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Analysis of Bed Temperature on Circulated Fluidized Bed Boiler Using Simple Multivariable Regression

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ABSTRACT

A Circulated Fluidized Bed (CFB) boiler is a type of steam boiler with more complex phenomena of fluidization and combustion occurring in the furnace. One of the operating problems is the temperature bed which is difficult to predict. Bed temperature prediction is important as a reference to know the combustion process and heat transfer along the furnace. The purpose of this study is multivariable data analysis to predict bed temperature based on historical data. The amount of historical data is then prepared for the dataset and passes through the stages of data cleansing, visualization, exploration, and engineering judgment. The parameters selected as control variables after going through the first principal analysis are 5 parameters, namely gross power, coal feed (X_1), primary air (PA) flow (X_2), secondary air (SA) flow (X_3), and average bed temperature (y). The dataset is then divided based on the load into 2 groups a low load of 20.03-30.00 MW and a high load of 30.01-54.41 MW. Each parameter is converted to the natural logarithm (ln) then multivariable regression is performed. The result is a low load model equation $y=767.0446X_1^{0.036081}X_2^{-0.09217}X_3^{0.085303}$ with Root Mean Square Error (RMSE) = 23.2813 and a high load model equation $y=822.4708X_1^{0.049569}X_2^{-0.01843}X_3^{0.004091}$ with RMSE = 4.8416. This model can be used to predict the average bed temperature at certain input conditions of coal feed, PA flow, and SA flow according to operating load. Prospects for bed temperature prediction with this multivariable can be developed using data-based machine learning so that the operating patterns obtained are more accurate and real-time forecast prediction.

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1. INTRODUCTION

Circulated Fluidized Bed (CFB) boiler is one type of boiler in steam power plants that is widely used and suitable for archipelagic countries such as Indonesia. CFB boilers have a small to medium electricity production capacity with a high combustion efficiency, making them suitable for areas with a small population (Koornneef *et al*., 2007). CFB boiler is a boiler with a fluidized bed system with relatively more uniform, efficient combustion and produces flue gas temperatures and low NO_x levels (Grochowalski *et al*., 2021).

Multi-fuel flexibility is an important feature of CFB boilers, especially with fluctuating fuel prices and availability conditions (Blaszczuk and Jagodzik, 2021). The combustion temperature in the combustion chamber is maintained at 800-900^oC. CFB boiler combustion efficiency is higher in the range of 99.5 – 98%. Contributing to high combustion efficiency includes better solid-gas mixing, higher combustion rates (especially for coarser particles), and continuous recirculation of hot unburnt carbon to the bottom of the furnace.

Low SO_x emission is another attractive advantage of CFB boilers. Based on commercial data CFB boiler does not contain emissions at 50-150 ppm or 20-150 mg/MJ. This consistently low emission level is due to the combustion temperature in the CFB boiler and the gradual supply of air so that it does not form high SO_x. Secondary air which is the largest primary excess air added to the top of the bed so that molecular nitrogen has a limited opportunity to form SO_x. Nitrogen is less likely to be oxidized at low temperatures at 750-950^oC in the CFB combustion with NO_x emission just 1/3-1/4 from conventional pulverized plants (Sun *et al*., 2015). CFB boilers are more widely accepted because of their diverse unit sizes and good environmental emission performance. The addition of limestone as sulfur capture in CFB boilers is an advantage over choosing pulverized boilers (Krzywanski and Nowak, 2012).

In CFB boilers, coal entering the bed area is also fluidized along with bed particles driven by primary air. In the fluidization process, combustion along the furnace also occurs with secondary air as combustion air and bed particles as heat conductors so that the heat temperature throughout the fluidization is evenly distributed. The combustion zone extends above the furnace up to 40 m and further into the cyclone. Thus, the refined carbon produced in the furnace takes a long time to burn as it travels through the height of the furnace. Unburned particles will enter the cyclone with flue gas exiting into the convective section and solid particles will drop down to the loop seal and recirculate into the bed furnace to complete the combustion process. Therefore, combustion efficiency will be better with reduced unburnt carbon. Fluidization and combustion are the key elements of the CFB boiler power plant (Adam *et al*., 2020).

CFB boiler involves the phenomenon of particle fluidization in fuel combustion, as a result, CFB boiler has a more complex system and operating pattern because it must condition the fluidization of particles as well as combustion in the bed. Complex operating patterns on CFB boilers result in operating problems. The rate of devolatilization and coke reaction will be faster if the bed temperature is higher, which also increases the boiler combustion efficiency.

Bed temperature is a key controlled variable in the combustion process. However, the upper layer temperature has been limited by the melting point of the ash as well as the desulfurization effect and NO_x emission (Hong *et al*., 2020). The bed area contains primary air (PA) from the air cap, secondary air (SA) from the air chamber, silica sand as bed particles, and coal as fuel. These components interact with each other in a single furnace. This condition is difficult to simulate and predict because it involves many parameters and operating phenomena.

