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MORALITY BEFORE KNOWLEDGE

Data-driven optimization of rice husk waste management through an integrated machine learning and community-based pyrolysis approach

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ABSTRACT

Background: Indonesia's energy landscape currently pivots between two bifaceted issues: the stagnation of the national energy transition and the inefficiencies of decentralized waste management. Despite East Java producing 9.27 million tons of dry-milled rice in 2024, the resulting 1.85 Mt of rice husk remains an underutilized bio-resource. This wasted potential coincides with a sluggish renewable energy trajectory, where the 15.25% share by mid-2025 significantly trails the 23% national target. **Methods:** A data-driven framework integrating feedstock characterization, experimental data, and literature benchmarks was applied to evaluate catalytic fast pyrolysis and upgrading pathways for rice husk. Machine-learning-assisted correlation analysis and multi-objective optimization Non-dominated Sorting Genetic Algorithm II (NSGA-II) were used to benchmark key process variables, product yields, and fuel quality trade-offs. **Findings:** The technical foundation, built on detailed feedstock characterization, reveals that the CFP process yields ~46.9 wt% bio-oil, which is further refined to a 32.2 wt% biodiesel-equivalent yield. To enhance operational precision, various ML algorithms were evaluated; the Extra Trees model coupled with NSGA-II demonstrated superior predictive performance with an R2 of up to 0.96 and an RMSE <1 MJ/kg for calorific value prediction, showing strong accuracy for O/C ratio and CO_2 fraction estimation. Techno-economic assessment confirms the framework's viability for pilot-scale implementation, projecting a positive NPV of IDR 50.4 million, an IRR of 23.78%, and a 2.93-year payback period. While sensitivity analysis highlights exchange rate volatility as a key financial risk, the model successfully positions farmers as active stakeholders in the value chain. **Conclusion:** The integrated CFP–ML framework demonstrates technical and economic viability for decentralized rice husk valorization, positioning farmers as active stakeholders in the renewable energy value chain and offering a scalable, bottom-up solution to support Indonesia's energy transition in agricultural regions. **Novelty/Originality of this article:** By synthesizing mechanistic process design with data-driven decision support, this study provides a scalable, bottom-up pathway for decentralized waste-to-energy systems in agricultural regions.

KEYWORDS: catalytic fast pyrolysis; hydrotreating; NSGA-II; rice husk; surrogate modeling.

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1. Introduction

Agricultural waste in Indonesia continues to accumulate without a comprehensive management strategy, despite its substantial potential as a renewable energy resource. This challenge is reflected in food loss and waste (FLW), which accounted for 40.9% of total national waste in 2023 (SIPSN, 2023). The accumulation of FLW has resulted in material losses estimated at 23-48 million tons annually, corresponding to economic losses of approximately 213-551 trillion rupiah (Pusparisa, 2023). Rice, as the national staple commodity, represents the largest contributor, accounting for 44% of total national FLW between 2000 and 2019, equivalent to approximately 12-21 million tons of unhusked rice waste per year (Ahdiat, 2023). As a central rice-producing region, East Java recorded 9.27 million tons of dry-milled grain (GKG) production in 2024 (BPS, 2024). Assuming a 20% rice husk fraction, the province alone generates an estimated 1.85 million tons of rice husk waste annually.

Beyond the issue of agricultural waste accumulation, Indonesia also faces structural challenges in its energy transition. According to the Biofuel Producers Association/*Asosiasi Produsen Biofuel Indonesia* (APROBI) Seminar held on 17 July 2025, the share of renewable energy reached only 15.25% by mid-2025, with an average annual growth rate of 0.475% since 2015, as reported by the Directorate General of New Renewable Energy and Energy Conservation/*Energi Baru Terbarukan dan Konservasi Energi* (EBTKE) of the Ministry of Energy and Mineral Resources/*Menteri Energi dan Sumber Daya Mineral* (ESDM). This trajectory remains significantly below the 23% national target stipulated in Presidential Regulation No. 22 of 2017. Furthermore, only approximately 2% of Indonesia's total renewable energy potential has been utilized to date. The coexistence of excessive agricultural waste and underutilized renewable energy resources highlights a critical opportunity to develop integrated waste-to-energy systems that address both challenges simultaneously.

While thermochemical conversion technologies such as pyrolysis have been widely studied for organic waste valorization, most existing studies emphasize either process optimization at the reactor scale or economic feasibility at the industrial scale, with limited integration of data-driven optimization and community-level deployment within a single framework. In particular, the application of machine learning in pyrolysis systems has primarily focused on specific feedstocks or slurry-based processes, and its role as a general benchmarking and decision-support tool for similar kinds of organic waste pyrolysis systems remains underexplored.

In response to these gaps, this study develops a data-driven rice husk waste management system that integrates thermochemical conversion, machine-learning-based surrogate modeling, and community-scale deployment. The proposed approach employs machine learning as a benchmarking and predictive tool to support decision-making in process operation and post-pyrolysis byproduct handling across organic waste pyrolysis systems, rather than as a feedstock-specific optimization strategy. By embedding technical optimization within a community-based deployment framework, this study aims to demonstrate a low-waste, scalable energy system that aligns with national energy transition goals. Furthermore, the feasibility of community deployment is assessed through simplified techno-economic and socio-economic indicators, providing a preliminary evaluation of practical implementation potential at the grassroots level. Together, this introduces an integrated bottom-up framework that couples surrogate modeling with community-oriented design. Unlike prior studies that either optimize specific reactors using black-box models or evaluate waste-to-energy systems without data-driven coupling, this study explicitly bridges surrogate modeling, mechanistic process design, and community-scale deployment within a single decision-support framework.

2. Methods

The methodological framework integrates primary and secondary data to support a data-driven decision process for rice husk pyrolysis and downstream upgrading. Primary data include feedstock characterization, pyrolysis performance indicators, and experimental datasets used to develop machine-learning-based surrogate models, while secondary data are obtained from literature benchmarks on organic waste and sludge pyrolysis. The overall workflow is structured into three main stages: feedstock characterization and process selection, catalytic fast pyrolysis with catalyst screening, and downstream upgrading via hydrotreating.

In the first stage, proximate and ultimate analyses are performed to quantify volatile matter, ash content, moisture, fixed carbon, and elemental composition (C, H, O, N, S). These properties serve as the initial decision basis for selecting the thermochemical conversion route. Rather than treating the processing pathway as a fixed design choice, this study formulates process selection as a data-driven decision problem. Correlation analysis and machine-learning-assisted benchmarking are employed to evaluate how feedstock properties influence product distributions, thereby informing the selection of catalytic fast pyrolysis over alternative routes such as torrefaction or conventional pyrolysis. This stage corresponds to the decision nodes that determine whether the system should be oriented toward bio-oil production and whether catalyst-assisted operation is required.

The core methodological focus, namely the selection of catalytic fast pyrolysis and the subsequent hydrotreating upgrading step. Machine-learning-assisted correlation analysis is used to identify the most influential variables governing bio-oil yield, biochar formation, and product quality. Specifically, heatmap-based correlation analysis and literature benchmarking are employed to quantify the roles of volatile matter, ash content, elemental composition, and temperature in controlling phase distribution and fuel properties. These correlations are then used as a decision-support layer to guide catalyst input selection, operating condition benchmarking, and the prioritization of hydrotreating as an upgrading pathway when high oxygen content and low H/C ratios are predicted.

Finally, the upgraded bio-oil stream is routed to hydrotreating when data-driven indicators suggest that direct fuel utilization would be limited by high oxygen content or instability. In this manner, machine learning is not applied as a direct "black-box optimizer" corresponding to a single predefined procedure, but rather acts as a benchmarking and decision-support layer that links feedstock properties, interpretable operating condition benchmarking, and product quality across the entire process chain. This integrated framework enables systematic evaluation of catalytic fast pyrolysis and hydrotreating as adaptive process choices for organic waste pyrolysis systems, rather than as predetermined unit operations, particularly in the context of further community deployment.

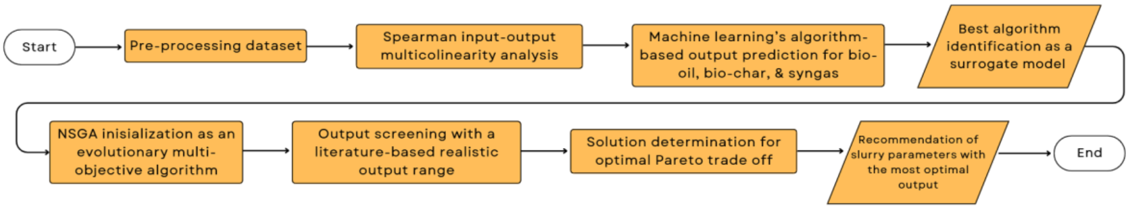

Fig. 1. Integrated ml slurry processing workflow

Following the process-level decision framework described before, Figure 1 illustrates the computational workflow that supports the data-driven selection of catalytic fast pyrolysis and downstream upgrading pathways. This workflow provides the analytical layer used to evaluate feedstock suitability, benchmark operating conditions, and guide the decision nodes through machine-learning-assisted modeling and multi-objective analysis.

