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Robust adaptive fuzzy logic power system stabilizer

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ABSTRACT

This paper introduces a robust adaptive fuzzy controller as a power system stabilizer (RFPSS) used to damp inter-area modes of oscillation following disturbances in power systems. In contrast to the IEEE standard multi-band power system stabilizer (MB-PSS), robust adaptive fuzzy-based stabilizers are more efficient because they cope with oscillations at different operating points. The proposed controller adopts a dynamic inversion approach. Since feedback linearization is practically imperfect, components that ensure robust and adaptive performance are included in the control law to compensate for modelling errors and achieve acceptable tracking errors. Two fuzzy systems are implemented. The first system models the nominal values of the system's nonlinearities. The second system is an adaptive one that compensates for modelling errors. A feedback linearization-based control law is implemented using the identified model. The gains of the controller are tuned via a particle swarm optimization routine to ensure system stability and minimum sum of the squares of the speed deviations. A bench-mark problem of a 4-machine 2-area power system is used to demonstrate the performance of the proposed controller and to show its superiority over other conventional stabilizers used in the literature.

1. Introduction

Electro-mechanical oscillations on the transmission grid are becoming a critical problem for the power systems; there are two distinct types of dynamic oscillations which have been known to present problems on power systems (Kundur, 1994). One type occurs when a generating unit (group of units) at a station is (are) swinging against the rest of the system. Such oscillations are called local mode oscillations. The characteristic frequency of a typical local mode is generally in the 1–2 Hz range, depending mainly on the impedance of the transmission system. The second type of oscillations, known as inter-area modes, are more complex because they usually involve combination of many machines on one part of a system swinging against machines on another part of the system. The characteristic frequency of inter-area modes of oscillations is generally in the range of 0.1 to 0.6 Hz. A power system stabilizer (PSS) is an electronic feedback control that is a part of the excitation system control for generating units. PSS acts to modulate the generator field voltage to damp power system oscillations.

Conventional power system stabilizers (CPSSs) are designed based on linear models representing the system's generators operating at a certain operating point (Awed-Badeeb, 2006; Chow, Boukarim, & Murdoch, 2004). The performance of these designed CPSSs is acceptable as long as the system is operating close to the operating point for which the system model is obtained. However, CPSSs are not able to provide satisfactory performance results over wider ranges of operating conditions. Considerable efforts have been directed towards developing adaptive PSS, e.g. (Hsu & Lious, 1987). The basic idea behind adaptive techniques is to estimate the uncertainties in the plant on-line based on measured signals (Astrom & Wittenmark, 1989). However, adaptive PSSs can only deal with systems of known structure. Furthermore, adaptive controllers cannot use human experience which is expressed in linguistic descriptions. This problem is overcome by using artificial intelligence (fuzzy logic, neural networks, decision trees)-based techniques for the design of PSSs.

Fuzzy systems work with a set of linguistic rules, which are put down by experienced operators. It is a model-free approach, which is generally considered suitable for controlling imprecisely defined systems (El-Metwally & Malik, 1995, 1996). In fuzzy control, the controller is synthesized from a collection of fuzzy If–Then rules which describe the behavior of the unknown plant. It has been applied to the design of PSSs in a number of publications (El-Metwally & Malik, 1995, 1996; Hassan, Malik, & Hope, 1991). In El-Metwally and Malik (1995, 1996), Hassan et al. (1991), the parameters of the fuzzy power system stabilizer (FPSS) are kept fixed after the design is completed. The performance of the FPSS depends on the operating conditions of the power system, although it is less sensitive than CPSSs.

The authors have proposed a design of a hierarchical fuzzy logic PSS for a multi-machine power system in Hussein, Elshafei, and Bahgat (2007). The scaling factors of the fuzzy controller are tuned automatically as the operating conditions of power system change.

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These scaling parameters are the output of another fuzzy logic system (FLS), which gets its inputs from the operating condition of the power system. An (indirect adaptive fuzzy)-based power system stabilizer for a multi-machine power system in Hussein, Elshafei, and Bahgat (2007) that consists of a fuzzy identifier for a nonlinear synchronous machine and a feedback linearization controller to damp frequency oscillations. This technique does not guarantee performance and robustness since cancellation is practically imperfect.

