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PREDICTION THE END-POINT PHOSPHORUS CONTENT OF MOLTEN STEEL IN BOF WITH MACHINE LEARNING MODELS

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Abstract

The main task in the production of steel in the basic oxygen furnace (BOF) is dephosphorization Therefore, the prediction and control of the end-point phosphorus content of molten steel is of great significance. Four machine learning regression models (Lasso, Random Forest, Xgboost, and Neural Network) were established to predict the end-point phosphorus content of molten steel in the BOF based on raw and auxiliary material data, process parameters, and production quality data. The prediction effect of the four models was further compared, and their prediction results were interpreted based on the interpretability of the models and the permutation importance method. The results showed that compared with linear regression and neural network regression model, two types of ensemble tree model have higher prediction accuracy, better stability with small data sets, and lower data preprocessing requirements. The factors influencing the end-point phosphorus (P) content in BOF were ranked in order of importance as: Tapping temperature > Turning down times > Steel scrap quantity> Operation habits of different working groups > Amount of oxygen injection> Sulfur and phosphorus content of molten iron > Addition amount of lime, limestone, and lightly burnt dolomite in the slag > Slag-splashing amount.

Keywords: *Converter steelmaking; Machine learning; Ensemble tree model; Model interpretability; Influencing factor ranking; End-point prediction*

1. Introduction

Rising raw material costs and fierce market competition requires iron and steel enterprises to constantly exploit their potential, optimize the production process, and refine operations in order to achieve effective, cost efficient and environmentally friendly production [1]. The ultimate goal of BOF steelmaking, a significant step in the steelmaking process, is to obtain molten steel with qualified composition and temperature while dephosphorization, as the core task of in steelmaking, is crucial for greening and high efficiency. Common research methods tend to evaluate and analyze the manufacturing process by establishing dephosphorization models. Metallurgical practitioners have proposed various mechanism models and empirical formulas based on metallurgical principles and their own experiences [2-5]. However, these models and formulas can neither accurately predict the end-point phosphorus (P) content in BOF nor analyze the dephosphorization process in depth because most steps in BOF steelmaking are multi-dimensional, multi-variable, non-linear, uncertain, and coupled with various factors [6]. A new solution is in urgent need.

The development and application of machine learning has inspired metallurgical practitioners to apply new technologies in addressing related issues such as end-point P content prediction in the BOF process etc. Li et al. [7] established a model based on Levenberg-Marquardt algorithm of BP neural network to predict the end-point phosphorus (P) content in the BOF process, which increased the convergence rate of the model and avoided the local minimum problem. Wang et al. [8] hybridized weighted K-Means clustering algorithm and the GMDH (Group Method of Data Handling) polynomial neural network techniques, and built a prediction model of end-point P content in BOF that is more advantaged than the BP neural network. He et al. [9] adopted principal component analysis to reduce the dimension of factors influencing the prediction, thus proposing a prediction model for end-point P content in BOF based on PCA and BP Neural Network. Sala et al. [10] used Ridge Regression and

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two types of ensemble tree models to form two data-driven prediction models for end-point components and temperature in BOF, one of which contained time series data while the other did not. The results showed the model with time series data had higher prediction accuracy. Zhou et al. [11] set the steelmaking process and the end-point P content as the constraint condition for the BP neural network based on metallurgical rules, and established a prediction model for end-point P content in BOF based monotone-constrained back-propagation (BP) neural network. Li et al. [12] applied Least Squares Twin Support Vector Machines to classify the end-point phosphorus partition ratio in BOF steelmaking based on slag components and tapping temperature, which achieved relatively high prediction accuracy. Li et al. [13] selected 11 basic machine learning models and integrated them with averaging and stacking, which further improved the prediction effect on steel quality.

In addition to the prediction of the end point phosphorus content of the converter, many researchers have also proposed new methods for the determination of other end point components. Liu et al. [14] proposed a novel method based on accurate and fast multi flame features extraction and general regression neural network (GRNN). Wang et al. [15] fully combined the characteristics of genetic algorithm and BP neural network, and a combined GA-BP neural network model was established. Chang et al. [16] proposed a new multi-channel graph convolutional network to integrate these correlations with the process variables to build a more accurate prediction model. Gu et al. [17] proposed an improved CBR model using time-series data (CBR_TM) to predict the end-point carbon content and temperature in the converter according to the data types of process parameters. Song et al. [18] established an intelligent case-based hybrid converter model to predict the converter endpoint and process operations.

Existing research is more concerned with the predictive accuracy of models and has served its purpose from the perspective of data, features and algorithms, etc. However, neural network models have poor interpretability, which makes metallurgical practitioners unable to conclude metallurgical rules from these models or apply them in improving manufacturing process.

The upper limit of machine learning is determined by the data and their features, and can only be approached by models and algorithms. Different data processing strategies have different focuses and can deal with different issues. Researchers should pay more attention to the algorithm's interpretability and make purpose-oriented choice. This study established two types of ensemble tree models (Random Forest [RF] and Xgboost [XGB]), a neural network model [BPNN] and a linear regression model (Lasso) based on integrated and processed raw data from BOF steelmaking. Furthermore, the results of the four models were compared and interpreted from the perspective of metallurgy.

2. Models Adopted

2.1. Ensemble methods and ensemble tree regression models

Bagging randomly selected n sampling sets from the original data set by bootstrap sampling, based on which n weak learners can be trained. The final strong learner can be obtained through conducting ensemble strategy with weak learners. RF is a representative algorithm in bagging, and its random selection of features gives it better generalization ability [19]. Besides, RF can sort all features by their importance for the predicted target while maintaining interpretability.

