A Comprehensive Investigation of Coal Blending Optimization: Methods, Applications, Challenges and Future Prospects

Yiheng Chen

sgych102@liverpool.ac.uk

School of Engineering, University of Liverpool, Liverpool, United Kingdom

Abstract. Coal blending optimization has become an important research topic, because it is able to improve fuel utilization, reduce operating costs and control pollutant emissions in both power generation and metallurgical production. This review aims to summarize representative coal blending optimization methods and clarify their applications in different industrial scenarios. To achieve this, the paper examines both traditional mathematical modeling approaches and recent Artificial Intelligence (AI)-hybrid methods, including MOPSO-based optimization, dynamic decision-making models, Support Vector Machine (SVM)-based prediction, XGBoost-SVR, hybrid residual prediction and reinforcement learning-enhanced evolutionary algorithms. Based on the comparison of these studies, this review discusses how the coal blending optimization gradually developed from static cost-oriented models to data-driven and multi-objective frameworks. This review also points out three main challenges faced by current studies which are AI interpretability, applicability and real-world complexity. It further outlines future prospects such as LLM-assisted explanation, transfer learning, domain adaptation and real-time optimization.

Keywords: Coal blending optimization, coke quality prediction, machine learning.

1 Introduction

Coal is a kind of fossil fuel which was formed millions of years ago by the ancient plant under high temperature and pressure. It was mainly composed of carbon, along with hydrogen, oxygen, nitrogen, sulfur, and small amounts of mineral impurities. Coal plays a critical role in electricity generation, steelmaking, chemical production, and high-temperature industrial processes. However, the performance, efficiency and environmental impact of coal utilization not only depend on the type of coal, but also depend on coal blending. Therefore, the optimization coal blending strategy has become a key issue in improving operational efficiency, reducing costs and controlling emissions.

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Early studies on coal blending optimization mainly used traditional mathematical modeling approaches. For instance, Li et al. focused on improving algorithmic performance by constructing Multi-Strategy Fusion Multi-Objective Particle Swarm Optimization (MSF-MOPSO) method to improve the convergence and diversity of Pareto solutions, thereby enhancing engineering robustness and applicability [1]. To solve the limitations of static models, Yan et al. proposed a hybrid dynamic coal blending framework that incorporated carbon trading, procurement strategies, and emission policies into a unified multi-objective decision-making system [2]. Nowadays, lots of studies in coal blending optimization tend to use Artificial Intelligence (AI) hybrid mathematical modeling methods. With the development of data-driven techniques, Zhao et al. integrated a Support Vector Machine (SVM)-based emission prediction model with a genetic algorithm to jointly optimize fuel costs and pollutant penalties, and this marks a transition toward prediction-assisted intelligent optimization [3]. Yuan et al. introduced coal petrography into coal blending and coking cost optimization, using Gaussian functions, Xgboost-based feature selection and Support Vector Regression (SVR) to predict coke quality, and then applying a modified particle swarm optimization algorithm to obtain the optimal blending scheme. Their study demonstrated that petrographic information could improve prediction performance and help reduce blending costs [4]. Liu et al. further proposed a hybrid residual prediction model with Random Forest feature extraction and integrated machine-learning predictors, together with an improved genetic algorithm, to solve coal allocation problems under strict constraints. Their results indicated that this method could achieve more accurate coke-quality prediction and lower-cost coal blending solutions [5].

The remainder of the paper is organized as follows. First, the optimization algorithm of coal blending strategy will be discussed in Section 2. Then, the application scenarios of coal blending optimization will be demonstrated in Section 3. In Section 4, this review will demonstrate the limitations and future prospects of coal blending optimization methods. Finally, Section 5 summarizes the main findings of this review and presents the overall conclusions.

2 Optimization algorithm of coal blending strategy

2.1 Traditional mathematical modeling approaches

MSF-MOPSO algorithm. Li et al. developed a MSF-MOPSO algorithm to solve the coal blending problem in thermal power plants [1]. Based on the conventional multi-objective particle swarm optimization (MOPSO), MSF-MOPSO integrates entropy-based leader selection, adaptive flight parameter adjustment, and adaptive constraint handling together to improve the convergence of the algorithm, maintain the diversity of the solution and improve the feasibility of candidate solutions. MSF-MOPSO firstly initializes and evaluates particles and preserves the nondominated solutions in an external repository. Then, algorithm selects an appropriate global leader from the repository, updates particle velocities and positions iteratively until a well distributed Pareto front is obtained. This optimization considers economic, safety, and environmental objectives at the same time, and the method is subject to multiple coal quality and blending constraints include calorific value, volatile matter, moisture, ash content, ash melting point, and the sum of blending ratios.

