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Research Article

Optimizing Biomass Synergy: Cost-Effective Reduction of Carbon Footprint in Coal-Fired Power Plants

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Abstract

Biomass is a renewable energy source that is easy to find in agricultural countries and can be quickly implemented by co-combusting CFPP in an effort to reduce GHG emissions. However, the integrated optimization of the blending process involving different coal ranks and biomass synergizing has yet to be achieved in order to meet the quality requirements of a number of CFPPs. This study offers an optimization approach for synergizing blending biomass in several coal-fired power plants (CFPPs). The objective is to reduce fuel costs and carbon dioxide emissions by taking into account CFPP's fuel quality requirements as well as constraints on CFPP demand, source supply capacity, and transportation alternatives. The optimization model used is mixed integer linear programming (MILP), which leverages OR-Tools in Google Colab to provide optimal solutions for the allocation of coal and biomass, whereas in the mathematical model, the amount of biomass that can be mixed into coal is limited in the range of 5% to 10%. Case studies conducted on 17 sources of coal, 1 biomass production facility, 3 alternative transportation capacities, and 4 CFPPs show that blending biomass with coal can reduce fuel costs by 2.77% and carbon dioxide emissions by 9.99% when compared to business as usual. This model offers a practical solution to reduce costs while simultaneously tackling climate change in accordance with the objectives outlined in the Paris Agreement.

Keywords: biomass; blending optimization; carbon footprint; linear programming; OR tools

1. Introduction

Blending is a commonly utilized process in various supply chains, where feedstocks of varying quality are merged to meet the specific requirements of end users (Fomeni, 2018). One of the research subjects that has been widely carried out is coal mixing between two or more types of coal with different qualities to meet certain requirements, such as the technical specifications of boilers for power plants (Yin et al., 2000). According to Sloss (2014), when the composition of coal blending aligns with the specifications of the boiler, there is potential for an increase in generator efficiency. The implementation of this approach has the potential to yield several benefits in the coal industry (Yorukoglu, 2017). The benefits of the blending implementation include a reduction in coal production, an extension of mine life, a decrease in overburden in open pit mines, a reduction in slagging that minimizes plant maintenance costs, an increase in profits, and a reduction in greenhouse gas emissions. Furthermore, research was also carried out to optimize coal mixing while considering costs, supply chains, and carbon dioxide emissions (Baskoro et al., 2022).

In the last few years, the existence of coal-fired power plants has been in the spotlight because it is the largest contributor to the increase in global carbon emissions (Xu et al., 2018) and affect air quality (Xu & Ge, 2020). The global community has increasingly expressed significant apprehension regarding the environmental impact of coal usage on the greenhouse effect and climate change (Xu et al., 2017). Primary energy consumption has increased over the last ten years as a result of societal and economic developments, with an average annual growth rate of 1.6% until 2030. To reduce the use of traditional fossil energy such as coal, support for the use of clean energy has become a trending topic, and biomass is one of the clean energies that is attracting attention (Zhang et al., 2019). So a lot of research has been done on the contribution of co-firing biomass in coal-fired power plants. The co-firing technique utilizes biomass derived from a range of sources, including wood chips, rice husks, and corn stalks (Xu et al., 2020). In the co-firing process, replacing some coal with biomass might lower the amount of greenhouse gases released, such as carbon dioxide, nitrogen oxides, and sulfur oxides (Roni et al., 2017). Hence, as the proportion of biomass fuel increases, there is a corresponding decrease in the emissions of greenhouse gases. Based on these advantages, several CFPPs have implemented the technique successfully (Smith et al., 2019).

However, the optimization of the blending process between biomass and various coal ranks has not yet been conducted in an integrated manner to satisfy the specific quality standards demanded by several CFPPs. The lack of coordination among CFPPs in planning fuel requirements is the cause of this problem. Each CFPP focuses on selecting the most cost-effective coal option available and does not integrate the planning of biomass; instead, it is solely determined by the availability of coal in the stockpile. Consequently, a scenario occurs wherein the fuel

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quality fails to fulfil the quality requirement of the CFPP boiler, thereby leading to elevated fuel expenses and greenhouse gas emissions.

