Design and Application of a Large-Scale Multi-Objective Dynamic Steel Allocation Optimization Model Integrating Thought Chains

Wei Wu[1], Mengmeng Liu[2], and Liya Wang[1, *]

[1] School of Science, North China University of Science and Technology, Tangshan 063210, China

[2] Yisheng Innovation Education Base, North China University of Science and Technology, Tangshan 063210, China

Abstract

In view of the problems of traditional steel distribution relying on manual experience, poor dynamic adaptability and multi-objective optimization imbalance, a multi-objective dynamic steel distribution optimization model integrating the thinking chain is proposed.The model is based on the scrap steel image data set, expands the data through StyleGAN3 and Improved-Diffusion models, improves robustness by Swin-IR ultra-resolution processing, and adopts Swin-Transformer and SE Attention mechanism optimization YOLOv8 to build a scrap steel grading model;Fusion reinforcement learning and cross-modal feature adaptive fusion technology, establish a multi-objective decision-making system including cost, quality and energy consumption, and combine metallurgical process knowledge map and reaction dynamics model to achieve constraint optimization.Through the dialogue and interactive interface, the optimal steel scheme can be output by entering the target steel type. Experimental verification shows that the control accuracy of the steel composition of the model has been increased by more than 15%, the energy consumption has been reduced by 8%, and the production cost has been reduced by 10%, providing technical support for the intelligent and low-carbon transformation of the steel industry.

Keywords

Steel Distribution Optimization; Thinking Chain; Multi-objective Optimization; Enhanced Learning.

1. Introduction

As the pillar industry of the national economy, the steel industry's production efficiency, product quality and low-carbon level directly affect the sustainable development of the industry [1].As the core process of steel production, the rationality of the steel distribution link directly determines the quality and stability of steel products, production energy consumption and enterprise operating costs [2].At present, in steel production, the traditional steel distribution method mainly relies on manual experience. There are disadvantages such as strong decision-making subjectivity and dynamic response lag, and it is difficult to adapt to complex working conditions such as fluctuations in raw material supply and product standard adjustment [3].Although some enterprises have introduced intelligent steel distribution systems, the existing models are mostly problems such as insufficient generalization ability, poor multi-objective balance and lack of integration with metall technology, resulting in limited accuracy and practicability of steel distribution schemes [4].

With the rapid development of artificial intelligence technology, algorithms such as machine learning, deep learning and reinforcement learning are increasingly widely used in the field of industrial

ISSN: 2414-1895 DOI: 10.6919/ICJE.202601_12(1).0008

optimization [5].Zhao Yuntao and others [2] proposed that multi-modal data fusion technology provides comprehensive data support for the steel distribution model. Guo Qingcheng [1] used neural network algorithms to build a relationship model between steel distribution components and product quality, which provided new ideas for steel distribution optimization.However, the existing research focuses on the adaptability of a single algorithm, lacks the adaptability of the dynamic production environment and the systematic consideration of multi-objective optimization, and fails to fully integrate metallurgical technology professional knowledge and real-time production constraints [6].

To this end, this paper designs a multi-objective dynamic steel distribution optimization model that integrates the thinking chain, and realizes the dynamic intelligent generation of steel distribution scheme through the coordinated optimization of scrap steel intelligent grading, cross-modal feature integration, multi-objective decision-making and metallurgical knowledge constraints.At the same time, a dialogue interactive interface is built. Users can quickly obtain the best steel matching solution by entering the target steel type, which aims to solve the pain points of traditional steel matching, improve the comprehensive efficiency of steel production, and help the industry achieve the "dual carbon" goal.

Do not number your paper: All manuscripts must be in English, also the table and figure texts, otherwise we cannot publish your paper. Please keep a second copy of your manuscript in your office. When receiving the paper, we assume that the corresponding authors grant us the copyright to use the paper for the book or journal in question.

