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Review

A Survey of Data-Driven Soft Sensing in Ironmaking System: Research Status and Opportunities

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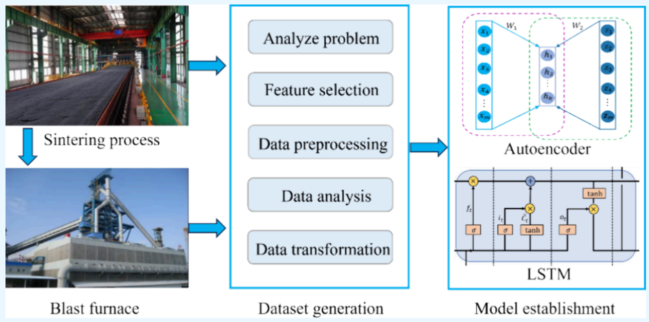

ABSTRACT: Data-driven soft sensing modeling is becoming a powerful tool in the ironmaking process due to the rapid development of machine learning and data mining. Although various soft sensing techniques have been successfully used in both the sintering process and blast furnace, they have not been comprehensively reviewed. In this work, we provide an overview of recent advances on soft sensing in the ironmaking process, with a special focus on data-driven techniques. First, we present a general soft sensing development framework of the ironmaking process based on the mechanism analysis and process characteristics. Second, we provide a detailed taxonomy of current soft sensing methods categorized by their predictive tasks (i.e., quality indicators prediction, state parameters prediction, etc.). Finally, we outline several insightful and promising directions, such as self-supervised learning and digital twins in the ironmaking process, for future research.

1. INTRODUCTION

Iron- and steelmaking has a significant impact on the development of the national economy, and blast furnace ironmaking accounts for about 70% of energy consumption in the entire steel-making process. With the emergence of the concept of "peak carbon dioxide emissions and carbon neutrality", intelligent ironmaking has become a new development trend in the modern manufacture field.[1] In order to achieve the goal of intelligent ironmaking, a growing number of researchers have started to establish a comprehensive industrial automatic system, including key performance indicators (KPIs) prediction, optimization, control, and decision-making. Accurate and efficient KPIs prediction, as an important prerequisite for industrial automation systems, has received widespread attention from both academic and industry fields.[2−6]

In the actual industrial processes, a large number of KPIs cannot be directly detected using instruments and measurements because of the harsh production environment.[7−10] In the traditional blast furnace ironmaking process, monitoring and estimation of KPIs mainly depend on the experience of the site-workers and offline testing. This manual method usually costs much time, and its accuracy is not high, causing difficulty in accurately controlling the product quality in real time. If the site-workers fail to make the correct decisions and judgments, it will impose an adverse impact on the product quality and even affect the normal operation. To settle this issue, soft sensing methods that establish the mapping relationships between KPIs and easy-to-measure variables have been widely used in the industrial processes.[11] In general, existing soft sensing modeling methods can be divided into three categories: mechanism-based methods, knowledge-based methods, and data-driven methods.

Mechanism-based modeling methods rely on the internal physicochemical reaction principle of the blast furnace ironmaking process, such as thermodynamics, fluid mechanics, law of conservation of energy, etc. If accurately established, these models can provide highly reliable and explanatory results with clear physical meanings. For example, Harvey et al.[12] put forward a global simulation strategy to optimize process parameters of the blast furnace based on classical thermodynamic calculations coupled with a direct search algorithm. This work[13] developed a static mechanism model by calculating the distributions of key process variables such as density and pressure of the gas phase, degree of iron ore reduction, and coke solution loss. Additionally, a multifluid mathematical simulator of the blast furnace was proposed to reproduce the field of velocity, temperature, and reaction in the furnace.[14] Despite the advantages of mechanism-based models, they still have some limitations.[15,16] For example, these

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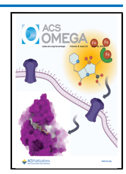

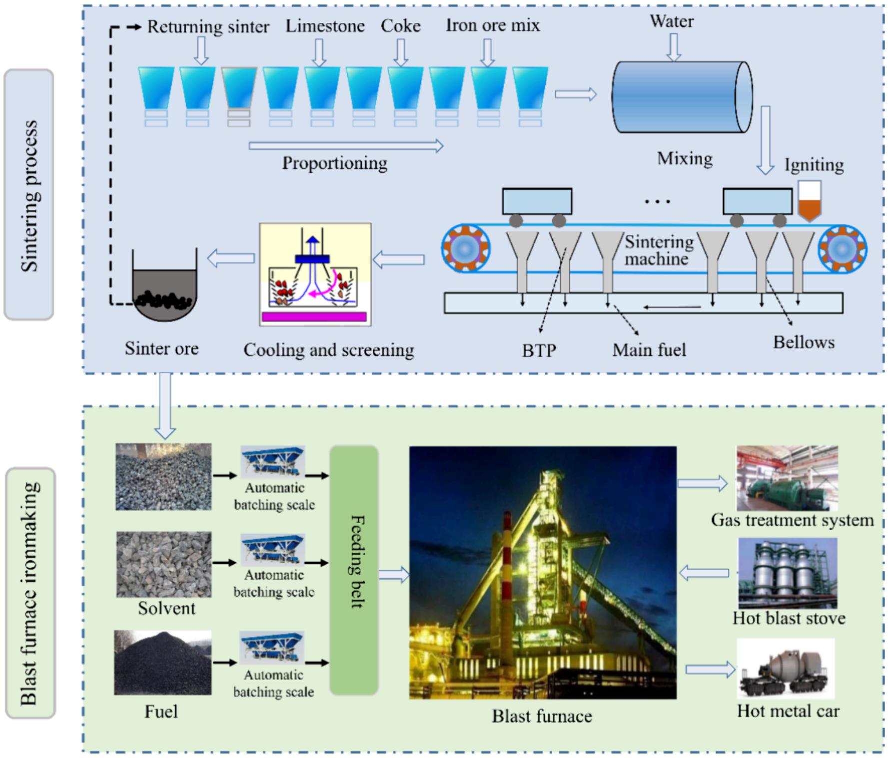

Figure 1. Process flowchart of the ironmaking process.

methods need a lot of expert knowledge, and it is hard to adjust relevant parameters in the blast furnace process dynamically. Besides, it is unrealistic to obtain complete and accurate physical and chemical reaction mechanisms due to the complex environment of the blast furnace.

Knowledge-based modeling methods mainly use expert experience and knowledge to infer and judge the qualitative relationships between different variables. The knowledge-based models usually include causal analysis, graphical reasoning, fuzzy reasoning, expert system, etc.[17−19] For example, three prototypical expert systems were proposed to cope with the complexity of the blast furnace based on physical models, uncertain knowledge, and rules of thumb.[20] An expert system based on LSTM network was developed to achieve the long-/short-term predictions of the iron temperature during tapping.[21] The experimental results on a real data set demonstrated that this system can provide a useful tool for the operators. Afterward, a new fuzzy control expert system[22] maximized the combustion and heat transfer efficiency of hot blast stoves. According to the studies mentioned above, it can be seen that the expert system has promoted the development of the automation level in the blast furnace ironmaking process. But qualitative system description and limited process analysis still hinder further improvements in the ironmaking production level. Besides, the expert system is heavily confined to the construction of the knowledge base, which equally brings some challenges for intelligent ironmaking.

Compared with the two methods above that rely heavily on the mechanism and knowledge of the ironmaking process, data-driven soft sensing models are mainly based on the understanding of data characteristics and distributions. In the modern ironmaking process, the data-driven modeling methods have increasingly received attention with the rapid development of data collection and storage technology, especially the Industrial Internet platform as a global information system.[23] The common data-driven soft sensing methods consist of traditional statistic learning models and deep learning models.[24,25] In the earlier stage, statistic learning algorithms such as principal component analysis,[26] partial least squares regression,[27] Support Vector Machines,[28] and Random Forest[29] have been widely used in the soft sensing modeling tasks of the ironmaking process. However, with the development of distributed control systems and information technology, a large amount of industrial data has been collected and stored at an increasingly fast speed. In this case, these shallow learning models above are hard to extract useful features from tremendous amounts of data. Fortunately, Hinton et al.[30,31] first proposed an unsupervised pretraining method to tackle the problem of gradient vanishment in 2006, which pushed the deep neural network to a new climax. Deep learning, with remarkable feature learning ability, has obtained many breakthroughs in computer vision,[32,33] natural language process,[34,35] and speech recognition.[36,37] Inspired by these successful applications, deep learning has also been widely used in the industrial processes, such as hierarchical Extreme Learning Machine,[38] Variable-wise Weighted Stacked Autoencoder (VW-SAE),[39] Gated Stacked Target-related Autoencoder (GSTAE),[40] etc. In addition, Autoencoder and Recurrent Neural Network have also been applied to predict the molten iron quality indicators in the blast furnace ironmaking process.[41,42] Accurate prediction of KPIs is a prerequisite for improving the quantity and quality of the product in the ironmaking process.

