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Real-time moisture control in sintering process using offline–online NARX neural networks

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ABSTRACT

Sinter is the main raw material for blast furnace iron making. To provide high quality sinter, the moisture content of the mixture in the sintering need to be in the best range. However, most of the sintering is still artificial water adding which leads to a great variation in the moisture content of the mixture. The present work proposes a sintering parameter identification model using a nonlinear autoregressive model with exogenous (NARX). By exploiting the real-time and historical performing data, we set up a mixture adding water model involved the water and the major mixtures among sintering. Then, a combination of offline deep supervisor learning and online self-learning NARX algorithm is proposed. Finally, in the experimental stage, the results suggest the proposed method can effectively predict the moisture with an acceptable degree of accuracy.

1. Introduction

The sintering of iron and steel industry is to mix iron ore, flux and fuel in a certain proportion, then add a proper amount of water and sinter on the sintering machine [1]. In sintering, water not only affects the quality of sinter, but also affects the production efficiency [1]. Therefore, water is one of the important causes that affect the sintering of iron and steel industry.

Iron ore sintering includes six steps (See Fig. 1): proportioning, mixing, ignition, breaking, cooling and screening. First, in the proportioning, these materials blend in proportion to form the raw mix. The silos store different kinds of iron ore, limestone, dolomite, lime, coke, blast furnace ash, dust removal and returned sinter. Second, in the mixing part, there are two mixers. The first mixing drum adds water to the raw mix and sends it to the second one. The second mixing is aimed at granulating. When the mixture falls on the conveyor belt, the moisture meter above the belt measures the water content. In step 3, a roller feeder carries out the mixture on the sinter machine. As the sinter trolley moving to the end, it reaches the sintering terminal and the sintering ends. In step 4, the sinter cake is broken up in a sinter breaker. Step 5 is sinter cooling. Finally, in the screen part, the qualified sinter is sent to the blast furnace. And the undersized sinter is sent back to the proportioning part as returned sinter.

Many studies have been made on the sintering process recently [2–5]. In sintering mixing research, Wu et al. [2] presents a three-step optimization method to find a coke ratio. In [3], the expert control scheme for moisture base of the expert system is built. But it relies on artificial experience. Wu et al. [4] proposed a model for on-line identification of two hard measured parameters: moisture content and evaporation coefficient of raw materials, by using a neural network for moisture control. By neural network PID controller, Giri and Roy [5] solves the mixture of water control in the presence of a lag problem. But the model of the system is difficult to determine.

Nonlinear large-scale systems control problems have attracted much attention in recent years [6–8]. In particular, Tong et al. [7] proposes a novel fuzzy adaptive output feedback decentralized optimal control scheme. The scheme nonlinear large-scale systems contain the unknown nonlinear functions and unmeasured states. NARX neural networks, popular in nonlinear control applications and other problems are as powerful as fully connected recurrent neural network [7]. NARX networks have a feedback which comes from the output neuron rather than from hidden states [9]. It has been successfully applied to many areas [11–14] such as NARX-Laguerre model [7], pattern classifier [10], proton exchange membrane fuel cell control [12], convergence bound in the frequency domain [14], etc. Some studies are improvements to NARX [15].

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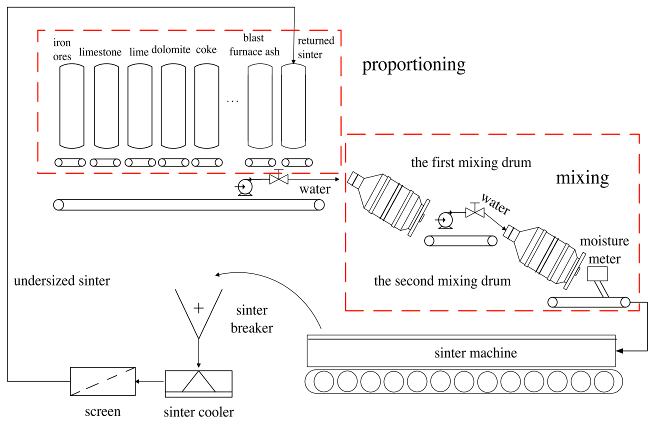

Fig. 1. Typical sintering process in iron and steel industry.

