Received March 5, 2022, accepted March 15, 2022, date of publication March 25, 2022, date of current version March 31, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3162424

Temperature Prediction for Reheating Furnace by Gated Recurrent Unit Approach

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This work was supported in part by the Ministry of Science and Technology, Taiwan, under Grant MOST 110-2221-E-035-092-MY3 and Grant MOST 109-2222-E-992-003-MY2.

ABSTRACT Reheating furnaces are used to homogeneously reheat the steel stock (Billets, blooms or slabs) at a temperature between 1000°C and 1250°C before hot rolling. Supply of accurate, stable, and reliable control of temperature is most important for reheating furnaces in hot-rolled steel production. The phenomenon of large time lags in temperature is an arduous problem that existed in the combustion system of furnaces, it causes control system big overshoot, continuous oscillation, and may even make the system unstable. In this paper, a prediction model based on gate recurrent unit (GRU) was established to forecast the inside temperature of the furnace by using temperature, fuel, and air time series. Moreover, this paper presents an approach which is combining a prediction model with a feedforward controller that can improve the stability of the temperature control system. Established prediction model of temperatures by collecting data from on-side, and evaluated the model and feedforward performance on the actual reheating furnace. Compared with other dynamic models (recurrent neural network and long short-term memory), the proposed models outperformed by 15.63% and 26.07% on average in terms of the mean absolute error and root mean square error, respectively. Moreover, the proposed control improve traditional PI controller by 33.43% and 19.92% on average in terms of the mean absolute error and root mean square error, respectively. The presented method can be used to reduce the temperature disturbances in the reheating furnaces.

INDEX TERMS Gate recurrent unit, combustion system, feedforward controller, furnace hearth temperature prediction.

I. INTRODUCTION

In the steel rolling line, a reheating furnace is ascribed to upstream equipment. It is used to heat up the temperature of stock and satisfy the requirement of the rolling process. Temperature uniformity on the slabs has influenced the life of rolling equipment and the whole steel rolling line operation. The regenerative reheating furnace considered here was composed of three zones: preheating zone, heating zone, and soaking zone respectively [1]. Each zone has over two pairs of regenerative burners [2] on the sides of the furnace, shown in Figure 1. The preheating was commonly used to heat cool stock, specific types of steel or determined by operators, the heating zone was used to heat up to typically between 1000°C and 1200°C and the soaking zone was used to heat temperature as possible uniformity to typically between 1100°C and 1200°C. In most cases, just enabling heating and soaking zone was satisfied slab production requirements.

That is almost impossible to directly obtain slab surface temperature or temperature distribution by using available measurement techniques currently [3]. Therefore, temperature control means controlling the zone temperature, which has measured from the thermocouple of the furnace inside in the combustion system, and its temperature regulation depends mainly on the control fuel flow. There are many control ways for temperature, such as manual control, fuzzy control, PI/PID single-loop control, etc., but cascade control is the most common and widely used in the reheating furnace.

Unfortunately, temperature variation has non-linear, inertia, and large time delay characteristics, so it is hard for the temperature to achieve demands in accurate control. Some research proposed prediction temperature to assist temperature control [4]–[6], but the prediction of the temperature of reheating furnaces is a challenging task.

The associate editor coordinating the review of this manuscript and approving it for publication was Qichun Zhang.

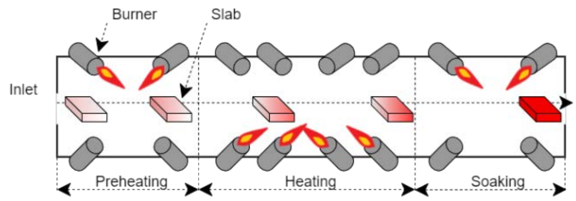

FIGURE 1. Typical bird view of a reheating furnace [1].

This study deals with the design of temperature prediction using gate recurrent units models, and carries out the feedforward control in the on-site temperature of the reheating furnace. Compare performance GRU with RNN and LSTM in predicting temperature, and design a simple structure of feedforward control. Because combine predict the temperature in advance and effective feedforward control strategy, it eliminates the time lag and accelerates response time in temperature control. This paper presents the main idea and demonstrates the performance of the method on temperature control of the combustion system, which has our proposed. The result shows that the proposed approach outperforms the common cascade controller in terms of temperature stability.

The remaining of the paper is organized as follows. Section 2 surveys the techniques of temperature prediction and control. Section 3 describes a method that is composed of a temperature prediction model and feedforward control. Section 4 presents the experimental results and analysis. Finally, conclusions are given in Section 5.

