Power System Stabilizer Using Adaptive Control Rules

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Abstract

This paper presents a power system stabilizer (PSS) using adaptive control rules. The PSS consists of an adaptive controller and a compensator to damp the oscillations of power system. The function of controller is to supply an adaptive control signal to the exciter or governor with the adaptive law, which can damp most of the power system's oscillations. The function of compensator is to delete the extra disturbance or uncertainty. The principle and equation derivation are introduced and analyzed. Simulations for the power system are demonstrated their performance and compare with the conventional PSS does.

Keywords: power system stabilizer, adaptive control, neural networks.

1. Introduction

In recent years, there are many published paper proposed adaptive PSS to damp the oscillations of power system. A number of adaptive stabilizer schemes have also been proposed [1-2]. With the power system stabilizer (PSS) based on recurrent neural network to damp the oscillations of the power systems are also introduced in recent years. The simulation results have been demonstrated that the performances are better than those of conventional PSS [3]. In those schemes the dynamic changes in the power systems network and load levels are compensated by the time-varying, self-adjusting controller so that the PSS performance is optimal in a wider range of operating conditions. Effective and uniform damping on a multimachine system often requires the use of multiple stabilizers at different nodes in the network. A scheme for coordinating the PSS signals enables the synthesis of complementary, non-conflicting and adequate inputs for uniform damping of the interconnected power system. Since the generating units that are often targeted for stabilization are geographically or physically separated over large distances, the control design schemes must include some decentralization philosophy to reflect practical limitations of controller elements. An adaptive model-following multimachine PSS design technique is presented in this research. With this scheme coordinated control signals are derived at the inputs of each generating unit using only local terminal measurements. To achieve this objective, a proposed recurrent neural network controller (RNNC) and compensator are chosen for each machine to control the dynamic interaction between that machine and the rest of the interconnected network. The effectiveness of the proposed technique is demonstrated on a multimachine power system using computer simulation studies. Results show improvement in the overall system damping characteristics using the proposed adaptive neural network PSS in comparison to conventional stabilizers.

2. The adaptive neural network control scheme

The PSS using adaptive control rules is designed to control the power system generator one by one. The simulation model for multi-machine is shown in Figure 1. The elements of state vector are phase deviation (Δδ), angular velocity deviation (Δω), field voltage deviation in q axis (Δe_q) and field voltage deviation (Δe_{FD},) respectively. The block diagram of the proposed adaptive control PSS for a multi-machine power system is illustrated in Figure 2**.** Since the state oscillations of the power system have to be damped, the control goal R is designed to be zero for low frequency oscillations. The RNNC to be applied here is the proposed two-layer RNNC, which is used to supply an adaptive control signal to the exciter or governor system. The compensated controller is used to make up or delete the unknown disturbance and extra uncertainties. The principle and mathematic derivation for the adaptive control PSS is derived as following:

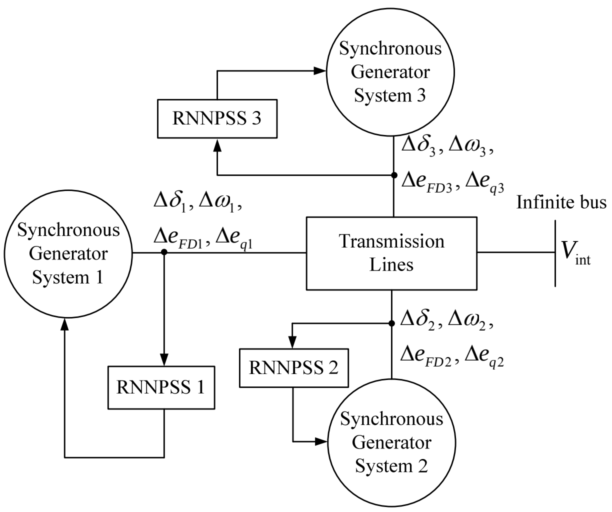


Figure 1 The block diagram of adaptive control scheme for the power system

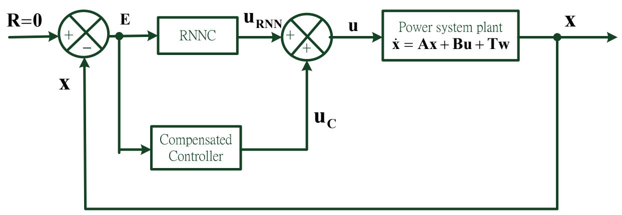


Figure 2 The block diagram of adaptive control scheme for the power system

the state equation of the power system is described by [1,5,6]

