Received: 20 July 2023 | Accepted: 20 August 2023

DOI: 10.1002/mgea.6

REVIEW

MGE ADVANCES
Materials Genome Engineering

Toward learning steelmaking—A review on machine learning for basic oxygen furnace process

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Abstract

Basic oxygen furnace (BOF) steelmaking is the most widely used process in global steel production today, accounting for around 70% of the industry's output. Due to the physical, mechanical, and chemical complexities involved in the process, conventional monitoring and control methods are often pushed to their limits. The increasing global competition has created a demand for new methods to monitor and control the BOF steelmaking process. Over the past decade, Machine Learning (ML) techniques have garnered substantial attention, offering a promising pathway to enhance efficiency and suitability of steel production. This paper presents the first comprehensive review of ML applications in the BOF steelmaking process. We provide an introduction to both fields: an overview of the BOF steelmaking process and ML. We analyze the existing work on ML applications in BOF steelmaking and synthesize common concepts into categories, supporting the identification of common use cases and approaches. This analysis concludes with the elaboration of challenges, potential solutions, and a future outlook for further research directions.

KEYWORDS

BOF steelmaking, data-driven modeling, industry 4.0, machine learning

1 | INTRODUCTION

The steel industry is characterized by a diverse range of steel types, each with unique characteristics such as chemical composition, heat treatments, and mechanical properties that are tailored to meet the demands of the market. With more than 3500 identified steel types, the industry has experienced remarkable growth and evolution, with approximately 75% of these steel types developed in the past 2 decades. Manufacturers have made significant strides in improving the quality and performance of steel, driven by advances in technology, innovation, and research.

Steel is one of the most versatile materials in terms of its properties and composition, strength to weight ratio, and its ability to be infinitely recycled into new products. In 2021, the production of world steel has reached the peak of 1950 Mt[1] while in 2022, steelmakers confronted energy crises and economic slowdowns, resulting in a 4% decline in worldwide production.[2] The use of steel is projected to increase in the future with the proliferation of infrastructural development. On the other hand, the steel industry is a significant contributor to global carbon emissions. According to the "International Energy Agency," the steel industry accounts for around 7% of global CO_2 emissions.

The steel industry is under pressure since there is a growing emphasis on industrial decarbonization policies like the European "Fit for 55" initiative, which aims to reduce emissions to 55% by 2030 compared to 1990 levels, targeting significant reductions in carbon emissions by 2050.[3] Such policies and increased demand in profound steel transformation in industrial activity and machine learning (ML) in steelmaking is a promising approach for sustainable and optimized steelmaking.

The industry's competitive nature necessitates advancements in quality monitoring, process optimization, and efficiency improvement. Industry 4.0,[4] incorporating the Internet of Things, cloud computing, and smart sensors, plays a vital role in pioneering innovative strategies. The fourth industrial revolution enables full traceability of the production process and real-time data collection. The immense data generated, however, introduces new challenges, which can be tackled through data-driven models, specifically ML algorithms. The escalating volume of available data in industrial plants emphasizes the crucial role of ML. The utilization of ML methods has the potential to address specific industrial needs, allowing for a more precise understanding and control of complex processes.

ML has demonstrated potential in various industrial applications, from smart manufacturing[5] to designing superalloys,[6] improving the understanding of mechanical properties of additively manufactured composite materials,[7] and predicting anisotropic mechanical properties in high-temperature alloys used in industry-grade applications.[8] In the context of the steel industry, ML techniques have found applications in predicting solidification cracking in stainless steels,[9] optimizing continuous steel casting,[10] and predicting mechanical properties of hot-rolled steel plates.[11]

The basic oxygen furnace (BOF) process is the most widely used steelmaking process in the world, accounting for more than 70% of global steel production. However, the BOF process is energy-intensive and has a significant carbon footprint. Monitoring the BOF steelmaking process poses a set of significant challenges arising from the intense heat, aggressive chemical environment, and violent mass movements involved. Research efforts focusing on end-point control of the BOF were initiated as far back as 1987, with initial models employing mathematical approaches for BOF end-point control.[12] Over time, monitoring systems such as the sub-lance system, flame spectroscopic system, and off-gas analysis system were implemented to provide dynamic tracking of the BOF process. Beyond their control functions, these systems generate a substantial volume of data. This wealth of information is incredibly valuable for the development of data-driven models in the BOF process.

A comparative analysis highlighting mathematical modeling, BOF process monitoring analysis, and data-driven modeling, specifically in the context of end-point carbon prediction, demonstrates a significant advantage for data-driven modeling. While mathematical modeling provides less than 70% accuracy and monitoring analysis improves this to a range of 80%–90%, data-driven prediction surpasses both with accuracy rates over 90%.[13] This validates the importance of focusing research and development efforts on data-driven methodologies for improved process control. ML techniques can be applied to various aspects of steelmaking, such as raw material selection, process control, and product quality prediction.[14]

This survey is the first of its kind to provide a comprehensive overview of over a decade's worth of active research in the sphere of steelmaking, specifically focusing on the use of ML in the BOF process. Our intention is to illuminate the fascinating intersection of these two areas, uncovering their potential for advancing this evolving industrial field. The structure of the paper is as follows: Section 2 delivers a brief yet comprehensive introduction to the BOF process (Section 2.1) and elaborates on the fundamental principles of ML (Section 2.2). In Section 3, we break down the methodology behind the data-driven modeling workflow, tailored specifically for the BOF process. Section 4 highlights some key examples of ML applications within the BOF process, along with an in-depth reporting of their results. Finally, Section 5 concludes the paper with an insightful look toward the future of research in this area, focusing on the development of more intelligent and sustainable steelmaking processes.

2 | BACKGROUND

2.1 | Overview of basic oxygen furnace

The BOF is a cylindrical converter with a rounded base, designed to accommodate capacities ranging from 60 to 400 tons.[15] Its operation involves temperature elevation and decarburization of hot metal through the injection of an oxygen jet at supersonic speeds. The distinguishing feature of BOF technology is its exothermic characteristic. The necessary heat for the process is generated from the oxidation of carbon and various other impurities such as silicon, manganese, and phosphorus present within the hot metal. The most prominent factors leading to a rise in temperature are the oxidation reactions of carbon and silicon.

However, the process' intricacy arises from factors like rapid heat generation, turbulent bath movement, the impact of the supersonic oxygen jet on the metal bath, multiphase flows, and the high-temperature dissolution and melting of scrap.[16]

BOF steelmaking has remarkably enhanced the speed of the steelmaking process. The process duration has been dramatically cut from the 5–7 h needed with the open-hearth furnace technology to less than 30 min.[17] The process commences with the hot metal at about 1200–1400°C, which is subsequently elevated to 1550–1700°C. This high-temperature state is essential for the conversion of high-carbon pig iron (4.5%–5%) to low-carbon steel (under 0.1%), a process facilitated by blowing pressurized oxygen into the converter through a water-cooled lance. This oxidizes the impurities by creating slag and off-gases and producing low-carbon steel.

Monitoring technologies used during the blowing process for endpoint prediction fall primarily into two categories: contact and noncontact measurements.[18] Contact

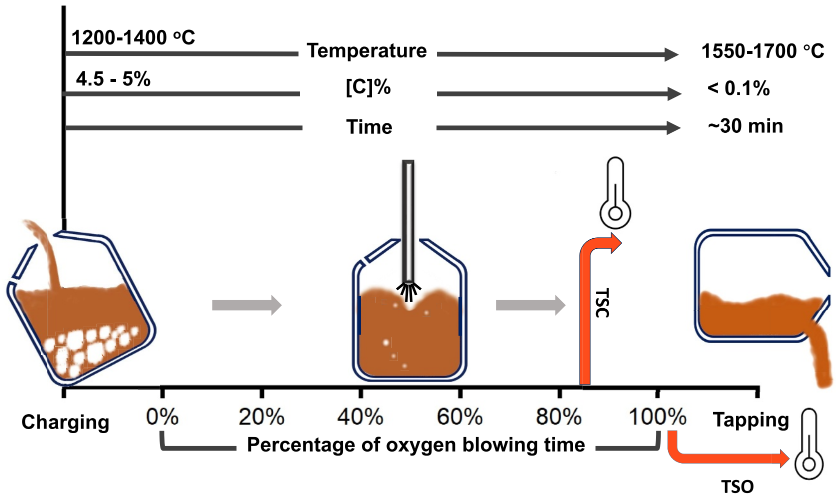

FIGURE 1 Schematic of the basic oxygen furnace process.

measurement, represented by the sub-lance measurement, is a single-use system requiring immersion into molten steel. The first sub-lance measurement, in-blow sampling—temperature sampling carbon (TSC), occurs between 80% and 90% of the oxygen blowing time, and the second sub-lance sampling, end-blow sampling—temperature sampling oxygen (TSO), occurs at the end of the blowing time. Noncontact measurements, exemplified by off-gas analyzers, estimate the carbon content based on the thermodynamics of off-gases. A detailed schematic of the BOF process is presented in Figure 1.

2.2 | Machine learning

ML, an innovative discipline, focuses on two intertwined aspects: the feasibility of developing computer systems that improve their performance through experience and the elementary statistical, computational, and information-theoretic principles that govern various learning entities, including digital, biological, and organizational systems.[19] This field provides computer systems with the capability to perform tasks such as prediction, diagnosis, planning, and recognition by learning from historical data.