II. RELATED WORK

This section reviewed recently related studies, which include temperature prediction and control. Reference [7] proposes the Smith predictive compensation combined with fuzzy PID control method, it establishes the mathematical model of the furnace temperature control system. The verified result has small overshoot, short response time and stability characteristics in software simulation. Reference [8] adapts PID algorithm of grey predicting's neural network to control the temperature, it was suitable for predicting a small sample of data accurately, easily and conveniently. The experimental results show that this method eliminates the overshoot of the temperature and decreases dynamic response time in the simulation. In reference [9], the extreme learning machine improved by restricted Boltzmann machine is used to predicted the change in the furnace temperature in advance. The air-fuel ratio and the burner switching time can be optimized, and besides, The melting efficiency of aluminum melting furnace is improved. In reference [2], the estimated zone temperatures model of the reheating furnace by using RBF-based RNN (RBF-RNN) approach, and a model based on the theory of heat transfer is derived to predict billet temperatures. The proposed method of this study combines an FNN decoupling controller (FNNDC) with a hybrid PSO (HPSO), it was used to control the zone temperatures in a real reheating furnace. The experimental results illustrated this control method saved a great deal of fuel, and reduce the error between the mean and target temperatures of a billet at the furnace exit. Yielded large economic benefits, decreased environmental pollution, and improved the quality of steel products.

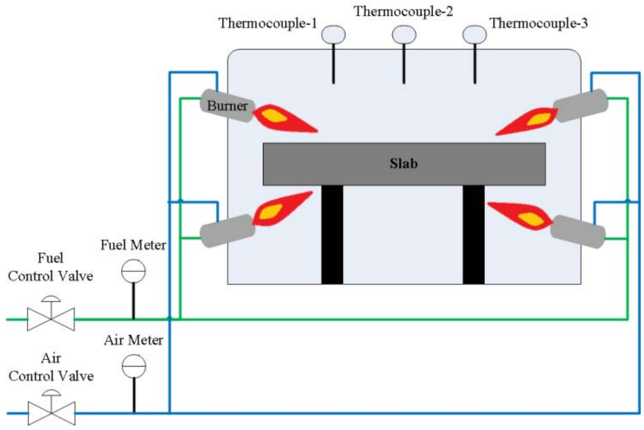

FIGURE 2. Section view of reheating furnace of each zone.

III. PROPOSED METHOD

A. FEATURES ACQUISITION

The drawing of the section view of the furnace was shown in Fig. 2. In a temperature time series, neighboring samples have high relationship. Table 1 shows the features collected which are used to establish the prediction model. The furnace inside temperature, air flow, and fuel flow data of each zone are simultaneously recorded every 1 second. The slope of the furnace inside temperature of each zone is also calculated every 1 second. The temperature slope is a physical quantity that describes in which direction and at what rate the temperature changes, so it is probably useful for predicting temperature. The temperature slope is evaluated as:

$$TS_t^x = TC_t^x - TC_{t-1}^x \tag{1}$$

B. GRU, GATED RECURRENT UNIT

Some researchers proposed Recurrent Neural Network to make predictions in time series [10]–[12]. However, the disadvantage of RNN is, it can not remember long term relationship and dependencies because of vanishing gradient, so it has only short-term memory [13], [14]. The LSTM model is an advanced RNN, it consists of forget gate, input gate and output gate, which can control the retention or discard of information in the sequence. It is also prevents the RNN model from forgetting long-term states [15]. The LSTM not only retains hidden state, but also has a cell state represented the model longer memory of past events. Therefore, the LSTM is very suitable for solving time series prediction problems [15]–[17]. However, the LSTM has larger amount of parameters than native RNN, which means search space more vast and training procedure needs more time, it is not benefit to search optimal solution.

The GRU model is a modified version of the LSTM model, it not only merges the forget gate and the input gate into an update gate but also drops the cell state, achieved

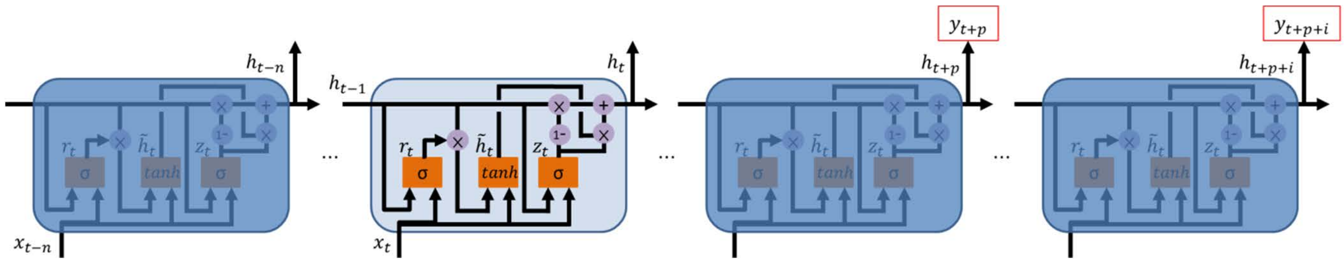

FIGURE 3. The GRU model for many-to-many [17].

