Metallurgical technologies / Металлургические технологии

UDC 669.1:001.89
DOI 10.17073/0368-0797-2023-6-638-644

Original article
Оригинальная статья

Prediction of carbon content in the metal of final blow period in BOF using neural network

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Abstract. Prediction and control of the carbon content after the end of oxygen blow in BOF converter are key points of steel production efficiency. One of the most accurate methods is the dynamic predicting method based on the use of intermediate sublance measurement (TSC probe) when about 85 – 90 % of total oxygen is consumed and on the final period model. Models of the final period are traditionally based on exponential or cubic functions, currently there are developments based on neural network technologies. We investigated the possibility of using a neural network to predict the final carbon content using the results of intermediate sublance measurement (TSO probe) when about 95 % of total oxygen is consumed. As a model of the final period, a two-layer neural network with one hidden layer and an activation function of the Softplus type for all neurons was implemented in software. The input vectors contain initial carbon content and oxygen consumption for the second blow values. The output vector contains the predicted final carbon content, the output training vector - actual final carbon content values. The network was trained on 700 heats data of the training set. The model trained in this way was tested on 232 heats data of the testing set. The prediction errors distribution and values of the mean absolute error and root mean square error for the training and testing sets are correspondingly close. They are also comparable with similar indicators of the heats, the final period of which was carried out without oxygen blow (only flux additions and/or nitrogen blow), and this indicates a high accuracy of the prediction.

Keywords: BOF, carbon content, sublance, mathematical simulation, prediction, final period, neural network

For citation: Shakirov M.K., Protopopov E.V., Zimin A.V., Turchaninov E.B. Prediction of carbon content in the metal of final blow period in BOF using neural network. *Izvestiya. Ferrous Metallurgy*. 2023;66(6):638–644. https://doi.org/10.17073/0368-0797-2023-6-638-644

Прогнозирование содержания углерода в металле заключительного периода продувки в кислородном конвертере с использованием нейронной сети

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Аннотация. Прогнозирование и управление содержанием углерода в металле по окончании продувки в кислородном конвертере являются ключевыми моментами в обеспечении эффективности производства стали. Наиболее точным методом является метод динамического прогнозирования, основанный на использовании информации промежуточного замера фурмой-зондом (блок типа TSC) в период израсходования порядка 85 – 90 % общего расхода кислорода на плавку и принятой модели заключительного периода продувки. Для прогнозирования традиционно используются модели заключительного периода на основе экспоненциальных или кубических функций, существуют разработки на основе нейросетевых технологий. В настоящем исследовании заключительный период плавки определили как период между первым и последним (перед выпуском плавки) замерами фурмой-зондом. В зависимости от результатов первого замера и требуемых параметров металла в этот период может производиться продувка кислородом, присадка флюсов, а также усреднительная продувка азотом. Была исследована возможность использования нейросети для прогнозирования конечного содержания углерода с использованием результатов промежуточного замера фурмой–зондом (блок типа TSO) в период израсходования порядка 95 % общего расхода кислорода на плавку. В качестве модели заключительного периода была программно реализована двухслойная нейросеть с одним скрытым слоем и активационной функцией типа Softplus для всех нейронов. Входные данные - содержание углерода промежуточного замера и расход кислорода на заключительный период продувки. Выходные данные – прогнозируемое конечное содержание углерода. Для обучения использовались данные по фактическому конечному содержанию углерода в металле. Нейронная сеть была настроена по данным 700 плавок обучающей выборки. Настроенная таким образом модель была дополнительно протестирована на данных 232 плавок, не использовавшихся при обучении. Получены близкие значения ошибок прогноза для обучающей и тестирующей выборок. Кроме того, полученные значения ошибок сопоставимы с изменениями содержания углерода для плавок без использования кислорода в заключительный период, что говорит о высокой точности прогноза.

