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Neural Network Stabilizing Control of Single Machine Power System with Control Limits

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***Abstract*—Power system stabilizers are widely used to generate supplementary control signals for the excitation system in order to damp out the low frequency oscillations. This paper proposes a stable neural network (NN) controller for the stabilization of a single machine infinite bus power system. In the power system control literature, simplified analytical models are used to represent the power system and the controller designs are not based on rigorous stability analysis. This paper overcomes the two major problems by using an accurate analytical model for controller development and presents the closed-loop stability analysis. The NN is used to approximate the complex nonlinear power system online and the weights of which can be set to zero to avoid the time consuming offline training process. Magnitude constraint of the activators is modeled as saturation nonlinearities and is included in the Lyapunov stability analysis. Simulation results demonstrate that the proposed design can successfully damp out oscillations. The control algorithms of this paper can also be applied to other similar control problems.**

I. INTRODUCTION

The power system generators are equipped with voltage regulators to control the terminal voltage. It is known that the voltage regulator has a detrimental impact upon the dynamic stability of the power systems. During a change in operating condition, oscillations of small magnitude and low frequency often persist for long periods of time and in some cases even present limitations on power transfer capability. The issue of power system stabilizing control has received a great deal of attention since 1960's. Power system stabilizers (PSSs) are designed to generate supplementary control signal in the excitation system to damp out low frequency oscillations [1].

Earlier research works on stabilizing control are based on linearized model. For example, the widely used conventional power system stabilizer (CPSS) is designed using the theory of phase compensation and introduced as a lead-lag compensator. To have the CPSS provide good damping over wide operating conditions, its parameters need to be fine tuned in response to all kinds of oscillations, which is a time-consuming job. To simplify this process, intelligent optimization algorithms (such as simulated annealing, genetic algorithm, and tabu search) are applied to offline determining the "optimal parameters" of CPSS by optimizing an eigenvalue based cost function. In the past decade, fuzzy logic and NN were applied online to adjust the parameters of CPSS based on the knowledge gained by offline training. Since power systems are highly nonlinear systems, with configurations and parameters changing with time, the designs based on linearized model cannot guarantee their performances in practical operating environment. Thus, adaptive controller designs based on nonlinear models are required for the power system [2].

In recent years, stabilizing control schemes using NN and fuzzy logic have been proposed. Most of the papers only demonstrated the effectiveness of the controller design via simulation while not the stability analysis. The reason for the lack of stability analysis is due to the complexity of the power systems. Moreover, industry will be reluctant to accept controller designs if stability cannot be guaranteed. Consequently, it maybe very difficult to adjust the parameters of the controllers and the simulation results may be difficult to reproduce. To overcome this problem, certain controller designs have appeared based on feedback linearization or differential geometric theory. One problem with these papers is that controller designs are usually based on simplified models, which overlook the complex dynamics of practical system. Furthermore, exact linearization requires the system model to be known exactly, imprecise model will greatly degrade their performance. While practical power system models are very difficult to be known exactly, this assumption can seldom be satisfied. Since the stabilizing and voltage controllers are all implemented in the excitation system, there is the possibility for these two kinds of controls to interact with each other, while few papers show the performance of voltage control under the PSS designs.

The paper tries to overcome the above mentioned problems by designing a stable adaptive neural network controller. The controller design is based on a full scale single machine infinite bus power system. Since the complex nonlinearity can be approximated using a neural network, the requirement on precise model is released. The weight updating rule of the NN is an unsupervised version of backpropagation through time which release the need for NN identifier. The initial weights of NN can be directly set to zero to avoid the time consuming offline training process which is necessary in some papers before the controllers can be used online. Since practical operating conditions require the magnitude of control signal to be within certain limit, this paper also investigate the stability of the closed loop system when the magnitude of the ideal control signal overshoot the limit. Simulations under different operating conditions show that the proposed PSS design not only can damp out the power system oscillations very well but also can limit the impact on the voltage control within acceptable range.

