A Novel Reference Model-Based Neural Network Approach to Temperature Control System

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Abstract. With the continuous development of deep learning, neural network with its excellent self-learning performance obtains a series of major breakthroughs in target detection, image recognition and so on. In this paper, the temperature control system based on a neural network combined with I-PD compensation is proposed. To improve the neural network self-learning efficiency, the reference model is introduced for providing the teaching signal of neural network. The system simulations are carried out in MATLAB/SIMULINK environment to verify the control efficiency of the proposed reference model based neural network control system. The experiments are carried out on the DSP based temperature control system platform, the results are compared to the conventional I-PD control system to verify the control efficiency.

1. Introduction

In recent years, thermal processing systems that incorporate temperature control are needed in order to achieve high-performance processing. Among the various thermal processing techniques, the PID control has become the most commonly used controller due to its simplicity and applicability, even for multi-point temperature control systems. However, if the thermal processing system has a large delay time, the transient response and the stability could not be guaranteed respected [1]-[9].

Based on the condition that most of the PID controllers cannot learn and adjust its parameter online to suit the variation of the thermal process system, the intelligent control theory has gained more and more attention in process control systems. As the multi-layer neural network with deep learning technology. By introducing the neural networks control into the thermal process system which has the strong nonlinear characteristic, the adaptive system can improve the control performance to the un-modelled dynamics and the bounded disturbances [10]-[14].

In this paper, a neural network approach for a temperature control system with a reference model has been proposed. The control system is driven by using the error between the reference model output and the real system output as the teaching signal of the neural network. By adding the neural network controller into the IPD control system, the control input can be appropriately adjusted. The control performance has been quickly tuned while system response reaches the steady state. In order to evaluate the proposed reference model based neural network control system, the simulations have been carried out in MATLAB/SIMULINK environment and the experiments have been carried out on a DSP based temperature platform.
2. Configuration of neural network with reference model system

In this section, we describe the configuration of the proposed neural network control system with the reference model is described. Figure 1 shows the block diagram of the reference model based neural network control system.

![Block diagram of reference model based neural network control system](image)

Figure 1. Block diagram of reference model based neural network control system

For simplicity, the controlled object is expressed as a first order plus time delay (FOPTD) model. In Figure 1, \(y_{\text{ref}}\) is the set reference value of the system, \(e_y\) is the teaching signal of the neural network controller, which is calculated by the error between the output \(y_r\) of reference model \(R_m\) and the output temperature \(y\), \(C\) is the conventional PID controller, in this paper I-PD configuration is employed, while the control input \(x\) is the sum of the neural network control output \(x_N\) and IPD output \(x_C\). Since the control object is the plant with time delay, the reference model \(R_m\) can be appropriately designed to provide the ideal temperature output with the same delay. The explanation of the control system can be divided into four main parts.

2.1. Control object with time delay

The control object is the thermal processing system which can be represented as the FOPTD system. With its large delay time, the transfer function of the plant can be expressed as equation (1), where \(K\) is the steady state gain of the output temperature against the input signal, \(T\) is the time constant of the plant, and the \(\tau\) is the delay time of the response.

\[
P(s) = \frac{K}{Ts + 1} e^{-\tau s}
\]  

(1)

2.2. I-PD control

Consider that the neural network controller needs time to learn and training the parameters, and mainly acting on the late time, the conventional I-PD controller is designed for the control of the initial state. The parameter of the I-PD controller is designed based on the Ziegler-Nichols rule (step response method). These values are decided by \(\tau\), \(K\) and \(T\) shown in equation (1). The I-PD parameter \(K_p\), \(T_i\) and \(T_d\) can be calculated as equations (2), (3) and (4), respectively.

\[
K_p = 1.2 \frac{T}{\tau}
\]  

(2)

\[
T_i = 0.5T
\]  

(3)

\[
T_d = 2\tau
\]  

(4)
2.3. Neural network controller

The multi-layer neural network (NN) controller has been introduced to the I-PD control system. In the proposed system, the NN controller has one input layer, two hidden layers and one output layer as shown in Figure 2, where the two hidden layers have 10 neurons.