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The solution to understanding patterns and troubleshooting operations is to perform simulations. One of the popular simulations that can be used to predict bed temperature furnaces is dynamic computational simulation or CFD (Computational Fluid Dynamics) and similar simulations such as Barracuda, Ansys Fluent, and others. However, simulations have complex models, are time-consuming, and are advanced computing hardware (Zhou *et al*., 2004). In addition, simulation software is expensive. Bed temperature has been predicted using machine learning simulations with data on air pressure, coal flow, primary airflow, secondary airflow, and steam mass (Grochowalski *et al*., 2021). However, this study uses machine learning simulations and requires complex model architectures for accurate predictions. This is an opportunity to have a simple model such as multivariable regression.

The purpose of this study is multivariable data analysis to predict bed temperature based on historical data and to determine the effect of the selected parameters on changes in bed temperature. Multivariable regression is a simple method that is often used to determine the relationship between the dependent and independent variables. Operational data analysis with multivariable regression can be used to observe the effect of input parameters on the operating pattern of the average bed temperature based on a data-driven model.

The model estimates the exact actual value with some error and the goal of regression is to minimize the sum of the squares of the vertical distances of the points from the line (Tunckaya and Koklukaya, 2015). This multivariable regression model is expected to be used to predict bed temperature with the most important parameters under operating conditions with various loads. With the correct preparation of data into the dataset, this method will provide a model quickly, accurately, and easily in real conditions as a consideration in decision-making.

2. METHOD

2.1. Process System Overview

In addition to historical data from the distributed control system (DCS) which is used as a dataset for processing, this research is also supported by auxiliary data such as process flow diagrams (PFD), piping and instrumentation diagrams (P&ID), general arrangement (GA) drawings, mechanical drawings, datasheets, operating philosophy, manual books, and data sampling. Auxiliary data is used to support and complement the process philosophy and validation data appropriately. The power plant in this study is one of the power plants using a CFB boiler in Indonesia.

Based on **Figure 1**, the block diagram of the combustion system starts with coal being burned in the CFB boiler, then the heat of combustion air (blue line) is used by the heat exchanger (HE) to heat water (green line) from the economizer to produce steam. The combustion gas goes to the cyclone with the bottom ash as the solid waste of the combustion. Hot gas or flue gas is passed on to heat water in the economizer and air in the primary air (PA) Heater and secondary air (SA) Heater.

The combustion gas then enters the Electrostatic Precipitator (ESP) to capture the remaining combustion ash (fly ash) and then flue gas is discharged into the environment through the chimney. The overall height of the boiler unit is 48 m with the steam drum positioned at 44 m. The height of the furnace is 41 m. The bed area is at a height of 7.6 m with a furnace width of 6.1 m.

Based on **Figure 2**, the schematic of the bed area at the combustion system in the CFB boiler has several areas, the bed area is the contact area between PA and silica sand as bed particles. Primary air is distributed through an air cap configured in the bed area. The lower furnace area is an area where fine coal fuel is exhaled with hot air and SA so that there is a mixing between bed material, air, and coal fuel. In this process, two phenomena occur, namely combustion and the hydrodynamics of the material bed and fluidized fuel along the furnace. The fuel will burn along the furnace to the upper furnace.

The fluidization flow then goes to the cyclone where in this area the unburned fuel and bed material carried will go down the cyclone to the loop seal while the flue gas will be forwarded to the convection area, namely high-temperature superheater (HTS), low-temperature superheater (LTS), and Economizer (Hong *et al*., 2020; Zhu *et al*., 2019). Particles that fall into the loop seal will be pushed by air to return to the bed furnace area. Carbon that is not burned will complete the combustion process in the furnace. This fluidization phenomenon repeats itself with a certain operating pattern at equilibrium conditions.