$$\dot{\mathbf{x}} = \mathbf{Ax}+\mathbf{Bu}+\mathbf{Tw} \qquad (1)$$

where the **x** is the state vector of the power system, **u** is the input vector, **w** is the disturbance and **A, B, T** are the parameter constant of the state equation. Since the parameter constant **B** is a 12 by 1 vector, in order to delete the disturbance **w**, the optimal input vector can be assumed by

$$\mathbf{u}^* = \mathbf{B}^T(\mathbf{BB}^T)^{-1}(-\mathbf{Tw}-\mathbf{Ax}_r+\dot{\mathbf{x}}_r-\mathbf{A}^*\mathbf{E}) \qquad (2)$$

Substitute Eq. (2) into (1) the $\dot{\mathbf{x}}$ can be obtained as

$$\begin{aligned}\dot{\mathbf{x}} &= \mathbf{Ax}+\mathbf{BB}^T(\mathbf{BB}^T)^{-1}\\ &(-\mathbf{Tw}-\mathbf{Ax}_r+\dot{\mathbf{x}}_r-\mathbf{A}^*\mathbf{E})+\mathbf{Tw}\end{aligned} \qquad (3)$$

Eq. (3) then becomes

$$\dot{\mathbf{x}} = \mathbf{Ax}-\mathbf{Ax}_r+\dot{\mathbf{x}}_r-\mathbf{A}^*\mathbf{E} \qquad (4)$$

$$\dot{\mathbf{x}}-\dot{\mathbf{x}}_r = \mathbf{Ax}-\mathbf{Ax}_r-\mathbf{A}^*\mathbf{E} \qquad (5)$$

Let

$$\dot{\mathbf{x}}-\dot{\mathbf{x}}_r = \dot{\mathbf{E}} \text{ and } \mathbf{x}-\mathbf{x}_r = \mathbf{E} \qquad (6)$$

$$\dot{\mathbf{E}}+(\mathbf{A}^*-\mathbf{A})\mathbf{E} = \mathbf{0} \qquad (7)$$

If $\mathbf{A}^*$ is chosen to correspond to the coefficient $(\mathbf{A}^*-\mathbf{A})$ of a Hurwitz matrix, that is a matrix whose eigenvalues are all negative. The damping of system oscillations will be achieved when $\lim_{t\to\infty}\mathbf{E}(t)=\mathbf{0}$ for any initial conditions. Nevertheless, the functions **A** and **B** aren't accurately known and the external disturbances are perturbed. Thus, the ideal controller $u^*(t)$ cannot be practically implemented. Therefore, the adaptive neural network control system has to be designed to approximate this ideal controller.

The proposed RNNC as shown in Figure 3 is a two layer recurrent neural network. The algorithm and formula derivations were discussed in [3, 6]. The control law for the adaptive RNNC system is assumed to take the following form:

$$\mathbf{u} = \mathbf{u}_{\mathbf{RNN}} + \mathbf{u}_{\mathbf{C}} \tag{8}$$

where $\mathbf{u}_{\mathbf{RNN}}$ is the main tracking controller to approximate the ideal controller $u^*(t)$. The $\mathbf{u}_{\mathbf{C}}$ is the compensated signal which can be used to make up the adaptive signal for the PSS between the ideal control effort and the RNNC effort.

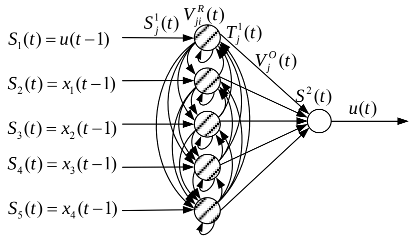


Figure 3. The structure of the RNNC

After the rearrangement, Eqs. (1), (2) and (8), the error equation can be expressed by:

$$\dot{\mathbf{E}} = -\overline{\mathbf{A}}\mathbf{E} + \mathbf{B}(\mathbf{u}^* - \mathbf{u}_{\mathbf{RNN}} - \mathbf{u}_{\mathbf{C}}) \tag{9}$$

where $\overline{\mathbf{A}} = (\mathbf{A}^* - \mathbf{A})$ is a Hurwitz matrix.