Hilali et al. (2023) have integrated coal blending planning, transportation planning, and supply and demand capacity considerations in their research to minimize costs and carbon dioxide emissions, but it is important to note that biomass was not part of their study models. Meanwhile, Nawaz and Ali (2020) conducted a study on blending biomass as a co-firing of coal based on supply already in the stockpile without addressing changes in the variation of coal quality characteristics or coal supply plans. This research was based on the supply already in the stockpile.

The utilization of biomass co-firing in existing coal-fired power plants represents a rapid and efficient approach to increasing the renewable energy mix (Arifin et al., 2023). This is also driven by the minor CFPP modifications required (Juan et al., 2018). Biomass also has quality characteristics similar to coal, such as caloric value, moisture content, and ash content, which affect boiler efficiency (Mehmood et al., 2012). Hence, the utilization of linear programming methodology is applicable for the computation of coal and biomass blending, as the amalgamation of these three quality attributes can be represented as a weighted mean.

This research aims to synergize the supply of biomass and coal into an optimized blending plan involving 4 PLTUs, 17 coal mines, and 1 biomass production facility. The mathematical model was built by considering the quality of coal from various mines and biomass so that they comply with the technical specifications of boilers, source of supply capacity, CFPP demand, and transportation selection, with the objective of reducing costs and carbon dioxide emissions.

The subsequent sections of this work are structured in the following manner: Section 2 provides an examination of the relevant literature pertaining to the study. The presentation of the research methodology was provided in Section 3, while the mathematical model was presented in Section 4. In Section 5, a proposed solution is put forth, and an analysis of the outcomes is presented. In the last section, we present the conclusion and recommendation.

2. Literature Review

Over the decades, studies on how to best combine the quality of coal have been conducted. Coal blending optimization is a widely employed practice within the mining industry, processing plants, and coal-fired power plants. Its primary objective is to ensure that the coal produced adheres to the required technical standards in terms of quality (Chakraborty & Mitra, 2019). A deterministic method with linear programming (Cutz et al., 2019) and mixed integer linear programming (Baskoro et al., 2022) were used in the research on coal blending optimization that was carried out. In addition, research was carried out utilizing heuristic techniques, such as particle search optimization (Gao & Li, 2019; Yuan et al., 2020), robust algorithms (Amini et al., 2022), and support vector machines (Zhao et al., 2019).

Yuan et al. (2020) developed a mathematical model to forecast the quality of coke generated by a coal processing plant. The prediction model generates coke production with a higher degree of accuracy and stability compared to the formula that was originally used. In the meantime, Gao and Li (2019) use the particle swarm optimization method to find the global optimal coal mix ratio in order to get the best solution from coal-quality alloys in the power plant. In addition, research and development were carried out on an optimization model for coal blending by including a transportation model, with supply and demand capacity being utilized as research and development optimization factors. In the research that was carried out by Hilali et al. (2023), a non-linear programming approach was used to simulate coal blending optimization and integrated supply chain operations. This method took into consideration many suppliers and several merchants. The capacity of the suppliers and the routes that the coal will travel are taken into account by the mathematical model in order to establish the optimal blending of coal for each order. The MILP model is used by Baskoro et al. (2022), which takes into account the characteristics of supply, demand, and transportation capacity in order to achieve the goal of reducing costs and carbon dioxide emissions as much as possible. The results suggest that the implementation of the direct shipping scenario will reduce fuel costs and mitigate carbon dioxide emissions.

Murele et al. (2020) developed an optimization model that aims to determine the optimal biomass fraction in mixed solid fuels to reduce carbon dioxide emissions. This study found that the integration of biomass into the energy supply chain can result in a reduction in carbon dioxide emissions of up to 4.32% with a blend of 5–8% biomass.

A comprehensive overview of the assessments conducted in the aforementioned domain is presented in Table 1.

