RESEARCH ARTICLE

Maintenance Scheduling Optimization for Sustainable Steel Ladle Fleet Operations

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ABSTRACT

An adequately managed steel ladle fleet is crucial for cost-efficient and sustainable steelmaking. While short-term dispatching decisions have been widely studied, the sustainability of long-term decisions, especially ladle maintenance optimization, remains unexplored. To address this gap, we present a novel mixed-integer quadratically constrained programming model that captures the complete ladle life cycle, integrating production and refractory degradation constraints to minimize the CO_2 emissions. State-of-the-art exact solvers can solve it efficiently while incorporating operational rules to mitigate end-of-horizon effects. Using historical data from an integrated steel plant, we analyze the refractory degradation patterns and optimize ladle deployment across three production scenarios. Our results suggest that relining a ladle during low-demand periods maintains direct emissions at comparable levels despite production variability. However, this strategy leads to approximately 60 % increase in material waste, highlighting a key sustainability trade-off. This approach also presents challenges in managing personnel and maintenance resources, as multiple relinings may be scheduled simultaneously. These findings provide valuable insights into how an inefficient maintenance policy affects economic and environmental performance. In conclusion, this study contributes to a more holistic understanding of sustainable steel ladle fleet operations, offering actionable strategies for balancing production efficiency, resource consumption, and emissions reduction in steelmaking.

KEYWORDS
Sustainability, Steel Ladles, Refractories, Maintenance Optimization, Maintenance Scheduling, MIQCP

1. Introduction

The iron and steel industry accounts for approximately 7–9 % of global greenhouse gas emissions and is under increasing pressure to adopt more environmentally responsible practices while meeting growing demand [1]. The development and implementation of breakthrough technologies are expected to significantly reduce emissions by replacing carbon-intensive processes with cleaner alternatives [2]. However, additional opportunities remain to enhance energy efficiency and decarbonize existing processes [3]. Advanced digital methods are crucial in addressing these challenges, especially in improving steel ladle operations.

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Ladles are vessels constructed with special refractory linings to withstand high temperatures. They are required for moving and processing molten steel within the melt shop and are essential for controlling steel quality and temperature [4]. The refractory lining degrades over its usage and must eventually be replaced once it reaches a safety threshold [5]. Hence, properly managing a steel ladle fleet is essential to guarantee safe, reliable, and efficient operations [6]. It prevents excessive refractory degradation and energy losses, reducing material waste and unlocking additional savings during steel refining operations.

Effectively managing a steel ladle fleet involves decisions across different time scales. Operational decisions have been studied in the context of steelmaking-continuous casting (SCC) scheduling [7–12]. The decisions involved are scheduling empty ladle operations (repairs and reheating) and assigning ladles to molten steel charges, for example. Recent research has also explored their impact on energy efficiency and sustainability [4, 6]. However, tactical decisions, in particular ladle maintenance scheduling, remain largely unexplored in the literature. These decisions determine when, which, and how many ladles should be available to meet production targets, directly impacting the efficiency of steelmaking operations.

This paper proposes a maintenance scheduling model to address the lack of understanding of sustainable tactical ladle deployment decisions. Assuming a production demand (set of charges) must be met, the model determines a maintenance schedule for the ladle fleet that minimizes the direct (Scope 1) emissions from heating the ladles with natural gas burners and indirect (Scope 3) emissions from refractory consumption. First, we discuss how refractory wear and direct emissions relate to the ladle's production rate, highlighting the impact of operational practices on sustainability. Incorporating these relationships into our model allows a more precise assessment of ladle deployment decisions. We then formulate the problem as a mixed-integer quadratically constrained programming (MIQCP) model and demonstrate its solution using state-of-the-art solvers while incorporating complex operational rules to mitigate end-of-horizon effects. Finally, we illustrate how the model can be systematically used to evaluate the sustainability of ladle operations.

To our knowledge, this is the first attempt to model and optimize steel ladle maintenance scheduling decisions. Besides, we minimize explicit sustainability indicators while considering the effect of the production rate on refractory degradation. It provides a more accurate tool to assist steelmakers in evaluating the sustainability of ladle operations in longer production horizons, extending the current state-of-the-art and opening new research directions. Furthermore, it allows us to derive additional operational recommendations for sustainable ladle deployment decisions. This includes, for example, how to synchronize the maintenance execution with periods of lower production demand to reduce direct CO_2 emissions. Ultimately, our main contribution is a novel method that offers a bridge between operational and tactical ladle fleet management decisions.

The remainder of this article is organized as follows. Section 2 reviews the related literature. Section 3 describes and formulates the sustainable ladle fleet maintenance optimization problem. Section 4 discusses the solution approach and rules to mitigate end-of-horizon effects. Section 5 presents the application of the proposed methodology to the Tata Steel, IJmuiden, use case. Moreover, the main takeaways are summarized in managerial insights, such as how relining ladles earlier can save on direct emissions. Next, the limitations are also highlighted based on the results. We conclude in Section 7 with the effects of the refractory lifetime on the ladle deployment decisions. Future research directions are also presented.

2. Literature Review

The current state of steelmaking-continuous-casting (SCC) scheduling and planning optimization has been recently reviewed by Lee et al. [13]. The authors highlighted that ladle operations are often simplified, even though they are indispensable transportation resources [14]. A few studies consider more detailed ladle dispatching decisions within SCC scheduling frameworks. Periodical repair operations have been investigated in [7, 8, 11]. Moreover, Armellini et al. [10] propose an integrated planning and scheduling problem, advancing the work from Fanti et al. [9]. They explore additional operational constraints, such as ladle cleanliness assignment constraints required to produce special steel grades.

The previous methods advanced the feasibility of the generated schedules in practice, but made limited consideration regarding sustainable ladle operations. They indirectly maximize energy efficiency by reducing empty-ladle processing times, which is also explored in other ladle dispatching models [12, 15]. Most recently, the implications of explicitly considering the refractory lining's thermal balance and degradation in the energy efficiency and sustainability of ladle dispatching decisions were studied [4, 6]. They provide a consistent method to quantify the economic and environmental impact of ladle operations from short-term decisions.

Although much progress has been made to improve operational decisions, optimizing tactical ladle deployment decisions remains unexplored. The existing related applications often focus on predicting the refractory lining's degradation or lifetime [5, 16, 17] and exploring their integration into condition-based or predictive maintenance systems [18–20]. Their goal is to determine when the next maintenance should be scheduled based on the current state of the refractory lining. The main benefits are safer operations, extending the ladle's lifetime, and improving maintenance resources management [18]. However, these solutions are often limited to short horizons and simplify the impact of operational decisions.

Condition-based and predictive maintenance are within the broader field of maintenance optimization strategies [21], which aims to determine the optimum balance between maintenance costs and benefits (reliability, quality, safety), subject to the system's constraints [22]. Other strategies, including prescriptive, preventive, corrective, and opportunistic maintenance, have been the subject of significant research [21–25]. Preventive policies are the most used in industrial facilities [17] and involve routine equipment maintenance, without considering its condition. Predictive maintenance is often employed for other stages within steel production, although it is less common for steel refining operations [17, 26].

The previous analysis highlights that limited progress has been reported in bringing the academic contributions into real applications in the steel industry, which was also generally observed by [22, 23, 25]. This is especially notable for prescriptive maintenance, which recommends the optimal action based on the output of predictive methods. Although it can significantly improve predictive strategies, related applications are rare. Contributing to that, steelmakers commonly employ proprietary solutions [27, 28], whose details and results are not often published. A related application is discussed in Lammer et al. [29], where the blast oxygen furnace refractory maintenance scheduling problem is presented. Although a different vessel is considered, the same concepts could be applied to the steel ladle. The authors use historical data to model refractory wear and the impact of maintenance activities to predict the degradation behavior and propose an adequate maintenance policy based on a target lifetime. The optimization is performed through a simple heuristic that constructs a feasible schedule. A limitation of their approach is that it only applies to a single vessel, not considering the interactions within a fleet of vessels.

