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REVIEW

Application of deep learning in iron ore sintering process: a review

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Abstract
In the wake of the era of big data, the techniques of deep learning have become an essential research direction in the machine learning field and are beginning to be applied in the steel industry. The sintering process is an extremely complex industrial scene. As the main process of the blast furnace ironmaking industry, it has great economic value and environmental protection significance for iron and steel enterprises. It is also one of the fields where deep learning is still in the exploration stage. In order to explore the application prospects of deep learning techniques in iron ore sintering, a comprehensive summary and conclusion of deep learning models for intelligent sintering were presented after reviewing the sintering process and deep learning models in a large number of research literatures. Firstly, the mechanisms and characteristics of parameters in sintering processes were introduced and analysed in detail, and then, the development of iron ore sintering simulation techniques was introduced. Secondly, deep learning techniques were introduced, including commonly used models of deep learning and their applications. Thirdly, the current status of applications of various types of deep learning models in sintering processes was elaborated in detail from the aspects of prediction, controlling, and optimisation of key parameters. Generally speaking, deep learning models that could be more effectively implemented in more situations of the sintering and even steel industry chain will promote the intelligent development of the metallurgical industry.

Keywords Deep learning · Sintering process · Modelling · Simulation technology · Intelligent sintering

1 Introduction

The iron and steel industry is an essential embodiment of a country's productive capacity and plays a fundamental role in national economic development and national defence construction [1]. In recent years, China has the world's largest crude steel yield, exceeding 1 billion tonnes by the year 2020 and reaching 1.065 billion tonnes for the first time [2]. At the same time, behind the huge productive capacity, China, as a responsible and committed developing country, still has the historical mission of "carbon peaking" and "carbon neutrality". Considering the global warming, the traditional ironmaking process needs to be transitioned to a more intelligent and environmentally friendly one. In particular, the sintering process is one of the highly energy-intensive stages of the ironmaking process, which relies mainly on coal and coke for the entire combustion process and generates large amounts of emissions of carbon [3, 4]. The sintering process is characterised by highly complex processes and nonlinear control processes, which are hard to describe with an accurate mathematical model. This situation makes the path to wisdomly face a challenge [5]. In dealing with these characteristics of the sintering process, deep learning, an important branch of machine learning that has emerged in recent years, has been introduced into steelmaking and is widely used as a nonlinear modelling algorithm that uses artificial neural networks as the basic architecture for

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feature extraction and knowledge learning from data [6–8]. It has become one of the most important tools for smartening up the steel industry. This paper provides an introduction to the principles of deep learning and a comprehensive account of previous work on the application of deep learning to the process of sintering and its advantages and disadvantages.

Since the concept of artificial intelligence was first introduced at the Dartmouth Conference in 1956, it has developed through highs and lows and is now in its third wave of development [9]. In the background of big data and strong computing computer developments, machine learning algorithms have made breakthrough advances in a variety of sectors such as computer visualisation, speech recognition and natural language processing, and their applications based on artificial intelligence (AI) technology have matured for industrial fields. Research on AI technology and its industrial applications are beginning to enter a new stage of development [10].

On the basis of machine learning and gradually developed deep learning, the two concepts are often confused. Machine learning is an important area of artificial intelligence, and its core is the ability of machines to acquire data to learn "for themselves". Instead of manually writing software programs to complete target tasks, machine learning allows the system to learn on its own to recognise situations and make predictive judgments; thus, machine learning systems can quickly process tasks by using knowledge and training from large-scale datasets [11], whereas deep learning is a subset of machine learning. It leverages machine learning techniques in conjunction with neural networks that emulate human decision-making to address practical problems [12]. Compared with machine learning, the cost of deep learning increases due to the need for large datasets to support its training. Therefore, according to the situation of different fields, we should choose the appropriate method. Taking image recognition as an example, the biggest advantage of machine learning is that its training and testing time is shorter than that of deep learning models, making it more suitable for low-computational applications, but the recognition accuracy is not high enough [13]. However, deep learning can extract feature information of different resolutions and obtain more complete image information. It has more powerful learning capabilities than machine learning and is more suitable to the needs of accurate image recognition [14].

Generally speaking, the main modelling approaches applied for the measurement and prediction of key parameters of sintering processes in the metallurgical industry are data-driven modelling [15]. Later, as data collecting technologies advanced, an increasing number of researchers began to concentrate on and conduct experiments using machine learning modelling approaches. Among them, support vector machine (SVM) [16], decision tree (DT) [17], and XGBoost [18] are the more commonly used modelling methods. In particular, for its excellent generalisation capability, SVM is well known in the machine learning community and is widely used in research areas such as industrial process monitoring, fault diagnosis, and prediction of key performance indicators [19]. In actual applications, however, the requirements for product quality and environmental protection in modern industry are increasing, and industrial processes are becoming more complex and larger in scale. Machine learning modelling methods rely excessively on manual feature extraction and expert knowledge; therefore, processing data with highly nonlinear, high-dimensional, strongly coupled, and dynamic process can be difficult to use these classic machine learning techniques.

It is encouraged to note that with the rise of deep learning and big data, sintering process monitoring has a new opportunity for development. Deep learning is also certainly going to inject new momentum into smart steel manufacturing. Deep learning algorithms can be divided into several areas such as classification, target detection, image segmentation, and sequence analysis, distinguished by the type of task and key techniques [20]. Because of its ability to automatically learn intricate features in data by layering representations from the lowest to the highest layers, deep learning has led to many advances in computer vision (CV), natural language processing (NLP), and speech recognition [21–24]. Vision-based deep learning algorithms combined with partial sequence analysis techniques can already be applied in important processes in the steel industry. This includes image classification techniques for sintering fire watching [25], target detection techniques for slab surface quality inspection [26], image segmentation techniques for conveyor belt runout detection [27] and slag picking identification of iron ladles [28], as well as blast furnace radar fabric identification [29] and steel plate size measurement by fusing convolutional neural networks (CNNs) [30] and long short-term memory (LSTM) [31] techniques.

Along with the rapid development of advanced sensor technology and distributed control systems in recent years, it is easy to obtain massive amounts of data from the sintering process. This state of being enables the expansion of deep learning neural network training sets. As a consequence, deep learning has received a great deal of attention and has been applied to the soft measurement of key parameters in industrial processes [32, 33]. For the sintering process, limited by its level of complexity and the high difficulties of data pre-processing, traditional inspection methods are unable to capture accurate and advanced features from complex data. It is only rational and necessary to investigate deep learning-based modelling approaches in the sintering process, drawing inspiration from successful application instances of other industrial processes. The ideal way to utilise and integrate cutting-edge deep networks into the sintering process is now a hot topic for academics to address.

2 Analysis of sintering process

Since the last century, with over more than 100 years of development in iron and steel industry, iron ore sintering has been used in more advanced applications, which include briquetting, granulation, sintering, and pelletising. With the development of iron ore beneficiation technology, low grade ores can be made available at higher grades by grinding and separation processes. However, in order to ensure the permeability of the blast furnace charge, this pulverised material must be briquetted before it can be injected into the furnace. In addition to this lumping requirement, the excellent blast furnace characteristics of sintered ore were also appreciated by the ironmaking process. Therefore, the sintering process eventually became the preferred choice for the briquetting of pulverised materials [34].