The emission of carbon dioxide is one of the most significant problems facing the environment today, and it is becoming a worry on a worldwide scale, particularly in the energy industry (Xu et al., 2017). The environmental repercussions of the coal supply for CFPPs are an additional significant concern that needs to be addressed. In comparison with other types of power plants, CFPP produces the most electrical energy while emitting more carbon dioxide into the atmosphere (Adebayo et al., 2021). For this reason, co-firing, another name for the process in which coal and other materials, are burned together to produce energy, is one strategy for lowering the emissions caused by the burning of fossil fuels in power plants (Wander et al., 2020). Currently, various co-firing technologies have been developed, such as mixing coal with green ammonia which results in a reduction in operating costs of 8.59% and a reduction in carbon dioxide emissions of 12.74% (Zhao et al., 2023). Co-firing experiments have also been conducted by combining fuels with distinct properties, such as coal, biomass and ammonia, in a single joint combustion that has been shown to substantially reduce carbon dioxide emissions (Cardoso et al., 2022). At this time, biomass co-firing is regarded as the simplest and quickest method. In CFPP, co-firing biomass results in lower investment costs and improved environmental impacts than just coal (Kommalapati et al., 2018). Additionally, co-firing biomass at CFPP results in lower costs associated with the generation of electricity (Xu & Ge, 2020) with a reduction in operating costs of 6.06% using rice husk (Xu et al., 2020). According to Gil and Rubiera (2018), the use of biomass as a fuel source has the potential to enhance the value derived from forest products and the agricultural sector in developing nations. There is an inverse relationship between the proportion of alternative fuels and the levels of greenhouse gas emissions. According to Tchapda and Pisupati (2014), biomass exhibits a lower sulfur content in comparison to coal. Consequently, the use of biomass does not contribute to air pollution and can enhance the efficiency of forest and agricultural resource utilization (Aviso et al., 2020). Hence, the utilization of co-firing with biomass is often regarded as a highly viable near-term strategy for mitigating CO_2 emissions (Križan et al., 2011). This is also supported by findings showing that strict energy conservation and pollution reduction policies will make economic capability unharmed (Yu et al., 2018).

Table 1
The state of the art in the area of fuel blending optimization

Authors	Parameters				Objective			Material		Location				Method
	Q	T	S	D	Cost	Emission	Others	Coal	Biomass	Mining	Processing	Power Plant	Others	
Gao & Li (2019)	√				√			√				√		PSO
Zhao et al. (2019)	√				√	√		√				√		SVM
Yuan et al. (2020)	√		√	√	√			√			√		√	MPSO
Amini et al. (2019)	√		√	√	√		√	√		√	√			RA
Aviso et al. (2020)				√	√	√		√	√			√		FMILP
Murele et al. (2020)		√	√	√	√				√				√	STN
Cutz et al. (2019)	√		√	√	√	√		√	√			√		LP
Peng et al. (2023)	√		√	√	√	√		√					√	NLP
Hilali et al. (2023)	√	√	√	√	√			√		√	√		√	NLP
Baskoro et al. (2022)	√	√	√	√	√	√		√		√	√	√		MILP
This research	√	√	√	√	√	√		√	√	√	√	√		MILP

Q: Quality; T: Transportation; S: Supply; D: Demand
MILP: Mixed Integer Linear Programming; RA: Robust Alghorithm; STN: State-Task Network
PSO: Particle Swarm Optimization; SVM: Support Vector Machine; NLP: Non-Linear Programming

The use of deterministic methods like linear programming (LP), mixed integer linear programming (MILP), and non-linear programming (NLP) has begun to be researched in the coal blending optimization model. This is in addition to the investigation of the use of co-firing, which is the combination of biomass with coal. A linear programming (LP) model is utilized by Cutz et al. (2019) in order to maximize the quantity of biomass that is co-fired with coal in order to make it economically advantageous for power plant retrofitting in four different nations. The findings of this research give recommendations for power plants that might potentially benefit from the retrofitting process by combining the combustion of biomass and coal. The MILP model was created by Aviso et al. (2020) in order to best plan a biomass-coal co-firing network by taking into consideration the characteristics of the power plant as well as the source of the biomass. This model also provides the option of using direct and indirect co-firing choices at each power plant by employing a fuzzy method.

