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# Decentralized nonlinear optimal predictive excitation control for multi-machine power systems

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ABSTRACT

This paper presents a novel decentralized nonlinear excitation controller based on a nonlinear optimal predictive control theory for multi-machine power systems to enhance their transient stability. A key feature of the proposed excitation controller is that it does not require online optimization and the huge computation burden is avoided. There are only two controller parameters, i.e. prediction horizon and control order, needed to be determined at the design stage. Moreover, as the proposed excitation controller only requires local and direct measurements used as input signals, it can be implemented locally and dispersedly for individual generators and is convenient for industrial applications. Case studies are performed based on a three-machine six-bus power system. Simulation results demonstrate the effectiveness of the proposed nonlinear excitation controller in terms of improving dynamic stability and robust performance under various operating conditions.



## 1. Introduction

Nowadays, the installation of the large generating units as well as high-response voltage regulators and the scale development of the interconnected power system make the stability problem become very exigent [1]. As one of the most effective and economical techniques, excitation control of large synchronous generators has attracted many researchers' attentions for improving dynamic performances and transient stability of power systems [2]. Since the power system is a large-scale system consisting of many lower-dimensional generator subsystems, decentralized control is preferred because they do not require the full state feedback and communication between different subsystems, which make the controller implementation more feasible and simpler [3,4]. On the other hand, various advanced control techniques, particularly in nonlinear control theories, have been successfully applied in excitation systems in order to take the nonlinearities of power systems into account, such as differential geometrical control [5–7], observer-based nonlinear control [8,9], nonlinear robust control [10,11], Hamiltonian control theory [12,13], Lyapunov control theory [14], fuzzy logic control [15–17] and so on.

Model predictive control (MPC) is now regarded as one of the major robust control techniques, which has received a great deal of attentions and has been successfully applied in industrial process control systems [18,19]. MPC improves insensitivity to parameter variations and external disturbances, and deals with the state and control constraints effectively. Although there are several formulations of the MPC scheme either in the way of the system model is obtained or in a formulation of the objective functions, all of them are based on the optimization of a cost function consisting of the difference between the actual output and the tracked trajectory. Various MPC schemes have been proposed for FACTS control [20–22], permanent-magnet synchronous motor [23], induction motor [24,25], and active power filter [26]. Conventionally, a nonlinear optimization problem should be solved online to determine the optimal control, which limits its application to slow nonlinear systems for a long-time [27,28]. Many researchers have made substantial efforts in applying predictive control to nonlinear systems with fast dynamics. Several nonlinear predictive control laws have been proposed to reduce the computational effort. In [29], a nonlinear optimal predictive control (NOPC) law based on the Taylor series expansion for continuous-time systems has been presented. The main advantages of this NOPC are that online optimization is no longer required and an explicitly analytical control law is given. Therefore, it is easy to be implemented in a real industrial process.

In this paper, a robust decentralized nonlinear excitation controller based on the NOPC is proposed to enhance the dynamic stability of multi-machine power systems. The proposed controller is a decentralized controller which only requires local and direct feedback measurements. Hence, it is convenient for industrial applications. Simulations results of a three-machine six-bus power system show that the proposed excitation controller can enhance

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transient stability of the power system under both small and large sudden disturbances.

The rest of the paper is organized as follows. Section 2 describes the mathematical dynamic model of a multi-machine power system. Then, a nonlinear predictive control approach is recalled briefly in Section 3. Section 4 designs a decentralized excitation controller based on the nonlinear predictive control approach for a multi-machine power system. In Section 5, simulation studies of a three-machine six-bus power system illustrate the effectiveness of the proposed design method. Finally, conclusions are given in Section 6.

## 2. Power system model

The dynamic model of a $n$-machine power system consisting of $n$ interconnected subsystems can be described as follows:

$$\begin{cases} \dot{\delta}_i = \omega_0(\omega_i - 1) \\ \dot{\omega}_i = (P_{mi} - P_{ei} - D_i(\omega_i - 1))/2H_i \\ \dot{E}'_{qi} = (u - E_{qi})/T'_{d0i} \end{cases} \tag{1}$$

where $i = 1,\ldots,n$ and

$$E_{qi} = E'_{qi} - (x_{di} - x'_{di})I_{di} \tag{2}$$

$$I_{qi} = \sum_{j=1}^{n} E'_{qj}(B_{ij}\sin\delta_{ij} + G_{ij}\cos\delta_{ij}) \tag{3}$$

$$I_{di} = \sum_{j=1}^{n} E'_{qj}(G_{ij}\sin\delta_{ij} - B_{ij}\cos\delta_{ij}) \tag{4}$$

