Chapter 15
Control and Communication Coordination for Industrial Digital Twins of Sintering Process

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15.1 Introduction

The emergence of artificial intelligence and big data technology has greatly accelerated the process of intelligent manufacturing in factories and promoted the industrial production processes toward digitization, networking, and intelligence. However, due to the coupling of each industrial process, big data analysis without the inherent model is not suitable for the complex environment of the factory. Digital twins (DTs) can facilitate the data interaction between physical space and cyberspace by establishing the twin models mapping physical space and adjusting manufacturing parameters timely according to the simulation and prediction of cyberspace, so as to improve production quality [1]. DTs closely integrate model-driven automation with data-driven artificial intelligence technology, providing a new paradigm for the development of intelligent manufacturing.

Establishing digital twin models of industrial processes requires vast amounts of field data, which are generated by various sensors and actuators and need to be transmitted to the edge data center through the field-level industrial network. The coordination of control and communication depends on the timeliness and

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reliability of industrial networks. However, traditional protocols such as Fieldbus and industrial Ethernet cannot guarantee deterministic transmissions for time-sensitive data. Besides, these industrial network protocols are rather sealed and work for specific hardware devices. Therefore, **the first key issue** is how to improve the interconnection among devices and collect industrial field-level data efficiently by exploring deterministic communication technologies.

In order to guarantee the highly real-time transmission for large amounts of time-critical streams between cyber and physical systems, Time-Sensitive Networking (TSN) developed by IEEE 802.1 TSN Task Group[2], extending Ethernet for safety-critical and real-time applications, is the critical technology to guarantee the determinacy. Notably, IEEE 802.1Qbv [3] defines a programmable gating mechanism, i.e., the time-aware shaper (TAS), which employs the time transmission gate and gate control list (GCL) to determine which queues of flows are selected for transmission. Meanwhile, the time of all devices should be synchronized based on IEEE 802.1AS-Rev [4] to guarantee the successful TAS deployment.

However, the characteristics of industrial processes result in new challenges of TSN configurations. Firstly, there are large amounts of tasks in the industrial field that have high requirements of real-time transmissions, such as time-sensitive safety control data flows. Secondly, on-site sensors and actuators are diverse, audio and video data are frequently generated, leading to heterogeneous data streams, which are low time-sensitive (LTS) flows, audio–video bridge (AVB) flows, and so on. Besides, safety data is not time triggered, which should be scheduled with the highest priority. The co-existence of time-triggered (TT) and sporadic flows should be considered for scheduling.

The real-time control and communication coordination depends on scheduling for different flows. The scheduling problem for different priorities is very challenging, even with the specification of the time gating mechanism. For the schedule synthesis problem of TT flows in the TSN network, there are several existing modeling methods, such as integer linear programming (ILP) [5] or mapping the scheduling problem to Satisfiability Modulo Theories (SMT) [6, 7] problem and No-wait Job-shop Scheduling Problem (NW-JSP) [8]. However, the common assumption in these works is the fixed routing paths, which prevents spatial isolations for TT flows. Therefore, it is necessary to improve the schedulability of TT flows through the co-designing of transmission scheduling and route planning. Moreover, in order to improve the scalability (computational efficiency of scheduling method) of the scheduling approaches, the iterated scheduling methods were proposed in [9, 10]. Nonetheless, the stream relevance of these works was based on the intuitive correlations between streams, which lacked data analysis. Therefore, a more objective and precise stream relevance metric needs to be constructed for iterated scheduling in TSN. Except for TT flows, there are other heterogeneous data flows such as AVB flows with bounded end-to-end latency requirements. Gate control list (GCL) schedule synthesis approaches of TT flows taking AVB flows into account were proposed in [11–13].

Because the production process has the characteristics of numerous process parameters, complex mechanisms, significant nonlinearity, and dynamic changes, it is difficult to accurately model the process only by data collection. Therefore, after collecting a large amount of heterogeneous field data, how to build digital twin models in combination with the process mechanism to improve production quality is **the second key issue**. Some successful DT-based applications can predict various physical and chemical components [14–17], as well as predict the performance indicators [18–21], etc. However, existing works ignore the production process and equipment limitations in the actual production process. It is necessary to combine domain knowledge with data-driven intelligent modeling technology to achieve accurate modeling of physical systems and then achieve the prediction of key production indicators.

In addition, there may be thousands of models in the production process. How to achieve on-demand interaction and resource allocation between digital twin models to improve the performance of the product/process in the physical space is **the third key issue**. At present, there have been some results in related research on industrial digital twins. Lu et al. [22] applied the federated learning scheme to build a digital twin edge network. Through the asynchronous model updating scheme, the network not only reduces data transmission overhead but also protects data privacy. In [23], a digital twin model construction method based on federated learning is proposed, and the global model loss function optimization algorithm is given under limited resources. In [24], the construction of the digital twin model is abstracted as a computing task, and a communication and computing resource allocation scheme based on reinforcement learning is proposed to maximize the utilization of network resources. Dong et al. [25] established the digital twin of 5G mobile edge computing network, which applied the twin to train the resource allocation optimization and normalized energy-saving algorithm based on reinforcement learning offline and then updated the scheme to mobile edge computing network. However, the existing research is still at the preliminary stage. How to realize the quality prediction, control decision-making, and network resource optimization of the industrial process based on the constructed digital twin model and then realize the coordination of control and communication still needs in-depth research.

In the rest of this chapter, we propose a scheme of control–communication coordination for industrial digital twins as well as the key technologies of TSN and digital twin modeling. Section 15.2 introduces the network architecture to enhance the real-time control and communication coordination in the environment of the smart factory. For a sintering process described in Sect. 15.3, Sect. 15.4 presents the deterministic and real-time communication protocol based on TSN. Sections 15.5 and 15.6 describe the intelligent modeling of the sintering process and the construction of the corresponding digital twins with the assistance of TSN techniques. Section 15.7 concludes the chapter.

15.2 Control–Communication Coordination Architecture for Industrial Digital Twins

In order to meet stringent production requirements in intelligent manufacturing, various resources in industrial networks need to be efficiently scheduled and managed to achieve production-oriented control and communication coordination. By constructing the digital twin models of process and network, it can provide a new way of resource management for network systems and improve the efficiency of resource utilization. Besides, it can realize the monitoring and management of all factors in the industrial production process and real-time closed-loop control of the whole process and then significantly improve the intelligent level of manufacturing. To this end, we propose a digital twin-assisted control and communication coordination architecture as shown in Fig. 15.1, including Field Industrial Internet of Thing (IIoT), Edge Data Middle Platform, and Industrial Cloud Platform. The whole architecture is optimized in a closed loop through bottom-up information flow and top-down control flow.