3. Methodology

The importance of blending coal and biomass to meet the boiler quality requirements of CFPPs, as well as considering a supply chain constrained by demand for CFPPs, production capacity from various sources, and available transportation options, has led to the modeling of supply chain network issues in this section of the article. The optimization process is depicted in the study model presented in Figure 1 below.

The optimization process is conducted in the planning of coal and biomass supply, considering the quality attributes and production capacity of each source to fulfill the quality and quantity requirements of each power plant. The optimization process encompasses the assessment of both the capacity and quality of seventeen coal mines (*CSi*) and one biomass production facility (*BSi*). The use of three different types of barges (*Sj*), each with a different capacity, facilitates the transportation of coal and biomass. The capacity of each barge varies, ranging from 7500 to 7700 MT, 10,000 to 10,400 MT, and 12,000 MT to 12,600 MT. The allocation of these barges is designated for four power plant destinations, where the blending process is conveniently conducted within the stockpile area to ensure compliance with quality standards and the fuel requirements of the power plant boilers. The optimization framework that is being utilized is based on mixed integer linear programming (MILP) and utilizes OR-Tools in Google Colab to produce optimal results concerning the distribution of biomass and coal.

The results were then compared with business as usual, which is the realization of coal blending implementation. From the data obtained, the costs incurred to fulfill the coal supply to the four CFPPs amounted to USD 691,260,791, and the CO_2 emissions produced were 22,697,124 tons of CO_2.

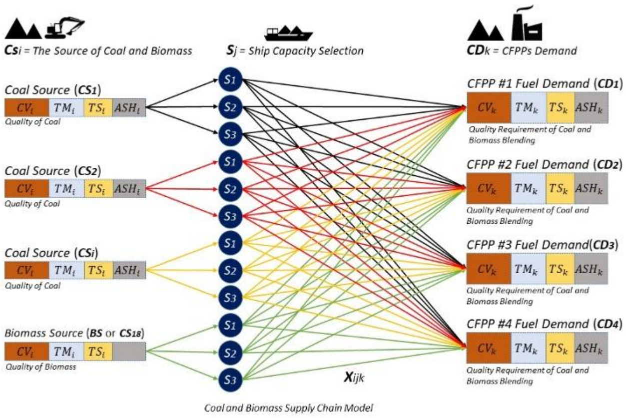

Fig. 1. Supply chain model

4. Mathematical Model

The mixed-integer linear programming approach is utilized for conducting calculations. This optimization involves iteratively calculating the amount of coal from mines or biomass from production facilities sent to CFPP using barges of various capacities. The aim of this optimization is to obtain the lowest fuel costs, consisting of coal purchasing costs, biomass purchasing costs, and transportation costs.

Meanwhile, it is assumed that CFPPs do not use carbon capture technology and release all of their carbon dioxide emissions into the atmosphere. The carbon dioxide emissions calculation formula refers to the Guidelines for National Greenhouse Inventories Volume 2 Energy (IPCC, 2006), and GHG emissions resulting from biomass burning are not taken into account in the electricity generation sector in the national GHG emissions inventory but are allocated to the forestry sector (land use, land-use change, and forestry), so that the use of biomass as fuel will reduce GHG emissions. The higher the biomass utilization, the lower the emissions produced, as long as the fuel mixture meets the quality requirements set by the CFPP. However, the amount of biomass that can be utilized will be limited to between 5 and 10% of total fuel use. This value is based on guidelines for biomass utilization for power plants, which state that biomass utilization is 5% and rarely exceeds 10% on a continuous basis (IEA, 2013). This is in line with the results of Murele et al. (2020) research, which resulted in the best optimization of biomass utilization in the range of 8–10%.

The initial step in the stage of optimization calculation involves the identification and formulation of a mathematical model that accurately represents the problem under consideration. The model encompasses three key components: a decision variable, an objective function, and a set of constraints.

