Two Neural Network Based Decentralized Controller Designs for Large Scale Power Systems

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Two Neural Network Based Decentralized Controller Designs For Large Scale Power Systems

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Abstract—This paper presents two 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 signals are calculated using local signals only, the transient and overall system stabilities can be guaranteed. NNs are used to approximate the unknown and/or imprecise dynamics of the local power system and the inter-connection terms, thus the requirements for exact system parameters are released. Simulation studies with a three machine power system demonstrate the effectiveness of the proposed controller designs.

Index Terms—Decentralized control, power systems, neural networks, and large scale system.

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 designs subsystem controllers separately, requiring local information and measurement only or with a minimum amount of information from other subsystems.

The traditional decentralized control strategies of power systems were designed 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 are reported based on nonlinear multimachine power system models [1-3]. However, there is a problem with the differential geometric based nonlinear controller designs. The problem is that exact feedback linearization requires the exact knowledge of the system dynamics. Imprecise knowledge will greatly degrade the performance of controller designs. Since it is impossible to make the assumption that the complex power system dynamics can be known exactly, the possible applications are limited by this assumption. In order to overcome the limitation of the above feedback linearization methods and to enhance robustness of systems, there appear numerous results on the decentralized nonlinear robust control of power systems [4-9]. As expected, these feedback linearization and backstepping techniques are modified to accommodate model uncertainties. In all these papers, the stability and robustness of the control system were demonstrated using Lyapunov analysis.

Neural networks have been proved 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 [10-12]. 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 subsystem, the stability of the overall system and the coordination of subsystem controllers can be guaranteed.

This paper presents two NN based decentralized controller designs for large scale power systems, one is for the excitation control and the other is for the steam valve control. For both controller designs, it can be concluded that all of the signals in the closed loop (system states and NN weights) are guaranteed to be uniformly ultimately bounded and eventually converge to a compact set. Simulation studies conducted with a three machine power system demonstrate the effectiveness of the proposed decentralized NN controllers.

II. Background

The following mathematical notions are required for system approximation using NNs and system stability analysis in the design of an adaptive controller.

A. Approximation Property of NN

The commonly used property of NNs for control is its function approximation and adaptation capacities [13]. Let $f(x)$ be a smooth function from $R^n \rightarrow R^m$, then it can be shown that, as long as x is restricted to a compact set $S \in R^n$, for any given positive number ε_N, there exist weights and thresholds such that

$$f(x) = W^T \varphi(x) + \varepsilon(x) \tag{1}$$

where x is the input vector, $\varphi(.)$ is the activation function, W is the weight matrix of the output layer and $\varepsilon(x)$ is the approximation error that satisfies $\varepsilon(x) \le \varepsilon_N$.

For the above function approximation, $\varphi(x)$ must form a basis [14]. For two layer neural networks, $\varphi(x)=\sigma(V^T x)$, where

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V is the weight matrix of the first layer and $\sigma(x)$ is a sigmoid function. If V is fixed, then W becomes the only design parameter. It has been shown in [15] that $\varphi(x)$ can form a basis if V is chosen randomly. The larger the number of the hidden layer neurons N_h, the smaller the approximation error $\varepsilon(x)$.

B. Stability of Systems

To formulate the controller, the following stability notion is needed. Consider the nonlinear system given by

$$\begin{aligned} \dot{x} &= f(x,u) \\ y &= h(x) \end{aligned} \tag{2}$$

where $x(t)$ is a state vector, $u(t)$ is the input vector and $y(t)$ is the output vector [16]. The solution to (2) is uniformly ultimately bounded (UUB) if for any U, a compact subset of R^n, and all $x(t_0) = x_0 \in U$ there exists an $\varepsilon > 0$ and a number $T(\varepsilon, x_0)$ such that $||x(t)|| < \varepsilon$ for all $t \geq t_0 + T$.

III. Dynamic Model Of Large Scale Power Systems

For a large scale power system with n interconnected generators, the following dynamic equations are widely used to represent the subsystems [1, 5, 7, and 17].

$$\begin{cases} \dot{\delta}_i = \omega_i \\ \dot{\omega}_i = -\dfrac{D_i}{2H_i}\omega_i + \dfrac{\omega_0}{2H_i}(P_{mi} - P_{ei}) \\ E'_{qi} = \dfrac{1}{T'_{d0i}}(E_{fi} - E_{qi}) \\ \dot{P}_{mi} = -\dfrac{1}{T_{mi}}P_{mi} + \dfrac{K_{mi}}{T_{mi}}X_{ei} \\ \dot{X}_{ei} = -\dfrac{K_{ei}}{T_{ei}R_i\omega_0}\omega_i - \dfrac{1}{T_{ei}}X_{ei} + \dfrac{1}{T_{ei}}P_{ci} \end{cases} \tag{3}$$

where $i=1,\dots,n$, δ_i is the power angle in rad, ω_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_{qi} 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.[6].

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

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

$$\begin{cases} P_{ei} = E'_{qi}\sum_{j=1}^{n} E'_{qj}B_{ij}\sin(\delta_i - \delta_j) \\ Q_{ei} = -E'_{qi}\sum_{j=1}^{n} E'_{qj}B_{ij}\cos(\delta_i - \delta_j) \end{cases} \quad \begin{cases} I_{di} = -\sum_{j=1}^{n} E'_{qj}B_{ij}\cos(\delta_i - \delta_j) \\ I_{qi} = \sum_{j=1}^{n} E'_{qj}B_{ij}\sin(\delta_i - \delta_j) \end{cases} \tag{4}$$

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 ith row and jth column element of nodal suseptance matrix at the internal nodes after eliminating all physical buses in p.u. [7].