Subsequently, a multi-objective evolutionary algorithm (NSGA-II) is employed to explore the trade-offs among competing objectives, including liquid yield, solid yield, gas formation, and fuel quality indicators. Candidate solutions are screened using literature-based feasibility thresholds to ensure physical consistency and process realism. The resulting Pareto front is then used as a decision-support tool to identify representative operating regions and benchmark optimal trade-offs, rather than to prescribe a single deterministic operating point.

In this framework, machine learning and multi-objective optimization serve as a benchmarking and recommendation layer. This layer supports process selection, catalyst utilization, and upgrading prioritization, aligning directly with the decision nodes shown in Figure 1. While the surrogate models are trained on sludge-derived slurry datasets, they are utilized here as a generic benchmarking tool to identify dominant feedstock–process–product relationships, rather than to predict specific rice husk CFP performance. This strategy allows for a systematic evaluation of catalytic fast pyrolysis and hydrotreating across heterogeneous organic wastes, ensuring both interpretability and adaptability for community-scale deployment.

3. Results and Discussion

3.1 Preliminary analysis of rice husk biomass and process design

As the initial analysis stage begins with proximate and ultimate analyses, an appropriate thermochemical conversion pathway is determined, with bio-oil fraction selected as the primary target of production. The obtained feedstock characteristics, particularly volatile matter content, ash fraction, moisture level, and oxygen composition, indicate that pyrolysis is a suitable process for oxygen removal through thermal decomposition (Tsai et al., 2007). Compared to other thermochemical techniques, fast pyrolysis remains the most suitable option, as it avoids excessive tar formation typical of slow pyrolysis and does not primarily produce non-condensable gases with limited technical readiness for scale-up, such as flash pyrolysis (Balat et al., 2009). Accordingly, catalytic fast pyrolysis (CFP) was selected as the primary conversion route to maximize liquid product formation while enabling in-situ upgrading of pyrolysis vapors.

The selection of catalytic fast pyrolysis further requires careful consideration of catalyst type shown in Table 1, as different catalyst classes exhibit fundamentally different mechanistic roles in controlling product distribution and bio-oil quality. Basic metal oxides such as CaO, Fe_2O_3, $Ca(OH)_2$, and K_2CO_3 primarily promote acid neutralization, decarboxylation, and decarbonylation reactions, leading to reduced char formation and increased yields of light oxygenated compounds. However, these catalysts generally increase water formation and retain a high fraction of oxygenated species, indicating that their primary function is oxygen removal rather than hydrocarbon upgrading. Boric oxide and alkali additives further enhance dehydration and deoxygenation, but at the expense of increased char and aqueous phase formation, thereby limiting improvements in liquid fuel quality.

In contrast, metal-modified mesoporous catalysts such as Al/MCM-41, Cu-MCM-41, Fe-MCM-41, and Zn-MCM-41 promote cracking reactions and partial deoxygenation, increasing hydrogen formation and reducing methoxy and carbonyl compounds. Nevertheless, due to their weak shape selectivity and broader pore size distribution, these catalysts exhibit limited control over aromatic formation and the final hydrocarbon spectrum. Acidic zeolites, particularly HZSM-5 and Pt/HZSM-5, exhibit a fundamentally different upgrading behavior. Owing to their strong Brønsted acidity and shape-selective microporous structure, HZSM-5 promotes extensive cracking, aromatization, and deoxygenation, resulting in increased yields of gasoline-range aromatics, reduced oxygen-to-carbon ratios, and substantial suppression of methoxy and heavy oxygenated compounds. The near-complete decomposition of aliphatic C-C bonds and elimination of more than 80% of methoxy groups reported for HZSM-5 further indicate its superior capability in controlling bio-oil chemical composition rather than merely enhancing deoxygenation.

Table 1. Comparative analysis of difference catalyst function for CFP

Catalyst Type	Impact Comparisons	Reference
CaO, Fe_2O_3	The presence of CaO was found to suppress the formation of heavy compounds such as phenols and anhydrosugars, while promoting the generation of cyclopentanones, hydrocarbons, and light products including acetaldehyde, 2-butanone, and methanol. In addition, CaO effectively reduced acid species. In contrast, Fe_2O_3 favored the formation of polycyclic aromatic hydrocarbons (PAHs)	Lu et al. (2010)
B_2O_3 (boric oxide), mixed with biomass	The process enhanced deoxygenation by removing approximately 50–80% of hydroxyl and methoxy functional groups, led to higher water and char production, and resulted in a reduction in gas yields.	Lim & Andresen (2011)
Al/MCM-41, Cu-Al/MCM-41, Fe-Al/MCM-41, Zn-Al/MCM-41	Lignocel predominantly generates hydrocarbon-rich products, whereas phenolic compounds. The application of catalysts generally increased phenol formation, with lower Si/Al ratios enhancing overall yields and improving product quality. Catalysts containing Fe and Cu resulted in the highest phenol production. In addition, Al/MCM-41 effectively reduced oxygenated compounds, while Cu/MCM-41 led to the most significant increase in H_2 concentration within the gas fraction.	Antonakou et al. (2006)
K_2CO_3 or $Ca(OH)_2$, mixed with biomass	K_2CO_3 exhibited higher catalytic activity by completely suppressing the formation of saccharides, aldehydes, and alcohols, while markedly decreasing the production of acids, furans, and guaiacols. This catalyst also enhanced the yields of alkanes and phenolic compounds. In contrast, $Ca(OH)_2$ lowered char formation, increased liquid yields, and promoted alcohol production, showing behavior opposite to that observed with K_2CO_3.	Wang et al. (2010)
Pt/HZSM-5 and HZSM-5	The use of HZSM-5 enhanced isomerization and hydrogenation reactions, leading to higher gas production and an increased C_4 iso-to-n-hydrocarbon ratio, while simultaneously reducing the yield of organic liquid products (OLP). The presence of steam further contributed to the decrease in OLP yield. Additionally, HZSM-5 was highly effective in breaking aliphatic C–O bonds and carbonyl functionalities, removing nearly 80% of methoxy groups.	Katikaneni et al. (1997), Ben & Ragauskas (2011)

(Dickerson & Soria, 2013)

Based on this comparative mechanistic assessment, HZSM-5 was selected as the primary catalytic material in this study because it provides simultaneous control over oxygen removal, aromatic hydrocarbon formation, and heavy oxygenate suppression. This mechanistic catalyst selection is later coupled with the machine-learning benchmarking layer to ensure consistency between empirical catalyst behavior and data-driven operating condition recommendations, vital for achieving a stable, energy-dense bio-oil result suitable for downstream hydrotreating and fuel upgrading.

Following the selection of HZSM-5 based on the comparative mechanistic assessment described above, the catalytic fast pyrolysis configuration adopted in this study is illustrated in Figure 2. As shown, the CFP system operates under an inert nitrogen atmosphere, where rice husk biomass is introduced through a feeding hopper and rapidly heated in the thermal zone (Furnace 1). In this zone, fast pyrolysis occurs, producing char, volatile vapors, and non-condensable gases under short vapor residence times. The resulting pyrolysis vapors subsequently pass through a downstream catalytic zone (Furnace 2) containing an external HZSM-5 catalyst. Owing to its hierarchical pore structure and strong acidity, HZSM-5 promotes cracking, partial deoxygenation, and aromatization of oxygenated pyrolysis intermediates, enabling preliminary upgrading of bio-oil vapors within the reactor.

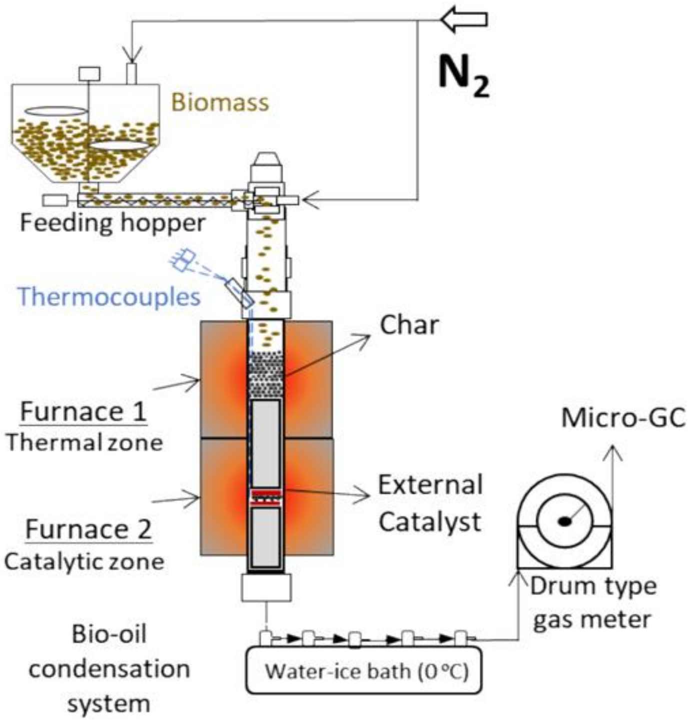

Fig. 2. Schematic of a catalytic fast pyrolysis system
(Pagano et al., 2025)

Solid char is separated prior to the catalytic section, while upgraded vapors are directed to a condensation system maintained at approximately 0°C using a water–ice bath to recover crude bio-oil. Non-condensable gases are quantified using a drum-type gas meter and subsequently analyzed by micro-scale gas chromatography (micro-GC). This configuration allows fast thermal decomposition and catalytic vapor upgrading to occur sequentially, forming a suitable precursor stream for subsequent bio-oil purification through hydrotreating. Other catalytic processes are available, such as conventional and flash pyrolysis.