Ключевые слова: кислородный конвертер, содержание углерода, измерительная фурма, математическое моделирование, прогнозирование, заключительный период, нейронная сеть

Для цитирования: Шакиров М.К., Протопопов Е.В., Зимин А.В., Турчанинов Е.Б. Прогнозирование содержания углерода в металле заключительного периода продувки в кислородном конвертере с использованием нейронной сети. *Известия вузов. Черная металлургия*. 2023;66(6):638–644. https://doi.org/10.17073/0368-0797-2023-6-638-644

Introduction

The accumulated operational experience with converters employing upper oxygen blow has compellingly demonstrated the process's advantages. These include high productivity, sufficiently durable unit lining, simple equipment design and operation, and technological flexibility regarding the composition of processed pigments [1 – 3]. However, achieving stable technological melting indicators and overall process efficiency depends significantly on the accuracy and correctness of determining the completion moment of the operation [4].

In the practice of organizing blowing, addressing this challenge typically involves using indirect characteristics to gauge the progress of blowing and the bath's behavior. Examples include:

– determining the completion moment of the blowing operation based on the oxygen consumption amount;

– observing the luminosity intensity of the exhaust gas plume above the converter;

– analyzing the chemical composition of exhaust gases;

– examining changes in indirect characteristics such as the bath's behavior (acoustic phenomena, lance vibration), observing the temperature of the water cooling the lance, and measuring the electrical conductivity of the bath, among others.

Simultaneously, the enumerated elements and methods for controlling the blowing process can be categorized as subjective factors, assuming a high level of competence among the process personnel. However, the rapidity of oxidative refining processes within the BOF, coupled with intense dust and gas emissions, and the fluctuating bath level with the potential for emissions or, conversely, slag coagulation, all contribute to the substantial complexity in managing the smelting process.

The scrutinized predictive models assume particular significance in the production of specialty steels, especially low-carbon steels, including void-free steels with minimal impurities (≤0.003 % C and 0.004 % N). In this context, the accurate prediction and control of carbon content in the metal during the final phase of the blowing operation emerge as a critical task. Effectively addressing this challenge facilitates an improvement and stabilization of technological performance.

Incorporating additional information for predicting smelting characteristics, the well-established methods for calculating residual carbon content in metal prior to release can be classified as follows [4; 5]:

– prediction through static models;

– prediction through dynamic models;

– intelligent prediction.

1. Static prediction

Static prediction employs what are known as static melt models, relying on calculations of thermal and material balances or statistical descriptions of the entire melt. Initial data include the chemical composition and temperature of the iron, the chemical composition of the solid metal charge and additional materials, along with results from previous melts and the required values of metal indicators at the end of blowing – primarily the chemical composition and temperature. This method facilitates the determination of the quantity of charge and additional materials, including assessment of the amount of oxygen consumed during the blowing period necessary to achieve the desired carbon content in the metal [6 – 8].

However, the accuracy of this method in predicting post-blowing melt parameters is not consistently stable due to the influence of numerous uncontrolled factors [9]. These factors may encompass variations in the chemical composition and physical properties of the metal charge, fluctuations in properties and quantities of additives, uncontrolled heat losses, losses of oxygen during different blowing periods, and more [7]. Theoretical [10 – 12] or static [13 – 15] models, including those based on neural networks, are the most commonly used approaches for static forecasting.

2. Dynamic prediction

It is established that the use of a sublance in combination with models for the final blowing period serves as a dynamic control tool, leading to a reduction in the melting cycle by significantly minimizing the time required for corrective operations (turndown, metal cooling) [15].

Models for the final period are constructed on a statistical description of the relationships between the ultimate values of melting parameters – primarily carbon content and temperature – their initial values, and the quantity of consumed oxygen [16]. In this scenario, the decarburization rate can be expressed as follows

$$-\frac{\partial C}{\partial \tau} = k(C - C_0), \qquad (1)$$

where k is the decarburization reaction rate constant, s^{-1}; C is the current concentration of carbon in the liquid metal, %; C_0 is the minimum achievable carbon concentration in liquid metal, characterizing mass and rate of carbon oxidation in the region of its low values, %; τ is the duration of oxygen blowing, s.