$$P_{ei} = E'_{qi}I_{qi} \tag{5}$$

where $\omega_0 = 2\pi f_0$ is the system speed in radians per second, $\delta_i$ is the rotor angle of the $i$th generator, $P_{mi}$ is the mechanical power of the $i$th generator, $P_{ei}$ is the electromagnetic active power of the $i$th generator, $I_{qi}$ and $I_{di}$ are the $q$-axis current and $d$-axis current of the $i$th generator, respectively, $D_i$ is the damping constant of the $i$th generator, $H_i$ is the inertia coefficient of the $i$th generator, $G_{ij}$ and $B_{ij}$ are the conductance and susceptance between the bus $i$ and bus $j$, respectively.

The Eq. (1) can be described as the following affine nonlinear system format:

$$\dot{\boldsymbol{x}}_i = \boldsymbol{f}_i(\boldsymbol{x}_i) + \boldsymbol{g}_i(\boldsymbol{x}_i)\boldsymbol{u}_i \tag{6}$$

where $\boldsymbol{x}_i = [\,\delta_i \quad \Delta\omega_i \quad E'_{qi}\,]^T$, $\boldsymbol{u}_i$, are the state vector and input vector of the $i$th generator model, respectively.

$$\boldsymbol{f}_i(\boldsymbol{x}_i) = \begin{bmatrix} \omega_0\Delta\omega_i \\ (P_{mi} - P_{ei} - D_i\Delta\omega_i)/2H_i \\ -E_{qi}/T'_{d0i} \\ \end{bmatrix} \tag{7}$$

$$\boldsymbol{g}_i(\boldsymbol{x}_i) = [\,0 \quad 0 \quad 1/T'_{d0i}\,]^T \tag{8}$$

During post-fault, the power system is expected to arrive to a stable state fleetly. In other words, the reference signal would be zero if we set up output vector as follows:

$$\boldsymbol{y}_i(t) = y_i = h_i(\boldsymbol{x}) = \Delta\delta_i = \int \Delta\omega_i \tag{9}$$

## 3. Review of nonlinear predictive control approach

### 3.1. Nonlinear optimal predictive control

Consider an affine nonlinear system as following:

$$\begin{cases} \dot{\boldsymbol{x}}(t) = \boldsymbol{f}(\boldsymbol{x}(t)) + \boldsymbol{g}(\boldsymbol{x}(t))\boldsymbol{u}(t) \\ \boldsymbol{y}(t) = \boldsymbol{h}(\boldsymbol{x}(t)), \quad i = 1,\ldots,m \end{cases} \tag{10}$$

where $\boldsymbol{x} \in R^n$, $\boldsymbol{u} \in R^m$, $\boldsymbol{y} = [y_1,\ldots,y_m]^T \in R^m$ are state, control, and output vectors, respectively.

The nonlinear optimal predictive control uses dynamic optimization algorithm, which confirms future control sequence based on a certain performance index, so the output $\boldsymbol{y}(t)$ will track a reference trajectory $\boldsymbol{y_r}(t)$ optimally. In any initial instant $t$, the performance index only relate to a period of limited future time $T$, while in the next instant, the optimal time frame will move ahead too. Therefore, the receding-horizon performance index adopted should be given by:

$$J = \frac{1}{2}\int_0^T (\hat{\boldsymbol{y}}(t+\tau) - \hat{\boldsymbol{y}}_r(t+\tau))^T(\hat{\boldsymbol{y}}(t+\tau) - \hat{\boldsymbol{y}}_r(t+\tau))\mathrm{d}\tau \tag{11}$$

where $T$ is the prediction horizon, $\hat{\boldsymbol{y}}(t+\tau)$, $\hat{\boldsymbol{y}}_r(t+\tau)$ are prediction output and future reference trajectory during the prediction horizon, respectively.

The following assumptions are given about the nonlinear system (10): (I) The zero dynamics are stable. (II) All states variables are available. (III) The output $\boldsymbol{y}(t)$ and the reference $\hat{\boldsymbol{y}}_r(t+\tau)$ are sufficiently many times continuously differentiable with respect to $t$.