Boosting, on the other hand, trains a weak learner 1 from the training set based on the original weights, and adjust weights of the samples according to the learning error rate of the weak learner 1 to obtain a weak learner 2. Repeat these processes untill the number of weak learners reaches n set in advance. The final strong learner is obtained by integrating these n weak learners via ensemble strategy. Unlike Adaboost, the Gradient Boosting Decision Tree (GBDT) adjusts the residual in each iteration to minimize sampling loss. Xgboost is an improved GBDT that uses a second-order Taylor expansion for better accuracy and excels in its higher operational efficiency, effective processing of missing values, and great generalization ability [20].

2.2. Neural network regression

The BP neural network (BPNN) is a type of multilayer feedforward neural network whose learning process is composed by signal forward-propagation and error back-propagation [21]. In neural network models with only one hidden layer, the BPNN mainly works in two stages: in the first stage, the sample's features are input from the input layer, and the signal is propagated forward through the hidden layer and reaches the output layer; in the second stage, the error between network's actual and expected value is propagated backward from the output layer to the hidden layer, then to the input layer. The weights of the neurons in all layers are adjusted based on the errors. The target can be achieved in weight adjustment of iterative calculation round by round.

2.3. Lasso regression

L1-regularized linear regression is usually called

Lasso regression. Compared to conventional linear regressions, Lasso regression adds a L1-regularized term to loss function. In the L1-regularized term, there is a constant coefficient α regulating the mean square error term and the weight of the regularized term in the loss function. The specific loss function of Lasso regression is as Eq. (1):

$$J(\theta)=\frac{1}{2}n(X\theta-Y)^{T}(X\theta-Y)+\alpha\|\theta\|_{1} \quad (1)$$

The number of samples is expressed as n, the constant coefficient as α, the L1 norm as $\|\theta\|_1$.

Lasso regression can minimize the coefficient for some features, even lowering some with a relatively small absolute value to 0. This would improve model's generalization capability [22]. As a linear regression model, Lasso can select different features to simplify the influencing factors and improve model's interpretability, which is of great benefit to the understanding of the steelmaking process in metallurgical practice.

3. Model establishment

3.1. Feature selection and data processing

The data in this paper are derived from the production data of a company's BOF plants. The steelmaking process in BOF is shown in Figure 1. Figure 1a is the slag-splashing furnace protection of BOF. Slag-splashing operation is mainly concerned with the slag-splashing timing and the amount of nitrogen injected. These two factors indirectly reflect the internal outline of the BOF and the physical and chemical properties of slag in the initial phase, which is related to dephosphorization. Figure 1b refers to the loading stage in steelmaking. The change of scrap ratio affects bath temperature, slagging rate, slag components, and slag-splashing effect etc. at the same time, influencing dephosphorization directly or indirectly; besides, the components, temperature, and adding amount of molten iron are initial conditions that directly influences dephosphorization process. Figure 1c represents the blowing stage, the most

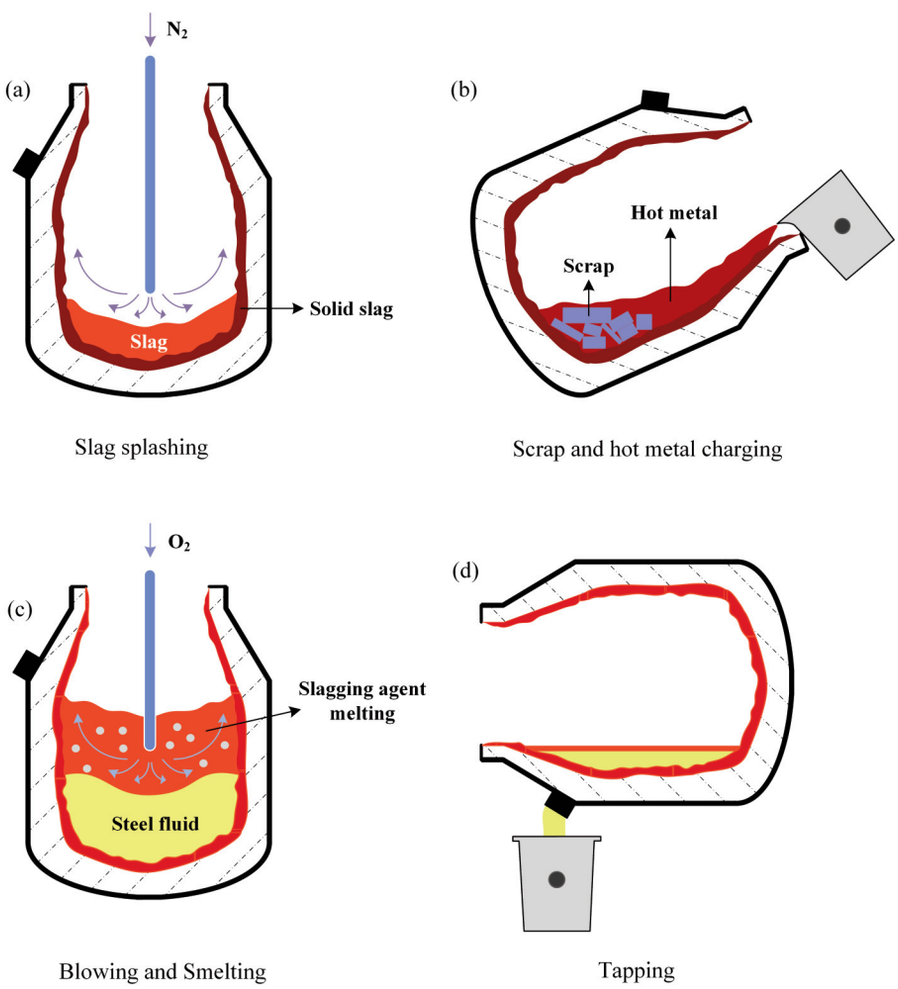

Figure 1. *Flow chart of steelmaking process in BOF.* ***a*** *Slag splashing;* ***b*** *Scrap and hot metal charging;* ***c*** *Blowing and smelting;* ***d*** *Tapping*