The present study focuses on the offline–online NARX algorithm for automatic control of mixture moisture. And the model has been applied to the actual industrial process. In an original approach, the two-stage NARX experimental modeling is introduced to real-time prediction and control for moisture in sintering. Since the optimal control strategy on the basis of complex nonlinear sintering system is difficult and time-consuming, we propose the deep learning model based on the massive historical data. On the one hand, the offline NARX model has captured most of the system behaviors, so it is not required to update largely or learn much in a short time. On the other hand, the online learning model emphasizes the learning and tracking the dynamics behaviors of the system in real time.

The remaining structure of this study is as follows. Section 2 states the problem to be investigated. In Section 3, the two stage NARX model is designed for parameter identification and moisture prediction. Section 4 compares the experimental results with modeling simulation results. Section 5 provides a conclusion and potential application for future work.

2. Description of moisture process in sintering mixture

In practice, for a real sintering process, the mixing machine is shown in Fig. 1. Different materials are mixed in the mixing machine into raw mix which includes slag, iron return fine, limestone, dolomite, quicklime, returned sinter, dousing ash, added water. The moisture content of the raw mix is measured by the moisture meter at the end of the second mixer. The relationship between the moisture content of the raw mix and different materials is

$$M(t) = \frac{\sum_{i=1}^{n} K_i(t) \times W_i(t) + D(t)W_r(t) + u(t)}{\sum_{i=1}^{n} W_i(t) + W_r(t) + u(t)} \tag{1}$$

where $M(t)$ is moisture meter value, $W_i(t)$ is the weight of the ith material, $W_r(t)$ is the weight of returned sinter, $u(t)$ is the water addition, $K_i(t)$is the moisture content of each material, $D(t)$ is the moisture of returned sinter,n is the quantity of material types. With direct computing, Eq. (1) leads to

$$u(t) = \frac{M(t) \times \left[\sum_{i=1}^{n} W_i(t) + W_r(t)\right] - \left[\sum_{i=1}^{n} K_i(t) \times W_i(t) + D(t) \times W_r(t)\right]}{1 - M(t)}. \tag{2}$$

For all the materials, affected by local weather, material sources, and product demand,$W_i(t)$, $K_i(t)$ $(i = 1, \ldots, n)$ change nonlinearly with time. For example, in summer rainy days, the increased moisture in the air can also cause the moisture content of the material, although the material is stored in the warehouse. The most important reason is the moisture content of returned sinter $D(t)$ is determined by the last raw materials. All these lead to a nonlinear relationship. Since the moisture content of the material does not change dramatically in a short time, the amount of water added at the next moment can be calculated according to the moisture at the previous moment. That is:

$$\begin{aligned} M(i+1) &= f_1[\omega_1(i), \omega_1(i-1), \ldots, \omega_1(i-d_x)], \\ \omega_1 &= [W_1, W_2, \ldots, W_n]^{\mathrm{T}}. \end{aligned} \tag{3}$$

So we can calculate the water addition by the follow formula

$$u(t) = \frac{[g - M(i+1)] \times \left[\sum_{i=1}^{n} W_i + W_r\right]}{1 - g} \tag{4}$$

where g is the target moisture value. In addition, the inertial characteristics of the mixer make a delay system. In the proportioning, the distance between the silo with various materials and the mixer is different, so the weight of each material measured at the same time point does not belong to the same water addition process. From the addition of water to the measurement of the moisture of the mixture, it takes two mixing processes that take about 8 min.

To identify the parameter in this process, we use NARX model (See Fig. 2). Moisture measurement value is the feedback quantity and target moisture are input into the NARX model. Then the controller adjusts the amount of water according to these parameters to complete the entire water addition process.

