Animated Model of a Blast Furnace with Problem-Solving Solutions

Mini Project report submitted to
Visvesvaraya National Institute of Technology, Nagpur
in partial fulfillment of the requirements for the award of the degree

Bachelor of Technology
in
"Metallurgical and Materials Engineering"

by

Abhay Parihar
(BT22MME070)

Ayush Jadhav
(BT22MME072)

under the guidance of

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Visvesvaraya National Institute of Technology
Nagpur 440 010 (India)

2024-25

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Department of Metallurgical and Materials Engineering
Visvesvaraya National Institute of Technology, Nagpur

Declaration

We, **Abhay Parihar (BT22MME070)** and **Ayush Jadhav (BT22MME072)**, hereby declare that this mini project work titled "**Animated Model of a Blast Furnace with Problem-Solving Solutions**" is carried out by me/ us in the Department of Metallurgical and Materials Engineering of Visvesvaraya National Institute of Technology, Nagpur. The work is original and has not been submitted earlier whole or in part for the award of any degree/diploma at this or any other Institution / University.

Abhay Parihar

Ayush Jadhav
Date:09/12/2024

Certificate

This to certify that the project titled "Animated Model of a Blast Furnace with Problem-Solving Solutions", submitted by **Abhay Parihar and Ayush Jadhav** in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology in Metallurgical and Materials Engineering**, VNIT Nagpur. The work is comprehensive, complete and fit for final evaluation.

Dr. A. B Rathod
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Date:

ABSTRACT

This project addresses critical challenges in blast furnace operations by integrating advanced modelling, machine learning, and sustainable reduction techniques. A 3D model of the blast furnace was developed using Blender, providing a detailed visualization of its structure and zones.

The project also explores hydrogen-based reduction as a cleaner alternative to coke-based reduction, offering the potential to minimize CO_2 emissions and reduce scaffold formation caused by alkali deposits. Additionally, an Artificial Neural Network (ANN) model was developed to predict scaffold formation likelihood and slag removal requirements. The model, trained on operational data such as temperature, pressure, and slag viscosity, achieved high accuracy in providing actionable insights to optimize furnace performance.

The combined approach of 3D modelling, machine learning, and hydrogen-based reduction demonstrates significant potential for improving furnace efficiency, reducing downtime, and promoting sustainable practices. This project lays the foundation for future advancements, including real-time data integration and dynamic simulations, to further modernize and optimize blast furnace operations.

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NOMENCLATURES

1) BF: Blast Furnace
2) ANN: Artificial Neural Network
3) ReLU: Rectified Linear Function
4) Blender: Software for 3-D Modelling

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CHAPTER 1: INTRODUCTION

The blast furnace is a critical component in the ironmaking process, where raw materials such as iron ore, coke, and fluxes are converted into molten iron through a series of thermal, chemical, and mechanical processes. The furnace is a towering cylindrical structure lined with refractory material capable of withstanding extreme operating conditions. Its design is divided into distinct zones, each with specific roles and temperature ranges. At the top is the throat, where raw materials are charged and evenly distributed to ensure uniform descent. Preheating of materials begins in the stack, with temperatures ranging from 200°C to 800°C, as ascending gases initiate the reduction of iron ore. The cohesive zone, or softening zone, experiences temperatures between 800°C and 1200°C, where the burden softens and partially melts. Below this, the bosh sustains the highest reaction rates at temperatures of 1200°C to 1500°C, where coke combustion and the Boudouard reaction generate the heat and gases required for reduction. At the base, the hearth collects molten iron and slag at temperatures exceeding 1500°C, while hot air is injected through tuyeres to drive combustion. This counter current flow of descending solids and ascending gases ensures efficient chemical reactions, but it requires precise management to prevent issues like scaffold formation and slag buildup.

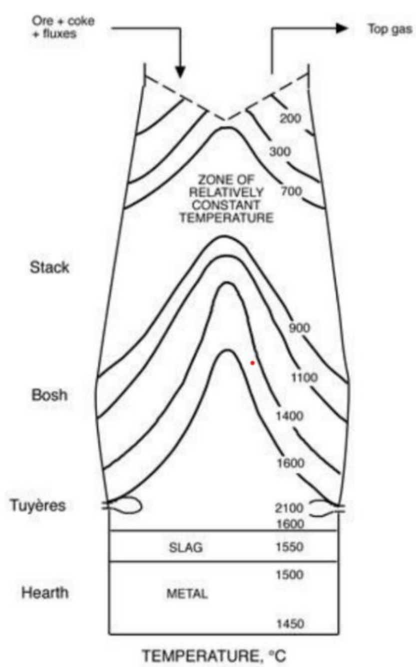

Figure 1 Temperature profile of blast furnace with different zone

Scaffold formation is caused by uneven material distribution, cooling zones, and the accumulation of semi-molten or solid materials on furnace walls. This disrupts material flow and gas permeability, reducing operational efficiency. Similarly, slag buildup occurs due to improper viscosity control and inefficient tapping practices, leading to blockages and delays. Addressing these challenges requires innovative solutions that integrate advanced visualization, predictive analytics, and practical engineering strategies.