TABLE 1. Features for establishment of the prediction model.

Features	Description
TC_t^1 (°C)	Measured temperature of thermocouple-1 of furnace hearth at each zone
TC_t^2 (°C)	Measured temperature of thermocouple-2 of furnace hearth at each zone
TC_t^3 (°C)	Measured temperature of thermocouple-3 of furnace hearth at each zone
F_t^{Air} (Nm^3/h)	Measured air flow of furnace at each zone
F_t^{Fuel} (Nm^3/h)	Measured fuel flow of furnace at each zone
TS_t^1 (°C)	The temperature slope of thermocouple-1 of furnace hearth at each zone
TS_t^2 (°C)	The temperature slope of thermocouple-2 of furnace hearth at each zone
TS_t^3 (°C)	The temperature slope of thermocouple-3 of furnace hearth at each zone

reduction of amount of parameters. A GRU unit is composed of reset gate and update gate, due to the simpler architecture, it is contributes to train faster and search optimal solution easily [13], [17]. The structure of a GRU unit is shown in one cell in Fig. 3.

In the first step, reset gate is calculated using both the hidden state from the previous time step and the input data at the current time step, it be reserved by applying a sigmoid function σ, as expressed in Eq (2).

$$r_t = \sigma\left(W_r \times x_t + U_r \times h_{t-1}\right) \tag{2}$$

where x_t is input data at the current time step, h_{t-1} is the hidden state from the previous time step, W_r and U_r are the weighting vectors respectively. The result values will be transformed to fall between 0 and 1 after using the sigmoid function σ. Therefore, the gate could filter between the less-important and more-important information in the subsequent steps. Next, decided the information which will be kept from the previous time steps together with the new inputs. 1) The previous hidden state is multiplied by the reset gate and then multiplied by a trainable weight. 2) The input data at the current time step is multiplied by a trainable weight. 3) Obtained result after summed value from 1) and 2), and that information will be passed to the *tanh* function. This equation expressed in Eq (3).

$$\tilde{h}_t = tanh\left(W_h \times x_t + U_h \times (r_t \times h_{t-1})\right) \tag{3}$$

The resultant value is obtained from *tanh* function that is means the candidate hidden state. If the value of r_t is equal to 1 then it means the whole information from the previous hidden state h_{t-1} is being considered. Likewise, if the value of r_t is 0 then that means the information from the previous hidden state is completely neglected.

Second, the update gate is computed using the previous hidden state and current input data using the same formula, like the reset gate. But each weight multiplied with the input and hidden state is independent and unique to each gate, which means the final vectors for the update gate are different from the reset gate, as expressed in Eq (4).

$$z_t = \sigma\left(W_z \times x_t + U_z \times h_{t-1}\right) \tag{4}$$

The purpose of the update gate is to help the model determine how much of the past information stored in the previous hidden state needs to be retained for the future. In the last step, obtaining the updated hidden state from the update gate and hidden state. Apply element-wise multiplication to (1-update gate) and hidden state from the previous time step. Next, summed with the output, which is from the update gate multiplied by the candidate hidden state, as expressed in Eq (5).

$$h_t = (1 - z_t) \times h_{t-1} + z_t \times \tilde{h}_t \tag{5}$$

The new and updated hidden state will obtained from the above operations. Furthermore, the model applied many to many, which means multi-input produced multi-output, shown in Fig. 3. Diversity model could be applied in various cases and improved accuracy in prediction probably.

In Table 1, the temperature, air flow and fuel flow of furnace hearth are sequences of data points indexed in time order. These features have high time series characteristics. Thus it is suitable for time series learning network, and chosen the GRU model in this study.

C. FEED-FORWARD CONTROL

The cascade control is a typical control system which is used to temperature control, it's extensively applied in combustion system of reheating furnaces [18], [19]. In this study, the feedforward control combined with cascade control is shown in Fig. 4. Whereas TIC is master controller, FIC_a and FiC_g are slave controllers, TE represents measure temperature of the furnace hearth, FT_a represents measure air flow, and FT_g represents measure fuel flow. The output of the master controller (TIC) is given as set point to the slave controller (FIC_g) and also given as set point to the slave controller (FIC_a) passing through air/fuel ratio (A/F Ratio) respectively at the same time. The FIC_a and FIC_g control the air flow and fuel flow respectively, two controllers adopt the double cross