With the consideration of the nonlinearity, delay and other practical features of the sintering process, we employ a typical NARX to build the model. In Fig. 2, the control inputs are the target moisture and the material amount. With a large amount of historical operating data, we first set up a feed forward controller. This is an offline NARX deep learning process. The result of the offline deep learning is a parameter identification model. This can be seen as a substitute for artificial experience control and would be used at the online control stage.

During the online NARX control, the control input is target moisture, material amount and the moisture measurement value. The online NARX control is first determined by offline model. And then, it is adjusted with the NARX training process, until the modeling result meets the accuracy requirement. The resulting neuron number of the hidden layer was chosen to be five to ensure realization control in this process. We use moisture measurement value as the feedback quantity and target moisture are input into the NARX model. Then the controller adjusts the amount of water according to these parameters to complete the entire water addition process.

3. Offline–online NARX moisture control model

3.1. Architecture of NARX

NARX model is widely used for nonlinear dynamic system identification and modeling. A NARX is composed of several layers with feedback connections. The output of the system is fed back to the input for a fixed number of time steps. The mathematical formulation for the NARX model can be represented as [1]

$$y(n+1) = \varphi(x(n-d_x), \ldots, x(n-1), x(n), y(n-d_y), \ldots, y(n)) \tag{5}$$

where $x(n)$ and $y(n)$ are the input and output of the system at discrete time step n, $d_x \geq 1$ and $d_y \geq 1$ are the input and output mem-

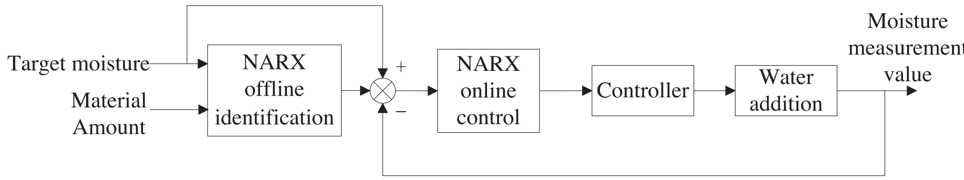

Fig. 2. Framework of water addition control process.

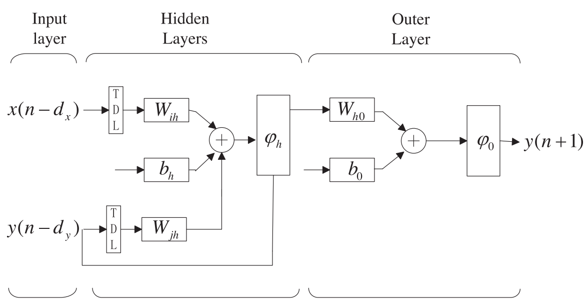

Fig. 3. Architecture of NARX.

ory orders respectively. $\varphi(\cdot)$ is a nonlinear mapping function. The output of the NARX can be fully written as [1]

$$y(n+1) = \varphi_0\left[b_0 + \sum_{h=1}^{Nh} W_{h0}\varphi_h(b_h + \sum_{i=0}^{d_x} W_{ih}x(n-i) + \sum_{j=0}^{d_y} W_{jh}y(n-j)) \right] \tag{6}$$

where W_{h0}, W_{ih} and W_{jh} are the network weight vectors, b_0 and b_h are the biases, φ_0 and φ_h are the activation functions of the output and hidden layers. There are two kinds of alternative architectures which are series-parallel architecture and parallel architecture. Fig. 2 depicts the series–parallel structure of a NARX neural network with one input layer, Nh hidden layers and one output layer respectively. d_x and d_y are the delayed inputs and outputs respectively. TDL represents the tapped delay line (Fig. 3).

3.2. Offline–online NARX mechanisms

For moisture control process, we propose a training method with a combination of offline training and online training. Offline training mode is used to establish the fundamental NARX model of moisture prediction. Online training mode is an enhancement for the fundamental NARX model. The basic training scheme is as follows. First, we take offline training for the NARX to obtain a fundamental model. Second, take an online training algorithm in place of the offline training algorithm to enhance the fundamental NARX. In other words, we firstly provide sufficient knowledge for the NARX under offline mode, and when the model works, we switch it to the online mode for self-learning.

