Neural Network based Temperature Predictor for Slabs in Continuous Reheating Furnaces

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***Abstract*—During operation of the continuous reheating furnace, it is generally impossible to measure the slab temperature distribution. Thus, it has to be predicted. In this work, three recurrent neural networks are built for estimation of temperature profile of slab, temperature at top, bottom and center. The training data is collected by measuring the temperature of a furnace and temperature distribution of slabs. A real static reheating furnace is used to simulate a continuous reheating furnace. Instead of moving slabs through different temperature zones of the continuous reheating furnaces along the horizontal line and measuring the slab temperature distribution, slabs are kept fixed but the temperature of the static reheating furnace varies with time. Therefore, this process is similar to the moving of slabs in the continuous reheating furnace. Then, the training data is used to train three recurrent neural networks to predict temperatures of the top layer, bottom layer and center layer of slabs multiple-step ahead. The experimental result showed that neural network based predictors work well. The error between the target and the neural network is rather small for the three layers.**

I. Introduction

Reheating furnace is widely used in many industrial processes such as hot rolling mills. The slabs go through the furnace and they are heated to desired temperatures about 1200 to 1300 ^oC [1]. As of their continuous motion in the furnace, their temperature distribution can not be measured, especially the inside layers. Thus, this temperature distribution must be approximately estimated. Some methods can be used such as physical models, finite impulse response (FIR), auto-regressive with exogenous variable (ARx), moving average with exogeneous variable (ARMAx) models, hybrid models and neural networks models. It is very difficult to build physical models because the operating conditions in the furnace are varying. The FIR, ARx and ARMAx models can not capture nonlinearities well. Neural network models are proved to be universal approximators [2] and able to be effectively realized [3]–[6]. Other hybrid models [7]–[10] are also used. In this work, recurrent neural networks based models are used to predict the temperature profile of slabs in a continuous reheating furnace. They are trained with the usage of Neural Network Toolbox in Matlab [11]. These models are tested on a real static reheating furnace (similar model can be found in [12]), which provides the same operation of reheating precess as the continuous reheating furnace. The predictors estimate the temperature at the top, the bottom and the center of slabs while they move through the furnace. The static furnace operates as a one-sided heat transfer system. Slabs are heated from the top side of the furnace. An electric heating furnace is applied in this case.

The paper includes five parts. The next section is a brief introduction of reheating furnaces and a real static furnace. In the third section, the network structure is provided, and then trained. The fourth section gives some experimental results and remarks. Conclusions and future works are made in the final section.

II. Reheating Furnace

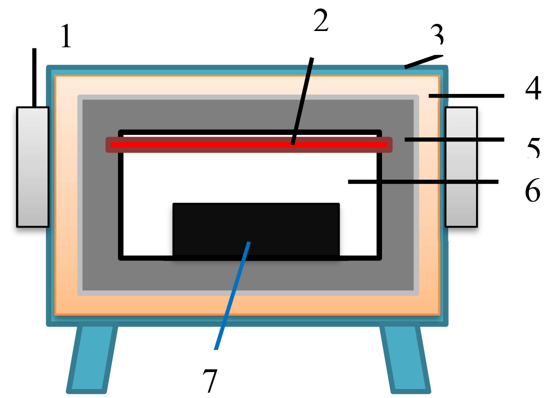

Fig. 1. Schematic Diagram of the Electric Resistant Heating Furnace

In general, there are two types of continuous reheating furnace in industry: walking beam furnace and pusher type furnace. In this paper, the second type is studied. In the pusher type furnace, the slabs are constantly in contact with the furnace's floor and each other. The slabs, that are pushed into the furnace, make the slabs in front of them move forwards. They move through different temperature zones along the furnace. This kind of motion is the same as the case that slabs are kept immobile but temperature varies in time. Thus, a static reheating furnace can be used in place of a continuous

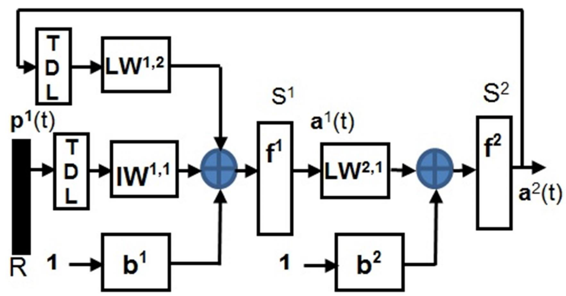

Fig. 2. Recurrent Neural Network Structure

reheating furnace for experimental purposes, such as testing temperature predictors for slabs. Based on this idea, a static reheating furnace is used to generate temperature samples of the furnace and also the slab. These samples are used as training data for training recurrent neural networks. In addition, with the usage of a static furnace, the cost for the test and design process of the predictors will be reduced a lot.

