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# The research progress and application status of ore blending technology: A review

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**Abstract:** Ore blending is essential for stabilizing production, reducing costs, and improving resource utilization in mineral processing. This review systematically traces its evolution through four stages: empirical, experimental, mathematical model-based, and systematic integration. Linear programming provides fast, interpretable solutions for clear grade constraints. Nonlinear intelligent algorithms (e.g., particle swarm optimization, genetic algorithms) achieve higher accuracy for multi-objective, polymetallic ores but require large datasets and sacrifice interpretability. Systematic blending, powered by 5G, AI, and digital twins, enables full-chain coordination with performance gains of>30%, yet requires significant investment. Four interconnected barriers hinder industrial adoption: multi-source data integration difficulties, low computational efficiency for real-time control, poor model adaptability across ore types (prediction errors up to 10%), and a shortage of interdisciplinary talent. Future directions include ore property-based experimental research with open-access global databases, hybrid intelligent models with real-time dynamic adjustment, and integrated medium-to-long-term blending systems using digital twins and IoT. By explicitly linking experimental data, model calibration, and system deployment, this review provides a structured reference for transitioning from experience-driven to data-intelligent, full-chain synergistic ore blending.

***Keywords:*** ore blending technology, ore property characteristics, intelligent optimization algorithm, systematic ore blending, industrial application

## 1. Introduction

The mineral resources sector, which includes the Mining and Mineral processing sectors, is essential to the country's economic and social development because it supplies the raw materials needed for manufacturing, the building of infrastructure, and the development of upscale industries (Napiermunn & Wills, 1988; D. Yu et al., 2025). However, the resource-intensive growth of the global economy in recent decades has resulted in an ever-increasing demand for mineral resources (Qin et al., 2026), accompanied by significant challenges like the depletion of high-grade mineral resources (Zeng et al., 2025), the complexity of low-grade ore properties, the upgrading of industrial production requirements, and the tightening of environmental protection constraints (Holmes et al., 2022).

To meet the technical, financial, and environmental demands of later procedures such as ore beneficiation, smelting, and additional processing, ore blending technology has been developed. This technology has become a key technique for optimizing resource allocation in the mining sector by systematically and scientifically blending and mixing ores with different grades, characteristics, and chemical compositions (Hatfield, 2013). It enables full utilization of the complementary benefits of various ores, improving resource utilization efficiency, stabilizing production process parameters, lowering operating costs, and minimizing environmental damage. With the increasing development of natural resources, its strategic significance is becoming more apparent (Saavedra et al., 2025a). Recent reviews have further emphasized the need for advanced ore-blending strategies to address the depletion of high-grade resources (X. Li et al., 2025).

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The design of ore blending schemes is fundamentally based on the intrinsic features of ore, including its mineral composition, particle size, and content of hazardous components(Williams & Holtzhausen, 2001). For example, ore blending allows these resources to complement one another's characteristics, even if low-grade ore has many impurities and high processing costs, and high-grade ore offers valuable attributes but has limited reserves (Flores-Castañeda et al., 2025). Ore-blending technology covers the three main steps of mining, beneficiation, and metallurgy (Yaqot & Menezes, 2023). However, previous research has been conducted in isolation, resulting in problems such as a separation between upstream and downstream operations and the disregard of variations in ore characteristics (Yifan Li et al., 2023). Cross-process coordination has emerged as a critical issue due to resource depletion and growing demands for industrial chain integration. As a result, ore blending has moved from an empirical, crude approach to exact modeling and from single-process optimization to cross-process collaborative optimization in recent years, thanks to clever algorithms, big data, and digital twin technologies (Bai et al., 2025). However, there are still significant barriers to the industrial deployment of advanced ore blending technologies, including challenges in integrating data from multiple sources, limited computational efficiency of complicated models, and poor adaptability of generic models to particular ore types(Nobahar et al., 2024).

The evolution and synergistic integration of the three major stages-mining, mineral processing, and metallurgy-serve as the analytical framework for this article, which focuses on the scientific foundations and industrial applications of ore blending technology. By addressing cutting-edge international advances, quantitative model comparisons, and studies of ore-type characteristics, it fills gaps in prior research. In addition to identifying obstacles to full-chain collaboration and outlining future possibilities, the study methodically evaluates technological developments across domains and reveals new trends in cross-disciplinary integration. This review systematically maps this evolution, compares methodologies, identifies industrial barriers, and proposes future directions. Additionally, it analyzes important technical measures for the control of hazardous elements and the optimization of process indicators in ore dressing, and it elaborates in detail on the application characteristics and performance differences of various intelligent optimization algorithms (such as particle swarm optimization, genetic algorithms, and neural network algorithms) in ore dressing based on specific industrial data. The objective is to promote the high-quality development of the mineral resources industry through the innovation and application of ore dressing technology and to offer a more thorough, in-depth, and practically relevant academic reference for the research and industrial application of ore dressing technology.

## 2. Ore blending technology

The main goal of ore blending is to maintain the stability and effectiveness of later manufacturing processes while balancing the amounts of advantageous and detrimental elements in the raw materials (Cheremisina et al., 2026). Ore blending is fundamentally a multi-constraint, multi-objective optimization issue from a mathematical and technical standpoint (Saavedra et al., 2025b).

Over the course of a century, ore blending technology has evolved and can be broadly divided into four major stages: empirical methods, experimental methods, mathematical modelling (linear mathematical models and non-linear intelligent models), and system integration (Ke et al., 2017; Liu et al., 2019) (Fig. 1). Early production relied on laboratory testing and manual experience, which could only meet the blending requirements for simple ore types (Bao, 2023). As the composition of raw materials in mines became more complex, linear programming-based mathematical models gradually became the mainstream approach (Erarslan et al., 2001; Zhou et al., 2022). In the modern era, intelligent optimization algorithms and fuzzy theory were introduced, effectively resolving the challenges of non-linear, multi-objective optimization(L. Chen et al., 2022). Three main goals have continually propelled technological advancements: providing real-time control, enhancing dosage accuracy, and responding to complex operational conditions (Z. Feng et al., 2023b; Singh et al., 2020).

The theory, performance, and application scope of ore blending techniques vary significantly (Ke et al., 2017), as illustrated in Fig. 1. Non-linear optimization methods (e.g., swarm intelligence) provide greater adaptability and multi-objective solutions, yet suffer from complex parameter tuning and poor interpretability(Yi et al., 2021). New-generation system integration technologies deliver the best overall performance but are limited by high cost, data infrastructure requirements, and operational capabilities, and are currently deployed only in large-scale smart mines (Nobahar et al., 2024). The choice of technology must be flexible, based on ore properties, mine scale, and management needs. The evolution of ore blending technology reflects a continuous effort to overcome the limitations of existing methods and adapt to increasingly complex industrial scenarios (Hutson et al., 2024). Despite advances from human expertise to intelligent algorithms, current technologies still face drawbacks: traditional models can't account for uncertain operating conditions, intelligent algorithms lack robustness, and end-to-end system solutions are difficult to widely adopt. Current research focuses on on-site system deployment, model fusion, and algorithm refinement.

