A Multiobjective Evolutionary Feature Selection Framework for End-Point Molten Steel Temperature Prediction in Ladle Furnace Refining

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***Abstract*—Accurate prediction of the end-point temperature of molten steel in the ladle furnace (LF) is crucial for ensuring product quality and stable production, yet the complex high-temperature physical and chemical reactions lead to high-dimensional, strongly nonlinear, and highly coupled variables that make data-driven modeling challenging. In this paper, a multiobjective evolutionary feature selection (MOFS) framework is proposed for end-point molten steel temperature prediction in LF refining, which uses a unified multiobjective evolutionary optimization framework to jointly optimize feature selection and model hyperparameters, balancing prediction accuracy, feature subset size, and model complexity. Experiments on an industrial dataset demonstrate superior performance with fewer features and lower complexity, confirming its effectiveness for practical applications.**

Keywords—multiobjective optimization, feature selection, tabular data, LF refining, temperature prediction.

I. INTRODUCTION

Ladle furnace (LF) refining is an important procedure in secondary steelmaking, not only adjusting the temperature and chemical composition of molten steel but also regulating the production schedule of downstream continuous casting. The LF refining process includes multiple operation steps and involves complex physical and chemical reactions. [1]-[3]. Fig. 1 illustrates the workflow of the LF. Once the ladle arrives, slag making materials and deoxidizers are added, while power supply operations provide heat to adjust temperature. Alloying additions are added in several steps to meet the target.

Among various qualities, the end-point temperature of molten steel in LF refining is a key quality indicator, as it directly determines the downstream process. Inaccurate temperature control may lead to casting interruptions, excessive reheating, or increased production costs. Therefore, accurate prediction of molten steel temperature in LF refining is of great significance for improving product quality and operation efficiency in the entire steelmaking process.

Traditionally, temperature control in LF refining mainly relies on manual experience and direct temperature measurements during the refining process. Although these

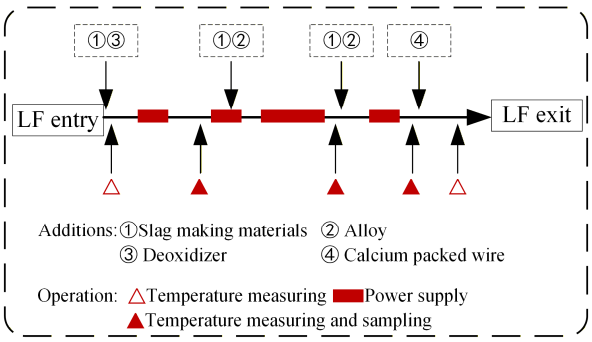

Fig. 1 Schematic workflow of the LF operation.

methods are widely used in industrial practice, they often cause instability and increase costs. As a result, it is difficult to achieve stable and efficient temperature control in LF refining using traditional experience- or measurement-based methods alone. With the increasing availability of industrial process data, data-driven approaches have been widely introduced to improve the accuracy of molten steel temperature prediction [4]-[6]. Srinivas et al. employed a genetic algorithm to estimate the parameters of a dynamic model for predicting molten steel temperature in the LF [7]. Xin et al. applied deep neural networks (DNN) to LF temperature prediction [8]. Some existing studies combine optimization algorithms with machine learning and deep learning models for more accurate predictions [2], [9].

However, the LF refining process involves a large number of variables with complex correlations and feature redundancy. Directly building prediction models using all available features not only increases model complexity but also raises the risk of overfitting. Therefore, feature selection (FS) is essential to identify useful variables, reduce the dimensionality of data, improve computational efficiency [10]-[11]. Moreover, different feature subsets usually exhibit different data distributions, which require adaptive adjustment of model hyperparameters to ensure predictive performance.