In recent years, there has been a proliferation of studies that adopted data-driven soft sensing modeling methods in the entire ironmaking process through literature analysis.[43−45] But there is no systematic review of data-driven soft sensing modeling in the entire ironmaking process. Although this

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work[1] has reviewed the current study status of prediction modeling, it is only limited in the sintering process and fails to provide advanced deep learning techniques for soft sensing. To fill the gap, in this paper, we give an in-depth illustration to the current soft sensing research status from the sintering process to the blast furnace. Our aim of this work is to provide valuable information for researchers and engineers to understand and design data-driven soft sensing models for industrial applications. The specific contributions are as follows:

(1) **General Framework**: A detailed description and characteristics analysis of ironmaking process are systematically introduced, and a general soft sensing development framework for KPIs prediction is outlined. This general framework can provide a practical guideline on data-driven soft sensing for researchers and engineers.

(2) **New Taxonomy**: Data-driven soft sensing modeling methods about KPIs prediction in the ironmaking process are summarized and categorized, including the sinter ore quality indicators, sintering state parameters, molten iron quality indicators, etc.

(3) **Insight into Promising Directions**: We discuss some potential research directions about soft sensing modeling in the ironmaking process, including self-supervised learning, digital twins, etc.

(4) **Real-World Data set**: We release a data set collected from a real ironmaking process so that researchers can use it as the benchmark to test their methods.

The outline of this survey is organized as follows. In Section 2, we briefly introduce the flowchart of the entire ironmaking process and analyze some important process characteristics. Then the current soft sensing modeling methods are systematically illustrated in Section 3. Future directions are provided and are discussed in Section 4. Finally, conclusions are drawn in Section 5.

2. BACKGROUND AND ANALYSIS OF IRONMAKING PROCESS

2.1. Description of Ironmaking Process. As shown in Figure 1, the entire ironmaking process consists of two key parts: the sintering process and the blast furnace ironmaking process. For convenience, we will illustrate the two parts independently.

Sintering process is a preliminary modus of the blast furnace ironmaking, and the quality of the sinter ore has a great impact on the energy consumption and carbon emission in the ironmaking process. In the modern ironmaking industry, the Dwight-Lloyd sintering machine is the most widely used in factories, as shown in Figure 1. First, the raw materials such as iron ore, limestone, coke, etc., are transformed into mixture according to the preset proportion. Then the mixed materials are blended by adding proper water for granulation, and transported to the mixture bunker through the belt conveyor. Next, the mixed materials start to fire in the ignition furnace, and the surface layer gradually burns from top to bottom with the moving of the trolley. Meanwhile, 24 bellows supply fresh air to support combustion and release exhaust gas. When the trolley arrives at the end position of sinter machine, the mixed materials are completely burned and the sinter ore is produced. Finally, sinter ore is crushed, screened, and transported to the blast furnace.

A typical blast furnace system mainly consists of the blast furnace body, the ore and coke feeding system, the hot blast system, the pulverized coal injection system, the top gas treatment system, and the iron treatment system. During the ironmaking process, sinter ore, solvent (limestone), and fuel (coke) are loaded from the top of the blast furnace. At the bottom of the blast furnace, hot air is blown into the reactor through the hot blast stoves. Under conditions of high temperature, carbon monoxide (CO) and hydrogen (H_2) are generated when the oxygen in the hot air chemically reacts with the carbon in the fuel. Next, when the hot gas flows upward with the pressure, the final products of the hot metal are formed through a series of physicochemical reactions. The details of the six systems mentioned above are as follows.

(1) Blast furnace body: It is a core equipment of the ironmaking process, containing the throat, shaft, belly, bosh, and hearth.

(2) Charging system: The charging system includes the skew bridge, stock house, scale car, coke bin, rotating chute, etc. The raw materials such as iron ore, coke, and limestone are gradually charged into the top of furnace layer by layer according to the preset proportion.

(3) Hot blast system: The hot air system includes the tuyere, hot blast stove, blower, etc. Its goal is to preheat the cold air generated by the blower at approximately 1200 °C and send it to the blast furnace.

(4) Pulverized coal injection system: It is mainly to inject compressed hot air together with pulverized coal into the hearth of the blast furnace.

(5) Top gas treatment system: The top gas treatment system of a blast furnace mainly includes the eliminator, downcomer, venturi scrubber, dust catcher, etc. Its main task is to purify and recycle the waste gas produced in the blast furnace smelting process.

(6) Iron treatment system: The impurities in the raw materials and solvents are combined to produce molten furnace slag. The pig iron is collected from the taphole and transported to the subsequent steelmaking process.

2.2. Analysis of Ironmaking Characteristics. For simplicity, we take the blast furnace, for example, to analyze the process characteristics (Figure 2). Blast furnace is considered as the most complex metallurgical reaction vessel in the ironmaking industry field, which contains various physical and chemical reactions, heat and mass transfer, multiphase and multi field coupling, strong coupling parameters, etc. These complex mechanisms bring great challenges for data-driven soft sensing modeling in the ironmaking process. To establish an accurate prediction model of KPIs, it is necessary to understand the detailed flow and characteristics of the entire ironmaking process, which will lay a solid foundation for soft sensing modeling.

2.2.1. Complex Mechanism. The blast furnace ironmaking is a complex physicochemical reaction process, including water decomposition, redox reaction, etc. For industrial soft sensing, incorporating the mechanism knowledge into the data-driven models is beneficial to improving the interpretability, which can provide reliable guidance for the site workers. The typical chemical reaction equations are as follows.

$$C + O_2 = CO_2,\ 2C + O_2 = 2CO \tag{1}$$

$$3Fe_2O_3 + CO = 2Fe_3O_4 + CO_2 \tag{2}$$

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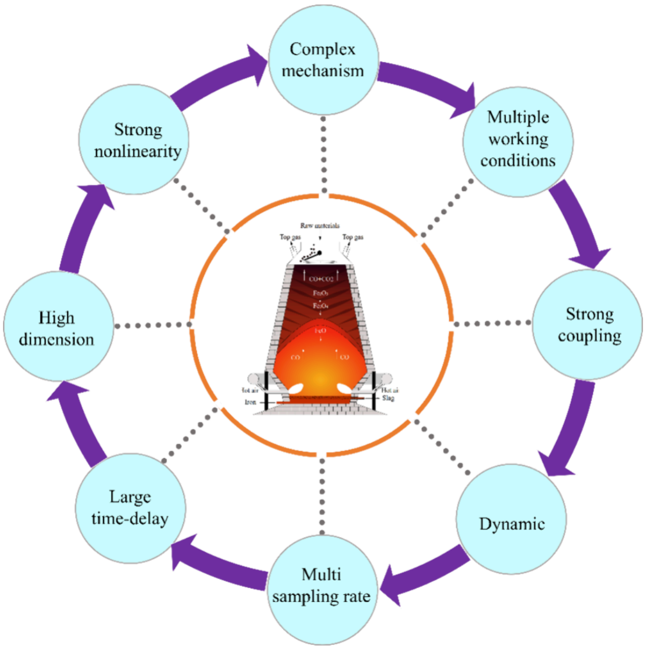

Figure 2. Characteristics analysis of the ironmaking process.

$$CaCO_3 = CaO + CO_2,\ MgCO_3 = MgO + CO_2 \tag{3}$$

$$FeCO_3 = FeO + CO_2,\ FeO + CO = Fe + CO_2 \tag{4}$$

2.2.2. Strong Nonlinearity. On one hand, the process parameters of the blast furnace body are nonlinear with molten iron quality (MIQ) indices, such as silicon content (Si), sulfur content (S), and phosphorus content (P). On the other hand, the relationships among process parameters are also nonlinear, such as pressure difference, gas permeability, hot air temperature, etc. For example, when the furnace temperature changes from hot to cool, the initial differential pressure decreases slightly and the gas permeability index increases greatly. When the furnace temperature is too low, the pressure difference increases and the gas permeability index decreases.

