

Application of Machine Learning Models in Optimizing the Gasification Process of Agricultural By-Products in the Mekong Delta of Vietnam

Thi-Huyen-Trang Vu¹, Mai-Phuong Nguyen², Thi-Mai-Trang Nguyen², Tuan-Tung-Duong Vu³, Ngoc-Ly Tran², Quoc-Dat Le³

¹Faculty of Mathematical Economics, Thuongmai University, Hanoi, Vietnam; email: trang.vth@tmu.edu.vn

²K60V2, Faculty of Mathematical Economics, Thuongmai University, Hanoi, Vietnam

³K60V1, Faculty of Mathematical Economics, Thuongmai University, Hanoi, Vietnam

Abstract— Faced with the challenges of energy security and climate change, this study proposes a solution applying advanced Machine Learning algorithms—including Random Forest, Support Vector Machine, and XGBoost—to simulate and optimize the gasification process of agricultural by-products (straw, rice husk) in the Mekong Delta, Vietnam. From this technological solution, the study addresses the core problem of determining the optimal operating parameters to maximize gas production and calorific value while minimizing impurities in a complex nonlinear reaction system. In terms of macro-level impact, the biomass energy density analysis shows that the Mekong Delta has enormous potential for energy conversion and greenhouse gas emission reduction. An Giang leads the region with a reduction of approximately 6–6.3 million tons of CO₂/year, followed by Dong Thap and Long An with 4–5 million tons of CO₂ each year. The research not only provides an AI model to support decision-making as an alternative to costly experiments, but also contributes a crucial scientific basis for strategic planning of renewable energy development and the circular economy in Vietnam.

Keywords— Biomass gasification, Machine learning, Multi - objective optimization, Agricultural by-products, Mekong Delta.

I. INTRODUCTION

In the context of Vietnam's commitment to achieving net-zero emissions by 2050 at COP26, utilizing agricultural by-products for renewable energy development is an urgent requirement. The Mekong Delta is the largest rice-producing region in the country, generating the highest proportion of rice straw and husks in total agricultural by-products annually. Compared to other by-products such as sugarcane bagasse or coconut shells, rice by-products are chosen because of their superior yield, concentrated distribution, stable seasonal supply, and the widespread practice of burning them in the fields, which causes greenhouse gas emissions and resource waste; therefore, the potential for environmental and economic impact when exploited is significantly greater. However, the gasification process of rice straw and husks is strongly affected by high humidity and high ash and silica content, making operational optimization complex. Therefore, applying machine learning (ML) to model and optimize multiple objectives (performance – air quality – emissions – cost) is a necessary approach, suitable for the specific biomass conditions of the Mekong Delta and aligned with the green energy transition recommended by the International Energy Agency (IEA).

II. THEORETICAL BASIC AND LITERATURE REVIEW

2.1. Theoretical basic

The gasification process comprises four main stages: drying, pyrolysis, combustion, and reduction – producing a synthesis gas mixture (CO, H₂). Gasification reactors are divided into four main groups: Updraft gasifiers, downdraft gasifier, fluidized bed gasifiers, and cyclone gasifiers; each type has its own characteristics in terms of heat distribution,

combustion efficiency, and emission levels. Differences in reactor configuration significantly alter syngas quality and operational stability. Gasification efficiency is influenced by feedstock including elemental composition (C, H, O, N), physical characteristics (moisture content, ash content), and operating conditions such as temperature, equivalence ratio (ER), steam-to-biomass (S/B) ratio. In this process, temperature is the most influential factor affecting reaction kinetics and gas composition; ER determines the degree of oxidation; and S/B governs the H₂/CO ratio. Typical by agricultural residues such as rice husks and straw have high ash, silica, and alkali metal content, increasing the risk of slag formation and affecting efficiency, requiring optimization of parameters suitable for each type of feedstock.

Given the complex nonlinearity of the system, traditional thermodynamic models still rely heavily on simplifying assumptions. Therefore, machine learning is considered a promising approach due to its ability to directly learn input-output relationships from data. Algorithms such as Random Forest, XGBoost, and SVM enable rapid prediction of gasification performance, syngas composition, and emissions, while also supporting multi-objective optimization under limited and heterogeneous experimental datasets.

