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OPTIMIZED USAGE OF FERROALLOYS IN STEELMAKING PROCESS USING MACHINE LEARNING

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***Abstract*:** The steelmaking industry strives for efficient and cost-effective production while achieving desired steel qualities. This paper investigates the application of machine learning (ML) for optimizing ferroalloy usage in the steelmaking process. We explore how ML models can be leveraged to predict the required amount of ferroalloys for specific steel grades based on various process parameters and historical data. This approach offers the potential to minimize ferroalloy consumption while maintaining steel quality consistency. The paper discusses the benefits of ML-based optimization, including reduced production costs, minimized environmental impact, and improved process control. We explore potential ML algorithms suitable for this task and outline the development process for an ML-based ferroalloy optimization system. Finally, the discussion addresses the challenges and future directions for implementing ML-based optimization in steelmaking.

***Keywords*:** Ferroalloys, Steelmaking, Machine Learning, Optimization, Process Control

I. INTRODUCTION

Steel is an alloy of iron and carbon containing less than 2% carbon and 1% manganese and small amounts of silicon, phosphorus, sulphur and oxygen.

It's the most important engineering and construction material around the world. Here's why it's so crucial:

1. Strength and Versatility: Steel is incredibly strong and can be shaped into countless forms, making it useful for everything from skyscrapers to surgical tools.

2. Everywhere in our lives: We encounter steel constantly - in cars, appliances, buildings, and even the tools used to make other things! It's a foundational material in our modern world.

3. Durable and Sustainable: Steel is built to last and can be recycled repeatedly without losing its properties.

Bhilai Steel Plant Overview

- Bhilai Steel Plant, located in Bhilai, Chhattisgarh, is India's first and main producer of steel rails, as well as a major producer of wide steel plates and other steel products.
- Founded in 1955 with the help of Russia (then The Soviet Union).
- Produces 6.56 MT of saleable steel every year.
- Comes under SAIL (Steel Authority of India Ltd.)
- Other 7 plants also come under SAIL, but BSP produces steel and products in a huge
- amount alone.
- 5 plants -> Finished steel products, 3 plants-> Ferro alloys and other chemicals.

Steelmaking Process in Bhilai Steel Plant

1. Iron Making

- Iron ore from Dalli Rajhra mines is crushed.
- Coal from Bokaro, Jharkhand is divided:
  - **Coking coal:** Baked into coke.
  - **Energy coal:** Burned for plant power.
- Limestone and dolomite clean the iron ore.

2. Making Coke

Coking coal is baked in airless ovens to produce strong coke.

3. Sintering

Mixture of iron ore, coke dust, and limestone/dolomite is heated to stick together.

4. Blast Furnace

- Coke, sinter, and limestone are added to the furnace with hot air (1500-2000°C).
- Iron ore melts, forming hot metal and slag.
- Hot metal is collected in ladles.

5. Steel Making

- **Twin Hearth Furnace:** Oxygen and additives remove impurities.
- **Basic Oxygen Furnace:** Oxygen is blown through hot metal for precision impurity removal.

6. Refining

- Molten steel is transferred to a ladle furnace to add elements like Mn or Si.
- Vacuum degassing removes gases like H and O.

7. Casting

Molten steel is poured into molds to form long bars, cut into slabs or blooms as they cool.

8. Cooling & Inspection

Steel is inspected for surface flaws and internal defects using sound waves and test samples.

9. Shaping

Heated slabs are rolled into shapes such as plates, beams, rails, bars, or wires.

10. Finishing

Steel is cut, straightened, cleaned, coated, or heat-treated for specific properties.

11. Shipping

Finished steel is securely packaged and shipped to various industries.

II. LITERATURE REVIEW

Review 1:

Ferroalloys are crucial in steelmaking, enhancing properties and enabling specialized grades. This review covers types, functions, recent advancements, and economic and environmental aspects.