2.1 Sintering process and its chemical reactions

The significance of sintering is that the lumping of pulverised ore from the mining process can be used to obtain high grade, high strength, good reducibility and good metallurgical properties of man-made clinker, which is conducive to meeting the permeability of the blast furnace, ensuring smooth operation and improving economic indicators. The sintering and lumping processes can also remove harmful impurities like sulphur, improve the quality of the charged material and undertake partial blast furnace smelting tasks. In addition, lumping can also be used to recycle iron-containing waste such as steel slag and dust sludge from the production process of steel mills, which reduces costs and protects the environment. Currently, there are two methods of lumping: pelletising and sintering, of which sintering is the main method [35, 36].

The flow of the iron ore powder sintering process is summarised below [37]. According to specifications, a range of raw materials comprising pulverised iron are combined with a certain amount of fuel and melting agent, then thoroughly combined, granulated, and delivered to the sintering equipment for ignition and sintering. The high temperature created by burning the fuel causes a number of physical and chemical events. Fusible material of some of the mixture softens and melts, creating a small quantity of liquid phase that wets the remaining unmelted ore particles. Under the influence of air extraction, the high-temperature area constantly moves in the direction of negative pressure, and after experiencing high temperatures, with a drop in temperature, the liquid phase material will bind mineral powder particles into blocks. This procedure is known as sintering [38]. Figure 1 depicts the flowchart for the sintering process.

The common belt sintering machine air extraction sintering process is top-down, and the main chemical reactions that occur in the sinter are as follows.

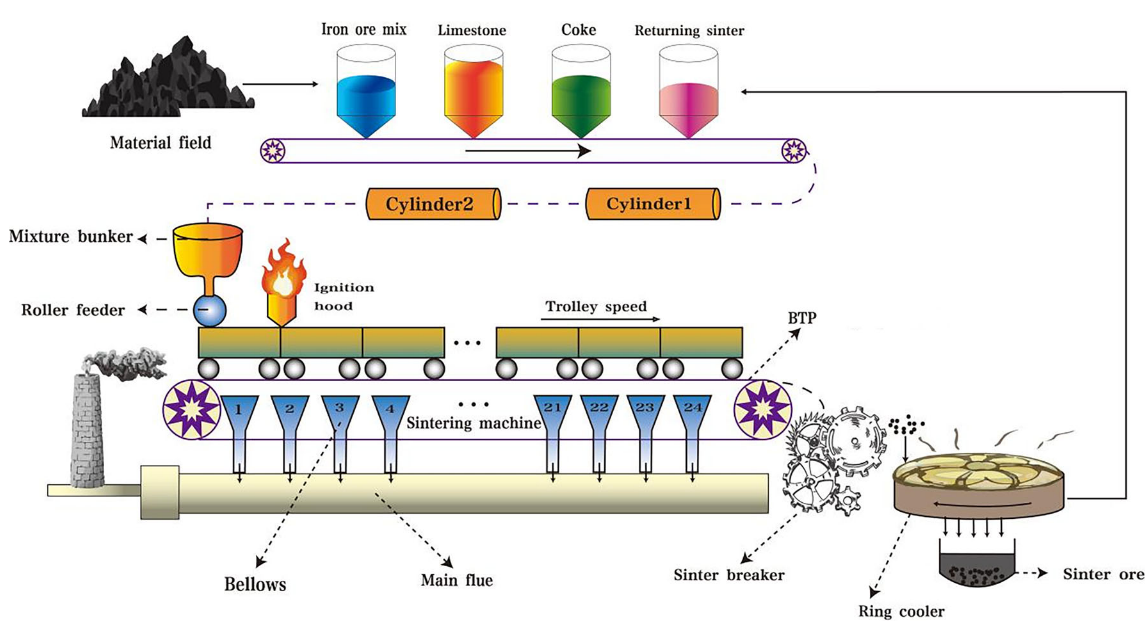

Fig. 1 Process flowchart of iron ore sintering

$$1/2O_2(g) + [C] = CO(g) \quad (1)$$

$$[C] + O_2(g) = CO_2(g) \quad (2)$$

$$3[FeS_2] + 8O_2(g) = [Fe_3O_4] + 6SO_2(g) \quad (3)$$

$$2[Fe_3O_4] + 3SiO_2(g) = 3(2FeO \cdot SiO_2) + O_2(g) \quad (4)$$

$$[Fe_3O_4] + CO(g) = 3[FeO] + CO_2(g) \quad (5)$$

The sintering process is an intricate system with a protracted process flow. The steps in the manufacturing line are primarily composed of the ingredients and mixing process, the sintering operation process, and the treatment of the sintered ore [39, 40].

2.2 Important parameters and characteristics of sintering process

As shown in Fig. 2, all variables affecting sinter quality and production efficiency can be broken down into raw material parameters, operational parameters, equipment parameters, state parameters, and index parameters in order to make the study more manageable. These parameters are closely linked and affect each other. For instance, the water-material ratio and sintering speed, which are key parameters influencing the sintering effect in the sintering process, determine the reaction rate. Additionally, the air permeability affects the sintering speed, and it is determined by the physical and chemical properties of the mixture as well as its water content. These factors collectively contribute to variations in burn-through point (BTP). FeO content, as an important index parameter, is also closely related to bed height, ignition temperature, water content, raw material parameters, etc. [41]. As shown in Table 1, there are many parameters and indicators in the sintering process, and they affect each other. Therefore, this point should be fully considered in the process characteristic analysis for industrial modelling and optimisation.

The performance and yield of the sintered ore are affected by a variety of factors throughout the automated, continuous, multi-station, multi-input, and multi-output sintering process. The primary features of the sintering process are complexity, highly nonlinearity, time-varying, and hysteresis.

2.3 Development of iron ore sintering simulation technology

The development of sintering theories and techniques has been accompanied by the development of sintering models and simulation techniques. Simulation is able to predict some of the behaviours in the sintering process, especially complex phenomena that are not easily grasped by experiments, like the mixing of sintered raw materials,