In this system, the reference value of the system $y_{\text{ref}}$ and the output temperature $y$ are set as the input signal of the neural networks. $x_N$ is the output value of the neural networks. The calculation process from the input $N_{\text{in}}$ to the output $N_{\text{out}}$ can be shown in Figure 3. Where the $W$ is the weight of neurons, $\theta$ is the offset value of every neuron, $\sigma$ is the neuron activation function.

\begin{equation}
NN_{\text{out}} = W_3 \ast \sigma(W_2 \ast \sigma(W_1 \ast NN_{\text{in}} + \theta_1) + \theta_2)
\end{equation}

Where $N_{\text{in}} = [y_{\text{ref}}, y]^T$ is the input vector, $W_1$, $W_2$ and $W_3$ are the weight matrixes, and the $N_{\text{out}} = [x_N]$ is the neural network output. With regards to the self-learning, the weight matrix needs to be updated. The learning rule of the weight can be calculated as equation (6), where $m$ is the neural network layer, $\alpha$ is the learning gain, $x$ is the input of each weight represent as $N_{\text{in}}$, $Y_1$ and $Y_2$, and $\delta$ is the derivation of the weight as equation (7).

\begin{equation}
W(m)^{n+1} = W(m)^n - \alpha \times \delta(m)^n \times x(m)^n
\end{equation}

\begin{equation}
\delta(m) = \nabla \sigma(z(m)) \times W(m+1) \times \delta(m)
\end{equation}

In order to improve the self-learning ability of the neural network controller, the ReLu neuron activation function as equation (8) has been applied.

\begin{equation}
f(x) = \begin{cases} 
  x & x > 0 \\
  0 & x \leq 0 
\end{cases}
\end{equation}

\begin{equation}
f'(x) = \begin{cases} 
  1 & x > 0 \\
  0 & x \leq 0 
\end{cases}
\end{equation}

2.4. Reference model-based NN control system

The Padé approximation method has been introduced to approximate the plant to equation (10), which is easier for the simulation to modify the reference model. The reference model setting is based on the approximated plant model, which is to improve the transient response speed by adding a gain $R$ to the plant time constant the approximated model is shown as equation (11). Approximation of dead time to $1^{st}$ order transfer function makes the controller realization easy, i.e. the memory to store the output can be saved.
\[
P(s) \approx \frac{K}{T_s + 1} \cdot \frac{1}{\tau_s + 1}
\]

(10)

\[
R(s) \approx \frac{1}{T \cdot R \cdot s + 1} \cdot \frac{1}{(\tau s + 1)^2}
\]

(11)

3. System simulation

In order to verify the proposed reference model-based NN control method, the simulation has been carried out in MATLAB/SIMULINK environment. In the simulation, the control object transfer is expressed as a FOPTD system as equation (12). Its approximated transfer function becomes equation (13), hence the reference model can be represented as equation (14), wherever in this proposal, \( R \) is set as 0.01.

\[
P(s) = \frac{2.36}{2626s + 1} e^{-524s}
\]

(12)

\[
P(s) \approx \frac{2.36}{2626s + 1 (524s + 1)^2}
\]

(13)

\[
P(s) \approx \frac{1}{26.26s + 1 (524s + 1)^2}
\]

(14)

The I-PD parameter was decided by the plant parameter as described before. The parameters were \( K_p = 10.3, T_i = 838, T_d = 209 \). Moreover, the hyper parameters of the neural network are decided as \( \alpha = 1 \times 10^{-9}, \beta = 2 \times 10^{-5} \). The initial values of the weight can be set as an optimal random value.