2.2.3. High Dimension. The blast furnace ironmaking is a large system with multiple working procedures and long processes involving hundreds of parameters. These parameters can be categorized as state parameters, control parameters, and quality indicators, as shown in Table 1. The state parameters mainly reflect the operation modes inside the blast furnace, and the site-workers can adjust relevant equipment if there are abnormal conditions. The control parameters are used to maintain normal operation, and the MIQ indices represent the quality of hot metal.

2.2.4. Large Time-Delay. It takes 6−8 h for a complete ironmaking process from blast furnace charging to hot metal formation. In general, the MIQ indices are tested by instruments every 20−30 min, but the process parameters are detected every minute. This large-scale time delay makes it difficult to choose appropriate variables for the input of soft sensing models. The reason is that the difference of sampling time makes only a part of the process variables have labels. In addition, it may destroy the inherent distribution pattern between the process variables and the target variable. A simple solution is to adjust the sampling time of process parameters forward or backward before establishing prediction models.

2.2.5. Multisampling Rate. In the blast furnace ironmaking process, different types of parameters have distinctive sampling times due to the inadequacy of measurement techniques. In general, process variables are collected with two or more rates, which are different from those of the target variable. For example, the raw materials are usually tested once a day, and the MIQ indices are about half an hour. But these process parameters are detected by advanced sensors every minute. For time series prediction, different sampling rates are directly connected to the performance of soft sensor. To address this problem, process variables are usually down-sampled to align the frequency of the target variable.

Table 1. Categorization of Key Parameters in the Ironmaking Process

State parameters	Control parameters	Quality indicators
South exploration (m)	Coke batch (ton)	Silicon content (Si)
Coke burden	Ore batch (ton)	Phosphorus content (P)
Sinter ore ratio (%)	Coke nut (ton)	Sulfur content (S)
Pellet ratio (%)	Solvent (ton)	Molten iron temperature (°C)
Lump ore ratio (%)	Lump ore (ton)	Manganese (Mn)
Blast ratio (%)	Pellet (ton)	Vanadium (V)
Blast pressure (MPa)	Flux of the cold air (m^3/h)	Titanium (Ti)
Top pressure (MPa)	Hot air temperature (°C)	Gas utilization rate (GUR)
Pressure difference (MPa)	Blast temperature (°C)	Burn-through point (BTP)
Top pressure flux ratio (%)	Flow rate of rich oxygen air (m^3/h)	FeO content (FeO)
Gas permeability	Blast humidity (g/m^3)	Tumble Strength (TS)

2.2.6. Dynamic. Blast furnace ironmaking is a continuous dynamic process, whose operation parameters change in real time during the production process. In this case, strong autocorrelations exist among these process parameters at different times, which is a very important characteristic for data-driven modeling in the ironmaking process. Taking the silicon content (SI) in hot metal as an example, we calculate the autocorrelation of SI as shown in Figure 3(a). We can observe that the current samples are strongly affected by the pervious samples, meaning that there exist dynamics in the ironmaking process.

2.2.7. Strong Coupling. There are no independent parameters in the ironmaking process, and they often mutually interact with each other. For example, reducing air volume can not only bring a decrease to the amount of coal gas in the bosh but also change the blast kinetic energy. Meanwhile, with the increase in coal gas, the speed of the blast furnace burden is accelerated. Similarly, we also study the correlations among process variables in the ironmaking process, as shown in Figure 3(b). It can be seen that the mutual coupling relationships between these variables are noticeable; thus, it is essential to consider the multivariable coupling characteristics in soft sensing modeling because new finds[46] have demonstrated that modeling the coupling relations among process variables contributes a lot to the accuracy of soft sensing.

2.2.8. Multiple Working Conditions. In the actual ironmaking production, the lists of ingredients may be constantly adjusted, according to the fluctuation of their price. Each list of ingredients represents a unique working condition. Thus, there are many different working conditions, causing the differences in data distributions. Faced with this situation, a single model cannot obtain good performance because the mapping relationship between process variables and the target variable

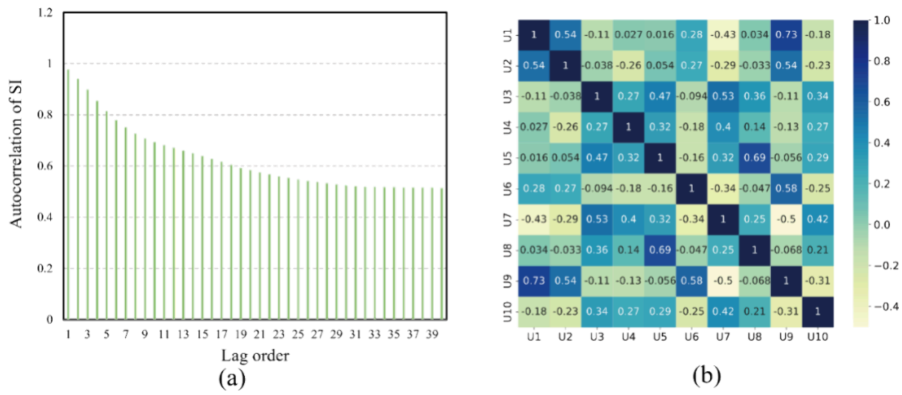

Figure 3. (a) The autocorrelation of SI in the ironmaking process; (b) correlation between process variables.

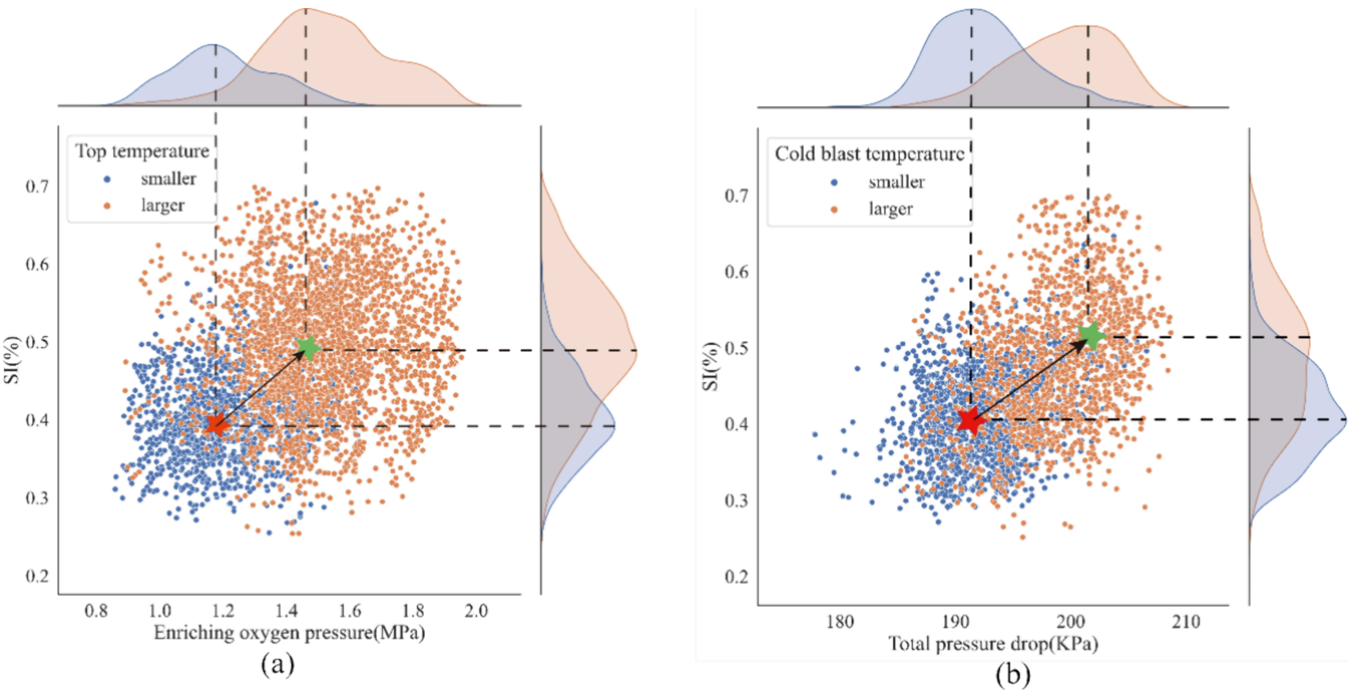

Figure 4. (a) The change trend of the relationship between enriching oxygen pressure and SI; (b) the change trend of the relationship between total pressure drop and SI.[46]

has changes. From Figure 4(a), we can find that the relationship between enriching oxygen pressure and SI varies over time due to different working conditions. When enriching oxygen pressure is small under certain working conditions, the distribution of SI is located in a small range. However, if working conditions shift, the content SI has become high. Similarly, Figure 4(b) also shows the distribution discrepancy caused by multiple working conditions. However, the traditional data-driven models assume that the training set and the testing set come from the same distribution, which is often unrealistic in the actual industrial processes. Thus, multiple working conditions can impose an adverse impact on soft sensing, and we need to take the distribution shift problem into account for data-driven modeling.