important stage of dephosphorization in steelmaking. The process is mainly affected by oxygen blowing operation and drossing process, in which the former one determines the dynamic condition while the latter one determines the thermodynamic condition by slag's physical and chemical properties. These two factors interact and couple with each other. In addition, turning down times indicates the effects of single/double slag operation and reblowing/un-reblowing on dephosphorization. The employees of the different groups have different operating habits and experiences, especially in adjusting the height of oxygen lance and the adding moment of various slagging agents. At the data level, such differences lead to fluctuation in the distribution of the same factor in the different groups.

Based on these facts, this work has considered all the features in the production data of BOF that can influence target prediction, mainly the addition of raw and auxiliary materials, the molten iron condition, and the operating coefficients in the manufacturing process etc. The details are as follows: Working group, carbon content in molten iron, silicon content in molten iron, manganese content in molten iron, phosphorus content in molten iron, sulfur content in molten iron, temperature of molten iron, quality of molten iron, quality of steel scrap, steel output, oxygen blowing time, oxygen blowing amount, turning down times, lime, limestone, raw dolomite, iron ore, light-burned dolomite, temperature of the first turning-down, reblowing time, tapping temperature, nitrogen blowing amount, slag-splashing time, iron mixing times. With the exception of the working groups, which belong to character data, all other process data are numerical data. Within these numerical data, 'pouring furnace' and 'iron mixing times' are integers (discrete ones) greater than 0, while the other data are continuous values. All process data do not include unstructured data such as time series data or image data. Brief notes on all features are listed in Table 1.

Extreme outliers were manually removed from the original data based on the feature distribution map and manufacturing experience, while other outliers were removed according to the 3σ principle. Missing values mainly include unrecorded data and null data. Unrecorded data, such as the temperature of molten iron and the steel scrap amount, were filled with the average value. Null data, such as raw dolomite and addition of limestone, were filled by 0; or by the default value, which was 1, such as turning down times and iron mixing times. Work groups A, B, and C were dumb-coded and expressed as [(1,0,0), (0,1,0), (0,0,1)], respectively. Eq. (2) was adopted for z-score standardization of data features.

$$y_i = \frac{x_i - \bar{x}}{s} \tag{2}$$

Figure 2 shows the correlation efficient between each feature. The correlation between each variable, and between the variables and their predicted targets, was analyzed by heat map. The results can serve as a reference for engineers and technicians in process optimization.

3.2. Model training

All model hyperparameters were determined using a grid search and cross-validation.

The main hyperparameters of RF are "n_estimators", "min_samples_split", "min_samples_leaf", "max_depth", "max_features".

Table 1. *List of influencing factors and their brief notes*

Influencing factors	Brief notes	Influencing factors	Brief notes
Work group A	F1	Oxygen blowing amount	F14
Work group B	F2	Turning down times	F15
Work group C	F3	Lime	F16
Carbon content in molten iron	F4	Limestone	F17
Silicon content in molten iron	F5	Raw dolomite	F18
Manganese content in molten iron	F6	Iron ore	F19
Phosphorus content in molten iron	F7	Light-burned dolomite	F20
Sulfur content of molten iron	F8	Temperature of the first turning-down	F21
Temperature of molten iron	F9	Reblowing amount	F22
Molten iron amount	F10	Tapping temperature	F23
Steel scrap amount	F11	Nitrogen blowing amount	F24
Steel output	F12	Slag splashing time	F25
Oxygen blowing time	F13	Iron mixing times	F26