Ferroalloys, rich in elements like manganese, silicon, and chromium, are essential in steelmaking for strength, ductility, and corrosion resistance. Manganese ferroalloys deoxidize, remove sulfur and oxygen, and enhance hardness and strength for HSLA steels. Silicon ferroalloys deoxidize steel and improve elasticity and magnetic properties for electrical steels. Chromium ferroalloys provide corrosion resistance and hardness in stainless steel.

Ferroalloys function by removing oxygen with manganese, silicon, and aluminum, removing sulfur with manganese, and alloying to create specialized grades like stainless steel (chromium, nickel) and high-temperature steel (molybdenum).

Recent advancements focus on efficiency, reduced environmental impact, and new alloys for high-strength, lightweight applications in automotive and aerospace industries. Although production is energy-intensive with significant environmental impacts, cleaner technologies and secondary materials are being adopted to reduce costs and improve sustainability.

Ferroalloys are vital in enhancing steel properties and enabling specialized grades. Advances in technology and sustainability will continue to drive improvements in production and environmental impact.

Review 2:

Steelmaking has evolved significantly to improve efficiency, cost-effectiveness, and sustainability. This review explores the Basic Oxygen Furnace (BOF) and Electric Arc Furnace (EAF) methods, recent technological advancements, and efforts to reduce environmental impacts. These processes are crucial for meeting global steel demand, with ongoing research focused on enhancing their efficiency and sustainability.

Steelmaking, involving the production of steel from iron ore or scrap metal, relies on specific processes to determine steel quality and properties. The BOF process uses oxygen to refine molten pig iron, offering high production rates, precise quality control, and cost-effectiveness, but generating significant CO2 emissions and requiring substantial raw materials. The EAF process melts scrap steel with electric arcs, offering flexibility in raw materials, lower CO2 emissions, and energy efficiency, though it can result in variable steel quality and high electricity costs.

Recent advancements aim to improve efficiency and reduce environmental impact. Carbon capture and storage (CCS) technology captures and stores CO2 emissions, while hydrogen-based steelmaking, such as the Hydrogen Direct Reduction (HDR) method, aims to produce steel with minimal CO2 emissions.

As demand for steel grows, the BOF and EAF processes remain essential. Technological advancements and sustainability efforts are key to developing more efficient and environmentally friendly steelmaking methods.

Review 3:

The ladle furnace (LF) is crucial in secondary steelmaking, offering precise control over the composition and temperature of molten steel. This review explores the LF's function, advantages, and technological advancements. It highlights the LF's role in producing high-quality steel, reducing impurities, and optimizing efficiency, along with recent developments aimed at enhancing energy efficiency and reducing environmental impact.

Ladle furnaces (LF) are vital in secondary steelmaking, refining the chemical composition and temperature of molten steel. They ensure high-quality standards required for various applications. LFs control temperature, adjust chemical composition, facilitate deoxidation and desulfurization, and modify non-metallic inclusions. These functions enhance steel quality, provide operational flexibility, and boost productivity.

Advantages of LFs include improved steel quality through better temperature and composition control, operational flexibility for quick adjustments, and enhanced productivity by reducing the load on primary units. Recent technological advancements focus on improving energy efficiency, reducing emissions, and enhancing process control. Innovations such as better insulation, optimized heating systems, and advanced dust and emission control systems reduce energy consumption and environmental impact. Automation and control systems, along with advanced stirring techniques like electromagnetic and gas stirring, improve process precision and reliability.

Ladle furnaces are pivotal in secondary steelmaking, ensuring precise control over temperature and composition, which leads to improved steel quality, flexibility, and productivity. Technological advancements have made LFs more energy-efficient and environmentally friendly. As demand for high-quality steel grows, ongoing innovations in LF technology are essential to meet industry requirements and environmental standards.

Review 4:

The Basic Oxygen Furnace (BOF) is vital in steelmaking, converting raw materials into high-quality steel. This review covers the BOF's development, operational principles, environmental impacts, and recent advancements, emphasizing its importance and ongoing improvements in efficiency and sustainability.