To our knowledge, no previous work in the literature has modeled and solved the steel ladle maintenance scheduling problem. Additionally, explicit sustainability indicators as an objective have not been explored yet. Lammer et al. [29] presents a similar application. However, they focus on a different vessel and use refractory wear models integrated into a heuristic method to determine a maintenance schedule. Our approach leverages the results from Ruela et al. [4, 6] and optimizes the maintenance for the entire ladle fleet over a longer horizon. It is a novel prescriptive maintenance model that enables a better understanding of how the short and long-term ladle dispatching decisions are connected and should be considered to achieve more sustainable operations.

3. Problem Formulation

This section describes the ladle maintenance scheduling problem within a steel plant. After that, it is modeled as a mathematical optimization problem to minimize the CO_2 emissions involved in ladle operations. The effect of ladle management practices on the refractory degradation and sustainability of the process is highlighted.

3.1. Ladle maintenance scheduling

Figure 1 provides an overview of the ladle life cycle, highlighting the key maintenance activities. The service period between maintenance events is called a *campaign*, consisting of multiple ladle cycles. Each *cycle* represents the activities performed between two consecutive molten steel charges. It involves executing minor repairs and optionally reheating the ladle to adjust its thermal condition. Minimizing cycle duration reduces energy losses and reheating requirements, increasing the amount of charges a ladle can process daily. This operational practice is essential for energy-efficient ladle dispatching, lowering direct emissions and contributing to more stable production [4].

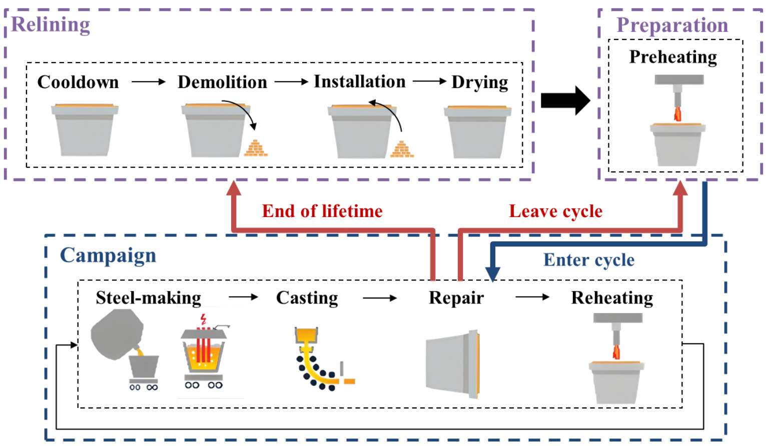


Figure 1.: The complete steel ladle life cycle.

Long-term maintenance, known as *relining*, is executed when the ladle reaches the end of its lifetime. It usually happens when the refractory lining reaches a critical safety thickness threshold after an inspection. The ladle is removed from the cycle and moved to a separate area to cool down before demolition begins. After that, a new refractory lining can be installed. This activity is conducted with limited equipment, facilities, and specialized personnel. Next, the ladle must undergo a controlled drying process to eliminate any free and chemically bound water present [30]. Before re-entering the cycle, repairs are performed, followed by *preheating* the ladle. This step, typically carried out using natural gas burners, is a significant source of direct emissions. Ensuring the refractory lining reaches the required temperature is essential to prevent thermal shock and excessive heat loss during molten steel tapping [31]. During lower production periods, a ladle may be temporarily removed from operation and require additional preheating before reuse. Hence, properly managing ladle deployment throughout a campaign and strategically synchronizing relining events can be leveraged to reduce direct CO_2 emissions. Optimizing these decisions not only enhances sustainability but also improves overall process efficiency.

3.2. Refractory degradation

Refractory degradation is caused by the thermomechanical and chemical wear mechanisms arising from the operational practices, ladle design, and process conditions [6]. Steel ladles are usually constructed with multiple refractory layers: working lining, permanent lining (safety and insulating layers), and shell [32]. The permanent lining is important to protect the shell from extreme temperatures and mechanical stresses [33]. The working lining is in contact with molten steel and needs to be regularly replaced, while the permanent refractory lining is designed to last through multiple campaigns.

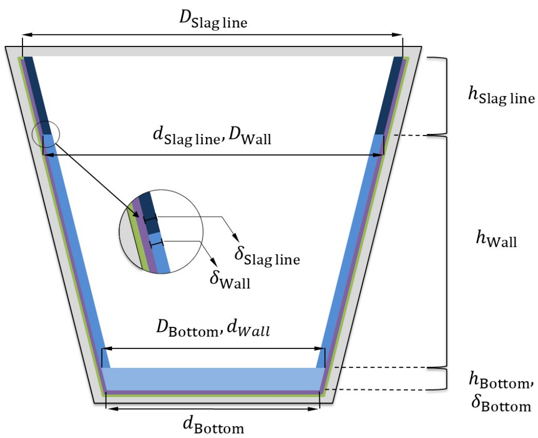


Figure 2.: Diagram of the steel ladle showing each relevant dimension. The shell, insulation, and safety linings are represented in gray, green, and purple, respectively.

The working lining can be divided into three main zones: the bottom, the wall, and the slag line (Figure 2). Each zone is designed with specific goals and exhibits different degradation behaviors. The slag line exhibits the highest wear rate due to chemical attack, as steelmaking byproducts (slag) penetrate the pores of the refractory material and react to form compounds that weaken its structure [34]. The wall zone is designed to minimize the dissolution of refractory elements into the steel to prevent contamination and defects in later processing stages. Finally, the bottom of the ladle endures the most severe thermomechanical stresses from the impact of molten steel, especially during tapping. Lower refractory temperatures considerably increase the risk of crack formation and can lead to early failures [35].

The slag line and bottom linings generally wear faster than the wall lining and are replaced more frequently. Therefore, campaigns can be categorized into two types: A and B. A *major* relining is necessary at the start of campaign A, where a new refractory lining is installed in all zones. Since the wall lining is designed to last two campaigns, a *minor* relining is performed before the start of campaign B, replacing only the slag line and bottom working linings. Consequently, campaign A is followed by campaign B in a cyclical manner (e.g., A $\rightarrow$ B $\rightarrow$ A $\rightarrow$ B $\cdots$). The ladles also exhibit different degradation behaviors depending on the campaign [16], introducing additional challenges in fleet availability management.

Indirect emissions from refractory consumption are expected in every relining. Moreover, spent refractories have different recycling/reuse capabilities and economic viability, directly impacting the waste generated after demolition [36]. Hence, scheduling a relining only when necessary and maximizing material usage are key aspects of sustainable ladle operations.

3.3. Mathematical Modeling

Based on the previous description, ladle maintenance scheduling involves answering the following main questions:

- Which ladles should leave/enter the cycle?
- How much to produce daily in each ladle?
- How to schedule a relining considering the fleet's availability?

Understanding how to answer these questions effectively is crucial to achieving sustainable and cost-effective ladle operations.

The proposed mathematical model determines how to utilize ladles to meet the production demand and when to schedule maintenance. It considers the degradation of the refractory lining thickness and direct emissions, which are influenced by the ladle's daily production rate. The model considers a scheduling horizon extending from weeks to months, using daily time steps. It also assumes that production demand is predetermined, specifying the number of charges to be produced each day. The following general assumptions are additionally made:

(1) All parameters are deterministic
(2) Ladles have the same design and thermal behavior.
(3) The charges are identical and can be processed by any ladle.
(4) All ladles enter and leave the cycle at the beginning and end of the day, respectively.
(5) There is no time dependence between charges within one production day.
(6) A ladle relining is non-preemptive, i.e., it cannot be interrupted.
(7) There are sufficient personnel and equipment to execute the relining activities.
(8) The ladle's campaign and initial thickness per zone are given.

