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Data-Driven Insights into Unburnt Ash Carbon Mitigation: An EDA Perspective

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Abstract: Electrical energy is primarily generated in thermal power plants. The boilers used in a thermal power plant is an important part of energy production. Predicting the important factors which leads to energy loss or wastage of the fossil fuel, coal will be majorly important because we could reduce the wastage before boilers are used. Since it will be the analysis of relationship between physical properties of the raw materials, e.g., coal, water, air , a one time analysis's results won't change because physical properties of a matter stays constant. A boiler requires coal, heat and air for input and excludes hot flue gas which could become a reliable source of heat, suitable for purposes of drying away moisture from industrial equipments ; the boiler also leaves unburnt carbon as waste, there are no further applications for it yet. Managing boilers would mean less or no wastage of coal. This analysis report is the detailed analysis of Boilers' Indirect method of calculating efficiency. It provides detailed analysis about unburnt carbon along with all the factors where heat is lost. The applied exploratory analysis on thermal energy production to ensure that coal is burns properly without any wastage, leaving less or no unburnt carbon.
Keywords: Exploratory Data Analysis, Energy Conservation, Matplotlib, Python, Pandas, Seaborn

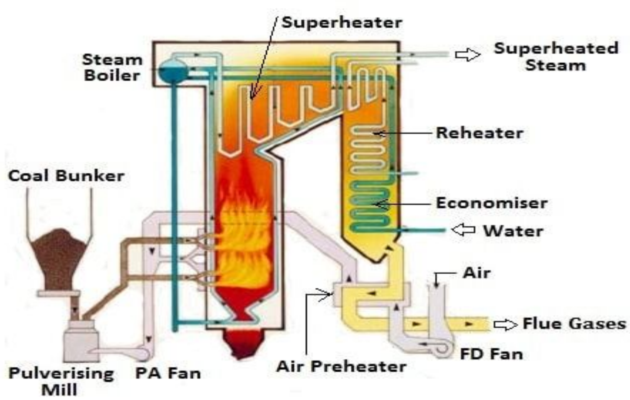
I. INTRODUCTION

A. From beginning, all the parameters

Novelty

Contribution

Thermal Energy power plants are the most common and most reliable sources of energy production throughout the world. Therefore governments put a lot of attention towards the conservation and proper utilization of coal. A boiler is connected with several inlets and outlets, each with a unique purpose and monitored with automatic sensors which would be automatically updated into Excel sheets.



Pulverized Coal-Fired Boiler

The team has conducted researches by following strict guidelines published by "Energy conservation department of India", it is important to follow the 30 pages long detailed methods of calculating the efficiency of boiler. Using this document for any research regarding coal combustion in India is mandatory by the government of India. Taking it as reference, we focus on Unburnt Carbon itself, which would directly affect efficiency of the boiler. The document consists of two methods: Direct and Indirect method. This experiment is conducted using Indirect method as it gives a detailed overview about all the efficiency loss, due to which factor and at which part of the boiler.

Therefore, the detailed analysis of 25 relevant variables in operating boilers focus towards the proper combustion of coal, aiming "Unburnt carbon"(coal) to decrease up to 0%.

Using EDA is an efficient solution to filter the 25 parameters into relevant and non-relevant parameters with line plots, along with the covariance heatmaps to find the covariance and standard deviation of the said parameters with unburnt carbon. Also for normalization and finding the most efficient amount, boxplot was used to emit outliers.

The data used is most recent, financial year of 2023 and few months of 2024, which were automatically updated in Excel by sensors in the boiler.

B. *Abbreviations and Acronyms*

EDA= Exploratory Data Analysis
df= datafarame ,
using python's 'pandas'
pd= pandas
np= numpy
df1= the first dataframe created, other dataframes will be produced out of this dataframe, on basis our requirements.
plt = python's module in matplotlib(matplotlib.pyplot)
sns = seaborn library
boxplot = a very informative graph which tells about the measure of central tendencies of a variable with numerical data.

