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The Effect of Coal and Biomass on the Generation of Fly Ash and Bottom Ash at the Coal-Fired Power Plant Asam Asam Unit 1-4, South Kalimantan

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ABSTRACT

Background: One of the main environmental challenges in Coal-Fired Power Plant (CFPP) operations is the large amount of Fly Ash and Bottom Ash (FABA) produced, which creates significant waste management issues. Reducing FABA production through biomass co-firing has become a potential solution, yet its effectiveness in actual operations remains underexplored. Asam Asam Power Plant Unit 1–4, with a capacity of 4 × 65 MW in South Kalimantan, is one of the power plants that utilize sawdust biomass in its operations.
Aims: This study aims to analyze the effect of coal and biomass consumption on FABA generation during 2022, 2023, and 2024.
Methods: The method employed is multiple linear regression using Minitab version 21.4.1 software, with coal consumption (X1) and biomass consumption (X2) as independent variables and FABA generation (Y) as the dependent variable.
Result: The results show that coal consumption has a positive relationship with FABA generation, while biomass consumption shows a negative relationship. ANOVA test results indicate that only coal consumption significantly affects FABA generation. A notable decrease in FABA production in 2024 signifies an increase in biomass utilization in the fuel mixture, highlighting its potential in reducing solid waste generation from CFPP operations. A simulation involving three biomass-coal blending scenarios demonstrated that incorporating 20% biomass into the fuel mix can reduce FABA generation by up to 27.79%.

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1. Introduction

A CFPP continues to be a major source of electricity in Indonesia, primarily relying on coal combustion to meet national energy demands (Pambudi *et al.,* 2023). However, the combustion of coal results in the generation of solid wastes, notably FABA, which present significant challenges for environmental management (Suripto *et al.,* 2024). The amount of FABA produced tends to increase with plant capacity and coal consumption (Rahim *et al.,* 2023). Fly Ash, typically released with flue gases, contains hazardous compounds such as heavy metals, which can contribute to air and soil pollution if not managed properly (Chen *et al.,* 2024). Meanwhile, Bottom Ash, which accumulates at the bottom of the boiler, poses long-term environmental risks despite its partial reuse in construction materials (Eom *et al.,* 2024).

To reduce the environmental impact of CFPP, biomass co-firing has emerged as a cleaner and more sustainable alternative (Apriliyanti & Nugraha, 2025). Biomass, such as sawdust, when burned alongside coal, is believed to reduce greenhouse gas emissions and may also affect the amount and characteristics of FABA generation (Yana *et al.,* 2022). Numerous international studies have examined the effects of co-firing on FABA generation. For instance, Wu *et al.* (2025) found that co-firing with biomass significantly reduced ash yield and changed its composition, making it less harmful. Moreover, Marganingrum *et al.* (2022) observed that the reduction in coal usage due to biomass substitution directly affected the volume of FABA generation.

Despite the increasing amount of research, most studies on biomass co-firing primarily focus on emission reductions or boiler performance, with limited attention given to its specific impact on FABA quantities, particularly in the Southeast Asian context (Zhai *et al.,* 2025). Furthermore, while some studies discuss the general potential of biomass in CFPP, quantitative analysis that links fuel consumption to FABA production over several years is still scarce (Bayu *et al.,* 2023).

CFPP Asam Asam Unit 1-4, located in South Kalimantan, is one of Indonesia's pioneers in using biomass co-firing with sawdust since 2021. However, there has been no comprehensive analysis that evaluates the correlation between coal and biomass consumption and FABA generation in this plant, particularly utilizing long-term operational data. Therefore, This study aims to analyze the effect of coal and biomass consumption on FABA generation during 2022, 2023, and 2024. Using multiple linear regression analysis, the study will provide empirical evidence on how biomass co-firing impacts FABA generation during actual plant operations. This study not only identifies historical patterns but also investigates the potential effects of different coal and biomass proportions in the fuel mix on FABA generation. In order to quantify the possible decrease in FABA under various operating situations, this study simulates various co-firing ratios, such as 10%, 20%, or 30% biomass substitution. The purpose of these forecasts is to assist decision-makers in assessing the best biomass blending techniques for reducing solid waste in CFPP operations.

2. Methods

2.1 Location

CFPP Asam Asam Unit 1-4, with a capacity of 4 x 65 MW, is located in Asam Asam Village, Jorong District, Tanah Laut Regency, South Kalimantan. CFPP Asam Asam Unit 1-4 serves as voltage support on the southern side of the interconnection system and is part of the base load in the Kalimantan interconnection power grid.

