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Design of model predictive controllers for adaptive damping of inter-area oscillations

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ABSTRACT

An adaptive damping controller design method by integrating online recursive closed-loop subspace model identification (SMI) with model predictive control theory is proposed in this paper. A reduced order state-space model which contains dominant low frequency oscillation modes is firstly identified online by using an closed-loop SMI algorithm. Then, an infinite horizon closed-loop optimal control is achieved based on model prediction which uses the current state of power system as the initial state. At each control step, the identified model is updated by using the new coming measurements and the optimal control action is solved again. Periodical online model and control updating identification and optimal control enables the proposed controller to adapt to operating condition variations and system parameter uncertainties. It is more robust than offline identification based damping controllers which could suffer from performance degradation under time varying and uncertain conditions. Simulation results demonstrate the effectiveness and robustness of the proposed controller in damping inter-area low frequency oscillations. The abilities to coordinate with power system stabilizers (PSSs) and other similar controllers in multi-machine power systems are also illustrated.

1. Introduction

Conventional power system damping controllers are usually based on linearization of detailed dynamic model of the system to be controlled [1,2]. The method may be suitable for small and moderate scale power systems, but is impractical for modern bulk power systems. Model order reduction (MOR) methods, such as dynamic equivalent [3] and model identification [4,5] have been proposed to design damping controllers for large scale systems, in which transfer functions or state-space models with reduced orders are derived from system dynamic responses. However, it is difficult for the MOR-based controllers to adapt to large changes in system operating conditions because of the fixed parameters they have employed. To overcome inherent shortcomings of conventional damping controllers, robust controllers [6,7] and adaptive controllers [8,9] have been developed from two different points of view to enhance robustness and to adapt wide range of operating conditions of power system.

Model predictive control (MPC) is an adaptive control strategy which has been applied in process control successfully [10]. Within the MPC, future behaviors of a process is firstly predicted based on an online and closed-loop identified model and by taking the current state of the process as the initial state. Then a sequence of controls can be obtained by solving an optimal control problem and the only first action of this sequence is applied to the plant. At each control step, the identified model is updated by using the new coming measurements then the optimal control action is solved and applied again. In recent years, a number of predictive control schemes have been presented for power system emergency control, voltage and transient stability control, as well as load frequency control [11–15]. These various studies illustrate that MPC can produce computationally reasonable power system control strategies. In [16], a multivariable adaptive power system stabilizer based on a subspace model identification (SMI) method [17] and the MPC strategy is proposed and locally implemented to damp multi-mode oscillations.

The core within the adaptive damping control strategy employing MPC is the online and closed-loop identification of a reduced-order system model. In this paper, an adaptive model predictive damping controller design method by integrating an online recursive closed-loop subspace model identification algorithm with MPC strategy is proposed. The method is different from MPC scheme proposed in [16] in two significant ways. Firstly, the 'multivariable output error state space' (MOESP) SMI method includes several algorithms which take different past measurements as instrumental variables [18]. In this paper, the 'recursive past output errors in variables-MOESP (RPOEIV-MOESP)' algorithm [19] is used for online and closed-loop model identification instead of the 'recursive past input-MOESP' (RPI-MOESP) algorithm in [16]. The RPI-MOESP algorithm may lead to bias error in the estimated model since it is an open-loop identification technique [20]. Sec-

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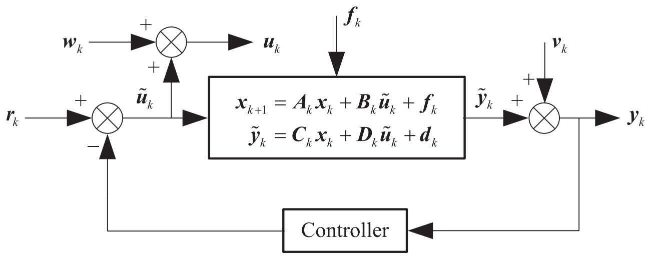

Fig. 1. Closed-loop structure of a system.

ondly, wide-area measurements that have good observability are selected as feedback signals. The controller proposed in this paper aims at damping inter-area oscillation modes which is the main concern of the power industry.

The integration of the RPOEIV-MOESP algorithm and the MPC strategy makes the adaptive model predictive damping controller proposed in this paper (hereafter denoted as RPOEIV-MPC) have following merits. Firstly, compared with conventional model identification methods, such as Prony [4], eigen-system realization algorithm (ERA) [21], prediction error method (PEM) [22], SMI methods are more popular because of their numerical simplicity, robustness, and their state-space form, which is convenient for control design [9]. And there is no underlying nonlinear iterative optimization and related problems such as convergence, local minima, and high computational burden. Secondly, online and successive model updating strategy within the controller enables it to effectively track and adapt to changes of system model and operating conditions, thus robustness of controller is enhanced.