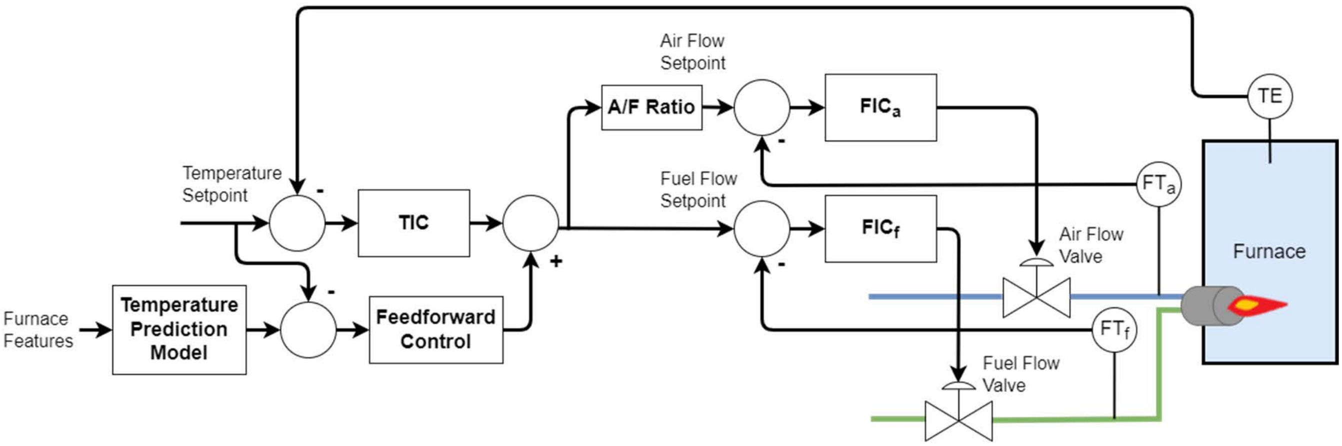

FIGURE 4. The architecture of the temperature controller.

Algorithm 1 Feedforward Control

Input:

1: $Diversity = T_{Setpoint} - T_{Predict}$

Output:

1: $if\ \left(Diversity > Deadband_{up}\right),\ thenCompensate = \min\{\frac{Diversity}{2}, 10\}$

2: $elseif\ (Diversity < Deadband_{low}),\ thenCompensate = \max\{\frac{Diversity}{2}, -10\}$

3: $elseCompensate = 0$

limiting method proposed in [18], [19], it effectively ensures response speed of the system and air-fuel ratio.

In order to increase response, extra added feedforward strategy is practicable. Feedforward Control can act proactively if there are any known upcoming disturbances. In this study, the feed-forward controller uses information from temperature prediction model to improve the control performance and eliminate long lag time. In order to prevent over response to disturbances or hunting, consider deadband design is necessary. Moreover, control compensation must be limited. The compensation obtained from feedforward controller, and additional increases total output of TIC. The procedure of the feedforward controller is described in Algorithm 1. Whereas $T_{Setpoint}$ is the value that we want the inside temperature of the furnace to achieve as steady as possible, $T_{Predict}$ is a forecasted temperature obtained from the temperature prediction model, *Diversity* is a disparity between $T_{Setpoint}$ and $T_{Predict}$, $Deadband_{up}$ and $Deadband_{low}$ are respectively upper limit and lower limit of deadband. The *Compensate* is an output of the feedforward control, and the sum of *Compensate* and the output of TIC is converted to the set point of the slave controllers.

IV. EXPERIMENTS AND RESULT ANALYSIS

We analyzed the predictive performance of the RNN, LSTM and GRU models. Next, we compare PI control to PI control with feedforward. The experimental process was carried out at a steel factory in Jiangsu, China.

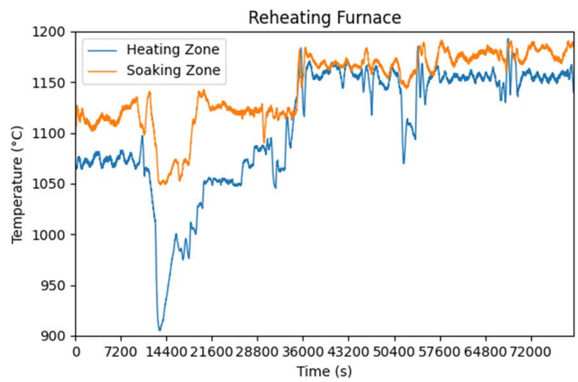

FIGURE 5. Training data.