Table 2. Proximate and Ultimate analysis of rice husk

Parameter	Value
Proximate	
Volatile Matter (%)	68.20
Ash Content (%)	16.10
Moisture Content (%)	12.67
Fixed Carbon (%)	15.70
Heating Value (KJ/Kg)	15,175
Ultimate	
Carbon Content(%)	45.2
Hydrogen Content (%)	5.8
Oxygen Content (%)	47.6
Nitrogen Content (%)	1.02
Sulphur Content (%)	0.21

(Efomah & Gbabo, 2015)

The purification of crude bio-oil obtained from catalytic fast pyrolysis is proposed to proceed through several possible upgrading pathways, among which hydrotreating is identified as a primary development option due to its effectiveness in improving chemical stability and reducing oxygen content. Hydrotreating is a hydrogen-based upgrading process that primarily proceeds via hydrodeoxygenation reactions, converting oxygenated functional groups into water, carbon monoxide, and carbon dioxide, thereby increasing the H/C ratio and calorific value of the upgraded oil (Lachos-Perez et al., 2023).

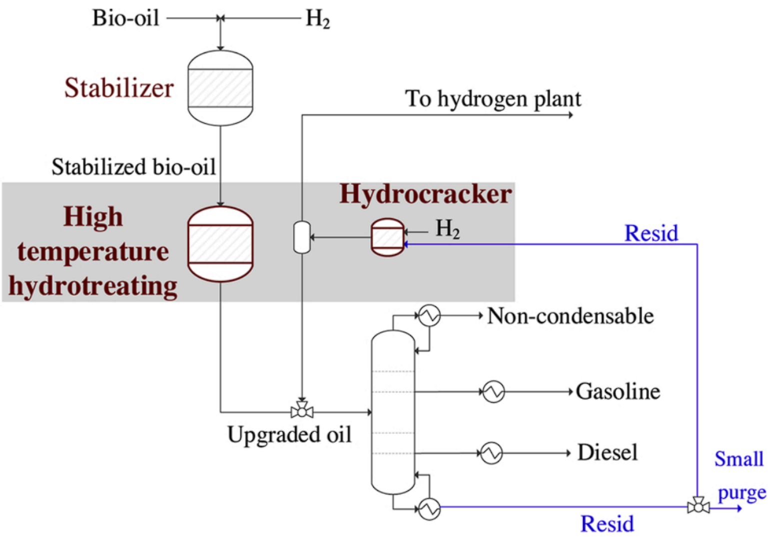

Fig. 3. Hydrotreating process diagram
(Wang et al., 2021)

As illustrated in Figure 3, hydrotreating-based upgrading can be configured as a multi-stage process. In the initial stabilization stage, bio-oil is subjected to moderate-temperature hydrotreating to hydrogenate reactive carbonyl and carboxyl compounds, producing a stabilized bio-oil that is less prone to polymerization and coke formation. This step is followed by a higher-temperature hydrotreating or hydrocracking stage, where deeper hydrodeoxygenation and cracking reactions occur, resulting in substantial oxygen removal and the formation of lighter hydrocarbon fractions (Wang et al., 2021).

Conceptually, this upgrading pathway can be divided into two temperature regimes. The first stage, operated at 100–300 °C, focuses on stabilization through hydrogenation of highly reactive oxygenated species. The second stage operates at 350–400°C under hydrogen pressure, aiming to achieve extensive hydrodeoxygenation and hydrocarbon enrichment. These reactions are typically facilitated by catalysts composed of noble metals, metal sulfides, or transition metals supported on acidic materials compatible with HZSM-5, enabling synergistic hydrogenation and cracking functionalities (Sanna et al., 2015). Hydrotreating systems are commonly designed to operate at pressures ranging from 1 to 30 MPa and temperatures between 200 and 500 °C in batch, downflow, or semi-continuous reactors, depending on scale and process objectives (Cheng et al., 2018).

Depending on operating severity and downstream separation, the upgraded products may be directed toward different utilization routes, including gasoline-range and diesel-range fuels, while non-condensable streams and excess hydrogen can be recycled or integrated with hydrogen production facilities. This flexibility positions hydrotreating as a strategic upgrading option within an integrated bio-oil valorization framework, providing a strong basis for the subsequent process flow diagram (PFD) design and system-level evaluation.

To integrate the entire technical workflow, a process flow diagram (PFD) is presented in Figure 4. The proposed configuration is designed as an integrated system for converting rice husk biomass into bio-oil and an upgraded liquid fuel through two main stages, Catalytic Fast Pyrolysis (CFP) and Hydrodeoxygenation (HDO) treatment, as proposed. In the initial stage, raw biomass is dried in a rotary biomass dryer (E-DRY) to reduce moisture content to below 8%, followed by size reduction using a grinder (E-GRD) to achieve particle sizes smaller than 2 mm. The dried material is then conveyed under an inert nitrogen atmosphere through a feed-lock hopper (T-FEED) to maintain oxygen-free conditions prior to entering the two-zone CFP reactor (R-CFP).

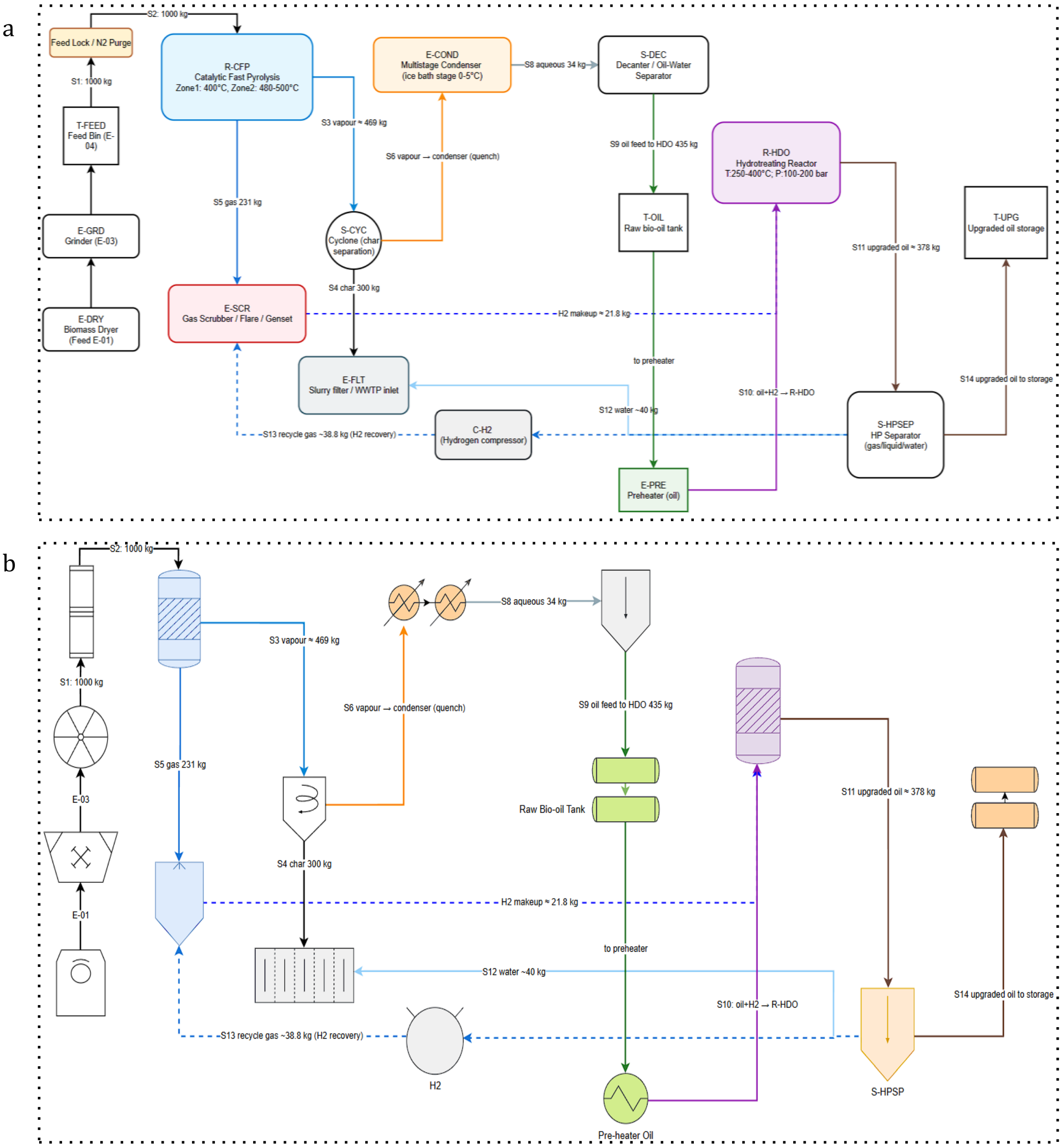

Fig. 4. Process flow diagram (PFD) of entire technical process (a) PFD with node-by-node process specifications; (b) PFD with schematic illustrations of the leading technical equipment

