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Bi-Objective Optimization in Steelmaking: Balancing Scrap Costs, Energy Consumption, and Steel Quality

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Abstract: In this paper, we present a bi-objective optimization approach for steelmaking, with a focus on scrap-loading. The first objective minimizes the costs associated with raw materials and energy, while the second one minimizes deviation from the required chemical composition of the final product. We analyze key metrics of scrapyard composition, such as size, similarity, and variance, and assess their impact on production outcomes. The results show that scrapyard configuration plays a crucial role in both cost and quality, with larger and optimized scrapyards leading to improved efficiency. By examining trade-offs using a lexicographic approach, this research provides valuable insights for bridging theoretical models with practical strategies aimed at achieving sustainable and cost-effective steel production.

Keywords: Steel production, scrap selection, bi-objective optimization, lexicographic approach

1. INTRODUCTION

In modern steelmaking, the optimization of the scrap-loading process plays a crucial role in improving both the quality of the chemical composition of the steel and the economic efficiency of the production process. As steel production increasingly relies on scrap as its primary raw material (World Steel Association, 2021), the variability in its chemical composition and market availability poses a significant challenge in achieving precise steel specifications. Scrap materials are inherently variable, both across different grades and within the same grade. These fluctuations in composition can affect key aspects of the production process, such as energy consumption, operational costs, and product quality. Therefore, achieving an optimal scrap blend is essential to minimize material waste, reduce energy use, and ensure the production of high-quality steel.

Some of the above-defined issues have already been addressed in the specialized literature. The classical blending problem applies not only to the steelmaking process but also to brass production (Sakallı et al., 2011) and other fields, where the final product results from mixing different components. The variability of scrap in steel production is another aspect addressed in the literature. Yang et al. (2018) address the issue using robust optimization and scheduling under time-of-use electricity tariffs, while Rong and Lahdelma (2008) propose fuzzy chance-constraint programming. Other studies mainly focus on the scheduling problem to minimize total costs (Tang et al., 2014; Hubert Missbauer and Stadler, 2009) or combine both scheduling and energy costs (Su et al., 2023). Additionally, a few works investigate the optimization of scrap cost and composition for single casting (Kowalik, 2019), which is also a key aspect of our study. This paper differs from the existing literature by examining how scrapyard composition affects final chemical properties, production costs, and energy consumption. Moreover, we use the theoretical chemical quality introduced by the scrap as a metric to evaluate the composition of the scrap load. By examining the relationships between scrap types, scrapyard composition, energy consumption, and cost-effectiveness, we provide insights into how steel producers can optimize their processes and define better-suited scrapyards. This work aims to develop a tool for steel production decision-makers to model scrap selection, highlighting the impact of scrapyard composition on outcomes. Unmanaged variations in scrap quality or cost could compromise profitability and limit the production of certain steel types, underscoring the need for a deeper understanding of scrapyard influence. To address this, our approach integrates theoretical modeling with the practical complexities of real-world steel production.

The remainder of this article is structured as follows. Section 2 outlines the optimization problem, while Section 3 presents a bi-objective mixed-integer programming formulation. Section 4 details the solution methodology. Section 5 focuses on our experimental analysis, describing the realistic instances used, the tests performed, and the results obtained. Finally, Section 6 discusses conclusions and potential directions for future research.

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2. PROBLEM DEFINITION

Let $R = A \cup S$ represent the set of raw materials, where S denotes the scraps set and A represents the ferroalloys set. Let E be the set of various chemical elements present in the raw materials. For a given type of steel, each chemical element $e \in E$ has a predefined minimum β^e_{min} and maximum β^e_{max} percentage, as well as a target value $\overline{q}^e$. Each raw material $r \in R$ has known chemical compositions α^e_r for each element $e \in E$, along with a price p_r, a liquid coefficient μ_r, and a specific energy parameter m_r. Together with the energy cost γ, these parameters determine the theoretical melting cost. The required production amount is determined each time a new steel batch needs to be produced. To achieve the desired quantity Q_{steel}, each material must be properly scaled by its liquid coefficient, which indicates how much raw input is converted into liquid steel. Since all materials are processed in an electric arc furnace (EAF), an important aspect is the furnace's maximum capacity, denoted as C^{max}, which must never be exceeded for operational and safety reasons. Another factor influencing the target chemical composition for a specific type of steel is the residual liquid mold already present in the EAF, denoted by λ^e, which accounts for the small amount of steel remaining from the previous casting. However, relying solely on this information overlooks important practical challenges in production. A key issue is that not all materials are handled in the same way. To address this, we introduce a parameter δ, which measures the ease of moving materials from the scrapyard to the EAF, without affecting ferroalloys. While industrial cranes generally operate on a kilo scale, accurately loading precise amounts into the furnace can be challenging. These handling difficulties can lead to delays or unintended variations in scrap composition. Hence, to better align the model with real-world production, two additional parameters are introduced: M_1, representing the available scrap supply, and M_2, the minimum scrap quantity required in the EAF that ensures efficiency. While adding smaller scrap amounts can be cost-effective, it may increase loading times and reduce overall productivity.

