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Artificial Intelligence Application in Bioenergy

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Abstract

Energy is considered an important input for economic development. The judicious use of energy helps conserve energy resources, protect the environment, and ensure energy security. Renewable energy has attracted significant attention as a clean, sustainable energy source. The limitations of renewable energy systems, such as process optimization, intermittent nature, and grid connectivity, pose hurdles to efficient deployment. Biomass, as a renewable energy source, can be used for bioenergy production and plays an important role in sustainable development; however, the major issue is the low efficiency of the production technology. Integrating artificial intelligence (AI), including machine learning (ML), deep learning (DL), reinforcement learning (RL), and natural language processing (NLP), delivers intelligent solutions to challenges in renewable energy systems, including energy efficiency improvement, grid integration, and predictive Maintenance. The AI application in renewable energy can enhance efficiency, reduce overall operational costs, and reduce energy waste. This paper provides a comprehensive review of the application of AI to renewable energy, specifically bioenergy systems.

1. Introduction

Energy, as an important asset for economic development, remains heavily reliant on fossil fuels. However, the use of fossil fuels and their combustion lead to the emission of harmful gases that contribute to serious global issues such as global warming and climate change (Vine, 2008). To tackle these issues, renewable energy (RE) has emerged as a promising energy resource with reliable, efficient, and sustainable characteristics. Solar, wind, and biomass energy, along with other RE, are expanding their production and applications by addressing the dual challenge of energy security and environmental sustainability. The transition to sustainable energy sources is marked by integrating renewable energy systems (RES) into existing grid infrastructure. RES offers several benefits, such as being a clean energy source with minimal or no greenhouse gas emissions, which help mitigate climate change. Technological advancements and research are making RES more affordable than fossil fuels. The issues with fossil fuels and recent awareness have led to the use of bioenergy and biofuels as alternative energy sources (Ang et al., 2022; Peng et al., 2013; Su'ait et al., 2025).

Biomass energy is widely available and utilized as a renewable energy source all over the world, and agro-residues as major contributor as a feedstock for bioenergy production (Reid et al., 2020). Bioenergy, a renewable energy source, plays an important role in sustainable development; however, the major issue lies in the low efficiency of the production technology. Biomass, as a renewable energy source, has utility for both heat and power generation (Narnaware et al., 2017). The production of bioenergy on a commercial scale and improving the efficiency of bioenergy processes are two major challenges that need to be addressed. Design, optimization, and scaling of bioenergy conversion systems, as well as the adoption of high-tech processes and improved infrastructure, should be considered. This review focuses on the application of artificial intelligence (AI) to renewable energy for optimizing operations

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and efficiency. The study discusses the challenges in integrating AI with bioenergy and prospects for future implementation.

Biomass conversion can be achieved via two major routes, i.e., (a) Biochemical conversion and (b) Thermochemical conversion, as shown in Figure 1. Biochemical conversion technologies include processes such as anaerobic digestion (AD) and fermentation. During anaerobic digestion, organic substrate is converted into biogas by microbial activity in a closed digester. The organic matter undergoes an AD process in an oxygen-free environment to produce biogas. Biogas consists primarily of methane (CH_4) and carbon dioxide (CO_2), with trace amounts of other gases. Several materials, such as animal manure, sewage, paper waste, agricultural waste, municipal solid waste, and agro-processing industry waste, can be used as feedstock for individual or co-digestion. Biogas, which is a good fuel for household applications and power generation. Recently, biogas conditioning has achieved methane content exceeding 90 percent, enabling compression to produce compressed biogas (CBG) (Gustafsson et al., 2020; Kapdi et al., 2005). Ethanol, a liquid fuel, is produced from sugar through fermentation. The transformation of biomass into ethanol is regarded as the most environmentally friendly liquid fuel and an alternative to fossil fuels. It has wide application in the transportation, pharmaceutical, and beverage industries, as well as in electricity production. Efficient fermentation technology can help scale up bioethanol production for industrial applications (Balat, 2007; Igwebuike et al., 2024; Jayakumar et al., 2022; Lin Shuzo Tanaka, 2006).

