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An integrated scheme of neural network and optimal predictive control

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Abstract: An approach of adaptive predictive control with a new structure and a fast algorithm of neural network (NN) is proposed. NN modeling and optimal predictive control are combined to achieve both accuracy and good control performance. The output of nonlinear network model is adopted as a measured disturbance that is therefore weakened in predictive feed-forward control. Simulation and practical application show the effectiveness of control by the proposed approach.

Key words: neural network (NN); optimal predictive control; nonlinear objective

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1 Introduction

Optimal predictive control is a popular method in the linear system theory. It can effectively simplify the design of controller and achieve satisfied control performance. Therefore, it is widely applied in such environments as linear system or light nonlinear system. However, it can result in large errors when used in heavy nonlinear system.

The robust adaptive control, which has been investigated since 1980s to deal with the problem of dynamic disturbance, can in some degree guarantee the stability of close-loop system. Unfortunately, due to the fact of sacrificing the control accuracy to obtain the robustness in the linear model, it can hardly be applied into heavy nonlinear system.

Multi-layer feed-forward neural network (NN) is capable of identifying a nonlinear object to the most degree [1, 2]. By designing good network structure and algorithms to overcome such shortcomings of traditional NN as slow-speed learning and convergence, an accurate model can be obtained. In addition, it can be combined with the approach of adaptive optimal predictive linear control. In this way, the new controller based on this approach can be applied to the real online control without undermining the control accuracy. Its control structure is illustrated in **figure 1**, where NNM is the neural network model identifier, and NNC is the neural network controller.

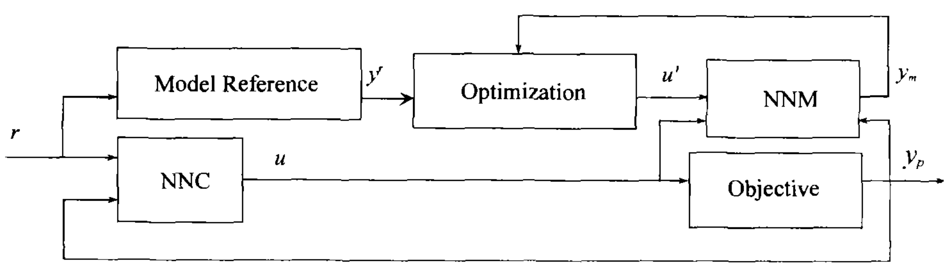

Figure 1 Control structure of a new controller.

2 Algorithm of adaptive predictive control

Consider the single-input and single-output discrete nonlinear control objective below:

$$y(k)=f(y(k-1), y(k-2), \cdots, y(k-n); u(k-1), u(k-2), \cdots, u(k-m)) \quad (1)$$

where $y(k)$ is the object output, $u(k)$ is the system input, and $f(\cdot)$ is a nonlinear function.

The following equation is adopted as a network model to identify a nonlinear objective [3, 4]:

$$y(k)=\boldsymbol{\Phi}^{\mathrm{T}} x(k-1)+N(x(k-1)+\varepsilon(k)) \quad (2)$$

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where

$$x(k-1)=[y(k-1), y(k-2), y(k-n); u(k-1), u(k-2), \cdots, u(k-m)]^{\mathrm{T}}$$

$$\boldsymbol{\Phi}=[a_1, a_2, \cdots, a_n; b_1, b_2, \cdots, b_m]^{\mathrm{T}},$$

where $\boldsymbol{\Phi}$ is a vector that needs to be determined for the NN structure as shown in **figure 2.** $N(x(k-1))$ represents the network nonlinear model output. The model error is represented with $\varepsilon(k)$.

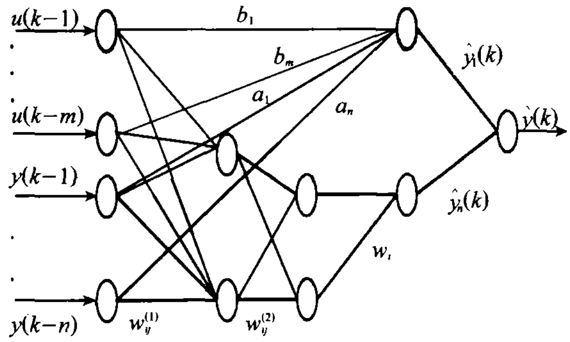

Figure 2 Neural network identification model.

Through equation (2), the value of one-step forward prediction is obtained from the following model [5, 6]:

$$\hat{y}(k+1)=\boldsymbol{\Phi}^{\mathrm{T}}(k)x(k)+N(x(k)) \tag{3}$$

At the k-th sampling point, the control variable $u(k)$ is determined to minimize the following metrics [7]:

$$J=\frac{1}{2}(\hat{y}(k+1)-y_r(k+1))^2-\frac{\rho}{2}(u(k)-u(k-1))^2 \tag{4}$$

where $y_r(k)$ is the expectation of the system output, and ρ is a weighted factor.

The state variable $x(k)$, the prediction value $\hat{y}(k+1)$ and the control variable $u(k)$ are all functions of invariable k. To simplify, when $u(k)$ is solved from equation (4), it will be replaced with $u(k-1)$ in calculating $N(x(k))$, *i.e.*

$$\hat{N}(K)=N(\bar{x}(k)) \tag{5}$$

where

$$\bar{x}(k)=[y(k), y(k-1), \cdots, y(k-n+1); u(k-1), u(k-2), \cdots, u(k-m+1)]^{\mathrm{T}}.$$

Then it is natural to obtain the value of $u(k)$ by minimizing J, *i.e.*

$$\frac{\partial J}{\partial u(k)}=0 \tag{6}$$

Wherein, the following control rule can be obtained:

$$u(k)=\frac{\rho}{b_1^2(k)}u(k-1)+\frac{b_1(k)}{b_1^2(k)+\rho}[a_1(k)y(k)+a_2(k)y(k-1)+\cdots+a_n(k)y(k-n+1)+b_2(k)u(k-1)+b_3(k)u(k-2)+\cdots+b_m(k)u(k-m+1)+\hat{N}(K)-y_r(k+1)] \tag{7}$$

where $a_i(k)$ and $b_j(k)$ ($i=1, 2, \cdots, n, j=1, 2, \cdots, m$) are parameters in vector $\boldsymbol{\Phi}$ at k-th time point.