Inside the reactor, operated at temperatures of 400–500 °C under an N_2 atmosphere, thermocatalytic decomposition occurs in the presence of an HZSM-5 catalyst, converting lignocellulosic components into a mixture of organic vapors, non-condensable gases, and solid char. Solid particles are separated using a cyclone separator (S-CYC). At the same time, the vapor fraction is sequentially condensed in a multistage condenser (E-COND) equipped with two cooling zones (quench and ice bath). The resulting condensate is subsequently routed to an oil–water decanter (S-DEC) for phase separation, yielding raw bio-oil that is transferred to a storage tank (T-OIL), whereas the aqueous phase is directed to the wastewater treatment system (E-FLT–WWTP).

The second stage involves upgrading via hydrotreating (R-HDO) to improve bio-oil quality into a biodiesel-range fuel. Prior to upgrading, the bio-oil feed is preheated in a shell-and-tube heat exchanger (E-PRE) to approximately 150 ^{o}C and mixed with high-pressure hydrogen supplied by a hydrogen compressor skid (C-H_2), which also facilitates hydrogen recycle from the high-pressure separator (S-HPSEP). In the HDO reactor, operated at 250-400 ^{o}C and 100–200 bar, hydrodeoxygenation reactions remove oxygen-containing functional groups from bio-oil compounds, producing an upgraded oil along with water and light gaseous by-products. These three phases are separated in a three-phase high-pressure separator (S-HPSEP), where the liquid upgraded fuel is sent to the upgraded oil storage tank (T-UPG), the aqueous phase is routed to filtration (E-FLT), and hydrogen-rich gas is recompressed and recycled through C-H_2 to enhance hydrogen utilization efficiency. Residual non-condensable gases and process emissions are treated in a gas scrubber (E-SCR) prior to final disposal through a flare system (FLARE).

Table 3. Utilities specification for each process unit

Code	Process Unit	Primary Process	Parameters	Input / Output
E-DRY	Biomass Dryer	Reduce rice husk moisture content prior to grinding.	120–180 °C; 1 atm; 1 batch	In: S1 (wet rice husk) 1 t Out: dried rice husk 0.95 t
E-GRD	Grinder / Hammer Mill	Grind rice husk to a particle size < 2 mm.	Ambient; 1 atm	In: 950 kg Out: 950 kg powder
T-FEED	Feed Hopper	Provide buffering and automatic feeding to the reactor.	Ambient; N_2 inert; < 1 vol% O_2	In: 950 kg Out: 950 kg
Feed Lock	Lock Hopper (N_2 purge)	Maintain an inert atmosphere during feeding.	< 2 bar; N_2 blanket	In: 950 kg Out: 950 kg
R-CFP	Catalytic Fast Pyrolysis Reactor	Convert biomass into bio-oil, gas, and char via HZSM-5 catalysis.	Zone 1: 400 °C; Zone 2: 480–500 °C; 1 atm	In: 950 kg Out: S3 vapor 469 kg; S4 char 300 kg; S5 gas 231 kg
S-CYC	Cyclone Separator	Separate solid char from gas/vapor.	450–480 °C; 1 atm	In: S3 vapor 469 kg Out: S4 char 300 kg; S6 vapor 469 kg
E-COND	Multistage Condenser (Quench + Ice Bath)	Condense bio-oil vapor into a liquid phase.	Stage 1: 40 °C; Stage 2: 0–5°C; 1 atm	In: S6 vapor 469 kg Out: S7 liquid (435 kg aqueous) + 34 kg
S-DEC	Oil–Water Decanter	Separate the bio-oil and aqueous phases from the condensate.	25–40 °C; 1 atm	In: S7 469 kg Out: S9 oil 435 kg; S8 (aq) 34 kg
T-OIL	Raw Bio-oil Tank	Store crude bio-oil prior to upgrading.	Ambient–60 °C; 1 atm	In: S9 oil 435 kg Out: feed to R-HDO
E-PRE	Preheater (Shell & Tube HE)	Increase the bio-oil temperature prior to hydrotreating.	120–150 °C; 10–15 bar	In: S9 oil 435 kg Out: S10 (oil + H_2) ≈ 455 kg
C-H_2	Hydrogen Compressor Skid	Compressed recycle and make-up H_2 gas.	Outlet 100–200 bar; 25 °C	In: S13 H_2 gas 38.8 kg Out: H_2 make-up + recycle ≈ 60 kg
R-HDO	Hydrotreating Reactor	Convert bio-oil into biodiesel via hydrogenation.	250–400 °C; 100–200 bar	In: S10 oil + H_2 ≈ 455 kg Out: S11 oil ≈ 378 kg; S12 water ≈ 40 kg; S13 gas ≈ 38.8 kg

S-HPSEP	3-Phase HP Separator	Separate the HDO effluent into oil, water, and gas phases.	50–80 °C; 100–200 bar	In: R-HDO effluent Out: S11 oil ≈ 378 kg; S12 water ≈ 40 kg; S13 gas ≈ 38.8 kg
T-UPG	Upgraded Oil Storage	Store the final biodiesel product.	Ambient; 1 atm	In: S11 378 kg Out: S14 product to storage
E-SCR	Gas Scrubber / Flare System	Clean syngas (CO, CO_2, CH_4) and route it to the flare/genset.	30–50 °C; 1 atm	In: S5 gas 231 kg + minor vent Out: clean gas to flare/genset
E-FLT	Slurry Filter / WWTP Inlet	Filter char and wastewater from the slurry stream.	Ambient; 1 atm	In: S4 300 kg + S8/S12 ≈ 74 kg Out: slurry solid ≈ 300 kg; WW ≈ 74 kg
HOT-OIL	Thermal Oil Heater	Provide heating duty for E-DRY and E-PRE.	180–250 °C; 3 bar	Thermal loop fluid
ICE-BATH / CHILLER	Cooling / Refrigeration Unit	Provide cooling for E-COND Stage 2.	0–5 °C	Cooling brine circuit
N_2-GEN	Nitrogen Generator	Supply inert gas to the system.	5 Nm^3/h; 99.9% N_2	N_2 to T-FEED, R-CFP
FLARE	Flare Stack	Incinerate off-gas (H_2 / CO / VOC).	700–1000 °C; 1 atm	Off-gas from E-SCR and C-H_2
WWTP	Wastewater Treatment	Treat liquid effluent from E-FLT and S-DEC.	Ambient	Effluent 74 kg

3.2 Characterization and multicollinearity analysis of rice husk pyrolysis

Based on the heatmap analysis of bio-oil synthesis, the most influential variable affecting bio-oil yield is volatile matter (r = 0.43), followed by hydrogen content (r = 0.25) and nitrogen content (r = 0.24). This indicates that feedstocks with high volatile and hydrogen content tend to produce greater quantities of bio-oil. Conversely, ash content shows a strong negative correlation with bio-oil yield (r = –0.43), suggesting that high ash concentrations hinder the conversion of feedstock into liquid products. These findings are consistent with those reported by Jerzak et al. (2024), who observed that moderate temperatures and volatile-rich feedstocks such as sewage sludge and microalgae can maximize bio-oil yields to over 35%. However, elevated pyrolysis temperatures result in a significant decrease in bio-oil yield due to secondary decomposition reactions.

Accordingly, sewage slurry is adopted in this study as a reference domain to delineate an optimal pyrolysis severity window, because its volatile-rich character and well-documented temperature sensitivity provide a robust empirical basis for identifying conditions that favor liquid formation before secondary cracking dominates. This slurry-informed operating envelope is then transferred to rice husk-derived streams as an informed starting point, while explicitly accounting for the stronger ash-related inhibition expected in high-mineral feedstocks to avoid systematic overestimation of bio-oil yield.