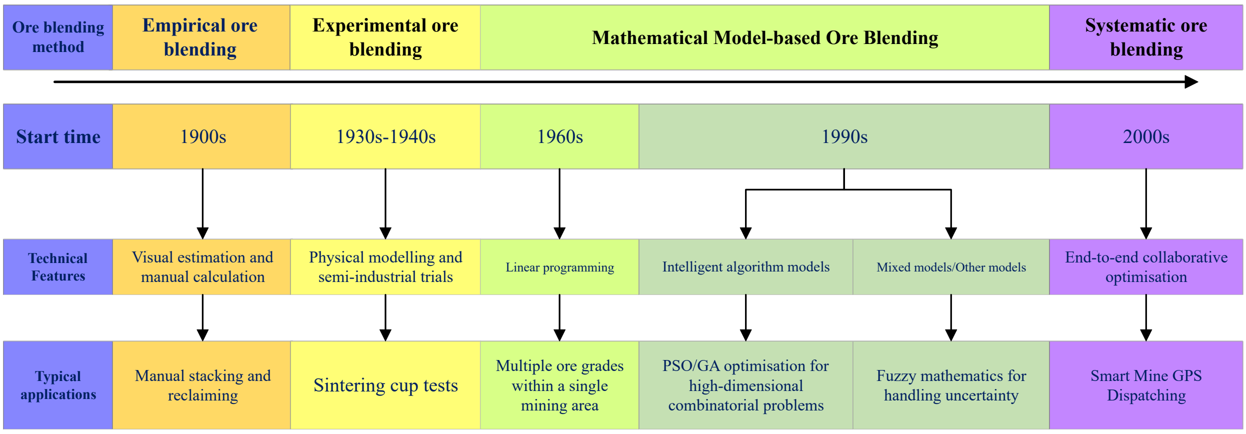


Fig. 1. Evolution roadmap of ore blending technology

### 2.1. Empirical ore blending

Empirical ore blending offers the benefits of low implementation complexity and quick on-site adjustment, making it appropriate for small-scale operations with straightforward ore types and low precision requirements. It determines blend proportions mainly through operators' field experience and straightforward mass-balance calculations without systematic experimentation or mathematical optimization (Chu et al., 2023). However, the lack of a closed-loop feedback mechanism, heavy reliance on operator expertise, and limited quantitative understanding of key ore qualities are intrinsic limitations of this early approach to ore blending technology. Its main scientific drawback is that it cannot accurately predict non-linear interactions among various ore components, such as how variations in goethite content affect sinter bed permeability and strength in iron ore sintering, which frequently results in fluctuations in downstream process stability. This is because it cannot establish a predictive relationship between ore characteristics and blend performance (Tang et al., 2024). As a result, over the past 20 years, empirical blending has been largely abandoned in large-scale, contemporary mineral processing facilities, making up less than 10% of production decisions in medium-to-large businesses. However, it still exists in specialized situations like emergency backup or small-scale private mines with inadequate funding and technical infrastructure.

### 2.2. Experimental ore blending

Experimental ore blending is a technology that involves mixing two or more ore samples at different ratios in laboratory tests to determine the optimal blending scheme, which then guides industrial production. Its core principle is to establish a quantitative relationship between blending ratios and process performance indicators through systematic experiments. This approach originated between the 1930s and 1950s, evolving alongside the standardization of mineral processing science and the widespread adoption of sintering processes (Zhang et al., 2022). Physical simulation methods, such as sintering pot tests and flotation batch tests, transformed ore blending decisions from empirical intuition to scientific laboratory validation. To this day, these methods remain essential for verifying the compatibility of new ore types. As the most widely used ore blending approach, experimental ore blending has been applied to various ores, including phosphorite, iron ore, nickel ore (Prasojo et al., 2013), gold ore (Nwaila et al., 2019), and others (Saldaña et al., 2019). The methodology is founded on a comprehensive investigation of ore properties and follows a complete technical workflow, as illustrated in Fig. 2. This workflow integrates all key steps: sample collection, characteristic analysis, test design, blending trials, scheme optimization, and industrial application, clearly distinguishing the stages of sample characterization, experimental design, and industrial scale-up.

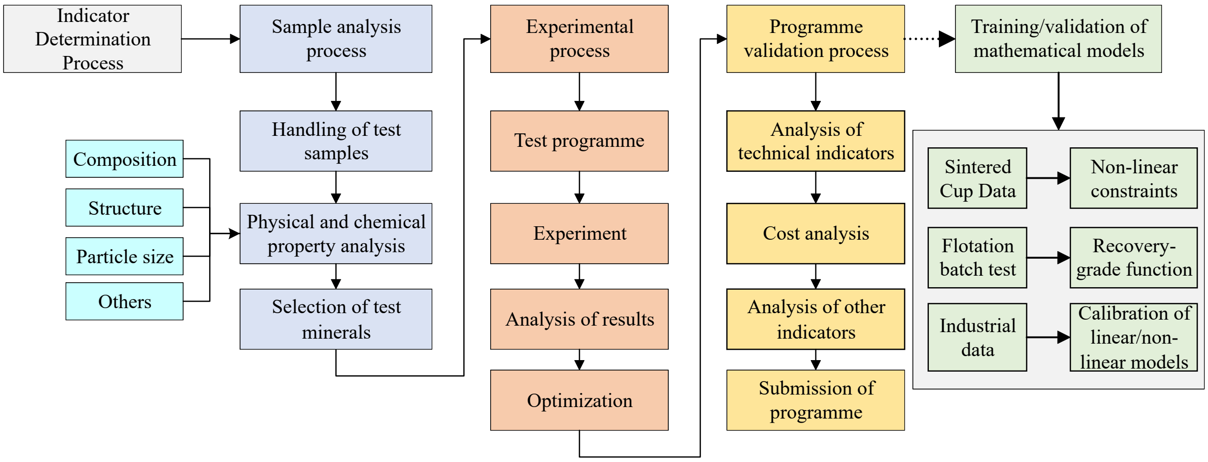


Fig. 2. Flow chart of experimental ore blending

All kinds of mineral resources can be blended using pilot ore. Ores can be broadly classified into two primary types: single-metal ores and complex multi-component ores. The study focuses on technical approaches that vary in breadth depending on the complexity of the ore composition.

### 2.2.1. Experiments on ore blending for simple ore

Phosphate ore, iron ore, manganese ore, and nickel ore are examples of single-component ores. The goals of ore blending for these ores are specific and well-defined. The main goals of experimental ore blending are to increase the target mineral's utilization efficiency, keep hazardous components below process-permissible levels, simplify operations, and ensure consistent product quality (Farid et al., 2023). Short research cycles and simple optimization are characteristics of experimental designs that mainly concentrate on manipulating a single variable (ore blending ratio). This article offers a thorough analysis of the literature on iron and phosphate ores.

#### 2.2.1.1. Phosphate ore blending

Phosphate ore blending enhances resource utilization and stabilizes beneficiation performance by mixing ores of different genetic types and chemical compositions (Liu et al., 2018). This approach improves flotation efficiency, reduces reagent usage and grinding fineness, and effectively removes impurities such as silicon and magnesium (Käyhkö et al., 2022; Liu et al., 2022). Table 1 summarises common phosphate ore blending strategies and their documented outcomes in reverse flotation, including synergistic impurity removal and grade improvement.

Table 1. Summary of phosphate ore blending strategies and their performances in reverse flotation

| Blending strategy | Key effects | References |
|---|---|---|
| Calcium-magnesium+ calcium-silicon | Synergistic removal of Mg and Si impurities; improved concentrate grade | (Deng, 2015; H. LI et al., 2023) |
| High-magnesium + low-magnesium | Significant increase in $P_2O_5$ grade; reduction of MgO content in concentrate | (Li et al., 2020) |
| Siliceous + carbonate | Satisfactory reverse flotation performance | (Xie et al., 2021) |
| Comprehensive engineering integration | Green, efficient, energy-saving development | (Y. Chen et al., 2022) |

#### 2.2.1.2. Iron ore sintering blend

The cost of sinter raw materials makes up around 80% of the total cost of producing sinter, which is the main burden material in blast furnace smelting (Zhang et al., 2014). To cut expenses and achieve effective resource allocation, it is crucial to optimize the sinter raw material blending structure. Optimization of ore mineral composition (Aladejebi et al., 2025; Wu et al., 2020; Zhou et al., 2023) and optimization of sintering process parameters (Li et al., 2014; Wu et al., 2019; Yang et al., 2022) are the two primary dimensions along which research in this field has been carried out. The primary iron ore sintering blending techniques, such as ore characteristic optimization, raw material matching (Chen, 2023), process parameter adjustment, industrial scale-up, and cross-process collaboration, are listed in Table 2 along with their main results.