The static reheating furnace, which is an electric resistance reheating furnace as shown in Fig 1, is built in the laboratory. It consists of voltage supply connector (1), heating element (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. The temperature profile of the sheet is measured by using three thermocouples. It includes temperature at top, center and bottom of the sheet. Temperature of the heated sheet can reach about $1200 \quad {}^oC$ in 6 to 7 hours. The main aim is to keep the heated sheet at desired temperature and temperature distribution closely equal. Thus, the furnace's temperature must be controlled. Hence, the predicted temperature for the sheet will certainly enhance performances of the control system.

III. Recurrent Neural Network, Design and Training

A recurrent neural network consists of multiple layers where each layer's output can be fed back that layer or previous layers through a tapped delay lines (TDL) block. This block contains delay systems of transfer function z^{-1} in series. If the input to the TDL block is $u(t)$ then the output of the block is $u(t-1) \quad ... \quad u(t-m)$, where m is the number of delay systems z^{-1} in the TDL block. Fig. 2 shows an example of recurrent neural networks. This network includes 2 layers, the number of neurons for each layer is S^1 and S^2, respectively. $\mathbf{f}^1$, $\mathbf{f}^2$ and $\mathbf{b}^1$, $\mathbf{b}^2$ are vectors of transfer functions and vectors of biases for layer 1 and layer 2, respectively. The block $IW^{i,j}$ is a matrix of weights connecting the *j-th* input to the input of the *i-th* layer. The block $LW^{i,j}$ is a matrix of weights connecting the *j-th* layer's output to the input of the *i-th* layer. For neural network, it is proved that the network can approximate any nonlinear function with any degree of accruracy [2]. However, training recurrent neural networks becomes more difficult because of their feedback connections.

In this work, three recurrent neural networks are trained to predict a slab's temperature profile at the top, the center and the bottom, respectively. The input to these networks is the temperature of the furnace. The network's structure is chosen the same as shown in Fig. 2, where $\boldsymbol{f}^1$ is a vector of $tansig$ functions and f^2 is a $tansig$ functions, $S^2 = 1$. $S^2 = 6$ for the first network, $S^2 = 7$ for the second network and $S^2 = 6$ for the third network. Each TDL block has 2 delays $[1 : 2]$. The training data consists of 5118 measured samples from the furnace and slab with sampling time of 5 seconds. The trial and error method is used to determine the number of neurons in the first layer, which is tested within the range of 6 and 10 neurons. The Marquardt training algorithm [13], which is built in Matlab, is applied to train these networks. The measured temperature data is filtered and then normalized to the interval $[-1 \quad 1]$. This will avoid the saturation of the $tansig$ function. Thus, the possible occurrence of spurious valleys can be reduced [14]. The transfer function of the filter is chosen as follows

$$\begin{aligned} H(z) = \quad & 0.0288 + 0.1431z^{-1} + 0.3281^{-2} \\ & + 0.3281z^{-3} + 0.1431z^{-4} + 0.0288z^{-5} \end{aligned} \tag{1}$$

Recurrent neural network training consists of two phases [15]: open-loop network training and close-loop network training. For the first phase, the training time is very short in second, but the latter takes a lot of time in hours. The weights and biases, obtained from the first stage, will be used as initial parameters for the second stage training. The close-network training is performed step by step as the number of samples, which is used to train at a time, increases after each successful training. This procedure can avoid spurious valleys during training [14]. In fact, a recurrent neural network can be designed and trained to predict all three layers' temperature at the same time. However, this can not be implemented since the network structure are more complicated. Thus, three different neural networks are applied in this case.

IV. Experimental Results

A sheet of diatomite is used to generate temperature samples for networks training. After all three networks were trained, they are verified with the usage of training data and new data. The new data, which is not used for network training, consists of 5006 samples. Each sample includes furnace's temperature and temperature of three layers of slab. For the training data, outputs from networks, targets and errors are plotted in Fig. 3, 4 and 5. For the new data, outputs from networks, targets and errors are plotted in Fig. 6, 7 and 8. The maximum absolute error for each network is shown in Tab. I. In can

Networks for	Training Data (%)	New Data (%)
Top Layer	1.3	2.9
Center Layer	1.7	13
Bottom Layer	1	8.6