4.1. Decision variable

x_{ijk} = Coal or biomass amount delivered from mine *i* using capacitated barge *j* to CFPP *k*

notation:

i = The *i*-th coal mine or biomass production facility, where *i* = 1, 2, ..., 18

j = Choice of barge capacities with capacities of 7,500 MT; 10,000 MT; and 12,000 MT; where *j* = 1, 2, 3

k = CFPP, to which coal is shipped, where *k* = 1, 2, 3, 4

4.2. Objective Function

Minimize fuel and transportation cost

$$Z = \sum_{i=1}^{17} \sum_{j=1}^{3} \sum_{k=1}^{4} (FC_i + TC_{ijk})\, x_{ijk} + \sum_{i=18} \sum_{j=1}^{3} \sum_{k=1}^{4} (FC_i + TC_{ijk})\, x_{ijk} \qquad (1)$$

or

$$Z = \sum_{i=1}^{18} \sum_{j=1}^{3} \sum_{k=1}^{4} c_{ijk}\; x_{ijk} \qquad (2)$$

where,

FC_i = Cost of coal or biomass from mine *i*

TC_{ijk} = Transportation costs from the mine *i*

c_{ijk} = Total mining costs *i*

4.3. Constraints

Meanwhile, the reduction in CO_2 emissions produced by the CFPPs is obtained by setting constraints on biomass demand. The higher the demand for biomass, the lower the emissions produced, as long as the blended fuel meets the quality requirements. The other constraints are shown below.

Coal and biomass sources

$$\sum_{i=1}^{18} x_{ijk} \le CS_i + BS_i \qquad (3)$$

where,

CS_i = Coal source i = 1,2,…,17

BS_i = Biomass source i = 18

CFPPs demand

$$\sum_{k=1}^{4} x_{ijk} \geq Dbb_k + Dbio_k \quad (4)$$

Biomass demand

$$Dbio_{k\,min} \leq \sum_{k=1}^{4} x_{ijk} \leq Dbio_{k\,max} \quad (5)$$

where,

Dbb_k = CFPP coal demand k = 1,2,3,4

$Dbio_k$ = CFPP biomass demand k = 1,2,3,4

The amount of biomass is set at a minimum of 5% and a maximum of 10% of the CFPP fuel requirements.

Coal and biomass quality

$$CV_{min} \leq CV_{ij} \leq CV_{max} \quad (6)$$

$$TM_{min} \leq TM_{ij} \leq TM_{max} \quad (7)$$

$$ASH_{min} \leq TS_{ij} \leq TS_{max} \quad (8)$$

$$ASH_{min} \leq ASH_{ij} \leq ASH_{max} \quad (9)$$

Non-negative

$$x_{ijk} \geq 0 \quad (10)$$

Binary constraints

Each variable value for the decision variable is binary (0 or 1). This shows that the value of the variable is 1 when it is used and 0 if it is not used.

$$\alpha = 0 \; atau \; 1 \; \forall \; x_{ijk} \quad (11)$$

where,

CV_{ij} = Coal and biomass caloric value from the source
CV_k = CFPP caloric value requirement
TM_{ij} = Coal and biomass total moisture from the source
TM_k = CFPP total moisture requirement
TS_{ij} = Coal and biomass total sulphur from the source
TS_k = CFPP total sulphur requirement
ASH_{ij} = Coal and biomass ash content from the source
ASH_k = CFPP ash content requirement

The MILP approach is employed for conducting calculations, utilizing the Google OR-Tools application for assistance. The initial step in the optimization calculation stage involves the identification and formulation of a mathematical model that accurately represents the problem under consideration.

5. Results and Discussion

5.1 Validation in biomass blending optimization

Fuel demand and quality are constraints that must be met so that the CFPP can produce energy optimally. The number of fuel requests that are the same between businesses as usual (BaU) and the optimization results confirm that the optimization calculations have been carried out accordingly. Table 2 shows the amount of coal and biomass that resulted from the optimization calculation, which is compared based on the BaU data.