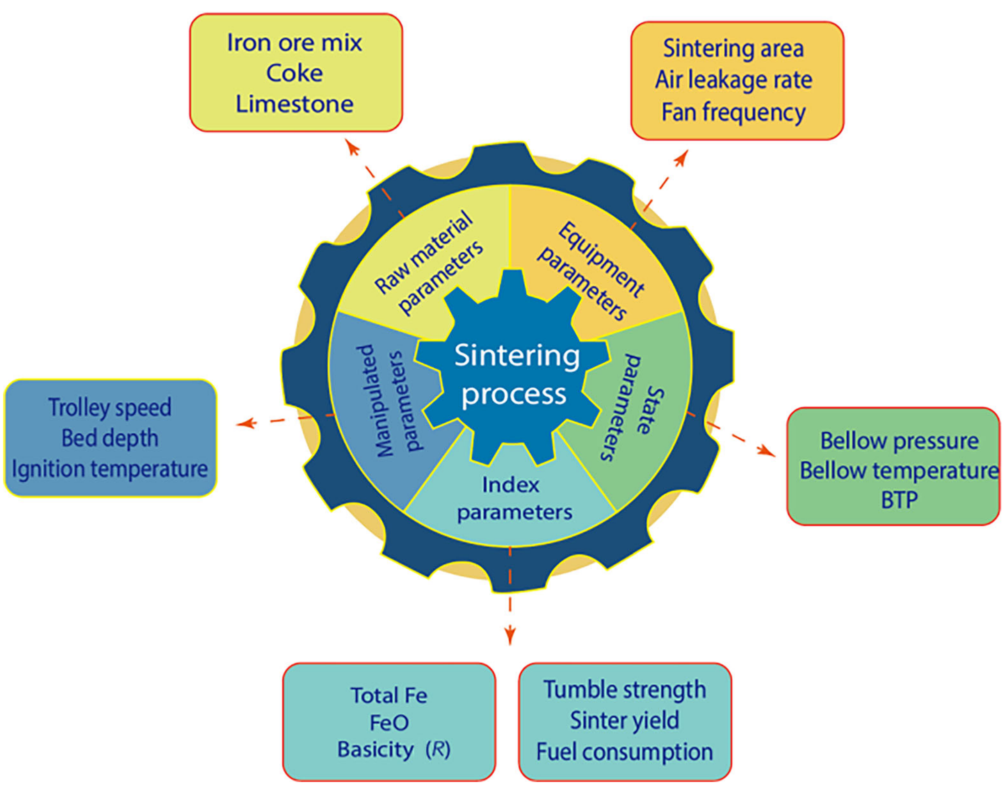

Fig. 2 Parameters in sintering process

Table 1 Main parameters affecting sintering process

Type of variable	Parameter	Effect on sintering process	Correlation parameter
Raw material parameter	Fuel (Coke)	FeO content can be increased by increasing fuel consumption appropriately	Amount of fuel will affect sintering temperature and sintering speed
	Limestone	Limestone plays roles in regulating basicity and improving air permeability of sintering process	Mixture ratio and particle size will affect use effect of limestone
Operational parameter	Trolley speed	Too fast: incomplete sintering, low yield Too slow: prolonging sintering time	It is affected by sintering temperature, material layer thickness, raw material parameters and other factors
	Ignition temperature	Too low: undermelting of sinter surface Too high: reduced permeability	It is affected by bed depth and air leakage rate
Equipment parameter	Sintering area	Too small sintering areas can lead to increased energy consumption and flue gas emissions	It is influenced by particle size of raw materials and directly affects sintering temperature and sintering time
	Fan frequency	Increased frequency boosts oxygen content for better combustion but increases flue gas flow	It affects ignition temperature and sintering temperature
State parameter	Bellow pressure	Too low: incomplete fuel combustion Too high: reduced combustion temperature	It mainly affects ignition temperature
	BTP	Changes in location of BTP can affect amount of returning ore and yield of finished product	It is influenced by parameters such as sintering rate, bed depth and permeability
Index parameter	FeO	Too high: poor reducibility Too low: lower strength of sintered ore	It is affected by mix composition, layer thickness and permeability, basicity, etc.
	Basicity	Low basicity leads to a reduction in tumble strength and reducibility	It is influenced by factors such as mix composition, fuel ratio and sintering temperature
	Tumble strength	Higher strength results in less pulverised sinter and better gas permeability	It is influenced by raw material parameters, basicity, bed depth, sintering speed, etc.

granulation behaviour, the state of the high-temperature zone of sintering, movement, etc. The key to modelling and simulating is to select and construct a reasonable model and to form a stable system with a mapping structure in order to accurately represent the changing laws of the process system. The production of blast furnace ironmaking depends on large part on the sintering of iron ore; thus, it is crucial to model, simulate, and optimise the sintering process in order to increase automation and implement intelligent manufacturing [42].

From the perspective of information perception and intelligence, for the simulation of the whole process and system parameters of sintering, the mechanism model is generally chosen for modelling, in which the simulation for the equipment and process in the sintering process is more suitable to use the field model [43, 44]. The data-driven model can be used to mine the data information in the sintering process. These two modelling approaches are the mainstream methods for sintering process modelling at present.

2.3.1 Mechanism model

This approach is based on the study of the sintering process mechanism and the phenomena associated with the system parameters in order to model the characteristic parameter architecture. The high degree of coupling between the parameters of the system model requires the division of the model into functions and subsystems based on two levels of parameter resolution and model synthesis. Analysis is to decompose the overall functional modules and process forms of the system hierarchically and selectively decouple the relevant parameters, so that certain process analysis can be done in raw materials preparation, high-temperature sintering and waste heat utilization. Comprehensively considering the overall development of the system, the main functional modules and process forms are fully integrated, and the relevant scattered parameters are correlated and coupled to form a relatively complete model system, as shown in Fig. 3.

The analytical model achieves the purpose of model simplification by highlighting the main reactions and omitting secondary factors. The main models formed include combustion mechanism, heat distribution of material layer, composition and distribution of sintering flue gas, etc. Model synthesis is to systematically build various analytical models and consider the entire sintering process to meet the needs of sintering process control optimization. Among these, mechanism-based modelling involves the analysis of physical and chemical principles to create an accurate mathematical model. This approach requires a deep and clearly understanding of the entire industrial process mechanism. Usamentiaga et al. [45] presented a sensor for monitoring sintering burn-through points based on infrared thermography. The procedure they proposed was on the basis of the collection of infrared and thermal images at the end of sintering process, which was a mechanism-based modelling approach. However, sintering is a rather complex process with continuously changing physical and chemical reactions, and it is difficult to construct an exact mathematical model.

Field state modelling, as a branch of mechanism modelling, received some attention as well. The sintering thermal process is a coupling of multiple field information such as heat, mass, momentum and chemical reactions. In a systematic and comprehensive analysis of the sintering process, the unit processes must be modelled and then coupled with multiple related unit processes to carry out a holographic simulation of the integrated field states [46, 47]. Methods for implementing such numerical simulations rely heavily on existing software frameworks for modular extensions, as well as autonomous programming using common computer platforms and software, and are therefore currently used as a means of implementing mechanism models.

2.3.2 Data-driven model

Since the sintering process is a dynamic system with many influencing factors, complex mechanisms, strong coupling and large lags, in practice, a multilevel process information computer management system in an enterprise can collect and store a large amount of information related to product quality, yield, and cost parameters. Data mining of the production process or sintering test data information allows the establishment of a data-driven fusion model, as shown in Fig. 4. These models do not require deep mechanistic knowledge of the sintering process, only specific parameters are selected as inputs and outputs of the model, and various mathematical and artificial intelligence algorithms are used to establish the mapping function between the input and output parameters. The main applications of the data-driven fusion model are sintering parameter prediction and sintering process optimisation, where the keys are modelling data and updating of model parameters, as well as the fusion and self-learning training process. The parameters include directly measurable parameters, indirectly measurable parameters and their correlations; the optimisation covers raw materials preparation, sintering operations and process systems. In particular, data-driven models can be used to predict specific parameters that