An important assumption made is how the charges are processed (Items 4 and 5). In actual operations, the charges are scheduled and processed irregularly during the day, requiring different operational practices. This approximation may lead our model to overestimate the direct emissions calculated. It is not in our scope to incorporate more detailed ladle dispatching decisions [4], as it would make the proposed maintenance model intractable. This improvement should be the subject of future research.

The indices, sets, parameters, and decision variables are now described. The constraints and objective functions are presented next.

Sets and Indexes

T	The set of time steps: $\{1, \ldots, t^{\text{Max}}\}$
N	The set of ladles: $\{1, \ldots, n^{\text{Max}}\}$
P	The set of daily production levels: $\{0, 1, \ldots, p^{\text{Max}}\}$
C	The set of campaigns: {A: 0, B: 1}
L_z	The set of ladle zones: $\{\text{Slag line (SL)}, \text{Wall (WL)}, \text{Bottom (BT)}\}$
L_s	The set of refractory lining states: $\{\text{Good (GD)}, \text{Moderate (MD)}, \text{Worn-out (WO)}\}$

Decision variables

Continuous variables

$E_{n,t}$	The amount of CO_2 emissions for ladle n at time t
$W_{n,t,z}$	The amount of wear ladle n undergoes in zone z at time t
$\delta_{n,t,z}$	The refractory thickness for zone z in ladle n at time t
$\delta^{\text{Final}}_{n,s}$	Auxiliary variable containing the refractory thickness of ladle n for condition s at the end of the horizon
$\delta^{\text{Res}}_{n,t,z}$	The residual lining at the end of a campaign for zone z in ladle n at time t

Binary and Integer variables

$U_{n,t}$	Indicates if ladle n is active at time t
$U^{\text{In}}_{n,t}$	Indicates if ladle n is entering the cycle at time t
$U^{\text{Out}}_{n,t}$	Indicates if ladle n is leaving the cycle at time t
$Z^a_{n,t}$	Indicates if maintenance starts when ladle n is in campaign A at time t
$Z^b_{n,t}$	Indicates if maintenance starts when ladle n is in campaign B at time t
$Z^c_{n,t}$	Indicates the campaign for ladle n at time t
$Y_{n,t,p}$	Indicates if ladle n is operating at time t with production level p
$K_{n,t}$	Auxiliary integer variable used in the campaign definition calculation
$S_{n,s}$	Auxiliary binary variable indicating if ladle n is in state s at the end of the horizon

Parameters

d_t	The production demand at time t

$\Delta W_{p,z,c}$	The refractory wear in zone z to produce p charges in campaign c
e_p^{Cycle}	The CO_2 emissions to produce p charges per ladle (Scope 1)
e^{Preheat}	Preheating CO_2 emissions (Scope 1)
e^{Minor}	Indirect CO_2 emissions in a minor relining (Scope 3)
e^{Major}	Indirect CO_2 emissions in a major relining (Scope 3)
t^{Relining}	The relining duration
t^{Prep}	The preparation time after a relining (drying + pre-heating)
t^{Cool}	The preparation time before a relining (cooldown + demolition)
M	A sufficiently large positive number
δ_z^{Max}	The refractory thickness for zone z after a relining
$\delta_{n,z}^{\text{Init}}$	The initial refractory thickness for ladle n and zone z
δ_z^{GD}	Remaining thickness bound for ladle in condition "Good" for zone z
δ_z^{WO}	Remaining thickness bound for ladle in condition "Worn-out" for zone z
Z_n^{Init}	The initial campaign for ladle n
U_n^{Init}	Indicates if ladle n is in the cycle at the beginning of the scheduling horizon

3.3.1. Production constraints

The production demand d_t must be met at each time step t:

$$\sum_{n\in N}\sum_{p\in P} Y_{n,t,p}\cdot p = d_t,\ \forall t\in T \tag{1}$$

$$\sum_{p\in P} Y_{n,t,p} = 1,\ \forall n\in N, \forall t\in T \tag{2}$$

where Equation 2 ensures that only one production level p is selected. Additionally, there is no production when the ladle is inactive:

$$1 - Y_{n,t,0} = U_{n,t},\ \forall n\in N, \forall t\in T \tag{3}$$

Next, the direct emissions of ladles in the cycle are calculated based on the production level:

$$\sum_{p\in P} Y_{n,t,p}\cdot e_p^{\text{Cycle}} = E_{n,t},\ \forall n\in N, \forall t\in T \tag{4}$$

Furthermore, we can define a lower bound on the number of ladles in the cycle at each time step based on the maximum production rate:

$$p^{\text{Max}}\cdot\sum_{n\in N} U_{n,t} \geq d_t,\ \forall t\in T \tag{5}$$

Adding this constraint will remove potentially infeasible solutions from the search process.

3.3.2. Scheduling constraints

A 3-bin formulation [37] is employed to determine if the ladle is entering or leaving the cycle:

$$U_{n,t} - U_{n,t-1} = U_{n,t}^{\text{In}} - U_{n,t}^{\text{Out}},\ \forall n \in N, \forall t \in T, t > 1 \tag{6}$$

$$U_{n,t}^{\text{In}} + U_{n,t}^{\text{Out}} \leq 1,\ \forall n \in N, \forall t \in T \tag{7}$$

Equation 7 ensures that the ladle can only enter or leave the cycle. Moreover, an already active ladle is considered to be entering the cycle at the first time step:

$$U_{n,1} = U_{n,1}^{\text{In}},\ \forall n \in N \tag{8}$$

Since each campaign has a dedicated indicator variable, it is necessary to ensure that there is at most one relining per ladle at a time:

$$Z_{n,t}^{a} + Z_{n,t}^{b} \leq 1,\ \forall n \in N, \forall t \in T \tag{9}$$

Moreover, the ladles must remain inactive for t^{Cool} before a relining begins and can only enter the cycle again after t^{Relining} days, with an additional preparation time of t^{Prep} days:

$$\begin{aligned} &\sum_{v \in T_v} U_{n,v} \leq M \cdot (1 - Z_{n,t}^{a} - Z_{n,t}^{b}),\ \forall n \in N, \forall t \in T, \\ &\qquad T_v = [\max\{1, t - t^{\text{Cool}}\}, \cdots, \min\{t^{\text{Max}}, t + t^{\text{Prep}} + t^{\text{Relining}}\}] \end{aligned} \tag{10}$$

where $M = t^{\text{Cool}} + t^{\text{Relining}} + t^{\text{Prep}}$ is a large-enough constant. Finally, if the ladle was in the cycle at the beginning of the horizon, it must wait for at least two days before a relining:

$$\sum_{v \in T_v} (Z_{n,v}^{a} + Z_{n,v}^{b}) \leq 1 - U_{n}^{\text{Init}},\ \forall n \in N, T_v = [1, \cdots, t^{\text{Cool}}] \tag{11}$$

3.3.3. Campaign ordering constraints

The campaign at each time step can be determined with the following set of equations:

$$Z_{n}^{\text{Init}} + \sum_{v \in T_v} (Z_{n,v}^{a} + Z_{n,v}^{b}) = K_{n,t} \cdot 2 + Z_{n,t}^{c},\ \forall n \in N, \forall t \in T, T_v = [1, \cdots, t] \tag{12}$$

$$Z_{n,t}^{c} - Z_{n,t-1}^{c} = Z_{n,t}^{a} - Z_{n,t}^{b},\ \forall n \in N, \forall t \in T, t > 1 \tag{13}$$

$$Z_{n,1}^{c} - Z_{n}^{\text{Init}} = Z_{n,1}^{a} - Z_{n,1}^{b},\ \forall n \in N \tag{14}$$

Equation 12 is the linear formulation of the modulo operator assuming two campaign types. It ensures that Z_c results in a value of 0 or 1 (remainder of the division by two), meaning the ladle is in campaign A or B, respectively. Finally, Equation 13 identifies when there is a change in the campaign, and Equation 14 ensures that the initial ladle campaign Z_{n}^{Init} is respected.

