Intelligent Alloy Charging in RH Vacuum Treatment: A Neural Network Approach to Feed Optimization

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Alloy charging in RH (Ruhrstahl-Heraeus) vacuum treatment is a critical step in achieving precise chemical composition and meeting diverse steel grade requirements. Traditionally, alloy addition strategies have relied heavily on engineers' experience and empirical knowledge, leading to inconsistencies across operators and suboptimal material usage. To address this issue, this study proposes an intelligent alloy optimization model based on historical RH refining records and expert rules, implemented through a neural network architecture. Focusing on non-oriented electrical steel as a case study, the proposed model learns from past process data to predict optimal alloy dosing for specific refining targets. By minimizing operator-dependent variation, the model establishes consistent and rational alloying standards. An optimization model is also integrated to recommend cost-effective charging strategies tailored to each steel grade. Experimental validation shows that the model achieves a Mean Absolute Percentage Error (MAPE) of approximately 3.5% in predicting the final concentration of alloying elements in molten steel, with recommended feed amounts closely aligning with target specifications. These results demonstrate the model's potential to enhance process consistency, reduce cost, and support intelligent decision-making in RH vacuum refining.

Keywords: RH vacuum, Neural network, Feed optimization

1. INTRODUCTION

In steelmaking plants, RH (Ruhrstahl-Heraeus) vacuum refining stations play a vital role in adjusting the chemical composition of molten steel to meet a wide range of customer specifications. Each steel grade requires tailored alloy additions during refining, and these decisions have traditionally relied on the professional judgment and accumulated experience of individual process engineers. However, differences in dosing habits and risk management standards among engineers often lead to significant variation in alloy input amounts, even for the same steel grade and refining targets.

Recent statistics indicate that alloying costs in steel refining have been increasing annually, making precision and cost-efficiency in alloy charging a critical factor in maintaining a steelmaker's competitiveness. In particular, non-oriented electrical steel, commonly referred to as "silicon steel" due to its high silicon content—is widely used in electrical and electromechanical applications. To meet strict compositional specifications, RH refining for this type of steel typically requires more than 2 tons of silicon-based alloys per heat. These alloys are mainly composed of high-purity ferrosilicon, the cost of which has surged by 2–3 times in recent years. As such, implementing a stable and intelligent method to optimize silicon alloy feeding during refining can significantly reduce overall alloy consumption and production costs.

To date, most research and patents related to RH refining—both in China and abroad— have focused on estimating element recovery rates using statistical analysis or empirical equations. For example, Baosteel's 2005 patent " Alloying control method in process of RH refinement" (CN1704484A)[1] divides the refining process into two stages, before and after deoxidation and temperature rise. It proposes measuring the free oxygen content in molten steel and applying empirical formulas to determine the required alloy amounts. Post-deoxidation, a linear programming (LP) model is used to identify the lowest-cost alloy combination that satisfies all target concentration constraints. Building upon this, Baosteel later developed another patent in 2017, "Steel-smelting alloy puts into amount control method" (CN107179703A)

[2], which uses statistical methods to calculate the recent average and historical average recovery rates for each alloy. These recovery rates are then transformed into a "learning recovery rate" and applied in a predictive formula for estimating post-addition concentrations of each element. Finally, an LP model determines the optimal alloy combination under cost-minimizing objectives. However, LP-based approaches may become unsolvable under overly restrictive composition constraints. To address this, Baosteel introduced another patent in 2020, "Control method of steelmaking alloy input amount" (CN110764412A)[3], which incorporates relaxation terms into the optimization model. When infeasibility is encountered, the algorithm increases the allowable upper or lower limits of specific element targets and penalizes the objective function accordingly to retain cost minimization goals. International efforts have followed similar directions. For instance, SSAB Iowa[4] developed a chemistry-based method to estimate element recovery rates and compiled them into a quick-reference table. A linear programming model is then applied to find the lowest-cost alloy plan, and this system has been practically implemented at SSAB's Ladle Metallurgy Furnace (LMF).

Despite the usefulness of these methods, most existing RH refining studies and patents rely solely on empirical or statistical models that consider only alloy type, addition amounts, and elemental content. In reality, the post-addition composition in molten steel is influenced by a range of refining process parameters, including bath temperature, weight, initial composition, and oxygen blowing conditions. To address these complexities, this study proposes a novel approach by leveraging complete historical RH refining records, including both alloy addition and all relevant process parameters. Through machine learning techniques, we identify key factors affecting alloy efficiency and develop a neural network-based predictive model to improve accuracy. This model is further integrated with an optimization framework to recommend cost-effective alloy dosing strategies tailored to individual steel grades. The resulting intelligent system not only reduces variability caused by operator experience but also establishes rational feeding standards derived from data, helping to minimize alloy costs in RH refining operations.