Hybrid dynamic coal blending method. Yan et al. proposed a hybrid dynamic coal blending method, which is used to deal with multiple environmental objectives under a carbon emissions allocation mechanism [2]. Different from traditional static coal blending approaches, the method proposed by Yan et al. combines the dynamic programming and multi-objective decision-making framework to reflect seasonal demand changes, inventory status, and carbon quota allocation in different periods. This model optimizes coal purchasing, blending, combustion, storage, and carbon quota trading decisions over a multi-stage production cycle under uncertainty. This optimization not only looks for the biggest benefits for the power plant but also minimizes the carbon and PM10 emissions. Also, this model considers several constraints, including basic electricity supply requirements, coal quality limits, inventory capacity, carbon quota availability, and non-negativity conditions. Through combining decision making and environmental policy constraints, this method achieves a balance between economic performance and environmental protection in coal-fired power plants.

2.2 AI hybrid modeling approaches

SVM based coal blending optimization model. Zhao et al. proposed a coal blending optimization model based on SVM shown in Fig. 1, this model is used to decrease pollutant emission costs in coal-fired power plants [3]. In this method, SVM was used to establish the NOx prediction model based on actual operating data from a 300 MW boiler, while the concentration of SO_2 was calculated according to the material balance based on sulfur content in blended coal. This method firstly predicts the amount of pollution. Then, the approach combines coal price, pollutant removal cost and emission punishment in a Genetic Algorithm (GA) framework to obtain the minimum operating cost. This optimization aims to reduce coal blending cost and pollutant emissions while maintaining boiler safety at the same time. This model also sets several constraints, including lower heating value, sulfur mass fraction, nitrogen mass fraction, volatile matter fraction, and ash content in blended coal. This hybrid SVM–GA framework provides a practical data-driven approach for economical and environmentally oriented coal blending optimization.

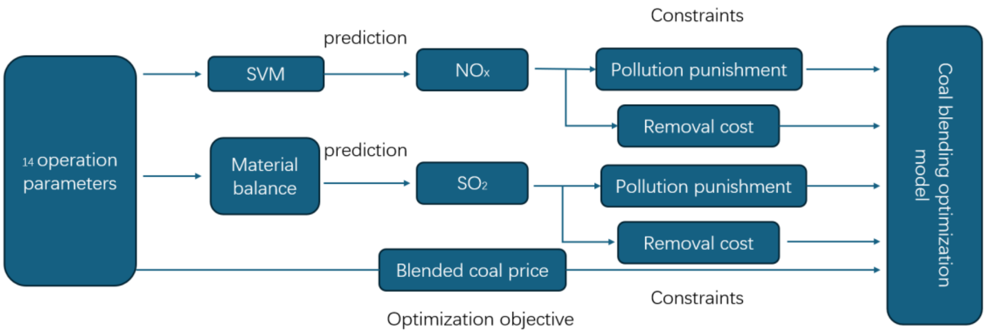

Fig. 1. The model of coal blending optimization structure (Picture credit : Original).

Xgboost-SVR and MPSO-based coal blending optimization. Yuan et al. proposed a hybrid data-driven method for coal blending and coking cost optimization based on coal petrography [4]. This approach used Gaussian functions to extract vitrinite reflectance distribution features and combined the vitrinite reflectance distribution features with traditional coal quality indicators. Then, Xgboost was used to evaluate the importance of the feature and select representative variables, while using SVR to predict key coke quality indices, including Coke

Strength after Reaction (CSR), Coke Reactivity Index (CRI), M40, and M10. After establishing the prediction model, the research adopted a MPSO algorithm to minimize coal blending cost. The optimization's objective of this approach is to reduce raw coal consumption cost, subject to the constraints of multiple coal quality, coke quality and processing conditions. This hybrid framework shows the value of combining machine learning with intelligent optimization in coal blending studies.

Hybrid residual prediction model with improved genetic algorithm. Liu et al. presented a coal allocation optimization method based on a hybrid residual prediction model and an improved genetic algorithm [5] shown in Fig. 2. In this framework, random forest was first used to extract features and reduce dimensions. In order to indicate different coke quality, several machine learning regressors were trained, including Xgboost, Adaboost, LightGBM and SVR. To further improve the robustness and prediction accuracy, this approach introduced the residual prediction and integrated the selected sub-models into a hybrid residual prediction model. On this basis, this approach proposed P-awGA, an improved genetic algorithm. This algorithm combined prior knowledge with adaptive random initialization and enhance convergence and solution feasibility under strict constraints. The goal of this method is to minimize coal allocation cost under constraint of coke quality, inventory, and coal structure, such as M40, M10, CSR, CRI, ash, sulfur, stock limits, and blending ratio requirements.

