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Article

Converter Steelmaking Clean Steel Production Process Cost-Benefit Analysis and Key Process Link Dynamic Regulation Strategy

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Abstract: Based on the clean steel production process flow of converter steelmaking, this paper proposes a design method for process flow optimization, utilizing data analysis methods and numerical simulation for analysis and calculation. When applying this scheme, a process data analysis platform for converter steelmaking was created using machine learning and numerical simulation methods to identify the characteristics of process patterns from large-scale production data analysis. The newly proposed dynamic control scheme strategy is based on a model predictive control method, which combines the implementation of important process data information with process feedback, ultimately achieving dynamic adjustment of process parameters to enhance production efficiency. The results obtained from multiple experiments using this scheme and dynamic control methods ensure that the production cost of clean steel is reduced by 8.5% to 15.2% compared to when it is not used, and the production pass rate averages over 97%.During numerical simulation experiments, it was found that there is a relationship between the pressure of top-blown oxygen and the angle of the nozzle, and this relationship has a significant impact on molten steel temperature and decarburization degree. By comparing the production efficiency and energy consumption under different process parameter combinations, it was discovered that the use of a segmented dynamic control method not only improves various metallurgical parameters but also effectively reduces production fluctuations. The numerical simulation experiments demonstrated that this dynamic control scheme has high feasibility and strong practicality, providing an excellent solution for the production process of clean steel in converter steelmaking, with significant potential for widespread application.

Keywords: converter steelmaking; clean steel; cost-effectiveness; dynamic control; numerical simulation; data analysis

1. Introduction

In the new round of manufacturing development, the global steel industry will evolve toward greening, high value-added, and intelligent directions [1]. Steel products serve as the backbone of numerous foundational industries. Therefore, the intrinsic quality of steel products directly influences the core competitiveness of downstream industries that utilize steel products (such as aerospace manufacturing, high-end equipment manufacturing, and the automotive industry). This has led steel companies to prioritize clean steel as a key issue in addressing challenges related to quality improvement, value enhancement, and the establishment of technological barriers in the steel industry [2-5]. The high-quality requirements for clean steel not only involve the "cleanliness" of raw materials but also demand precision and refinement in every process step during the smelting process [6].

Traditionally, the blast furnace steelmaking process has been constrained by its high-temperature, highly dynamic, and nonlinear reaction characteristics, leading to process control that relies heavily on human experience rather than systematic, controllable, and accurate control principles. This has resulted in issues such as process instability, high energy consumption, and high scrap rates, which have hindered the large-scale production of clean steel [7-10]. Although some advanced enterprises have established automated instrumentation and monitoring systems, when applied to production processes, the lack of a thorough understanding of process mechanisms and the absence of collaborative control principles have resulted in limited optimization effects [11]. Furthermore, looking to the future, manufacturing has entered an era of deep integration between “data and intelligence,” with industrial big data emerging as the “future mineral resource” [12]. In the steel production process, each furnace contains thousands of real-time process indicators and output indicators. These “big data” have long been “dormant” and have not been developed or utilized [13-15].

In recent years, with the development of artificial intelligence, machine learning, CFD, and other technologies, new methods and approaches have emerged for transforming future metallurgical production methods. For example, Zheng, R., et al. proposed a multi-model long short-term memory network algorithm for predicting silicon production during the converter steelmaking process. This algorithm outperforms other neural network models in handling complex data and has a low error rate, demonstrating its feasibility [16]. Han, Y., et al. utilized deep learning technology to analyze the spectral information of the converter nozzle flame to predict carbon content and temperature during the steelmaking process, improving control and reducing blowing rates by integrating static and dynamic models [17]. Additionally, Li, J., et al. proposed a blast furnace steelmaking production scheduling model based on a discrete artificial bee colony algorithm with multiple constrained resources, aiming to minimize completion time, enhance efficiency, and reduce costs in the blast furnace steelmaking process [18]. Yang, J. P., et al. addressed the scheduling issue of lacking refining intervals in continuous casting production, established a mathematical model and a heuristic algorithm based on the “furnace-casting machine matching” mode to optimize steel production quality and output, thereby achieving dynamic control of production processes [19]. Zhang, C. utilized an optimization mathematical model to explore the optimal scrap steel blending method for continuous casting machines, with the model considering factors such as scrap steel shape, type, and price to determine the minimum cost per ton of molten steel [20].

