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Review:

Data-driven soft sensors in blast furnace ironmaking: a survey*

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Abstract: The blast furnace is a highly energy-intensive, highly polluting, and extremely complex reactor in the ironmaking process. Soft sensors are a key technology for predicting molten iron quality indices reflecting blast furnace energy consumption and operation stability, and play an important role in saving energy, reducing emissions, improving product quality, and producing economic benefits. With the advancement of the Internet of Things, big data, and artificial intelligence, data-driven soft sensors in blast furnace ironmaking processes have attracted increasing attention from researchers, but there has been no systematic review of the data-driven soft sensors in the blast furnace ironmaking process. This review covers the state-of-the-art studies of data-driven soft sensors technologies in the blast furnace ironmaking process. Specifically, we first conduct a comprehensive overview of various data-driven soft sensor modeling methods (multiscale methods, adaptive methods, deep learning, etc.) used in blast furnace ironmaking. Second, the important applications of data-driven soft sensors in blast furnace ironmaking (silicon content, molten iron temperature, gas utilization rate, etc.) are classified. Finally, the potential challenges and future development trends of data-driven soft sensors in blast furnace ironmaking applications are discussed, including digital twin, multi-source data fusion, and carbon peaking and carbon neutrality.

Key words: Soft sensors; Data-driven modeling; Machine learning; Deep learning; Blast furnace; Ironmaking process

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1 Introduction

With the acceleration of the carbon neutrality target, green intelligent manufacturing has become an inevitable trend in the development of the manufacturing industry. Iron and steel manufacturing occupies a pivotal position in the industrial field, and blast furnace ironmaking is one of the most energy-consuming processes in the iron and steel industry (Yu and Tan, 2022). Therefore, iron and steel enterprises urgently need stable and efficient intelligent operations in the ironmaking process to achieve the goal of producing better-quality, low-carbon, green, and sustainable products.

The majority of the world's steel is extracted from iron ores, and blast furnace ironmaking is a key stage in the overall production process (Geerdes

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et al., 2020). The whole structure of the blast furnace is depicted in Fig. 1. The principal process flow of blast furnace ironmaking is as follows: Solid fuels (coke, coal, etc.), iron-containing raw materials (sinter, pellets, and lump ore), and fluxes (dolomite, limestone, manganese ore, etc.) are continuously fed into the feeding and distribution system in layers from the top to the bottom of the blast furnace. The main process is completed in the mutual contact reaction between the furnace charge and the coal gas. Specifically, the furnace burden steadily descends from the top, while the high-temperature gas generated from bubbling hot air and coal components rises from the bottom. Molten iron is eventually produced through a series of complex physical and chemical reactions. The impurities in the ores react with the flux to form slag. The slag eventually falls down to the hearth area and is mixed into the molten iron. The molten iron flows through the tap hole, and the slag is discharged through the skimmer (Azzedine et al., 2021). The major blast furnace concern is to produce high-quality molten iron in the production process at reduced production costs. To realize this goal, real-time monitoring and control of the blast furnace ironmaking process are required.

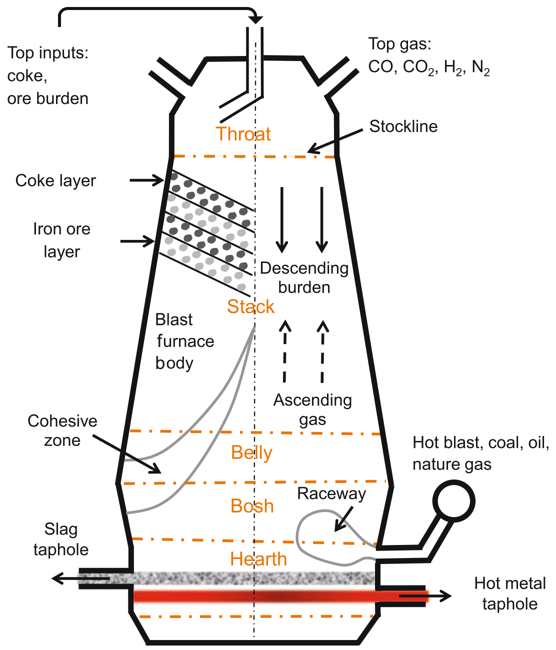

Fig. 1 Schematic of the blast furnace

In blast furnace ironmaking, the most important molten iron quality (MIQ) indices are the silicon content, molten iron temperature, gas utilization rate (GUR), etc. These MIQ indices generally reflect the operating status and energy consumption of the blast furnace ironmaking process. For example, the silicon content indicates the reserving condition of coke and can reflect the thermal state of the blast furnace. Low silicon content is preferred from the perspective of energy efficiency, but there is a boundary to avoid hearth cooling. The molten iron temperature, also known as the hot metal temperature (HMT), is also required to estimate the MIQ and control the blast furnace conditions. GUR reflects the energy consumption, cast iron quality, and the distribution of gas flow in a blast furnace.

Direct measurement of these MIQ indices is difficult primarily due to the complicated running environment. For example, the internal reactions of the blast furnace are extremely sophisticated with various physical and chemical reactions, nonuniform heat transfer, and multiphase fluids (Geerdes et al., 2020). In addition, unfavorable factors such as high temperature, high pressure, and a corrosive environment are involved in the blast furnace ironmaking process. Therefore, the internal status of the blast furnace should be evaluated using the existing observable states, that is, the inflow and outflow together with the conditions at the furnace boundaries (Saxén et al., 2013). Soft sensors are a key technique that can be used for indirect measurement of these MIQ indices based on other easy-to-measure process variables.

At an early stage, the soft sensor models derived from first principles were expected to be established for the indirect measurement of these MIQ indices. However, due to the complicated internal phenomena of the blast furnace, it was difficult to develop first-principles-based models with sufficient prediction accuracy. Nevertheless, efforts to develop physical models have continued. As a result, successful applications of a blast furnace operation guidance system based on a physical model have been reported (Hashimoto et al., 2019a, 2019b). This system is based on a transient two-dimensional (2D) model of a blast furnace (Hashimoto et al., 2018), which is integrated with nonlinear model predictive control (MPC) and moving horizon estimation.

Compared with the first-principles-based models, data-driven models do not require detailed prior process knowledge and are derived directly from process data. Data-driven models aim to use artificial intelligence methodologies (including machine learning, deep learning, and big data analytics) to predict the MIQ indices of the blast furnace. With the advance in data acquisition systems, enormous amounts of data are generated in the blast furnace ironmaking process. The availability and increasing quantity of data have enabled data-driven soft sensor models to be widely and successfully applied to the blast furnace ironmaking process (Zhang XM et al., 2019a).

There have been investigations of data-driven models in the industrial domain, but few investigations have involved data-driven soft sensors in blast furnace ironmaking. The advancement of the Internet of Things, big data, and artificial intelligence has prompted increased research attention on this subject, but despite this interest, there has been no comprehensive survey of the development of data-driven soft sensors in blast furnaces. This paper seeks to remedy that situation, and makes the following contributions:

1. We summarize the evolution of data-driven soft sensors in blast furnace ironmaking. The state-of-the-art studies of data-driven soft sensors in blast furnace ironmaking are categorized and discussed from the perspectives of modeling methods and engineering applications. Within each type of method, the different model variants and their application performances are discussed.

2. We discuss some promising future directions for data-driven soft sensors in blast furnace ironmaking, followed by some of our thoughts and insights on the limitations and challenges faced by the blast furnace ironmaking field.

3. This review serves not only as a friendly guide for new researchers in the field of blast furnace ironmaking, but also as a dictionary for experienced researchers looking for possible directions in future work.

4. To our knowledge, this is the first exhaustive survey of data-driven soft sensors in blast furnace ironmaking.

2 Backgrounds

Data-driven soft sensors have been proposed as a valuable tool in many industrial fields to solve practical problems such as measuring system back-up, what-if analysis, real-time prediction for plant control, sensor validation, and fault diagnosis strategies (Fortuna et al., 2007; Zhang XM et al., 2020a; Du et al., 2021; Gao S et al., 2022; Yan et al., 2022). The environment in which measuring devices commonly work is hostile and maintenance and calibration will result in unnecessary workload and cost, so it is not beneficial or economical to install and use physical sensors to monitor abundant process variables (Jiang YC et al., 2021a). Furthermore, the existence of unexpected faults and time delays in the physical sensors can impair the efficiency of the control strategy. When it comes to the MIQ indicators, such as silicon content measured in the actual blast furnace case, a typical approach is to determine the silicon content index in the laboratory through offline sample analysis, which results in discontinuous measurements (Warne et al., 2004). Therefore, soft sensors provide an effective solution for these problems that can indirectly measure the target indicator based on some easily measurable process variables. As a result of developments in modern data acquisition systems, enormous amounts of data are generated every day in the steel industry. Data-driven soft sensors have gained increasing attention owing to the fact that large databases are being established and analysis of complex systems is desired.

The construction procedure of data-driven soft sensors is shown in Fig. 2. It includes mainly data collection and filtering, model structure selection, model identification, and model validation. Appropriate data collection strategies, such as feature selection and filtering, are important to reveal the current system's pivotal information. Noises should be filtered, and missing data or outliers caused by faults in measuring and transmission devices or unexpected disturbances, which may spoil the model quality, need to be identified. In addition, expert experience and knowledge sometimes need to be considered in the model construction process.

Moreover, different soft sensor structures are selected depending on the specific application circumstances. In terms of the blast furnace case, mechanistic modeling can be cumbersome and it is difficult to perform parameter identification with satisfying results. Data-driven models are thus introduced which use rich historical and online data to achieve high accuracy for multiple blast furnace tasks. Conventional data-driven soft sensor models are involved mainly

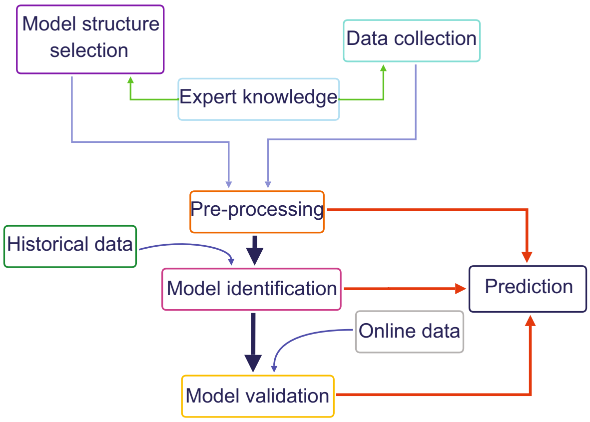

Fig. 2 Construction procedure of data-driven soft sensors

with various statistical learning and machine learning techniques, and are later extended to the scope of deep learning with different network structures (Sun and Ge, 2021).