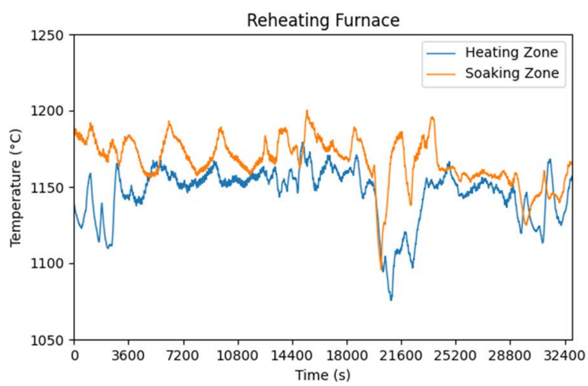

FIGURE 6. Testing data.

A. DATA AND ENVIRONMENT

The heating and soaking zone is enabled when slab production or heat insulation. The preheating zone is determined enabled according to slab temperature before entry into the furnace, if it's necessary. So we don't discuss preheating zone in this paper.

We chose continuous 34 hours data on October 2021, 24 hours ahead of data as training, 10 hours behind of data as testing, and shown in Fig. 5 and Fig. 6 below.

TABLE 2. Parameters of establishment model.

Parameters	Cells	Layers
P1	60	3
P2	60	5
P3	60	7
P4	90	3
P5	90	5
P6	90	7

There are many statistical indicators which are used to determine the predictive performance of the model [13], [15], [20], [21]. In this study, evaluated the performance of model by using the coefficient of determination (R^2), the mean square error (MSE), the mean absolute error (MAE), the maximum error ($MaxError$), and the minimum error ($MinError$). The coefficient of determination is very good at measuring the degree of similarity between the actual data and the predicted values. R^2, MAE, MSE, $MaxError$ and $MinError$ can be evaluated as:

$$MSE = \frac{1}{n}\sum\nolimits_{i=1}^{n}(o_i - y_i)^2 \tag{6}$$

$$MAE = \frac{1}{n}\sum\nolimits_{i=1}^{n}|o_i - y_i| \tag{7}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(o_i - y_i)^2}{\sum_{i=1}^{n}\left[o_i - \frac{1}{n}\sum_{i=1}^{n}o_i\right]^2} \tag{8}$$

$$MaxError = |o_i - y_i| \tag{9}$$

$$MinError = |o_i - y_i| \tag{10}$$

where o_i is the actual value, y_i is the predicted value. When the R^2 value equals to 1 and the MSE value verges on 0, the performance of this model is outstanding.

B. TAINING

The past 60 seconds are selected as input variables to the training samples, each second contains 8 features from Table 1. The output variables are the forecasted temperature of thermocouple-2 of furnace hearth after the next 13 to 17 seconds (i.e. TC^2_{t+13} (°C) ,TC^2_{t+14} (°C) ,TC^2_{t+15} (°C) , TC^2_{t+16} (°C) , TC^2_{t+17} (°C)). The 15th second prediction temperature (TC^2_{t+15} (°C)) is selected as inside temperature in advance, and prediction model is obtainable by training the samples. The epochs (max training time) are set as 100, the nodes and layers of the model are adjustable parameters. In order to find the optimal parameters for different neural network structures (namely RNN, LSTM and GRU), we designed 6 set parameters shown in Table 2.

From this table, each model has different optimal parameters for each zone, that's also what we want. The GRU model has the lowest MSE for the heating zone when the number of cells and layers were respectively 90 and 7, whereas for the soaking zone the number of cells and layers were respectively 60 and 5.

TABLE 3. Training result.

Training		P1	P2	P3	P4	P5	P6
Heating Zone	RNN	**0.2784**	0.3398	0.5693	0.4482	1.0553	0.4970
	LSTM	0.8298	0.5128	**0.4170**	0.6957	0.5117	0.8857
	GRU	1.1347	0.2289	0.3087	0.2527	0.2226	**0.2180**
Soaking Zone	RNN	0.7093	1.5032	0.4948	**0.4532**	0.4737	0.7482
	LSTM	**0.2910**	0.3067	0.3881	0.4243	0.3034	0.4471
	GRU	0.4211	**0.2907**	0.4822	0.3577	0.3651	0.6135

TABLE 4. Testing result.

