is the input vector to the NN,  $\varepsilon_i$  is the bounded NN approximation error given by  $|\varepsilon_i| \leq \varepsilon_{iM}$ .

Thus, the actual control signal can be chosen as

$$u_i = -K_i r_i - [0 \quad \Lambda_i^T] \dot{x}_i - f_i(\cdot) - \text{sgn}(r_i) \hat{W}_i^T \Phi_i(X_i) \quad (18)$$

The Lyapunov function for the  $i$ th subsystem is chosen according to

$$V_i = \frac{1}{2} r_i^2 + \frac{1}{2} \tilde{W}_i^T \Gamma_i^{-1} \tilde{W}_i \quad (19)$$

where  $\tilde{W}_i$  is the weight estimation error defined as

$$\tilde{W}_i = \hat{W}_i - W_i \quad (20)$$

and  $\Gamma_i > 0$  is another design parameter.

Taking the derivative of  $V_i$  to get

$$\begin{aligned} \dot{V}_i &= -K_i r_i^2 - |r_i| \hat{W}_i^T \Phi_i(X_i) + r_i \Delta_i(x) + \tilde{W}_i^T \Gamma_i^{-1} \dot{\tilde{W}}_i \\ &\leq -K_i r_i^2 - |r_i| \tilde{W}_i^T \Phi_i(X_i) + |r_i| \varepsilon_{iM} + \tilde{W}_i^T \Gamma_i^{-1} \dot{\tilde{W}}_i \end{aligned} \quad (21)$$

Thus the Lyapunov function for the overall system becomes

$$V = \sum_{i=1}^n V_i \quad (22)$$

Note that

$$\sum_{i=1}^n \sum_{j=1}^n \delta_{ij}(|x_{j1}|, |x_{j2}|) = \sum_{i=1}^n \sum_{j=1}^n \delta_{ji}(|x_{i1}|, |x_{i2}|) \quad (23)$$

Thus

$$\dot{V} \leq \sum_{i=1}^n \left[ -K_i r_i^2 - |r_i| \tilde{W}_i^T \Phi_i(X_i) + \tilde{W}_i^T \Gamma_i^{-1} \dot{\tilde{W}}_i + |r_i| \varepsilon_{iM} \right] \quad (24)$$

The weight updating rule is chosen according to

$$\dot{\tilde{W}}_i = \Gamma_i |r_i| \Phi_i(X_i) - \alpha_i \Gamma_i \tilde{W}_i \quad (25)$$

Then (24) becomes

$$\dot{V} \leq \sum_{i=1}^n (-K_i r_i^2 - \alpha_i \tilde{W}_i^T \tilde{W}_i + |r_i| \varepsilon_{iM}) \quad (26)$$

If  $W_{i\max}$  is defined as the bound of  $W_i$ , then we have

$$-\alpha_i \tilde{W}_i^T \tilde{W}_i \leq -\alpha_i |\tilde{W}_i|^2 + \alpha_i |\tilde{W}_i| |W_i| \leq -\frac{\alpha_i}{2} |\tilde{W}_i|^2 + \frac{\alpha_i}{2} W_{i\max}^2 \quad (27)$$

In addition to (27), we have

$$\varepsilon_i^M |r_i| \leq \frac{r_i^2}{2} + \frac{1}{2} \varepsilon_{iM}^2 \quad (28)$$

Thus,

$$\dot{V} \leq \sum_{i=1}^n \left[ -(K_i - \frac{1}{2}) r_i^2 - \frac{\alpha_i}{2} |\tilde{W}_i|^2 + \frac{\alpha_i}{2} W_{i\max}^2 + \frac{1}{2} \varepsilon_{iM}^2 \right] \quad (29)$$