Model identification is carried out based on diverse strategies that correspond to the selected model. In general, a loss function is developed to depict the bias from the practical condition. Then, various nonlinear optimization algorithms, including gradient descent and genetic algorithms, are implemented. Eventually, the constructed model should be validated. A common way to test the model is using K-fold cross-validation (Masson et al., 1999). Confidence levels have also been introduced as an approach for model validation (Papadopoulos et al., 2001).

3 Data-driven soft sensors in the blast furnace

In this section, the state-of-the-art studies of the applications of data-driven soft sensors in the blast furnace ironmaking process are surveyed. Each subsection below corresponds to a category in Fig. 3. The modeling methods are classified mainly according to the model structures and prior suggestions.

3.1 Fuzzy models

Fuzzy models are based on fuzzy logic with a mathematical system that analyzes analog input values in terms of logical variables that take on continuous values between 0 and 1. Although alternative approaches, such as genetic algorithms and neural networks (NNs), can perform just as well as fuzzy logic in many cases, fuzzy logic solution to the problem can be cast in a form that human operators can understand. Therefore, fuzzy models are often employed as an alternative for blast furnace prediction and control tasks that were traditionally performed by humans.

Zhang WL et al. (2016) proposed a fuzzy model to measure the pressure of the blast furnace gas system with a multiobjective hierarchical genetic algorithm. In the modeling process, a Levenberg-Marquart Bayesian regularization algorithm was used to alleviate the fuzzy model overfitting problem. The performance of the proposed fuzzy model was validated using a series of real blast furnace data, and the results were compared with those of the G-fuzzy model, least-squares support vector machine (LSSVM), and echo state network (ESN). Li JP et al. (2018) created a nonparallel hyperplane fuzzy classifier (NHFC) to determine the tendency of molten iron silicon content according to the blast furnace operation data. In NHFC, the cross-classification problem was transformed into a binary classification by embedding high-dimensional blast furnace data into a 2D space. Compared with the traditional support vector machine (SVM) and LSSVM, NHFC exhibits better interpretability and higher classification accuracy.

Takagi-Sugeno fuzzy models, also known as T-S fuzzy models, have attracted great attention due to their capability to approximate any nonlinear system with arbitrary precision. Li JP et al. (2021b) constructed a novel multi-input multi-output (MIMO) T-S fuzzy model by employing an output transfer matrix. In the MIMO T-S fuzzy model, the low-rank learning of the correlation matrix was presented to identify the correlation between variables. Additionally, the issue of missing MIQ can be managed through a complete complementary matrix derived from the original incomplete matrix. Furthermore, Li JP et al. (2022) proposed a Bayesian-based T-S (BSTS) fuzzy model that exploits the Bayesian method to recognize the consequent parameters of the T-S-based model. In the BSTS fuzzy model, the sparse prior is used to intensify the stability of the fuzzy model with strong generalization ability. Experimental results have shown that the BSTS fuzzy model achieved a smaller root-mean-square error (RMSE) and a higher prediction hit rate than the ANFIS, SpareFIS, H-spareFIS, and genfis3 models.

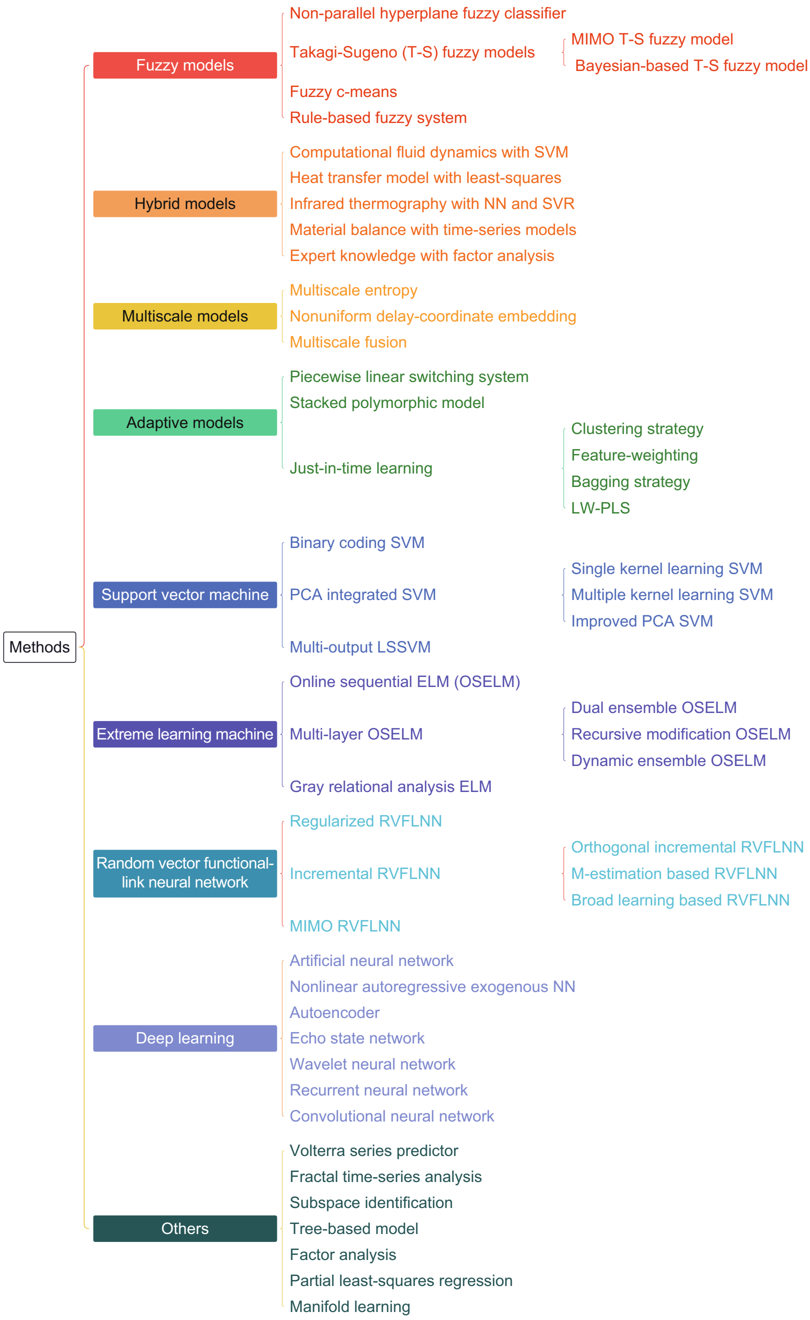

Fig. 3 Models of data-driven soft sensors in the blast furnace

Li S et al. (2022) proposed a blast furnace coke ratio model that combines fuzzy c-means (FCM) clustering with grid-search-optimized support vector regression (SVR). The proposed model is referred to as FCM-GS-SVR. In FCM-GS-SVR, FCM is used to determine the different operation conditions. Experimental results showed that the FCM-GS-SVR model achieved higher accuracy and stability for the coke ratio prediction of molten iron than the decision tree, original SVR, and GS-SVR with a raceway computational fluid dynamics (CFD) model. Lughofer et al. (2021) developed a rule-based fuzzy model to predict silicon concentration, temperature, and cooling capacity from a large database collected at a particular blast furnace process. The rule-based fuzzy model is developed based on a novel feature ranking approach and a unique granular rule extraction procedure. The rule-based fuzzy model is validated on two separate test data sets, demonstrating that it maintains stable predictive behavior and outperforms other data-driven methods including deep neural networks (DNNs). For the fuzzy models, the determination of fuzzy rules is the key to ensuring the accuracy of the models. Therefore, how to design appropriate fuzzy rules for the complex blast furnace ironmaking process is a challenge.

3.2 Hybrid models

In blast furnace ironmaking, the hybrid model refers to a modeling method that combines some prior knowledge with the traditional data-driven model to obtain better accuracy. For example, hybrid models are built by combining data-driven models with expert experience, fluid dynamics, mass/energy balance, etc.

Zhou P et al. (2018e) presented a soft sensor to detect the cohesive zone information in the blast furnace based on the online measurement of the cooling water information with offline CFD. The shape and position of the cohesive zone under different circumstances were recorded in a database according to the offline CFD computation. Therefore, the final position and shape of the cohesive zone were acquired through the match operation in the database. Li JL et al. (2021) constructed a hybrid prediction model that combines off-line CFD computation and SVM to track the position of the cohesive zone in the blast furnace. The CFD model was performed in the form of an axisymmetric 2D steady-state simulation in the blast furnace shaft. The internal information of the cohesive zone, such as the fluid flow, heat, and mass transfer, was obtained through the CFD calculation, and the prediction of the cohesive position was accomplished by SVM. Pan et al. (2018) developed a temperature measurement method that combines a temperature reduction model and infrared thermography technology to detect the molten iron temperature in the blast furnace. The infrared thermal image of the molten iron after the skimmer was analyzed by thermography technology, and the corresponding temperature can be obtained. A temperature reduction model was also derived to identify the relationship between the molten iron temperatures at the taphole and skimmer. Thus, the molten iron temperature at the taphole was indirectly determined by a temperature reduction model and the molten iron temperature after the skimmer.

Jiang ZH et al. (2018) proposed a hybrid model consisting of a heat transfer model and a main pipeline temperature drop model to predict the molten iron temperature in the taphole of a blast furnace. The molten iron temperature at different positions in the main pipeline based on the heat transfer model was employed as the input of the parametric identification in the temperature drop model. A least-squares optimization method was selected to recognize the respective parameters and predict the molten iron temperature at the taphole. Li YR and Yang (2021) presented a genetic algorithm based model that combines domain knowledge to perform the silicon content prediction task in ironmaking by adjusting different genetic mutations and crossover operators. In addition, the interpretable features were extracted from the industrial modeling by redefining the populations.

Azadi et al. (2022) developed a hybrid dynamic model to predict the molten iron silicon content and the slag basicity during the blast furnace ironmaking process. The relationship between the input variables is depicted by a first-principles-based steady-state model. A data-driven model was constructed to compensate for the insufficiency of the mechanistic model. Hu YF et al. (2022) constructed a comprehensive evaluation model based on factor analysis and expert knowledge to reduce CO_2 emissions in the blast furnace ironmaking process. The status of the blast furnace was classified into four classes: good, normal, poor, and warning. Although the hybrid models are usually better than their prototype data-driven methods due to the introduction of reasonable prior knowledge, in some cases, it is difficult to obtain accurate prior knowledge.