2.2. Literature review

Research on energy systems and biomass thermochemical processes is witnessing a strong shift from traditional thermodynamic models to data-driven approaches. Gao et al. (2023) demonstrated that syngas quality is influenced by multiple factors such as feedstock characteristics and reactor configuration, but traditional studies often only evaluated these factors individually. In the context of gasification systems

containing extremely complex nonlinear interactions, artificial intelligence (AI) and machine learning are increasingly being applied as comprehensive optimization tools to overcome the limitations of traditional physical equations (Zhang et al., 2024).

Core machine learning algorithms have been developed and proven over decades. Random Forest, proposed by Breiman (2001), uses bootstrap sampling and random feature selection to minimize overfitting, proving particularly effective with noisy experimental engineering data. Meanwhile, the Support Vector Machine (SVM) algorithm developed by Cortes and Vapnik (1995) demonstrates excellent generalization capabilities in multidimensional spaces, even when the training sample size is limited (Nakayama et al., 2017). Most recently, Extreme Gradient Boosting (XGBoost), introduced by Chen and Guestrin (2016) – a direct successor to Friedman's Gradient Boosting (2001) – has made breakthroughs in accuracy by directly integrating L1 and L2 regularization terms and using second-order derivative information to optimize the loss function.

Within the domain of biomass gasification, these foundational algorithms have yielded many significant experimental results. Ascher et al. (2023) found that models based on Gradient Boosting (such as GBDT) can achieve excellent predictive performance ($R^2 \approx 0.90$), while identifying biomass particle size and steam/biomass ratio (S/B) as the strongest influencing factors on gas yield. Following a similar approach, the study by Shafizadeh et al. (2023) demonstrated that the decision tree-based model outperformed Support Vector Regression with an R^2 above 0.88, highlighting the dominant role of ash content and reactor temperature in determining the process the output. Extending to the control problem, Gil et al. (2023) successfully applied the Gaussian Process Regression model to locate the ideal gasification coordinates for each specific biomass type.

Although machine learning models have demonstrated enormous potential, a comprehensive review of the literature reveals a significant research gap regarding specificity and generalizability. Much of the current work is limited to the use of a single feedstock or a fixed reactor configuration, lacking multivariate integration. This deficiency is particularly evident when compared to the energy problem in the Mekong Delta – a region possessing vast resources of straw and rice husk by-products but exhibiting highly variable physicochemical properties. To date, there has been a complete absence of a specialized optimization model that simultaneously integrates the diversity of reactor configurations and the specific biomass characteristics of this region. To break through limitations, this research was conducted to fill the gap by integrating advanced algorithms (RF, XGBoost, SVM) on a diverse empirical database, thereby establishing ideal operating scenarios that directly serve the sustainable energy development strategy in the Mekong Delta.

III. RESEARCH DATA AND METHODOLOGY

3.1. Research data

To develop a machine learning model system, the study built a database of 103 observations extracted from 20

experimental works and a reputable overview of the gasification of rice by-products. The data collected covers many levels, ranging from industrial scale through a fluidized bed furnace system of 20 tons/day (Park et al., 2021) to laboratory scale with pyrolysis-gasification optimization models (Kusworo et al., 2023), combined with physicochemical parameters systematized from in-depth reports (Dafiqurrohman et al., 2023). The diversity of furnace technology, temperature range, and equivalence ratio (ER) from these sources helps the dataset to be well distributed, truly reflecting the complexity of the system in practice. This is a solid foundation for building a characteristic space with 14 input and 5 output borders, which are detailed in Table 1 below.

