



A Circular-Economy-Driven Interval Type-2 Fuzzy Modelling Approach for Reliable EFB Biomass Power Generation

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Abstract. The transition to green technology and circular agro-industrial systems requires biomass-to-energy conversion processes that remain reliable under uncertain feedstock conditions. Palm oil empty fruit bunches (EFB) are abundant residues in Indonesia and represent a strategic renewable-energy resource, yet their operational use is constrained by stochastic moisture accumulation, biological heterogeneity, and fluctuating calorific value. This paper develops a systems-engineering and Interval Type-2 Fuzzy Logic System (IT2FLS) framework for improving the reliability of EFB-based biomass power generation. The biomass supply chain is formulated as a multi-input single-output closed-loop system that separates controllable logistics decisions from uncontrollable environmental and biological disturbances. The proposed IT2FLS uses a footprint of uncertainty to represent ambiguous membership boundaries and to dampen noise that conventional Type-1 fuzzy models cannot explicitly capture. A full-factorial rule base of 27 rules was evaluated using daily simulation data for one operating year. Results show that IT2FLS reduced root mean square error from 58.14 MWh to 15.82 MWh and mean absolute percentage error from 12.4% to 3.1%, while increasing the coefficient of determination from 0.821 to 0.985. Control-surface analysis further reveals a moisture-driven veto effect, whereby high water content suppresses energy output even when calorific value is high. The framework supports adaptive pretreatment, storage, and scheduling decisions for resilient circular-economy implementation in palm oil agroindustry.

Keywords: Empty fruit bunch · Biomass power generation · Interval Type-2 fuzzy logic · Circular economy · Systems engineering · Waste valorization

1 Introduction

Green technology and circular-economy strategies have become central to agro-industrial transformation, particularly in countries where agricultural processing generates large volumes of organic residues. Indonesia's palm oil industry is a major contributor to national economic activity, but it also produces substantial solid residues, including shells, fibers, and empty fruit bunches (EFB) [1, 2]. The valorization of EFB into renewable energy can reduce waste accumulation, improve resource efficiency, and support national decarbonization targets. These benefits are consistent with the broader waste-management perspective emphasized in agro-industrial innovation, where prevention, cleaner production, life-cycle thinking, and integrated environmental assessment are required to transform residues into value-added resources [3–5].

Despite this potential, EFB-based biomass power generation is operationally difficult because the feedstock is not a standardized industrial fuel. Its moisture content can increase rapidly during rainfall, open-yard storage, and humid transport, while its calorific value varies with agronomic, biological, and seasonal factors [6, 7]. These variations degrade boiler efficiency because high-moisture biomass consumes useful heat for evaporation before combustion can produce net power. As a result, biomass power plants face uncertainty not only in the quantity of feedstock delivered, but also in the energy actually recoverable from each ton of EFB.

From a systems-engineering perspective, the EFB-to-energy pathway is a dynamic system with interacting logistics, environmental disturbances, conversion efficiency, and feedback decisions [8, 9]. Conventional operational approaches, including deterministic calculations, proportional-integral-derivative control, rule-based heuristics, and Type-1 Fuzzy Logic Systems (T1FLS), are often insufficient under high uncertainty. T1FLS can represent linguistic knowledge such as “dry”, “normal”, or “wet”, but it assigns crisp membership grades and therefore assumes that the boundary between states is known precisely. Such an assumption is weak in agro-industrial contexts where sensor noise, biological heterogeneity, and weather-driven variability are unavoidable [10, 11].

Interval Type-2 Fuzzy Logic Systems (IT2FLS) provide a more robust alternative because they allow uncertainty inside the membership functions themselves. Their footprint of uncertainty (FOU) represents a bounded region between upper and lower membership functions, making them suitable for systems where expert knowledge and sensor data are imprecise. Although Type-2 fuzzy control has been explored in energy forecasting and renewable-energy control, its integration with a systems-engineering architecture for EFB biomass supply chains remains underdeveloped [12, 11].