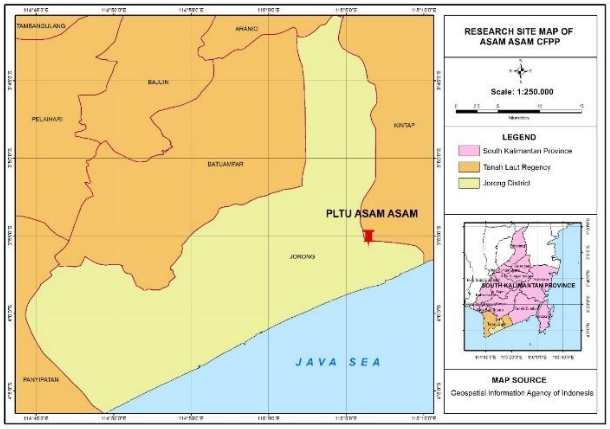

Figure 1. Research Location.

2.2 Research Approach

This research adopts a quantitative approach utilizing a Multiple Linear Regression (MLR) method to analyze the relationship between coal and biomass consumption and FABA generation. The objective is to assess both the partial and simultaneous effects of the two independent variables (coal and biomass consumption) on the dependent variable (FABA generation). The study flowchart that follows is designed to give clarity on the procedure and sequence of analysis:

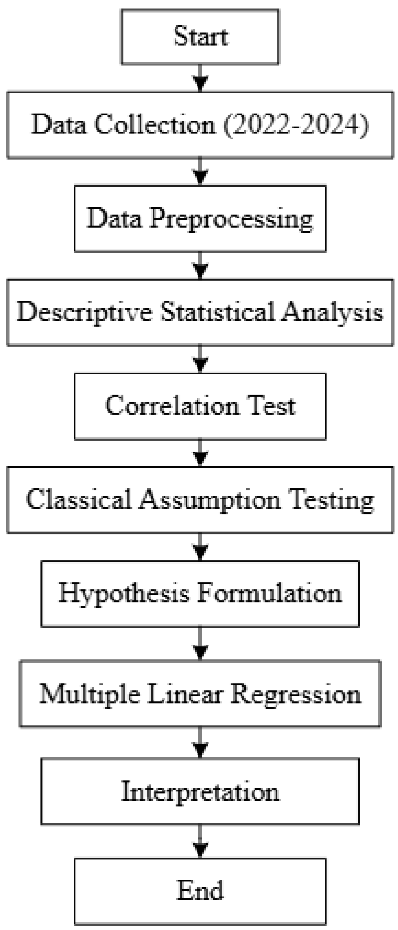

Figure 2. Research Flowchart.

2.3 Data Collection

The operational reports of CFPP Asam Asam Unit 1-4 provided the secondary data used in this research. The data span a period of three years (2022-2024) and includes: coal consumption (X_1) measured in ton, biomass consumption (X_2) measured in ton, FABA generation (Y) measured in ton, and gross production measured in kWh. Coal and biomass consumption are chosen as independent variables because they are the main fuels that directly impact the combustion process and consequently the generation of solid by-products like FABA. Gross production serves a key to assess the correlation between electricity output and FABA generation, providing insight into waste intensity

2.4 Data Preprocessing

Using linear trends to interpolate missing values and guaranteeing unit consistency across all datasets were examples of data preparation (Zhang *et al.,* 2023). Boxplots were used to visually identify outliers, and the correctness of the data (Mazarei *et al.,* 2025).

2.5 Preliminary Statistical Analysis

The dataset was summarized using descriptive statistics, and multicollinearity was examined and correlations between variables were assessed using Pearson correlation analysis (Sundus *et al.,* 2022). By doing these actions, the data was guaranteed to be appropriate for regression analysis.

2.6 Classical Assumption Testing

The regression model was validated using traditional assumption testing. Multicollinearity was examined using the Variance Inflation Factor (VIF), autocorrelation was examined using the Durbin–Watson statistic, and normality was evaluated using the Kolmogorov-Smirnov test based on p-values (Iheaka, 2025). By looking at the p-values of X_1 and X_2, heteroscedasticity was assessed; findings larger than 0.05 suggested homoscedasticity.

2.7 Hypothesis Development

To evaluate the relationship between coal and biomass consumption and the amount of FABA generation, this study formulates both partial and simultaneous hypotheses. The statistical analysis of multiple linear regression is based on these hypothesis.

For the partial hypotheses:

- $H_{0\text{-}1}$: Coal consumption (X_1) significantly affects FABA generation (Y).
- $H_{a\text{-}1}$: Coal consumption (X_1) does not significantly affect FABA generation (Y).
- $H_{0\text{-}2}$: Biomass consumption (X_2) significantly affects FABA generation (Y).
- $H_{a\text{-}2}$: Biomass consumption (X_2) does not significantly affect FABA generation (Y).

For the simultaneous hypotheses:

- $H_{0\text{-}2}$: Coal consumption (X_1) and biomass consumption (X_2) have a significant effect on FABA generation (Y).
- $H_{a\text{-}2}$: Coal consumption (X_1) and biomass consumption (X_2) do not have a significant effect on FABA generation (Y).

2.8 Regression Analysis

The MLR used is: $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \in$.