The main objective of the problem is to minimize the total cost, which is the sum of the scrap cost and the energy cost associated with the melting process, while also optimizing the final steel chemical composition (quality). We refer to this problem as the Cost-Quality Scrap Selection Optimization Problem (CQ-SSOP).

3. MATHEMATICAL FORMULATION

In this section, we present a Mixed-Integer Quadratic Programming (MIQP) formulation for the CQ-SSOP. To this end, we introduce the following sets of decision variables. For each scrap $s \in S$, x_s represents the amount required for production, l_s denotes the integer quantity of scrap, and z_s is a binary variable, equal to 1 if scrap s is used, and 0 otherwise. For each ferroalloy $a \in A$, we define y_a as the amount used in the production process. Additionally, we introduce an auxiliary variable q, representing the quantity of steel molded in the EAF. Then, the problem can be formulated as follows:

$$f_1 = \min \sum_{s \in S} (p_s + m_s \cdot \gamma) x_s + \sum_{a \in A} (p_a + m_a \cdot \gamma) y_a \quad (1)$$

$$f_2 = \min \sum_{e \in E} \left(\frac{\sum_{s \in S} \alpha^e_s \cdot x_s + \lambda^e - \overline{q}^e}{\theta^e} \right)^2 \quad (2)$$

subject to

$$\sum_{s \in S} \alpha^e_s \cdot x_s + \sum_{a \in A} \alpha^e_a \cdot y_a + \lambda^e \leq \beta^e_{max} \cdot q, \quad \forall e \in E \quad (3)$$

$$\sum_{s \in S} \alpha^e_s \cdot x_s + \sum_{a \in A} \alpha^e_a \cdot y_a + \lambda^e \geq \beta^e_{min} \cdot q, \quad \forall e \in E \quad (4)$$

$$q = \sum_{s \in S} \mu_s \cdot x_s + \sum_{a \in A} \mu_a \cdot y_a \quad (5)$$

$$q \geq Q_{steel} \quad (6)$$

$$\sum_{s \in S} x_s + \sum_{a \in A} y_a \leq C^{\max} \quad (7)$$

$$x_s \leq M_1 \cdot z_s, \quad \forall s \in S \quad (8)$$

$$x_s \geq M_2 \cdot z_s, \quad \forall s \in S \quad (9)$$

$$x_s = \delta \cdot l_s, \quad \forall s \in S \quad (10)$$

$$z_s \in \{0,1\}, \; x_s \geq 0, \; l_s \in \mathbb{Z}^+_0, \quad \forall s \in S \quad (11)$$

$$y_a \geq 0, \quad \forall a \in A. \quad (12)$$

The objective function (1) minimizes the total cost, which includes both the market price of the raw materials and the energy costs associated with melting scraps and ferroalloys. The objective function (2) measures the deviation from the predetermined quality target point $\overline{q}^e$ for each chemical element in the scrap. This deviation is scaled by a factor of θ^e to normalize the impact of different chemical ranges across elements. The squared deviation is then minimized to reduce the discrepancy between the actual and desired chemical composition. Constraints (3) and (4) enforce the upper and lower limits for each chemical element required to produce the specified steel type. These constraints account for contributions from scraps, ferroalloys, and the residual liquid mold in the furnace. Since the chemical composition requirements depend on the total steel produced, these limits are scaled based on the actual production volume. Constraint (5) ensures that the total amount of scrap and ferroalloy used is consistent with the desired steel production amount, which is essential for meeting the chemical requirements dictated by constraints (3) and (4). Constraints (6) and (7) impose weight restrictions: the first guarantees a minimum steel production quantity, while the second ensures that the total load does not exceed the EAF capacity. Constraints (8) and (9) regulate the quantity of selected scrap $s \in S$. If scrap s is selected, its quantity must be within the predefined bounds M_1 (maximum) and M_2 (minimum), reflecting real-world handling limitations in the production process. Constraint (10) accounts for the practical conditions of the production environment, allowing for more precise resource management. Finally, the variable domains and integrality restriction are specified in Constraints (11) and (12).