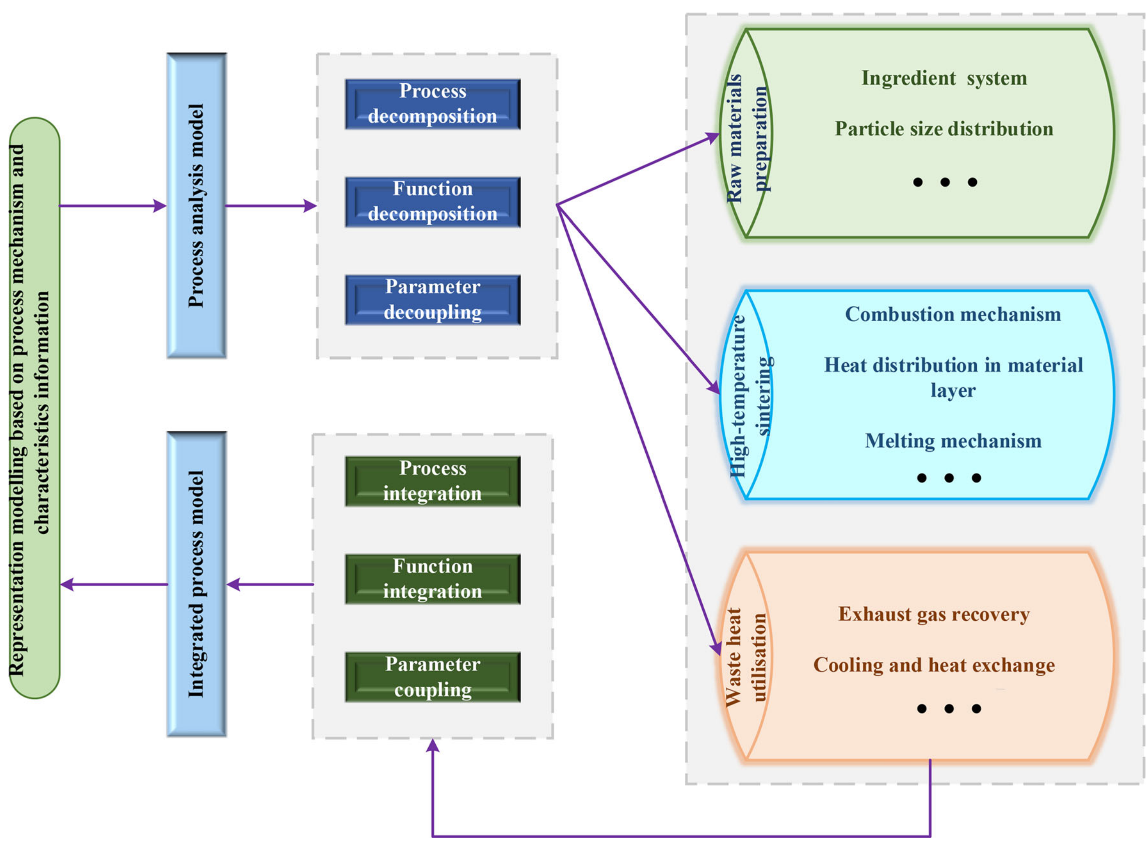

Fig. 3 Mechanism modelling system

cannot be measured directly or where there is a lag in the measurement process, like sintering endpoint, sintering product composition indicators, sintering flue gas composition, etc.

Classic data-driven modelling approaches mainly consist of multivariate statistical analysis approach and machine learning modelling approach. Common statistical analysis methodologies include principal component analysis (PCA) [48], independent component analysis (ICA) [49], and partial least squares (PLS) [50]. Using the concept of dimensionality reduction, PCA is a method for condensing datasets. It is a linear transformation created to reduce a large number of individual indicators to a handful of composite indications. ICA uses a decomposition matrix to multiply the data in order to recover the original source. The primary distinction between ICA and PCA is the requirement for a predetermined number of independent sources for decomposition in ICA. This implies that the user must have an understanding of the information ahead and certain specific data features that cannot be picked at random. PLS, in contrast, permits the simultaneous use of principal component analysis, multiple linear regression, and correlation analysis between two sets of data. The modelling method of machine learning has been introduced in the introduction and will not be repeated here. At present, the main research direction of sintering modelling is to combine deep learning model to improve accuracy while retaining the advantages of fast and low computational load of machine learning modelling.

In simple terms, data-driven decisions and actions are based on massive amounts of data. It is a model based on data analysis and machine learning techniques. As one of the important new branches of machine learning, deep learning is currently an important method to achieve data-driving and has shown great potential in many fields as well as soft sensing scenarios [51]. Deep learning is a hot topic in artificial intelligence, with its excellent recognition and classification ability to use a large amount of data to train models, so as to build data-driven models with better performance in prediction, classification and decision-making. At the same time, deep learning has a clear advantage in improving the efficiency of sample labelling, which helps us achieve the transition from model-driven modelling to data-driven modelling [52]. From this, we can foresee that deep learning will unlock the intelligent future of data-driven modelling.

Both sintering process modelling techniques have been applied in practical production, and Table 2 summarises the research progress of these two modelling methods.

In the current analysis of iron ore sintering processes, modelling from a deep learning perspective has become a powerful tool and a research hotspot, regardless of the modelling method.

3 Commonly used deep learning models and their applications in sintering

The existence of numerous applications linked to emerging technologies like big data, the internet of things, and cloud computing has caused an accelerated increase in the magnitude of data. A major research challenge nowadays is