The correlation heatmap further reveals that, in addition to volatile matter, hydrogen (r = 0.25), nitrogen (r = 0.24), and carbon content (r = 0.22) are positively correlated with bio-oil yield. This supports the notion that volatile organic compounds, such as lipids, proteins, and carbohydrates in rice husk, serve as primary precursors for bio-oil via thermal cracking and volatilization. Jerzak et al. (2024) also emphasized that highly volatile fractions facilitate the release of light molecular species. In contrast, hydrogen stabilizes free radicals during thermal decomposition, thereby promoting the formation of stable aromatic compounds and liquid hydrocarbons.

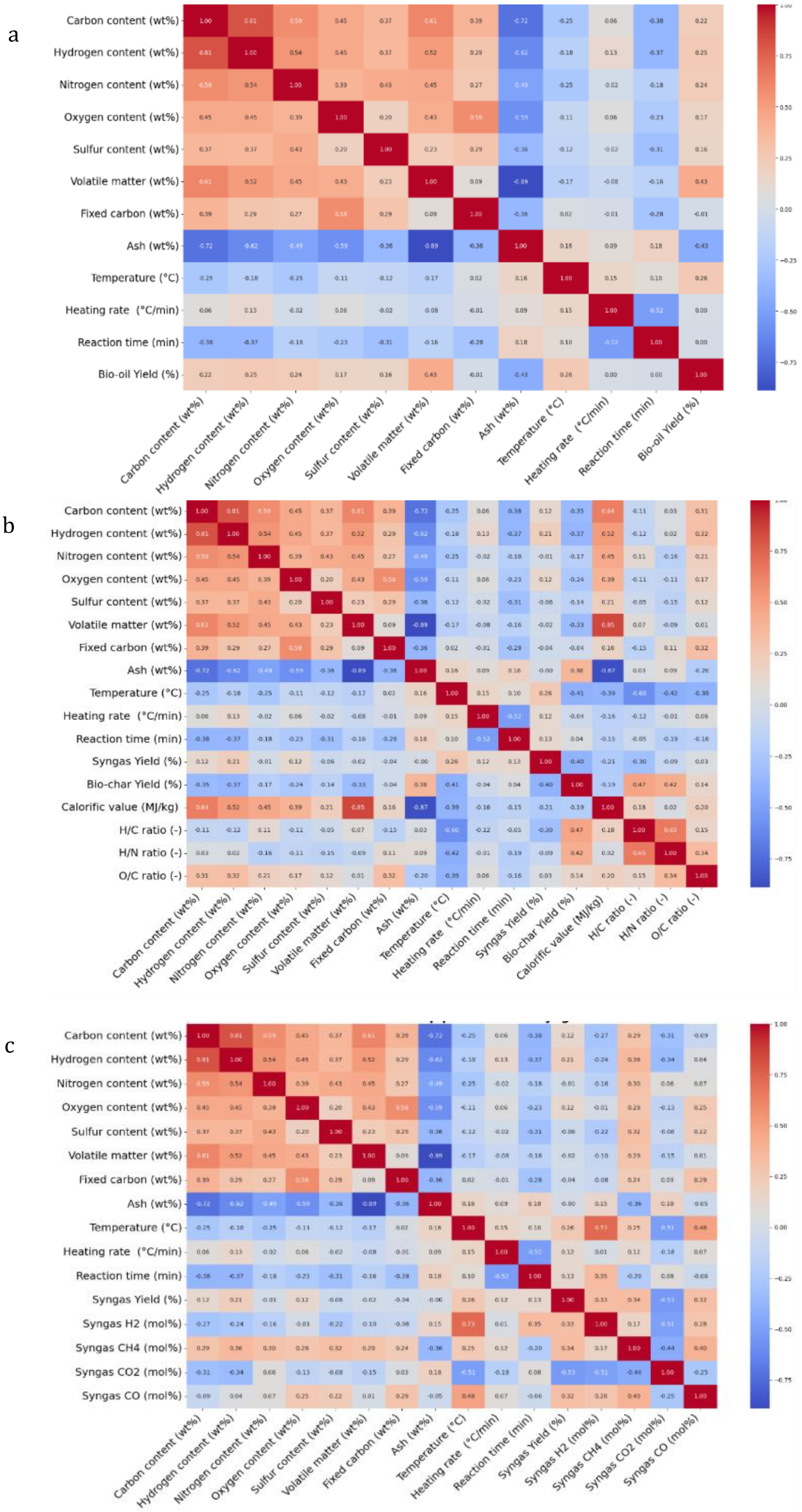

Fig. 5. Multicollinearity heatmap on rice husk pyrolysis (a) for bio-oil synthesis; (b) for biochar synthesis; (c) for syngas synthesis

In the context of biochar production, the heatmap reveals a positive correlation between biochar yield and ash content (r = 0.38), suggesting that inorganic constituents and thermally stable carbon structures are more resistant to degradation and therefore accumulate in the solid phase during pyrolysis. In contrast, the negative correlation with temperature (r = -0.39) indicates that, as temperature increases, the thermal decomposition of rice husk waste into bio-oil and syngas becomes more pronounced. The energetic characteristics of biochar are further reflected by a strong positive correlation with calorific value (r = 0.64) and a strong negative correlation with ash content (r = –0.87). Additionally, the atomic H/C (r = –0.60) and O/C (r = –0.39) ratios exhibit negative correlations with rising temperature, confirming that carbonization and deoxygenation processes intensify under higher thermal conditions (Vershinina et al., 2022).

3.3 Multi-objective optimization for slurry pyrolysis benchmark

In multi-objective optimization of rice husk pyrolysis, machine learning (ML) serves as a surrogate modeling approach to replace complex, computationally expensive physical simulations. The pyrolysis of sewage sludge entails nonlinear interactions among various process parameters (including temperature, residence time, and intrinsic feedstock properties) that are challenging to model using conventional mechanistic methods. ML enables rapid prediction of key outputs, such as bio-oil yield, biochar characteristics, and syngas composition, solely from historical datasets.

Table 4. Machine learning performance analysis as a surrogate model

Target	Best Model	R2 Score	RMSE	MSE	MAPE
Calorific value (MJ/kg)	ExtraTrees	0.961892	0.58985	0.347923	0.054316
O/C ratio (-)	ExtraTrees	0.852925	0.151034	0.022811	0.48897
Bio-char Yield (%)	ExtraTrees	0.845811	6.894357	47.53216	0.22996
Syngas CO_2 (mol%)	ExtraTrees	0.81222	8.363523	69.94851	0.23576
Bio-oil Yield (%)	ExtraTrees	0.760497	6.015574	36.18713	0.20994
Syngas H_2 (mol%)	ExtraTrees	0.704197	6.930259	48.02849	1.54E+15
H/C ratio (-)	LGB	0.644423	0.185279	0.034328	0.33422
Syngas Yield (%)	LGB	0.637678	6.77032	45.83723	0.25237
Syngas CO (mol%)	ExtraTrees	0.60967	4.36807	19.08003	8.46E+14
H/N ratio (-)	ExtraTrees	0.584614	1.684675	2.83813	0.1868
Syngas CH4 (mol%)	ExtraTrees	0.572841	4.366069	19.06256	1.38E+15

Model evaluation revealed that the Extra Trees Regressor achieved the highest predictive performance, with a coefficient of determination (R^2) up to 0.96 and a root mean square error (RMSE) of less than 1 MJ/kg for calorific value estimation. This model also exhibited superior accuracy in predicting the oxygen-to-carbon (O/C) ratio and syngas CO_2 content, owing to its robustness against noisy data and its ability to capture complex feature interdependencies. Light Gradient Boosting Machine (LightGBM) proved effective for predicting the hydrogen-to-carbon (H/C) ratio and overall syngas yield, although its performance was slightly inferior. Nonetheless, some outputs (particularly CH_4 and CO concentrations in the syngas) remained prone to substantial predictive errors, indicating the need for improved data preprocessing or exploration of alternative modeling architectures.

