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A Review on AI/ML applications in biomass systems

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ABSTRACT :

Biomass gasification is a clean technology that converts organic materials into syngas, which can be used for heat and electricity. The efficiency of gasification depends on factors like temperature, feedstock type, and reactor design, which vary with different biomass types. Manual optimization of these parameters is complex and time-consuming due to their nonlinear behavior. Machine Learning (ML) algorithms like SVR, Random Forest, and Gradient Boosting help predict and optimize syngas yield and composition based on input variables (e.g., temperature, moisture, equivalence ratio). ML models trained on experimental data enable accurate predictions, reduce the need for experiments, and support real-time decision-making for clean energy planning.

1. Introduction

Bioenergy is energy generated from organic material, including agricultural waste, wood residues, and animal manure. Bioenergy production from biomass and biogas is one of the most important renewable energy sources for sustainability. Biomass can be converted into useful energy forms such as syngas, bio-oil, and biochar through thermochemical processes (e.g., gasification and pyrolysis), and biogas is produced through anaerobic digestion of organic waste (e.g., manure, food waste) and is made up of a mixture of carbon dioxide and methane. The above technologies can produce renewable energy and aid waste management, reduce carbon emissions and support rural economies.

Despite the benefits of bioenergy systems, there are still technical and operational challenges. The properties of biomass vary significantly based on the feedstock and can result in inconsistent performance of the gasifier technology. In addition, tarring, excessive moisture, ash deposits, and process instability can compromise the efficiency of the energy conversion process. Moreover, controlling parameters such as temperature, pressure, and stoichiometric air-to-fuel ratio is tedious and difficult. All these limitations can lead to changes in the quality of syngas and hinder the ability to alter operating conditions to accommodate various feedstocks.

Biomass-based bioenergy play a critical role in the global shift to a low-carbon and sustainable energy system. They offer clean, renewable and stable energy sources with the capacity to complement intermittent renewables, such as solar and wind. By utilizing resources available locally, they also promote energy security, reduce fossil fuel reliance, and support job growth in rural and developing regions. When smart control and predictive technologies are incorporated, these systems can operate more efficiently, reduce costs, and be more environmentally sustainable.

Artificial Intelligence (AI) and Machine Learning (ML) have emerged as valuable tools to overcome the constraints of biomass and geothermal energy systems. For example, in biomass gasification, ML frameworks (such as Artificial Neural Networks (ANN), Support Vector Regression (SVR), Random Forest (RF), and Gradient Boosting (XGBoost)) can forecast syngas composition, yield of biochar, and efficiency of the gasification process based on operating parameters such as temperature, moisture content, and feedstock. This approach streamlines experimentation and can lead to significant real-time process enhancement.

Similarly, in geothermal energy, AI/ML methods are being used to detect drilling faults in real-time, as well as to forecast reservoir properties, and generate power forecasts. Models such as Long Short-Term Memory (LSTM) Networks, and Federated Learning (FL), allow for accurate data transfer between geothermal plants without compromising privacy. These methods also yield improved accuracy of forecasting, along with improved safety and operational safety.

Through data-driven solutions integrated with physical knowledge, AI and ML are evolving into smart, adaptive, predictive control systems. In a fatigued workforce, these technologies enable substantial reductions in human error, enhanced efficiencies, and ultimately, sustainable and intelligent energy futures.

2. Working of Bioenergy System

2.1 Working of Bioenergy System (Biomass and Biogas)

Bioenergy systems convert organic waste feedstocks, including agricultural residues, woody materials, and animal waste into usable energy services: heat, electricity, or fuels, via biochemical (specifically anaerobic digestion) or thermochemical systems (e.g., gasification). The gasification of biomass process described in the preceding report involves the thermochemical conversion of solid biomass via gasification into a combustible gas mixed product known as syngas. The syngas is a mixture of carbon monoxide (CO), hydrogen (H_2), and methane (CH_4) and can be used to produce electricity and heat or for use in biofuels.

2.2 Working Steps:

2.2.1 Feedstock Preparation and Collection

- A biomass feedstock, such as wood, rice husk, or crop residues, is collected, dried, and size-reduced to facilitate uniform feeding.

2.2.2 Gasification Process

- The biomass is fed into the gasifier reactor to undergo four steps:
- Drying: Heat is used to remove moisture from the biomass.
- Pyrolysis: The biomass thermally breaks down into char, tar, and volatile gases.
- Oxidation: In the presence of an insufficient supply of oxygen, the biomass partially burns to produce heat.
- Reduction: The resulting gases (CO_2, H_2O) react with char to produce the syngas ($CO + H_2 + CH_4$).

2.2.3 Gas Cleaning and Cooling

- The syngas is cleaned of tar, ash, and particulates to enhance the quality of the gas.