The paper is organized as follows. Section II presents a brief background on universal approximation property of neural networks and stability of nonlinear system. Section III introduces the single machine infinite bus power system model. The neural network controller design is introduced in section IV. Simulation results are provided in section V, and finally the conclusion in Section VI.

II. BACKGROUND

The following mathematical notions are required for the development of adaptive output feedback NN controller.

A. Approximation Property of NN

The commonly used property of neural network for control is its function approximation property [3]. Let $f(x)$ be a smooth function from $R^n \rightarrow R^m$, then it was shown that, as long as x is restricted to a compact set $S \in R^n$, for some sufficiently large number of hidden-layer neurons, 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. Equation (1) means a neural network can approximate any continuous function in a compact set. In fact, for any choice of a positive number ε_N, one can find a neural network such that $\varepsilon(x) \leq \varepsilon_N$ for all $x \in S$. For suitable function approximation, $\varphi(x)$ must form a basis [4]. For two layer neural networks, $\varphi(x)$ is defined as $\varphi(x)=\sigma(V^T x)$, where V is the weight matrix of the first layer and $\sigma(x)$ is the sigmoid function. If V is fixed, then the only design parameter in the NN is W and the NN becomes a function link network (one layer neural network) which is easier to train. It has been shown in [5] that $\varphi(x)$ can forms a basis if V is chosen randomly. The larger the number of the hidden layer neurons N_h, the smaller the approximation error $\varepsilon(x)$. Barron shows that the neural network approximation error $\varepsilon(x)$ for one-layer NN is fundamentally bounded by a term of the order $(1/n)^{2/d}$, where n is the number of fixed basis functions and d is the dimension of the input to the NN [10].

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 [6]. 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. MODEL OF SINGLE MACHINE POWER SYSTEM

Fig. 1 shows the configuration of the single machine infinite bus power system. The system consists of a synchronous generator, an exciter, an automatic voltage regulator (AVR) and a transmission line which connect the generator bus to the infinite bus. The control signal is added to the inputs of AVR.

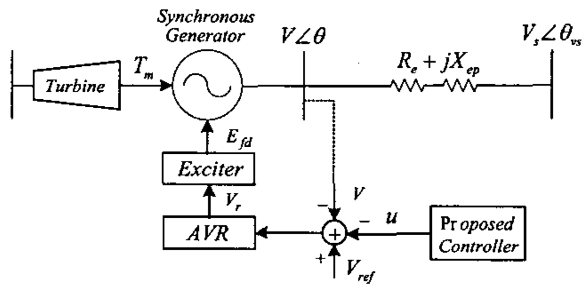

Fig. 1: Single machine infinite bus power system configuration

The dynamics of the single machine power system are expressed using a Flux-Decay model as in (3). The first three equations represent the dynamics of the synchronous generator, the fourth and fifth equations represent the dynamics of the exciter and AVR respectively [7].

$$\begin{aligned} &\frac{d\delta}{dt} = \omega - \omega_s \\ &\frac{2H}{\omega_s}\frac{d\omega}{dt} = T_m - E_q' I_q - (X_q - X_d') I_d I_q - D_{fw}(\omega - \omega_s) \\ &T_{d0}' \frac{dE_q'}{dt} = -E_q' - (X_d - X_d') I_d + E_{fd} \\ &T_e \frac{dE_{fd}}{dt} = -E_{fd} + V_r \\ &T_a \frac{dV_r}{dt} = -V_r + K_a(V_{ref} - V - V_{pss}) \end{aligned} \tag{3}$$

where, I_d, I_q and V are subjected to the constraints of (4) and (5) respectively:

$$\begin{aligned} 0 &= R_e I_d - (X_q + X_{ep}) I_q + V_s \sin(\delta - \theta_{vs}) \\ 0 &= R_e I_q + (X_d' + X_{ep}) I_d - E_q' + V_s \cos(\delta - \theta_{vs}) \end{aligned} \tag{4}$$

$$V = \sqrt{V_d^2 + V_q^2} \tag{5}$$

with

$$\begin{aligned} V_d &= R_e I_d - X_{ep} I_q + V_s \sin(\delta - \theta_{vs}) \\ V_q &= R_e I_q + X_{ep} I_d + V_s \cos(\delta - \theta_{vs}) \end{aligned} \tag{6}$$

