

Optimization of the Biomass Supply Chain for Co-Firing at Adipala Power Plant to Improve Cost Efficiency

Chandra Kharisma Margatama ^{1,2} & Darwin ^{1,3}

¹ Faculty of Industrial Technology, Bandung Institute of Technology, Bandung
Jl. Ganesha No. 10, Bandung
Email: 29423018@mahasiswa.itb.ac.id ² & angin.bandung@gmail.com ³

Abstract. The utilization of biomass as a renewable energy source is becoming increasingly important to reduce dependence on fossil fuels and decrease carbon emissions. However, the efficient distribution of biomass in the co-firing system at the Adipala Steam Power Plant (PLTU) faces significant challenges related to high logistics costs. This research aims to optimize the distribution costs of biomass in the co-firing system at PLTU Adipala using Linear Programming (LP) methods. The main objective of this study is to determine the optimal amount of biomass needed to meet the energy requirements of the power plant with efficient distribution costs, as well as to identify supply chain strategies that can enhance cost efficiency. The method employed is a Linear Programming optimization model that considers factors such as transportation costs, supply capacity, and biomass needs according to the primary energy mix quota. The research findings indicate that the application of LP can reduce logistics costs and improve the efficiency of biomass distribution. These findings make a significant contribution to enhancing the efficiency of biomass supply chain management at PLTU Adipala and can serve as a reference for the development of renewable energy policies in Indonesia. In conclusion, the application of LP in biomass supply chain management can provide efficient and sustainable solutions, as well as promote the reduction of carbon emissions in the energy sector.

Keywords: *Biomass, Co-firing, Linear Programming, Cost Efficiency, Adipala Power Plant.*

1 Introduction

The energy problem in Indonesia is becoming increasingly urgent as energy demand rises and dependence on fossil fuels decreases. High reliance on fossil energy has the potential to harm the environment, increase carbon emissions, and accelerate global climate change. Therefore, the transition to renewable energy is a crucial step in ensuring sustainable energy resilience. Biomass, as a renewable energy source, has significant potential in Indonesia. The country is rich in biomass resources from the agricultural and forestry sectors, such as palm oil waste, rice husks, and sawdust (Renewable Energy Agency, 2021), which can be utilized to support energy resilience and reduce carbon emissions.

However, despite the vast potential of biomass, its utilization in the energy sector, particularly in Steam Power Plants (PLTU), remains limited. One of the main factors hindering the optimization of biomass utilization is the challenges in managing an efficient biomass supply chain. High logistics costs, which include the collection, transportation, and storage of biomass, often serve as a major barrier to the distribution of biomass to power plants. Parikha (2004) reported that approximately 40% to 60% of the biomass available in Indonesia is not maximally utilized, leading to a waste of resources that could serve as alternative fuel.

As a solution to reduce dependence on fossil fuels, co-firing technology, which combines biomass with coal in the combustion process at power plants, has been introduced. This technology not only helps reduce carbon emissions but also accelerates the transition to a more sustainable energy system. In Indonesia, co-firing technology is being implemented in several power plants, including the Adipala Power Plant, aiming to enhance the contribution of renewable energy and reduce carbon emissions (Dreves, 2022). Although this technology is promising, its implementation requires efficient biomass distribution to support the operational sustainability of the power plant.

However, beyond the challenges in combustion technology, a primary constraint in the application of co-firing lies in the management of the biomass supply chain, which requires careful and efficient planning. Price variability of biomass, limited transportation capacity, and inadequate infrastructure in some regions further exacerbate this issue. Therefore, a more systematic approach is needed to optimize the biomass supply chain so that biomass distribution to power plants can be conducted at efficient costs and improve operational smoothness.