In the field IIoT, we deployed a large number of sensing devices (temperature sensors, pressure sensors, infrared thermal imagers, vibration sensors, etc.), transmission nodes (TSN switches), and control devices (PLCs) to monitor the production status of the sintering process. The modeling of the digital twin requires the real-time acquisition of a large number of production data. Therefore, we adopt TSN as the backbone of the architecture to ensure the reliable transmission of field

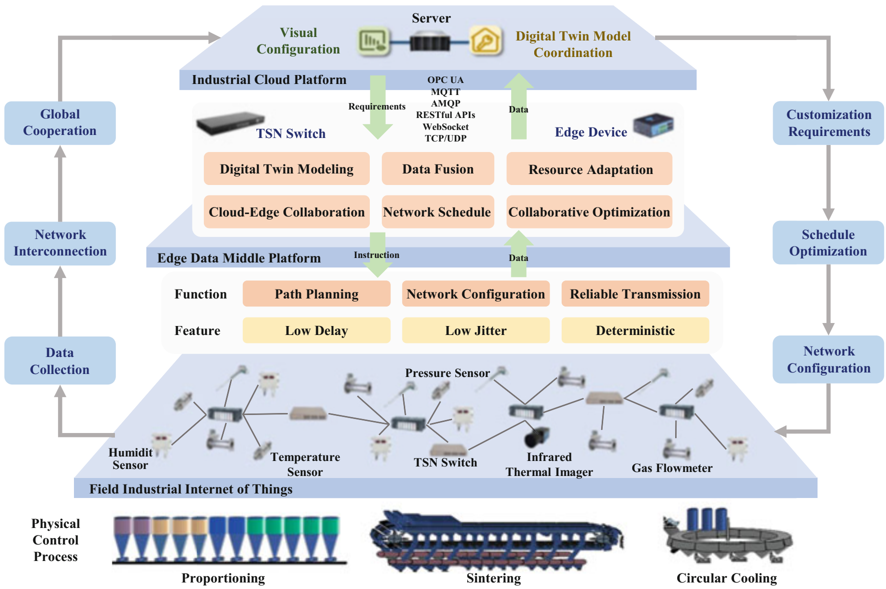

Fig. 15.1 A digital twin-assisted control and communication coordination architecture

perception data, which can meet the network transmission quality requirements of 1-ms delay and 1-μs jitter. At the same time, to ensure the performance of heterogeneous data transmission, some multi-priority data scheduling mechanisms are proposed. After receiving the path planning instruction from the TSN switch at the edge layer, the field layer TSN switch configures the network to achieve reliable transmission on demand. This layer ensures the data penetration of the whole sintering process and the acquisition of high-quality data (low data packet loss rate, accurate data time label, etc.), thus reducing the difficulty of data pretreatment and improving the reliability of algorithms.

The edge data middle platform is deployed with TSN switches for communication and edge devices for control and computing. The management and virtual mapping of production factors such as network, process, and equipment are all completed at this layer. In order to realize the integration and unification of massive scattered and chaotic multi-source data, edge equipment analyzes and processes the data according to the obtained multi-dimensional information and constructs digital twin models of different units based on process mechanism and expert experience to achieve accurate characterization of the production process. At the same time, the quality prediction, quality optimization, and quality traceability models are constructed. The path and network resources are dynamically adjusted according to the requirements of the upper layer. The configuration instructions are issued through the TSN switch to achieve cloud–edge collaboration. Network adaptation reduces the energy consumption of node communication, improves the utilization rate of network resources, and lays a foundation for control performance under dynamic resource conditions. With the support of digital twin technology, the edge data middle platform not only supports more intelligent and flexible system decisions of the top layer but also supports broader and more agile perceptual control of the bottom layer.

In the industrial cloud platform, based on the built digital twin models, a digital twin network for key processes is constructed. Physical entities and various service applications are connected through standardized north–south interfaces. When facing different production needs, the industrial cloud platform can schedule multiple digital twin models on-demand to build a virtual testbed, which can be used to dynamically optimize production resources and adjust and match network optimization schemes. The virtual testbed can efficiently simulate complete process for optimization and then deploy to the industrial site after full verification with the help of optimization algorithms, management methods, and experts' knowledge. Finally, it realizes the re-optimization of process flow, improving production efficiency, and achieves intelligent decision-making and efficient innovation. This layer pays more attention to the comprehensive utilization of field information. With the help of the flexible scheduling of the digital twin model, the resource demand can be predicted accurately, and the communication and control cooperation mechanism between the edge layer and the field layer can be designed. Then, the device states and resource arrangement can be adjusted timely through the feedback of the network operation state to improve and optimize the overall performance. In the bidirectional action, the potential factors of production are connected with the task requirements of the upper layer to meet the demands of intelligent production of the sintering process.

15.3 Sintering Production Line

The process of sintering production is a method of heating powdery materials at a high temperature and sintering them into blocks under incomplete melting conditions. In this process, under the action of a certain high temperature, the surface of iron ore particles softens and melts to produce a certain amount of liquid phase, and they act with other unmelted ore particles. After cooling, the raw materials in the liquid phase solidify and bind into blocks. This process is called sintering.

Obviously, the sintering process is a blocking process in high temperature with complex physical and chemical reactions. The obtained product is called sinter ore and they present irregular pores. The heat energy required for sintering is provided by burning the carbon introduced by material proportioning and the excess air introduced by the exhaust bellows. During this whole process, a series of procedures should be considered such as the materials proportioning, mixing, sintering, crushing, cooling, sifting, and waste gas treatment. Taking the 3 #360 sinter plant of Guangxi Liuzhou Iron & Steel (Group) Company as an example (Fig. 15.2), the sintering production process is briefly introduced.

The first procedure of sintering is mineral proportioning. In order to ensure physical properties, chemical composition stability, and proper permeability of the sintering process, it is necessary to accurately mix multiple iron-containing raw materials and add flux and fuels, according to the quality requirements of sintering product. A well-performed proportioning enables high productivity of blast furnace ironmaking. Generally, the linear programming method can be adopted in sintering proportioning optimization. The optimization output is usually the optimal ratio of chemical composition, such as the TFe, MgO, and R of sinter ore under certain objectives. There are other algorithms for sintering proportioning, such as the Monte Carlo method and genetic algorithm.

The second procedure is the sintering process. Firstly, the sintering feed is carried out, that is, the hearth layer and the sinter mixture are evenly placed on the sintering strand in turn (the hearth layer for sinter is at the bottom of the sinter mixture). Then, ignition and thermal insulation are carried out by coal gas. As the sintering pallet travels toward the end of sinter machine, the sintering is performed from top to bottom under the action of air suction by the sinter bellows. Generally, the materials in the sinter strand can be divided into sinter layer (product), combustion layer, preheating and drying layer, over wet layer, and original sinter ore layer (sinter mixture) from top to bottom. After ignition, five layers appear one after another and move downward. Finally, when the sintering strand moves to the end of the sintering machine, the combustion belt just reaches the bottom of the material layer in the vertical direction of the pallet.

