Volume 10, Issue 6, June – 2025 International Journal of Innovative Science and Research Technology
ISSN No: 2456-2165 https://doi.org/10.38124/ijisrt/25jun759

LRF Optimization

Tagoor Paramathma Jayamangala[1]; Sangaraju Preetham Raju[2]; Sravya Bolla[3]; Nitish C[4]; V. Harika[5]; Praveen Kumar Burra[6]; Bharani Kumar Depuru[7*]

[1,2,3,4]Research Associate, AiSPRY
[5,6]Research Team Leader, AiSPRY
[7]Director, AiSPRY

Corresponding Author: Bharani Kumar Depuru[7*]

Publication Date: 2025/06/23

Abstract: For high-quality steel ladle refining furnace is necessary for temperature, deoxidization, desulphurization, and inclusion removal as well as for fine-tuning composition of molten steel grades such as bearing steel where fatigue life is greatly impacted by total oxygen concentration. However, the LRF process is complicated with strong coupling effects, non-linear correlations and changeable input conditions, making precise prediction difficult and control difficult. Traditional methods often result in low precision, increased material consumption, eg, ferroalloys and off-specification heats, necessitating extensive and expensive post-production testing. Oxygen ingress from sources like carryover slag (FeO+MnO) and argon stirring reoxidizes steel, consuming costly deoxidizers like aluminum and reducing their yield This study offers a data-driven strategy to maximize alloy additions in the process at the ladle refining furnace (LRF) stage, which are essential for regulating an ultimate chemical composition quality of steel with the objective of minimizing material cost while ensuring compliance with grade-specific chemical specifications. The study leverages historical plant data, comprising heat-wise opening and final chemistries, ferroalloy addition records, and cost-recovery profiles for grade steel. We explore and compare three mathematical optimization strategies: Linear Programming(LP), Bayesian Optimization (BO) using both Optuna and Scikit-Optimize, and Genetic Algorithms (GA) via the pymoo library This study emphasizes the difficulties in optimizing in actual steelmaking settings and suggests modeling enhancements to match algorithmic results with a metallurgical reality.The findings highlight the need of pre-validating data related to domain expertise, the necessity of hybrid modeling techniques, and the incorporation of physical process behavior with optimization logic.

Keywords: *Ladle Refining Furnace (LRF), Steelmaking Optimization, Ferroalloy Addition, Alloy Cost Minimization, Linear Programming (LP), Bayesian Optimization (BO), Genetic Algorithm (GA), Process Control, Metallurgical Modeling, Data-Driven Decision Making, Deoxidization and Desulphurization, Industrial Process Optimization, Physical Constraints, Recovery Rate Modeling, Cost-Efficient Alloy Design, Machine Learning in Metallurgy, Multi-Objective Optimization, Feasibility Analysis, Process Variability in Steel Production*

How to Cite: Tagoor Paramathma Jayamangala; Sangaraju Preetham Raju; Sravya Bolla; Nitish C; V. Harika; Praveen Kumar Burra; Bharani Kumar Depuru; (2025) LRF Optimization. *International Journal of Innovative Science and Research Technology*, 10(6), 1540-1549. https://doi.org/10.38124/ijisrt/25jun759

I. INTRODUCTION

In new steel making, faces increasingly rigid quality specifications driven by the various and demanding uses of steel grades, specialized across various industries [1][4]. This evolving demand for precision necessitates advanced refining processes beyond the primary steelmaking stage. The Ladle Refining Furnace (LRF), a cornerstone of secondary steelmaking, plays an essential role in meeting these exacting requirements [2][3]. It functions as a versatile metallurgical unit capable of fine-tuning a molten steel's temperature and composition, deoxidizing, desulphurizing, and removing inclusions [1][6]. This critical link guarantees that future continuous casting of steel runs smoothly in the production chain and makes a substantial contribution to the overall quality of the finished steel product [4][5]. Given the growing complexity of steel uses such as bearing steel for enhanced fatigue life underscores the need for tighter control overall compositions and inclusion of content [4][9]. This elevates a role of secondary refining from a general purification step to a precision engineering phase where the ultimate goal is to produce precisely specified steel with minimal deviations [6] [10]. Achieving this consistency directly impacts the operational efficiency by decreasing the frequency and scope of post-production testing samples [8] [12].

Traditionally, decisions regarding alloy additions during the LRF stage have relied heavily on operator experience and empirical rules [1][4]. While this approach has been serviceable, it often leads to suboptimal outcomes such as excessive alloy consumption, increased production costs, and occasional deviations from target chemical

ISSN No: 2456-2165 https://doi.org/10.38124/ijisrt/25jun759

compositions [3][6]. These challenges underscore the need for a more systematic and data-driven approach to optimize the LRF process [2][7].

This study proposes a comprehensive methodology that leverages historical plant data, including heat-wise chemical compositions, alloy addition records, and cost-recovery profiles develop predictive models for alloy optimization by employing and comparing three optimization techniques: Linear programming (LP), Bayesian optimization (BO), Genetic Algorithms (GA) via the pymoo library [8][9]. We aim to identify strategies that minimize material costs while ensuring compliance with grade-specific chemical specifications [6] [10].

This study adopts a structured data-driven approach, aligned with the CRISP-MLQ methodology [Fig.1], to enhance process optimization at the Ladle Refining Furnace (LRF) stage of steel manufacturing [9] [12]. The dataset comprises detailed plant-level information, including heat-wise opening and final chemical compositions, alloy addition quantities, and cost-recovery parameters for various ferroalloys [1] [11]. Exploratory Data Analysis (EDA) was conducted to identify elemental deviations and consumption trends, revealing critical focus areas such as aluminum volatility and sulfur sensitivity [6][9]. Preprocessing steps included the alignment of alloy naming conventions, removal of outlier heats, and filtering of invalid or infeasible entries based on metallurgical constraints[5][12]