Where:

Y : FABA generation (ton)
X_1 : Coal consumption (ton)
X_2 : Biomass consumption (ton)
β_0 : Intercept

$\beta_1 \& \beta_2$: Regression coefficients
$\in$: Error term

To obtain the MLR equation, this study uses Minitab software version 21.4.1, which provided regression coefficients, R^2, ANOVA tables, and residual plots. After building the regression model, a number of fictitious coal-to-biomass cofiring ratios, including 90:10, 80:20, and 70:30, are simulated in order to perform scenario analysis. These simulations anticipate FABA generation under different fuel mixes while maintaining a constant total fuel input using the well-established regression equation. In order to help the development of evidence-based co-firing policies, this scenario study aims to forecast how expanding biomass substitution may lower FABA production in real-world scenarios.

3. Results and Discussion

3.1 Existing Operational Conditions at the CFPP Asam Asam Unit 1-4

The demineralized water cycle and the fuel cycle are the two main operational cycles that are observed at the Asam CFPP Units 1-4. Freshwater from the Asam River is used to start the water cycle. It is then processed in the Water Treatment Plant (WTP) to create demineralized water. This water passes through the condenser and turbine system after being kept in the Cold Condensate Storage Tank (CCST). The feedwater is compressed and heated further before going into the boiler after being heated in the Low-Pressure Heater (LPH) and High-Pressure Heater (HPH) and having the gas removed in the deaerator. The turbine-generator system is powered by high-pressure steam produced by combustion of the water inside the boiler. The closed loop is then completed by condensing and recirculating the resultant steam.

Co-firing sawdust biomass and coal is part of the fuel cycle, and it has been used at the plant from October 2021. With the help of forced and primary air fans, fuel is mixed, ground up, and delivered to the boiler, where it is burned. FABA are solid wastes and flue gas produced by this operation. While Fly Ash is caught by the Electrostatic Precipitator (ESP) prior to flue gas being released through the stack in accordance with emission regulations, Bottom Ash settles in the Submerged Scraper Conveyor.

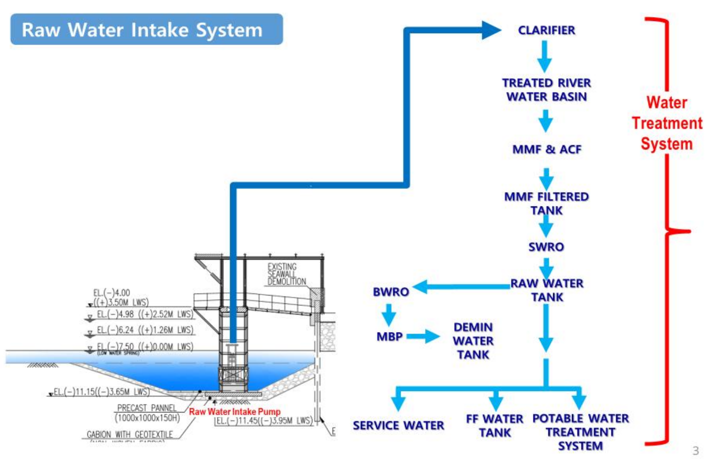

Figure 3. Water Treatment System.

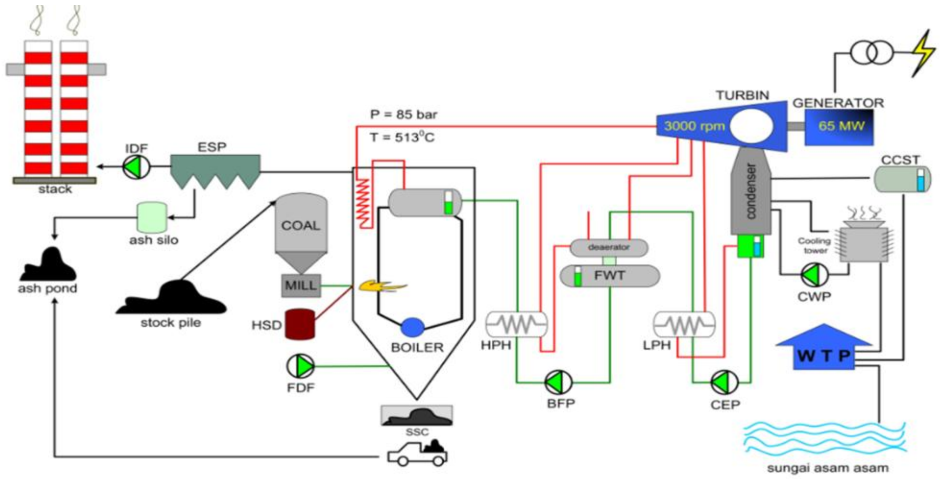

Figure 4. CFPP Asam Asam Unit 1-4 Cycle.