In above equations, δ is the rotor angle, ω is the speed, E_{fd} is the field voltage, V_r is the output of the automatic voltage regulator (AVR), T_m is the mechanical torque, V is the terminal voltage at the generator bus, V_{ref} is the reference signal used to control the terminal voltage, R_e and X_{ep} form the impedance of the transmission line between the generator and infinite bus, $V_s\angle\theta_{vs}$ are the voltage of the infinite bus, and V_{pss} is the control signal. Table I shows the value of the parameters in above model.

TABLE I
SYSTEM PARAMETERS

$T_{d0}'=6.0$	$X_d=0.8958$	$X_d'=0.1198$	$X_q=0.8645$
$H=6.4$	$\omega_s=377$	$D_{fw}=0.0125$	$T_e=0.314$
$T_a=0.01$	$K_a=20$	$R_e=0.025$	$X_{ep}=0.085$

The control objective is to stabilize the speed ω to $\omega_s=2\pi f$ for different operating conditions. The system can be linearized via input-output feedback [8]. Since the control signal appears in the fourth order derivative of ω, the linearized system is fourth-order rather than the original fifth-order system. Since the uncontrolled state δ satisfies $\dot{\delta}=\omega-\omega_s$, δ is bounded when ω is stabilized to ω_s. So the system is stable even though δ does not appear as one of the states in the feedback linearized system.

Define $\bar{e}=[e_1 \quad e_2 \quad e_3 \quad e_4]^T=[\omega \quad \dot{\omega} \quad \ddot{\omega} \quad \dddot{\omega}]^T-[\omega_s \quad 0 \quad 0 \quad 0]^T$ then the error dynamics of the system can be expressed in the *Brunovsky Canonical Form* as

$$\begin{aligned}\dot{e}_1 &= e_2\\ \dot{e}_2 &= e_3\\ \dot{e}_3 &= e_4\\ \dot{e}_4 &= f(\bar{x})+g(\bar{x})u+d\end{aligned} \tag{7}$$

where u stands for the control signal and d stands for a bounded disturbance with $|d|\le d_M$, $\bar{x}$ stands for δ, ω, E_q', E_{fd}, Vr. $f(\bar{x})$ and $g(\bar{x})$ are given as:

$$\begin{aligned}
f(\bar{x}) &= \sin[2(\delta-\theta_{vs})][(k_7-k_6)(4\dot{\delta}^3-\ddot{\omega})-6k_8\dot{\delta}\dot{\omega}]\\
&-\cos[2(\delta-\theta_{vs})][6(k_7-k_6)\dot{\delta}\dot{\omega}+4k_8\dot{\delta}^3-k_8\ddot{\omega}]\\
&+[k_9\cos(\delta-\theta_{vs})-k_{10}\sin(\delta-\theta_{vs})]\\
&[2\ddot{E}_q'\dot{\delta}+3E_q'\dot{\omega}+2k_{11}k_{14}\dot{E}_q'\dot{E}_{fd}-2k_{11}(k_{14}-k_{17})\dot{E}_q'^2]\\
&-[k_9\sin(\delta-\theta_{vs})+k_{10}\cos(\delta-\theta_{vs})]\\
&[3\dot{E}_q'\dot{\delta}^2+3E_q'\dot{\delta}\dot{\omega}+(k_{14}-k_{17})\ddot{E}_q'-k_{14}k_{19}(\dot{E}_{fd}-k_{27}V_r+k_{28}V_t-k_{28}V_{ref})]\\
&+k_{12}\ddot{\omega}+2k_{11}k_{14}k_{19}E_q'(\dot{E}_{fd}-k_{27}V_r+k_{28}V_t-k_{28}V_{ref})\\
&+2k_{11}\dot{E}_q'[k_{14}\dot{E}_{fd}-(k_{14}-k_{17})\dot{E}_q']+2[k_{11}(k_{17}-k_{14})+2k_{11}]\dot{E}_q'\ddot{E}_q'\\
&+[k_{16}\cos(\delta-\theta_{vs})-k_{18}\sin(\delta-\theta_{vs})]\{[k_9\sin(\delta-\theta_{vs})+k_{10}\cos(\delta-\theta_{vs})\\
&+2k_{11}E_q']\ddot{\delta}+2k_{11}\dot{E}_q'\dot{\delta}+[k_9\cos(\delta-\theta_{vs})-k_{10}\sin(\delta-\theta_{vs})]\dot{\delta}^2\}\\
&-[k_9\sin(\delta-\theta_{vs})+k_{10}\cos(\delta-\theta_{vs})+2k_{11}E_q']\cdot\\
&[k_{16}\sin(\delta-\theta_{vs})+k_{18}\cos(\delta-\theta_{vs})]\dot{\delta}^2
\end{aligned} \tag{8}$$