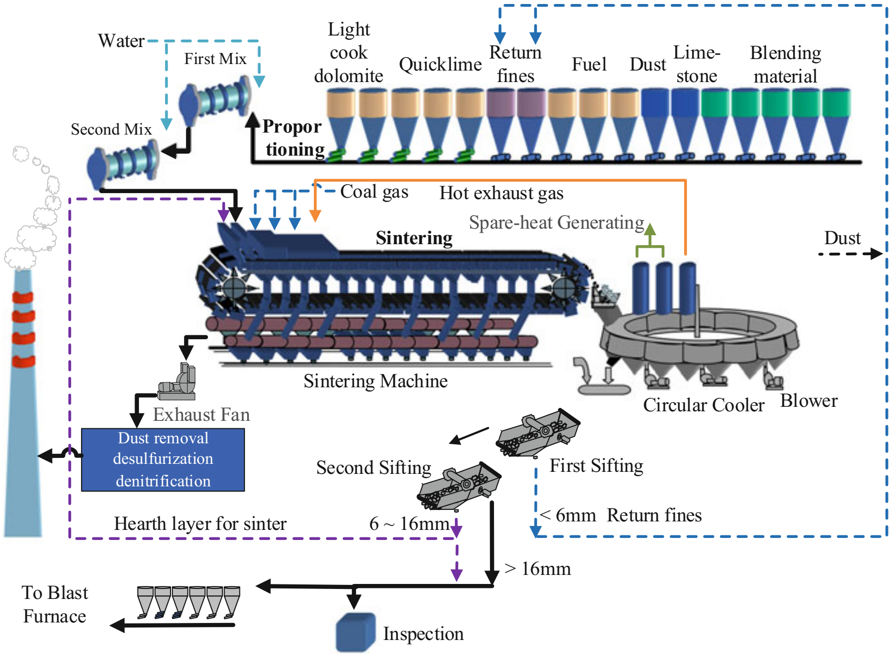

Fig. 15.2 The illustration of the sintering process

At the end of the sintering pallet, the sinter ore falls and is crushed by single roll crusher. After that, considering the high temperature of the sinter ore, it is firstly cooled before being discharged to the belt conveyor. The cooling is undertaken by the circular cooler. After cooling, the sinter ore is transferred to the screening system by belt conveyor. In addition, for the sinter ore as the product of sintering, it is also necessary to collect samples and conduct physical and chemical inspection before they are sent to the blast furnace.

The quality of sinter ore directly affects the quality of iron. Among the evaluation indices of sinter quality, tumble strength (TS), ferrous iron content, total iron, and alkalinity are the most critical. TS reflects the physical strength performance of the sinter, which is used to evaluate the abrasion resistance, collision resistance, and low-temperature reduction pulverization rate of sinter [26]. And the content of FeO of sinter ore reflects the chemical properties, which can be used to evaluate the reducibility of sinter. Higher TS is always accompanied by a high content of FeO, which will reduce the reducibility of the sinter ore and prolong the smelting cycle of sinter ore in the blast furnace. On the contrary, lower TS can increase the powder content of sinter ore and have a negative impact on the blast furnace smelting. Both of them will cause a lot of economic losses.

15.4 Deterministic Communication Based on Time-Sensitive Networking

For digital twin models, the synchronization performance of virtual–real interactions is critical due to frequent data interaction between digital twins and physical systems. Thus, the deterministic and real-time transmission of large amount of time-sensitive data is the key to ensure the performance of the digital twin model. Traditional Ethernet cannot provide deterministic and real-time guarantees due to the best-effort (BE) services, and several real-time Ethernet variants are proposed by corresponding organizations to enhance the real-time property of Ethernet. However, these standards are mostly close to each other and require special hardware support, which causes poor interoperability. TSN, an Ethernet extension breaking these limitations, aims to provide deterministic delay and low jitter for time-sensitive industrial applications.

There are vast types of flows, which include low time-sensitive (LTS) flows with bounded end-to-end delay requirements like audio–video bridging (AVB) flows, and BE flows with no time guarantees. For example, in the sintering process, there are mixture moisture data obtained by the infrared moisture analyzer between two mixing cylinders, high-resolution camera data, sintering machine temperature, Trolley speed data, waste gas temperature, and concentration of the components data, which have different priorities. Although the TSN standard specifies the behavior of the time gating mechanism, the schedule synthesis to achieve the differentiated transmission in the same physical medium under the TSN network for multiple types of flows with different priorities is still challenging.

To improve the schedulability of scheduling instances for TT flows, we propose a co-design approach of transmission scheduling and route planning for TT flows with considering queue assignment [27]. Specifically, the complete co-design constraints of multi-queue scheduling and route planning with deterministic and low delay guarantees are constructed for TT flows, which include queue assignment, conflict avoidance, stream sequence, and real-time and routing constraints. The queue assignment constraint describes the mapping relationships between queues and TT flows on egress port of TSN switches. The conflict avoidance constraint guarantees the deterministic forwarding behavior of TT flows on the egress port, which consists of windows-domain non-overlapping and frame isolation constraints. An illustrative example of conflict avoidance constraint is depicted in Fig. 15.3. The real-time constraint is constructed to ensure that the end-to-end delay of TT flows is lower than the corresponding deadline. The stream sequence constraint describes the transmission sequence of TT flows from talker to listener, i.e., the transmission of TT flows must follow the sequential order on the transmission routing path. The routing no-loop constraint is constructed to avoid the closed loop of the transmission path. Then, the constraint satisfaction problem (CSP) is mapped into SMT problem by an improved mapping method based on Listeners, which solves the indefinite routing problem caused by the introduction of route planning.

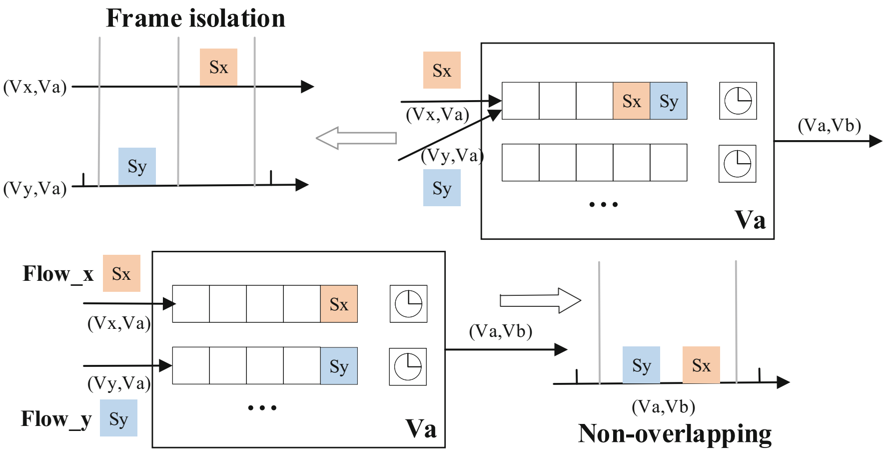

Fig. 15.3 The illustration of conflict avoidance on a shared link

Due to the high computational complexity of TT flows scheduling problems in TSN (i.e., NP-Complete), the above approaches are time consuming and thus are suitable for small and medium scheduling instances. The iterated scheduling methods are proposed for improving scalability (computational efficiency of scheduling method). To construct a more objective and precise stream relevance metric for iterated scheduling in TSN, a semi-supervised learning approach [28] on stream partitioning for iterated scheduling is proposed. Specifically, a large-scale TT stream unlabeled dataset and a small labeled dataset of all possible stream attributes that may influence each flow set's final schedulability are first constructed. The labels are the schedulability under different stream partitioning settings. The stream attributes include a period, a size, a deadline, the number of frames, packets, queues, a sender, a receiver, and a link speed. The scopes of TT stream attributes are selected according to the typical industrial automation applications in the white paper [29] to cover realistic scenarios.