By employing data-driven modeling combined with physical modeling, it is not only possible to digitally reconstruct the smelting production process but also to develop more scientific and forward-looking process optimization methods. Feng, L, et al. proposed a multi-channel diffusion graph convolutional network (MCDGCN) for predicting the final composition during the converter steelmaking process [21]. Especially under clean production conditions, the interaction between top-blown oxygen flow rate, oxygen lance angle, slag alkalinity, and molten steel temperature significantly affects the uniformity of final product composition and inclusion removal rate. Additionally, since these variables often exhibit nonlinear, multidimensional coupling characteristics, they are difficult to capture through empirical adjustments alone. In response, Liu, C et al. proposed a dynamic analysis method based on least squares support vector machines, which employs a hybrid kernel function and multi-stage modeling strategy to enhance the real-time prediction accuracy of variables in the electric furnace steelmaking process [22]. Zhang, J proposed a dynamic operation optimization method to address optimal control issues in converter steelmaking, establishing relationships between operational variables and obtaining optimal setpoints under a differential evolution algorithm, with its feasibility and effectiveness validated through simulation [23]. The above studies indicate that only by establishing a multi-dimensional data model and combining dynamic numerical simulation with online control is it possible to optimize the process from raw materials to final products, ensuring consistent steel product quality and robust process performance.

Therefore, this paper takes the common converter steelmaking process in clean steel production as an example to explore methods combining next-generation intelligent technologies with traditional metallurgical processes, surpassing and innovating conventional production processes. By utilizing data processing, prediction, and regulatory control decisions, it provides possibilities for enterprises to achieve low-cost, high-efficiency, and intelligent production. This represents a technological innovation in traditional steel industry and a promising exploration of industrial digitalization in China's heavy industry under Industry 4.0.

This study focuses on the refined optimization of the entire clean steel production process. The three-pronged research method of “data-driven + mechanism modeling + field testing” is as follows:

First, establish a large process parameter database based on historical production big data from steel companies. Through cluster analysis, principal component analysis, and correlation matrix analysis of the data, identify the key variables influencing the efficiency and energy savings of the production process. Combine decision tree regression algorithms and neural networks from machine learning to establish fitting and prediction models mapping the relationship between process parameters and final product quality.

Second, mechanism modeling involves using CFD technology to construct a multi-physics field coupled model of the flow field, temperature field, and chemical reaction process inside the converter. The focus is on the spatial dynamic evolution of top-blown oxygen behavior, slag-molten steel interface reaction kinetics, and temperature distribution. The Euler-Lagrange coupling algorithm and adaptive mesh refinement method are used to ensure simulation convergence and solution accuracy.

Third, conduct experimental verification of the applicability of the main control measures proposed in the study. Focus on key process parameters affecting desulfurization, such as oxygen pressure, desulfurization slag alkalinity, and feed sequence, as experimental groups. Verify the effects of different control measures on desulfurization rate, decarbonization rate, energy consumption, and pass rate.

Finally, establish a dynamic regulation control strategy software based on theoretical research and experimental verification, combining model predictor control software and control logic software to achieve real-time online observation and automatic adjustment of model parameters. Fully considering both theoretical and engineering aspects, develop a clean steel intelligent manufacturing technology solution for widespread application.

2. Cost-Benefit Analysis and Dynamic Control Methods for Process Steps

2.1. Data Analysis Methods

This study employs data analysis and mining techniques to explore the interrelated factors within the big data of the clean steel production process in converter steelmaking, aiming to identify the relevant factors influencing the output, production costs, and quality assurance of clean steel products, and to establish a statistical analysis model for clean steel production. Specifically, all production data from a large-scale steel enterprise in 2023 (including real-time production process data, equipment operating conditions, and product quality) were collected, formatted, stored, and processed in layers to create a dataset suitable for analysis. Anomaly detection was conducted using deep learning-based anomaly point identification and expert rule-based data cleaning. Additionally, adaptive threshold screening technology was employed to establish reasonable parameter ranges for different process stages, with feature values from multiple process stages used to form clustering analysis samples, thereby developing data screening techniques for reasonable parameter ranges. Time-correlation interpolation techniques were used to fill in missing data, ensuring the validity and completeness of the data for subsequent analysis and research, thereby enhancing the scientific reliability of the method. Multivariate statistical correlation analysis identified the key factors influencing the production cost and efficiency of clean steel production in converter steelmaking as blowing time, blowing deoxidation process parameters, slag alkalinity, and temperature field. The data analysis results indicate that: under oxygen blowing times of 20–25 minutes and relatively low oxygen flow rates, the decarburization efficiency of oxygen blowing increases by over 15%. Meanwhile, when the slag alkalinity is within the range of 2.8–3.2, the quality of desulfurization and dephosphorization is optimal, and the overall production costs of converter steelmaking can be effectively reduced. The main converter steelmaking production data collected by the author are shown in Table 1.