Since there is historical operating data in the sintering control system which contains the amount of mixing, artificial water and moisture, we can take full advantage of it with an appropriate offline training algorithm to obtain a fundamental NARX model. Specifically, for the water addition control process, the input of the offline NARX network is composed of the mixing weight vector$x(n) = (x_1(n), \ldots, x_7(n))^{\mathrm{T}}$, added water weight $u(n)$ and the output moisture$y(n)$, as well as their delays. That is

$$\mathrm{Input}(n) = [x(n-d_x), \ldots, x(n), u(n-d_x), \ldots, u(n), y(n-d_y), \ldots, y(n)]^{\mathrm{T}}. \tag{7}$$

The NARX output is

$$\mathrm{Output}(n) = \hat{y}(n). \tag{8}$$

We consider offline NARX estimation via the Levenberg Marquardt (LM) algorithm for efficient supervised learning.

LM is a fast and reliable second-order local method, which combines advantages of steepest descent (first-order) and Gauss–Newton (second-order) methods. Thus, compared with other training methods, L M algorithm typically requires more memory but less time.

Its general weight updates for epoch $h+1$ can be expressed by

$$W_{h+1} = W_h - (H_h + \mu I)^{-1} J_h r_h.$$

Here, W is the weight matrix, h is the epoch, H stands for the Hessian matrix, μ is a variable scalar, I is the identity matrix, J represents the Jacobian matrix and r is the residual error vector. The Hessian matrix can be approximated as$H_h = J_h^T J_h$. When the scalar μ is zero, this is just Newton's method, using the approximate Hessian matrix. When μ is large, this becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift toward Newton's method as quickly as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function is always reduced at each iteration of the algorithm. In our model, the hidden layer of the neural network consists of 21 layers. And there are about 7 million training samples available.

Of course, if more historical operating data is taken to train our model, the problem may be avoided to some extent. But it is hard to make the model omniscient about the moisture of a real sintering process just base on its limited historical operating data. So an online self-learning mechanism for our model should be built. For online NARX model, the training set comes from real time data in nearly 8 min. The online learning rate should be relatively small value. On the one hand, the online learning mode emphasizes the learning and tracking the dynamics behaviors of the system in real time; On the other hand, the offline NARX model has captured most of the system behaviors, so it is not required to update largely or learn much in a short time.

4. Application to real-time moisture control

4.1. Input data pretreatment

All the input data used in the model comes from the server of the factory's real-time monitoring system. To make the results obtained are reliable, the data object we need to process is a full data record set for nearly two years (1.1.2016–31.12.2017) in the factory. The data recording step is 4 s. The total amount of data is 12,096,000 (See Table 1). As shown in Table 1, the moisture measurement is the output quantity of the control process, and the other materials are input quantities.

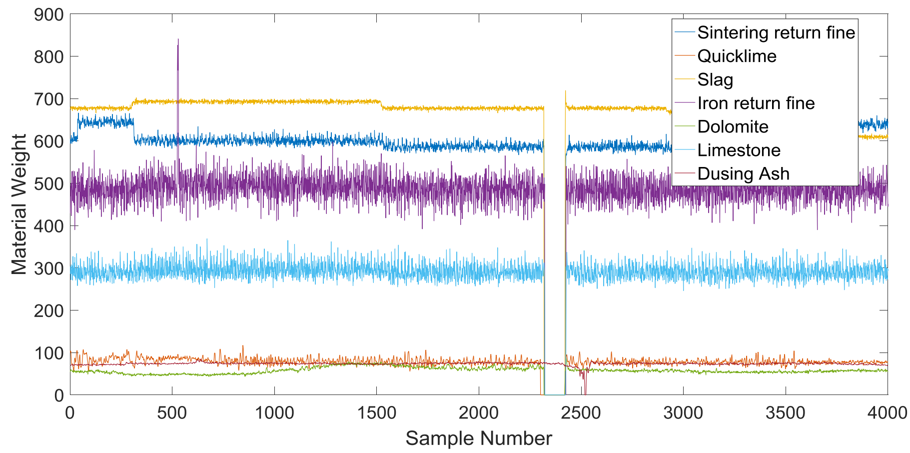

Fig. 4. Material weights in different scale sizes.