and

$$g(\bar{x})=k_{14}k_{19}k_{28}[k_9\sin(\delta-\theta_{vs})+k_{10}\cos(\delta-\theta_{vs})+2k_{11}E_q'] \tag{9}$$

The feedback linearization process and the definition of k_1 - k_{28} can be found in [8].

IV. NN CONTROLLER DESIGN

A. Assumptions

Assumption 1: $g(\bar{x})$ is bounded and the sign of which is known. That is, $g(\bar{x})$ is either positive or negative. Without losing generality, we shall assume $g(\bar{x})>0$. Furthermore, there exists two positive constants g_m and g_M, such that $g_M>g(\bar{x})>g_m>0$.

Assumption 2: The derivative of $g(\bar{x})$ is bounded, which means there exist a positive constant g_{dM}, such that $|\dot{g}(\bar{x})|\le g_{dM}$.

Remark: For this single machine power system, $g(\bar{x})$ is given by $K_1[K_2\sin(\delta-\theta_{vs}+\phi)+K_3E_q']$, where

$$K_1=\frac{k_a}{T_eT_{d0}'T_a}>0$$

$$K_2=\frac{\omega_s}{2H}\sqrt{[(k_1^2+k_2k_3)k_4-k_3]^2+(2k_1k_2k_4-k_1)^2}>0$$

$$K_3=\frac{R_e\omega_s[R_e^2+(X_q+X_{ep})^2]}{H[R_e^2+(X_d'+X_{ep})(X_q+X_{ep})]^2}>0$$

$$\phi=\arctan[\frac{2k_1k_2k_4-k_1}{(k_1^2+k_2k_3)k_4-k_3}] \tag{10}$$

Assumptions 1 and 2 hold for the single machine power system because of the range of the variables and the inertia of the system.

B. Neural Network Controller Design

Define the filtered error r as

$$r=[\Lambda^T \quad 1]\bar{e} \tag{11}$$

where $\Lambda=[\lambda_1 \ \lambda_2 \ \lambda_3]^T$ is an appropriately chosen coefficient vector such that $e\to 0$ as $r\to 0$, (i.e. $s^3+\lambda_3 s^2+\lambda_2 s+\lambda_1$ is Hurwitz).