4. LEXICOGRAPHIC APPROACH

Solving a multi-objective program requires specialized methods to identify Pareto-optimal solutions. Some approaches, such as the lexicographic method, follow an *a-priori* strategy, where the decision-makers specify their preferences by establishing a strict priority order among objectives (see, for instance, Bonomi et al., 2024, 2025). In contrast, a-posteriori methods, including the weighted sum approach, the ϵ-constraint method, and NSGA-inspired heuristics, generate or approximate the set of Pareto-optimal solutions, allowing decision-makers to explore trade-offs before making a selection.

In this work, we employ a two-step lexicographic optimization approach. The method proceeds as follows. In the first step, one objective function (f_P) is optimized, disregarding the other one. In the second step, the non-prioritized objective function (f_{NP}) is optimized while imposing a constraint on the deterioration of the first objective. Let f_P^* be the optimal value obtained in the first step. In the second step f_{NP} is optimized under the additional constraint:

$$f_P \leq f_P^*(1+w)$$

where $0 \leq w \leq 1$ represents the maximum allowed percentage degradation of f_P with respect to f_P^*. We denote this general two-step optimization procedure as $(f_{NP}|f_P, w)$.

In our specific case, either f_1 and f_2 can be prioritized, allowing us to either minimize total cost first and maximize steel quality second, or reverse the order. Furthermore, by adjusting the w parameter, we can control trade-offs between the two objectives. Since f_2 is a quadratic function, the model formulation changes depending on its priority. When f_2 is the non-prioritized objective, the model remains quadratic in the objective function. Conversely, when f_2 is prioritized, it introduces a quadratic constraint. Although the inclusion of quadratic elements increases the complexity of the problem, all resulting models can still be efficiently solved using state-of-the-art commercial solvers.

5. EXPERIMENTAL ANALYSIS

This section presents the experiments conducted to derive managerial insights. In particular, Section 5.1 describes the generation of benchmark instances, while Sections 5.2 and 5.3 analyze the results obtained under two scenarios: one where no deterioration of the prioritized objective is allowed, and another where a controlled deterioration is permitted.

The mathematical model was implemented in Java 21. All experiments were conducted on a Manjaro 23.1 system equipped with a Ryzen 5 5600U 12-core processor and 42 GB of RAM, using Gurobi 10.0.1 as MIQP solver. All available threads were used during the experiments.

5.1 Instances

The instance generation process begins by defining the reference quality point $\overline{q}^e$ for each chemical element as the midpoint between its minimum and maximum requirements when steel production is at its minimum (i.e., when $q = Q_{steel}$). To normalize these values, we use the parameter θ^e, which represents the difference between the maximum and minimum quantities under minimal production. Additionally, the liquid mold composition, λ^e, is defined as the mean composition across all steel types. The parameter δ is defined as 100 Kg, while M_1 is set at 50000 Kg and M_2 at 2000 Kg.

A key aspect of the instance generation is the variety of steel types considered. The real-world chemical compositions of all steel types are crucial for ensuring both the applicability of the analysis and the accuracy of the model. To achieve this, we randomly select 10 different steel types from the standards defined in Bringas (2004). For each selected type, we generate 9 additional variants by randomly sampling the percentage of each chemical element within its allowed range defined by the standard. These variants, together with the original steel types, result in a total of 100 different steel types and chemical compositions for testing our model.

The primary focus of our analysis is on the scrapyard composition and its impact on the solution. We define three indicators to characterize the scrapyard: 1) the number $|S|$ of different scrap types allowed in the scrapyard, 2) the similarity (Sim) between the scrapyard and a target chemical composition, and 3) the internal chemical dispersion ($Disp$) of the scrapyard. We consider 3 values for each parameter, resulting in 27 unique scrapyard combinations. To mitigate sampling effects, we generate 10 scrapyards for each combination, producing a total of 270 scrapyards.