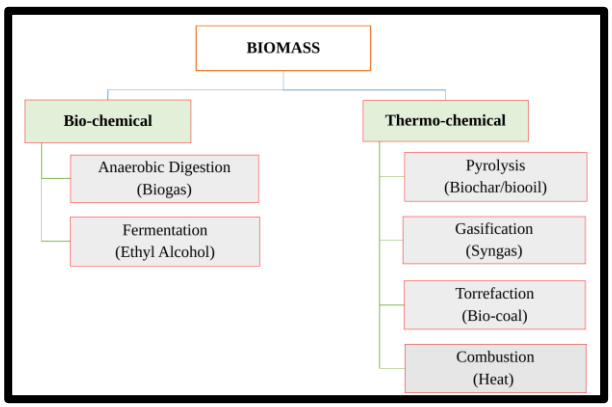


Figure 1. Biomass conversion technologies

Despite several benefits, the RES also faces limitations, such as the intermittent nature of solar and wind energy, which can lead to unreliable power generation. Grid power feeding becomes more challenging, and fulfilling peak demand can be hampered. Conventional grids also face issues from RESs, such as voltage fluctuation, variation in frequency due to the unpredictable and stochastic character of RESs (Basit et al., 2020). The transition of the world to industrialization, urbanization, and improved living standards has created parallel challenges in the generation of wet organic waste. These wastes need proper handling and disposal to prevent environmental degradation through contamination, greenhouse gas emissions, and human health hazards, (Minghua et al., 2009; Sharma et al., 2019). Biomass and bioenergy production face challenges in handling the wide variety of biomass from different sources, ensuring process control, and managing the supply chain (Liao, 2021). This review focuses on the application of AI to renewable energy for optimizing operations and efficiency. The study discusses the challenges in integrating AI with bioenergy and prospects for future implementation.

2. Artificial Intelligence for RES

The challenges that modern energy systems face are being addressed through the integration of AI, including machine learning (ML), deep learning (DL), reinforcement learning (RL), and natural language processing (NLP), which provides intelligent solutions. These tools are useful in analyzing data to learn, discover patterns, and make necessary adjustments with minimal human intervention. The AI provides a promising prospect in the improvement of efficiency, reliability, and economic viability of the systems (Ejiyi et al., 2025; Xiang et al., 2025). AI can be successfully applied to the biomass and bioenergy production processes. AI can mimic human intelligence to perform various tasks. Depending on the task performed and the algorithms used, AI can be classified into different categories. Liao and Yao have given the classification of I in four different types, which include a. symbolic AI, b. machine learning (ML), c. heuristics, and d. hybrids & others (Liao, 2021).

AI and energy convergence began in early 2000, particularly with the global focus on clean energy adaptations. Initially, AI was used for predictive analysis and optimization algorithms to improve energy efficiency in conventional power systems. Later, the expansion of renewable energy began using AI to manage the complex operations required to integrate RE into existing grids (Algburi et al., 2025; Ochoa-Barragán et al., 2026). AI is a sophisticated system or machine that performs human-like tasks, requiring human-like supervision and intelligence. An ML algorithm is a

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subset of an AI algorithm that employs statistical methods to predict and derive insights from data, and to make decisions based on identified patterns. Deep learning (DL) is a subset of ML characterized by the use of artificial neural networks (ANNs), which enable intelligent systems to autonomously train on extensive datasets and execute a range of intricate tasks (Ejiyi et al., 2025; Mira et al., 2023). As AI applications across industries gain increasing attention, the energy industry is using them for demand forecasting, grid operation optimization, predictive maintenance, and supporting decentralized energy production.

The development of AI and ML techniques, along with thermochemical conversion (TCC) processes, can address complex, nonlinear problems, optimize parameters, forecast production yields, and enable real-time control. Processes such as bio-oil, biochar, and syngas production have effectively used ML algorithms, as reported by several studies (Shoaei et al., 2024). Likewise, Elmaz et al. reported that decision tree regression and a multilayer perceptron-based ML model were used to predict syngas composition (Elmaz et al., 2020). Some studies reported the solid biochar yield via the biomass pyrolysis process using the AI models RF and eXtreme gradient boosting (XGBoost) (Pathy et al., 2020; Zhu et al., 2019). The use of ML algorithms such as deep neural networks (DNNs) and RF has been reported for predicting biochar properties related to absorption, using three regression models: RF, XGBoost, and DNN. RF and XGBoost were used in hydrothermal carbonization (HTC) to analyze the solid and to optimize the carbon stability index (CSI) and return on energy investment (REI), which are important indicators for determining carbon sequestration potential and energy efficiency, respectively (Zhu et al., 2023). Zhang et al. used a random forest (RF) model to predict bio-oil properties based on biomass characterization and pyrolysis conditions (Tang et al., 2020). Table 1 presents the application of various AI techniques with utility in the energy domain.