The use of a sublance facilitates the measurement and sampling of metal for chemical analysis without the need for tilting, which typically involves interrupting oxygen purge and tilting the converter. In this scenario, two measurements are usually conducted for each melting operation: one during oxygen blowing (after 85 – 90 % of the estimated total oxygen amount has been consumed) and another at the conclusion of the oxygen blowing process.

The first measurement uses TSC probes (*temperature*, *sample*, *carbon*): metal temperature and carbon content are determined based on the liquidus temperature of the melt, and a sample is taken. To enhance result reliability, the oxygen blowing intensity is reduced during this measurement period. The first "dynamic" measurement serves as input for the final period model, which calculates the necessary amount of oxygen and potential coolant required to achieve the desired temperature and carbon content during metal tapping.

Following the oxygen blowing phase, measurements are conducted using TSO probes (*temperature*, *sample*, *oxygen*): the metal's temperature is determined, its oxidation is assessed, carbon content is calculated, and a metal sample is taken.

However, in domestic converter shops, TSC probes are currently not employed, and measurements are instead carried out using TSO probes during the blowing period, corresponding to a lower (less than 0.15 %) carbon content in the metal.

The use of a measuring sublance helps eliminate the influence of fluctuations in the properties of charge materials, thereby enhancing the accuracy of predicting the final carbon content for converter smelting compared to static prediction methods. Some Japanese manufacturers have achieved predicting accuracy of over 90 % within an interval of ±0.02 % C [17].

Another variation of dynamic carbon content prediction involves an approach based on utilizing indirect indicators of the decarbonization process, such as the results of exhaust gas composition analysis. The primary drawback of this option, coupled with the impact on the results of analyzing the amount of air drawn from the atmosphere in the gas discharge tract operation mode with partial combustion of exhaust gases, is the presence of a delay (time delay) in the initial information for calculation.

3. Intelligent prediction

Intelligent prediction of carbon content in the melt, as per the aforementioned characteristics, involves employing additional indirect information about the progress of the process, such as the vibration of the oxygen lance, the level of slag-metal emulsion, acoustic characteristics of the blowing progress, and more.

The initial application of this approach includes the development of a model for the final blowdown period based on a neural network [18].

Specifically, to predict carbon content, a network is employed with input neurons corresponding to carbon content measured by the sublance of the probe, the amount of oxygen, and coolant consumed during the final period. The positive results obtained allow for conclusions regarding the effectiveness of the method used.

The development and implementation of such approaches underscore the advantages of predicting carbon content in the final blowing period using neural networks compared to exponential, cubic, and carbon oxidation models based on analysis of the chemical composition of exhaust gases. Notably, these studies were conducted using experimental data from intermediate measurements employing only TSC probes [17; 19 – 21].

Therefore, it appears pertinent to evaluate the suitability of neural networks for describing the final period of blowing, particularly for predicting the final carbon content in the metal based on intermediate measurement data from TSO probes commonly used in the industry.

Research methodology

In this current study, the final blowing period was defined as the conditional interval between the first and last (prior to heat release) sublance measurements. Depending on the outcomes of the first measurement and the required final parameters of the metal, activities such as oxygen blowing, flux addition, and averaging nitrogen blowing can be conducted during this period.

The study aimed to assess the accuracy of predicting the final carbon content in the metal using intermediate measurements by TSO probes, accounting for approximately 95 % of the estimated total oxygen consumption for melting. Additionally, the results obtained were compared with similar ones derived from technology utilizing TSC probes.

The data analyzed in this study were derived from ongoing production heats conducted in a 350-ton converter equipped with a measuring lance under the direct supervision of the authors.

The melts chosen for training and testing the carbon content prediction specifically involved cases where only oxygen blowing was employed in the final period.

The determination of initial carbon content relies on sublance measurements conducted before the commencement of the final period, while the final content is ascertained through chemical analysis of a metal sample taken with a sublance at the end of blowing. Table 1 provides the initial (C_1) and final (C_2) carbon content, along with the change in carbon concentration resulting from the final period ($\Delta C^{\text{final}} = C_2 - C_1$) and the oxygen consumption for the operation. The values are presented in Table 1 as a ratio of the range of change in the numerator to the average value in the denominator.