In this control strategy, an optimal RNN to approximate the ideal control law is assumed to be

$$\begin{aligned}\mathbf{u}^* &= \mathbf{u}^*_{\mathbf{RNN}}(\mathbf{E}, \mathbf{V}_j^{\mathbf{O}*}, \mathbf{V}_{ji}^{\mathbf{R}*}) + \boldsymbol{\varepsilon} \\ &= (\mathbf{V}_j^{\mathbf{O}*})^{\mathrm{T}}\mathbf{T}_j^{1*} + \boldsymbol{\varepsilon}\end{aligned} \tag{10}$$

where $\boldsymbol{\varepsilon}$ is a minimum reconstructed error, $\mathbf{V}_j^{\mathbf{O}*}, \mathbf{V}_{ji}^{\mathbf{R}*}$ and $\mathbf{T}_j^{1*}$ are optimal parameters of $\mathbf{V}_j^{\mathbf{O}}, \mathbf{V}_{ji}^{\mathbf{R}}$ and $\mathbf{T}_j^1$, respectively. Thus, the RNN control law is assumed to be expressed by

$$\begin{aligned}\mathbf{u} &= \mathbf{u}_{\mathbf{RNN}}(\mathbf{E}, \mathbf{V}_j^{\mathbf{O}*}, \mathbf{V}_{ji}^{\mathbf{R}*}) + \mathbf{u}_{\mathrm{C}} \\ &= (\hat{\mathbf{V}}_j^{\mathbf{O}})^{\mathrm{T}}\hat{\mathbf{T}}_j^1 + \mathbf{u}_{\mathrm{C}}\end{aligned} \tag{11}$$

where $\hat{\mathbf{V}}_j^{\mathbf{O}}, \hat{\mathbf{V}}_{ji}^{\mathbf{R}}$ and $\hat{\mathbf{T}}_j^1$ are estimations of the optimal parameters. The systems will provide to be stable by tuning the parameters of RNNC, the performance of the simulation results will be introduced later.

Subtracting Eq. (11) from Eq. (10), an approximation error $\tilde{u}$ can be obtained by

$$\begin{aligned}\tilde{\mathbf{u}} &= \mathbf{u}^* - \mathbf{u} \\ &= (\mathbf{V}_j^{\mathbf{O}*})^{\mathrm{T}}\mathbf{T}_j^{1*} + \varepsilon - (\hat{\mathbf{V}}_j^{\mathbf{O}})^{\mathrm{T}}\hat{\mathbf{T}}_j^1 - \mathbf{u}_{\mathrm{C}} \\ &= (\tilde{\mathbf{V}}_j^{\mathbf{O}})^{\mathrm{T}}\mathbf{T}_j^{1*} + (\hat{\mathbf{V}}_j^{\mathbf{O}})^{\mathrm{T}}\tilde{\mathbf{T}}_j^1 + \varepsilon - \mathbf{u}_{\mathrm{C}}\end{aligned} \tag{12}$$

where $\tilde{\mathbf{V}}_j^{\mathbf{O}} = \mathbf{V}_j^{\mathbf{O}*} - \hat{\mathbf{V}}_j^{\mathbf{O}}$ and $\tilde{\mathbf{T}}_j^1 = \mathbf{T}_j^{1*} - \hat{\mathbf{T}}_j^1$. The linearization technique transforms the multidimensional receptive-field basis functions into a partially linear form such that the expansion of $\tilde{\mathbf{T}}_j^1$ in Taylor series can be expressed by

$$\begin{aligned}\tilde{\mathbf{T}}^1 &= \begin{bmatrix}\tilde{\mathbf{T}}_1^1 \\ \cdot \\ \cdot \\ \cdot \\ \tilde{\mathbf{T}}_j^1\end{bmatrix} \\ &= \begin{bmatrix}\dfrac{\partial \mathbf{T}_1^1}{\partial \mathbf{V}_{ji}^{\mathbf{R}}} \\ \cdot \\ \cdot \\ \cdot \\ \dfrac{\partial \mathbf{T}_k^1}{\partial \mathbf{V}_{ji}^{\mathbf{R}}}\end{bmatrix}_{\mathbf{V}_{ji}^{\mathbf{R}} = \hat{\mathbf{V}}_{ji}^{\mathbf{R}}} (\mathbf{V}_{ji}^{\mathbf{R}*} - \hat{\mathbf{V}}_{ji}^{\mathbf{R}}) \\ &= \mathbf{T}_{\mathrm{V}}^1\tilde{\mathbf{V}}_{ji}^{\mathbf{R}} + \mathbf{O}_{\mathrm{V}}\end{aligned} \tag{13}$$