TABLE 1: Statistics describing the variables of the model

Table of Contents	Minimum	Maximum	Medium	SD
C (%)	34.6	51.67	40.831	3.957
H (%)	4.23	6.21	5.185	0.411
N (%)	0.0	1.58	0.53	0.469
O (%)	30.7	52.9	38.835	5.299
S (%)	0.0	0.2	0.082	0.056
Ash (%)	5.34	23.9	14.981	4.15
Volatile Matter (%)	55.4	76.28	65.65	4.077
Fixed carbon (%)	13.0	19.8	15.431	1.856
Temperature (°C)	500.0	950.0	767.398	68.781
Equivalence Ratio (ER)	0.0	0.37	0.232	0.095
Steam-to-Biomass Ratio (S/B)	0.0	1.5	0.044	0.214
Size (mm)	0.094	35.4	5.952	4.641
Humidity (%)	3.58	19.03	10.348	2.751
Feeding Speed (kg/h)	0.04	833.0	67.636	161.528
H ₂ (%)	1.1	39.17	7.529	6.608
CO (%)	1.84	35.34	13.734	7.064
CH ₄ (%)	0.17	18.5	6.268	5.228
Gas Yield (kg/m ³)	0.85	3.11	1.974	0.393
Tar (mg/Nm ³)	0.95	10000.0	1885.879	3462.009

Source: Author's calculations from Google Colab

However, the variables have significant differences in scale and units (% , °C, kg/h, mm), as shown by the standard deviation and the wide range of variable values in Table 1. If not handled appropriately, this discrepancy can skew the target function optimization process and reduce the model's ability to converge. Therefore, all data is normalized before training to bring variables to the same value domain, reduce the influence of large-margin variables, and increase digital stability during optimization. This approach ensures that the model effectively exploits the nonlinear relationship between raw material characteristics, operating conditions and syngas quality.

3.2. Research methods

To address nonlinearity and map the complex relationship between biomass characteristics, operating conditions and syngas quality, the study implements and matches three advanced machine learning algorithms:

Random Forest (RF) Model: Proposed by Breiman (2001), RF is an integrated learning method based on bagging techniques. This algorithm builds a "forest" of multiple independent decision trees on random subsets. According to the analysis of Liaw and Wiener (2002), the core strength of RF is the random selection of characteristic sets at each split node, which helps to reduce the correlation between trees, thereby

minimizing variance and minimizing overfitting for noisy experimental data.

Extreme Gradient Boosting (XGBoost) Model: Developed by Chen and Guestrin (2016) based on Friedman's (2001) Gradient Boosting platform, XGBoost works on a sequential learning mechanism. Unlike RF, each next-generation decision tree in XGBoost is trained to correct the residue (error) of the previous combination of trees through loss function optimization. The breakthrough of this algorithm is the direct integration of the regularized elements (L1, L2) into the target function and the use of quadratic derivatives, which allows the model to control complexity well, converge quickly, and excellently dissect multidimensional interactions in the thermodynamic process.

Support Vector Machine (SVM) Model: Introduced by Cortes and Vapnik (1995), SVM is set up as Support Vector Regression (SVR) for continuous forecasting. Unlike tree-like models, this algorithm searches for global solutions through the principle of maximizing the margin of separation. For nonlinear data systems such as biomass gasification, SVRs use a multiplication function technique (most commonly Radial Basis Function - RBF) to map data to a characteristic space with a higher number of dimensions, allowing for flexible regression surface construction while maintaining stability and generalization capacity even when sample size is limited.