3. REVIEW OF SOFT SENSING METHODS IN IRONMAKING PROCESS

3.1. General Frameworks of Data-Driven Soft Sensing Modeling for Ironmaking Process. Aiming to these characteristics in the ironmaking process, we developed a general design pipeline of data-driven soft sensing modeling shown in Figure 5, including mechanism analysis, auxiliary variable selection, data preprocessing, model establishment, and online application deployment.

Step 1: We need to conduct mechanism analysis for the ironmaking process and define a soft sensing modeling problem according to the requirements of the actual factories.

Step 2: After determining the target variable, we select some key auxiliary variables using some statistical analysis methods, such as ranking-based approaches,[47] wrapper approaches,[48] and embedded approaches,[49] coupling with some prior knowledge.[50]

Step 3: Next, the corresponding sensors are installed in the ironmaking field to collect and restore the historical data, including production data, machine data, operation data, process data, product data, quality data, and energy consumption data.

Step 4: However, these raw data usually have some problems such as locked variables, missing values, and random noise, so preliminary data preprocessing is an essential step.

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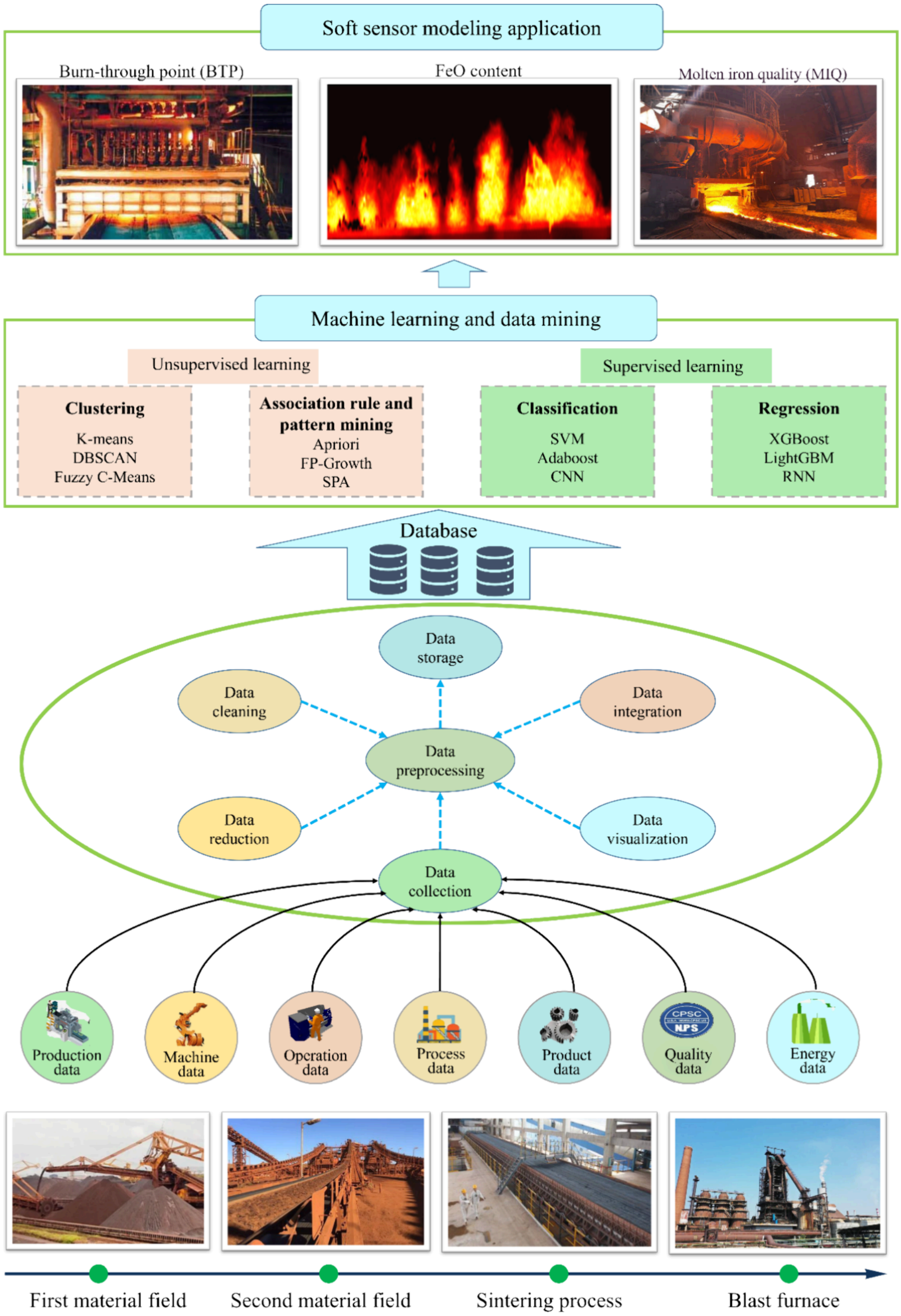

Figure 5. Data-driven soft sensing modeling procedures in the ironmaking process.

Because there is a classic saying, " garbage in, garbage out" in the data mining field,[51] meaning that data quality can be a limiting factor for soft sensing modeling, a series of popular data preprocessing methods are adopted to enhance data quality before being fed into machine learning models (e.g., data cleaning, data reduction, data transformation, and data visualization).

Step 5: Then model selection plays a crucial role in soft sensing development, which decides the upper limit of prediction performance. At this stage, a consistent fact is that the structures of soft sensing models are established on the understanding of data characteristics of the ironmaking process (Section 2.2), which is a fundamental work for algorithm designers in the industrial field.

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Table 2. Representative Methods for Soft Sensing Applications in the Sintering Process

Task	References	Introduction of methods
Quality indicators	Xie et al.[58]	Integrated model combining multisource information fusion and LSTM network for FeO content prediction.
	Bai et al.[60]	Combination model of adaptive particle swarm optimization (APSO) algorithm and least-squares support vector machine (LSSVM) algorithm.
	Jiang et al.[61]	Polymorphic measurement method of FeO content of sinter based on heterogeneous features of infrared thermal images.
	Ye et al.[64]	TS model combined with a local thermal nonequilibrium (LTNE) model for tumble strength prediction.
	Chen et al.[65]	Semisupervised just-in-time learning framework using a Gaussian mixture model (GMM).
State parameters	Liu et al.[68]	BTP prediction system based on gradient boosting decision tree (GBDT) algorithm and decision rules.
	Cao et al.[69]	Steady-state subspace model (SSSM) for predicting the exhaust-gas tempera- ture (EGT) of BTP.
	Du et al.[81]	The fuzzy time series prediction method with the Fuzzy C-Means clustering.
Energy consumption indicators	Hu et al.[78]	The real-time dynamic prediction model of CCR based on broad learning.
	Hu et al.[63]	Weighted kernel-based fuzzy C-means (WKFCM)-based broad learning model (BLM) to predict CCR.
	Chen et al.[80]	Semisupervised linear−nonlinear least-square learning network (LLLN) for CCR.

Step 6: Finally, the established soft sensing model is trained and tested in the offline data and then deployed into the actual industrial system for the KPIs intelligent prediction.

Overall, the data-driven soft sensing modeling methods can be divided into two categories: traditional machine learning models and deep learning models. We will illustrate the current research status in the ironmaking process from two aspects, respectively.

3.2. Soft Sensing Modeling Methods Based on Traditional Machine Learning Models. *3.2.1. Soft Sensing Modeling Methods for Sintering Process.* Based on the data-driven soft sensing development procedures mentioned above, a large number of prediction models about KPIs have been established for the sintering process in the past few years, as shown in Table 2. These KPIs are mainly classified into three categories: quality indicators, state parameters, and energy consumption indicators. The details are introduced in the following sections.

