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Optimizing Biomass Pre-Treatment Technologies for BBJP Plants in Indonesia: A Multi-Criteria Decision Making Approach

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Abstract. The challenges of energy consumption and environmental sustainability are pronounced in the dynamic landscape of contemporary industries driven by Industry 4.0 technologies. Indonesia, heavily reliant on fossil fuels, charts a course toward a clean energy future with a National Energy Transition Roadmap for Net Zero Emission by 2060. This transition involves innovative strategies such as biomass co-firing and waste utilization in Solid Recovered Fuel (SRF) plants, known as Bahan Bakar Jumputan Padat (BBJP) plants. To optimize these BBJP plants, this study employs Multi-Criteria Decision Making (MCDM) methodologies, specifically the Analytical Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), to evaluate and select pre-treatment technologies. Criteria include capacity, conversion process, waste type, electricity consumption, operational ease, land requirement, and investment cost. Comparing bio-drying, thermal drying, and mechanical drying, AHP ensures consistent criterion weights, with TOPSIS ranking bio-drying as the most favorable, followed by thermal and mechanical drying. The study acknowledges global waste management challenges and introduces a mobile-modular containerized BBJP/SRF plant model, addressing installation, maintenance, scalability, and adaptability issues. While recognizing challenges, especially in pre-treatment processes, the research emphasizes the need for efficient and cost-effective solutions. Practical implications include enhanced decision-making in biomass drying, identification of technology advantages and disadvantages, and a commitment to address challenges for sustainable implementation. The study contributes to Indonesia's energy transition discourse, advocating the pivotal role of BBJP plants in balancing Industry 4.0 demands and environmental protection, providing insights for stakeholders and decision-makers in advancing sustainable waste-to-energy initiatives.

Keywords: Industry 4.0, Bahan Bakar Jumputan Padat (BBJP), Multi-Criteria Decision Making (MCDM), Analytical Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Bio Drying, Thermal Drying, Mechanical Drying.

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1. Introduction

In the era of Industry 4.0, characterized by the integration of intelligent sensors, Internet of Things (IoT), artificial intelligence (AI)/machine learning (ML), cloud computing, big data and analytics, virtual reality (VR)/augmented reality (AR), intelligent robotics, 5G communications, and 3D printing, the industrial sector has witnessed a significant evolution. While these technological advances have substantially improved production processes, addressing challenges in energy consumption and environmental sustainability has become paramount [1]. The escalating demand for electrical energy, driven by the reliance on data centers, cloud computing, and web servers, poses a critical issue globally. This demand is further intensified by the simultaneous growth in the global population and shifts in lifestyle. Nations, including Indonesia, are thus forced to reassess their energy landscapes to balance Industry 4.0 demands with environmental preservation. Indonesia, like many other parts of the world, relies heavily on fossil fuels coal, gas, and oil for electrical energy production. Coal dominates the energy mix, constituting 50-65% of Indonesia's power plant performance [2]. This reliance contributes significantly to greenhouse gas emissions and environmental challenges. In response to global commitments, Indonesia aligns itself with the principles of the 2015 Paris Agreement. The challenge lies in achieving a global temperature reduction of no more than 2°C while balancing national energy sources, budget constraints, and the Trilemma Energy index (security, equity, and sustainability) [3]. To realize clean and sustainable energy, Indonesia crafted the National Energy Transition Roadmap targeting Net Zero Emission (NZE) by 2060. This roadmap emphasizes renewable energy-based power plants and innovative approaches, including biomass co-firing in existing coal-fired power plants. This co-firing method faced initial opposition due to environmental concerns but gained support through proposals like the energy plantation forest (EPF) program[4].