3.3 Multiscale models

Multiscale models are a type of modeling method in which important features at multiple scales of time or space are considered. The multiscale modeling and analysis of the blast furnace ironmaking process have received much attention over the past few decades.

For example, Li J and Gao (2010) exploited multiscale entropy to investigate the complexity of the blast furnace at different time scales. They analyzed specific cases of dissimilarly sized blast furnaces and found that the sulfur series tended to be more complicated than the silicon series in terms of time complexity, and the large blast furnace was prone to be steadier than the small blast furnace. Gao CH et al. (2011b) carried out a multiscale recognition model to conduct the real-time monitoring of the blast furnace system from the perspective of silicon and sulfur content. It turned out that various dynamic phenomena, i.e., chaos, randomicity, and limit cycle, existed with different contribution rates in the blast furnace system. Furthermore, Chu and Gao (2014) proposed a data-driven multiscale model that can recognize the variables most relevant to the output. The model integrates these input variables with the output to construct a linear or nonlinear multiscale model. Experiments showed that the multiscale-data-driven model had better performance than the traditional data-driven model over a fixed scale. Moreover, Gao CH et al. (2021) discussed the multiscale features of the blast furnace system and presented a multiscale prediction method derived from the nonuniform delay-coordinate embedding using Taylor expansion. The discrete binary particle swarm optimization was used to optimize the relevant parameters including the time lag and the embedding dimension. The results showed that the proposed nonuniform delay-coordinate embedding model was superior to the uniform embedding model and lower embedding dimension model.

An et al. (2019) concentrated on the multiscale fusion model to adjust the GUR in the blast furnace. The multiscale characteristics between the GUR and the operations were studied, and a decomposition method together with a reconstruction method was introduced to obtain a short-time-scale part and a long-time-scale part of the GUR. Finally, different time-scale models were fused to predict the GUR. Shen et al. (2020) adopted an approach similar to the methods in An et al. (2019) and designed a control strategy for the hot-blast supply and burden distribution for the multiscale features during the blast furnace procedure. Specifically, a reinforcement learning algorithm for burden distribution control was proposed to improve the GUR trend on a long time scale. Yin et al. (2020) presented an interval multiscale prediction model to predict the GUR in the blast furnace. A multiscale point prediction model based on SVM was established. Moreover, an interval prediction model was optimized using the multiobjective optimization method and considering the interval prediction index and the point prediction model. Experimental results demonstrated that the interval multiscale prediction model was more accurate than the point prediction model.

3.4 Adaptive models

Adaptive models are popular modeling methods for dynamic systems and have been widely used in the blast furnace ironmaking process. Several adaptive strategies, such as piecewise linear switching, adaptive weighting, and just-in-time (JIT) learning, have been adopted to construct adaptive models in blast furnace ironmaking.

For example, Saxén et al. (2016) presented a self-organizing model based on the identification of piecewise linear switching systems to predict the silicon content in the blast furnace. The approach assumes that the mode switches in a random manner, and the authors presented a switched linear model to seize the complicated dynamic features of the process. Numerical cases and industrial data were studied to validate the effectiveness of the adaptively switched method. Wen et al. (2018) developed a model-free adaptive control method based on compact form dynamic linearization (CFDL) to manage the multivariate MIQ system by extending the original single-input single-output (SISO) system to the MIMO system. Experimental results showed that it outperformed the conventional data-driven MPC while guaranteeing the bounded-input bounded-output stability of the entire system.

Fang and Jiang (2020) proposed an adaptively weighted echo state network (AW-ESN) for interval prediction of silicon content in the blast furnace using the ensemble approach. Bootstrap was first used to reshape the training data into subsets. The AW-ESN was introduced to approximate the silicon content while establishing interval predictions. Fang et al. (2020) presented an adaptively stacked polymorphic model to forecast the silicon content online. First, an adaptive uncertain fuzzy clustering algorithm was used to simplify the computation burden and refine the existing data. Then, AW-ESN and time difference AW-ESN were stacked to construct polymorphic models. Finally, the ensemble submodels were adopted to mitigate the overfitting problem. The application results suggested that the adaptive polymorphic model possessed a better trend-tracking capability than AW-ESN and ESN.

JIT learning is a machine learning method that can update the predictive model when a quality prediction is required for a query sample. The JIT learning methods have been proven to have the ability to cope with changes in process characteristics as well as nonlinearity. Liu Y and Gao (2015) proposed a JIT model integrated with a support vector clustering (SVC) based outlier detection for online prediction of the silicon content in blast furnace ironmaking. A local model was well preserved using the strategy of updating a healthy relevant data set in a sensible way. A healthier relevant data set was constructed to build a more reliable local prediction model. Moreover, the historical data set was updated repetitively in a reasonable way. Experimental results in an industrial blast furnace demonstrated that the SVC-based JIT least-squares support vector regression (LSSVR) model performed better than SVC-LSSVR, JIT-SVR, and LSSVR in terms of RMSE and hit rate criteria.

Chen K and Liu (2017) presented a JIT learning prediction strategy with flexible feature-weighting for online quality prediction in the blast furnace. A unique similarity criterion was introduced into a dual-objective joint-optimization system to quantify the weight shared between similar samples. In addition, the hyperparameter in the dual-objective system was automatically calculated, thus avoiding the arduous cross-validation work. Ding et al. (2017) developed an ensemble non-Gaussian local regression (ENLR) model by implementing the JIT learning strategy to predict silicon content. Independent component analysis (ICA) was performed to acquire the hidden information between the chosen similar data. Next, a local stochastic model was built using Gaussian process regression (GPR), and the resulting probabilistic results were used as the final prediction. The effectiveness of ENLR was compared with those of three local modeling methods including JIT-GPR (JGPR), JIT-LSSVR (JLSSVR), and ICA-JLSSVR on the silicon content prediction task. The results showed that ENLR outperformed other models in prediction accuracy.

Chen K et al. (2017) described a JIT correntropy-data-driven model to predict silicon content during the ironmaking process. A correntropy SVR was used to alleviate the influence of extreme operating conditions. In addition, the JIT learning method was introduced in the correntropy SVR by a clustering strategy and a refreshing data set. Finally, higher prediction accuracy was achieved by the JIT correntropy model as compared with JLSSVR, correntropy SVR, and LSSVR. He X et al. (2019) proposed a bagging JIT model with a semi-supervised learning method (BJSM). The entire model combines JIT learning, bagging, and the semi-supervised extreme learning machine (SELM) to obtain robust prediction performance. Experimental results indicated the effectiveness of BJSM over the local SELM and JLSSVR models in terms of the RMSE and hit rate criteria.

Zhou P et al. (2021a) proposed a JIT recursive multi-output LSSVR (M-LSSVR) model which was highly efficient in handling multivariable prediction and control of blast furnaces. This method integrates M-LSSVR based on multitask transfer learning with the JIT learning strategy. An incremental learning algorithm was introduced to conservatively prune the model to optimize the speed. In the meantime, an inverse decremental learning algorithm was employed to preserve the size of the model. The proposed JIT recursive M-LSSVR control was compared with the global prediction modeling-based LSSVR and JLSSVR nonlinear predictive control. The resulting integral of absolute error (IAE) values and the integral of squared error (ISE) values of the molten quality control of the proposed JIT recursive M-LSSVR method were lower than those of other models.

Locally weighted partial least-squares (LW-PLS) regression is a JIT modeling method, where partial least-squares (PLS) is used to build a local regression model based on the similarity between the query and historical samples. Zhang XM et al. (2020b) developed a fast locally weighted PLS (FLW-PLS) regression model, which aims to reduce the cumbersome computation of the traditional LW-PLS. The core idea is to employ the exact Euclidean-locality-sensitive hashing algorithm to reduce the computational complexity caused by the linear search of similar data in conventional LW-PLS. Experimental results proved that FLW-PLS can process large-scale industrial data in a much shorter time without a significant loss of prediction accuracy as compared to LW-PLS. Note that the prediction accuracy of the JIT learning model is highly dependent on the similarity between the query sample and historical data. Therefore, how to calculate an appropriate similarity that fully considers the relationship between process variables and quality variables is very important.

3.5 Support vector machine

In machine learning, SVM is a popular supervised learning algorithm for classification. SVM uses kernel tricks to construct hyperplanes in high-dimensional spaces and can perform nonlinear classification efficiently. In addition, SVM can be generalized to the regression domain in the form of SVR. Over the past few years, SVM or SVR has been widely used in the blast furnace ironmaking process.

Jian et al. (2011) presented a sliding-window smooth SVR (SW-SSVR) to capture the inner thermal state of the blast furnace. The SW-SSWR model focuses on the changing trend of silicon content, and the fluctuation trends can be easily tracked with a time-forgetting factor in the model. Experimental results showed that SW-SSVR outperformed SSVR and SVR in prediction accuracy and computation efficiency. Liu Y et al. (2011) proposed an effective outlier detection method based on an SVC strategy without any assumption of data distribution. SVR online modeling was then followed after the detection process to predict the silicon content online. This proposed method is referred to as SVC-SVR. Experimental results showed that the SVC-SVR model had better performance than the Mahalanobis distance SVR, resampling by half-means SVR, and the smallest half-volume SVR models.

Wang ZY et al. (2011) developed a model that integrates kernel principal component analysis (KPCA) into the LSSVM framework to predict the molten iron silicon content of the blast furnace. In LSSVM, KPCA is used as a data preprocessing method to extract the principal features of the data. Jian et al. (2012) developed a multi-kernel SVM of the Hilbert space to analyze the nonlinear blast furnace system. Experimental results indicated that multi-kernel SVM was more competitive than single kernel learning LSSVM or ordinary LSSVM. Jian and Gao (2013) proposed a binary coding SVM to predict molten iron silicon trends, which can provide guidance for blast furnace control. The upper error bound of the prediction results was also estimated for practical manufacturing. The test results showed that compared to the traditional one-against-all and one-against-one strategies, the proposed binary coding SVM was capable of conducting multiclass categorization for the blast furnace system with $\log_2 N$ binary classifiers.