Coal_QualityFC: Fixed Carbon percentage in coal, indicating the solid combustible residue after volatile materials are driven off.
Coal_QualityVM: Volatile Matter percentage in coal, representing combustible gases released during heating.
Coal_QualityMoisture: Moisture content percentage in coal, affecting its heating value and combustion efficiency.
Coal_QualityAsh: Ash content percentage in coal, non-combustible mineral matter remaining after complete combustion.
Coal_QualityGCV: Gross Calorific Value of coal in KCal/Kg, representing the total heat content of the fuel.
Flue_Gas_AnalysisAVG_O2_at_APH_IbyL: Average oxygen percentage at Air Preheater inlet, indicating combustion efficiency.
Flue_Gas_AnalysisLeakage_across_APH: Percentage of air leakage across the Air Preheater, affecting overall efficiency.
Flue_Gas_AnalysisAvg O2_at _APH_ObyL: Average oxygen percentage at Air Preheater outlet, reflecting combustion and leakage.
Flue_Gas_AnalysisAir_IbyL_temp_FD_outlet: Temperature of air at Forced Draft fan outlet in degrees Celsius, influencing combustion.
Flue_Gas_AnalysisFlue_Gas_temp_APH_ObyL: Flue gas temperature at Air Preheater outlet in degrees Celsius, indicating heat recovery efficiency.
Unburnt_AnalysisBottom_Ash_Carbon: Percentage of unburnt carbon in bottom ash, reflecting combustion efficiency.
UnburntESP_Ash_Carbon: Percentage of unburnt carbon in Electrostatic Precipitator ash, indicating combustion completeness.
UnburntCyclone_Ash_Carbon: Percentage of unburnt carbon in cyclone ash, reflecting combustion efficiency in cyclone section.
UnburntAPH_Ash_Carbon: Percentage of unburnt carbon in Air Preheater ash, indicating overall combustion efficiency.
AirAnalysisTheoretical_Air: Theoretical air required for complete combustion in Kg/Kg Coal.
AiAnalysisExcess_Air: Percentage of excess air supplied above theoretical requirement for combustion control.
AirAnalysisActual_Air Supplied: Actual air supplied for combustion in Kg/Kg Coal, including excess air.
AirAnalysisMassofDry_Flue_Gas: Mass of dry flue gas produced per Kg of coal burned.
UnburntLOSSESP_Ash: Heat loss percentage due to unburnt carbon in Electrostatic Precipitator ash.
UnburntLOSSBottom_Ash: Heat loss percentage due to unburnt carbon in bottom ash.
UnburntLOSSCyclone_Ash: Heat loss percentage due to unburnt carbon in cyclone ash.
UnburntLOSSAPH_Ash: Heat loss percentage due to unburnt carbon in Air Preheater ash.
Sensible_Heat_Loss: Percentage of heat loss in flue gases due to their elevated temperature.
Efficiency: Overall boiler efficiency percentage, considering various heat losses.
Hydrogen: Hydrogen content percentage in coal, affecting moisture formation during combustion.

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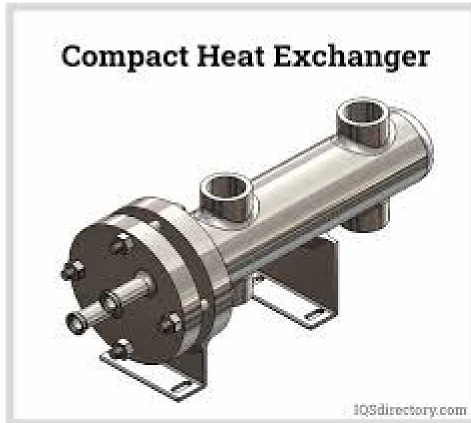
C. Parts Of A Boiler In A Thermal Power Plant Include

1) Steam Drum

A vital component in a high pressure boiler that produces steam to run the turbine

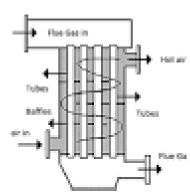


2) Heat Exchanger

Allows heat to be exchanged between two substances, usually water and gas, without mixing them

3) Circulator Pumps

Used for heating domestic water or heating



4) Air Preheater

Heats the combustion air entering the boiler, resulting in increased fuel efficiency

5) Superheater

Increases the temperature of the steam generated by a boiler

6) Safety valve

Prevents excessive pressure buildup in the boiler

7) Strainer

Functions as a filter to retain solid elements in the fluid supply

8) Sight glass

A glass tube used in steam boilers to visually indicate the water level

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9) Steam stop valve

Controls the flow of steam exiting the boiler

10) Condenser

A key component of a steam power plant, and the efficiency of the thermal power plant depends on its efficiency

11) Furnace

Burns a fossil fuel or, in some installations, waste fuels

12) Alternator

Copulates to the steam turbine and produces electrical energy when the turbine turns it

.

D. Units

Coal_QualityFC = %
Coal_QualityVM = %
Coal_QualityMoisture = %
Coal_QualityAsh = %
Coal_QualityGCV= KCal/Kg
Flue_Gas_AnalysisAVG_O2_at_APH_IbyL = %
Flue_Gas_AnalysisLeakage_across_APH = %
Flue_Gas_AnalysisAvg O2_at _APH_ObyL = %
Flue_Gas_AnalysisAir_IbyL_temp_FD_outlet = DEG C
Flue_Gas_AnalysisFlue_Gas_temp_APH_ObyL = DEG C
Unburnt_AnalysisBottom_Ash_Carbon = %
UnburntESP_Ash_Carbon = %
UnburntCyclone_Ash_Carbon = %
UnburntAPH_Ash_Carbon = %
AirAnalysisTheoretical_Air = Kg/Kg Coal
AiAnalysisExcess_Air = % of The Air
AirAnalysisActual_Air Supplied = Kg/Kg Coal
AirAnalysisMassofDry_Flue_Gas = Kg/Kg Coal
UnburntLOSSESP_Ash = %
UnburntLOSSBottom_Ash = %
UnburntLOSSCyclone_Ash = %

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UnburntLOSSAPH_Ash = %
Sensible_Heat_Loss = %
Efficiency = %
Hydrogen = %