Waste management emerges as a global challenge, leading to the deployment of *Bahan Bakar Jumputan Padat* (BBJP) for sustainable waste-to-energy conversion. Operational BBJP plants, located strategically, are modest in number but demonstrate potential for expansion. A paradigm shift is underway with the introduction of a mobile-modular containerized BBJP/SRF plant model. This innovation streamlines waste-to-energy conversion, offering advantages like ease of installation, maintenance flexibility, scalability, and adaptability to diverse land configurations. The modular BBJP plant comes in scalable capacities (10, 20, 50, and 100 Tons Per Day), offering a dynamic solution. Containerized modules, transportable via trailer trucks, enhancing mobility, enabling deployment in remote waste source locations and minimizing the need for extensive waste mobilization to centralized facilities. However, challenges, such as the pre-treatment process, must be addressed to optimize BBJP. Transitioning from fixed-conventional BBJP plants to the mobile-modular containerized model signifies a significant leap in sustainable waste-to-energy efforts [5]. .

The study highlights challenges in BBJP plant pre-treatment, emphasizing the urgent need for a cost-effective solution. Current conditions lack efficiency, prompting a search for an affordable and efficient treatment model. This acknowledgment underscores the commitment to enhancing waste-to-energy sustainability. The optimization process for co-firing programs involves meticulous selection of pre-treatment technology, considering factors like capacity, conversion processes, waste types, electricity consumption, operational ease, land requirements, and investment costs. Implementing the Multi-Criteria Decision Making (MCDM) method is crucial for determining the optimal alternative based on predefined criteria weights.

2. Methods

In this comprehensive section, we expound upon the meticulous methodology employed to determine the optimal pre-treatment technology for BBJP (Solid Recovered Fuel) plants, utilizing the sophisticated Multi-Criteria Decision Making (MCDM) approach. The criteria guiding this decision-making process are thoughtfully curated from pertinent literature studies, ensuring relevance to the case at hand.

2.1. Identification of Criteria

The criteria enlisted in the decision-making process encompass a diverse set of parameters crucial for evaluating pre-treatment technologies. These criteria, along with their detailed descriptions, provide a holistic framework for assessing the technologies. The table below encapsulates this identification process:

Table 1. Identification of Criteria for Determining Pre-Treatment Technology for BBJP Plants [6]

No.	Criteria	Description
1	Capacity	Describes the production capacity of the considered pre-treatment technology, with options: small, large, or very large.
2	Conversion Process	Describes the type of solid recovered fuel (RDF/SRF) conversion process used by the pre-treatment technology, with options: biological (slow), thermal (fast), or mechanical (fast).
3	Type of Waste	Describes the type of waste that can be processed by the pre-treatment technology, with options: organic, organic and non-organic, or organic only.
4	Electricity Consumption	Describes the level of electricity consumption required by the pre-treatment technology, with options: small, large, or medium.
5	Operational Ease	Describes the level of operational ease of the pre-treatment technology, with options: easy, easy with specialized expertise, or easy but requires specialized expertise.
6	Land Requirement	Describes the type of land utilization needed by the pre-treatment technology, with options: distributed, centralized, or centralized with a larger size.
7	Investment Cost	Describes the level of investment cost required by the pre-treatment technology, with options: low, high, or very high.

The criteria for selecting pre-treatment technology for BBJP Plants (Solid Recovered Fuel from waste biomass) are strategically chosen to facilitate a thorough and effective evaluation process. Capacity is crucial, directly influencing production scale and aligning with energy efficiency goals. Conversion Process choice—biological, thermal, or mechanical—affects fuel quality and overall energy conversion efficiency. The Type of Waste criterion recognizes diverse waste compositions, ensuring technology optimization for specific types and maximizing efficiency. Electricity Consumption considerations aim for sustainability, favoring lower consumption to reduce operational costs and support sustainable energy goals. Operational Ease's impact on practical implementation and long-term success emphasizes user-friendliness and adoption feasibility. Land Requirement addresses spatial needs, aiding in system planning and adaptation to diverse settings. Lastly, Investment Cost balances economic viability, ensuring technology aligns with financial parameters and BBJP Plants' long-term objectives. This comprehensive evaluation framework, encompassing technical, economic, and operational aspects, guarantees the selected pre-treatment technology effectively meets the specific needs and goals of BBJP Plants in utilizing waste biomass for energy production.