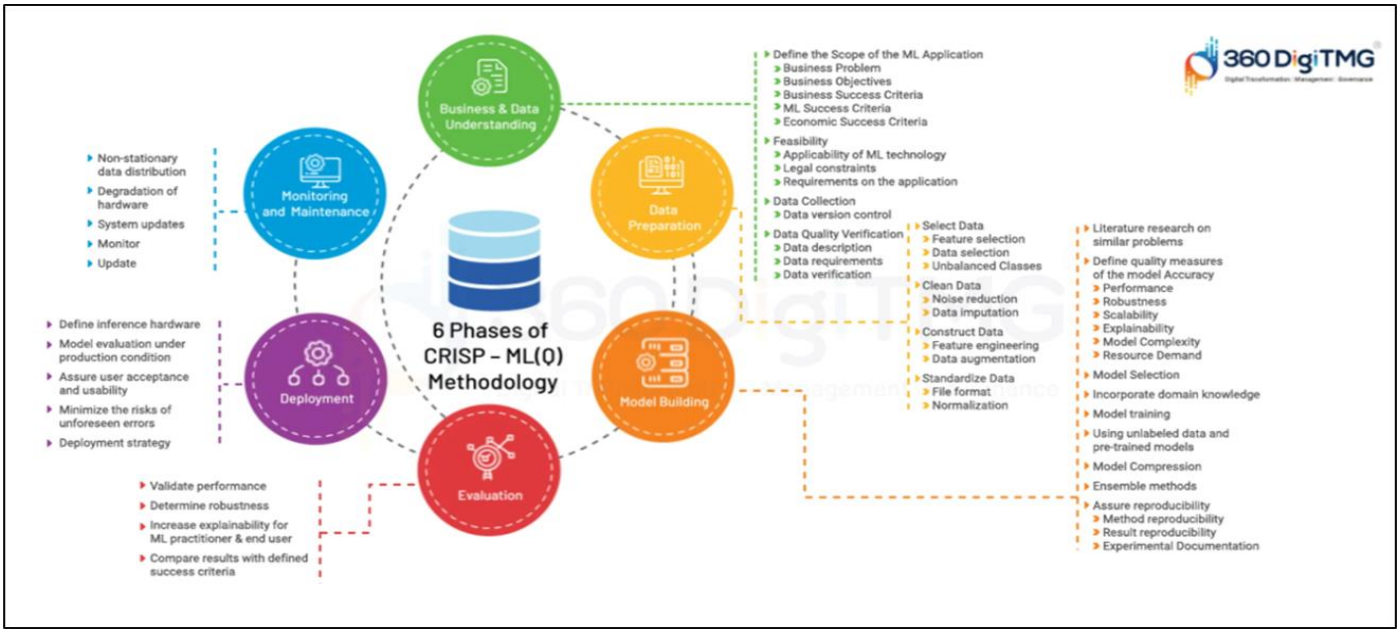


Fig 1 CRISP-ML (Q) Methodological Framework, Outlining its Key Components and Steps Visually.
(Source: -Mind Map - 360DigiTMG)

The core optimization objective was framed as a cost minimization problem, subject to constraints dictated by grade-specific chemistry targets [2][8]. Three modeling techniques were evaluated: Linear Programming (LP), Bayesian Optimization (BO) via Optuna and Scikit-Optimize, and Genetic Algorithms (GA) implemented through the pymoo library [9] [10]. Each model integrated alloy compositions, recovery percentages, and cost per kilogram to simulate the impact of alloy additions on final steel chemistry [7] [11]. A feasibility check module was embedded to pre-validate input conditions and improve model reliability [10] [12]. Ultimately, the framework is intended to serve as a decision-support system, guiding plant operators in determining optimal alloy addition strategies for improved cost-efficiency and chemical compliance across steel grades [6][8].

II. METHODOLOGY AND TECHNIQUES

To optimize alloy addition in the LRF procedure, a structured machine learning and mathematical modeling framework was developed. This approach aims to improve decision-making for alloy usage, reduce material costs, and ensure the final steel chemistry remains within specification limits. Historical plant data—including heat-wise chemical compositions, opening and final alloy addition records, cost data, and recovery efficiencies—served as the foundation for modelling.

➢ *Data Collection:*

Data was extracted from Level-2 process automation and metallurgical quality control systems. It includes heat-wise chemistry data—opening and final element percentages for multiple elements such as C, Mn, Al, S, Si, etc.—alloy addition records (quantity of ferroalloys added per heat across various alloy types), alloy properties dataset (composition, recovery percentage, and cost per unit for each alloy), and grade specifications (min, max, and aim chemical limits per steel grade).

ISSN No: 2456-2165 https://doi.org/10.38124/ijisrt/25jun759

➢ *Optimization Modeling:*

The optimize algorithms were explored to determine cost-effective alloy additions. Linear Programing, a mathematical approach aiming to minimize total cost, lead to constraints related to final chemistry targets. Bayesian Optimization (BO), leveraging probabilistic models via Optuna and Scikit-Optimize, was used to handle non-convex, sparse, and high-dimensional search spaces. Genetic Algorithms (GA), a population-based metaheuristic method, used the Pymoo library to evolve candidate solutions through selection, crossover, and mutation.

➢ *Workflow:*

The overall methodology consists of the following steps:

- Data Cleaning & Standardization: Aligning alloy names across datasets, removing invalid rows, and calculating element deltas (Final – Opening).
- Feasibility Check: Verifying whether the heat is suitable for optimization by checking if any element exceeds its maximum threshold before alloy additions.