3.3.4. Refractory degradation constraints

The refractory thickness at each time step is calculated as:

$$\delta_{n,1,z} = \delta^{\text{Init}}_{n,z} - W_{n,1,z} + \delta^{\text{Max}}_{z} \cdot (Z^a_{n,t} + Z^b_{n,t}) - \delta^{\text{Res}}_{n,1,z},\ \forall n \in N, \forall z \in [\text{SL}, \text{BT}] \tag{15}$$

$$\delta_{n,1,z} = \delta^{\text{Init}}_{n,z} - W_{n,1,z} + \delta^{\text{Max}}_{z} \cdot Z^b_{n,t} - \delta^{\text{Res}}_{n,1,\text{WL}},\ \forall n \in N \tag{16}$$

$$\delta_{n,t,z} = \delta_{n,t-1,z} - W_{n,t,z} + \delta^{\text{Max}}_{z} \cdot (Z^a_{n,t} + Z^b_{n,t}) - \delta^{\text{Res}}_{n,t,z},\ \forall n \in N, \forall t \in T, t > 1, \forall z \in [\text{SL}, \text{BT}] \tag{17}$$

$$\delta_{n,t,z} = \delta_{n,t-1} - W_{n,t,z} + \delta^{\text{Max}}_{z} \cdot Z^b_{n,t} - \delta^{\text{Res}}_{n,t,\text{WL}},\ \forall n \in N, \forall t \in T, t > 1 \tag{18}$$

Equations 15 and 16 enforce the initial thickness of each ladle according to the respective refractory zone. Equations 17 and 18 determine the refractory mass balance. After each relining, the refractory thickness needs to be replenished to δ^{Max}_{z}. This step requires calculating the residual refractory thickness:

$$\delta^{\text{Res}}_{n,t,\text{WL}} = \delta_{n,t-1,z} \cdot Z^b_{n,t},\ \forall n \in N, \forall t \in T, t > 1 \tag{19}$$

$$\delta^{\text{Res}}_{n,1,z} = \delta^{\text{Init}}_{n,\text{WL}} \cdot Z^b_{n,1},\ \forall n \in N \tag{20}$$

$$\delta^{\text{Res}}_{n,t,z} = \delta_{n,t-1,z} \cdot (Z^a_{n,t} + Z^b_{n,t}),\ \forall n \in N, \forall t \in T, t > 1, \forall z \in [\text{SL}, \text{BT}] \tag{21}$$

$$\delta^{\text{Res}}_{n,1,z} = \delta^{\text{Init}}_{n,z} \cdot (Z^a_{n,1} + Z^b_{n,1}),\ \forall n \in N, \forall z \in [\text{SL}, \text{BT}] \tag{22}$$

Note that Equations 19 and 21 introduce bilinear terms from the multiplication of variables Z_a, Z_b by δ. Section 4 will further discuss the solution approach. Equations 20 and 22 establish that the residual is the initial thickness if maintenance is scheduled at the first time step. Finally, the refractory wear is determined based on the actual campaign:

$$\sum_{p \in P} Y_{n,t,p} \cdot \Delta W_{p,z,\text{A}} \leq W_{n,t,z} + M_z \cdot Z^c_{n,t},\ \forall n \in N, \forall t \in T, \forall z \in L_z \tag{23}$$

$$\sum_{p \in P} Y_{n,t,p} \cdot \Delta W_{p,z,\text{A}} \geq W_{n,t,z} - M_z \cdot Z^c_{n,t},\ \forall n \in N, \forall t \in T, \forall z \in L_z \tag{24}$$

$$\sum_{p \in P} Y_{n,t,p} \cdot \Delta W_{p,z,\text{B}} \leq W_{n,t,z} + M_z \cdot (1 - Z^c_{n,t}),\ \forall n \in N, \forall t \in T, \forall z \in L_z \tag{25}$$

$$\sum_{p \in P} Y_{n,t,p} \cdot \Delta W_{p,z,\text{B}} \geq W_{n,t,z} - M_z \cdot (1 - Z^c_{n,t}),\ \forall n \in N, \forall t \in T, \forall z \in L_z \tag{26}$$

A tight bound uses the maximum wear for each zone z, which can be obtained from the model parameters.

Finally, a desirable result is to generate the minimum amount of refractory residual possible. This constraint is enforced by considering a constraint only to allow worn-out ladles to be relined:

$$\delta^{\text{Res}}_{n,t,z} \leq \delta^{\text{WO}}_{z},\ \forall n \in N, \forall t \in T, \forall z \in L_z \tag{27}$$

3.3.5. Objectives

The objectives are to minimize CO_2 emissions involved in the management of the ladle fleet:

$$\min \sum_{n\in N}\sum_{t\in T} E_{n,t} + \sum_{n\in N}\sum_{t\in T} U^{\text{In}}_{n,t}\cdot e^{\text{Preheat}} - \sum_{n\in N} e^{\text{Preheat}}\cdot U^{\text{In}}_{n,1}\cdot U^{\text{Init}}_{n} + \sum_{n\in N}\sum_{t\in T} Z^{a}_{n,t}\cdot e^{\text{Minor}} + \sum_{n\in N}\sum_{t\in T} Z^{b}_{n,t}\cdot e^{\text{Major}} \quad (28)$$

The first term represents the direct emissions from reheating the ladles during the cycle, depending on the production rate. Next, the preheating emissions required before a ladle enters the cycle are included. If a ladle is used at the first time step of the horizon, the preheating emissions are only considered if the ladle is not already in the cycle (U^{Init}_{n}). Moreover, the indirect emissions from refractory material consumption (e^{Minor} and e^{Major}) are added for each maintenance event. Note also that rewriting this objective in terms of costs is straightforward and entails only replacing the emissions coefficients with appropriate values.

Finally, the solution that minimizes reheating emissions also reduces waiting times and maximizes the number of cycles per ladle per day. However, this results in shorter campaign durations, potentially increasing relining frequency and, consequently, indirect and preheating emissions. Therefore, the optimizer should choose a maintenance policy that balances these sources of emissions. It enables us to investigate the implications of different deployment decisions on the sustainability of ladle fleet operations while considering the refractory degradation and its thermal behavior.

4. Methodology

4.1. End-of-horizon effects

The proposed model requires the definition of an adequate scheduling horizon, which is much smaller in practice: a steel plant often operates for decades without significant interruptions or indefinitely. Moreover, specifying a very long horizon is impractical due to the uncertainty of the demand forecasts and in terms of computational effort. Hence, the optimal solution for the short horizon may not be optimal in the long term [38].

Most end-of-horizon mitigation techniques are studied in the lot-sizing problem literature [39]. In general, they incorporate a measure of the final inventory into the objective function that reflects the characteristics of the future production demand. However, the inventory is conceptually different from the final refractory thickness. Thus, it is not straightforward to extrapolate the existing methods to our model. Therefore, we propose two empirical rules employed in practice to handle end-of-horizon effects:

(1) **Remaining thickness distribution:** A reliable fleet should have ladles with lifetimes (or remaining thickness) evenly distributed. It ensures fluctuations in production do not disrupt operations and that enough capacity is available to carry the molten steel charges. This behavior can be modeled by categorizing the ladle's refractory lining into three conditions (L_s). Using the slag line (since it undergoes the highest erosion rate) as our reference lining, this rule can be

included in the model with the following set of equations:

$$\sum_{s\in L_s} S_s = 1,\ \forall n \in N \tag{29}$$

$$\sum_{s\in L_s} \delta^{\text{Final}}_{n,s} = \delta_{n,t^{\text{Max}},\text{SL}},\ \forall n \in N \tag{30}$$

$$\delta^{\text{Final}}_{n,\text{WO}} \le \delta^{\text{WO}}_{\text{SL}} \cdot S_{n,\text{WO}},\ \forall n \in N \tag{31}$$

$$\delta^{\text{Final}}_{n,\text{WO}} \ge 0,\ \forall n \in N \tag{32}$$

$$\delta^{\text{Final}}_{n,\text{MD}} \le \delta^{\text{GD}}_{\text{SL}} \cdot S_{n,\text{MD}},\ \forall n \in N \tag{33}$$

$$\delta^{\text{Final}}_{n,\text{MD}} \ge \delta^{\text{WO}}_{\text{SL}} \cdot S_{n,\text{MD}},\ \forall n \in N \tag{34}$$

$$\delta^{\text{Final}}_{n,\text{GD}} \le \delta^{\text{Max}}_{\text{SL}} \cdot S_{n,\text{GD}},\ \forall n \in N \tag{35}$$

$$\delta^{\text{Final}}_{n,\text{GD}} \ge \delta^{\text{GD}}_{\text{SL}} \cdot S_{n,\text{GD}},\ \forall n \in N \tag{36}$$

$$\sum_{n\in N} S_{n,s} \le \lceil \frac{n^{\text{Max}}}{|L_s|} \rceil,\ \forall s \in L_s \tag{37}$$

$$\sum_{n\in N} S_{n,s} \ge \lfloor \frac{n^{\text{Max}}}{|L_s|} \rfloor,\ \forall s \in L_s \tag{38}$$

Equations 29 – 36 are used to determine the condition of each ladle based on the thickness of the slag line lining at the end of the scheduling horizon. Finally, Equations 37 and 38 enforce that the fleet has evenly distributed ladle conditions. If the fleet size is an even number, they can be replaced by a single equality constraint.

(2) **Campaign distribution**: A reliable fleet should also have evenly distributed campaigns. A fleet with only ladles in campaign A reduces the overall production capacity. On the other hand, having all ladles in campaign B increases the risk of ladle breakouts that could affect production continuity. Hence, one approach to model this rule is to constrain the number of ladles in A and B campaigns at the end of the scheduling horizon to be close to the average fleet size:

$$\sum_{n\in N} Z^{c}_{n,t^{\text{Max}}} \le \frac{n^{\text{Max}}+1}{2} \tag{39}$$

$$\sum_{n\in N} Z^{c}_{n,t^{\text{Max}}} \ge \frac{n^{\text{Max}}-1}{2} \tag{40}$$

Similar to the previous rule, Equations 39 and 40 can be replaced by an equality constraint when the fleet size is even.

The previous rules make the problem considerably harder, but are required to ensure the model outputs are closer to actual operations. Converting them into soft constraints can help avoid infeasible solutions, especially when enforced at every time step. Without these constraints, the model will generate solutions where all ladles are fully worn out by the end of the horizon, which is not desired in practice.

4.2. Solution Approach

As mentioned in Section 3.3.4, the proposed mathematical model contains quadratic constraints from the multiplication of binary and continuous variables. Hence, it can be classified as a mixed-integer quadratically constrained problem (MIQCP). This paper employs state-of-the-art exact solvers to solve the proposed optimization problem. They provide optimality guarantees and allow the solution of representative instances with complex constraints, which is sufficient for understanding sustainable steel ladle maintenance decisions. It is important to highlight that the computational effort is expected to increase considerably with the instance's size, especially for a larger fleet and scheduling horizon. More sophisticated methods, such as heuristics or decomposition approaches, should be explored in future works.

5. Results

This section shows the proposed maintenance scheduling problem's evaluation and application to the Tata Steel, IJmuiden, use case [40]. The model is executed for actual demand profiles extracted from historical data. Its implementation is initially verified, and the insights obtained for a stable production scenario are discussed. After that, the impact of production demand variability is evaluated for two typical scenarios, and their effect on ladle deployment decisions is further analyzed. Next, our findings are summarized into actionable managerial insights, and the model's limitations are discussed.

The refractory wear rate data analysis is presented in Appendix A. It considers historical data for two years of production and highlights how refractory degradation is affected by production rate and campaign. Appendix B discloses the remaining model parameters. The methods used to calculate the direct and indirect emissions coefficients are provided in the Supplementary material.

The optimization problem was implemented in Python 3.10 with Pyomo 6.9.2. All experiments were executed using Gurobi 12.0.1 on a 128-core system (AMD EPYC 7702P) with 256GB RAM and Ubuntu 22.04 operating system. The problem is solved in two steps: first, we focus on finding a feasible solution by setting the parameter *MIPFocus* to 1 [41]. If a solution is found, we set *MIPFocus* to 2 and solve the problem focusing on proving optimality, starting from the previous solution until the specified termination conditions are met. Empirical results showed that even finding a feasible solution can be challenging. Hence, this approach provided significant improvements.

After solving each instance, the decision variables are stored for further analysis. It includes the scheduling decisions, such as if the ladle is entering or leaving the cycle, the number of charges produced, the remaining thickness and residuals, and the direct and indirect emissions. They are saved for each time step and ladle. The parameters are also stored to enable us to track all the experiments executed consistently. Furthermore, we also store the solver parameters, optimality gap, objective function, and runtime results for each instance.

5.1. Example evaluation

To validate and illustrate the proposed model's outputs, instances requiring a fleet of six ladles with a scheduling horizon of 45 days were generated to enable solving the problem with a reasonable computational effort. The demand scenario selected for evaluation features a stable production demand and contains 851 charges in total, which is displayed in Figure 3. Table 1 displays the fleet's initial condition. It consists of ladles with equally distributed campaigns and refractory lining conditions. Additionally, the ladles in good condition (1 and 2) correspond to a new lining and are not initially in the cycle. This heterogeneous fleet is considered to allow us to investigate the effect of the ladles' initial condition on the deployment decisions. Finally, the solver termination conditions are 10 000 s or a 0.1 % optimality gap.

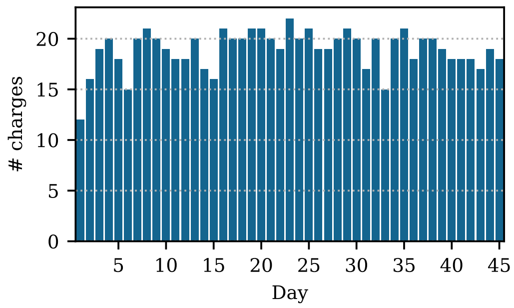


Figure 3.: Stable production demand profile example extracted from historical data.

Ladle	U^{Init}	Z^{Init}	$\delta^{\text{Init}}_{\text{WL}}$	$\delta^{\text{Init}}_{\text{BT}}$	$\delta^{\text{Init}}_{\text{SL}}$
1	0	B	90	250	150
2	0	A	150	250	150
3	1	B	62	121	69
4	1	A	119	122	80
5	1	B	47	59	30
6	1	A	97	28	27

Table 1.: The ladle fleet's initial condition.

Figure 4 displays the maintenance schedule obtained. Initially, notice that each ladle has a different refractory degradation profile per zone and campaign. For example, in campaign A of Ladle 5, the bottom lining wears out completely before the slag line. In contrast, the opposite is observed in campaign B of Ladle 6, where the slag line is fully consumed first. In addition, a relining is always scheduled when the working lining is worn out, showing a small residual thickness. Moreover, the wall lining is only replaced at the end of the B campaign, while the slag line and bottom linings are replaced at all maintenance events. The campaign ordering constraints are also correctly enforced, and the provided relining, preparation, and cooldown durations are respected during maintenance. These results show that all the operational constraints are being applied, and the model implementation is correct. We now analyze the deployment decisions in detail, aiming to answer the central questions from Section 3.3. An additional question is answered to evaluate the impact of the rules employed to mitigate end-of-horizon effects.