2.2. Technology Ranking

By adhering to this rigorous methodology, the article aims to present a nuanced and data-driven perspective on the pre-treatment technology selection for BBJP plants. The inclusion of criteria weights, normalization processes, and comprehensive ranking ensures a robust foundation for decision-making, emphasizing the multi-faceted nature of technology evaluation. It is crucial to acknowledge that while these methodologies offer valuable insights, other external factors like environmental considerations, sustainability metrics, and regulatory compliance must also be factored into the final decision-making process.

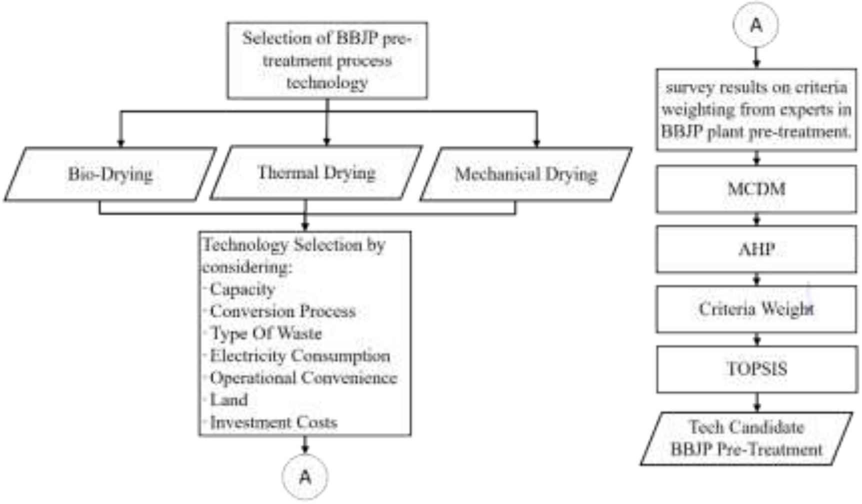

Figure 1. Research Methodology

2.3. Biomass Pre-Treatment Technologies

The selection of pre-treatment technology for biomass drying is a nuanced process, contingent upon the type of biomass utilized, desired outcomes, and available resources. Each technology presents its own set of advantages and drawbacks, necessitating a comprehensive evaluation of these factors to determine the most suitable choice.

1) Bio-drying stands out as a pre-processing technology for biomass drying, leveraging microorganisms in a bio-activator to degrade organic matter within the biomass. This process unfolds within a closed-box reactor, maintaining controlled temperature and humidity. Microorganisms consume organic matter in the biomass, generating heat and water vapor that effectively dries the biomass. The resulting product boasts biological stability, requiring minimal preparation [7].
2) Thermal drying represents another pre-processing technology for biomass drying, relying on heat to evaporate moisture within the biomass. Executed in dryers, which can take the form of rotary drums, fluidized beds, or belt conveyors, heat sources may include burning fossil fuels, biomass, or utilizing residual heat from other processes. This process enhances heating value and combustion efficiency of biomass, concurrently reducing required capacity [8].
3) Mechanical drying is a pre-processing technology for biomass drying that employs mechanical methods such as centrifugation or pressing to eliminate moisture from the biomass. Implemented in mechanical dryers, including screw presses, belt presses, or centrifuges, this process is particularly suitable for biomass with high moisture content, such as sludge or fertilizer [9].

In the quest for an optimal pre-treatment technology, the selection among these methods requires careful consideration of specific project requirements, resource availability, and the nature of the biomass in question. Each technology offers a distinctive approach to biomass drying, and the choice should align with the overarching goals of the biomass utilization project. The following sections delve deeper into the evaluation and comparison of these technologies based on key criteria, providing insights into their respective strengths and areas of application.