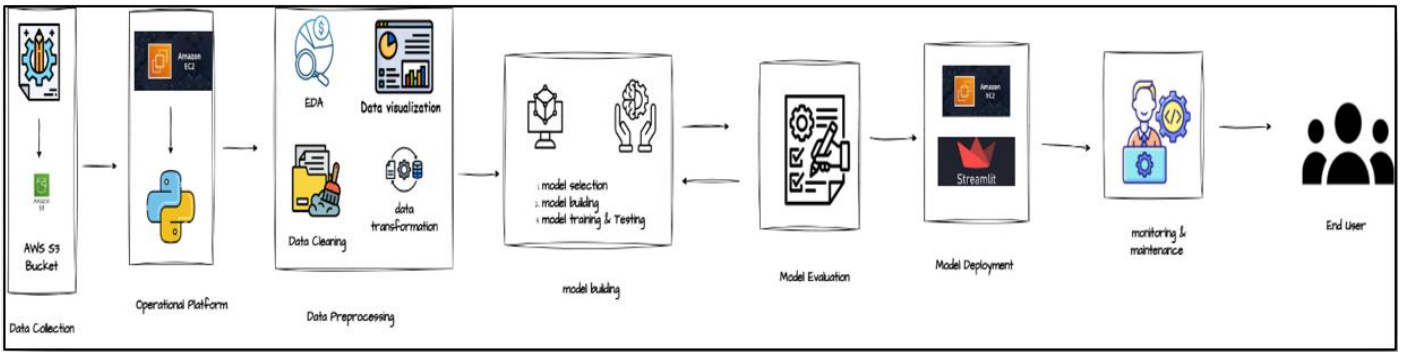


Fig 2 Architecture Diagram

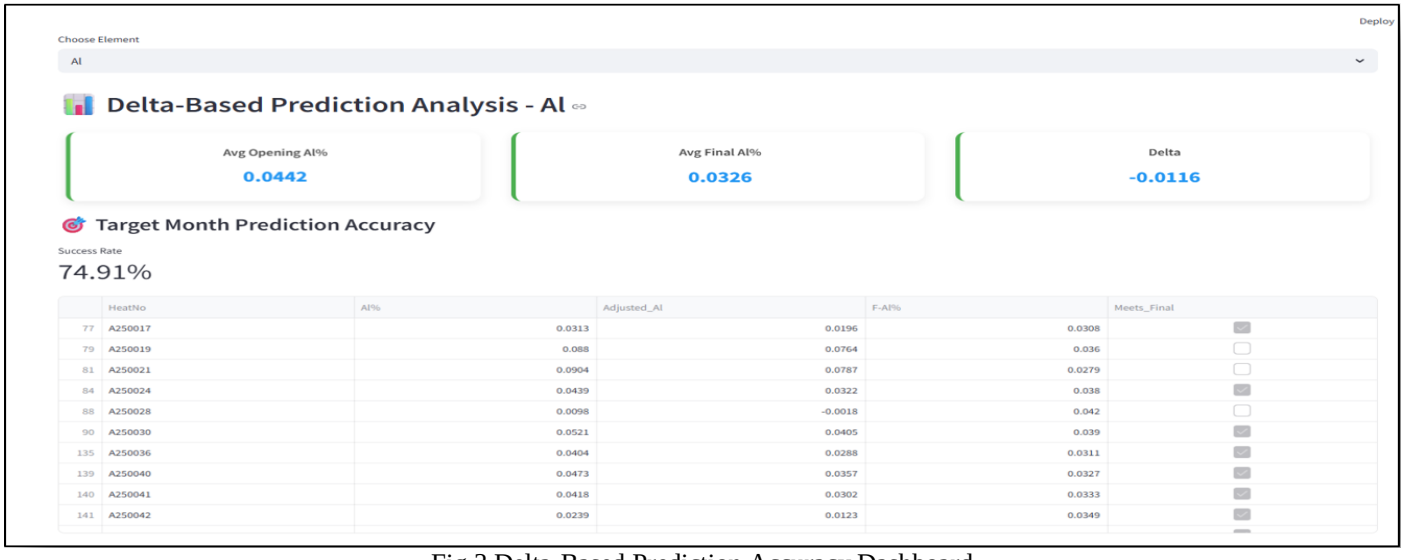
- Model Formulation: Defining the cost function and chemistry constraints using domain-informed parameters.
- Optimization Execution: Running the selected algorithm to find optimal alloy quantities.
- Result Validation: Ensuring solutions meet chemical constraints and business requirements (e.g., total alloy addition ≤ 2 tons).

➢ *Exploratory Data Analysis (EDA) and Data Visualization:*

To build a reliable optimize model for the LRF stage, an extensive Exploratory Data Analysis (EDA) was conducted to know the underlying patterns, distributions, and interdependencies in the metallurgical data. This phase was critical in evaluating feasibility from an optimize point of view and refining preprocess strategies.

➢ *Statistical Summary of Data:*

To determine a range, central tendency, and dispersion of values, descriptive statistics were calculated for major chemical and process variables. C (carbon) showed a relatively tight range around aim values, reflecting controlled deoxidation practices. S (sulphur) displayed high variance across heats, suggesting sensitivity to slag behavior, purging conditions, and other uncontrollable factors. Al (aluminum) values were often above target ranges at the opening, affirming client feedback that Al levels are initially kept high to counter losses from argon purging. Power and holding time distributions helped correlate process duration with chemical stabilization trends.



	HeatNo	Al%	Adjusted_Al	F-Al%	Meets_Final
77	A250017	0.0313	0.0196	0.0308	☑
79	A250019	0.088	0.0764	0.036	☐
81	A250021	0.0904	0.0787	0.0279	☐
84	A250024	0.0439	0.0322	0.038	☑
88	A250028	0.0098	-0.0018	0.042	☐
90	A250030	0.0521	0.0405	0.039	☑
135	A250036	0.0404	0.0288	0.0311	☑
139	A250040	0.0473	0.0357	0.0327	☑
140	A250041	0.0418	0.0302	0.0333	☑
141	A250042	0.0239	0.0123	0.0349	☑

Fig 3 Delta-Based Prediction Accuracy Dashboard

ISSN No: 2456-2165 https://doi.org/10.38124/ijisrt/25jun759

➢ *Key Observations:*

several heats exhibited opening chemistry already exceeding max limits especially for al and s directly impacting optimization feasibility missing or zero alloy entries were frequent in specific heats indicating either manual additions outside of logging systems or lack of addition affecting data reliability elemental deltas x showed that alloy additions successfully increased key elements eg mn al but some elements such as ca and s remained unaffected confirming minimal control through alloying alone [Fig.3]

➢ *Data Correlation Analysis:*

To examine relation among variables, correlation matrix & heatmaps were created. Notable findings include strong correlation between Mn and Mn-alloy inputs (HCFeMn, MCFeMn), confirming their impact on Mn uplift. Al drops during processing aligned with longer purging times, verifying volatility and process-related loss. S levels showed weak correlation with alloying, supporting domain feedback that sulphur control depends on slag and oxygen management rather than alloy.

➢ *Key Observations:*

Strong correlations between particular alloy additions and the associated element changes in the final chemistry were shown by correlation analysis. For instance, FeMn correlated strongly with Mn and FeAl with Al, confirming the predictive link between input alloys and chemical outputs. Notably, there was a somewhat negative association between Al and S, which is consistent with metallurgical knowledge that aluminum helps reduce sulfur. These correlations validate the structure of the optimization model and suggest that a predictive framework can effectively use alloy additions to estimate final chemistry. It also supports feature selection strategies for modeling efforts output. [Fig.4]

