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Intelligent Control of a Boiler-Turbine Plant Based on Switching Control Scheme

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Abstract

This paper reports on our present achievement toward the intelligent control of a boiler-turbine power-plant based on switching control scheme, recently revived by some active reports. To overcome strong nonlinearity emerging in load following operations of boiler-turbine power plants, which is not efficiently compensated by the conventional PI-based gain scheduling control, neural-based nonlinear feedforward switching control scheme is employed.

Owing to its 2-degree freedom type installment in the control system and proper switching of nonlinear feedforward control by monitoring contribution of inverse dynamics error to control error, effective suppression of nonlinearity is achieved.

1. Introduction

Large steam boiler-turbine power plants are increasingly required to adapt its operation to both (low) base load demand and high peak demand where rapid and smooth load following is desired in actual operation. PID(PI)-based gain scheduling control is one of the most widely used methods to perform practically reasonable operation under such situations, but still fails sometimes to get enough performance because of the unsatisfactory suppression of process nonlinearity. While linear adaptive control is now one of practical control methods for slowly changing nonlinear plants[1], its direct application to nonlinear-intensive process might lead to unacceptable transient deviation and instability.

Recently, revival concepts of switching control scheme was actively presented by some groups to overcome such limitations of conventional adaptive control[2],[3],[4]. Some of them are still based on linear control theory, but their potential applicability seems to be so wide to cover nonlinear control scheme. In this paper, we apply this switching control scheme to the load following control of boiler-turbine plants. For effective compensation of process nonlinearity, neural feedforward structure is employed, and pre-learned-fixed neural controllers and an adaptive neural controller are switched each other based on the magnitude of error of estimated inverse dynamics.

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2. System description

Plant and basic controller representations

we consider the following single input-single output (SISO) nonlinear discrete time system as the target plant:

$$\sum : \begin{array}{l} x(k+1) = f_0(x(k), u(k)) \\ y(k) = h_0(x(k)) \end{array} \tag{1}$$

where $u, y \in R, x \in R^n$ are the input, output and state respectively , and f_0, h_0 are unknown C^∞(smooth)-functions, with $f_0(0,0)=0, h_0(0)=0$. Then following theorem was proved by Levin and Narendra[5].

Theorem 1:[6] Let the linearization Σ_l around the equilibrium state (0, 0) of the system Σ be observable. Then the system can be locally represented by an input-output model of the form:

$$\begin{aligned} y(k+1) = F(&u(k), u(k-1), \ldots, u(k-n+1), \\ &y(k), y(k-1), \ldots, y(k-n+1)) \end{aligned} \tag{2}$$

where F is a smooth function of its arguments. □

Because of no theoretically confirmed method to design a regulator for system (2), we assume this input-output nonlinear system has a smooth inverse representation applicable for nominal feedforward controller design.

$$u_f(k) = \hat{f}(r(k+1), y(k), \ldots, y(k-n+1), u(k-1), \ldots, u(k-n+1)) \tag{3}$$

In building the above control input, the inverse dynamics is approximately estimated using general function approximator, for example, orthogonal polynomial, neural network, RBF network, and so on.

Control structure and switching scheme

While the stability of linear version of the above one-step ahead control is assured under reasonable condition if using proper parameter estimation method, we have no guarantee that the above control scheme with any estimation method should surely stabilize the target system. Considering this subtlety in control performance, we employ 2-degree of freedom type configuration for control depicted in Fig.1, in which feedback controller is expected to work to keep the overall system stable when control error is small. Then, control input to the target system is constructed as follows.

$$\begin{aligned} u_0(k) &= C(z^{-1})e(k) \\ u(k) &= u_f(k) + u_0(k) \end{aligned} \tag{4}$$

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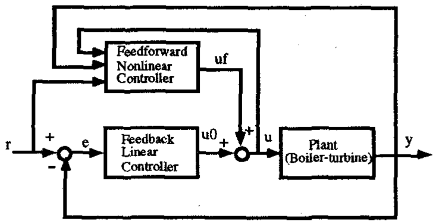

Fig. 1 2-degee of freedom type control

We also adopt switching control strategy between nonlinear controllers based on the same idea as [3], that is, powerful nonlinear approximator which could cover whole I/O space of interest is not available and we need to separate the I/O space into small regions so that approximator such as neural network can approximate nonlinear relation on each region. For building efficient switching scheme, we need to set a proper performance index function which tells us a timing of controller switching. The following theorem on relation between inverse dynamics error, $e_u(k-1) = \hat{u}(k-1) - u(k-1)$ and control error, $e(k) = r(k) - y(k)$ holds for control system described above.

Theorem 2: Supposing that control (3), (4) be applied for system (2) whose output is near around the control reference enough, then the contribution of inverse dynamics error to control error, $\Delta e(k)$ is approximately expressed as follows.

$$|\Delta e(k)| = \left| \left. \frac{\partial \hat{f}(y(k), \psi(k-1))}{\partial y(k)} \right|_{y(k)=r(k)} \right|^{-1} |e_u(k-1)| \qquad (5)$$

where $\psi(k-1) = (y(k-1) \ldots y(k-n) \;\; u(k-1) \ldots u(k-n))$

Proof: With Taylor expansion of $\hat{u}(k-1)$ around $y(k) = r(k)$, neglecting the residual terms, we directly get the above result. □

The relation (5) allows us to evaluate the suitabilities of FF-NN controllers based on their inverse-modeling errors, e_u and switch into the most capable one in the present control region.

3. Simulation results

We conducted the load following control simulation for boiler/turbine plant model to demonstrate the effectiveness of our switching control scheme. Under some moderate assumptions, we consider to control generated power of turbine using throttle valve as the only control input. Power demand changes rapidly from 60MW to 120MW around t=3000 and from 120MW to 50MW around t=6000. While a simulation result by conventional PI-gain scheduling control in Fig.2, Fig.3 shows the corresponding control result by switching of four fixed and one adaptive neural FF control models. PI-gain scheduling control was also employed as the FB controller mechanism.

Though with small overshoots, notable performance improvement was confirmed for both transient and steady state characteristics.

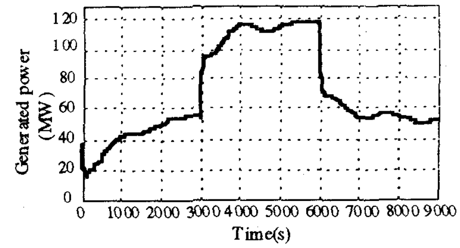

Fig. 2 PI-gain scheduling control

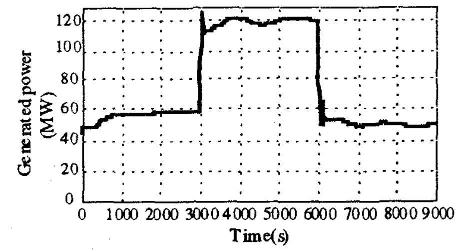

Fig. 3 PI-gain scheduling control + NN FF switching control

4. Conclusion

We developed a nonlinear switching control scheme based on feedforward structure and confirmed its usefulness through simulations for a simplified model of a boiler-turbine power generation plant.

While the switching scheme based on model error, inverse dynamics error in our case, seems to work well, we still need to understand further about error compensating mechanism through the cooperation between feedforward nonlinear controller and linear controller to improve and make the total control system more robust and reliable.

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