To predict the carbon content at the end of the final blowing period, a two-layer neural network with one hidden layer was employed. The input data included the actual carbon content in the metal before the start of the final period C1 and the actual oxygen consumption in the final period O_2^{final}. The output data consisted of the predicted carbon content in the metal C_2^{predict} at the end of the final period. Training utilized data on the actual final carbon content from the metal sample. The activation function for the network was defined by the equation

$$Y = \ln(1 + e^x). \tag{2}$$

The initial and final carbon content, along with oxygen consumption data, were normalized using the following equation

$$C_i^* = \frac{C_i - C_{\min}}{C_{\max} - C_{\min}}, \tag{3}$$

where C_i is the actual parameter value; $C_{\min}$ and $C_{\max}$ are the minimum and the maximum values of the parameter, respectively.

A training set comprising data from 700 melts was used, with the results tested on data from 232 subsequent melts that followed the training set in chronological order. Of these, 56 melts were conducted under the direct supervision of the authors.

Table 1

Parameters of the final oxygen blow period

Таблица 1. **Параметры заключительного периода продувки с использованием кислорода**

C_1, %	C_2, %	ΔC^{final}, %	$O_2^{\text{зп}}$, nm³
0.026 – 0.168 / 0.055	0.017 – 0.117 / 0.039	0 – 0.099 / 0.016	411 – 4012 / 1156

The network was trained using a backpropagation algorithm, specifically the gradient descent method. Throughout the training process, the sum of squared deviations between the actual C_2 and the predicted carbon content C_2^{predict} in the metal was minimized.

The accuracy of prediction was evaluated using the following indicators:

– *mean error*, calculated as

$$ME = \frac{1}{N}\sum_{i=1}^{N}\left(Y_i - \hat{Y}_i\right), \tag{4}$$

where N is the number of observations; Y_i, $\hat{Y}_i$ are the actual and the predicted values of the parameter, respectively;

– *mean absolute error*, calculated as

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Y_i - \hat{Y}_i\right|, \tag{5}$$

– *root mean square error*, calculated as

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Y_i - \hat{Y}_i\right)^2}. \tag{6}$$

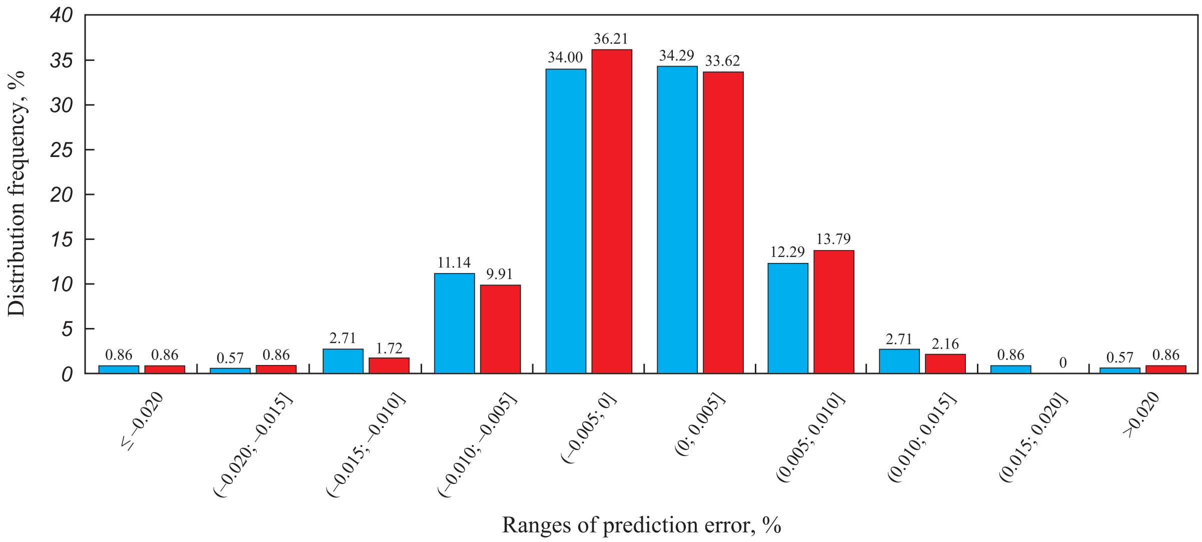
Results and discussion

As a result of training and subsequent testing of the neural network on the corresponding experimental data arrays, a distribution of prediction errors of the final carbon content in metal $C_2 - C_2^{\text{predict}}$ was obtained (see Fig.).