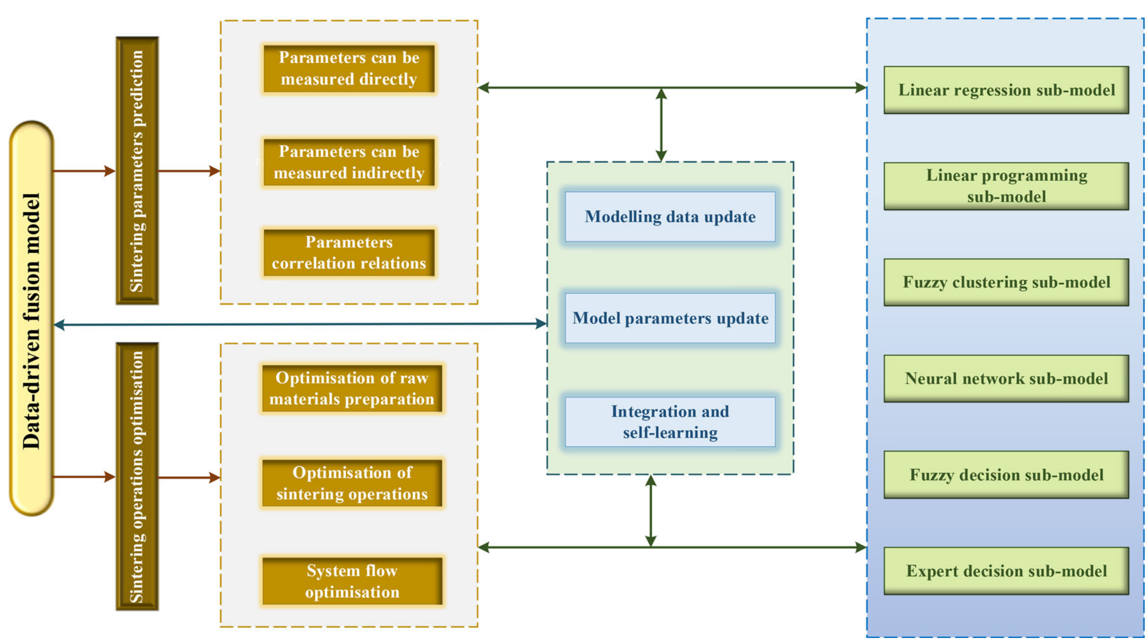

Fig. 4 Data-driven modelling system

Table 2 Research progress in application of numerical simulation techniques

Model	Reference	Research progress presentation
Mechanism model	Waters et al. [53]	A mathematical model of granulation process was developed, and particle size distribution was predicted by combining particle size distribution of raw materials, amount of moisture added and physical properties of raw materials
	Venkataramana et al. [54]	A combined mathematical model for simulating granule size distribution and cold material sinter bed permeability was developed
	Nyembwe et al. [55]	Granulation effect of sintered mixtures with addition of concentrates and small pellets was investigated, and applicability of model was verified
	Zhao et al. [56]	A fuel particle sub-model was developed based on analysis of sintering characteristics to investigate influence of fuel properties on sintering conditions
	Hou et al. [57]	A coke dust combustion model was developed to analyse effects of large particle fuels on sintering conditions under different distribution methods
	Pahlevaninezhad et al. [58]	A model of iron ore sintering based on coke combustion reaction was developed
Data-driven model	Donskoi et al. [59, 60]	An empirical model for optimising performance of sintered ores containing texture information was developed and sintering performance was analysed for different texture parameters
	Li et al. [61]	A recurrent neural network (RNN)-based dynamic temporal feature unfolding and extraction framework was developed to improve prediction of FeO content in sintering process
	Jiang et al. [62]	Combination of heat transfer mechanisms and LSTM-based data-driven models was used to implement online prediction of FeO content
	Gao et al. [63]	A mathematical model for predicting tumble strength of sinter was developed using artificial neural network techniques
	Du et al. [64]	A fuzzy time series modelling method based on fuzzy c-mean clustering was proposed to accurately predict BTP
	Ye et al. [65]	A data-driven prediction of tumble strength based on local thermal non-equilibrium (LTNE) model is proposed to solve problem of uncertainty in thermochemical reaction equations of sintered beds

how to efficiently and swiftly extract usable information from redundant and complicated data. Deep learning techniques have advanced in numerous fields recently, including speech recognition, image processing, and natural language processing [66]. Table 3 classified deep learning models according to their typical application scenarios. The specific model structures and application status were introduced in detail in the following sections [67–83].

To obtain a unified representation of data, deep learning is the mapping of different data into the same implicit space, which enables the automatic learning of features on heterogeneous data from multiple sources [84]. Autoencoders, restricted Boltzmann machines (RBMs), convolutional neural networks, recurrent neural networks, deep belief networks, deep neural networks, generative adversarial networks, and multi-model fusion neural networks are among the most widely used deep learning models [85]. Table 4 compares the advantages and disadvantages of different types of deep learning models [73, 86–88]. According to extensive research by researchers, various models of deep learning have made breakthroughs in many fields, and applying deep learning to the steel metallurgy industry is an inevitable trend.

3.1 Autoencoder model structure and its applications in sintering

In 1986, Geoffrey Hinton, the father of deep learning, first proposed autoencoders to build deep learning architectures for unsupervised learning. The main purpose of the application was data compression and abstraction of valid data [89, 90]. The autoencoder network consists of a decoder and an encoder, as shown in Fig. 5. During training, usually, both encoder and decoder are needed. When applying data dimensionality reduction, only the encoder is needed. Similar to other deep learning structures, the working area of autoencoder (AE) is also in the neuron layer and trained by back propagation [91]. The basic idea is that in order to extract prospective characteristics, the input data are simply reconfigured to create the output data. An input layer, a hidden layer, and an output layer make up the fundamental structure.

The application of autoencoders in the steel industry focuses on the directions of building data-driven soft sensors and recognizing heterogeneous image datasets from multiple sources. A soft measurement model based on weighted integrated semi-supervised stacked autoencoder for online detection and prediction of moisture in sintered mixes was proposed by Jiang et al. [92]. A sintering data

Table 3 Classification of application domains of deep learning models

Application domain	Reference	Deep learning model
Image identification	Bhatt et al. [67]	CNNs
	Hosseini, et al. [68]	CNNs
	Liu et al. [69]	CNNs
	Naskath et al. [70]	DBN
	Bayraci and Susuz [71]	DNN
Natural language recognition	Mac et al. [72]	AE
	Shankar and Parsana [73]	AE
	Xiao and Zhou [74]	RNN
Video recognition	Limsupavanich et al. [75]	RNN
	Dharejo et al. [76]	RNN
	Tao et al. [77]	DBN
	Putin et al. [78]	DNN
Fault diagnosis	Yang et al. [79]	AE
	Zhu et al. [80]	RNN
	Su et al. [81]	DBN
	Gai et al. [82]	DBN
	Lee et al. [83]	DNN

DBN—Deep belief network; DNN—deep neural network

Table 4 Advantages and disadvantages of different types of deep learning models

Deep learning model	Structural characteristics	Advantage	Disadvantage
AE [73]	Its basic structure includes input layer, hidden layer, and output layer	Main feature of AE network is simple structure, which can be used for data feature extraction and dimensionality reduction and has a certain generalization ability	It can only obtain implicit expression by training model in an unsupervised way, resulting in insufficient expression ability
CNNs [86]	An input layer, a convolutional layer, a pooling layer, a fully connected layer, and an output layer make up structure of a convolutional neural network	Compared with other deep learning algorithms, it has better classification accuracy and can process data with translation invariance	Calculation process of such models is complex, data quality is high, and sensitivity to label attributes may affect performance
RNN [87]	Its basic structure consists of an input layer, a hidden layer and an output layer, but neurons are linked to each other in hidden layer	It can remember input information of last time and process input of any length, so that it is suitable for processing sequence data	Operational speed is relatively slow, and gradient frequently tends to vanish
DBN [70]	It is obtained by superimposing multiple restricted Boltzmann machine (RBM) and back propagation (BP) networks	It can be used for both supervised and unsupervised learning and allows entire neural network to generate training data according to maximum probability	Because of back propagation process in multiple hidden layers, learning time of network is prolonged, energy consumption is high, and learning efficiency is low
DNN [88]	In addition to input layer and output layer, DNN also contains several hidden layers	Due to its powerful nonlinear fitting ability, such networks can achieve adaptive learning and network optimization	Training process requires a lot of data and computing resources, and network cannot handle changes in time series