IV. RESULTS AND DISCUSSION

4.1. Machine Learning Model Selection Results

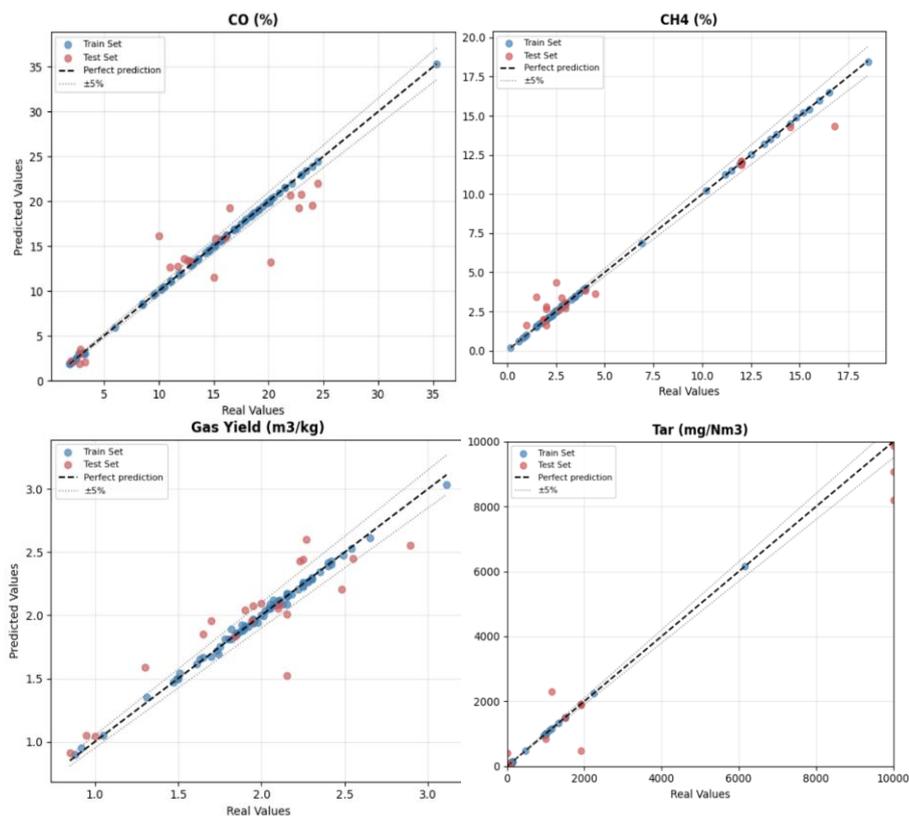


Figure 1. Correlation between actual and predicted values of the XGBoost model.

Source: Calculations by the authors from Google Colab

The study evaluated three learning algorithms including Support Vector Machine, Random Forest, and Extreme Gradient Boosting (XGBoost) for predicting input parameters (biomass characteristics, operating conditions) to predict gasification performance indicators, gas yield, and gas stream composition (including H₂, CO, CH₄, and Tar). The results of the file comparison test can be detailed in Table 2.

TABLE 2. Performance comparison of various machine learning models.

Evaluation Metrics	SVM	Random Forest	XGBoost
Overall Average	0.4899	0.7362	0.7523
Weighted R ²	-0.4276	0.9053	0.9212
Average RMSE	960.8659	249.2106	227.1282
Average MAE	558.3187	147.1006	128.1958
R ² - H ₂ (%)	0.3734	0.3890	0.6050
R ² - CO (%)	0.8600	0.8153	0.8088
R ² - CH ₄ (%)	0.7882	0.9035	0.9546
R ² - Gas Yield	0.8555	0.6677	0.4719
R ² - Tar	-0.4276	0.9053	0.9212

Source: Author's calculation via Google Colab

The results show a clear differentiation in the nonlinear data processing capabilities of the machine learning models. Although the SVM model demonstrated high predictive accuracy for gas yield with an R² of 0.8555, it failed to capture the complex stochastic nature of tar formation with a negative R² (-0.4276). The RF algorithm significantly improved tar prediction with an R² of 0.9053 but still had limitations in capturing fluctuation in H₂ concentration with an R² of only 0.3890.

Above all, XGBoost, with its continuous error correction learning mechanism, optimally suppressed data perturbations, achieving the highest weighted composite coefficient of determination of 0.9212. This algorithm not only maintains high accuracy for major combustible gases such CH₄ as and CO with R² values of 0.9546 and 0.8088 respectively, but also successfully isolates the H₂ bottleneck with R² = 0.6050 while excellently controlling Tar (R²= 0.9212). With an RMSE of 227.1282, the lowest among all three models, XGBoost was selected as the core model for SHAP analysis and system optimization.

To visually illustrate the generalization capabilities of the chosen algorithm, Figure 1 shows the correlation between the actual and predicted values of the XGBoost model on the independent test set.

It can be observed that the predicted data points closely follow the ideal diagonal (dashed line y = x), with most observations falling within the allowable error range (±5%). In particular, for the two target variables with the largest dispersion, Tar, XGBoost demonstrates extremely impressive trend tracking capabilities, thereby confirming the reliability of this machine learning algorithm before application to establishing biomass plant operation scenarios.

