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LPV-based power system stabilizer: Identification, control and field tests

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ABSTRACT

This paper shows the design and tests of an LPV power system stabilizer aimed at improving the damping of electromechanical oscillations in power systems. In order to capture the dynamic model for control design, LPV models were estimated from experimental data. The generator active and reactive powers were used as scheduling parameters. The control problem is formulated as a parameterized linear matrix inequality, which the positivity condition is relaxed through a sum-of-squares decomposition. The controller ensures stability and H_∞ performance for a set of operating conditions. Field tests were carried out on a 10-kVA machine and on a 350-MVA hydroelectric generator.

1. Introduction

Power system stabilizers (PSSs) are controllers used to improve the damping of electromechanical oscillations in multimachine power systems, ensuring reliability and efficiency in the operation of interconnected systems. If these oscillations are not properly damped, the power system operating condition may become unstable, leading to system outages and safety concerns. In order to mitigate such lack of damping for these oscillations modes, an auxiliary component of damping torque is generated using PSS controllers. This stabilizing signal (PSS output) modulates the automatic voltage regulator (AVR) reference (Kundur, 1994; Rogers, 2000). In IEEE/CIGRE Joint Task Force on Stability Terms and Definitions (2004) this study area was defined as small-disturbance (or small-signal) rotor angle stability.

Although power systems are highly nonlinear systems that operate in a constantly changing environment, the standard PSS is designed using a linearized model of the power system (Kundur, 1994). In this scenario, the PSSs should preserve the small-signal system stability even under these variations and disturbances. However, even if the system remains stable, the damping level can be less than the adequate value.

The research topic on advanced control theory applied to power system operation and performance improvement has been an active area given the importance of such kind of plant. In light of these reasons, over the last years robust (Konara & Annakkage, 2016; Martins & Bossa, 2014), self-tuning adaptive (Tavakoli & Seifi, 2016), LMI-based (Werner, Korba, & Yang, 2003), and gain-scheduling approaches (Nogueira et al., 2014) have been proposed to design PSSs that are able to ensure both stability and performance over a range of operating conditions. Linear parameter varying (LPV) systems is a recent approach both to deal with parametric uncertainty and to approximate nonlinear dynamic systems (Sename, Gaspar, & Bokor, 2013). Explicit dependence on time-varying exogenous parameters (scheduling parameters) is the main characteristic of LPV systems.

The synthesis of LPV controller ensures the closed-loop system stability and performance for all trajectories of the scheduling parameters. Real-time measurements of the scheduling parameters are used to adapt them according to system variations. Furthermore, online convergence is not necessary in LPV controllers, resulting in less computational effort in executing the control law when compared with self-tuning regulators. These reasons justify the fact that LPV control is currently referred to as modern gain-scheduled control (Leith & Leithead, 2000; Rugh & Shamma, 2000).

Taking into account that deviations from the nominal operating condition of a power system can be represented in the form of structured uncertainty, an LPV model has the capability to approximate the nonlinear dynamics for a given region of interest. Recent works have applied the LPV theory to design controllers for power systems. Schaab, Hahn, Wolkov, and Stursberg (2017) present simulation results of an LPV controller applied to power systems containing synchronous

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generators as well as wind energy conversion systems. The design of a decentralized LPV PSS and simulation tests on the 50-generator IEEE test system are presented in Qiu, Vittal, and Khammash (2004). Using the same benchmark simulation model, in Liu, Vittal, and Elia (2006) is evaluated the performance of an LPV supplementary damping controller implemented in a Thyristor Controlled Series Capacitor (TCSC). Regarding to transitory stability, an LPV voltage regulator with rotor angle as scheduling parameter is proposed in He, Liu, and Mei (2010). In this paper, simulation tests were performed on a single-machine infinite-bus power system.

Many papers published so far, on the subject of adaptive control and its recent variants have been constrained only to carry out performance evaluation by means of computational tests applied to simplified models of the system. It is known that such computational models are obtained by neglecting several important phenomena, implying a considerable failure risk, when implemented in a real power system, due to the fact that a generating unit is a critical equipment regarding to its requirement for remaining in continuous operation and subjected to very restrictive safety and regulation rules. Therefore, it is not so easy to grant permission for performing field tests in such system.

In order to overcome these issues, laboratory scale electric power systems can be used to validate advanced control methods on a real environment. Following this, in Nogueira, Barra Jr., Da Costa Jr., Barreiros, and De Lana (2015) an LPV based PSS (LPV-PSS) was designed and tested in a 10-kVA reduced-scale electric power system, which is subjected to a wide range of operating conditions. Active power deviation signal is processed to synthesize an appropriate control signal providing additional damping torque to the system. Due to inherent strong nonlinear dependence which exists between the relative damping of the target oscillation mode and the power system loading condition, the average value of the generated active power has been chosen as the scheduling variable. The LPV-PSS was designed through a parameterized LMI (PLMI) formulation (Gilbert, Henrion, Bernussou, & Boyer, 2010), where a central polynomial is used to specify a target to the closed-loop poles. A solution for the PLMI was obtained through a sum-of-squares relaxation (Apkarian & Tuan, 2000; Scherer & Hol, 2006).

This work aims to extend the preliminary results shown in Nogueira et al. (2015). Important topics as LPV model validation, choice for the central polynomial, conditions for the sum-of-squares relaxation, and LPV controller implementation, are addressed. In addition, field tests carried out on a 350-MVA generating unit of the Tucuruí Hydroelectric Power Plant, North Region of Brazil, are presented and discussed.