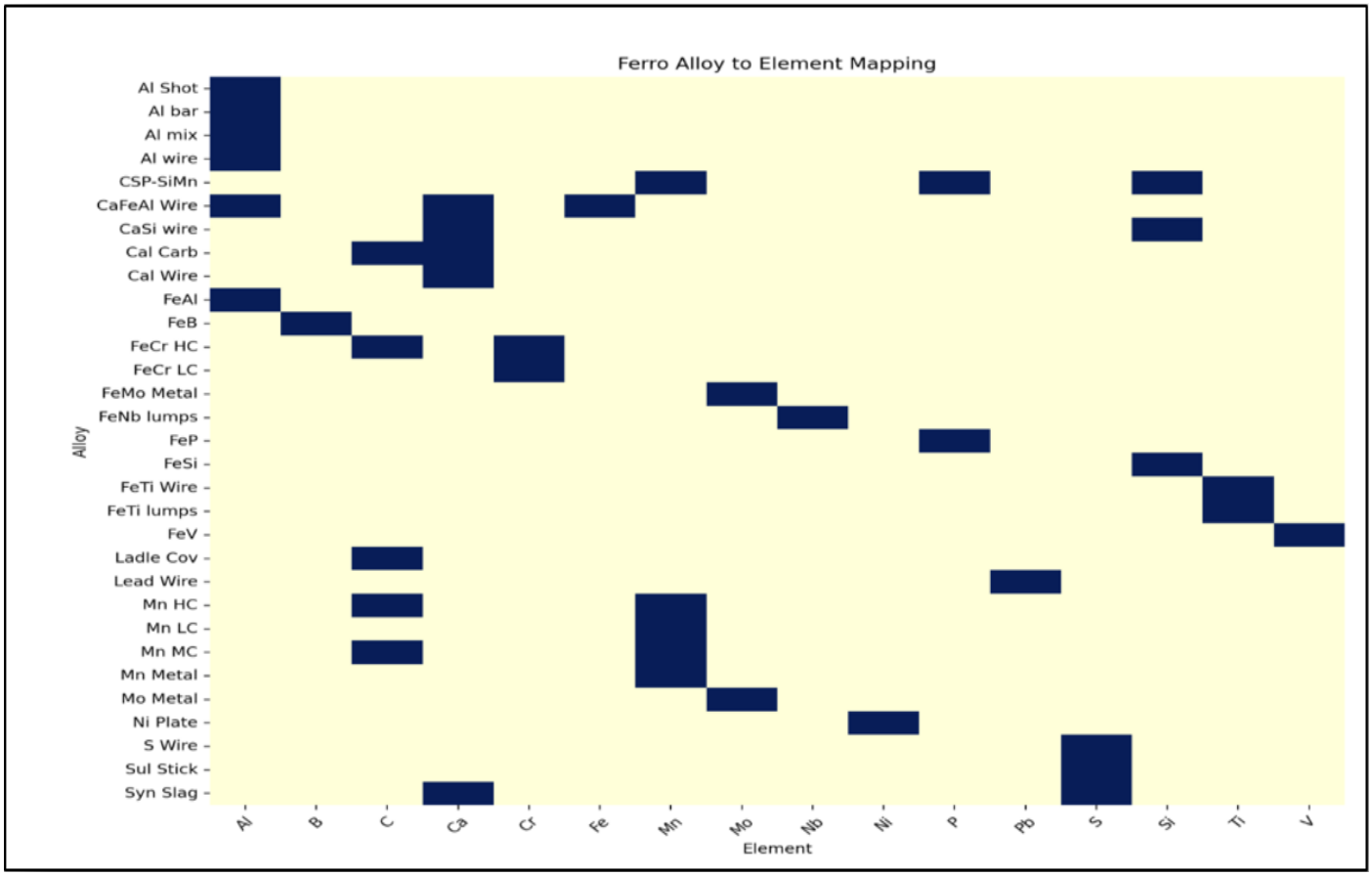


Fig 4 Ferroalloy-to-Element Contribution Heatmap Illustrating Alloy Influence on Chemical Composition

➢ *Distribution Analysis:*

Analyzing the distribution of key parameters is essential for detecting data skewness. To achieve this, histograms, box plots, and quantile-quantile (Q-Q) plots were utilized.

➢ *Key Observations:*

Element distributions across heats indicated that while some (like C and Mn) followed near-normal distributions, others (such as Al and S) were highly skewed. Aluminum showed a right-skewed distribution with a long tail of over-addition, consistent with operational practices aimed at compensating for volatility. Sulphur displayed a wider and often non-normal spread, pointing to process unpredictability. These skewed and multimodal distributions highlight the non-linearity in the chemical behavior during refining, reinforcing the limitations of linear models. This variability strengthens the case for using metaheuristic and probabilistic approaches like Genetic Algorithms and Bayesian Optimization. [Fig.5]

ISSN No: 2456-2165 https://doi.org/10.38124/ijisrt/25jun759

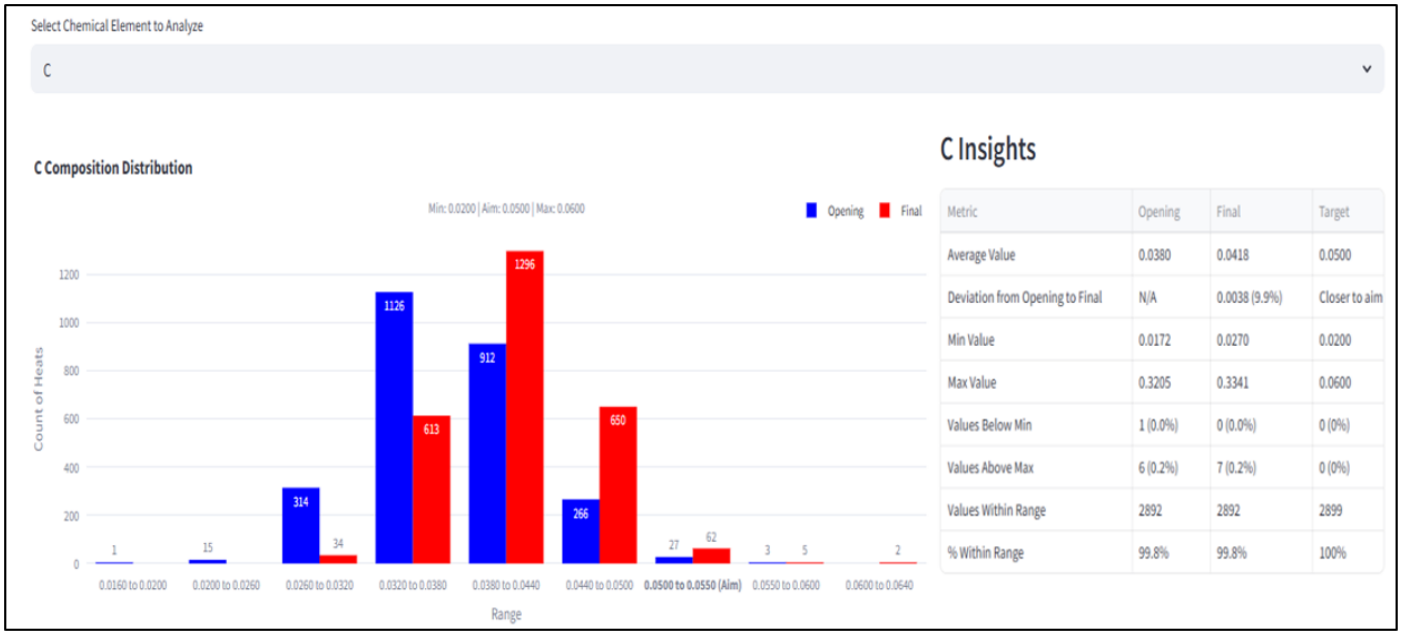


Fig 5 Composition Distribution and Statistical Insights Comparing Opening Vs Final Values

➢ *Outlier Detection*

To detect outliers, a combination of statistical methods and visualization techniques was applied.