4.2. Explaining the thermodynamic mechanism code through SHAP diagrams.

To overcome the "blackbox" barrier of XGBoost, the SHAP method was applied to quantify the contribution of each input variable to the forecast result, thereby clarifying the core physicochemical laws.

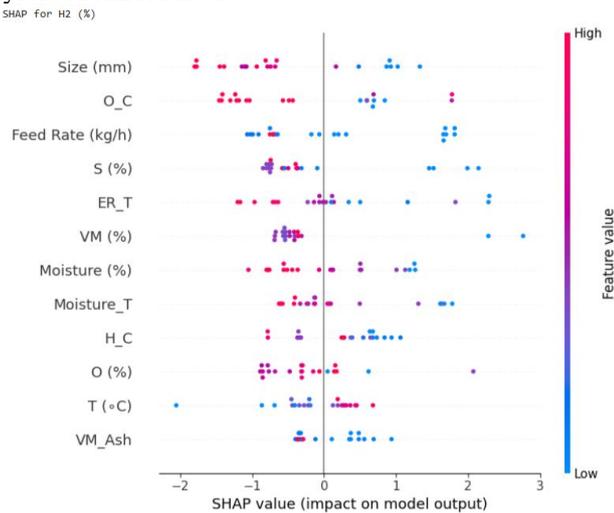


Figure 2a. SHAP plot of H₂

SHAP analysis reveals the governing mechanisms of the two most unpredictable factors in biomass gasification: H₂ and Tar.

Combustion gas (H₂) generation mechanism: Small biomass particle size is the most powerful driver of production. Grinding the biomass increases the surface area, optimizing heat transfer to the particle core, thereby promoting deep thermal decomposition and reforming reactions. Conversely, high feed

rates reduce residence time, preventing H₂ generation reactions from completing.

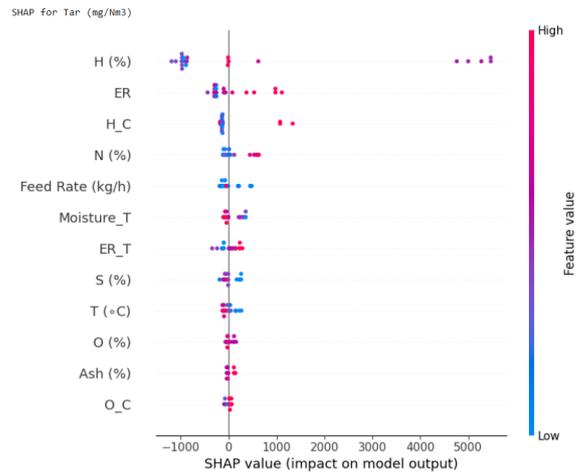


Figure 2b. SHAP plot of Tar

Source: Calculations by the authors from Google Colab

The mechanism of tar formation and decomposition: SHAP analysis indicates that the intrinsic hydrogen content (H%) in the feedstock is the primary factor governing tar formation through the condensation of aromatic rings. However, increasing the equivalence ratio (ER) and temperature plays an effective role in suppressing tar formation. High temperatures provide sufficient thermal energy to cleave the chemical bonds of tar compounds, while the oxygen supplied at higher ER participates in partial oxidation reactions, promoting in-situ tar oxidation within the combustion chamber.

4.3. Multi-objective optimization and determination of operating conditions

From the SHAP analysis results, the study noted a significant trade-off: Operating conditions such as high temperature and elevated ER promote tar decomposition and maximize gas yield, but also act as drivers of CH₄ degradation.

