Electric Power Systems Research 80 (2010) 1428–1436

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

Damping inter-area modes of oscillation using an adaptive fuzzy power system stabilizer

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ARTICLE INFO

Article history:
Received 3 June 2009
Received in revised form 15 April 2010
Accepted 8 June 2010
Available online 16 July 2010

Keywords:
Fuzzy logic system
Fuzzy identification
Feedback linearization
Variable-structure algorithm
Swarm optimization technique

ABSTRACT

This paper introduces an indirect adaptive fuzzy controller as a power system stabilizer used to damp inter-area modes of oscillation following disturbances in power systems. Compared to the IEEE standard multi-band power system stabilizer (MB-PSS), indirect adaptive fuzzy-based stabilizers are more efficient because they can cope with oscillations at different operating points. A nominal model of the power system is identified on-line using a variable structure identifier. 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

An interconnected power system, depending on its size, has many modes of oscillations [1]. In the analysis and control of system stability, two distinct types of system oscillations are usually recognized. One type is associated with units at a generating station swinging with respect to the rest of the power system. Such oscillations are referred to as local plant mode of oscillations. The second type of oscillations is associated with the swinging of many machines in one part of the system against machines in other parts. These are referred to as inter-area mode of oscillations. The basic function of power system stabilizers (PSSs) is to add damping to both types of system oscillations and to enhance the overall stability of the power system over a broad range of operating conditions and disturbances.

Conventional PSSs (CPSSs) [1] use transfer functions designed for linear models representing the generators at a certain operating point. However, as they work around a particular operating point of the system for which these transfer functions are obtained, they are not able to provide satisfactory results over wider ranges of operating conditions.

Considerable efforts have been directed towards developing adaptive PSS, e.g. [2]. The basic idea behind adaptive techniques is to estimate the uncertainties in the plant on-line based on measured signals [3]. However, adaptive PSSs deal with systems of known structures. Furthermore, adaptive controllers cannot use human experience which is expressed in linguistic descriptions. This problem is overcome using artificial intelligence (fuzzy logic, neural networks, and 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 [4,5]. In Fuzzy control, the controller is synthesized from a collection of fuzzy If-Then rules which describe the behavior of the unknown plant. Fuzzy logic systems provide nonlinear mapping from an input data vector space into a scalar output space, which are general enough to perform control and identification of nonlinear systems.

The authors have proposed an (indirect adaptive fuzzy)-based power system stabilizer for a multi-machine power system in [6]. This power system stabilizer consists of a fuzzy identifier for a nonlinear synchronous machine and a feedback linearization controller to damp frequency oscillations. This technique suffers a robustness problem due to the integration of the updated parameter. In [7] a design of a hierarchical fuzzy logic PSS for a multi-machine power system is introduced. The scaling factors of the fuzzy controller are tuned automatically as the operating conditions of power system change. These scaling parameters are the output of another fuzzy-logic system (FLS), which obtains its inputs from the operating condition of the power system. An online adaptive neuro-fuzzy power system stabilizer for multi-machine power systems is derived in [8]. This system is divided into two subsystems, a recursive least square identifier with a variable forgetting factor for

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doi:10.1016/j.epsr.2010.06.004

the generator and a fuzzy logic based adaptive controller to damp oscillations. An adaptive power system stabilizer using on-line self-learning fuzzy systems is proposed in [9]. The authors present a new adaptive fuzzy power system stabilizer which consists of an identifier to estimate the power system. The identifier is trained by recursive least square algorithm and the fuzzy logic controller is trained by a steepest descent algorithm to damp the oscillations. The steepest descent algorithm to train fuzzy logic controller suffers the possibility of being slow as it could get trapped in local minima [9].

In this paper, an indirect adaptive fuzzy power system stabilizer is proposed. The stabilizer's control law is determined as a function of the error in the plant's output (generator speed deviation) and the output of a fuzzy identifier. Actual speed and actual speed deviation of the associated generator are taken as inputs to the fuzzy identifier. These inputs to the identifier are obtained online and assumed to be measured from the output of the plant. The output of the fuzzy identifier is the estimate of the unknown nonlinearities of the model. These are used in a feedback linearization framework to provide the necessary damping to the power system.

The paper proceeds as follows. In Section 2, a basic idea of variable-structure adaptive fuzzy control used in this paper is presented. In Section 3, the proposed identification and control design procedure is given. In Section 4, an overview of particle-swarm based optimization is given with the procedure to optimally compute the controller gains. In Section 5, a description of the test system is given. In Section 6, the simulation results that demonstrate the effectiveness of the proposed controller are presented and compared with those of the conventional controller using the 4-machine 2-area bench-mark test power system. Conclusions are stated in Section 7.

2. Basic idea of variable-structure adaptive fuzzy control

Consider the class of nonlinear systems described by

$$y^{(r)} = f(\underline{x}) + g(\underline{x})u \tag{1}$$

where $f(\cdot)$ and $g(\cdot)$ 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, and $y^{(r)}$ is the rth derivative of the output y. It is assumed that $g(x) \neq 0$ for all values of $\underline{x}$ and is bounded in the compact set.

System (1) can also be represented using state-space modeling as

$$\dot{\underline{x}} = A\underline{x} + \underline{b}(f(\underline{x}) + g(\underline{x})u)$$

with

$$A = \begin{bmatrix} \underline{0}_{(n-1)\times 1} & I_{(n-1)\times(n-1)} \\ 0 & \underline{0}_{1\times(n-1)} \end{bmatrix}, \quad \underline{b} = \begin{bmatrix} \underline{0}_{(n-1)\times 1} \\ 1 \end{bmatrix}.$$

Only x and u are available for measurements. The output signal y is required to follow a desired-output signal y_m.