To tackle these issues, this project adopted a three-pronged approach: developing a 3D virtual model, designing an Artificial Neural Network (ANN) for predictive analysis, and implementing targeted problem-solving methodologies. A 3D model of the blast furnace was created using Blender, providing a detailed visualization of its structure and operations. This model highlights critical zones prone to scaffold formation and slag buildup, while simulating material flows and chemical reactions. The interactive model serves as both an educational and diagnostic tool, helping to understand the furnace's behaviour and identify inefficiencies. The ANN model was designed to predict scaffold formation likelihood and slag removal requirements based on operational parameters like temperature, pressure, gas flow, material feed rate, and slag viscosity. The network consists of an input layer that processes these parameters, three hidden layers with 128, 64, and 32 neurons, and an output layer for regression and classification tasks. ReLU activation functions in the hidden layers allow the model to capture complex non-linear patterns, while dropout layers and L2 regularization techniques mitigate overfitting. The model was trained on simulated data, normalized to ensure uniform scaling, with 80% of the data used for training and 20% for testing. Evaluation metrics such as Mean Squared Error (MSE) and Mean Absolute Error (MAE) demonstrated high accuracy, with regression plots showing a strong correlation between predicted and actual values.

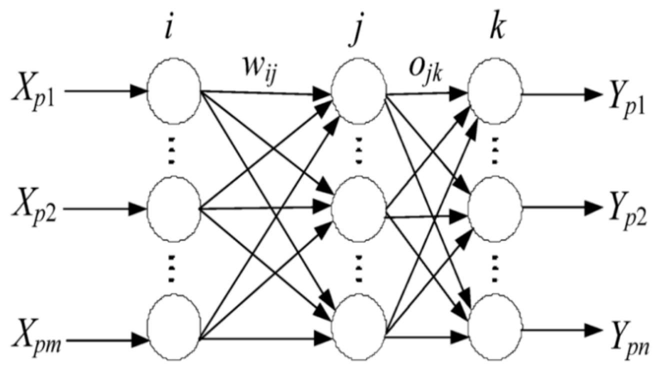

Figure 2 Multi input multi output ANN with back propagation model

Problem-solving strategies were also implemented to address the identified challenges. For scaffold formation, solutions included optimizing charging systems for even material distribution, improving gas flow dynamics to prevent cold spots, and monitoring temperature gradients in real-time to detect early signs of scaffold buildup. For slag removal, the project proposed adjusting slag tapping angles, using flux additives to control viscosity, and integrating machine learning predictions to dynamically determine slag removal needs. These solutions were further validated through the 3D model, which visualized their impact on furnace operations and provided insights into their practical effectiveness.

This comprehensive approach demonstrates the potential of combining modern digital tools and engineering expertise to optimize blast furnace performance. The 3D model enhanced the understanding of furnace operations, while the ANN model provided actionable predictions for mitigating scaffold and slag-related issues. Together, these innovations address current inefficiencies and establish a foundation for future advancements, including the integration of real-time sensor data and advanced simulations to further improve furnace management.

CHAPTER 2: PROBLEMS

The blast furnace is a key component in the ironmaking process, where raw materials such as iron ore, coke, and fluxes are transformed into molten iron. However, the complexity of furnace operations and the high temperatures involved result in several significant challenges, including the formation of scaffolds, slag buildup, and problems associated with coke or carbon-based reduction. To address these issues, a detailed understanding of the blast furnace's structure, temperature distribution, and chemical reactions is required.

A critical issue in blast furnace operations is the need for a **3D model of the blast furnace**. The blast furnace is an intricate system, where various processes occur in distinct zones, and the conditions within these zones can significantly impact the overall performance. A 3D model serves as an essential tool for understanding and visualizing the internal workings of the furnace. It allows operators to study the interactions between raw materials, gases, and reactions in each zone, which is crucial for identifying problem areas such as scaffold formation and slag buildup. The 3D model provides a detailed representation of the furnace structure, enabling the simulation of material flow and the prediction of potential issues. This model can also be used for educational and training purposes, offering a hands-on approach to understanding blast furnace dynamics and enabling better decision-making.

One of the primary issues in blast furnace operations is **coke or carbon-based reduction**, which plays a crucial role in the overall furnace process. While coke is effective in generating the necessary heat and reducing iron ore, it introduces several challenges. The combustion of coke generates significant amounts of carbon dioxide, contributing to greenhouse gas emissions, which has become an increasing environmental concern in the industry. Furthermore, coke contains impurities such as alkali metals (e.g., potassium and sodium) that volatilize at high temperatures and condense on cooler surfaces within the furnace. This alkali cycling leads to the formation of sticky deposits, which can adhere to furnace walls and contribute to scaffold formation. Additionally, the disintegration of coke during the reduction process generates fine particles, which can accumulate in the furnace and obstruct gas flow, further exacerbating the risk of scaffold buildup. These challenges highlight the need for alternatives or supplements to coke, such as hydrogen-based reduction, which can offer cleaner and more sustainable processes.