3.2 Data Preprocessing

To guarantee preparedness for statistical modeling, all datasets underwent a methodical data cleaning procedure after the initial data collection. This included verifying the types of variables, converting numeric values into standardized formats, and eliminating superfluous characters (such as commas, needless whitespace, and hyphens). After data cleaning, the biomass consumption for May 2022 was recorded as zero. This figure accurately reflects the operational conditions of that month, as co-firing was not implemented due to specific constraints at the plant. Therefore, we retained this value as a valid entry instead of treating it as a missing value. Outlier detection was conducted using visual diagnostics with boxplot (Arimie *et al.,* 2020). No significant outliers were observed in coal consumption, biomass consumption, and FABA generation data across all three years. This suggests operational consistency in fuel use and combustion residuals.

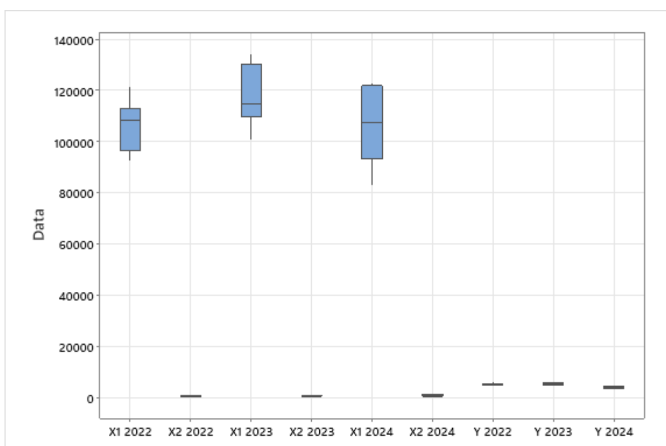

Figure 5. Boxplot Data

3.3 Descriptive Statistical Analysis

Table 1 provides a summary of the dataset's descriptive statistics for the years 2022–2024. The mean and median values for each variable are fairly close together, suggesting a distribution that is largely symmetric, however small variations in certain instances point to minor skewness. Interestingly, not all variables have a specified mode (shown by "*"), suggesting that no single value appears more than once in the datasets; hence, there is no dominant or frequently recurring value.

Table 1. Descriptive Statistical Analysis.

Variable	Mean	Median	Mode	Skewness
X_1 2022	106,548	108,354	*	-0.34
X_2 2022	573.10	540.90	*	-0.04
Y 2022	5,179	5,101	*	0.46
X_1 2023	118,144	114,496	*	0.23
X_2 2023	632.20	628.10	*	-0.47
Y 2023	5,411	5,460	*	-0.04
X_1 2024	1,065,071	107,277	*	-0.21
X_2 2024	1,009	961	*	0.47
Y 2024	3,904	3,952	*	-0.25

The distribution's symmetry, indicated by low skewness and minimal differences between the mean and median, supports the suitability of the dataset for parametric analyses such as MLR (Rehman *et al.*, 2024).

3.4 Correlation Test

To evaluate the relationship between two parameters, Pearson's correlation coefficient can be used. This method determines both the direction and strength of the relationship between the variables. A positive correlation coefficient signifies a direct relationship, indicating that an increase in one variable is associated with an increase in the other variable.