Table 2. Summary of iron ore sintering blending strategies and their key findings

| Strategy category | Ore/parameter combination | Key effects/outcomes | References |
|---|---|---|---|
| Ore characteristic optimization | Varying $Al_2O_3$ in blended ore | Clarified influence mechanism on sintering indexes | (JIN et al., 2023) |
| | V–Ti ores + ordinary ores | Enhanced sintering strength of V–Ti blends | (Zhou et al., 2015) |
| Raw material optimization | Iron ore + CIC | Improved sintering performance; new raw material option | (Wu et al., 2019) |
| | Australian ore fines ≤45% | Optimal sintering test effect | (Zhang et al., 2014) |
| | Five candidate schemes | Optimal scheme identified via lab validation | (Liu et al., 2019) |
| | South Africa NFM 4% + NFC 12% + Malaysia 39% + Australia 36% + sintering dust 9% | Improved granulation and high-temperature behavior | (W. Zhang et al., 2025) |
| Process parameter optimization | Ferromanganese ore with different fuel ratios | Experimental basis for manganese ore sintering | (Lu et al., 2022) |
| Cross-process collaboration | Pellet ratio in blast furnace throat | Theoretical basis for sintering-BF collaborative optimization | (He et al., 2024) |

The effective use of strategic resources and large-scale industrial application have been the main emphasis of iron ore blending research in recent years (Aladejebi et al., 2025). Additionally, research has expanded from single process optimization to collaborative cross-process optimization. In summary, empirical proportioning has given way to a science-based method that integrates ore properties, process parameters, and industrial scalability in iron ore sintering blending. Establishing quantitative blending models, adding real-time quality feedback, and investigating cross-process integration should be the main goals of future initiatives.

### 2.2.2. Experiments on ore blending for multi-component ores

Experimental ore blending for complex mineral resources has shifted from single-process optimization to multi-objective, multi-mineral synergistic control (Desai et al., 2023). Key applications include copper-zinc (Coutinho et al., 2023), platinum (Prasojo et al., 2013), gold, and geometallurgical ores (Hatfield, 2013). Table 3 summarizes blending strategies for such multicomponent ores, highlighting that recovery efficiency depends on mineralogy and geological factors beyond grade alone. To address refractory ores, two complementary trends have emerged. First, deep integration with mathematical models (machine learning, linear programming) uses experimental data to build predictive simulations, reducing laboratory testing, shortening cycles, and lowering costs. Second, coupling with innovative processes, such as low-temperature magnetization roasting and superconducting magnetic separation, overcomes utilization bottlenecks for low-grade and complex ores, broadening the method's scope. As the link between lab testing and industrial production strengthens, experimental blending will achieve greater industrial value, promoting scientific and accurate ore blending practices.

Table 3. Summary of experimental ore blending strategies for multicomponent ores

| Ore type/strategy category | Ore/parameter combination | Key effects/outcomes | References |
|---|---|---|---|
| Copper–zinc polymetallic ore | Low-grade copper ore ≤20% | Ensured separation efficiency of Cu–Zn ores | (Luo et al., 2021) |
| | Blending experiments | Improved stability of processing indices | (Hong et al., 2019) |
| Copper ore (oxide + sulfide) | Oxide ore 20%–30% | Cu grade >20%, Cu recovery >85% | (Huang et al., 2021) |
| Platinum group ores | Flotation + grinding tests | Provided an efficient utilization approach | (Van Tonder et al., 2010) |
| Gold ores | Blended gold ores | Identified minerals affecting leaching efficiency | (Nwaila et al., 2019) |
| General polymetallic deposit | Mineral deposit (copper) | Cu recovery affected by geological/mineralogical factors beyond Cu assay | (Tungpalan et al., 2021) |

Beyond individual case studies, experimental ore blending remains the cornerstone of modern ore processing, enabling precise control over raw material quality and process parameters. However, its effectiveness is severely limited by ore complexity. For polymetallic ores such as Cu–Zn, the number of required trials is three to five times higher than for single-mineral ores (e.g., phosphate, iron), leading to prolonged research cycles and heightened industrial scale-up risks. Moreover, key blending parameters vary significantly across different polymetallic systems. For copper-zinc ores, low-grade fractions must be strictly limited to ensure separation efficiency; in copper oxide–sulfide blends, an optimal oxide ratio exists. For platinum group metals, gold, and other polymetallic ores, recovery depends not only on grade but also on mineralogy, geology, and leaching behavior. This underscores the critical role of process mineralogy in polymetallic ore blending. Consequently, experimental blending alone is insufficient for complex ores and must be integrated with mathematical models. In this framework, experimental blending provides essential training and validation data for building reliable, data-driven models. Without such high-quality experimental data, even the most sophisticated algorithms cannot achieve accurate predictions or robust optimization.

### 2.3. Mathematical model-based ore blending

The 1950s saw the emergence of mathematical models for ore blending. In 1963, linear programming was first systematically applied to coal blending to meet power plants' demands for specific calorific value and sulfur content (Erarslan et al., 2001). The adoption and refinement of this approach were accelerated by the introduction of commercial computers in universities and major corporations, which enabled the solution of complex linear equation systems (Das & Ragunathan, 2015). Owing to growing requirements for blending precision, along with rapid advances in computer technology and mathematical optimization theory, mathematical model-based blending has become the primary research focus in contemporary ore blending technology (Ma et al., 2024). This methodology builds on experimental data and production practice to develop mathematical models that describe the relationships among blending ratio, ore characteristics, and process performance indicators (Ke et al., 2016). By solving for the optimal blending scheme using optimization algorithms, it overcomes the deficiencies of traditional experimental blending, such as long cycles and poor dynamic adaptability, enabling precise and rapid optimization (Sun et al., 2018). Although linear models enabled efficient industrial applications, their linear assumptions fail to capture complex mineral–process relationships. This limitation drove the adoption of nonlinear and intelligent algorithms, neural networks, genetic algorithms, and particle swarm optimization, which better handle multi-objective trade-offs (technical, environmental, economic). Ore blending thus evolved from static linear programming to dynamic optimization. Critically, all these models are parameterized, calibrated, or validated using experimental blending data, creating a lab-to-algorithm loop. Hence, experimental data underpins every model, from linear regression to deep neural networks. To provide a clear comparison between the two modeling paradigms, Table 4 summarizes their key differences in terms of typical methods, constraint handling, computational efficiency, interpretability, suitable scenarios, industrial cases, and representative references.