E. Equations

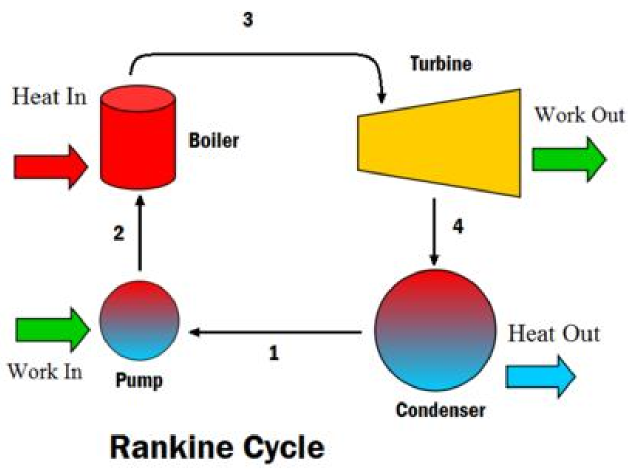
Boiler Efficiency:

η=(Energy output)/(Energy input) X 100

Boiler efficiency(Indirect Method) = 100 – Boiler Losses

Heat loss(Q) **Q = U * A * ΔT**

Rankine Cycle



The **Rankine cycle** or **Rankine Vapor Cycle** is the process widely used by power plants such as coal-fired power plants or nuclear reactors. In this mechanism, a fuel is used to produce heat within a boiler, converting water into steam which then expands through a turbine producing useful work. This process was developed in 1859 by Scottish engineer William J.M. Rankine.[1]

Thermal Efficiency of Rankine Cycle: The thermal efficiency of the Rankine cycle is the ratio between the work produced by the steam turbine that has been reduced by the pump work, with the incoming heat energy from the boiler.

The heat energy from the fuel is transferred to the working fluid i.e. water. The calorific value absorbed by water vapor can be calculated using the following formula:

$$Q_{in} = m\,(h_F - h_D)$$

The superheated steam produced by the boiler then goes to the steam turbine. Heat energy from water vapor is then converted into kinetic energy, shown by the F-G line in the image above. The reduction of the enthalpy can be used to calculate the magnitude of the motion energy produced by the steam turbine using the following formula:

$$W_{out} = m\,(h_F - h_G)$$

The steam coming out from the steam turbine enters the condenser to be condensed back into liquid phase. Here the heat energy not converted into kinetic energy, because the energy is used to convert the water into steam (latent heat). The decreases of the enthalpy (G-C line) can be used to calculate the thermal energy of condensed water using the following formula:

$$Q_{out} = m\,(h_G - h_C)$$

In the next process, the condensate water is pumped to the boiler to increase its pressure. Shown by the C-D line, water does not experience much increase in enthalpy. This means that the energy given to the air is not too significant. Incoming energy values can be calculated using the following formula:

$$W_{in}=m(h_D-h_C)$$

So now we can calculate the thermal efficiency by using the formula below:

Thermal Efficiency = [(Work Output — Work input)/Heat entered into the system]

II. RANKINE CYCLE EFFICIENCY FORMULA

Thermal Efficiency = [(Work Output — Work input)/Heat entered into the system]

III. RANKINE CYCLE EFFICIENCY

Rankine Cycle Efficiency = $[m\,(hF - hG) - m\,(hD - hC)\,] / [m\,(hF - hD)]$

A. Some Common Mistakes

1) The word "data" is plural, not singular.
2) Neglecting data quality checks: Failing to identify and address missing values, outliers, or inconsistencies in the dataset.
3) Overlooking data distributions: Not examining the shape, central tendency, and spread of variables, which can lead to incorrect assumptions about the data.
4) Ignoring correlations: Failing to investigate relationships between variables, potentially missing important insights or multicollinearity issues.
5) Overreliance on summary statistics: Not complementing numerical summaries with visualizations to gain a more comprehensive understanding of the data.
6) Inadequate data visualization: Using inappropriate chart types or poorly designed visualizations that obscure rather than reveal patterns in the data.
7) Confirmation bias: Focusing only on patterns that confirm preexisting hypotheses while ignoring contradictory evidence.
8) Inadequate documentation: Not keeping a clear record of the EDA process, making it difficult to reproduce or explain findings later.

B. Methodology

1) Data Collection

- Access the Excel sheets containing automatically updated sensor data from the boiler.
- Ensure data covers the financial year 2023 and relevant months of 2024.
- Verify that all 25 relevant variables are included in the dataset.
- Cross-check data collection methods with the guidelines published by the Energy Conservation Department of India. https://beeindia.gov.in/sites/default/files/4Ch1.pdf