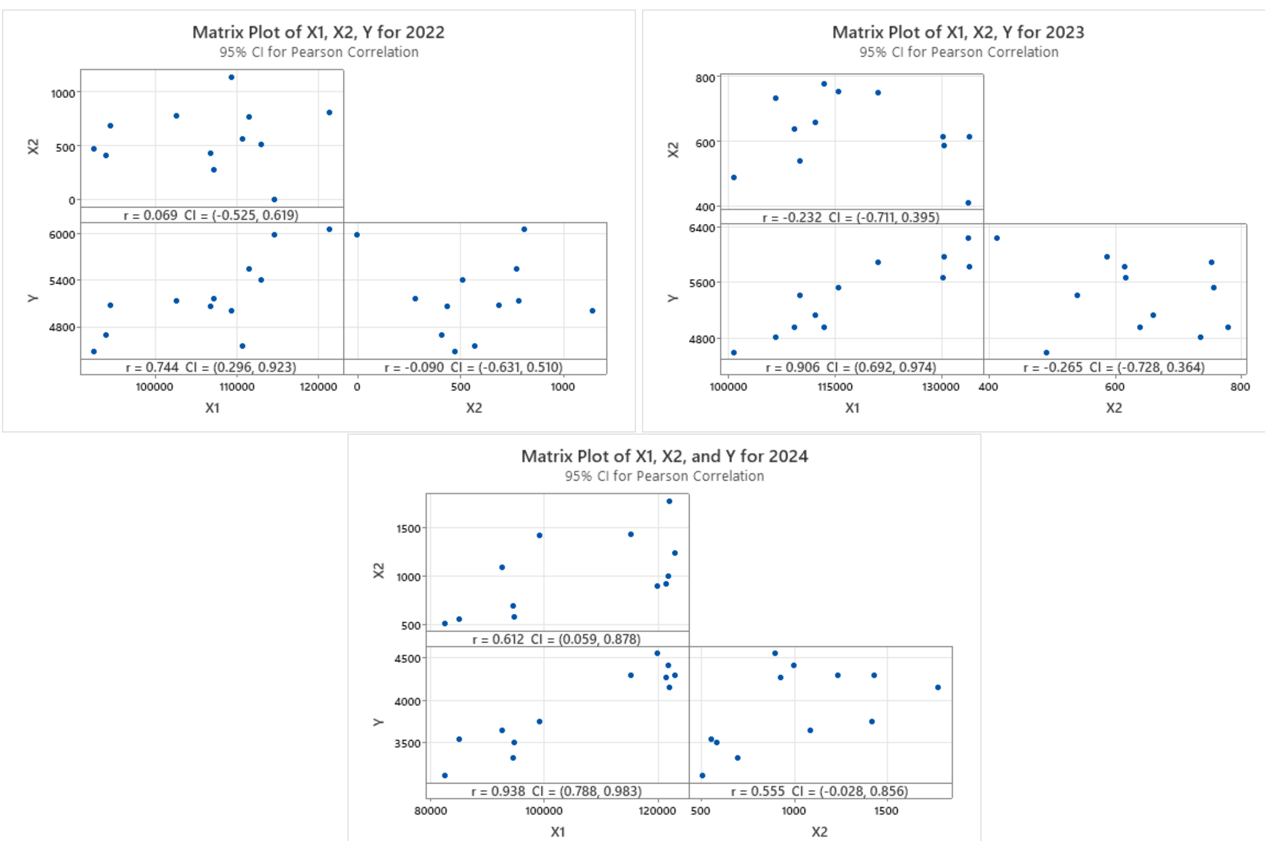

Figure 6. Matrix Plot of Pearson Correlation.

The correlation analysis conducted over the period of 2022 to 2024 reveals a consistent pattern in the relationship between fuel consumption and FABA generation. In 2022, coal consumption (X1) exhibited a moderately strong positive correlation with FABA generation (Y) (r = 0.744) (Anggara *et al.,* 2024), while biomass consumption (X_2) showed a very weak negative correlation with Y (r = -0.090). The interrelationship between X_1 and X_2 was weakly positive (r = 0.069), suggesting that the degree of biomass substitution for coal remained limited during this year.

In 2023, the correlation between coal consumption and FABA generation increased significantly (r = 0.906), whereas the relationship between biomass and FABA became slightly more negative (r = -0.265), indicating an emerging inverse trend. Concurrently, the correlation between X_1 and X_2 shifted toward a slightly stronger negative association (r = -0.232), which aligns with an observed pattern of partial fuel switching (Rahim *et al.,* 2023).

By 2024, the correlation between coal consumption and FABA generation had reached a very strong level (r = 0.938). Interestingly, the correlation between biomass consumption and FABA generation reversed direction, showing a moderate positive relationship (r = 0.555), which may suggest a shift in the operational role of biomass in the combustion process. The inter-fuel correlation also increased to a moderate positive value (r = 0.612), potentially reflecting a more integrated and planned approach to fuel co-firing. These findings indicate evolving co-firing dynamics and their influence on FABA generation over the three-year period.

3.5 Classical Assumption Testing

The classical assumption test is a statistical requirement conducted in multiple linear regression analysis using ordinary least squares (OLS). In OLS, there is one dependent variable and multiple independent variables. The classical assumptions for multiple linear regression tests include normality test, multicollinearity test, autocorrelation test, and heteroscedasticity test.

3.5.1 Normality Test

Normality testing was conducted using Minitab software with the Kolmogorov-Smirnov method, yielding the p-value shown below.

Table 2. Normality Test.

Year	Variable	P-Value	P-Value Residual
2022	X_1	0.300	
	X_2	0.799	0.155
	Y	0.466	
2023	X_1	0.198	
	X_2	0.636	0.268
	Y	0.385	
2024	X_1	0.223	
	X_2	0.693	0.572
	Y	0.225	

The table indicates that all variables for 2022-2024 have a p-value more than 0.05 , which suggests that this data is normally distributed. The p-value for the residual normality test in 2022, 2023, and 2024 were 0.155, 0.268, and 0.572 (> α 0.05), which leads to the conclusion that the data is normally distributed and meets the requirements for linear regression.

3.5.2 Multicollinearity Test

Based on the calculations in Minitab software, the VIF values were found to be < 10, indicating that there is no multicollinearity in the data and that it meets the criteria for performing linear regression tests (Daoud, 2017).

Table 3. Multicollinearity Test.

Year	Variable	VIF
2022	X_1	1.000
	X_2	1.000
2023	X_1	1.060
	X_2	1.060
2024	X_1	1.600
	X_2	1.600

3.5.3 Autocorrelation Test

The autocorrelation test was conducted using the Durbin–Watson (DW) statistic. A DW value close to 2 indicates no autocorrelation; a value less than 2 (approaching 0) suggests positive autocorrelation; and a value greater than 2 (approaching 4) indicates negative autocorrelation (Uyanto, 2020). Based on calculations performed using Minitab software, the DW values were 2.045, 2.221, and 2.163, respectively, indicating that all three regression models satisfy the assumption of no autocorrelation.