3.2.1.1. Soft Sensing Methods of Quality Indicators. Sinter ore is the primary raw material of the blast furnace, and its quality has a great impact on the yield, quality, and energy consumption of the ironmaking process. However, testing its quality indicators is usually very time-consuming and expensive. Therefore, how to achieve an accurate prediction of quality indicators is a challenging problem. These quality indicators are divided into two types: chemical composition and physical metallurgical properties. The former mainly includes ferrous oxide (FeO), calcium oxide (CaO), total iron (TFe), and silicon dioxide (SiO_2), and the latter contains two representative indicators: tumbler strength (TS) and basicity.[52] For example, if the FeO content of sinter ore is too high, then the coke and fuel consumption in the entire ironmaking process will increase, causing a heavy economic burden to enterprises. On the contrary, too low FeO may impose an adverse influence on the yield and quality of molten iron. How to accurately predict FeO content is an urgent problem.

To cope with this problem, many researchers explore data-driven methods to timely and accurately monitor the FeO content.[53−57] To begin with, Xie et al.[58] developed an intelligent framework combining adaptive particle swarm optimization (APSO) algorithm and least-squares support vector machine (LSSVM) algorithm to predict FeO content. On the basis of this study, a knowledge and data fusion model was designed to realize online prediction of FeO content according to the temperature distribution mechanism.[59] Moreover, the experimental results in a sintering plant demonstrated that the proposed model was effective and feasible. In order to combine multiple data, a multisource information fusion scheme was creatively proposed to achieve the FeO content prediction based on infrared thermal image data of sinter cross section and process data. The prediction results show that the extracted multisource features reach a good performance and meet the needs of practical engineering.[60,61]

Apart from chemical compositions, TS, as a critical metallurgical and intrinsic property, is also essential to the wear resistance and anticollision performance of the sintered ore.[62] In general, high strength sinter ore helps to reduce the industry dust output dosage and improve efficiency of the blast furnace, while too low strength can affect the permeability of material surface.[63] Under this background, Ye et al. developed a TS estimation method based on LSSVM and local thermal nonequilibrium (LTNE) model, and the proposed scheme was verified in the sinter pot tests.[64] In addition, the testing time of TS takes several hours, making the labeled samples scarce. To solve the imbalanced samples problem, a semisupervised just-in-time learning framework using a Gaussian mixture model (GMM) was devised to predict TS in the sintering process.[65]

These data-driven soft sensing models have exhibited some improvements for quality indicators in the sintering process. However, it is usually time-consuming and expensive to obtain labeled samples in the sintering process. These works have not solved the label scarcity problem. For example, the FeO content is estimated by some experienced experts in the sintering factory, while process variables are collected by sensors every minute. The sample imbalance between process variables and FeO content needs to be overcome using semisupervised regression. In addition, we can use meta learning[66] to solve the few-shot problem for soft sensing in the future. A key step of meta learning is to construct auxiliary tasks to transfer knowledge to the target task.

3.2.1.2. Soft Sensing Methods of State Parameters. At the same time, these quality indicators are also closely connected with some key state parameters, including the burn through point (BTP), mixture moisture, ignition temperature, and bed permeability state. Among these parameters, BTP is the most important thermal state parameter for site-workers, which stands for the location where the materials are thoroughly burned. According to the engineering practice experience, the desired position of BTP is approximately located in the

Table 3. Representative Methods of Soft Sensing Applications in the Blast Furnace

Task	References	Introduction of methods
Upper part of blast furnace	Li et al.[82]	Online sequential extreme learning machine (OS-ELM) for GUR.
	Shi et al.[83]	Hybrid model combining fuzzy C-means and statistical methods for GUR.
	Zhang et al.[85]	The TS fuzzy neural network (TS-FNN) for GUR.
	Su et al.[84]	Hybrid model (W-PCA-ML-ELM) for predicting the permeability index
Middle part of blast furnace	Jiao et al.[86]	Three-dimensional (3D) parallel process model for blast furnace.
	Li et al.[87]	Prediction model of the CZ combining an offline computational fluid dynamics (CFD) calculation with SVM
	Baniasadi et al.[88]	The extended discrete element method (XDEM) for softening process.
	Zhou et al.[89]	Soft sensing model of CZ using the offline CFD and online measurement method.
Lower part of blast furnace	Tang et al.[90]	Silicon content prediction based on SVR and chaos particle swarm optimization.
	Zhou et al.[91]	Hammerstein model for the prediction of MIQ using the least-squares support vector machine-based nonlinear subspace identification method.
	Lv et al.[92]	Data-driven robust modeling is proposed for an online estimation of MIQ using improved random vector functional-link networks (RVFLNs)
	Guo et al.[93]	Multioutput LS-SVR (M-LS-SVR) using multitask transfer learning technology for MIQ.
	Yang et al.[94]	Multi time scale inception-time network to predict the silicon content.
	Li et al.[95]	Genetic algorithm based method to construct interpretable features for industrial modeling.
	Hua et al.[96]	Nonlinear Takagi−Sugeno (T−S) fuzzy model for the hot metal silicon content.

penultimate bellow. If the actual BTP falls before the optimal position, the sintering burden is burned out in advance, giving rise to excessive coal consumption. Oppositely, the delay of BTP may lead to insufficient combustion and affect the sintering quality. In view of this situation, the accurate BTP intelligent prediction has received many researchers' interests.[67] Some representative works are as follows. Liu et al.[68] used the gradient boosting decision tree (GBDT) algorithm and decision rules to predict BTP considering process knowledge and data characteristics dynamically. Cao et al.[69] built a dynamic steady-state subspace model (SSSM) to predict the exhaust-gas temperature of BTP. Hu et al.[70] proposed the weighted kernel just-in-time learning (WKJITL) and fuzzy broad-learning system (FBLS) to obtain a timely response to the current BTP. Besides, the moisture of the sintering mixture is also an important parameter for sintering quality control. To provide the constructive guidance for the site-workers, Jiang et al.[71] developed a moisture detection system by combining expert knowledge and heterogeneous image features, and its performance has also been verified in the actual sintering factory.

Although these studies have made some progress in the past few years, these models only focus on the current step prediction and cannot achieve the multistep prediction because the site-workers needed sufficient time to implement maintenance in advance. To achieve the multistep prediction tasks, popular time series models can be used for BTP prediction such as transformer, informer, etc.[72] For the BTP prediction, we also need to consider two problems. First, random noise is very common in the sintering field, and we should pay attention to the antinoise model to improve the BTP prediction accuracy. Second, a distribution shift often occurs in the sintering process, which causes the training set and the test set to have different distributions. Traditional data-driven models are based on independent and identically distributed assumption. Transfer learning may be a new path to tackle the distribution shift problem. Domain adaptation, as an important branch of transfer learning, has become extremely popular in industrial fault diagnosis. How to apply domain adaptation to the BTP prediction is a worthwhile problem. The core of domain adaptation is to reduce the distribution discrepancy between the training set and the test set using metric or adversarial learning. Thus, domain adaptation-based BTP multistep prediction is promising to break the bottleneck of distribution shift in the sintering process.

3.2.1.3. Soft Sensing Methods of Energy Consumption Indicators. In addition, reducing energy consumption is of great significance to meet the requirements of "peak carbon dioxide emissions and carbon neutrality" in the iron and steel industry. To improve the energy efficiency, comprehensive coke ratio (CCR) is defined to measure the carbon efficiency.[73] Through the literature analysis, the researches about CCR mainly focus on two aspects: multiple operating conditions problem[74] and semisupervised learning.[75] For one thing, the multiple working conditions problem is very common, as described in section 2.2, which can bring distribution differences in the training set and testing set. To deal with this problem, researchers[76,77] used an improved fuzzy C-means (FCM) clustering method and affinity propagation clustering algorithm to identify the optimal working condition and then established the least-squares support vector machine (LS-SVM) submodels to predict CCR. To eliminate noise of the actual production data, a hybrid model combining the maximum entropy clustering algorithm and broad learning was proposed for the real-time dynamic prediction of CCR.[78] Afterward, an original prediction framework called weighted kernel-based fuzzy C-means (WKFCM)-based broad learning model (BLM) was proposed to achieve fast and effective carbon efficiency modeling.[79] For another, the lack of labeled samples is still a challenging problem that needs to be taken into consideration for the construction of the prediction system. In this case, Chen et al.[80] proposed a semisupervised linear−nonlinear least-squares learning network (LLLN) for the CCR prediction.