2.4. Advantages and Disadvantages of Pre-Treatment Technologies

This section delves into a comprehensive analysis of the strengths and weaknesses inherent in various pre-treatment technologies utilized for biomass drying, namely Bio-Drying, Thermal Drying, and Mechanical Drying. The detailed breakdown is presented in **Table 2.**

Table 2. Comparative Analysis of Pre-Treatment Technologies for Biomass Waste [6, 7 & 8]

Pre-Treatment Technology	Advantages	Disadvantages
Bio-Drying	a. Low energy consumption b. Low capital cost c. Low operational cost d. Produces biologically stable products	a. Prolonged drying time b. Limited to specific biomass types c. Requires enclosed container with controlled temperature and humidity
Thermal Drying	a. High drying rate b. Suitable for various biomass types c. Can recover residual heat d. Enhances heating value and biomass combustion efficiency	a. High energy consumption b. High capital cost c. High operational cost d. Greenhouse gas emissions
Mechanical Drying	a. High drying rate b. Suitable for high moisture content biomass c. Low energy consumption	a. High capital cost b. High operational cost c. Limited to specific biomass types

The table meticulously outlines the advantages and disadvantages associated with each pre-treatment technology for biomass drying. The positive aspects encompass factors such as low energy consumption, low capital and operational costs, high drying rates, suitability for various biomass types, and more. Conversely, the drawbacks include prolonged drying times, limitations to specific biomass types, the need for enclosed containers with controlled conditions, high energy consumption, high capital and operational costs, and greenhouse gas emissions. The selection of the most suitable pre-treatment technology necessitates a thorough consideration of the merits and demerits associated with each technology. It also requires a nuanced understanding of specific processing conditions and needs in biomass treatment. This comprehensive evaluation ensures an informed decision-making process that aligns with both efficiency and sustainability goals in biomass processing.

2.5. Multi-Criteria Decision Making (MCDM)

Michael Scoot Morton initially introduced the concept of Multi-Criteria Decision Making (MCDM) or Decision Support Systems (DSS) in 1971. MCDM is an information system designed to assist management in deciding semi-structured issues. The goal of MCDM is to generate various alternatives that users can interactively use in the decision-making process [8]. MCDM is a procedure used to find the best alternative from a set of feasible options [9]. MCDM with an optimization approach is highly useful in ranking, especially when complex criteria need to be considered simultaneously [10]. Decision Support Systems consist of building global preference relationships for a group of evaluated alternatives. The evaluation uses several selection criteria, where each option is assessed against these criteria, including measures that may conflict. Using MCDM or DSS, management can optimize decision-making by considering various relevant factors and criteria. This approach helps in complex situations where many alternatives and measures must be evaluated holistically. Thus, MCDM or DSS can be an effective tool in making better and data-driven decisions[11]. Some characteristics of MCDM that need to be considered include:

1. Consists of several criteria or attributes used as a selection basis.
2. These criteria often have conflicts with each other.
3. There is uncertainty in the decision-making process, such as subjective assessments, uncertain data, and incomplete information.
4. Sometimes, the final result of the MCDM process does not provide a clear conclusion or a single alternative as the best.
5. The considered alternatives are different objects with equal opportunities to be chosen by decision-makers.

6. Decision matrices are often used to visualize the relationship between alternatives and criteria in MCDM. The decision matrix M is m x n, where m represents the number of other options, and n represents the number of evaluated criteria.

In Multi-Criteria Decision Making (MCDM) for Bahan Bakar Jumputan Padat (BBJP) or Solid Recovered Fuel (SRF) plants, criteria identification and evaluation are meticulous processes. Factors like production capacity and investment costs are curated based on literature studies, with weights assigned through methodologies such as the Analytical Hierarchy Process (AHP) or stakeholder consensus [12]. Data normalization maintains parameter consistency, and weight calculation leads to comprehensive evaluations. The Technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS) refines decision-making, evaluating alternatives based on proximity to the ideal solution [13]. TOPSIS involves matrix normalization, weighted normalization, identifying perfect and non-ideal solutions, calculating separation measures, and determining scores. The integrated AHP and TOPSIS methodology quantitatively ranks pre-treatment technologies for BBJP or SRF plants, emphasizing the multi-faceted nature of technology evaluation and ensuring a robust foundation for sustainable energy decision-making [14]. This approach acknowledges external factors like environmental considerations and regulatory compliance, providing a comprehensive and data-driven perspective on technology selection. The final ranking based on TOPSIS scores determines the most favorable and preferred pre-treatment technology for the envisioned project.

