Neural Network based Model Reference Control for Electric Heating Furnace with Input Saturation

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***Abstract*—In this paper, a recurrent neural network based controller is designed for an electric heating furnace with input saturation. First, a recurrent neural network is used as a mathematical model of the electric heating furnace. The network is trained with training data of power in percentage and furnace temperature measured from the furnace. Then, this network is applied to design a recurrent neural network controller based on the model reference control method, which guarantees the input constraint of the plant. The plant network and the controller network are combined to form a closed neural network. During the closed neural network training, only parameters of the network controller are updated, and that of the plant network are kept unchanged. Experimental results show that the neural network controller provides the same performance as the PI and MPC controllers, and it satisfies the input constraint.**

I. Introduction

Heating furnaces [1] have been largely used in industry. The control of a heating kiln consists of regulating both the temperature of the furnace and that of the slab as required by the technology. Various control methods for the heating furnace temperature have been studied and applied. The modular neural network in [2] was used to predict set-points for temperature of each zone in the reheating furnace in steel industry. Neural network based decoupling PID controllers for the electric heating kiln were designed and verified via simulations in [3]. Recently, a multi discrete-time first-order plus time delay based predictive controller was proposed for the electric heating in [4].

Neural networks were approved as universal approximators in [5]. They were used for modeling of plate rolling processes in [6]. These networks were applied to estimate the temperature profile of the slab based on temperatures of the top and bottom surface of the slab. The similar work but using recurrent neural networks for the electric heating furnace can be found in [7]. In [8], the average temperature of the slab was predicted with the usage of neural networks. In [9], the roll-force model was also built based on neural networks. Adaptive neural networks were used to estimate temperature of steel slabs after rolling in [10]. Neural networks based modeling of slab temperature can be seen in papers [11], [12], [13].

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An optimal temperature control for the furnace and slab was proposed in [14]. Model predictive control [15], [16], [17], [18], [19] for the reheating furnace were applied in industry.

Some of these existing controllers can deal with plants in the presence of input saturation, such as PID in [20] and MPC controllers, but they need mathematical models. One control method without using any mathematical model in [21] can be also applied. Although the neural network based model reference controllers are applied in practice, there has not been any stability analysis of the neural network based model reference control system yet, but there were stability criteria for recurrent neural networks such as [22]. Thus, in this work, a reference model controller based on neural networks is designed for the electric heating furnace with input saturation. The proposed controller is verified and compared to existing methods through experiments.

The work consists of 4 parts. In section 2, the electric heating furnace in laboratory is presented. In section 3, the design of the model reference control based on neural network for the electric heating is provided, and experimental results are included. The final section provides discussions and future works.

II. Electric Heating Furnace Control System

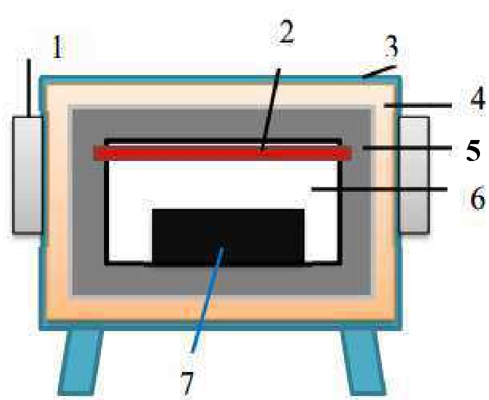

Fig. 1. Furnace Structure

The structure of an electric heating furnace in the laboratory is shown in Fig 1. It consists of voltage supply connectors (1), resistors (2), furnace housing (3), thermal insulation material (4), anti-fire brick (5), furnace chamber (6), and slab (7). For experiments, a sheet of diatomite is heated in the furnace to generate temperature samples of the slab and the furnace. The temperature of the furnace is measured by using a thermocouple. The main aim is to keep the furnace temperature at desired value. Thus, the furnace temperature must be controlled.

The furnace control system in the laboratory contains a computer with Matlab/Simulink, a thermalcouple Cromen-Alumen type K, ADC/DAC converters and a triac control circuit. The control signal will be computed from the computer based on the used controller. Then, it will be sent to the triac control circuit, which regulates the ratio of the power of the electric heating furnce to the maximum power. This means that the input to the electric heating furnace is limited to the interval $[0; 1]$.

In the next section, the neural network based model reference control will be introduced and applied to the electric heating furnace.

III. Neural network based model reference control

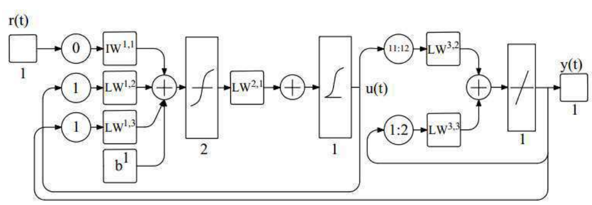

Fig. 2. Neural network controller and plant neural network block diagram

In this section, a neural network controller based on model reference control will be designed for the electrich heating. Fig. 2 shows the neural networks based model reference control system, where $r(t)$ is the setpoint, $u(t)$ is the control signal or neural network controller's output, $y(t)$ is the plant network's output during the design process or furnace temperature while the system is under real-time control mode, $IW^{1,1}$ is the input weight matrix, $LW^{i,j}$ is the layer weight matrix, which connects the output of j^{th} layer to the input of the i^{th} layer for $i = 1, 2, 3$ and $j = 1, 2, 3$, and b^1 is the bias of the first layer.