Testing		R2	MSE	MAE	MinEr	MaxEr
Heating Zone	RNN	0.9986	0.4333	0.5238	0.0000	2.9149
	LSTM	0.9985	0.4765	0.5534	0.0000	3.0319
	GRU	**0.9988**	**0.3698**	**0.4725**	0.0000	**2.7922**
Soaking Zone	RNN	0.9979	0.5029	0.5506	0.0000	4.0484
	LSTM	0.9985	0.3427	0.4470	0.0000	4.4355
	GRU	**0.9989**	**0.2706**	**0.3994**	0.0000	**3.2740**

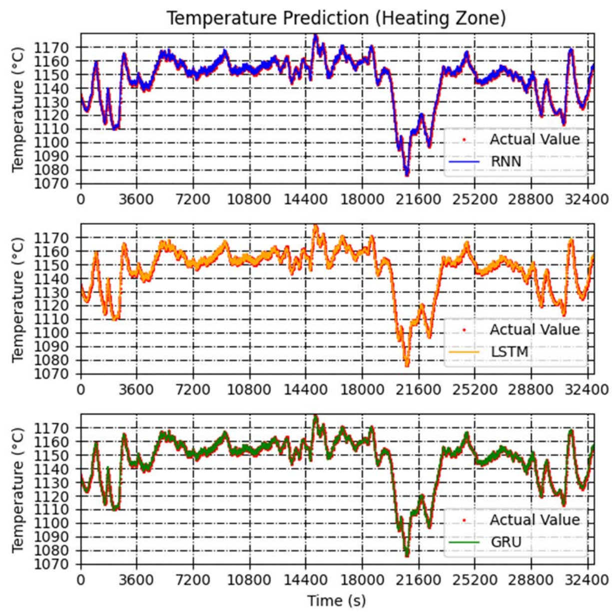

FIGURE 7. Temperature prediction of heating zone.

C. TESTING

In the testing step, compared the performance of GRU with RNN and LSTM. The RNN model selected parameters when the number of cells and layers were respectively 60 and 3 for heating zone, whereas for the soaking zone the number of cells and layers were respectively 90 and 3. The LSTM model selected parameters when the number of cells and layers were respectively 60 and 7 for heating zone, whereas for the soaking zone the number of cells and layers were respectively 60 and 3.

Fig. 7-8 displays the comparison between actual values and predicted data of the three models. The three models have good performance in predicting temperature, so the

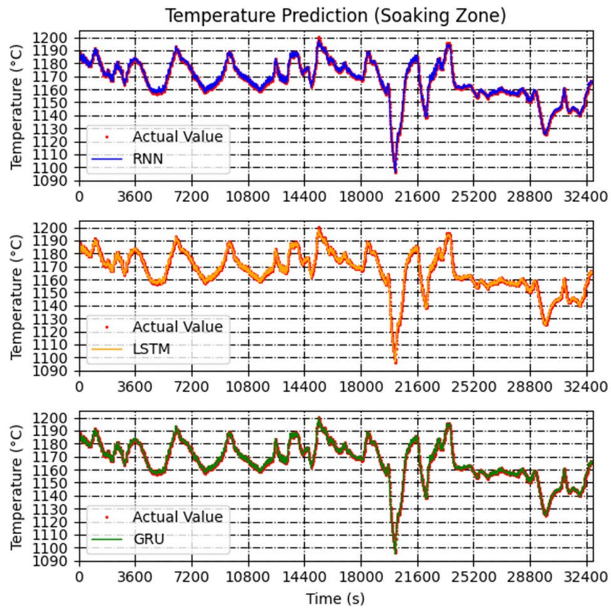

FIGURE 8. Temperature prediction of soaking zone.

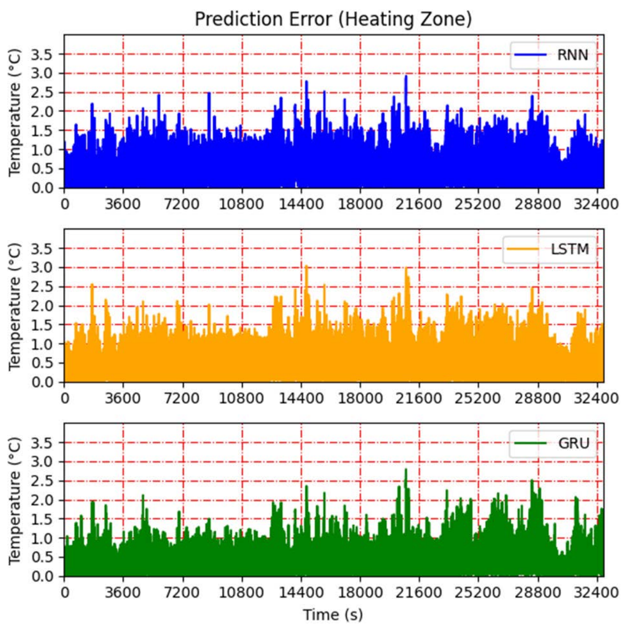

FIGURE 9. Prediction error of heating zone.

prediction curves are almost overlapping. To go a step further, we showed the prediction error of three models for each second in Fig. 9-10, and the prediction error is obtained from |o_i-y_i |. For a clearer comparison, the R^2, MSE, MAE, $MaxError$, and $MinError$ of each model are listed in Table 4. The R^2 for RNN, LSTM, and GRU are 0.9986, 0.9985, and 0.9988 in heating zone and 0.9979, 0.9985, and 0.9989 in soaking zone. The MSE of the three models are 0.4333, 0.4765, and 0.3698 respectively in heating zone, and 0.5029, 0.3427, and 0.2706 respectively in soaking zone. In addition, the MAE of the three models are 0.5238, 0.5534, and 0.4725 respectively in heating zone, and 0.5506, 0.4470, and 0.3994 respectively in soaking zone.

