Constrained Power Plant Coordinated Predictive Control Using Neurofuzzy Model[1)]

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Abstract In unit steam-boiler generation, a coordinated control strategy is required to ensure a higher rate of load change without violating thermal constraints. The process is characterized by nonlinearity and uncertainty. While neural networks can model highly complex nonlinear dynamical systems, they produce black box models. This has led to significant interest in neuro-fuzzy networks (NFNs) to represent a nonlinear dynamical process by a set of locally valid and simpler submodels. Two alternative methods of exploiting the NFNs within a generalised predictive control (GPC) framework for nonlinear model predictive control are described. Coordinated control of steam-boiler generation using the two nonlinear GPC methods show excellent tracking and disturbance rejection results and improved performance compared with conventional linear GPC.

Key words Coordinated control, neuro-fuzzy networks, GPC

1 Introduction

Modern power plant is a complex arrangement of pipework and machinery with a myriad of interacting control loops and support systems. All the main control loops must respond to a central command structure, which sets their individual setpoints and controls the behaviour of the plant. The coordinated control (CC) scheme is responsible for driving the boiler-turbine-generator set as a single entity, harmonising the slow response of the boiler with the faster response of the turbine-generator, to achieve fast and stable unit response during load tracking manoeuvres and load disturbances.

Model predictive control (MPC) has emerged to be an effective way of power plant control. The application of a decentralized predictive control scheme was proposed in [1] based on a state space implementation of GPC for a combined-cycle power plant, in which a two-level decentralized Kalman filter was used to locally estimate the states of each of the subprocess. In another related work[2], a comparison of control performance obtained with a linear state space model-based GPC and dynamic performance predictive controller applied in a gas turbine power plant simulation was presented. A nonlinear long-range predictive controller based on neural networks is developed in [3] to control the power plant process.

In using GPC for nonlinear system, since the on-line optimization problem is generally nonconvex, the on-line computation demand is high for any reasonably nontrivial systems. Using a neural network to learn the plant model from operational process data is one solution. Neurofuzzy networks (NFNs)[4] are derived from fuzzy logic. Therefore, expert knowledge in linguistic form can be incorporated into the network through the design of the fuzzy rules. This feature is extremely useful to incorporate the knowledge of experienced operators into the network[5].

This article describes how this nonlinear neurofuzzy modelling technique can be integrated within an MPC framework. It also discusses how constraint handling can be incorporated in the nonlinear control scheme. Two methods are proposed for nonlinear MPC based on an identified neurofuzzy network model of the plant. Coordinated control in steam-boiler generation is presented to illustrate the effectiveness of the proposed NFNs-based-GPC.

2 Neuro-fuzzy network modelling

Consider the following general single-input single-output nonlinear dynamic system:

$$y(t)=f[y(t-1),\cdots,y(t-n_y'),u(t-d),\cdots,u(t-d-n_u'+1),e(t-1),\cdots,e(t-n_e')]+e(t)/\Delta \quad (1)$$

where $f[\cdot]$ is a smooth nonlinear function such that a Taylor series expansion exists, $e(t)$ is a zero mean white noise and Δ is the differencing operator. n_y', n_u', n_e' and d are respectively the known orders

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and time delay of the system. Let the local linear model of the nonlinear system (1) at the operating point $O(t)$ be given by the following Controller Auto-Regressive Integrated Moving Average (CARIMA) model:

$$\bar{A}(z^{-1})y(t) = z^{-d}B(z^{-1})\Delta u(t) + C(z^{-1})e(t) \tag{2}$$

where $\bar{A}(z^{-1}) = \Delta A(z^{-1})$, $B(z^{-1})$ and $C(z^{-1})$ are polynomials in z^{-1}, the backward shift operator. Note that the coefficients of these polynomials are a function of the operating point $O(t)$. The nonlinear system (1) is partitioned into several operating regions, such that each region can be approximated by a local linear model. Since NFNs are a class of associative memory networks with knowledge stored locally[4], they can be applied to model this class of nonlinear systems. A schematic diagram of the NFN is shown in Fig. 1. B-spline functions are used as the membership functions in the NFNs for the following reasons[4]:

1) B-spine functions can be readily specified by the order of the basis function and the number of inner knots.

2) They are defined on a bounded support, and the output of the basis function is always positive, *i.e.*, $\mu_k^j(x) = 0$, $x \notin [\lambda_{j-k}, \lambda_j]$ and $\mu_k^j(x) > 0$, $x \in (\lambda_{j-k}, \lambda_j)$.

3) The basis functions form a partition of unity, *i.e.*, $\sum\limits_j \mu_k^j(x) \equiv 1$, $x \in [x_{\min}, x_{\max}]$.

4) The output of the basis functions can be obtained by a recurrence equation.