ML encompasses three paradigms—supervised, unsupervised, and reinforcement learning—and finds application across various disciplines. These categories are explained in Figure 2. Its common tasks include regression, classification, clustering, dimensionality reduction, and anomaly detection.

Supervised learning methods, such as support vector machines (SVM), decision trees, ensemble models, and neural networks, work with labeled data and are primarily used for regression and classification tasks as they infer an underlying function mapping inputs to outputs.[20]

In contrast, unsupervised learning algorithms like *k*-means, hierarchical clustering, principal component analysis,

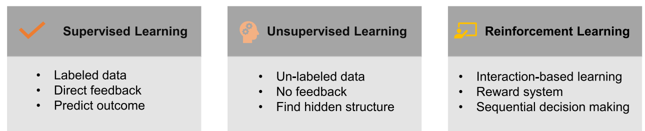

FIGURE 2 Three main paradigms of machine learning.

and auto-encoders operate on unlabeled data and serve clustering and dimensionality reduction tasks. These techniques help uncover hidden structures or simplify complex datasets.[21]

Reinforcement learning[22] employs strategies like Q-learning to optimize sequential decision-making tasks through a reward–penalty feedback loop.

The efficacy of ML models critically depends on the quality and volume of data as well as the suitability of the chosen algorithm. Hence, the role of sophisticated data analysis and appropriate algorithm selection is emphasized to achieve accurate outcomes.

The selection of ML models significantly influences data analysis effectiveness and is often guided by data characteristics and problem complexity. As depicted in Figure 3, simpler models like linear regression may be adequate for tasks with less complex relationships, whereas more complex tasks may require sophisticated methods like neural networks or ensemble models.

Complex models require careful attention to hyperparameters, which are specific parameters set prior to the training process. These hyperparameters, such as the learning rate in neural networks or the number of neighbors in K-nearest neighbors (k-NN), impact the model's training and final performance. Hyperparameter tuning can significantly improve model accuracy and generalization, with techniques like grid search and random search being commonly used for this optimization.

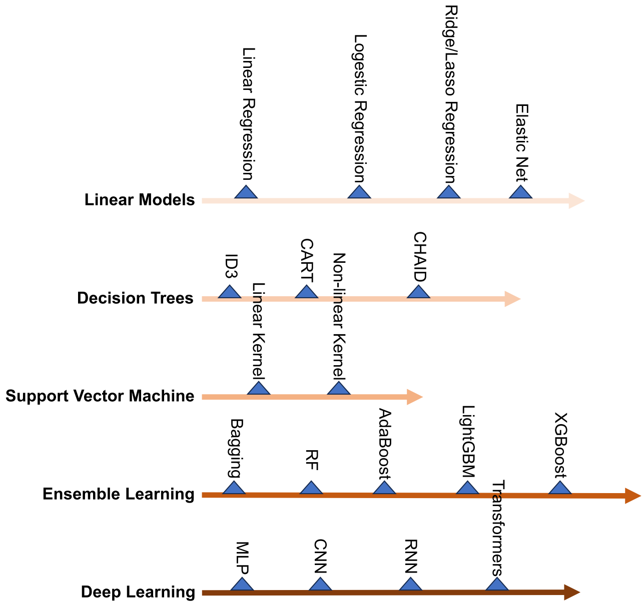

FIGURE 3 A machine learning model complexity spectrum. A two-dimensional complexity increment is depicted with the vertical axis spanning from simpler linear models at the top to deep learning models at the bottom. The horizontal axis shows the progression within each category, for instance, within deep learning models from multilayer perceptron to transformers. As we move downward and rightward, models demand more data and potentially offer improved accuracy, subject to the specific nature of the data.

To evaluate the performance of a model with selected hyperparameters on unseen data, a technique called cross-validation is employed. Cross-validation partitions the data and averages results from multiple splits, thereby providing a robust measure of model performance, reducing overfitting, and leading to a more generalizable model.

In sum, ML's versatility and adaptability, underpinned by its diverse range of methodologies, algorithms, model complexity considerations, and hyperparameter fine-tuning, underscore its capacity to address a broad spectrum of problems, depending on the nature of available data and specific task requirements.

3 | DATA-DRIVEN MODELING WORKFLOW FOR BOF PROCESS

In the context of designing and deploying data models for industrial processes, the Cross-Industry Standard Process for Data Mining (CRISP-DM) has emerged as the de facto methodology.[23] This data-driven approach comprises six key stages: business understanding, data understanding, data fusion and preparation, modeling, evaluation, and deployment. These stages create a coherent and iterative workflow, facilitating an effective and efficient integration of data-driven models into industrial processes. The following sections delve into a tailored application of this workflow for the BOF process, shedding light on the practical aspects and challenges of implementing a data-driven modeling approach in a complex industrial setup.

3.1 | BOF database

The data-driven modeling of the BOF process leverages a comprehensive database comprising steel production data sourced from industrial BOF converters across several countries, including China,[24] India,[25] and Sweden.[26] This database incorporates diverse types of data—static tabular data, time-series data, and image data—dictated by the underlying BOF technology and the data collection strategies adopted by the respective companies.

The static data segmented into process parameters, blowing parameters, additives information, sampling test results during the process, and end-of-blow features. Process parameters consist of elements such as liquid iron information (the hot metal's composition, temperature, and quantity), scrap information, and furnace information (generic details like the furnace and lance ID). On the other hand, blowing parameters encapsulate data like blowing time, the total oxygen volume blown. Additive information includes the type and quantity of heat additives—like dolomite and limestone—introduced during the blow.

At the conclusion of the process, the end-of-blow features such as the final temperature and elemental composition are gathered through sub-lance sampling (TSO) and lab analysis, respectively. Additionally, certain facilities collect sampling test results during the process with sub-lance sampling (TSC) at an estimated 80%–90% mark of the blowing time.

Time-series data, encompassing off-gas data, vessel vibration, and audiometry measurements are collected throughout the blowing process, while flame information primarily includes flame images and flame radiation spectrum captured during the process. Figure 4 reveals that static features have been predominantly employed for BOF data-driven modeling. Despite the significant role of process time-series features, their availability has been limited to a few BOF datasets.[26–28] In Brämming et al.,[29] a comprehensive blend of all available features—process parameters, image, off-gas data, and vessel vibration audiometry measurements—was utilized to estimate foam height and endpoint phosphorus prediction.

3.2 | Data preprocessing

In the data-driven modeling of the BOF process, data preprocessing plays a crucial role in transforming raw data into a format amenable to further analysis. While preprocessing generally follows a standard framework, encompass data cleaning, missing value handling, outlier detection, and data normalization, two aspects stand out in the context of the BOF process: feature extraction and feature engineering.

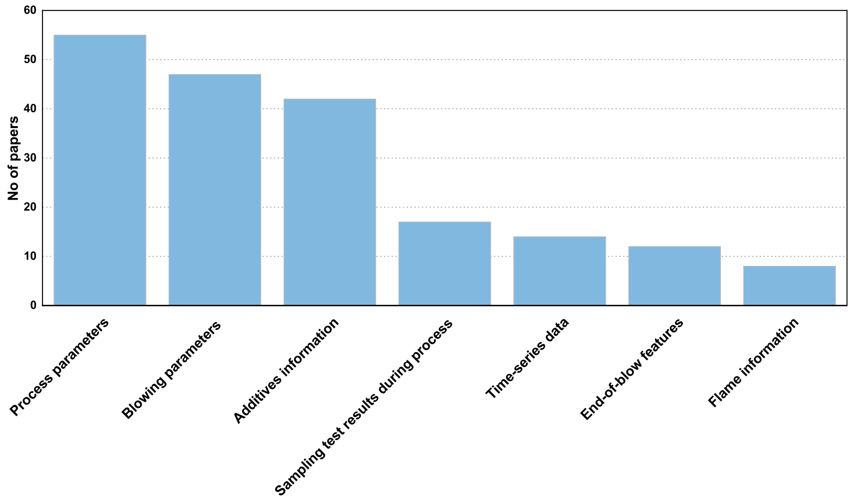

FIGURE 4 Distribution of feature usage in the input of machine learning models of basic oxygen furnace. The bar plot illustrates the count of papers employing various types of input features, categorized by the feature type.

Importantly, industrial datasets, including those obtained from the BOF process, are inherently noisy and often contain substantial sparsity. This characteristic makes the preprocessing step not just beneficial but necessary for the subsequent analysis to be effective and accurate.

Feature extraction, usually employed in conjunction with various feature importance methodologies, aids in identifying the most relevant features. In the context of BOF studies, various methodologies for feature importance, such as statistical tests, correlation analysis,[30] or ML techniques like principal component analysis[31] are often employed. This process enhances the efficacy of the modeling phase by ensuring that the resulting models accurately capture inherent data patterns, ultimately facilitating more reliable predictions. An example of effective feature extraction is demonstrated in the work by Qi et al.,[32] where optimal feature subset selection was performed to improve regression accuracy.

Feature engineering, on the other hand, leverages domain knowledge and well established principles to derive new, informative features based on existing data.[26,33] Feature engineering serves as a bridge between the raw data and the domain expertize, thereby enabling a more integrative approach to modeling that combines both data-driven and physical-based methods. This aspect is illustrated in the work by Bae et al.,[26] where thermodynamic principles were used to extract and incorporate engineered features into BOF datasets, thereby enhancing the value of data-driven modeling of the BOF process.