3.5.4 Heteroscedasticity Test

The heteroscedasticity test was conducted by analyzing the residuals versus fitted values plot in Minitab software (Jarantow *et al.,* 2023). If the plot displays a random scatter without a discernible funnel-shaped pattern, it indicates the absence of heteroscedasticity. Based on the residual plot output from Minitab, the residuals appear randomly and evenly dispersed, suggesting that heteroscedasticity is not present and the data satisfy the assumptions required for linear regression analysis.

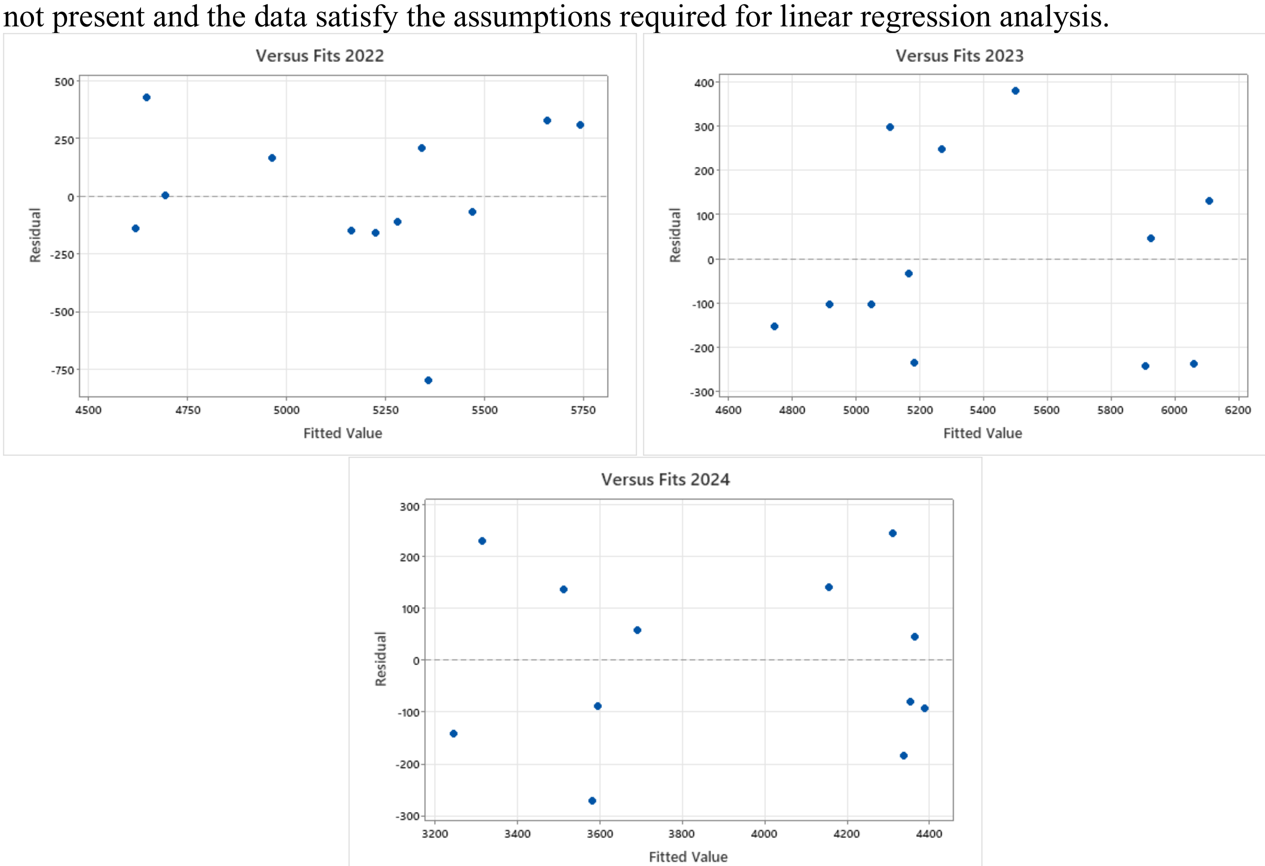

Figure 7 Residual Plot Graphic.

3.6 Hypothesis Formulation

Hypothesis formulation testing is a typical technique used in data analysis to ascertain the accuracy of an estimated regression model obtained from the data (Song, 2024). Therefore, this method is closely related to the accuracy of the conclusions drawn. H_0: $\beta = 0$ = There is no relationship between variable Y and variable X in the established regression model. H_a: $\beta \neq 0$ = There is a relationship between variable Y and variable X in the established regression model. Based on the regression F-value (6.04, 21.08, and 32.99) being greater than the F-table (3.10), the null hypothesis (H_0) is rejected, and the alternative hypothesis (H_a) is accepted, concluding that there is a relationship between variable Y and variable X in the established regression model.