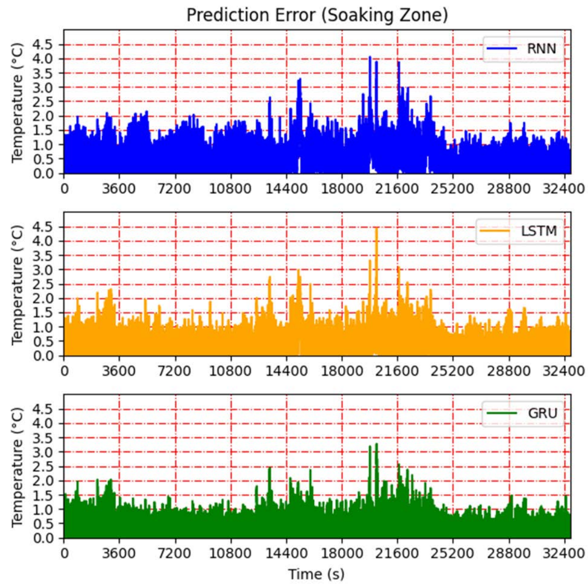

FIGURE 10. Prediction error of soaking zone.

Results show that RNN model is better than LSTM model for predicting temperature in the heating zone, but the LSTM model is better than RNN model for predicting temperature in the soaking zone. Compared GRU to RNN and LSTM, the GRU model has lower prediction error than those of the other models in the heating and soaking zone, it means the GRU model has more predictive performance in heating and soaking zone. The temperature varies of heating zone is more than soaking zone, so It's easier to get an accurate model of soaking zone. Besides, some other factors, such as the maximum error and minimum error of the model, it will also affect the choice of the optimal model.

D. PRACTICAL APPLICATION EXPERIMENT

Based on the analysis above, we selected the GRU model to combine feedforward in the PI controller, named the F-PI controller. The prediction model was executed on the host-computer, the proposed system architecture as Fig. 11. The host-computer implemented functions that are used to received features from PLC and feedback predicting temperature to PLC every 1 second. The tasks of PLC were collected information from on-site equipment, transferred features to the host-computer, and determined the position of the control valve. We conducted the prediction model as feedforward control, and evaluated control efficiency in the heating and soaking zone. There are many variables in the reheating furnace, so it's impossible if the same situation of the test.

The testing situation describe as

1) The steel type was SWRCH22A.
2) Slab Temperature before entry reheating furnace: 30°C $\sim$ 150°C.
3) Both set point of PI and F-PI controllers are 1080° in the heating zone.
4) Both set point of PI and F-PI controllers are 1152° in the soaking zone.

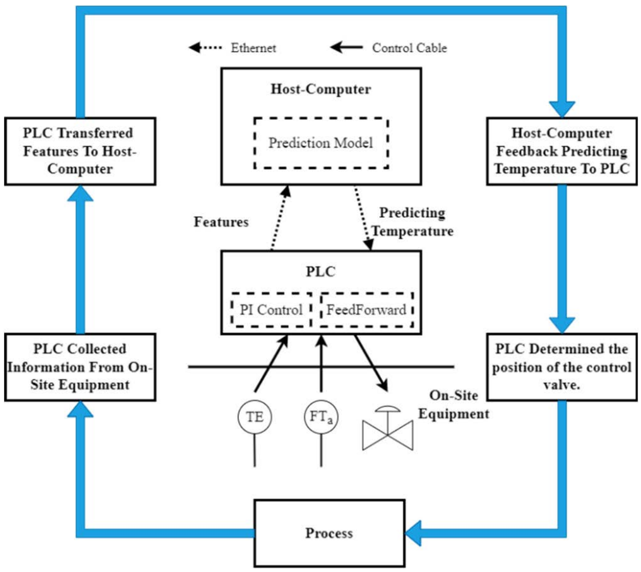

FIGURE 11. Proposed system architecture.