For scrapyard size, we consider values of 8, 12, and 18 scrap types. This allows us to assess how variations in scrapyard size influence production, which is particularly relevant in plants where handling large quantities of different scrap types is logistically challenging. Additionally, it provides insights into how raw material shortages affect production and how adjustments can mitigate these effects.

The parameter Sim measures how closely a scrapyard matches a target chemical composition. The target, defined by the decision maker, can vary depending on the context. In our study, the mean composition for steel types was used. Three classes are defined based on cosine similarity, which computes the cosine of the angle between two vectors (the target chemical composition and the scrapyard composition) as a metric to quantify their difference: low (L), medium (M), and high (H). These classes differ by 5%.

The parameter $Disp$ quantifies the chemical dispersion within the scrapyard. It is computed as the mean of the variance of each chemical element, normalized by its allowed chemical range. Three classes are identified: low (L), medium (M), and high (H).

5.2 Trade-off results when f_P worsening is not allowed

In this set of experiments, we analyze the average cost and quality of a single casting across all combinations of scrapyards, parameters, and steel types under the constraint that the primary objective cannot deteriorate with respect to its optimal value.

Table 1 presents the results obtained from solving $(f_2|f_1, 0)$, where the total cost is divided into the contribution given by the ferroalloy cost (Fa), the scrap cost (Sc), and the energy cost (En). Several insights emerge from this cost assessment. When both scrapyard size and similarity are at their lowest, a high proportion of ferroalloys is used, leading to increased costs. This suggests that while smaller scrapyards may be logistically efficient, they can drive up overall production costs. Notably, the average amount

		$\|S\| = 8$				$\|S\| = 12$				$\|S\| = 18$			
		Cost Components %			Total Cost	Cost Components %			Total Cost	Cost Components %			Total Cost
Sim	*Disp*	Fa	Sc	En	Avg [StDev]	Fa	Sc	En	Avg [StDev]	Fa	Sc	En	Avg [StDev]
L	L	17.9	73.2	9.3	637.34 [320.91]	3.4	86.1	10.5	491.95 [117.05]	4.0	85.1	11.0	471.43 [131.01]
L	M	29.2	63.2	8.8	779.07 [430.57]	9.2	81.1	9.8	550.29 [214.46]	5.3	84.3	10.4	519.50 [221.44]
L	H	22.5	69.4	11.3	722.01 [429.64]	12.1	78.6	9.5	576.66 [267.22]	7.6	81.4	11.1	493.37 [173.76]
	Avg:	23.2	68.6	9.8	**712.81 [393.71]**	8.2	82.0	10.0	**539.63 [199.58]**	5.7	83.6	10.8	**494.77 [175.40]**
M	L	10.2	79.6	10.4	521.60 [182.81]	5.8	83.7	10.6	502.78 [225.51]	5.0	84.0	11.1	459.66 [133.65]
M	M	15.3	74.9	11.8	565.55 [234.46]	5.6	83.9	11.5	488.76 [144.98]	2.9	85.6	11.7	438.99 [105.08]
M	H	19.0	72.3	18.8	642.22 [314.55]	6.3	82.8	12.1	484.82 [178.28]	2.1	87.0	11.3	458.53 [87.21]
	Avg:	14.9	75.6	13.7	**576.46 [243.94]**	5.9	83.5	11.4	**492.12 [182.92]**	3.3	85.5	11.4	**452.39 [108.65]**
H	L	6.5	83.0	10.7	481.64 [137.70]	4.6	83.2	12.7	443.1 [130.56]	3.0	84.7	12.4	427.41 [112.00]
H	M	4.4	84.5	12.8	474.49 [121.03]	5.1	83.5	13.0	452.59 [127.45]	4.3	83.4	12.4	423.69 [128.99]
H	H	13.2	76.7	12.9	525.39 [231.35]	7.9	80.8	12.9	472.85 [159.30]	4.8	82.9	12.4	424.32 [117.58]
	Avg:	8.0	81.4	12.1	**493.84 [163.36]**	5.9	82.5	12.9	**456.17 [139.10]**	4.1	83.7	12.4	**425.14 [119.52]**
Overall Avg:		15.4	75.2	11.9	**594.37 [267.00]**	6.7	82.6	11.4	**495.97 [173.87]**	4.3	84.3	11.5	**457.43 [134.52]**