Table 2
Comparison of coal and biomass usage between BaU and blending optimization scenarios

Source	Business as Usual (tons)	Optimization (tons)
CS01	74,822	150,000
CS02	3,686,050	3,007,685
CS03	2,076,318	775,000
CS04	613,128	615,000
CS05	385,320	-
CS06	327,268	-
CS07	682,420	-
CS08	729,052	-
CS09	273,940	-
CS10	52,310	525,000
CS11	134,055	1,067,660
CS12	1,054,433	-
CS13	37,424	-
CS14	1,389,081	139,500
CS15	678,812	2,825,000
CS16	201,841	2,025,000
CS17	109,073	125,000
Biomass	-	1,250,500
TOTAL	12,505,347	12,505,345

The entire biomass consumption for the four CFPPs amounts to 1,250,500 tons, which corresponds to 10% of the overall fuel use. The present composition adheres to the biomass demand restrictions allowed for each CFPPS, where the recommended practice is to incorporate approximately 5–10% biomass into coal for burning. The augmentation of biomass supply as a fuel source for coal-fired power plants (CFPP) presents numerous challenges that need careful consideration and resolution (Yudiartono et al., 2023). One of the factors to consider is the requirement for extensive land areas in order to cultivate biomass raw materials (Maulidia et al., 2019). Despite these challenges, the utilization of biomass makes a significant contribution to the achievement of sustainable development goals and holds the potential to ensure energy security for an expanding global population (Ekpeni et al., 2014). The need for large amounts of biomass will support the increase in the agricultural industry and biomass processing industry (Saleem, 2022).

5.2 Biomass blending results in significant fuel cost of CFPP reduction

Calculations for optimizing biomass blending show that the costs required to purchase and deliver fuel in accordance with the requirements are USD 672,645,231 or 2.77% lower than business as usual. Therefore, it can be concluded that optimizing the blending of biomass into coal results in a cost efficiency of USD 18,615,560, as shown in Table 3.

Table 3
Comparison of fuel costs between BaU and blending optimization scenarios

Source	Business as Usual (USD)	Optimization (USD)
CS01	4,584,361	9,246,849
CS02	214,390,107	174,205,790
CS03	108,472,429	40,402,231
CS04	35,357,079	35,239,500
CS05	20,641,387	-
CS06	18,170,877	-
CS07	36,226,221	-
CS08	39,205,782	-
CS09	15,018,581	-
CS10	2,782,892	27,854,410
CS11	6,918,007	54,509,234
CS12	59,688,813	-
CS13	2,129,426	-
CS14	73,491,586	7,254,000
CS15	37,621,315	156,276,829
CS16	10,813,780	107,914,790
CS17	5,748,147	6,495,896
Biomass	-	53,245,704
TOTAL	691,260,791	672,645,231

The efficiency of fuel costs was also demonstrated through research conducted by Furubayashi (2022), where the use of biomass as a fuel for power plants will reduce energy costs in Akita prefecture, Japan. The cost advantage of biomass over coal can be attributed to its comparatively lower calorific value. Hence, the significant quantity of biomass used plays a crucial role in enhancing cost-effectiveness while maintaining fuel quality integrity. The balance framework reveals that the quantity of the biomass mixture plays a crucial role in determining the ultimate calorie requirements of the boiler. This result is supported by Hodžić and Kadić (2023), who state that the efficiency of the combustion process depends on several factors, such as the type and quality of fuel as well as the technology used.

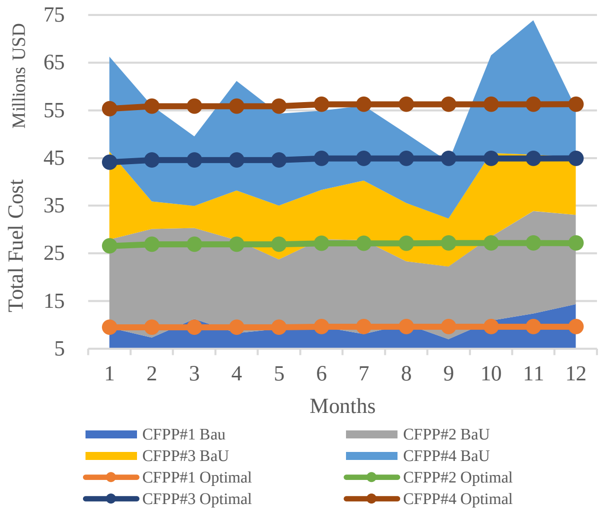

Fig. 2. Comparative analysis of fuel expenses between the standard operational approach and the optimized outcomes on a monthly basis for each CFPP.