2) Data Architecture

- Import required Python libraries: pandas (as pd), numpy (as np), matplotlib.pyplot (as plt), and seaborn (as sns).
- Load the Excel data into a pandas DataFrame (df1).
- Display the first few rows using df1.head() to verify successful data import.
- Use df1.info() to check data types and identify any missing values.

```
[4]: df1.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 337 entries, 0 to 336
Data columns (total 26 columns):
 #   Column                                  Non-Null Count  Dtype
---  ------                                  --------------  -----
 0   Date                                    336 non-null    object
 1   Coal_QualityFC                          337 non-null    float64
 2   Coal_QualityVM                          337 non-null    float64
 3   Coal_QualityMoisture                    337 non-null    float64
 4   Coal_QualityAsh                         337 non-null    float64
 5   Coal_QualityGCV                         337 non-null    float64
 6   Flue_Gas_AnalysisAVG_O2_at_APH_IbyL     330 non-null    float64
 7   Flue_Gas_AnalysisLeakage_across_APH     337 non-null    float64
 8   Flue_Gas_AnalysisAvg O2_at _APH_ObyL    330 non-null    float64
 9   Flue_Gas_AnalysisAir_IbyL_temp_FD_outlet 337 non-null    float64
 10  Flue_Gas_AnalysisFlue_Gas_temp_APH_ObyL 337 non-null    float64
 11  Unburnt_AnalysisBottom_Ash_Carbon       337 non-null    float64
 12  UnburntESP_Ash_Carbon                   328 non-null    float64
 13  UnburntCyclone_Ash_Carbon               337 non-null    float64
 14  UnburntAPH_Ash_Carbon                   337 non-null    float64
 15  AirAnalysisTheoretical_Air              337 non-null    float64
 16  AiAnalysisExcess_Air                    330 non-null    float64
 17  AirAnalysisActual_Air Supplied          330 non-null    float64
 18  AirAnalysisMassofDry_Flue_Gas           330 non-null    float64
 19  UnburntLOSSESP_Ash                      328 non-null    float64
 20  UnburntLOSSBottom_Ash                   337 non-null    float64
 21  UnburntLOSSCyclone_Ash                  337 non-null    float64
 22  UnburntLOSSAPH_Ash                      337 non-null    float64
 23  Sensible_Heat_Loss                      337 non-null    float64
 24  Efficiency                              328 non-null    float64
```

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3) Feature Engineering

-Remove unwanted, or constant, non-relevant data.
-Create different dataframes for different objectives.
-Nomenclature of columns should not clash, easily understandable,
-Performing PCA(Principal component analysis) leads to data loss and hence shall be used carefully and I personally don't encourage that.

4) Data Cleaning

- Handle missing values:
- For numerical data, consider imputation techniques (mean, median, or mode) based on the nature of the variable.
- For categorical data, either create a "Missing" category or use mode imputation.
- Rewrite nill values 'NaN' to mean values of that particular column

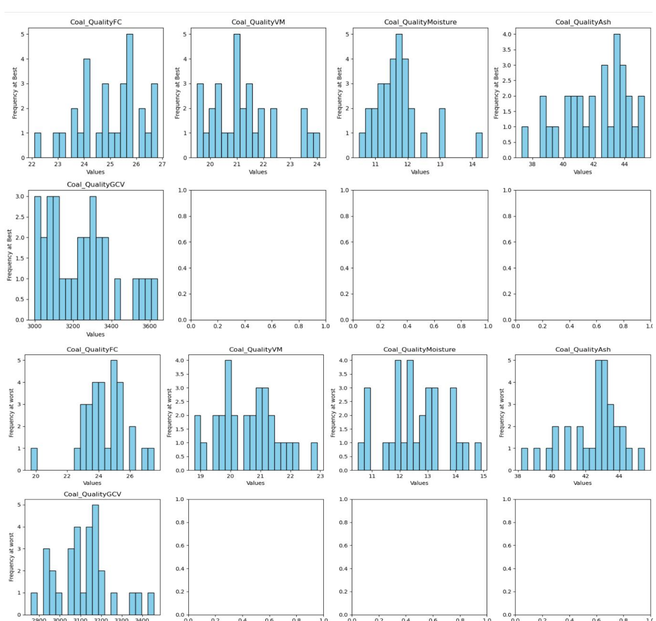
```
#Data about Boilers is very critical, Boiler 12 gets faulty many times, that is why some data is missing from start.
#So decision is to be taken with every value I replace
#We will continue diminishing Na values, Mentor's order to keep them 0
df1["Flue_Gas_AnalysisAVG_O2_at_APH_IbyL"].fillna(value=(df1["Flue_Gas_AnalysisAVG_O2_at_APH_IbyL"].mean()), inplace=True)
df1["Flue_Gas_AnalysisAvg O2_at _APH_ObyL"].fillna(value=(df1["Flue_Gas_AnalysisAvg O2_at _APH_ObyL"].mean()), inplace=True)
df1["UnburntESP_Ash_Carbon"].fillna(value=(df1["UnburntESP_Ash_Carbon"].mean()), inplace=True)
df1["AiAnalysisExcess_Air"].fillna(value=(df1["AiAnalysisExcess_Air"].mean()), inplace=True)
df1["AirAnalysisActual_Air Supplied"].fillna(value=(df1["AirAnalysisActual_Air Supplied"].mean()), inplace=True)
df1["AirAnalysisMassofDry_Flue_Gas"].fillna(value=(df1["AirAnalysisMassofDry_Flue_Gas"].mean()), inplace=True)
df1["UnburntLOSSESP_Ash"].fillna(value=(df1["UnburntLOSSESP_Ash"].mean()), inplace=True)
df1["Efficiency"].fillna(value=(df1["Efficiency"].mean()), inplace=True)
```

- Changes in dataframe(df1) won't be reflected in actual dataset and will give us a consistent unbiased dataframe ready for further analysis.
- Ensure percentage values are stored as floats.
- Address inconsistencies:
- Check for and correct any anomalies in units (e.g., ensure all temperature values are in °C).
- Standardize variable names for consistency, this is very important as each column name was specifically designed , since we had to architecture the whole dataframe.