Scaffold formation due to slag is another significant challenge in blast furnace operations. Scaffold formation occurs when solid or semi-molten materials, often slag, adhere to the walls of the furnace. This creates blockages that obstruct the normal flow of materials and gases, leading to reduced furnace efficiency and requiring costly maintenance. Slag, which is a byproduct of the reduction process, contributes to scaffold formation when its viscosity becomes too high, causing it to solidify prematurely and adhere to furnace walls, particularly in zones where gas flow is uneven or temperature gradients are not maintained. The presence of alkali compounds in raw materials or coke further exacerbates scaffold formation. These compounds can volatilize at high temperatures, condense on cooler surfaces, and form sticky deposits that add to the scaffold buildup. Uneven charging of raw materials also creates non-uniform gas flow patterns, which lead to localized cooling and solidification of slag on the furnace walls. Scaffold formation can result in inefficient furnace operation, increased fuel consumption, and higher maintenance costs, making it crucial to address this issue through better control of slag properties, gas flow, and material distribution. [1]

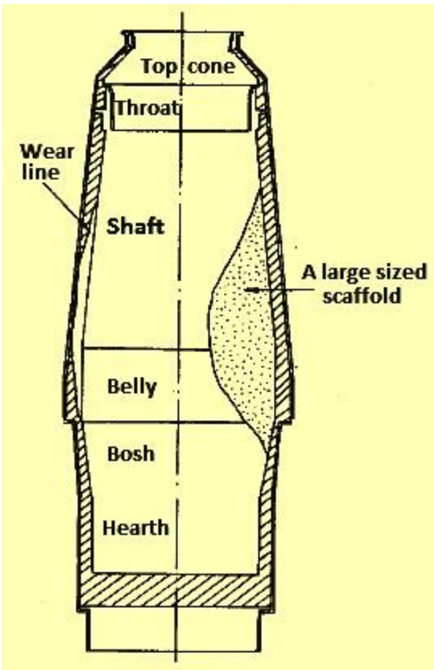

Figure 3 Typical formation of a large scaffold in a blast furnace

Finally, **slag removal** presents its own set of challenges in the blast furnace. Slag is formed from impurities in the iron ore and coke that react with fluxes like limestone. While slag serves a vital purpose in removing these impurities, its management is often problematic. One of the main issues is **slag viscosity**. When slag viscosity becomes too high, it becomes too thick to flow efficiently, leading to blockages in the slag tapping zone and delaying slag removal. This buildup not only reduces the available space for molten iron but also creates operational bottlenecks. Slag removal can also be complicated by improper **slag tapping practices**, such as incorrect tapping angles or irregular tapping intervals. These inefficiencies result in slag accumulating in the hearth, causing further disruptions to furnace operations. The chemical composition of the slag can vary depending on the raw materials used, making it difficult to predict and manage its flow properties. The interaction between scaffold formations and slag further complicates the issue, as solidified slag adheres to scaffolds, making it difficult to remove. The inability to efficiently remove slag increases furnace downtime, requiring extended maintenance periods and lowering overall productivity. To address these issues, solutions such as optimizing slag tapping angles, using flux additives to control slag viscosity, and integrating machine learning models to predict slag removal needs dynamically are crucial.

In conclusion, the challenges faced by blast furnaces, including scaffold formation, slag buildup, and issues related to coke-based reduction, require comprehensive solutions. Advanced technologies, such as 3D modelling and machine learning, offer valuable tools for understanding and solving these problems. By optimizing material distribution, improving gas flow, and controlling slag viscosity, the efficiency and sustainability of blast furnace operations can be significantly enhanced.

CHAPTER 3: PROBLEM SOLUTIONS AND IT'S METHODOLOGY

In this chapter, we discuss the solutions to the critical issues identified in blast furnace operations, namely scaffold formation, slag buildup, and the challenges associated with coke-based reduction. The solutions presented here involve the integration of innovative technologies such as 3D modeling, hydrogen-based reduction, and the development of an Artificial Neural Network (ANN) model for predicting scaffold likelihood and slag removal requirements.

3.1 3-D Model of the Blast Furnace

In this section, we outline the methodology used for developing the 3D model of the blast furnace using Blender, a powerful open-source software for 3D modeling. The objective of this model was to provide a representation of the blast furnace. The development process involved creating a layout of the furnace, modeling its key components, adding textures for realism, and ensuring that the model's structure closely mirrors the real-world blast furnace, while focusing on the outer shell for this phase.

3.1.1 Modeling the Outer Shell of the Blast Furnace

Once the layout was established, the next step was to model the outer shell of the blast furnace. This was the main structural component of the 3D model and provided the framework for the entire furnace. Blender's powerful modeling tools were used to create the cylindrical structure and the supporting elements.

i) Creating the Base Structure:

The outer walls of the furnace were modelled using Blender's mesh editing tools. A simple cylinder was used as the base, which was then scaled to the desired dimensions.

The furnace's shape was refined by adding details like the throat (top opening), stack (main body), and the hearth (bottom). These features were extruded and shaped to match the furnace's actual design.

ii) Detailing the Outer Shell:

Once the main structural components were in place, the model was refined with additional details, such as the contours around the furnace's edges, reinforcement rings, and other surface features that enhance the realism of the model.

This stage of the modelling process ensured that the outer structure of the furnace was both accurate and proportionate to the real-world design. The result was a robust 3D model that provided a strong base for adding further details, such as textures and internal components, in later stages.