3. Results and Discussion

This chapter provides detailed guidelines for composing the full text, encompassing the article section, the systematic chapter, and their respective contents. These explicit instructions serve as a comprehensive framework, directing the entirety of the editorial process for the article, as illustrated in Figure 1. Authors are expected to adhere closely to these guidelines to ensure the coherence and quality of the written content throughout the publication process.

3.1. Analytical Hierarchy Process (AHP)

This research utilizes the Analytical Hierarchy Process (AHP) method to prioritize criteria in selecting RDF/SRF waste treatment technologies [16]. The pairwise criteria matrix weights are determined based on a questionnaire provided to experts and practitioners directly involved in the BBJP Plant execution at TPSA Begedung.

1) Step 1: Pairwise Criteria Matrix

   In this step, researchers embark on the formation of a pairwise comparison matrix as a method to evaluate the relative significance among criteria. The essence of this comparison is encapsulated by the term a_{ij}, signifying the degree of importance attributed to criterion i in relation to criterion j. This matrix serves as a fundamental tool, providing a structured approach for researchers to systematically analyze and quantify the hierarchical relationships existing among the diverse set of criteria under consideration.

Table 3. Pairwise Comparison Matrix

Criteria	Capacity	Conversion Process	Type of Waste	Electricity Consumption	Operational Convenience	Land	Investment Cost
Capacity	1	5	7	3	6	4	1/2
Conversion Process	1/5	1	3	1	4	2	1/3
Type of Waste	1/7	1/3	1	1/4	1/2	1/3	1/4
Electricity Consumption	1/3	1	4	1	3	2	1/2

Operational Convenience	1/6	1/4	2	1/3	1	1/3	1/2
Land	1/4	1/2	3	1/2	3	1	1/3
Investment Cost	2	3	4	2	2	3	1
Total	4	11	24	8	19 1/2	12 2/3	3 2/5

2) Step 2: Normalization of Pairwise Criteria Matrix

The pairwise comparison matrix (A) undergoes a normalization process to yield the Relative Weight Matrix (W), which signifies the relative importance of each criterion on a scale ranging from 0 to 1. This normalization is achieved by dividing each element a_{ij} by the total of the corresponding column. The resulting Relative Weight Matrix provides a nuanced understanding of the influence of individual criteria in the decision-making process. This method ensures that each criterion's contribution is appropriately scaled, facilitating a more accurate representation of their relative significance in the overall evaluation.

Table 4. Normalized Pairwise Comparison Matrix

Criteria	Capacity	Conversion Process	Type of Waste	Electricity Consumption	Operational Convenience	Land	Investment Cost
Capacity	0,2443	0,4511	0,2917	0,3711	0,3077	0,3158	0,1463
Conversion Process	0,0489	**0,0902**	0,1250	0,1237	0,2051	0,1579	0,0976
Type of Waste	0,0349	0,0301	0,0417	0,0309	0,0256	0,0263	0,0732
Electricity Consumption	0,0814	0,0902	0,1667	0,1237	0,1538	0,1579	0,1463
Operational Convenience	0,0407	0,0226	0,0833	0,0412	0,0513	0,0263	0,1463
Land	0,0611	0,0451	0,1250	0,0619	0,1538	0,0789	0,0976
Investment Cost	0,4887	0,2707	0,1667	0,2474	0,1026	0,2368	0,2927
Total	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000

The normalized value w_{12} is calculated by dividing the corresponding element a_{12} by the total of the second column in matrix A.

$$w_{12} = \frac{a_{12}}{\sum_{i=1}^{n} a_{i2}} \text{ For the given values in } A:$$

$$w_{12} = \frac{1}{5 + 1 + 1/3 + 1 + 1/4 + 1/2 + 3}$$

$$w_{12} = \frac{1/5}{11.75} \approx 0.0902$$

So, the value of 0.0902 in the normalized matrix W for w_{12} is obtained by normalizing the comparison value a_{12} in A based on the total of the second column. This process is repeated for each element in the matrix to obtain the complete normalized matrix W.