For simplification, define  $\rho = \sum_{i=1}^n \frac{\alpha_i W_{i\max}^2 + \varepsilon_{iM}^2}{2}$ . If the

selection of design parameters  $K_i$  and  $\alpha_i$ , such that  $K_i > \gamma + 1/2$ , and  $\alpha_i \geq \gamma \lambda_{\max}(\Gamma_i^{-1})$ , then we get

$$\dot{V} \leq -\gamma \sum_{i=1}^n [r_i^2 + \tilde{W}_i^T \Gamma_i^{-1} \tilde{W}_i] + \rho \leq -\gamma V + \rho \quad (30)$$

*Theorem 1:* Consider the closed-loop system consisting of system (7), the controller (18), and the NN weight updating laws (25). For bounded initial conditions, we have the following conclusion.

All signals in the closed loop system remain uniformly ultimately bounded, and the system states  $x$  and NN weight estimates  $\hat{W}$  eventually converge to a compact set  $\Omega$ .

$$\Omega = \left\{ r, \hat{W} \mid V < \frac{\rho}{\gamma} \right\} \quad (31)$$

*Proof:* From (31), it can be seen that if  $r_i$  and  $\tilde{W}_i$  are outside of the compact set defined as (31), then  $\dot{V}$  will remain negative definite until the systems state and the weight estimate errors enter the  $\Omega$ . Thus,  $r_i$  and  $\tilde{W}_i$  are uniformly ultimately bounded. Furthermore, since  $W_i$  exist and are bounded, then  $\hat{W}_i$  are also bounded. Considering (14) and the boundedness of  $r_i$ , we can conclude that  $x_i$  is bounded. Using (18), we conclude that control signal  $u$  is also bounded.

Thus, all signals in the closed loop system remain bounded, and the system states  $x$ , and NN weight estimates

$\hat{W}_i$  eventually converge to a compact set  $\Omega$ . Further analysis of the compact set can be found in [9].

### B. NN Based Decentralized Steam-Valve Control

According to backstepping, the design procedure is described using three steps [9].

*Step 0:* First consider the  $i$ th subsystem. Define the error between the actual and desired system output as

$$e_i = x_{i1} - x_{i1d} \quad (32)$$

Then the filtered tracking errors can be defined as

$$z_{i0} = [\lambda_i \quad 1] \bar{e}_i \quad (33)$$

where  $\bar{e}_i = [e_i, \dot{e}_i]$ ,  $\lambda_i > 0$  such that  $x_{i1} \rightarrow x_{i1d}$  as  $z_{i0} \rightarrow 0$  (i.e.  $s + \lambda_i = 0$  is Hurwitz).

Taking the derivative of (33) and using (12) to get

$$\dot{z}_{i0} = \lambda_i x_{i2} + f_{i0}(x_{i2}) + \xi_{i1} + \Delta_i(\cdot) \quad (34)$$

By viewing  $\xi_{i1}$  as the virtual control signal, the ideal value of which can be chosen according to

$$r_{i0}^* = -K_{i0} z_{i0} - [\lambda_i x_{i2} + f_{i0}(x_{i2})] - \text{sign}(z_{i0}) \sum_{j=1}^n \delta_{ji} |x_{i1}| \quad (35)$$

where  $K_{i0} > 0$  is the design parameter.

Based on NN approximation theory and applying the Assumptions, the latter part of the above equation can be approximated by using two NNs.

$$W_{i01}^T \Phi_{i01}(X_{i01}) + \varepsilon_{i01} = \lambda_i x_{i2} + f_{i0}(x_{i2}) \quad (36)$$

$$W_{i02}^T \Phi_{i02}(X_{i02}) + \varepsilon_{i02} = \sum_{j=1}^n \delta_{ji} |x_{i1}|$$

where  $X_{i01} = [x_{i2}, 1]^T$ ,  $X_{i02} = [|x_{i1}|, 1]^T$ , and the approximation errors are bounded according to  $|\varepsilon_{i01}| \leq \varepsilon_{i01}^M$  and  $|\varepsilon_{i02}| \leq \varepsilon_{i02}^M$ .