Table 1
Material quality and measurement moisture records.

Time (s)	Slag (t/h)	Iron return fine (t/h)	Limestone (t/h)	Dolomite (t/h)	Quicklime (t/h)	...	Added water (t/h)	Moisture measurement (%)
0	593	316	434	25	79	...	113	6.83
4	605	322	433	25	79	...	113	6.54
8	617	312	429	24	79	...	113	6.26
12	615	317	402	24	78	...	113	6.60
16	605	321	431	24	80	...	113	5.71
...	...	...	...	...	...	...	...	...

Table 2
Input and output variables in using narxnet.

Input variables								Output
x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	y
Slag	Iron return fine	Limestone	Dolomite	Quicklime	Sintering return fine	Dusing ash	Added water	Moisture measurement

The original data we deal with has 23 properties (corresponding to 23 kinds of materials). The principal component analysis was used to extract 7 kinds of materials as the main factors affecting the moisture of the mixture (See Fig. 4). This reduces the complexity of the NARX algorithm. Moreover, as shown in Fig. 4, the attribute data is in different magnitude scales. Therefore, the data should be normalized and outlier before use. Also, Fig. 4 shows the weight of these materials in mixing progress is not always stable. The material weight will greatly change, and the value of material even becomes to zero when the sintering machine stops working or returns to work. And measuring the moisture content of each material precisely is really difficult.

4.2. Offline NARX training and online real-time control

To obtain a fundamental NARX model, we use Matlab's narxnet structure with eight input variables as in Eq. (5). As shown in Table 2, the moisture measurement is the output layer in the narxnet, and the others are the input layers in the narxnet.

The hidden layer is set to 21 layers and the output layer with one neuron, trained using the LM algorithm (trainlm in Matlab). In the hidden layer a logistic sigmoid function has been chosen as the neurons' activation function. A linear function has been selected for the neuron of the output layer. During training, our dataset was divided into three blocks: 90% of data in the training sample, 5% in the validation sample and 5% in the test sample. The training was stopped when the forecasts for the validation sample ceased to improve significantly (See Fig. 5).

Table 3
Values of RMSE and RMSEr with different steps.

Time interval (s)	RMSE	RMSEr
4	2.01073e^−0	9.26925e^−1
8	3.30428e^−0	8.58377e^−1
12	4.73875e^−0	8.17515e^−1

In Fig. 5, at the left part, the blue line, green line and red line represent the mean squared error (MSE) of training data, validation data and test data respectively. Validation data modifies parameters of the model based on the training data. At the 9th iteration, the model has the best performance.

To evaluate sample values against predicted values, three error indices were used: coefficient of determination (R), root mean squared error (RMSE), relative root mean squared error (RMSEr). The coefficient of determination investigates the correlation between predicted and sample values. In Fig. 7, the scatter plots clearly illustrate that the NARX output value has a high correlation with the target value. The root mean squared error (RMSE) calculates the error variance independently from sample size (See Fig. 5 for detail). Relative RMSE helps to assess absolute RMSE values and makes comparison of different wells easier. A low value is

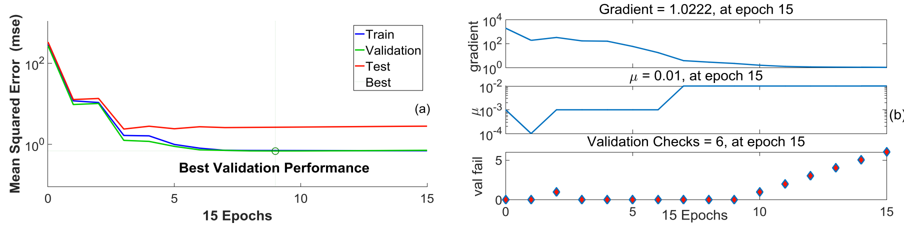

Fig. 5. (a) The best validation performance is at epoch 9; (b) The NARX training is terminated at 15 epoch.