Table 4. Comparison table: Linear blending model vs. non-linear blending model

| Comparison aspect | Linear model | Nonlinear model |
|---|---|---|
| Typical methods | Linear programming, goal programming, integer programming | PSO, GA, neural network, deep reinforcement learning |
| Constraint handling | Linear equality/inequality | Highly nonlinear, multi-peak, multiple constraints |
| Computational efficiency | Very fast (<1 second) | Slow (10-50 times slower than linear) |
| Interpretability | High (solution directly interpretable) | Low (black-box, especially neural networks) |
| Suitable scenarios | Clear grade constraints, no interaction among components | Polymetallic symbiosis, high-temperature sintering, complex flotation kinetics |
| Industrial cases | Phosphate stockpile blending, Choghart iron mine (Iran) | Copper smelting, polymetallic open-pit, sintering blending |
| Representative references | (Ali et al., 2018) | (Z. Feng et al., 2023a) |

### 2.3.1. Linear ore blending model

Linear programming (LP) models represent the earliest mathematical approach to ore blending and remain widely used due to their interpretability and computational efficiency. Classical single-objective LP was originally designed for grade and production control in mining (Chanda & Dagdelen, 1995). Its inherent limitation, a single objective function, spurred the development of multi-objective, integer, and goal programming variants. For example, Chen et al. (2012) developed a multi-objective optimization model for Kunyang Phosphate Mine, solved it using MATLAB, and improved economic benefits by integrating the model with management systems. Meanwhile, mining software such as DIMINE has incorporated mixed-integer programming and 0-1 integer programming (L. Wu et al., 2012) to enhance the accuracy and efficiency of open-pit ore blending.

To overcome the structural constraints of LP models, researchers have integrated them with other computational and geospatial technologies. Although LP alone cannot capture nonlinear interactions, combining it with neural networks allows iterative constraint adjustment (Gu et al., 2010). Combining LP with machine learning and techniques like Lagrange relaxation and ordinary least squares can enhance adaptability to complex constraints and solution efficiency (Nelis & Morales, 2021). In addition, LP and nonlinear programming have been jointly applied to iron-making system optimization (Shen et al., 2017). Beyond these technical integrations, linear goal programming has been validated in international mining contexts. For the Choghart iron ore mine in Iran, Gholamnejad and Kasmaee (2012) developed a linear goal programming model that enabled rational blending of low-grade and high-phosphorus stockpiles. Industrial applications in Chinese mines further demonstrate the practical value of LP-based ore blending. Ke et al. (2016) established an LP model for Wulongquan Mine, increasing resource utilization by 16.09%. Zhou et al. (2022) used LP to optimize sinter blending, reducing raw material costs while maintaining sintering performance. To address the challenge of precise iron ore proportioning in sintering, Ren et al. (2022) proposed an automatic batching algorithm based on the Cartesian product and successfully implemented it in industrial production. For a large polymetallic open-pit mine in Inner Mongolia, Wang et al. (2017) developed an automatic optimization technique based on goal programming, achieving rapid and accurate blending solutions.

LP models have progressed from single-objective to multi-objective, multi-constraint, and full-process integration, growing from individual blends to entire supply chains, mining, beneficiation, and smelting. Future ore blending LP models will emphasize full-process cooperation, dynamic intelligence, and multi-technology integration. Applications will range from individual blending operations to coordinated mining, transportation, and processing optimization (Azzamouri & Giard, 2018; Farghaly et al., 2021). Downstream adaptability will be improved by combining LP with metallurgical performance prediction models. To achieve both economic and environmental benefits, future models will integrate green and low-carbon targets by introducing energy consumption and carbon emission limits.

### 2.3.2. Nonlinear ore blending model

Ore blending is a highly nonlinear, multi-conflicting, heavily constrained, high-dimensional optimization problem by nature (Campos et al., 2024). For complex engineering scenarios like grade fluctuations, polymetallic symbiosis, and the synergistic optimization of cost, quality, and energy consumption, traditional linear programming, empirical trial-and-error methods, and conventional operations research techniques are insufficient (Pedro et al., 2023). As a result, several nonlinear models have been widely used in the mining sector due to the quick growth of intelligent computers and data-driven technologies, making nonlinear ore blending models a prominent field of study. This has created a diverse research landscape focused on intelligent optimization algorithms, along with the coexistence of conventional mathematical techniques and cutting-edge technologies. With an emphasis on intelligent algorithm-based models (particle swarm optimization, genetic algorithms, neural networks, and their hybrids), as well as other general nonlinear models, this section methodically reviews the state of research on nonlinear ore blending models from two perspectives: model construction and solution techniques (B. Li et al., 2023).

#### 2.3.2.1. Nonlinear ore blending models based on intelligent algorithms

Intelligent optimization techniques have become the norm for solving nonlinear ore blending issues because they perform better in high-dimensional, nonlinear, and multi-constrained environments. They can be divided into four groups: particle swarm optimization, genetic algorithms, neural network methods, and hybrid intelligence algorithms.

(1) Particle swarm optimization and its improvements

Particle swarm optimization (PSO) has been recognized as one of the earliest and most popular intelligent algorithms in ore blending owing to its straightforward structure, rapid convergence, and few parameters (S. Li et al., 2026). Recent efforts have primarily focused on enhancing global search capability and solution accuracy through improved mechanisms and hybrid variations (F. Yu et al., 2025). In the context of dynamic and multi-objective ore blending (Chen et al., 2023) proposed a multi-round PSO that effectively handles highly nonlinear constraints in medium- and long-term dynamic blending by splitting ore blocks and designing particle flight rules. Hu et al. (2013) developed a particle search approach using kernel particles and dual attractors to optimize excavation and transportation costs in an open-pit mine production planning model. For sintering blending, Feng et al. (2022) designed a region-division-based limited multi-objective PSO incorporating adaptive angle partitioning and a dual external archive to balance cost and total iron content. (Ma, Li, et al., 2023) constructed a PSO-VIKOR collaborative optimization framework that integrates energy balance constraints into a sintering proportioning model for iron ore, flux, and fuel. Dai et al. (2023) presented an optimization model for material layer fuel distribution that combines mechanism models and algorithms, reducing the fuel ratio and improving fuel content in the upper layer, thereby enhancing sinter quality uniformity. In addition to PSO, other swarm intelligence algorithms have also been applied to ore blending. Wu et al. (2022) developed a multi-metal, multi-objective blending model based on the artificial bee colony (ABC) algorithm, achieving recovery rate increases of 8.95%, 12.20%, and 8.33% for tungsten, molybdenum, and bismuth, respectively. Li et al. (2024) adopted an enhanced PSO with linearly decreasing inertia weight and a contraction factor for copper smelting blending, significantly reducing raw material costs. Wang et al. (2025) proposed an improved beluga whale optimization algorithm (IBWO) incorporating chaotic mapping and Lévy flight, which achieved a 31.2–165.9% increase in convergence speed and a 14.69–17.93% increase in average profit.

(2) Genetic algorithms and multi-objective extensions

Genetic algorithms and their multi-objective variants, owing to their powerful global search capability, have become mainstream approaches for solving large-scale, multi-constraint ore blending optimization problems (Zhou et al., 2025). Early studies, such as (Chakraborty & Chakraborty, 2012), applied a multi-objective GA to coal blending to simultaneously optimize raw material cost and washing indicators, while Li and Cui (2013) achieved grade stabilization and maximized resource utilization in phosphate rock stockyard blending through an enhanced multi-objective GA. Since the introduction of NSGA-II by Deb et al. (2000), which employs fast non-dominated sorting and elitism, continuous improvements have been made in convergence and solution set quality: Wang et al. (2019) enhanced population diversity in sintering blending by improving non-dominated sorting and deduplication operations; Singh et al. (2020) obtained the Pareto optimal set by using NSGA-II to address the yield–quality bi-objective optimization issue in sintering. (Gu et al., 2021) sequentially proposed an adaptive GA and an enhanced MOEA/D algorithm for refined modeling of polymetallic blending, substantially improving computational efficiency and overall metal recovery. In recent years, research has further extended to novel algorithms and complex constraints. Li et al. (2024) proposed an improved multi-objective beluga whale optimization algorithm (IMOBWO) for sintering blending, achieving a balanced optimization of cost and total iron grade; Luo et al. (2025) improved NSGA-II with an SDN-enhanced dominance relationship to reduce energy consumption while stabilizing grade in multi-unloading-point phosphate ore blending; and Xiang et al. (2025) integrated an improved matter-element extension model with NSGA-II for polymetallic open-pit blending. At Dabaoshan Mine, production accuracy improved by 1.035–2.828%, and Cu/S grade deviations by 7.021% and 33.027%. However, the method still lacks diversity-convergence balance, dynamic adaptability, transferability, physics fusion, and high-dimensional support.