2.2.4 Energy Generation and Use

- The cleaned syngas is used in engines or turbines on site or burned directly for heat applications.

2.2.5 By-Products

- The by-products encompass biochar, which has a role as a soil conditioner to improve agricultural productivity and carbon sequestration.

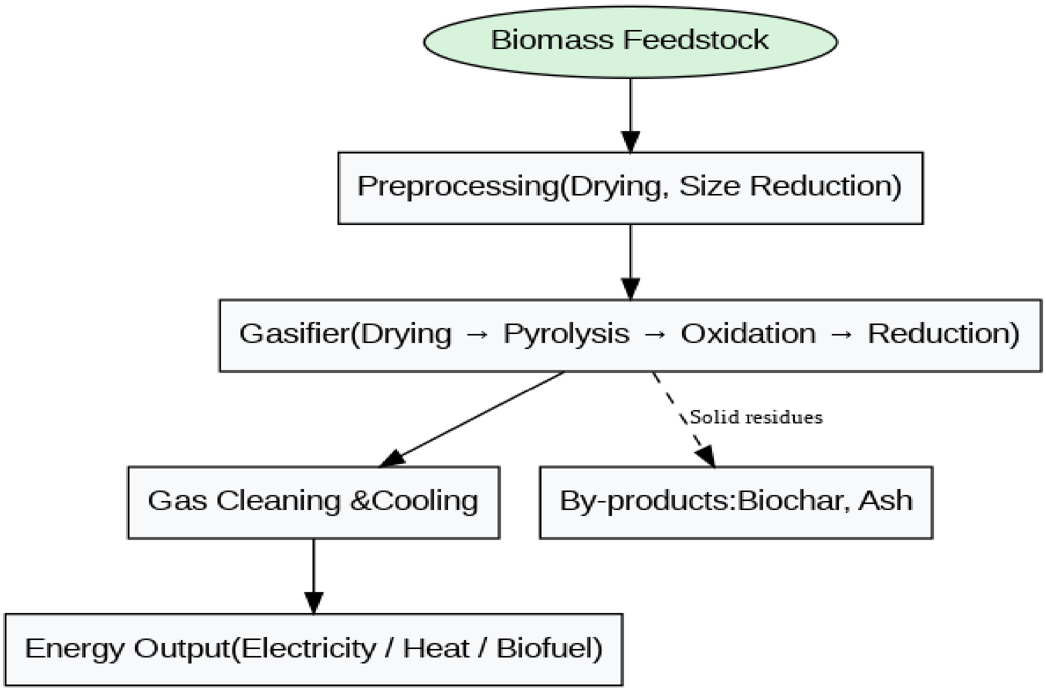

Fig.1 Block Diagram for Working of Biomass Gasification System

3. Issues Relating to Bioenergy Systems

Bioenergy System's Challenges

Biomass feedstocks (e.g., rice husks, wood chips, bagasse) possess varying moisture, ash, and carbon content. Because of this variability, the gasification process is inconsistent, leading to an unstable syngas composition and decreased efficiency. Tar compounds are formed during gasification, condensing in the pipelines causing plug-ups of gasifiers and other equipment. Plug-ups lead to elevated maintenance costs and downtime of the operational facility. Feedstocks with high moisture levels require more energy input for drying, leading to less thermal efficiency of the system. In addition, feedstock that possesses high ash levels cause slagging and fouling of the interior of the reactor. Gasification is dependent upon multiple, interrelated parameters, (e.g., temperature, airfuel ratio, and pressure). Notably, these variables are nonlinear, meaning that manual control is complex, often leading to inconsistent performance of the gasifier. The initial capital and ongoing costs associated with gasifiers and the low conversion efficiencies of biomass systems make them less competitive than fossil fuels in the absence of government incentives. The lack of large, experimental datasets to inform predictive models limits the development of accurate predictive models for optimizing gasification performance and predicting fuel properties.

4. AI/ML Techniques

Machine learning (ML) and artificial intelligence (AI) are essential for improving the sustainability and efficiency of biomass gasification operations. They are widely used for feedstock classification, process parameter optimization, gas composition prediction, and operational failure diagnosis. Artificial Neural Networks (ANNs) are one of the most popular methods among them. ANNs, which are modeled after the human brain, are made up of layers of interconnected neurons that learn from input-output data. They are useful for modeling the correlations between feedstock attributes and energy yield, estimating the Higher Heating Value (HHV) of biomass by proximate or ultimate analysis, and predicting the composition of syngas (ratios of CO, H_2, and CH_4). Their ability to handle nonlinear data, increase prediction accuracy, and facilitate real-time modeling are their main advantages.