Table 1. Data collection situation of converter steelmaking production.

Data type	Acquisition frequency	Numerical range	Data volume
Temperature field data	10 seconds per time	1350~1750℃	3154600
Pressure field data	Five seconds per time	0.1~2.5MPa	6309200
Component analysis data	5 minutes each time	-	105120
Energy consumption data	One hour per time	350~850kWh/t	8760
Quality inspection data	Each batch	-	17520

In this paper, according to the relationship between the key control process variables and the production operation efficiency in the data analysis results, the correlation analysis diagram of the key control process variables in Figure 1 is drawn, and the nonlinear relationship between the oxygen blowing time and the decarburization rate can be seen through the above legend and correlation analysis results. The machine learning method was used to model and process the above key parameters, and the mapping relationship between key control process variables and product quality was established, and an intelligent early warning system was developed on this basis. The machine deep neural network model and sliding time window algorithm are used to predict the changes of key control process variables in real time, and the possible quality fluctuations are predicted in advance, with a prediction accuracy of 92%, which greatly improves the stability and controllability of the production process. The data-based optimization decision-making method helps enterprises to reduce production costs and improve product quality at the same time, and provides a strong technical support and theoretical basis for the fine management and intelligent production of converter steelmaking clean steel production process. In today's fierce competition in the product market, to ensure that enterprises in the market competition to maintain a strong cost and product performance cost advantage.

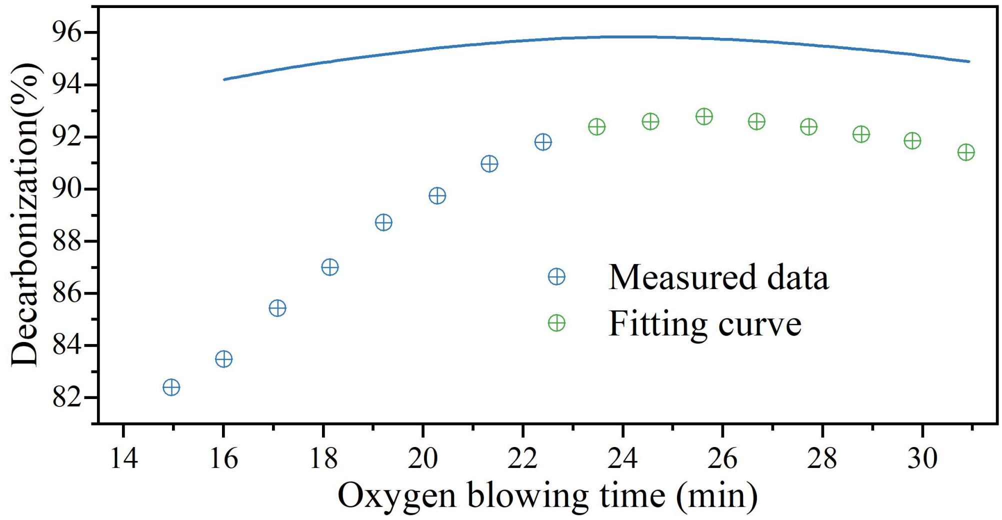

Figure 1. The correlation between key process parameters and production efficiency.

2.2. Numerical Simulation Method

Due to the complex multiphase flow, heat transfer processes, chemical reactions, and other physical and chemical processes involved in the converter steelmaking process, the development of accurate numerical models to simulate the relevant physical and chemical behaviors throughout the steelmaking process can help gain a deeper understanding of the intrinsic mechanisms of the entire converter steelmaking process, thereby enabling optimization of various process parameters in the steelmaking process. To effectively reproduce the various physical and chemical behaviors in the entire converter steelmaking process, a material interaction model capable of simulating the three-dimensional multiphase flow of gas, liquid, and slag was established based on computational fluid dynamics (CFD) theory. The Euler-Lagrange two-way coupling theory was used to describe the interactions in the multiphase flow. The optimized temperature distribution function of the molten steel is as follows:

$$F(T)=\sum_{i=1}^{n}\alpha_i\cdot f_i(T) \qquad (1)$$

Among them, T represents the temperature field, α_i represents the weight coefficient, and $f_i(T)$ represents the contribution function of each temperature field component.