This paper refines and extends an EFB biomass-energy manuscript using the Springer LNCS format. The contributions are threefold. First, it formalizes EFB power generation as a multi-input single-output (MISO) closed-loop system that distinguishes controllable managerial variables from uncontrollable disturbances. Second, it designs an IT2FLS rule base for estimating energy output under stochastic moisture and calorific-value uncertainty. Third, it compares IT2FLS

against a T1FLS benchmark and interprets the results in the context of circular-economy waste valorization and resilient renewable-energy management.

2 Materials and Methods

2.1 Systems-Engineering Architecture

The proposed architecture models biomass-to-energy conversion as a closed-loop system in which operational decisions are continuously updated based on feedstock quality and predicted energy output. The system separates the controllable input vector, denoted by $u(t)$, from the uncontrollable disturbance vector, denoted by $w(t)$. In this study, $u(t)$ represents the scheduled biomass volume, while $w(t)$ contains moisture content and calorific value. Energy output is expressed as

$$y(t) = f(u(t), w(t)) + \epsilon(t), \quad (1)$$

where $y(t)$ is the expected power-generation output, $f(\cdot)$ is the nonlinear conversion relationship, and $\epsilon(t)$ denotes stochastic noise caused by measurement error, weather variability, and unobserved process disturbances.

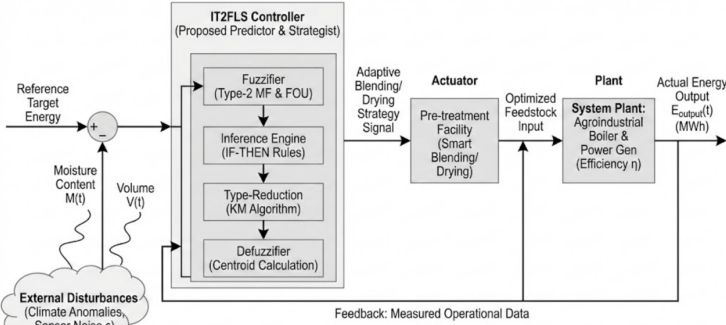


Diagram 1: Integrated IT2FLS-based Adaptive Control Architecture for Biomass-to-Energy Conversion under High Uncertainty

Fig. 1. Integrated IT2FLS-based adaptive-control architecture for EFB biomass-to-energy conversion under high uncertainty.

Figure 1 illustrates the adaptive-control concept. EFB volume is treated as a managerial decision variable, whereas moisture and calorific value are treated as disturbance variables. This distinction is important because it prevents the model from falsely treating weather-driven and biological variability as fully controllable. The controller therefore supports decisions such as scheduling, storage prioritization, and pretreatment intensity rather than assuming perfect feedstock stability.

2.2 Interval Type-2 Fuzzy Logic Formulation

An Interval Type-2 Fuzzy Set (IT2FS), denoted as $\tilde{A}$, is characterized by a membership grade that is itself uncertain within a bounded interval. It can be written as

$$\tilde{A} = \{((x, \mu), 1) \mid x \in X, \mu \in J_x \subseteq [0, 1]\}, \quad (2)$$

where X is the universe of discourse and J_x is the interval of possible membership grades for input x . The FOU is defined as the union of all primary memberships:

$$FOU(\tilde{A}) = \bigcup_{x \in X} J_x. \quad (3)$$

This FOU is bounded by an upper membership function and a lower membership function, allowing the model to represent ambiguous linguistic boundaries such as the transition between “normal” and “wet” EFB.

The inference mechanism uses Mamdani reasoning. For rule r , the firing strength is represented by an interval $[\underline{f}^r, \bar{f}^r]$. Type reduction is performed using the Karnik–Mendel procedure to obtain a centroid interval $[y_l, y_r]$, and the crisp output is calculated as

$$y = \frac{y_l + y_r}{2}. \quad (4)$$

This output represents the predicted energy production in MWh.