Finding the best hyperplane for classification or regression tasks is how Support Vector Machines and Support Vector Regression (SVM/SVR) work. These models are used in biomass applications to categorize biomass kinds from analytical data and forecast biogas and biochar production based on temperature and feedstock composition. They are errorresistant and perform accurately even with limited datasets. To improve accuracy and reduce overfitting, the ensemble learning technique Random Forest (RF) constructs several decision trees and averages their predictions. RF's strong interpretability and durability make it especially useful for forecasting biochar yield, syngas quality, and handling big datasets with missing or noisy data. Gradient Boosting techniques, such as LightGBM and XGBoost, build sequential decision trees that use gradient descent optimization to iteratively repair past errors, improving predictive performance. They are used to simulate thermal decomposition rates and forecast yields of biohydrogen and bio-oil. For large-scale data, these models are quick, precise, and effective. In the meantime, gasification parameters like temperature and gas yield are continuously monitored using Long Short-Term Memory (LSTM) networks, a type of deep learning model intended for sequential or time-series data that provides superior predictive control due to its capacity to capture long-term dependencies. Convolutional Neural Networks (CNNs) are also utilized for spatial or grid-like data analysis, including image-based biomass quality assessments, feedstock type identification, and surface pattern analysis in reactors. They are effective for visual analysis in biomass systems because of their capacity to automatically extract hidden spatial elements.

5.Literature Review

Research into bioenergy, particularly biomass gasification, has demonstrated how machine learning (ML) algorithms can improve control, predict fuel properties, and optimize yield. Pascarella et al. (2025) established a large-scale PYRIS dataset to improve predictive modeling for biomass pyrolysis processes, with XGBoost significantly improving performance predicting bio-liquid yields over traditional methodologies, but noted that the data standardized key attributes of the dataset could improve the utility of the dataset. Similarly, Jin et al. (2025) developed a hybrid SVBoost model to predict the strength of hybrid biomass random compressed pellets, achieving an R^2 value of 0.93 and optimizing for production parameters (e.g., ratio, temperature, and holding time).

As it relates to sustainability, Abbaspour and Fazlollahtabar (2025) developed a MultiLayer Perceptron (MLP) model combined with Rough Set Theory, to rank strategies for net-zero biomass power plants and recognizing that sustainably sourced biomass and effective policies are instrumental in achieving carbon-neutrality. Abdelfattah et al. (2025) and Hai et al. (2023) utilized Random Forest (RF) and Decision Tree models, respectively, to predict biochar yield and surface area, citing process temperature and residence time as the most important factors contributing to performance.

Research is also underway related to advanced techniques like Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN), for time-dependent and spatial approaches to biomass processes. The literature has shown that LSTM networks can effectively monitor dynamic gasification systems continuously, while CNN networks for instance can analyze spectral or image data related to the classification characteristics of different feedstocks. Additionally, this combined AI or machine learning predictive control and real-time monitoring has the potential to reduce human intervention and improve syngas quality and energy yield. Overall, the literature suggests that AI and ML will continue to reshape bioenergy systems by improving efficiency, reducing experimental costs, and allowing for adaptive and sustainable operation. Future works, while still developing sites for data commissions and verifiability, will run into challenges related to data deficiency, variability in feedstock, and the literature has much left to be discovered in terms of model interpretability.

In order to offer continuous real-time data streams for machine learning algorithms, emerging trends also emphasize the integration of Internet of Things (IoT) devices and sensor-based data capture in biomass gasifiers. Closed-loop control can be achieved by integrating these data-driven insights with AI-enabled controllers to allow systems to independently modify process parameters like air-to-fuel ratio, reactor temperature, and pressure. In addition to increasing productivity, this automation reduces operational errors, which results in lower energy losses and more reliable product quality.

Explainable AI (XAI) frameworks have also started to be investigated in the literature in order to better understand complex models and increase user confidence in algorithmic decisions. To identify the input variables that most significantly affect gasification results, methods like SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) are being used. For example, research has shown that factors like reaction temperature, volatile matter, and carbon content have the biggest effects on energy conversion efficiency and emission control. Scaling AI applications in the energy sector, where decision transparency and dependability are crucial, depends on interpretability.

Additionally, feedstock classification and preprocessing optimization have demonstrated the capabilities of modeling, control, and machine learning. AI algorithms can quickly determine the moisture, ash, and lignin content of biomass prior to conversion by employing spectral imaging and pattern recognition, allowing for improved feedstock selection and mixing techniques. This guarantees increased energy yield and consistent reactor functioning. Process parameter tuning has been further improved by integration with optimization techniques like Particle Swarm Optimization (PSO) and Genetic techniques (GA), facilitating the production of bioenergy that is both economically viable and sustainable.

The body of research indicates that bioenergy research is undergoing a paradigm shift due to AI and ML. These technologies are increasing energy output, lowering operating uncertainty, and fostering environmental sustainability by enabling predictive, adaptive, and intelligent gasification systems. Future studies should concentrate on creating cohesive, high-quality datasets, enhancing model generalization across various biomass types, and establishing hybrid AI frameworks that integrate machine learning and mechanistic models. These initiatives will open the door for reliable, comprehensible, and self-sufficient bioenergy systems that can be crucial to the world's shift to clean, renewable energy.