Differentiating (11) and substituting (7) to get

$$\dot{r}=[0 \quad \Lambda^T]\bar{e}+f(\bar{x})+g(\bar{x})u+d \tag{12}$$

According to the theory of feedback linearization, the desired control signal can be chosen as

$$u^*=-K_v r-\frac{1}{g(\bar{x})}\{f(\bar{x})+[0 \quad \Lambda^T]\bar{e}\} \tag{13}$$

where K_v is a selected positive constant. Now approximate $-\frac{1}{g(\bar{x})}\{f(\bar{x})+[0 \quad \Lambda^T]\bar{e}\}$ by using a NN, such that

$$\hat{W}^T\Phi(\bar{x},\bar{e}) = -\frac{1}{g(\bar{x})}\{f(\bar{x}) + [0 \quad \Lambda^T\}\bar{e} = f_n(\bar{x},\bar{e}) \tag{14}$$

Define the ideal control signal v (without magnitude constraint) as:

$$v = -K_v r + \hat{W}^T\Phi(\bar{x},\bar{e}) \tag{15}$$

Then the actual control signal applied to the power system is given by:

$$u = \begin{cases} v & while|v| \le u_{\max} \\ u_{\max}\, sign(v) & while|v| > u_{\max} \end{cases} \tag{16}$$

where $u_{\max}$ is the maximum allowed control signal magnitude. The structure of the controller is shown in Fig. 2. It has multi-loop structure with an inner nonlinear adaptive NN loop used to estimate the nonlinear dynamics of the single machine power system and an outer PD tracking loop. The next step is to determine an appropriate weight updating rule so that the closed-loop stability of the single machine power system can be guaranteed. The performance of the proposed adaptive neural network controller is described by theorem I.

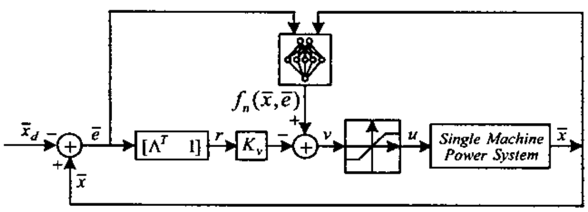

Fig. 2. Neural network feedback linearizing controller

Assume there is a constant weight, W, that can approximate (14) within designated precision, such that

$$W^T\Phi(\bar{x},\bar{e}) = -\frac{1}{g(\bar{x})}[f(\bar{x}) + [0 \quad \Lambda^T]\bar{e} + \varepsilon \tag{17}$$

where ε is the approximation error, which is bounded by $|\varepsilon| \le \varepsilon_N$. Assume W is bounded by W_{max}, that is, $\|W\| \le W_{\max}$. Rearrange (17) as an expression of $f(\bar{x})$ and substitute which into (12) to get

$$\dot{r} = -K_v g(\bar{x})r - g(\bar{x})\tilde{W}^T\Phi(\bar{x},\bar{e}) + g(\bar{x})\varepsilon + d \tag{18}$$

where $\tilde{W}$ is the weights approximation error and is defined as:

$$\tilde{W} = W - \hat{W} \tag{19}$$

Theorem 1: Assume the unknown disturbance d, the weight approximation error ε are bounded by known constants such that $|d| \le d_N$, $|\varepsilon| \le \varepsilon_N$ respectively. Select the weight updating rule as

$$\dot{\hat{W}} = -\Gamma r\Phi(\bar{x},\bar{e}) - \alpha\Gamma\|r\|\hat{W} \tag{20}$$

where α, $\Gamma > 0$ are the adaptation gains and the gain K_v satisfying

$$K_v > \frac{g_{dM}}{2g_m^2} \tag{21}$$

Then the filtered error $r(t)$ and the weight estimation error $\tilde{W}$ are uniformly ultimately bounded.

Proof: The proof is done in two cases.