If  $\xi_{i1}$  is the actual control signal, the virtual control signal can be chosen as

$$\hat{r}_{i0} = -K_{i0} z_{i0} - \hat{W}_{i01}^T \Phi_{i01}(X_{i01}) - \text{sgn}(z_{i0}) \hat{W}_{i02}^T \Phi_{i02}(X_{i02}) \quad (37)$$

*Remark 3:* During the following controller design, it is necessary to take the derivative of the virtual control signal. The procedure cannot proceed if the virtual control signal is not continuously differentiable. This problem can be solved by approximate of the discontinuous sign function with a continuous function. A choice of the function is  $f_1(x) = (1 - e^{-kx})(1 + e^{-kx})$  with  $k > 0$ . When  $|x|$  is approximated by  $f_2(x) = x f_1(x)$ . It is easy to verify that the estimation error is bounded [6].

Thus,  $X_{i02} = [f_2(x_{i1}), 1]^T$  is selected to replace  $[|x_{i1}|, 1]^T$  as the NN input and the realizable virtual control signal becomes

$$r_{i0} = -K_{i0} z_{i0} - \hat{W}_{i01}^T \Phi_{i01}(X_{i01}) - f_1(z_{i0}) \hat{W}_{i02}^T \Phi_{i02}(X_{i02}) \quad (38)$$

Define

$$z_{i1} = \xi_{i1} - r_{i0} \quad (39)$$

Choose the Lyapunov function for this step as

$$V_0 = \sum_{i=1}^n V_{0i} = \sum_{i=1}^n \left( \frac{1}{2} z_{i0}^2 + \frac{1}{2} \tilde{W}_{i01}^T \Gamma_{i01}^{-1} \tilde{W}_{i01} + \frac{1}{2} \tilde{W}_{i02}^T \Gamma_{i02}^{-1} \tilde{W}_{i02} \right) \quad (40)$$

where  $\Gamma_{i01} = \Gamma_{i01}^T > 0$  and  $\Gamma_{i02} = \Gamma_{i02}^T > 0$  are the adaptation gain matrices.

Choose the weights updating rules for  $\hat{W}_{i01}$  and  $\hat{W}_{i02}$  as

$$\dot{\hat{W}}_{i01} = \Gamma_{i01} [z_{i0} \Phi_{i01}(X_{i01}) - \alpha_{i01} \hat{W}_{i01}] \quad (41)$$

$$\dot{\hat{W}}_{i02} = \Gamma_{i02} [z_{i0} |\Phi_{i02}(X_{i02}) - \alpha_{i02} \hat{W}_{i02}]$$

According to the bound analysis in [7], we know the following expressing is valid.

$$\dot{V}_0 \leq \sum_{i=1}^n \left( -c_{i01} z_{i0}^2 + z_{i0} z_{i1} - c_{i02} |\tilde{W}_{i01}|^2 - c_{i03} |\tilde{W}_{i02}|^2 + c_{i04} \right) \quad (42)$$

with  $c_{i01} = K_{i0} - \frac{3}{2} > 0$ ,  $c_{i02} = \frac{\alpha_{i01}}{2} > 0$ ,  $c_{i03} = \frac{\alpha_{i02} - 1}{2} > 0$ , and

$$c_{i04} = \frac{\alpha_{i01}}{2} |W_{i01}|^2 + \frac{\alpha_{i02} + C_{i02}^2}{2} |W_{i02}|^2 + T_{i02} |W_{i02}| + \frac{1}{2} T_{i02}^2 + \frac{1}{2} \varepsilon_{i02}^{M^2} + \frac{1}{2} \left( \varepsilon_{i01}^M + \frac{d_{i0}^M}{g_{i0}^m} \right)^2$$

where  $C_{i02}$  is a constant as long as  $k$  and the NN parameters (number of input neurons, number of hidden neurons, and type of transfer functions) are decided [7].