2. The Overall Design of the Large Model Optimized with Steel

2.1 Model Architecture

The multi-objective dynamic steel distribution optimization model integrating the thinking chain consists of 5 parts: scrap steel data processing module, scrap steel grading module, dynamic steel distribution decision-making module, metallurgical knowledge integration module and dialogue interaction module.

The scrap steel data processing module is responsible for data set construction, data enhancement and super-resolution processing, providing high-quality data support for follow-up model training.The scrap steel grading module realizes the accurate identification of scrap steel material and thickness through the improved YOLOv8 model, and outputs multi-modal characteristics;Based on the enhanced learning framework and cross-modal integration technology, the dynamic steel distribution decision-making module builds a multi-objective decision-making system and generates the initial steel distribution scheme; the metallurgical knowledge integration module introduces the process knowledge atlas and reaction dynamics model to constrain and optimize the initial scheme and avoid process risks;The dialogue interaction module provides users with a convenient operation interface to realize the rapid response of the target steel type input and the output of the steel distribution scheme.

2.2 Core Design Concept

The core design concept of the model lies in the collaborative optimization of "data-driven + knowledge guidance + thinking chain":Based on multimodal data, the core attributes of scrap steel are excavated through data enhancement and feature fusion;Take the knowledge of metallurgical technology as a constraint to ensure the engineering feasibility of the steel distribution scheme;Take the learning-driven thinking chain as the core to achieve multi-objective dynamic balance and decision optimization.Improve the generalization ability of the model through pre-training-fine-tuning paradigm, and dynamically adjust the priority of each target with the help of the adaptive weighting mechanism, so that the model can adapt to the complex and changeable production environment [7].

ISSN: 2414-1895 DOI: 10.6919/ICJE.202601_12(1).0008

3. Key Technologies and Implementation Methods

3.1 Data Processing and Grading Model Construction of Scrap Steel

3.1.1 Data Set Construction

In order to simulate the actual waste recycling scenario, 100 tons of all kinds of scrap steel were collected from the Chinese waste market, divided into 5 categories according to the thickness range (<3mm, 3-6mm, 6-10mm, >10mm) and garbage,Use Label Image software to annotate rectangular boxes in YOLO format, and divide training sets and verification sets at a 9:1 scale.The data set contains key attribute information such as original images, boundary box coordinates, pixel-level split mask and material categories and thickness ranges, providing comprehensive data support for model training.

3.1.2 Data Enhancement and Super-resolution Processing

Two generation models are used to solve the problem of insufficient data volume: First, StyleGAN3 generates a confrontation network, learns the characteristics of scrap steel images through the confrontation training of generators and discriminators, and generates realistic scrap steel images to expand the data set;The second is the Improved-Diffusion diffusion model, which generates high-quality scrap steel images through the process of gradual noising and denoising. For the low-quality images in the collection process, the Swin-IR model is used for super-resolution reconstruction to improve the clarity of the image and enhance the ability of the model to recognize the characteristics of scrap steel.

3.1.3 Build a Scrap Steel Grading Model

Optimized based on the YOLOv8 target detection algorithm, and integrate the Swin-Transformer architecture and SE attention mechanism to build a scrap steel grading model.Swin-Transformer can balance the local details and global structural information of the scrap steel image, so that the model can capture the subtle features and overall shape of the scrap steel at the same time;The SE attention mechanism can automatically highlight the key characteristics of scrap steel classification and suppress redundant information interference.The optimized model is specially adapted to the scrap steel grading scene to improve the accuracy of material and thickness recognition.

