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Continuous Manufacturing Process Sequential Prediction using Temporal Convolutional Network

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Abstract

In the era of intelligent manufacturing, the continuous manufacturing industry will benefit from digitalization technologies such as digital twins. This paper proposes a temporal convolutional network sequence-to-sequence (TCN-StS) model as a data-driven simulation tool for the construction of digital twins. The proposed model captures time delay information through temporal convolution operation and thus better predicts the process state variations than recurrent neural networks on an actual industrial sintering dataset and shows good robustness over time. This study sheds new light on process sequence-to-sequence modelling through convolutional networks.

Keywords: sequence-to-sequence; temporal convolution; digital twin

1. Introduction

The continuous process is ubiquitous in steel, chemical, pharmaceutical, and other manufacturing industries. Prediction and operation decision-making in traditional continuous manufacturing processes rely on the knowledge reserve and cognitive level of operators, which severely restricts the safe and efficient operation of the production process. Over the decades, the soaring development of big data and artificial intelligence has brought transformational opportunities for the digitization of the process industry. The concept of digital twin (Glaessgen and Stargel, 2012; Gockel et al., 2012), initially proposed by the National Aeronautics and Space Administration (NASA), has recently been transplanted and deemed as the future solution to the manufacturing industry (Rosen et al., 2015).

Sequence-to-sequence modelling is the closest approach as a digital twin, as it uses the historical operation sequences to capture the dynamics of the process and predict the future evolution. Chou et al. first designed a sequence-to-sequence soft sensor model and performed excellently for product impurity predictions of an industrial distillation column (Chou et al., 2020). Kang et al also built a sequence-to-sequence model and achieved rolling predictions in the process of vapor-recompression C3 (Kang et al., 2021). Although canonical recurrent neural networks such as LSTMs and GRUs are considered by most deep learning practitioners synonymous with sequence modelling, Bai et al indicated that temporal convolutional networks (Lea et al., 2016) outperformed recurrent neural networks across a diverse range of tasks and datasets, while demonstrating longer effective memory (Bai et al., 2018).

These recent researches illustrate the importance of sequence-to-sequence modelling for the manufacturing industry and the potential of convolutional neural networks as a positive option for sequential modelling. This paper proposes a temporal convolutional network sequence-to-sequence (TCN-StS) model to achieve continuous manufacturing process sequential prediction. The model is applied to the sintering process in the iron-making industry and tested in an actual industrial dataset.

2. Methodology

2.1. Process description

The sintering process is an important thermochemical process in the blast furnace ironmaking system. It involves the heating of fine iron ore with flux and coke fines or coal to produce a semi-molten mass that solidifies into porous pieces of sinter with the size and strength characteristics necessary for feeding into the blast furnace.
This process is a typical continuous manufacturing process (Figure 1). Firstly, iron ore, coke, limestone, and returning sinter are mixed and then fed in a moving trolley to form a uniform sintering bed. Next, the igniter ignites the surface of the bed, and the blower under the moving trolley generates negative pressure in the bellow below the bed through the exhaust. As the trolley gradually moves to the end of the sintering machine, the combustion continues to develop downward (Zhou et al., 2019). In the end, the raw ore powder will gradually form sintered ore with a certain particle size, which will enter the subsequent blast furnace ironmaking production as iron material.