Based on the large-scale TT flow unlabeled dataset, a sparse autoencoder (SAE) is proposed to obtain a sparse and low-rank representation of stream attributes, representing the original input signal to the greatest extent. However, this low-rank representation can only reconstruct the input signal now without any capability of signifying the stream relevance or conflict degrees. Thus, a classifier is added at the SAE top encoding layer and fine-tunes the learned SAE with labeled samples provided in the TT flow labeled dataset. Then, an objective and pervasive evaluation metric on TT flow relevance is constructed based on the low-rank representation of each TT flow without any prior domain knowledge requirements. The evaluation metric on stream relevance provides a data-driven measurement for subsequent stream partitioning. Moreover, the metric can be an additional term on stream relevance or conflicts to guide stream partitioning method such as graph-based approaches and clustering approaches, if accurate domain knowledge is available.

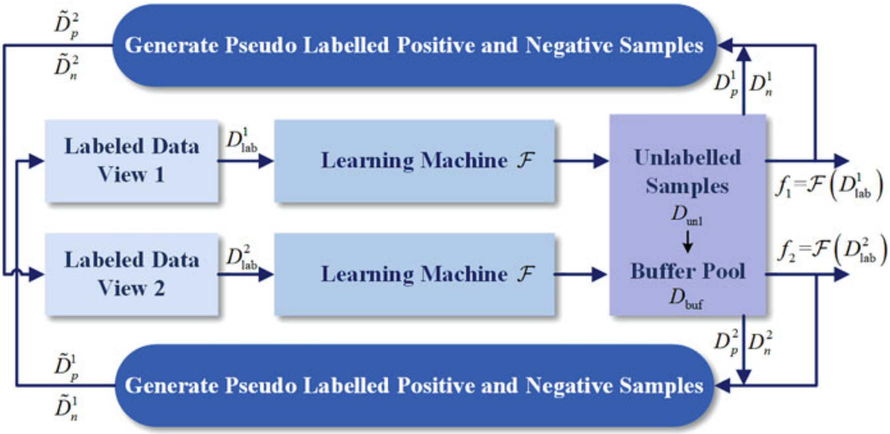

Fig. 15.4 The illustration of the semi-supervised co-training method

To explore a large amount of unlabeled data, a semi-supervised co-training method is proposed to exploit the multi-view relationship of time-triggered stream partitioning, as shown in Fig. 15.4. Each labeled flow set is separated into two views, in particular, divide the streams into two groups on average. To start with, a small portion of labeled training samples is used for learning and stored as the original models. Then the LLR of unlabeled samples is extracted and the pseudo labels are generated by the original models. Next, the original learning models are fine-tuned using an updated training set, which contains labeled training samples and unlabeled training samples with pseudo labels. At last, the second and third steps are iterated until the updated training set becomes stable. The extensive experiments on the TT flow dataset are constructed to demonstrate the effectiveness and performance of the proposed SSL-SP approach, which includes the schedulability comparison, effect of classifiers, dataset size, and parameter setting. The proposed SSL-SP approach obtains the highest schedulability on the TT flow dataset compared to existing iterated scheduling methods.

Nevertheless, the above works focus on the scheduling problem of TT flows from different aspects without considering the impact of TT flow schedule on other flows like AVB flows with bounded end-to-end latency requirements. To achieve the transmission in the same physical medium under TSN network for TT flows, LTS flows, and BE flows, the work [30] proposes a transmission framework by coordinating TAS and cyclic queuing and forwarding (CQF) simultaneously. Under this framework, TT flows are scheduled on the premise of reducing the impact on periodic and aperiodic LTS flows. The flows transmission architecture on the egress port of TSN switch is depicted in Fig. 15.5. The TT flows (i.e., HTS flows), LTS flows, and BE flows are buffered in the egress queue based on the priority mapping table (i.e., assigned internal priority value) and forwarded to the next TSN switch or the nearest edge computing (EC) device based on the predefined GCL schedule.

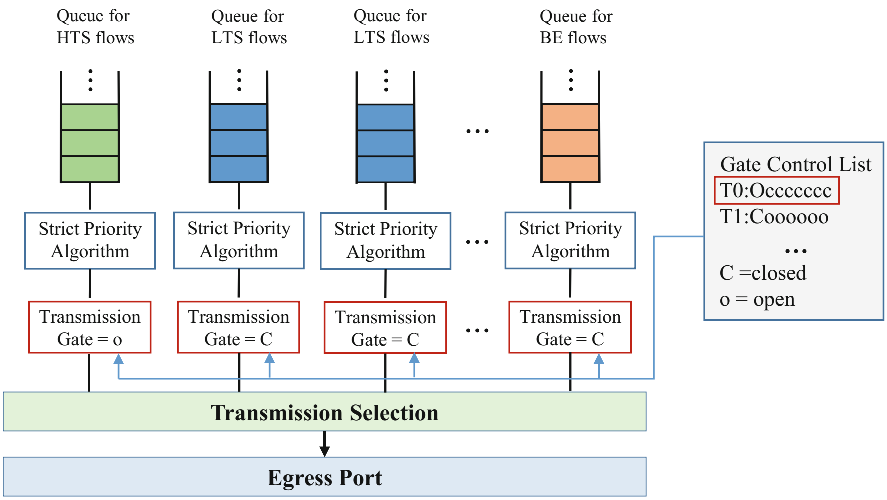

Fig. 15.5 Mixed flows transmission at the egress port of TSN switch

Specifically, the network designer provides the flow sets, including the crucial parameters such as the lower bound and upper bound of the sampling period, the class measurement interval of LTS flows, length of the frames, etc. The network designer then chooses the cycle time and scheduling unit if the flow sets are schedulable. Otherwise, the network designer needs to tune the flows sets by changing the network topography or adding other TSN switches. The network manager then formulates and solves a constrained optimization problem, whereby the objective function is the estimated average delay of LTS flows on the premise of ensuring the constraints of the LTS flows. The decision variable represents the packet injection time of HTS flows. If there exist feasible solutions to the scheduling problem, then the schedules of HTS flows can be generated by the feasible solutions otherwise tune the flows sets. Finally, by merging the schedules of HTS flows and LTS flows, the configurations of the specific egress port on the TSN switch are finished.

To make the coordinated transmission framework practical and achieve fine-grained scheduling of HTS flows, a parameter selection approach is developed by choosing the proper cycle time and the minimum scheduling unit. Moreover, to further reduce the average delay of LTS flows under the coordinated transmission framework, a scheduling problem by planning the packet injection time of each HTS flow is formulated. And then, an injection time grouping algorithm (ITG) is designed by grouping flows of the same period to reduce the computation complexity. Simulation results show the effectiveness of the ITG algorithm.

