전력계통 안정화를 위한 적응 퍼지 여자 제어기

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Adaptive Fuzzy Excitation Controller for Power System Stabilization

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Abstract— **We propose a robust adaptive fuzzy controller for the transient stability and voltage regulation of a single-machine infinite bus power system. The proposed control scheme is based on the input-output linearization to eliminate the system nonlinearities. To deal with uncertainties due to a parameter variation or a fault, we introduce fuzzy systems with universal function approximating capability which estimate the uncertainties on-line.**

Keywords— **Adaptive Fuzzy Control, excitation control, transient stability**

I. Introduction

Power systems are large scale nonlinear systems and have uncertain dynamics due to a variety of effects such as lightening, severe storms and equipment failures. This requires the control system to have the ability to handle potential instability and poorly damped power angle oscillations due to their effects. Transient and dynamic stability considerations are among the most important issues in the reliable and efficient operation of power systems. However, conventional controllers that are designed based on the linearized model of power systems cannot deal with such a situation due to their nonlinear dynamics. That is, the conventional controller yields the satisfactory performance if the system is operating within a certain range of the design point and the disturbance is not so large as to push the system in the highly nonlinear region. To cope with this problem of uncertainty and nonlinearity, various studies have been carried out recently[1], [2], [3], [4], [5], [6], [7].

In this paper, we present an adaptive fuzzy control scheme for single-machine infinite bus (SMIB) power systems. It is based on a static feedback input-output linearization[9]. Unlike conventional adaptive nonlinear methods, the proposed algorithm does not require the system to be linear in the uncertain parameters. In addition, since the proposed controller is trained on-line, it can track the plant variations to adjust its own parameters accordingly. First, adaptively input-output linearizing control using fuzzy systems is designed to eliminate the nonlinearities. Then, a robust control term which makes tracking error remain in a neighborhood of the operating point is introduced.

II. Power System Model

A. Dynamic equations of the system

Under some standard assumptions, the motion of the generator can be described by a classical model with flux decay dynamics[8]. In this model, the generator is modeled as the voltage behind direct axis transient reactance. The block diagram of the system is illustrated in Fig. 1. The

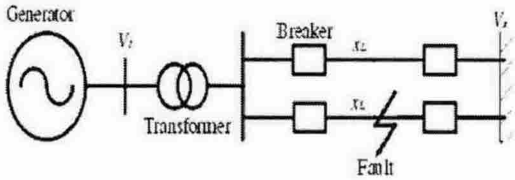

Fig. 1. Single-machine infinite bus system

mechanical and electrical equations of the ith machine are as follows.

$$\dot{\delta}(t) = w(t) \quad (1)$$

$$\dot{w}(t) = -\frac{D}{H}w(t) + \frac{w_0}{H}(P_m - P_e(t)) \quad (2)$$

$$\dot{E}_q(t) = \frac{1}{T'_{d0}}(E_f(t) - E_q(t)) + \frac{x_d - x'_d}{x'_{ds}} V_s \sin\delta(t) w(t) \quad (3)$$

$$P_e(t) = \frac{V_s E_q}{x_{ds}} \sin\delta(t) \quad (4)$$

where $\delta(t)$ is the power angle, $w(t)$ the relative speed, P_m the mechanical input power which is assumed to be constant, P_e the active electrical power delivered by the generator, w_0 the synchronous machine speed, E_q the EMF in the q-axis, E_f the equivalent EMF in the excitation coil, x_d the d-axis reactance of the generator, x'_d the q-axis transient reactance of the generator, D the per unit damping constant, H the per unit inertia constant. The parameters are defined as

$$x_s = x_T + \frac{x_L}{2} \quad (5)$$

$$x_{ds} = x_d + x_T + \frac{x_L}{2} \quad (6)$$

$$x'_{ds} = x'_d + x_T + \frac{x_L}{2} \quad (7)$$

$$T'_{d0} = \frac{x'_{ds}}{x_{ds}} T_{d0} \quad (8)$$

where x_T is the reactance of the transformer, x_L is the reactance of the one transmission line, and T_{d0} is the direct axis transient short-circuit time constant.

The output under consideration is the magnitude of the terminal voltage

$$V_t = \left\{ \left(\frac{x_s}{x_{ds}} E_q \sin\delta \right)^2 + \left(\frac{1}{x_{ds}} (x_s E_q \cos\delta + x_d V_s) \right)^2 \right\}^{\frac{1}{2}} \quad (9)$$

From the model discussed above, we can see that the power system is highly nonlinear.