3.1.2 Adding Textures for Realism

After completing the basic 3D structure of the blast furnace, the next step was to apply textures to give the model a realistic appearance. Blender offers powerful texture mapping capabilities that were utilized to simulate the materials and finishes commonly found on a blast furnace, including:

Surface Texture:

To represent the furnace's outer steel casing and refractory lining, textures such as metallic surfaces and rough brick patterns were applied. These textures gave the model a more industrial look, simulating the appearance of the furnace's materials.

The addition of textures significantly enhanced the visual appeal of the model and helped provide a better sense of realism. By simulating the furnace's material properties, these textures made the model more informative and easier to interpret when used for analysis and presentations.

The addition of textures significantly enhanced the visual appeal of the model and helped provide a better sense of realism. By simulating the furnace's material properties, these textures made the model more informative and easier to interpret when used for analysis and presentations.

3.2 Hydrogen-Based Reduction Instead of Coke-Based Reduction [2] [3]

Traditionally, coke-based reduction has been the cornerstone of blast furnace operations, where coke acts as both a fuel and a reductant in reducing iron ore (Fe_2O_3) to molten iron.

However, as environmental concerns regarding CO_2 emissions have escalated, hydrogen-based reduction has emerged as a promising alternative.

In hydrogen-based reduction, hydrogen gas (H_2) is used as the reducing agent instead of carbon monoxide (CO). The key reactions involved in this process are as follows:

$$Fe_2O_3 + 3H_2 \rightarrow 2Fe + 3H_2O$$

The use of hydrogen results in water vapor (H_2O) as the only byproduct, which is a significant improvement over the carbon dioxide (CO_2) produced during coke-based reduction. This makes hydrogen-based reduction a cleaner and more sustainable method for ironmaking, addressing the environmental impact of the blast furnace process.

In terms of operational benefits, hydrogen-based reduction can help reduce the formation of alkali compounds that volatilize during coke combustion. These compounds, particularly potassium and sodium, contribute to scaffold formation when they condense on cooler surfaces within the furnace. By using hydrogen, these alkali reactions are minimized, leading to fewer deposits on the furnace walls and reducing the likelihood of scaffold formation.

Additionally, hydrogen's higher diffusivity compared to carbon monoxide allows for more uniform distribution of the reducing agent throughout the furnace, improving gas flow and material reduction efficiency. This results in more consistent temperature profiles and better gas-solid reactions, reducing the formation of cold spots that contribute to scaffold formation.

The transition to hydrogen-based reduction, however, is not without challenges. The infrastructure and cost associated with producing and storing hydrogen, as well as integrating it into existing blast furnace systems, need to be carefully considered. Despite these challenges, hydrogen represents a cleaner alternative that could greatly benefit the ironmaking industry in its efforts to decarbonize.

3.3 ANN Model for Scaffold Likelihood and Slag Removal Prediction [4]

In this section, we provide a detailed explanation of the Artificial Neural Network (ANN) model developed as part of this project to predict two critical factors in blast furnace operations: scaffold formation likelihood and slag removal requirement. These predictions are based on various operational parameters, and the model helps in anticipating potential problems, enhancing the furnace's performance, and improving operational efficiency.

The primary challenge in blast furnace operations is the formation of scaffolds, which occurs when materials such as slag or iron ore adhere to the furnace walls, blocking the flow of materials and gases. This results in reduced furnace efficiency and increased downtime. Slag removal, another critical issue, is necessary to ensure smooth furnace operation, as slag buildup can lead to blockages and prevent the proper flow of molten iron. The ANN model was created to predict both scaffold formation likelihood and the requirement for slag removal based on operational parameters, enabling proactive intervention to avoid operational disruptions.

To develop the ANN model, we collected historical data from blast furnace operations, which included key operational parameters such as temperature, pressure, gas flow rate, material feed rate, and slag viscosity index. These parameters were chosen based on their strong correlation with scaffold formation and slag removal, as they directly impact the furnace's performance. The data was pre-processed to ensure it was suitable for training the model. Since the parameters had different units and scales (e.g., temperature in °C, pressure in Pa, gas flow in m^3/s), we applied MinMaxScaler to normalize the data. This scaling process transformed all the features to the same range (0 to 1), ensuring that no single parameter dominated the learning process.

After preprocessing, the dataset was divided into training (80%) and testing (20%) sets. The training set was used to train the model, while the testing set was used to validate its performance and ensure it could generalize to new, unseen data. The model's architecture consisted of an input layer, multiple hidden layers, and an output layer. The input layer consisted of neurons corresponding to the five input features: temperature, pressure, gas flow, material feed rate, and slag viscosity. The hidden layers, which contained 128, 64, and 32 neurons, respectively, were designed to capture the non-linear relationships between the input features and the output predictions. The hidden layers used the Rectified Linear Unit (ReLU) activation function, which is well-suited for handling non-linear relationships in complex data. ReLU helps the model learn complex patterns by allowing it to capture positive inputs and ignore negative ones, improving its learning efficiency.