The BOF, or LD converter, transformed steelmaking in the mid-20th century by replacing the Bessemer process. It uses oxygen blowing to remove impurities from molten pig iron and scrap steel, producing precise, high-quality steel.

Despite its productivity benefits, the BOF generates significant CO2 and other emissions. Mitigation efforts include alternative technologies and emission controls. Recent advancements focus on improving efficiency and sustainability, such as better refractory materials, AI-driven process optimization, and carbon capture.

The BOF is essential for producing high-quality steel. Continuous innovation aims to reduce its environmental impact, helping the steel industry meet demand sustainably.

III. METHODOLOGY

Our main objective is to optimize the use of ferroalloys in steelmaking. This balanced approach will prevent excess ferroalloys from being added to the molten steel, ultimately achieving cost-effectiveness.

For this, we are preparing a machine learning model. This model will predict the optimal amount of ferroalloys to be added to the molten steel liquid, preventing excess use and ensuring a cost-effective process.

What are Ferroalloys?

Ferroalloys are metal alloys composed primarily of iron (Fe) and a high percentage of one or more other elements, such as manganese (Mn), chromium (Cr), or silicon (Si). They are not used in their final form but rather act as additives in the steelmaking process.

Ladle Furnace

Ladle furnace, or ladle metallurgy furnace, is an important part of the secondary steelmaking process. This process represents a phase in steelmaking where liquid steel is refined and its composition is adjusted, typically through the addition of ferroalloys.

This process occurs in several steps:

- **Preparation of Ladle:** First, the ladle furnace is prepared. The ladle is placed in an insulated chamber to minimize heat loss and maintain high temperatures.
- **Charging:** Next, the ladle is charged with liquid steel. This steel usually comes from the primary steelmaking process, such as from a basic oxygen furnace (BOF) or an electric arc furnace (EAF).
- **Heating:** The steel in the ladle furnace is heated to the desired temperature. Electricity is often used for this purpose to ensure the steel reaches the appropriate temperature uniformly. Stirring may also be employed to distribute heat evenly.
- **Alloy Addition:** Once the steel reaches the desired temperature, ferroalloys are added to the ladle. Ferroalloys, such as ferrochrome, ferromanganese, and ferrosilicon, are used to introduce desired alloying elements. This addition process is carefully controlled to achieve the desired composition.
- **Refining and Degassing:** After the addition of ferroalloys, the steel is further refined and degassed. This helps remove unwanted impurities and improves the cleanliness and quality of the steel.
- **Temperature Adjustment:** If necessary, the temperature of the steel in the ladle furnace is adjusted to maintain the desired temperature.
- **Pouring:** In the final step, the refined liquid steel is poured from the ladle into casting machines or ingot molds for further processing.

Machine Learning Implementation

Machine learning (ML) is a branch of AI that trains algorithms to learn from data, identify patterns, make predictions, and improve over time without explicit programming.

What It Does

- Learns from data to make predictions or decisions.
- Identifies hidden patterns in data sets.
- Improves performance with more data and experience.

Types of Machine Learning

- **Supervised Learning:** Uses labeled data to learn input-output relationships and predict outputs for new data.
- **Unsupervised Learning:** Finds patterns in unlabeled data, grouping similar points or identifying anomalies.
- **Reinforcement Learning:** Learns through interactions with an environment, optimizing actions to maximize rewards.

Here, we have used Supervised Learning

Steel Industry Automation

Steel industry automation leverages technology to reduce human involvement and streamline production, ranging from basic tasks to full integration. Here's a summary of automation levels and benefits:

- **Level 0:** Sensors, actuators, and motors.
- **Level 1 (Basic Auto):** PLCs (Programmable Logic Controllers) and HMI (Human Machine Interface) automate tasks using sensor/actuator data.
- **Level 2 (Process Ctrl):** SCADA (Supervisory Control and Data Acquisition) monitors production, enabling adjustments and data collection.
- **Level 3 (Production Ctrl):** MES integrates with SCADA and ERP for optimized production.
- **Level 4 (Enterprise Management):** ERP manages all business functions for real-time decision-making.