Table 1. Costs distribution

of scrap used across all combinations remains consistent, with about 4 scrap types used per casting. Thus, costs are strongly influenced by the scrapyard composition. Regarding size, we can observe a cost decrease of more than 16% when increasing scrapyard size from 8 to 12, with an additional reduction of 7% from 12 to 18. These results highlight the significant impact of scrapyard size on production costs. However, determining the optimal size can be challenging due to exogenous factors such as raw material availability, which can affect both the daily scrapyard size and costs. In terms of results stability when these exogenous events occur, the chemical dispersion of a scrapyard is more easily managed than its similarity, as the latter depends heavily on market and customer demands. The impact of the chemical dispersion $Disp$ is less straightforward and appears to be correlated with the parameter Sim. The data suggest that mid-level dispersions minimize costs, whereas low or high dispersions tend to increase them. Therefore, decision-makers should aim to create scrapyards with balanced but not excessively sparse chemical distributions to reduce costs. Notably, energy consumption remains largely unaffected by scrapyard size, similarity, or chemical dispersion. This implies that energy costs related to scrap selection are relatively stable and do not exhibit strong dependencies on the defined scrapyard parameters.

Sim	*Disp*	$\|S\| = 8$	$\|S\| = 12$	$\|S\| = 18$
L	L	2.26	1.02	0.46
L	M	3.69	1.57	0.55
L	H	2.70	1.58	0.77
	Avg:	2.88	1.39	0.60
M	L	3.75	1.11	0.79
M	M	2.96	2.26	0.92
M	H	4.48	2.25	0.64
	Avg:	3.73	1.87	0.79
H	L	3.67	2.01	0.96
H	M	3.71	2.98	1.83
H	H	4.80	2.99	1.66
	Avg:	4.06	2.66	1.48
Overall Avg:		3.56	1.97	0.95

Table 2. Square deviation from $\overline{q}_e$

Table 2 presents the results of $(f_1|f_2, 0)$, i.e., the optimization of the final chemical quality as the primary objective. The results confirm previous trends, highlighting that an increase in scrapyard size positively impacts the final chemical quality across all parameter combinations. Specifically, increasing the size from 8 to 12 improves the chemical quality by approximately 44%, while further increasing it from 12 to 18 leads to an additional 51% improvement. A notable difference compared to cost minimization is that increasing Sim negatively affects the chemical quality. Moving from low to medium similarity leads to an average worsening of quality across all sizes of approximately 32%, while moving from medium to high results in a further reduction of about 46%. This highlights the importance of accurately estimating future production requirements to maintain fine control over chemical quality. $Disp$ also plays a key role. Low dispersion enhances chemical quality, as chemically similar scraps make it easier to achieve target compositions. Conversely, high dispersion introduces greater variability, making it more challenging to meet exact chemical specifications. In summary, chemical quality is more sensitive to future production requirements (captured by Sim) but can be improved by maintaining low chemical dispersion ($Disp$) and larger scrapyard sizes.

5.3 Trade-off results when f_P worsening is allowed

Since our model includes two objective functions, understanding the interplay between them is crucial. Figures 1 and 2 illustrate how the objectives relate to each other under different percentage worsening of the prioritized objective function (reported on the horizontal axis). Figure 1 presents the results of $(f_1|f_2, w)$ for different values of w (0, 5, 10, 25, 50, 75, and 100). The case $(f_2|f_1, 0)$ is also added with the label "Optimal". Figure 2 shows the results for $(f_2|f_1, w)$, with the same possible values of w, and as "Optimal" the case in which $(f_1|f_2, 0)$. Both figures display results for all 27 parameter combinations in a 3×3 grid. The columns represent increasing $Disp$ (from left to right), while the rows represent increasing Sim (from top to bottom). Within each plot, the three different sizes are analyzed. This approach allows us to evaluate how the worsening of one objective function impacts the other, helping decision-makers identify strategies and promising trade-offs.