Several studies have been conducted to enhance the cost efficiency of co-firing operations, one of which is the optimization of the biomass supply chain carried out by Nunes and Silva (2023), focusing on the logistics of collecting residual biomass. Other research by Atashbar et al. (2016), Sun and Fan (2020), Lo et al. (2021), and Ba et al. (2016) also emphasizes the importance of a holistic understanding of the supply chain in the residual biomass sector. To deepen the study of improving efficiency in biomass logistics, this research is based on the model by Rentizelas et al. (2009), which uses Linear Programming (LP) to optimize cost functions that include biomass logistics activities between storage locations in agricultural areas and central power plants, as well as construction and expansion costs of storage facilities. Other studies have also utilized linear programming to schedule biomass deliveries in the supply chain, both for centralized power plants and decentralized heat and power plants.

Therefore, this study aims to optimize the distribution costs of biomass in the co-firing system at the Adipala Power Plant using Linear Programming (LP) methods. Through LP, this research will identify optimal solutions in managing the biomass supply chain that can minimize operational costs and enhance biomass distribution efficiency. Overall, this study aims to determine the optimal

amount of biomass needed to meet the energy requirements of the Adipala Power Plant with the most efficient distribution costs, as well as to identify supply chain strategies that can improve cost efficiency and support renewable energy sustainability. The benefits of this research will not only provide significant contributions to biomass supply chain management in Indonesia but also serve as a reference for the development of future renewable energy policies and support the achievement of national carbon emission reduction targets.

2 Optimization Model

2.1 Objective Function

This research focuses on optimizing the supply chain of residual biomass with the aim of minimizing logistics costs while enhancing the efficiency and sustainability of the supply chain. The study employs an Operations Research-based approach, such as linear programming, to evaluate and optimize various scenarios of collection, transportation, storage, and processing of residual biomass. Below is the cost modeling related to the logistics of residual biomass from the study by Nunes and Silva (2023):

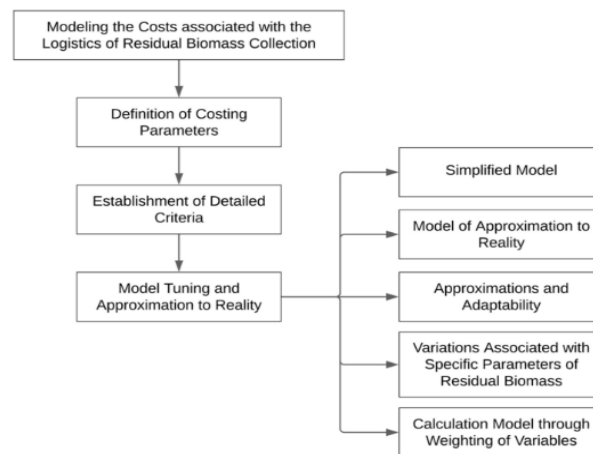


Figure 1. Conceptual Model

- Nunes and Silva (2023) developed a model that can be divided into five stages as follows:
 1. Definition of cost parameters
 2. Development of detailed criteria
 3. Building a simple model and adjusting it to reality and adaptability approaches

4. Variations related to specific parameters in the residual biomass calculation model through variable weighting
5. Optimization

2.2 Cost Parameters and Detailed Criteria

2.2.1 Cost Function

Given the focus of this research on minimizing logistics costs, this study develops a biomass logistics cost model based on Nunes and Silva (2023), following the availability of data and existing business processes of the company. The cost components consist of two main components: the cost of purchasing biomass material and logistics costs. The consideration of including the cost of purchasing biomass material in the research model is to observe how dynamics change with variations in raw material prices or logistics/shipping. Meanwhile, logistics costs include loading costs, vehicle fuel costs, labor costs for delivery, vehicle costs, and other shipping costs.

The cost of purchasing biomass material is calculated by multiplying the unit price by the quantity. The equation is as follows:

$$C_{xi} = x_i * P_{xi} \quad (1)$$

Where:

C_{xi} : Total cost of purchasing biomass material from source i (Rp).

x_i : Quantity of biomass from source i (ton)

P_{xi} : Price of biomass (Rp/ton).

Meanwhile, the loading cost of biomass onto vehicles is calculated using a labor cost approach. First, the number of laborers needed is estimated using a labor load approach that describes labor productivity.