3) Step 3: Consistency Analysis of Weighting

After obtaining the Relative Weight Matrix (W), a consistency analysis of the weighting is performed to ensure the reliability of these weights. In this step, the Weight Vector (W^*) and Consistency Index (CI) are calculated to evaluate the consistency among criterion preferences.

Table 5. Consistency Analysis of Weighting

Criteria	Capacity	Conversion Process	Type of Waste	Electricity Consumption	Operational Convenience	Land	Investment Cost	Weighted sum value	Criteria weight	Consistency measure
Capacity	**0,2443**	0,4511	0,2917	0,3711	0,3077	0,3158	0,1463	2,1281	0,2443	8,7099
Conversion Process	0,0489	**0,0902**	0,1250	0,1237	0,2051	0,1579	0,0976	0,8484	0,0902	9,4029
Type of Waste	0,0349	0,0301	**0,0417**	0,0309	0,0256	0,0263	0,0732	0,2627	0,0417	6,3048
Electricity Consumption	0,0814	0,0902	0,1667	**0,1237**	0,1538	0,1579	0,1463	0,9201	0,1237	7,4377

Operational Convenience	0,0407	0,0226	0,0833	0,0412	**0,0513**	0,0263	0,1463	0,4118	0,0513	8,0299
Land	0,0611	0,0451	0,1250	0,0619	0,1538	**0,0789**	0,0976	0,6234	0,0789	7,8965
Investment Cost	0,4887	0,2707	0,1667	0,2474	0,1026	0,2368	**0,2927**	1,8055	0,2927	6,1688

λmax	7,7072
CI	0,1179
CR	**0,0893**

Example Consistency Calculation:

1. Calculation of Weight Vector (W^*) : $w_{ij} = \frac{a_{jl}}{\sum_{i=1}^{n} a_{0j}}$, For example, $w_{11} = \frac{1}{4}, w_{32} = \frac{1/4}{3/4} = \frac{1}{3}$.
2. Calculation of Weight Vector (W^*) : $W^* = \frac{1}{n}\sum_{j=1}^{n} w_{ij}$, With $n = 7, W^*$ represents the average of each column in the W matrix
3. Calculation of Consistency Index (CI) : $CI = \frac{\lambda_{\max} - n}{n-1}$, Where $\lambda_{\max}$ is the maximum eigenvalue
4. Calculation of Consistency Ratio (CR) : $CR = \frac{CI}{RI}$, With RI being a pre-determined consistency index
5. $CI = \frac{\lambda_{\max} - 7}{7-1}$, $\lambda_{\max}$ is computed from eigenvalue calculations and can be set at 7.7072.
   $$CI = \frac{7.70\pi 2 - 7}{6}, CI \approx 0.1179$$
6. $CI = \frac{\lambda_{\max} - 7}{7-1}$, $CR = \frac{CI}{RI}$ (With $RI = 1.32$)
   $CR \approx \frac{0.1179}{1.32} = CR \approx 0.0893$

In this example, CI is approximately 0.1179, and CR is 0.0893, which is below the consistency threshold (typically 0.1). This indicates that the generated criterion weights can be considered consistent.

3.2. *TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution)*

TOPSIS is a decision-making method employed to evaluate and select alternatives based on the Euclidean distance between each alternative and the ideal best and worst solutions [17]. In the context of the provided decision matrix, here is a detailed description of each step in the TOPSIS process

1) Step 1: Entering Matrix Values and Calculating Total Column Squares

   In this step, the decision matrix values are entered, and the total sum of squares per column is calculated. This process is undertaken to normalize the matrix values in the subsequent step.