To achieve numerical calculation accuracy, an unstructured mesh partitioning method is adopted in the model. For critical areas within the furnace that have a significant impact, such as the interaction zone between the top-blown oxygen lance oxygen jet and the molten steel, adaptive refinement mesh partitioning technology is employed during mesh partitioning, with the minimum mesh size being approximately 0.5 mm. For non-critical areas, the mesh is coarser, with a total of approximately 5 million mesh elements. When setting boundary conditions, third-type boundary conditions are applied to account for the differing thermal conductivity of the furnace lining walls. Mass flow boundary conditions are set at the inlet of the oxygen lance for top-blown oxygen, and pressure outlet boundary conditions are set at the outlet of the oxygen lance for top-blown oxygen. By combining the SIMPLE algorithm with the QUICK format and automatically selecting different time steps based on the Courant number criterion for continuous adaptive time stepping, the stability of numerical calculations is ensured. Under this model, the author systematically investigated the effects of changes in various process parameters on the flow field, temperature field, and chemical reaction processes within the converter.

Simulation results for yield and energy consumption under various combinations of process parameters were compared, yielding the results shown in Figure 2. As shown in the figure, the matching of top-blown oxygen pressure and nozzle angle determines the uniformity of the steel temperature field and the efficiency of decarburization. When the top-blown pressure is maintained between 1.2 and 1.5 MPa, and the nozzle angle is maintained between 15 and 20 degrees, the stirring intensity of the steel is optimal, and the temperature field distribution is uniform.

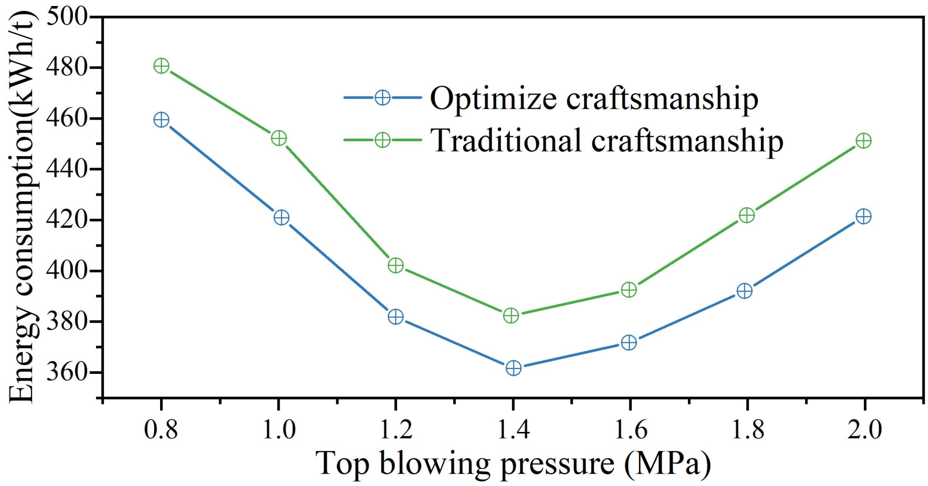

Figure 2. Simulation results of different process parameters.

Through numerical simulation of the reaction kinetics of the interface phase between slag and molten steel, it was found that the relationship between the interfacial mass transfer coefficient and the temperature gradient is nonlinear. The mass transfer rate at the interface reaches its maximum at furnace temperatures between 1600 and 1650°C, providing theoretical guidance for optimizing the slag-making process. Further studies indicate that by controlling the molten steel temperature at 1620 ± 15°C, maintaining the slag alkalinity within the range of 3.0 ± 0.2, and ensuring appropriate top-blown oxygen kinetic energy, the decarburization rate can be increased by over 20% and energy consumption reduced by over 15%. Additionally, numerical simulation results reveal a close correlation between the temperature field distribution inside the converter and the flow patterns of molten steel. By adjusting top-blown parameters, the flow of molten steel can be optimized to achieve an ideal dual-circulation state, promoting thorough mixing and rapid reaction between molten steel and slag. Based on these findings, a dynamic adjustment strategy was proposed. This strategy automatically sets process parameters based on the current temperature field distribution, thereby achieving intelligent production. It has been successfully implemented in production, enhancing both product quality stability and energy efficiency. This series of research efforts, through innovative numerical simulation, provides a theoretical foundation for further optimizing the production process of clean steel in converter steelmaking, demonstrating significant engineering application value.