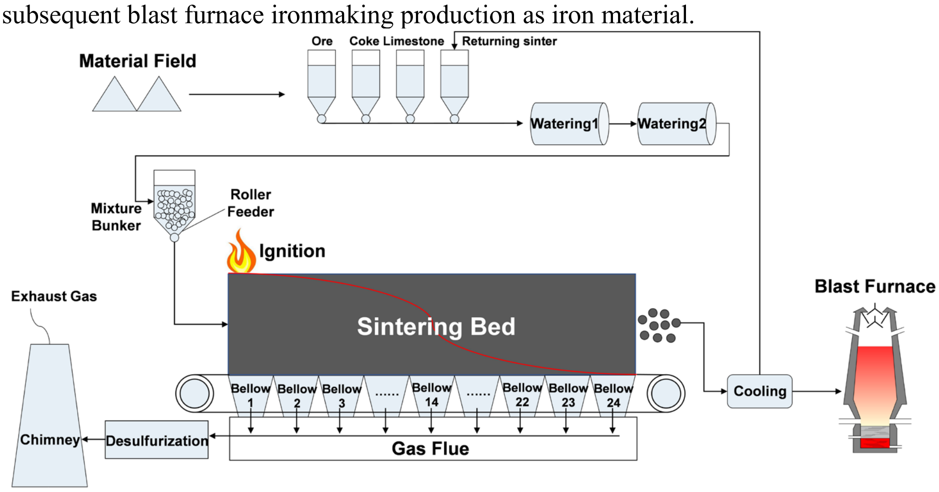

Figure 1. Sintering process schematic.

The sintering process owns the following two characteristics:

Time delay. There is a time interval between the change of process variables in the sintering system and its downstream variables, which is called mechanism time lag. In addition, for the same batch of raw materials, because different variables are measured at different times, there will be a technical time lag. The coexistence of the two types of time delays makes the sintering process exhibit strong time-delay characteristics.

Non-linearity. In the sintering process, a large number of chemical reactions such as coke combustion and limestone decomposition and a two-dimensional three-phase complex heat and mass transfer relationship exist at the same time, so the sintering system variables present obvious nonlinear relationship characteristics.

An industrial sintering process dataset of 27,000 samples was obtained and used in this study. The dataset was collected from 2019/12/05 to 2019/12/24 with a sampling frequency of 1 min. There are 15 key variables including 9 operating variables (OVs) and 6 state variables (SVs) in the process (Table 1).

Table 1. Key variables of the process.

Variable	Notation
Sintering bed thickness	OV1
Ignition intensity of row A	OV2
Ignition intensity of row B	OV3
Ignition temperature	OV4
Trolley speed	OV5
Round roller speed	OV6
Seven roller speed	OV7
Frequency of No.1 exhaust fan	OV8
Frequency of No.2 exhaust fan	OV9
Bellow 14 negative pressure	SV1
Bellow 22 negative pressure	SV2
Bellow 14 gas temperature	SV3
Bellow 22 gas temperature	SV4
End point of sintering	SV5
End point temperature of sintering	SV6

2.2. Temporal convolutional network sequence-to-sequence (TCN-StS) Model

The basic temporal convolutional network is a one-dimensional fully convolutional network with zero padding applied to make sure that the output sequence has the same length as the input sequence. To keep the convolution operation causal, which means for every i in {0, …, input_length－1}, the i-th element of the output sequence only depends on the elements of the input sequence with indices {0, …, i}, zero-padding is applied only on the left side of the input tensor.

Nevertheless, it is very challenging to apply basic causal convolution directly to long-term sequence problems due to its ability to look back only in a linear order in the depth of the network. Dilated convolution, which enables an exponentially large receptive field, eliminates this problem. Formally, for a one-dimensional sequence input $\mathrm{x} \in \mathrm{R}^n$ and a filter $\mathrm{f}: \{0, \dots, \mathrm{k}-1\} \rightarrow \mathrm{R}$, the dilated convolution operation F on elements s of the sequence is defined as Eq. (1).

$$\mathrm{F}(s) = (\mathbf{x} *_d f)(s) = \sum_{i=0}^{k-1} f(i) \cdot \mathbf{x}_{s-d \cdot i} \tag{1}$$

where d denotes the dilation factor, k is the filter size, and $\mathrm{s} - \mathrm{d} \cdot \mathrm{i}$ accounts for the direction of the past.

Besides, to avoid the gradient exploding/vanishing problems in deep neural networks, residual blocks with skip connections initially designed in ResNet (He et al., 2015) are used in TCN. The skip connection is a branch leading out to a series of transformations $\boldsymbol{F}$, whose outputs are added to the input $\mathbf{x}$ of the block as Eq. (2).

$$\mathrm{o} = \mathrm{Activition}(\mathbf{x} + (\boldsymbol{F}(\mathbf{x}))) \tag{2}$$

Within a residual block, two layers of dilated causal convolution, rectified linear unit (ReLU) activation, weight normalization, and spatial dropout are stacked. Figure 2(a) illustrates the TCN architecture.