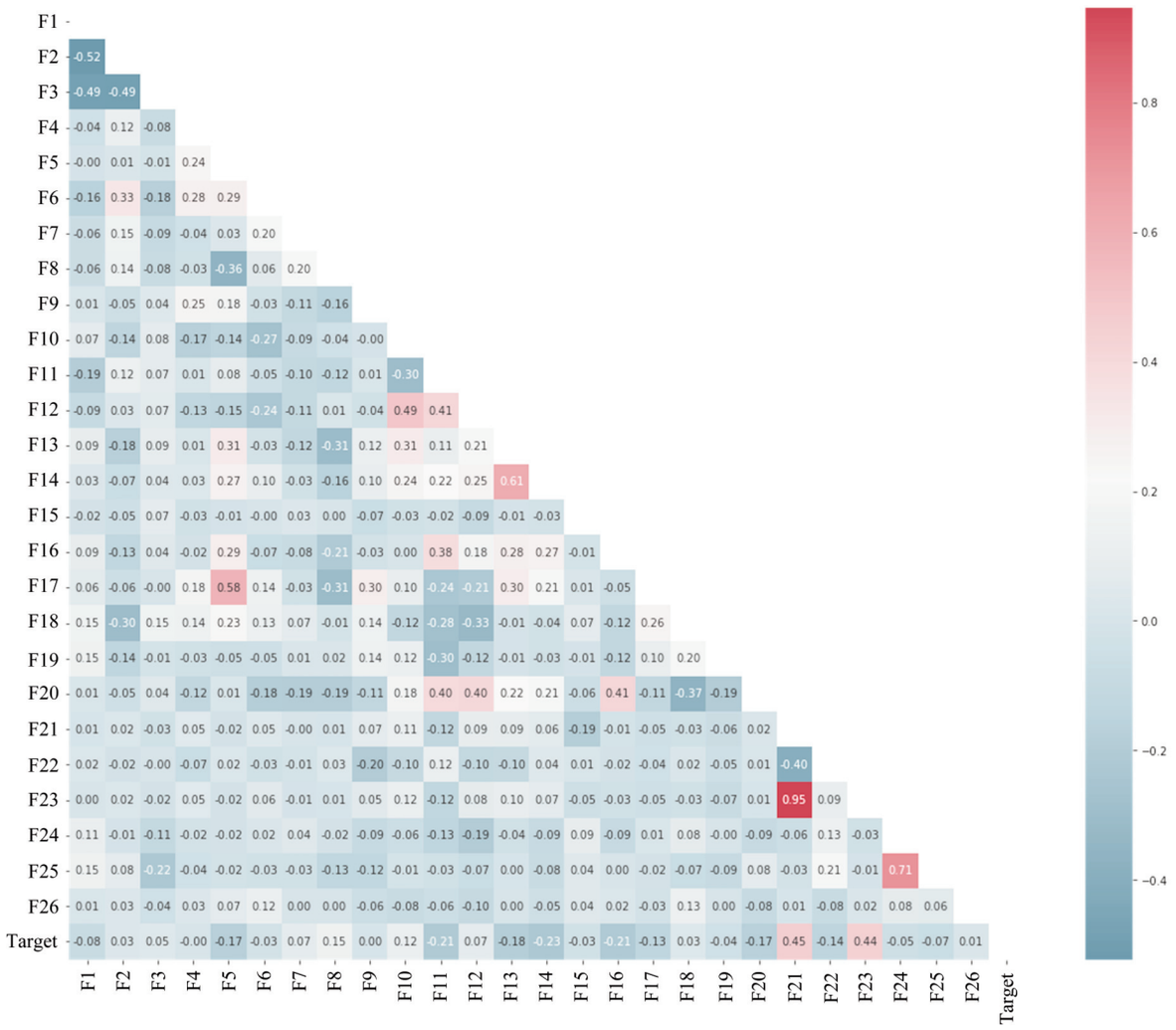

Figure 2. *Correlation efficient among feature variables*

"n_estimators" represents the number of trees in the forest. If it is too small, the model would easily not fit correctly. When the number of trees exceeds a certain level, the improvement would be limited. In this paper, the number varied between 20 and 300, with a step size of 10. "min_samples_split" represents the minimum number of samples required to split an internal node. It was set between 2 and 32 with a step size of 2. "min_samples_leaf" restricts the minimum number of samples for a leaf node. It was set between 1 and 16 with a step size of 1. "max_depth" were not limited to pursue a smaller training error. These three parameters were used to avoid overfitting to improve the generalization of the model. "max_features" can be set to "auto". Only when the number of features is large should we consider limiting the maximum number to control the generation time of the decision tree. All other hyperparameters were set to default values.

The following hyperparameters are optimal for the RF regression model. The number n of weak learners was set to 250. Minimum samples split was set to 2, and minimum samples leaf nodes to 8.

For XGBoost, the main hyperparameters that had to be adjusted were "n_estimators", "max_depth", "min_child_weight", "gamma", and "learning_rate". the other framework parameters, booster and objective, were just set as default parameters in the regression task. The "learning_rate" shrinks the feature weights to make the boosting process more conservative after each boosting step. A smaller "learning_rate" means more iterations of the weak learners to reach the model's optimal results, but it would take more time. In this paper, we fix a learning rate first, and adjust "n_estimators". The "learning_rate" was set at 0.01~0.3. "n_estimators" represents the number of trees, and the model would be too complex when it is too large. It was set between 10 and 200 with a step size of 10. "max_depth" controls maximum depth of a tree. Increasing this

value makes the model more complex and more likely to overfit. It was set between 2 and 20 with a step size of 2. “min_child_weight” represents minimum sum of instance weight (hessian) needed in a child. The larger it is, the more conservative the algorithm will be. “gamma” is an important hyperparameter used by XGB to prevent overfitting, and it represents the minimum loss reduction required to make further partition on a leaf node of the tree. The larger “gamma” is, the more conservative the algorithm will be. The parameter was gradually increased from 0 to 1. The above hyperparameters are the main objects of adjustment. Only when the model remains overfitting after their adjustment, other hyperparameters are considered.

The following hyperparameters are optimal for the XGB regression model. The subtree number was set to 120, weight reduction factor for each weak learner to 0.08, max depth of tree structure to 6, minimum child weight to 90, and gamma to 0.

The BP neural network was structured as a hidden layer with 15 neurons. Experimentally, more complex structure tends to lead to model overfitting. The activation function was the ReLU function because it is faster to train, avoids the problem of vanishing gradients and is suitable for most neural networks, especially MLP and CNN. “max_iter” is the maximum number of iterations. It was set between 10~1000. The solver was “lbfgs”. However, for small datasets, “lbfgs” can converge faster and perform better. If the solver is “lbfgs”, the regressor would not use minibatch and “learning_rate”. “Alpha” stands for the strength of the L2 regularization term. It prevents the neural network from overfitting and was set between 0.00001~0.1, and the search followed the logarithmic scale. The final L2 regularization term α=0.01.