15.5 Intelligent Modeling for Sintering Process

As described in Sect. 15.3, the prediction of key indicators is crucial to the quality control of sinter. Taking TS as an example, high TS reduces the reducibility of the sinter ore, while low TS results in low strength. Both cases will cause dramatic economic losses. Therefore, designing the prediction model of key indicators to maintain them within an appropriate range in practical production not only has positive impacts on the production of the blast furnace in the aspect of quality and quantity but also helps reduce cost.

However, the sintering process is usually non-linear in view of its industrial chemistry, physical, and mechanical components. Besides, the invisibility of the process and the various time lags make the prediction of the content of TS and FeO nontrivial. In order to achieve accurate quality prediction, the mapping relationship between key indicators and process parameters should be explored, and the mechanism model of the process should be established. At the same time, inspired by machine learning and big data technology, data-driven methods become effective for establishing quality prediction models, which can handle nonlinear approximation problems well. More and more studies begin to focus on data-driven quality prediction in industrial applications.

In terms of TS prediction, some scholars integrated artificial intelligence methods for TS prediction [14–17]. The idea of these hybrid ensemble prediction methods were mainly divided into two types. One is to establish a TS prediction model and then optimize the parameters in the model [14, 15]. The other is to process the data first to weaken some characteristics and then use the processed data to establish prediction models [16, 17]. The data-driven modeling method is not restricted by strict mathematical assumptions and constraints and can reflect the complex relationship between sintering data, which makes the data-driven TS prediction more accurate.

However, the current research work on TS prediction has the following three restrictions. First, the previous works ignore the non-uniform distribution of sintering materials along the width of sintering bed in the practical production process, which makes the low prediction accuracy and cannot satisfy the actual requirements for sub-regional parameters control in sintering production. Second, limited by the capabilities of sensors, the data and features obtained from sintering site are limited. It is difficult for data-driven methods to use data with limited features to establish accurate prediction models. Third, the previous works ignore the inherent time delay in the sintering process and the TS detection process, which means that the data of the same time tag cannot represent the production process of the same batch of sinter materials. Furthermore, the TS prediction model established by the mismatching input and output data will lead to low prediction accuracy. In general, the previous work deviated from the actual production to a certain extent.

To solve the above problems, we proposed a novel TS prediction scheme and a data-driven TS prediction model in [31]. The TS prediction scheme is shown in Fig. 15.6. First, considering the non-uniform distribution of materials in the

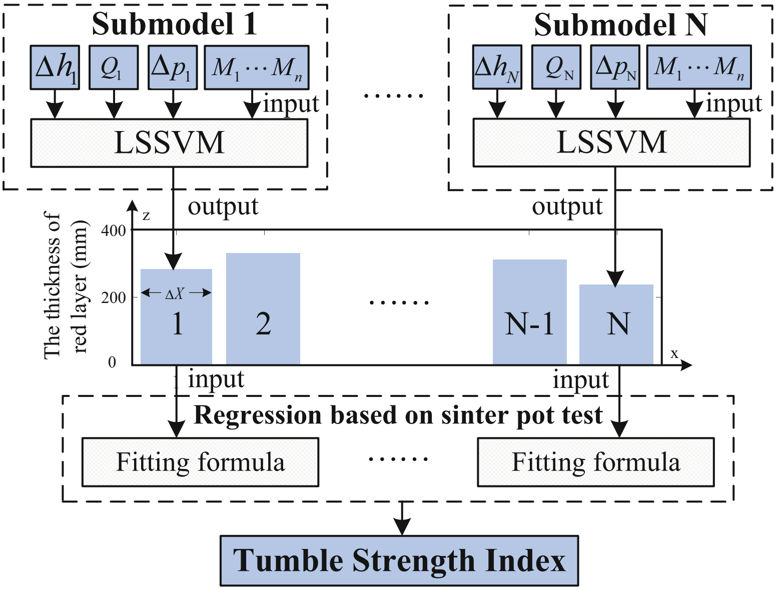

Fig. 15.6 TS prediction scheme

sintering bed and the inherent time delay in the sintering and TS measuring process, we combined local thermal non-equilibrium (LTNE) to establish the TS model (15.1):

$$TS(t + t_f + t_c) = \frac{\int_0^{X_f} \int_{Y_s}^{Y_f} \int_0^{h(t,t_c;x,y)} g(\Delta h, Q, \Delta p, M_1, ..., M_n; x, t) dxdydz}{\int_0^{X_f} \int_{Y_s}^{Y_f} \int_0^{h(t,t_c;x,y)} dxdydz}, \quad (15.1)$$

where t_c is the cooling time, t_f the time gap between the head and the tail, Q the air volume, Δh the height of the mixed materials, Δp the pressure of bellows, and $M_1, ..., M_n$ the composition of sintering mixed materials. The model was more in line with the actual sinter production. Based on the TS model, Q, Δh, Δp, $M_1, ..., M_n$ were selected as the inputs of TS prediction model. Based on the TS model, a more practical data-driven TS prediction scheme for on-site application is proposed. To satisfy the requirements of sub-regional parameters control, the sintering bed is divided into several segments along the width direction, and the TS value in each segment is predicted. This scheme made the TS prediction value worthier for practical sinter production.

To solve the problem of inaccurate modeling caused by limited data features, the thickness of the red layer of the sintering bed tail section was introduced as an intermediate variable, and the sinter pot test data was used to expand the limited feature. By setting up an infrared thermal imaging camera at the tail of the sintering bed, the red layer information was obtained and processed in time, so as to obtain

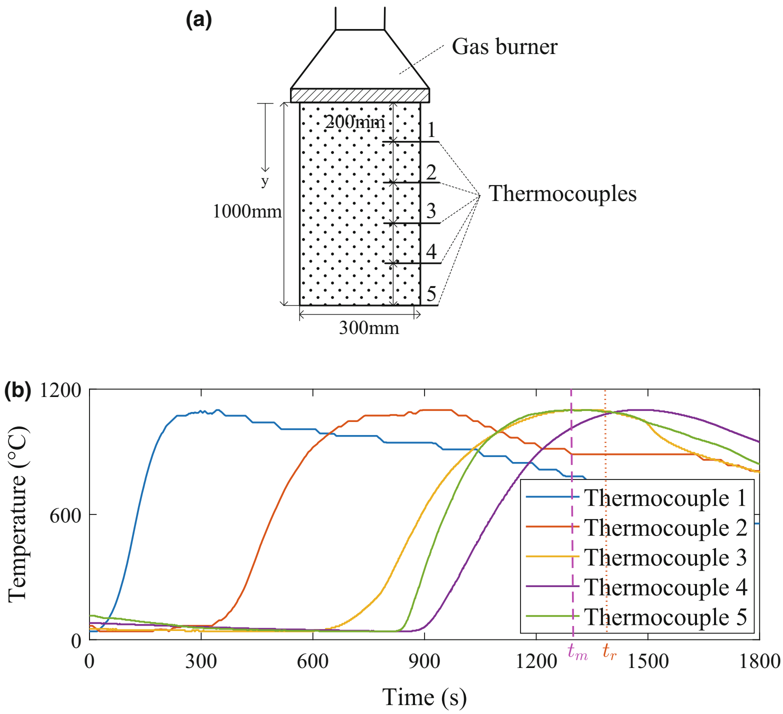

Fig. 15.7 Temperature test in the sinter pot. (**a**) Thermocouple distribution in the sinter pot. (**b**) Temperatures fluctuations in the test