Table 1. Applications of AI Techniques in RES

AI technique	Application	Benefits	Limitations	References
Machine Learning (ML)	Predictive maintenance, load forecasting	High accuracy in pattern recognition	Requires large datasets for training	(Ajibade et al., 2023; Khan et al., 2026)
Deep Learning (DL)	Fault detection in solar/wind farms	Automated feature extraction	Computation ally intensive	(Arun et al., 2024; Song et al., 2026)
Reinforcement Learning (RL)	Energy grid optimization	Adapts to dynamic energy demands	Complex implementation on in real systems	(Michailidis et al., 2025; Perera & Kamalaruban, 2021)
Random Forest (RF)	Air quality index prediction	Resistant to overfitting, handles high dimensional data well	Less interpretable	(Sankarananth et al., 2023)
Long Short-Term Memory (LSTM)	Long-term air quality prediction	Suitable for sequential data and captures long-term dependencies	Requires significant computational l resources	(Sankarananth et al., 2023)
XGBoost	Prediction performance, stability of smart grid	Accurate, handles missing data well	High computational cost, sensitivity to hyperparameters	(Hussain et al., 2025; Lu et al., 2026)
Convolutional Neural Network (CNN)	Power generation forecasting, Image data processing	Better extracting features from images	Requires a large amount of training data	(Babalhavaeji et al., 2023; Yousef et al., 2023)

3. Role of AI in Renewable Energy Systems

AI has emerged as a revolutionary technology that can be applied in optimizing the performance of RES by taking on different roles, as shown in Figure 2. The ML algorithms, such as artificial neural networks (ANNs), support vector machines (SVMs), decision trees (DTs), and hybrid

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methodologies, are some AI models that have wide application in analyzing complex data, its patterns, and correlation to optimize systems (Garg et al., 2025; Majji et al., 2023; Ming et al., 2023) as depicted in Table 2. AI applications in renewable energy use some major technologies, including ML, neural networks, and advanced algorithms. AI can play an important role in predictive maintenance for RES, such as solar PV systems, wind turbines, and others. The trained AI algorithm can analyze large amounts of data, including temperature, vibrations, performance indicators, output patterns, and weather patterns. AI can predict potential issues, suggest maintenance requirements, reduce downtime, and optimize energy output by analyzing weather data. AI can forecast energy output from RES, helping grid operators manage energy demand and supply more effectively. The major objectives of integrating AI in RETs are energy conservation, improving efficiency, and sustainability. Recent research shows that AI has emerged as a powerful tool capable of making human-like decisions to monitor, optimize, and manage RES, thereby improving energy efficiency, grid integration, and predictive maintenance, as depicted in Figure 3.

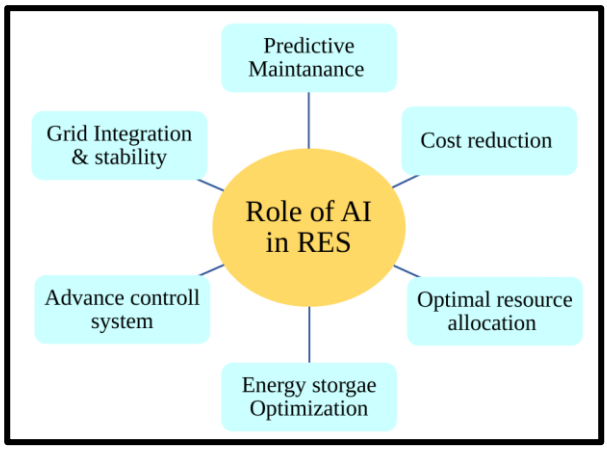


Figure 2. Application of AI in improving RET (Ukoba et al., 2024)