It consists of two recurrent neural networks and a reference model. The referene model is skipped from the figure for simplicity. The first two-layer plays as a controller and the last layer is designed as a model of the plant. First, the plant network is trained, and then the controller network is trained such that the plant output tracks the output of the reference model. While the controller network is trained, the parameters of the plant network are fixed.

The plant network's weights are determined through the training process based on the plant's input and output measured from practice. In this case, the input is the percentage of the power applied to the furnace, and the temperature of the furnace is considered as the output. The network for the plant (the last layer in Fig. 2) is a recurrent neural network with only one neuron, linear transfer function, input delays of 11 and 12, and output delays of 1 and 2. The training data for the plant network is obtained from the step response of the furnace (see the blue curve or target in Fig. 3). When the plant network training is completed, the network output is compared with the furnace temperature as in Fig. 3 (bottom figure). The obtained error between the network output and the target is quite small after 500 seconds. The parameters of the plant network are gained as follows $LW^{3,2} = [6.71 \quad -6.70]$ and $LW^{3,3} = [1.99 \quad -0.99]$. This trained plant network will be used for the design of the neural network controller later.

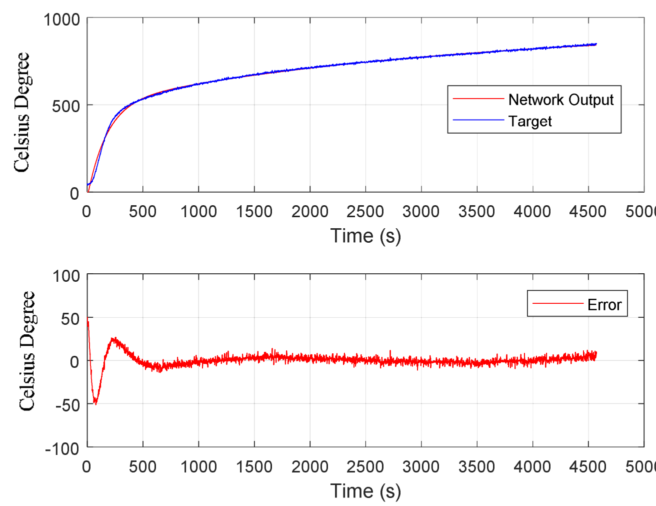

Fig. 3. Plant network's output and furnace's step response

The training data for the network controller includes some desired set-points and the corresponding responses from the reference model, which is chosen as a first-order transfer function. It is obtained from Matlab/Simulink as shown in Fig. 4. In this figure, the input is set-points in black and the target is the reference model's output in blue.

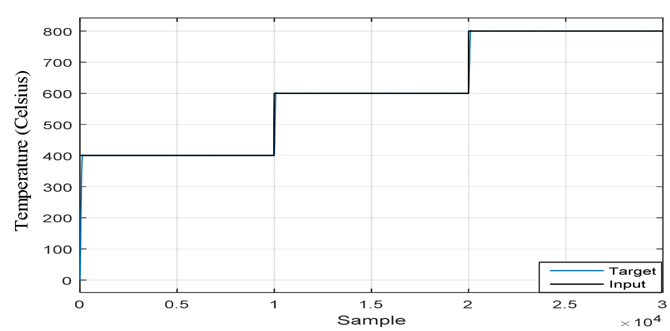

Fig. 4. Training data for the neural network controller

The structure of neural network controller is shown in Fig. 2. It is the first two-layer recurrent neural network, which has 2 neurons in the first layer with tansig transfer function, one neuron in the second layer with logsig transfer function, 0 delay in the input, 1 delay in the feedback from the output of the controller network, 1 delay in the feedback from the output of the furnace. Since the logsig function is used as transfer function for the output layer of the network controller, the output of the network controller will be within the interval $[0, 1]$. This makes sure that the input constraint of the plant, the percentage of power applied to the furnace, will be satisfied.

After the controller network training is done, the parameters of the controller are obtained as follows $IW^{1,1} = [0.034 \quad 0.026]^T$, $LW^{1,2} = [1.22 \quad -0.12]^T$, $LW^{1,3} = [0.041 \quad -0.025]$, $b^1 = [-0.55 \quad 0.93]^T$, and $LW^{2,1} = [-13.15 \quad 14.47]$. Then, the network controller is applied to regulate the furnace temperature with different reference signals. In addition, it is also compared to the classical PI controller and the MPC controller. The experimental results for two cases are shown in Fig. 5 and Fig. 7, respectively.