To address the above challenges, this paper proposes a multiobjective evolutionary feature selection framework for end-point molten steel temperature prediction in LF

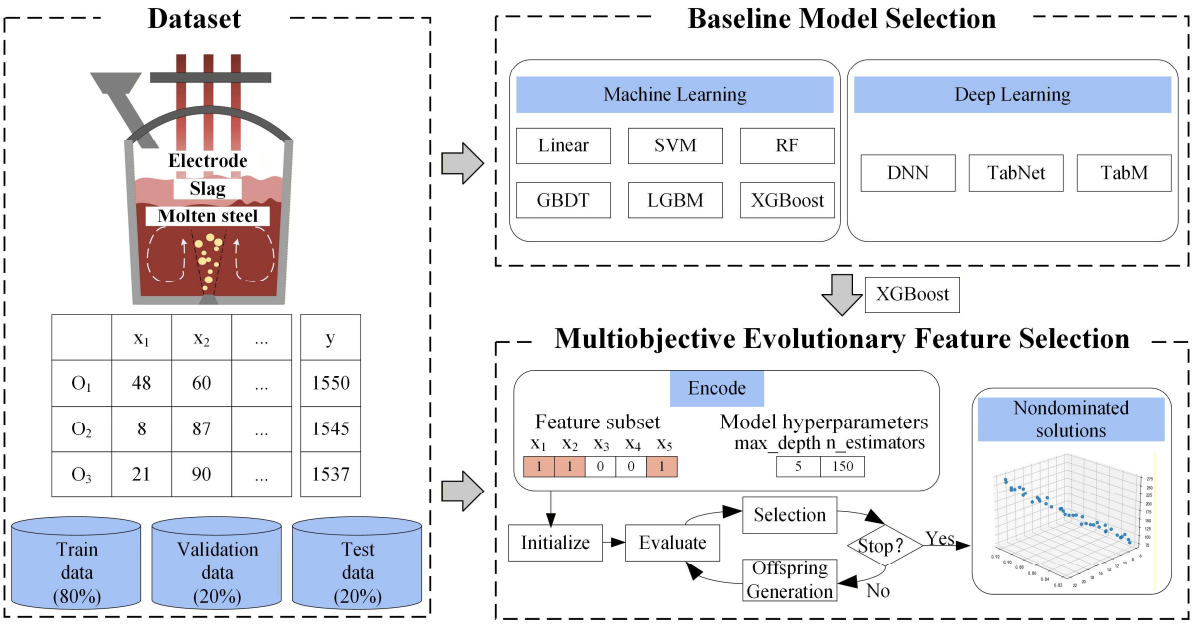

Fig. 2 Overall framework of the proposed method.

refining, jointly considering prediction accuracy, feature subset size, and model complexity. By jointly optimizing feature selection and model configuration, the proposed method explores the trade-off between prediction accuracy and model complexity, and the main contributions of this work can be summarized as follows:

- A multiobjective evolutionary feature selection framework is proposed, which integrates feature selection and model hyperparameter optimization into a unified optimization process.
- A three-objective optimization formulation is constructed to balance prediction accuracy, feature subset size, and model complexity.
- Extensive experiments on real industrial LF refining data are conducted. The comparison with traditional prediction models and feature selection methods shows that this framework has advantages in achieving high prediction accuracy with fewer input features and lower model complexity.

II. Related Work

A. Tabular Data Learning

Tabular data is one of the most widely used data formats in real-world, owing to its structured representation with rows as instances and columns as attributes [12]. Such data are widely observed in industrial applications, including intelligent manufacturing [13] and quality prediction [14]-[17].

Varying feature importance, missing values, outliers, and data quality constraints, which typically require domain knowledge of the features to handle. These factors increase the difficulty of learning on tabular data. A supervised tabular dataset consists of N samples and e features, organized as rows and columns in a table. Each sample $O_i \in \mathbb{R}^e$ is represented by an e-dimensional feature vector, where features may be numerical or categorical. Each sample is associated with a target value y_i, which can be discrete for classification tasks or continuous for regression tasks.

Although deep neural networks (DNNs) have demonstrated remarkable success in domains such as computer vision and natural language processing by learning hierarchical representations directly from raw data, their early applications to tabular data were often limited and struggled to outperform tree-based approaches [18]-[20]. The performance of tabular learning models is highly dependent on dataset characteristics, such as variables distributions, noise levels, data scale, and relationships among variables [21].