Therefore, the main paper's novelty is to provide useful LPV-PSS design techniques which assure both the performance and the stability of power systems. Namely, the main contributions of the paper are: (i) to address the difficult problem of designing an adaptive PSS in order to provide enough damping for a set of allowed operating conditions; (ii) to propose a design method which complies with standard safety and operational rules stated for large power systems; (iii) to propose and apply a LPV system identification strategy tailored for safe operation in power plants; (iv) to adapt and apply, for that important engineering problem, some recently proposed computation relaxation tools in order to address the NP-hard problem of solving an infinite set of LMIs for LPV-PSS design; (v) to implement and to assess performance of the adaptive LPV-PSS in a large power plant, providing invaluable practical information of interest of both engineers and researchers.

2. LPV system identification methodology

2.1. LPV-ARX model structure

The dynamic model used to capture the dominant modes of the plant can be represented as a discrete-time LPV model given by:

$$A(z,\boldsymbol{\theta})\,y(k) = B(z,\boldsymbol{\theta})\,u(k) + e(k), \tag{1}$$

where $u(k)$ and $y(k)$ are the system input and output, respectively, z^{-1} is the backward-shift operator, $\boldsymbol{\theta} = \left[\theta_1 \theta_1 \dots \theta_p\right]$ is a vector with scheduling parameters, and $e(k)$ is the estimation error. The model can also be presented in a transfer function form:

$$G(z,\boldsymbol{\theta}) = B(z,\boldsymbol{\theta}) / A(z,\boldsymbol{\theta}). \tag{2}$$

Note that the scheduling parameters are time-varying discrete signals related to the system operating condition. For simplicity, the time index k is omitted ($\boldsymbol{\theta}(k) := \boldsymbol{\theta}$). The parameterized polynomials $B(z,\boldsymbol{\theta})$ and $A(z,\boldsymbol{\theta})$ have the form:

$$B(z,\boldsymbol{\theta}) = b_1(\boldsymbol{\theta})\,z^{-1} + b_2(\boldsymbol{\theta})\,z^{-2} + \cdots + b_{n_b}(\boldsymbol{\theta})\,z^{-n_b}, \tag{3a}$$

$$A(z,\boldsymbol{\theta}) = 1 + a_1(\boldsymbol{\theta})\,z^{-1} + \cdots + a_{n_a}(\boldsymbol{\theta})\,z^{-n_a}, \tag{3b}$$

where n_b and n_a are the degree of the parameterized polynomials. If the vector $\boldsymbol{\theta}$ has only one scheduling parameter, the terms $b_i(\boldsymbol{\theta})$ and $a_j(\boldsymbol{\theta})$ can be fixed functions with polynomial dependence on θ, such as:

$$b_i(\theta) = b_{i1} + b_{i2}\theta + \cdots + b_{iN}\theta^{N-1},\ i = 1, \dots, n_b, \tag{4a}$$

$$a_j(\theta) = a_{j1} + a_{j2}\theta + \cdots + a_{jN}\theta^{N-1},\ j = 1, \dots, n_a. \tag{4b}$$

Note that by selecting $N = 2$, there is an affine dependence on θ, and for $N = 1$, the resulting model is a conventional ARX (autoregressive with exogenous input) model. For this reason, the model presented in Eq. (1) is named LPV-ARX. When the scheduling vector $\boldsymbol{\theta}$ is set by two or more variables, $b_i(\boldsymbol{\theta})$ and $a_j(\boldsymbol{\theta})$ become multivariable polynomials. This work evaluates LPV models with only one scheduling parameter.

Model (1) can be represented in a matrix regression form. Consider a $\boldsymbol{\Theta}$ matrix with dimension $n \times N$ ($n = n_b + n_a$), composed by the parameters to be identified:

$$\boldsymbol{\Theta} = \begin{bmatrix} a_{11} & \cdots & a_{1N} \\ \vdots & \ddots & \vdots \\ a_{n_a 1} & \cdots & a_{n_a N} \\ b_{11} & \cdots & b_{1N} \\ \vdots & \ddots & \vdots \\ b_{n_b 1} & \cdots & b_{n_b N} \end{bmatrix}, \tag{5}$$

and the extended regression matrix $\boldsymbol{\Psi}$ composed by the plant collected data:

$$\boldsymbol{\Psi}(k) = \boldsymbol{\phi}(k)\,\boldsymbol{\pi}(k) = \begin{bmatrix} -y(k-1) \\ \vdots \\ -y\left(k-n_a\right) \\ u(k-1) \\ \vdots \\ u\left(k-n_b\right) \end{bmatrix} \left[1 \ \ \theta \ \ \theta^2 \dots \ \theta^{N-1}\right]. \tag{6}$$

From (5) and (6) the estimated output $\hat{y}(k)$ is calculated through (7):

$$\hat{y}(k) = \left\langle \hat{\boldsymbol{\Theta}}(k), \boldsymbol{\Psi}(k) \right\rangle, \tag{7}$$

where $\hat{\boldsymbol{\Theta}}$ is the matrix with estimated parameters, and $\langle \boldsymbol{A}, \boldsymbol{B} \rangle$ is the inner product between matrices $\boldsymbol{A}$ and $\boldsymbol{B}$, $\langle \boldsymbol{A}, \boldsymbol{B} \rangle = \mathrm{trace}\left(\boldsymbol{A}^T \boldsymbol{B}\right)$.

2.2. LPV least mean squares

The LPV identification method applied herein is based on the LPV least mean squares (LPV-LMS) algorithm presented in Bamieh and Giarré (2002), which highlights the formal persistence of excitation as a necessary condition to acquire input–output data set with the scheduling variable varying as much as possible between its limit values. Therefore, during the data acquisition both system input and scheduling variable should be excited. The literature of LPV identification often considers this method as the global approach. However, systems with slow dynamics scheduling variables often need a large data set to comply with such requirement, although it leads to long term experiment, which is not suitable for many practical applications in real systems. The LPV