(3) Neural Networks and Deep Learning Methods

Neural networks are important for ore blending modeling and quality prediction because of their powerful nonlinear mapping capabilities (Noriega & Pourrahimian, 2024; Peng & Nie, 2022). Regarding neural networks and deep learning methods, relevant research has evolved from simple nonlinear mapping prediction into a multi-layered technical system encompassing end-to-end modeling, interpretability analysis, and real-time decision support (Fan et al., 2024; Moraga et al., 2024). Early work, such as Fan et al. (2012), constructed a BP neural network to predict sintering indicators and optimize fuel and moisture ratios, achieving an accuracy of 86.67%–96.67%; Baek and Choi (2019) employed a deep neural network to forecast ore production and crusher utilization in underground mines, attaining a coefficient of determination as high as 0.99. Subsequently, research extended toward full-process optimization: S. Liu et al. (2021) proposed an ABC-BP neural network-based blending model targeting the overall mineral processing recovery rate; Wang et al. (2023) realized end-to-end prediction from copper concentrate blending to smelting using a PSO-tuned neural network. In terms of model interpretability, Tsae et al. (2023) integrated an artificial neural network with the Shapley method to analyze input variable importance; Ma, Zhang et al. (2023) combined SA2PSO with random forest to build a sintering blending recommendation model that balances cost, quality, and carbon emissions. In recent years, the potential of deep learning in real-time decision-making has been gradually explored. Zeb et al. (2024) predicted the gold concentrate grade of a flotation process half an hour in advance, and Chiarot Villegas et al. (2024) developed a Q-learning-based deep reinforcement learning model that achieved 90% crusher supply coverage during shift changes with sub-millisecond execution times. Sayedahmed (2025) proposes the use of an artificial neural network (ANN) model, specifically the radial basis function neural network (RBFNN), to classify blend quality in Egypt's Aswan region, confirming the model's effectiveness in identifying and improving blend quality. It also delves into the application of deep learning algorithms to forecast the gold concentrate grade of a flotation process half an hour in advance, a valuable tool for short-term decision-making, e.g., for optimizing operations and process control. Although neural network methods demonstrate great potential in prediction accuracy and end-to-end modeling, key bottlenecks still constrain their in-depth application in ore blending, including insufficient interpretability due to their black-box nature, heavy reliance on large-scale labeled data, the difficulty of adapting to dynamic working conditions with their offline and static characteristics, and inadequate integration of physical prior knowledge.

(4) Hybrid intelligent algorithms

Regarding hybrid intelligent algorithms, the research motivation stems from the inherent limitations of single algorithms in striking a balance between global exploration and local exploitation (Z. Li et al., 2026), as well as between convergence speed and population diversity. Zhao et al. (2012) integrated the global convergence of particle swarm optimization with the positive feedback mechanism of ant colony optimization to achieve fast and accurate solutions for sintering blending; Li et al. (2017) hybridized genetic algorithms and particle swarm optimization for multi-objective blending in deep bauxite mines, yielding better stability and convergence speed.  proposed an MOPSO-PIO hybrid algorithm to improve population diversity management for polymetallic open-pit blending, while (Rothwell et al., 2020) designed a hybrid grey wolf–particle swarm algorithm for short-term multi-element collaborative mining blending. These works have preliminarily validated the effectiveness of complementary algorithmic advantages, demonstrating superior solution performance over single algorithms on specific problems. However, most hybrid strategies remain at the level of simple serial concatenation or stage switching at the operational level, lacking in-depth mechanism design for synergistic effects between algorithms, resulting in limited hybrid gains; meanwhile, the expansion of parameter space and increased computational complexity are highlighting the need for more principled integration strategies that maximize synergistic effects while controlling computational costs.

#### 2.3.2.2. Other nonlinear ore blending models

Beyond intelligent algorithms, nonlinear ore blending models based on traditional mathematical programming, fuzzy mathematics, statistical analysis, and refined constraint modeling still play an irreplaceable role in specific scenarios (Karimi et al., 2022). In terms of traditional mathematical optimization, Yi et al. (2021) employed the response surface method to optimize sinter porosity to improve strength; Zhang et al. (2011) constructed a nonlinear programming model based on a multi-role decision support system to optimize blast furnace blending costs; S.-l. Wu et al. (2012) combined a "two-step method" with the simplex method, achieving stepwise decoupling of the proportioning calculations for iron ore and other materials, thereby significantly improving solution efficiency; and S. Feng et al. (2023) constructed an automatic multi-decision sintering blending model based on the OLS algorithm, capable of screening and proportioning 43 kinds of raw materials within 10 seconds, meeting the demands of variable-material production. In the realm of statistical analysis and fuzzy mathematics, GU et al. (2024) integrated clustering techniques to establish a multi-objective blending model, achieving grade-consistent unit division for blasted ore piles; Fernández-González et al. (2016) combined linear and partial correlation analysis with Sugeno fuzzy clustering to reveal complex interrelationships among variables and constructed a low-cost sintering blending model; and Bao et al. (2023) employed response surface Box–Behnken design and desirability function methodology to establish a nonlinear regression model between sintering raw material ratios and quality indicators, achieving multi-objective comprehensive optimization. Moosavi et al. (2014) integrated Lagrangian relaxation with genetic algorithms to address long-term open-pit mine production scheduling problems, enhancing large-scale problem-solving capability; and Huang et al. (2019) established a cost-minimization sintering blending model based on the complementarity of basic iron ore properties, achieving a blending cost reduction of 0.19%–4.19% and a fuel consumption reduction of 1.16–3.79 kg per ton of sinter. These methods provide a wealth of modeling tools for nonlinear ore blending problems from the perspectives of mechanism simplification, uncertainty representation, and constraint refinement.

Based on the previous examination of the principles and mechanisms of various non-linear ore blending techniques, there are clear distinctions between the different approaches in terms of search strategies, convergence behavior, reliance on problem structure, and data requirements. Particle Swarm Optimization (PSO), Genetic/Multi-objective Evolutionary Algorithms (GA/NSGA-II/III), Neural Networks/Deep Learning, Hybrid Intelligent Algorithms, and Traditional Mathematical Programming are systematically summarized in Table 5 along three dimensions: benefits, drawbacks, and relevant scenarios.