### 3.2. Output prediction

The optimal tracking problem is based on the idea that at any time $t$, to design within a moving time frame located at time $t$ taking $\boldsymbol{x}(t)$ as the initial condition of a state trajectory $\hat{\boldsymbol{x}}(t+\tau)$ driven by an input $\hat{\boldsymbol{u}}(t+\tau)$ with associated prediction $\hat{\boldsymbol{y}}(t+\tau)$. The system dynamics in the moving horizon time frame located at time $t$ are described by:

$$\begin{cases} \dot{\hat{\boldsymbol{x}}}(t+\tau) = \boldsymbol{f}(\hat{\boldsymbol{x}}(t+\tau)) + \boldsymbol{g}(\hat{\boldsymbol{x}}(t+\tau))\hat{\boldsymbol{u}}(t+\tau) \\ \hat{\boldsymbol{y}}(t+\tau) = \boldsymbol{h}(\hat{\boldsymbol{x}}(t+\tau)) \end{cases} \tag{12}$$

where $0 \leqslant \tau \leqslant T$, and

$$\boldsymbol{h}(\hat{\boldsymbol{x}}(t+\tau)) = [h_1(\hat{\boldsymbol{x}}(t+\tau)),\ldots,h_m(\hat{\boldsymbol{x}}(t+\tau))]^T \tag{13}$$

If relative degree of the system (10) is $\rho$, when the control order is chosen to be $r$, to make the $r$th derivative of the control input appear, the Taylor expansion of the output $\hat{\boldsymbol{y}}(t+\tau)$ must be no less than $(\rho + r)$th order. Repeating differentiation up to $\rho + r$ times of the output $\hat{\boldsymbol{y}}(t)$ with respect to time, substituting into the system (10), the $\hat{\bar{\boldsymbol{Y}}}(t)$ can be obtained:

$$\hat{\bar{\boldsymbol{Y}}}(t) = \begin{bmatrix} \hat{\boldsymbol{y}}^{(0)} \\ \hat{\boldsymbol{y}}^{(1)}\cdots \\ \hat{\boldsymbol{y}}^{(\rho)} \\ \hat{\boldsymbol{y}}^{(\rho+1)}\cdots \\ \hat{\boldsymbol{y}}^{(\rho+r)} \end{bmatrix} = \begin{bmatrix} \boldsymbol{h}(\boldsymbol{x}) \\ L_f^1\boldsymbol{h}(\boldsymbol{x})\cdots \\ L_f^{\rho}\boldsymbol{h}(\boldsymbol{x}) \\ L_f^{\rho+1}\boldsymbol{h}(\boldsymbol{x})\cdots \\ L_f^{\rho+r}\boldsymbol{h}(\boldsymbol{x}) \end{bmatrix} + \begin{bmatrix} \boldsymbol{0}_{m\times1} \\ \boldsymbol{0}_{m\times1}\cdots \\ \boldsymbol{0}_{m\times1} \\ \boldsymbol{H}(\hat{\bar{\boldsymbol{u}}}) \end{bmatrix} \tag{14}$$

where $\boldsymbol{H}(\hat{\bar{\boldsymbol{u}}}) \in R^{m(r+1)}$ is a matrix given as follows:

$$\boldsymbol{H}(\hat{\bar{\boldsymbol{u}}}) = \begin{bmatrix} L_gL_f^{\rho-1}\boldsymbol{h}(\boldsymbol{x})\hat{\boldsymbol{u}}(t) \\ \boldsymbol{P}_{11}(\hat{\boldsymbol{u}}(t),\boldsymbol{x}(t)) + L_gL_f^{\rho-1}\boldsymbol{h}(\boldsymbol{x})\dot{\hat{\boldsymbol{u}}}(t) \\ \vdots \\ \boldsymbol{P}_{r1}(\hat{\boldsymbol{u}}(t),\boldsymbol{x}(t)) + \ldots + \boldsymbol{P}_{rr}(\hat{\boldsymbol{u}}(t),\ldots,\hat{\boldsymbol{u}}^{(r-1)}(t),\boldsymbol{x}(t)) + L_gL_f^{\rho-1}\boldsymbol{h}(\boldsymbol{x})\hat{\boldsymbol{u}}^{(r)}(t) \end{bmatrix} \tag{15}$$

where $\hat{\bar{\boldsymbol{u}}} = [\,\hat{\boldsymbol{u}}(t)^T \quad \dot{\hat{\boldsymbol{u}}}(t)^T \quad \ddot{\hat{\boldsymbol{u}}}(t)^T \quad \ldots \quad \hat{\boldsymbol{u}}^{(r)}(t)^T\,]$, and $\boldsymbol{P}_{11}$, $\boldsymbol{P}_{21}, \boldsymbol{P}_{22}, \ldots, \boldsymbol{P}_{r1}, \ldots, \boldsymbol{P}_{rr}$ are complicated nonlinear functions of the elements in the optimized vector $\hat{\bar{\boldsymbol{u}}}(t)$.