3.3 | Modeling

The modeling of the BOF process has witnessed the application of various ML techniques over the past decade, ranging from conventional regression models to more recent deep learning approaches. The predominant method utilized is supervised learning aimed at achieving regression tasks, see Figure 5a. However, hybrid models, which merge unsupervised learning for clustering sparse BOF data and apply different models on each cluster, have also found application.[34,35] A recent notable trend is the use of deep reinforcement learning to capture the dynamic nature of the BOF process.[36]

Early research into the data-driven modeling of the BOF process primarily hinged on case-based reasoning (CBR). CBR groups instances based on their behavior, thereby enabling a representation of a variety of heats and providing crucial insights into the BOF process.[37,38]

Support vector machines for regression (SVR) emerged as an effective tool to capture nonlinear relationships within the data, with the choice of kernel function, particularly the radial basis function kernel, significantly affecting the model's performance. The modeling of BOF data using SVR has been explored in various studies,[39,40] and advancements have been made using an improved twin support vector regressor.[41,42]

Since their introduction into the BOF field in 2002,[43] the use of artificial neural networks (ANN) has seen a steady rise. Most of these models are based on multilayer perceptron (MLP) networks,[31,44,45] but many studies fail to report network configurations such as the number of layers and neurones. Notably, Bae et al. applied a three-layer MLP model in their work and used different configurations for predicting three BOF endpoints.[26] Wang et al. provided a detailed account of their use of a one-dimensional convolutional neural network (CNN) and its network structure.[46]

Several hybrid models combining different methodologies have also been effective in enhancing prediction

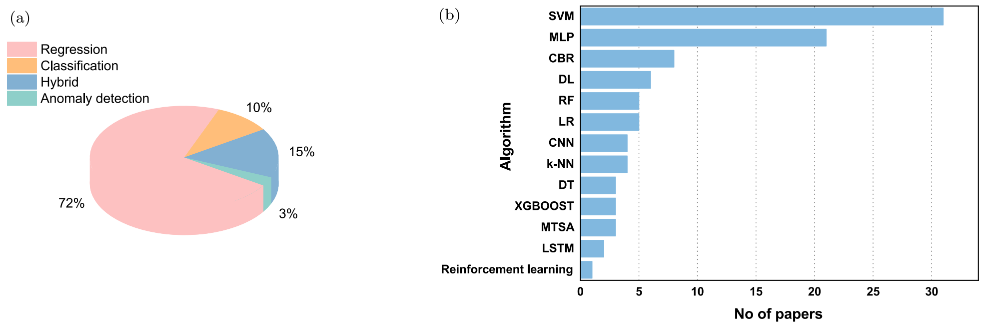

FIGURE 5 The statistical distribution of ML techniques applied to the BOF process. (a) Task-wise distribution showcasing the variety of tasks to which ML techniques are applied in the BOF process. (b) Model-wise distribution presenting the range of different ML models utilized in BOF data-driven modeling. BOF, basic oxygen furnace; ML, machine learning.

accuracy in the BOF process. For instance, weighted *k*-means clustering, coupled with distinct ANN for each cluster, was successfully applied by Wang et al.[47] Feng et al. combined various algorithms such as SVR, random forest (RF), and ANN with Bayesian integration and achieved promising results.[48] Jiang et al. introduced a hybrid approach merging multiple linear regression (MLR) and Gaussian process regression (GPR) to simultaneously capture global trends and local noise-induced fluctuations.[49]

Several studies have also embarked on comparative assessments of different ML algorithms. In one such study, Laha et al. compared RF, ANN, and SVR.[25] Zhang et al. compared RF, Gradian boost regressor (GBR), CNN, and metallurgical mechanism model (MMM), finding that RF and GBR outperformed the other models.[50] In a more comprehensive comparative study, Bae et al. demonstrated that ANN and SVR significantly outperformed other ML techniques in predicting temperature, carbon, and phosphorus endpoints.[26]

Recently, there has been an increasing interest in incorporating novel deep learning (DL) methodologies such as transfer learning,[51] graph neural networks (GNNs),[52] CNNs,[46] auto-encoder Bayesian network,[24] and reinforcement learning.[36] The application of recurrent neural networks (RNNs), specifically long short-term memory (LSTM), has been explored for handling time-series data.[53] A deep learning framework based on fully connected networks (FCN) and CNN has been developed for regression tasks, taking into account both static and multivariate time series information.[28]

The increasing diversity of modeling techniques applied to the BOF process can be seen visually in Figure 5b, which displays a statistical plot of the distribution of model types over the past decade. This diversity illustrates the dynamic nature of data-driven modeling in the BOF process and provides a strong indication of the potential for continued innovation and advancement in this field.

On the other hand, in light of the observations from Figure 3 (complexity of ML models) and Figure 5b (model-wise distribution in BOF data-driven modeling), it is notable that while simpler models such as SVM have been extensively used, the inherent complexity of the BOF process calls for more sophisticated methodologies. Ensemble models, which combine the strengths of multiple models, and deep learning models, capable of handling high-dimensional and sequential data, have started to emerge. Future research should focus on these more complex models, underscoring the potential of deep learning and ensemble techniques for a comprehensive understanding and prediction of the BOF process.

3.4 | Evaluation

Performance evaluation is an integral aspect of any ML process, as it allows for the quantification of model performance through the comparison of predicted and actual results. A crucial component of evaluation frameworks across various fields is the use of performance metrics or error measures. These metrics serve as mathematical constructs, providing a means to measure the proximity between expected and actual outcomes. These measures commonly involve mean absolute error (MAE) and root mean squared error (RMSE), among others, and are conceptually tied to the scientific notions of distance and similarity.

In regression tasks within ML, performance metrics are employed to compare the predictions generated by the trained model with the actual (or observed) data from the test dataset. The outcome of these comparisons plays a pivotal role in decision-making processes associated with the selection of appropriate ML algorithms for implementation.

With regard to regression, we advise readers to refer to Botchkarev[54] for an understanding of metrics such as MAE, mean squared error, and root mean square error. Additionally, Hossin and Sulaiman[55] provides insights into the coefficient of determination (*R*-squared) and various classification metrics.

In addition to these conventional metrics, a hit rate (HR) is frequently used in ML predictive models for BOF endpoints.[24,32,37] Often, it is introduced either as the primary evaluation metric or in combination with more common regression evaluation metrics such as *R*-squared or RMSE. The HR is mathematically defined as follows:

$$\mathrm{HR} = \frac{N(|\mathrm{Predicted} - \mathrm{Actual}| < \epsilon)}{N(\mathrm{Test\ samples})}$$

In this equation, the tolerance ϵ is adjusted according to the target range. For instance, the reported tolerance for endpoint temperature has been ± 15, ± 10, and ± 5, while for endpoint carbon, most studies have reported tolerance values of ± 0.02, ± 0.01, and ± 0.005.[56]

The use of HR as a performance metric in the evaluation of ML models for the BOF process has certain limitations. Its reliance on the data range and the chosen tolerance, ϵ, makes it difficult to compare across different studies due to the inherent variability. Furthermore, the HR does not inherently measure goodness of fit, a key aspect for regression tasks, which most studies entail (see Figure 5a). However, when used alongside traditional regression metrics like R-squared or RMSE, the HR offers an additional perspective on model performance, showing how frequently model predictions fall within a specified tolerance. This can be valuable in industrial scenarios where a certain margin of error is acceptable.

In summary, while the HR should be used cautiously due to its limitations, it can complement a multimetric evaluation framework. Future studies should aim for transparency when reporting HR results and provide clear justification for the choice of tolerance, improving interpretability and comparability.

4 | ANALYSIS OF ML USE CASES IN BOF

In this section, we delve into an analysis of recent developments in the utilization of ML for modeling the BOF process. Our investigation pivots around three key categories where ML is increasingly being employed: endpoint predictions, anomaly detection, and specific use cases. Despite the relatively less frequent application of anomaly detection using BOF data, this area has been prioritized due to its increasing relevance and future potential in this field.

The most prevalent application of ML in the BOF process has been in the realm of endpoint predictions. This aspect specifically addresses the prediction of endpoint temperature and chemical compositions, key elements that influence the final properties of the steel produced. The array of studies and use cases that have emerged in this area are discussed in depth in Subsection 4.1, with corresponding studies and related use cases collated in Tables 1–4.

In addition to endpoint predictions, the role of ML in anomaly detection is gaining prominence. Anomaly detection is integral to identifying and mitigating potential disruptions, thus ensuring the smooth operation of the BOF process. We discuss this increasingly significant aspect in Subsection 4.2 and summarize relevant studies in Table 5.

We also shed light on lesser-known but emerging areas of ML application in the BOF process in Subsection 4.3. These novel applications illustrate the versatility of ML and its potential to disrupt traditional BOF operations.

4.1 | Endpoint predictions

The application of ML in the BOF steelmaking process has shown profound impacts, particularly in predicting the endpoint. The endpoint is a critical juncture in the steelmaking process where the desired composition and temperature of the molten steel are achieved. Its accurate determination, influenced by several parameters such as elemental concentrations and impurity levels, is indispensable for producing high-quality steel conforming to desired specifications. The importance of accurate endpoint prediction lies in its direct impact on steel's final properties. An optimal chemical composition minimizes the necessity for adding expensive alloys in subsequent stages, while an appropriate end-of-blow temperature prevents energy inefficiencies and potential disruptions in the workflow.