➢ *Key Insights:*

Outlier detection revealed that several heats had chemical values well outside acceptable limits, particularly for Sulphur and Aluminum. These outliers were likely caused by process disturbances or deviations from standard operating procedures. Their presence significantly impacted optimization feasibility, especially for methods like Linear Programming that assume rigid constraints. Identifying and removing or flagging these heats is critical to avoid skewing model training and evaluation. This analysis also emphasizes the importance of preprocessing and feasibility checks before running any optimization, ensuring the models are applied only to relevant, solvable cases. [Fig.6]

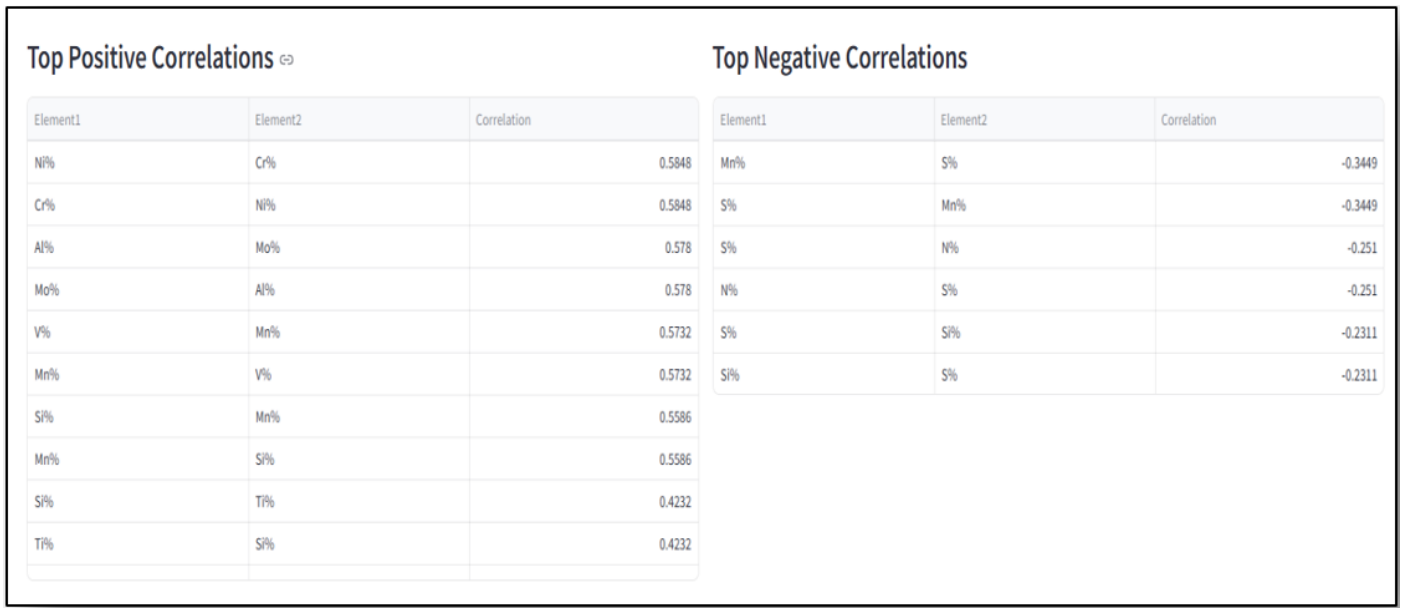


Fig 6 Top Correlated Element Pairs – Positive and Negative Relationships in Heat Chemistry Data

➢ *Heat and Process Time Tracking:*

The systematic LRF process time by converted it to minutes and enabling time-based trend analysis. The metric is central to understand how long refining takes per heat, which is crucial because over-processing leads to energy inefficiency and under-processing risks unmet chemistry targets.

➢ *Power Consumption Monitoring:*

The app calculates total Power Consumption per heat and introduces a derived metric called Power Efficiency (kWh/min). These indicators enable granular analysis of energy use trends across heats and refining durations, helping optimize operational cost.

ISSN No: 2456-2165 https://doi.org/10.38124/ijisrt/25jun759

➢ *Chemical Element Binning & Deviation Analysis:*

For each chemical element (e.g., C, Mn, Al), the app bins opening and final values based on aim, min, and max targets. This enables visual tracking of how far heats deviate from specification and whether corrective actions push chemistries closer to desired ranges.

➢ *Insightful Statistical Profiles:*

The application creates an element-wise table of metrics, including average opening/final values, deviations, count of values out-of-range, and percentage within target limits. This empowers metallurgists to immediately identify unstable or problematic elements like Al or S across heats.

➢ *Refining Time Impact on Chemistry:*

Elements such as Al frequently display negative correlations between LRF process time and the delta (final - opening) in element percentages, which is consistent with domain-specific findings that Al tends to decrease with time as a result of volatility and argon purging.

➢ *Aim Proficiency Analysis:*

The system computes how often each element is within its prescribed range (both before and after refining) and how closely the values match the aim point. This is crucial for identifying inefficiencies in alloy addition strategies or inconsistent refining practices.

➢ *Prediction Accuracy from Element Drift:*

Using average changes in chemistry, the app predicts final values and compares them against target tolerances for months, i.e., January, February. This statistical model allows early-stage validation of expected success and flags elements with poor predictability.

➢ *Monthly and Hourly Heat Volume Trends:*

The app visualizes the number of heats processed per month and hour of the day. This, in order to prevent overload or inefficient operations. Knowledge helps the labor planning by detecting peak refining hours and optimizing shift scheduling.

➢ *Elemental Trendlines Across Heats:*

For selected elements, the app plots line graphs chemical evolution across heat numbers. This helps in visually identifying drifts, sudden changes, or stabilization trends that can correlate with operational events or input material changes.

➢ *Correlations Between Elements:*

The app computes heatmaps for opening and final chemistry to detect inter-element correlation. Secure positive or negative correlations often reveal alloying behavior or counteractive chemistry (e.g., Al vs O), guiding multi-element alloy strategies.

➢ *Power Efficiency and Chemical Success:*

The model explores how efficiently power is used here to bring each element into its target range. Elements like Al, that are volatile or influenced by temperature, show distinct power-consumption behavior affecting cost optimization strategies.

➢ *Refining Time vs. Success Rate:*

A final powerful insight links LRF refining time with chemistry success rate by binning process times, e.g., short, medium, long. These tools help set procedures and yield time targets by figuring out areas where process time results in declining returns or where success rates plateau.

➢ *Data Preprocessing:*

- Handling Missing Values: Rows with missing values in critical columns such as opening/final chemistry and ferroalloy additions were dropped to maintain data integrity and avoid introducing bias through imputation.
- Feature Selection: Only essential columns related to chemical composition, alloy additions, and cost/recovery were retained. Non-contributing columns (e.g., Ladle Number, Date) were excluded to streamline modeling.
- Normalization & Scaling: Not applied at this stage since LP, BO, and GA models operate on physical quantities (kg, %, ₹) and rely on real-scale inputs for interpretable outputs.
- Type Casting & Conversion: All chemical and alloy values were explicitly cast to float to ensure compatibility with mathematical operations used in optimization routines.
- Alloy Column Mapping: A mapping dictionary was applied to unify alloy names between the heat sheet and composition/recovery datasets to build consistent input dictionaries.
- Feature Engineering: ΔX columns (e.g., ΔC, ΔMn) were created to calculate the difference between final and opening chemistry for each element, providing insight into alloy impact per heat.
- Outlier Handling: Heats with chemical values beyond max limits (flagged by QC) were treated as outliers and excluded from optimization datasets based on client input.
- Feasibility Filtering: A custom feasibility check was implemented to exclude heats where over-limit elements (e.g., Sulphur, Aluminum) could not be corrected via alloy additions.