Table 6. Matrix Values and Calculating Total Column Squares

Criteria		Capacity	Conversion Process	Type of Waste	Electricity Consumption	Operational Convenience	Land	Investment Cost
Bio-Drying	**Field Report**	Small	Slow	Organic	Small	Easy	Distributed	Small
	Score (1-5)	1	1	1	3	3	3	3
Thermal Drying	**Field Report**	Large	Fast	Organic and Non-Organic	Large	Easy and requires expertise	Centralized	Large
	Score (1-5)	3	3	3	1	2	3	1
Mechanical Drying	**Field Report**	Large	Fast	Organic and Non-Organic	Moderate	Easy and requires expertise	Centralized	Large
	Score (1-5)	3	3	3	2	2	3	1
Total Squares		**19**	**19**	**19**	**14**	**17**	**27**	**1**

2) Step 2: Normalizing the Decision Matrix with Total Column Squares

   After calculating the total sum of squares per column, the decision matrix is normalized by dividing each matrix element by the corresponding total sum of column squares. This is done to standardize the scale of values for each criterion.

Table 7. Matrix Values and Calculating Total Column Squares

Criteria	Capacity	Conversion Process	Type of Waste	Electricity Consumption	Operational Convenience	Land	Investment Cost
Bio-Drying	0,229415734	0,22941573	0,229415734	0,801783726	0,727606875	0,577350269	0,904534034
Thermal Drying	0,688247202	0,6882472	0,688247202	0,267261242	0,48507125	0,577350269	0,301511345
Mechanical Drying	0,688247202	0,6882472	0,688247202	0,534522484	0,48507125	0,577350269	0,301511345

3) Step 3: Assigning Weights to the Normalized Decision Matrix

In this step, weights are assigned to the normalized decision matrix. These weights reflect the importance of each criterion in the decision-making process. Each value in the normalized decision matrix is multiplied by the corresponding weight.

Table 8. Weighted Decision Matrix

Criteria	Capacity	Conversion Process	Type of Waste	Electricity Consumption	Operational Convenience	Land	Investment Cost
Weighted	0,244328098	0,84838644	0,26270125	0,920128624	0,411787492	0,623404974	1,805511369
Bio-Drying	0,05605271	0,1946332	0,0602678	0,737744156	0,29961941	0,35992303	1,633146481
Thermal Drying	0,16815813	0,58389959	0,1808034	0,245914719	0,199746273	0,35992303	0,54438216
Mechanical Drying	0,16815813	0,58389959	0,1808034	0,491829438	0,199746273	0,35992303	0,54438216

4) Step 4: Determining Ideal Best and Ideal Worst

Ideal Best (V+) and Ideal Worst (V-) are solutions that have the highest and lowest values for each criterion. In this context, V+ and V- values have been identified for each criterion.

Table 9. Ideal Best (V+) and Ideal Worst (V-) Values

Criteria	Capacity	Conversion Process	Type of Waste	Electricity Consumption	Operational Convenience	Land	Investment Cost
V+	0,16815813	0,58389959	0,1808034	0,737744156	0,29961941	0,35992303	1,633146481
V-	0,05605271	0,1946332	0,0602678	0,245914719	0,199746273	0,35992303	0,54438216

5) Step 5: Calculating Euclidean Distance and Criterion Scores

Table 10. Euclidean Distance, Criterion Scores, and Ranking for Biomass Waste Pre-Treatment Technologies

Criteria	Ed+	Ed-	Psi	Rank
Bio-Drying	0,4226	1,1989	0,739	1
Thermal Drying	1,1989	0,4226	0,261	2
Mechanical Drying	1,1207	0,4890	0,304	3

In the final step, Euclidean Distance (Ed+) and (Ed-) are calculated for each alternative. Euclidean Distance represents the distance between each alternative and the ideal best solution (Ed+) and the ideal worst solution (Ed-). Criterion scores (Psi) are also computed as the ratio of Ed- to (Ed+ + Ed-). Alternatives are ranked based on the criterion scores generated. The rankings are determined based on the Criterion Scores (Psi), where a lower score indicates better performance. According to the TOPSIS analysis, Bio-Drying emerges as the most favorable pre-treatment technology for biomass drying, securing the top rank with a Psi score of 0.739. Thermal Drying follows closely behind with a Psi score of 0.261, while Mechanical Drying takes the third position with a Psi score of 0.304. These results offer valuable insights into the relative performance of each pre-treatment technology, aiding decision-makers in selecting the most suitable alternative for biomass drying applications.