In this context, ML-based approaches have been extensively applied to estimate the endpoints, primarily focusing on temperature and carbon content, as summarized in Tables 1 and 2.

Gu et al.[53] integrated CBR and LSTM models to improve endpoint predictions, showing higher accuracy than traditional SVR and ANN models. Furthermore, some studies[52,76] have expanded the ML application scope to simultaneous prediction of multiple endpoint targets, departing from the more common singular focus approach. However, potential data bias from substantial sample reduction in certain studies calls for a careful interpretation of the results.[41,61,82]

Several ML models, as collated in Table 3, have been deployed to predict endpoint phosphorus, while less focus has been given to endpoint sulfur, with the existing studies listed in Table 4. These explorations signify the expanding frontiers of ML application in the BOF process, with notable successes and room for further advancements.

4.2 | Anomaly detection in the BOF process

In the BOF steelmaking process, meticulous process monitoring and accurate anomaly detection are paramount for preserving operational stability, process reliability, and the resultant steel quality. Various operational anomalies, such as the prevalent splashing phenomenon, can introduce substantial challenges related to safety, environmental consequences, operational efficiency, and quality control. The splashing phenomenon, characterized by an eruption of molten steel due to improper operations leading to a buildup of carbon oxides in the molten pool, regularly arises in the BOF process.[88] This anomaly not only degrades the quality of the produced steel but also poses severe safety hazards, potentially leading to injuries, decreased efficiency, environmental pollution, and difficult operational conditions.

The mitigation of risks associated with such anomalies necessitates the development of robust methods for automatic anomaly detection, root cause diagnosis, and the prediction of future occurrences. Despite the significance of this

TABLE 1 Endpoint temperature prediction.

Ref.	Training samples	Type of features	ML task	Method	Evaluation metric
[51]	2000	Process parameters and blowing parameters	Regression	Auto-encoder network	Hit rate and RMSE
[41]	200	n/a	Regression	SVR	RMSE, MAE, and hit rate
[26]	9708	Process parameters, blowing parameters, additives information, sampling test results during process, and time-series data	Regression	MLP, SVR, XGBoost, LR, DT, and k-NN	Hit rate
[48]	3750	Process parameters and blowing parameters	Bayesian integration of SVR, RF, and ANN	Regression	Hit rate
[57]	2000	Blowing parameters and sampling test results during the process	Regression	SVR	Hit rate
[58]	846	Process parameters, blowing parameters, additives information, and time-series data	Regression	CBR + LSTM	Hit rate
[36]	320	Process parameters, blowing parameters, additives information, and time-series data	Regression	Deep reinforcement learning	MAE and hit rate
[40]	1500	Process parameters, blowing parameters, and additives information	Regression	SVR	MAE, RMSE, and hit rate
[24]	200	Process parameters, blowing parameters, additives information, and time-series data	Regression	Bayesian auto-encoder	RMSE and MAE
	1000	Process parameters, blowing parameters, additives information, sampling test results during process, and time-series data			
[56]	2000	Process parameters and blowing parameters	Regression	Deep learning	Hit rate
[59]	743	Process parameters, blowing parameters, additives information, and sampling test results during the process	Regression	ANN, SVR	RMSE and hit rate
[60]	150	Process parameters, blowing parameters and additives information	Regression	SVR	Hit rate
[61]	62	Process parameters, blowing parameters, and additives information	Regression	MLP	Hit rate
[62]	60[a]	Process parameters, blowing parameters, additives information, and sampling test results during the process	Regression	Extreme learning	Hit rate
[63]	4808	Process parameters, blowing parameters, additives information, and time-series data	Regression	Ridge regression, RF, gradient boosted regression tree	RMSE and *R*-squared
[64]	800	Process parameters, blowing parameters, and additives information	Regression	MLP	Hit rate
[65]	100	Process parameters, blowing parameters, and additives information regression	SVR	Hit rate	
[66]	420[a]	Process parameters, blowing parameters, additives information, and flame information	Regression	CBR + expert system model	Hit rate
[67]	150	Process parameters, blowing parameters, additives information, and sampling test results during the process	Regression	ANN	Hit rate
[68]	872[a]	Process parameters, blowing parameters, additives information, and time-series data	Regression	Multivariate adaptive regression splines, ANN, SVR, RF, k-NN	RMSE and *R*-squared
[69]	1629	Process parameters, blowing parameters, and additives information	Classification	SVM	Precision, recall, F1-score, and accuracy

TABLE 1 (Continued)

Ref.	Training samples	Type of features	ML task	Method	Evaluation metric
[70]	250	Blowing parameters and sampling test results during the process	Regression	ANN	RMSE and hit rate
[71]	n/a	Process parameters and time-series data	Regression	SVR	EMSE
[72]	4332[a]	Process parameters, blowing parameters, additives information, time-series data	Regression	Evolutionary neural network	R-squared and hit rate
[28]	7158[a]	Process parameters, and time-series data	Regression	CNN	RMSE
[39]	1400	Process parameters, blowing parameters, and additives information	Regression	SVR	MAE
[73]	450	Blowing parameters and sampling test results during process	Regression	SVR	Hit rate
[42]	1000	Process parameters, blowing parameters, and additives information	Dimension reduction + regression	PCA + SVR	RMSE, MAE, and hit rate
[74]	90	Process parameters, blowing parameters, and additives information	Regression	SVR	MAE and hit rate

Abbreviations: ANN, artificial neural networks; CBR, case-based reasoning; CNN, convolutional neural network; LSTM, long short-term memory; MAE, mean absolute error; ML, machine learning; MLP, multilayer perceptron; n/a, not applicable; RF, random forest; RMSE, root mean squared error; SVR, support vector machines for regression.

[a]It is not specified whether these are total samples or training samples.

aspect, anomaly detection has seen less focus in BOF data analysis compared to other application areas, as is evident from the studies summarized in Table 5.

Addressing this gap, Qian et al. made significant strides in detecting the splashing phenomenon within the BOF process.[27] The authors proposed a novel method capable of converting irregularly gathered observations into smoothly differentiated functions, effectively highlighting the traits of splashing anomalies. This method successfully handles strong linear correlations within the data, thereby significantly improving anomaly detection. With a testing dataset of 665 off-gas records of CO and CO_2 during the BOF process, the method exhibited an impressive detection accuracy of 97%.

Moreover, other anomalies such as slopping and drying have been identified using multivariate time-series analysis (MTSA). This analysis incorporates dynamic data from vessel vibrations, audio meter measurements, and off-gas data as reported in Brämming et al.[29] for slopping and[87] for drying and splashing.

This highlights the necessity for further research into the application of ML for time-series data analysis within the BOF process. Given the depth and complexity of such data, its comprehensive analysis could provide valuable insights into the incidence and prediction of a range of anomalies, thereby improving overall operational efficiency and safety.

4.3 | Additional ML applications in the BOF process

Beyond the explored areas of endpoint predictions and anomaly detection, ML exhibits promising potential in other facets of the BOF process.

In Rahnama et al.'s study,[30] ML analysis was applied to process data from a pilot plant. The main objectives were to identify correlations between operational parameters and reactor performance, with reactor performance defined as the rate of decarburization. The researchers trained a neural network based on the pilot plant dataset, developing a regression model to predict the decarburization rate. This model was then employed to predict the decarburization rate in an industrial BOF furnace based on the lance height and total oxygen flow.

Further, in the work by Wang et al.,[80] a real-time method for predicting carbon content during the second blow period of the BOF process was proposed. The authors transformed the conventional time-based exponential decarburization model into an oxygen-based variant. Then, they used a CBR method, a data-driven approach, to define the key parameter in the decarburization model.

Bramming et al.[29] embarked on a complex task of monitoring several critical control parameters during the converter steelmaking process to prevent undesired events, such as slopping.

Lastly, Sun et al.[89] dealt with the crucial task of accurately determining the endpoint of converter steelmaking. They assembled an experimental dataset comprising 1236 flame images of the furnace mouth, categorized into early, middle, and late stages of converter steelmaking. To analyze this image data, they employed a CNN model, specifically the DenseNet architecture, resulting in a remarkable accuracy of 96% in blowing endpoint judgment.

These diverse applications, summarized in Table 6, highlight the versatility of ML in enhancing different aspects of the BOF process. Each study offers a unique perspective

TABLE 2 Endpoint carbon prediction.