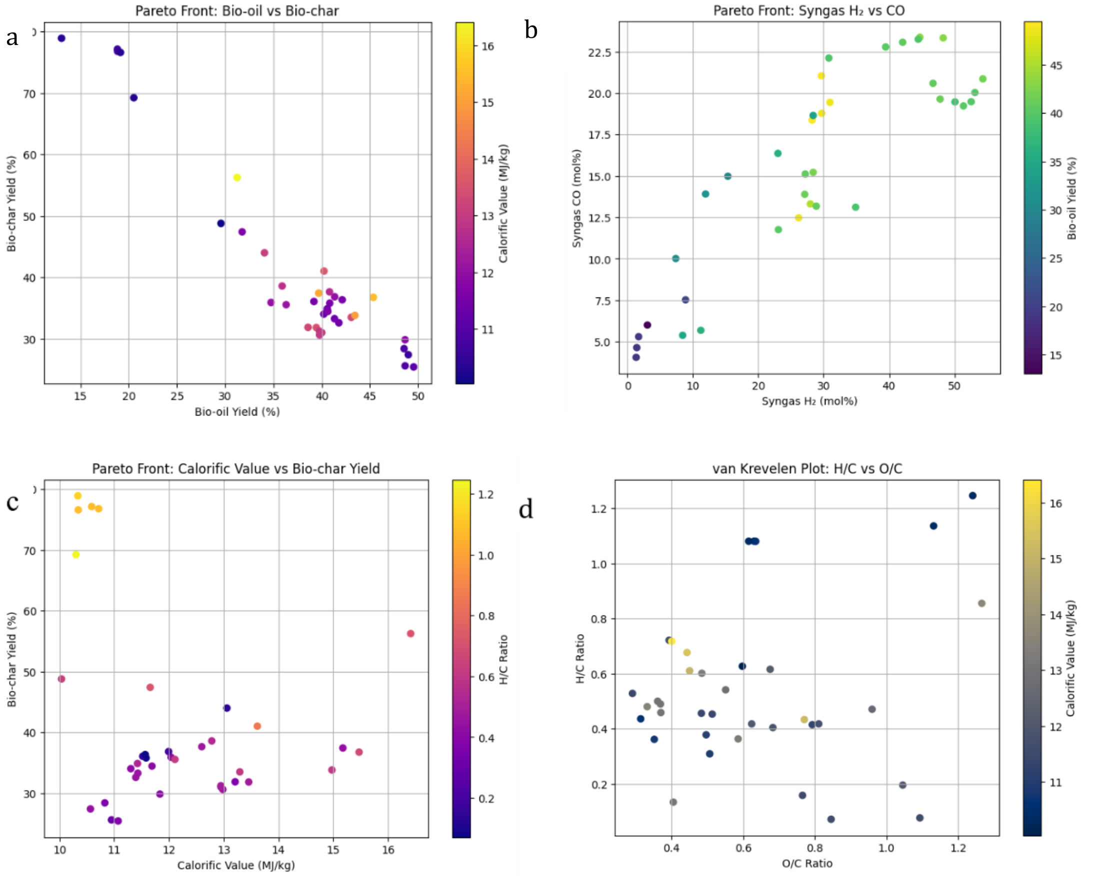

Fig. 6. Pareto front on multi-objective optimization for (a) bio-oil vs bio-char; (b) syngas H_2 vs CO_2; (c) calorific value vs bio-char yield; (d) H/C vs O/C

The Figure 6 above, illustrate key trade-offs among major product streams resulting from sewage sludge-derived slurry pyrolysis. Two-dimensional plots capture the trade-offs among bio-oil yield and bio-char yield, hydrogen and carbon monoxide fractions in syngas, and calorific value versus bio-char yield, with color gradients encoding auxiliary parameters such as H/C ratio or bio-oil yield. The van Krevelen diagram visualizes atomic-level energy quality indicators (H/C vs. O/C ratios) and serves as a diagnostic tool for assessing feedstock energy potential. Furthermore, the three-dimensional plot delineates the distribution and balance among bio-oil, bio-char, and syngas yields in relation to total product output, thereby reflecting the overall energy conversion efficiency of the process.

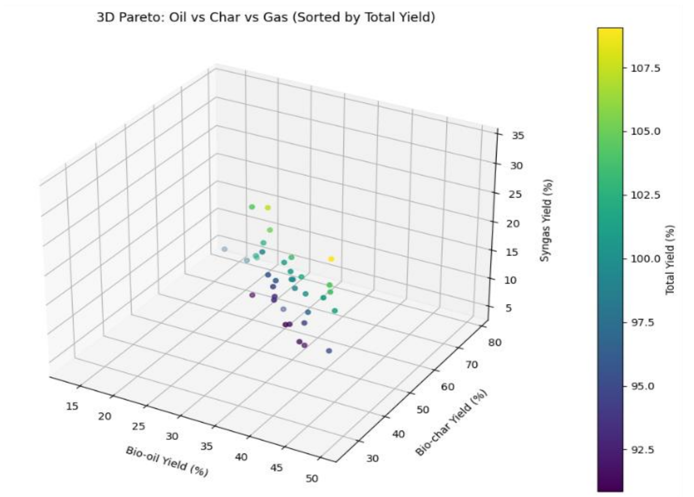

Fig. 7. 3D Pareto interpretation for multi-objective optimization yields

Appendix 1 presents the optimal combinations of input parameters (including sludge composition, proximate analysis data, and operational conditions) that yield the best outcomes for each specific optimization target: highest bio-oil yield, maximum bio-char production, highest calorific value, and lowest oxygen-to-carbon (O/C) ratio. In addition to reporting the corresponding input and output values, Appendix 1 emphasizes the inherent trade-offs among product characteristics. It highlights the interrelationships among mass balances across the bio-oil, syngas, and biochar fractions.

3.4 Optimization of technical parameter on process design

According to Table 5, the catalytic fast pyrolysis (CFP) process for rice husk conversion to syngas and bio-oil requires high temperatures, low heating rates, and short vapor residence times (Balat et al., 2009). Elevated temperatures facilitate the rapid pyrolysis of cellulose, hemicellulose, and lignin, with hemicellulose decomposing between 470–530 K, cellulose between 510–620 K, and lignin between 550–770 K (Demirbas & Arın, 2002). For optimal rice husk CFP, the recommended temperature range is 850–1250 K, with a heating rate of 10–200 K/s, utilizing finely ground biomass and an oxygen-free environment (Balat et al., 2009). The bio-oil production process should involve rapid heating and quenching to yield intermediate liquid products. Vapor residence time should be maintained below 2 seconds, with aerosols and pyrolysis vapors cooled to form bio-oil, while extended gas residence time favors increased syngas production. For improved results, rice husk particles should have a residence time of 0.5–10 seconds and a particle size not exceeding 1 mm (Balat et al., 2009).

Table 5. Optimal parameters for catalytic fast pyrolysis of biomass

Pyrolisis Technology	Main products	Optimal temperature (K)	Heating rate (K/s)	Particle size (mm)	Solid residence time (s)
Fast	Bio-oil and syngas	850–1250	10–200	<1	0.5–10

(Balat et al., 2009)

Solid yields are lowest during the CFP process. As shown in Table 5, bio-char production yield decreases significantly to below 50% when the temperature exceeds 683 K. Therefore, optimal temperatures for bio-char formation are below 575 K, with particle sizes ranging from 5 to 500 mm and longer residence times to promote char formation. Higher temperatures are unfavorable because they increase tar production during CFP (Balat et al., 2009). Consequently, slow pyrolysis is recommended for maximizing biochar yield (Elliot et al., 1991).

Table 6. Various results of solid biowaste pyrolysis in relation to temperature

Temperature (K)	Char yield (%)	Liquids yield (%)	Gas yield (%)
507	97.0	0.0	3.0
584	76.2	15.9	7.9
655	62.9	25.4	11.7
683	49.0	35.0	16.0

(Küçük & Demirbaş, 1997)

3.5 Value chain and techno-economic analysis

The proposed system is embedded within a value chain framework that emphasizes a zero-waste and integrated agricultural energy system. In this framework, farmers are positioned as key upstream actors responsible for supplying rice husk residues, thereby directly linking agricultural waste management with renewable energy production. Rather than being treated as passive waste generators, farmers participate as incentivized suppliers within a community-based value chain, enabling mutual benefits for both the farming community and the designed system.

Through structured collection and distribution of rice husk residues, farmers contribute to reducing localized waste accumulation while simultaneously converting an otherwise discarded by-product into an additional income stream. This arrangement provides economic incentives through waste-based compensation schemes, transforming agricultural residues into monetizable resources. From the system perspective, the availability of locally sourced feedstock reduces procurement costs and logistical complexity, supporting operational continuity at the community scale. This reciprocal relationship forms the foundation of grassroots energy communities, where value creation and waste mitigation occur simultaneously within a localized supply network.

From a technical standpoint, the value chain is underpinned by the conversion performance of rice husk through the HZSM-5-assisted catalytic fast pyrolysis process. Based on literature benchmarks, the CFP process yields approximately 46.90% (w/w) bio-oil from rice husk feedstock (Cai et al., 2018). Accordingly, the processing of one metric ton of rice husk is expected to generate approximately 469 kg of crude pyrolysis bio-oil. This intermediate product subsequently undergoes upgrading via hydrotreating, where oxygen content is reduced to approximately 20% to enhance fuel stability and combustion efficiency. Literature-reported upgrading efficiencies indicate a biodiesel-equivalent conversion rate of 32.20% (w/w) relative to the bio-oil feed (Wang et al., 2021; Fermoso et al., 2017), corresponding to 151.02 kg of upgraded fuel product.