B. State equation with output modification

In this paper, we consider the following modified output equation to deal with oscillation of the power angle and to improve characteristic of internal dynamics as in [3]

$$\begin{aligned} h &= V_t + \alpha \dot{w}_F \\ \dot{w}_F &= -b w_F + b w \end{aligned} \quad (10)$$

where the modified output h is equal to V_t in the steady-state and w_F is obtained through the low-pass filtering of $w (b > 0)$. Using the modified output, oscillation of δ can be removed and the stability of the closed-loop system comes to depend on α if b, the break frequency, is fixed, which will be shown through root-loci analysis and simulations. From (1), (2), (3) and (10), we can get the nonlinear state equation as

$$\dot{\mathbf{x}}(t) = a(\mathbf{x}) + b(\mathbf{x}) u \quad (11)$$

where $\mathbf{x} = [\delta \ w \ E_q \ w_F]^T, u = E_F$ and

$$a(\mathbf{x}) = \begin{bmatrix} w \\ -\frac{D}{H} w + \frac{w_0}{H}(P_m - P_e) \\ -\frac{1}{T'_{d0}} E_q + \frac{x_d - x'_d}{x'_{ds}} V_s \sin\delta w \\ -b w_F + b w \end{bmatrix} \quad (12)$$

$$b(\mathbf{x}) = \begin{bmatrix} 0 \\ 0 \\ \frac{1}{T'_{d0}} \\ 0 \end{bmatrix} \quad (13)$$

$$(14)$$

The control objective is to maintain voltage regulation and synchronism of δ despite of the parametric uncertainties due to a sudden fault.

III. Adaptive Fuzzy Controller Using Input-Output Linearization

A. Input-output linearizing controller

To perform the input-output linearization, we must differentiate (14) with respect to the time. First, let $F_1 = \frac{x_s}{x_{ds}} E_q \sin\delta$ and $F_2 = (x_s E_q \cos\delta + x_d V_s)/x_{ds}$, we have

$$\begin{aligned} \frac{\partial F_1}{\partial \mathbf{x}} &= \left[\ \tfrac{x_s}{x_{ds}} E_q \cos\delta \quad 0 \quad \tfrac{x_s}{x_{ds}} \sin\delta \quad 0 \ \right] \\ \frac{\partial F_2}{\partial \mathbf{x}} &= \left[-\tfrac{x_s}{x_{ds}} E_q \sin\delta \quad 0 \quad \tfrac{x_s}{x_{ds}} \cos\delta \quad 0 \ \right] \end{aligned} \quad (15)$$

Since $h = V_t - \alpha b(w_F - w)$ and $V_t = (F_1^2 + F_2^2)^{\frac{1}{2}}$, we have

$$\begin{aligned} \frac{\partial h}{\partial \mathbf{x}} &= \frac{\partial V_t}{\partial \mathbf{x}} + \alpha b \left[\ 0 \quad 1 \quad 0 \quad -1 \ \right] \\ &= \frac{1}{V_t} \left(F_1 \frac{\partial F_1}{\partial \mathbf{x}} + F_2 \frac{\partial F_2}{\partial \mathbf{x}} \right) + \alpha b \left[\ 0 \quad 1 \quad 0 \quad -1 \ \right] \\ &= \begin{bmatrix} -\frac{x_s x_d}{x_{ds}^2 V_t} E_q V_s \sin\delta \\ \alpha b \\ \frac{x_s}{x_{ds}^2 V_t} (x_s E_q + x_d V_s \cos\delta) \\ -\alpha b \end{bmatrix}^T \end{aligned} \quad (16)$$

Using the above result of (16) in conjunction with (12) and (13), we can get $\dot{h}$ as follows

$$\begin{aligned} \dot{h} &= L_a h + L_b h u \\ &= -\frac{\omega x_s x_d}{x_{ds}^2 V_t} E_q V_s \sin\delta \\ &\quad + \alpha b \left(-\frac{D}{H}\omega + \frac{\omega_0}{H}(P_m - P_e) \right) \\ &\quad + \frac{x_s}{x_{ds}^2 V_t} (x_s E_q + x_d V_s \cos\delta) \\ &\quad \times \left(-\frac{1}{T'_{d0}} E_q + \frac{x_d - x'_d}{x'_{ds}} V_s \omega \sin\delta \right) \\ &\quad + \alpha b (b\omega_F - b\omega) \\ &\quad + \frac{1}{T'_{d0}} \frac{x_s}{x_{ds}^2 V_t} (x_s E_q + x_d V_s \cos\delta) u \end{aligned} \quad (17)$$

where $L_a h$ and $L_b h$ are Lie derivatives of h with respect to $a(\mathbf{x})$ and $b(\mathbf{x})$, respectively.