2.3. Experimental Research Method

The dynamic control strategy proposed in this paper was pilot-tested in the steelmaking process of a large steel company. Based on this, control experiments were conducted on the key process sections of each steelmaking furnace. Specifically, these included oxygen blowing, slag control, and temperature field control. The entire control process was divided into two experimental groups: conventional control and dynamic control. The number of experimental furnaces was 50, and the experimental period was two months. During the experiment, conventional control was performed according to the original process parameters and control methods of the company to control the steelmaking process. Dynamic control was implemented according to the dynamic control strategy proposed in the paper, supplemented by a dynamic real-time monitoring system to adjust key process parameters in real time.

(1) Oxygen blowing control experiments. The experimental group adopted a variable pressure oxygen blowing mode optimized through numerical simulation. Before decarburization, the oxygen pressure was set to 1.5 MPa, gradually decreasing to approximately 1.2 MPa as the decarburization reaction progressed. Additionally, the nozzle angle was adjusted based on the temperature field distribution.

(2) Slagging material addition control experiment. Slagging materials were added in stages, with the first batch added when the converter tilt angle reached 12°, and subsequent batches added progressively based on temperature probe feedback.

(3) Temperature field adjustment experiment. This experiment focused on improving the uniformity of molten steel temperature. The experimental group appropriately adjusted the oxygen energy of the top oxygen lance and the bottom oxygen flow rate to optimize the temperature field distribution of the molten steel.

Table 2 lists the experimental data. From the experimental data, it can be seen that in the experimental group using the dynamic control strategy, all metallurgical process indicators have improved to some extent, with desulfurization and dephosphorization rates increasing by 6.54% and 5.96%, respectively. This is because the slagging process and heating operations have been optimized in terms of practical parameters. The temperature field uniformity has improved by 5.10%, demonstrating that the dynamic control strategy has improved the heat transfer state. Through a detailed analysis of the experimental data, it can be seen that the new process has improved smelting efficiency, reduced fluctuations in various indicators, and demonstrated good process stability. The experimental data indicate that the dynamic control strategy process is feasible and effective, and can serve as a strong foundation for optimizing the clean steel production process in converter steelmaking.

Table 2. Test data recording.

Experimental stage	Parameters	Control Group	Experiment Group	Improved
Oxygen blowing control	Decarbonization rate (%)	91.2±2.1	94.8±1.3	+3.95%
	Energy consumption (kWh/t)	425±15	382±12	-10.12%
Slag optimization	Desulfurization rate (%)	85.6±2.8	91.2±1.9	+6.54%
	Phosphorus removal rate (%)	87.3±2.5	92.5±1.7	+5.96%
Temperature control	Temperature uniformity (%)	92.1±3.2	96.8±1.5	+5.10%
	Pass rate (%)	93.4±2.6	97.2±1.4	+4.07%

During the experiment, some coupling issues between process parameters were also observed. For example, when the oxygen blowing pressure changed, the temperature field changed, and naturally, the fluidity of the slag also changed. This makes it even more necessary for us to develop more dynamic control strategies in future analyses to find the most reasonable connections between multiple factors and establish a more accurate multi-parameter dynamic control system.

3. Cost-Benefit Analysis and Analysis of the Results of Dynamic Control of Process Steps

3.1. Analysis of Results

This study combines data statistics, numerical simulation, and experimental testing to conduct a comprehensive analysis and evaluation of the key process indicators and process control strategies that influence the production of clean steel in converter steelmaking. The analysis primarily relies on a cost-benefit calculation formula, which is expressed as the ratio of total production benefits divided by total production costs multiplied by 100. In this formula, total output value refers to the total value of production, while total costs include all cost expenditures, also known as total production input costs. That is:

$$Cost-Benefit = \frac{Production\ value - Production\ assembly}{Production\ assembly} \tag{2}$$