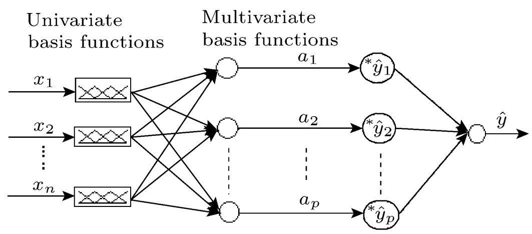

Fig. 1 B-spline neuro-fuzzy network

The multivariate basis function is obtained by the tensor products of the univariate basis functions:

$$a_i(x) = \prod_{k=1}^{n} \mu_{A_k^i}(x_k), \text{ for } i = 1, 2, \cdots, p \tag{3}$$

where n is the dimension of the input vector x, and $p = \prod\limits_{i=1}^{n}(R_i + k_i)$, the total number of weights in the NFN. k_i and R_i are the order of the basis function and the number of inner knots, respectively. The output of the NFN with p fuzzy rules is:

$$\hat{y}(k) = \frac{\sum\limits_{i=1}^{p} \hat{y}_i(k)a_i(x)}{\sum\limits_{i=1}^{p} a_i(x)} = \sum_{i=1}^{p} \hat{y}_i(k)a_i(x) \tag{4}$$

3 Neurofuzzy predictive control

3.1 Local model-based generalized predictive control (LMB-GPC)

The neurofuzzy network provides a global nonlinear plant representation from a set of locally valid CARIMA models together with a weight function, producing a value close to one in parts of the operating space where the local model is a good approximation and a value approaching zero elsewhere (Fig. 2). Notice that this is the main property of the B-spline neuro-fuzzy networks. An alternative way of developing nonlinear controller is to use the same operating regime based model directly with a model based control framework. The resultant global controller is expected to give better plant-wide control performance than the equivalent linear controller, simply because global modeling information may be used to determine the control input at each sample time. It is assumed to constitute a linear representation of the process at any time instant and may then be used by a GPC controller to represent the process dynamics locally. Since the model is regarded as linear and valid, the control sequence can be solved analytically at each sample instant.

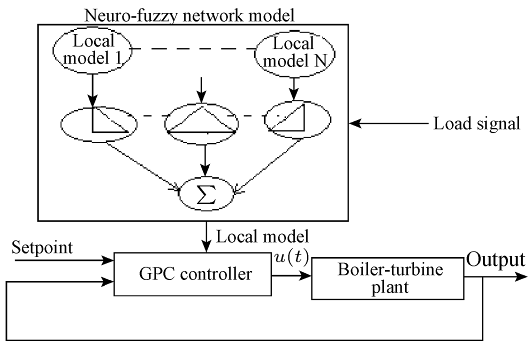

Fig. 2 Local model-based generalized predictive control

3.2 Composed controller generalized predictive control (CC-GPC)

The control structure here consists of the family of controllers and the scheduler. At each sample instant the latter decides which controller, or combination of controllers, to apply to the process. Generally, the controllers are tuned about a model obtained from experiments at a particular equilibrium point, since linear model and controllers are quite well understood. The technique is very similar to T-S controller or gain scheduling controller. They are constructed by interpolating between the members of a family of linear controllers. Here, these interpolating functions are realized by B-spline neuro-fuzzy networks.

As already described, the neurofuzzy network consists of a set of locally valid submodels together with an appropriate interpolation function. A controller is then designed about each of the local models. The interpolated outputs are then summed and used to supply the control commands to the process (Fig. 3). The interpolation function effectively smoothes the transition between the local controllers. In addition, the transparency of the nonlinear control algorithm is improved as the operating space is covered using controllers rather than models.

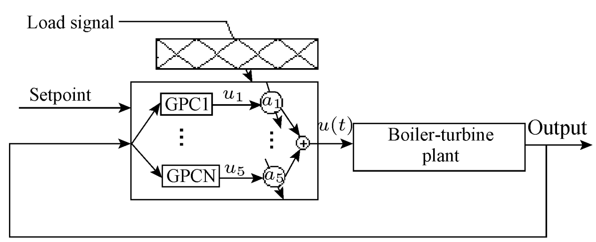

Fig. 3 Composed controller generalized predictive control

3.3 Constraint handling

One of the main application benefits of using a linear predictive controller is its ability to handle process constraints directly within the control law. The inclusion of constraints in LMB-GPC is straightforward, since the least squares solution to the chosen cost function may be replaced by a constrained optimization technique such as quadratic programming. The drawback is the increasing computation required to solve for the control sequence at each sample instant. While the same approach is applied to the CC-GPC, a problem arises, as there is no way of knowing that the summation of all of the controller outputs will not in fact violate a process constraint. Notice that we are using a B-spline neuro-fuzzy network, in which the third property in Section 2 signifies that the basis functions form a partition of unity. In such a way, the summation of all the controller outputs will not in fact violate a process constraint, since they are weighted sum by the normalized B-spline neuro-fuzzy network. Take consideration of a second order B-spline neuro-fuzzy network. At any time instant, if one variable accounts for 80% of the total output, another variable will surely account for 20% of the total output. This may be the main attracting factor of the B-spline neuro-fuzzy network while applying to constraint GPC. Choosing of other kind of NFNs can not guarantee non-violation of a process constraint.