In the LRF optimization project, data preprocessing played a crucial role in ensuring that the input provided to the optimization algorithms was both reliable and representative of the true process dynamics. Initially, rows with missing or null values were dropped—particularly those involving opening and final chemistries or alloy addition values—as these are foundational to calculating element-wise deltas and assessing the effect of alloying on heat quality. No imputation was done to avoid artificially biasing the chemistry or cost data, which could distort optimization outcomes.

We also performed standard type casting to convert all chemical composition and alloy weight columns into float format, ensuring compatibility with mathematical models. To maintain consistency across datasets, alloy names from the heat sheet were mapped to standard identifiers used in the cost and recovery sheets through a well-defined mapping

ISSN No: 2456-2165 https://doi.org/10.38124/ijisrt/25jun759

dictionary. Feature engineering steps included computing ΔX (delta) values for each element, representing the difference between final and opening chemistries, which helps track the effectiveness of alloy additions. Outlier removal was performed based on domain knowledge—heats flagged by the client for deviating from acceptable chemical limits were excluded. Additionally, a custom feasibility check was implemented to filter out heats where over-limit elements such as Aluminum and Sulphur exceeded their maximum permissible values and could not be adjusted downward via alloy additions. These preprocessing steps ensured clean, consistent, and context-aware inputs for the downstream Linear Programming, Bayesian Optimization, and Genetic Algorithm models.

III. RESULTS AND DISCUSSION

This section offers the conclusions and revelations obtained from implementing three optimization strategies: Linear Programming (LP), Bayesian Optimization (BO), and Genetic Algorithm (GA) for determined optimal ferro alloy additions in Ladle Refining Furnace (LRF) process. The objective was to minimize alloy cost while satisfying strict target chemical ranges for each steel heat.

➢ *Model Performance and Optimization Outcomes:*

The three algorithms were independently applied on historical LRF process data, incorporating per-heat opening chemistry, ferroalloy additions, cost, and recovery percentages. LP was modeled using equality and inequality constraints for each element to ensure the final composition lies within the target ranges. However, the model frequently returned infeasible solutions, primarily because it cannot adjust or reduce already high chemical values (like Sulphur or Aluminum), due to the unidirectional nature of alloy additions.

Bayesian optimization applied by both Optuna and Scikit-Optimize showed better flexibility through penalty-based formulations. Yet, in many cases, the output was either zero alloy recommendation or excessively high penalty-induced cost. This was attributed to limited optimization space and overlapping constraints, where certain elements, e.g., Al, S, were already outside the permissible range in the initial state.

In contrast, the GA-based approach provided comparatively better flexibility and interpretability. By defining soft bounds and nonlinear search spaces, GA attempted to satisfy multi-criteria constraints. However, feasibility checks had to be introduced before model execution to filter out heats where no amount of addition could correct the chemical balance. Even then, several heats failed optimization due to real-world metallurgical complexities not accounted for in the model.

➢ *Key Insights*

- Constraint Conflicts: LP failed for heats where elements like Al or S were above the upper bound. Since LP cannot subtract chemical values, this caused infeasibility.
- Penalty-Based Methods: BO managed to provide solutions but often defaulted to zero additions due to excessively high penalties or incompatible constraints.
- Search-Based Flexibility: GA worked better by iterating across a population, but only when feasible starting chemistries were pre-validated.
- Feasibility Checks: A critical part of success in GA was the use of a feasibility check function that screened out infeasible heats early in the process.
- Alloy Mapping & Preprocessing: Correctly mapping heat sheet alloy names to the alloy master data was crucial for consistency in cost, recovery, and chemistry calculations.

➢ *Visualizations and Comparative Analysis*

Compare results, cost output, and recommended alloy weights were logged for each model per heat. Visual plots were generated to compare actual vs. target chemistry, highlighting how different models approached optimization. GA provided the most aligned result when initial chemistry was within range. LP and BO frequently returned null or impractical solutions. [Fig.7]

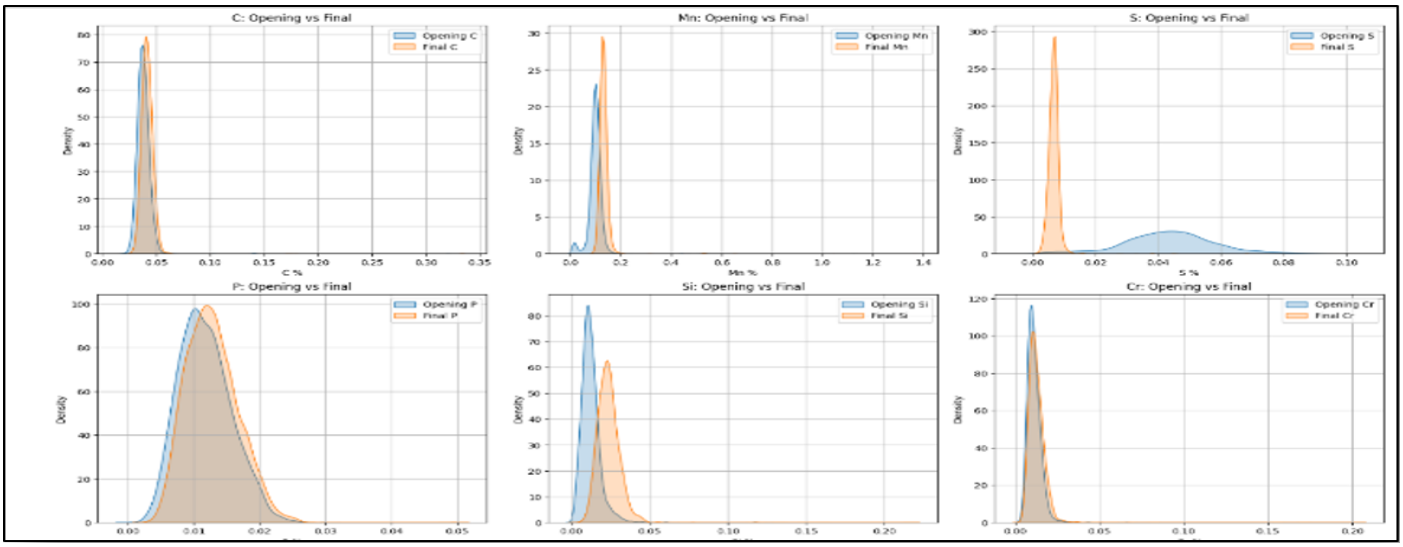


Fig 7 Top Correlated Element Pairs – Positive and Negative Relationships in Heat Chemistry Data

ISSN No: 2456-2165 https://doi.org/10.38124/ijisrt/25jun759

IV. COMPARATIVE ANALYSIS OF OPTIMIZATION TECHNIQUES

➢ *Linear Programming Method overview:*

Because linear programming is effective at resolving resource allocation issues when faced with linear constraints, it was chosen as the original baseline model. The goal was to minimize the total cost of alloy additions while ensuring the final chemical composition falls within defined lower and upper bounds for each key element, e.g., C, Mn, Si, Al.