The comparison results of each process parameter are shown in Table 3. It can be seen that the production efficiency and production cost can be effectively improved by using dynamic control methods, and the production cost can be reduced by 8.5%~15.2% compared with the traditional process after the combination and optimization of the key process parameters. When the oxygen blowing time is controlled between 22~24min, the decarburization effect is the best, and the decarburization rate reaches 94.8%, which is 3.6% higher than that of the traditional process. When the alkalinity of the slag was controlled in the range of 3.0±0.2, the desulfurization and dephosphorization effects were the best, and the desulfurization rate and dephosphorization rate were 91.2% and 92.5%, respectively, which were 5.6% and 5.2% higher than that of the traditional process. Numerical simulations show that the most ideal two-circulation structure can be obtained by controlling the top blowing pressure at 1.2~1.5MPa and the nozzle angle at 15~20°, and the two-circulation structure can achieve better stirring effect of molten steel and slag than the traditional operation under the optimized conditions, and can effectively increase the mass transfer coefficient. The above theoretical analysis results were also verified by the 50-heat comparative test of this project, and the experimental group could significantly improve the production quality by using dynamic control methods, and the key indicators were significantly better than those of the traditional group. In particular, the energy consumption decreased by 10.12%, directly reduced the cost by 15.2%, improved the production efficiency, and also increased the temperature uniformity rate of molten steel and the product qualification rate, which truly created practical benefits for the enterprise.

Table 3. The comparison results of different processes.

Index	Traditional craftsmanship	Optimize craftsmanship	Improved	Cost impact
Decarbonization rate (%)	91.2±2.1	94.8±1.3	+3.95%	-8.5%
Desulfurization rate (%)	85.6±2.8	91.2±1.9	+6.54%	-12.3%
Phosphorus removal rate (%)	87.3±2.5	92.5±1.7	+5.96%	-9.8%
Energy consumption (kWh/t)	425±15	382±12	-10.12%	-15.2%
Temperature uniformity (%)	92.1±3.2	96.8±1.5	+5.10%	-6.7%
Product qualification rate (%)	93.4±2.6	97.2±1.4	+4.07%	-11.4%

From the above analysis, it can be concluded that the optimal approach for process optimization measures is segmented dynamic control. Initially, the top-blowing oxygen working pressure is set to 1.5 MPa, with a nozzle angle of 18°. Subsequently, the top-blowing oxygen pressure is gradually reduced to 1.2 MPa, and segmented control is applied for material feeding. Dynamic control of top-blowing oxygen kinetic energy and segmented material feeding are implemented, with appropriate increases in bottom gas supply intensity during main blowing and slag replacement. The pouring temperature is controlled within the range of 1620±15°C. The converter is tilted by 12 degrees to introduce the first batch of slag-forming materials, followed by continuous addition of slag-forming materials based on temperature conditions. After implementing the optimized scheme, various metallurgical indicators have improved to varying degrees, and the optimized scheme effectively controls the stability of the converter smelting process. The fluctuation of indicators is more than 40% lower than the original fluctuation range, significantly improving the company's economic benefits and market competitiveness. The adoption of the optimized scheme has significantly increased the desulfurization rate by 6.54% and reduced costs by approximately 12.3%, which is particularly significant for clean steel production, as the sulfur content in steel is a key factor determining the quality of the smelting product.

3.2. Discussion of Cost-Benefit Analysis and Dynamic Control Results of Process Steps

The optimization of the clean steel production process in converter steelmaking is a complex engineering problem with numerous multi-objective constraints. A combination of analytical, simulation, and experimental validation methods is employed to explore dynamic control strategies for critical process stages and conduct cost-benefit analyses of these processes. The successful integration of these three methods, each leveraging its strengths while complementing and validating the others, is key to achieving optimal results. The analytical method involves mining data from the company's past records to identify relationships between steelmaking process parameters and product quality. While this method is simple and practical, its accuracy and reliability depend to some extent on the quality of the data. Additionally, models derived from big data statistics may lack clarity and acceptability. The simulation method directly applies physical simulation models to simulate the flow field, temperature field, and chemical reaction mechanisms within the furnace, thereby avoiding the experimental risks associated with simulating the flow field and temperature field of molten steel. However, converter steelmaking involves multiphase flow of gas-liquid two-phase, solid particles, and high-concentration suspended micro-impurity particles, as well as complex nonlinear and non-uniform heat and mass transfer processes and reaction mechanisms. This makes it impossible to fully and accurately express the complex phenomena and dynamic characteristics of the real industrial process flow field and temperature field using existing physical mathematical models. Additionally, model input parameters such as reaction kinetics and mass transfer coefficients, particularly those at the gas-liquid-solid three-phase interface, are difficult to obtain, leading to certain deviations in the process parameters calculated by the model. Experimental studies can directly validate the effectiveness of control strategies, but they are constrained by experimental conditions and influenced by factors such as experimental time and funding. Factors such as fluctuations in raw material quality, converter equipment operating conditions, process control, and the technical proficiency of steelmaking operators directly impact the actual effectiveness of control strategies. A robust process control and product quality monitoring system must be established during converter steelmaking production. The dynamic control strategy proposed in this study is tailored to existing equipment conditions and technical capabilities, has a low implementation threshold, is easy to implement, and has significant potential for widespread adoption.