However, there are several directions that are worth pursuing. First, these models have not considered the detection and correction of abnormal data during the sintering process. In fact, there are a large amount of noisy data in the actual production, which can degrade the performance of soft sensing. Second, in the WKFCM model, the impact of various fuzzification coefficients needs to be further studied and the kernel parameters should be optimized to improve its accuracy. Third, we need to achieve real-time prediction and develop intelligent decision-making strategy for the sintering factory

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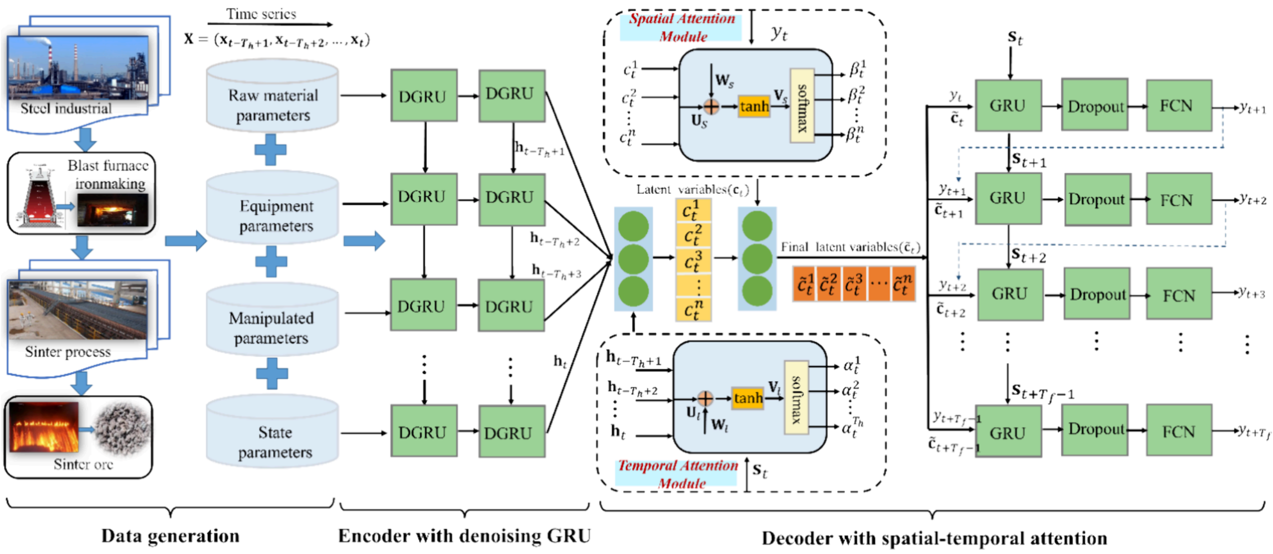

Figure 6. BTP multistep prediction based on denoising spatial-temporal encoder-decoder framework.[101]

based on the established prediction models. In this way, these prediction models can bring economic benefits to the enterprises. Nowadays, online soft sensing is at an initial exploration stage, and it is essential to design reliable online prediction strategies for real industrial applications.

3.2.2. Soft Sensing Modeling Methods for Blast Furnace. As a core part of the ironmaking process, the blast furnace not only generates a substantial amount of carbon dioxide emissions but also needs the most energy consumption. If some KPIs in the blast furnace can be measured in advance, it will provide sufficient time for the workers to adjust relevant process parameters to maintain normal operation. However, KPIs are usually hard to estimate using sensors due to the harsh environment, such as high temperatures, high pressure, etc. To monitor the operation conditions in real time, it is essential to develop accurate soft sensing models to predict some KPIs in the production. It is empirically argued that an accurate estimation of molten iron quality (MIQ) indices is fundamental to the optimization and control of operation parameters in the blast furnace. For example, these studies mainly consist of three aspects: upper, middle, and lower part, as shown in Table 3. The details are provided as follows.

The research about the upper part of the blast furnace mainly focuses on the top gas. For example, the gas utilization rate (GUR) is a typical KPI that is used to reduce energy consumption and improve operation status. Therefore, Li et al.[82] proposed a novel online sequential extreme learning machine (OS-ELM) to predict GUR. However, OS-ELM cannot divide different working conditions. To this end, Shi et al.[83] used fuzzy C-means clustering and a statistical model to study the relationships between gas flow center distribution and GUR based on image data. Apart from GUR, Su et al.[84] proposed a hybrid model based on the multilayer extreme learning machine, the principal component analysis, and wavelet transform to predict the permeability index. These soft sensing models are mainly based on the ELM, which is a shallow model and cannot capture much useful information from a large amount of data. Moreover, the collected data sets may be incomplete due to various reasons, e.g., sensors breakdown, human errors, uncontrollable factors, etc. Latent factor analysis is effective in extracting inherent latent features from incomplete data for building the soft sensing model.

In the middle part of the blast furnace, the position of the cohesive zone (CZ) is closely related to operation stability. To begin with, Jiao et al.[86] built a three-dimensional (3D) parallel process model using computational fluid dynamics (CFD). On the basis of this study, Li et al.[87] combined an offline CFD calculation method and SVM to monitor the CZ position in real time. Specifically, this work established an axisymmetric two-dimensional steady-state CFD model to simulate the fluid flow, heat transfer, and the heat transfer in the blast furnace shaft, and then used SVM to predict the location of CZ. Baniasadi et al.[88] proposed an extended discrete element method (XDEM) to model complex gas−solid flow during the softening process. Recently, a soft sensing method of CZ has been proposed using the offline CFD calculation method and online detection of cooling water.[89] These models are based on a single working condition, ignoring the essence of complex working conditions in the ironmaking process. Therefore, it is important to extract domain-invariant temporal features across different working conditions, which could meet the requirements of industrial applications.

As for the lower part, there are several related studies, especially molten iron quality (MIQ) indices.[90] For example, Tang et al.[90] established an SVR model to predict silicon content and used chaos particle swarm optimization to select the optimal parameters. Afterward, Zhou et al.[91] developed a least squares SVR-based nonlinear subspace identification method for the prediction of MIQ indices. At the same time, an improved random vector functional-link network (RVFLN) was proposed for the silicon content prediction.[92] In order to solve the multiple output problem, Zhou et al.[93] proposed a multitask transfer learning technology to construct multioutput LS-SVR (M-LS-SVR). To cope with the multiple sampling rate problem, Yang et al.[94] designed a multi time scale inception-time network to predict the silicon content in the ironmaking process. These works have solved some common problems for MIQ prediction, but the stability and reliability of these models are not desirable. In the ironmaking process, uncertainty quantification factors often occur, and the generalization of soft sensing needs to be further explored.

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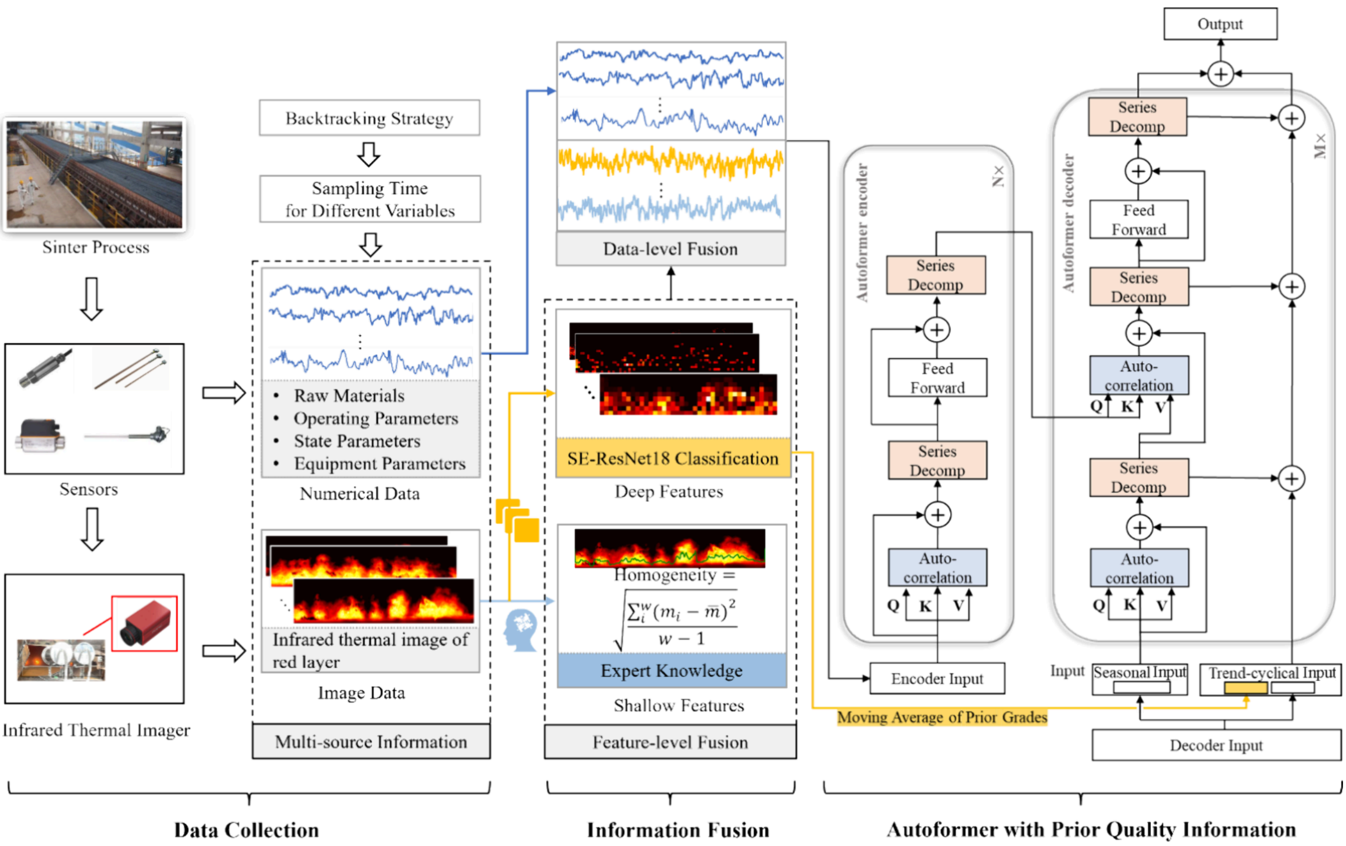