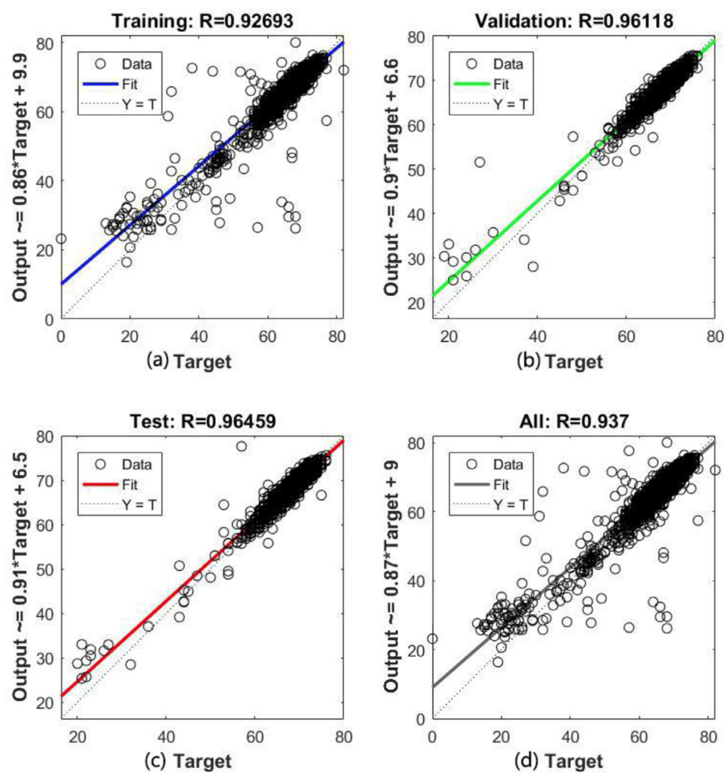

Fig. 6. Scatter plot of correlation between target and predict values.

best for RMSE and RMSEr (See Table 3 for detail)

$$R = \frac{\sum_{k=1}^{n}(x_k - \bar{x})(y_k - \bar{y})}{\sqrt{\sum_{k=1}^{n}(x_k - \bar{x})^2 \sum_{k=1}^{n}(y_k - \bar{y})^2}} \tag{9}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{n}} \tag{10}$$

$$RMSEr = \sqrt{\frac{\sum_{i=1}^{n}\left(\frac{y_i - \hat{y}_i}{y_i}\right)^2}{n}} \tag{11}$$

where x_k and y_k are the measured data, $\bar{x}$and $\bar{y}$ averages of data, n the number of sample.

In Fig. 6, the blue, green and red line represent the coefficient of determination (R) of training data, validation data and test data respectively. And black line represents the coefficient of determination of the whole data. We get the model of the moisture of mixture by training the training data, and use the validation data to prevent the model from overfitting. We use validation data to modify parameters of the model by small rate iteration, finally we determine the quality of the model by test data. The sintering progress is often stable. The weight of mixture will change when the sintering machine stops working or returns to work. This is the reason why the noise of scatter plots appears.

Table 4
Offline–online control moisture values.

Time(s)	Offline predictive values	Online control values	Target values
0	6.83%	6.71%	6.80%
4	6.54%	6.83%	6.80%
8	6.26%	6.69%	6.80%
12	6.60%	6.74%	6.80%
16	5.71%	6.77%	6.80%
...	...	...	...