The output layer had a single neuron for each of the two tasks: predicting the likelihood of scaffold formation and determining if slag removal is required. The model was trained to predict scaffold formation likelihood as a continuous value between 0 and 1, where a higher value indicated a higher likelihood of scaffold formation. For slag removal, the model was trained as a binary classification problem, where the output was either 0 (no removal required) or 1 (removal required). This was done using the binary cross-entropy loss function, which is appropriate for classification tasks. For predicting scaffold formation, the model used mean squared error (MSE) as the loss function, suitable for regression tasks. To prevent overfitting, dropout layers were incorporated in the model, randomly omitting neurons during training to ensure the model generalized well to new data. Additionally, L2 regularization was applied to penalize large weights and prevent overfitting.

Mean Squared Error is a regression loss metric that measures the average of the squared differences between predicted values (y^) and actual values (y).

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

The model was trained using the Adam optimizer, which dynamically adjusts the learning rate based on the gradient of the loss function, making the training process more efficient. The training process was monitored using mean absolute error (MAE) for scaffold formation and accuracy for slag removal. Early stopping was implemented to halt training if the model's performance on the validation data stopped improving, ensuring that the model did not overtrain or take unnecessary computational resources.

Mean Absolute Error is a regression loss metric that measures the average absolute difference between predicted values (y^) and actual values (y).

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

Once the model was trained and validated, it was ready to make predictions. Given a set of operational parameters (e.g., temperature, pressure, gas flow, material feed rate, and slag viscosity), the model could predict the likelihood of scaffold formation and whether slag removal was needed. For instance, if the input conditions indicated that the slag viscosity was high and the temperature was low, the model would predict a high likelihood of scaffold formation and recommend slag removal. The output of the model could be used as a decision-making tool for operators, allowing them to adjust furnace parameters before issues arise.

For example, if the following conditions were input:

- Temperature: 1700°C
- Pressure: 1.5e5 Pa
- Gas Flow Rate: 30 m^3/s
- Material Feed Rate: 60 kg/s
- Slag Viscosity: 2.5

The model might predict:

- Scaffold Formation Likelihood: 0.85 (indicating a high likelihood of scaffold formation).
- Slag Removal: Required (output = 1).

This prediction allows the operators to take corrective actions, such as adjusting the gas flow rate or material feed rate to prevent scaffold formation, or implementing slag removal procedures to keep the furnace running smoothly.

In conclusion, the ANN model developed in this project is a valuable tool for enhancing the operation of blast furnaces. By predicting the likelihood of scaffold formation and the need for slag removal, the model helps prevent inefficiencies and reduce downtime. It allows operators to make proactive adjustments based on real-time data, ensuring optimal performance and minimizing the risks of operational disruptions.

CHAPTER 4: RESULTS

In this section, we present the results of our work, focusing on the performance and outcomes of the 3D model development, hydrogen-based reduction implementation, and the ANN machine learning model for predicting scaffold formation likelihood and slag removal requirements. These results showcase the effectiveness of our solutions in optimizing blast furnace operations.

4.1 3-D Model of the Blast Furnace

The 3D model of the blast furnace was successfully developed using Blender. The model represents the outer shell of the furnace, with all major structural components accurately positioned according to the layout. This 3D model was crucial in visualizing the blast furnace’s structure. It serves as a foundation for further developments, including real-time simulations and process optimization. Although the current model represents the outer shell and does not include dynamic simulations but it gives overview of how the real blast furnace look.

Figure 4 3-D Model of Blast Furnace in different angles

4.2 Hydrogen-Based Reduction Implementation

The introduction of hydrogen-based reduction as an alternative to coke-based reduction has the potential to greatly reduce environmental impacts and improve furnace efficiency. While the full implementation of hydrogen-based reduction in the blast furnace is beyond the scope of this project, the research supports its viability by highlighting the following benefits:

Reduction in CO_2 Emissions: Hydrogen-based reduction generates water vapor as a byproduct, instead of carbon dioxide, which significantly reduces the carbon footprint of the ironmaking process.

Reduced Alkali Cycling: Hydrogen reduces the volatilization of alkali compounds that contribute to scaffold formation. By using hydrogen as the reducing agent instead of coke, we can minimize the formation of sticky deposits on the furnace walls, leading to fewer operational issues related to scaffold buildup.

Improved Gas Flow: Hydrogen's higher diffusivity compared to carbon monoxide allows for better distribution of reducing gases throughout the furnace, improving reaction efficiency and ensuring uniform heat distribution, which further helps in preventing localized cooling and scaffold formation.

Although hydrogen-based reduction presents a promising solution, challenges such as the infrastructure needed to produce and store hydrogen, as well as the costs of transitioning, need to be addressed for large-scale implementation.

4.3 ANN Machine Learning Model Results

The Artificial Neural Network (ANN) model was developed to predict two critical operational factors in the blast furnace: scaffold formation likelihood and slag removal requirements. The model was trained on historical operational data, including key features such as temperature, pressure, gas flow, material feed rate, and slag viscosity.

The model predicted the likelihood of scaffold formation based on the operational parameters. The output of the model ranged from 0 to 1, where a value closer to 1 indicates a higher likelihood of scaffold formation. The performance of the model was evaluated using Mean Absolute Error (MAE) and Mean Squared Error (MSE).