The Lasso regression model only needs to be optimized for the hyperparameter “alpha”. This is a constant that multiplies the L1 term, controlling the regularization strength. It ranged from 0.00001 to 10, and the final L1-regularized term α=0.00005.

All four models suit regression issues with multiple features, and their effects were all evaluated by Eq. (3), the mean absolute error (MAE), and Eq. (4), the mean squared error (MSE).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|predicted_i - actual_i\right| \quad (3)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(predicted_i - actual_i\right)^2 \quad (4)$$

4. Comparison of model’s prediction results

Figure 3 compares the evaluation indexes MAE and MSE of four models. Two indexes were obtained through simple cross validation. Simple cross-validation here refers to cross-validation performed only once in data split. Figure 3 shows that MAE and MSE of two ensemble learning models were smaller than those of Lasso and BPNN models. More specifically, Lasso surpassed BPNN while RF was slightly ahead of XGB. This is because ensemble models are based on cart decision tree compared to linear regression models, which gives them a higher accuracy in regression. Besides, the multi-model ensemble methods, bagging and boosting, were adopted by two ensemble models, which improved their fitting accuracy and generalization capability at the same time and guaranteed better performance than the single-models BPNN and Lasso. The Lasso model outperformed the BPNN since it can reduce the number features and avoid the problem of overfitting in linear regression by adding the L2-regularized term. Compared with the other three models, BPNN’s performance may be limited by restricted sample amount, which lowered its fitting accuracy.

It should be noted that the actual end-point P content is 0.030 % on average, and the minimum absolute error of the prediction is 0.0046 %, which is 15.3 % off the average. In the actual production process, the P content is measured by direct reading spectrometer, which also causes certain errors in the sampling and location of the measurement points. From the stand of converter steelmaking’s requirements, such an error is acceptable.

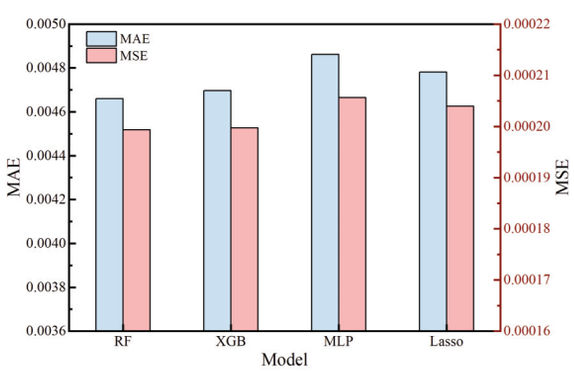

Figure 3. *Evaluation indexes for four models*

Figure 4 shows the learning curves of four models evaluated by index MAE (score). Cross-validation score comparison results of the four learning curves in Figure 4 were in line with their performance in Figure 3, yet they all had lower error than in Figure 3 that adopted single cross validation. This is because the learning curves were drawn with cross-validation conducted via the ShuffleSplit function (n_splits=100, test size=0.2). This means that the score of each point was calculated as the average error of 100 random samplings, thus lowering error fluctuation. By Combining results from Figure 3 and Figure 4, the accuracy of different models was ranked as RF > XGB > Lasso > BPNN.