B. Multiobjective Feature Selection

In practice, capturing nonlinear relationships among variables often requires considerable manual experience and domain knowledge, directly affecting prediction accuracy and model robustness [22]. As a result, manually selected features are often suboptimal for complex industrial prediction tasks. This limitation has motivated increasing interest in adaptive feature selection and optimization strategies that can automatically identify optimal feature subsets while balancing multiple competing objectives, such as predictive accuracy, feature sparsity, and model complexity.

In general, feature selection (FS) usually requires considering several objectives at the same time. Rather than optimizing a single performance metric, industrial applications typically involves other objectives, including reducing feature dimensionality to improve interpretability and generalization, and controlling model complexity or computational cost to satisfy real-time or resource-limited deployment requirements. So the multiobjective feature selection (MOFS) can be generally formulated as a vector optimization problem:

$$\min_{Z\in\{0,1\}^e} F(z) = \left(f_1(z), f_2(z), ..., f_q(z)\right) \quad (1)$$

where z denotes a binary feature selection vector, $f_q(z)$ represents the objective functions associated with feature selection. To address such conflicting objectives, various MOFS approaches have been proposed [23]. For example,

Jiao *et al.* guided the evolutionary search of MOFS by exploiting promising feature subsets obtained from single-objective FS tasks through different direction vectors [24]. Chen *et al.* enhanced PSO-based feature selection by incorporating correlation-guided updating and surrogate-assisted strategies [25].

III. Proposed Method

A. Overall Framework

The overall framework of the proposed method is illustrated in Fig. 2, aiming to construct an accurate and efficient molten steel temperature prediction model for LF refining by jointly considering feature selection and model complexity control. Industrial LF refining data are collected and preprocessed, divided into training set, validation set, and test set, and a comprehensive baseline comparison is conducted, where XGBoost is selected as the base model due to its superior accuracy and robustness. Feature selection and XGBoost hyperparameter optimization are formulated as a multiobjective evolutionary optimization problem and solved using the NSGA-III algorithm, where the training set is used to fit the model and the validation set evaluates predictive performance, feature subset size, and model complexity to guide the search; the Pareto front is constructed on the validation set, and non-dominated solutions are evaluated on the test set to report final performance.

B. Baseline Model Selection

Before conducting multiobjective optimization, an appropriate baseline prediction model is first determined. Considering the complex nonlinearity and strong feature interactions in the LF refining process, multiple representative machine learning and deep learning models are evaluated as candidate predictors. The candidate models include linear regression, kernel-based methods, ensemble learning models, and neural network–based approaches. All models are trained under identical data preprocessing and evaluation settings to ensure fair comparison. Through systematic benchmarking, XGBoost demonstrates consistently superior predictive performance and robustness on the LF refining dataset. Moreover, XGBoost provides flexible model complexity control through tree-based structures and hyperparameters, making it particularly suitable for joint optimization with feature selection in a multiobjective evolutionary framework.

C. Multiobjective Evolutionary Feature Selection

After determining XGBoost as the baseline predictor, feature selection is formulated as a multiobjective evolutionary optimization problem. The objective is to identify informative feature subsets while maintaining high prediction accuracy and controlling model complexity. In the proposed framework, each individual is encoded as a hybrid chromosome that jointly represents feature selection decisions and XGBoost hyperparameters. As shown in Fig. 3, each chromosome is composed of two segments. The first segment is a binary vector of length e, where each bit denotes whether a feature is selected. The second segment encodes the XGBoost hyperparameters, including the number of estimators, the maximum tree depth, and the learning rate, using integer and continuous genes.

Algorithm 1 Pseudo-code of MOFS

Input: The dataset X, the population size P, the maximum iterations G, the feature dimension e and the search region of hyperparameters Ω_θ.
Output: Pareto-optimal feature subsets and hyperparameter configurations.

Initialize a population P^0, where each individual $\mathrm{I} = \{z, \theta\}$ consists of a binary feature selection vector $z \in \{0,1\}^e$ and a hyperparameter vector $\theta \in \Omega_\theta$
for $g = 1, 2, ..., G$ **do**
  for $p = 1, 2, ..., P$ **do**
    Select features according to z.
    Train prediction model using hyperparameter θ.
    Evaluate the multiobjective fitness values $F(z, \theta)$.
  end for
  Generate a new offspring population.
  Next parent population through elitism.
end for
Select the optimal solution from the Pareto front.
Return the selected feature subset and hyperparameter configuration.