The simulation has been carried out with the following condition. The control performance was evaluated both in a positive direction and a negative direction. The reference value of the temperature was set as a repetitive step signal with an amplitude of 5 deg C, the offset of the reference is 100 deg C. The time response is shown in Figure 4. The control input with the summation of the neural network output and the I-PD output is shown in Figure 5.

![Figure 4](image4.png)

**Figure 4.** Output of NN controller and I-PD controller

Also, each positive and negative direction’s response need to be analyzed. Focusing on the reference from 100 deg C to 105 deg C as the positive direction and 105 deg C to 100 deg C as the negative direction, each step response is plotted on the same figure as in Figures 6 and 7, respectively.
From the simulation results, no matter the positive direction control or the negative direction control, the system response with the neural network control in regards to rising time and settling time is improved from the conventional I-PD control. Moreover, since the first step response is almost the same as the last step response, the learning process has been done at the beginning of the first step. The system response follows to the reference model, although there is a little deviation. As a result, the control efficiency has been improved by comparing to the conventional I-PD control.

4. Experimental results

Experiments with the proposed reference model-based neural network control method were carried out based on the platform that equips DSP as the temperature controller as is shown in Figure 8. The system has four coupling channels, each channel has two independent heaters and one temperature sensor. The temperature sensor can transfer temperature 0-400 deg C to 0-10 VDC output voltages. In addition, the heaters are driven by PWM signals. The temperature can be controlled through controlling the duty ratio of the PWM signals.

In this proposal, the channel Ch1 is defined as the input channel (heating channel) and Ch4 is defined as the output channel. The step response method was introduced for the system identification. The plant can be identified as equation (15). Based on the identified plant model, the reference model can be obtained as equation (16).
\[ P(s) = \frac{3.052}{2161s + 1} e^{-615s} \]  
\[ R_m = \frac{1}{21.61s + 1} \frac{1}{615s + 1} \]

The parameters of the I-PD controller are obtained by Ziegler-Nichols method, thus, the parameters \( K_p = 1.38 \), \( T_i = 1231 \) and \( T_d = 308 \). The initial layer offset \( \theta_1 = \theta_2 = 0 \), the learning gain \( \alpha = 1.2 \times 10^{-12} \), while the training gain \( \beta = 2 \times 10^{-10} \). And the initial weight of the NN controller has been optimized.

In the experiments, to verify the control efficiency of the proposed method, the results were compared to conventional I-PD control system both with the feed-forward gain \( k_f = 0 \) (slow) and \( k_f = 1 \) (fast). The experiments were carried out by controlling the temperature of Ch1 from 100 deg C to 105 deg C. The results of output temperature are shown in Figure 9, while the control input is shown in Figure 10.

![Figure 9. Experiment results of transient response](image)

![Figure 10. Control input of IPD+NN system and conventional IPD system](image)

From Figure 9, the conventional I-PD controller with feed forward gain \( k_f = 0 \) has the longest response while no overshoot, and I-PD controller with feed-forward \( k_f = 1 \) has the fastest transient response, however, have an overshoot as 1.5 deg C. By introducing the NN controller, the transient response has been improved, the system has the transient response as fast as conventional I-PD with feed-forward gain \( k_f = 1 \), and has no overshoot. Thus, the system response has been improved, and the efficiency of the proposed control method has been successfully evaluated.

5. Conclusion
In this paper, a reference model-based neural network controller for temperature control system has been proposed. The control system is driven by using the error signal between system output and reference model output as the teaching signal of the neural networks. The NN system configuration combined with I-PD control has been described. And then, the proposed design method has been applied to a first order plus time delay plant. Simulation has been carried out in MATLAB, and the results have been quantitatively compared to the convention I-PD control method with the summation of squared error. The experiments have been carried out on a DSP based temperature system platform, the results also have been compared to the conventional I-PD control system to evaluated the improvement taken in the transient response. The control efficiency of the proposed method has been successfully evaluated.

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