Case 1: $|v| \le u_{\max}, u = v$

- *Filtered Error Bound*

Select the Lyapunov function candidate $V \in R$ as [10]

$$V = \frac{r^2}{2g(\bar{x})} + \frac{1}{2}\tilde{W}^T\Gamma^{-1}\tilde{W} \tag{22}$$

Evaluating the derivative of V to get

$$\dot{V} = \frac{r\dot{r}}{g(\bar{x})} - \frac{\dot{g}(\bar{x})r^2}{2g(\bar{x})^2} + \tilde{W}^T\Gamma^{-1}\dot{\tilde{W}} \tag{23}$$

Substituting the error dynamics (18) into (23) to get

$$\dot{V} = -(K_v + \frac{\dot{g}(\bar{x})}{2g(\bar{x})^2})r^2 + \tilde{W}^T[\Gamma^{-1}\dot{\tilde{W}} - r\Phi(\bar{x},\bar{e})] + r\varepsilon + \frac{rd}{g(\bar{x})} \tag{24}$$

Substituting (20) into (24)

$$\dot{V} = -(K_v - \frac{g_{dM}}{2g_m^2})r^2 + \alpha|r|\tilde{W}^T(W - \tilde{W}) + r\varepsilon + \frac{rd}{g(\bar{x})} \tag{25}$$

Rewrite (25) as

$$\begin{aligned} \dot{V} &\le -(K_v - \frac{g_{dM}}{2g_m^2})r^2 \\ &\quad -\alpha|r|\{[\|\tilde{W}\| - \frac{W_{\max}}{2}]^2 - \frac{W_{\max}^2}{4}\} + |r|(\varepsilon_N + \frac{d_M}{g_m}) \\ &\le -|r|\{(K_v - \frac{g_{dM}}{2g_m^2})|r| - [\frac{W_{\max}^2}{4}\alpha + \varepsilon_N + \frac{d_M}{g_m}]\} \\ &\quad -\alpha|r|[\|\tilde{W}\| - \frac{W_{\max}}{2}]^2 \\ &\le -|r|\{(K_v - \frac{g_{dM}}{2g_m^2})|r| - [\frac{W_{\max}^2}{4}\alpha + \varepsilon_N + \frac{d_M}{g_m}]\} \end{aligned} \tag{26}$$

Since K_v is chosen according to (21), $\dot{V}$ is negative as long as

$$\|r\| > \frac{\frac{W_{\max}^2}{4}\alpha + \varepsilon_N + \frac{d_M}{g_m}}{K_v - \frac{g_{dM}}{2g_m^2}} \tag{27}$$

- *Weight Estimation Error Bound*

Choose the Lyapunov function the same as (22), now reevaluate $\dot{V}$

$$\dot{V}=-Kr^2+\alpha\|r\|[-\tilde{W}^T\tilde{W}+\tilde{W}^TW]-r\varepsilon+\frac{rd}{g(x)}$$
$$\leq -Kr^2-\alpha\|r\|[\|\tilde{W}\|^2-W_{\max}\|\tilde{W}\|-\frac{\varepsilon_N+\frac{d_M}{g_m}}{\alpha}] \tag{28}$$

It can be seen that $\dot{V}<0$ as long as $\|\tilde{W}\|^2-W_{\max}\|\tilde{W}\|-\frac{\varepsilon_N+\frac{d_M}{g_m}}{\alpha}>0$, so the weights estimation error bound is given by

$$\|\tilde{W}\|>\frac{W_{\max}+\sqrt{W_{\max}^2+\frac{4(\varepsilon_N+\frac{d_M}{g_m})}{\alpha}}}{2} \tag{29}$$

Case 2: $|v|>u_{\max}, u=u_{\max}sign(v)$

Define $\Delta u=u-v$, with Δu satisfying $|\Delta u|\leq\Delta u_{\max}$. Substitute $u=v+\Delta u$ into (12), similarly, we can get

$$\dot{r}=-K_v g(\bar{x})r-g(\bar{x})\tilde{W}^T\Phi(\bar{x},\bar{e})+g(\bar{x})\varepsilon$$
$$+d+g(\bar{x})\Delta u \tag{30}$$