If f and g were known, a feedback linearization technique could be used to derive the required control law [11]. The feedback control law would be

$$u = \frac{1}{g(\underline{x})}[-f(\underline{x}) + y_m^{(r)} + \underline{k}^T \underline{e}_1], \tag{2}$$

where $\underline{e}_1 = [e_1, \dot{e}_1, \ldots, e_1{}^{(r-1)}]^T$, $e_1 = y_m - y$ is the tracking error. $\underline{k} = [k_r, \ldots, k_1]^T$ is the vector of design parameters. The design parameters should be selected such that the roots of the characteristic equation $s^r + k_1 s^{r-1} + \cdots + k_r = 0$ are in the left-hand side of the s-plane to ensure stability [10]. In this paper, particle swarm optimization (PSO) technique is used to search for the optimum values of the design parameters k_i, $i = 1, 2, \ldots, r$.

Since the functions f and g are unknowns, an identifier is implemented to derive some fuzzy mappings $\hat{f}(\underline{x}/\underline{\theta}_f)$ and $\hat{g}(\underline{x}/\underline{\theta}_g)$ that are estimates of the functions f and g, respectively. These fuzzy mappings are function of $\underline{x}$ and are parameterized in terms of the vectors $\underline{\theta}_f$ and $\underline{\theta}_g$. The vectors $\underline{\theta}_f$ and $\underline{\theta}_g$ correspond to the centroids of the consequents of the fuzzy mappings $\hat{f}(\underline{x}/\underline{\theta}_f)$ and $\hat{g}(\underline{x}/\underline{\theta}_g)$, respectively.

We use a series-parallel identification model [12],

$$\dot{\hat{\underline{x}}} = -\alpha\hat{\underline{x}} + \alpha\underline{x} + \hat{f}(\underline{x}/\underline{\theta}_f) + \hat{g}(\underline{x}/\underline{\theta}_g)u, \tag{3}$$

where α is a positive design parameter that determines the dynamics of the identifier error model. The parameter is chosen heuristically with a guideline that increasing the parameter speeds up the estimator convergence and reduces the final error. However, this could come at the expense of increased sensitivity to unstructured uncertainties and measurement noise [13]. The goal of the identification scheme is to determine an adaptive law to compute the parameter vectors $\underline{\theta}_f$ and $\underline{\theta}_g$ such that all the signals in the identification model must be uniformly bounded and the error $\underline{x} - \hat{\underline{x}}$ is as small as possible.

Based on the design algorithm given in [12,13], we choose $\hat{f}(\underline{x}/\underline{\theta}_f)$ and $\hat{g}(\underline{x}/\underline{\theta}_g)$ to be fuzzy systems characterized by the singleton fuzzifier, the center average defuzzification, the product inference and the Gaussian membership function. As such, it is possible to represent $\hat{f}(\underline{x}/\underline{\theta}_f)$ and $\hat{g}(\underline{x}/\underline{\theta}_g)$ as

$$\hat{f}(\underline{x}/\underline{\theta}_f) = \underline{\theta}_f^T \underline{p}(\underline{x}) \tag{4}$$

$$\hat{g}(\underline{x}/\underline{\theta}_g) = \underline{\theta}_g^T \underline{p}(\underline{x}) \tag{5}$$

where

$$\underline{p}(\underline{x}) = [p_1(\underline{x}) \ldots p_k(\underline{x}) \ldots p_M(\underline{x})]^T$$

$$\underline{\theta}_f = [\theta_f^1 \ldots \theta_f^k \ldots \theta_f^M]^T$$

$$\underline{\theta}_g = [\theta_g^1 \ldots \theta_g^k \ldots \theta_g^M]^T.$$

$p_k(\underline{x})$ is called the fuzzy basis function (FBF) and is given by,

$$p_k(\underline{x}) = \frac{\prod_{i=1}^n \mu_{F_i^{ji}}(x_i)}{\sum_{j_1=1}^{m_1} \cdots \sum_{j_n=1}^{m_n} \prod_{i=1}^n \mu_{F_i^{ji}}(x_i)} \tag{6}$$

where $\mu_{F_i^{ji}}(x_i)$ is the membership function assigned to the jth linguistic variable in the jth rule.

Collect the $p_k(\underline{x})$s into vector $\underline{p}(\underline{x})$, θ_f^ks and θ_g^ks into vectors $\underline{\theta}_f$ and $\underline{\theta}_g$, respectively. Let $\underline{e}_2 = \underline{x} - \hat{\underline{x}}$, then the unknown parameters are updated according to [11,12] as

$$\dot{\underline{\theta}}_f = \Gamma_f \underline{e}_2^T \underline{b}\underline{p}(\underline{x}) \tag{7}$$

$$\dot{\underline{\theta}}_g = \Gamma_g \underline{e}_2 \underline{b}\underline{p}(\underline{x})u, \tag{8}$$

where Γ_f and Γ_g are diagonal matrices.

Practically, (7) and (8) lead to a robustness problem due to the integration of $\underline{\theta}_f$ and $\underline{\theta}_g$. Techniques such as projection algorithm and sigma modification are used to improve the system response by avoiding the robustness problem. In [13,14], a – free of integration – variable structure algorithm that does not suffer robustness problems is presented. From [13,14], the ith element of $\underline{\theta}_f$ and $\underline{\theta}_g$ are, respectively, given by

$$\theta_f^i = -\overline{\theta}_f^i \ \text{sat}[(\underline{x} - \hat{\underline{x}})^T \underline{b}] + \theta_f^i(0) \tag{9}$$