➢ *How it was implemented:*

Decision variables represented the alloy quantities to be added per heat. Constraints enforced the final chemistry as the sum of opening values plus additions from alloys adjusted by recovery percentages. The problem was formulated using PuLP and solved using the CBC solver.

➢ *Observations:*

Strict equality constraints led to infeasibility when the initial element concentration, e.g., Al or S, exceeded target limits. LP cannot model nonlinear behavior like elemental volatility or losses during argon purging. LP makes the assumption that every constraint must be met at once, which isn't always feasible because of physical and chemical limits.

➢ *Bayesian Optimization Method overview:*

The optimization problem was modeled as a black-box function using Bayesian Optimization, in which the method balances exploration and exploitation of the search in an effort to determine the alloy configuration with the lowest cost space. Both Optuna and Scikit-Optimize (skopt) were explored for implementation.

➢ *How it was implemented:*

BO treated the objective function as cost penalty, where penalty was added if final chemistry deviated from allowed ranges. Alloys were treated as continuous variables with defined upper-lower bounds. Multiple trial evaluations were used to find the cost-optimal combination.

➢ *Observations:*

For many heats, the BO returned zero quantities for alloy additions because any change would incur a severe punishment for breaking constraints. BO is sensitive to both the initial conditions and the punishment settings, and performance was inconsistent across heats due to the probabilistic nature. BO may converge prematurely if the cost surface is flat near boundary regions. That all the constraints must be satisfied simultaneously leads isn't always possible due to chemical interactions and physical limitations.

➢ *Genetic Algorithm Method overview:*

Complex, nonlinear, and multi-dimensional problems with restrictions can be effectively solved using evolutionary optimization techniques such as Genetic Algorithms. In this study, the GA was implemented using the Pymoo framework and was specifically tailored to reflect the practical dynamics of alloy recovery and chemical interactions in the steel refining process.

➢ *Implementation details:*

In the GA configuration, the objective function assessed both the overall alloy cost and the quantities of various alloys to be added to each candidate solution or individual, which was encoded as a vector and applied penalty terms when the resulting chemical composition deviated from specified limits. The algorithm used standard evolutionary mechanisms—selection, crossover, mutation—to iteratively improve the population, ultimately converging toward cost-effective and chemically feasible alloying strategies.

➢ *Observations:*

Computationally expensive for batch processing. Model success highly depended on initial chemistry values. Recovery rate could not optimize if chemical deviation exceeded alloy correction capability.

➢ *Model Deployment and Real-Time Monitoring:*

In the study, deployment of One View, the optimized model was not run in a live production setting. Rather, the focus remained on designing and validating multiple optimized frameworks—Linear Programming, Bayesian Optimization, Genetic Algorithms—to evaluate the feasibility and alignment with real-world steel processes at the LRF stage.

Although model deployment is yet to be realized, the groundwork was laid for future integration into a real-time decision-support system for the melt shop. The envisioned deployment pathway includes embedding the selected optimization model—preferably GA-based—into a plant-level monitoring tool or SCADA interface that can automatically suggest optimal ferroalloy additions based on live chemical composition data and heat status.

Such integration will allow operators to receive intelligent alloy addition recommendations in real-time, reducing manual trial-and-error, minimizing material wastage, and improving turnaround time. The model, once validated across different steel grades and heat profiles, can be deployed using Python-based microservices and a lightweight front-end interface (e.g., Streamlit or Flask), enabling seamless interaction with Level-2 automation systems.

While real-time monitoring and feedback loops were not implemented in the current phase, the simulation results and model architecture are fully aligned for production deployment in subsequent phases of the project.

➢ *Discussion and Implications*

The analysis of optimization techniques—Linear Programming (LP), Bayesian Optimization (BO), and Genetic Algorithms (GA)—for ferroalloy additions at the Ladle Refining Furnace (LRF) stage revealed critical challenges and practical insights. While LP offered a structured cost-minimization framework, it struggled with infeasibility when input chemistries exceeded target maxima due to its inability to handle complex real-world metallurgical interactions. BO approaches demonstrated flexibility in navigating non-linear search spaces but often converged to

ISSN No: 2456-2165 https://doi.org/10.38124/ijisrt/25jun759

suboptimal or infeasible solutions due to strict constraints and limited exploration. GA showed the most promise, allowing non-linear modeling and constraint flexibility, though it required careful feasibility checks and problem tuning.

The findings emphasize that accurate modeling of chemical volatility (e.g., aluminum loss due to purging) and real-time adjustment is essential for actionable optimization. Integrating metallurgical domain knowledge—such as sulfur's behavior and aluminum's volatility—significantly improves model realism. These findings highlight the necessity of hybrid models that combine process-based limitations with data-driven learnings. When such optimization systems are implemented successfully, they can lower material costs, improve process stability, and support real-time decision-making in steelmaking operations.

➢ *Key Takeaways:*

Optimization of ferroalloy additions in the LRF stage is critical for minimizing cost while maintaining chemical compliance in steel grades. Traditional linear programming methods often fail in practical scenarios due to their inability to handle over-limit starting chemistries. Bayesian optimization techniques provide flexibility but require careful constraint tuning to avoid convergence on infeasible solutions. Genetic algorithms proved to be the most robust approach, effectively handling non-linearities and metallurgical constraints with improved feasibility. Domain knowledge, such as sulfur and aluminum behavior, is essential in aligning optimization logic with real-world process dynamics. Pre-validation through feasibility checks ensures the optimization model starts from a chemically viable baseline. The project highlights the need for hybrid approaches combining data-driven algorithms with physical process understanding. This work lays the foundation for future real-time closed-loop alloy addition systems to aid melters in decision-making during production. [Fig.8]