where $\tilde{\mathbf{T}}_j^1 = \tilde{\mathbf{T}}_j^{1*} - \hat{\mathbf{T}}_j^1$, $\tilde{\mathbf{T}}_j^{1*}$ is the optimal parameter of $\hat{\mathbf{T}}_j^1$, $\hat{\mathbf{T}}_j^1$ is the estimated parameter of $\tilde{\mathbf{T}}_j^{1*}$, $\tilde{\mathbf{V}}_{ji}^{\mathbf{R}} = \mathbf{V}_{ji}^{\mathbf{R}*} - \hat{\mathbf{V}}_{ji}^{\mathbf{R}}$, $\mathbf{O}_{\mathrm{V}}$ is a vector of higher-order terms

$$\mathbf{T}_{\mathrm{V}}^1 = \begin{bmatrix}\dfrac{\partial \mathbf{T}_1^1}{\partial \mathbf{V}_{ji}^{\mathbf{R}}} & \cdots & \dfrac{\partial \mathbf{T}_k^1}{\partial \mathbf{V}_{ji}^{\mathbf{R}}}\end{bmatrix}^{\mathrm{T}}_{\mathbf{V}_{ji}^{\mathbf{R}} = \hat{\mathbf{V}}_{ji}^{\mathbf{R}}}.$$

Eq. (13) can be rewritten by

$$\mathbf{T}_j^{1*} = \hat{\mathbf{T}}_j^1 + \mathbf{T}_{\mathrm{V}}^1\tilde{\mathbf{V}}_{ji}^{\mathbf{R}} + \mathbf{O}_{\mathrm{V}} \tag{14}$$

Substituting Eq. (14) into Eq. (12), the approximation error $\tilde{\mathbf{u}}$ can be expressed as:

$$\begin{aligned}\tilde{\mathbf{u}} &= \tilde{\mathbf{V}}_j^{\mathbf{OT}}(\hat{\mathbf{T}}_j^1 + \mathbf{T}_{\mathrm{V}}^1\tilde{\mathbf{V}}_{ji}^{\mathbf{R}} + \mathbf{O}_{\mathrm{V}}) + \hat{\mathbf{V}}_j^{\mathbf{OT}}(\mathbf{T}_{\mathrm{V}}^1\tilde{\mathbf{V}}_{ji}^{\mathbf{R}} + \mathbf{O}_{\mathrm{V}}) + \boldsymbol{\varepsilon} - \mathbf{u}_{\mathrm{C}} \\ &= \tilde{\mathbf{V}}_j^{\mathbf{OT}}\hat{\mathbf{T}}_j^1 + \hat{\mathbf{V}}_j^{\mathbf{OT}}\mathbf{T}_{\mathrm{V}}^1\tilde{\mathbf{V}}_{ji}^{\mathbf{R}} + \tilde{\mathbf{V}}_j^{\mathbf{OT}}\mathbf{T}_{\mathrm{V}}^1\tilde{\mathbf{V}}_{ji}^{\mathbf{R}} + \mathbf{V}_j^{\mathbf{O*T}}\mathbf{O}_{\mathrm{V}} + \boldsymbol{\varepsilon} - \mathbf{u}_{\mathrm{C}} \\ &= \tilde{\mathbf{V}}_j^{\mathbf{OT}}\hat{\mathbf{T}}_j^1 + \hat{\mathbf{V}}_j^{\mathbf{OT}}\mathbf{T}_{\mathrm{V}}^1\tilde{\mathbf{V}}_{ji}^{\mathbf{R}} - \mathbf{u}_{\mathrm{C}} + \mathbf{D}\end{aligned} \tag{15}$$

where $\mathbf{D} = \tilde{\mathbf{V}}_j^{\mathbf{OT}}\mathbf{T}_{\mathrm{V}}^1\tilde{\mathbf{V}}_{ji}^{\mathbf{R}} + \mathbf{V}_j^{\mathbf{O*T}}\mathbf{O}_{\mathrm{V}} + \boldsymbol{\varepsilon}$ is the uncertainty term, and this term is assumed to be bounded with a small positive constant δ ($let\,|D| \le \delta$). After rearrangement, the Eqs. (12), (15) and (9) can be rewritten by