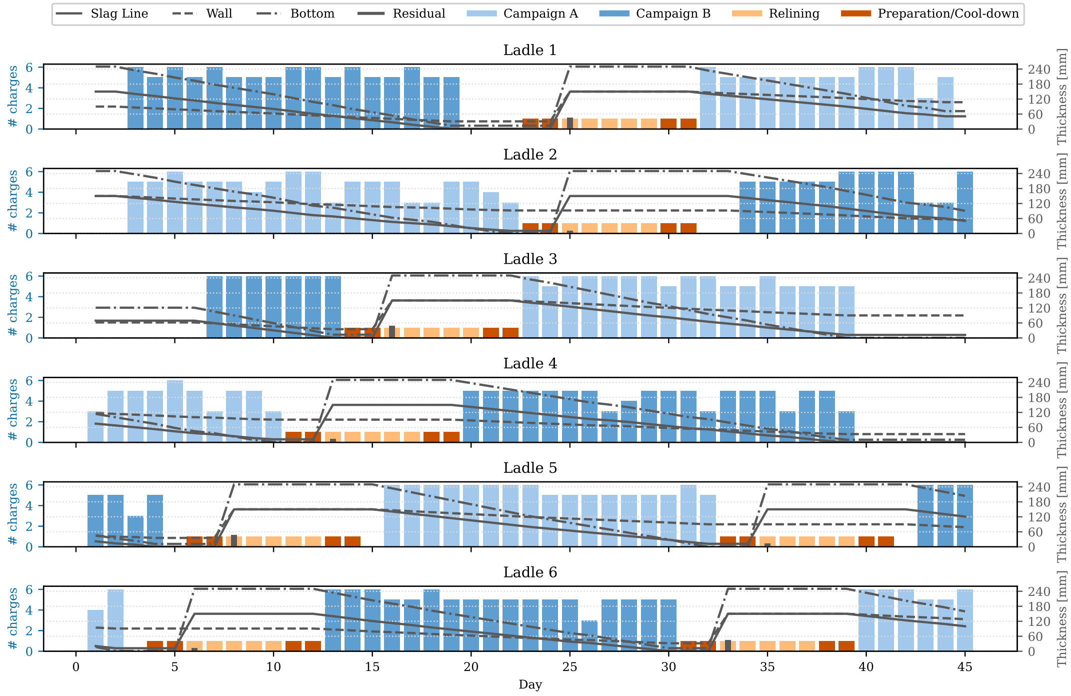


Figure 4.: The maintenance schedule obtained for the scenario with stable production demand. For all ladles, the number of charges produced daily is displayed alongside the relining schedule in the primary axis. Moreover, the refractory lining degradation profile and the total residual thickness are displayed on the secondary axis.

5.1.1. Which ladles should leave/enter the cycle?

This question lets us understand the recommended operational practices to reduce preheating emissions. Analyzing the ladles deployed at the beginning of the horizon reveals that Ladles 4, 5, and 6, which were already in the cycle, were selected. This choice is justified because it prevents preheating emissions from activating ladles 1 and 2. These ladles are only deployed later to ensure production continuity, as soon as the initially worn-out ladles require relining.

An additional observation is that, although already in the cycle, Ladle 3 is not used at the beginning of the horizon. The slightly lower initial production demand influenced this choice (see Figure 3), which required a smaller active fleet to be fulfilled. If this ladle had been recently preheated, it would have resulted in unnecessary preheating. This insight highlights the importance of planning ladle operations for a longer horizon and how proactive maintenance scheduling can be leveraged to reduce emissions.

5.1.2. How much to produce daily in each ladle?

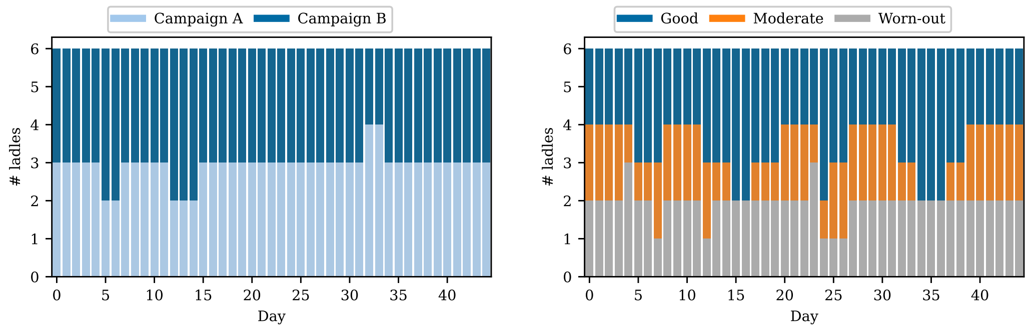
Notice from Figure 4 that ladles are not continuously operated with the maximum daily production rate, despite this being the most emission-efficient practice. This result suggests it is more efficient to distribute the production demand across ladles in the cycle more evenly to reduce the reheating emissions. It prevents a small number of ladles from having poor thermal management while the remaining ladles operate at maximum energy efficiency. The previous insight also highlights how the production demand directly affects the sustainability of ladle operations, which will be further explored in Section 5.2.

5.1.3. How to schedule a relining considering the fleet's availability?

The ladles are operated mainly with uninterrupted campaigns to prevent unnecessary preheating emissions and refractory wear. In addition, each ladle enters the cycle right after completing its preparation. As a result, significant disruptions in relining resource availability or processing time may require schedule adjustments to maintain its feasibility. This result indicates limited flexibility to accommodate variations in relining, preparation, or cooldown durations. In the worst case, such disturbances could lead to production breaks due to insufficient ladles in the cycle, highlighting the potential need for deploying additional ladles to ensure operational continuity.

5.1.4. How do the end-of-horizon mitigation rules affect the deployment decisions?

Figure 5 presents the fleet's campaign and refractory lining state throughout the scheduling horizon. Note that, even though we are only enforcing the end-of-horizon constraints at the last step, the distributions do not vary significantly on a daily basis. This result allows us to conclude that enforcing them for each time step is too strict or can reduce the flexibility in the deployment decisions. Moreover, practitioners can use this information to understand at which moment it might be more interesting to relax or enforce these constraints.



(a) Campaign.

(b) Refractory lining condition.

Figure 5.: The fleet's campaign and refractory lining condition over the scheduling horizon.

5.2. Evaluation of demand variability

As previously observed, the production demand is directly connected to the deployment decisions. To further investigate its influence, we evaluate two additional scenarios extracted from historical data: (a) one sudden reduction in the demand (Dip) and (b) multiple demand reductions (Unstable). They represent typical situations faced in actual production. The model was executed with the same initial ladle configuration and parameters from Section 5.1.

Figure 6 compares the maintenance schedule obtained for each demand profile. Notice how the exact moment the maintenance starts shifts in response to a lower de-

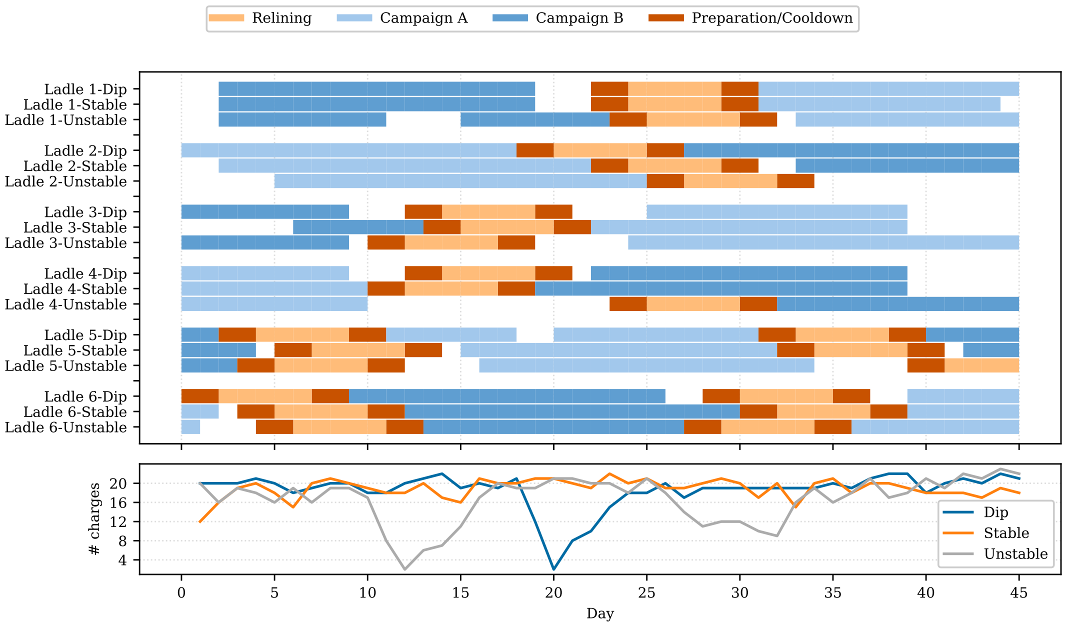


Figure 6.: Gantt chart of the maintenance schedule obtained under different demand scenarios.