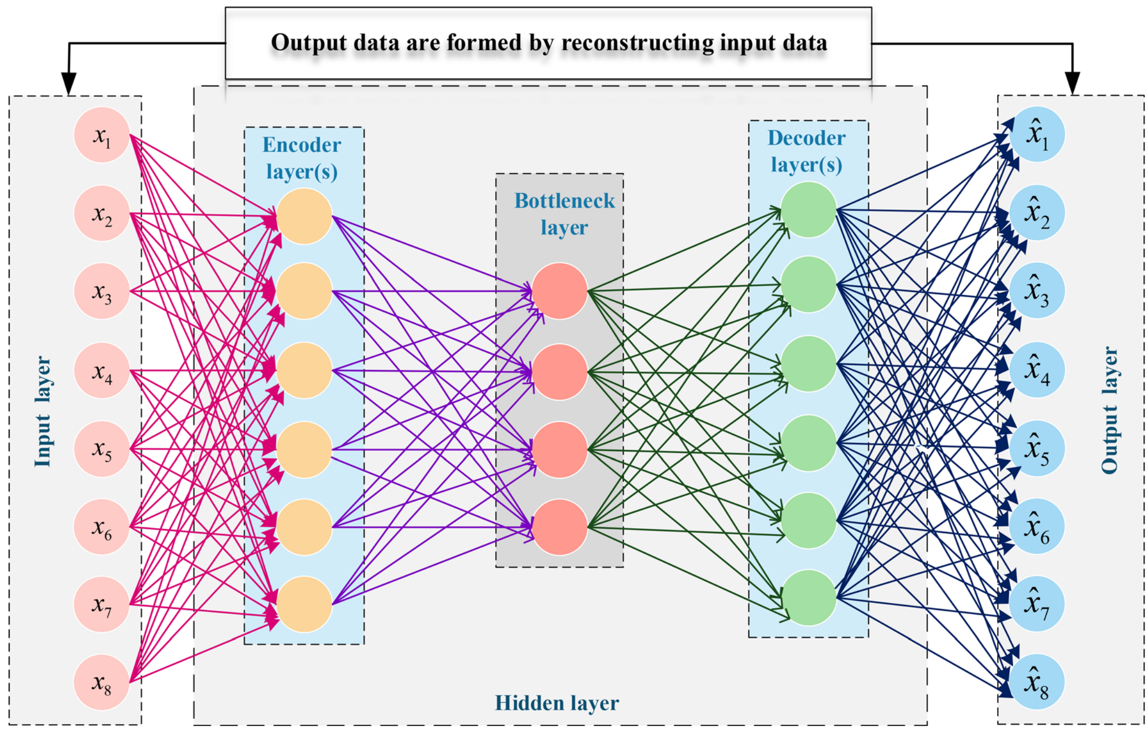

Fig. 5 Structure of autoencoder network. x_1, x_2, …, x_8—Input variables; $\hat{x}_1, \hat{x}_2, \ldots, \hat{x}_8$—output variables

fusion method based on multimodal autoencoders can accurately identify surface defects in sintered ores [93]. And Yu and Yan [94] used stack denoising autoencoder to realize fault diagnosis in sintering process. Maged et al. [95] proposed a variation-based autoencoder-long short-term memory deep learning T^2 graph, which was applied to intelligent fault diagnosis of sintering process. Chen et al. [96] employed autoencoders for intelligent modelling of industrial processes, validated their approach with sintering process cases, and developed digital twins to enable accurate production quality prediction. Wang et al. [97] used the raw process data to train the autoencoder neural network to accurately capture defective products and achieve automatic prediction of product quality in sintering process.

3.2 Convolutional neural networks model structure and its applications in sintering

CNNs are multilayer perceptrons that were once mainly used for the recognition of two-dimensional graphics and are able to create a corresponding mapping between the original input and the desired output. In recent years, they have begun to be used to solve multidimensional data in image recognition problems [98]. An input layer, a convolutional layer, a pooling layer, a fully connected layer, and an output layer make up the structure of a convolutional neural network. An illustration of the working of a convolutional neural network is shown in Fig. 6.

Convolutional and pooling layers are alternately connected as the first few layers in the standard CNNs algorithmic model, followed by a connection to a fully connected layer. After the works of the convolutional and pooling layers are completed, the fully connected layer maps these features to a space of linear classifications, and finally, the output layer outputs the classified results under the classification function processing [99].

Convolutional neural networks are one kind of widely used models in the modelling of various detection and prediction of iron ore sintering processes.

CNN models have completely surpassed traditional algorithms in image classification techniques; especially, significant progress has been made in the application for judging the endpoint of iron ore sintering. In order to achieve the determination of the sintering endpoint, after obtaining the image data of the sintering section, the CNN algorithm is used to extract the flame feature information, which can achieve highly reliable and real-time image classification, accurately determine the sintering endpoint and reduce the reliance on manual fire watching. Li et al. [20] acquired images from video of sintering sections and annotated the data with the experience of sintering workers watching the fire. They investigated the expansion of the sintered dataset using generative adversarial networks

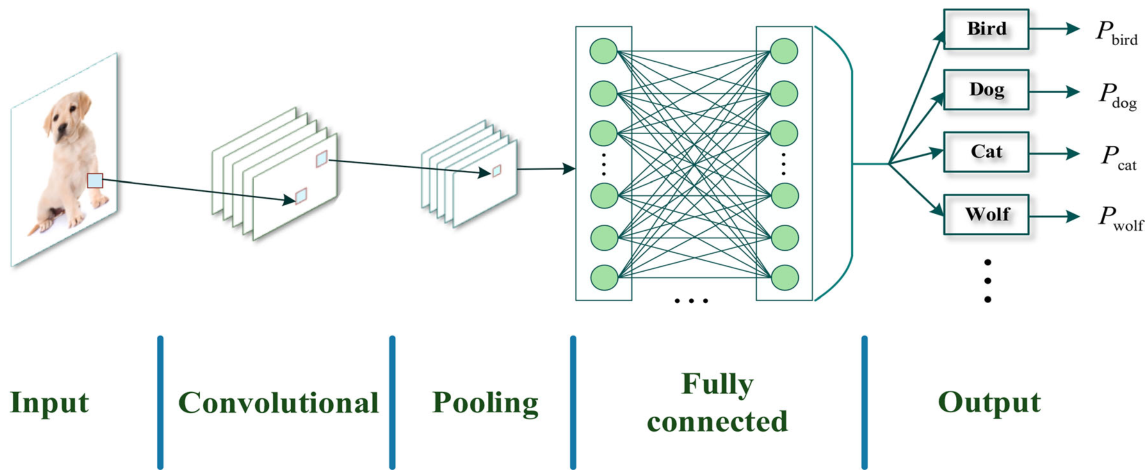

Fig. 6 Working principle of convolutional neural networks. P_{bird}—Output categorized as a bird; P_{dog}—output categorized as a dog; P_{cat}—output categorized as a cat; P_{wolf}—output categorized as a wolf

(GAN) [100] and proposed a classification model combining attention mechanisms [101] with ResNet, to rescale the feature data, to train the model using the expanded sintered dataset and to test it using production data. The results show that the classification accuracy of the algorithm can reach over 99% and the processing speed was 15 frames/s. Meira et al. [102] used CNNs to develop deep learning models with edge computing capabilities to identify quasi-particles in the sintering process of mixed pellets and to determine the particle size distribution from image data of the sintering process, and their model achieved an accuracy of 98.6% in the training validation of the images. Meira et al. [103] proposed implementation of Mask-R-CNN algorithm for segmentation of quasi-particle sizes classes in pellet sintering processes using datasets created from real images of industrial environments. Hu and Mao [104] combined LSTM and improved GAN to design a rotary kiln temperature prediction model that can effectively display important information on the time dimension. The optimisation of sinter composition is a very important aspect in the steel industry, and traditional composition optimisation methods can hardly cope with the efficient demands of large-scale production and complex working conditions. Sinter composition optimisation using a regressive convolutional neural network model can improve feature extraction, predict the optimum ratio of sintering raw materials, and give reasonable input parameters for sintering raw materials during the sintering process [105]. In practice, the sinter basicity should be controlled around 2.0, when both the calcium ferrite content and the drum index reach their maximum. Based on the ore-phase datasets, Zhi et al. [106] conducted experiments on a CNN-based basicity prediction model for ore-phase photographs and achieved more accurate prediction results. The predominant transport method in sintering production is belt transport. In order to eliminate the impact of belt damage and material blockage on production, Xiao et al. [107] proposed a CNN-based study on the detection, classification and location of sintered foreign objects, and this detection model achieved high accuracy under experimental conditions. The FeO content in sintered ore is a key indicator in blast furnace ironmaking, which still requires manual sampling and detection in actual production. Zhang et al. [108] proposed an online detection model for FeO content based on CNN and sinter tail infrared images, which can control the detection error within $\pm$ 0.5%.