The equation is as follows:

$$N_{Li} = x_i / BL_i \quad (2)$$

Where:

N_{Li} : Number of loading laborers (people)

BL_i : Load per laborer (tons/person)

Second, the number of laborers is multiplied by the wage to obtain the total loading cost at each supplier, using the formula:

$$C_{Li} = N_{Li} * WL_i \quad (3)$$

Where:

C_{Li} : Total loading cost from source i (Rp).

WL_i : Wage per laborer (Rp/person).

Third, the loading price is calculated by dividing the total loading cost by the amount of biomass provided by the supplier using the following formula:

$$P_{Li} = C_{Li}/x_i \quad (4)$$

Where:

P_{Li} : Loading price(Rp/ton)

The vehicle fuel cost is calculated by considering the distance from the supplier's location to the power plant, fuel consumption and price, and vehicle carrying capacity. First, this study calculates the total fuel cost per trip using the following formula:

$$CF_i = 2 * DF_i * F_i * PFL_i \quad (5)$$

Where:

CF_i : Total fuel cost per trip (Rp)

DF_i : Distance from source to power plant (km)

F_i : Total fuel required (liter/km)

PFL_i : Fuel price (Rp/liter)

Second, following the study by Nunes and Silva (2023), this study considers the use of vehicle carrying capacity by adding a beta (β) parameter that describes vehicle utilization. The formula is as follows:

$$PF_i = CF_i / \beta * Cap_i \quad (6)$$

Where:

PF_i : Fuel price per biomass (Rp/ton).

Cap_i : Maximum vehicle capacity (ton).

β : Vehicle carrying capacity parameter ($0 < \beta \leq 1$)

The total labor cost for transportation is then used to calculate the labor cost per unit of biomass, taking into account the vehicle carrying capacity, using the formula:

$$PT_i = CT_i / (\beta * Cap_i) \quad (7)$$

Where:

PT_i : Transportation labor cost per biomass (Rp/ton).

β : Vehicle carrying capacity parameter ($0 < \beta \leq 1$).

Cap_i : Maximum vehicle capacity (ton).

2.2.2 Constraint Function

To ensure the optimal amount of biomass with efficient costs in the company's business process, this study considers several constraint functions as follows:

Supplies from suppliers meets the minimum quota demand of the power plant. The biomass demand from the power plant from suppliers can be in the form of a quota, which in this study is described by the alpha (α) parameter. The larger indicates a greater need for the power plant to be supplied by suppliers, with the restriction $0 < \alpha \leq 1$. The parameter $\alpha = 1$ indicates that all biomass needs must be supplied by suppliers.

The supply-demand constraint can be written as follows:

$$dD \leq \sum_{i=1}^n x_i \leq D \quad (8)$$

Where:

D : Biomass demand of the power plant (ton).

x_i : Amount of biomass from supplier i (ton).

d : Quota/target biomass from suppliers ($0 < d \leq 1$).

The amount of biomass delivered does not exceed the supply capacity of biomass at each supplier. In this case, not all supplies from suppliers may be delivered to the power plant due to high costs. This means that the optimal amount of biomass delivered is at most equal to the biomass supply per supplier. The constraint function is:

$$x_i \leq g_i \quad (9)$$

Where:

x_i : Amount of biomass delivered from supplier i (ton).

g_i : Biomass supply from supplier i (ton)

Non-negativity or the amount of biomass delivered cannot be negative:

$$x_i \geq 0 \quad (10)$$

2.2.3 Cost Minimization Function

Based on the cost functions and constraints above, the cost minimization model in this study can be written as follows:

$$\text{Min}_{x_i} \sum_{i=1}^n x_i * [P_{xi} + P_{Li} + P_{oi} + (P_{Fi} + P_{Ti} + P_{Ri})] \quad (11)$$

or

$$\text{Min}_{x_i} \sum_{i=1}^n x_i * \left[P_{xi} + P_{Li} + P_{oi} + \left(\frac{C_{Fi} + C_{Ti} + C_{Ri}}{(\beta * Cap_i)} \right) \right] \quad (12)$$

with constraints:

$$D \leq \sum_{i=1}^n x_i \leq D \quad (13)$$

$$x_i \leq g_i \quad (13)$$

$$x_i \geq 0 \quad (14)$$

Where:

x_i : Amount of biomass delivered from supplier i (ton).