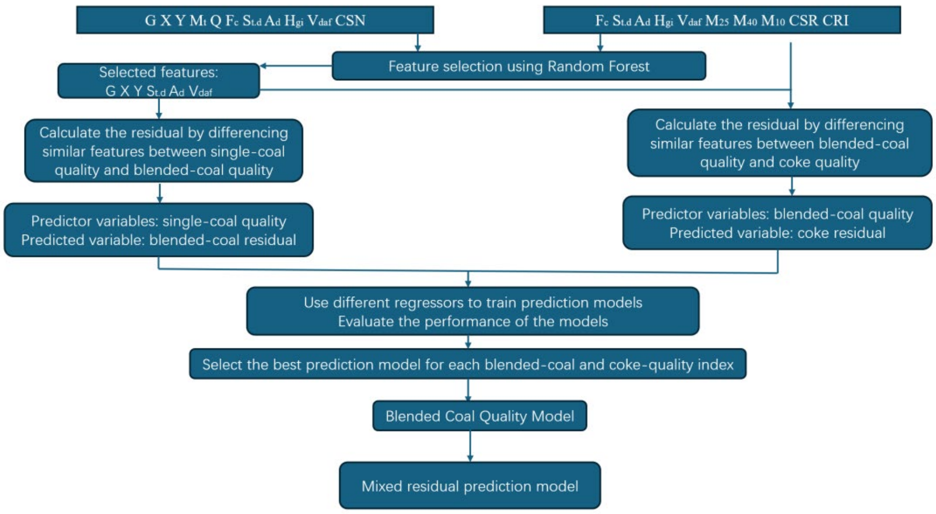

Fig. 2. Flowchart of hybrid residual prediction model (Picture credit : Original).

Reinforcement learning-enhanced evolutionary algorithm for coal blending optimization. Li et al. developed a reinforcement learning-enhanced evolutionary method, termed QNSGAIII [6]. This method is used to optimize multi-objective coal blending in metallurgical coke production. Four Back Propagation Neural Networks (BPNN) were built to predict key coke quality indices which are M40, M10, CRI, and CSR. Then, the predictions were integrated into a constrained multi-objective optimization model. The workflow combines coke quality prediction with Q-learning-guided NSGA-III optimization, where a Q-learning agent is able to adaptively adjust crossover and mutation probabilities according to the population state during evolution. This model also imposes several constraints such as blending-ratio limits, non-negativity and acceptable ranges of coke quality indicators. This optimization minimizes blending cost, ash content, sulfur content, M10 and CRI, while maximizing M40 and CSR.

3 The application of coal blending in different scenarios

3.1 Burning power

In the burning power scenario, coal blending is mainly used to support stable, economical, and clean operation of coal-fired power plants. The aim is not only decreasing the fuel expenditure, avoiding combustion risks caused by slagging and flame instability, but also satisfying the regulations on SO_2, NOx, PM10, and carbon emissions [1-3]. In power generation, coal blending models mainly include multi-objective coal blending models, hybrid dynamic coal blending models and pollutant-cost-oriented optimization models. Coal blending models in power generation not only consider the basic coal quality and blending-ratio limits, but also consider the environmental constraints such as sulfur content, ash content, pollutant emission limits, carbon allowance availability and operating requirements of desulfurization and denitrification systems.

3.2 Metallurgical coke production

Coal blending is mainly used to support stable coke production and make sure that the final coke quality satisfies the requirements of blast-furnace in metallurgy. The aim is to achieve a balance between production cost and coke performance while reducing the risk of producing coke caused by insufficient strength or excessive reactivity. From the perspective of optimization objectives, existing studies usually combine quality prediction with intelligent optimization, which decreases the raw coal or coal blending cost while improving key coke quality indices [4-6]. The typical objective includes reducing ash content, sulfur content, M10, and CRI and increasing M40 and CSR, so that both economic efficiency and metallurgical performance can be enhanced [5,6]. Part of the studies also introduce multiple predictive models to improve the accuracy of coke quality estimation before optimization [4,5]. Coal blending models in metallurgy. From the perspective of constraints, metallurgical coal blending models usually focus on coke quality limits such as CRI, CSR, M10, M40, ash, sulfur, volatile matter, bonding properties, inventory limits and blending-ratio requirements [4-6]. These constraints ensure the optimized coal blending scheme is not only cost-effective but also feasible for industrial coking practice.