The feedback linearizing control[9] for (17) is

$$u = \frac{1}{L_b h} \{ -L_a h + \dot{y}_R + ce \} \quad (18)$$

where $c > 0$ is the design constant, y_R is the reference voltage, $e (= y_R - h)$ is the regulation error. Applying (18) into (17) results in an error dynamic equation such as

$$\dot{e} + ce = 0, \quad (c > 0) \quad (19)$$

Thus, the tracking error e disappears exponentially.

But a fault on the transmission line causes the variation in the parameters x_s, x_{ds} and x'_{ds}. With the variation of these parameters, $L_a h$ and $L_b h$ can have parametric uncertainties. If the uncertainties in $L_a h$ and $L_b h$ satisfy the linear parameterization condition, we can use the conventional adaptive input-output linearization technique. But $L_a h$ and $L_b h$ in (17) are not the case and to cope with the problem, we will use fuzzy systems which approximate the deviations from the nominal models of $L_a h$ and $L_b h$.

B. Brief Description of Adaptive Fuzzy Systems

Adaptive fuzzy systems can be viewed as fuzzy logic systems whose rules are automatically generated through training process. A fuzzy rule base consists of a set of fuzzy IF-THEN rules. In this paper, we consider the case where the fuzzy rule base consists of $N = \Pi_{j=1}^{n} N_j$ rules for a multi-input and single-output (MISO)and the output of the fuzzy system can be written as [10]

$$y = \theta^T \xi(\mathbf{x}) \tag{20}$$

where θ is a collection of consequent parameters and $\xi(\mathbf{x})$ is a collection of firing strengths. The fuzzy system in the form of (20) is the most frequently used one in control application.

C. Design of the control law and adaptation laws

Observing (17) reveals some insights on the uncertainties. First, the term related to ω_F has no uncertainty. Secondly, thus, the variations in the $L_a h$ and $L_b h$ due to a fault are the functions of $\mathbf{x}_1 = [\delta\ \omega\ E_q]^T$ and $\mathbf{x}_2 = [\delta\ E_q]^T$, respectively, since V_t is the function of δ and E_q. We consider (17) as the nominal model of the system and the real plant dynamics are assumed to be described by

$$\dot{h} = (L_a h + d_1(\mathbf{x}_1)) + (L_b h + d_2(\mathbf{x}_2))\, u \tag{21}$$

where $d_i(\mathbf{x}_i), i = 1, 2$ denote uncertainties due to a variation or fault of the power system. We estimate the d_i's using two fuzzy systems. Once we determine the membership functions for $\mathbf{x}_1$ and $\mathbf{x}_2$, then we obtain m_1 dimensional vector $\xi_1(\mathbf{x}_1)$ and m_2 dimensional vector $\xi_2(\mathbf{x}_2)$. Using these vectors we can rewrite (21) as

$$\begin{aligned} \dot{h} &= \left(L_a h + \theta_1^{*T}\xi_1(\mathbf{x}_1) + v_1(\mathbf{x}_1)\right) \\ &\quad + \left(L_b h + \theta_2^{*T}\xi_2(\mathbf{x}_2) + v_2(\mathbf{x}_2)\right) u \end{aligned} \tag{22}$$

where

$$\begin{aligned} \theta_1^* &= \arg\min_{\theta_1 \in \Omega_1} \left[\sup_{\mathbf{x}\in\Omega_{x_1}} \left\{ \theta_1^T \xi_1(\mathbf{x}_1) - d_1(\mathbf{x}_1) \right\} \right] \\ \theta_2^* &= \arg\min_{\theta_2 \in \Omega_2} \left[\sup_{\mathbf{x}\in\Omega_{x_2}} \left\{ \theta_2^T \xi_2(\mathbf{x}_2) - d_2(\mathbf{x}_2) \right\} \right] \end{aligned} \tag{23}$$

and v_1, v_2 are reconstruction errors which are assumed to satisfy the following:

Assumption 1 On the compact region Ω_{x_1} and Ω_{x_2}

$$|v_1(\mathbf{x}_1)| \le \psi_1^* s_1(\mathbf{x}), \forall \mathbf{x}_1 \in \Omega_{x_1} \tag{24}$$

$$|v_2(\mathbf{x}_2)| \le \psi_2^* s_2(\mathbf{x}_2), \forall \mathbf{x}_2 \in \Omega_{x_2} \tag{25}$$

where $\psi_1^* \ge 0$ and $\psi_2^* \ge 0$ are unknown bounding parameters and $s_1(\mathbf{x}_1) : \Omega_{x_1} \to R^+$ and $s_2(\mathbf{x}_2) : \Omega_{x_2} \to R^+$ are known smooth bounding functions.

Let us define

$$\begin{aligned} \hat{f}(\mathbf{x}, \theta_1) &= L_a h + \theta_1^T \xi_1(\mathbf{x}_1) \\ \hat{g}(\mathbf{x}, \theta_2) &= L_b h + \theta_2^T \xi_2(\mathbf{x}_2) \end{aligned} \tag{26}$$

where θ_1 and θ_2 are the estimates of the optimal paramters θ_1^* and θ_2^*, respectively. We propose the control input as

$$\begin{aligned} u &= \frac{1}{\hat{g}(\mathbf{x}, \theta_2)} \left(-\hat{f}(\mathbf{x}, \theta_1) + \dot{y}_R + ce + \beta \right) \\ &= u_c + \frac{\beta}{\hat{g}(\mathbf{x}, \theta_2)} \end{aligned} \tag{27}$$

where u_c is the so-called certainty equivalent control and β is the additional control action. The β is needed to improve robustness with respect to the norm-bounded reconstruction errors. We choose β as follows;

$$\beta = \frac{\psi(t)}{1-\gamma} p(t) \tag{28}$$

where γ is a small positive design constant and $p(t)$ is

$$p = s \cdot \tanh\left(\frac{es}{\varepsilon}\right) \tag{29}$$

and $s = s_1 + s_2|u_c|$, $\varepsilon > 0$ is a small positive design constant. Scalar $\psi(t)$ is the estimation of $\psi^* = \max\{\psi_1^*, \psi_2^*\}$. The adaptive laws for θ_1, θ_2 and ψ are chosen as

$$\dot{\theta}_1 = -\gamma_1 \left[e\xi_1 + \sigma(\theta_1 - \theta_1^0) \right] \tag{30}$$

$$\begin{aligned} \dot{\theta}_2 &= -\gamma_2 \left[e\xi_2 u + \sigma(\theta_2 - \theta_2^0) \right] \\ \dot{\psi} &= \gamma_\psi \left[ep - \sigma(\psi - \psi^0) \right] \end{aligned} \tag{31}$$

where θ_1^0, θ_2^0 and ψ^0 are the initial estimates of θ_1, θ_2 and ψ, respectively.

Theorem 1. Consider the SMIB system described by (11) with the modified output of (10). The robust adaptive tracking design described by the control law (27) with the parameter adaptive laws (30),(31) guarantees that

(a) all the signals and parameter estimates are uniformly ultimately bounded, and

(b) given any $\mu > \sqrt{2\rho}$ there exists $T(\mu)$ such that for $t \ge T$,

$$|e(t)| \le \mu$$

IV. Simulations

In this section, the performance of the example system with the proposed robust adaptive fuzzy controller is tested. The parameters of the generator used in the simulations are as follows:

$$\begin{aligned} &x_d = 1.863, x_d' = 0.257, \omega_0 = 314.159, \\ &D = 5.0, H = 8.0, x_T = 0.127, x_L = 0.4853, \\ &T_{d0} = 6.9, P_m = 1.0, V_s = 1.0 \end{aligned}$$

The pole-loci of linearized zero dynamics around the operating point are shown in Fig. 2 when $b = 0.04$. The linearized zero dynamic equations are in appendix. As $|\alpha|$ increases, the damping of roots of the characteristic equation increases. Therefore, the damping effect can be obtained for appropriate value of α and we have chosen it as $\alpha = -2.2$. After several simulations, we have chosen the universes of discourse for δ, w and E_q as $[0, \pi]$, $[-1, +1]$ and $[0, 10]$, respectively. Number of fuzzy membership functions is all 4. Thus, the fuzzy basis function vectors ξ_1 and