Table 7. Financial projection of proposed system

Item (mil.) /year	2025	2026	2027	2028	2029	2030
Cash Inflow	713.8	749.5	787.0	826.3	867.7	911.0
Cash Outflow	763.2	761.0	728.7	702.9	682.2	665.7
Taxable Income			58.27	123.4	185.4	245.3
Earnings After Tax and Depreciation	-49.36	-11.48	12.81	27.15	40.79	53.97

The system is proposed for pilot-scale implementation, and the financial projection is developed to evaluate its economic feasibility during the initial deployment phase. Table 9 summarizes the techno-economic assessment for the 2025–2030 period. In the first year of operation (2025), the project recorded a negative taxable income of IDR 49,367,206.48, reflecting capital recovery and operational ramp-up typical of early-stage deployment. During this period, cash inflow amounts to IDR 713,860,967.63, while cash outflow is IDR 763,228,174.10. Despite this initial deficit, the investment remains financially viable, as indicated by a positive Net Present Value (NPV) of IDR 50,428,772.68 and an Internal Rate of Return (IRR) of 23.78%.

Table 8. Key techno-economic indicators based on projected financial performance

Techno-Economic Key Parameters	Value
Net Present Value (IDR)	50,428,772.68
Return on Investment (%)	12.82
Internal Rate of Return (%)	23.78
Payback Period (year)	2.93

Operational stabilization in subsequent years leads to a marked improvement in financial performance. By 2026, losses will decrease, and earnings before interest, taxes, depreciation, and amortization (EBITDA) will show positive growth, reflecting improved process utilization and enhanced value capture across the supply chain. By 2030, annual cash inflow is projected to reach IDR 911,087,591.11, with a Return on Investment (ROI) of

12.82%. The estimated Payback Period (PBP) of 2.93 years indicates that the initial investment can be recovered in less than three years, underscoring the economic robustness and scalability potential of the proposed system.

3.6 Sensitivity analysis

Sensitivity analyses were conducted in this study to evaluate the robustness of the financial performance of the catalytic fast pyrolysis and hydrotreating-based rice husk waste management system to various technical and economic uncertainties. In economic modeling, sensitivity analysis serves as a formal robustness test that examines how variations in model outputs can be quantitatively attributed to variations in fundamental input parameters (Hermeling & Mennel, 2008). Specifically, it translates uncertainty in basic economic parameters into uncertainty in key output indicators, thereby providing a prerequisite for drawing reliable economic conclusions from numerical simulations (Hermeling & Mennel, 2008).

Table 9. Sensitivity analysis results when there is a 10% increase in the value of the dollar

Item (mil.) /year	2025	2026	2027	2028	2029	2030
Cash Inflow	IDR 785.2	IDR 824.5	IDR 865.7	IDR 909.0	IDR 954.4	IDR 1.002.1
Cash Outflow	IDR 831.0	IDR 830.0	IDR 795.9	IDR 768.6	IDR 746.8	IDR 729.4
Taxable Income			IDR 69.7	IDR 140.3	IDR 207.6	IDR 272.7
Earnings After Tax and Depreciation	-IDR 45.83	-IDR 5.52	IDR 15.35	IDR 30.87	IDR 45.67	IDR 60.01

Although the baseline financial projections show positive economic viability, key economic parameters (with a first-order focus on exchange rate fluctuations as a representative macroeconomic uncertainty) are dynamic and have the potential to change at the real implementation stage, especially in the context of community-scale systems. In this study, the exchange rate is selected as a first-order macroeconomic proxy due to its direct influence on both imported hydrogen and catalyst costs in the proposed system. Accordingly, the present sensitivity analysis aims to identify the financial and technical parameters that have the most influence on the key economic viability indicators, namely Net Present Value (NPV), Internal Rate of Return (IRR), and Payback Period (PBP), under a deterministic one-factor sensitivity framework.

Table 10. Baseline techno–economic analysis results

Techno-Economic Key Parameters	Value
Net Present Value (IDR)	73,158,972.51
Return on Investment (%)	13.59
Internal Rate of Return (%)	33.61
Payback Period (year)	2.92

Although the present analysis focuses on exchange rate variation as a dominant macroeconomic uncertainty, other parameters such as bio-oil upgrading yield, product selling price, and operating cost are also expected to influence system feasibility. These parameters are therefore recommended as future sensitivity dimensions to be explored as more operational data become available from pilot-scale deployment. Based on the results presented in Table 10, a 10% increase in the dollar exchange rate leads to an increase in NPV by 31.06%, ROI by 6%, and IRR by 41.33%, accompanied by a reduction in PBP by 0.01 years (approximately 3.65 days). These results indicate that exchange rate fluctuations exert a strong influence on financial performance indicators. However, under practical deployment conditions, currency depreciation may simultaneously increase both revenue and imported cost components, suggesting that net profitability will depend on the balance between export-linked product pricing and imported input expenditures.

Table 11. Sensitivity analysis results when there is a 5% increase in demand

Item (mil.) /year	2025	2026	2027	2028	2029	2030
Cash Inflow	IDR 824.5	IDR 865.7	IDR 909.0	IDR 954.4	IDR 1.002	IDR 1,002.1
Cash Outflow	IDR 862.4	IDR 863.0	IDR 828.9	IDR 801.6	IDR 779.8	IDR 729.4
Taxable Income			IDR 80.0	IDR 140.3	IDR 222.6	IDR 272.7
Earnings After Tax and Depreciation	-IDR 45.83	IDR 2.722	IDR17.62	IDR 33.61	IDR 48.91	IDR 63.78

Furthermore, parameter changes will be made when there is a 5% increase in product demand. If there is an increase in product demand, the NPV value will increase by 94.34%, ROI by 13.02%, and IRR by 108%. From a community deployment perspective, the sensitivity analysis highlights the importance of financial robustness under market and macroeconomic uncertainty. Since farmer income, feedstock supply continuity, and local participation are directly linked to system profitability, maintaining positive NPV and short payback periods under parameter variations is essential to sustain long-term community engagement. This underscores the need for adaptive pricing mechanisms, flexible incentive schemes, and modular scaling strategies to mitigate financial risks at the grassroots implementation level.

Table 12. Techno–economic key parameters under a 5% demand increase scenario

Techno-Economic Key Parameters	Value
Net Present Value (Rp)	98,007,694.13
Return on Investment (%)	14.49
Internal Rate of Return (%)	49.49
Payback Period (year)	2.91

3.7 *Proposed methods for community deployment*

Beyond techno-economic feasibility, the proposed value chain is designed to be deployable within a community-based framework that positions local actors as active participants rather than passive resource providers. In Indonesia, the relevance of end-to-end and community-integrated waste management systems is increasingly reflected in ongoing industrial practices. One such example is the circular economy initiative implemented by CAP in collaboration with local community groups, including KSM Sehati, through the Integrated Waste Processing Facility/*Instalasi Pengolahan Sampah Terpadu* (IPST) Asari in Cilegon. This initiative demonstrates an operational model in which community-based waste collection, industrial processing, and product valorization are integrated within a single deployment framework.

Fig. 8. Field visit to integrated waste processing facility

A tangible outcome of this system is the development of PLUSRI, a derived oil product obtained from processed plastic waste, which is currently being evaluated for internal company use as a substitute fuel for corporate vehicle fleets (Figure 9). The existence of PLUSRI indicates that community–industry integrated waste-to-fuel pathways are not merely conceptual, but can be translated into standardized fuel products with defined specifications and targeted end-use applications. This precedent is particularly relevant to the present study, as it provides empirical evidence that pilot-scale waste valorization systems can be embedded within industrial value chains while maintaining strong linkages to community-level feedstock supply.

Fig. 9. PLUSRI, a derived oil product for company use
(Bakti Barito Foundation, n.d.)

The experience from IPST Asari illustrates that community involvement can be effectively operationalized within industrial waste management frameworks, not merely as a social add-on but as a functional component of system continuity and resource recovery. This approach is consistent with findings from community-based economic studies, which emphasize that sustainable local development emerges when communities are engaged as subjects of economic activity, supported by capacity building, shared ownership, and collaborative governance structures (Wahib & Susanto, 2024). Within this framework, rice husk suppliers in the proposed system are integrated not simply as feedstock providers, but as stakeholders embedded within a localized energy value chain, contributing to both material supply and system resilience.

This deployment philosophy aligns with bottom-up approaches to economic and supply chain design, which emphasize decentralized decision-making and the utilization of locally generated operational data over centralized, top-down planning. Shapiro (1998) argues that bottom-up analytical systems are particularly effective in environments characterized by uncertainty, heterogeneity, and dynamic constraints, as decisions are informed by transactional and operational data rather than aggregated strategic assumptions. In contrast, top-down economic models rely heavily on centralized forecasts and averaged parameters, which may inadequately represent local variability in community-scale systems.

For community-based bioenergy systems, such bottom-up characteristics are especially relevant, as feedstock availability, quality, and logistics reliability vary spatially and temporally across agricultural communities. By structuring the value chain around decentralized feedstock aggregation and pilot-scale processing hubs, the proposed system enhances adaptability to local conditions while reducing dependence on large-scale coordination mechanisms. The integration of machine learning surrogate models further reinforces this bottom-up analytical framework. Rather than functioning as centralized optimization tools detached from operational realities, surrogate models are trained on process-level data to capture nonlinear relationships among feedstock properties, operating conditions, and product yields. This data-driven approach enables localized optimization and adaptive decision support, consistent with bottom-up analytical information systems that translate operational data into actionable insights (Shapiro, 1998).