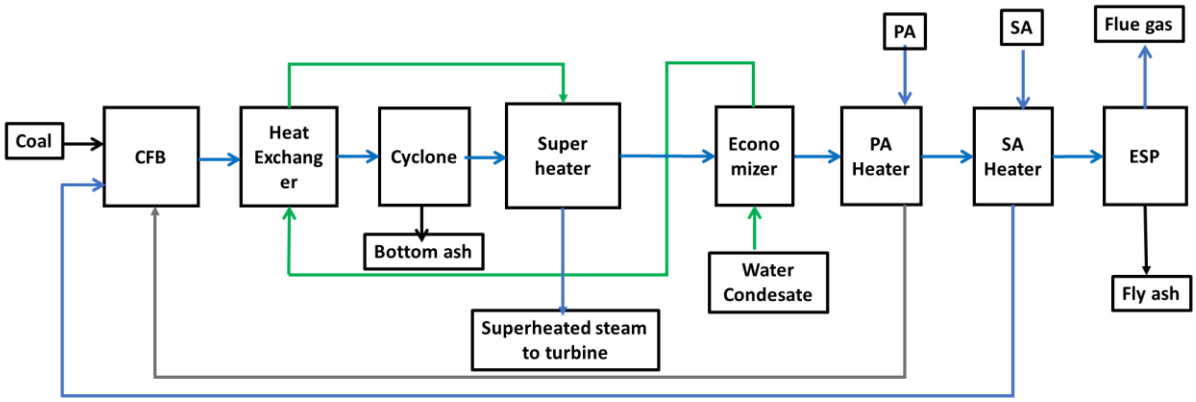

Figure. 1 Block diagram combustion system CFB boiler.

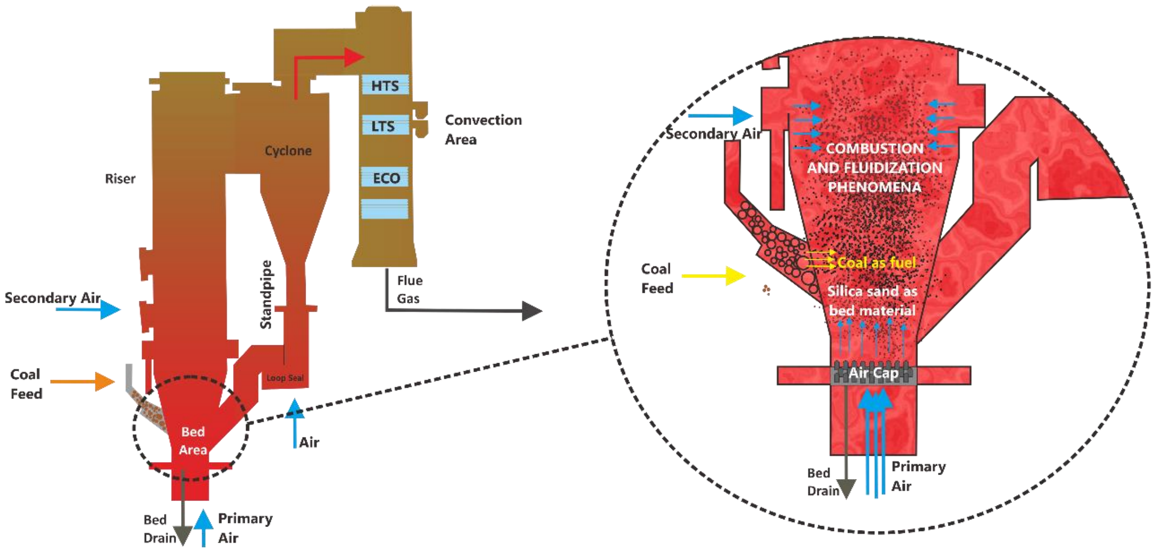

Figure 2. Schematic of bed area at combustion system CFB boiler.

2.2. Description of the Research

Before the data is processed, the data goes through several stages. The following are the stages which are divided into 2 groups, namely pre-processing data and processing data. Based on **Figure 3**, the process begins with a literature study on CFB boilers. The next stage is to determine the operating limits. Operational limits are determined in the CFB boiler area without considering the processes before and after the boiler such as coal handling and turbine system. Other supporting systems such as water treatment systems and electrical

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systems are also not included in this scope. The operating limitations reviewed include the coal combustion system starting from the coal and air input in the furnace to the flue gas conditions at the chimney output. The assumptions set in this study are the specifications and conditions of the input coal particles which are considered constant, the quality and condition of the silica sand bed material are considered uniform, and environmental conditions such as weather and humidity outside the scope.

The next stage is data collection. Data processing using Microsoft Excel software from raw data to datasets and model equations. Operational data collection is carried out from DCS with a data retrieval time of 3 months (February – April 2022) per five minutes. The number of parameters that have been successfully collected is 58 parameters with a data volume of 58 x 25,029 data. The data that has been collected then goes through the cleansing stage. Cleansing is done by eliminating empty data or incomplete data, error data, and inconsistent data (Hamid *et al*., 2022).

At this stage, the amount of data will be reduced because every single data error detected, then one column per time will be deleted for all parameters. This is necessary so that the validity of the historical-time consistency and the relationship between parameters is maintained. Not all parameters are used as datasets in the operation data analysis. Approaches and engineering judgments are carried out on the above parameters. Parameters are separated into independent and dependent variables. Independent variables include input parameters that can be controlled, such as coal flow rate, air flow rate, and gross power. The dependent variable is a variable whose changes are influenced by independent variables and other conditions or interactions. These dependent variables are temperature and pressure at various points in the CFB boiler.