4 Coordinated control in steam-boiler generation

The CC scheme is shown in Fig. 4, where the active power of the boiler N_E and the steam pressure P_T are governed by both the fuel consumption M and the steam valve setting μ_T. The existing scheme for load control is the fixed parameter PI controller, which could obviously be well tuned in one operating point. The proposed two kinds of neurofuzzy predictive controllers are now incorporated into the system. Here, $W_{N\mu}(s)$ is the transfer function relating the steam valve setting to the load power, and $W_{NM}(s)$ is the transfer function between the fuel consumption and the load power.

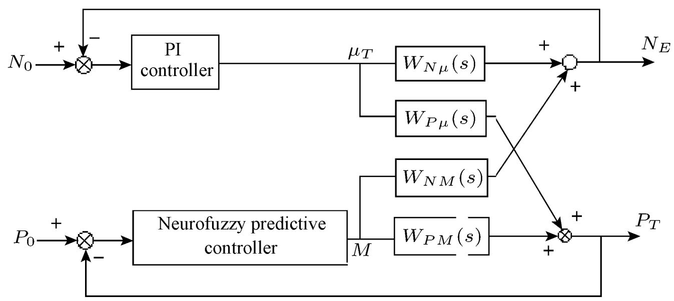

Fig. 4 Load control system in boiler-following mode

A valid neurofuzzy model of the plant, which is an essential tool for the improvement of the control system, has been established in [6]. The response of the steam turbine is fast, giving a time constant in $W_T(s)$ of approximate 9s. A PI controller is used to control the steam valve, which is designed to react quickly to a change in the load power demand. In contrast, the boiler has a much slower response with a considerably larger time constant. A neurofuzzy predictive controller is used to control the boiler, by using the two methods presented in Section 3. As analyzed in the above section, constraints could be incorporated into the NFNs GPC system. In the controllers, positions of valve actuators are constrained to [0 1], and their change rates are limited to: $-0.005 \leqslant \dot{u}_1 \leqslant 0.005$, $-1.0 \leqslant \dot{u}_2 \leqslant 0.02$. u_1 and u_2 represent fuel delivery and steam valve, respectively.

In the CC-GPC, the nonlinear controller consists of five local controllers, each of which is designed about one of the local models, and thus each with a set of tuning parameters. At each sample instant the load signal was fed to the interpolation membership function of the B-spline NFNs, which in turn generates the activation weights for each of the local controllers. Each local controller was assumed to be linear and hence the control sequence for each could be solved analytically. Since the B-spline membership function was chosen to be second order, there are two controllers working at any time instant. In the LMB-GPC, the NFNs model for the process was used with a GPC algorithm. At each sample instant the load signal was fed to the interpolation function of the NFNs. Each of the five sets of local model parameters was then passed through this B-spline interpolation function to form a local model, which accurately represents the process around that particular operating point. This local model may be assumed linear and is used by the GPC controller. Also notice that, since the B-spline membership function was chosen to be second order, there are two local models working at any instant time. The LMB-GPC strategy requires only one set of tuning parameters. The internal model of a single GPC controller is updated at each sample instant.

The linear GPC is obtained by minimizing the following cost function:

$$J = E\{\sum_{j=1}^{N} q_j[\hat{y}(t+j) - y_r(t+j)]^2\} + \sum_{j=1}^{M} \lambda_j[\Delta u(t+j-1)]^2 \tag{5}$$

subject to $u_{\min} < u(t+i-1) < u_{\max},\ \Delta u_{\min} < u(t+i-1) < \Delta u_{\max},\ \text{for } i = 1, 2, \cdots, m$

The controller parameters are chosen as $Q = I$, and $\lambda = 0.1 \times I$. The sampling interval is chosen to be 30s. The prediction horizon N is set to a relatively large value of 10 (300s), which can guarantee itself to be larger than the process setting time. To investigate the effect of the control horizon M on the performance of NFGPC, several values of M are tested. For small M, the closed-loop response is sluggish. Reasonably good performance is obtained for $M = 6$. There is, however, little improvement when M is increased further. This test and trial process results in a practically stable controller.

Sliding pressure mode.