Ref.	No. of samples	Type of features	ML task	Method	Evaluation metric
[26]	9708	Process parameters, blowing parameters, additives information, sampling test results during process, and time-series data	Regression	MLP, SVR, XGBoost, LR, DT, and k-NN	Hit rate
[53]	1109	Process parameters, blowing parameters, additives information, and sampling test results during process	Classification	CBR + LSTM	Hit rate
[58]	846	Process parameters, blowing parameters, additives information, and time-series data	Regression	CBR + LSTM	Hit rate
[36]	320		Regression	Deep reinforcement learning	MAE and hit rate
[51]	2000	Process parameters and blowing parameters	Regression	Auto-encoder network	Hit rate and RMSE
[24]	200	Process parameters, blowing parameters, additives information, and time-series data	Regression	Bayesian auto-encoder	RMSE and MAE
	1000	Process parameters, blowing parameters, additives information, sampling test results during process, and time-series data			
[75]	25	Blowing parameters, and flame information (radiation spectrum)	Regression + classification	SVC + SVR	Hit rate
[76]	2331	Process parameters, blowing parameters, additives information, and end-of-blow features	Regression	GNN	*R*-squared, MAE, RMSE and hit rate
[41]	200	n/a	Regression	SVR	RMSE, MAE and hit rate
[56]	2000	Process parameters and blowing parameters	Regression	Deep learning	Hit rate
[77]	150	Flame information (radiation spectrum)	Classification	SVC	Accuracy
[32]	750		Regression	k-NN	Hit rate
[60]	150	Process parameters, blowing parameters, and additives information	Regression	SVR	Hit rate
[61]	62	Process parameters, blowing parameters, and additives information	Regression	ANN	Hit rate
[62]	60[a]	Process parameters, blowing parameters, additives information, and sampling test results during process	Regression	Extreme learning	Hit rate
[64]	800	Process parameters, blowing parameters, and additives information	Regression	ANN	Hit rate
[44]	15,000[a]	Process parameters and blowing parameters	Regression	MLP	Hit rate
[57]	2000	Blowing parameters and sampling test results during the process	Regression	SVR	Hit rate
[65]	100	Process parameters, blowing parameters, and additives information	Regression	SVR	Hit rate
[78]	170	Process parameters, blowing parameters, and additives information	Regression	SVR	Hit rate
[79]	1094	Process parameters, blowing parameters, additives information, and sampling test results during process	Clustering + regression	CBR + SVM	Hit rate
[67]	150	Process parameters, blowing parameters, additives information, and sampling test results during process	Regression	ANN	Hit rate

TABLE 2 (Continued)

Ref.	No. of samples	Type of features	ML task	Method	Evaluation metric
[68]	872[a]	Process parameters, blowing parameters, additives information, and time-series data	Regression	Multivariate adaptive regression splines, ANN, SVR, RF, k-NN	RMSE and R-squared
[70]	250	Blowing parameters and sampling test results during process	Regression	ANN	RMSE and hit rate
[40]	1500	Process parameters, blowing parameters, and additives information	Regression	SVR	MAE, RMSE and hit rate
[72]	4332[a]	Process parameters, blowing parameters, additives information, and time-series data	Regression	Evolutionary neural network	R-squared and hit rate
[14]	6510	Process parameters, blowing parameters, and additives information	Regression	MLP	R-squared
[63]	4808	Process parameters, blowing parameters, additives information, and time-series data	Regression	Ridge regression, RF, gradient boosted regression tree	RMSE and R-squared
[28]	7158[a]	Process parameters and time-series data	Regression	CNN	RMSE
[39]	1400	Process parameters, blowing parameters, and additives information	Regression	SVR	MAE
[80]	1000	Process parameters, additives information, and sampling test results during the process	Regression	CBR	Hit rate
[73]	450	Blowing parameters and sampling test results during the process	Regression	SVR	Hit rate
[42]	1000	Process parameters, blowing parameters, and additives information	Dimension reduction + regression	PCA + SVR	RMSE, MAE and hit rate
[74]	90	Process parameters, blowing parameters, and additives information	Regression	SVR	MAE and hit rate
[81]	150	Flame information (radiation spectrum)	Classification	SVC	MAE and accuracy

Abbreviations: ANN, artificial neural networks; CBR, case-based reasoning; CNN, convolutional neural network; GNN, graph neural networks; LSTM, long short-term memory; MAE, mean absolute error; ML, machine learning; MLP, multilayer perceptron; n/a, not applicable; RF, random forest; RMSE, root mean squared error; SVR, support vector machines for regression.

[a]It is not specified whether these are total samples or training samples.

and contributes novel methods to improve the efficiency and quality of steel production, reinforcing the transformative potential of ML in the steelmaking industry.

5 | CONCLUSION AND FUTURE RESEARCH DIRECTIONS

As we enter the era of the fourth industrial revolution, the convergence of big data analytics and ML methodologies opens up new possibilities for data-driven modeling in the steel industry. This thorough review seeks to build a bridge between ML applications and the BOF steelmaking process. Our objective is to highlight the potential opportunities and challenges that await in this innovative field. To the best of our understanding, this is the first survey that presents an exhaustive analysis of ML techniques in relation to their use in the BOF process. Our research underscores the pivotal role of ML in steering the shift toward intelligent, efficient, and sustainable steel production.

Existing research has provided key insights into the applications of ML techniques. However, most studies up to this point have primarily employed shallow models on relatively small datasets. Although these models have their merits, they may not fully encapsulate the intricacies of real-world steelmaking processes, which may limit their predictive performance and generalizability. Reflecting on the current state of research, the main limitations observed can be grouped into four key areas:

- **Data underutilization**: Most studies leverage small datasets for training and not fully utilizing the wealth of data available in steel plants as shown in Figure 6. It should be acknowledged, however, that obtaining high-quality, large volume data is challenging due to various constraints in the industrial environment.
- **Temporal features and process dynamics**: Many studies neglect the potential of time-series data and the inherent dynamics of the BOF process. Furthermore, the operational applicability of some models is limited by the use of

TABLE 3 Endpoint phosphorous prediction.

Ref.	No of samples	Type of features	ML task	Method	Evaluation metric
[26]	9708	Process parameters, blowing parameters, additives information, sampling test results during the process, and time-series data	Regression	MLP, SVR, XGBoost, LR, DT, and k-NN	Hit rate
[31]	1600	Process parameters, blowing parameters, additives information, sampling test results during process, and end-of-blow features	Dimension reduction + regression	PCA + ANN	Hit rate and *R*-squared
[45]	700	Process parameters, blowing parameters, and additives information	Regression	MLP	Hit rate
[50]	668	Process parameters, blowing parameters, and additives information	Regression	Ridge regression, SVR, RF, CNN, GBR, and metallurgical model	Hit rate
[82]	140	Process parameters, blowing parameters, and additives information	Regression	Deep extreme learning	Hit rate
[83]	1500	Process parameters, blowing parameters, additives information, sampling test results during process, and end-of-blow features	Regression	SVR	Hit rate
[76]	2331	Process parameters, blowing parameters, additives information, and end-of-blow features	Regression	GNN	*R*-squared, MAE, and RMSE
[29]	691	Process parameters, blowing parameters, end-of-blow features, time-series data, and image	Regression	Multivariate data analysis	*R*-squared
[44]	15,000[a]	Process parameters and blowing parameters	Regression	ANN	Hit rate
[78]	170	Process parameters, blowing parameters, and additives information	Regression	SVR	Hit rate
[84]	3085	End-of-blow features	Classification	SVM	Accuracy
[38]	1500[a]	Process parameters, blowing parameters, additives information, sampling test results during process, and end-of-blow features	Regression	CBR	Hit rate
[34]	1084	Process parameters, blowing parameters, and additives information	Dimension reduction + regression	PCA + MLP network	RMSE
[72]	4332[a]	Process parameters, blowing parameters, additives information, and time-series data	Regression	Evolutionary neural network	*R*-squared and hit rate
[14]	6510	Process parameters, blowing parameters, and additives information	Regression	MLP	*R*-squared
[85]	16,000	Process parameters and additives information	Clustering + classification	(*k*-means & DT) + SVM	Accuracy
[32]	750	Process parameters and blowing parameters	Regression	k-NN	Hit rate
[63]	4808	Process parameters, blowing parameters, additives information, and time-series data	Regression	Ridge regression, RF, and gradient boosted regression tree	RMSE and *R*-squared
[28]	7158[a]	Process parameters and time-series data	Regression	CNN	RMSE
[39]	1400	Process parameters, blowing parameters, and additives information	Regression	SVR	MAE
[86]	1350	Process parameters, blowing parameters, and additives information	Regression	Linear regression	Hit rate
[47]	1500	Process parameters, blowing parameters, additives information, sampling test results during process, and end-of-blow features	Clustering + regression	*k*-means + ANN	Hit rate

Abbreviations: ANN, artificial neural networks; CBR, case-based reasoning; CNN, convolutional neural network; GBR, gradian boost regressor; GNN, graph neural networks; MAE, mean absolute error; ML, machine learning; MLP, multilayer perceptron; RF, random forest; RMSE, root mean squared error; SVR, support vector machines for regression.

[a]It is not specified whether these are total samples or training samples.

TABLE 4 Endpoint sulfurous prediction.

Ref.	No. of samples	Type of features	ML task	Method	Evaluation metric
[83]	1500	Process parameters, blowing parameters, additives information, end-of-blow features, and sampling test results during the process	Regression	SVR	Hit rate
[76]	2331	Process parameters, blowing parameters, additives information, and end-of-blow features	Regression	GNN	*R*-squared, MAE, and RMSE
[14]	6510	Process parameters, blowing parameters, and additives information	Regression	MLP	*R*-squared
[63]	4808	Process parameters, blowing parameters, additives information, and time-series data	Regression	Ridge regression, RF, and gradient boosted regression tree	RMSE and *R*-squared

Abbreviations: GNN, graph neural networks; MAE, mean absolute error; ML, machine learning; MLP, multilayer perceptron; RF, random forest; RMSE, root mean squared error; SVR, support vector machines for regression.

TABLE 5 Anomaly detection.

Ref.	No. of samples	Type of features	ML task	Method	Evaluation metric
[27]	500	Time-series data	Anomaly detection	Multivariate time-series analysis + SVM	Detection rate
[29]	691	Process parameters, blowing parameters, end-of-blow features, time-series data, and image	Regression	Multivariate data analysis	Hit rate
[87]	375[a]	Process parameters, blowing parameters, additives information, and time-series data	Anomaly detection	Time-series data analysis	Accuracy

Abbreviation: ML, machine learning.