A. Model for excitation controller design

Since the time constants of the turbine control loop is much larger than that of the excitation control loop, the mechanic power input to the generator is assumed to be constant, that is $P_{mi}=P_{mi0}$. For simplification, the third state variable is substituted with the electrical power deviation ΔP_{ei}, defined as $\Delta P_{ei}=P_{ei}-P_{mi0}$. After transformation, the model used for the decentralized excitation controller can be expressed as (5).

$$\begin{cases} \dot{\delta}_i = \omega_i \\ \dot{\omega}_i = -\dfrac{D_i}{2H_i}\omega_i - \dfrac{\omega_0}{2H_i}\Delta P_{ei} \\ \Delta\dot{P}_{ei} = -\dfrac{1}{T'_{doi}}\Delta P_{ei} + \dfrac{1}{T'_{doi}}v_{fi} + \gamma_i(\delta,\omega) \end{cases} \tag{5}$$

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 ith subsystem. v_{fi} and $\gamma_i(\delta,\omega)$ are defined according to (6) and (7) respectively. The process resulting the following equations can be found in [5].

$$\gamma_i(\delta,\omega) = E'_{qi}\sum_{j=1}^{n}\dot{E}'_{qj}B_{ij}\sin(\delta_i - \delta_j) - E'_{qi}\sum_{j=1}^{n}E'_{qj}B_{ij}\cos(\delta_i - \delta_j)\omega_j \tag{6}$$

$$v_{fi} = I_{qi}E_{fi} - (x_{di} - x'_{di})I_{qi}I_{di} - P_{mi} - T'_{d0i}Q_{ei}\omega_i \tag{7}$$

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 (7) 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. Similar to the bound analysis in [17], the following assumption is proposed.

Assumption 1: The E_{fi} may rise by up to k times of the E_{qi} with $k>1$.

Remark 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 [7], $\gamma_i(\delta,\omega)$ is bounded according to

$$|\gamma_i(\delta,\omega)| \le \sum_{j=1}^{n}(\gamma_{i1j}|\sin\delta_j| + \gamma_{i2}|\omega_j|) \le \sum_{j=1}^{n}(\gamma_{i1j}|\delta_j| + \gamma_{i2}|\omega_j|) \tag{8}$$

where γ_{i1j} and γ_{i2j} are unknown constants decided by system parameters.

For simplification, define a new set of state variables $x_i = [x_{i1} \quad x_{i2} \quad x_{i3}]^T = [\delta_i - \delta_{i0} \quad \omega_i \quad \dot{\omega}_i]^T$ so as to transform the system model into a format as (9).

$$\begin{cases} \dot{x}_{i1} = x_{i2} \\ \dot{x}_{i2} = x_{i3} \\ \dot{x}_{i3} = f_i(.) + u_i + \Delta_i(x) \end{cases} \tag{9}$$

where $f_i(.)=k_{i1}x_{i2}+k_{i2}x_{i3}$ with $k_{i1\sim3}$ defined as $k_{i1}=-D_i/(2H_iT_{d0i}')$, $k_{i2}=-D_i/(2H_i) -1/T_{d0i}'$, $k_{i3}=-\omega_0/(2H_iT_{d0i}')$

correspondingly, $\Delta_i(x)=-\omega_0/(2H_i)\gamma_i(x)$, and the newly introduced control signal u_i is defined as $u_i=-\omega_0/(2H_iT_{d0i}')v_{fi}$.

After transformation, the bound of the interconnection terms can be expressed as (10).

$$|\Delta_i(x)| \le \sum_{j=1}^{n} \delta_{ij}(|x_{j1}|,|x_{j2}|) \tag{10}$$

B. Model for the steam valve controller design

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

$$\begin{cases} \dot{\delta}_i = \omega_i \\ \dot{\omega}_i = -\dfrac{D_i}{2H_i}\omega_i + \dfrac{\omega_0}{2H_i}(P_{mi}-P_{ei}) \\ \dot{P}_{mi} = -\dfrac{1}{T_{mi}}P_{mi} + \dfrac{K_{mi}}{T_{mi}}X_{ei} \\ \dot{X}_{ei} = -\dfrac{K_{ei}}{T_{ei}R_i\omega_0}\omega_i - \dfrac{1}{T_{ei}}X_{ei} + \dfrac{1}{T_{ei}}P_{ci} \end{cases} \tag{11}$$

For this steam valve control model, P_{ei} is the inter-connection term. According to [7], P_{ei} is bounded by (12).

$$|P_{ei}| \le \sum_{j=1}^{n} g_{ij}|\sin\delta_j| \le \sum_{j=1}^{n} g_{ij}|\delta_j| \tag{12}$$

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 (11) can be transformed into (13).

$$\begin{cases} \dot{\delta}_i = \omega_i \\ \dot{\omega}_i = k_{i4}\omega_i + k_{i5}\Delta P_{mi} + k_{i6} - k_{i5}P_{ei} \\ \Delta\dot{P}_{mi} = k_{i7}\Delta P_{mi} + k_{i8}\Delta X_{ei} \\ \Delta\dot{X}_{ei} = k_{i9}\omega_i - k_{i10}\Delta X_{ei} + k_{i10}P_{ci} \end{cases} \tag{13}$$

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 (14).

$$\begin{cases} \dot{x}_{i1} = x_{i2} \\ \dot{x}_{i2} = f_{i0}(x_{i2}) + \xi_{i1} + \Delta_i(x) \\ \dot{\xi}_{i1} = f_{i1}(\xi_{i1}) + \xi_{i2} \\ \dot{\xi}_{i2} = f_{i2}(x_{i2},\xi_{i2}) + u_i \end{cases} \tag{14}$$

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 (15).

$$|\Delta_i(x)| \le \sum_{j=1}^{n} \delta_{ij}|x_{j1}| \tag{15}$$

IV. 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 ith subsystem. Define the filter error r_i as

$$r_i = [\Lambda_i^T \quad 1]^T x_i \tag{16}$$

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 $x_i\to 0$ as $r_i\to 0$ (i.e. $s^2+\lambda_{i2}s+\lambda_{i1}=0$ is Hurwitz).