For about the online real-time moisture control, in practice, take an online training algorithm in place of the offline training algorithm to enhance the fundamental NARX. We find that the performance of the NARX model on online mode improves slightly as expected compared with the model under offline mode (See Table 4). In term of this case, the NARX under online mode can learn and track the system dynamics, and adapt to the time-

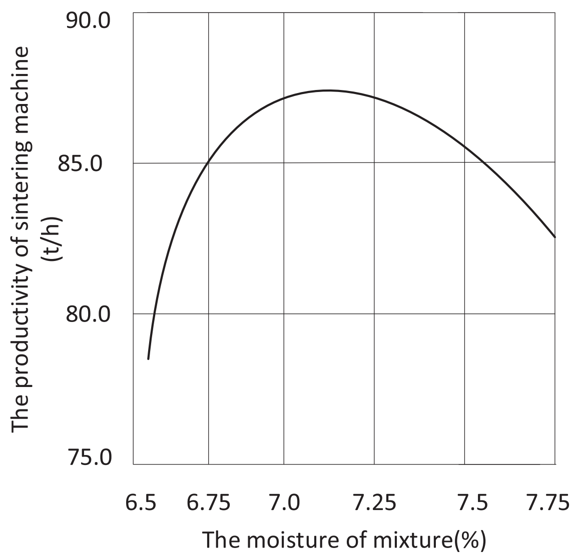

Fig. 7. Productivity of sintering machine.

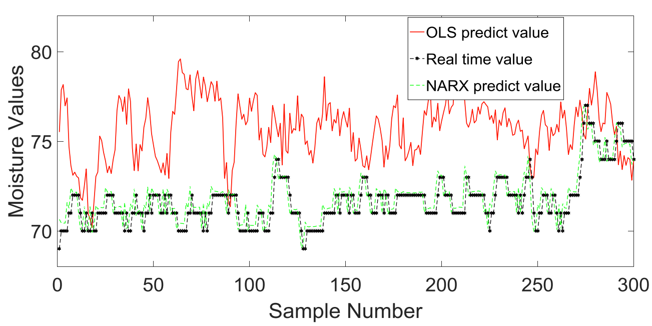

Fig. 8. Verification of offline–online NARX and OLS in moisture prediction.

Table 5
RMSE and RMSEr of two strategies.

	OLS	NARX
RMSE	10.0532e^−1	2.01073e^−0
RMSEr	12.3750e^−0	9.26925e^−1

variable demand and the real-time dynamics. Therefore, the improvement on performance is reasonable.

As is shown in Fig. 7, the efficiency of the sintering progress will satisfy our requirement, when the moisture content of the mixture is between 6.75% and 7.5% [16]. If the moisture content of mixture is below 6.75%, the index of granulation of mixture will be worse. Breathability and thermal conductivity of mixture will also be worse. In this situation, the max temperature will be not enough so that the quality of sinter cannot satisfy our requirement. If the moisture content of mixture is over 7.5%, the mixture will be very wet, which will hinder the flow of mixture. Breathability will be worse. The quality of sinter cannot satisfy our requirement. The Working condition will also affect the efficiency of the sintering process. Based on the artificial experience, the target value of moisture is 6.8%.

As is shown in Fig. 8, the red line and green dotted line represent the predict value by ordinary least square (OLS) [17] and NARX, respectively. The black line represents the target value. Obviously, the predicted value of the NARX model is closer to the target value. We learn that the RMSE is reduced to 2.01073e^−0, and the RMSEr is reduced to 9.26925e^−1 by utilizing NARX (See Table 5).

5. Conclusions

This study illustrates the application of NARX modeling technique for sintering moisture control process. By exploiting the real-time and historical performing data, considering the nonlinear and time delay, we set up an offline–online self-learning NARX algorithm to control the moisture in sintering process. In the experimental stage, the results suggest the proposed method can effectively predict the moisture with an acceptable degree of accuracy. Following study will make further effort to validate the model and combine an optimal control algorithm with it to realize real-time optimal control of the real moisture control process.

Acknowledgments

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