5) Data Exploration

- Calculate basic statistics for each variable:
- Use df1.describe() for an overview of numerical variables.
- For initial differences, group by "unburnt_ash_cabon" will help us get best and worst results.

For Best,



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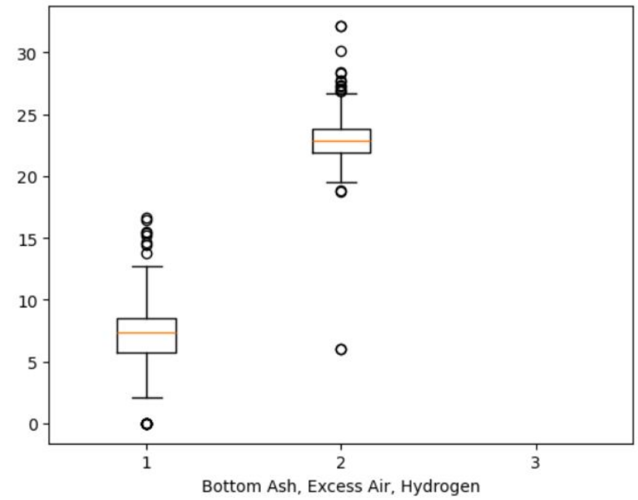
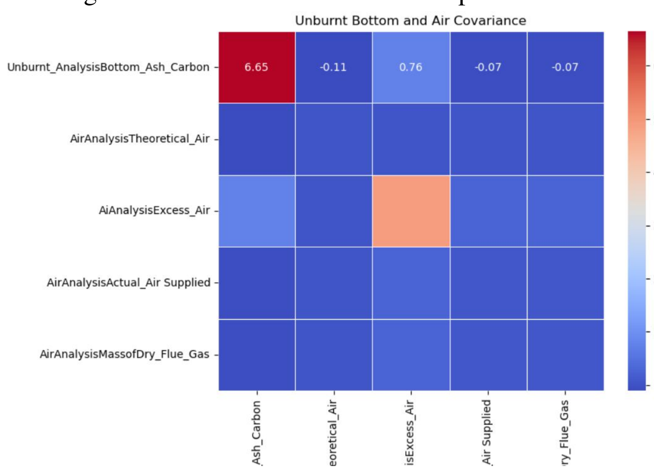
For worst, - Create box plots for each numerical variable to visualize distributions and identify potential outliers, why the said variables in boxplot were selected to analyse will be shown later



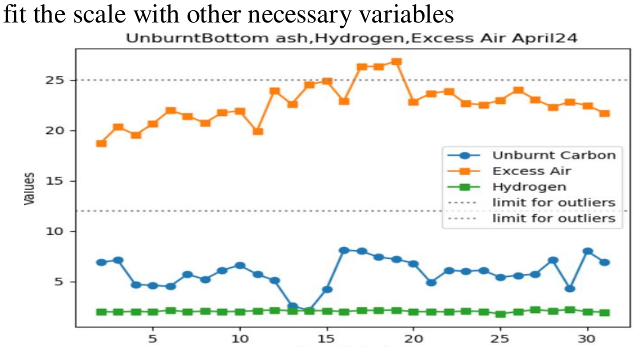
Hydrogen is a constant, varies minutely in decimals at most and hence column 3 shows not even a point in new version of matplotlib.
- Analyze the distribution of key variables, particularly Carbon quality, air quality, shown in step 4(Data Exploration)
Understand which factors affect the most for different types of ashes, bottom ash is the main ash, while other ashes are just flown from bottom ash to other locations, meaning minute or no relation with initial parameters to monitor.



AiAnalysisExcess_Air is the most effective parameter for unburnt ash and hence reason for increasing quantity of other ashes

6) Data Visualization

- Create line plots to visualize trends over time for key variables, refer the boiler thermodynamics and visualize relevant variables more.
- Normalize variables like GCV to fit the scale with other necessary variables



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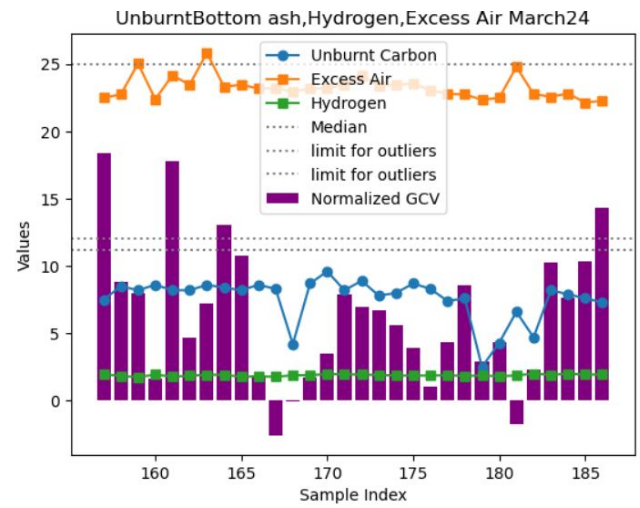
- This anomalous behaviour of Hydrogen led to create a boxplot along with other variables I needed information