2. EXPERIMENTAL METHOD

To develop an intelligent model for optimized alloy charging, it is first essential to understand how alloy additions are transformed into the final chemical composition of molten steel during RH vacuum treatment. This transformation involves complex physical and chemical reactions, which traditionally require expert knowledge to interpret. However, with recent advancements in machine learning, it has become feasible to extract and model these intricate processes directly from large-scale production data. In this study, we treat production conditions and alloy input quantities as model inputs, and the resulting elemental concentrations in molten steel as model outputs. Through machine learning, we aim to capture the underlying nonlinear relationships governing chemical changes during refining, allowing us to build a predictive model for the alloying process. Once the predictive model is validated for accuracy, it can be integrated with an optimization algorithm to back-calculate the minimum-cost alloy combination that satisfies specified compositional targets for different steel grades.

Typical machine learning models are often regarded as "black boxes." While they may achieve high predictive accuracy, they lack interpretability and may yield seemingly correct predictions even with unreasonable inputs, thereby reducing trust and usability in industrial applications. To overcome this limitation, the model in this study is designed based on a domain-informed expert model structure. As shown in Equation (1), the final concentration C_{final} is expressed as a function of the initial concentration C_{init}, alloy input amount, and element recovery rate R.

$$C_{final} = C_{init} + Alloy\ Input \times R \quad \text{.....(1)}$$

In this formulation, alloy additions increase the element concentration only when the input is greater than zero, which implies $C_{final} > C_{init}$. However, in real-world refining processes, this assumption does not always hold. Alloy additions may increase the total mass of the molten steel, thereby diluting concentrations, or may react with other elements and reduce specific elemental content. To address these phenomena, we extend the model by incorporating two correction factors: one representing concentration enhancement mechanisms, such as targeted alloy recovery or inter-element synergy; and another accounting for concentration depletion phenomena, encompassing dilution and reactive losses.

Equation (1) is thus reformulated into Equation (2), which expresses the predicted concentration as a function of known variables and two unknown correction terms $f(x)$ and $g(x)$, both modeled via neural networks. Here, x represents relevant process parameters that may affect elemental concentrations.

$$C_{final} = C_{init} + Alloy\ Input \times f(x) - g(x) \quad \text{....(2)}$$

Figure 1 illustrates the neural network structure corresponding to Equation (2). The model accepts three types of input features: (1) process and environmental parameters, (2) alloy input quantities, and (3) initial chemical compositions. The process/environmental inputs are fed into two sub-networks that model $f(x)$

and $g(x)$, which then contribute correction terms to the final predicted concentration. Arithmetic operations are used to combine these values according to Equation (2) to yield the final output.

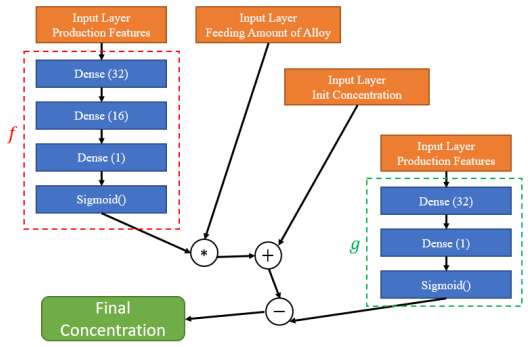


Fig.1. Neural Network Architecture Integrating Machine Learning and Expert-Based Modeling.

Based on the trained predictive model, we can estimate the incremental alloy requirement to increase an elemental concentration by a specific percentage. This capability enables the use of optimization algorithms to determine the most cost-effective alloy combination. The cost-minimizing alloy optimization problem is formulated as follows. In the objective function (Equation 3) PA_{ij} denotes the quantity of alloy j used to supply element i, and A_C_j is the unit cost of alloy j. Constraints (Equation 4), A_{R_j} is the predicted concentration increase per kg of alloy j, provided by the machine learning model; $PBRA_i$ is the total increase in the concentration of element i; GK_U_i and GK_{L_i} are the lower and upper bounds of the required concentration for element i, and TOL_i is the acceptable tolerance range during refining.

$$\text{Minimize}: \sum(PA_{ij} \times A\_C_j) \quad \text{..... (3)}$$

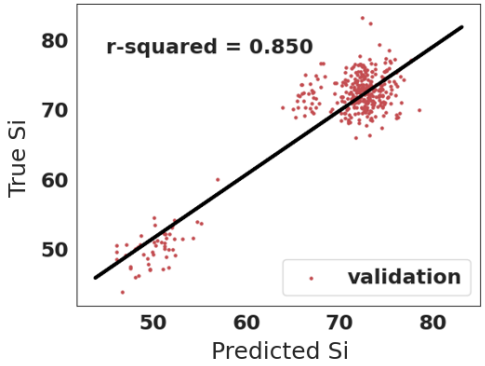
$$\text{Subject To}: \quad PA_{ij} * A_{R_j} = PBRA_i$$