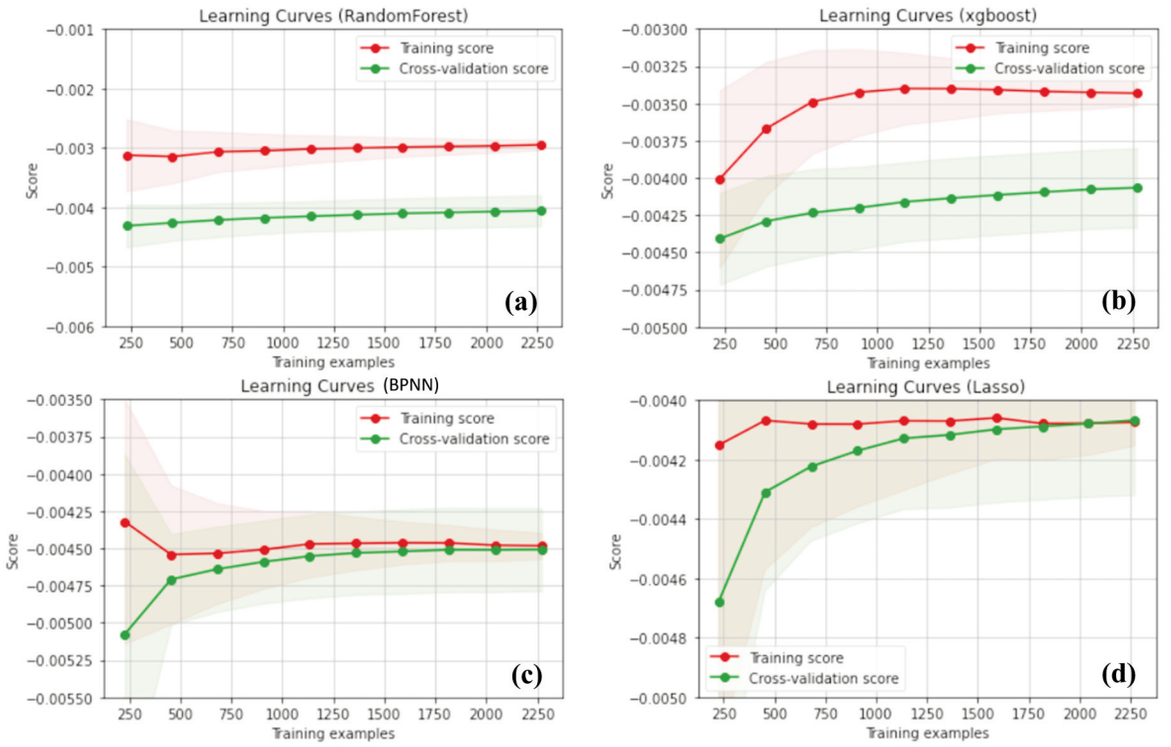

Figure 4. *Model learning curves with multi-sampling*

Figure 5 shows the learning curves with a single sampling. This means that all scores were obtained by a single sampling, i.e. the split n was set to 1 in the ShuffleSplit function. Figure 5a and Figure 5b show that the learning curves of the ensemble tree models tend to smooth out rapidly, reflecting RF and XGB's stability in processing this problem type. Their performance remained good even with a small data set. Figure 5c and Figure 5d indicate that BPNN and Lasso require at least 1,500 data items. Lasso showed poor stability with relatively small datasets and the BPNN's learning curve gradually converges when the data reaches 1,600 items. All this suggests that BPNN and Lasso have higher requirements for the amount of data and have a larger error with small data set. RF and XGB, on the other hand, do not require normalization or standardization of the original data. The XGB algorithm can even deal with missing values by itself, making its application easier. Considering the above results, two types of ensemble tree models had better stability in small data set and lower requirements on data processing than BPNN and linear regression models.

5. Model interpretation and analysis

Metallurgical practitioners mostly optimize the manufacturing process by selecting influencing factors and controlling variables based on their own experience, which requires a lot of time and effort. However, with machine learning, technicians can perform optimization by integrating the evaluation results into multi-models, selecting influencing factors and determining their priorities.

Figure 6 compares the importance of all influencing factors. RF and XGB measured their importance (parameter as gain) via the extent of gain brought by splitting the different features based on the decision tree. A larger gain reflects a greater importance. BPNN measures importance by the permutation importance, which means to observe the change of index after permuting one certain feature. A greater change in the index refers to higher importance [23]. For better comparison, importance calculation results of RF, XGB, and BPNN model were unified into percentage and drawn as a histogram.

On the one hand, the three models have different mathematical theories and bases for calculating importance. On the other hand, each model evaluates via relatively single index that differs from the others. This led to different importance sorting of all features, and the results of one model cannot represent the actual situation in manufacturing practice. Therefore, the average value of RF, XGB, and MLP was taken as a comprehensive and final evaluation of the feature's importance. The coefficient of linear regression was adopted to assess whether the feature's influence was positive or negative. It should be mentioned that a positive influence here means a higher coefficient