To enhance the robustness and performance, following a similar approach in Elshafei (2003), a robust adaptive fuzzy power system stabilizer (RFPSS) is designed in this paper. The control law is based on feedback linearization. Since feedback linearization can hardly be exact, the control law is augmented to include adaptive and robust components so that the system can cope with modelling uncertainties and achieve acceptable electro-mechanical oscillation damping.

2. Adaptive fuzzy logic control

Consider the class of nonlinear systems described by

$$\dot{\underline{x}} = \underline{f}(\underline{x}) + \underline{b}u \tag{1}$$

$$y = z(\underline{x}) \tag{2}$$

Where $f(\cdot)$ and $z(\cdot)$ are unknown real continuous nonlinear functions, $u \in R$ and $y \in R$ are the input and the output of the system, respectively. $\underline{x} = (x, \dot{x}, \ldots, x^{(n-1)})^T \in R^n$ is the system state vector.

Differentiating (2) once yields

$$\dot{y} = \frac{\partial z(\underline{x})}{\partial(\underline{x})}\underline{f}(\underline{x}) + \frac{\partial z(\underline{x})}{\partial(\underline{x})}\underline{b}u \tag{3}$$

Assume $\frac{\partial z(\underline{x})}{\partial(\underline{x})}\underline{b} = 0$, i.e., the nonlinear system (1) and (2) has a relative degree not equal to one. Define $h(\underline{x})$ to be

$$h(\underline{x}) = \frac{\partial z(\underline{x})}{\partial(\underline{x})}\underline{f}(\underline{x})$$

Therefore, (3) can be written as

$$\dot{y} = h(\underline{x}) \tag{4}$$

Differentiating (4) once yields

$$\ddot{y} = \Delta(\underline{x}) + \beta(\underline{x})u \tag{5}$$

where $\Delta(\underline{x})$ and $\beta(\underline{x})$ are given by

$$\Delta(\underline{x}) = \frac{\partial h(\underline{x})}{\partial(\underline{x})}\underline{f}(\underline{x}), \quad \beta(\underline{x}) = \frac{\partial h(\underline{x})}{\partial \underline{x}}\underline{b}$$

Designing a control signal $u(t)$ that stabilizes (5) will guarantee that the overall system is stable.

Choose the control law as

$$u = \frac{1}{\beta(\underline{x})}[-\Delta(\underline{x}) + v] \tag{6}$$

We select v such that the output $y(t)$ would track a reference trajectory y_d. This is achieved by assuming

$$v = \ddot{y}_d - \underline{k}^T\underline{e} \tag{7}$$

In the ideal case, the positive constant vector $\underline{k}$ determines the location of the closed loop poles of the error model. The error model is defined as

$$\underline{e} = \begin{bmatrix} e \\ \dot{e} \end{bmatrix} = \begin{bmatrix} y - y_d \\ \dot{y} - \dot{y}_d \end{bmatrix} \tag{8}$$

The reference signal y_d and its derivative signal $\dot{y}_d$ are assumed to be smooth such that the reference signal second derivative $\ddot{y}_d$ exists.

To adapt to various operating conditions, the nonlinear functions $\Delta(\underline{x})$ and $\beta(\underline{x})$ can be estimated on-line. Fuzzy logic provides an attractive technique to represent such nonlinearities. The power of fuzzy models stems from the universal approximation theorem (Wang, 1995). From the implementation point of view, adaptive fuzzy systems are attractive since they depend linearly on the parameters to be estimated. The control law becomes

$$u = \frac{1}{\hat{\beta}(\underline{x})}[-\widehat{\Delta}(\underline{x}) + v] \tag{9}$$

$$\widehat{\Delta}(\underline{x}) = \underline{\hat{\theta}}_{\Delta}^T\underline{\zeta}(\underline{x}) \tag{10}$$

$$\hat{\beta}(\underline{x}) = \underline{\hat{\theta}}_{\beta}^T\underline{\zeta}(\underline{x}) \tag{11}$$

where

$$\underline{\hat{\theta}}_{\Delta}^T = \left[\hat{\theta}_{\Delta}^1 \cdots \hat{\theta}_{\Delta}^i \cdots \theta_{\Delta}^M\right]$$

$$\underline{\hat{\theta}}_{\beta}^T = \left[\hat{\theta}_{\beta}^1 \cdots \hat{\theta}_{\beta}^i \cdots \hat{\theta}_{\beta}^M\right]$$