It's noteworthy that the distribution of prediction errors for the testing set closely aligns with that of the training set. The indication that over 90 % of errors fall within the range of ±0.010 %, and approximately 70 % of melts fall within the range of ±0.005 %, suggests a sufficiently high accuracy in predicting the final carbon content in the metal.

For a comprehensive comparison, the achieved prediction accuracy indices for both the training and testing sets were contrasted with similar indices obtained from melts that did not involve the use of oxygen in the final period of blowing. In these comparative melts, lime and/or limestone additives were employed, and averaging nitrogen blowing occurred through an oxygen lance. The initial values of C_1, derived from the results of the first sublance probe measurement, were used as the predicted values for the final carbon content C_2^{predict} (Table 2). Accuracy indicators were then calculated according to Eqs. (4) – (6).

The results indicate that the accuracy indicators characterizing the prediction for both the training and



Distribution of prediction errors of the final carbon content:
– training set; – testing set

Распределение ошибок прогноза конечного содержания углерода:
– обучающая выборка; – тестирующая выборка

testing sets have close values. Additionally, these values are comparable with those observed in melts conducted without the use of oxygen in the final period. Changes in carbon content ($C_2 - C_1 = C_2 - C_2^{\text{predict}}$) for such melts are evidently associated with the heterogeneity of the chemical composition throughout the bulk of the metal bath. In other words, the data obtained (Table 2) suggest that the achieved prediction accuracy is on par with changes in the carbon content in the metal, potentially linked to the heterogeneity of the bath and, possibly, errors in determining the carbon content during measurements using sublance. The prediction accuracy of the proposed model for the final period, within the ranges of ±0.005 and ±0.010 % for the testing set, was reported as 70 and 94 %, respectively.

The authors in [22] demonstrated, for technology employing TSC probes, that a final period model based on a neural network allows achieving a prediction error for the carbon content in the metal within the ranges of ±0.005, ±0.010, ±0.015 and ±0.020 %, corresponding to 25, 54 71 and 91 % of cases. The analysis conducted indicates that these indicators outperform those for exponential, cubic models, and the carbon oxidation model based on an analysis of the chemical composition of exhaust gases.

However, it's worth noting that in this case, the average initial value of carbon content was 0.244 % which is significantly higher than that in the present study.

To optimize the obtained results, future research can explore options and assess the impact of updating the training set to adapt the model to changing conditions during the converter campaign.

Conclusions

The accurate prediction of carbon content in the metal is crucial for effective management during the final smelting period in a BOF. The findings of this study align with the results reported in works [21; 22], affirming the feasibility of employing a neural network for predicting the carbon content in the metal during the final blowing period in a BOF.

Table 2

Comparison of parameters of training, testing sets and heats without oxygen in the final period

Таблица 2. **Сравнение показателей плавок обучающей, тестирующей выборок и плавок без использования кислорода в заключительный период**

Set	Number of melts	*ME*, %	*MAE*, %	*RMSE*, %
Training set	700	$-1.36 \cdot 10^{-7}$	0.0044	0.0060
Testing set	232	$-1.09 \cdot 10^{-5}$	0.0043	0.0060
Without O_2	330	$2.53 \cdot 10^{-4}$	0.0040	0.0048

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E. V. Protopopov – technological description of the task, justification of the research direction, analysis of the results.
A. V. Zimin – statement of the research tasks, formulation of conclusions.
E. B. Turchaninov – statement of the research tasks, data analysis.

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Received 25.04.2023
Revised 11.09.2023
Accepted 25.09.2023

Поступила в редакцию 25.04.2023
После доработки 11.09.2023
Принята к публикации 25.09.2023