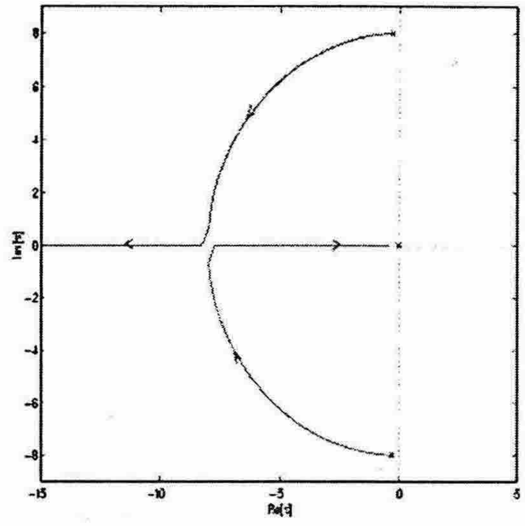

Fig. 2. Pole-loci of linearized zero dynamics

ξ_2 are 64 and 16 dimensional vectors, respectively. The controller parameters are as follows:

$$c = 100, \sigma = 0.1, \epsilon = 0.001,$$
$$\gamma_1 = 100, \gamma_2 = 0.1, \gamma_\psi = 10,$$
$$\gamma = 0.1, y_R = 1.0, b = 0.04$$

We consider a symmetrical 3-phase short-circuit fault that occurs on a transmission line. The fault is assumed to occur in the middle of the one transmission line. Before the fault occurs, it is assumed that the system is in steady-state. It should be emphasized that since the variation of the system is unknown, the new equilibrium point is indeterministic. However, knowledge of the post-fault equilibrium is not required for the stabilizing control. Fig. 3 shows the responses of the system using the proposed fuzzy controller with $\alpha = 0$ and $\alpha = -2.2$. We can see that the oscillation in the power angel is dampen out quickly when $\alpha = -2.2$.

From the result of Fig. 3, we can see that the adaptive fuzzy controller with the modified output can maintain the stability of the system as well as damp out the power angle rapidly.

V. Conclusions

In this paper, We have proposed robust adaptive fuzzy contoller for single-machine infinite bus system. The adaptive fuzzy control scheme based on the input-pseudo output linearization has been applied to regulate the terminal voltage and to damp out quickly the oscillation of the power angle. We have shown that the closed-loop system is stable in the Lyapunov standpoint. Simulation results show that both transient stability and voltage regulation can be achieved effectively by using the proposed control scheme.

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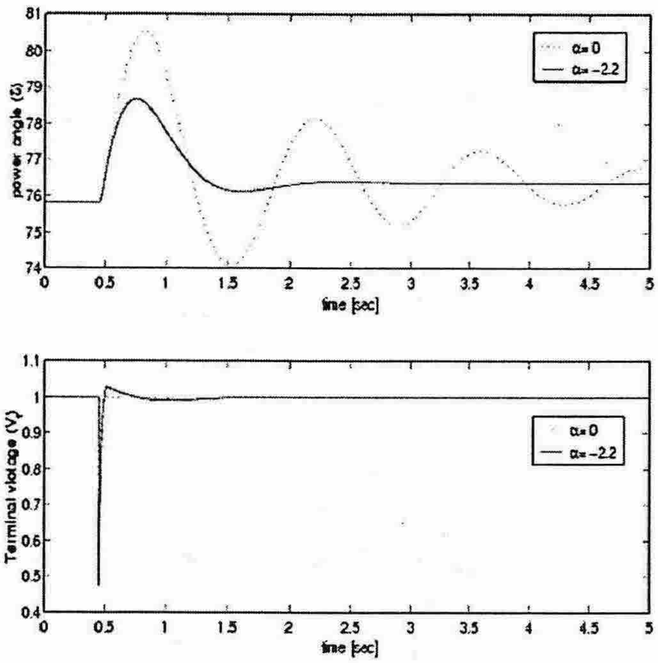

Fig. 3. System responses in the case of the 3-phase short-circuit fault at t=0.5 sec.

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