2.3 Rule-Base Design and Experimental Setup

The model uses three inputs: biomass volume, moisture content, and calorific value. Each input has three linguistic states. Biomass volume is described as low, medium, and high; moisture content as dry, normal, and wet; and calorific value as low, medium, and high. With three inputs and three states per input, the full-factorial design contains $3^3 = 27$ fuzzy rules. The output variable, energy production, is represented as low, medium, or high. Table 1 introduces representative rules from the complete rule base to show how the linguistic input combinations are translated into energy-output classes. The selected rules cover low, medium, and high operating conditions and also illustrate how wet biomass can limit the output class even when biomass volume or calorific value is favourable.

As shown in Table 1, the rule base embeds both additive and restrictive operating logic. Dry biomass with high volume and high calorific value supports a high-output classification, whereas wet biomass shifts the conclusion downward because part of the available heat is consumed by moisture evaporation. Rule 27 is especially important because it demonstrates the conservative behaviour required for biomass boilers: even when biomass volume and calorific value are high, wet feedstock is assigned only a medium energy-output class. This structure allows the IT2FLS to represent expert operational knowledge while preserving uncertainty in the membership boundaries.

Table 1. Representative fuzzy rules used in the IT2FLS model.

Rule	IF–THEN statement
1	IF biomass volume is low AND moisture is dry AND calorific value is low THEN energy output is low.
3	IF biomass volume is low AND moisture is dry AND calorific value is high THEN energy output is medium.
14	IF biomass volume is medium AND moisture is normal AND calorific value is medium THEN energy output is medium.
21	IF biomass volume is high AND moisture is dry AND calorific value is high THEN energy output is high.
25	IF biomass volume is high AND moisture is wet AND calorific value is low THEN energy output is low.
27	IF biomass volume is high AND moisture is wet AND calorific value is high THEN energy output is medium.

Daily operating data for 365 simulated days were used to compare IT2FLS with a T1FLS benchmark. The benchmark used the same input variables and rule logic but relied on crisp Type-1 membership functions. Model performance was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and coefficient of determination (R^2). The comparative design is intentionally conservative: the improvement can therefore be attributed primarily to the treatment of uncertainty rather than to different input variables.

3 Results

3.1 Control-Surface Behaviour

The simulation surfaces show that energy output is nonlinear with respect to both biomass volume and moisture content. Figure 2 indicates that under dry conditions, increasing biomass volume produces an approximately monotonic increase in energy output. However, when moisture exceeds the wet-region threshold, the surface slope becomes sharply negative. This pattern is consistent with the physical behavior of biomass boilers, because latent heat is consumed for moisture evaporation before useful heat is available for power generation.

Figure 3 shows the interaction between calorific value and moisture. A critical “veto effect” appears: high calorific value does not guarantee high energy output when moisture is excessive. In operational terms, this means that procurement strategies based only on nominal heating value are biased and potentially misleading. Moisture control, covered storage, and pretreatment become priority interventions because they preserve the usable fraction of the biomass energy content.

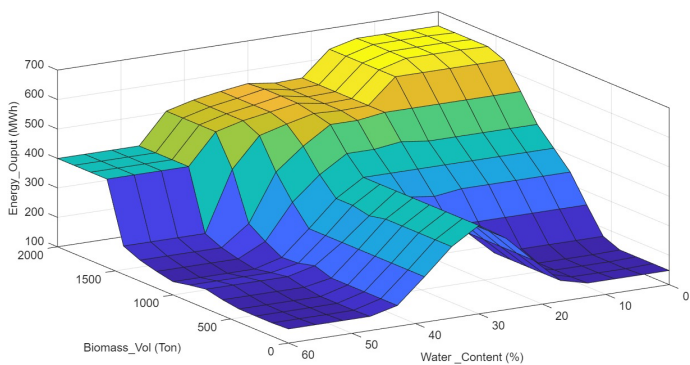


Fig. 2. Simulated control surface describing the effect of biomass volume and moisture content on energy output.