3.1 Energy efficiency improvement

AI can analyze large datasets from RES systems, such as solar PV and wind turbines, and identify patterns that help optimize system operations for greater efficiency and sustainability. The ML techniques are highly effective for deriving insights that support better energy management practices. AI has become critically important in real-time optimization of renewable energy technologies, resulting in improving response and efficiency of renewable energy conversion systems (Sohail, 2026). AI significantly works towards energy management, optimization, energy generation, energy storage, and demand side response to minimize the operational cost, reduce the transmission losses, and improve overall efficiency (Ohalete et al., 2023; Uzorka et al., 2026). Energy conversion can be optimized using ML-based predictive modeling. GA effectively optimizes several objectives to balance power output and costs. Deep learning (DL), reinforcement learning (RL), and digital twin techniques are also applied to energy system optimization to achieve sustainability (Ali et al., 2023; Garg et al., 2025; Khosravi et al., 2024).

3.2 Grid Integration

The integration of renewable energy into existing grids faces significant challenges, including grid instability and intermittency, infrastructure mismatches, and operational stress. AI forecasting the variability in renewable energy generation could predict fluctuations in RE supply and, accordingly, optimize grid management through better grid integration. The AI integration in renewable energy infrastructure transforms into a more intelligent, decentralized, and iterative system (Celik et al., 2022; Uzorka et al., 2026). Overcoming the issues in grid integration, AI enables the RES transition with the existing power system by real-time adaptation with the grid, intelligent automation, and a predictive control mechanism (Sohail, 2026).

3.3 Predictive Maintenance

AI technologies can be more useful for predictive maintenance of RES, which involves analyzing operational data to predict potential failures and maintenance requirements. Working life and downtime can be greatly reduced with AI predictive maintenance. The spaciotemporal graph neural network model helps understand performance metrics across several photovoltaic (PV) systems, which is helpful for planning maintenance strategies. The condition and performance of the subsystems and components significantly affect the performance of the RES, such as solar PV systems, wind turbine systems, and power electronic converters. These components are prone to degradation due to environmental factors, and mechanical wear and tear. AI can enable predictive maintenance by analyzing large volumes of sensor data to generate actionable insights and detect faults before failure (Bello et al., 2024; Marangis et al., 2025; Uzorka et al., 2026).

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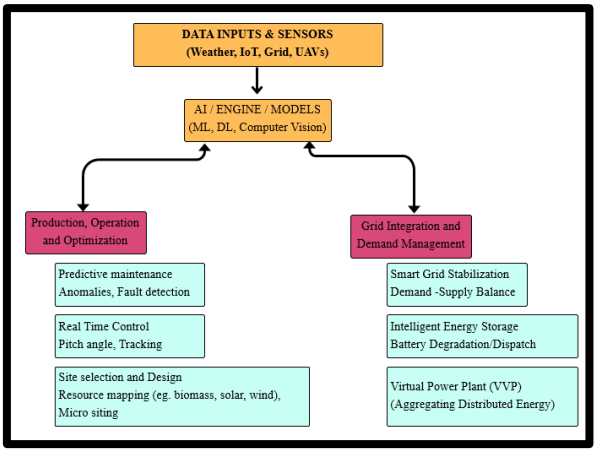


Figure 3. Role of artificial intelligence in renewable energy systems

Table 2. AI techniques for renewable energy, its utility, and benefits

Renewable Energy Domain	Challenges	AI Techniques applicable	AI utility	Key benefits
Solar Energy	Intermediate solar radiation, Shading, solar soiling, and faults in inverters	Artificial Neural Networks (ANN) Long Short-Term Memory (LSTM) Support Vector Machines (SVM) Convolutional Neural Networks (CNN)	Forecasting Solar PV power using meteorological data Maximum Power Point Tracking (MMPT) under partial shading conditions	Maximize power efficiency Reduction in manual inspections Minimize grid uncertainty due to clouds
Wind Energy	Wind speed variability Mechanical stress on wind turbine blades High offshore maintenance cost	Deep Learning (DL) Random Forest (RF) Reinforcement Learning (RL) Reinforcement Genetic Algorithm (GA)	Modelling of wind speed and wake effect for precise forecasting Predictive maintenance for gearbox, bearing, blades Real-time pitch and yaw angle optimization	Extend lifetime and reduction in downtime Optimize the capture under erratic conditions Minimize operation and maintenance cost
Biomass and Bioenergy	Heterogeneous feedstock, supply chain management, complexity in AD and gasification	ANN Adaptive Neuro-Fuzzy Inference System (ANFIS) Machine Learning (ML)	Predicting syngas composition based on variable ER and temperature Process parameters (pH, Temperature) optimization for maximizing biogas yield,	Efficient fuel use, syngas quality Optimized biogas yield, fast experimental validation
Smart grid & Hybrid System	Supply demand balance, integration of multiple RES	Reinforcement Learning (RL) Multi-Agent System (MAS) Fuzzy Logic Controllers (FLC)	Forecasting real-time load demand Dynamic economic dispatch scheduling Intelligent grid management by switching seamlessly between different RES Controlling grid fluctuation by automatic voltage and frequency control	Prevents blackout and stabilize voltage Maximize microgrid self-consumption