3.2 Construction of Dynamic Steel Distribution Decision Model

3.2.1 Reinforced Learning Framework Design

Build a reinforced learning environment based on the dynamic Markov decision-making process to meet the variability and real-time needs of the smelting process.Multi-dimensional information such as visual characteristics, three-dimensional point cloud characteristics, text semantic characteristics and furnace condition parameters of state space fusion scrap steel;The action space is defined as a time-varying adjustment strategy for the ratio of various scrap steel to ensure that the ratio scheme meets the actual requirements of production;The reward function comprehensively considers the dynamic weight of the three major goals of cost, quality and energy consumption, and adjusts the importance of each goal in real time according to the production priority.The near-end strategy optimization algorithm (PPO) is used for strategy update. By limiting the range of policy updates, performance instability problems in the process of model training is avoided, and the reliability of steel distribution decisions is improved.

3.2.2 Cross-modal Feature Fusion

In response to the needs of multi-source data fusion in scrap steel and steel, pre-training-fine-tuning paradigm and adaptive weighting mechanism are used to realize the efficient integration of cross-modal information such as images, point clouds and semantics.In the pre-training stage, general feature representation is learned on large-scale industrial data. In the fine-tuning stage, the model parameters are optimized in combination with steel-specific tasks, and regularized processing is added to improve the generalization ability of the model.The adaptive weighting mechanism can dynamically adjust the importance of different modal data according to data characteristics and

Volume 12 Issue 1, 2026
DOI: 10.6919/ICJE.202601_12(1).0008

changes in the production environment, fully explore the deep value of multi-source data, and provide comprehensive information support for steel matching decision-making.

3.2.3 Multi-objective Decision-making System

Standardize the three core goals of cost, quality and energy consumption, and build a unified quantitative evaluation system.Cost objectives cover raw material costs, transportation costs and other direct costs, and eliminate dimension differences through normalization;The quality target is quantified based on the deviation between the molten steel composition and the target value, and intuitively reflects the impact of the steel matching scheme on the product quality;Energy consumption targets adopt logarithmic scaling to balance the numerical differences with other targets.

Introduce the non-dominant sorting genetic algorithm (NSGA-II) to solve the multi-objective optimization problem, identify the optimal solution through non-dominant sorting, calculate the congestion to maintain population diversity, and search for the Pareto optimal solution in combination with genetic operations to provide a multi-objective optimization scheme for steel matching decision-making.

3.3 Metallurgical Knowledge Integration and Constraint Optimization

3.3.1 Application of the Principle of Reaction Kinetics

Based on the basic principles of metallurgical thermodynamics, a model of the evolution of steel water composition is established, and the law of change of the content of carbon and other key elements with temperature and time is dynamically described.By analyzing the rate characteristics and influencing factors of metallurgical reactions, it provides a theoretical basis for the steel matching scheme, ensures that the steel matching ratio can adapt to the law of component change in the smelting process, and improves the control accuracy of steel water composition.

3.3.2 Knowledge Atlas Construction and Reasoning

Construct a metallurgical process knowledge atlas, and transform professional knowledge such as steel grade characteristics, process rules, elemental reaction relationships, etc. into structured graph data.The graph attention network is introduced to realize knowledge reasoning, automatically learn the correlation between different knowledge nodes, provide explainable knowledge support for scrap steel grading and steel matching decision-making, and help the model understand the metallurgical process constraints.

3.3.3 Constraint Optimization Processing

The Lagrange multiplier method is used to deal with component restrictions, process specifications and other constraints in the production process, and the optimization problem with constraints is transformed into unconstrained optimization problems for solution.By dynamically updating the multiplier parameters, it is ensured that the steel distribution scheme realizes multi-objective optimization of cost, quality and energy consumption on the premise of meeting all production constraints, taking into account theoretical optimization and engineering feasibility.

3.4 Dialogue Interactive Interface Design

Build a lightweight dialogue interactive interface and integrate natural language processing technology to achieve accurate identification of user needs.Users can enter the target steel type (such as Q235B, No. 45 steel, etc.) and key parameters (such as output, quality level, cost budget, etc.),The system automatically calls the steel distribution optimization large model for quick calculation, and outputs the optimal steel distribution scheme including scrap steel category, proportion, alloy addition and process parameters.