The rest of the paper is organized as follows. The RPOEIV-MOESP algorithm is firstly presented in Section 2. Section 3 describes the model predictive damping control strategy. Then Section 4 gives the test results of the identification algorithm and the RPOEIV-MPC controllers on the 10-machine-39 bus New England system. At last, conclusions of the paper are drawn in Section 5.

2. Online recursive closed-loop subspace identification algorithm

2.1. Modeling of power system

Around a stable operating point, a power system can be described using a closed-loop structure shown in Fig. 1.

The system excluding the controller can be written as

$$\begin{aligned} \boldsymbol{x}_{k+1} &= \boldsymbol{A}_k\boldsymbol{x}_k + \boldsymbol{B}_k\tilde{\boldsymbol{u}}_k + \boldsymbol{f}_k, \quad \boldsymbol{u}_k = \tilde{\boldsymbol{u}}_k + \boldsymbol{w}_k \\ \tilde{\boldsymbol{y}}_k &= \boldsymbol{C}_k\boldsymbol{x}_k + \boldsymbol{d}_k, \quad \boldsymbol{y}_k = \tilde{\boldsymbol{y}}_k + \boldsymbol{v}_k \end{aligned} \tag{1}$$

where $\boldsymbol{x}_k \in R^{n\times 1}$, $\tilde{\boldsymbol{u}}_k \in R^{m\times 1}$ and $\boldsymbol{y}_k \in R^{l\times 1}$ denote the state, control input and plant output vectors, respectively; $\boldsymbol{u}_k \in R^{m\times 1}$ and $\boldsymbol{y}_k \in R^{l\times 1}$ denote the measured input and output vectors, respectively. $\boldsymbol{A}_k \in R^{n\times n}$, $\boldsymbol{B}_k \in R^{n\times m}$ and $\boldsymbol{C}_k \in R^{l\times n}$ are system matrices. $\boldsymbol{f}_k \in R^{n\times 1}$ is an exogenous perturbation vector, including random load switching, and set-point and topology changes actuated by faults, line and generator tripping, and load shedding [23,24]. $\boldsymbol{d}_k \in R^{l\times 1}$ is the output disturbance vector. $\boldsymbol{w}_k \in R^{m\times 1}$ and $\boldsymbol{v}_k \in R^{l\times 1}$ are input and output measurement noises, respectively. $\boldsymbol{w}_k$ and $\boldsymbol{v}_k$ are assumed to be zero-mean, white noises. $\boldsymbol{w}_k$, $\boldsymbol{v}_k$ and $\boldsymbol{f}_k$ are statistically independent of $\boldsymbol{x}_k$ and $\tilde{\boldsymbol{u}}_k$. Moreover, in Fig. 1, $\boldsymbol{r}_k \in R^{m\times 1}$ is the measurable reference. The controller is assumed to be causal and stabilizing.

In the following, a brief review of the direct approach for solving the closed-loop identification problem, i.e., the RPOEIV-MOESP algorithm is firstly presented. Then, several aspects on applying the algorithm to power system damping control are discussed.

2.2. RPOEIV-MOESP algorithm

Based on the subspace identification algorithms for multivariable dynamic errors-in-variables model presented in [18,19], a new RPOEIV-MOESP algorithm is proposed in this paper for power system oscillation damping controller design. The essential elements of this RPOEIV-MOESP algorithm are given as follows. The fundamental proofs of the identification algorithm can be found in [18,19], and they hold for the proposed algorithm as well.

Step 1. Excitation: Design an excitation signals $\boldsymbol{P}_d$ and feed it to reference input $\boldsymbol{r}_k$ in order to persistently excite the system.