4. AI for Bioenergy

Particularly in the field of bioenergy, AI has been applied primarily in three areas: detection, production, and energy use. The detection involves the biomass cultivation, feedstock production, and harvesting required for bioenergy systems. It may include composition analysis, image classification, monitoring crop growth, predicting biomass yield, and feedstock distribution/mapping, among others.

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(Shi et al., 2023). ANNs consist of interconnected nodes that work more effectively like a human brain. ANNs model processes for optimization and anticipate outcomes from varying substrates (Kunatsa & Xia, 2022). AI-driven models are increasingly employed in bioenergy forecasting for operations such as biofuel production, conversion process optimization, and effective supply chain management. AI can help in addressing the real challenges in biomass energy systems, pertaining to optimizing biomass fuel use, reducing greenhouse gas emissions, and scalability for sustainable energy production (Xiang et al., 2025). AI plays an important role in enhancing the yield while reducing the environmental footprint. Some of the models, like the Adaptive Neuro-Fuzzy Inference System (ANFIS) and the Multilayer Perceptron (MLP) led to improved methane production and lower carbon emission from biofuels (Ifaei et al., 2023; Wei et al., 2021).

For detection, the use of ANN models has been studied and reported by several authors, who focused on the prediction of biomass yield (Vacchiano, 2013), prediction of the above-ground biomass in forestry (Shaharum et al., 2019), estimation of bioenergy crop yield based on the drone images using support vector machine (SVM) and random Forest (RF) (Liu et al., 2019) and estimation of biomass characterization for elemental composition (C, H, O) based on proximate analysis using Adaptive Neuro-fuzzy Inference System (ANFIS) with Particle Swarm Optimization (PSO) (Olatunji, 2019). Production or process includes biomass conversion processes, such as thermochemical or biochemical processes, their pretreatment, and bioenergy production. Additionally, related activities such as bioenergy valorization, process optimization, economic feasibility, and environmental sustainability are involved. In production or processing, AI-based models are used for processes such as gasification, torrefaction, pyrolysis, and AD. An ANN model was reported to be used for the prediction of bio-hydrogen production in a downdraft gasifier with a water–gas shift unit (Safarian et al., 2021). A biogas flow prediction in the AD process using partial least squares regression (PLSR), locally weighted regression, and the ANN model reported by Beltramo and Hitzmann (Beltramo & Hitzmann, 2019). Energy use in bioenergy is associated with the decision-making in bioenergy utilization and optimization of the bioenergy supply chain (BSC), which is important for the operation of bioenergy systems focusing on the conveyance of feedstock, its inventory, end use of the energy produced, energy planning, and site selection (Shi et al., 2023). Strandgard and Turner have reported the application of DSS using four different mathematical models for the scheduled delivery of forest biomass (Strandgard et al., 2022).

4.1 AI in biochemical processes

The application of AI in biochemical conversion technology for producing biomethane through anaerobic digestion has been reported by several studies. Monitoring the parameters like pH, alkalinity, and volatile fatty acid concentration (VFAs), composition of biogas (CH_4, CO_2, and others), methane yield, and enzymatic activity. ANN model used to optimize the bioethanol content in industrial fermentation processes, with an R^2 accuracy of 0.91 (Pereira et al., 2020). ANN, RF, and hybrid ML models have shown a versatility of AI applications for optimization of Lipase production and enzymatic performance, which accelerated the process in enzyme-assisted biofuel systems (Ge et al., 2023). Heating value is an important parameter in biomass energy production. Determining the chemical characterization of biomass requires time and money. Alruqi et al. have reported using one baseline approach, linear regression (LR), and three highly robust and efficient ML algorithm, i.e., RF, Adaptive Boosting (AdaBoost), and XGBoost, were employed for prediction of higher heating value (HHV) based on characterization data of the biomass like percentage of carbon content (C%), hydrogen content(H%), nitrogen content (N%), and oxygen content (O%) content in biomass (Alruqi et al., 2024). Figure 4 shows the application of AI techniques in different biochemical conversion processes.