The analysis in Figure 1 shows that maintaining tight control over chemical quality comes at a significant cost, as expected. Specifically, even a small 5% deterioration in quality can reduce costs by approximately 100 €/ton. Increasing the scrapyard size lowers costs, with a linear

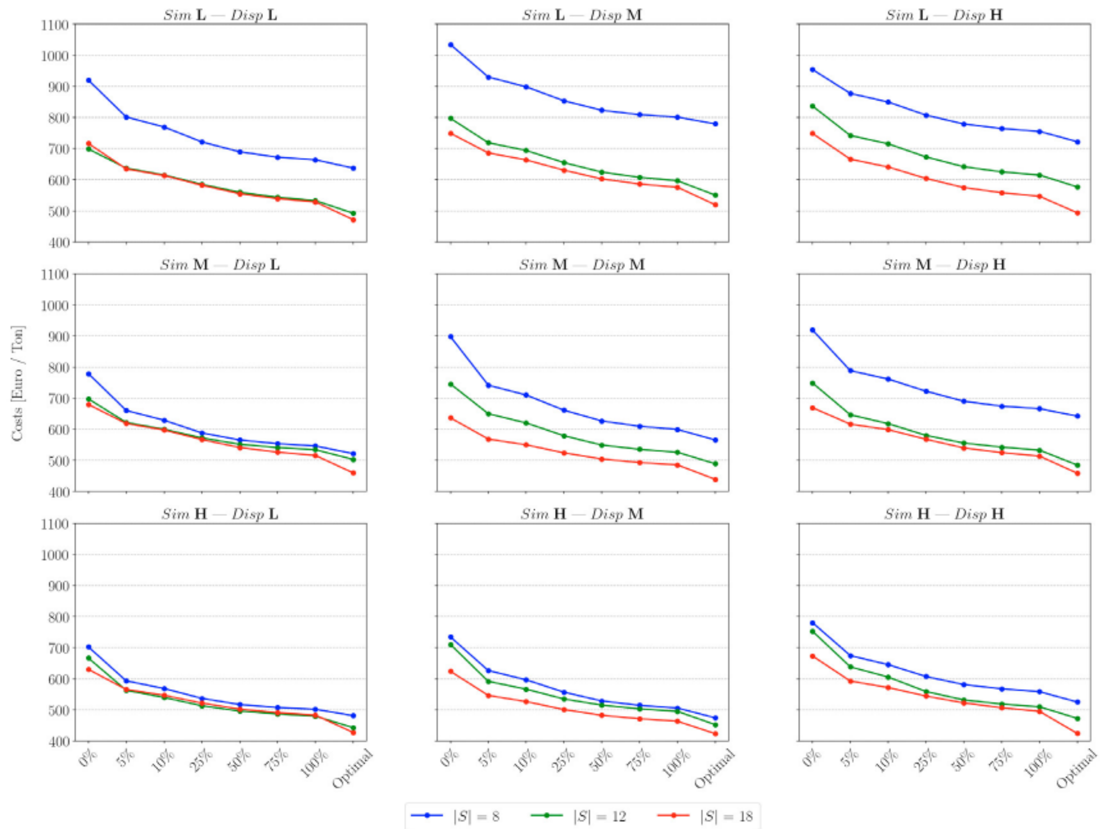

Fig. 1. Costs evolution using $(f_1|f_2, w)$

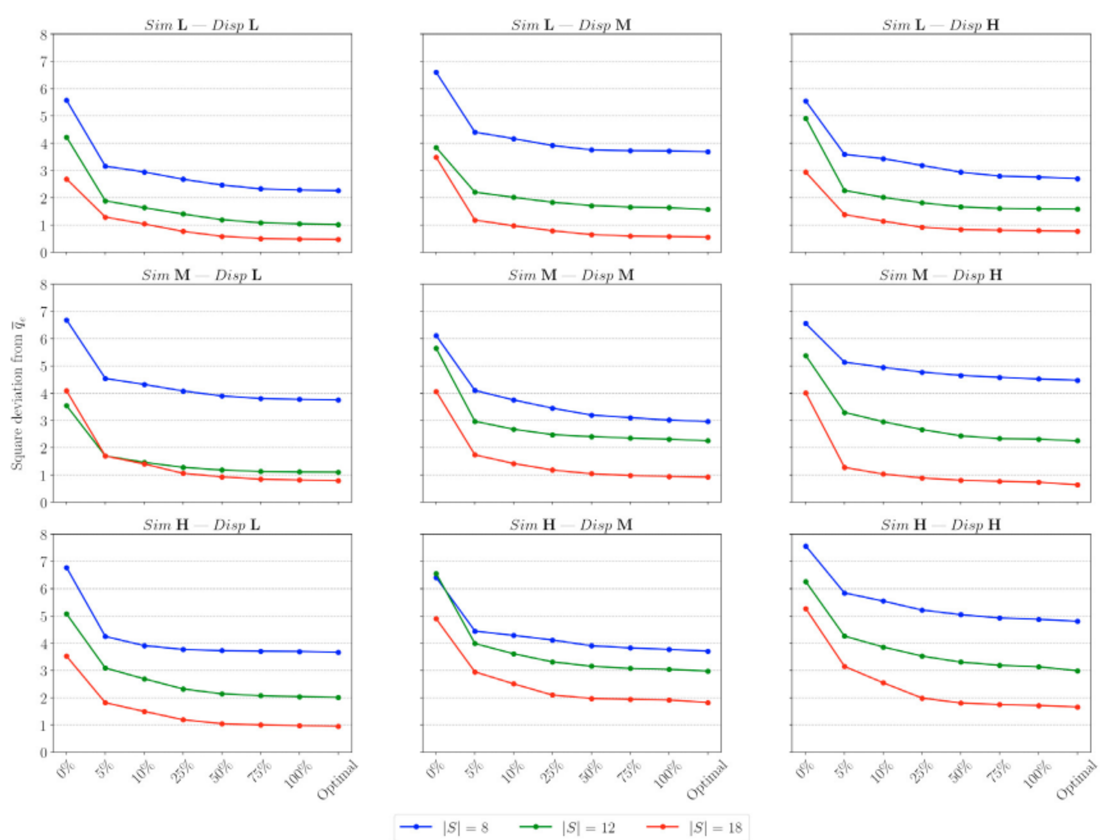

Fig. 2. Square deviation evolution using $(f_2|f_1, w)$

decrease across all sizes. However, for certain parameter combinations, the cost difference between sizes 12 and 18 becomes negligible, a result that did not emerge while analyzing just one objective function at a time. This indicates that returns diminish as the scrapyard size increases, suggesting that the maximal efficiency could be achieved at a certain size beyond which further expansion is not cost-effective. It is important to note that these figures do not account for the logistical costs of managing larger scrapyards. A deeper analysis incorporating these factors could identify the true optimal size. It is also relevant to note that as Sim increases, size-related cost differences are reduced. Moreover, a small scrapyard consistently results in the highest costs across all combinations, while the cost difference between sizes 12 and 18 depends more on Sim and $Disp$.

In Figure 2, we can see that a modest 5% increase in costs leads to a significant quality improvement. However, beyond this point, improvement reaches a plateau or decreases slightly. As seen in the chemical quality analysis of Section 5.2, larger scrapyards consistently yield better results. Unlike the cost trends, there is always a measurable quality improvement when scrapyard size increases. Interestingly, quality improvements are not directly linked to the Sim or $Disp$ parameters in isolation, but rather to their interaction.

6. CONCLUSION