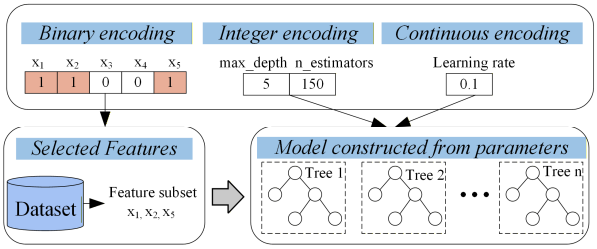

Fig. 3. Hybrid individual encoding strategy

Three conflicting objectives are simultaneously optimized: maximizing prediction accuracy, minimizing the number of selected features, and reducing model complexity. The objective functions used in the proposed optimization framework are illustrated as follows:

$$\min F(s) = \left(f_1(s), f_2(s), f_3(s)\right) \tag{2}$$

$$f_1(s) = -R^2(s) \tag{3}$$

$$f_2(s) = \sum_{j=1}^{e} m_j \tag{4}$$

$$f_3(s) = d \times n \tag{5}$$

where s denotes an individual encoding both the feature subset and the model hyperparameters. m_j denotes if the j-th feature is selected. f_1 represents the negative coefficient of determination R^2 on the validation set. f_2 denotes the number of selected features, encouraging sparse and interpretable models. And f_3 is defined as the product of the maximum tree depth and the number of trees in XGBoost. The maximum tree depth and the number of trees are two of the most important factors determining the complexity of tree-based models. Their product provides a simple yet effective proxy for model complexity.

To effectively handle the multiobjective optimization problem, the NSGA-III algorithm is employed as the evolutionary search strategy, as it is well suited for problems with multiple conflicting objectives and can maintain

population diversity through a reference point–based selection mechanism. NSGA-III evolves the population toward a set of non-dominated solutions that capture various trade-offs among accuracy, input dimensionality, and model complexity. These solutions provide flexible configurations that can be selected according to practical requirements in LF refining applications.

IV. EXPERIMENTS

A. Dataset Description

The dataset used in this study was collected from an industrial ladle furnace (LF) refining process in a steel plant located in China. The input variables consist of 25 process-related features. The output variable is the final molten steel temperature measured at the end of the LF refining stage. A total of 13,130 samples were collected after data cleaning and preprocessing, which were randomly divided into training, validation, and test sets in a ratio of 6:2:2. For the baseline model selection, training is performed on the training set, while performance is evaluated on the test set. During the multiobjective optimization process, the validation set is employed to compute the R^2 score as one of the optimization objectives. The test set is reserved for final evaluation.

B. Evaluation Metrics

In the experiments, commonly used evaluation metrics in regression tasks are adopted, including: Mean absolute error (MAE), root mean squared error (RMSE) and hit rate (HR).

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|\hat{y}_i - y_i\right| \tag{6}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2} \tag{7}$$

$$\mathrm{HR} = \frac{1}{N}\sum_{i=1}^{N} H_i \tag{8}$$

$$H_i = \begin{cases} 1, & \text{if } \left(\left|\hat{y}_i - y_i\right| < k\right) \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

where N denotes the number of test samples, $\hat{y}_i$ and y_i are the predicted and real values of the i-th sample, respectively. And k represents the error limit, which is set to 5℃.

C. Experimental Setup

1) Experimental Environment: The experiments were conducted on a computer equipped with an Intel Core i5-9300H CPU, 16 GB RAM, and an NVIDIA GeForce GTX 1650 GPU.

2) Parameter Settings: In the optimization, each solution is encoded as a binary–integer vector. A 25-dimensional binary vector is used for feature selection, where 1 indicates a selected feature and 0 indicates an unselected feature. For the XGBoost model, the learning rate is selected from {0.01, 0.05, 0.1}. The maximum tree depth is limited to the range of 2 to 15, and the number of trees is constrained between 50 and 300. The settings of NSGA-III are as following. The population size is 30. Simulated binary crossover and polynomial mutation are applied with probabilities of 1.0 and 1/D, respectively, where D is the number of decision variables. The algorithm runs for 150 generations.