Taking the derivative of r_i to get

$$\dot{r}_i = [0 \quad \Lambda_i^T]x_i + f_i(.) + u_i + \Delta_i(x) + d_i \tag{17}$$

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

$$u_i = -K_i r_i - [0 \quad \Lambda_i^T]x_i - f_i(.) \tag{18}$$

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 conclude that there is a NN such that

$$W_i^T\Phi_i(X_i) + \varepsilon_i = \sum_{j=1}^{n} \delta_{ji}(|x_{i1}|,|x_{i2}|) \tag{19}$$

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

Thus, the actual control signal can be chosen as

$$u_i = -K_i r_i - [0 \quad \Lambda_i^T]x_i - f_i(.) - \mathrm{sgn}(r_i)\hat{W}_i^T\Phi_i(X_i) \tag{20}$$

The Lyapunov function for the ith subsystem is chosen according to

$$V_i = \frac{1}{2}r_i^2 + \frac{1}{2}\tilde{W}_i^T\Gamma_i^{-1}\tilde{W}_i \tag{21}$$

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

$$\tilde{W}_i = \hat{W}_i - W_i \tag{22}$$

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

Taking the derivative of V_i to get

$$\begin{aligned} \dot{V}_i &= -K_i r_i^2 - |r_i|\hat{W}_i^T\Phi_i(X_i) + r_i\Delta_i(x) + \tilde{W}_i^T\Gamma_i^{-1}\dot{\hat{W}}_i \\ &\le -K_i r_i^2 - |r_i|\tilde{W}_i^T\Phi_i(X_i) + |r_i|\varepsilon_{iM} + \tilde{W}_i^T\Gamma_i^{-1}\dot{\hat{W}}_i \end{aligned} \tag{23}$$

Thus the Lyapunov function for the overall system becomes

$$V = \sum_{i=1}^{n} V_i \tag{24}$$

Note that

$$\sum_{i=1}^{n}\sum_{j=1}^{n} \delta_{ij}(|x_{j1}|,|x_{j2}|) = \sum_{i=1}^{n}\sum_{j=1}^{n} \delta_{ji}(|x_{i1}|,|x_{i2}|) \tag{25}$$

Thus

$$\dot{V} \le \sum_{i=1}^{n}\left[-K_i r_i^2 - |r_i|\tilde{W}_i^T\Phi_i(X_i) + \tilde{W}_i^T\Gamma_i^{-1}\dot{\hat{W}}_i + |r_i|\varepsilon_{iM}\right] \tag{26}$$

The weight updating rule is chosen according to

$$\dot{\hat{W}}_i = \Gamma_i|r_i|\Phi_i(X_i) - \alpha_i\Gamma_i\hat{W}_i \tag{27}$$

Then (24) becomes

$$\dot{V} \le \sum_{i=1}^{n}(-K_i r_i^2 - \alpha_i\tilde{W}_i^T\hat{W}_i + |r_i|\varepsilon_{iM}) \tag{28}$$

Since

$$-\alpha_i \tilde{W}_i^T \hat{W}_i \le -\alpha_i \left|\tilde{W}_i\right|^2 + \alpha_i \left|\tilde{W}_i\right|\left|W_i\right| \le -\frac{\alpha_i}{2}\left|\tilde{W}_i\right|^2 + \frac{\alpha_i}{2} W_{i\max}^2 \quad (29)$$

and

$$\varepsilon_i^M \left|r_i\right| \le \frac{r_i^2}{2} + \frac{1}{2}\varepsilon_{iM}^2 \quad (30)$$

Thus,

$$\dot{V} \le \sum_{i=1}^{n}[-(K_i - \frac{1}{2})r_i^2 - \frac{\alpha_i}{2}\left|\tilde{W}_i\right|^2 + \frac{\alpha_i}{2}W_{i\max}^2 + \frac{1}{2}\varepsilon_{iM}^2] \quad (31)$$

For simplification, define $\delta = \sum_{i=1}^{n} \frac{\alpha_i W_{i\max}^2 + \varepsilon_{iM}^2}{2}$. If the selection of design parameters K_i and α_i, such that $K_i>\gamma+1/2$, and $\alpha_i \ge \gamma\lambda_{\max}(\Gamma_i^{-1})$, then we get

$$\dot{V} \le -\gamma \sum_{i=1}^{n}\left[r_i^2 + \tilde{W}_i^T \Gamma_i^{-1} \tilde{W}_i\right] + \delta \le -\gamma V + \delta \quad (32)$$

Theorem 1: Consider the closed-loop system consisting of system (8), the controller (17), 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 Ω.

$$\Omega = \left\{ r, \hat{W} \middle| V < \frac{\delta}{\gamma} \right\} \quad (33)$$

Proof: From (33), it can be seen that if r_i and $\tilde{W}_i$ are outside of the compact set defined as (33), then $\dot{V}$ will remain negative definite until the systems state and the weight estimate errors enter the Ω. 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 (16) and the boundedness of r_i, we can conclude that x_i is bounded. Using (20), 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 Ω.