the thickness of the red layer in each segment of the sintering bed tail section. In addition, sinter pot tests were conducted to obtain the fitting formula between the thickness of the red layer and TS. The sinter pot test is designed as a simulation of the industrial sinter process with a standard laboratory process. It overcomes the challenge of exploring the relationship between sintering parameters and the quality of sinter ore under complex and uncertain conditions. The demonstration of the sinter pot is quite simple. The pot is cylindrical with a depth of 1000 mm and a diameter of 300 mm. As shown in Fig. 15.7a, five thermocouples are inserted in the pot at depths of 200 mm, 400 mm, 600 mm, 800 mm, and 1000 mm, respectively. In 8 sinter pot tests, we obtained the TS and temperatures of 5 thermocouples. Figure 15.7b shows the temperature fluctuations in a test.

In order to determine the thickness of the red layer, an interpolation method was adopted to reconstruct the temperature field. Based on the BTP model and practical control strategy in the sintering process, there was 5.9% of the time gap between the beginning and thermocouple 5 appearing maximum temperature for cooling down at the end of the sintering bed. This means that in the sinter pot test, the time to calculate the thickness of the red layer is 5.9% of the time gap after the thermocouple reaches the maximum temperature. Figure 15.8 shows the temperature field changing in the sinter pot and the demonstration of the red layer.

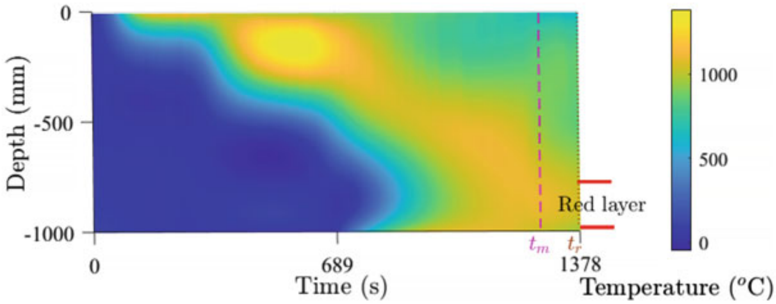

Fig. 15.8 Temperature distribution in the sinter pot

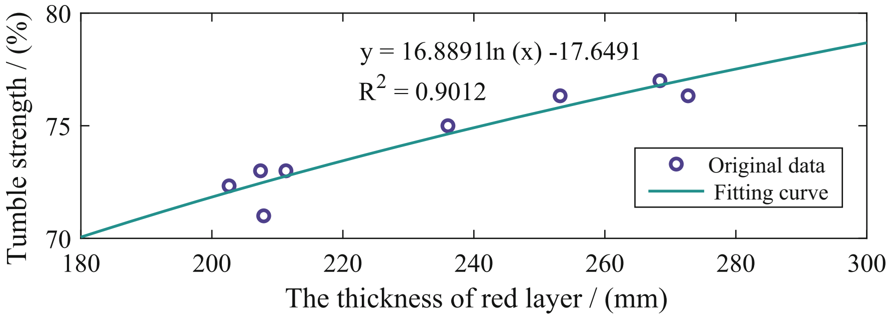

Fig. 15.9 Fitting curve of the thickness of red layer and TS

The fitting curves of the thickness of the red layer and TS are shown in Fig. 15.9. So far, the fitting formula between the thickness of the red layer and TS is expressed as:

$$\theta = 16.8891 \ln(\vartheta) - 17.6491, \tag{15.2}$$

where θ is TS value (%) and ϑ the thickness of red layer (mm).

Further, to solve the problem of time-tag mismatching of input and output data, the LSSVM predictive sub-models were trained by time-matched data of input and red layer thickness. The expanded data features and the time-matched input and output data lead to more accurate predictions. Finally, through the input data and the trained LSSVM prediction sub-models, the prediction value of red layer thickness in each segment was obtained, and then the TS prediction value was calculated by the fitting formula.

The proposed TS prediction scheme was applied to a 3#360 sinter plant of Guangxi Liuzhou Iron & Steel (Group) Company, and the experiments obtained higher prediction accuracy and verified the effectiveness of the proposed method. What's more, it is worth mentioning that the lack of data features and the time-tag mismatching of input and output data are common problems in complex industrial systems. Our proposed scheme provides novel ideas for solving these problems.

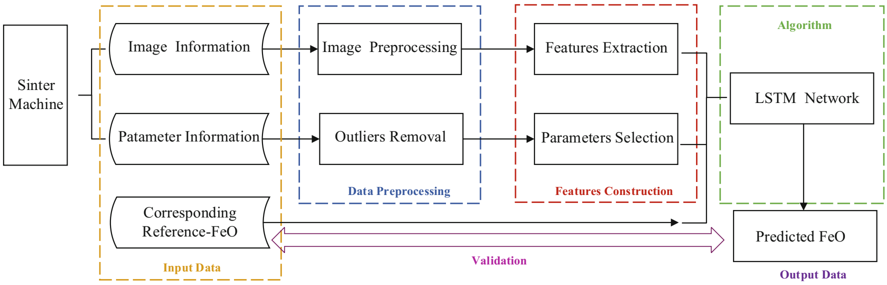

Fig. 15.10 Flow chart of the research scheme routine

In terms of FeO prediction, the LSTM network is widely used in the field of the industry considering its superiority in processing information of time series in recent years. This model is used by Elsaid et al. [18] to predict the aircraft engine vibrations and by Chen et al. [19] to make predictions of mechanical state. In the field of sinter quality prediction, Liu et al. [20] based on the operating parameters carry out research for forecasting the sinter composition by introducing the LSTM. Jiang et al. [21] introduce the heat transfer function to predict the content of FeO using a LSTM-based data-driven model.

Besides, though the overall sintering process is invisible due to the cover of the sintering pallets, we can observe the sintering state at the end of the sintering pallets and capture this information with the camera. These render it accessible to make predictions taking the information from images into consideration. Moreover, the parameters of the sintering process are also used as the features together with the features extracted from images to construct the multi-source feature vector, which can serve to eliminate the errors. They are then as the input of the LSTM network. Furthermore, in order to eliminate the errors caused by the complex large time delay [32], the reference-FeO at the end of the sintering pallets is obtained and it is used as the target output of the LSTM network. Finally, the deep learning model, LSTM network, is utilized to predict the content of FeO with the input of multi-source information and the target output of corresponding reference-FeO.