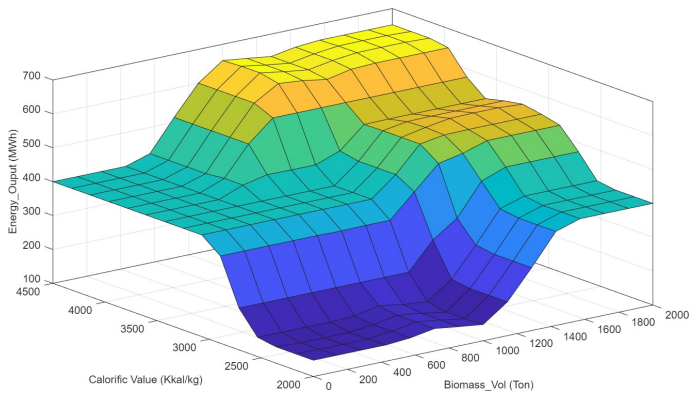


Fig. 3. Simulated interaction between calorific value and moisture content, showing the moisture-driven veto effect.

3.2 Type-1 Fuzzy Benchmark

The T1FLS benchmark performs acceptably in low-noise periods but becomes unstable during high-variance moisture conditions. Figure 4 shows that the Type-1 prediction curve reacts aggressively to noisy input variation. This produces overshoot and undershoot during simulated rainy-season periods, indicating that the model follows short-term noise rather than the underlying energy-output trend.

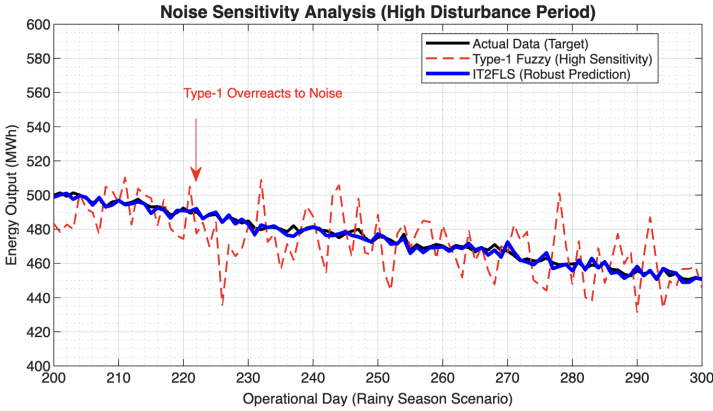


Fig. 4. Type-1 fuzzy benchmark during a high-disturbance period. The benchmark tends to overreact to noisy input variation.

The T1FLS achieved an overall RMSE of 58.14 MWh and MAPE of 12.4%. During stable dry-season conditions its RMSE was 22.45 MWh, but during unstable rainy-season conditions RMSE increased to 89.30 MWh. This confirms that Type-1 inference is vulnerable when membership boundaries are uncertain.

3.3 Comparative Performance of IT2FLS

The proposed IT2FLS substantially improves prediction accuracy and stability. Table 2 compares the benchmark and proposed model. IT2FLS reduced MAE from 42.5 MWh to 12.3 MWh, RMSE from 58.14 MWh to 15.82 MWh, and MAPE from 12.4% to 3.1%. The R^2 score increased from 0.821 to 0.985, indicating that the IT2FLS explains nearly all observed variation in the simulated output.

The improvement is especially relevant for biomass power operation because large errors can produce incorrect feedstock scheduling and supply–demand mismatch. The FOU acts as a damping mechanism by preventing the inference system from treating every short-term fluctuation as a meaningful change in feedstock quality.

Table 2. Comparative performance of Type-1 fuzzy logic and IT2FLS.