mand, scheduling the relining more often around these periods. It is especially visible for Ladles 2 and 4: a relining is scheduled around the 20th and 30th day, coinciding with significant reductions in production demand. This insight suggests that steelmakers can mitigate the increase in direct emissions by strategically scheduling relining during periods of lower demand. However, Ladles 1 and 6 have similar deployment patterns across all scenarios, indicating that changes in production demand do not affect the maintenance schedule of all ladles. Therefore, emissions are mainly prevented by accurately identifying which ladles require schedule adjustments.

Figure 7 displays the amount of relining resources used over time. First, note that no more than two resources are used simultaneously for the Stable and Dip scenarios, and their utilization is more evenly distributed throughout the entire horizon. On the other hand, up to four resources are required in the Unstable scenario around the 30th day. Since it may not always be possible or cost-effective to increase the availability of maintenance resources, this result allows steelmakers to anticipate potential bottlenecks caused by demand variability. It highlights that sufficient relining resources should be available to ensure the maintenance schedule remains feasible.

Table 2 summarizes the emissions and refractory residuals obtained in each scenario. Notice that the total direct emissions (e^{Direct}) are similar across all scenarios. This observation shows that optimizing the fleet's maintenance schedule is important to compensate for production instabilities, although it has limited capabilities to reduce direct emissions. Further reducing the direct emissions requires different actions. Changing the reheating practice should be carefully evaluated to balance refractory wear, steel temperature losses, and safe operations [4, 6]. Further possibilities involve using more energy-efficient refractory linings [42], which should be combined with porous burners [43] with optimized control to reduce natural gas consumption [44]. Replacing natural gas with alternative fuels is currently the subject of research [45] and must be considered once it becomes a mature technology.

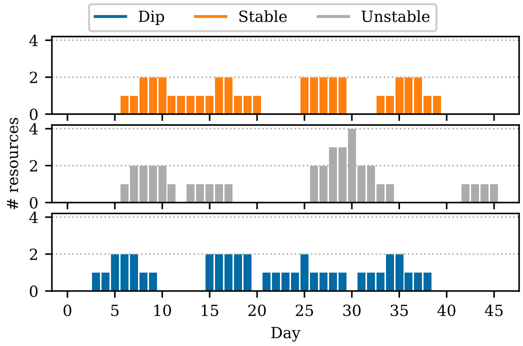


Figure 7.: The number of relining resources used over time.

Demand	Charges	δ^{Res}	e^{Cycle}	e^{Preheat}	e^{Direct}	e^{Total}
Stable	851	0.2801	0.0557	0.1281	0.1839	0.7087
Unstable	748	0.4592	0.0647	0.1192	0.1840	0.7811
Dip	835	0.4506	0.0518	0.1306	0.1824	0.7173

Table 2.: The refractory residuals (mm) and CO_2 emissions (tons) for the three demand scenarios. Values are normalized by the number of charges.

Finally, even though the total production per scenario differs, the same number of relinings is required. For the production horizon considered, the variability in the production leads mainly to an inefficient usage of refractory materials. As displayed in Table 2, the amount of refractory residuals increases by approximately 60 % with production variability. Therefore, relining the ladles earlier reduced direct emissions since there was no penalization on the residuals in the objective function. Adjusting the value of parameter δ^{WO} in our model can be used to apply more strict limits on the refractory residuals. It can be used to better understand the compromise between emissions and waste generation.

5.3. Limitations

The results were evaluated under deterministic parameters. More specifically, the duration of the relining and preparation activities can be highly uncertain in practice and affected by factors not included in the model. For example, workers may be unavailable on weekends or holidays. Extending our proposed model to determine a ladle fleet that is robust to uncertain parameters could be the subject of future research. Employing stochastic or robust optimization methods is an interesting direction to achieve this goal.

Moreover, a limitation of the proposed end-of-horizon mitigation approach is that it does not exclude ladles undergoing relining from the calculation. Hence, alternative methods should be investigated to quantify the fleet's reliability and how to incorporate them into the model efficiently. However, our approach remains valid, offering practical rules that can be directly formulated as linear equations.

In addition, the objective function does not consider the CO_2 emissions involved in recycling, reusing, and landfilling spent refractories. Their precise calculation is complex because each refractory material may have different recycling/reuse capabilities [36]. It is also hard to obtain accurate data on the destination of spent refractories, which can vary significantly between steel plants [46]. Hence, this improvement to the objective function can be the subject of future research.

Finally, the refractory wear measurements are uncertain, and the degradation is also affected by other process conditions besides the production rate [6, 16]. Clustering the historical data with additional relevant variables is an interesting approach to improve this aspect [29]. Hence, it is relevant to investigate how different refractory wear profiles affect the optimal maintenance schedule.

6. Managerial insights

The following operational insights derived from the results can be leveraged to improve decision-making in steel plants:

- Proactive ladle maintenance scheduling has limited potential to reduce direct CO_2 emissions. It can, however, determine the ideal moment to reline a ladle and how to distribute the production more efficiently across the fleet to prevent excessive direct emissions.
- The campaign and refractory condition constraints applied at the end of the scheduling horizon are sufficient to ensure a well-distributed fleet. Enforcing them at every time step may be overly restrictive and could reduce operational flexibility.
- Additional relining resources (personnel, equipment, facilities) may be occasionally necessary to achieve sustainable operations in the face of production variability. If desired, the model can be easily extended to constrain the available resources.

Even though the proposed model is a hard-to-solve optimization problem, high-quality solutions were obtained in less than three hours for the scenarios evaluated. These instances are valid representations of the challenges faced in several steel plants. It highlights that exact methods are still applicable and can yield valuable insights. However, exploring heuristics or decomposition methods is recommended for larger fleet sizes or extended scheduling horizons to enhance computational efficiency.

Therefore, the model could already be integrated into the production planning and scheduling routines. Its weekly or monthly execution is still feasible since its solution requires a reasonable computational effort. It can allow practitioners to anticipate challenges in the ladle fleet's management. For example, different production plans can be evaluated to define an adequate fleet size and targets for each ladle's daily production rate. Bottlenecks in the availability of maintenance resources can also be proactively addressed.

Finally, given that the production plan is constantly updated due to unexpected events, such as new orders, availability of raw materials, and equipment downtime, it is recommended to re-execute the model whenever significant deviations occur. Investing in laser scanning technology is recommended for smooth integration within operations. It will reduce the time required to configure the initial condition of the ladles for the model and allow for faster decision-making in the face of production disruptions.

7. Conclusion

A novel steel ladle maintenance scheduling model considering the refractory's thermal and degradation behavior was proposed and solved with state-of-the-art exact solvers. The objective is to minimize the direct emissions from reheating and preheating the ladles and the indirect emissions from material consumption required in a ladle relining. Rules from actual operations were used to mitigate end-of-horizon effects. Moreover, historical data from Tata Steel, IJmuiden, was analyzed to determine the refractory degradation patterns.