As shown in Fig. 15.10, we propose a data-driven prediction method for sinter composition FeO based on multi-source information and LSTM network in [33]. The image information, the parameter information of vibration, and temperature are introduced as multi-source features to reflect the content of FeO of sinter ore. Besides, the values of reference-FeO at the end sintering strand are obtained as the target output of the LSTM network. Then, the multi-source information is input to the LSTM network to learn the non-linear relationship between multi-source features and target output. The experimental results show that the data-driven prediction scheme based on multi-source features has better prediction performance, and the absolute error is less than 0.5 compared with reference-FeO, which meets the practical needs of engineering.

Table 15.1 Digital twin models

Category of models		Number of models
Proportioning model	Automatic/manual	24
Mechanism model	Mapping relation	4
Quality prediction	Sintering	9
	Pelletizing	28
	Blast furnace	28
Quality backtracking	Abnormal position	13

Based on the data-driven method, 106 models, such as proportioning optimization, process mechanism, quality prediction, and quality backtracking, were established in Guangxi Liuzhou Iron & Steel (Group) Company, as shown in Table 15.1. The simultaneous evolution of cyberspace and physical space provides decision support for improving quality and efficiency.

15.6 Digital Twins Coordination of the Sintering Process

Based on the coordination architecture in Sect. 15.2, TSN technology, and various data-driven models, control and communication coordination can be realized on the industrial cloud platform. In order to optimize the production process, distributed digital twin models need to be coordinated. In the rest of this chapter, we will introduce control–communication coordination for industrial digital twins of the sintering process, mainly based on TSN and digital twin technology. The development of the digital twin accelerates the intelligent reform of the manufacturing process.

Facing various production demands, a whole process coordination and optimization digital twin network of multiple twins is constructed. Digital twin models are extracted on-demand to simulate the production process in a virtual way, which can gain more efficient network resource allocation. In addition, they predict key process indicators and adjust production process parameters to achieve better production performance.

The network configurations of TSN can be generated by simulating the on-demand interaction of each twin through a digital twin network. If these configurations are directly distributed to the physical network, the normal production process may be affected. In case of production failure, the impact cannot be estimated. Based on the service mapping model of the digital twin network of production collaborative optimization, virtual testing is carried out before parameters arrangement. After network resource allocation and process parameters optimization on the cloud platform, configuration parameters are arranged to the industrial site with less trial and error costs. In this way, the utilization efficiency of production resources is improved.

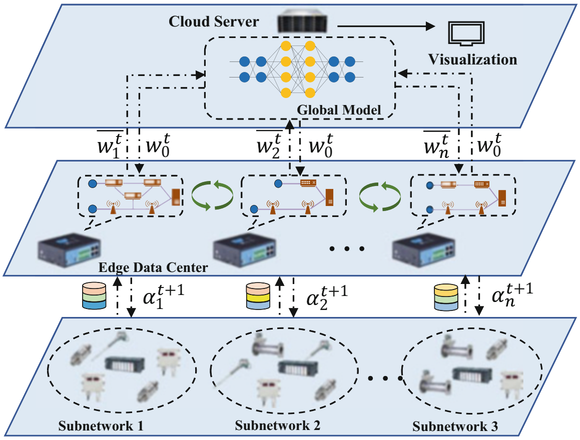

Fig. 15.11 Coordination framework for distributed digital twins

Since the industrial field covers a wide range, different edge devices serve individual regions, and the digital twin models built on each edge device are various. In order to coordinate the local model and the global model, we iteratively update model parameters between each edge device and cloud server through distributed learning technology. Specifically, after each edge device collects massive heterogeneous data, it extracts, converts, loads, cleans, and processes the data to construct digital twin datasets for training various functions in the production process. Then various industrial production functional models, i.e., various forms of deep neural networks, are trained distributed based on these datasets. The digital twins trained on each edge device of the whole production process interact with the industrial cloud platform to serve various production demands as shown in Fig. 15.11. The local model at device i is shown as follows:

$$F(\omega_i^t) = \frac{1}{D_i} \Sigma_{x_i, y_i \in D_i} f(\omega_i^t, x_i, y_i), \tag{15.3}$$

where ω_i^t is the network parameter of device i after t iterations, D_i is the dataset on the edge device i, x_i, y_i is the data sample, and $f(\omega_i^t)$ is the difference between the value output by the network and the true value of the data. $F(\omega_i^t)$ is the loss function obtained by averaging the value for the whole dataset. The network parameter update process is shown in Fig. 15.11 and following formulas:

$$\bar{\omega_i^t} = \omega_i^{t-1} - l_r \nabla_\omega F(\omega_i^{t-1}), \tag{15.4}$$

$$\omega_0^t = \beta_1 \bar{\omega_1^t} + \beta_2 \bar{\omega_2^t} + \cdots + \beta_n \bar{\omega_n^t}, \tag{15.5}$$

where $\bar{\omega_i^t}$ is the local updated network parameters of device i, and l_r denotes the learning rate. In formula (15.5), ω_0^t indicates the global network parameter, and the

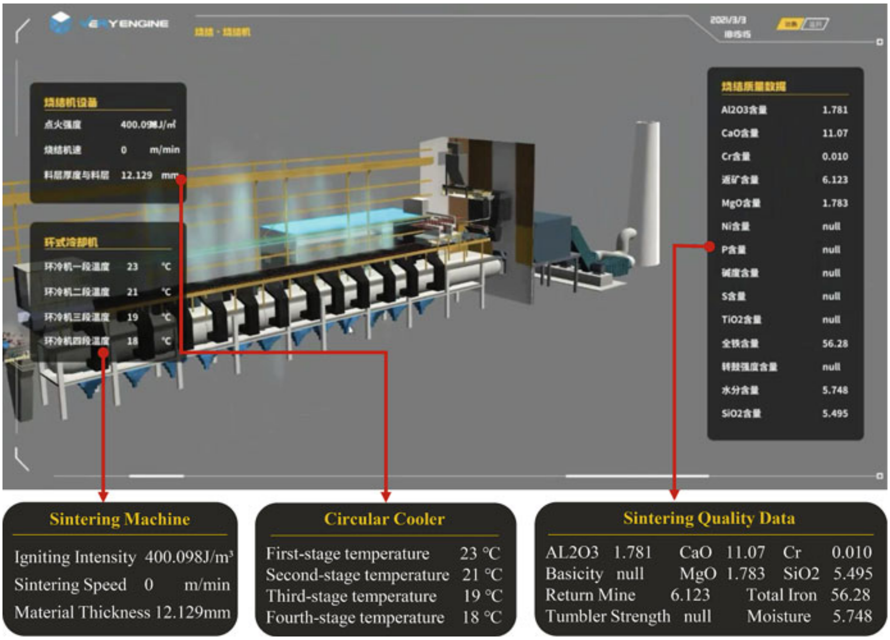

Fig. 15.12 Digital twin platform for sintering quality prediction

update process is a weighted learning process. After T local training iterations, the edge device will upload the model to the cloud server. The industrial cloud platform will integrate all collected models and get a global loss function recorded as $F(\omega_k)$ after k iterations. At the same time, this parameter will be broadcasted to each edge device for update. This process will be repeated until the preset accuracy is met.