Xu et al. (2016) presented an SVR model optimized by the dynamic multi-swarm particle swarm optimizer with a new cooperative learning strategy (DMS-PSO-CLS), which achieved better generalization performance in silicon content prediction of a blast furnace. The optimizer was a derivative form of DMS-PSO which exploits the merits of DMS-PSO and the cooperative learning strategy to improve both the convergence speed and prediction accuracy of SVR. Experimental results indicated that the proposed DMS-PSO-CLS achieved better accuracy with higher convergence speed to optimize the SVR parameters compared with PSO and DMS-PSO. Wu et al. (2018) employed SVR to identify the burden distribution parameters to improve the energy consumption efficiency of the blast furnace. A probabilistic case-matching model was then constructed by the target data to forecast the trend of the carbon-monoxide utilization rate (CMUR). Zhou P et al. (2018b) presented an M-LSSVR based inverse system identification method for prediction and control of the blast furnace system. First, M-LSSVR was constructed using multitask transfer learning technology. Then, M-LSSVR was used to identify the inverse system model of the controlled blast furnace ironmaking process by means of the multiobjective parameter optimization algorithm. The application results on the real data showed that the proposed method had obvious superiority in the prediction and control of the MIQ indices of the blast furnace.

Luo et al. (2020) developed an AdaBoost-based weighted SVM (W-SVM) ensemble predictor to cope with the imbalanced binary classification problem existing in the silicon content prediction of the blast furnace. The different performances of the classifier served as criteria for the dynamic weight distribution to enhance the reliability. Experiments on five benchmark data sets demonstrated higher efficiency and accuracy of the AdaBoost-based W-SVM compared with SVM, W-SVM, extreme learning machine (ELM), and online sequential ELM (OSELM). Zhai et al. (2020) exploited a genetic algorithm based on SVR to select features, and exploited SVR to predict the fuel ratio (FR) in the blast furnace ironmaking process. Chen SH and Gao (2020) presented a partly transparent soft-margin SVM (pTsm-SVM) model to handle the silicon classification tasks in the blast furnace process. In pTsm-SVM, an intelligent algorithm is first used to mine linear prior knowledge from data, and the prior knowledge is then integrated into SVM. Experimental results indicated that the pTsm-SVM model was more effective than the soft-margin SVM from the perspective of Cohen's Kappa coefficient.

Li WY et al. (2021) proposed an improved SVM model based on principal component analysis (PCA) and CFD to estimate the raceway depth from thermal images in a blast furnace. The thermal images were generated using a raceway CFD model. PCA was implemented to reduce the data dimensionality and extract crucial features of the data. SVM was used to construct the mapping between raceway depth from CFD simulations and extract features from PCA. Wang ZY et al. (2021) performed a comparative study on the prediction of hot metal quality of the blast furnace by SVM and ELM. After linear and nonlinear correlation analysis, feature selection, and normalization, the application results showed that SVM exceeded ELM in both the average absolute error and hit rate.

3.6 Extreme learning machine

ELM is a single hidden layer feedforward neural network training algorithm that has higher learning speed and better generalization performance than traditional methods. ELM has been widely used in many fields such as classification, regression, clustering, sparse approximation, compression, and feature learning.

In blast furnace ironmaking, Zhou P et al. (2015a) proposed a data-driven dynamic model incorporating ELM with PCA for the online prediction of silicon content in the blast furnace. The most critical variables were extracted from multiple factors with the help of PCA. Then, a new ELM framework with a self-feedback structure was developed which has an input node at a previous time to store the data feature across the time domain. The test results indicated that the proposed ELM with self-feedback had higher accuracy compared to the artificial neural network (ANN) with self-feedback and ELM without self-feedback.

Yang et al. (2016) presented a modified ELM to measure the silicon content in molten metal. The original random weight generation method was replaced by a modified pruning algorithm to optimize the weight. Compared to the back-propagation (BP) algorithm and SVM, the model proved to be more accurate from the tests on the industrial data set. Zhang HG et al. (2016) employed the PCA technique to reduce the dimension of the hidden layer output matrix of ELM to obtain a soft sensor for molten iron temperature in a blast furnace. The training procedure was accelerated without major information loss. Experimental results showed that the proposed model had better generalization performance and stability than ANN, SVM, and optimally pruned ELM (OP-ELM).

Su et al. (2018) described a novel multi-layer ELM architecture called W-PCA-ML-ELM to predict the permeability index of the blast furnace. W-PCA-ML-ELM was designed based on PCA and wavelet transform. PCA was used to simplify the last hidden layer output matrix that is usually not in the full column rank. The wavelet transform was applied to tackle the noise existing in the production data. The application results showed that the proposed W-PCA-ML-ELM was superior to weighted ELM (W-ELM), W-P-ELM, and W-ML-ELM in prediction accuracy. Zhang HG et al. (2018) developed a W-ELM model for the prediction of silicon content in molten iron. The imbalanced operating data and outliers tended to reduce the confidence of the existing models, so an outlier detection based on W-ELM was performed. Experimental results showed that the proposed W-ELM model had better predictive performance compared to common ELM and LSSVM methods.

Li YJ et al. (2019) developed an improved ELM called GR-ELM to predict the GUR of the blast furnace. GR-ELM was designed based on gray relational analysis (GRA) and a residual modification mechanism. The input attribute optimization was carried out using GRA and the entropy weight method. The residual modification mechanism was implemented due to the limited capacity of ELM. The mutual information between the process variables and the output was used to determine the corresponding time delay. Experiments showed that GR-ELM outperformed ANN, SVM, and random forest (RF). Furthermore, Li YJ et al. (2020) proposed a kernel ELM algorithm to find the appropriate burden surface distribution of the blast furnace. The problem was handled as a multiobjective optimization issue, and a modified two-stage intelligent optimization strategy was adopted to set the initial values of the burden surface. Feedback compensation was used to enhance the reliability of the optimization strategy. Su et al. (2020) developed an improved multi-layer OSELM model, called EVFF-ML-OSELM, to predict the silicon content online. Compared with the conventional ML-OSELM, a variable forgetting factor (VFF) and an ensemble strategy were incorporated into EVFF-ML-OSELM. The VFF was used to realize dynamic prediction and the ensemble strategy was employed to fix the overfitting problem. Simulation results demonstrated that the EVFF-ML-OSELM model had a higher prediction accuracy than OSELM, WOS-ELM, and ML-OSELM.

Wang P et al. (2022) proposed a multiobjective nonlinear ensemble learning model based on ELM to predict silicon content. The model adopted an evolutionary algorithm to select the pivotal features and considered the nonlinear and coupling relationships between features in the modeling process. All parameters of each ELM including the structure parameters were taken as decision variables, and they were optimized fusing a modified nondominated sorting differential evolution algorithm. The ensemble strategy was based on differential evolution, rather than a linear combination of the individual results. Experimental results suggested that the novel ensemble method outperformed the linear average and ordinary multiobjective evolutionary ensemble learning methods. Li YJ et al. (2022) proposed a novel dual ensemble OSELM (DE-OSELM) for silicon content prediction considering the time-varying characteristics of the blast furnace ironmaking process. In DE-OSELM, the recursive modification based online sequential ELM (RM-OSELM) was first constructed to address the dynamic issues. A combination of the output weights corresponding to OSELM and RM-OSELM was introduced to form a final updating rule for sequential implementation. Experimental results indicated that DE-OSELM converged faster than OSELM and was more accurate than RM-OSELM.

Li YJ et al. (2021) combined the broad learning based W-ELM prediction model with a twin information fusion based pre-setting model to determine the setting values of the burden surface in the blast furnace. In addition, the knowledge mining based feedback compensation model, data-based production status evaluation, and knowledge-based adjustment model were integrated to adjust the setting values of the burden surface according to the change in the production status. Hu TH et al. (2021) developed a novel ELM based on multiobjective evolutionary optimization and nonlinear ensemble learning to depict the silicon content during the ironmaking process. A modified discrete multiobjective evolutionary algorithm was adopted to optimize the input features of the base learners. Then, ELM was used to combine the previous base learners to enhance the credibility of the model. Test results showed that the accuracy of the new ELM was improved compared to the ELM using fixed feature selection.

3.7 Random vector functional-link neural network

Similar to ELM, random vector functional-link neural network (RVFLNN) has a single-layer feedforward neural network structure. In RVFLNN, the weights and biases of the hidden neurons are randomly generated within an appropriate range, while the output weights are computed by a simple closed-form solution. RVFLNN has attracted significant attention due to its superior performance in several different domains such as visual tracking, classification, and regression.

In blast furnace ironmaking, Zhou P et al. (2015b) proposed an online sequential RVFLNN (OS-RVFLNN) with PCA and self-feedback structure for the multivariate prediction of MIQ in the blast furnace. PCA was used to choose the most relevant indicators from redundant input variables. Then, an output self-feedback structure was implemented based on the original OS-RVFLNN. The proposed OS-RVFLNN with feedback connections proved to be faster and more precise than ordinary OS-RVFLNN and ANN with self-feedback. Zhou P et al. (2018c) presented a Cauchy distribution weighted M-estimation based robust RVFLNN (Cauchy-M-RVFLNN) for an online approximation of MIQ. In addition, canonical correlation analysis (CCA) was performed to recognize the most pivotal variables influencing the quality indices. Finally, comparative experiments demonstrated that the proposed Cauchy-M-RVFLNN produced better prediction accuracy and stronger stability than LSSVR, robust LSSVR, and ordinary RVFLNN.

Furthermore, Zhou P et al. (2019) developed an improved orthogonal incremental RVFLNN (I-OI-RVFLNN) model to achieve a compressed model structure and reduce the computational effort for quality prediction in the blast furnace ironmaking process. The Schmidt orthogonalization method was employed to orthogonalize the output matrix of the hidden layer. The hidden nodes were prefixed in numbers to cut out the dispensable nodes in conventional incremental RVFLNN. Experimental results showed that the proposed I-OI-RVFLNN achieved much better performance in convergence speed and accuracy than I-RVFLNN and OI-RVFLNN. Zhou P et al. (2020) presented a robust online sequential RVFLNN (ROS-RVFLNN) with a forgetting factor for the data modeling in a blast furnace. A similar Cauchy distribution function weighted M-estimator was exploited to boost the stability of the model. Compared with OS-RVFLNN and robust RVFLNN, the proposed ROS-RVFLNN was more resistant to stochastic interruptions and more accurate through real industrial tests.