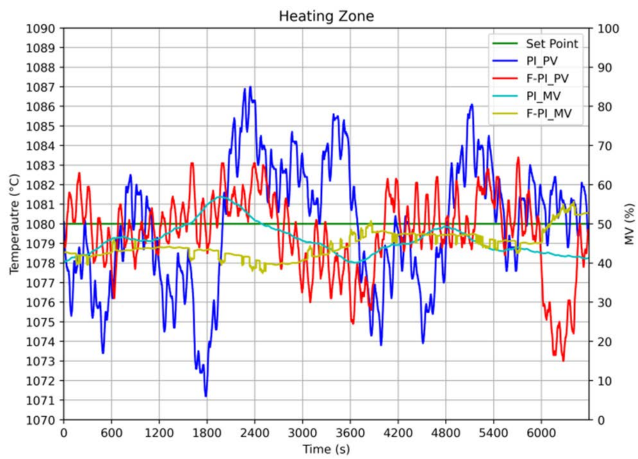

FIGURE 12. Control efficiency of heating zone.

5) Same parameters of controllers such as proportional and integral term.
6) Running times and production of the two control models are respectively 2 hours and 131.1 tons.
7) Measured temperature of thermocouple-2 is selected as TIC process value.

The set point is the target value for the combustion system, whereas the process value is the actual temperature in furnace of heating and soaking zone. The input variables are obtained from PLC then output predicting the temperature of 15th second of advance to PLC, this process was carried out every second.

Fig. 12-13 presents the control effectiveness of PI and F-PI (PI with feedforward) for heating and soaking zone. The results show that feedforward activation when temperature over or under set point $\pm$ 3°C, so the temperature could be heated up or down in advance. In addition, the temperature values more close to the set point for F-PI controller. However, the performance of F-PI is almost the same as PI controller in the soaking zone. Because of the temperature variation smoothly in the soaking zone, the feedforward is hardly enabled.

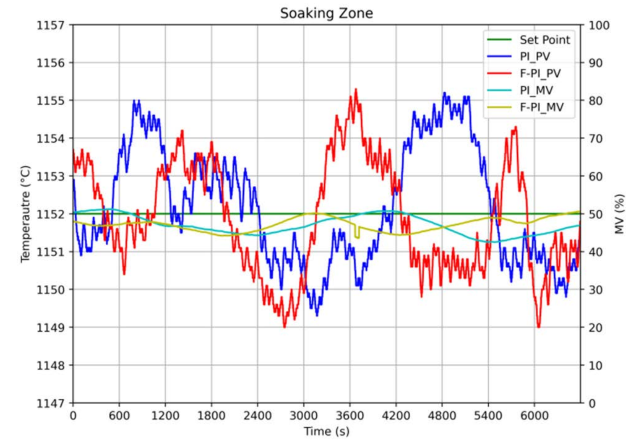

FIGURE 13. Control efficiency of soaking zone.

TABLE 5. Comparisons of performance for temperature control.

	Heating Zone			Soaking Zone		
	PI	F-PI	Improve	PI	F-PI	Improve
MAE	2.70	**1.57**	41.85%	1.32	**1.29**	2.27%
MSE	10.57	**4.39**	58.47%	2.37	**2.17**	8.44%
RMSE	3.25	**2.09**	35.69%	1.54	**1.47**	4.55%
MaxError	8.80	**7.00**	20.45%	**2.70**	3.00	-11.11%
MinError	0.00	0.00		0.00	0.00	
Total Fuel	18890.29	**18271.10**	3.28%	**9107.46**	9123.94	-0.18%

In heating zone, the *MAE* for PI and F-PI controllers are 2.70 and 1.57, the *MSE* for PI and F-PI controllers are 10.57 and 4.39, and the *RMSE* for PI and F-PI controllers are 3.25 and 2.09. In soaking zone, the *MAE* for PI and F-PI controllers are 1.32 and 1.29, the *MSE* for PI and F-PI controllers are 2.37 and 2.17, and the *RMSE* for PI and F-PI controllers are 1.54 and 1.47. The F-PI controller exhibited the lower *MAE*, *MSE*, *RMSE* and *MaxError* values in heating zone, whereas the lower *MAE*, *MSE* and *RMSE* values in soaking zone. This thus implies that the F-PI has more effective on temperature control. The aforementioned values are listed in Table 5. Notably, temperature smooth control affected fuel burnup possibility.

V. CONCLUSION

This study proposes an applied GRU model to forecast the 15th second inside temperature of the reheating furnace in advance, and feedforward control for heating and soaking zone. Compared with other dynamic models, namely RNN and LSTM models, the predictive performance of the GRU model significantly outperformed the other two dynamic models. Moreover, the combined predictive model with PI controller for feedforward of the combustion system of reheating furnace. Compared with PI controller, the proposed controller with feedforward provides more accurate control on temperature, it not only improves rolling mill production line stability but also reduces fuel burnup and carbon reduction possibility if the temperature is unnecessary.

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