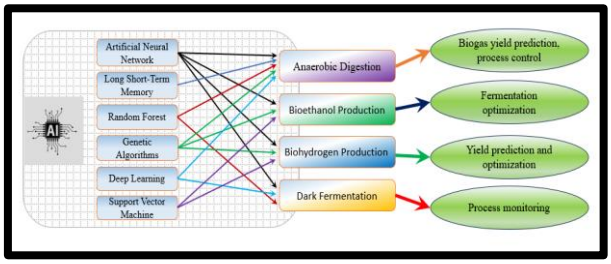


Figure 4. Artificial intelligence application in biochemical processes

4.2 AI in thermochemical process

Thermochemical conversion technology converts biomass into gaseous or liquid products that can be transformed into sophisticated energy, such as transportation fuels or electricity. These processes operate at higher temperatures and

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include technologies like gasification, pyrolysis, torrefaction, liquefaction, and combustion. Gasification is a partial oxidation of biomass that produces a gaseous product called syngas, or producer gas. Pyrolysis involves the thermal breakdown of the biomass in an inert environment to produce liquid, solid, and gaseous products. Liquefaction yields liquid energy products from biomass via chemical reactions using solvents such as water, ethanol, and acetone. During biomass pyrolysis, several physical and chemical reactions occur, which can be optimized to improve the pyrolysis products, such as bio-oil, biochar and pyrolysis gases.

Biomass gasification faces a major barrier: tar formation. The use of an ANN approach for predicting tar at a lab scale and correlating the results with experimental data demonstrated that the ANN model achieved good accuracy. ANN simulation software, ASPEN Plus modelling, is widely used for analyzing biomass gasification by predictive determination of syngas composition and lower and higher heating value of biomass feedstock. Feedforward networks, one of the ANNs forms, are widely applied for optimization of biomass conversion (Garg et al., 2025). Zaman and Ghosh reported a study on the application of a hybrid ANN-Aspen Plus Framework for biomass gasification and gas turbine integration to optimize the biomass to power performance, real-time optimization and carbon dioxide utilization (Zaman & Ghosh, 2021). Hydrothermal liquefaction is one of the technologies that can handle high-moisture feedstock to produce solid biochar, liquid bio-oil, and gaseous products. The major factors influencing bioenergy production via hydrothermal liquefaction include feedstock quality, reaction time, temperature, catalyst type, and others. (Sahoo et al., 2018). Gopirajan et al. used an ML algorithm with an AI-enabled decision support system to optimize operating parameters and predict output yield, achieving about 94% accuracy between predicted and experimental results (Varadharajan & Panchamoorthy, 2021). During thermochemical conversion at elevated temperatures, biomass undergoes numerous physical and chemical transformations, yielding a wide array of intermediate products (Neves et al., 2011). Researchers have investigated diverse optimization and monitoring approaches to enhance the production of pyrolysis products (bio-oil, biochar, pyrolysis gases). It focused on optimizing process parameters and implementing a better supervision system, which improved system operation through real-time data collection and monitoring (Singh et al., 2020; Wang et al., 2012; Yu et al., 2020; Ullah et al., 2021). Devasahayam reported a prediction of hydrogen based on feedstock particle size during the co-gasification process using the DL model (Devasahayam, 2023). Figure 5 shows the application of AI techniques in different thermochemical conversion processes and their specific use.