To implement the control goal, the steps below are generally followed:

(1) Identify the model parameters of the non-liner objective by the approach in reference [1] during each sampling time interval;

(2) Compute the control variable $u(k)$ at k-th time point by equation (7);

(3) Use new data to identify these parameters and return to step 1 in the next sampling interval.

3 Results from simulation and analysis

Consider the following nonlinear objective

$$y(k)=\frac{0.5[y(k-1)y(k-2)(y(k-3)-1)u(k-2)+u(k-1)]}{1+y^2(k-2)+y^2(k-3)} \tag{8}$$

and adopt the network model described in equation (2), where $\boldsymbol{\Phi}=[a_1, a_2, b_1]^{\mathrm{T}}$ and $x(k-1)=[y(k-1), y(k-2), y(k-3)]^{\mathrm{T}}$. The structure of the neural network is with three cells for the input layer, three cells for the first-hidden layer, twelve cells for the second-hidden layer, one cell for the output layer (refer to figure 2). The learning speed is given with 0.01.

First, the network was offline trained with 100 sample-data groups. After 5 000 epochs, the result was adopted as the initial value to be applied into online identification of the network. Then, the above algorithm was employed to design the controller and the adaptive close-loop control system. Finally, the reference input signal $y_r=-0.5$ was adopted as the input for both traditional optimized predictive systems and modified systems, and the yields are illustrated in **figures 3** and **4.**

It is obvious that the system with the modified approach is with rapid dynamic response and no error in a static state as shown in figure 3. In comparison, the system with the traditional approach will be out of control in the end (see figure 4).

Furthermore, multiple simulation tests were carried out to verify the anti-interference capability of the new

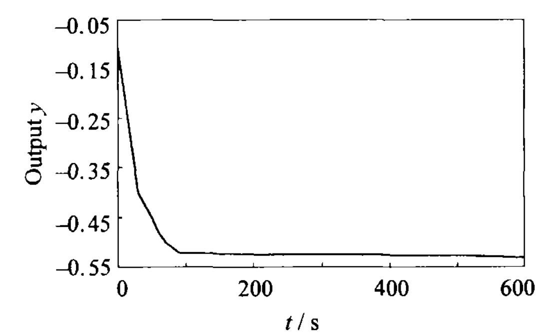

Figure 3 Output results by the modified approach.

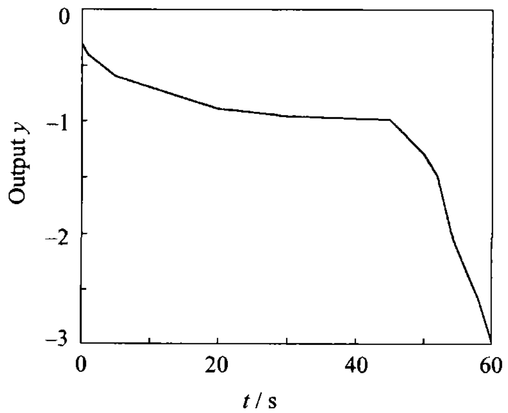

Figure 4 Output results by the traditional approach.

approach, where the interference was caused by the variation of the objective parameter values, the objective dimensions and the outside factors. Therefore, the new approach is better than the traditional one in accuracy and computing speed.

4 Applications

It is a critical issue to control the coiling temperature of hot rolling strip steel for best quality. The main goal is to make actual coiling temperature as close as possible to the target coiling temperature [8]. On the one hand, if the actual coiling temperature is much higher than that of the target, the strip steel will turn soft into a solid ball. On the other hand, if the actual coiling temperature is too lower than that of the target, the strip steel will turn stiff and be hard for coiling. To that end, the error between the actual coiling temperature and the target should be limited in the range of ±30 ℃. Otherwise, the texture and performance of the strip steel will be suffered.

It is a major concern of steel plant engineers to accurately control the temperature of hot strips. However, it is difficult to implement accurate control by the traditional method, due to the complicated onsite environment. The above control algorithms has been applied in real production and satisfied effects has been achieved. The average hit rate of actual measured temperature falling in the target range is improved by 5%. The curves in **figure 5** show the coiling temperature of strip steels for the target value, the actual value before and after the modification, respectively.

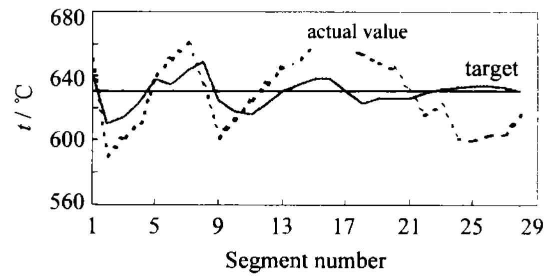

Figure 5 The control results of the coiling temperature of strip before (dash line) and after (real line) modification.

5 Conclusion

Traditional control methods are not sufficient to meet the requirements of today's large-scale industrial production. An adaptive optimal control approach based on the artificial neural network is proposed. Simulation and application demonstrate that this approach is effective and practical for controlling non-linear systems.

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