*Step 1:* Taking the derivative of (39) and using (12) to get

$$\dot{r}_{i0} = \phi_{i0}(\cdot) + \frac{\partial \alpha_{i0}}{\partial x_{i2}} \Delta_{i0}(\cdot) + \frac{\partial \alpha_{i0}}{\partial \hat{W}_{i02}} \Gamma_{i02} |z_{i0}| \Phi_{i02}(X_{i02}) \quad (43)$$

where

$$\phi_{i0} = \frac{\partial r_{i0}}{\partial x_{i1}} x_{i2} + \frac{\partial r_{i0}}{\partial x_{i2}} [f_{i0}(x_{i2}) + \xi_{i1}] + \frac{\partial r_{i0}}{\partial \hat{W}_{i01}} \dot{\hat{W}}_{i01} - \frac{\partial r_{i0}}{\partial \hat{W}_{i02}} \Gamma_{i02} \alpha_{i02} \dot{\hat{W}}_{i02} \quad (44)$$

Thus

$$\dot{z}_{i1} = f_{i1}(\xi_{i1}) + \xi_{i2} - \phi_{i0} - \frac{\partial \alpha_{i0}}{\partial x_{i2}} \Delta_{i0}(\cdot) - \frac{\partial \alpha_{i0}}{\partial \hat{W}_{i02}} \Gamma_{i02} |z_{i0}| \Phi_{i02}(X_{i02}) \quad (45)$$

Define

$$z_{i2} = \xi_{i2} - \alpha_{i1} \quad (46)$$

By viewing  $\xi_{i2}$  as the virtual control signal, the ideal virtual control signal  $r_{i1}^*$  can be chosen according to

$$r_{i1}^* = -z_{i0} - K_{i1} z_{i1} - [f_{i1}(\xi_{i1}) - \phi_{i0}] - \text{sign}(z_{i1}) \left\{ \frac{\partial \alpha_{i0}}{\partial x_{i2}} \left[ \sum_{j=1}^n \delta_{ji} |x_{i1}| \right] + \Gamma_{i02} |z_{i0}| \right\} \quad (47)$$

According to NN approximation theory, we know that there exist two NNs, such that one NN satisfies

$$W_{i11}^T \Phi_{i11}(X_{i11}) + \varepsilon_{i11} = f_{i1}(\xi_{i1}) - \phi_{i0} \quad (48)$$

with  $X_{i11} = [x_{i1}, x_{i2}, \xi_{i1}, W_{i01}, W_{i02}, 1]^T$  and  $|\varepsilon_{i11}| \leq \varepsilon_{i11}^M$ .

and another NN satisfies

$$W_{i12}^T \Phi_{i12}(X_{i12}) + \varepsilon_{i12} = \left| \frac{\partial \alpha_{i0}}{\partial x_{i2}} \left[ \sum_{j=1}^n \delta_{ji} |x_{i1}| \right] + \Gamma_{i02} |z_{i0}| \right| \quad (49)$$

with  $X_{i12} = [|z_{i0}|, |x_{i1}|, \left| \frac{\partial \alpha_{i0}}{\partial x_{i2}} \right|, 1]^T$  and  $|\varepsilon_{i12}| \leq \varepsilon_{i12}^M$ .

Similar to Step 0, change the input vector to the NN to

$$X_{i12} = [f(z_{i0}), f(x_{i1}), f\left(\frac{\partial \alpha_{i0}}{\partial x_{i2}}\right), 1] \quad (50)$$

Correspondingly, the realizable control signal becomes

$$r_{i1} = -z_{i0} - K_{i1} z_{i1} - \hat{W}_{i11}^T \Phi_{i11}(X_{i11}) - f_1(z_{i1}) \hat{W}_{i12}^T \Phi_{i12}(X_{i12}) \quad (51)$$

Choose the Lyapunov function for this step as

$$V_1 = V_0 + \sum_{i=1}^n \left( \frac{1}{2} z_i^2 + \frac{1}{2} \tilde{W}_{i1}^T \Gamma_{i1}^{-1} \tilde{W}_{i1} + \frac{1}{2} \tilde{W}_{i2}^T \Gamma_{i2}^{-1} \tilde{W}_{i2} \right) \quad (52)$$

where  $\Gamma_{i1}, \Gamma_{i2} > 0$  are the adaptation gain matrices,  $\tilde{W}_{i1}$  and  $\tilde{W}_{i2}$  are the weights estimation errors.