The deployment strategy also draws on principles of community system design, which emphasize that technological systems must be embedded in existing social and operational practices to achieve long-term adoption and sustainability. Agostini et al. (2002) demonstrated that community systems are most effective when they augment daily routines and local interactions rather than functioning as externally imposed infrastructures. Accordingly, the proposed system aligns rice husk collection, logistics scheduling, and incentive mechanisms with established agricultural workflows to minimize participation barriers and sustain engagement.

From a supply chain perspective, the system is conceptualized as an integrated, multi-stage chain incorporating reverse logistics for agricultural residues. As articulated in supply chain design theory, effective resource recovery systems require coordination among upstream suppliers, processing nodes, and downstream markets to optimize overall system performance rather than the performance of isolated components (Beamon, 1998). Within this framework, community-based feedstock aggregation functions as the upstream node, while the pilot-scale pyrolysis unit serves as the central processing hub, converting low-value residues into energy-dense intermediates and final fuel products.

By integrating bottom-up participation, localized logistics, modular processing, and data-driven optimization, the proposed deployment model supports both technical efficiency and social sustainability. Compared to top-down, centralized energy infrastructures, this approach enhances system resilience by reducing exposure to supply disruptions, enabling incremental scaling through replication across agricultural clusters, and continuously adapting operational strategies using locally generated data. The resulting framework provides a theoretically grounded and practically viable pathway for implementing pilot-scale pyrolysis systems within agricultural communities while remaining aligned with broader techno-economic and supply chain optimization objectives.

Beyond its immediate application, this framework also offers a transferable blueprint for decentralized bioenergy deployment across agricultural regions with comparable residue availability and community structures, highlighting the need for future policy frameworks that support modular replication, standardized community contracts, and data-enabled governance to enable scalable and regionally adaptive waste-to-energy systems.

4. Conclusions

This study represents a strategic advancement in the development of renewable bioenergy systems by integrating technological innovation, artificial intelligence, and agricultural community engagement within a unified sustainable energy framework. By combining HZSM-5-based catalytic fast pyrolysis (CFP) with a two-stage hydrotreating process, rice husk biomass is effectively converted into bio-oil and biochar, achieving optimized conversion efficiency. While literature-recommended CFP temperatures span 850–1250 K, the present design adopts a moderate dual-zone configuration (400–500°C) as a pilot-scale compromise between liquid yield, catalyst stability, and community-scale operability. Under these conditions, thermocatalytic reactions conducted at residence times of 2–3 s, followed by hydrogenation employing Ni–Mo/Al_2O_3 catalysts, achieve up to 90% deoxygenation, yielding liquid bio-oil fractions of up to 46.9 wt%.

Machine-learning-based optimization using Extra Trees and LightGBM models enables accurate prediction of product yields, calorific values, and elemental ratios (e.g., C/H), achieving coefficients of determination (R^2)> 0.95, thereby allowing precise control over product quality and enabling adaptive operation under biomass feedstock variability. From a techno-economic perspective, the system demonstrates strong financial feasibility, with an internal rate of return (IRR) of 23.78%, a return on investment (ROI) of 12.82%, a payback period of 2.93 years, and a net present value (NPV) of approximately Rp50.4 million, based on a modular process design with a capacity of 1 ton feedstock per batch.

By integrating digitalized supply chain management and volume-based compensation mechanisms, the proposed framework enhances energy efficiency and accelerates decarbonization within the agricultural sector, while simultaneously establishing an inclusive business model that positions farmers as integral stakeholders in a low-carbon, intelligent, and globally competitive national energy ecosystem.

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Author Contribution

H.Y.M. contributed to the conceptualization of the study, biomass and process pathway design, community deployment framework, and the drafting of the original manuscript. H.Y.M. also conducted personal field visits to IPST Asari, performed site observations, and led the analysis of community-based deployment strategies and policy implications. M.D.A. was responsible for process engineering analysis, catalyst study and selection for catalytic fast pyrolysis, hydrotreating process design, bio-oil upgrading methodology, data acquisition, and interpretation of the thermochemical conversion results. B.A. contributed to the development and implementation of machine learning surrogate models for benchmarking slurry and biomass pyrolysis, decision-support modeling for operating condition selection, and correlation analysis between optimal process parameters and catalytic fast pyrolysis performance of rice husk. D.E.K. supported the biochemical and upgrading aspects of the study, including literature review, interpretation of hydrotreating reactions, technical validation, and primary administrative responsibilities including manuscript formatting, submission preparation, and overall document refinement. R.A.N. conducted the techno-economic analysis, financial modeling, market-related assessments, and the sensitivity analysis evaluating the robustness of key economic indicators under parameter variations.

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Ethical Review Board Statement

This study does not involve human participants, personal data, or clinical experimentation. The research is based on secondary data from publicly available literature and permitted industrial information. Therefore, ethical review board approval was not required.

Informed Consent Statement

This research does not involve human subjects. The authors confirm that industrial information discussed during site visits and technical interactions was selectively documented and reported only when it was publicly available or explicitly permitted by the respective sources. No confidential, proprietary, or restricted process information, internal data, or industrial roadmaps obtained through discussions or site interactions was recorded, documented, or disclosed in this study.

Data Availability Statement

The datasets used in this study were compiled exclusively from publicly available peer-reviewed publications reporting experimental results on biomass and sludge pyrolysis, as well as from permitted open-source industrial information. The primary source of machine learning training and validation data was derived from the study by Shahbeik, H., Rafiee, S., Shafizadeh, A., Jeddi, D., Jafary, T., Lam, S. S., Pan, J., Tabatabaei, M., and Aghbashlo, M. (2022), entitled "Characterizing sludge pyrolysis by machine learning: Towards sustainable bioenergy production from wastes," published in *Renewable Energy* (Vol. 199, pp. 1078–1092), https://doi.org/10.1016/j.renene.2022.09.022. No confidential, proprietary, or restricted industrial data were used in this study. All additional data supporting the findings of this study are available within the article and its supplementary materials or from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that this research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The industrial entities mentioned in this manuscript did not influence the study design, data analysis, interpretation of results, or the decision to publish, and are referenced solely as benchmarks representing existing state-of-the-art practices.

Declaration of Generative AI Use

During the preparation of this work, the authors used ChatGPT (OpenAI) to refine language quality, improve grammatical accuracy, and enhance the manuscript's clarity and academic tone. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the integrity, originality, and accuracy of the publication.

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Appendix 1. Recommended input–output parameters for pyrolysis

Input											
Solutions	Ultimate analysis					Proximate analysis			Operating conditions		
	Carbon content (wt%)	Hydrogen content (wt%)	Nitrogen content (wt%)	Oxygen content (wt%)	Sulfur content (wt%)	Volatile matter (wt%)	Fixed carbon (wt%)	Ash (wt%)	Temperature (°C)	Heating rate (°C/min)	Reaction time (min)
Top Bio-oil Yield	50.468	5.751	7.349	33.628	0.810	62.967	0.944	12.058	1030.55	58.121	101.750
Top Bio-char Yield	37.277	4.055	9.562	3.815	1.216	47.997	14.755	35.800	227.400	9.738	23.672
Balanced Yield (≈100%)	50.567	6.232	7.368	32.266	1.985	64.708	7.393	13.204	562.612	9.600	101.750
Top Calorific Value	35.239	4.694	1.257	36.691	0.344	71.720	1.414	16.425	307.477	9.201	59.278
Minimum O/C Ratio	36.862	5.212	8.585	15.926	0.996	60.797	7.947	28.505	765.870	10.729	75.608

Output											
Solutions	Bio-oil	Syngas					Bio-char				
	Bio-oil Yield (%)	Syngas Yield (%)	Syngas H_2 (mol%)	Syngas CH_4 (mol%)	Syngas CO_2 (mol%)	Syngas CO (mol%)	Bio-char Yield (%)	Calorific value (MJ/kg)	H/C ratio (-)	H/N ratio (-)	O/C ratio (-)
Top Bio-oil Yield	49.519	29.419	28.240	13.726	28.631	18.362	25.432	11.072	0.378	4.921	0.497
Top Bio-char Yield	13.042	4.586	3.071	4.680	83.476	6.001	78.918	10.336	1.136	10.785	1.131
Balanced Yield (≈100%)	42.121	21.515	28.399	14.629	32.557	15.215	36.362	11.567	0.071	3.917	0.845
Top Calorific Value	31.237	7.825	7.402	8.946	51.065	10.015	56.254	16.416	0.718	10.622	0.401
Minimum O/C Ratio	40.566	25.290	46.719	10.601	21.585	20.585	34.885	11.426	0.528	6.229	0.291