Li WP and Zhou (2020) proposed a robust regularized RVFLNN algorithm to predict the MIQ indices. CCA was carried out for the feature selection of the prediction model, and a Gaussian distribution weighted M-estimation was constructed to temper the influence of outliers. The L1 regularization and L2 regularization based on the least-squares loss function were implemented to achieve the sparseness of the output matrix. Experiments using industrial data from a blast furnace indicated that the proposed robust regularized RVFLNN outperformed LS-RVFLNN and Huber-M-RVFLNN in terms of estimation accuracy and modeling stability. Li JP et al. (2021a) proposed a MIMO-RVFLNN to exploit the correlations among the multivariate MIQ indices. An output space transfer matrix was employed to alleviate the effect of the missing values in quality indices. The corresponding optimization algorithm with guaranteed convergence proof was given. The simulation results of a blast furnace illustrated that the proposed MIMO-RVFLNN obtained better prediction performance than the Cauchy distribution weighted M-RVFLNN and the robust multitask LSSVR. Zhou P et al. (2021b) developed an improved incremental RVFLNN to predict the quality of the molten iron without input-output direct links or output bias. The proof of the model's ability to fit a continuous function with fewer hidden nodes was given compared to the original structure. The terminal condition of the incremental algorithm was stated by the difference in RMSE between two successive iterations. Experimental results on benchmark simulations and real blast furnace data showed that the improved incremental RVFLNN had better performance in terms of prediction accuracy and efficiency.

3.8 Deep learning

Unlike SVM, ELM, and RVFLNN, deep learning has a deep architecture, which usually contains multiple hidden NN layers, to learn data representation with multiple abstract levels. Compared with shallow learning methods, deep learning methods have significant ability to extract the inherent characteristics of data and deal with nonlinear processes. Deep learning has produced very promising results in different fields, including the ironmaking process.

In the field of blast furnace ironmaking, different types of NNs have been developed and widely used. For example, Radhakrishnan and Mohamed (2000) presented an NN-based soft sensor to predict the quantity of the hot metal and slag, as well as their silicon and sulfur compositions, in the blast furnace. Jiménez et al. (2004) developed a data-driven model based on NNs to predict the molten iron temperature of the blast furnace. The model incorporated the time factor as an internal parameter in the NN architecture to cope with sequential information and was validated through actual plant data. Rajesh et al. (2010) discussed the application of NN modeling in the blast furnace ironmaking process, including the prediction of molten iron silicon, burden distribution, and heat levels.

Zhao J et al. (2011) developed an ESN-based two-stage method to forecast the generated gas amount and consumption demand in the blast furnace. The ESN-based two-stage method was constructed by combining ESN with gray correlation. The test results indicated that the ESN-based two-stage method outperformed the radial basis function, SVM, and original ESN on real-world data. Yuan et al. (2015) proposed a novel multivariate method for MIQ prediction on the basis of PCA and a dynamic genetic NN. A hybrid optimization algorithm consisting of adaptive genetic algorithms and BP was adopted to bypass the local minima and improve the convergence speed. An et al. (2016) constructed an

Elman neural network to capture the dynamic characteristics of the missing temperature information caused by the faulty temperature sensor on the blast furnace wall. In addition, the correlation between temperature sensors was derived according to the maximal information coefficient (MIC) to enhance the reliability of the current model.

Zhou P et al. (2018d) presented a wavelet neural network (WNN) designed to minimize the 2D probability density function (PDF) shaping of modeling errors for hearth temperature prediction in blast furnaces. The modeling error PDF was tracked using kernel density estimation (KDE), and the quadratic sum of 2D deviations was then computed as a performance metric for WNN optimization. According to the experimental results, compared with the traditional WNN, the target PDF modeling loss function adopted in the improved WNN showed better generalization performance when used as a criterion for the optimization process. Cui et al. (2018) constructed a time-series NN for the hearth temperature prediction based on multi-information fusion, taking account of tuyere images and other process features. The validation was conducted using the online data and tuyere images of a 2500 m^3 blast furnace in a steel plant, and the application results showed that the proposed model effectively improved the prediction precision compared with DNN and WNN without the tuyere images. Pan et al. (2018) presented a data-driven model with a compensation method based on an ensemble neural network and SVR for molten iron temperature measurement from the perspective of infrared computer vision. The texture features influenced by dust were derived through the temperature-level co-occurrence matrix and the neighboring temperature-level-dependence matrix, and the ensemble neural network and SVR were employed to compensate for the errors caused by dust.

Zhao XD et al. (2020) presented an ameliorated moth-flame optimization (AMFO) algorithm to identify the parameters of a fast learning network (FLN) to predict molten iron silicon content in the blast furnace. The Gaussian mutation produces flames, and the modified position updating mechanism of moths constitutes a crucial part of the proposed algorithm to dodge the local minima. Experimental results indicated that the AMFO-FLN model achieved a more stable hit ratio and higher precision compared with the conventional moth-flame optimization (MFO). Xie and Zhou (2020) constructed a robust stochastic configuration network (RSCN) based on KDE to detect MIQ during the blast furnace ironmaking process. The model implements an incremental method by adding neurons one by one using the original stochastic configuration network (SCN) algorithm. KDE was introduced into the construction process of SCN in the form of probability density estimates for each training set. Meanwhile, determination of the output weight of the proposed RSCN was improved as compared to the abnormality that occurred when the traditional RSCN output weight was calculated in the multi-output situation. The performance of the proposed RSCN proved to be better than those of SCN and RVFL.

Diniz et al. (2021) presented an intelligent algorithm for the long-term prediction of silicon content in the blast furnace using maximal overlap discrete wavelet packet transform (MODWPT) and nonlinear autoregressive (NAR) networks. The silicon content time sequence was decomposed into several subsequences by MODWPT, and each subsequence was trained by an NAR network to yield the final prediction results. Experimental results showed the superiority of the NAR network against the nonlinear input-output model. Cardoso and di Felice (2021) proposed an NN model with Bayesian regularization, and applied it to predict the molten iron silicon content. This Bayesian regularization based NN model was more robust than conventional BP networks and can also avoid cumbersome cross-validation in the modeling process. Experimental results showed that the Bayesian regularization based NN model was superior to the genetic algorithm based multiobjective NN model.

3.8.1 Autoencoder

An autoencoder is a type of NN used to learn data encodings in an unsupervised manner (Kramer, 1991). In an autoencoder, the encoder is used to generate a low-dimensional feature representation from inputs, while the decoder is used to reconstruct the inputs from the encoder's output by minimizing a loss function. An autoencoder is specifically useful for data denoising, dimensionality reduction, and feature extraction. In the field of blast furnace ironmaking, a number of autoencoder-based models have been proposed and widely used. For example, Zhou P et al. (2018a) proposed an improved RVFLNN model which combines an autoencoder and PCA to estimate multivariable MIQ indices online. In RVFLNN, an autoencoder was first used to extract representative features from real industrial data. Then, PCA was introduced to reduce the complexity of the hidden layer output matrix and settle the multicollinearity by reducing the number of hidden nodes. Finally, the RVFLNN algorithm was used to carry out the online prediction of the MIQ indices in the blast furnace ironmaking process. Application results on a blast furnace demonstrated that the improved RVFLNN had better predictive performance than the conventional RVFLNN and autoencoder-RVFLNN. Liu C et al. (2020) developed a stacked autoencoder (SAE) based deep learning framework to perform the prediction task in the blast furnace. First, SAE was used to extract the intrinsic features by means of unsupervised learning. A sparse Bayesian regression (SBR) layer was designed as the top layer to predict the mean value and estimate the uncertainty boundary of the prediction. To further boost the accuracy of the network, a smart algorithm based on an improved differential evolution (IDE) was introduced to select model hyperparameters, which can avoid the cumbersome effort of setting them manually. Experimental results validated the deep learning model's superiority in accuracy and error bar approximation compared with IDE-SVR, IDE-LSSVM, IDE-KELM, and IDE linear regression stacked autoencoder (IDE-LRSAE). Zhu et al. (2022) proposed a multi-gate mixture-of-experts SAE (MMoE-SAE) model to predict the silicon content of molten iron in the blast furnace ironmaking process. MMoE-SAE was built based on a multi-gate hybrid expert structure, and had a selected series of SAE networks as experts. Application results showed that MMoE-SAE had better prediction performance than SAE and Bagging-SAE. He BC et al. (2022) proposed a faster dynamic feature extractor (called TempoATTNE-DFE) and used it to predict the silicon content of an industrial blast furnace. In TempoATTNE-DFE, a new encoder-decoder structure is developed which can be implemented in parallel for data sequences. The results showed that TempoATTNE-DFE had higher computational efficiency in offline training and online prediction of the blast furnace application.

3.8.2 Nonlinear autoregressive exogenous neural network model

Nonlinear autoregressive exogenous neural network (NARX) is a recurrent dynamic NN and is a good predictor for time-series data modeling. NARX has been widely used to model an extensive variety of nonlinear dynamic systems, such as the blast furnace system. Zhou P et al. (2018c) proposed a robust multi-output LSSVR (R-M-LSSVR) based NARX modeling method to estimate and control the MIQ indices of the blast furnace online. They employed an NARX model to extract the nonlinear dynamics of the process at first. Consequently, a multitask transfer learning method was presented to construct an M-LSSVR model. Moreover, an M-estimator was introduced to improve the stability of the M-LSSVR model. Experimental results showed that the prediction accuracy of the R-M-LSSVR model was higher than those of M-LSSVR and M-estimator. Fontes et al. (2020) combined FCM and NARX to form a soft sensor (FCM-NARX) for the prediction of temperature and silicon content of molten iron. FCM was used to group the existing data, i.e., to determine the corresponding operational conditions, and the NARX model provided accurate predictions of molten iron temperature and silicon content. The experiments verified the superiority of the FCM-NARX model as compared to the conventional NARX model.

Azadi et al. (2020) constructed an NARX model for simultaneous multistep prediction of blast furnace gas utilization, pressure drop, and top gas temperature, which is crucial in the analysis of the operation status. In this framework, a new set of fast and slow dynamic features were reconstructed to obtain multiscale features in the time dimension. Jiang YS et al. (2020) presented an NARX model to identify the moisture content of the mixture during sintering in the blast furnace. Current and historical data were used to construct a model to control the moisture in the sintering process. Finally, to improve the stability of the online model, offline deep learning with a supervised method was fused with the online NARX model in a self-learning manner. Experimental results showed that the NARX model outperformed the ordinary least-squares model.

3.8.3 Recurrent neural network

Recurrent neural networks (RNNs), including long short-term memory (LSTM), are deep neural models that consider process dynamics and outperform most traditional data-driven models in sequence prediction problems. LSTM is a special type of RNN whose core components are a sequence input layer and an LSTM layer. LSTM can learn long-term dependencies between time steps of sequence data. In blast furnace ironmaking, RNN and LSTM have been used to manage quality prediction. For example, Jiang K et al. (2018) presented a fusion model that combines eXtreme Gradient Boosting (XGBoost) with LSTM to predict the silicon content online. First, the trend of silicon content was approximated by polynomial regression fitting in a sliding window. Then, the variables most relevant to the output were automatically picked by XGBoost. Finally, a fusion model based on XGBoost and LSTM was constructed to implement the intelligent prediction of the changing trend of silicon content. The prediction results showed the superiority of the fusion model compared to LSTM and XGBoost. Furthermore, Jiang K et al. (2020) proposed a stacked denoising autoencoders based RNN (SDAE-RNN) to classify the variation trend of the silicon content online in the blast furnace. First, the abstract features were extracted using SDAE. Then, a multilevel feature fusion algorithm was used to combine the raw features, shallow features, and abstract features to generate a multilevel fusion feature vector. The multilevel fusion feature vector and corresponding silicon content trend label were used to train the RNN model to classify the variation trend of silicon content. The results demonstrated that the SDAE-RNN model outperformed PCA-SVM, PCA-RNN, and SAE-RNN in classification accuracy.