6. Results

Table 1: Summary of Bioenergy

S. No.	Author(s) & Year	Energy System	AI/ML Technique(s)	Application / Focus Area	Key Findings / Results
1.	Pascarella et al. (2025)	Bioenergy (Biomass)	XGBoost, Explainable AI	Prediction of bio-liquid yield from pyrolysis dataset (PYRIS)	XGBoost achieved best accuracy (MAE ≈ 2.28); emphasized need for standardized data.
2.	Jin et al. (2025)	Bioenergy	SVBoost (Hybrid), SHAP, LIME	Prediction and optimization of hybrid biomass pellet strength	High predictive accuracy (R^2 = 0.93); identified optimal temperature and feed ratio.
3.	Abbaspour & Fazlollahtabar (2025)	Bioenergy	MLP + Rough Set Theory	Ranking of sustainability strategies for net-zero biomass power plants	MLP achieved R^2 = 0.97; “sustainable biomass sourcing” ranked as top factor.
4.	Abdelfattah et al. (2025)	Bioenergy	Decision Tree, SHAP	Biochar yield prediction from pyrolysis data	Decision Tree achieved highest R^2 (0.771); residence time and temperature most influential.
5.	Alruqi et al. (2024)	Bioenergy	XGBoost, RF, AdaBoost, SHAP	Prediction of Higher Heating Value (HHV) from ultimate analysis	XGBoost yielded R^2 = 0.9967; carbon content most positive, nitrogen most negative factor.
6.	Hai et al. (2023)	Bioenergy	Random Forest	Prediction of biochar yield & surface area from agricultural biomass	RF model R^2 = 0.85; temperature and particle size key parameters.
7.	Mahdavi et al. (2025)	Bioenergy	ML + MPC (Model Predictive Control)	Integration of solar greenhouses and biomass gasification for hydrogen	Enhanced energy sharing and hydrogen yield; proposed smart control framework.

8.	Fernández Montenegro et al. (2025)	Bioenergy	FCN (Deep Learning)	Biomass monitoring via hyperspectral imaging	Mean absolute error < 4%; validated realtime, noninvasive biomass estimation.
9.	Nielsen et al. (2024)	Bioenergy	LDA, K-NN, RF	Pellet manufacturing optimization using vibration data	F1-score = 100%; realtime roller gap detection improved efficiency.
10.	Shi et al. (2023)	Bioenergy	ANN, SVM, RF	AI in bioenergy systems (yield prediction, efficiency)	Found ANN and RF most accurate; highlighted need for generalized models.

The reviewed bioenergy studies unequivocally demonstrate the growing significance of AI and ML techniques in enhancing predictive modeling and optimizing biomass conversion processes. In predicting important parameters like syngas composition, biochar yield, and Higher Heating Value (HHV), ensemble learning algorithms like Random Forest (RF) and XGBoost have continuously shown superior accuracy. Neural models such as Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) proved highly effective for nonlinear and time-dependent process modeling, while Convolutional Neural Networks (CNN) offered new possibilities for image-based feedstock classification and monitoring. Better comprehension of variable influences like temperature, residence time, and carbon content was made possible by the incorporation of Explainable AI (XAI) tools like SHAP and LIME, which improved the interpretability of complex models.

7. Conclusions

Process optimization, predictive modeling, and system automation have greatly improved with the use of artificial intelligence (AI) and machine learning (ML) in bioenergy, especially in biomass gasification and biochar production. In the reviewed studies, it is evident that algorithms like Random Forest (RF), XGBoost, Support Vector Regression (SVR), and Artificial Neural Networks (ANN) are capable of accurately predicting important parameters like biochar yield, Higher Heating Value (HHV), and syngas composition. These models enable precise control and increased efficiency in bioenergy conversion systems by accurately capturing complex nonlinear relationships among process variables like temperature, feedstock composition, and residence time.

The ability to analyze time-series and image-based data for feedstock classification and real-time system monitoring has been further enhanced by sophisticated deep learning models, such as Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN). Additionally, by integrating Explainable AI (XAI) techniques like SHAP and LIME, ML-driven predictions have become more transparent and reliable, aiding operators and researchers in comprehending the variables affecting system behavior.

All things considered, bioenergy systems are becoming intelligent, data-driven, and adaptable technologies with the ability to self-optimize and perform predictive control thanks to AI and ML-based approaches. In order to create reliable and understandable bioenergy solutions, future research should concentrate on creating standardized datasets, enhancing model generalization across various biomass types, and developing hybrid AI frameworks that integrate physical and data-driven models.

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