$$\begin{aligned}\dot{\mathbf{E}} &= -\overline{\mathbf{A}}\mathbf{E} + \mathbf{B}(\mathbf{u}^* - \mathbf{u}) \\ &= -\overline{\mathbf{A}}\mathbf{E} + \mathbf{B}\tilde{\mathbf{u}} \\ &= -\overline{\mathbf{A}}\mathbf{E} + \mathbf{B}[\tilde{\mathbf{V}}_j^{\mathbf{OT}}\hat{\mathbf{T}}_j^1 + \hat{\mathbf{V}}_j^{\mathbf{OT}}\mathbf{T}_{\mathrm{V}}^1\tilde{\mathbf{V}}_{ji}^{\mathbf{R}} - \mathbf{u}_{\mathrm{C}} + \mathbf{D}]\end{aligned} \tag{16}$$

Considering the dynamic system to be a controllable system, the input **u** as expressed in Eq. (1), has to be designed as Eq. (11) with the adaptation laws for proposed recurrent neural networks parameters as shown in Eqs. (17)–(18), and the compensated control $\mathbf{u_c}$ is designed as Eq. (19) with the estimation law given in Eq. (20), These η_1 , η_2 and η_3 are the coefficient constants of the adaptive control law which can be set to be positive values. Simulation results will be demonstrated that the performances of the proposed adaptive RNN control system can be a controllable stable system.

$$\dot{\hat{\mathbf{V}}}_{\mathbf{j}}^{\mathbf{O}} = \boldsymbol{\eta}_1 \hat{\mathbf{T}}_{\mathbf{j}}^{1} \mathbf{E}^{\mathrm{T}} \mathbf{PB} \tag{17}$$

$$\dot{\hat{\mathbf{V}}}_{\mathbf{ji}}^{\mathbf{R}} = \boldsymbol{\eta}_2 \mathbf{T}_{\mathbf{V}}^{1\mathrm{T}} \hat{\mathbf{V}}_{\mathbf{j}}^{\mathbf{O}} \mathbf{E}^{\mathrm{T}} \mathbf{PB} \tag{18}$$

$$\mathbf{u}_{\mathrm{C}} = \hat{\boldsymbol{\delta}} \mathbf{sgn}(\mathbf{E}^{\mathrm{T}} \mathbf{PB}) \tag{19}$$

$$\dot{\hat{\boldsymbol{\delta}}} = \boldsymbol{\eta}_3 \left| \mathbf{E}^{\mathrm{T}} \mathbf{PB} \right| \tag{20}$$

3. Computer simulations

For the derivations above, the simulation has to be executed for the effectiveness of the adaptive control strategy. The simulations were taken with the comparisons between the The linear quadratic regulator (LQR) PSS, feed-forward neural network (FNN) PSS and proposed adaptive control. The system matrix **A**, **B**, and **T** are given by [5-7].

The simulation for adaptive neural network PSS, FNNPSS and LQR can be explained as following:

3.1 The proposed adaptive neural network PSS

The input **u** of the adaptive neural network control method is according to Eq. (11).

$$\mathbf{u} = \mathbf{u}_{\mathrm{RNN}}(\mathbf{E}, \mathbf{V}_{\mathbf{j}}^{\mathbf{O}*}, \mathbf{V}_{\mathbf{ji}}^{\mathbf{R}*}) + \mathbf{u}_{\mathrm{C}} = (\hat{\mathbf{V}}_{\mathbf{j}}^{\mathbf{O}})^{\mathrm{T}} \hat{\mathbf{T}}_{\mathbf{j}}^{1} + \mathbf{u}_{\mathrm{C}}$$

The structure of RNNC is chosen as Figure.2. The mathematical calculations are in [3]. The weights update is used by Eqs. (17)-(20). with $\boldsymbol{\eta}_1$, $\boldsymbol{\eta}_2$, and $\boldsymbol{\eta}_3$ being 0.01, 0.012, 0.012, respectively. The **P** is a 12 by 12 unit matrix.