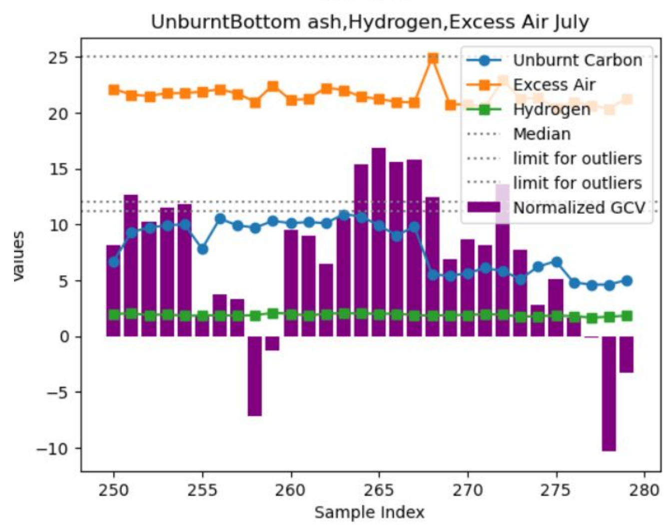
```
'Hydrogen not visible because distribution is too small to plot, proof in cell  below'
```

```
hmean=np.mean(df1['Hydrogen'])
hmax=np.max(df1['Hydrogen'])
print(hmean, hmax)
```

```
1.940667540059524 2.33779917
```

- Combine analysis from one category variable with other category variables, such as the excess air plotted along with coal-GCV, FC, and unburnt ash carbon.





7) Pattern Recognition

- Analyze monthly trends using for whole year using a single function, just edit certain parameters and it prints all 12 months of data:

```
def monthly_plot(df1):
    s=0
    months=["April","April24","September","October","November","December","March24","May","June","July","Jan24"]
    normalized_gcv = (df1['Coal_QualityGCV'] - 3000) * 30 / (3500 - 3000)
    normalized_median=(((np.median(df1['Coal_QualityGCV'])- 3000) * 30) / (3500 - 3000))
    for i in range(1,340,31):
        j=i-30
        monthly=df1[j:i]
        plt.plot(monthly['Unburnt_AnalysisBottom_Ash_Carbon'], label='Unburnt Carbon', marker='o')
        plt.plot(monthly['AiAnalysisExcess_Air'], label='Excess Air', marker='s')
        plt.plot(monthly['Hydrogen'], label='Hydrogen', marker='s')
        plt.xlabel('Sample Index')
        plt.ylabel('Values')
        plt.bar(monthly.index, normalized_gcv[j:i], color='purple', label='Normalized GCV')
        plt.axhline(y=normalized_median, color='gray', linestyle=':', label='Median')

        plt.axhline(y=12, color='gray', linestyle=':', label='limit for outliers')
        plt.axhline(y=25, color='gray', linestyle=':', label='limit for outliers')
        plt.title('UnburntBottom ash,Hydrogen,Excess Air '+months[s])
        plt.legend()
        plt.show()
        s+=1
monthly_plot(df1)
```

- Use the function to efficiently compare plots from different months and edit the function as per your preferences.

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8) Documentation

- Record insights from each analysis step in a separate markdown cell or text file.

```
''' FC seems to be higher, best between 24-26.
    VM is similar, 21 recommended.
    Moisture less than 12 recommended ( practically we dont get it exact 0 but we can try to keep it below 12)
    Ash(analysis via lab), the lower the better, doesnt actually affect other factors in more than a linear way.
    GCV more than 3200, best at 3300. Can have std dev. of 100.
'''
```

- Summarize key findings, such as:
- Factors most strongly correlated with Unburnt Carbon.
- Seasonal patterns in boiler efficiency. Metrics such as Outliers, mean, median are very helpful to compare data with.
- Identify potential areas for deeper analysis, such as:
- Create bookmark and timestamp during your research break.
- Optimization strategies for further analysis.

9) Iteration

- Based on initial findings, refine the analysis:
- Focus on variables with strong correlations to Unburnt Carbon.
- Investigate the impact of coal quality on Unburnt Carbon, flue gas composition, and overall efficiency.
- Explore additional relationships:
- Analyze the impact of air supply parameters on Unburnt Carbon.
- Investigate the relationship between Flue Gas Analysis variables and efficiency.
- Consider advanced statistical techniques:
- Perform regression analysis to model Unburnt Carbon based on key predictors.

```
""" SUMMARY FOR BEST (based on above histograms)
    GCV=more than 3200, 3300 recommended
    FC=25.7
    ASH CARBON= Possible to go 0, like min 40% of the time
    EXCESS AIR= 23%(min 22%)
    FLUE GAS 02(INLET/OUTLET)= between 3 and 4 is good, doesnt matter cause it is the output byproduct
    FLUE GAS OUTLET TEMP= Less than 150, can go lower to atmospheric temperature
    FLUE GAS FD TEMP(OUTLET)= 45 Recommended

"""
```

By following this expanded methodology, a comprehensive analysis of the boiler's performance can be conducted, with a focus on reducing Unburnt Carbon and improving overall efficiency.