Metric	Type-1 fuzzy benchmark	IT2FLS proposed	Improvement
MAE (MWh)	42.5	12.3	71.0%
RMSE (MWh)	58.14	15.82	72.8%
MAPE (%)	12.4	3.1	75.0%
R^2	0.821	0.985	—

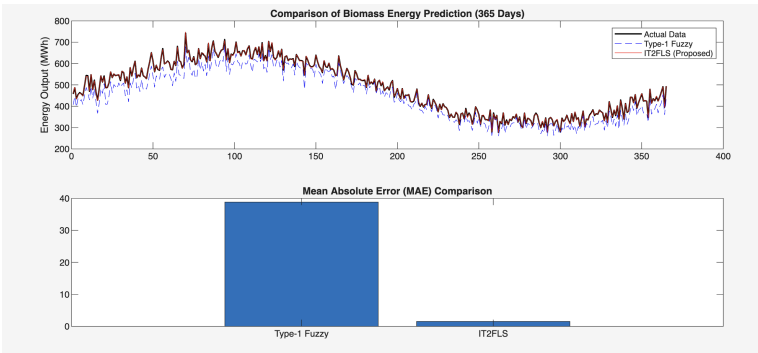


Fig. 5. Comparative prediction behavior of the proposed IT2FLS and the Type-1 fuzzy benchmark.

4 Discussion

The results confirm that explicit uncertainty modelling is essential for resilient EFB biomass power generation. The original manuscript correctly identified moisture and calorific value as dominant uncertainty sources, but the refined interpretation clarifies that they should not be treated as equivalent decision variables. Biomass volume is directly schedulable, whereas moisture and calorific value are only partially controllable through storage design, drying, blending, and procurement selection. This correction avoids managerial bias by distinguishing what plant operators can decide from what they can only mitigate.

The observed moisture veto effect is the most important operational insight. High calorific value is often interpreted as evidence of superior fuel quality, yet the simulation shows that excessive moisture can suppress energy output even under high heating-value conditions. This supports a shift from volume-based biomass scheduling to quality-aware scheduling. In practice, plant managers should prioritize covered storage, pre-drying, rapid transport after harvest, and blending strategies that stabilize boiler input quality.

The framework also connects the biomass-energy model to broader agro-industrial waste-management innovation. The embedded presentation emphasized that agroindustry generates liquid waste, emissions, and solid residues, and that future development must be aligned with environmental protection, efficient resource use, and life-cycle thinking. EFB energy conversion fits within

this hierarchy because it reduces solid waste while generating renewable energy. However, conversion efficiency determines whether the process genuinely supports circular economy goals. Poorly controlled high-moisture combustion can reduce energy gains and increase operational inefficiency, so intelligent control is not merely a technical addition but a sustainability requirement.

Several limitations remain. First, the evaluation relies on simulated daily data rather than full-scale plant measurements. Second, the membership functions and FOU parameters were expert-designed; future work should optimize them using genetic algorithms, particle swarm optimization, or adaptive neuro-fuzzy learning. Third, the study focuses on EFB combustion for power generation and does not compare alternative EFB valorization routes such as biochar, bio-oil, activated carbon, or cellulose nanocrystals, all of which were identified in the waste-technology material as relevant circular-economy pathways [13–15]. Future research should therefore combine IT2FLS control with techno-economic and life-cycle assessment to compare competing waste-valorization options.

5 Conclusion

This study presents a refined LNCS-ready manuscript for an IT2FLS-based decision framework to improve the reliability of EFB biomass power generation. The framework integrates systems-engineering logic with Interval Type-2 fuzzy modelling to distinguish controllable biomass scheduling from uncontrollable moisture and calorific-value disturbances. Compared with a Type-1 fuzzy benchmark, IT2FLS reduced RMSE by 72.8%, reduced MAPE to 3.1%, and increased R^2 to 0.985. The control-surface analysis reveals that moisture creates a veto effect over calorific value, making adaptive pretreatment and storage management central to reliable renewable-energy production. The proposed approach strengthens circular-economy implementation in palm oil agroindustry by converting solid waste into energy while improving operational resilience under uncertainty.

Disclosure of Interests The author has no competing interests to declare that are relevant to the content of this article.