3.8.4 Convolutional neural network

Convolutional neural network (CNN) is a particular type of NN that has a weight-sharing architecture with convolution and pooling operations. The convolution operation aims to extract features from the data using multiple convolution kernels or filters, which can retain the data spatial information. The pooling operation aims to reduce the dimensionality of features extracted from convolution operations. Over the past few years, CNNs have been widely used in many applications such as image recognition, face recognition, video analysis, and blast furnace ironmaking. For example, Wang GP et al. (2021) proposed an attention-CNN-indRNN model to predict silicon content in the ironmaking process. In the attention-CNN-indRNN model, a CNN is used to extract the furnace condition features, and is then integrated with the attention mechanism and the indRNN (Li S et al., 2018) model. The test results validated the effectiveness of the attention-CNN-indRNN model compared to LSTM and ANN. Lay-Ekuakille et al. (2021) described the utilization of the sensed images to capture the effects of high temperatures at the inlet of a blast furnace, and proposed two comparative algorithms based on a CNN and monadic technique based on the harsh environment during the ironmaking process. Virtual sensors were introduced according to sinogram and back projection sub-techniques. Experiments showed that the CNN-based deep learning model brought excellent results when compared with the monadic method.

However, although deep learning has made significant progress in the field of blast furnace ironmaking, training deep models with a large number of free parameters is a complex optimization problem. In addition, the interpretability of deep learning needs to be further explored to help operators understand the learning and decision-making process.

3.9 Others

In this subsection, some other statistical or machine learning methods applied to the blast furnace ironmaking process are reviewed, such as fractal analysis, tree-based models, factor analysis, and manifold learning.

Gao CH et al. (2011a) developed three types of data-driven models based on the Volterra series to predict the molten iron silicon content from a tiny blast furnace. The kernels of three different types of low-order Volterra filters were updated across the sliding window. The results showed a high percentage of target hits compared with Taylor models, suggesting that the Volterra predictor could handle the dynamic behaviors of the silicon sequence. Furthermore, Zhang ZY et al. (2022) performed six kinds of compact Volterra models, including linear, second-order, and third-order types corresponding to the single input and two inputs, for silicon prediction. The ability of the Volterra series to reflect the significant inertia of the blast furnace was thoroughly explored by referring to high-order Volterra models. Experimental results indicated that the compact Volterra models had better performance than the original Volterra models and Taylor expansion models.

Li YQ et al. (2020) developed a novel prediction method for the blast furnace gas using the recurrence plot (RP) and recurrence quantification (RQ) analysis. RP and RQ projected the outputs relevant to the potential five factors to high-dimensional spaces and represented their dynamics with a 2D recurrence of states. In the end, five parameters quantified the respective influence on the blast furnace gas output. Consequently, the internal dynamics correlation among the blast furnace data was demonstrated in both qualitative and quantitative ways.

Fractal analysis assesses the fractal characteristics of data. It is a potential tool to mathematically assess and understand the behaviors of complex systems like the blast furnace. Zhou L et al. (2011) employed the Horton-Strahler topological classification fractal pattern, a conventional fractal method, to distinguish the fluctuation of the silicon sequence at different scales quantified by the Hurst index. The tests of the silicon series from large, medium, and small blast furnaces presented the fractal characteristics along with the obvious local singularity, which can be unified by the Horton-Strahler topological classification. Finally, some operation strategies were given to maintain stability of the blast furnace according to the sequence analysis. Luo et al. (2019) attempted to evaluate the density distribution for the return intervals of extreme temperature fluctuation in the blast furnace by identifying the fractal feature of the data using rescaled range analysis (R/S) analysis and the Hurst coefficient. The comparison between two blast furnaces showed the superiority of the novel density evaluation over the standard KDE based on 100 000 Kolmogorov-Smirnov (K-S) tests.

Subspace identification methods have gained great significance in practice and are appropriate for both prediction and control in MIMO systems. Zeng et al. (2010b) presented a data-driven predictive control method using the subspace identification method for the blast furnace ironmaking process. Some practical issues, namely constraint handling and control objective, are studied during the modeling of MPC. Simulation results revealed the effectiveness of MPC combined with the subspace identification method against the classical proportional-integral-differential (PID) control. Song et al. (2016) developed a more complicated data-driven nonlinear subspace modeling method for multivariate prediction of MIQ. Correlation analysis and CCA were merged to select the most prominent factors as the input variables for modeling. In addition, a data-driven state-space model of MIQ prediction was constructed based on the subspace identification with LSSVM for the Hammerstein system. The computational burden was reduced by replacing the nonlinear parts of the kernel functions with the approximated polynomial parts in the Hammerstein model. Industrial experiment results showed higher accuracy and shorter computing time of nonlinearity fitted by the interpolation method than M-LSSVR.

Tree-based models are popular machine learning algorithms because of their understandability and simplicity. In tree-based models, the target variable can take categorical or continuous values, so tree-based models are suitable for classification or regression tasks. Several tree-based models, such as the classification and regression tree (CART), gradient boosting decision tree (GBDT), XGBoost, and Light Gradient Boosting Machine (LightGBM), have been developed and widely used in industrial processes. Luo and Chen (2020) exploited XGBoost and LightGBM to predict molten iron silicon content in a blast furnace. The test results on real industrial data showed that XGBoost and LightGBM exhibited better prediction performance than the traditional Lasso, RF, SVM, and GBDT algorithms. Zhang XM et al. (2019b) proposed an ensemble pattern trees model to predict the molten iron temperature in the blast furnace. A bagging strategy was employed to aggregate a set of pattern trees to improve the stability of the model to random perturbations. Moreover, a variable criterion was derived from the ensemble model to quantify the influence of the process variables on the MIQ. The validation results showed that the ensemble pattern tree model outperformed PLS, decision trees, RF, and ANN.

Factor analysis is a statistical method used to reduce a large number of variables into a smaller number of factors. Factor analysis is also introduced into the blast furnace regression problem due to the interdependence of variables in the ironmaking process. For example, Li HY et al. (2021) built a comprehensive evaluation and prediction system based on factor analysis to predict the blast furnace status. In addition, the AdaBoost method was used to perform long-term prediction of the blast furnace status index in advance.

Manifold learning is a kind of nonlinear dimension reduction method that refers to the concept of the topological manifold. It is a prevailing machine learning method designed to determine the low-dimensional subspace embedded in a high-dimensional space. Manifold learning has also been introduced in the blast furnace to handle the complicated data distribution. For example, Zeng et al. (2010a) proposed a two-stage model based on manifold learning to identify the covered patterns in a high-ranked blast furnace system, which eventually contributes to the control and modeling of the blast furnace system. First, dimension reduction was performed by locality preserving projection (LPP), where the input space was projected into the embedded low-dimensional space, and the relationship of input space before and after the projection was illustrated by flexible least-squares (FLS). FLS involved the measurement error and the dynamic error to recognize the time-varying features of the system. Simulation results showed that the proposed two-stage model based on manifold learning can follow the trend of silicon content in the blast furnace system.

4 Discussion

In this section, data-driven soft sensors are first discussed from the perspective of application areas. Then, some possible future research directions for data-driven soft sensors in blast furnace ironmaking are presented.

4.1 Application areas of data-driven soft sensors in blast furnace ironmaking

The typical application areas of data-driven soft sensors in blast furnace ironmaking are classified as follows: silicon content prediction and tendency forecasting, molten iron temperature prediction, GUR prediction, and control of the blast furnace condition. Fig. 4 shows the application distribution of soft sensors in blast furnace ironmaking. The percentages of the model types used to implement each specific application are thoroughly described in Fig. 5. The representative models corresponding to each application field and their references are shown in Fig. 6.

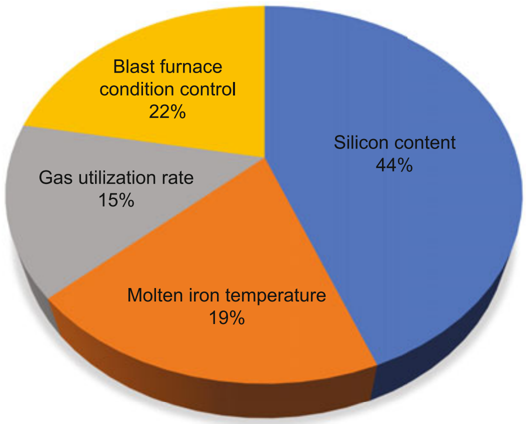

Fig. 4 Typical application distribution of soft sensors in blast furnace ironmaking

4.1.1 Silicon content

Silicon content is an important indicator that reflects the chemical heat of molten iron. The silicon content can have a significant impact on the properties of the final steel product, so it is important to monitor it during the ironmaking process. Fig. 5a lists some data-driven soft sensor studies conducted in the silicon content prediction task. As can be seen in Fig. 5a, deep learning, SVM, ELM, RVFLNN, and adaptive models are the main approaches applied to the silicon content prediction task. Among them, deep learning is the most widely used modeling algorithm. In blast furnace ironmaking, there are two main ways to deal with the silicon content task: real number prediction and tendency prediction. For real number prediction, when the query sample arrives, the real value of silicon content is predicted. For tendency prediction, the changing trend of silicon content needs to be predicted.