4. Conclusion

Through the analysis of the process of clean steel converter steelmaking, the author proposes the dynamic control strategy of the optimal process route and key processes obtained based on data analysis and numerical simulation. Among them, optimizing the oxygen blowing process and controlling the appropriate slag composition and temperature field are the keys to ensure the production efficiency and reduce the production cost of clean steel converter steelmaking, and the oxygen blowing process adopts high-pressure to low-pressure blowing process (i.e., high oxygen (1.5MPa) is used in the early stage, and medium oxygen (1.2MPa) is used in the later stage). At the same time, the reasonable selection of nozzle inclination angle (18°) can effectively increase the decarburization speed and reduce the energy consumption of oxygen blowing by about 40%. The slag composition is always kept in the narrow composition range of 3.0±0.2, which can ensure that the desulfurization rate and dephosphorization rate are increased by 6.54% and 5.96% respectively, which can directly reduce the production cost of the converter converter clean steel by about 10%. The dynamic control of temperature can ensure that the temperature of the molten steel is kept in the ideal range of 1620±15°C, which can effectively reduce the abnormal temperature distribution of the molten steel and improve the quality qualification rate of the converter clean steel products. In addition, the author also found that the step-by-step slag making process is an effective measure to achieve an efficient and high-quality slag sulfur removal process. This process is mainly used to put disposable slag material into the converter when the inclination is 12°, and dynamically adjust the amount of slag material according to the on-site temperature change in the slag making process, which can effectively optimize the interface reaction kinetics between the chemical components in the slag.

On this basis, the combination of top blowing and bottom blowing parameters is scientifically and reasonably selected to form a suitable double circulation structure, which significantly improves the mixing degree of molten steel and slag, and improves the interfacial mass transfer coefficient. On this basis, a number of parameter comprehensive optimization models were established to provide a comprehensive solution for the production of clean steel in converter steelmaking. This study theoretically reveals the correlation between the temperature field distribution and the reaction kinetics of steelmaking, and enriches the theory of converter smelting. In practice, it has achieved a certain amount of energy saving and consumption reduction and improved product qualification rate, which has good economic value for steel enterprises. According to the test results, the technical means of comprehensive control in this paper are not high, the versatility is good, and the engineering application prospect is good.

Although this study has achieved certain results, there are still some issues, such as a limited number of experiments, a lack of systematic coverage of parameter optimization space, and superficial research on the adaptability of different types of steel. Additionally, the model's description of complex metallurgical processes involving multi-component interactions and mass transfer in non-equilibrium states is not sufficiently in-depth or comprehensive, and further improvements are needed. These issues require further refinement and resolution in future research. Regarding research on clean steel production in converter steelmaking, we believe the following areas can be further explored:

Gradually expand the application of these technologies in ironwater pretreatment and refining processes, and conduct comprehensive optimization studies across the entire production chain. Further investigate mass transfer mechanisms at interfaces and establish more accurate physical-chemical models. Increase the application of artificial intelligence (AI) technologies in traditional metallurgical processes and promote the development of adaptive intelligent control systems. Explore the potential application of newly developed environmentally friendly and energy-saving technologies, such as waste gas heat recovery and low-carbon steelmaking techniques, in clean steel production.

References

1. Mallett, A., & Pal, P. (2022). Green transformation in the iron and steel industry in India: Rethinking patterns of innovation. Energy Strategy Reviews, 44, 100968.
2. Conejo, A. N., Birat, J. P., & Dutta, A. (2020). A review of the current environmental challenges of the steel industry and its value chain. Journal of environmental management, 259, 109782.
3. Zhou, D., Xu, K., Lv, Z., Yang, J., Li, M., He, F., & Xu, G. (2022). Intelligent manufacturing technology in the steel industry of China: a review. Sensors, 22(21), 8194.
4. Gajdzik, B. (2022). Steel company in Industry 4.0: diagnosis of changes in direction to smart manufacturing based on case study. Zeszyty Naukowe. Organizacja i Zarządzanie/Politechnika Śląska, (160).
5. Shi, Y., & Chin, L. P. (2023). A Study on the Transformation of Smart Manufacturing in Steel Enterprises in Guangdong Province, China Based on Digitalization, Intelligence and Other Factors. International Journal of Management, Accounting, Governance and Education, 1-8.