Figure 2 shows a comparison of fuel costs between businesses as usual and optimization results from a monthly perspective for each CFPP. The graph shows that cost optimization results tend to be the same each month, while business as usual scenarios show cost fluctuations from month to month. From the data available, the tendency for low costs in March, August, and September is due to the use of coal with a lower calorific value than the specifications required by the CFPPs.

5.3 Impact of biomass blending optimization on co_2 emissions

The reduction in emissions can be attributed to the utilization of biomass as an energy source. In the present scenario, the emissions arising from the utilization of biomass are not factored into the calculations within the electric power industry in order to avoid redundant computations (IPCC, 2006). Reducing CO_2 emissions, which is one of the objectives of this study, shows significant results compared with business as usual. According to the data presented in Table 4, there is a notable decline of 9.99% in the CO_2 emissions released by CFFPs, as evidenced by the reduction from 22,697,124 to 20,427,542 tons of CO_2.

Table 4
Comparison of CO_2 emissions between BaU and blending optimization scenarios

CO_2 emissions	CFPP#1 (tons CO_2)	CFPP#2 (tons CO_2)	CFPP#3 (tons CO_2)	CFPP#4 (tons CO_2)
BaU	3,942,936	6,968,288	7,250,669	4,535,271
Optimization	3,548,673	6,271,486	6,525,615	4,081,768

The findings presented in Table 4 align with the research conducted by Xu et al. (2020), which asserts that the utilization of coal-biomass co-firing methods in power plants is a viable approach for mitigating CO_2 emissions. The utilization of the blending mechanism has demonstrated its efficacy in improving the optimization of biomass and coal supply for CFPP, taking into account factors such as feedstock quality, transportation, and efficiency (Juan et al., 2019).

Considering these variables, the model possesses the capacity to facilitate efficient decision-making processes aimed at mitigating fuel expenses and curbing greenhouse gases within power plants. This is particularly relevant for developing nations that heavily rely on coal-fired power plants and possess ample biomass resources (Gil & Rubiera, 2018).

In order to effectively accomplish the objectives delineated in the Paris Agreement, it is imperative to implement a gradual reduction in coal utilization until the point at which coal-fired power plants are rendered obsolete. This is crucial, as CFPPs impede the comprehensive decarbonization of the electricity sector. However, the utilization of biomass as a means of co-firing with coal is an optimal strategy in the near term for achieving maximum reductions in CO_2 emissions (Križan et al., 2011). The MILP model demonstrates a reduction in CO_2 emissions of 9.99%, which aligns with the findings of a case study conducted in the Philippines. Their case study revealed that a substitution of 3.8% of coal usage for electricity generation can lead to a 5.9% decrease in GHG emissions (Dang et al., 2015).

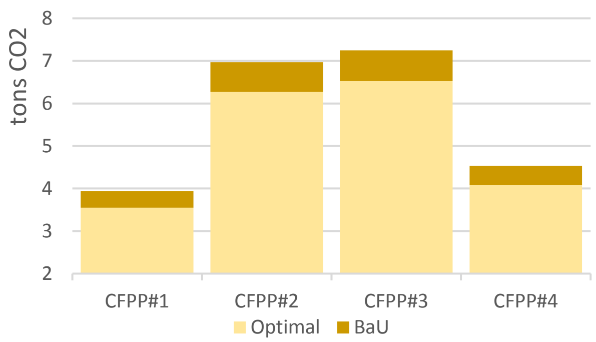

Fig. 3. CO_2 emissions saved through biomass synergy at each CFPP

Figure 3 presents the comparison of carbon dioxide emissions generated in the business as usual scenario with the optimized scenario. The graphic clearly illustrates a decline in carbon dioxide emissions at each CFPP.