Step 2. Identification: When time instant $k = 2s + N - 1$, identify system matrices $\boldsymbol{A}_k$ and $\boldsymbol{C}_k$ after collecting a sequence of input vector $\{\boldsymbol{u}_1, \boldsymbol{u}_2, \ldots, \boldsymbol{u}_k\}$ and output vector $\{\boldsymbol{y}_1, \boldsymbol{y}_2, \ldots, \boldsymbol{y}_k\}$ the by using POEIV-MOESP algorithm, where s and N indicate the number of block rows and columns of block Hankel matrices, respectively. Then the matrix $\boldsymbol{B}_k$ can be computed out by using the least square algorithm. The essential of the RPOEIV-MOESP algorithm is identifying system model from noisy input–output measurements $\{\boldsymbol{u}_k, \boldsymbol{y}_k\}$ using appropriate instrumental variables under the condition that there exists input measurement noise (i.e., $\boldsymbol{w}_k \neq \boldsymbol{0}$) and input and output measurement noises are correlated. Specifically,

(i) Build block Hankel matrices

$$\boldsymbol{U}_{k,s,N} = \begin{bmatrix} \boldsymbol{u}_k & \boldsymbol{u}_{k+1} & \cdots & \boldsymbol{u}_{k+N-1} \\ \boldsymbol{u}_{k+1} & \boldsymbol{u}_{k+2} & \cdots & \boldsymbol{u}_{k+N} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{u}_{k+s-1} & \boldsymbol{u}_{k+s} & \cdots & \boldsymbol{u}_{k+s+N-2} \end{bmatrix} \tag{2}$$

$$\boldsymbol{U}_{k+s,s,N} = \begin{bmatrix} \boldsymbol{u}_{k+s} & \boldsymbol{u}_{k+s+1} & \cdots & \boldsymbol{u}_{k+s+N-1} \\ \boldsymbol{u}_{k+s+1} & \boldsymbol{u}_{k+s+2} & \cdots & \boldsymbol{u}_{k+s+N} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{u}_{k+2s-1} & \boldsymbol{u}_{k+2s} & \cdots & \boldsymbol{u}_{k+2s+N-2} \end{bmatrix} \tag{3}$$

where the first subscript of $\boldsymbol{U}_{k,s,N}$ indicates the time index of the top-left element of the matrix. Similarly, $\boldsymbol{Y}_{k,s,N}$ and $\boldsymbol{Y}_{k+s,s,N}$ can also be constructed.

(ii) Calculate the projection matrix using RQ factorization

$$\begin{bmatrix} \boldsymbol{U}_{k+s,s,N}\boldsymbol{U}_{k,s,N}^T & \boldsymbol{U}_{k+s,s,N}\boldsymbol{Y}_{k,s,N}^T \\ \boldsymbol{Y}_{k+s,s,N}\boldsymbol{U}_{k,s,N}^T & \boldsymbol{Y}_{k+s,s,N}\boldsymbol{Y}_{k,s,N}^T \end{bmatrix} = \begin{bmatrix} \overline{\boldsymbol{R}}_{11}^N & \boldsymbol{0} \\ \overline{\boldsymbol{R}}_{21}^N & \overline{\boldsymbol{R}}_{22}^N \end{bmatrix} \begin{bmatrix} \boldsymbol{Q}_1^N \\ \boldsymbol{Q}_2^N \end{bmatrix} \tag{4}$$

then singular value decomposition (SVD) of the projection matrix $\overline{\boldsymbol{R}}_{22}^N$ is conducted as

$$\overline{\boldsymbol{R}}_{22}^N = \boldsymbol{USV}^T = [\,\boldsymbol{U}_1 \quad \boldsymbol{U}_2\,] \begin{bmatrix} \boldsymbol{S}_1 & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{S}_2 \end{bmatrix} \begin{bmatrix} \boldsymbol{V}_1^T \\ \boldsymbol{V}_2^T \end{bmatrix} \tag{5}$$

The system order n can be determined by inspecting a "large" reduction in the singular values in $\boldsymbol{S}$, and then $\boldsymbol{U}_1$ and $\boldsymbol{S}_1$ can be subsequently obtained by partitioning the singular value decomposition.

(iii) Calculate the extended observability matrix $\boldsymbol{\Gamma}_s$ and compute $\boldsymbol{A}_k$ and $\boldsymbol{C}_k$

$$\boldsymbol{\Gamma}_s = \boldsymbol{U}_1\boldsymbol{S}_1^{1/2}, \boldsymbol{A}_k = [\underline{\boldsymbol{\Gamma}}_s]^{\dagger}\overline{\boldsymbol{\Gamma}}_s \tag{6}$$

where $(\cdot)^{\dagger}$ denotes the Moore–Penrose pseudo-inverse. $\underline{\boldsymbol{\Gamma}}_s$ and $\overline{\boldsymbol{\Gamma}}_s$ are obtained by removing the last and the first l rows of $\boldsymbol{\Gamma}_s$, respectively. The matrix $\boldsymbol{C}_k$ can be determined from the first l rows of $\boldsymbol{\Gamma}_s$.