As shown in Fig. 6, the deep learning models widely used for real number prediction of silicon content are autoencoder, NARX, LSTM, gated recurrent unit (GRU), and CNN. Autoencoders attempt to improve the prediction performance of ANN by pre-training. NARX aims to handle the temporality in the blast furnace by dynamically identifying the historical patterns. LSTM and GRU are popular RNN modeling methods that can capture

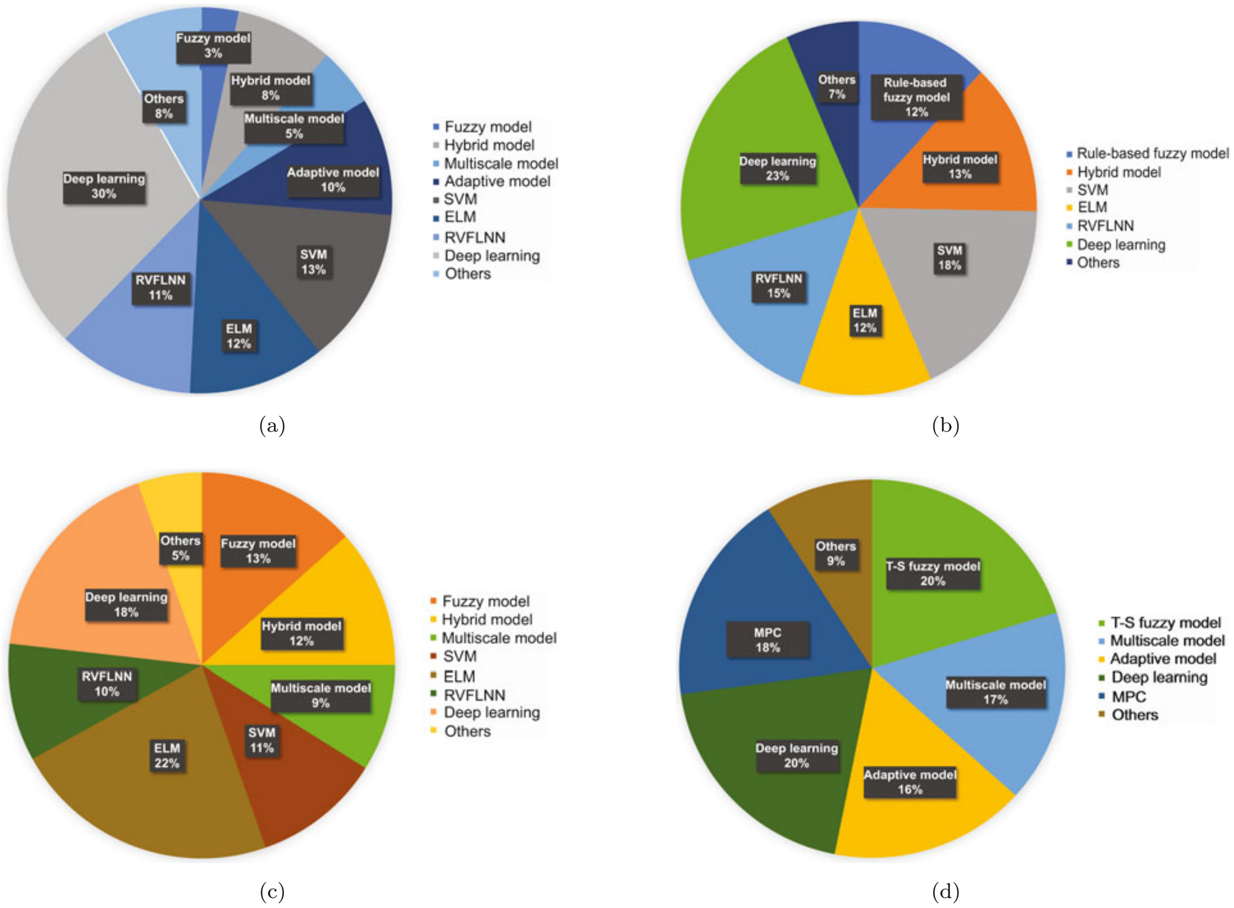

Fig. 5 Model distribution in different application tasks: (a) silicon content; (b) molten iron temperature; (c) gas utilization rate; (d) blast furnace condition control

the long-term dependencies of input data and have been widely adopted in blast furnace ironmaking. CNN is a deep learning algorithm designed to learn the spatial features of blast furnace data through convolution and pooling operations. Other popular modeling methods are variants of SVM, ELM, and RVFLNN. For example, ELM and RVFLNN are introduced with sequential design and incremental training to improve the ability of the original model for long-term prediction. In addition, some other studies (i.e., Volterra series model, multiscale model, and adaptive model) have been developed to deal with the real number silicon content prediction task.

Compared with real number silicon content prediction, it is more convenient and realistic to estimate the tendency of the silicon content (Waller and Saxén, 2003). As shown in Fig. 6, the most commonly used algorithms are the fuzzy classifier, Horton-Strahler topological classification, multiscale recognition, XGBoost, multilevel feature fusion of mutual information, and binary coding SVM models. For example, because of adequate resilience to the inevitable time delay and coupling phenomena in the blast furnace, the fuzzy classifier is usually used in tendency prediction. In the Horton-Strahler topological classification model, a multiscale trend decomposition of silicon content is conducted to recognize the latent patterns for every scale series.

4.1.2 Molten iron temperature

Molten iron temperature is an essential index that reflects the thermal state of the blast furnace and the final quality of molten iron (Zhou B et al., 2016). Fig. 5b shows that the most frequently preferred modeling algorithms for the molten iron temperature prediction task are deep learning, SVM, RVFLNN, hybrid model, ELM, and rule-based fuzzy model. Similar to the silicon content prediction task,

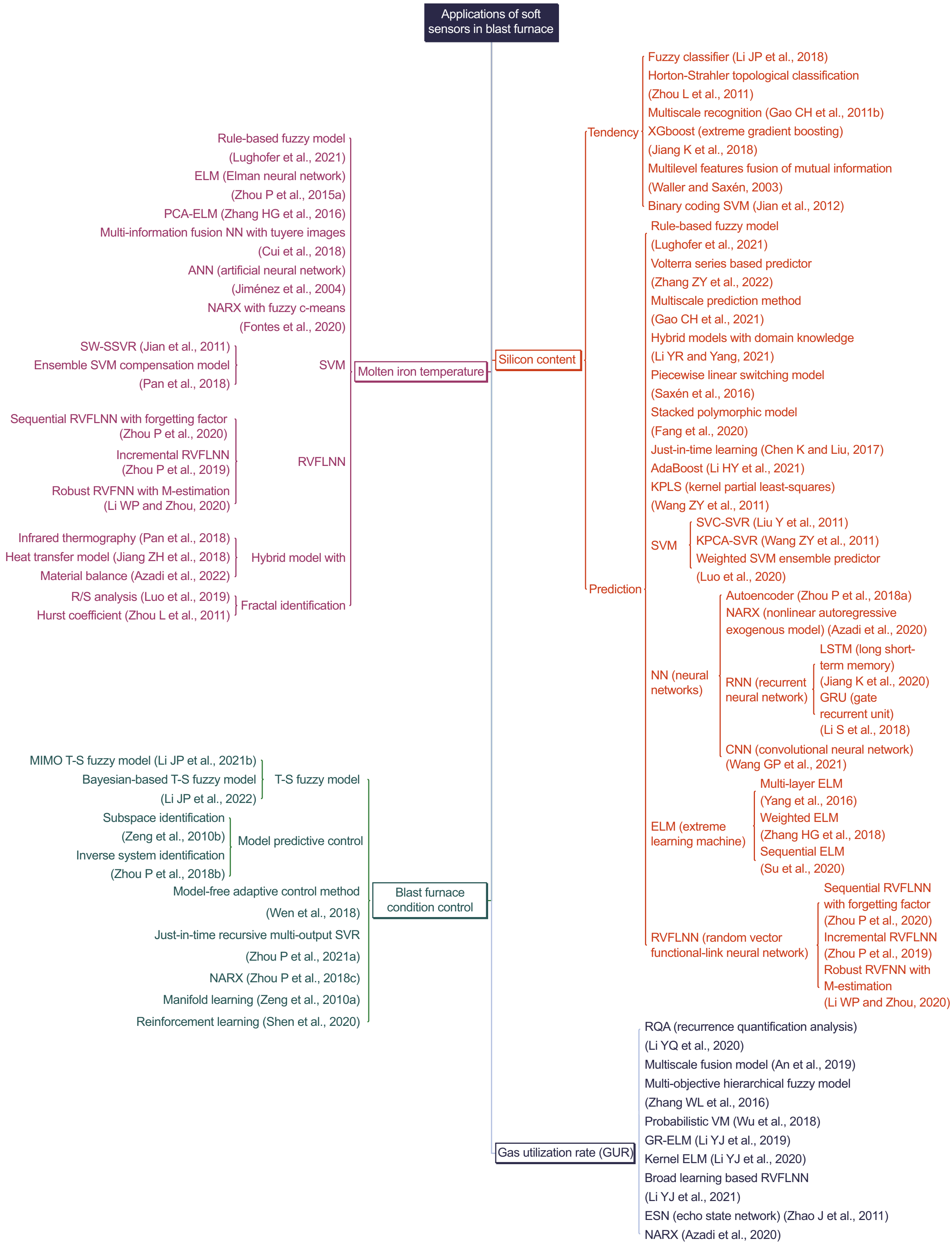

Fig. 6 Applications of soft sensors in blast furnace ironmaking

deep learning is the most frequently used modeling method for the molten iron temperature task.

As shown in Fig. 6, the frequently employed deep learning models for online prediction of molten iron temperature include ANN and NARX. For example, an ANN model with a multi-information fusion of tuyere images is applied to improve the performance of molten iron temperature prediction. In addition, an NARX model with the FCM strategy is employed and shows better performance than the original NARX. Other modeling methods in the molten iron temperature task are basically derived from SVM, ELM, and RVFLNN prototypes. For instance, the ensemble approach is commonly used to enhance the stability and convergence speed of SVM. Similar to the design in the silicon content task, sequential design and incremental training are introduced in the optimization of ELM and RVFLNN to improve the prediction accuracy. Furthermore, to alleviate the collinearity issues that exist in data, PCA techniques are often implemented before using SVM, ELM, and RVFLNN for prediction.

In addition to the commonly used modeling algorithms, fractal identification models and hybrid models have been employed in the molten iron temperature prediction task. For example, the R/S analysis statistical model using the Hurst index has been proposed to investigate the time series of molten iron temperature. This approach allows for the extraction of easily interpretable fractal features. Hybrid models combining machine learning and infrared thermography, heat transfer models, and material balance are used to forecast molten iron temperature, and are known for their accuracy and partial explainability.

4.1.3 Gas utilization rate

GUR is the ratio of the carbon dioxide content to the total carbon monoxide and carbon dioxide content in the top gas flow. A high GUR means adequate burning of coal and reduced consumption. Fig. 5c shows that ELM, deep learning, fuzzy model, hybrid model, SVM, and RVFLNN are the main approaches for predicting the blast furnace GUR.