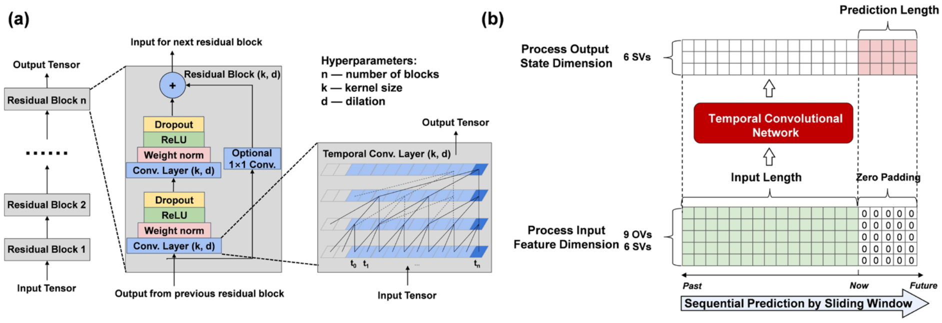

Figure 2. Proposed TCN-StS model. (a) Temporal convolutional network (TCN) architecture. (b) Sequence-to-sequence prediction demonstration.

A sequence-to-sequence prediction manner is proposed in Figure 2(b). At time T, a sequence of shape (input length, feature dimensions) are combined with zero values of shape (output length, feature dimensions). This sequence represents the history from time $(\mathrm{T}-\text{input length})$ to T. The model output is a sequence of shape (output length, output dimension) predicting the process state from time $\mathrm{T}+1$ to $(\mathrm{T}+\text{output length})$. Formally, the TCN-StS model produces the mapping as Eq. (3).

$$\hat{\mathbf{y}}_{\mathrm{T}+1}, \hat{\mathbf{y}}_{\mathrm{T}+2}, \cdots, \hat{\mathbf{y}}_{\mathrm{T}+\mathrm{out\_len}} = \mathrm{TCN\_StS}\left(\mathbf{x}_{\mathrm{T}-\mathrm{in\_len}}, \cdots, \mathbf{x}_{\mathrm{T}-1}, \mathbf{x}_{\mathrm{T}}\right) \tag{3}$$

3. Result and discussion

The dataset is split into 70 % training, 10 % validating, and 20 % testing. Each feature of the original dataset is standardized separately. The input feature dimension is 15 containing 9 OVs and 6 SVs while the output dimension is 6. An input length of 40 minutes is set according to the time delay of the sintering process and predictions are made by the TCN-StS model for the time length of 5, 10, 15, and 20 minutes.

Figure 3(a) presents a snapshot of sequential prediction for SV6. The prediction sequence shows good coincidence with the true sequence, especially at shorter prediction lengths such as 5 minutes and 10 minutes. The predictions shift away from the true values at longer prediction lengths. Two canonical recurrent neural networks, RNN and LSTM are adopted for comparison. The mean squared errors (MSEs) and mean absolute errors (MAEs) of the three models are given in Table 2. The TCN-StS model has lower MSEs and MAEs at all prediction lengths. The results indicate TCN-StS model outperforms recurrent neural networks at the sintering process sequential prediction.

Table 2. Sequential prediction accuracy of RNN, LSTM, and TCN-StS model.