B. NN Based Decentralized Steam-Valve Control

According to backstepping, the design procedure is described using three steps [18].

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

$$e_i = x_{i1} - x_{i1d} \quad (34)$$

Then the filtered tracking errors can be defined as

$$z_{i0} = [\lambda_i \quad 1]\overline{e}_i \quad (35)$$

where $\overline{e}_i = [e_i, \dot{e}_i]$, $\lambda_i>0$ such that $x_{i1}\text{->}x_{1d}$ as $z_{i0}\text{->}0$ (i.e. $s+\lambda_i=0$ is Hurwitz).

Taking the derivative of (35) and using (14) to get

$$\dot{z}_{i0} = \lambda_i x_{i2} + f_{i0}(x_{i2}) + \xi_{i1} + \Delta_i(.) \quad (36)$$

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

$$r_{i0}^* = -K_{i0}z_{i0} - [\lambda_i x_{i2} + f_{i0}(x_{i2})] - sign(z_{i0})\sum_{j=1}^{n}\delta_{ji}\left|x_{i1}\right| \quad (37)$$

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.

$$\begin{aligned} &W_{i01}{}^T \Phi_{i01}(X_{i01}) + \varepsilon_{i01} = \lambda_i x_{i2} + f_{i0}(x_{i2}) \\ &W_{i02}{}^T \Phi_{i02}(X_{i02}) + \varepsilon_{i02} = \sum_{j=1}^{n}\delta_{ji}\left|x_{i1}\right| \end{aligned} \quad (38)$$

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

If ξ_{i1} is the actual control signal, the virtual control signal can be chosen as

$$\hat{r}_{i0} = -K_{i0}z_{i0} - \hat{W}_{i01}{}^T\Phi_{i01}(X_{i01}) - \operatorname{sgn}(z_{i0})\hat{W}_{i02}{}^T\Phi_{i02}(X_{i02}) \quad (39)$$

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 $f_2(x)=xf_1(x)$. It is easy to verify that the estimation error is bounded [11].

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

$$r_{i0} = -K_{i0}z_{i0} - \hat{W}_{i01}^T\Phi_{i01}(X_{i01}) - f_1(z_{i0})\hat{W}_{i02}^T\Phi_{i02}(X_{i02}) \quad (40)$$

Define

$$z_{i1} = \xi_{i1} - r_{i0} \quad (41)$$

Choose the Lyapunov function for this step as

$$V_0 = \sum_{i=1}^{n} V_{0i} = \sum_{i=1}^{n}\left(\frac{1}{2}z_{i0}^2 + \frac{1}{2}\tilde{W}_{i01}^T\Gamma_{i01}^{-1}\tilde{W}_{i01} + \frac{1}{2}\tilde{W}_{i02}^T\Gamma_{i02}^{-1}\tilde{W}_{i02}\right) \quad (42)$$

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

$$\begin{aligned} &\dot{\hat{W}}_{i01} = \Gamma_{i01}[z_{i0}\Phi_{i01}(X_{i01}) - \alpha_{i01}\hat{W}_{i01}] \\ &\dot{\hat{W}}_{i02} = \Gamma_{i02}[|z_{i0}|\Phi_{i02}(X_{i02}^{'}) - \alpha_{i02}\hat{W}_{i02}] \end{aligned} \quad (43)$$

According to the bound analysis in [11], we know the following expressing is valid.

$$\dot{V}_0 \le \sum_{i=1}^{n}\left(-c_{i01}z_{i0}^2 + z_{i0}z_{i1} - c_{i02}\left|\tilde{W}_{i01}\right|^2 - c_{i03}\left|\tilde{W}_{i02}\right|^2 + c_{i04}\right) \quad (44)$$

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

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

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 [11].

Step 1: Taking the derivative of (41) and using (14) to get

$$\dot{r}_{i0} = \phi_{i0}(.) + \frac{\partial \alpha_{i0}}{\partial x_{i2}} \Delta_{i0}(.) + \frac{\partial \alpha_{i0}}{\partial \hat{W}_{i02}} \Gamma_{i02} |z_{i0}| \Phi_{i0}(X_{i02}) \tag{45}$$

where

$$\phi_{i0} = \frac{\partial r_{i0}}{\partial x_{i1}} x_{i2} + \frac{\partial r_{i0}}{\partial x_{i2}} [f_{i0}(x_{i2}) + \xi_{i1}] + \frac{\partial r_{i0}}{\partial \hat{W}_{i01}} \dot{\hat{W}}_{i01} - \frac{\partial r_{i0}}{\partial \hat{W}_{i02}} \Gamma_{i02} \alpha_{i02} \hat{W}_{i02} \tag{46}$$

Thus

$$\dot{z}_{i1} = f_{i1}(\xi_{i1}) + \xi_{i2} - \phi_{i0} - \frac{\partial \alpha_{i0}}{\partial x_{i2}} \Delta_{i0}(.) - \frac{\partial \alpha_{i0}}{\partial \hat{W}_{i02}} \Gamma_{i02} |z_{i02}| \Phi_{i02}(X'_{i02}) \tag{47}$$