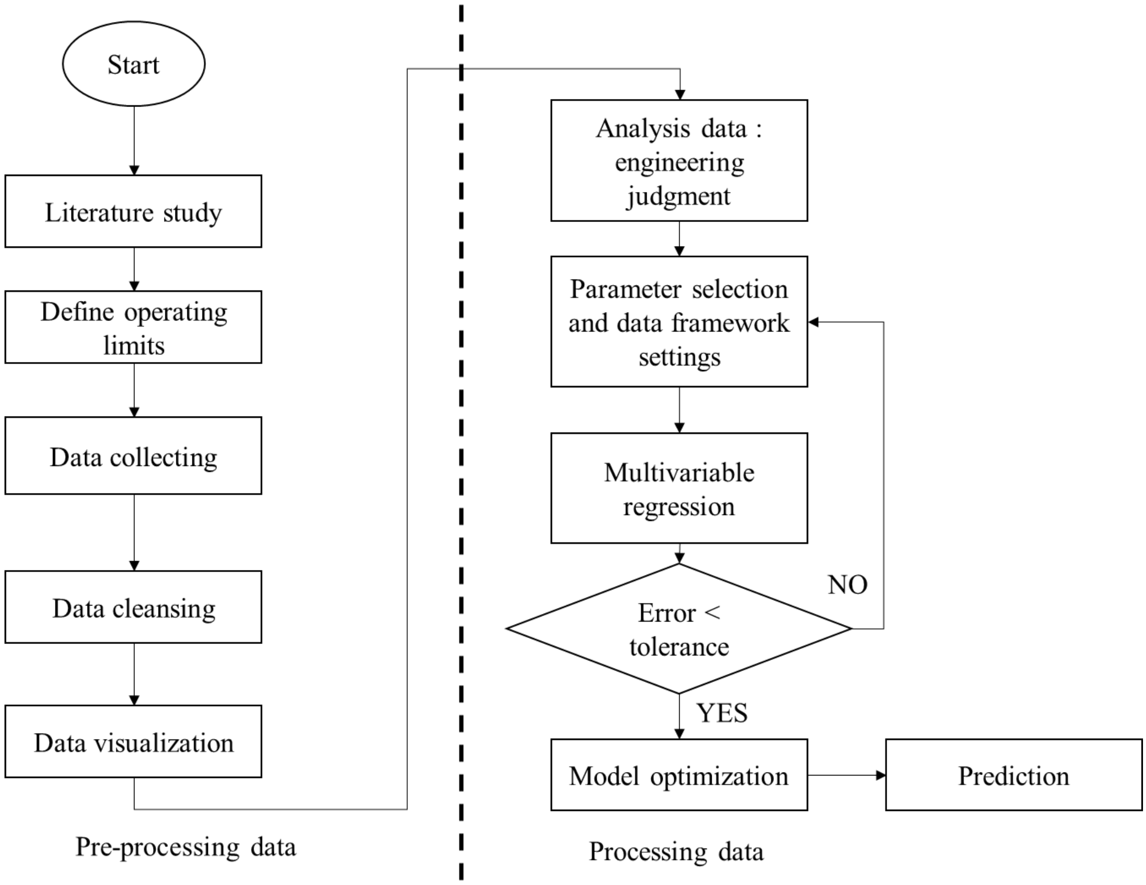

Figure. 3 Research process flow to determine predictive models.

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3. RESULT AND DISCUSSION

3.1. Pre-processing Data Analysis

At the cleansing stage, it will detect a lot of empty or unreadable data such as not a number (NaN). In addition, inconsistent and unnecessary data will also interfere with the accuracy of the data, for example when the unit is not operating and if the instrumentation is damaged it will give a lot of error data. When the data is cleaned, the historical data time series is no longer valid because a lot of data is discarded. After passing through the cleansing stage, the dataset is then visualized by plotting each parameter. The following is a sample dataset plotting visualization.

Figure 4 is the sample plotting visualizations between parameters. There is a lot of data that has been successfully visualized. It takes engineering and process skills to read and understand data visualization. After the visualization stage then to the data processing stage. Data processing begins with engineering judgment on data visualization. The data that has been successfully visualized is then analyzed using the first principle and rule of thumb, whether the data is appropriate or an error.