Benefits

- **Efficiency:** Optimizes resource allocation and process control.
- **Safety:** Reduces human involvement in hazardous tasks.
- **Quality:** Minimizes human error, enhancing product quality.

Technologies

- **Common:** PLCs, SCADA, MES.
- **Advanced:** Machine learning for process optimization and predictive maintenance.

For Developing Machine Learning Model, we have used Google Colaboratory (Colab) platform. It is a cloud-based platform for running Python code. It eliminates the need for setup and provides free access to powerful computing resources like GPUs. This makes Colab ideal for machine learning projects, allowing you to train models without worrying about hardware limitations. You can access Colab through a web browser and collaborate with others in real-time.

Design and Implementation

System Architecture

Figure 3.1: System Architecture

- **Operator Input:** Initial steel composition, process features, target composition.
- **Prediction Model:** Estimates ferroalloy additions to reach target composition.
- **Recommendations:** Suggests types and amounts of ferroalloys for efficient production.
- **Operator Review:** Operator can adjust recommendations based on experience or real-time conditions.
- **Implementation & Feedback:** Implemented additions, final composition measured, and it can be fed back to improve model accuracy.

The optimization algorithm evaluates different ferroalloy combinations to achieve the desired steel composition efficiently based on specified criteria (e.g., cost minimization, alloy utilization maximization).

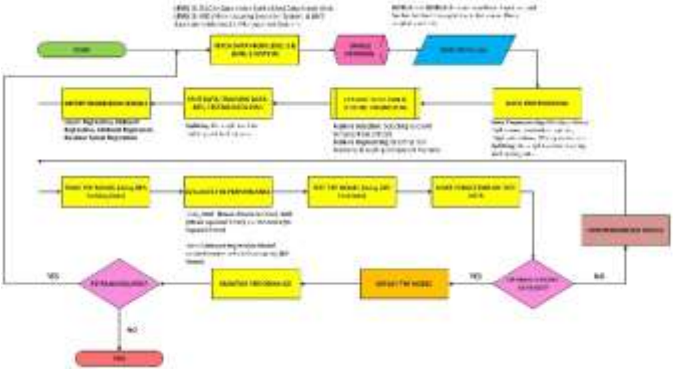

Figure 3.2: Flowchart for Design and Implementation Process

1. Data Collection

- Gathered from Level-2 (SCADA) and Level-3 (MES, LIMS) systems.
- Retrieved via Oracle database queries.
- Includes chemical compositions and ferroalloy additions.

2. Data Preprocessing

- Handled missing values, duplicates, errors, and categorical data.
- Used ydata Profiling for data exploration.

3. Feature Selection and Engineering

- **Selection:**
  - Used pandas profiling and correlation heatmaps.
  - Performed manual feature selection.
- **Engineering:**
  - Encoded categorical variables without creating new features.

4. Splitting the Dataset

- Training set: 80%
- Testing set: 20%

5. Regression Models

- Evaluated models: Linear Regression, Random Forest, XGBoost, CatBoost.
- Best performance: CatBoost with an R-squared score of ~82%.

6. Training the Model

- Trained on 80% of the data.

7. Evaluating Performance

- Metrics: MAE, MSE, R-squared score.
- Best model: CatBoost.

8. Testing the Model

- Evaluated on 20% testing set.

9. Making Predictions

- Predictions made on test data and displayed.

10. Model Deployment

- Deployed if performance is satisfactory.

11. Hyperparameter Tuning

- Performed if model accuracy needs improvement.

12. Retraining the Model

- Retrain with more data if necessary, repeating preprocessing and evaluation steps

IV. RESULT & ANALYSIS

Regression analysis is crucial for understanding relationships between dependent (target) and independent (predictor) variables, especially in multivariate contexts. We evaluated several regression models: Random Forest, Linear Regression, CatBoost, and XGBoost, to determine their performance on our dataset.