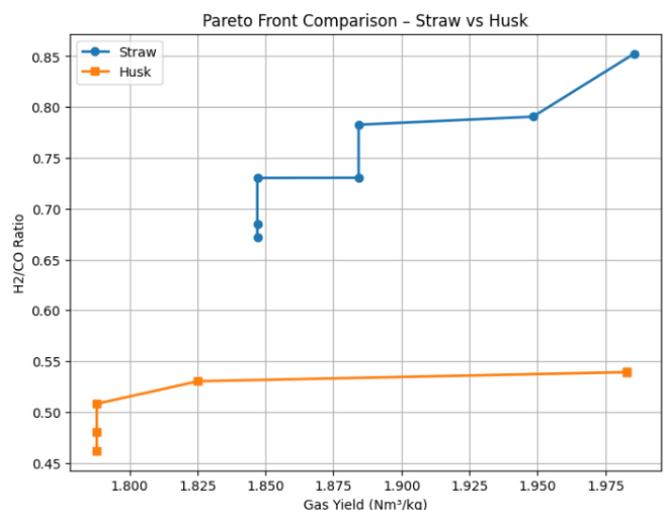


Figure 3. Pareto front diagram of straw and chaff

Source: Calculations by the authors from Google Colab

To address this optimization challenge, a multi-objective optimization algorithm was implemented to establish a Pareto frontier, aiming to identify the optimal operational setpoints for rice straw and rice husk.

Based on the Pareto frontier, three strategic operational scenarios - maximizing productivity, minimizing tar formation, and the equilibrium state - are derived in Table 3. Among these, the equilibrium scenario represents the optimal operating point, effectively harmonizing economic viability with emission abatement costs.

TABLE 3. Selection of optimal operating conditions

	Straw – Max Yield	Straw – Min Tar	Straw – Balanced	Husk – Max Yield	Husk – Min Tar	Husk – Balanced
T (°C)	825	750	850	825	750	825
ER	0.27	0.25	0.29	0.27	0.25	0.29
Moisture (%)	11	11	11	11	11	11
Size (mm)	10	10	10	2	2	8
Feed Rate (kg/h)	5	10	10	5	5	10
Gas Yield (m ³ /kg)	2.043	1.983	2.043	2.03	1.98	2.03
Tar_ph ys	245.209	122.919	130.284	137.673	15	15

Source: Calculations by the authors from Google Colab

For rice straw, optimal operating conditions is established at a temperature of 850°C and ER=0.29. High thermal intensity and optimized equivalence ratio create a dual effect: maintaining the Gas Yield at its Peak specific gas yield of 2.043 m³/kg while simultaneously reducing the Tar content to a safe level of 130.284 mg/Nm³.

For rice husk, the optimal configuration of 825°C along with ER = 0.29 and a particle size of 8 mm highlights the superior gasification characteristics of this feedstock. At this steady-state equilibrium, the gas yield reached 2.03 m³/kg while the tar content was negligible, remaining at only 15 mg/Nm³.

This set of optimized operational setpoints serves as input specifications for assessing commercial electricity potential and quantifying CO₂ reduction capabilities across the Mekong Delta economic region in the following section.

4.4 Assessing the potential and application of the model.

In the Mekong Delta, agricultural profile is characterized by intensive cultivation of high-yield rice varieties. Continuous crop rotation of 2-3 crops per year not only ensures a huge and consistent supply of by-products but also results in highly homogenous physicochemical properties of the biomass feedstock of the biomass. Specifically, straw and husks from these rice varieties are characterized by a porous structure, a very high volatile matter content (58.3% - 68.6%), and extremely low sulfur content (< 0.1%). These characteristics make them ideal, easily combustible, and environmentally friendly input materials for industrial-scale gasification systems.

Based on that context, the study applied the XGBoost algorithm and Pareto optimization to establish a balanced scenario, determining the optimal specific gas yield 2.043 m³/kg for rice straw and 2.030 m³/kg for rice husk. By integrating these operational coordinates into the actual agricultural production dataset for the period 2020-2024 in the Mekong Delta, the study drew two key conclusions:

Breakthrough in energy security: Rice straw shows overwhelming potential, capable of providing 21,500 to over 23,000 GWh/year, equivalent to the output of many large-scale coal-fired power plants. At the same time, rice husk contributes an extremely stable distributed electricity source at 3.000 – 3.500 GWh/year.

Dual emission mitigation impact: The biomass conversion process creates a mechanism of dual action: (1) producing clean electricity to directly replace coal/gas power and (2) eliminating harmful CH₄ and soot emissions from open burning of straw in the fields. Thanks to this, the entire Mekong Delta region has the potential to reduce approximately 30 million tons of CO_{2eq} per year.