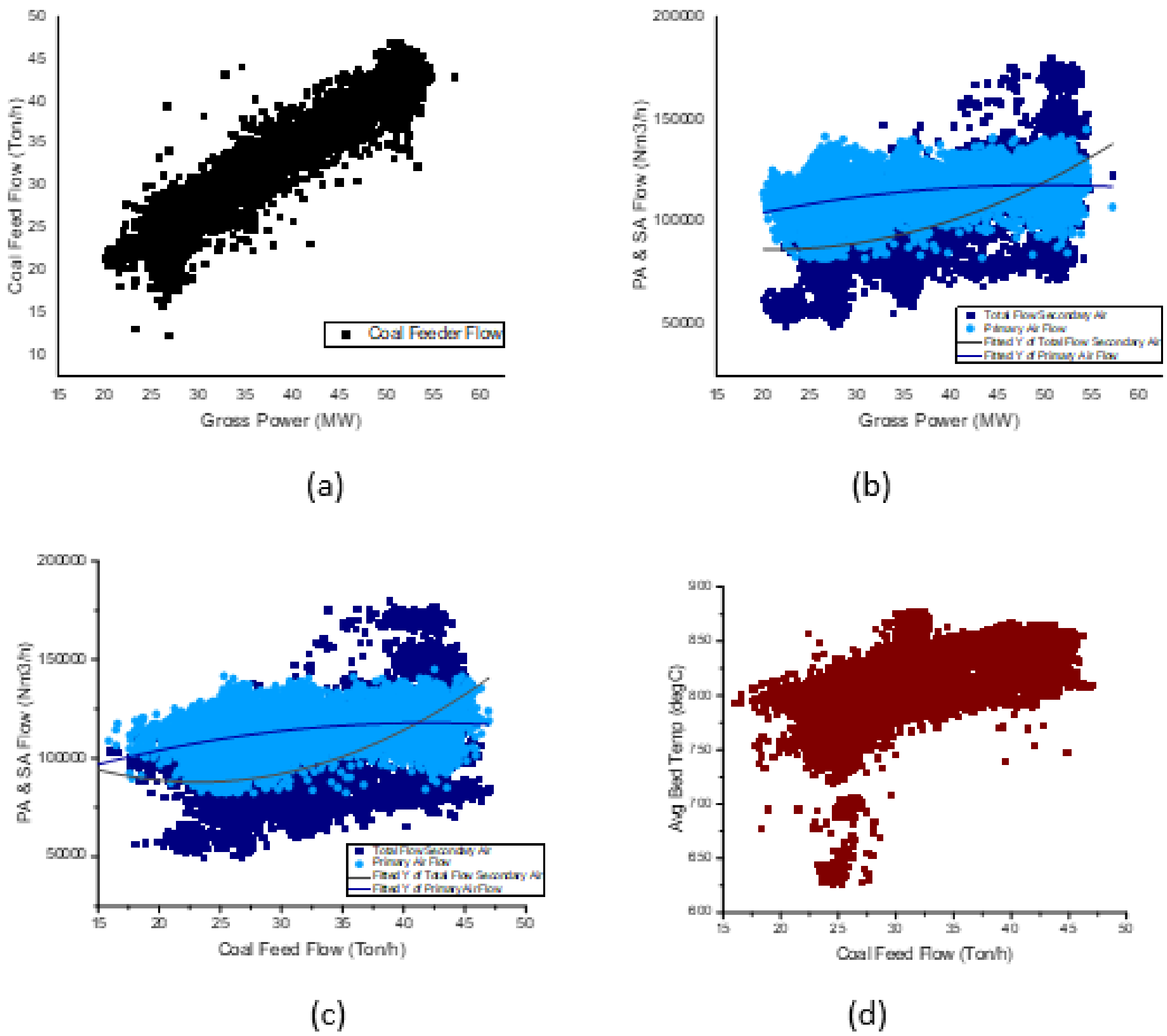

Figure 4. Dataset visualization plotting (a) Coal Feed Flow vs. Gross Power; (b) PA & SA flow vs. Gross Power; (c) PA & SA flow vs Coal Feed; (d) Avg Bed Boiler vs Coal Feed Flow.

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Figure 4(a) shows a linear profile of the relationship between coal feed flow and gross power where the coal feed flow required will be higher as the gross power increases. **Figure 4(b)** is the relationship between PA and SA flow for each operating load, while **Figure 4(b)** is the relationship between PA and SA flow to coal feed consumption. in **Figures 4(b)** and **4(c)**, there is an interesting similarity in that PA is maintained at a constant condition even though gross power and coal feed change, while SA tends to follow fluctuations in coal feed and gross power. This shows that the PA is made constant to maintain fluidization conditions in the furnace. The SA changed to maintain the air supply in the coal feed combustion process. **Figure 4(d)** shows the average bed temperature with coal feed flow, showing a fluctuating bed temperature profile with a large temperature range. It is necessary to study to find out the parameters related to bed temperature and develop a model to get the correlation. The next stage is determining the parameters and setting the data framework.

Bed temperature is influenced by many factors, including boiler load, coal feed rate, primary air rate, and sludge discharge (Lv *et al*., 2017). The parameters that have the most influence on the operating conditions of the boiler are selected especially the average bed temperature. Selected 3 main parameters as input, namely coal flow (ton/h), primary airflow (Nm^3/h), secondary air flow (Nm^3/h), and gross power output parameter (MW) with a predictable target of average bed temperature (°C). Gross power is used as the basis for grouping operating data. The data is divided into 2, namely in low load conditions and high load conditions. This group aims to increase accuracy by reducing the operating range. The data framework can be seen in **Tables 1** and **2**.