3.7 Multiple Linear Regression

Regression equations are algebraic expressions that represent regression lines. When analyzing two variables, X and Y, we can describe two regression lines: one for the regression of X on Y and the other for the regression of Y on X. The first regression line predicts probable values of X based on different values of Y, while the second line predicts probable values of Y based on given values of X. Therefore, we obtain two distinct regression equations.

Table 4. Equation of Multiple Linear Regression.

Year	Equation
2022	$Y = 846 + 0.042\ X_1 - 0.024\ X_2$
2023	$Y = 768 + 0.041\ X_1 - 0.027\ X_2$
2024	$Y = 867 + 0.029\ X_1 - 0.037\ X_2$

From the Table 4, the following can be interpreted:

1. Intercept = 846, 768, and 867 predicts the amount of FABA generated when both coal consumption and biomass consumption are zero. In this case, X = 0 falls outside the range of independent variables, so the regression model cannot be interpreted.
2. For every 1-ton increase in coal consumption, assuming biomass consumption remains constant, FABA generation will increase by 0.042 tons in 2022, 0.041 tons in 2023, and 0.029 tons in 2024.
3. For every 1-ton increase in biomass consumption, assuming coal consumption remains constant, FABA generation will decrease by 0.024 tons in 2022, 0.027 tons in 2023, and 0.037 tons in 2024.

3.8 Interpretation

The interpretation of this study is structured into several key components: ANOVA testing, analysis of correlation and determination coefficients, aptness test, assessment of biomass influence on FABA and electricity generation, and simulation-based comparison of biomass and coal contributions to FABA generating.

3.8.1 ANOVA Testing

Based on the results of the ANOVA test, coal consumption (X_1) has a p-value (0.007, 0.006, and 0.000) < α 0.05 and T-value (3.450, 6.210, and 6.550) > T-table (2.262), which indicates that coal consumption (X_1) has a significant effect on FABA generating (Y). This confirms that coal is the main contributor to ash formation due to its higher ash content and more incomplete combustion compared to biomass. Meanwhile, biomass consumption (X_2) has p-value (0.530, 0.693, and 0.841) > α 0.05 and T-value (-0.650, -0.410, and -0.210) < T-table (2.262), showing that biomass consumption (X_2) does not have a significant effect on FABA generating (Y). The weak statistical relationship is further reflected in the observed negative correlation between biomass consumption and FABA output. A plausible explanation for this observation lies in the combustion characteristics of biomass. Biomass generally contains lower levels of ash-forming components, such as fixed carbon and minerals, and higher volatile matter compared to coal (Kim *et al.,* 2024). Consequently, increasing the proportion of biomass in co-firing tends to reduce the total ash produced per unit of energy generated (Murphy *et al.,* 2023). Additionally, when biomass is co-fired in smaller proportions, it may enhance combustion efficiency, leading to more complete combustion and a lower generation of FABA (Turner *et al.,* 2023).

Table 5. ANOVA Test.

Year	Variable	T-Value	P-Value	T-Table
2022	X_1	3.450	0.007	2.262
	X_2	-0.650	0.530	
2023	X_1	6.210	0.000	
	X_2	-0.410	0.693	
2024	X_1	6.550	0.000	
	X_2	-0.210	0.841	

Based on the regression p-value (0.022, 0.000, and 0.000) < α 0.05, it can be concluded that coal consumption (X_1) and biomass consumption (X_2) simultaneously have a significant effect on FABA generating (Y). This suggests that there may be interaction effects or indirect contributions of biomass within the combustion process, which require further investigation (Bhoi *et al.,* 2023). Practically, these findings highlight the potential of biomass co-firing as a strategy to reduce greenhouse gas emissions and decrease FABA generating, especially when biomass replaces a portion of high-ash coal (Turner *et al.,* 2023). However, the fact that biomass alone does not significantly impact fuel ash behavior indicates that its effects are context-dependent—more pronounced at higher substitution levels or with certain types of biomass (Bhoi *et al.,* 2023). Therefore, optimizing biomass ratios and understanding fuel properties are essential for effective co-firing implementation (Kim *et al.,* 2024).

3.8.2 Analysis of Correlation and Determination Coefficients

Based on the correlation coefficient values (0.757, 0.776, and 0.938), there is a relatively strong relationship between coal and biomass consumption and the quantity of FABA generated. Regarding the coefficient of determination, in 2022, 47.83% of the variation in FABA generation can be explained by coal and biomass consumption, while the remaining 52.17% is attributed to other factors not included in the regression model. In 2023, coal and biomass consumption accounted for 51.48% of the variation in FABA generation, with the remaining 48.52% influenced by external variables. In 2024, 85.33% of the FABA generation was determined by coal and biomass consumption, whereas 14.67% resulted from variables outside the model.

Table 6. Correlation and Determination Coefficients.