4 Discussion

4.1 Challenges

Although AI-based coal blending methods have shown good performances in power generation and metallurgy, some challenges still exist. The first challenge is AI interpretability. Recent years, many researches have introduced different data-driven and hybrid intelligent methods, such as SVM, SVR, XGBoost, BPNN, ensemble regression models and reinforcement learning-enhanced evolutionary algorithms to improve the accuracy of the prediction and optimize the performance [3-6]. However, these methods depend on the complex model structures and nonlinear mappings between coal properties, process conditions and final quality indicators. As a result, it is difficult to understand why a particular coal blending scheme is recommended by the model or how each variable influences the output for those plant operators. Although these studies present strong predictive and optimization capability, their decision logic is not always transparent from the perspective of engineering [3-6]. This limitation in interpretability might reduce the trust of users, and when an inappropriate coal blending scheme is produced, it is also difficult to trace the source of error and make corrections in time.

The second challenge is applicability. Most existing models are constructed based on data from a specific power plant, coke plant, coal source or operating environment [1-6]. For example, some methods are designed for thermal power plants under fixed combustion specifications and pollutant-control requirements [1-3], while others are established for metallurgical coke production with particular coke quality indicators such as CSR, CRI, M40, and M10 [4-6]. Although these models have good performance in corresponding scenery, their applicability to other plants or industries is still uncertain. Differences in coal quality, equipment conditions, inventory structure, production strategies and environmental policies all might affect performance of the model [1-6]. As a result, the model trained in a specific industrial scenery cannot be directly transferred into another scenery.

The third challenge is the real-world complexity. In practical applications, coal blending is not the simple optimization question composed by a few input variables and prediction targets. In power generation, coal blending must consider fuel cost, coal quality fluctuations, boiler safety, pollutant emission limits, carbon allowance constraints, inventory conditions and changing electricity demand [1-3]. In metallurgical applications, the situation becomes even more complicated. Not only raw coal cost should be controlled, but also the coke quality indices and strict production constraints such as ash, sulfur, volatile matter, blending ratios and stock limits should be considered [4-6]. Although many studies have already introduced multi-objective optimization, dynamic decision-making and hybrid prediction-optimization frameworks, real industrial systems are still more complicated than most model assumptions [1-6]. In other words, significant differences still exist between the simplification of the model and the complexity of real operational.

4.2 Future prospects

To deal with challenge of limited AI interpretability, Large Language Models (LLMs) could be considered. In the future, LLMs could be integrated as an explanation layer between optimization models and operators. For example, an LLM can not only convert prediction results, sensitivity information and constraint interactions into explanations which can be understanded more easily, but also explain why a certain coal proportion is recommended. In this way, LLMs increase the practical value of the coal blending decision-making system through enhancing transparency, knowledge communication and human-AI collaboration instead of replacing existing predictive or optimization models. To improve applicability in different plants and operating environments, transfer learning and domain adaptation could be two important solutions. Future research should focus on how to transfer learned knowledge from one plant or coal blending task to another with limited retraining cost. Transfer learning could help reuse feature representations, prediction patterns or optimization experience learned from data-rich scenarios. Domain adaptation could reduce distribution differences caused by changes in coal properties, equipment conditions and operating policies. This direction would be valuable for plants which lack large-scale historical datasets. More generally, transfer learning and domain adaptation could reduce the dependence of AI-based coal blending methods on isolated case studies and be more suitable for wider industrial deployment. To cope with the complexity in real world, future coal blending research should move from offline modeling toward real-time optimization. Therefore, future frameworks should integrate online sensing, process monitoring, prediction updating and dynamic optimization into a closed-loop decision system. Real-time optimization adjusts coal blending schemes in time according to the changes in raw material quality and operating conditions instead of relying on static plans generated from historical data. In addition, the combination of real-time optimization and digital monitoring platforms could also improve the robustness and practical value of AI-based coal blending in power generation and metallurgical production. Furthermore, the performance of coke quality prediction also has a direct impact on the effectiveness of coal blending decisions and should be further considered. Improving the accuracy and robustness of coke quality prediction models is therefore essential for enhancing overall system performance. Recent studies based on deep learning, such as those by Qiu et al. [7-10], have demonstrated promising results in capturing complex nonlinear relationships between coal properties and coke quality. Future research could further explore advanced deep learning architectures, multi-modal data fusion, and interpretable modeling approaches to improve prediction performance.

5 Conclusion

This review has shown that coal blending optimization is a key method to improve operational efficiency, reduce the costs and control emissions. By examining traditional mathematical approaches and recent AI-hybrid methods, this paper demonstrates that coal blending research has gradually evolved from static optimization toward data-driven, prediction-assisted and multi-objective decision-making frameworks. The main contribution of this review is to provide a structured overview of representative optimization algorithms, their applications in power generation and metallurgical coke production and the major challenges that still limit wider industrial adoption. In particular, the discussion highlights that future progress should not only pursue higher predictive accuracy, but also emphasize interpretability, transferability and real-time adaptability, so that coal blending systems can become more practical and reliable in real industrial environments.

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