In the first case, the reference signal is constant, and the reference is changing in the second case. For the constant reference signal, the settling time produced by the neural network, MPC and PI controllers are 120, 120, and 180 seconds, respectively. The overshoot in percentage made by these controllers are 2, 6 and 3, respectively. The control signal, power produced by differenct controllers and applied to the furnace in percentage, is shown in Fig. 6. For the first 150 seconds, the neural network controller produces smaller power than the others, and for the remaining time, the power oscillates with larger amplitute than the others.

For the second case, the neural network gave the same performance as PI and MPC controllers. The control signal is shown in Fig. 8, which swings with larger magnitude. In both cases, the control signal lies inside the range $[0; 1]$ for all controllers.

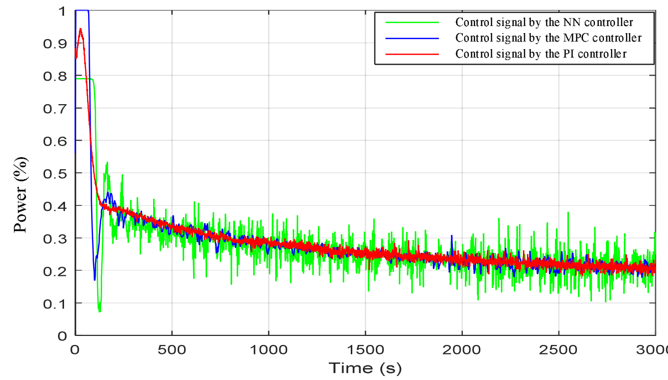

Fig. 6. Control signal with different controllers

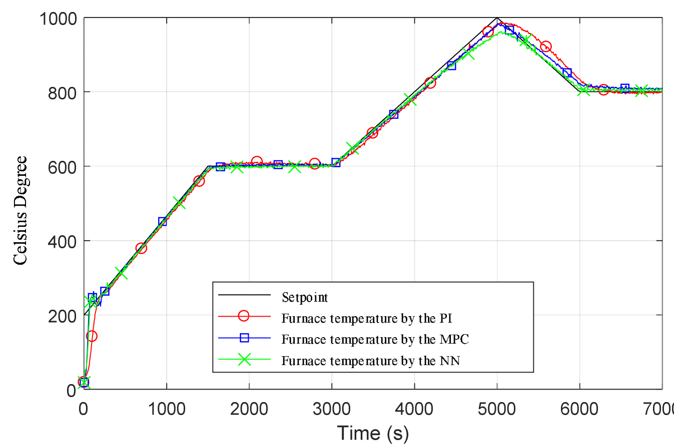

Fig. 7. Furnace temperature with a reference signal

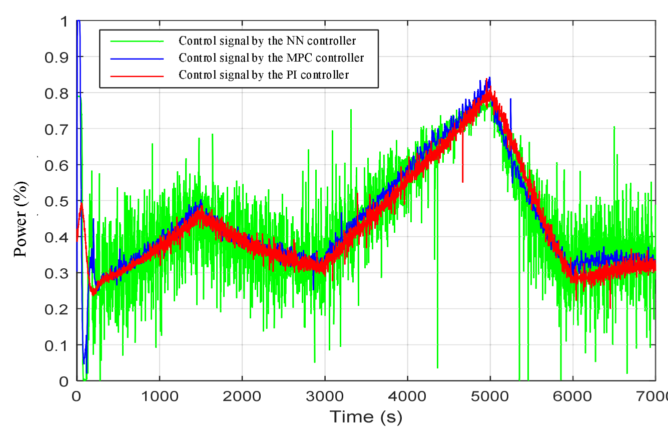

Fig. 8. Control signal with different controllers

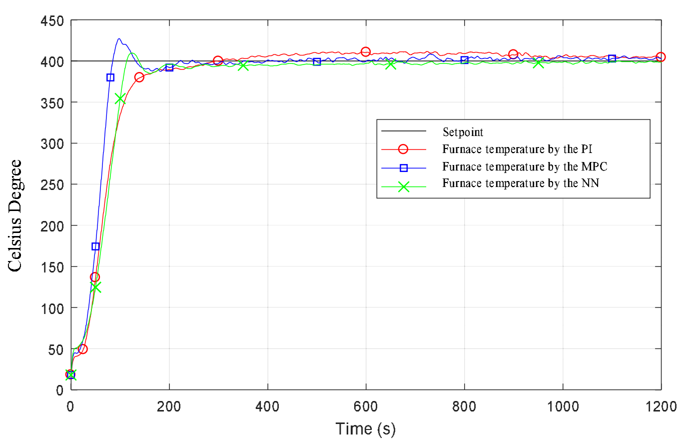

Fig. 5. Furnace temperature with different controllers

IV. Conclusion

In the paper, the first recurrent neural network is used as the model of the electric heating furnace and the other one is designed as the model reference controller. Experimental tests for the furnace in the laboratory show that the network controller provides very good performance in comparison with the PI and MPC controllers. The advantage of the proposed controller is that there is no need of the mathematical model of the electric heating furnace but only the information about the power applied to the furnace and its corresponding temperature. Moreover, it is unnecessary to solve any optimization problem online as the MPC controller, that means less computational load. In addition, it can deal with the input constraint of the plant, which is restricted to the range $[0, 1]$.

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