Based on the parameter selection and dataset settings, the dataset volume for which multivariable regression will be performed is 5 x 14298 for low load and 5 x 3151 for high load. After the preparation of the dataset is complete, the next step is to perform multivariable regression.

Table 1. Data framework setting low load.

Parameters	Unit	Range
Gross Power	MW	20.03 – 30.00
Coal Feed	Ton/h	12.30 – 39.48
Primary Air Feed	Nm^3/h	82236.41 – 141685.94
Secondary Air Feed	Nm^3/h	49042.90 – 131281.33
Avg Bed Temp	°C	625.82 – 836.31

Table 2. Data framework setting high load.

Parameters	Unit	Range
Gross Power	MW	30.01 – 57.17
Coal Feed	Ton/h	20.74 – 46.96
Primary Air Feed	Nm^3/h	82350.21 – 145065.64
Secondary Air Feed	Nm^3/h	55652.74 – 179676.90
Avg Bed Temp	°C	810.00 – 844.99

3.2. Data Analysis by Multivariable Regression

Multivariable regression describes how one dependent variable is influenced by one or more independent variables (Pulido-Arcas *et al*., 2016). The input parameters are coal feed (X_1), primary airflow (X_2), secondary air flow (X_3) and output parameters of average bed temperature (y) are set as target parameters to be predicted. In this equation, regression

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analysis uses "least squares" to fit the line through a series of observations. Modeling begins by changing the variables X_1, X_2, X_3 and y in natural logarithmic (ln) form as follows (Eq. (1)):

$$y=AX_1^{\beta_1}X_2^{\beta_2}\ldots X_n^{\beta_n} \tag{1}$$

The Eq. (1) is then linearized to form Eq. (2).

$$\ln(y)=\ln\left(AX_1^{\beta_1}X_2^{\beta_2}\ldots X_n^{\beta_n}\right) \tag{2}$$

The linear equation obtained as follows (Eq. (3))

$$\ln(y)=\ln(A)+\beta_1\ln(X_1)+\beta_2\ln(X_2)\ldots\ldots+\beta_n\ln(X_n) \tag{3}$$

After each parameter is converted into natural logarithmic (ln) form, multivariable regression is performed using Excel in the multivariate regression analysis data section. Based on the results of multivariable regression, the model for low load is obtained as follows (Eq. (4)):

$$y=767.0446X_1^{0.036081}X_2^{-0.09217}X_3^{0.085303} \tag{4}$$

and for high load as follows (Eq. (5)):

$$y=822.4708X_1^{0.049569}X_2^{-0.01843}X_3^{0.004091} \tag{5}$$

After the multivariable regression was performed, the model was then tested for the level of error using the RMSE (Root Mean Square Error) approach to determine the value of the deviation or difference between predictions and historical field data (Hu *et al*., 2020) (Eq. (6)).

$$RMSE=\sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(y_i-\hat{y}_i\right)^2} \tag{6}$$

If the RMSE shows a number that is too high beyond the specified tolerance, the dataset framework setting process is repeated by adjusting the data. After the error is lower than the tolerance, the next step is plotting the prediction data and field operation data to be able to know the visualization of predictions from the model.

Both models are then tested for accuracy. The model was tested with the same PA, SA, and Coal Feed operating data and obtained the predicted average bed temperature. The actual average bed temperature (y_1) and the predicted average bed temperature (y_1') were then tested using the RMSE method and the error for low load was RMSE = 23.2813 and high load was RMSE = 4.8416. The plotting of the actual and predicted average bed temperature is shown in **Figure 5**.

Based on **Figures 5(a)** and **5(b)**, the distribution profile of the actual average bed temperature (y_1) on gross power and coal feed at low loads is relatively distributed with a wide range, while in **Figures 5(c)** and **5(d)**, the profiles distribution of average bed temperature is more stable. This is what causes the low load average bed temperature (y_1') to show a large RMSE of 23.2813. stable profile at high load average bed temperature provides good performance against the predicted results with RMSE 4.8416. At low loads, the combustion and fluidization patterns still tend to be unstable with a bed temperature range of 625.82-836.31°C, while the temperature at high load is in the range of 810-844.99°C. The optimum combustion range for CFB boilers is 800-900°C. Therefore, at low loads seen in the blue line area (m) and (n), the operating pattern tends to be unstable with a wide range of average bed temperatures. Both models also show an interesting fact where the coal feed parameter (X_1) shows a positive value, which means that as the amount of coal burned increases the temperature increases on the average bed temperature, as well as the SA flow parameter (X_2) which shows a positive value. However, it is different from the Primary Air Flow (X_2) parameter where the rank of the model shows a negative value, this has the opposite impact from the SA flow where the greater the PA flow input, the lower the average bed temperature.