IV. EXPERIMENTAL SETUP

Includes dataset and experimental setup done.

1) Data Collection: Access Excel sheets containing automatically updated sensor data from the boiler for the financial year 2023 and relevant months of 2024. Verify inclusion of all 25 relevant variables and cross-check data collection methods with Energy Conservation Department of India guidelines.
2) Data Loading: Import required Python libraries (pandas, numpy, matplotlib.pyplot, seaborn). Load Excel data into a pandas DataFrame (df1). Use df1.head() to verify successful data import and df1.info() to check data types and identify missing values.
3) Data Cleaning: Handle missing values using appropriate imputation techniques. Remove duplicate entries with df1.drop_duplicates(). Correct data types, ensuring percentage values are floats and temperature values are in the appropriate numeric type. Address inconsistencies in units and standardize variable names.
4) Data Exploration: Calculate basic statistics using df1.describe() for numerical variables and df1[column].value_counts() for categorical variables. Create box plots to visualize distributions and identify potential outliers. Analyze the distribution of key variables, particularly Unburnt Carbon, using histograms.
5) Data Visualization: Create line plots to visualize trends over time for key variables. Generate a correlation heatmap to identify relationships between variables. Create scatter plots to visualize relationships between Unburnt Carbon and other key variables.
6) Feature Engineering: Create new DataFrames grouped by Unburnt Carbon, monthly aggregated data, and coal quality parameters.
7) Pattern Recognition: Analyze monthly trends using line plots for key variables such as Unburnt Carbon, Efficiency, and Sensible Heat Loss. Use box plots to understand the nature of these key variables.
8) Documentation: Record insights from each analysis step, summarizing key findings such as factors strongly correlated with Unburnt Carbon, seasonal patterns in boiler efficiency, and the relationship between coal quality and Unburnt Carbon. Identify potential areas for deeper analysis.

9) Iteration: Refine the analysis based on initial findings, focusing on variables strongly correlated with Unburnt Carbon. Investigate the impact of coal quality on Unburnt Carbon, flue gas composition, and overall efficiency. Explore additional relationships, such as the impact of air supply parameters on Unburnt Carbon and the relationship between Flue Gas Analysis variables and efficiency. Consider advanced statistical techniques like regression analysis and time series analysis for modelling and forecasting Unburnt Carbon levels. This comprehensive methodology enables a thorough analysis of the boiler's performance, emphasizing the reduction of Unburnt Carbon and improvement of overall efficiency.

A. *Figures and Tables*

TABLE I. FACTORS AFFECTING UNBURNT ASH CARBON

Table Head	Analysis Outcomes		
	Factors for unburnt carbon (worst)	*minimum*	*maximum*
copy	GCV FC ASH CARBON EXCESS AIR FLUE GAS O2 FLUE GAS OUTLET TEMP FLUE GAS FD TEMP(OUTLET)	 3100 25 10% % 3 <150 <40	 3200 25.7 16% <22% 4 150 40

Table Head	Analysis Outcomes		
	Factors for unburnt carbon (best)	*minimum*	*maximum*
copy	GCV FC ASH CARBON EXCESS AIR FLUE GAS O2 FLUE GAS OUTLET TEMP FLUE GAS FD TEMP(OUTLET)	 3200 25.7 0% 22% 3 0 45	 3300 25.7 3% >23% 4 <150 45

Fig. 1.Example of a figure caption. (*figure caption*)

The table you described contains variables related to boiler performance and efficiency, focusing on unburnt ash carbon. Here's an explanation of the variables and their significance:

1) GCV (Gross Calorific Value): Represents the total heat content of the fuel. Higher GCV indicates better quality coal.
2) FC (Fixed Carbon): The solid combustible residue left after volatile materials are driven off. Higher FC generally indicates better coal quality.
3) ASH CARBON: Represents the amount of unburnt carbon in ash. Lower values indicate more efficient combustion.
4) EXCESS AIR: The amount of air supplied above the theoretical air required for complete combustion. Optimal levels ensure efficient combustion while minimizing heat loss.
5) FLUE GAS O2: Oxygen content in flue gas. Indicates combustion efficiency and predict excess air levels.
6) FLUE GAS OUTLET TEMP: Temperature of flue gas leaving the boiler. Lower temperatures generally indicate better heat transfer efficiency.
7) FLUE GAS FD TEMP (OUTLET): Temperature of flue gas at the forced draft fan outlet. Affects overall system efficiency. The table's minimum and maximum ranges for best and worst conditions provide benchmarks for optimal boiler operation.