Define

$$z_{i2} = \xi_{i2} - \alpha_{i1} \tag{48}$$

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

$$\begin{aligned} r_{i1}^* &= -z_{i0} - K_{i1} z_{i1} - [f_{i1}(\xi_{i1}) - \phi_{i0}] \\ &\quad - sign(z_{i1}) \left\{ \left| \frac{\partial \alpha_{i0}}{\partial x_{i2}} \right| \left[\sum_{j=1}^{n} \delta_{ji}(|x_{i1}|) \right] + \Gamma_{i02} |z_{i0}| \right\} \end{aligned} \tag{49}$$

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

$$W_{i11}^T \Phi_{i11}(X_{i11}) + \varepsilon_{i11} = f_{i1}(\xi_{i1}) - \phi_{i0} \tag{50}$$

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

$$W_{i12}^T \Phi_{i12}(X_{i12}) + \varepsilon_{i12} = \left| \frac{\partial \alpha_{i0}}{\partial x_{i2}} \right| \left[\sum_{j=1}^{n} \delta_{ji}(|x_{i1}|) \right] + \Gamma_{i02} |z_{i0}| \tag{51}$$

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

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

$$X_{i12} = [f(z_{i0}), f(x_{i1}), f(\frac{\partial \alpha_{i0}}{\partial x_{i2}}), 1] \tag{52}$$

Correspondingly, the realizable control signal becomes

$$r_{i1} = -z_{i0} - K_{i1} z_{i1} - \hat{W}_{i11}^T \Phi_{i11}(X_{i11}) - f_1(z_{i1}) \hat{W}_{i12}^T \Phi_{i12}(X'_{i12}) \tag{53}$$

Choose the Lyapunov function for this step as

$$V_1 = V_0 + \sum_{i=1}^{n} \left(\frac{1}{2} z_{i1}^2 + \frac{1}{2} \tilde{W}_{i11}^T \Gamma_{i11}^{-1} \tilde{W}_{i11} + \frac{1}{2} \tilde{W}_{i12}^T \Gamma_{i12}^{-1} \tilde{W}_{i12} \right) \tag{54}$$

where $\Gamma_{i11}, \Gamma_{i12} > 0$ are the adaptation gain matrices, $\tilde{W}_{i11}$ and $\tilde{W}_{i12}$ are the weights estimation errors.
The weights updating rules are chosen as

$$\begin{aligned} \dot{\hat{W}}_{i11} &= \Gamma_{i11}[z_{i1} \Phi_{i11}(X_{i11}) - \alpha_{i11} \hat{W}_{i11}] \\ \dot{\hat{W}}_{i12} &= \Gamma_{i12}[|z_{i1}| \Phi_{i12}(X'_{i12}) - \alpha_{i12} \hat{W}_{i12}] \end{aligned} \tag{55}$$

Similar to Step 0, taking the derivative (54) and using (55) to get

$$\begin{aligned} \dot{V}_1 &= \dot{V}_0 + \sum_{i=1}^{N} \left[z_{i1} \dot{z}_{i1} + \tilde{W}_{i11}^T \Gamma_{i11}^{-1} \dot{\tilde{W}}_{i11} + \tilde{W}_{i12}^T \Gamma_{i12}^{-1} \dot{\tilde{W}}_{i12} \right] \\ &\le \sum_{i=1}^{n} \begin{bmatrix} z_{i1} z_{i2} - c_{i01} z_{i0}^2 - c_{i02} |\tilde{W}_{i01}|^2 - c_{i03} |\tilde{W}_{i02}|^2 + c_{i04} \\ -c_{i11} z_{i1}^2 - c_{i12} |\tilde{W}_{i11}|^2 - c_{i13} |\tilde{W}_{i12}|^2 + c_{i14} \end{bmatrix} \end{aligned} \tag{56}$$

where $c_{i11} = K_{i1} - \frac{3}{2} > 0$, $c_{i12} = \frac{\alpha_{i11}}{2} > 0$, $c_{i13} = \frac{\alpha_{i12} - 1}{2} > 0$ and

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

Step 2: Taking the derivative of (53) to get

$$\begin{aligned} \dot{r}_{i1} &= \phi_{i1} + \frac{\partial r_{i1}}{\partial x_{i2}} \Delta_i(.) + \frac{\partial r_{i1}}{\partial \hat{W}_{i02}} \Gamma_{i02} |z_{i0}| \Phi_{i02}(X_{i02}) \\ &\quad + \frac{\partial r_{i1}}{\partial \hat{W}_{i12}} \Gamma_{i12} |z_{i1}| \Phi_{i12}(X_{i12}) \end{aligned} \tag{57}$$

where

$$\begin{aligned} \phi_{i1} &= \frac{\partial \alpha_{i1}}{\partial x_{i1}} x_{i2} + \frac{\partial \alpha_{i1}}{\partial x_{i2}} [f_{i0}(x_{i2}) + \xi_{i1}] + \frac{\partial \alpha_{i1}}{\partial \xi_{i1}} \dot{\xi}_{i2} + \frac{\partial \alpha_{i1}}{\partial \hat{W}_{i01}} \dot{\hat{W}}_{i01} \\ &\quad - \frac{\partial \alpha_{i1}}{\partial \hat{W}_{i02}} \Gamma_{i02} \alpha_{i02} \hat{W}_{i02} + \frac{\partial \alpha_{i1}}{\partial \hat{W}_{i11}} \dot{\hat{W}}_{i11} - \frac{\partial \alpha_{i1}}{\partial \hat{W}_{i12}} \Gamma_{i12} \alpha_{i12} \hat{W}_{i12} \end{aligned} \tag{58}$$