Table 5. A comparison of the benefits and drawbacks of various non-linear ore blending methods

| Method Category | Key Advantages | Main Limitations | Typical Use Cases |
|---|---|---|---|
| PSO | Simple structure, fast convergence, few parameters; suitable for continuous variables | Premature convergence in high dimensions; multi-objective handling lacks adaptive balancing | Dynamic ore blending, sintering recipe optimization |
| GA/NSGA | Strong global search; handles discrete/mixed variables; Pareto-based multi-objective | Slow convergence, parameter-sensitive; poor adaptation to dynamic conditions | Large-scale, multi-constraint ore allocation (multiple metals/unloading points) |
| Neural Networks | Excellent nonlinear mapping; supports end-to-end & real-time predictions (with RL) | Black-box, low interpretability; data-hungry; offline training fails with temporal drift | Nonlinear processes (sintering, BF), quality prediction, short-term decisions |
| Hybrid Algorithms | Combines exploration & exploitation strengths; highly adaptable | Complex structure, expanded parameter space; shallow mixing yields limited gains | High-dimensional, dynamic, multi-constraint complex problems |
| Traditional Mathematical Programming | Interpretable, solid theory; no training data; efficient for small-scale problems | Requires convexity/differentiability; no global guarantee for non-convex problems; poor scalability | Small, well-constrained problems (e.g., sintering porosity optimization) |
| Fuzzy & Statistical Methods | Handles uncertainty & complex relationships; integrates with response surfaces/clustering | Subjective membership functions; result stability sensitive to parameters | BF cost optimization, high-temperature performance prediction, multi-objective integration |

In conclusion, the idea of "proceeding from simple to complex and making a priori judgements" can be applied when choosing algorithms for realistic ore blending systems. This involves first determining the problem's convexity and scale, then identifying the types of variables and the number of objectives, and lastly assessing the requirements for data availability and interpretability. To further close the gap between data-driven and mechanism-driven approaches, future research could concentrate on knowledge-guided evolutionary optimization techniques and lightweight, interpretable deep learning frameworks.

Despite the advantages of nonlinear models in handling complex constraints, their industrial adoption remains limited due to three factors: (1) high parameter sensitivity requiring extensive tuning; (2) lack of interpretability ('black-box' nature) hindering operator trust; and (3) reliance on large volumes of high-quality historical data that are often unavailable in small-to-medium mines. In contrast, linear programming continues to dominate routine production due to its robustness, speed, and transparency.

### 2.4. Systematic ore blending

Systematic ore blending refers to the process of optimizing the entire supply chain—from mining and transportation to port blending, and on to sintering and blast furnace smelting at steelworks—through coordinated efforts across the entire process. Its core characteristic lies in the integrated coordination of multiple levels (strategic planning, tactical production scheduling, and operational control), multiple stakeholders (mining companies, port operators, and steel producers), and multiple objectives (cost, ore grade, energy consumption, carbon emissions, and logistics efficiency). Systematic ore blending, a crucial link between geological resources and beneficiation and smelting processes, has emerged as a research hotspot in the mining and metallurgical domains as global mineral resource development increasingly moves toward intelligence, precision, and green transformation (Zhang et al., 2026). In essence, systematic ore blending serves as an integration platform that consolidates the strengths of empirical rules, experimental findings, and mathematical models into a unified, full-chain framework. It does not replace the previous approaches but rather orchestrates them — using empirical heuristics for rapid decisions, experimental data for validation, and mathematical models for optimisation — to achieve end-to-end coordination from mine to smelter. Research on systematic ore blending has progressively moved from single-process optimization to full-process collaboration, and from experience-driven to data-intelligence-driven approaches, thanks to new information technologies like Industry 4.0, 5G + Industrial Internet (Cerqueus et al., 2025), and artificial intelligence(Runkana et al., 2024). Mines, ports, and steel companies are all part of the diverse technological system that has developed. Typical industrial cases from these sectors are listed in Table 6.

Table 6. Summary table of typical industrial cases for system ore blending

| Sector | Enterprise/Mine | Key technology/system | Main effect | Reference |
|---|---|---|---|---|
| Mining | Nan'niu molybdenum mine (China) | Pre-shift blending model + in-shift dynamic dispatching | Daily grade close to plant target | (J. Li et al., 2025) |
| | Ansteel Qidashan mine | Dynamic ore blending dispatching (4G/5G + BeiDou) | Transportation efficiency +5.5% | (Yao et al., 2023) |
| | Luoyang molybdenum (intelligent dispatch) | 5G+AI intelligent dispatching, UAV modelling, unmanned measurement | Promotes smart mining development | (Wang et al., 2026) |
| | Codelco Chuquicamata+Radomiro Tomic, Chile | Multi-mine sulfide ore blending | Compensates open-pit grade decline; 63% sulfide extraction capacity from RT treated | (Codelco, 2024) |
| Port | Intelligent mobile/precision blending system | PID constant-flow control + electronic scale feedback | High-precision blending, chute blockage warning | (Wen & Chen, 2026) |
| Mining + Port | BHP WAIO Newman Hub, Australia | CSMS + Blasor + BOLT | Pit-blend-ship continuous flow | (Patton et al., 2025) |
| | Mineral Resources Onslow Iron, Australia | Mine-to-ship integrated system; | First ore on ship ahead of schedule | (Deswik, 2024) |
| Steel | Steel Plant A (China) | Blending-sintering-BF model + neural network + error tracing | Fuel ratio −15.8 kg/t, benefit 1.39–6.94 USD/t HM | (Xiao et al., 2025) |
| | Online batching system | Machine learning + intelligent algorithm | Batching cost −4.10 USD/t | (B. Liu et al., 2021) |

In the mining sector, research on systematic ore blending focuses on grade balance, dispatching optimization, and multi-objective collaborative control. Chen et al. (2023) developed an ant colony-based mathematical model with an integrated sharing system to improve grade stability, while (Sun et al., 2025) addressed complex geological conditions at the Zhongguan iron mine via multi-objective optimization of iron grade, sulfur, lumpiness and moisture. (Yao et al., 2023) combined 4G/5G, BeiDou and IoT to create a dynamic dispatching system that raised transportation efficiency by 5.5% at the Ansteel Qidashan mine, and (Wang et al., 2026) demonstrated 5G+AI at Luoyang Molybdenum through intelligent dispatching, unmanned surveying and UAV modelling. In ports, (Wen & Chen, 2026) developed a PID-based constant-flow precision blending system with real-scale feedback, air cannons and vibrators, achieving high-accuracy blending and chute blockage warning. (Zheng, 2022) further improved mobile belt conveyors using 5G, remote control and video monitoring, decoupling blending from loading/unloading to enhance flexibility. In steel enterprises, (Yang Li et al.,

2023) shifted from local to global line-cost optimisation, and (Xia et al., 2023) built a web-based pre-integrated model balancing benefit and cost. (Xiao et al., 2025) linked ore blending, sintering and blast furnace operations with a neural-network-based cross-process model plus error tracking, reducing the fuel ratio by 15.8 kg/t (benefit 1.39–6.94 USD/tHM). (Guo et al., 2025) combined machine learning, GA, and linear programming; (S. Liu et al., 2021) proposed an online batching system that lowered costs by 4.10 USD/t; and (Xu et al., 2025) used a local linear iteration method (MATLAB+MySQL) to solve nonlinear blending within 10 seconds, cutting sinter cost by 0.81 USD/t.

Methodologically, traditional operations research has been superseded by data-driven and hybrid intelligent models. (Saavedra et al., 2025b) examined data science and machine learning for real-time decision-making, feature engineering and data quality; (Duanni et al., 2024) combined deep residual networks with LSTM to predict FeO content from image and time-series data; and (Cerqueus et al., 2025) discussed AI applications in production planning, fault diagnosis and smart manufacturing under Industry 4.0. Together, these efforts have built a multi-level technical system covering mines, ports and steel plants, showing clear trends toward full-process integration, model coordination and data-driven operation. Systematic ore blending is evolving from a single-process optimizer into a platform supporting efficient resource use and low-carbon output. Nevertheless, key bottlenecks remain: data silos and cross-enterprise sharing barriers, insufficient real-time performance of nonlinear models, poor generalizability and high maintenance costs, lack of interactive trade-off mechanisms for multi-objective conflicts, and integration difficulties with existing linear programming systems. Future advances will likely come from edge intelligence, digital twins, federated learning, knowledge-data dual-driven methods, and autonomous driving integrated with 5C edge control. These directions will drive systematic blending toward real-time, autonomous, and globally optimized solutions (Nobahar et al., 2026).