The weights updating rules are chosen as

$$\dot{\hat{W}}_{i1} = \Gamma_{i1} [z_{i1} \Phi_{i1}(X_{i1}) - \alpha_{i1} \hat{W}_{i1}] \quad (53)$$

$$\dot{\hat{W}}_{i2} = \Gamma_{i2} [z_{i2} \Phi_{i2}(X_{i2}) - \alpha_{i2} \hat{W}_{i2}]$$

Similar to Step 0, taking the derivative (52) and using (53) to get

$$\begin{aligned} \dot{V}_1 &= \dot{V}_0 + \sum_{i=1}^n \left[ z_{i1} \dot{z}_{i1} + \tilde{W}_{i1}^T \Gamma_{i1}^{-1} \dot{\tilde{W}}_{i1} + \tilde{W}_{i2}^T \Gamma_{i2}^{-1} \dot{\tilde{W}}_{i2} \right] \\ &\leq \sum_{i=1}^n \left[ z_{i1} z_{i2} - c_{i01} z_{i0}^2 - c_{i02} |\tilde{W}_{i01}|^2 - c_{i03} |\tilde{W}_{i02}|^2 + c_{i04} \right. \\ &\quad \left. - c_{i11} z_{i1}^2 - c_{i12} |\tilde{W}_{i11}|^2 - c_{i13} |\tilde{W}_{i12}|^2 + c_{i14} \right] \end{aligned} \quad (54)$$

where  $c_{i11} = K_{i1} - \frac{3}{2} > 0$ ,  $c_{i12} = \frac{\alpha_{i11}}{2} > 0$ ,  $c_{i13} = \frac{\alpha_{i12}}{2} > 0$  and

$$\begin{aligned} c_{i14} &= \frac{\alpha_{i11}}{2} |W_{i11}|^2 + \frac{\alpha_{i12} + C_{i12}^2}{2} |W_{i12}|^2 + T_{i12} |W_{i12}| + \frac{1}{2} T_{i12}^2 \\ &\quad + \frac{1}{2} \left( \varepsilon_{i11}^M + \frac{d_{i1}^M}{g_{i1}^m} \right)^2 + \frac{1}{2} \varepsilon_{i12}^M \end{aligned}$$

Step 2: Taking the derivative of (51) to get

$$\begin{aligned} \dot{r}_{i1} &= \phi_{i1} + \frac{\partial r_{i1}}{\partial x_{i2}} \Delta_i(\cdot) + \frac{\partial r_{i1}}{\partial \hat{W}_{i02}} \Gamma_{i02} |z_{i0}| \Phi_{i02}(X_{i02}) \\ &\quad + \frac{\partial r_{i1}}{\partial \hat{W}_{i12}} \Gamma_{i12} |z_{i1}| \Phi_{i12}(X_{i12}) \end{aligned} \quad (55)$$

where

$$\begin{aligned} \phi_{i1} &= \frac{\partial \alpha_{i1}}{\partial x_{i1}} x_{i2} + \frac{\partial \alpha_{i1}}{\partial x_{i2}} [f_{i0}(x_{i2}) + \xi_{i1}] + \frac{\partial \alpha_{i1}}{\partial \xi_{i1}} \dot{\xi}_{i2} + \frac{\partial \alpha_{i1}}{\partial \hat{W}_{i01}} \dot{\hat{W}}_{i01} \\ &\quad - \frac{\partial \alpha_{i1}}{\partial \hat{W}_{i02}} \Gamma_{i02} \alpha_{i02} \hat{W}_{i02} + \frac{\partial \alpha_{i1}}{\partial \hat{W}_{i11}} \dot{\hat{W}}_{i11} - \frac{\partial \alpha_{i1}}{\partial \hat{W}_{i12}} \Gamma_{i12} \alpha_{i12} \hat{W}_{i12} \end{aligned} \quad (56)$$