The model is then tested using operating data. Testing was conducted to determine the effect of each parameter. The amount of data is made in 100 increments with the parameters changing according to the minimum and maximum values in the operating data. While the other parameters are fixed by using the average value. then obtained 3 graphs of average bed temperature for each PA, SA, and coal feed as follows.

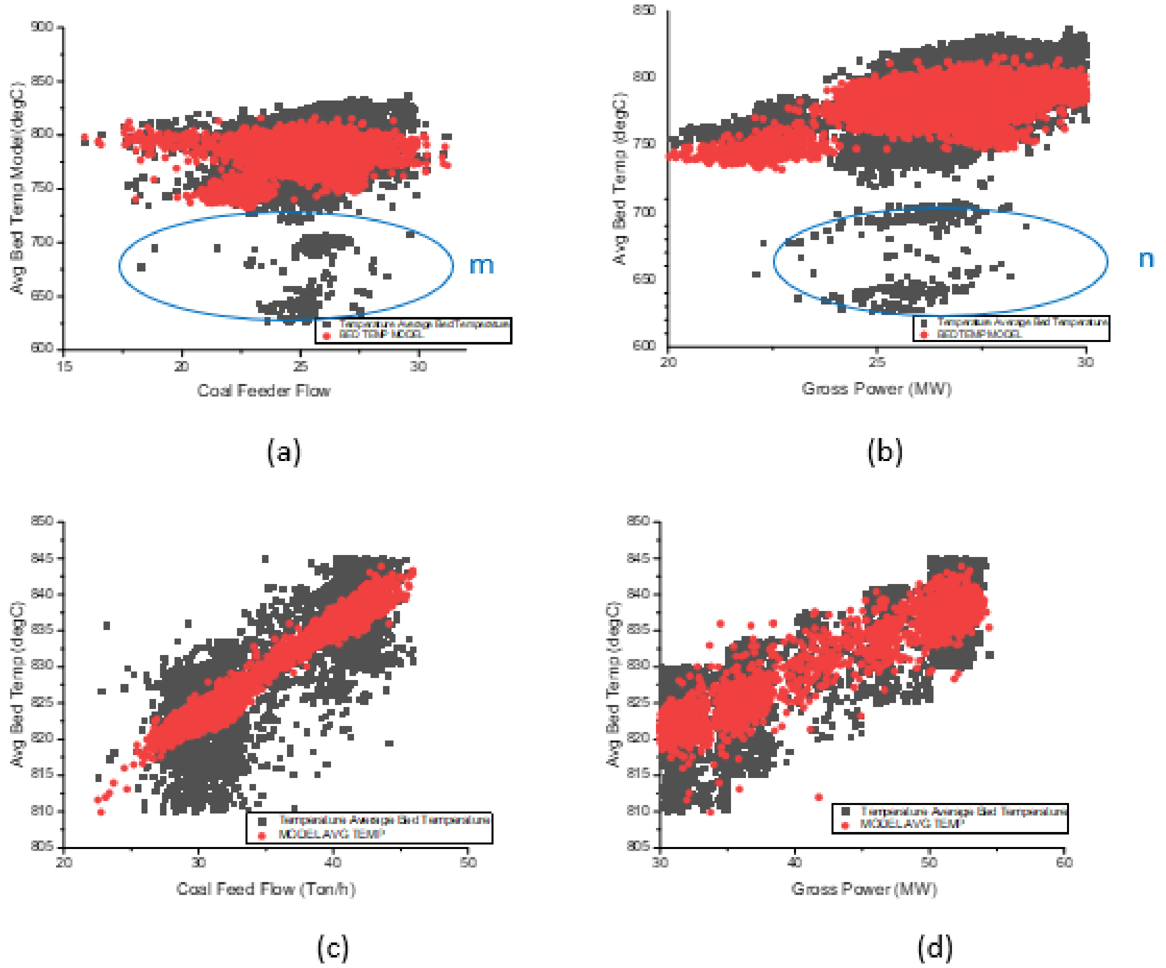

Figure 5. (a) Avg bed temp vs low load coal feed; (b) Avg bed temp vs. gross power low load; (c) Avg bed temp vs high load coal feed; (d) Avg bed temp vs gross power high load.

In **Figure 6(a),** the consistent data is PA = 108492.92 Nm^3/h and SA = 89147.42 Nm^3/h. The coal feed range used according to low load operating data is 12.30 - 39.48 ton/h. The graph shows a positive profile as the coal feed increases, the average temperature bed will also increase, as well as **Figure 6(c)** with parameter constant PA = 108492.92 Nm^3/h, coal feed = 25.03 ton/h, and SA range is 82350.21 - 116705.77 Nm^3/h. However, in **Figure 6(b)** with constant coal feed = 25.03 ton/h, SA= 108492.92 Nm^3/h and PA range is 82236.41 – 141685.94 Nm^3/h show different results. If the PA value increases, the average bed temperature will decrease.