### 2.5. Summary

The four ore blending techniques vary significantly in terms of accuracy, cost, data reliance, and real-time responsiveness, according to the analysis above (Table 7). Experimental beneficiation is appropriate for low-grade, multi-impurity ores where interaction effects need to be validated but there is a lack of large-scale data; however, it suffers from high computational cost and limited combinatorial exploration. Despite being free and fast, empirical blending is only suitable for small-scale facilities with basic mineralogy and no history data due to its low accuracy (improvement <10%) and poor reproducibility. Using linear programming, NSGA III, or DRL, model-based dressing provides multi-objective, strongly nonlinear optimization with gains of 15–30% when sufficient and precise historical data are available. Nonlinear models, however, converge slowly (NSGA III needs 800–1,200 iterations), making them appropriate for offline situations that don't demand real-time reaction, like high temperature metallurgy or polymetallic ores. At the highest level, system-level ore allocation combines 5G, AI, and digital twins to enable global coordination and real-time disturbance reaction, resulting in performance gains of more than 30%. This strategy focuses on integrated supply chains that include massive mines, ports, and steelworks, but it is costly and has substantial end-to-end data collection issues.

To further provide a quantitative benchmark for practitioners under a representative industrial scenario (medium-scale polymetallic mine, 5000 t/d, 3 deleterious elements, 2 process objectives), Table 8 compiles estimated performance indicators for the four ore blending approaches based on literature data. These values illustrate relative differences in solution time, prediction accuracy, improvement potential, and data requirements, addressing the lack of quantitative comparison noted in previous reviews.

To guide practitioners in selecting appropriate strategies based on ore complexity and data availability, a hierarchical decision-making framework is established (Fig. 3). The framework first differentiates paths according to mineralogical complexity and data scale: for low complexity and small datasets, empirical or experimental blending is directly adopted. When complexity is high and data are abundant, the process branches by the number of objectives and real-time requirements – linear programming is applied to single-objective scenarios; NSGA-III/DRL offline optimisation is used for multi-objective scenarios without real-time constraints; and system-level blending with digital twins is deployed for multi-objective scenarios requiring real-time closed-loop control. This framework provides a clear trade-off among accuracy, cost, data dependency, and response speed, offering a practical logic for tailoring ore blending solutions to different technical capabilities and production scenarios.

Table 7. A comparison of four ore blending techniques- including empirical, experimental, model-based, and systematic approaches

| Stage | Principle | Advantage | Limitation | Suitable for | Representative references |
|---|---|---|---|---|---|
| Empirical | Operator experience | Simple, fast | Low accuracy, experience-dependent | Small mines | (He, 2019; Zhao et al., 2023) |
| Experimental | Lab-scale tests | Reliable, intuitive | Long cycle, high cost | New ore types | (Li et al., 2020) |
| Mathematical (linear) | LP/GP/MILP | Fast, interpretable | Cannot handle nonlinearity | Clear grade constraints | (Wang et al., 2017) |
| Mathematical (nonlinear) | PSO/GA/NN | High accuracy, multi-objective | Parameter-sensitive, black-box | Polymetallic / sintering | (Wang et al., 2025) |
| Systematic | 5G+AI+digital twin | Full-chain synergy | High investment, integration difficulty | Large integrated enterprises | (Xiao et al., 2025) |

Table 8. Quantitative performance comparison of ore blending methods under a typical medium-scale polymetallic mine scenario (estimated ranges from literature)

| Indicator | Empirical | Experimental | Linear | Nonlinear | Systematic |
|---|---|---|---|---|---|
| Solution time per batch (seconds) | < 1 | 3600–7200* | < 1 | 30–300 | 1–10 |
| Grade prediction error (RMSE, %) | > 15% | 5–10% | 8–12% | 3–6% | 2–4% |
| Recovery improvement vs. empirical baseline | – | +5–10% | +8–15% | +15–25% | +20–30% |
| Number of constraints handled | ≤ 3 | ≤ 5 (manual) | 5–15 | 10–30 | 20–50+ |
| Objectives handled simultaneously | 1 | 1–2 | 1–2 | 3–6 | 3–10 |
| Convergence iterations (typical) | N/A | N/A | N/A (direct solve) | 200–1200 (GA/NSGA-III) | 50–200 (real-time adaptation) |
| Data required (historical cases / lab runs) | none | 20–50 runs | 50–200 rows | 500–5000 rows | 5000+ rows + real-time sensor |
| Interpretability (1=low, 5=high) | 5 | 5 | 5 | 2–3 | 2–4 |
| Implementation cost (relative) | Very low | Medium | Low–Medium | Medium–High | Very high |
| Typical payback period (months) | N/A | 6–12 | 3–8 | 6–18 | 12–36 |

*For experimental blending, "solution time" refers to the laboratory cycle (sampling, sample preparation, batch flotation/sintering tests), not computational time.

**Note:** All values are typical ranges extracted from the cited literature (e.g., linear programming: Zhou et al., 2022; nonlinear algorithms: Xiang et al., 2025; systematic blending: Xiao et al., 2025; Yao et al., 2023) and illustrate relative performance trends rather than absolute guarantees.

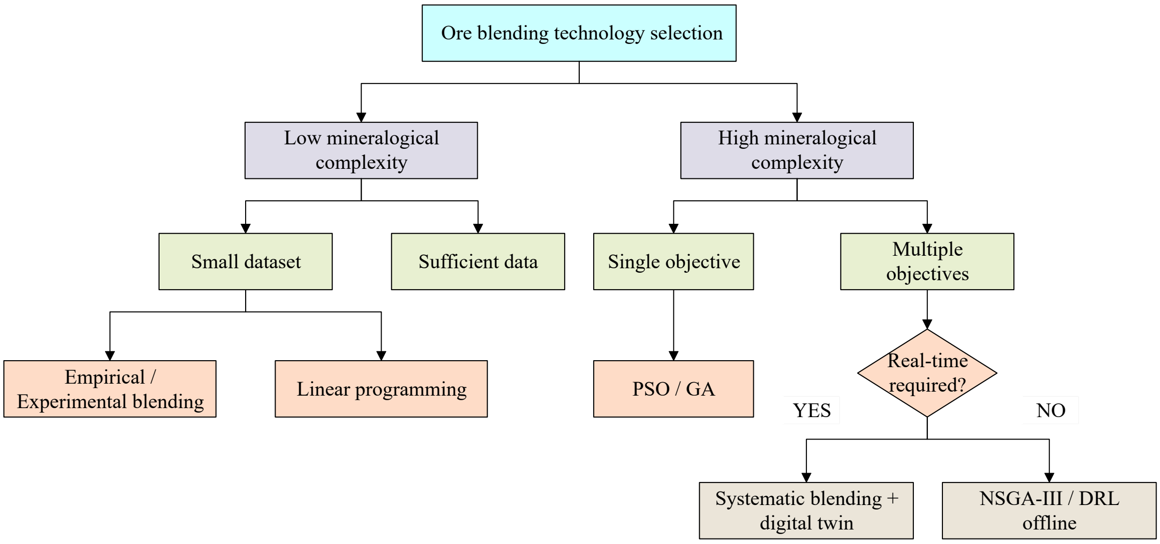


Fig. 3. A hierarchical decision-making framework for selecting ore blending strategies based on ore complexity and data availability

## 3. Barriers in industrial application

Although advanced ore blending methods have demonstrated great promise, their widespread industrial application is hampered by four interrelated obstacles (Fig. 4). These obstacles feed off one another in a vicious cycle: insufficient data leads to poor model training, which results in poor adaptability (prediction errors up to 10%); inaccurate models necessitate manual tuning, which exacerbates computational inefficiency; resolving this complexity calls for interdisciplinary talent (mineral processing + data science), which is hard to come by; without qualified staff, neither data standards nor models can be improved (Deloitte, 2025).