P_{Li} : Price of biomass material from supplier i (Rp/ton).

P_{oi} : Loading price of biomass (Rp/ton).

P_{Fi} : Fuel price per biomass (Rp/ton).

P_{Ti} : Labor cost per biomass (Rp/ton).

P_{Ri} : Vehicle rental price per biomass (Rp/ton).

C_{Fi} : Total fuel cost per trip (Rp).

C_{Ti} : Total labor cost per trip (Rp).

C_{Ri} : Total vehicle rental cost per trip (Rp).

Cap_i : Maximum vehicle carrying capacity (ton).

β : Vehicle carrying capacity parameter ($0 < \beta \leq 1$).

D : Biomass demand of PLTU Adipala (ton).

α : Parameter share suplai biomassa untuk PLTU Adipala

g_i : Biomass supply per supplier i (ton)

i : Supplier index ($i = 1, 2, \dots, 8$)

To obtain the optimal solution from the cost minimization model above, this study uses linear optimization methods. Linear optimization is a mathematical technique used to find the optimal solution to a problem with linear constraints. This study uses GLPK (GNU Linear Programming Kit), a software library designed to solve linear and integer linear optimization problems. GLPK supports problem formulation using standard linear optimization formats and has a programming interface that allows integration with various languages.

3 Result and Discussion

Data Overview and Division

The data in this research is processed from data presented by PT PLN and PLTU Adipala with the following details:

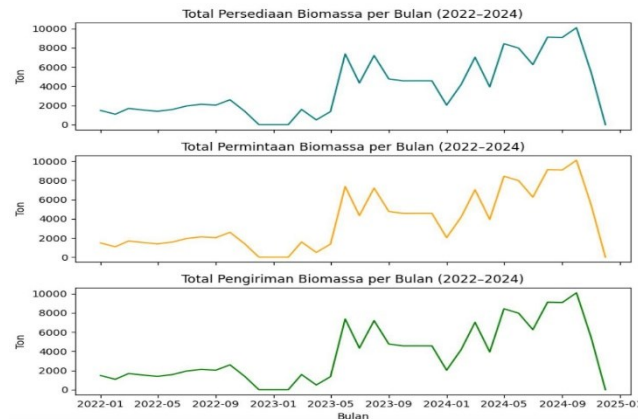


Figure 2. Overview of Biomass Inventory, Demand, and Supplier Deliveries period 2022–2024

Figure 2 displays the trend of total biomass inventory, biomass demand, and biomass deliveries from suppliers each month during the period from 2022 to 2024. In the biomass inventory graph, it can be seen that the inventory amount was relatively low and stable in 2022, then began to experience a significant increase from early 2023, peaking at the end of 2024 with a value approaching 10,000 tons. However, in the last month at the beginning of 2025, the inventory dropped drastically to nearly zero.

In line with the inventory, the biomass demand graph also shows a similar pattern. Biomass demand remained relatively stable and low throughout 2022, then surged sharply from early 2023. Demand peaked at the end of 2024 at around 10,000 tons, before dropping sharply at the beginning of 2025. This trend indicates a significant increase in biomass needs during the 2023 to 2024 period, which aligns with the rising inventory.

In the biomass delivery graph, the volume delivery pattern also follows a similar trend to inventory and demand. Biomass deliveries, which were relatively small and stable in 2022, began to increase sharply from early 2023, then fluctuated but remained at a higher range, peaking at the end of 2024 close to 10,000 tons. A sharp decline also occurred at the beginning of 2025. Overall, the graph shows a strong synergy between inventory, demand, and biomass deliveries during the same period.