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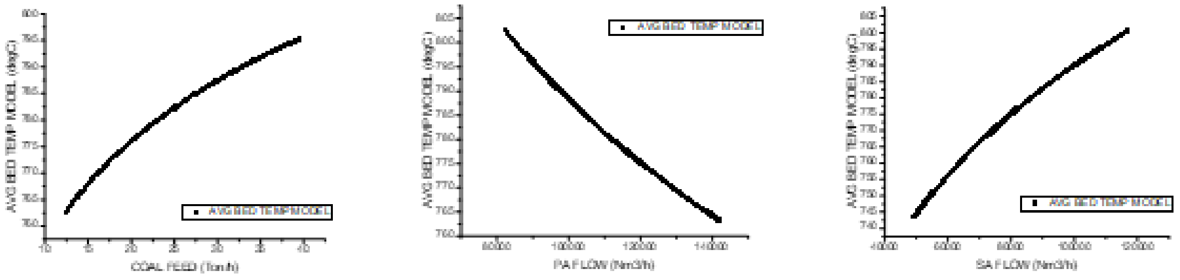
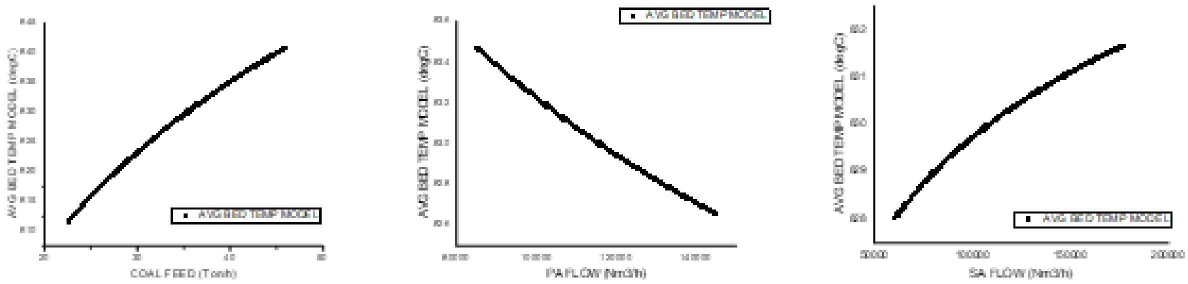


(a) (b) (c)

Figure 6. Simulation of the effect of coal feed, PA, and SA on the average bed temperature at low load model.

Temperature profile at low load also occurs at medium to high load. **Figure 7(a)** shows in the coal feed range of 22.51-45.90 with a fixed PA of 145065.6 Nm^3/h and a fixed SA of 107092.14 Nm^3/h, the profile is directly proportional. The higher the coal feed, the higher the temperature. The resulting profile is similar to the SA variation. for the range of SA 60261.99 – 176596.56 Nm^3/h, coal feed remained at 35.26 and PA remained at 115921.92 Nm^3/h, the profile obtained was equally proportional. However, in **Figure 7(b)** the PA flow range is 85036.19 – 145065.6 Nm^3/h, coal feed remained at 35.26, and SA flow remained at 107092.14 Nm^3/h showing the inversely proportional results. The greater the PA flow rate, the average temperature bed will decrease. This is following the theory that the main role of PA flow in the CFB boiler is used as fluidizing air in the particle bed and SA flow is used as combustion air which is exhaled in the middle of the furnace.



(a) (b) (c)

Figure 7. Simulation of the effect of coal feed PA, and SA on the average bed temperature at high load model.

4. CONCLUSION

The multivariable regression model shows that the performance and operating pattern of the CFB boiler differ depending on the power load generated. The obtained average bed temperature model is $y=767.0446X_1^{0.036081}X_2^{-0.09217}X_3^{0.085303}$ for low load and high load is $y=822.4708X_1^{0.049569}X_2^{-0.01843}X_3^{0.004091}$ with coal feed as X_1, PA flow as $X_2$and SA flow as X_3. Based on the parameter model, the higher the coal feed flow (X_1) and the SA flow X_3), the greater the effect of increasing the temperature bed. However, if the PA flow X_2) value is greater, the effect on the temperature bed will decrease. The simple model can be used to predict average bed temperature as a reference in decision-making and optimization. This model can be used accurately in boilers that have processed historical data, but it is not certain that it can be used in other boilers. Suggestions for future research are to collect

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historical data on various types of CFB boiler capacities and designs to become big data. The dataset can be processed using multivariable regression and machine learning to obtain an accurate model used by various types of CFB boilers.

5. AUTHORS' NOTE

The authors declare that there is no conflict of interest regarding the publication of this article. The authors confirmed that the paper was free of plagiarism.

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