Figure 7. MIF-Autoformer for soft sensing modeling of FeO content in the sintering process.[106]

In summary, these soft sensing methods have not explicitly modeled the coupling characteristics among the process variables. These MIQ models are based on fully connected methods, such as LSTM-based methods. In practice, these process variables are connected in non-Euclidean topologies.[46] A recent study[97] also unveiled that learning latent representations among process variables is helpful to improve the performance of soft sensing. Graph neural networks are good at dealing with non-Euclidean data; thus, it is promising to develop advanced graph soft sensing models for soft sensing. For graph networks, how to construct a suitable process graph is a key for soft sensing. Nowadays, dynamic graph networks have been used in time series prediction.[98] Motivated by these findings, we can establish global and local dynamic graph networks to describe the time-varying characteristics of the ironmaking process. Besides, to deal with poor data with missing values and outliers, we can introduce prior knowledge to generate association graphs, which is beneficial for engineers to understand the mechanism of the industrial system.

3.3. Soft Sensing Modeling Methods Based on Deep Learning Models. With the development of sensor technologies and the accumulation of massive data, traditional shallow models struggle to capture deep features from various data such as image, text, etc. Recently, more and more researchers have started to turn their attention to deep learning-based soft sensing modeling applications in the ironmaking process.[99,100] However, now deep learning-based soft sensing model is relatively rare in the ironmaking process; we will introduce three representative soft sensing methods in detail in the following subsections.

3.3.1. Denoising Spatial-Temporal Encoder-Decoder Framework for BTP Multistep Prediction. In order to alleviate the disturbance of industrial noise, a denoising spatial-temporal encoder-decoder (DSTED) framework was proposed to achieve the BTP multistep prediction in advance, which can provide sufficient time for site-workers to adjust the trolley speed to maintain the normal operation of sintering process.[101] DSTED is made up of three modules: the data generation module, encoder module, and decoder module, as depicted in Figure 6. First, we determine the process variables that are related to BTP and collect raw data from sintering process. After data preprocessing, the generated time series are fed into the encoder network with denoising GRU. Then the spatial−temporal attention mechanism is embedded into the decoder network to extract the dynamic correlations between the hidden features and the BTP. Eventually, a fully connected layer is adopted to predict BTP using the output of the decoder network.

Recently, Yan et al.[102] have also proposed the CBMP model to capture the temporal features and spatial features simultaneously. In the CBMP model, a spatial−temporal recalibration block was developed to quantify the contributions of spatial−temporal features for fine-grained modeling. However, these models also have some limitations. For example, these models have not considered the error accumulation problem in the multistep prediction task. Because the predicted value of the last step is directly fed to the next step, it causes error disturbance and degrades its prediction accuracy. In this case, they only obtain three-step prediction and have not achieved long-term prediction. In fact, it is better to achieve more steps and provide sufficient time for site workers to adjust relevant process parameters for normal production. For time series prediction, the latest transformer-based models such as Flowformer,[103] FEDformer,[104] Meta-

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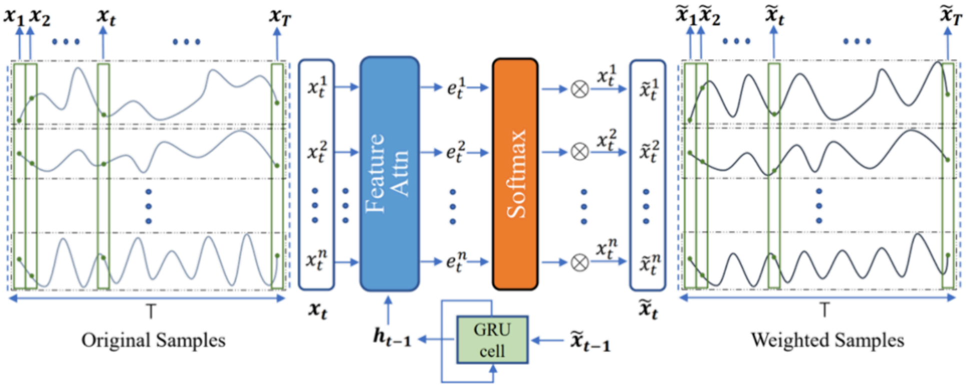

Figure 8. Context-aware enhanced GRU network model for the prediction of hot metal silicon content.[107]

former,[105] etc. have obtained the outstanding performance on the long-term series prediction tasks. Flowformer replaces the original multihead self-attention with flow-attention, which can reduce the nontrivial information aggregation. The experimental results reveal that it has linear computation complexity and achieves desirable accuracy on extensive prediction tasks. In order to capture the global trend, FEDformer adopts frequency analysis to extract important features from time series by seasonal-trend decomposition. Recent works show that the simple MLPs can substitute for an attention mechanism, and the model still has reasonable performance. Inspired by this idea, Metaformer utilizes a general framework using a spatial pooling operator. For the BTP long-term prediction, these models may be a good choice in the future.

3.3.2. Multisource Information Fusion Autoformer for FeO Soft Sensing Modeling. To make full use of process variables and image data in the sintering process, a multisource information fusion Autoformer (MIFAutoformer) model[106] was developed to predict FeO content in real-time, as shown in Figure 7. First, we select some relevant process variables according to expert knowledge including raw material parameters, operation parameters, state parameters, etc. Then we adopt a convolutional network SE-ResNet to extract the deep features of the infrared images of the sinter cross-section. Next, we combine the two kinds of features based on the backtracking time of the label data. Finally, the fused features are fed into the Autoformer to capture complex temporal patterns in the time series and achieve soft sensing of the FeO content. The MIFAutoformer model has been applied to a sintering process, and the experimental results confirm that the MIFAutoformer outperforms the existing baselines.

The MIFAutoformer model mainly fuses process data and image data at the feature level, ignoring the data-level and decision-level fusion. It is essential to fuse the raw process data and deep image information at the data preprocessing stage in the sintering process. Moreover, the time complexity and parameter size of MIFAutoformer are relatively high compared to Transformer, which makes model training time-consuming. It is necessary and feasible to establish a lightweight prediction model for FeO soft sensing in the future. Pretraining methods have been widely used for other domains such as time series prediction. We can use pretraining and fine-tuning to enhance the efficiency of the developed models. Moreover, this model has not also incorporated expert knowledge into deep learning models, leading to unreliable guidance for the engineers in the factory. Purely data-driven models are black models lacking interpretability. For the sintering factory, it is hard to deploy the black models into the industrial system. Therefore, we need to combine mechanism knowledge and achieve accurate FeO soft sensing.

3.3.3. Context-Aware Enhanced GRU for MIQ Prediction. Additionally, with the rapid improvement in computing power, deep learning-based soft sensing methods have been used to achieve MIQ prediction. For example, Li et al.[107] proposed a context-aware enhanced GRU Network with feature-temporal attention to predict silicon content in hot metal, as shown in Figure 8. First, to solve the mismatch between the process variables and silicon content, a temporal self-attention mechanism was embedded into the GRU to automatically learn the weights of different times. Moreover, the causal convolution-based self-attention was also incorporated into GRU to boost the local context-awareness of the model. The context-aware enhanced GRU has been packaged and deployed on the Industrial Internet platform through Docker in a steel plant in the south of China.