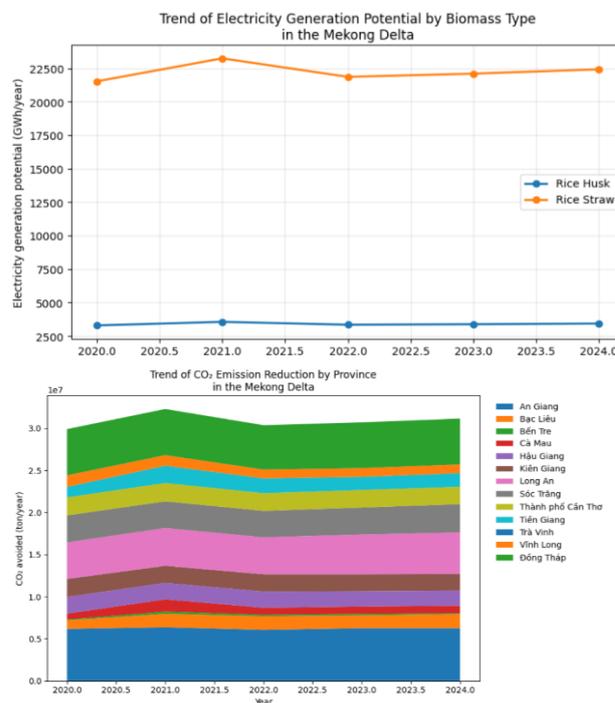


Figure 4. Potential energy and CH₄ reduction trends in the Mekong Delta region during the period 2020-2024

Source: Calculations by the authors from Google Colab

V. CONCLUSION

This study implemented a machine learning framework to optimize gasification parameters for agricultural residues. The XGBoost model exhibited superior predictive performance (Weighted R² = 0.9212), effectively addressing tar formation challenges. Based on the Pareto frontier, an 'Equilibrium Scenario' was identified: straw yielded 2.043 m³/kg and controlled Tar at 130 mg/Nm³ (at 850°C, ER = 0.29); rice husk yielded 2.03 m³/kg and approached 0 Tar (at 825°C, ER = 0.29). When applying these parameters to the Mekong Delta, the

estimated power generation potential of the entire region reaches over 26,000 GWh/year, while contributing to a reduction of approximately 30 million tons of CO_{2eq}/year through the replacement of fossil fuels and the cessation of open burning.

To realize this potential, the study proposes three core intervention groups. Firstly, regarding spatial planning: Applying a centralized model combining Biomass pelletization for rice straw in the core cluster (An Giang, Kien Giang, Dong Thap), and a Decentralized grid model for rice husk directly at rice mills. Secondly, regarding technology: Integrating a "Digital Twin" to automatically maintain the system at the optimal coordinates (825-850°C, ER = 0.29), helping to In-situ tar thermal cracking in the combustion chamber and reduce capex for the gas filtration system. Thirdly, regarding climate finance: Support the recovery of fly ash for organic fertilizer production, while promoting pioneering localities to create MRV profiles to monetize 30 million tons of CO_{2eq} on the carbon credit market, aiming for Net Zero 2050.

However, this study still has certain limitations in terms of data and scope of evaluation. The reliance on secondary empirical data sources may create marginal biases when applied to rice varieties with unique soil characteristics in the Mekong Delta. Furthermore, the current model only addresses the optimization problem from a thermodynamic engineering perspective, not encompassing the risks of supply chain logistics fluctuations and investment costs. To overcome these barriers, the next research direction should focus on deploying pilot-scale gasification systems locally to collect primary data, thereby refining and improving the accuracy of the AI algorithm. Simultaneously, integrating Technical-Economic Analysis (TEA) and Life Cycle Assessment (LCA) methods into the model will be a necessary step to comprehensively measure commercial viability before deploying industrial-scale biomass power projects.