D. Experimental Results

1) Comparison with Different Models: Several regression models are compared for molten steel temperature prediction. All models are trained on the training set and evaluated on the test set, with results averaged over five runs using different random seeds. The mean and standard deviation of the results are reported in Table I. We can observe that tree based models outperform complex deep learning models, such as TabNet and TabM. It can also be observed that XGBoost achieves the best overall prediction performance in terms of accuracy, outperforming the other baseline models. The superior performance is likely due to its ability to model complex nonlinear relationships and handle interactions among features effectively. Therefore, XGBoost is selected as the base learner in the optimization, where feature selection and model hyperparameters are further optimized using a multiobjective evolutionary algorithm.

TABLE I. COMPARISON WITH DIFFERENT MODELS

Model	MAE	RMSE	HR
Linear	3.7045 ± 0.0575	6.1146 ± 0.1312	0.7788 ± 0.0081
SVM	3.6111 ± 0.0401	6.0160 ± 0.1355	0.7882 ± 0.0073
RF	3.7319 ± 0.0536	6.3436 ± 0.0726	0.7797 ± 0.0118
GBDT	3.4346 ± 0.0688	5.8147 ± 0.1498	0.8043 ± 0.0111
LGBM	3.4590 ± 0.0690	5.8079 ± 0.1638	0.8034 ± 0.0095
DNN	3.6471 ± 0.0550	6.1135 ± 0.1520	0.7906 ± 0.0019
TabNet	3.5915 ± 0.0316	5.8626 ± 0.0549	0.7897 ± 0.0051
TabM	3.6379 ± 0.1174	6.0222 ± 0.2700	0.7883 ± 0.0095
XGBoost	**3.4150** ± 0.0705	**5.8046** ± 0.1578	**0.8085** ± 0.0096

2) Multiobjective Optimization Results: Fig. 4 shows the three-dimensional Pareto front obtained by the NSGA-III. Each point represents a non-dominated solution defined by a specific feature subset and XGBoost configuration. The optimization simultaneously considers three conflicting objectives, including prediction accuracy, the number of features, and model complexity. To ensure high prediction accuracy in practical applications, a representative solution is selected based on the maximum R^2 value. To further evaluate the effectiveness of the proposed optimization, the selected solution is compared with the baseline XGBoost model using default hyperparameters and all available features. HR is the average result over five runs. As shown in Table II, the proposed model reduces the number of input features by nearly 50% and adopts a much lighter model configuration, while achieving higher prediction accuracy In addition, Fig. 5 presents a scatter plot of predicted values and true values. It can be observed that most predictions fall within an acceptable error range, indicating that the model trained with the selected optimal configuration can provide reliable predictions that may support production decision-making.

TABLE II. COMPARISON WITH DIFFERENT CONFIGURATIONS

Model	Features	Max tree depth	Trees	HR
Default-XGBoost	25	10	250	0.8085
MOFS-XGBoost	**13**	**3**	**161**	**0.8158**

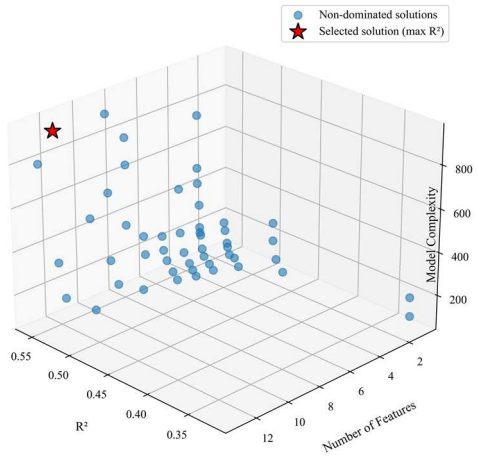

Fig. 4. Non-dominated solutions.