The ladle deployment decisions and their sustainability were analyzed for different production demand profiles extracted from historical data. First, the optimal maintenance schedule for a stable production demand under a heterogeneous initial fleet configuration was evaluated. The results showed that using worn-out ladles at the beginning of the horizon is important to ensure future production continuity. Moreover, operating with uninterrupted campaigns is key to reducing direct CO_2 emissions from reheating the ladles. The results also suggested that the proposed empirical rules at the end of the horizon are sufficient to ensure a well-distributed fleet throughout the horizon. We also observed that the solution may not be robust to relining and preparation/cooldown duration variations. It suggests that extra ladles would be needed to accommodate disturbances in the timing of the maintenance operations, which should be evaluated in future works.

The impact of the demand variability was also evaluated for two additional typical scenarios, and the results lead to an interesting insight: it is possible to obtain similar direct emissions by synchronizing the moment a ladle enters or leaves the cycle with lower production periods. However, this maintenance policy requires additional maintenance resources for a more unstable production demand, which could be infeasible or not cost-effective in practice. Another observation is that the number of relinings required remained the same across the scenarios, even under a lower production demand. Nevertheless, the amount of refractory residuals was significantly lower for the stable production. It showed that the optimal policy allowed more waste to be generated to save on direct CO_2 emissions. Further investigation into this trade-off could be the subject of future research.

Our results demonstrated the importance of optimizing the ladle fleet's maintenance schedule for more sustainable operations. However, future works must address the limitations to allow its adoption in actual operations. First, a more efficient solution approach should be investigated to enable the solution of larger fleet sizes and longer production horizons, such as heuristics or decomposition methods. Moreover, quantifying and including the emissions from refractory residuals in the objective can also be further explored. Finally, investigating the impact of the uncertain model parameters is essential to offer additional insights into the robustness of the ladle fleet. It will further support steelmakers in making better decisions during their decarbonization journey.

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Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request. The data are not publicly available due to confidentiality agreements with industry partners.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix A. Wear rate data analysis

The wear rate coefficients were estimated with laser scan measurements collected between 2023 and 2024 at Tata Steel, IJmuiden. The interested reader can find more details about the dataset in ref. [16]. We aim to determine the ladles' average wear rate per campaign and daily production rate. First, we calculate the campaign's daily production rate as the ratio between the total amount of charges processed and the number of days between two relinings. Figure A1 displays the daily production rate's distribution. A first observation is that most values are concentrated between 3 and 5 charges per day. Note also that operating at a rate of more than 1, 2, and 6 charges per day is less common in practice. Hence, we categorize the production rate into four levels for a more balanced and representative dataset to estimate the wear rate.

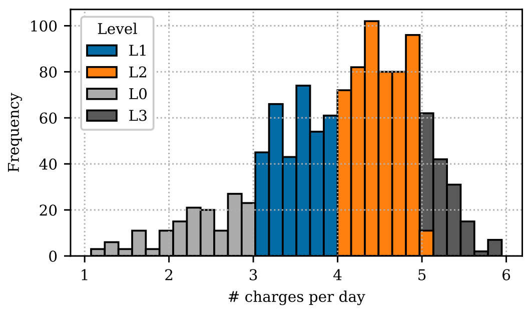

Figure A1.: Histogram of the average production rate for each campaign.

The wear rate is calculated as the difference between a new lining thickness and the last measurement taken before relining divided by the number of charges processed by the ladle in a campaign. Next, outliers are removed with the IQR rule to exclude extreme wear rate values from the analysis. Figure A2 displays the wear rate distribution considering the categorization previously proposed. The model considers the median value of each level and campaign, which are summarized in Table A1. The reported values are normalized by the maximum wear rate for confidentiality reasons.

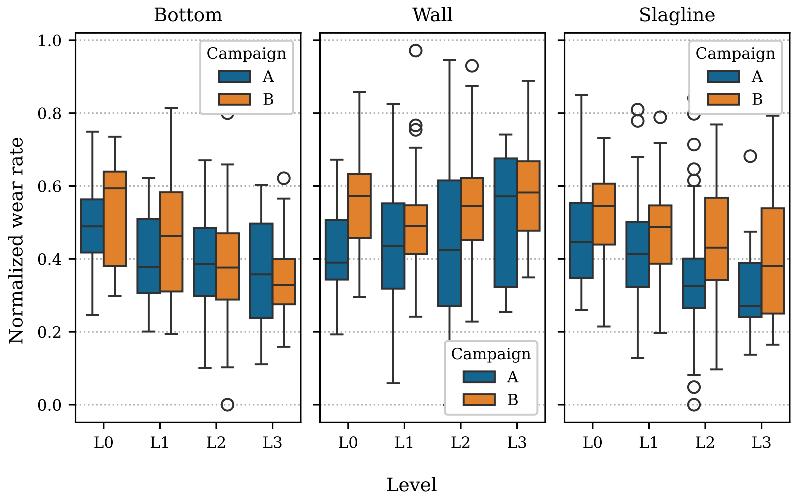

Figure A2.: Boxplot of the wear rate for each production level and campaign.

Table A1.: Wear rate for each zone per production rate and campaign.

p	Level	Campaign	Bottom	Slag Line	Wall
1, 2, 3	L0	A	0.906	0.505	0.161
		B	1.000	0.545	0.189
4	L1	A	0.806	0.492	0.168
		B	0.882	0.522	0.176
5	L2	A	0.813	0.457	0.166
		B	0.804	0.499	0.185
6	L3	A	0.788	0.435	0.189
		B	0.762	0.479	0.191

Appendix B. Parameters

The methods used to calculate the emissions coefficients are available in the supporting information. Tables B1 and B2 display the remaining model parameters used.

General		Per zone			
Parameter	Value	Parameter	Slag line	Bottom	Wall
t^{Cool} [days]	2	δ^{WO} [mm]	49.5	82.5	49.5
t^{Relining} [days]	5	δ^{GD} [mm]	99	165	99
t^{Prep} [days]	2	δ^{Max} [mm]	150	250	150
e^{Minor} [tCO_2]	35.127				
e^{Major} [tCO_2]	76.522				
e^{Preheat} [tCO_2]	9.915				

Table B1.: Model parameters.

p	6	5	4	3	2	1
e_p^{Cycle} [tCO_2]	0	0.224	0.895	1.498	4.241	7.085

Table B2.: Reheating emissions for each daily production rate per ladle.

Author biographies

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Paul van Beurden is trained as a physical chemist and holds a PhD in computational chemistry (Eindhoven University of Technology, Netherlands, 2003). At present, Paul is working as a Knowledge Group Leader at Tata Steel Nederland, based in IJmuiden, Netherlands. His current focus includes leading projects related to steel industry decarbonization, energy efficiency & waste heat recovery, and the integration of digitalization and AI in steel production. Prior to Tata Steel, he gained experience as a Researcher at the former Energy Research Centre of the Netherlands (ECN, currently part of TNO), where he worked on emission reduction, hydrogen production, and CO_2 capture. Dr. van Beurden is a member of the IEA IETS Digitalization Working Group and the AIST Digitalization Applications Technology Committee.

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René Hofmann is a Full Professor at TU Wien and Head of the Institute for Energy Systems and Thermodynamics. Mr. Hofmann has many years of industrial, research project and publication experience in the field of energy systems, habilitated in the field of design and operation optimization for industrial energy systems and teaches methods for modeling, simulation and optimization of thermal processes. He was active as a Senior Process Engineer with R&D at Josef Bertsch GmbH & Co. KG, Austria and his current research include net-zero sector-coupled energy systems and AI for energy systems. Mr. Hofmann is active in the executive committee of the International Energy Agency Technology Collaboration Program Industrial Energy Related Technology and Systems.