Thus,

$$\begin{aligned} \dot{z}_{i2} &= f_{i2}(x_{i2}, \xi_{i2}) + u_i - \phi_{i1} - \frac{\partial \alpha_{i1}}{\partial x_{i2}} \Delta_i(.) \\ &\quad - \frac{\partial \alpha_{i1}}{\partial \hat{W}_{i02}} \Gamma_{i02} |z_{i0}| \Phi_{i02}(X_{i02}) - \frac{\partial \alpha_{i1}}{\partial \hat{W}_{i12}} \Gamma_{i12} |z_{i1}| \Phi_{i23}(X_{i12}) \end{aligned} \tag{59}$$

The desired control can be selected as:

$$\begin{aligned} u_i^* &= -z_{i1} - K_{i2} z_{i2} - [f_{i2}(x_{i2}, \xi_{i2}) - \phi_{i1}] \\ &\quad - sign(z_{i2}) \left\{ \left| \frac{\partial \alpha_{i1}}{\partial x_{i2}} \right| \left[\sum_{j=1}^{N} \delta_{ji}(|x_{i1}|) \right] + \Gamma_{i02} |z_{i0}| + \Gamma_{i12} |z_{i1}| \right\} \end{aligned} \tag{60}$$

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

$$W_{i21}^T \Phi_{i21}(X_{i21}) + \varepsilon_{i21} = f_{i2}(x_{i2}, \xi_{i2}) \tag{61}$$

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

$$X_{i21} = [x_{i1}, x_{i2}, \xi_{i1}, \xi_{i2}, W_{i01}, W_{i02}, W_{i11}, W_{i12}, 1] \tag{62}$$

and another neural network satisfying

$$\begin{aligned} & W_{i2,2}^T \Phi_{i22}(X_{i22}) + \varepsilon_{i22} \\ &= |z_{i2}| \left\{ \left| \frac{\partial \alpha_{i1}}{\partial x_{i2}} \right| \left[\sum_{j=1}^{N} \delta_{ji}(|x_{i1}|) \right] + \Gamma_{i02} |z_{i0}| + \Gamma_{i12} |z_{i1}| \right\} \end{aligned} \tag{63}$$

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

$$X_{i22} = [|z_{i0}|, |z_{i1}|, |x_{i1}|, \left| \frac{\partial \alpha_{i1}}{\partial x_{i2}} \right|, 1] \tag{64}$$

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

$$u_i = -z_{i1} - K_{i2} z_{i2} - \hat{W}_{i21}^T \Phi_{i21}(X_{i21}) - sign(z_{i2}) \hat{W}_{i22}^T \Phi_{i22}(X_{i22}) \tag{65}$$

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

$$\begin{aligned} \dot{\hat{W}}_{i21} &= \Gamma_{i21}[z_{i2} \Phi_{i21}(X_{i21}) - \alpha_{i21} \hat{W}_{i21}] \\ \dot{\hat{W}}_{i22} &= \Gamma_{i22}[|z_{i2}| \Phi_{i22}(X'_{i22}) - \alpha_{i22} \hat{W}_{i22}] \end{aligned} \tag{66}$$

The Lyapunov function for the overall system is selected as

$$V = V_1 + \sum_{i=1}^{n} V_{2i} = V_1 + \sum_{i=1}^{n} \left(\frac{1}{2} z_{i2}^2 + \frac{1}{2} \tilde{W}_{i2}^T \Gamma_{i2}^{-1} \tilde{W}_{i2} \right) \tag{67}$$

Evaluating (67)'s derivative and using the same analysis as [11] to get

$$\dot{V} \le \sum_{i=1}^{n}\left[-\sum_{k=0}^{2} c_{ik1} z_{ik}^{2} - \sum_{k=0}^{2} c_{ik2}\left|\tilde{W}_{ik1}\right|^{2} - \sum_{k=0}^{2} c_{ik3}\left|\tilde{W}_{ik2}\right|^{2} - \sum_{k=0}^{2} c_{ik4}\right] \quad (68)$$

where $c_{i21} = K_{i2} - 1 > 0$, $c_{i22} = \dfrac{\alpha_{i21}}{2}$, $c_{i23} = \dfrac{\alpha_{i22}}{2}$, and $c_{i24} = \dfrac{\varepsilon_{i21}^{M} + \varepsilon_{i22}^{M} + \alpha_{i21}\left|W_{i21}\right|^{2} + \alpha_{i22}\left|W_{i22}\right|^{2}}{2}$.

Theorem 2: Consider the closed-loop system consisting of system (11), the desired output x_d, the controller (65), and the NN weight updating laws (43), (55) and (66). 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 *Ω*.

$$\Omega = \left\{ X, \Xi, \hat{W}_{i01}, \hat{W}_{i11}, \hat{W}_{i12}, \hat{W}_{i02}, \hat{W}_{i12}, \hat{W}_{i22} \,\middle|\, V < \frac{\delta}{\gamma} \right\} \quad (69)$$

Since the proof for this theorem is similar to Theorem 1, limited by pages number, the proof is omitted here.

V. Simulation Study

The proposed decentralized NN controller designs are evaluated with a three-machine power system described in [7]. For convenience, the configuration and the parameters of the example power system are shown in Fig.1 and Table 1 respectively.

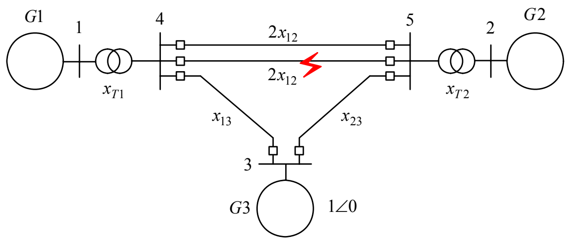

Fig. 1. Configuration of the three-machines power system.