Sliding pressure mode is an "instructive" development in power plant coordinated control. In the sliding pressure mode, the steam pressure setpoint was incremented every 10 minutes from 11Mpa to 19Mpa, leading to a load increase from 140MW to 300MW. This was done in order to move the process across a wide operating range. The "tuning knobs" of the neuro-fuzzy GPC are chosen as discussed above. Simulations were taken under both unconstraint and constraint conditions. The sliding pressure responses are shown in Fig. 5. It is readily apparent that the linear GPC controller could not offer satisfactory results in most of the cases. This is because its internal model was generated at a load "Medium" where the plant gain is moderate. The nonlinear GPC controllers show good sliding pressure response. Overall, there seems to be very little difference between the two nonlinear controllers during this test.

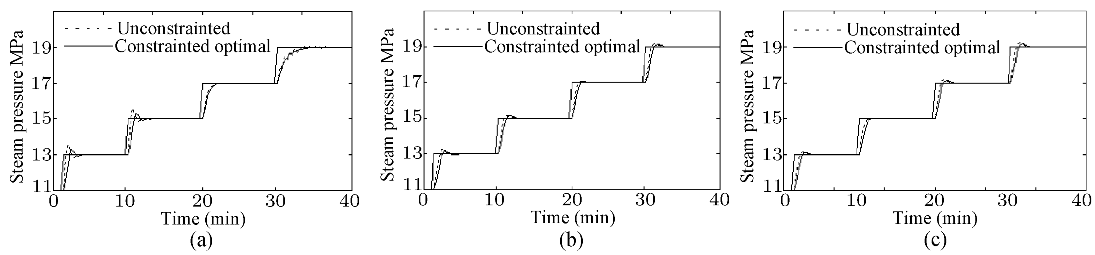

Fig. 5 Sliding pressure response under (a) linear GPC (b) local model-based GPC (c) composed controller GPC

Boiler following mode

Boiler following or "constant pressure" mode is the most commonly used mode in power plant coordinated control. It utilizes the main steam governor as a fast-acting load controller, since opening the governor valves and releasing the stored energy in the boiler meets short-term increases in electrical demand. Fig. 6(a) shows the steam pressure transient process while load increases from 260MW to 290MW. The opening of the steam valve leads to a quick increase in the load, as energy stored in the boiler is being released. The steam pressure is restored to its original level by increasing the fuel delivery, after being decreased. All the three controllers give a similar performance, since the plant dynamic is within one operating region and the tuning parameters of the linear controller are valid within this region. Fig. 6(b) shows steam pressure response while load increases from 240MW to 300MW. The nonlinear controllers exhibit superior action, since the tuning parameters of the linear controller were specified at one region and the plant dynamic changes across two regions.

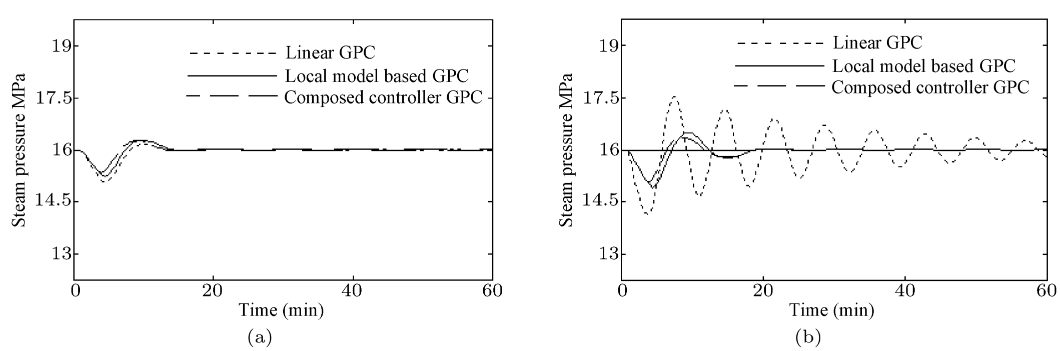

Fig. 6 Steam pressure transient process under boiler following mode

5 Conclusion

GPC can produce excellent results compared to conventional methods. One limitation of GPC is that it is mostly based on a linear model. It would lead to large difference between the actual and predicted output values, especially when the current output is relatively far away from the operating point at which the linear control model was generated. Introducing NFNs could help to solve this problem.

In the CC-GPC, a set of local controllers were combined through NFNs to form a local controller network. This technique has the added attraction of improving the overall control transparency, since the operating space is decomposed using controllers rather than models. In the LMB-GPC, the accuracy of the internal model used by the nonlinear controller was significantly improved by utilizing a nonlinear NFNs model of the process. The proposed nonlinear GPC controllers were applied in the simulation of the power plant coordinated control, which is the kernel system of unit steam-boiler. Better results are obtained when compared with the linear GPC.

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