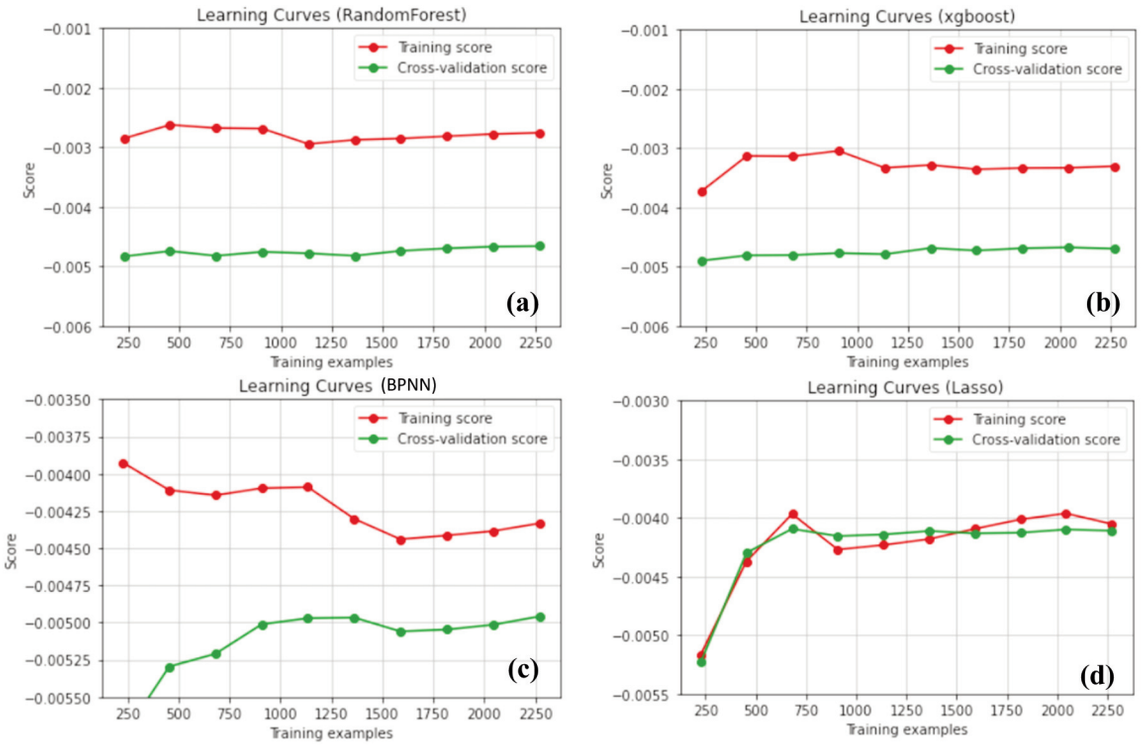

Figure 5. *Learning curves with single-sampling*

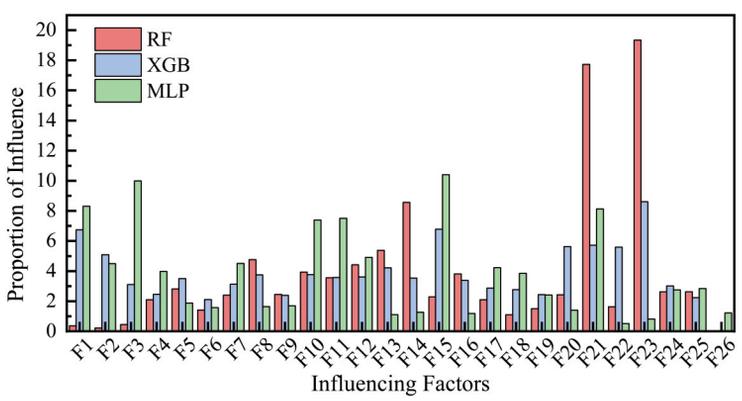

Figure 6. *Comparison of different influencing factor's importance*

value relating to a higher end-point P content, but it is actually a negative influence in metallurgical practice. Figure 7 shows comprehensive importance evaluation results. The comprehensive evaluation score was shown in the left vertical coordinate, and the coefficient of the linear regression model was drawn in point and line chart the values of which can be checked by the right vertical coordinate.

All influencing factors were divided into 11 groups based on the BOF operations. As shown in Figure 7, the importance of all groups were ranked as follows: Tapping temperature in BOF (F21, F23) > Turning down times (F15) > Material addition and Steel output (F10, F11, F12) > Work groups (F1, F2, F3) > Oxygen blowing operation (F13, F14) > Molten iron components (F4~F8) > Slagging agents (F16~F20) > Slag-splashing operation (F24, F25) > Reblowing amount (F22) > Molten iron temperature (F9) > Iron mixing times (F26).

Based on the sorting of operation processes and the coefficient of the linear regression model shown in Figure 7, it can be concluded that the first group, including F21 (First turning down temperature) and F23 (Tapping temperature), contains the most significant influencing factors. These two temperatures differ when the composition and temperature of the molten steel are not qualified. For the qualified ones, first turning down temperature is the tapping temperature. For that are not qualified , another operation is conducted for adjustment, and the

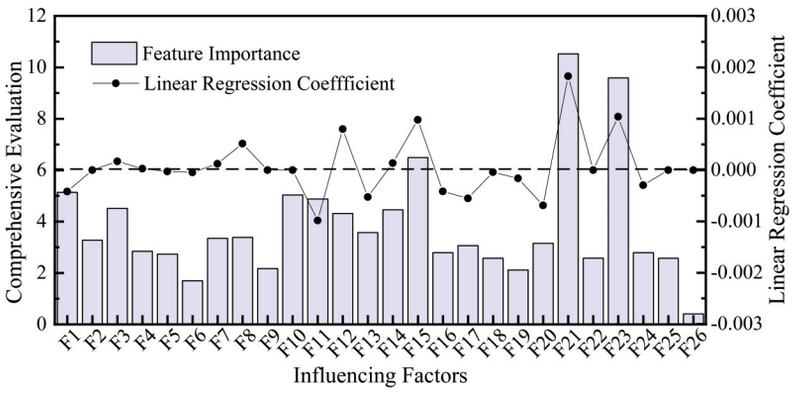

Figure 7. *Comprehensive evaluation on feature's importance*

temperature detected then is the tapping temperature. Temperature plays an important role in dephosphorization. The higher the temperature, the worse the dephosphorization [24]. The coefficient of both F21 (first turning down temperature) and F23 (tapping temperature) in the linear regression model were the maximum positive values, suggesting higher tapping temperature is related to larger end-point P content, which is in line with manufacturing experience and dephosphorization mechanism. F15 (turning down times) of the second group also had relatively greater importance. F15 larger than 1 indicated the possibility of reblowing or second slag formation blowing (double-slag process). Turning down times was positively related to end-point P content. Combining Figure 2's correlation analysis, turning down times was most strongly correlated with work group 3, which suggested their poorer stability than other work groups. In the third group, F10 (molten iron amount), F11 (steel scrap amount), and F12 (steel output), linear regression coefficient indicated the addition of steel scrap amount was negatively related to end-point P content while steel output is in positive relation. Since the Lasso model can reduce variables, it lowered the molten iron amount's coefficient to 0 (molten iron amount and steel output have collinear relation), which means that employees only need to optimize steel scrap amount. The fourth group, work group also played a certain role. To the end-point P content, the influence of work group A was negative, of group B insignificant, of group C positive. This indicates that work group C should learn more experience from group A. As for the fifth group, oxygen blowing operation, containing F13 (oxygen blowing time) and F14 (oxygen blowing amount), influenced the predicted object to a certain extent. Longer F13 was related to a higher oxidation in molten pool, and thus lower end-point P content. F14 is in positive influence for end-point P content, which could be due to the fact that a too high F14 value leads to more rapid temperature rising in molten pool, inhibiting dephosphorization or even triggers rephosphorization [25]. This indicated that personnel should pay more attention to the controlling of oxygen blowing amount. The sixth group included the molten iron components F4~F9. In the molten iron, S and P had a positive effect on end-point P content while others did not have a significant influence, suggesting that technicians can improve the dephosphorization effect by controlling the molten iron components. The seventh group discussed the influence of slagging agent addition, among which the most significant ones were lime, limestone, and light-burned dolomite. All these were negatively related to end-point P content. For the eight group, including F24 (nitrogen blowing amount) and F25 (slag splashing time), it was shown that higher F25 can raise the oxidation of molten pool in the primary stage, and assist dephosphorization in the early stage. Both the importance score and the linear regression model coefficient showed that F9 (molten iron temperature), F22 (reblowing amount), and F26 (iron mixing times) contained in last three groups had relatively small influence on the end-point P content.