$$GK_{U_i} + TOL_i \leq PBRA_i \geq GK_{L_i} - TOL_i \text{..... (4)}$$

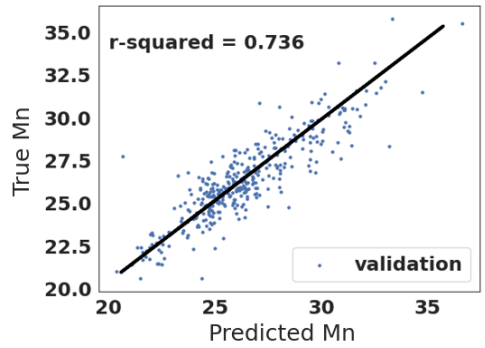
3. RESULTS AND DISCUSSION

3.1 Performance of the Predictive Model

The training and evaluation of the proposed alloy concentration prediction model were based on historical RH refining records of a specific non-oriented electrical steel grade collected from 2021 to 2022. A total of 1,804 heats were available, from which 20% (361 heats) were randomly selected as the test set. Two key alloy elements, silicon (Si) and manganese (Mn), commonly used in the refining of electrical steels, were chosen as the prediction targets. The predictive results are shown in Figure 2. For Si concentration, the model achieved a Mean Absolute Error (MAE) of 2.42 points, a Root Mean Square Error (RMSE) of 3.10 points, a Mean Absolute Percentage Error (MAPE) of 3.50%, and an R^2 score of 0.85. For Mn concentration, the model achieved MAE of 0.90 points, RMSE of 1.22 points, MAPE of 3.39%, and R^2 of 0.736. Note that one point corresponds to 100 ppm in element concentration.



(a)



(b)

Fig.2. RH Vacuum Refining Steel Composition Prediction Model: (a) Si Concentration and (b) Mn Concentration Prediction Results.

3.2 Optimization Results for Alloy Charging

The predictive model described above was formulated according to Equation (2), in which the terms $f(x)$ and $g(x)$ represent learned correction factors from the neural network. Once the process parameters and initial concentrations are given, the model can compute corresponding coefficients for $f(x)$ and $g(x)$. With all terms in Equation (2) known, the model can be integrated with a linear programming framework to derive

optimal alloy charging solutions.

The optimization problem is defined in Equation (5). The objective is to determine the minimum-cost combination of alloy inputs that satisfies the target refining concentrations of both Si and Mn.

- Let Si_i and Mn_i represent alloys contributing to the enrichment of Si and Mn, respectively.
- C_i and C_j are their corresponding unit costs.
- Si_{init} and Mn_{init} are the initial concentrations prior to alloy addition.
- $Si_{f(x)}$, $Si_{g(x)}$ and $Mn_{f(x)}$, $Mn_{g(x)}$ are model-derived coefficients based on real-time process data.
- Si_c and Mn_c are the resulting final concentrations.
- Target constraints require that $Si_c \geq Si_{target}$ and $Mn_c \geq Mn_{target}$.

Minimize：$\sum(Si_i \times C_i) + \sum(Mn_i \times C_j)$

Subject To： $Si_{init} + \sum(Si_i * Si_{f(x)}) - Si_{g(x)} = Si_c$

$$Mn_{init} + \sum(Mn_j * Mn_{f(x)}) - Mn_{g(x)} = Mn_c$$

$$Si_c \geq Si_{target}$$

$$Mn_c \geq Mn_{target} \quad \text{..... (5)}$$

The intelligent system developed in this study has been validated using 23 actual heats. The statistical evaluation of these heats showed a MAE of 2.69 points for Si and 1.28 points for Mn, confirming that the predictive performance remains stable under real-world conditions. Additionally, the optimized alloy input recommendations successfully met the refining targets, demonstrating both the practical applicability and economic benefits of the proposed system.

4. CONCLUSIONS

This study presents a data-driven framework for intelligent alloy feeding optimization in RH vacuum refining, with a focus on non-oriented electrical steel. By integrating domain knowledge into a neural network architecture, the proposed model effectively captures the complex physicochemical interactions between alloy additions and molten steel composition. Unlike conventional empirical or rule-based approaches, the model accounts for a wide range of refining process parameters, improving prediction accuracy and adaptability.

Experimental results using 1,804 historical RH refining records demonstrated that the model achieves high predictive performance, with a MAPE of 3.50% for Si and 3.39% for Mn concentrations. Furthermore, the model was integrated with a linear programming optimizer to recommend minimum-cost alloy charging strategies under given compositional targets. Validation using 23 actual refining heats confirmed the system's practical effectiveness, with consistent accuracy and successful target achievement.

The proposed system not only reduces operator-dependent variability in alloy feeding but also enables steelmakers to establish rational, data-driven dosing standards. By minimizing alloy consumption while ensuring product quality, the intelligent model provides a promising solution for cost control and process optimization in RH vacuum treatment.

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