MAE: The model achieved a low MAE on both the training and testing datasets, indicating that the predicted scaffold likelihood was close to the actual outcomes. MSE: The MSE was also within an acceptable range, suggesting that the model performed well in minimizing the difference between the predicted and actual values.

The model was able to accurately identify high-risk areas where scaffold formation was more likely, based on input parameters. For example, higher slag viscosity and lower temperature were correlated with a higher likelihood of scaffold formation. This insight enables operators to adjust furnace parameters in advance, preventing potential issues before they disrupt furnace operations. The model also predicted whether slag removal was required based on the operational parameters. This binary classification (0 = no removal required, 1 = removal required) was evaluated using accuracy as the performance metric. The model showed high accuracy in predicting whether slag removal was necessary based on the data provided.

Accuracy: The model achieved an accuracy rate of over 85% on the test data, indicating that it was able to correctly predict slag removal requirements in the majority of cases. Confusion Matrix: The confusion matrix revealed that the model had a low false positive rate (i.e., predicting removal when it wasn't required) and a reasonable false negative rate (i.e., failing to predict removal when it was required), which is crucial for preventing unnecessary maintenance interventions.

By predicting the need for slag removal, the ANN model helps optimize furnace operations by reducing downtime and improving the efficiency of slag tapping processes. It also assists operators in ensuring that slag is removed at the right time, preventing blockages and optimizing furnace throughput.

```
Enter the temperature (°C):  1800
Enter the pressure (Pa):  150000
Enter the gas flow rate (m³/s):  35
Enter the material feed rate (kg/s):  65
Enter the slag viscosity index:  2.0
1/1 [==============================] - 0s 13ms/step
Slag removal is not required.
```

```
Enter the temperature (°C):  1800
Enter the pressure (Pa):  150000
Enter the gas flow rate (m³/s):  35
Enter the material feed rate (kg/s):  65
Enter the slag viscosity index:  2.0
1/1 [==============================] - 0s 13ms/step
Slag removal is not required.
```

CHAPTER 5: CONCLUSION

This project aimed to enhance the understanding and optimization of blast furnace operations through the development of innovative solutions, including a 3D model, hydrogen-based reduction, and an Artificial Neural Network (ANN) machine learning model. Each of these components provides valuable insights and predictive capabilities to improve furnace efficiency, reduce downtime, and contribute to sustainable practices in ironmaking. The 3D model created using Blender serves as an essential tool for visualizing the blast furnace structure. Although it currently focuses on the outer shell and does not include dynamic simulations, the model provides a strong foundation for further developments in process optimization and operator training. The hydrogen-based reduction approach, explored as an alternative to traditional coke-based reduction, promises significant environmental benefits by reducing carbon dioxide emissions. The research indicates that hydrogen-based reduction could help mitigate scaffold formation by minimizing the volatilization of alkali compounds present in coke. Although the full implementation of hydrogen-based reduction would require substantial infrastructure changes, its potential for cleaner and more efficient ironmaking is promising and warrants further exploration. The ANN model developed to predict scaffold formation likelihood and slag removal requirements offers a data-driven solution for optimizing furnace operations. By training the model on historical operational data, it was able to predict when scaffold formation is likely and when slag removal is needed. The model achieved high accuracy in predicting both scaffold formation and slag removal, providing actionable insights that can help operators make informed decisions and adjust furnace parameters before problems occur. This proactive approach minimizes downtime, reduces maintenance costs, and improves the overall efficiency of the blast furnace. Together, these solutions provide a comprehensive framework for improving blast furnace operations. The combination of 3D visualization, predictive machine learning, and sustainable practices paves the way for future advancements in furnace technology, leading to more efficient, cost-effective, and environmentally friendly ironmaking processes. Further integration of real-time data and dynamic simulations could enhance the predictive accuracy and performance of these tools, allowing for smarter and more adaptable furnace operations.