[a]It is not specified whether these are total samples or training samples.

some of the end-of-blow features to predict other end-of-blow features, thereby neglecting the dynamics of the process.

- **Model simplicity**: Despite the complexity of the BOF process, simpler models have been predominantly used (refer to Tables 1–6 and Figure 5b).
- **Evaluation and transparency**: A common limitation lies in the prevalent use of HR as a performance metric, which may not truly reflect model performance. Additionally, there is a need for clearer differentiation between training and testing accuracy, alongside better transparency about the model structures. The lack of transparency in reporting model structure poses challenges in replicability and comparative study.

As shown in Figure 7, there has been a notable increase in published papers on this subject, with a peak in 2022 and a trend that suggests continued growth in 2023. Looking ahead, the focus should pivot toward harnessing the richness of data available in this domain and implementing advanced deep learning techniques. The key directions proposed for future research are given below:

- **Data expansion**: Enhancing performance and robustness of ML models requires larger and more diverse datasets. These should capture the variability in operational conditions, raw materials, and product specifications. Emphasis should be placed on sensor time-series data to better represent the complex industrial scenarios, while the challenges and costs of sensor implementation must also be weighed.
- **Advanced deep learning techniques**: Advanced deep learning techniques such as RNNs, CNNs, and autoencoders have demonstrated value in complex industrial scenarios,[98] and there is a particularly untapped potential for their application in the analysis of multivariate sensor data in the steelmaking process. Transfer learning can also accelerate model training and enhance predictive performance, especially when steelmaking-specific data is limited.[99]
- **Multitask learning**: The BOF process involves multiple, highly correlated endpoints that require simultaneous prediction. Multitask learning can effectively leverage these correlations, improving prediction accuracy and efficiency. Notably, graph neural networks provide a suitable model architecture for this approach.[52]

Ultimately, the successful application of these advanced ML models will signify the dawn of a new era in the steelmaking industry, truly embodying the transformative power of ML toward sustainable, efficient, and intelligent steelmaking. It is through such advancements that the steel industry will continue to innovate, evolve, and meet the challenges of tomorrow.

TABLE 6 Other applications of ML in the BOF process.

Ref.	Application	No. of samples	Types of features	ML task	Method	Evaluation metric
[89]	Blowing endpoint judgment	989	Flame information (image)	Classification	CNN (DenseNet)	Accuracy
[37]	Blowing oxygen volume prediction	4000	Process parameters and additives information	Regression	k-NN + CBR	Hit rate and RMSE
[43]	Predict oxygen and coolant requirements of reblowing	1600	Sampling test results during the process and end-of-blow features	Classification, regression	ANN	MAE
[90]	Total oxygen volume prediction	1300	Process parameters and end-of-blow features	Regression	ANN + incremental learning	Hit rate and *R*-squared
[90]	Second blow oxygen volume prediction	1000	Process parameters, additive information, sampling test results during process, and end-of-blow features	Regression	ANN + incremental learning	Hit rate and *R*-squared
[44]	Second blow oxygen volume and coolant mount prediction	15,000[a]	Process parameters and end-of-blow features	Regression	ANN	*R*-squared
[91]	Oxygen blowing volume and coolant amount prediction	n/a	Process parameters and end-of-blow features	Regression	CBR + SVM	RMSE and hit rate
[92]	Predict coolant requirements of reblowing and amount of coolant prediction	300	Blowing parameters, additives information, and sampling test results during the process	Classification and regression	Fuzzy network and relevance vector machine	Hit rate and RMSE
[49]	Blowing oxygen volume prediction	1381	Process parameters and additives information	Regression	Multiple LR + GPR + *k*-means clustering	RMSE, MAE, and hit rate
[25]	Yield of steel prediction	50	Process parameters, blowing parameters, and additives information	Regression	SVR, RF, ANN, and neuro-fuzzy inference system	MSE, RMSE, and *R*-squared
[71]	Multiple element (C, Mn, Si, S, and P) prediction	n/a	Process parameters and time-series data	Regression	SVR	EMSE
[93]	Oxygen consumption prediction	1273[a]	Process parameters and end-of-blow features	Regression	DT + SVR and DT + MLP	MAE and RMSE
[34]	Oxygen content of end-of-blow prediction	1084	Process parameters, blowing parameters, and additives information	Dimension reduction + regression	PCA + MLP network	RMSE
[94]	Blowing stage judgment	41	Flame information (image)	Classification + regression	MLP	Recognition rate
[30]	Decarburization rate prediction	1100	Blowing parameters and time-series data	Regression	ANN	*R*-squared
[63]	Endpoint Mn prediction	4808	Process parameters, blowing parameters, additives information, and time-series data	Regression	Ridge regression, RF, and gradient boosted regression tree	RMSE and *R*-squared
[39]	Percentage of iron content of slag prediction	1400	Process parameters, blowing parameters, and additives information	Regression	SVR	MAE
[46]	Endpoint oxygen prediction	1200	Process parameters, blowing parameters, and additives information	Regression	CNN	Hit rate
[95]	Oxygen consumption prediction	901	Process parameters and additives information	Clustering + regression	*k*-means clustering + LR	*R*-squared and hit rate

TABLE 6 (Continued)

Ref.	Application	No. of samples	Types of features	ML task	Method	Evaluation metric
[74]	Oxygen blowing volume and coolant amount prediction	90	Process parameters, blowing parameters, and additives information	Regression	SVR	MAE and hit rate
[96]	Blowing endpoint time	350	Flame information (radiation spectrum)	Regression	SVR	n/a
[97]	Blowing endpoint judgment	60[a]	Flame information (image and radiation spectrum)	Classification	SVM	Accuracy

Abbreviations: ANN, artificial neural networks; BOF, basic oxygen furnace; CBR, case-based reasoning; CNN, convolutional neural network; GPR, Gaussian process regression; LSTM, long short-term memory; MAE, mean absolute error; ML, machine learning; MLP, multilayer perceptron; n/a, not applicable; RF, random forest; RMSE, root mean squared error; SVR, support vector machines for regression.

[a]It is not specified whether these are total samples or training samples.

FIGURE 6 Dataset size distribution in ML for BOF studies. This plot illustrates the range of dataset sizes used in the training of ML models, spanning from less than 200 to between 5000 and 10,000. Note that only the papers that clearly mention the size of the training samples in their models are counted. Despite the vast amounts of data available in steel plants, it is evident that most studies have yet to fully leverage this resource. BOF, basic oxygen furnace; ML, machine learning.

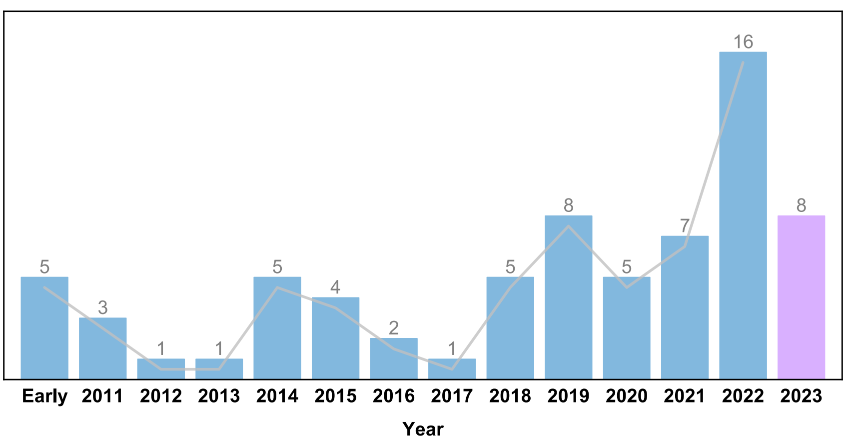

FIGURE 7 Yearly distribution of published papers on ML for the BOF. This chart illustrates the annual count of papers published on the application of ML techniques to the BOF process. A peak is evident in 2022, and the amount of research published in 2023 thus far suggests a continued upward trend in this area of study. BOF, basic oxygen furnace; ML, machine learning.

AUTHOR CONTRIBUTIONS

Maryam Khaksar Ghalati: Software; methodology; investigation; writing – original draft; conceptualization. **Jianbo Zhang**: Investigation and review. **G. M. A. M. El-Fallah**: Investigation. **Bogdan Nenchev**: Investigation. **Hongbiao Dong**: Supervision; conceptualization; writing – review.