TABLE I
Maximum Absolute Error

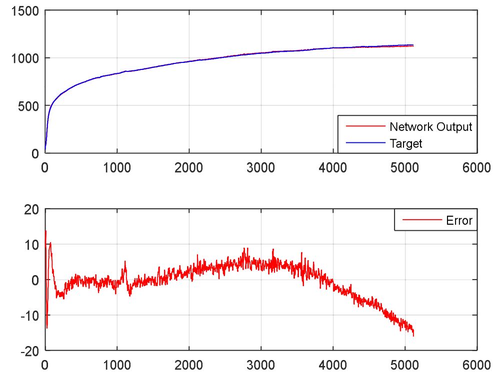

Fig. 3. Network Output, Target and Error for the Top Layer

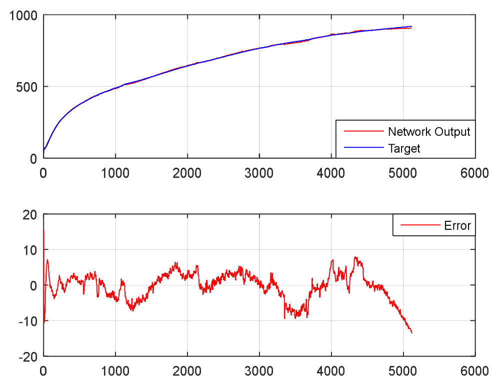

Fig. 4. Network Output, Target and Error for the Center Layer

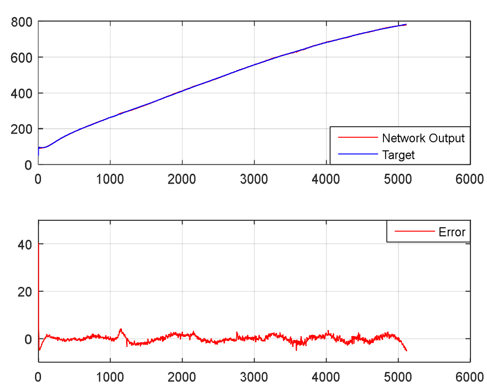

Fig. 5. Network Output, Target and Error for the Bottom Layer

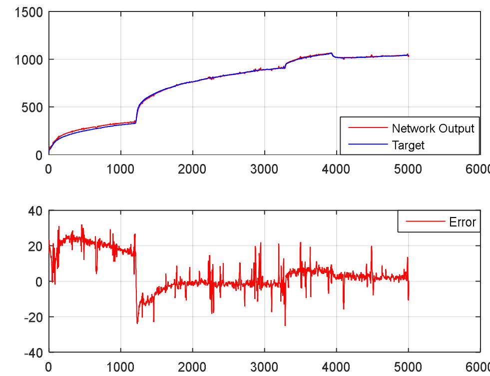

Fig. 6. Network Output, Target and Error for Top Layer

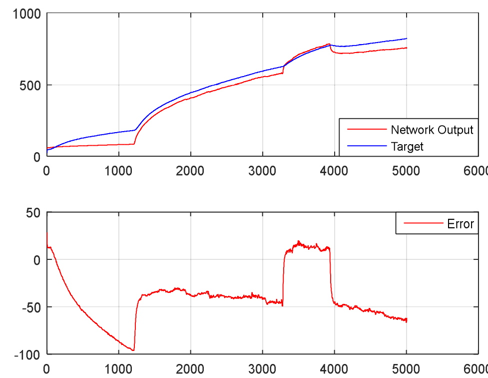

Fig. 7. Network Output, Target and Error for Center Layer

be concluded that the average error is pretty small when the networks are tested on training data, but it is quite big as the second and third networks are validated with the usage of new data. However, the first network, which predicts the temperature of the top layer, stills work well for the new training data as the absolute error is smaller than 2.9%. This can be understood because the slab is heated from its top side.

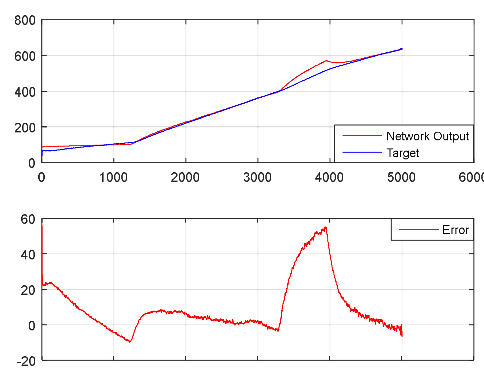

Fig. 8. Network Output, Target and Error for Bottom Layer

V. Conclusion

In the work, three recurrent neural networks are designed and trained to predict slab's temperature profile at top, center and bottom layers multi-step ahead. The experimental results for a sheet of diatomite proved that the first network predict well the temperature of the top layer of the sheet, but the other networks estimate not so well as the first one. For future application of the recurrent neural network based predictors, these networks must be tested on a continuous reheating furnace.

Future work focuses on improving the predictable capacity of the recurrent neural networks for the sheet and providing estimated values for controllers.

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