Figure 3. Average Biomass Transaction Cost per Supplier, Period 2022- 2024

Figure 3 displays the average price of biomass material per supplier from 2022 to 2024 in millions of rupiah. From this horizontal bar graph, it can be seen that the supplier Ngelosari has the highest average price, approximately 15.65 million rupiah. This indicates that the biomass supplied by Ngelosari has a relatively higher transaction value compared to other suppliers.

Next, the suppliers Pagelaran and Alas Malang occupy the following positions with average prices of approximately 11.78 million rupiah and 8.34 million rupiah, respectively. The biomass prices from these two suppliers are also relatively high, indicating a significant price variation among the main suppliers. Meanwhile, suppliers Jatiroto, Jatiजार1, and Purwasaba have lower average prices, approximately 6.77 million rupiah, 3.21 million rupiah, and 2.30 million rupiah, respectively.

On the other hand, some suppliers such as Jatiजार2, Wates, Kutaliman1, and Kutaliman2 show very low average prices, with some approaching zero. This may indicate differences in quality, volume, or transaction methods that affect biomass prices at those suppliers. Overall, this graph illustrates a wide variation in biomass prices among suppliers over the past three years.

Finally, Figure 3 shows the trend of average demand and biomass inventory with a rolling 30-day calculation for each supplier from January 2022 to the end of 2024. Each panel of the graph represents one supplier and shows two lines, namely demand (D) and inventory (g). From the overall graph, it can be seen that most suppliers began to show significant activity in biomass demand and inventory in the middle to the end of the observation period.

Suppliers such as Alas Malang, Jatiजार1, Jatiroto, Ngelosari, and Pagelaran exhibit relatively high and dynamic fluctuations in demand and inventory during this period. For instance, Alas Malang and Pagelaran show significant spikes in inventory that correlate with increasing demand. Conversely, suppliers such as

Kutalimam1, Kutalimam2, and Wates have very low or nearly invisible activity in the graph, indicating minimal contributions to biomass volume during this period.