3.3 Recurrent neural network model structure and its applications in sintering

RNNs are powerful in their ability to store data in a time series. The more popular ones are the deep residual RNN and LSTM RNN architectures [109]. Input, implicit, and output layers contribute to the architecture of a recurrent neural network. As shown in Fig. 7, the RNN network neurons are connected to each other in the hidden layer. The original information is preserved, and the current data are only related to the previous data. The network structure is relatively simple; thus, it can handle sequence data better.

Due to the complexity of industrial processes, it is very difficult to carry out online inspection of key quality indicators. Offline inspection methods rely excessively on manual experiences, the inspection time is long, and the information obtained is difficult to correct the production process in a timely manner.

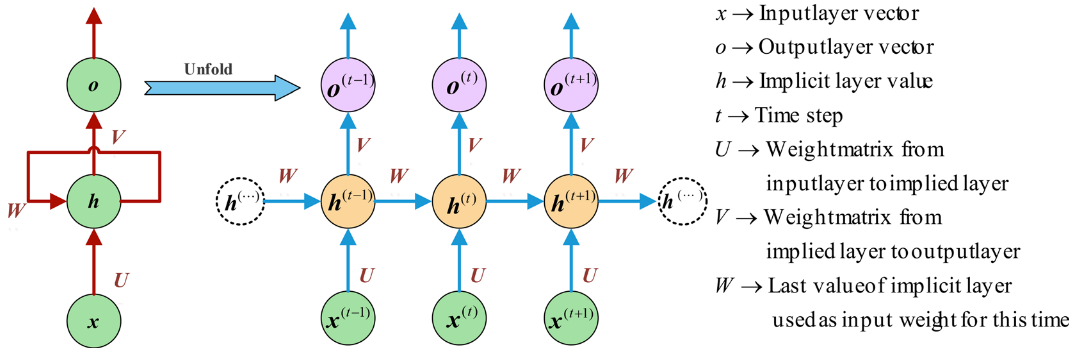

Fig. 7 Structure of RNNs

Recurrent neural networks have greater advantages in addressing latent variable prediction and dynamic feature extraction. Li et al. [61] conducted an investigation on dynamic time features unfolding and extraction for sinter quality prediction and used RNN to predict key quality parameters, which effectively improved the accuracy of FeO content prediction. RNNs are frequently employed in the learning of sequence data. Chunjie Yang and his colleagues presented a semi-supervised dynamic feature extraction framework based on sequence preliminary training and tuning to further improve the accuracy of FeO content prediction in actual sintering processes [110]. They used various RNN variants, such as LSTM and gated recurrent unit (GRU) units. To cope with the complex nature of the sintering process data, based on previous researches, their team combined RNN with gated recurrent units and partial least squares (GRU–PLS), and the GRU–PLS model has the lowest error in the prediction of FeO of the final sintered ore compared to other models [111]. Based on the mechanistic analysis, researchers mitigated the effect of noise by adding a denoising gate to the GRU and then proposed a denoising spatial–temporal encoder–decoder multistep prediction model for prediction of the BTP in advance [112, 113]. Yan et al. [114] proposed a multistep prediction model for BTP using RNN combined with 3D convolution to simultaneously learn spatial–temporal features from low to high levels, which was also effective and accurate. Li et al. [115] used long short-term memory and genetic algorithm-recurrent neural network (GA-RNN) to detect the chemical composition of sintered raw materials and established a GA-RNN based sinter quality prediction model to guide the sinter production process. Zhang et al. [116] designed a hybrid deep neural network model that contained a gated recurrent unit network and a deep convolutional neural network to predict sintering temperature by extracting multivariate coupled dynamic features, while incorporating a parallel GRU that uses historical data as input can improve the accuracy of capturing sintering temperature time-series dynamic features. Chen et al. [117] proposed a dynamic spatio-temporal graph attention network based on RNN to construct a multivariate time series prediction model for long-term prediction of sintering temperature.

3.4 Deep belief network and deep neural network model structures and applications in sintering

In 2006, Geoffrey Hinton developed a deep belief network model for the problem of nonlinear separability [118]. DBN simplifies the inference process based on logical belief networks and has a very similar hierarchical structure to BP networks. In a nutshell, Fig. 8 illustrates how many RBMs, and BPs are superimposed to create the DBN [119], where X denotes the input data, and O and Y denote the model output data and its labels, respectively. Unsupervised preliminary training and supervised back-propagation procedures make up the training process.

Deep learning network is a kind of neural network model which is able to spontaneously extract valid information from large amounts of data. This deep learning method is capable of having different structures and parameters for different application requirements, but the length of its training process may change as the training set changes in size [120]. The training process of DNN mainly includes setting up the DNN structure according to the requirements, interlayer transmission in the hidden layer to obtain the error, and back propagation to update the parameters according to the error minimisation principle, as shown in Fig. 9 [85].

DBNs are highly extensible learning algorithms that cannot only identify features and classify data, but also generate data. Yuan et al. [121] used DBN to predict the secondary chemical composition of sinter and established a prediction model. The pre-training under the unsupervised algorithm combined with the BP neural network optimization model achieved good simulation results. The outstanding feature representation capabilities of DBNs

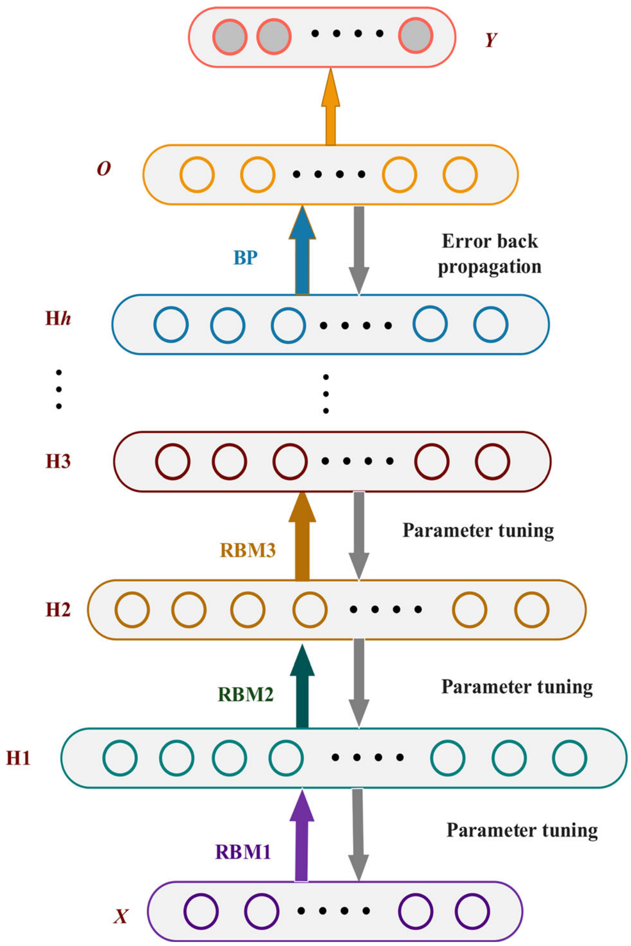

Fig. 8 Structure of DBN. H1, H2, …, H*h*—Hidden layer 1, hidden layer 2, …, hidden layer *h*

enable them to be used extensively in soft sensor modelling. Yuan et al. [122] proposed a new supervised DBN (SDBN) by adding quality information to the training phase to provide a new idea for soft sensor detection and prediction in the sintering process. This SDBN was combined with a restricted Boltzmann machine to extract soft sensor quality related features and applied to sintered ore FeO content prediction, which obtained superior prediction performance compared to DBN and stacked self-encoders [123]. How to improve the carbon efficiency of the sintering process has been a hot topic of research in recent years. Zhou et al. [124] proposed a DBN-based hybrid prediction model for CO/CO_2 and used a semi-supervised algorithm to test the actual operational data and achieved good simulation results.