As shown in Fig. 6, different ELM models, such as GR-ELM and kernel ELM, have been established for GUR prediction. In addition, ESN is often applied in GUR prediction with a large reservoir to avoid the strenuous optimization process in common deep learning. NARX is also applied to handle the high auto-correlation of GUR historical data. In addition, fuzzy models are often proposed with multiobjective training algorithms to conduct multitasking control of GUR. SVM is commonly used for interval prediction of GUR using probabilistic case-matching models. Furthermore, RVFLNN is typically employed with incremental training methods such as broad learning, which can compensate for the influence of extreme GUR patterns. Other models including RQ analysis and multiscale fusion models have also been proposed to predict GUR with high reliability and interpretability.

Previous works have mostly been based on the process variables to infer the GUR. However, there is also research that is trying to directly identify the gas distribution through images during the industrial combustion process (Liu Y et al., 2017). CNNs and deep belief networks (DBNs) are the main approaches for extracting the critical information from flame images, whereas they both demand large-scale labeled images to fully reveal the deep features embedded in images. The generative adversarial network (GAN) is a commonly used augmentation method to compensate for the insufficiency of labeled samples. These vision-based techniques combined with appropriate augmented methods may provide a novel solution for online GUR measurement.

4.1.4 Blast furnace condition control

Blast furnace condition control usually refers to the control of the final MIQ. According to Fig. 5d, the T-S fuzzy model, deep learning, MPC, multiscale model, and adaptive model are common methods applied to blast furnace condition control. As shown in Fig. 6, T-S fuzzy models are frequently applied control algorithms for MIQ control. T-S fuzzy models can integrate quantitative and qualitative knowledge in the limited fuzzy rules, which is helpful in guaranteeing the ultimate control performance. In addition, deep learning methods, including NARX and reinforcement learning, are implemented in blast furnace condition control. Due to the multiple control targets and specific characteristics in a real blast furnace, multitask transfer learning is usually combined with these methods to achieve better control performance.

MPC is another common approach for controlling the blast furnace through different identification methods derived from existing data. For example, MPC with subspace identification is employed to realize a control-oriented nonlinear state-space model for the control of quality indices. Nonlinear dynamic modeling enables the full utilization of historical information. Another method of model identification with MPC is to apply inverse system identification, to make the system be a pseudo-linear one with a linear transitive matrix, which intensifies the explainability of the control strategy. In addition, some robust control strategies are implemented by incorporating manifold learning (such as LPP) to improve control stability. Moreover, adaptive approaches such as JIT recursive multi-output SVR can serve as an alternative way to control the system without modeling identification.

In practice, for blast furnace condition control, an operation guidance system has been successfully implemented in multiple blast furnaces of the JFE Steel Corp. (Hashimoto et al., 2018, 2019a), which is based on the transient 2D model, moving horizon estimation, and nonlinear MPC. This application would encourage researchers and engineers to use first principles in the situation where it is difficult to measure the internal conditions of a process such as a blast furnace.

In summary, as illustrated in Fig. 5, the number of deep learning studies in blast furnace ironmaking is exponentially growing due to its significant contributions to improving model prediction and control performance. In contrast to shallow learning approaches, deep learning is characterized by a significant increase in the number of successively connected neural layers. The increased number of layers and transformations can reveal higher-level data features and more abstract concepts, as well as reveal more complex and hierarchical relationships. Thus, using deep learning to achieve high prediction accuracy of data-driven models in an end-to-end manner is a current trend.

4.2 Possible future research directions of data-driven soft sensors in the blast furnace

Despite the great success of data-driven soft sensors in blast furnace ironmaking, there are still some challenges and future work to be considered.

4.2.1 Digital twin modeling

A blast furnace is a complex system, including a blast furnace body and many subsystems such as burden distribution, coal injection, and hot air. These systems cooperate with each other and their spatiotemporal relationships are complex. A model that could continuously change and update with the physical counterpart in a synchronous manner would be helpful for operators to mirror and monitor the blast furnace ironmaking system with an eye toward achieving and maintaining maximum efficiency throughout the production process. Digital twin is a virtual model that is designed to accurately mirror a physical object. A digital twin can span the lifecycle of a system, update from real-time data, and use simulation, machine learning, and inference to help decision-making. For example, by using digital twins in conjunction with intelligent algorithms, organizations can enable data-driven operational monitoring and optimization, develop innovative products and services, and enable value creation and business model diversification (Glaessgen and Stargel, 2012). For the blast furnace, it is equipped with various sensors related to important functional areas. These sensors generate data on different aspects of physical object performance, such as temperature, energy consumption, and pressure. Once these data are obtained, the digital twin model can be used to investigate performance issues, run simulations, generate possible improvements, and so on, which can then be applied to the original physical object. Because data-driven models face difficulty in predicting variables that are not measured, it is necessary to introduce digital twin modeling combined with first principles in the blast furnace. Actually, researchers have paid attention to the application of digital twins in the industry from the perspective of intelligent manufacturing (Jiang YC et al., 2021b). So, to achieve smooth control and high production efficiency of the blast furnace system, it is of great significance to further study digital twin approaches that are integrated with physical models in the blast furnace.

4.2.2 Multi-source data fusion modeling

As mentioned earlier, blast furnace ironmaking is a complex production process with characteristics such as complex physical and chemical reactions, multiphase flow of solid, liquid, and gas, high uncertainty, time-varying, large time delay, and multi-disturbance factor coupling. Therefore, relying on a single data source or a single type of data may not be sufficient to establish an accurate prediction model. On the other hand, in blast furnace ironmaking, the collected data are commonly multi-source (i.e., raw material, process, product, machine, environment, and operator data) and heterogeneous (i.e., structured or unstructured data). Therefore, it is reasonable to use comprehensive data to build a predictive model to predict the blast furnace MIQ indices. Multi-source data fusion is a technique designed to combine information from multiple sources and sensors to enable analysis and decision-support reasoning that cannot be realized by a single sensor or source. By integrating heterogeneous data from different sources through the data fusion technique, the comprehensiveness, availability, and extensibility of data can be greatly improved. An et al. (2013) proposed a multi-source information fusion strategy based on reliability theory and Kalman filters to detect the burden surface temperature of the blast furnace. However, there are relatively few related studies on multi-source data fusion modeling of blast furnace ironmaking, especially in data-driven soft sensing. Thus, further research on the application of multi-source data fusion in data-driven soft sensor models is attractive and challenging.

4.2.3 Parallel and distributed modeling

As the scale of blast furnace data collection grows, processing the data becomes more urgent. A possible solution is to use parallel and distributed algorithms that can run faster and greatly reduce the training time. In parallel computing, many processes are executed simultaneously to improve the computing speed and efficiency. In parallel computing, large computational tasks are divided into sub-tasks, which can then be solved simultaneously through different processors. A variety of parallel computing strategies, such as bit-level parallelism, instruction-level parallelism, data parallelism, and task parallelism, have been proposed. Distributed computing, on the other hand, aims to use distributed systems to increase the available computing power, which enables larger and more complex computational tasks to be performed on multiple machines. Compared with parallel computing, distributed computing has higher scalability and resilience. However, there are few studies on parallel and distributed modeling of blast furnace ironmaking, thus offering research study options for the future.

4.3 Carbon peaking and carbon neutrality

The iron and steel industry is a major contributor to carbon emissions. For example, in China, the carbon emissions of the iron and steel industry account for 22% of the total carbon emissions (Yu and Tan, 2022). Thus, the iron and steel industry has a vital role to play in helping China achieve its carbon peak and carbon neutrality goals. However, the widespread use of coal-based blast furnaces in steel production leads to high carbon emission intensity, which means that the steel industry faces challenges in emission reduction. Therefore, how to reasonably use modern information technology, such as artificial intelligence and big data analysis, to help the iron and steel industry achieve the goal of carbon neutrality and emission peak is interesting and meaningful work. In general, data-driven soft sensors are advanced measurement and control systems that use data analysis, machine learning, and deep learning technologies to improve the efficiency and sustainability of industrial processes. By providing more accurate and real-time process information, data-driven soft sensors could be used to identify and control the variables that have the greatest impact on carbon emissions, such as the distribution of fuel consumed. Data-driven soft sensors can also be involved in the development and application of new technologies and new processes to help the ironmaking industry achieve carbon neutrality and emission peak targets. By providing detailed and accurate data about the process, data-driven soft sensors can support the development of new materials, fuels, and control strategies that reduce emissions and improve process sustainability. As a case in point, data-driven soft sensors could be used to evaluate the performance of new types of fuels or catalysts in the blast furnace, and to optimize the design of carbon capture and storage systems used in the process.

5 Conclusions

This paper aims to provide an overview of data-driven soft sensing techniques for blast furnace ironmaking. By reviewing the state-of-the-art data-driven soft sensing algorithms in blast furnace ironmaking, it can be confirmed that data-driven soft sensors have great potential for academic research and industrial applications. From an industrial point of view, data-driven soft sensors have great potential as efficient tools to improve the automation degree, efficiency, performance, and product quality of blast furnace ironmaking systems. From an academic point of view, data-driven soft sensors can be a multi-disciplinary integration research topic covering statistical learning, machine learning, deep learning, pattern recognition, system recognition, expert experience knowledge, and so on. However, there are still some challenges and future work that need to be considered. For example, it will be interesting to further study the blast furnace digital twin system to help operators mirror and monitor the blast furnace ironmaking process. It is also of great significance to use the multi-source data fusion technique to combine information from multiple sources and sensors to improve the performance of reasoning analysis and decision support. Furthermore, with the explosive growth of collected blast furnace data, the current data-driven soft sensing models are tending to be lightweight and run faster, and thus parallel and distributed computing strategies are encouraged to improve the computing speed and efficiency of soft sensing models. It would also be interesting and meaningful to design and use data-driven soft sensors to help the steel industry achieve carbon neutrality targets and make the ironmaking process more sustainable and efficient.

This survey will motivate more researchers to strive to overcome the above challenges of soft sensing technology for blast furnace ironmaking. In the next decade and beyond, it is expected that more innovative ideas and more advanced soft sensing technologies will be developed and applied to solve various problems in blast furnace ironmaking. Consequently, the overall benefits of soft sensing are inspiring for their further application toward smarter, low-carbon, and more sustainable industrial processes.

Contributors

Yueyang LUO and Xinmin ZHANG drafted the paper. Long DENG, Chunjie YANG, and Zhihuan SONG helped organize the paper. Xinmin ZHANG and Manabu KANO revised and finalized the paper.

Compliance with ethics guidelines

Yueyang LUO, Xinmin ZHANG, Manabu KANO, Long DENG, Chunjie YANG, and Zhihuan SONG declare that they have no conflict of interest.

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