ANNEXURE

Annexure 1: Python Code for ANN Model

The complete Python code for developing, training, and using the Artificial Neural Network (ANN) model for predicting scaffold formation likelihood and slag removal requirements.

```
[1]: !pip install opencv-python

Requirement already satisfied: opencv-python in c:\users\ayush\anaconda3\envs\mdsp\lib\site-packages (4.9.0.80)
Requirement already satisfied: numpy>=1.17.0 in c:\users\ayush\anaconda3\envs\mdsp\lib\site-packages (from opencv-python) (1.26.4)

[2]: !pip install scikit-learn

Requirement already satisfied: scikit-learn in c:\users\ayush\anaconda3\envs\mdsp\lib\site-packages (1.4.2)
Requirement already satisfied: numpy>=1.19.5 in c:\users\ayush\anaconda3\envs\mdsp\lib\site-packages (from scikit-learn) (1.26.4)
Requirement already satisfied: scipy>=1.6.0 in c:\users\ayush\anaconda3\envs\mdsp\lib\site-packages (from scikit-learn) (1.12.0)
Requirement already satisfied: joblib>=1.2.0 in c:\users\ayush\anaconda3\envs\mdsp\lib\site-packages (from scikit-learn) (1.4.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\ayush\anaconda3\envs\mdsp\lib\site-packages (from scikit-learn) (3.4.0)
```

```
[1]: import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
import matplotlib.pyplot as plt

# Load the CSV data
data_path = "blast_furnace_conditions_with_slag.csv"
data = pd.read_csv(data_path)

# Define input (X) and target (y) variables
X = data[["Temperature (°C)", "Pressure (Pa)", "Gas Flow Rate (m³/s)",
          "Material Feed Rate (kg/s)", "Slag Viscosity Index"]]
y = data["Scaffold Likelihood (0-1)"]

# Normalize the data
scaler_X = MinMaxScaler()
scaler_y = MinMaxScaler()
X_scaled = scaler_X.fit_transform(X)
y_scaled = scaler_y.fit_transform(y.values.reshape(-1, 1))

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y_scaled, test_size=0.2, random_state=42)

# Define the ANN model
model = Sequential([
    Dense(64, activation='relu', input_shape=(X_train.shape[1],)),
    Dense(32, activation='relu'),
    Dense(1, activation='linear')  # For regression output
])

# Compile the model
model.compile(optimizer='adam', loss='mse', metrics=['mae'])

# Train the model
history = model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=200, verbose=0)

# Plot regression plots for training and validation
train_pred = model.predict(X_train)
test_pred = model.predict(X_test)

plt.figure(figsize=(10, 5))

# Training regression plot
plt.subplot(1, 2, 1)
plt.scatter(y_train, train_pred, alpha=0.7, edgecolors='k', label='Train Data')
plt.plot([0, 1], [0, 1], 'r--', label='Ideal Fit')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Training Data Regression Plot')
plt.legend()
plt.grid()
```

```python
# Validation regression plot
plt.subplot(1, 2, 2)
plt.scatter(y_test, test_pred, alpha=0.7, edgecolors='k', label='Test Data')
plt.plot([0, 1], [0, 1], 'r--', label='Ideal Fit')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Validation Data Regression Plot')
plt.legend()
plt.grid()

plt.tight_layout()
plt.show()

# Plot training and validation loss
plt.figure(figsize=(10, 5))
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Training and Validation Loss Over Epochs')
plt.xlabel('Epochs')
plt.ylabel('Mean Squared Error (Loss)')
plt.legend()
plt.grid()
plt.show()

# Plot training and validation MAE
plt.figure(figsize=(10, 5))
plt.plot(history.history['mae'], label='Training MAE')
plt.plot(history.history['val_mae'], label='Validation MAE')
plt.title('Training and Validation MAE Over Epochs')
plt.xlabel('Epochs')
plt.ylabel('Mean Absolute Error')
plt.legend()
plt.grid()
plt.show()
```

[6]:
```python
import numpy as np

def predict_slag_removal(model, scaler_X):
    # Collect user input for parameters
    temperature = float(input("Enter the temperature (°C): "))
    pressure = float(input("Enter the pressure (Pa): "))
    gas_flow = float(input("Enter the gas flow rate (m³/s): "))
    material_feed = float(input("Enter the material feed rate (kg/s): "))
    slag_viscosity = float(input("Enter the slag viscosity index: "))

    input_data = [temperature, pressure, gas_flow, material_feed, slag_viscosity]

    input_data_scaled = scaler_X.transform([input_data])

    prediction = model.predict(input_data_scaled)

    return 1 if prediction >= 0.5 else 0

slag_removal_prediction = predict_slag_removal(model, scaler_X)

if slag_removal_prediction == 1:
    print("Slag removal is required.")
else:
    print("Slag removal is not required.")
```

```
Enter the temperature (°C):  1800
Enter the pressure (Pa):  150000
Enter the gas flow rate (m³/s):  35
Enter the material feed rate (kg/s):  65
Enter the slag viscosity index:  2.0
1/1 [==============================] - 0s 13ms/step
Slag removal is not required.
```

```
Enter the temperature (°C):  1700
Enter the pressure (Pa):  1.5e5
Enter the gas flow rate (m³/s):  30
Enter the material feed rate (kg/s):  60
Enter the slag viscosity index:  3.2
1/1 [==============================] - 0s 31ms/step
Slag removal is required.
```

Annexure 2: Dataset Sample

Table 1 Sample of Dataset (Input Operating Parameters in Blast Furnace) for ANN Model Training

Temperature (°C)	Pressure (Pa)	Gas Flow Rate (m^3/s)	Material Feed Rate (kg/s)	Slag Viscosity Index	Scaffold Likelihood (0-1)	Slag Removal Required (0/1)
1750	150000	30.5	60.2	2.8	0.65	1
1700	140000	28.3	58.0	3.5	0.80	1
1800	155000	35.0	65.0	2.1	0.40	0
1650	145000	29.5	59.5	3.8	0.90	1