Year	R-sq (%)	R-sq (adj) (%)
2022	57.32	47.83
2023	60.30	51.48
2024	88.00	85.33

3.8.3 Aptness Test

Since the regression F-value (6.04, 21.08, and 32.99) is greater than the F-table value (3.10), the null hypothesis (H_0) is rejected, and the alternative hypothesis (H_a) is accepted, concluding that there is a significant relationship between variable Y and variable X in the established regression model (Matson & Huguenard, 2007).

3.8.4 Assessment of Biomass Influence on FABA and Electricity Generation

The influence of biomass consumption on FABA generation and electricity output was evaluated by analyzing data collected from 2022 to 2024. The analysis utilized annual records of biomass consumption (in tons), electricity production (in MWh), and FABA generation (in tons).

Table 7. Biomass Consumption, Gross Production, and FABA Generating.

Year	Biomass Consumption (ton)	Gross Production (MWh)	FABA Generating (ton)
2022	6,440.66	1,704,105.80	62,152.94
2023	7,172.85	1,859,374.60	64,926.29
2024	11,520.75	1,670,902.11	46,849.84

Based on Table 7, there was a significant increase of 78.87% in biomass consumption in 2024 compared to 2022; however, the amount of FABA generated dropped sharply by 24.6%. This indicates a negative relationship between biomass consumption and FABA generation. The reduction in FABA is attributed to the combustion characteristics of biomass, which typically contains lower levels of ash and fixed carbon, along with higher volatile matter compared to coal. These properties lead to more efficient combustion and result in less solid residue. The highest electricity production occurred in 2023, reaching 1.86 GWh with a biomass consumption of 7,172.85 tons and FABA generation of 64,926.29 tons. In 2024, despite a substantial increase in biomass consumption, electricity output declined compared to the previous two years. This suggests that a higher biomass input does not necessarily lead to increased electricity production, particularly if the biomass is used in excessive amounts or has a low calorific value. Optimizing the co-firing ratio is essential to simultaneously improve combustion efficiency and reduce FABA generation.

3.8.5 Simulation-Based Comparison of Biomass and Coal Contributions to FABA Generating

The simulation was carried out by varying the proportion of coal and biomass mixtures under three scenarios: Scenario 1 consisted of 100% coal and 0% biomass; Scenario 2 used 90% coal and 10% biomass; and Scenario 3 applied 80% coal and 20% biomass. Increasing the biomass ratio to 20% in coal-fired power plants is considered technically feasible, as the risks of slagging, fouling, and corrosion remain within acceptable operational thresholds (Aditya et al., 2022). The simulation employed the 2024 regression model: $Y = 867 + 0.029\ X_1 - 0.037\ X_2$.This model was selected due to its highest adjusted R-squared value, indicating that it provides the best representation of the relationship between coal consumption, biomass usage, and FABA generation among the models evaluated.

Table 8. Comparison Biomass Ratio to FABA Generating.

Scenario	Coal (ton)	Biomass (ton)	FABA Generating (ton)
1	46,849.84	-	2,225.65
2	42,164.85	4,684.98	1,916.44
3	37,479.87	9,369.97	1,607.23

As shown in Table 8, increasing the proportion of biomass in the fuel mix consistently leads to a significant reduction in estimated FABA generation. Transitioning from 0% to 20% biomass results in approximately a 27.79% decrease in FABA output. This reflects the inverse relationship between biomass consumption and ash formation. This trend aligns with the chemical and physical properties of biomass, which generally contains fewer ash-forming elements and promotes more efficient combustion due to its higher volatile matter content (Schlupp *et al.,* 2024).

The reduction of FABA not only minimizes land requirements for waste disposal but also decreases the potential for soil and water contamination. The utilization of FABA as construction materials—such as paving blocks, bricks, and land filler—implemented at the Asam Asam CFPP exemplifies a circular economy practice that aligns with the Sustainable Development Goals (SDGs). The findings of this study also support the Indonesian government's policy framework, particularly Regulation of the Minister of Energy and Mineral Resources No. 11 of 2021 concerning the Implementation of Electricity Business, which promotes biomass co-firing as a pathway toward clean energy transition.

4. Conclusions

The study reveals that coal consumption significantly contributes to FABA generation, whereas biomass consumption does not exhibit a statistically significant effect. This finding aligns with the inherent characteristics of biomass, which typically contains lower levels of ash and fixed carbon, as well as higher volatile matter, resulting in more efficient combustion and reduced solid residues. A simulation involving three biomass-coal blending scenarios demonstrated that incorporating 20% biomass into the fuel mix can reduce FABA generation by up to 27.79%. The regression model from 2024 was selected due to its highest adjusted R-squared value, indicating superior predictive performance compared to other models. Although increased biomass consumption does not consistently correlate with higher electricity production, optimal co-firing configurations can mitigate the environmental impact of combustion waste without compromising energy efficiency. With a coordinated technical and policy approach, biomass co-firing presents a viable strategy for coal-fired power plants in Indonesia to reduce emissions and solid waste sustainably.

5. References

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