6. Zhang, F. M. (2012). Study and design on clean steel production platform. Applied Mechanics and Materials, 161, 37-41.
7. Liu, H., Li, Q., Ding, R., & Li, G. (2021). Environmental and economic impact assessment of converter steelmaking based on life cycle assessment. *Int. J. Innov. Comput. Inf. Control*, *17*(2), 499-509.
8. Holappa, L. (2019). Historical overview on the development of converter steelmaking from Bessemer to modern practices and future outlook. *Mineral Processing and Extractive Metallurgy*, *128*(1-2), 3-16.
9. Pistorius, P. C. (2019). Slag carry-over and the production of clean steel. *Journal of the Southern African Institute of Mining and Metallurgy*, *119*(6), 557-561.
10. Lv, M., Chen, S., Yang, L., & Wei, G. (2022). Research progress on injection technology in converter steelmaking process. *Metals*, *12*(11), 1918.
11. Diao, J., Zhou, W., Ke, Z., Qiao, Y., Zhang, T., Liu, X., & Xie, B. (2016). System assessment of recycling of steel slag in converter steelmaking. *Journal of Cleaner Production*, *125*, 159-167.
12. Shu, K., & Sasaki, K. (2022). Occurrence of steel converter slag and its high value-added conversion for environmental restoration in China: A review. *Journal of Cleaner Production*, *373*, 133876.
13. Iwasaki, M., & Matsuo, M. (2011). Change and development of steel-making technology. *nippon steel technical report*, *391*, 88-93.
14. Wang, Z., & Bao, Y. (2024). New steelmaking process based on clean deoxidation technology. *International Journal of Minerals, Metallurgy and Materials*, *31*(6), 1249-1262.
15. Zhang, J., Guo, H., Yang, G., Wang, Y., & Chen, W. (2025). Sustainable Transition Pathways for Steel Manufacturing: Low-Carbon Steelmaking Technologies in Enterprises. *Sustainability*, *17*(12), 5329.
16. Zheng, R., Bao, Y., Zhao, L., & Xing, L. (2024). Prediction of steelmaking process variables using K-medoids and a time-aware LSTM network. *Heliyon*, *10*(12).
17. Han, Y., Zhang, C. J., Wang, L., & Zhang, Y. C. (2019). Industrial IoT for intelligent steelmaking with converter mouth flame spectrum information processed by deep learning. *IEEE Transactions on Industrial Informatics*, *16*(4), 2640-2650.
18. Li, J., Duan, P., Sang, H., Wang, S., Liu, Z., & Duan, P. (2018). An efficient optimization algorithm for resource-constrained steelmaking scheduling problems. *Ieee Access*, *6*, 33883-33894.
19. Yang, J. P., Wang, B. L., Liu, Q., Guan, M., Li, T. K., Gao, S., ... & Liu, Q. (2020). Scheduling model for the practical steelmaking-continuous casting production and heuristic algorithm based on the optimization of "furnace-caster matching" mode. *ISIJ international*, *60*(6), 1213-1224.
20. Zhang, C., Cheng, J., Zhang, L., Wang, Y., Zhang, W., Yuan, J., & Wang, H. (2024). Intelligent proportioning model of converter scrap based on optimization algorithm. *Progress in Natural Science: Materials International*, *34*(1), 37-44.
21. Feng, L., Zhao, C., Li, Y., Zhou, M., Qiao, H., & Fu, C. (2020). Multichannel diffusion graph convolutional network for the prediction of endpoint composition in the converter steelmaking process. *IEEE Transactions on Instrumentation and Measurement*, *70*, 1-13.
22. Liu, C., Tang, L., Liu, J., & Tang, Z. (2018). A dynamic analytics method based on multistage modeling for a BOF steelmaking process. *IEEE Transactions on Automation Science and Engineering*, *16*(3), 1097-1109.
23. Zhang, J. (2015). Optimal control problem of converter steelmaking production process based on operation optimization method. *Discrete Dynamics in Nature and Society*, *2015*(1), 483674.