DNNs are more careful and efficient in solving practical complex nonlinear problems than shallow modelling approaches. This feature has led to its application in the field of industrial control. The problem of lags in sinter composition testing directly affects the quality and yield of the sintered product. Liu et al. [125] proposed a

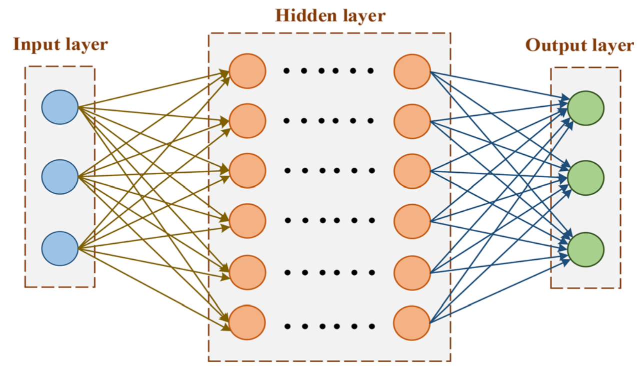

Fig. 9 Structure of DNN

comprehensive sinter composition prediction system based on DNN and LSTM, which can monitor and control the changes of sinter components in real time with lower average square error and average absolute error than that of existing methods. Wang et al. [126] proposed a sintering state recognition model based on prior knowledge and deep neural networks, which eliminated the negative effects arising from sample imbalance and achieved an accuracy rate of 92% for overall sintering state assessment. The application of the Industrial Internet of Things in the steel industry is currently in its initial stage, and how to effectively optimise system resources is a critical technical issue. Fan et al. [127] utilised the deep neural network partition mechanism and the allocation of communication and computing resources to achieve collaborative optimisation and minimise system delay. Wu et al. [128] used unsupervised deep neural network and semi-supervised deep neural network as the prediction model when studying the optimisation of transfer learning for sintering densification prediction. Compared with the traditional sintering density prediction model, the accuracy gradually improved. The problem of scarcity of sintered data can be solved more quickly.

It can be seen that researchers have made a lot of attempts on deep learning models in iron ore sintering process. The application effects of different models in sintering are compared in Table 5.

The energy consumption and environmental emissions from the fundamental industrial process of steel making make up a significant percentage of a nation's industry. However, compared to other industries, there are still some gaps in the level of automation and information technology in the iron and steel industry. Along with the rapid development of deep learning technology, process modelling and simulation incorporating sintering theory and large-scale production data information are one of the important tools for future technological innovation in iron ore sintering and the entire iron and steel metallurgical industry, and deep learning algorithms have a wide range

Table 5 Application comparison of deep learning model in sintering process

Application field	Type of model	Application effect
Fault diagnosis in sintering process	AE	This model can reduce influence of false outliers, reduce fault false positive rate, reduce calculation cost, and improve fault detection rate
Sintering image recognition	CNNs	Utilization of this model for extracting flame characteristic information can decrease reliance on manual fire observation, and with a classification accuracy of 99% for sintering section images, BTP can be accurately determined while particle size distribution in mixed pellet sintering process can be judged with an accuracy exceeding 98%
Prediction of sintering temperature and burn-through point	RNN	It enables multistep prediction of BTP and enhances accuracy of predictions. Furthermore, it facilitates long-term forecast in addition to improving sintering temperature prediction accuracy
Prediction of sinter composition	CNNs	It can optimise composition of sinter and predict optimal ratio of sintered raw materials by using mineral phase photos
	DNN	In this regard, the model solves problem of lagging component detection and reduces impact of data scarcity and sample imbalance
Quality prediction of sintered products	RNN	It can improve prediction accuracy of FeO content in sintering process and reduce measurement error
	DBN	In terms of FeO content prediction, prediction effect is better than that of AE model, and it is better in improving carbon efficiency in CO/CO_2 mixed prediction model

of application prospects in the analysis and prediction of various process aspects of iron ore sintering [20].

4 Conclusions

By summarising and generalising a large amount of literature, we can find that the applicable scenarios of different deep learning models in the steel industry are quite distinct. For the different needs of modelling the sintering process, various types of deep learning models have their own outstanding advantages. With the gradual completion of industrial data and the development of deep learning algorithms, deep learning has broad application prospects in iron ore sintering and even the entire steel industry and will become a new round of technological innovation in the future development of the industry. However, many of the studies of deep learning models in the sintering process are in the stage of experiments and simulation of actual production data, and fewer cases have actually been put into the production system for use. The utilisation of deep learning modelling methods to improve the accuracy and stability of the detection and prediction of key indicators in the sintering process, and to achieve optimal control, still requires more in-depth theoretical research:

1. AE network is commonly used in natural language recognition, but in the industrial field, due to its simple structure, AE is only applicable to the intelligent fault diagnosis aspect, and the application in the sintering process is currently in a gap. Intelligent fault diagnosis modelling of sintering process based on AE has great research prospects.
2. CNNs have the advantage of being able to handle large amounts of static image data. In particular, sinter tail infrared images, sinter section flame images, mixed pellet images, as well as mineral phase photographs are recognised, classified, and calibrated, and on the basis of expanding the training dataset, online detection, and prediction modelling are then carried out.
3. The advantages of RNNs lie precisely in dynamic temporal feature unfolding and extraction as well as learning of sequence data. Therefore, it is suitable for processing video images data during the sintering process. Moreover, RNNs have derived some variants, such as GRU and LSTM, which are more accurate in the extraction of such time-dynamic sequence features as sintering burn-through point and sintering temperature and can be used for long-term monitoring and prediction of such parameters.
4. CNN models are generally considered if various types of image data need to be classified and analysed during the sintering process. Examples include extracting flame features in red-hot images of the sinter tail to improve prediction of BTP accuracy, analysing photos of mineral phases to optimise the composition of sintered ores, detecting foreign objects on the sintering conveyor belt, etc. RNNs are more suitable for processing time series data and capturing time series dynamic features with high accuracy. Since this network enables online detection, it is more advantageous for sinter ore quality prediction during the sintering process, which allows long-term prediction of

parameters like sintering temperature. The most prominent feature of DBNs is their excellent scalability, and their excellent feature rendering capability is more suitable for soft sensor modelling, but the disadvantages are also obvious, which are low network efficiency and long learning time. Therefore, these models are generally combined with CNN or RNN to improve the accuracy and speed of predictive modelling. The DNN model is capable of deep modelling for nonlinear problems and can reduce system latency. It is more suitable for fast allocation of communication and computational resources in combination with Internet of Things technology during sintering process.

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Declarations

Conflict of interest All authors disclosed no relevant relationships.

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