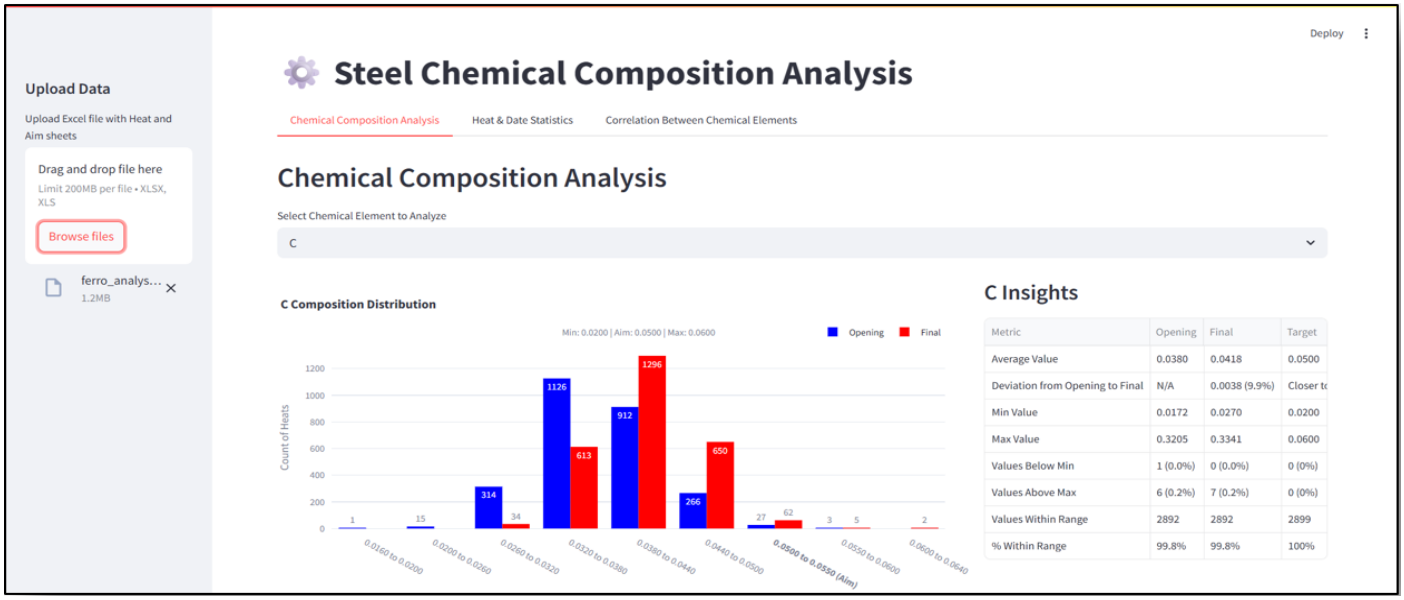


Fig 8 Steel Chemical Composition & Elemental Deviation Dashboard for Predictive Alloy Optimization.

V. CONCLUSION

This study demonstrates the feasibility of applying optimization algorithms to minimize ferroalloy usage and cost in the Ladle Refining Furnace (LRF) process while ensuring compliance with grade-specific chemical targets. Through comparative analysis of Linear Programming, Bayesian Optimization, and Genetic Algorithms, we found that GA provided the most practical and flexible solution, capable of handling real-world complexities such as over-limit elements and non-linear interactions. The integration of domain-specific insights—particularly the metallurgical behavior of elements like sulfur and aluminum—proved crucial in refining model performance and ensuring feasible outputs. While LP and BO struggled with hard constraints and rigid assumptions, GA accommodated variability and delivered more reliable recommendations for alloy additions. This work sets the foundation for building decision-support systems in steelmaking, enhancing cost-efficiency and operational control. Future efforts should focus on integrating process parameters like temperature, slag composition, and sampling intervals to improve prediction robustness and real-time deployability

ACKNOWLEDGEMENT

We acknowledged that with the consent from 360DigiTMG, we have used the CRISP-ML(Q) Methodology (ak.1) and the ML Workflow which are available as open-source in the official website of 360DigiTMG(ak.2).

➢ *Funding and Financial Declarations:*

- The authors affirm that no financial support, grants, or funding were obtained during the research or the manuscript preparation.
- The authors confirm that they have no financial or non-financial conflicts of interest to disclose.

ISSN No: 2456-2165 https://doi.org/10.38124/ijisrt/25jun759

➢ *Data Availability Statement:*

The datasets utilized, generated, and/or analyzed during the current study are not publicly accessible due to internal data privacy policies. However, they can be obtained from the corresponding author upon reasonable request.

FUTURE SCOPE

Future work on LRF optimization can explore integrating dynamic process variables such as temperature fluctuations, slag basicity, and oxygen ppm to improve model accuracy and real-time adaptability. Incorporating time-series data on alloy addition cycles and purging behavior could further enhance prediction precision. The use of hybrid modeling techniques that combine data-driven algorithms with physics-based metallurgical models holds promise for greater reliability. Additionally, developing a real-time recommendation system for melters, integrated with SCADA or Level 2 automation systems, can support smarter and faster decision-making. Scaling the model across different steel grades and incorporating constraints for operational sequencing (e.g., sequential alloy additions) will expand industrial applicability. Finally, incorporating reinforcement learning could help optimize sampling frequency and alloy dosing in closed-loop control systems.

REFERENCES

[1]. LF Refining Process Optimization Strategy https://www.clausiuspress.com/assets/default/article/2024/07/12/article_1720783774.pdf
[2]. Exergy Analysis and Optimization of Ladle Furnace Refining Process https://www.sciencedirect.com/science/article/abs/pii/S1006706X10601653
[3]. Optimization of Desulfurization Process Through Studying the Ladle Refining Furnace Parameters https://absb.researchcommons.org/journal/vol25/iss2/4/
[4]. Optimizing Ladle-Refining Performance During Treating Special Steel Melts for Aviation Technology https://www.researchgate.net/publication/347029473_Optimizing_ladle refining_performance_during_treating_special_steel_melts_for_aviation_technology
[5]. An Experimental Investigation on Utilization of Ladle Refined Furnace Slag in Geotechnical Applications https://www.sciencedirect.com/science/article/pii/S2405844024020358
[6]. Optimization of Aluminum Deoxidation Practice in the Ladle Furnace https://www.researchgate.net/publication/232871353_Optimization_of_Aluminum_Deoxidation_Practice_in_the_Ladle_Furnace
[7]. Prediction of Ladle Furnace Refining Endpoint Temperature Based on Particle Swarm Optimization Algorithm and Long Short-Term Memory Neural Network https://link.springer.com/article/10.1007/s11837-024-06983-8
[8]. Quantifying Flexibility Provisions of the Ladle Furnace Refining Process https://www.sciencedirect.com/science/article/abs/pii/S0306261923005421
[9]. Temperature Prediction Model for Ladle Furnace Based on Machine Learning https://journals.sagepub.com/doi/10.1177/03019233241240246
[10]. Optimisation of the Thermal Process in Ladle Metallurgy in Terms of Energy Intensity https://bibliotekanauki.pl/articles/2174906.pdf
[11]. Program for Exergy Analysis of Steel Refining in a Ladle Furnace https://tecnologiammm.com.br/article/10.4322/2176-1523.20253159/pdf/tmm-22-e3159.pdf
[12]. Computational Study of Non-Isothermal Slag Eye Formation and Its Effects on Ladle Refining https://arxiv.org/abs/2308.06798