Annexure 3: Model Performance Metrics

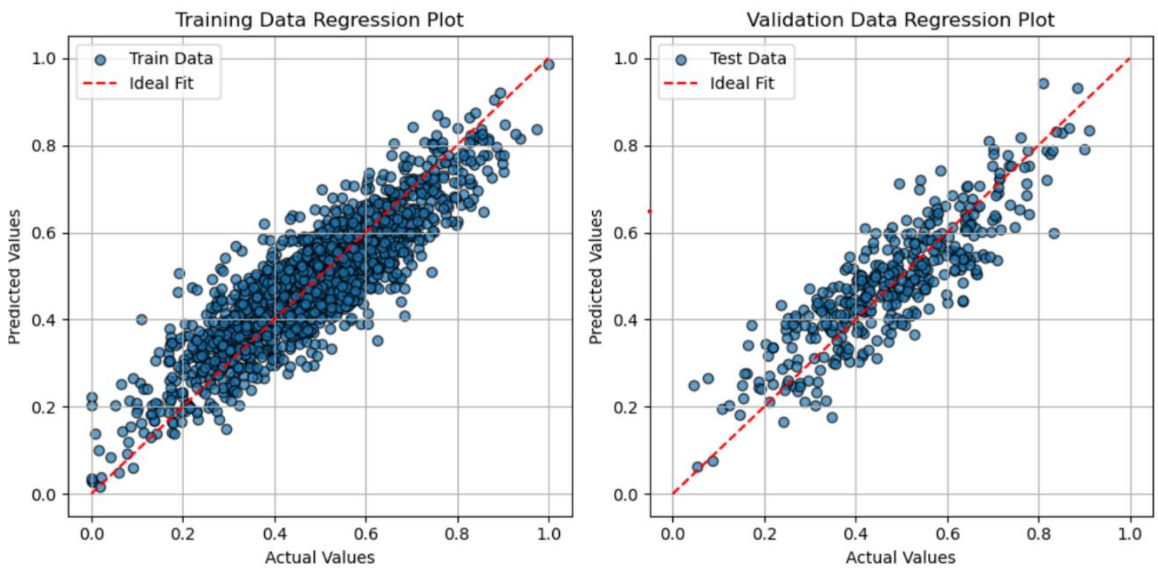

Figure 5 Predicted values v/s Actual values for Training Data (left) and Validation Data (right)

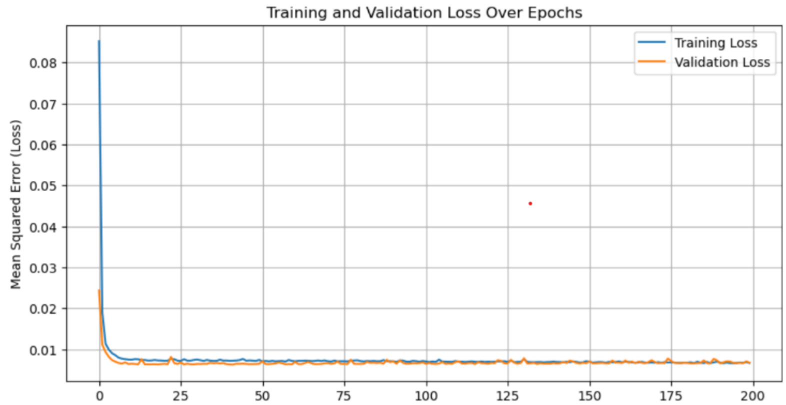

Figure 6 Mean Squared Error v/s Epochs plotting

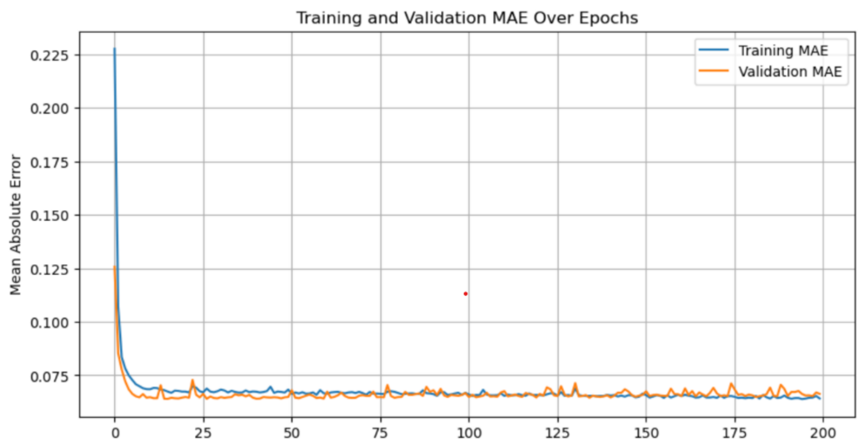

Figure 7 Mean Absolute Error v/s Epochs plotting

Annexure 4: Chemical Reactions in the Blast Furnace

Key reactions occurring in the blast furnace:

1. **Reduction of Iron Ore**:

$$Fe_2O_3 + 3CO \rightarrow 2Fe + 3CO_2$$

2. **Coke Combustion**:

$$C + O_2 \rightarrow CO_2$$

3. **Slag Formation**:

$$CaCO_3 \rightarrow CaO + CO_2$$

$$CaO + SiO_2 \rightarrow CaSiO_3$$

Annexure 5: Hydrogen-Based Reduction Research

Reaction:

$$Fe_2O_3 + 3H_2 \rightarrow 2Fe + 3H_2O$$

Benefits:

- 90% reduction in CO_2 emissions.
- Minimized scaffold formation due to reduced alkali cycling.

References

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