TABLE I
Generator and Transmission Line Parameters

Symbol	Generator No. 1	Generator No. 2
D (p.u.)	5	3
H (s)	4	5.1
T_m (s)	0.35	0.35
K_m	1.0	1.0
K_e	1.0	1.0
T_e (s)	0.1	0.1
R	0.05	0.05
Ω_0 (rad/s)	377	377
x_{12}=0.55p.u	x_{13}=0.53p.u.	x_{23}=0.6p.u.

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 G1 and G2. 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 initial operating points are chosen as

$$\begin{aligned} &\delta_{10} = 1.0608\,\text{rad}, \mathrm{P}_{\mathrm{m}10} = 1.10\,p.u., V_{t10} = 1.0\,p.u. \\ &\delta_{20} = 1.0584\,\text{rad}, \mathrm{P}_{\mathrm{m}20} = 1.01\,p.u., V_{t20} = 1.0\,p.u. \end{aligned} \quad (70)$$

The design parameters for the two decentralized excitation controllers are the same according to (71).

$$\begin{aligned} &\Lambda_1 = \Lambda_2 = [25,\ 10]^T,\ K_1 = K_2 = 5 \\ &\Gamma_1 = \Gamma_2 = 5,\ \alpha_1 = \alpha_2 = 5,\ k = 5 \end{aligned} \quad (71)$$

Simulation results when there is no excitation controller are shown in Figs. 2~3 and the simulation results under the proposed NN based excitation control are shown in Figs. 4~7.