Nevertheless, this work[107] used the silicon content of the last step as the input of soft sensing model, which can be seen as a deficiency for the engineering application. Because the silicon content tends to be unknown in actual production, it is unrealistic to utilize the label data. Meanwhile, this model did not consider the distribution shift phenomenon caused by the fluctuation of raw materials and dynamic working conditions. In the ironmaking process, a well-trained model in the laboratory cannot work well in the field testing because of much random disturbance. How to improve the generalization ability of the soft sensing model is also a promising direction.

4. FUTURE DIRECTIONS AND OPPORTUNITIES

4.1. The Time-Delay Problem between Variables in Ironmaking Process.

Since ironmaking is a long process, it takes several hours from raw material acquisition to product generation, which results in a time delay between process variables and quality variables. For example, sampling time for process variables may be one min, whereas it may take several hours to test the quality variables in the laboratory once a time. In addition, when the working conditions change, the time delays of these variables are different, causing a mismatch between the input variables and the output variables. Nowadays, some scholars have carried out related research on this problem. For example, Yao et al.[108] proposed a semisupervised dynamic feature extracting (SSDFE) network to optimize the time-delay parameters in the training process. But these works still cannot effectively solve the time-delay

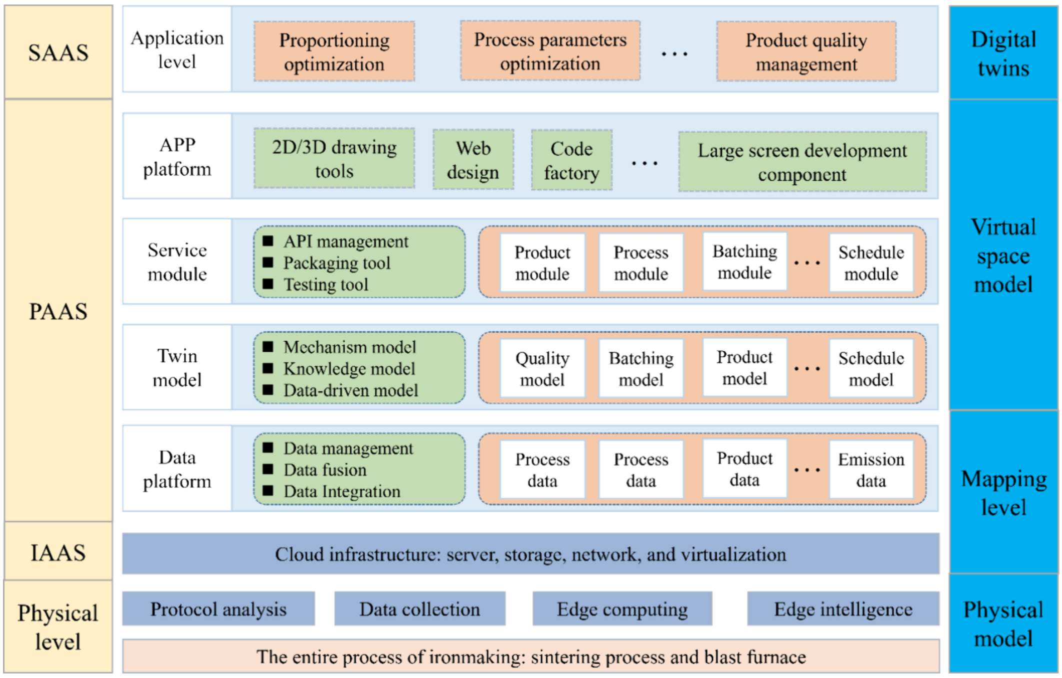

Figure 9. Flowchart of digital twins in the ironmaking process.

problem in the ironmaking process. This challenging problem will be a popular research topic in the future.

4.2. Knowledge Extraction and Fusion in Ironmaking Process. At present, soft sensing modeling methods of the ironmaking process mainly focus on the data-driven level, ignoring expert knowledge such as complicated physicochemical reaction mechanism, which leads to the poor interpretability for the black box models. In the actual factory, researchers cannot explain why the established models work, which brings a strong unreliability to engineering applications. In order to increase interpretability, incorporating expert knowledge into data-driven models will be a promising idea. For example, Li et al.[109] mined the internal rules of the industrial processes by constructing high-quality interpretable features. Chen et al.[110] adopted a graph neural network to establish the relationships among process variables, which realizes the automation of knowledge in industrial processes. But these works have not considered the mechanism of the physicochemical process. To solve this problem, we are faced with two challenges: (1) how to extract knowledge from the ironmaking process according to the principles of physical metallurgy and (2) how to properly embed mechanism knowledge into neural networks.

4.3. Multitask Learning for Quality Variables in Ironmaking Process. Most soft sensing models in the ironmaking process focus on predicting the single quality variable and have yet to predict multiple quality variables simultaneously. In the ironmaking process, complex coupling relationships exist among different quality variables, but now most studies have not solved this problem. Therefore, this is also a promising direction to explore the complex coupling relationships of quality variables. To our knowledge, multitask learning[111−113] can model the interactive relationships between different objects. Following this idea, it is empirically feasible to construct distinct tasks according to multiple quality variables and learn their correlations by a loss function in the neural network. For multitask learning, the two key problems need to be solved: (1) how to design the main and auxiliary tasks and (2) how to define and optimize the loss function.

4.4. Self-Supervised Learning for Lack of Labeled Samples in Ironmaking Process. As described in section 2, it will take several hours to test the quality variables in the actual factory; thereby, the labeled samples are very scarce. However, there are a large number of unlabeled samples because the process variables are collected every 1 min through PLCs in the ironmaking field. It is essential to explore an effective method to leverage rare labeled samples and abundant unlabeled samples. Recently, the well-known self-supervised learning has obtained satisfactory performance on the small labeled data set by learning useful representations from enormous unlabeled samples in the computer vision domain, such as MoCo, SimCLR, BYOL, etc.[114−116] Self-supervised learning aims to mine valuable features for the downstream tasks from unlabeled data sets by designing auxiliary tasks, boosting its feature extraction ability. For the ironmaking process, it is natural and rational to construct an unlabeled data set using the abundant process variables and generate a small labeled data set to achieve the soft sensing modeling task. Therefore, self-supervised learning will become a very interesting direction in the ironmaking process in the future.

4.5. Industrial Internet Platform for Ironmaking Process Based on Digital Twins. In order to apply these theoretical studies to engineering practice, we provide an Industrial Internet platform for ironmaking process based on digital twins,[117,118] as shown in Figure 9. The whole ironmaking system platform mainly consists of four parts: physical level, Infrastructure-as-a-Server (IAAS) level, Platform-as-a-Service (PAAS) level, and Software-as-a-Service (SAAS) level. First, the physical level contains the entity of the ironmaking production line and the corresponding automation system. Then the data are collected and stored in the IAAS layer through protocol analysis, edge computing, and data integration. The main techniques are implemented in the PAAS layer, including data platforms, digital twin models,

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APP platforms, and microservice modules. Finally, our developed intelligent models are deployed into the SAAS layer as industrial APPs, including optimization for ironmaking proportioning, optimization design of process parameters, product quality prediction, control of process parameters, fault diagnosis, and intelligent maintenance. Based on the Industrial Internet platform, the site-workers can monitor the operation conditions of actual production in real-time and then take the corresponding measures to maintain normal operation of the ironmaking process.

5. CONCLUSION

The data-driven modeling methods have increasingly drawn attention in the ironmaking process with the rapid accumulation of a huge amount of industrial data. In this Review, we provide a systematic survey of data-driven soft sensing modeling methods from various aspects in the ironmaking process. After that, a general soft sensing modeling framework is summarized to present general guidance for researchers and engineers. In particular, we review and analyze traditional machine learning and deep learning models for soft sensing in the ironmaking process, which is beneficial to researchers to understand the current study status quickly. In order to track the frontier progress of data-driven models, some worthwhile topics such as self-supervised learning are outlined to inspire new ideas and techniques for future research on the ironmaking process.

■ ASSOCIATED CONTENT

Data Availability Statement

We have published a real silicon content data set for researchers to carry out some interesting scientific topics. Our data and codes are available at https://github.com/ylkyc/ironmaking-zju.

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Notes

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