3.2 The linear quadratic regulator (LQR) stabilizer [6]

The control input is **u = - Kx = - [K₁ K₂]x**,

$$\mathbf{K}_1 = \begin{bmatrix} 2.4104 & -76.5612 & 3.5553 & 0.0725 & -1.2351 & -211.8305 \\ 0.1960 & 3.3675 & 0.0364 & 0.0005 & -0.0726 & -20.1852 \\ -0.4233 & -12.7616 & 0.0344 & 0.0004 & -0.2825 & -9.4848 \end{bmatrix}$$

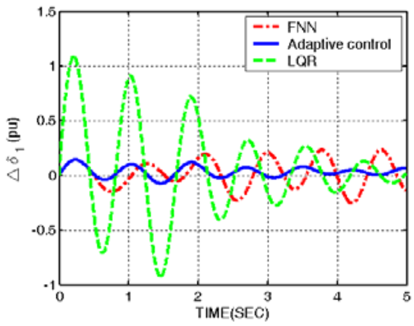
$$\mathbf{K}_2 = \begin{bmatrix} 0.0411 & 0.0005 & 0.3662 & -136.2018 & 0.0268 & 0.0003 \\ 3.1244 & 0.0640 & 0.0414 & -5.8995 & -0.0057 & -0.0001 \\ 0.0002 & -0.0001 & 0.0129 & -193.8797 & 3.1371 & 0.0617 \end{bmatrix}$$

The poles of the closed-loop system **A-BK** are $-40.6712 \pm j38.8362$, $-38.8845 \pm j36.5313$, $-36.5320 \pm j34.5999$, $-1.7979 \pm j7.8165$, $-0.8126 \pm j4.3389$ and $-0.6283 \pm j7.5563$.

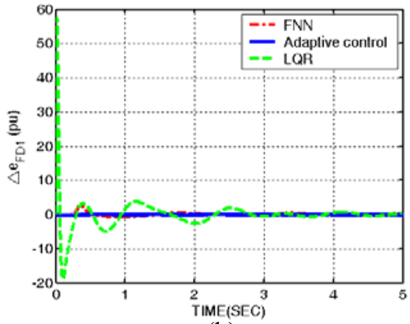
3.3. The feed-forward neural network power system stabilizer (FNNPSS)

The FNNPSS was used to determine the optimal learning rates for η_I^O and η_C^O, which are 0.0057 and 0.0315 respectively. The initial weight values of FNNPSS, $W_{ji}^I(t)$, $W_{kj}^O(t)$ and $V_{ji}^O(t)$, $V_{ji}^O(t)$, are all chosen arbitrarily to be between 0.1~0.5. The FNNPSS Training Algorithm was used to update the weight values and calculate the power system state outputs.

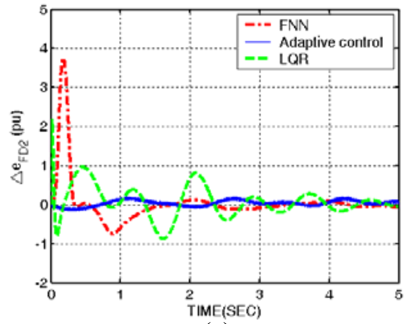
The simulation was executed by using the MatLAb 6.5e. software. the results are shown in Figures 4. The disturbances were set to be $\Delta T_{m1} = 0.01$ p. u., $\Delta T_{m2} =$ 0.01 p. u. and $\Delta T_{m3} = 0.01$ p. u. respectively. Figures 4 reveal the response performance of machine 1, 2 and 3 for $\Delta\delta_1$, Δe_{FD1} , Δe_{FD2} , and Δe_{FD3} , respectively. The performances of adaptive neural network PSS are obviously better than the FNNPSS and LQR methods. The damping effect are outstanding on the $\Delta e_{FD1}, \Delta e_{FD2}$ and Δe_{FD3} compare to other PSSs. The time to damp both the $\Delta\delta_1$ and Δe_{FD1} are within 0.1 *ms*. these figures indicate the power system oscillations were effectively damped by adaptive control PSS.



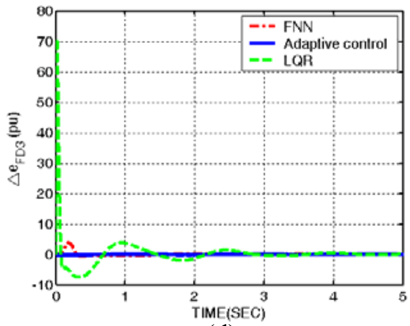
(a)



(b)



(c)



(d)

Figure 4 The performance of damping results (a) $\Delta\delta_1$, (b) Δe_{FD1} (c) Δe_{FD2}, (d) Δe_{FD3} for multimachine system.

4. Conclusions

The adaptive control PSS reveal the improvement in dynamic responses of power system being achieved. The performance of the proposed PSS using adaptive control rules are demonstrated better than FNNPSS and LQR PSS. The control method indicates that the power system oscillations were effectively damped.

5. References

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