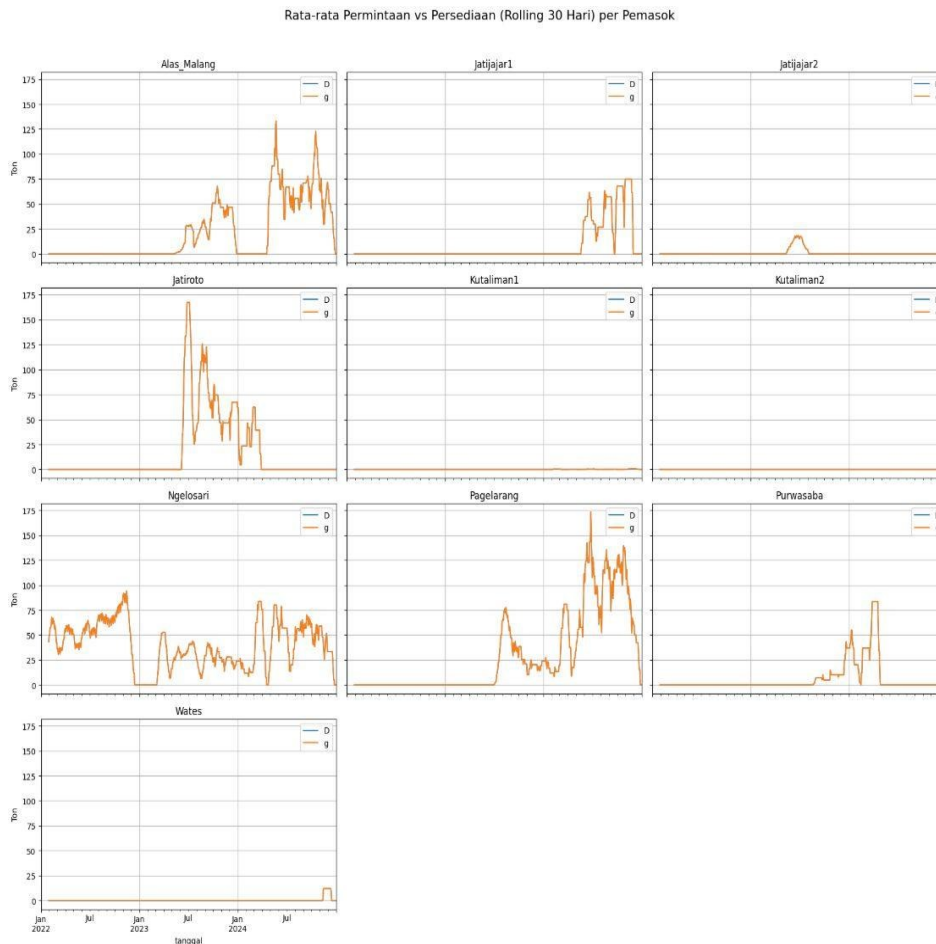


Figure 4 . 30 days Rolling Average of Demand and Inventory per Supplier

Additionally, suppliers such as Jatijajar2 and Purwasaba show limited activity with sporadic increases in demand and inventory. Overall, this graph provides a detailed picture of how biomass demand and inventory fluctuate among each supplier, reflecting market dynamics and material availability at each supplier location over the last 3 years.

In the optimization analysis, this study uses three suppliers with the highest supply from ten suppliers. The three biomass sawdust suppliers are Ngelosari, Pagelaran, and Alas Malang, which are considered to have more consistent data

within the range of 2022-2024 for Ngelosari and 2023-2024 for Pagelaran and Alas Malang.

This study aims to identify optimal strategies in the distribution of biomass from the three main suppliers to reduce supply costs and improve the efficiency of the biomass supply chain system. The optimization results show a significant gap between actual conditions and optimal conditions in terms of supply volume and total supply costs per month. Based on biomass supply volume, on average, biomass suppliers provide volumes that are much higher than the optimal needs calculated through the optimization model, resulting in several months where suppliers do not consistently distribute biomass.

For the supplier Ngelosari, the actual supply recorded is 1,340 tons per month, while the optimal need is only 853.65 tons, resulting in an excess supply of 486.35 tons. Similarly, Pagelaran shows the largest difference, with an actual supply of 1,898 tons, while the optimal supply is only 520.28 tons, indicating an excess supply of 1,377.72 tons. Alas Malang also does not escape this, with an actual supply of 1,632 tons, exceeding the optimal supply of 470.36 tons, resulting in an excess supply of 1,161.64 tons. This excess supply poses risks of logistical inefficiencies, stockpiling, and potential damage or waste of biomass raw materials.

Table 1. Results of Biomass Supply Chain Optimization

Supplier	Unit	Ngelosari	Pagelarang	Alas Malang
Result				
Average Supply Biomassa	Ton/Month	1340	1898	1632
Optimal Biomass Supply	Ton/ Month	853,65	520.28	470.36
Diff.		486,35	1.377,72	1.161,64
Total Average Cost	IDR/Month	6.200.981.884	721.379.654	671.482.482
Total Minimal Cost	IDR/Month	3.617.105.345	184.335.702	650.056.991
Diff.		2.583.876.539	537.043.952	21.425.491

Based on total supply costs, the optimization model also identifies significant cost-saving potential if the company switches to an optimal supply scheme. In the case of Ngelosari, the current average cost is 6.2 billion rupiah per month. However, with optimal supply volume arrangements, this cost can be reduced to only 3.6 billion rupiah, representing a potential saving of 2.58 billion rupiah per month. Pagelaran can also drastically reduce its costs from 721 million rupiah to only 184 million rupiah per month, providing a potential saving of 537 million

rupiah. Meanwhile, Alas Malang is the most efficient supplier in terms of alignment between actual and optimal supply. The actual cost of 671 million rupiah differs by only about 21 million rupiah from its optimal cost of 650 million rupiah.