However, in the Lasso model the features of coefficients close to 0 can occur in two cases. One is caused by the existence of L1 regular term. This can be solved by reducing the hyperparameter "Alpha". When the coefficient deviates from 0, we can clarify the extent and direction of the influence, but the model's generalization capability may also be impaired at this time. Another situation is that the feature itself has little influence on end-point P in the linear regression model. However, this only means that this feature is unimportant just in Lasso model. The assesment of their influencing extent must be coupled with the importance ranking given by the other three algorithms.

In conclusion, removing factors with relatively small influence and those that cannot be improved in each group, the following factors must be classified as important: Tapping temperature in BOF > Turning down times > Steel scrap amount > Group's operation habit > Oxygen blowing amount > S and P content in molten iron > addition of lime, limestone, lightly-burnt dolomite in slagging agents > Slag splashing

amount. Of all these factors, the first 6 had a positive influence while the lasttwo had a negative one.

6. Conclusions

1. The influencing factors of end-point P content mainly include raw and auxiliary material addition, the condition of the molten iron, the coefficients of the process operation, and the working habits of the employees. Four machine learning models were established to predict the end-point P content in BOF. The accuracy of the four models was ranked as follows: RF > XGB > Lasso > BPNN. Compared with the BPNN and the linear regression model (Lasso), two types of ensemble tree models showed lower error and better stability with small data sets, and lower data processing requirements.

2. Through a comprehensive consideration of the evaluation results of RF, XGB, BNPP, and the Lasso model, the influencing factors of end-point P content in the BOF were ranked by importance: Tapping temperature in BOF > Turning down times > Steel scrap amount > Work group's operation habits > Oxygen blowing amount > S and P content in molten iron > addition of lime, limestone, lightly-burntdolomite in slagging agents > Slag splashing amount. Among all these, the first six were of positive influence while the last two were of negative influence. The optimization of manufacturing process can be guided by interpreting prediction results of these models.

3. The production of BOF steel is a complicated process. There are still a number of key data that cannot be directly included into regression calculation, such as the voiceprint data in sonar slag-reducing technique, the mouth flame image data of the converter, and time series data such as the oxygen lance position, the lime loading model, the bottom blown pattern, and the change of gas composition etc. These data contain important information about changes in the overall metallurgical process. An effective processing or conversion method for them is in urgent need. Including these key data in the regression analysis can help engineers and technicians to better understand and analyze the steelmaking process.

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Author's contributions

Yi Kang: Conceptualization, Methodology, Programming, Validation, Formal analysis. Meng-meng Ren: Investigation, Writing - review & editing. Junxue Zhao: Supervision, Funding acquisition. Li-bin Yang: Resources, Investigation. Zhen-kai Zhang: Investigation, Formal analysis. Ze Wang: Investigation, Writing - review & editing. Geng Cao: Data preprocessing, Software.

Data Availability Statement

Research data are not shared.

Conflict of Interest

The authors declare no conflict of interest.

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PREDVIĐANJE KONAČNOG SADRŽAJA FOSFORA U RASTOPU ČELIKA U BAZNOM KISEONIČNOM KONVERTORU MODELIMA MAŠINSKOG UČENJA

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Apstrakt

Glavni zadatak u proizvodnji čelika u baznom kiseoničkom konvertoru (BOF) je defosforizacija. Zbog toga je predviđanje i kontrola konačnog sadržaja fosfora u rastopu čelika od velike važnosti. Četiri modela regresije mašinskog učenja (Lasso, Random Forest, Ksgboost i Neural Netvork) su primenjena za predviđanje krajnjeg sadržaja fosfora u tečnom čeliku u BOF-u na osnovu podataka o sirovim i pomoćnim materijalima, parametrima procesa i podacima o kvalitetu proizvodnje. Upoređen je efekat predviđanja četiri modela i rezultati predviđanja su interpretirani na osnovu interpretabilnosti modela i metode važnosti permutacije. Rezultati su pokazali da u poređenju sa linearnom regresijom i modelom regresije neuronske mreže, dva tipa modela ansambla stabla imaju veću tačnost predviđanja, bolju stabilnost sa malim skupovima podataka i niže zahteve za prethodnu obradu podataka. Faktori koji utiču na krajnji sadržaj fosfora (P) u BOF-u rangirani su po važnosti: Temperatura izlivanja > Vreme gašenja > Količina čeličnog otpada > Radne navike različitih radnih grupa > Količina injektiranog kiseonika > Sadržaj sumpora i fosfora u rastopljenom gvožđu > Dodatak količina kreča, krečnjaka i lagano sagorelog dolomita u sredstvima za šljaku > količina prskanja šljake.

Ključne reči: *Konverterska proizvodnja čelika; Mašinsko učenje; Model ansambla stabla; Interpretabilnost modela; Rangiranje faktora uticaja; Predviđanje krajnjeg sadržaja*