- *Filtered Error Bound*

Choose the Lyapunov function candidate same as (22) and substituting (30) into (22) to get

$$\dot{V}=-(K_v+\frac{\dot{g}(\bar{x})}{2g(\bar{x})^2})r^2+\tilde{W}^T[\Gamma^{-1}\dot{\tilde{W}}-r\Phi(\bar{x},\bar{e})]$$
$$+r\varepsilon+\frac{rd}{g(\bar{x})}+r\Delta u \tag{31}$$
$$\leq -|r|\{(K_v-\frac{g_{dM}}{2g_m^2})|r|-\frac{W_{\max}^2}{4}\alpha-\varepsilon_N-\frac{d_M}{g_m}-\Delta u_{\max}\}$$

Equation (27) is negative as long as

$$|r|>\frac{\frac{W_{\max}^2}{4}\alpha+\varepsilon_N+\frac{d_M}{g_m}+\Delta u_{\max}}{K_v-\frac{g_{dM}}{2g_m^2}} \tag{32}$$

- *Weight Estimation Error Bound*

Similar as case 1, the weight estimation bound is given by

$$\|\tilde{W}\|>\frac{W_{\max}+\sqrt{W_{\max}^2+\frac{4(\varepsilon_N+\frac{d_M}{g_m}+\Delta u_{\max})}{\alpha}}}{2} \tag{33}$$

Remark 1: In the adaptive control literature, the unboundedness of parameter estimates when persistence of excitation (PE) fails to hold is known as "parameter drift". This phenomenon has been referred to as "weight overtraining" in the NN literature. The PE condition ensures that parameter drift does not occur. However, it is difficult to verify or guarantee the PE condition. Hence this theorem relaxes the PE condition.

Remark 2: The weights of the hidden layer are randomly chosen initially between 0 and 1 and held constant and therefore not tuned. The initial weights of the output layer are just set to zero and then tuned online according to (20). There is no preliminary off-line learning phase, and stability will be provided by the outer tracking loop until the NN learns. This is a significant improvement over other NN control techniques where one must find some initial stabilizing weights, generally an impossible feat for complex nonlinear systems.

Remark 4: A single NN is used to approximate both nonlinearities of $f(\bar{x})$ and $g(\bar{x})$ with an expression shown in (14). No need to use two neural networks to approximate $f(\bar{x})$ and $g(\bar{x})$ separately. This results in a well defined controller structure.

Remark 5: Note that (32) and (33) is a local stability result since the control input was restricted to lie within certain limits. It can also be seen from these equations that the error bounds are proportional to Δu_{max}. Larger u_{max} will result in larger error bound. However, the tracking error bound can be made arbitrarily small by increasing K_v [9].

V. Simulation Results

The neural network based PSS design is tested under different operating conditions, which are 3-phase short circuit fault at the infinite bus (Figs 3-5), change of operating points (Fig 6) and change of impedance between the generator bus and the infinite bus (Fig 7). The NN has 10 inputs corresponding to the systems states, error dynamics and bias respectively.

$$[\delta \quad \omega \quad E_q^{'} \quad E_{fd} \quad V_r \quad e_1 \quad e_2 \quad e_3 \quad e_4 \quad 1]^T \tag{34}$$

The hidden layer has 15 neurons. The weights of the input layers are set to random numbers between 0 and 1 and held fixed. The activation function of the hidden layer is hyperbolic tangent function. The initial weight of the output layer W is set to zero and updated with time. Other parameters are set as follows: $K_v=0.01$, $\Lambda=[512\ 192\ 24^T]$, $u_{max}=0.5$, $\Gamma=10$, and $\alpha=10$. From the simulation results, it can be seen that the proposed controller can damp out oscillations very well. It can be seen that the neural network can adapt to changes in the operating condition in a fast manner which is the reason why offline line training is unnecessary.