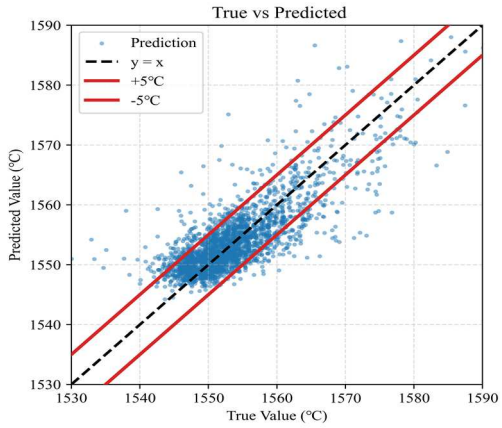

Fig. 5. Scatter plot of predicted versus true values with ±5 °C error bounds for the selected optimal model.

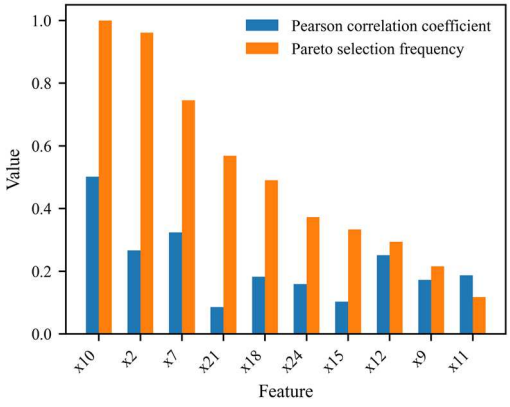

Fig. 6. PCC and Pareto selection frequency of top 10 features.

3) Comparison with Different FS Methods: We compare different feature selection methods for molten steel temperature prediction. All methods are evaluated using XGBoost with the same data partition to ensure fairness, and the number of selected features is fixed to 13. Three feature selection methods are compared: Pearson correlation coefficient (PCC) selection, XGBoost importance-based selection (XGB), and the proposed multiobjective evolutionary feature selection (MOFS). Each method is repeated five times. As shown in Table III, the proposed method achieves higher prediction accuracy while maintaining lower model complexity, demonstrating its ability to balance accuracy and efficiency.

TABLE III. COMPARISON WITH DIFFERENT FS METHODS

Method	MAE	RMSE	HR
PCC	3.4218 ± 0.0643	5.8391 ± 0.1751	0.8094 ± 0.0052
XGB	3.4185 ± 0.0560	5.8052 ± 0.1616	0.8090 ± 0.0077
MOFS	**3.3755 ± 0.0541**	**5.7550 ± 0.1518**	**0.8158 ± 0.0072**

4) Analysis of Feature Selection Results: To better understand the feature selection results, we compare the PCC with the Pareto-based feature selection frequency obtained from the proposed MOFS. As shown in Fig. 6, electrical energy consumption and entry temperature are selected with very high frequencies, indicating that thermal balance is the primary factor influencing the LF endpoint temperature. The calcium carbide addition is frequently selected, even though its PCC is relatively low. This indicates that the impact of these variables is primarily nonlinear and results from coupled chemical reactions, highlighting the ability of MOFS to capture complex feature interactions beyond simple linear effects. In addition, the initial elements content (e.g., Mn, V, and Nb) are selected by many Pareto-optimal solutions, suggesting that these variables affect the molten steel temperature indirectly through reaction kinetics. Overall, the comparison between PCC and Pareto-based selection frequency demonstrates that the proposed multiobjective framework can identify physically meaningful features that would be overlooked by conventional correlation-based methods.

V. CONCLUSION

To address the difficulty of balancing prediction accuracy, feature dimensionality, and model complexity in LF end-point molten steel temperature prediction, a multiobjective evolutionary feature selection (MOFS) framework was proposed, in which feature subset selection and XGBoost hyperparameter optimization are jointly formulated as a three-objective optimization problem. Prediction accuracy, feature subset size, and model complexity are optimized simultaneously using the NSGA-III algorithm, enabling the model to automatically identify important and useful features while controlling computational complexity. Experimental results on real industrial LF refining data demonstrate that the proposed method achieves higher prediction accuracy than the baseline models and conventional feature selection methods, while using nearly 50% fewer input features and a lighter model configuration. These results indicate that the proposed framework can effectively reduce feature redundancy and improve prediction performance, providing a practical and efficient solution for end-point molten steel temperature prediction in LF refining.

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