4. Experimental Verification and Result Analysis

4.1 The Optimization Effect of the Steel Distribution Scheme

Three typical steel grades (Q235B, No. 45 steel, 304 stainless steel) are selected for comparative experiments. The performance of the traditional artificial steel distribution scheme and the model scheme in this article are shown in Table 1.The results show that the component control accuracy of the steel distribution scheme generated by the model is improved by 16.3% on average, the production cost is reduced by 10.2% on average, the production energy consumption is reduced by 8.5% on average, and the response time of the scheme is controlled within 3 seconds, which is significantly better than the traditional manual steel distribution method.

Table 1. Performance comparison of steel distribution scheme

Steel type	Steel distribution method(%)	Component control accuracy(%)	Production cost reduction rate(%)	Reduction rate of energy consumption(%)	Program response time (s)
Q235B	Artificial steel	82.5	0	0	30-60
	Model steel	99.2	11.5	9.3	2.8
No. 45 steel	Artificial steel	81.3	0	0	40-70
	Model steel	98.5	9.8	7.9	2.5
304 stainless steel	Artificial stee	79.8	0	0	50-80
	Model steel	97.3	9.3	8.3	2.7

4.2 Stability Test

The same steel type (Q235B) was input 100 times in a row for stability test. The results showed that the component deviation fluctuation rate of the model output steel scheme was ≤0.5%, the cost fluctuation rate was ≤1.2%, and the energy consumption fluctuation rate was ≤0.8%, indicating that the model has good stability and reliability.

5. Conclusion

This paper designs a multi-objective dynamic steel distribution optimization model that integrates the thinking chain. Through the intelligent grading of scrap steel, cross-modal feature integration, enhanced learning-driven multi-objective decision-making and metallurgical knowledge constraint optimization, the precision and intelligent generation of the steel distribution scheme is realized. The built dialogue interactive interface simplifies the operation process, and users can quickly obtain the best steel matching scheme by entering the target steel grade.Experimental verification shows that the model is superior to the traditional manual steel distribution method in terms of component control accuracy, cost saving and energy consumption reduction, which provides an effective technical path for the steel industry to solve the pain points of steel distribution and realize low-carbon intelligent transformation.

ISSN: 2414-1895 DOI: 10.6919/ICJE.202601_12(1).0008

Acknowledgments

This work is supported by Research Project of North China University of Science and Technology College Students Innovation and Entrepreneurship Training Program Project, Project Number: S202510081025.

References

[1] Guo Qingcheng. Structural design and optimization of copper-based composite materials based on BP neural network and multi-objective optimization [D]. Xi'an University of Technology, 2024.

[2] Zhao Yuntao, Deng Xinhui. Attention feature fusion attitude estimation network based on multimodal data [J]. Liquid crystal and display, 2025, 40 (04): 598-606.

[3] Hao Shengtao. Research on the classification and measurement system and data collection method of steelmaking scrap steel [J]. Shanxi Metallurgy, 2023, 46 (07): 192-194.

[4] Digital modeling of scrap steel in Zhanjiang Base of Baosteel [J]. Angang Technology, 2022, (06): 11.

[5] Hayashi S, Tamaki W, TOMOTA Y. Relationship between scrap mixing and steel products for electric furnace [J]. Tetsu-to-Hagane, 2005, 91 (1): 147-149.

[6] Huang X, Liu X, Liu Y, et al. Element Detection in Scrap Steel Using Portable LIBS and Sparrow Search Algorithm-Kernel Extreme Learning Machine (SSA-KELM)[J]. SPECTROSCOPY AND SPECTRAL ANALYSIS, 2024, 44 (9): 2412-2419.

[7] Alvarez E A, Trashorras A J G, Cuesta J M S, et al. Steel mill slags energy potential: the case of the steel factory of Arcelor-Mittal in Asturias (Spain)[J]. Clean Technologies and Environmental Policy, 2012, 14: 869-877.