5.4 Sensitivity Analysis of Biomass Variable: Price and Calorific Value

Sensitivity analysis determines the extent to which the same decision will persist by changing an element or by combining other elements, then determines the effect on the analysis results. In the sensitivity analysis of optimizing biomass blending, changes in the biomass price variable show changes in total costs. The increase in biomass prices by 34.96% resulted in an increase in total costs to USD 691,260,791, illustrating the high sensitivity of operational costs to fluctuations in biomass prices. This emphasizes the need to take changes in biomass prices seriously in the decision-making process for optimizing fuel blends. Figure 2 illustrates the periodic changes in biomass prices, namely at 10%, 20%, 30%, and 40% increments.

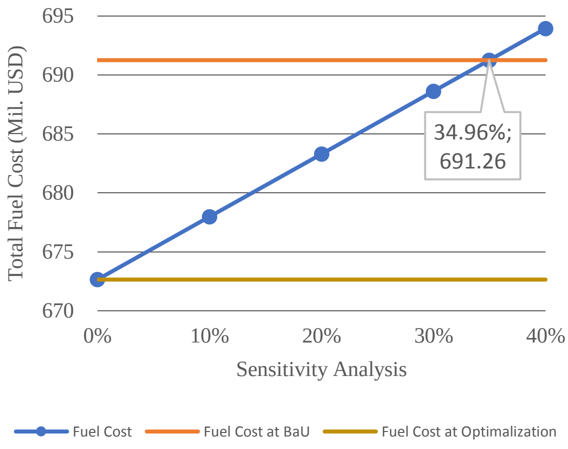

Fig. 4. Conducting sensitivity analysis on changes in biomass costs variable to ensure optimal adjustments to total fuel costs

Apart from that, the biomass calorific value variable also has a moderate role in influencing the quality of the fuel combination. Following the sensitivity analysis, it was found that the optimal calorific value for biomass is between 2512 and 3600 kcal/kg. This makes sure that the mixed fuel's calorific value stays within the CFPP standards. A fairly wide range of values illustrates the significance of adjusting the calorific value of biomass to achieve the required efficiency in fuel blending. The biomass calorific value range shown in Figure 5 shows how changes in biomass calorific value affect total fuel costs, which stay within the ideal range of USD 671,808,535 to USD 681,414,835.

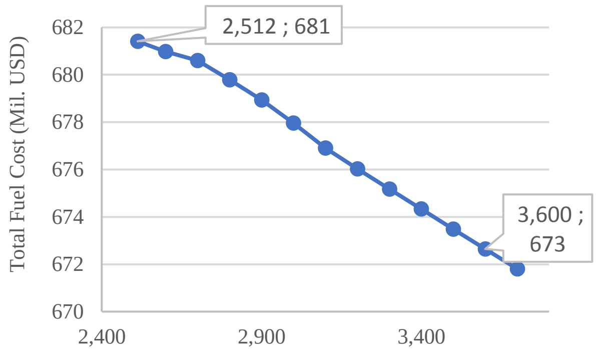

Fig. 5. Conducting sensitivity analysis on changes in biomass calorif value variable to ensure optimal adjustments to total fuel costs.

6. Conclusion

The MILP model has been built to optimize co-firing biomass blending by considering the fuel quality required by the CFPP, production capacity, CFPP demand, and transportation selection. The calculation results show that the cost of procuring and transporting fuel is USD 672,645,231, which results in a cost efficiency of 2.77% compared to business as usual conditions. Additionally, it is important to mention that there has been a significant reduction of 9.99% in carbon dioxide emissions produced by the four CFFPs. Optimization showing a decrease in carbon dioxide emissions from 22,697,124 to 20,427,542 tons of CO_2 supports this assertion.

The validation calculation demonstrates that there is no significant difference in the amount of fuel between the business as usual and the optimization results. It is important to note that the optimization results yield fuel-quality output that adheres to the technical specifications of the CFPP boiler. This compliance ensures that the fuel used for combustion will result in an efficient net plant heat rate and greater energy production. However, a comparison is not feasible due to the scarcity of available data. Therefore, further research is recommended to examine whether optimizing biomass blending outcomes can be correlated with the net plant heat rate and energy production output of the power plant. It is intended to examine the potential advantages of the biomass blending process in terms of cost reduction, plant efficiency enhancement, and improvement in the plant's merit order rating.

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