Up to now, this technical scheme has been applied in Guangxi Liuzhou Iron & Steel (Group) Company. The quality prediction, quality retrospective, and quality optimization services are provided. In terms of quality prediction service, high-quality and stable production data are obtained through real-time state detection. Then, quality prediction services can be provided based on reliable data. We have built more than 100 prediction models to achieve the prediction of key indicators such as chemical composition and physical properties, as shown in Table 15.1. Based on this, a digital twin platform for sintering quality prediction is formed, as shown in Fig. 15.12, which can provide an important reference for the production site. Figure 15.13 shows the quality prediction curves of TS and FeO drawn based on platform data from November 17 to November 25, 2021. The prediction accuracy is more than 93.75% and over 90.00%, respectively.

At the same time, the forecast service provides early warning. That is, when the forecast value is abnormal, the quality retrospective service is activated to locate the production processes where the abnormality occurs. After that, the occurrence of abnormality is reported to the quality optimization service in time, and the

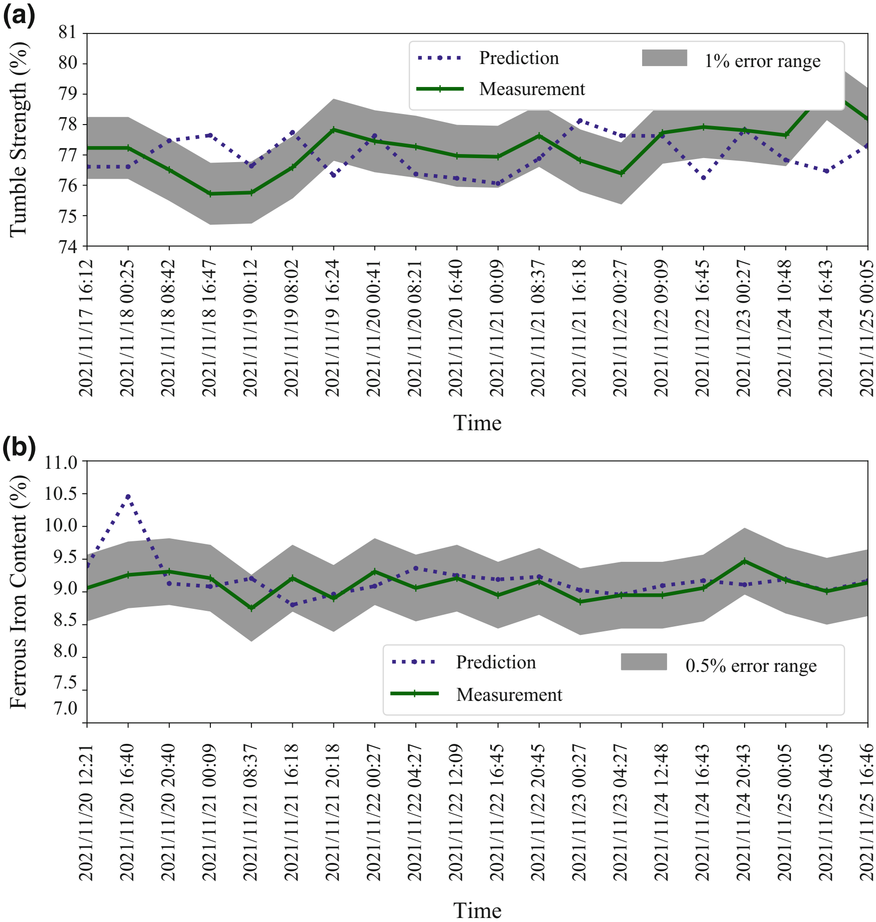

Fig. 15.13 Quality prediction of sintering process. (**a**) Results of TS prediction. (**b**) Results of FeO prediction

optimization suggestions given by the optimization model are used to provide important guidance to the on-site operators.

In terms of quality forecasting services, through real-time analysis of production data such as raw material ratio, operating status (machine speed, valve opening, etc.), observation status (exhaust gas temperature, wind box negative pressure, etc.), the quality prediction of sinter ore is achieved. Accurate prediction of quality indicators provides an important reference for the production site. As shown in Table 15.2, we predict the key indicators 20 minutes in advance, and the prediction accuracy of key indicators is more than 90%.

As for quality optimization, we first analyze the entire pre-iron process and establish a batching optimization model for a single process. Based on this, the

Table 15.2 Quality prediction accuracy and time in advance

Category of models	Number of models	Time scale	Spatial scale	Prediction in advance (hour)	Prediction accuracy
Sintering	9	Minute (forecast period) Hour (forecast advance time)	Equipment/process/production line	2	>90%
Pelletizing	28	Minute (forecast period) Hour (forecast advance time)	Equipment/process/production line	2	>90%
Blast furnace	28	Minute scale (changes with the updating frequency of molten iron quality)	Blast furnace/process/production line	1/3	>92.00%

analysis of the quality correlation between multiple processes is conducted and a proportioning optimization model is established. For the sinter mixture and sinter ore, the corresponding total iron or cost is the optimization target. Constraints are quality conservation constraints, ingredient constraints, inventory constraints, and harmful element constraints of the corresponding process, etc. As for the optimization algorithm, the simple method, gray wolf method, or whale optimization algorithm are utilized to optimize the quality for single process. After that, multi-processes joint batching optimization (mixing material and sinter) is performed. By analyzing the quality relationship between each process and introducing nonlinear convergence factors, Levy flight strategies, etc., joint optimization is achieved under these analyses and constraints. Finally, the proposed proportioning plan satisfies both the requirements of the sinter mixture and the sinter ore.

Furthermore, combined with production cost, process flow, iron grade quality, and other constraints, an economical ore procurement plan was given to substantially save production costs through sintering proportioning optimization. As for quality backtracking, the intelligent fault diagnosis of the production process has been realized by studying the safe intervals and correlation weights of various performance indicators of key processes.

15.7 Summary

To improve the production quality of the sintering process, this chapter firstly introduced a new multi-tier coordination architecture to cooperate control and communication for industrial digital twins, which addressed the field network for smart manufacturing and facilitated the integration of CT, OT, and IT. TSN and its scheduling algorithms were introduced to improve the synchronization and end-to-end performances of communication between cyber and physical systems, such as digital twins and sintering plants. To guarantee the transmission performance of heterogeneous data in the sintering process, some cooperative design methods and mixed transmission framework of route planning considering queue allocation are discussed. This chapter also presented several mechanism and data-driven modeling methods, which laid a solid foundation for more than 100 digital twin functional models. The proposed digital twins' coordination was applied through the on-demand interaction on the industrial cloud platform. The technical scheme is verified over a 3#360 sinter plant of Guangxi Liuzhou Iron & Steel Company and could predict key indicators 20 minutes in advance. The prediction accuracy of TS and FeO is more than 93.75% and 90.00% under normal operating conditions, respectively, which provide important references for improving the quality of the sinter.

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