1. Initial Model Performance

- **Random Forest Regression**
  - MAE: 21.54, MSE: 2219.49, R^2: 0.6980
  - Moderate fit with some underfitting due to high MSE.
- **Linear Regression**
  - MAE: 23.11, MSE: 2468.78, R^2: 0.6936
  - Similar to Random Forest, likely underfitting the data.
- **CatBoost Regression**
  - MAE: 20.295, MSE: 2329.24, R^2: 0.7942
  - Best initial performance, capturing data complexity well.
- **XGBoost Regression**
  - MAE: 20.852, MSE: 2094.27, R^2: 0.7431
  - Good fit, better than Random Forest but not as good as CatBoost.

2. Cross-Validation (CatBoost)

- MAE: 20.34, MSE: 2606.212, R^2: 0.782
- Consistent performance, indicating robustness and minimal overfitting.

3. Enhanced Performance with MultiOutputRegressor

- **Random Forest**
  - MAE: 17.1981, MSE: 1501.92, R^2: 0.8196
  - Significant improvement, better fit without overfitting.
- **Linear Regression**
  - MAE: 18.1780, MSE: 1704.98, R^2: 0.803
  - Improved performance, but still simpler model limitations.
- **CatBoost**
  - MAE: 16.7601, MSE: 1432.46, R^2: 0.827
  - Highest accuracy, excellent predictive performance.
- **XGBoost**
  - MAE: 17.34, MSE: 1541.00, R^2: 0.8145
  - Significant improvements, balanced performance.

REGRESSION ALGORITHMS USED	MULTIVARIATE ANALYSIS			MULTIVARIATE ANALYSIS (USING MultiOutputRegressor(), and adding more features)		
	MAE	MSE	R2-SCORE	MAE	MSE	R2-SCORE
Random Forest	21.54	2219.49	0.6980	17.1981	1501.92	0.8196
Linear Regression	23.11	2468.78	0.6936	18.1780	1704.98	0.803
Categorical Boosting	20.295	2339.24	0.7942	16.7601	1432.46	0.827
XGBoost	20.852	2094.27	0.7431	17.3497	1541.00	0.8145

Figure 5.1: Results of various Regression Algorithms

Plots

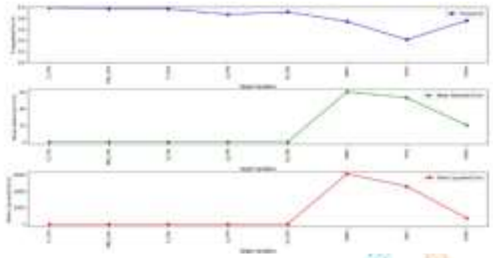

Figure 4.1: Accuracy Plots

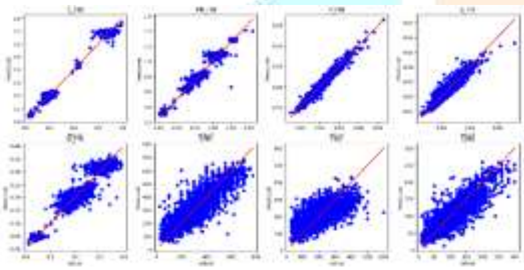

Figure 4.2: Scatter Plots

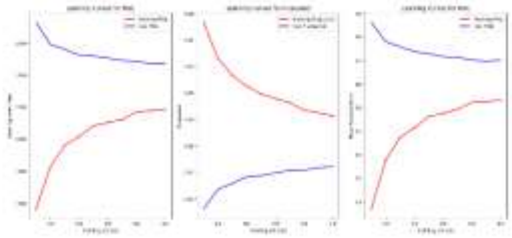

Figure 4.3: Learning Plots

V. CONCLUSION

Machine learning offers a powerful toolkit for optimizing ferroalloy usage in steelmaking, leading to significant cost savings, improved quality control, and a more sustainable manufacturing process. By focusing on practical advancements in model interpretability, data standardization, and targeted applications, the steel industry can harness the full potential of ML. As research and development progress, ML will continue to play a crucial role in shaping a more efficient and sustainable future for steelmaking.

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