Thus,

$$\begin{aligned} \dot{z}_{i2} &= f_{i2}(x_{i2}, \xi_{i2}) + u_i - \phi_{i1} - \frac{\partial \alpha_{i1}}{\partial x_{i2}} \Delta_i(\cdot) \\ &\quad - \frac{\partial \alpha_{i1}}{\partial \hat{W}_{i02}} \Gamma_{i02} |z_{i0}| \Phi_{i02}(X_{i02}) - \frac{\partial \alpha_{i1}}{\partial \hat{W}_{i12}} \Gamma_{i12} |z_{i1}| \Phi_{i12}(X_{i12}) \end{aligned} \quad (57)$$

The desired control can be selected as:

$$\begin{aligned} u_i^* &= -z_{i1} - K_{i2} z_{i2} - [f_{i2}(x_{i2}, \xi_{i2}) - \phi_{i1}] \\ &\quad - \text{sign}(z_{i2}) \left\{ \frac{\partial \alpha_{i1}}{\partial x_{i2}} \left[ \sum_{j=1}^N \delta_{ji}(|x_{i1}|) \right] + \Gamma_{i02} |z_{i0}| + \Gamma_{i12} |z_{i1}| \right\} \end{aligned} \quad (58)$$

Similarly, one NN is used to approximate  $f_{i2}(x_{i2}, \xi_{i2})$  as

$$\hat{W}_{i21}^T \Phi_{i21}(X_{i21}) + \varepsilon_{i21} = f_{i2}(x_{i2}, \xi_{i2}) \quad (59)$$

where  $|\varepsilon_{i21}| \leq \varepsilon_{i21}^M$  and the NN input is defined as

$$X_{i21} = [x_{i1}, x_{i2}, \xi_{i1}, \xi_{i2}, W_{i01}, W_{i02}, W_{i11}, W_{i12}, 1]^T \quad (60)$$

and another neural network satisfying

$$\begin{aligned} \hat{W}_{i22}^T \Phi_{i22}(X_{i22}) + \varepsilon_{i22} \\ = |z_{i2}| \left\{ \frac{\partial \alpha_{i1}}{\partial x_{i2}} \left[ \sum_{j=1}^N \delta_{ji}(|x_{i1}|) \right] + \Gamma_{i02} |z_{i0}| + \Gamma_{i12} |z_{i1}| \right\} \end{aligned} \quad (61)$$

where  $|\varepsilon_{i,n-k,2}| \leq \varepsilon_{i,n-k,2}^M$  and the NN input is defined as

$$X_{i22} = [|z_{i0}|, |z_{i1}|, |x_{i1}|, \left| \frac{\partial \alpha_{i1}}{\partial x_{i2}} \right|, 1]^T \quad (62)$$

Since this is the last step, there is no need to approximate  $\text{sign}(\cdot)$  using  $f_1(\cdot)$ . Finally, the actual control signal can be chosen as

$$u_i = -z_{i1} - K_{i2} z_{i2} - \hat{W}_{i21}^T \Phi_{i21}(X_{i21}) - \text{sign}(z_{i2}) \hat{W}_{i22}^T \Phi_{i22}(X_{i22}) \quad (63)$$