ACKNOWLEDGMENTS

The authors would like to acknowledge funding from NISCO UK Research Centre at School of Engineering, University of Leicester.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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REFERENCES

1. https://worldsteel.org 2023.
2. Gajdzik B, Wolniak R, Grebski W. Process of transformation to net zero steelmaking: decarbonisation scenarios based on the analysis of the polish steel industry. *Energies*. 2023;16(8):3384.
3. F. F. 55. European Commission; 2018.
4. Ghobakhloo M. Industry 4.0, digitization, and opportunities for sustainability. *J Clean Prod*. 2020;252:119869.
5. Wang J, Ma Y, Zhang L, Gao RX, Wu D. Deep learning for smart manufacturing: methods and applications. *J Manuf Syst*. 2018;48:144-156.
6. Conduit B, Jones NG, Stone HJ, Conduit GJ. Design of a nickel-base superalloy using a neural network. *Mater Des*. 2017;131:358-365.
7. Udu AG, Osa-uwagboe N, Adeniran O, Aremi A, Ghalati MK, Dong H. A machine learning approach to characterise the mechanical properties of additively manufactured fiber-reinforced plastics. Preprints, SSRN 4515794. 2023.
8. Mahalle G, Salunke O, Kotkunde N, Gupta AK, Singh SK. Neural network modeling for anisotropic mechanical properties and work hardening behavior of Inconel 718 alloy at elevated temperatures. *J Mater Res Technol*. 2019;8(2):2130-2140.
9. Feng S, Zhou H, Dong H. Using deep neural network with small dataset to predict material defects. *Mater Des*. 2019;162:300-310.
10. Cemernek D, Cemernek S, Gursch H, et al. Machine learning in continuous casting of steel: a state-of-the-art survey. *J Intell Manuf*. 2021:1-19.
11. Yang X, El-Fallah GM, Tao Q, et al. Dimensionality reduction for machine learning using statistical methods: a case study on predicting mechanical properties of steels. *Mater Today Commun*. 2023;34:105162.
12. Takawa T, Katayama K, Hoteiya M, Hirayama N. The development of a mathematical model of endpoint control system for top and bottom blowing process in BOF. *Tetsu-to-Hagané*. 1987;73(7):836-843.
13. Wang Z, Liu Q, Liu H, Wei S. A review of end-point carbon prediction for BOF steelmaking process. *High Temp Mater Process*. 2020;39(1):653-662.
14. Nenchev B, Panwisawas C, Yang X, et al. Metallurgical data science for steel industry: a case study on basic oxygen furnace. *Steel Res Int*. 2022;93(12):2100813.
15. Cavaliere P, Cavaliere P. *Clean Ironmaking and Steelmaking Processes: Efficient Technologies for Greenhouse Emissions Abatement*. Springer; 2019.
16. Sajeevkumar NM. Mathematical model for heat transfer in oxygen steelmaking process. Ph.D. thesis. Swinburne University of Technology, Melbourne, Australia; 2022.
17. Sarkar R, Gupta P, Basu S, Ballal NB. Dynamic modeling of LD converter steelmaking: reaction modeling using Gibbs' free energy minimization. *Metall Mater Trans B*. 2015;46(2):961-976.
18. Sandlöbes S, Senk D, Sancho L, Diaz A. In-situ measurement of CO- and CO_2-concentrations in BOF off-gas. *Steel Res Int*. 2011;82(6):632-637.
19. Jordan MI, Mitchell TM. Machine learning: trends, perspectives, and prospects. *Science*. 2015;349(6245):255-260.
20. Hastie T, Tibshirani R, Friedman JH, Friedman JH. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. Vol 2. Springer; 2009.
21. Alloghani M, Al-Jumeily D, Mustafina J, Hussain A, Aljaaf AJ. A systematic review on supervised and unsupervised machine learning algorithms for data science. *Supervised Unsupervised Learn Data Sci*. 2020:3-21.
22. Mnih V, Kavukcuoglu K, Silver D, et al. Human-level control through deep reinforcement learning. *Nature*. 2015;518(7540):529-533.
23. Shearer C. The CRISP-DM model: the new blueprint for data mining. *J Data Warehous*. 2000;5(4):13.
24. Liu C, Tang L, Liu J. A stacked autoencoder with sparse Bayesian regression for end-point prediction problems in steelmaking process. *IEEE Trans Autom Sci Eng*. 2019;17(2):550-561.
25. Laha D, Ren Y, Suganthan PN. Modeling of steelmaking process with effective machine learning techniques. *Expert Syst Appl*. 2015;42(10):4687-4696.
26. Bae J, Li Y, Ståhl N, Mathiason G, Kojola N. Using machine learning for robust target prediction in a basic oxygen furnace system. *Metall Mater Trans B*. 2020;51(4):1632-1645.
27. Qian Q, Fang X, Xu J, Li M. Multichannel profile-based monitoring method and its application in the basic oxygen furnace steelmaking process. *J Manuf Syst*. 2021;61:375-390.
28. Sala DA, Van Yperen-De Deyne A, Mannens E, Jalalvand A. Hybrid static-sensory data modeling for prediction tasks in basic oxygen furnace process. *Appl Intell*. 2022:1-11.
29. Brämming M, Björkman B, Samuelsson C. BOF process control and slopping prediction based on multivariate data analysis. *Steel Res Int*. 2016;87(3):301-310.
30. Rahnama A, Li Z, Sridhar S. Machine learning-based prediction of a BOS reactor performance from operating parameters. *Processes*. 2020;8(3):371.
31. He F, Zhang L. Prediction model of end-point phosphorus content in BOF steelmaking process based on PCA and BP neural network. *J Process Control*. 2018;66:51-58.
32. Qi L, Liu H. Feature selection of BOF steelmaking process data based on denary salp swarm algorithm. *Arabian J Sci Eng*. 2020;45(12):10401-10416.
33. Viana Júnior MA, Silva CA, Silva IA. Hybrid model associating thermodynamic calculations and artificial neural network in order to predict molten steel temperature evolution from blowing end of a BOF for secondary metallurgy. *REM-Int Eng J*. 2018;71(4):587-592.
34. Liu Z, Cheng S, Liu P. Prediction model of BOF end-point P and O contents based on PCA–GA–BP neural network. *High Temp Mater Process*. 2022;41(1):505-513.
35. Chen C, Wang N, Chen M. Prediction model of end-point phosphorus content in consteel electric furnace based on PCA-extra tree model. *ISIJ Int*. 2021;61(6):1908-1914.
36. Liu C, Tang L, Zhao C. A novel dynamic operation optimization method based on multiobjective deep reinforcement learning for steelmaking process. *IEEE Transact Neural Networks Learn Syst*. 2023:1-15.