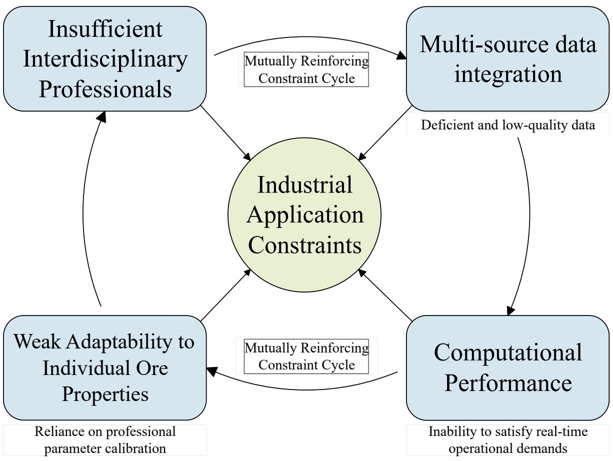


Fig. 4. Industrial application constraint cycle: Key factors and their mutually reinforcing relationships hindering ore blending technology upgrading

### 3.1. Difficulties in multi-source data integration

Integrating data from mines, processing facilities, smelters, and transportation links is necessary for intelligent and systematic ore blending; nevertheless, these entities frequently run separate systems with disparate standards, formats, and storage. Missing values, mistakes, and redundancies are common in both organized (grades, volumes) and unstructured (pictures, videos) data types (Z. Zhang et al., 2025). For instance, a significant global mining company had to deal with varying data standards across several iron ore locations and a 15% missing rate, which resulted in model inaccuracies that prevented large-scale deployment (Wang et al., 2024).

### 3.2. Computational efficiency of complex models

Nonlinear and systematic models have significant computational complexity since they are multi-objective, multi-constraint, and high-dimensional. The majority of businesses lack the on-site resources necessary to solve these models quickly enough to make real-time improvements. Furthermore, complicated models are prone to local optima and sensitive to initial values and parameter calibration (Hanhiniemi & Powell, 2022). Real-time optimization was not possible for a well-known European steel company due to solution timeframes of two hours per blending scheme; they were compelled to reduce the model structure at the expense of accuracy (Zeb et al., 2025).

### 3.3. Adaptability of general models to specific ore types

The majority of blending models in use today are generic and do not adequately account for the inherent qualities of certain ores (e.g., hematite vs. magnetite, high phosphorus vs. low phosphorus phosphate). These models frequently exhibit lower forecast accuracy when applied to particular ore types because of differences in mineral composition, physicochemical characteristics, impurity occurrence, and downstream response. For instance, a generic iron ore blending model might be effective for magnetite, but it could result in prediction errors of up to 10% for hematite with a high impurity content when it comes to sintering performance (Sinche Gonzalez, 2020). The absence of deep adaptive mechanisms to capture differential behavior is the primary culprit.

### 3.4. Shortage of interdisciplinary talent and industrial experience

Advanced ore blending integrates mineral processing, computer science, AI, IoT, and mathematical optimization. Professionals with a broad skill set are needed for its application and research. But there is a severe lack of such talent in the industry. With limited ability to create and implement sophisticated models, most enterprise employees remain focused on traditional mineral processing. Data science and intelligent optimization are infrequently included in mining education courses (Deloitte, 2025). As a result, even well-designed models frequently don't get deployed or maintained correctly.

## 4. Development trends

Against the backdrop of continuously depleting global mineral resources, increasing complexity of ore properties, and escalating demands on production processes, ore blending technology is poised for new development opportunities. Considering the current state of research progress and industrial practice, three core trends are expected to shape the future of ore blending technology research. These trends correspond directly to the previously identified barriers.

### 4.1. Ore property-based experimental research and open-access databases

The design of blending schemes is fundamentally based on ore characteristics. In the future, systematic experimental studies on various ore types and their downstream impacts will be conducted, with an increasing emphasis on the intrinsic correlations between ore attributes and blending outcomes. The proposed open-access database will be a crucial step in addition to this. In order to provide high-quality data support for training and validating intelligent models, such a database would integrate chemical, mineralogical, particle size, physicochemical, blending, and process performance data for different ores (iron, copper, manganese, phosphate) worldwide. This would address the current challenges associated with multi-source data integration (Moyo et al., 2025).

### 4.2. Hybrid intelligent models with real-time dynamic adjustment

The foundation of contemporary technology is still mathematical model-based blending. Future intelligent models will go toward real-time dynamic adjustment and hybrid architectures. On the one hand, computational efficiency restrictions can be overcome by integrating neural network prediction with evolutionary algorithm optimization to produce accurate modeling and effective solutions. However, incorporating reinforcement learning enables real-time learning and adaptive adjustment. This will address the limited adaptability of fixed models by automatically updating blending schemes in response to dynamic changes in ore characteristics and production conditions. Environmental indicators like $CO_2$ emissions will increasingly be included in multi-objective models (Powell & Morrison, 2007).

### 4.3. Integrated medium-to-long-term blending systems for resource consolidation

The need for long-term resource usage planning grows as high-grade resources become scarcer. Traditional mixing does not support long-term allocation across the entire industrial chain and is often limited to short-term, local applications. Integrated medium-to-long-term blending systems will be the main focus of future technologies. An integrated system including the whole mining-industrial chain (mine, processing, smelting, and transportation) can be created using big data, IoT, and digital twins. In order to improve resource allocation efficiency, port-centered cross-enterprise collaborative blending hubs (such as the "Precision-Blended Ore" multimodal alliance) can connect several mines and businesses. This allows for centralized blending and unified distribution.

## 5. Conclusions

Ore blending technology has evolved from empirical judgment to experimental validation, mathematical optimization, and systematic integration across the mining–beneficiation–metallurgy chain. This review provides a critical synthesis of the four approaches, identifies persistent barriers, and outlines actionable priorities.

(1) Empirical blending is fast but inaccurate, suitable only for small-scale operations. Experimental blending offers reliable, ore-specific validation but is time-consuming and costly. Linear programming remains the workhorse for clear grade constraints due to its speed and interpretability. Nonlinear intelligent algorithms (PSO, GA, neural networks) achieve higher accuracy (recovery improvement 15–25%) for polymetallic or high-temperature processes, but require large datasets (≥500 samples), careful tuning, and sacrifice transparency. Systematic blending, integrating 5G, AI, and digital twins, delivers full-chain coordination with >30% performance gains, yet demands high investment and data infrastructure, currently feasible only in large smart mines.

(2) Four interconnected obstacles hinder industrial adoption: (i) multi-source data integration (inconsistent standards, missing values); (ii) low computational efficiency of nonlinear models for real-time control; (iii) poor model adaptability across ore types (prediction errors up to 10% when transferred); and (iv) shortage of interdisciplinary talent. These factors reinforce each other, slowing technology upgrading.

(3) Three directions are recommended: (i) ore property-based experimental research with open-access global databases to supply high-quality training data; (ii) hybrid intelligent models (neural networks + evolutionary optimization + reinforcement learning) for real-time dynamic adjustment; and (iii) integrated medium-to-long-term blending systems using digital twins and IoT to coordinate the entire mining–smelting chain.

In summary, transitioning from experience-driven to data-intelligent, full-chain synergistic blending requires not only algorithmic advances but also systematic data infrastructure, cross-disciplinary training, and context-aware method selection. This review provides a structured reference to support that transition and the sustainable development of global mineral resources.

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