These results indicate that the current biomass supply structure is not optimal. There is significant potential for savings if the three suppliers adjust their supply volumes to optimal levels. Strategies that can be implemented include: First, rescheduling distribution from Ngelosari and Pagelaran to avoid over-supply. Second, revising supplier contracts to align quotas with real needs based on optimization data. Finally, prioritizing distribution from Alas Malang due to its high efficiency in terms of cost and volume. Through this data-driven approach, the company can not only significantly reduce operational costs but also enhance logistical sustainability and overall efficiency of the biomass supply chain.

4 Conclusion

The optimization analysis reveals significant inefficiencies in the current biomass supply chain, particularly in terms of supply volume and cost. The actual supply from the three main suppliers—Ngelosari, Pagelaran, and Alas Malang—exceeds the optimal calculated demand by substantial margins, leading to excess inventory, logistical inefficiencies, and higher operational costs. Notably, Pagelaran and Ngelosari exhibit the largest discrepancies, with potential monthly cost savings of 537 million rupiah and 2.58 billion rupiah, respectively, if supply volumes are adjusted to optimal levels. Alas Malang, however, demonstrates better alignment between actual and optimal supply, suggesting its distribution strategy could serve as a model for improving overall supply chain efficiency.

To address these inefficiencies, strategic measures such as rescheduling distributions, revising supplier contracts, and prioritizing more cost-effective suppliers like Alas Malang are recommended. Implementing these data-driven adjustments would not only reduce operational costs but also enhance the sustainability and reliability of the biomass supply chain. By aligning supply volumes with actual demand, PT PLN and PLTU Adipala can minimize waste, optimize logistics, and ensure a more efficient and cost-effective biomass procurement process in the long term.

5 References

- [1] Atashbar, N. Z., Labadie, N., & Prins, C. (2016). Modeling and optimization of biomass supply chains: A review and a critical look. *IFAC-PapersOnLine*, 49(12). <https://doi.org/10.1016/j.ifacol.2016.07.742>.
- [2] Ba, B. H., Prins, C., & Prodhon, C. (2016). Models for optimization and performance evaluation of biomass supply chains: An Operations Research

- perspective. *Renewable Energy*, 87. <https://doi.org/10.1016/j.renene.2015.07.045>.
- [3] Dreves, H. (2022). Growing Plants, Power, and Partnerships through Agrivoltaics. National Renewable Energy Laboratory (NREL).
 - [4] Lo, S. L. Y., How, B. S., Leong, W. D., Teng, S. Y., Rhamdhani, M. A., & Sunarso, J. (2021). Techno-economic analysis for biomass supply chain: A state-of-the-art review. In *Renewable and Sustainable Energy Reviews* (Vol. 135). <https://doi.org/10.1016/j.rser.2020.110164>.
 - [5] Nunes, L. J. R., & Silva, S. (2023). Optimization of the Residual Biomass Supply Chain: Process Characterization and Cost Analysis. *Logistics*, 7(3). <https://doi.org/10.3390/logistics7030048>.
 - [6] Parikka, M. (2004). Global biomass fuel resources. *Biomass and Bioenergy*, 27(6). <https://doi.org/10.1016/j.biombioe.2003.07.005>
 - [7] Renewable Energy Agency, I. (2021). Renewable Energy Statistics 2021. In *Renewable Energy Statistic 2021* (Vol. 56, Issue December 2021).
 - [8] Rentizelas, A. A., Tatsiopoulou, I. P., & Tolis, A. (2009). An optimization model for multi-biomass tri-generation energy supply. *Biomass and Bioenergy*, 33(2). <https://doi.org/10.1016/j.biombioe.2008.05.008>
 - [9] Sun, O., & Fan, N. (2020). A Review on Optimization Methods for Biomass Supply Chain: Models and Algorithms, Sustainable Issues, and Challenges and Opportunities. In *Process Integration and Optimization for Sustainability* (Vol. 4, Issue 3). <https://doi.org/10.1007/s41660-020-00108-9>.