Model	5 min		10 min		15 min		20 min	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
RNN	0.32	0.38	0.46	0.48	0.55	0.54	0.62	0.57
LSTM	0.30	0.37	0.38	0.44	0.50	0.52	0.54	0.55
TCN-StS	**0.26**	**0.33**	**0.36**	**0.40**	**0.41**	**0.44**	**0.46**	**0.47**

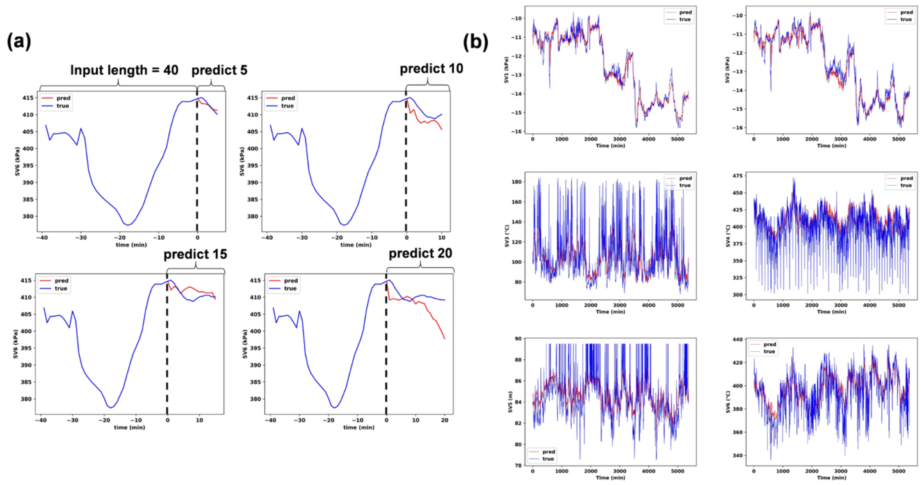

Figure 3. Prediction results. (a) A sequential prediction snapshot for SV6 at 5, 10, 15, and 20 minutes prediction length. (b) Prediction results at 10 minutes time points in the 10 minutes prediction sequence.

To better present the prediction performance over time, prediction results for each time point are extracted separately from the sequence. Figure 3(b) shows prediction results at 10 minutes time points in the 10 minutes prediction sequence. Prediction accuracies for each point in 10 minutes are shown in Figure 4. It can be found that as the prediction length increases, the prediction accuracy of all three models will become worse. For example, the TCN-StS model, with the average MSE of 0.36 and MAE of 0.40, shows the MSE and MAE of 0.24 and 0.33 at 1 min point, and 0.43 and 0.45 at 10 min point, respectively. The same growing trends are also found in RNN and LSTM models. Nevertheless, the TCN-StS model still has lower prediction errors than RNN and LSTM models at nearly all given time points, showing good robustness over time.

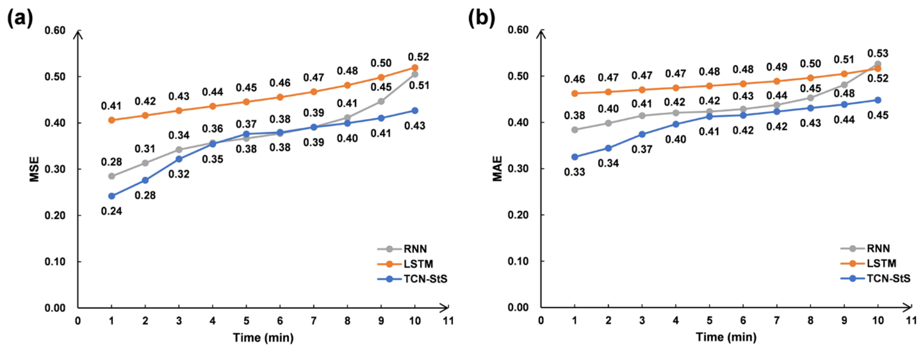

Figure 4. Prediction accuracy for each time point in the sequence. (a) Mean squared errors (MSEs). (b) Mean absolute errors (MAEs).

4. Conclusions

This paper designed a new convolutional-based sequence-to-sequence model architecture for continuous manufacturing process sequential prediction. Comparted to recurrent neural networks, the proposed TCN-StS model demonstrates better prediction accuracy at all given time lengths on an actual industrial dataset as well as a robust prediction capability over time. This study addresses the effectiveness of convolutional networks for sequence modelling and gives insights into utilizing sequence-to-sequence modelling as an effective simulation tool for constructing digital twins in the continuous manufacturing process.

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