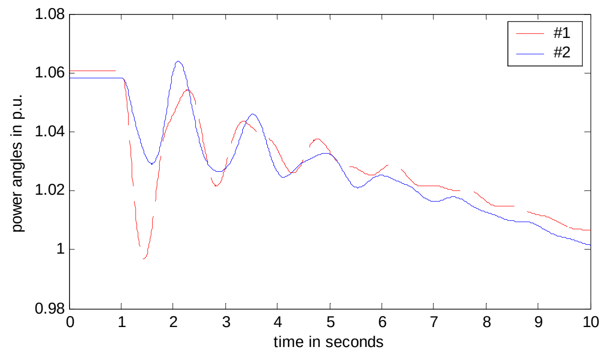

Fig. 2. Power angle responses without excitation controls

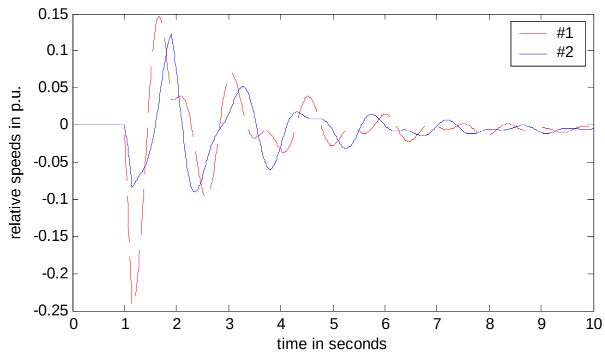

Fig. 3. Speed deviation responses without excitation controls

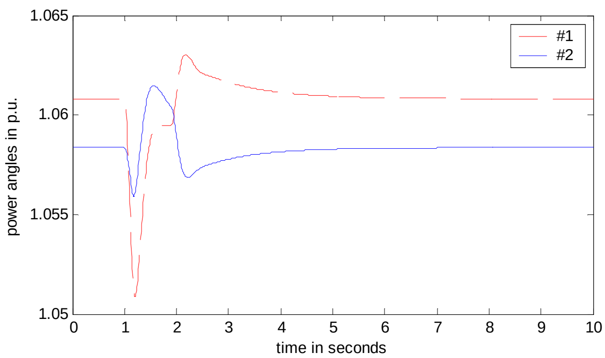

Fig. 4. Power angle responses under the decentralized excitation controls

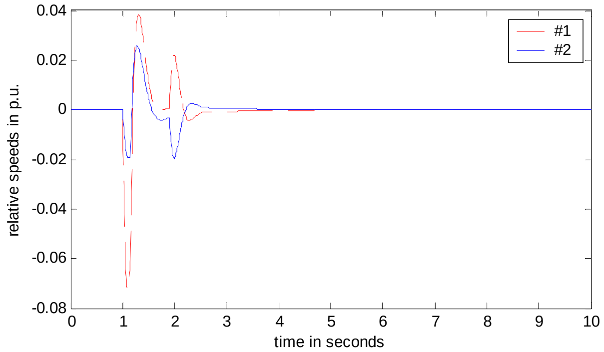

Fig. 5. Speed deviation responses under the decentralized excitation controls

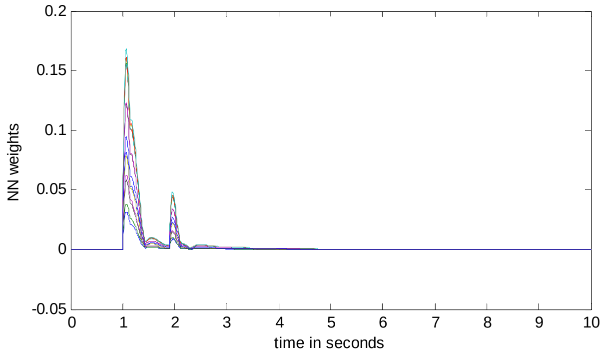

Fig. 6. Weights updating process of the excitation control for G1

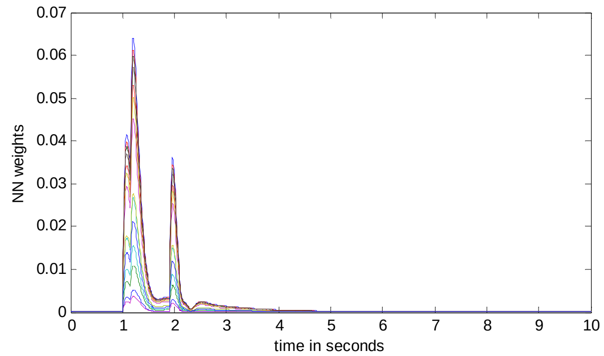

Fig. 7. Weights updating process of the excitation control for G2

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 Figs 2 and 3 that the system responses compose of different frequencies. This is because the interaction of between the subsystems' activities. From Figs. 4 and 5, it can be seen that the interactions have been successfully damped under the proposed decentralized excitation controls. Since there is no direct communication and coordination between the subsystem controllers, this performance is achieved by the analysis of the interconnection terms and the controller design.

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 (72).

$$\lambda_i = 5,\ K_{i0} = K_{i1} = K_{i2} = 5,\ k = 5$$
$$\Gamma_{i01} = \Gamma_{i02} = \Gamma_{i11} = \Gamma_{i12} = \Gamma_{i21} = \Gamma_{i22} = 5 \qquad (72)$$
$$\alpha_{i01} = \alpha_{i02} = \alpha_{i11} = \alpha_{i12} = \alpha_{i21} = \alpha_{i22} = 5$$

where i = 1, 2

Simulation results are shown in Figs 8~12.

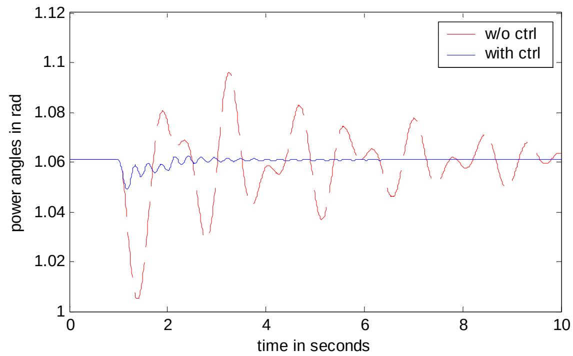

Fig. 8. Power angle responses comparison of G1

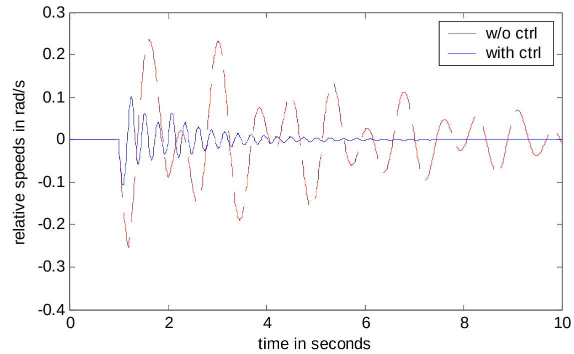

Fig. 9. Relative speed responses comparison of G1

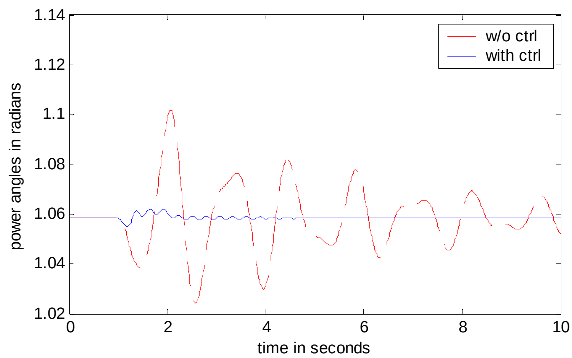

Fig. 10. Power angle responses comparison of G2

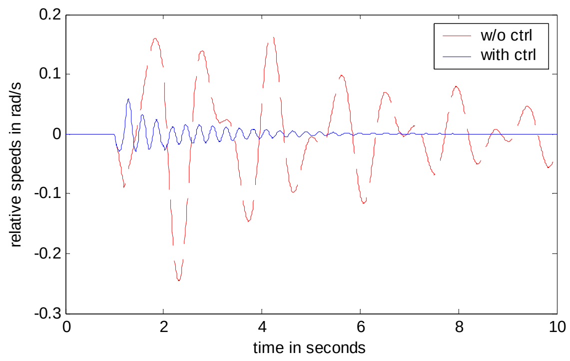

Fig. 11. Relative speed responses comparison of G2

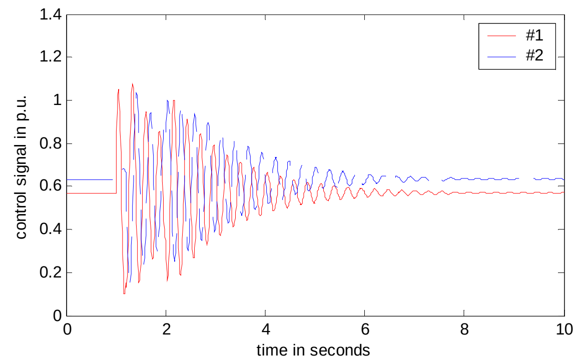

Fig. 12. Control signals responses of G1 and G2

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. Furthermore, from Figs 12, it can be observed that the control signals are bounded.

VI. 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 will includes the consideration of more practical power system model.

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