References

1. Maitah, M., Prochazka, P., Pachmann, A., Sredl, K., Rezbova, H.: Economics of palm oil empty fruit bunches bio briquettes in Indonesia. *International Journal of Energy Economics and Policy* **6**(1), 35–38 (2016)
2. Januari, A.D., Agustina, H.: Palm oil empty fruit bunches and the implementation of zero waste and renewable energy technologies. *IOP Conference Series: Earth and Environmental Science* **1034**, 012004 (2022). <https://doi.org/10.1088/1755-1315/1034/1/012004>
3. Indrasti, N.S., Fauzi, A.M.: *Produksi Bersih*. IPB Press, Bogor (2009)
4. Azzahro, H.U., Indrasti, N.S., Ismayana, A.: Penerapan produksi bersih pada industri kelapa sawit di PT YZ. *Jurnal Teknologi Industri Pertanian* **32**, 1–11 (2022). <https://doi.org/10.24961/j.tek.ind.pert.2022.32.1.1>

5. Bantacut, T., Suprihatin, Maulana, P.: Application of cleaner production in palm oil mill: A case study at PT Perkebunan Nusantara IV Adolina Business Unit Perbaungan North Sumatera Indonesia. *Chemical and Materials Research* **6**(12), 178–187 (2014)
6. Faizal, H.M., Jusoh, M.A.M., Rahman, M.R.A., Syahrullail, S., Latiff, Z.A.: Torrefaction of palm biomass briquettes at different temperature. *Jurnal Teknologi* **78**(9–2), 61–67 (2016). <https://doi.org/10.11113/JT.V78.9656>
7. Sukiran, M.A., Abnisa, F., Syafie, S., Wan Daud, W.M.A., Nasrin, A.B., Abdul Aziz, A., Loh, S.K.: Experimental and modelling study of the torrefaction of empty fruit bunches as a potential fuel for palm oil mill boilers. *Biomass and Bioenergy* **136**, 105530 (2020). <https://doi.org/10.1016/J.BIOMBIOE.2020.105530>
8. Khoddami, S., Mafakheri, F., Zeng, Y.: A system dynamics approach to comparative analysis of biomass supply chain coordination strategies. *Energies* **14**(10), 2808 (2021). <https://doi.org/10.3390/EN14102808>
9. Soren, A., Shastri, Y.: Resilient design of biomass to energy system considering uncertainty in biomass supply. *Computers & Chemical Engineering* **131**, 106593 (2019). <https://doi.org/10.1016/J.COMPCHENG.2019.106593>
10. Dharma, A., Robandi, I., Purnomo, M.H.: Application of Interval Type-2 Fuzzy Logic System in short term load forecasting on special days. *IPTEK The Journal for Technology and Science* **22**(2) (2011). <https://doi.org/10.12962/J20882033.V22I2.65>
11. Hemeyine, A.V., Abbou, A., Bakouri, A., Mokhlis, M., El Moustapha, S.M.O.M.: A robust Interval Type-2 fuzzy logic controller for variable speed wind turbines based on a doubly fed induction generator. *Inventions* **6**(2), 21 (2021). <https://doi.org/10.3390/INVENTIONS6020021>
12. Bukhtoyarov, V., Tynchenko, V., Bashmur, K., Kolenchukov, O., Kukartsev, V., Malashin, I.: Fuzzy neural network applications in biomass gasification and pyrolysis for biofuel production: A review. *Energies* **18**(1), 16 (2025). <https://doi.org/10.3390/EN18010016>
13. Raju, Tambunan, A.H., Setiawan, R.P.A.: Analisis energi proses pirolisis limbah kelapa sawit. Master's thesis, IPB University, Bogor (2016)
14. Abdullah, N., Sulaiman, F.: The properties of the washed empty fruit bunches of oil palm. *Journal of Physical Science* **24**(2), 117–137 (2013)
15. Sarfat, M.S., Setyaningsih, D., Fahma, F., Indrasti, N.S., Sudirman: Environmental impact assessment in the synthesis of antistatic bionanocomposite compared with the synthesis of polypropylene. *International Journal on Advanced Science, Engineering and Information Technology* **13**(1), 117–123 (2023). <https://doi.org/10.18517/ijaseit.13.1.16751>

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