3.3. Comparative Analysis of Pre-Processing Technologies: Strengths and Weaknesses

In delving into the specifics of the Analytical Hierarchy Process (AHP) employed for prioritizing criteria in the selection of RDF/SRF waste treatment technologies, a nuanced examination of its strengths and weaknesses is essential. AHP offers a systematic and structured approach, presenting a comprehensive decision-making framework. The method's incorporation of experts directly involved in the execution of the BBJP Plant at TPSA Begedung ensures a realistic and industry-specific viewpoint. The use of paired comparisons, however, introduces subjectivity into the process, potentially influencing the final weightings assigned to criteria. The complexity of these paired comparisons might also pose challenges, requiring careful attention to maintain accuracy in the evaluation process. The normalization step in AHP, transforming the pairwise criteria matrix into a Relative Weight Matrix (W), is a pivotal aspect. It provides a valuable insight into the relative importance of each criterion, offering a quantitative basis for decision-making. Nevertheless, the normalization process may face limitations in capturing dynamic changes in the needs and goals of the BBJP Plant over time. The industrial landscape is inherently dynamic, and the relevance of criteria may evolve, necessitating periodic reassessment. The consistency analysis of weighting, involving the calculation of the Weight Vector (W^*) and Consistency Index (CI), contributes to the reliability of the results. It ensures that the generated criterion weights align coherently with the decision-making process. However, the effectiveness of this analysis may be influenced by the evolving nature of industrial requirements. Regular reassessment and adjustment of weights might be crucial to maintaining the consistency and relevance of the decision-making framework.

3.4. Contextual Relevance to BBJP Plant in Indonesia:
In the specific context of the BBJP Plant in Indonesia, the strengths of the AHP approach become more apparent. Its systematic nature aligns with the industrial processes of the plant, providing a structured methodology for evaluating and prioritizing pre-processing technologies. The involvement of experts from the field ensures that the criteria selected, such as capacity, Conversion Process, type of waste, electricity consumption, operational convenience, land, and investment cost, are directly relevant to the plant's operations. However, the potential limitation of AHP in capturing dynamic changes becomes more critical in an industry where technological advancements and operational requirements evolve rapidly. The criteria and their respective weights might need periodic adjustments to reflect the evolving landscape of the BBJP Plant [18].

4. Conclusion
In summary, the thorough analysis of biomass drying pre-treatment technologies within BBJP (Solid Recovered Fuel) plants offers valuable insights for the transition to sustainable energy. The MCDM approach, integrating AHP and TOPSIS, proves robust for evaluating technologies through paired comparisons. Criteria, from production capacity to investment costs, are meticulously weighed and normalized, ensuring a nuanced assessment. AHP ensures consistent criterion weights, reflecting accurate relative importance. TOPSIS ranks technologies, with Bio-Drying as the preferred method, followed by Thermal Drying and Mechanical Drying. These rankings guide decision-makers toward sustainable energy alternatives. However, external factors like environmental considerations and regulatory compliance must also influence decisions. Balancing technical feasibility with environmental and societal impacts is crucial for a clean energy future. Integrating innovative technologies like Bio-Drying in Indonesia's energy transition showcases the nation's commitment to sustainability. This research contributes to Indonesia's energy discourse, emphasizing the role of BBJP plants in balancing Industry 4.0 demands with environmental protection. Future research should advance biomass drying pre-treatment technologies, exploring AI integration and intelligent monitoring for enhanced efficiency and sustainability. Real-world application requires systematic testing through pilot projects and large-scale implementations. Collaboration between academia, industry, and policymakers is essential for translating research into practical solutions, shaping Indonesia's evolving sustainable energy landscape.

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