$$\underline{\zeta}^T(\underline{x}) = [\zeta_1 \cdots \zeta_i \cdots \zeta_M]$$

The functions $\zeta_i, i = 1, \ldots, M$, are called the fuzzy basis function

$$\zeta_i = \frac{\mu_i}{\sum_{i=1}^M \mu_i}, \quad i = 1, \ldots, M$$

$\underline{\hat{\theta}}_{\Delta}$ is the vector of estimated parameters used to model $\Delta(\underline{x})$, and $\underline{\hat{\theta}}_{\beta}$ is the vector of estimated parameters used to model $\beta(\underline{x})$. According to the universal approximation theorem (Wang, 1995), there exist fuzzy systems that approximate the function $\Delta(\underline{x})$ and $\beta(\underline{x})$ with arbitrary accuracy.

In an adaptive system, the values $\theta_i, i = 1, \ldots, M$, are tuned on-line to ensure the fuzzy model is close enough to match the actual system. Expressions similar to (10) and (11) can model the nonlinear functions Δ and β, respectively. It follows from (5) and (8) that

$$\ddot{e} = \ddot{y} - \ddot{y}_d = \Delta(\underline{x}) + \beta(\underline{x})u - \ddot{y}_d \tag{12}$$

Using (7) and (9), it is possible to write $\ddot{y}_d$ as

$$\ddot{y}_d = \widehat{\Delta}(\underline{x}) + \hat{\beta}(\underline{x})u + \underline{k}^T\underline{e} \tag{13}$$

Substituting (13) into (12), the error model can be expressed as

$$\ddot{e} = \widetilde{\Delta}(\underline{x}) + \tilde{\beta}(\underline{x})u - \underline{k}^T\underline{e} \tag{14}$$

The error functions $\widetilde{\Delta}$ and $\tilde{\beta}$ are defined such that the estimation parameters error vectors, $\underline{\tilde{\theta}}_{\Delta}$ and $\underline{\tilde{\theta}}_{\beta}$ are given by

$$\underline{\tilde{\theta}}_{\Delta} = \underline{\theta}_{\Delta} - \underline{\hat{\theta}}_{\Delta}$$

$$\underline{\tilde{\theta}}_{\beta} = \underline{\theta}_{\beta} - \underline{\hat{\theta}}_{\beta}$$

Based on the universal approximation theorem, there are fuzzy systems Δ^* and β^* that can approximate Δ and β, respectively, with arbitrary degree of accuracy. Hence, it is possible to write

$$\Delta(\underline{x}) \approx \Delta^*(\underline{x}) = \underline{\tilde{\theta}}_{\Delta}^T\underline{\zeta}(\underline{x}) \tag{15}$$

$$\beta(\underline{x}) \approx \beta^*(\underline{x}) = \underline{\tilde{\theta}}_{\beta}^T\underline{\zeta}(\underline{x}) \tag{16}$$

Using (10), (11), (15) and (16) the error model (14) becomes

$$\ddot{e} = \underline{\tilde{\theta}}_{\Delta}^T\underline{\zeta}(\underline{x}) + \underline{\tilde{\theta}}_{\beta}^T\underline{\zeta}(\underline{x}) - \underline{k}^T\underline{e} \tag{17}$$

To derive the adaptation laws for $\underline{\tilde{\theta}}_{\Delta}$ and $\underline{\tilde{\theta}}_{\beta}$, consider the candidate Lyapunov function

$$V = \frac{1}{2}\underline{e}^T P\underline{e} + \frac{1}{2}\underline{\tilde{\theta}}_{\Delta}\Gamma_{\Delta}\underline{\tilde{\theta}}_{\Delta} + \frac{1}{2}\underline{\tilde{\theta}}_{\beta}\Gamma_{\beta}\underline{\tilde{\theta}}_{\beta} \tag{18}$$

The weighting matrices P, Γ_{Δ} and Γ_{β}, are positive definite. The time derivative of (18) along the trajectory (17) is

$$\dot{V} = -pke^2 + \underline{\tilde{\theta}}_{\Delta}^T\underline{\zeta}(\underline{x})pe + \underline{\tilde{\theta}}_{\beta}^T\underline{\zeta}(\underline{x})pe + \underline{\tilde{\theta}}_{\Delta}^T\Gamma_{\Delta}\dot{\underline{\tilde{\theta}}}_{\Delta} + \underline{\tilde{\theta}}_{\beta}^T\Gamma_{\beta}\dot{\underline{\tilde{\theta}}}_{\beta} \tag{19}$$