REFERENCES

- [1] Ascher, S., Wang, X., Watson, I., Sloan, W., & You, S. (2023). *Interpretable machine learning to model biomass and waste gasification*. *Bioresource Technology*, 370, 128682. <https://doi.org/10.1016/j.biortech.2022.128062>
- [2] Breiman, L. (2001). *Random forests*. *Machine Learning*, 45(1), 5–32. <https://doi.org/10.1023/A:1010933404324>
- [3] Chen, T., & Guestrin, C. (2016). *XGBoost: A scalable tree boosting system*. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD '16)* (pp. 785–794). ACM. <https://doi.org/10.1145/2939672.2939785>
- [4] Cortes, C., & Vapnik, V. (1995). *Support-vector networks*. *Machine Learning*, 20(3), 273–297. <https://doi.org/10.1007/BF00994018>
- [5] Dafiqurrohman, H., Safitri, K. A., Setyawan, M. I. B., Surjosatyo, A., & Aziz, M. (2022). *Gasification of rice wastes toward green and sustainable energy production: a review*. *Renewable and Sustainable Energy Reviews*. <https://clik.now/1NyW>
- [6] Friedman, J. H. (2001). *Greedy function approximation: A gradient boosting machine*. *The Annals of Statistics*, 29(5), 1189–1232. <https://doi.org/10.1214/aos/1013203451>
- [7] Gao, Y., Wang, M., Raheem, A., Wang, F. C., Wei, J., Xu, D., Song, X., Bao, W., Huang, A., Zhang, S., & Zhang, H. (2023). *Syngas production from biomass gasification: Influences of feedstock properties, reactor type, and reaction parameters*. *ACS Omega*, 8(35), 31620–31631. <https://doi.org/10.1021/acsomega.3c03050>
- [8] Gil, M. V., Jablonka, K. M., Garcia, S., Pevida, C., & Smit, B. (2023). *Biomass to energy: a machine learning model for optimum gasification pathways*. *Digital Discovery*, 2(4), 929–940. <https://doi.org/10.1039/d3dd00079f>
- [9] Kusworo, T. D., Kumoro, A. C., Al-Aziz, H., & Utomo, D. P. (2023). *Pyro-gasification of Rice Husk to Bio-fuel: An Optimization Study of Process Parameters*. *Periodica Polytechnica Chemical Engineering*, 67(2), 296-309. https://www.researchgate.net/publication/370877864_Pyro-gasification_of_Rice_Husk_to_Bio-fuel_An_Optimization_Study_of_Process_Parameters
- [10] Liaw, A., & Wiener, M. (2002). *Classification and regression by randomForest*. *R News*, 2(3), 18–22. Retrieved from https://cran.r-project.org/doc/Rnews/Rnews_2002-3.pdf
- [11] Nakayama, Y., Yata, K., & Aoshima, M. (2017). *Support vector machine and its bias correction in high-dimension, low-sample-size settings*. *Journal of Statistical Planning and Inference*, 191, 88–100. <https://doi.org/10.1016/j.jspi.2017.05.005>
- [12] Park, S. J., et al. (2021). *Gasification operational characteristics of 20-ton-per-day rice husk fluidized-bed reactor*. *Renewable Energy*, 168, 153–165. <https://doi.org/10.1016/j.renene.2021.01.045>
- [13] Shafizadeh, A., Shahbeik, H., Rafiee, S., Moradi, A., Shahbaz, M., Madadi, M., Li, C., Peng, W., Tabatabaei, M., & Aghbashlo, M. (2023). *Machine learning-based characterization of hydrochar from biomass: Implications for sustainable energy and material production*. *Fuel*, 347, 128467. <https://doi.org/10.1016/j.fuel.2023.128467>
- [14] Zhang, Y., Wang, J., Lai, S., & Wu, Z. (2024). *Prediction of syngas yield from biomass by gasification and related application*. *Applied and Computational Engineering*, 44, xx–xx. <https://doi.org/10.54254/2755-2721/44/20230456>
- [15] <https://thutuong.chinhphu.vn/quoc-te-an-tuong-voi-cam-ket-dat-phat-thai-rong-bang-0-cua-viet-nam-10940309.htm>, Accessed at 3:00p.m on 21/12/2025
- [16] <https://vaas.vn/vi/nong-nghiep-trong-nuoc/khai-thac-mo-vang-phe-phu-pham-nong-nghiep>, Accessed at 3:00p.m on 20/12/2025
- [17] <https://www.iea.org/>, Accessed at 10:00a.m on 21/12/2025