In this paper, we present a bi-objective optimization approach to the Cost-Quality Scrap Selection Optimization Problem in steel production. The problem minimizes costs associated with raw materials and energy consumption while ensuring a precise chemical quality of the steel through effective scrap selection. The developed mathematical model incorporates real-world constraints and parameters, offering a realistic and practical representation of the problem. This research serves as a valuable tool for decision-makers in the steel industry, promoting more sustainable and cost-effective production processes.

The experimental analysis highlights the significant impact of scrapyard features, namely size, similarity, and chemical dispersion, on both cost and quality. Larger scrapyards consistently lead to cost reductions and improved chemical quality. However, results suggest the existence of a threshold beyond which further increases in scrapyard size yield diminishing returns, outweighed by the added complexity and maintenance requirements. High chemical dispersion should be avoided to reduce costs, but no clear recommendation emerges for chemical quality based solely on dispersion. Similarity, while similarity helps reduce costs, it negatively affects chemical quality when optimized in isolation. We note that, in practice, managing high-quality scrapyards proves challenging, especially due to the difficulty of controlling their similarity over time.

Future research could explore strategies to mitigate the impact of supply chain disruptions, particularly with reductions in scrapyard size. A follow-up focusing on industry applications could apply our methodology in a more dynamic production planning solution, considering that we currently use factors such as λ^e and M_1, which link the individual casting to the larger planning aspect of the steel-making process. Another potential avenue for further investigation is examining the effects of daily electricity consumption patterns and price fluctuations on production costs. Finally, insights for designing scrapyards better tailored to the specific needs of individual steel-making companies could emerge by considering additional factors beyond those considered in this study.

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