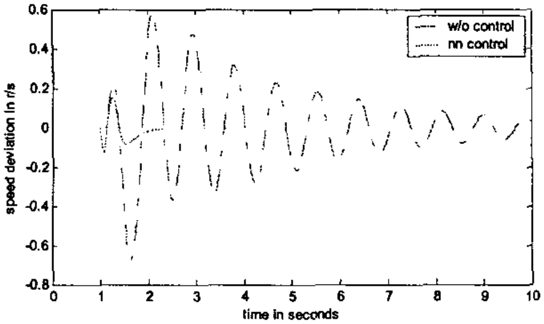

Fig 3. Speed deviation response to 100ms 3-phase short circuit fault ($P=0.5pu$, $Q=0.1pu$)

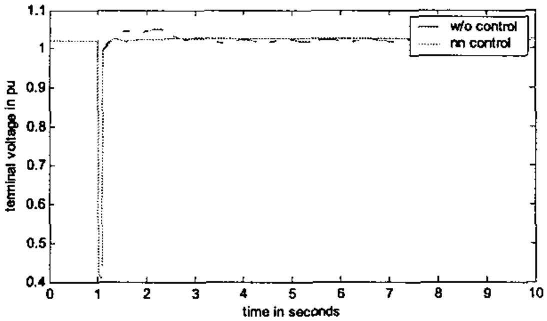

Fig 4. Terminal voltage response to 100ms 3-phase short circuit fault ($P=0.5pu$, $Q=0.1pu$)

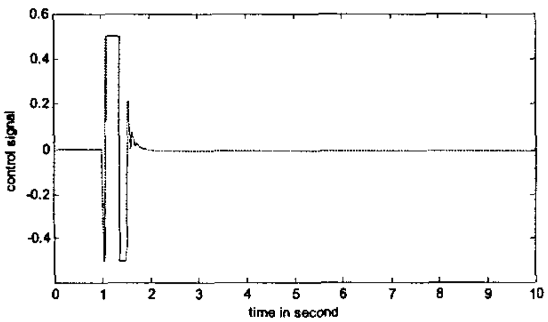

Fig. 5. Control signal response to 100ms 3-phase short circuit fault (P=0.5pu, Q=0.1pu).

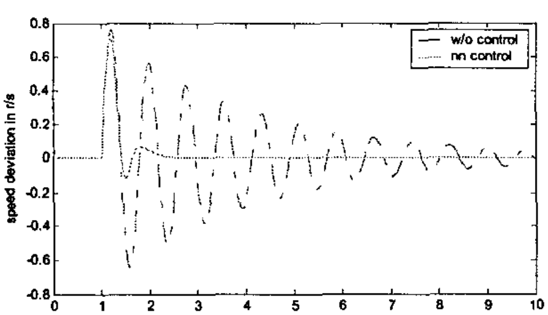

Fig. 6. Speed deviation response to a change of operating points ($P=0.5pu$, $Q=0.1pu$ to $P=0.7pu$, $Q=0.2pu$).

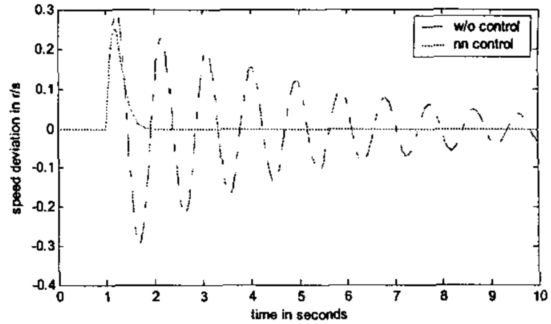

Fig. 7. Speed deviation response to a change of the impedance connected to the infinite bus ($R_e=0.025$, $X_{ep}=0.085$to$R_e=0.05$,$X_{ep}=0.17$)

VI. CONCLUSION

The design of power system stabilizer is an important issue in power system control. To overcome the problems of using oversimplified model and lacking of stability analysis in power system control, this paper proposes a stable neural network controller for a single machine infinite bus power system. The weight updating rule does not require the PE condition and can guarantee the stability of the closed loop system when the control signal is subject to magnitude constraints. Simulations under different operating conditions demonstrate the effectiveness of the proposed control algorithm. The proposed control scheme can also be applied to control similar class of nonlinear systems. Future research will include the design of stable decentralized controllers for multi-machine power systems.

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