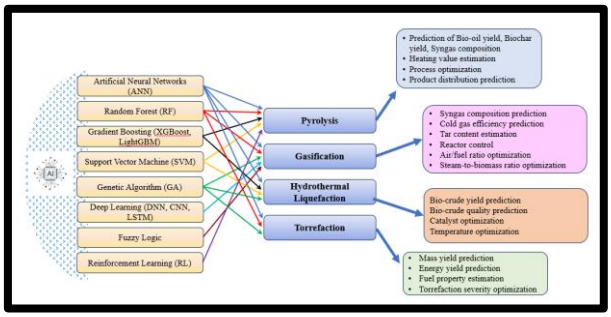


Figure 5. Artificial intelligence application in thermochemical processes

5. AI for Supply Chain Management of bioenergy

Biomass feedstock supply is an important part of sustainable bioenergy production. An efficient and effective biomass supply chain and logistics management are crucial to the operation of bioenergy plants (Gold & Seuring, 2011). In evaluating the bioenergy production system, several factors must be considered, including biomass resources, supply systems, employed biomass conversion technologies, and energy services, as shown in Figure 6. The delivery of biomass feedstock is generally tailored to specific operating conditions, such as climate and topography, feedstock, technologies, and final application, to optimize the supply chain network (McCormick & Kåberger, 2007).

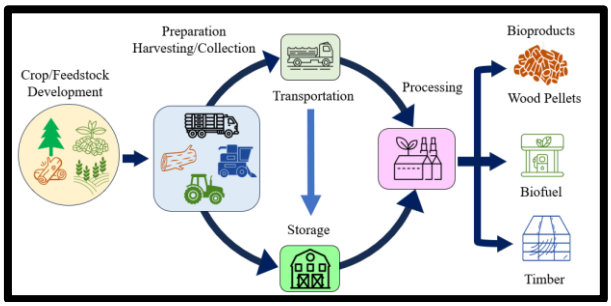


Figure 6. Biomass supply chain and logistics (Adapted from Nunes et al., 2020.)

Transportation is a crucial element of the biomass supply chain, and improving it may lead to profitability. Multimodal transportation,

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including rail, road, and barge routes, improves transportation efficiency (Nunes et al., 2020). Conventional biomass logistic methods frequently face difficulties due to the dynamic, nonlinear, and data-deficient characteristics of biomass supply. Several AI-based models can significantly enhance the biomass delivery management (BDM) model, thereby addressing these challenges as depicted in Table 3.

Table 3. AI techniques in supply chain management

Model/Technique	Applications in Logistics	Reference
Linear Programming (LP)	Minimizing transportation cost, Capacity and demand limitations, type of biomass, biomass processing facilities	(Nunes et al., 2020)
Integer Programming (IP)	Routing, scheduling, and allocation.	(Dixit et al., 2022)
Mixed-Integer Linear Programming (MILP)	Reduces costs, reduces the effects of biomass seasonality, and optimizes the number of travel trips within a timeframe.	(Li et al., 2024; Marufuzzaman & Ekşioğlu, 2016)
Agent-Based Modeling (ABM)	Decentralized logistics systems, dynamic system adaptation	(Bozdoğan et al., 2022)
Multi-Objective Optimization (MOO)	Cost management, utilization of time and resources, consolidation of packages to a single destination, and reducing costs and emissions.	(Sharifi et al., 2021; Wang & Feng, 2024)

Wesolowska et al. developed a novel ANN-based biomass delivery management (BDM) model that optimizes biomass logistics for a combined heat and power (CHP) plant operating on fluidized-bed gasification technology. The procurement and supply of biomass were managed based on technical, financial, and geographic parameters. The application of the ANN model enables selecting a supplier, optimizing the transportation route, and developing informed blending strategies through a novel biomass logistics approach (Wesolowska et al., 2025). Mathematical models such as Linear Programming (LP), Integer Programming (IP), Mixed Integer Linear Programming (MILP), Simulation Models, Stochastic Optimization models, Agent-Based Models (ABM), heuristics, metaheuristics, and multi-objective models can be used to plan, optimize, and evaluate multimodal transport logistics networks.

6. Conclusion

Renewable energy is experiencing a steady transition in its share of global energy and is important for achieving energy security and climate sustainability. Bioenergy is one of the major renewable energy sources, providing clean energy and environmental benefits. AI in renewable energy has significant applications in energy production, predictive maintenance, and grid management, as well as in optimization of bioenergy production processes and systems. AI tools, such as machine learning (ML), deep learning, and other AI techniques, have been instrumental in optimizing processes in bioenergy production and supply chain management. By applying artificial neural networks, support vector machines, and other artificial intelligence algorithms to enhance procedures such as biomass detection and production modelling, agricultural bioenergy producers can reduce costs and improve product quality. AI has great potential to make the renewable energy system more efficient in a sustainable energy economy.

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