Choose the weight updating rules for  $\hat{W}_{i21}$  and  $\hat{W}_{i22}$  as

$$\dot{\hat{W}}_{i21} = \Gamma_{i21} [z_{i2} \Phi_{i21}(X_{i21}) - \alpha_{i21} \hat{W}_{i21}] \quad (64)$$

$$\dot{\hat{W}}_{i22} = \Gamma_{i22} [z_{i2} \Phi_{i22}(X_{i22}) - \alpha_{i22} \hat{W}_{i22}]$$

The Lyapunov function for the overall system is selected as

$$V = V_1 + \sum_{i=1}^n V_{2i} = V_1 + \sum_{i=1}^n \left( \frac{1}{2} z_{i2}^2 + \frac{1}{2} \tilde{W}_{i2}^T \Gamma_{i2}^{-1} \tilde{W}_{i2} \right) \quad (65)$$

Evaluating (65)'s derivative and using the same analysis as before to get

$$\dot{V} \leq \sum_{i=1}^n \left[ -\sum_{k=0}^2 c_{ik1} z_{ik}^2 - \sum_{k=0}^2 c_{ik2} |\tilde{W}_{ik1}|^2 - \sum_{k=0}^2 c_{ik3} |\tilde{W}_{ik2}|^2 - \sum_{k=0}^2 c_{ik4} \right] \quad (66)$$

where  $c_{i21} = K_{i2} - 1 > 0$ ,  $c_{i22} = \frac{\alpha_{i21}}{2}$ ,  $c_{i23} = \frac{\alpha_{i22}}{2}$ , and

$$c_{i24} = \frac{\varepsilon_{i21}^M + \varepsilon_{i22}^M + \alpha_{i21} |W_{i21}|^2 + \alpha_{i22} |W_{i22}|^2}{2}$$

*Theorem 2:* Consider the closed-loop system consisting of system (9), the desired output  $x_d$ , the controller (63), and the NN weight updating laws (41), (53) and (64). If the NN transfer functions are selected to be smooth and bounded, and the NNs are large enough, such that they can approximate their objective functions accurately, then for bounded initial conditions, we have the following conclusion.

All signals in the closed loop system remain uniformly ultimately bounded, and the system states and NN weights eventually converge to a compact set  $\Omega$ .

$$\Omega = \left\{ X, \Xi, \hat{W}_{i01}, \hat{W}_{i11}, \hat{W}_{i12}, \hat{W}_{i02}, \hat{W}_{i12}, \hat{W}_{i22} \mid V < \frac{\rho}{\gamma} \right\} \quad (67)$$

Limited by pages number, proof for Theorem 2 is omitted.

#### IV. SIMULATION STUDY

The proposed decentralized controls are evaluated with a three-machine power system described in [8].

##### A. Simulations Results for Excitation Controls

The excitation controller design is evaluated with a 3-phase short circuit fault. The fault happened at the middle of one of the transmission lines between generators  $G_1$  and  $G_2$ . The fault happened at 1 second until it is cleared by disconnecting the faulted line at 1.2 second, and then the faulted line is restored at 2 second.

The design parameters for the two decentralized excitation controllers are the same according to (68).

$$\Lambda_{1-2} = [25, 10]^T, K_{1-2} = 5, \Gamma_{1-2} = 5, \alpha_{1-2} = 5, k = 5 \quad (68)$$

Simulation results are shown in Figs. 1 and 2.