37. Han M, Wang X. BOF oxygen control by mixed case retrieve and reuse CBR. *IFAC Proc Vol*. 2011;44(1):3575-3580.
38. Liang Y, Wang H, Xu A, Tian N. A two-step case-based reasoning method based on attributes reduction for predicting the endpoint phosphorus content. *ISIJ Int*. 2015;55(5):1035-1043.
39. Schlueter J, Odenthal H-J, Uebber N, Blom H, Morik K. A novel data-driven prediction model for BOF endpoint. In: *Proceedings of the Iron & Steel Technology Conference*; 2013:923-928.
40. Liu L, Li P, Chu M, Gao C. End-point prediction of 260 tons basic oxygen furnace (BOF) steelmaking based on WNPSVR and WOA. *J Intell Fuzzy Syst*. 2021;41(2):2923-2937.
41. Gao C, Shen M. End-point prediction of basic oxygen furnace (BOF) steelmaking based on improved twin support vector regression. *Metalurgija*. 2019;58(1-2):29.
42. Wang M, Gao C, Ai X, Zhai B, Li S. Whale optimization end-point control model for 260 tons BOF steelmaking. *ISIJ Int*. 2022;62(8):1684-1693.
43. Cox I, Lewis R, Ransing R, Laszczewski H, Berni G. Application of neural computing in basic oxygen steelmaking. *J Mater Process Technol*. 2002;120(1-3):310-315.
44. Fileti AF, Pacianotto T, Cunha AP. Neural modeling helps the BOS process to achieve aimed end-point conditions in liquid steel. *Eng Appl Artif Intell*. 2006;19(1):9-17.
45. Zhou K-X, Lin W-H, Sun J-K, et al. Prediction model of end-point phosphorus content for BOF based on monotone-constrained BP neural network. *J Iron Steel Res Int*. 2021:1-10.
46. Wang Z, Bao Y, Gu C. Convolutional neural network-based method for predicting oxygen content at the end point of converter. *Steel Res Int*. 2023;94(1):2200342.
47. Wang H-b, Xu A-j, Ai L-x, Tian N-y. Prediction of endpoint phosphorus content of molten steel in BOF using weighted K-means and GMDH neural network. *J Iron Steel Res Int*. 2012;19(1):11-16.
48. Feng K, Yang L, Su B, Feng W, Wang L. An integration model for converter molten steel end temperature prediction based on Bayesian formulas. *Steel Res Int*. 2022;93(2):2100433.
49. Jiang S-L, Shen X, Zheng Z. Gaussian process-based hybrid model for predicting oxygen consumption in the converter steelmaking process. *Processes*. 2019;7(6):352.
50. Zhang R, Yang J, Wu S, Sun H, Yang W. Comparison of the prediction of BOF end-point phosphorus content among machine learning models and metallurgical mechanism model. *Steel Res Int*. 2022:2200682.
51. Yang L, Liu H, Chen F. Just-in-time updating soft sensor model of endpoint carbon content and temperature in BOF steelmaking based on deep residual supervised autoencoder. *Chemometr Intell Lab Syst*. 2022;231:104679.
52. Chang S, Zhao C, Li Y, Zhou M, Fu C, Qiao H. Multi-channel graph convolutional network based end-point element composition prediction of converter steelmaking. *IFAC-PapersOnLine*. 2021;54(3):152-157.
53. Gu M, Xu A, Wang H, Wang Z. Real-time dynamic carbon content prediction model for second blowing stage in BOF based on CBR and LSTM. *Processes*. 2021;9(11):1987.
54. Botchkarev A. A new typology design of performance metrics to measure errors in machine learning regression algorithms. *Interdiscipl J Inf Knowl Manag*. 2019;14:045-076.
55. Hossin M, Sulaiman MN. A review on evaluation metrics for data classification evaluations. *Int J Data Mining Knowl Manag Process*. 2015;5(2):1.
56. Yang L, Liu H, Chen F. Just-in-time updating soft sensor model of endpoint carbon content and temperature in BOF steelmaking based on deep residual supervised autoencoder. *High Temp Mater Process*. 2023;42(1):20220270.
57. Gao C, Shen M, Liu X, Wang L, Chen M. End-point prediction of BOF steelmaking based on KNNWTSVR and LWOA. *Trans Indian Inst Metals*. 2019;72(1):257-270.
58. Gu M-q, Xu A-j, Yuan F, He X-m, Cui Z-f. An improved CBR model using time-series data for predicting the end-point of a converter. *ISIJ Int*. 2021;61(10):2564-2570.
59. Park TC, Kim BS, Kim TY, Jin IB, Yeo YK. Comparative study of estimation methods of the endpoint temperature in basic oxygen furnace steelmaking process with selection of input parameters. *Korean J Metal Mater*. 2018;56(11):813-821.
60. Gao C, Shen M, Wang L. End-point prediction of BOF steelmaking based on wavelet transform based weighted TSVR. In: *2018 37th Chinese Control Conference (CCC)*. IEEE; 2018:3200-3204.
61. Li W, Wang Q, Wang X, Wang H. Endpoint prediction of BOF steelmaking based on BP neural network combined with improved PSO. *Chem Eng Transact*. 2016;51:475.
62. Han M, Liu C. Endpoint prediction model for basic oxygen furnace steel-making based on membrane algorithm evolving extreme learning machine. *Appl Soft Comput*. 2014;19:430-437.
63. Sala DA, Jalalvand A, Van Yperen-De Deyne A, Mannens E. Multivariate time series for data-driven endpoint prediction in the basic oxygen furnace. In: *2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA)*. IEEE; 2018:1419-1426.
64. Feng M, Ll Q, Zou Z. An outlier identification and judgment method for an improved neural-network BOF forecasting model. *Steel Res Int*. 2008;79(5):323-332.
65. Gao C, Shen M-g, Liu X-p, Zhao N-n, Chu M-x. End-point dynamic control of basic oxygen furnace steelmaking based on improved unconstrained twin support vector regression. *J Iron Steel Res Int*. 2020;27(1):42-54.
66. Guo J-w, Zhan D-p, Xu G-c, et al. An online BOF terminal temperature control model based on big data learning. *J Iron Steel Res Int*. 2023:1-12.
67. Jun T, Xin W, Tianyou C, Shuming X. Intelligent control method and application for BOF steelmaking process. *IFAC Proc Vol*. 2002;35(1):439-444.
68. Kačur J, Flegner P, Durdán M, Laciak M. Prediction of temperature and carbon concentration in oxygen steelmaking by machine learning: a comparative study. *Appl Sci*. 2022;12(15):7757.
69. Li Q, Liu C, Guo Q. Support vector machine with robust low-rank learning for multi-label classification problems in the steelmaking process. *Mathematics*. 2022;10(15):2659.
70. Liu H, Yao S. End point prediction of basic oxygen furnace (BOF) steelmaking based on improved bat-neural network. *Metalurgija*. 2019;58(3-4):207.
71. Liu C, Tang L, Liu J, Tang Z. A dynamic analytics method based on multistage modeling for a BOF steelmaking process. *IEEE Trans Autom Sci Eng*. 2018;16(3):1097-1109.
72. Mahanta BK, Gupta P, Mohanty I, Roy TK, Chakraborti N. Evolutionary data driven modeling and tri-objective optimization for noisy BOF steel making data. *Digit Chem Eng*. 2023;7:100094.
73. Wang M, Li S, Gao C, Ai X, Zhai B. End-point dynamic control model for 260 tons BOF steelmaking based on PWWTSVR and LWOA. *Steel Res Int*. 2023:2200872.
74. Wang M, Gao C, Ai X, Zhai B, Li S. Hybrid end-point static control model for 80 tons BOF steelmaking. *Trans Indian Inst Met*. 2022;75(9):2281-2288.
75. Shao Y, Zhou M, Chen Y, Zhao Q, Zhao S. BOF endpoint prediction based on the flame radiation by hybrid SVC and SVR modeling. *Optik*. 2014;125(11):2491-2496.
76. Feng L, Zhao C, Li Y, Zhou M, Qiao H, Fu C. Multichannel diffusion graph convolutional network for the prediction of endpoint composition in the converter steelmaking process. *IEEE Trans Instrum Meas*. 2020;70(1):1-13.
77. Shao Y, Zhao Q, Chen Y, Zhang Q, Wang K. Applying flame spectral analysis and multi-class classification algorithm on the BOS endpoint carbon content prediction. *Optik*. 2015;126(23):4539-4543.
78. Gao C, Shen M, Liu X, Wang L, Chu M. End-point static control of basic oxygen furnace (BOF) steelmaking based on wavelet transform weighted twin support vector regression. *Complexity*. 2019;2019:1-16.
79. Han M, Cao Z. An improved case-based reasoning method and its application in endpoint prediction of basic oxygen furnace. *Neurocomputing*. 2015;149:1245-1252.

80. Wang X, Xing J, Dong J, Wang Z. Data driven based endpoint carbon content real time prediction for BOF steelmaking. In: *2017 36th Chinese Control Conference (CCC)*. IEEE; 2017:9708-9713.
81. Zhang C-J, Zhang Y-C, Han Y. Industrial cyber-physical system driven intelligent prediction model for converter end carbon content in steelmaking plants. *J Ind Inf Integrat*. 2022;28:100356.
82. Quan L, Li A, Cui G, Xie S. Using enhanced sparrow search algorithm-deep extreme learning machine model to forecast end-point phosphorus content of BOF. *Preprints.org*. 2021.
83. Shi C, Guo S, Wang B, Ma Z, Wu Cl, Sun P. Prediction model of BOF end-point phosphorus content and sulfur content based on LWOA-TSVR. *Ironmak Steelmak*. 2023:1-10.
84. Li H, Barui S, Mukherjee S, Chattopadhyay K. Least squares twin support vector machines to classify end-point phosphorus content in BOF steelmaking. *Metals*. 2022;12(2):268.
85. Phull J, Egas J, Barui S, Mukherjee S, Chattopadhyay K. An application of decision tree-based twin support vector machines to classify dephosphorization in BOF steelmaking. *Metals*. 2019; 10(1):25.
86. Wang Z, Xie F, Wang B, et al. The control and prediction of end-point phosphorus content during BOF steelmaking process. *Steel Res Int*. 2014;85(4):599-606.
87. Qian Q, Dong Q, Xu J, Zhao W, Li M. A metallurgical dynamics-based method for production state characterization and end-point time prediction of basic oxygen furnace steelmaking. *Metals*. 2022;13(1):2.
88. Ruuska J, Sorsa A, Ollila S, Leiviskä K. Analysis of splashing in basic oxygen furnace through systematic modelling. *IFAC-PapersOnLine*. 2015;48(17):171-176.
89. Sun K, Zhu Y. A blowing endpoint judgment method for converter steelmaking based on improved DenseNet. In: *2022 34th Chinese Control and Decision Conference (CCDC)*. IEEE; 2022: 3839-3844.
90. Fei H, Xianyi C, Zhenghai Z. Prediction of oxygen-blowing volume in BOF steelmaking process based on BP neural network and incremental learning. *High Temp Mater Process*. 2022;41(1): 403-416.
91. Han M, Li Y, Cao Z. Hybrid intelligent control of BOF oxygen volume and coolant addition. *Neurocomputing*. 2014;123:415-423.
92. Han M, Zhao Y. Dynamic control model of BOF steelmaking process based on ANFIS and robust relevance vector machine. *Expert Syst Appl*. 2011;38(12):14786-14798.
93. Liu Z, Zhong Z, Kaitian Z, Xinyue S, Yongzhou W. *Energy Technology 2021: Carbon Dioxide Management and Other Technologies*. Springer; 2021:95-110.
94. Liu H, Wang B, Xiong X. Basic oxygen furnace steelmaking end-point prediction based on computer vision and general regression neural network. *Optik*. 2014;125(18):5241-5248.
95. Wang D, Bao Y, Gao F, Xing L. Hybrid model for predicting oxygen consumption in BOF steelmaking process based on cluster analysis. *Steel Res Int*. 2023;94(1):2200595.
96. Xu L-f, Li W, Zhang M, Xu S-x, Li J. A model of basic oxygen furnace (BOF) end-point prediction based on spectrum information of the furnace flame with support vector machine (SVM). *Optik*. 2011; 122(7):594-598.
97. Zhou M, Zhao Q, Chen Y. Endpoint prediction of BOF by flame spectrum and furnace mouth image based on fuzzy support vector machine. *Optik*. 2019;178:575-581.
98. Choi K, Yi J, Park C, Yoon S. Deep learning for anomaly detection in time-series data: review, analysis, and guidelines. *IEEE Access*. 2021;9:120043-120065.
99. Maschler B, Weyrich M. Deep transfer learning for industrial automation: a review and discussion of new techniques for data-driven machine learning. *IEEE Ind Electron Mag*. 2021;15(2):65-75.

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How to cite this article: Ghalati MK, Zhang J, El-Fallah GMAM, Nenchev B, Dong H. Toward learning steelmaking—a review on machine learning for basic oxygen furnace process. *MGE Advances*. 2023;e6. https://doi.org/10.1002/mgea.6