Best conditions would typically show: - Higher GCV and FC - Lower ASH CARBON - Optimal EXCESS AIR - Lower FLUE GAS O2 - Lower FLUE GAS OUTLET TEMP and FLUE GAS FD TEMP (OUTLET)
Worst conditions would show opposite trends, indicating inefficient combustion and heat transfer. These parameters are crucial for monitoring and optimizing boiler performance, particularly in reducing unburnt carbon and improving overall thermal efficiency.

V. DISCUSSION

Tons of coal is burnt everyday in roughly each state in in each country with people unaware of how to reduce the fossil wastage. This research has bought various new insights towards the topic of reduction of "unburnt ash carbon" which is a proper waste product. Sharing this research, development in thermal plant giants have started , focusing on the outcomes of this research, and have found massive improvement with their unburnt coal wastage, and directly increasing the efficiency.

VI.ACKNOWLEDGMENT

I would like to acknowledge the valuable resources that contributed to this research paper. The study relied on various references from IEEE and other authors, as well as textbook definitions from Google and applications from physics-based journals. Special thanks to the Energy Conservation Department of India for providing essential guidelines and methodologies for calculating boiler efficiency. The data used in this study was collected from the most recent financial year (2023) and early months of 2024, automatically updated by sensors in the boiler. I am grateful for the availability of these resources, which were instrumental in conducting a comprehensive analysis of boiler efficiency and unburnt carbon reduction.

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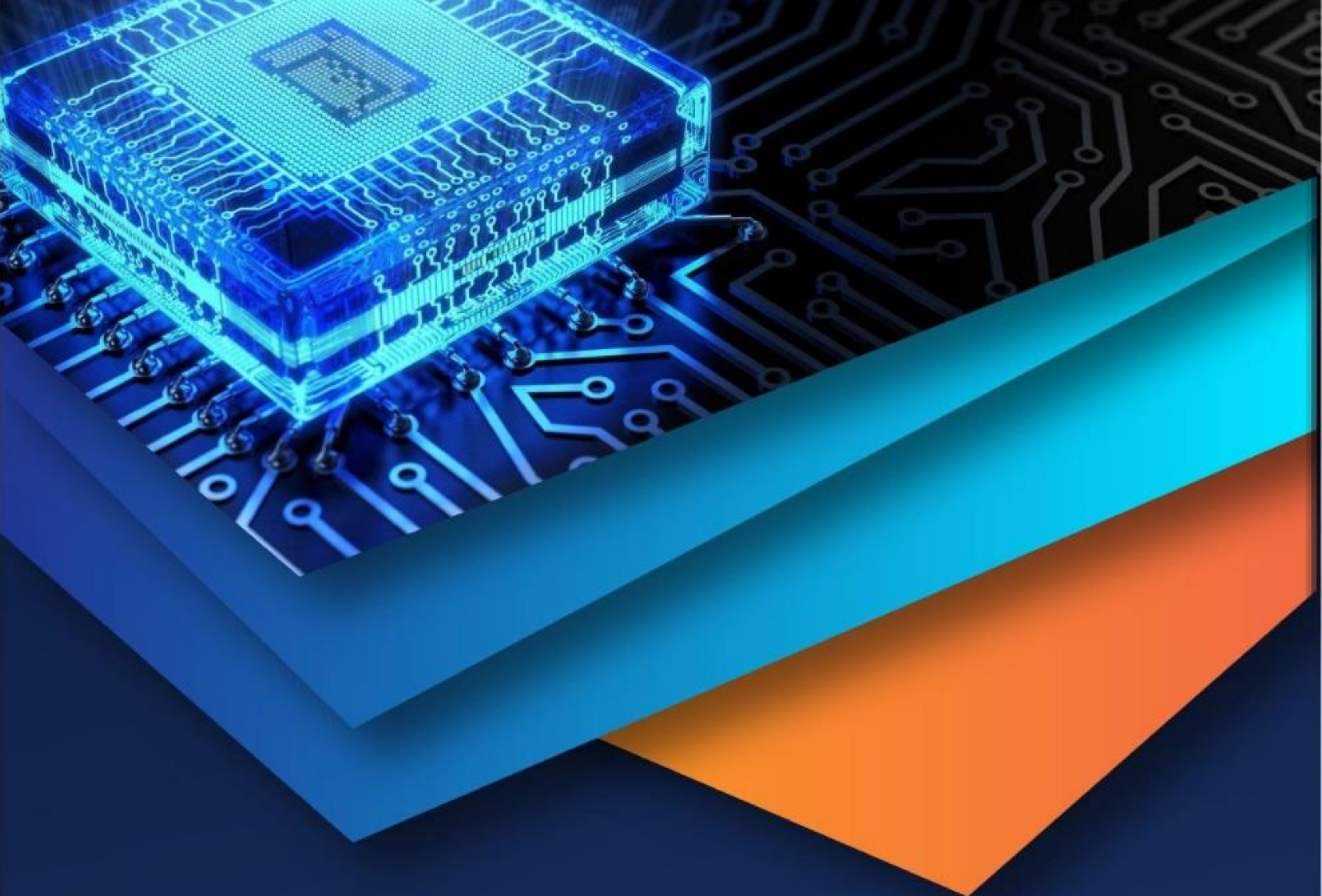

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