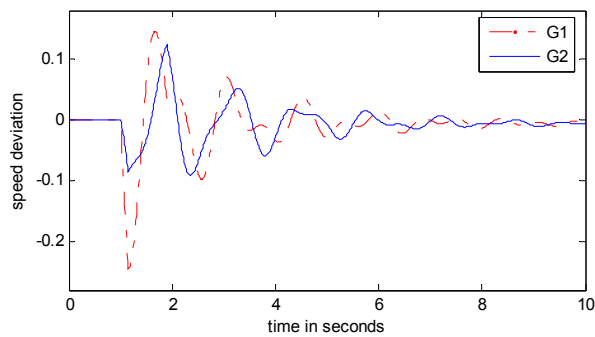


Fig. 1. Speed deviation responses without excitation controls

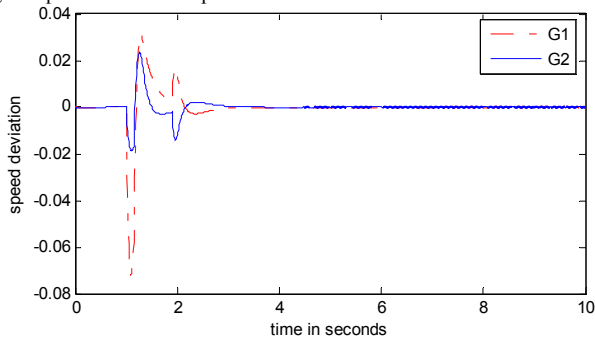


Fig. 2. Speed deviation responses under the decentralized excitation controls

It should be noted that when there are no excitation controls in the system, after the fault is cleared, the system will still converge, but the oscillation takes long time and the system may converge to another operating point other than the original one.

Furthermore, it can be seen from Fig. 1 that the system responses compose of different frequencies. This is because the interaction of between the subsystems' activities. From Fig. 2, it can be seen that the interactions have been successfully damped under the proposed decentralized excitation controls.

### B. Simulations Results for Steam Valve Controls

The proposed steam valve controller is evaluated under the same fault as the excitation controller.

The design parameters for all of the decentralized excitation controllers are the same according to (69).

$$\lambda_i = 5, K_{i,0-2} = 5, k = 5, \Gamma_{i,1-2,1-2} = 5, \alpha_{i,0-2,1-2} = 5 \quad (69)$$

where  $i = 1, 2$

Simulation results are provided in Figs 3 and 4.

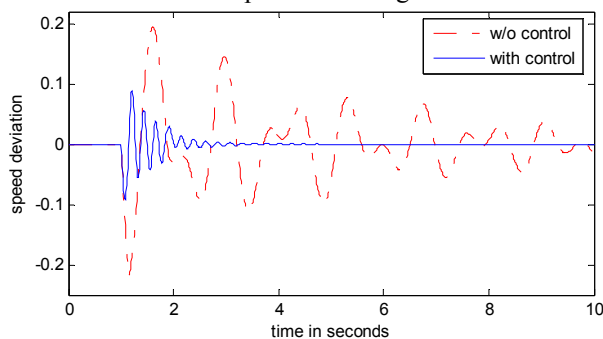


Fig. 3. Relative speed responses comparison of G1

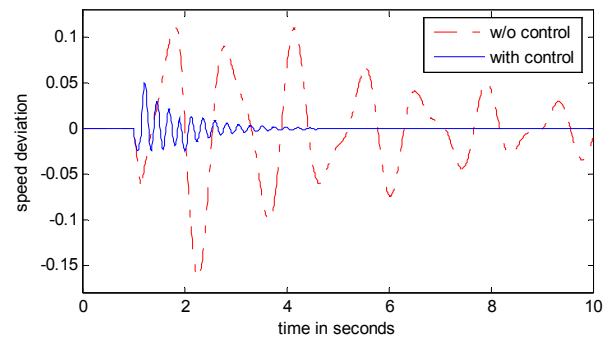


Fig. 4. Relative speed responses comparison of G2

From the above simulation results, it can be seen that although the subsystem controllers only take into account the local signals, the coordination of the control activities can be realized.

## V. CONCLUSION

This paper proposed two NNs based decentralized controller designs for the excitation and steam valve control of multimachine power systems. The controller designs are based on the bound analysis of the interconnection terms and rigorous Lyapunov stability analysis. The introduction of NNs eliminates the need for precise parameters of the system model. Simulation results demonstrate the effectiveness of the two controller designs. Future work includes consideration of more practical power system model and simplification of controller designs.

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