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(Review Article)

Application of artificial intelligence in bioenergy supply chain management from feedstock collection to power generation

Ifeanyi Kingsley Egbuna [1, *], Abubakar Dalhatu [2], Chidinma Anulika Nwafor [3], Chetachukwu Goodness Ezeifegbu [4], Fawaz Olabanji Nasir [5] and Frank Izuchukwu Iheakanwa [6]

[1] *Department of Supply Chain Management, Marketing, and Management, Wright State University, United States of America.*
[2] *Department of Material Science and Engineering, Taiyuan University of Technology, China.*
[3] *Department of Computer Science, David Umahi Federal University of Health Sciences, Nigeria.*
[4] *Department of Chemical Engineering, Federal University of Technology Owerri, Nigeria.*
[5] *Department of Mechanical Engineering, University of Ilorin, Nigeria.*
[6] *Department of Production Engineering, University of Benin, Nigeria.*

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Abstract

Artificial Intelligence is transforming the future of bioenergy supply chains, ranging from intelligent systems at feedstock collection levels to those at power generation. This extensive review offers a comprehensive history of Artificial Intelligence applications for optimizing efficiency, sustainability, and supply chain choices at all levels of the bioenergy supply chain. It also reveals how machine learning algorithms, prediction algorithms, and real-time analytics are being applied to streamline biomass collection, preprocessing, logistics, and conversion operations. Verified prominent innovations from relevant literatures from 2020 to 2025 include Artificial Intelligence based predictive maintenance, reducing downtime at bioenergy plants by 20 to 30% and up to 15% biomass conversion efficiency enhancement using adaptive control systems. Intelligent biomass haulage routing resulted in 10 to 25% fuel savings, reduced carbon emissions by 12% and feedstock classification accuracy up to 90% using high-end image recognition and sensor fusion. Artificial Intelligent sinventory systems also increased feedstock utilization by 18%, energy demand forecast models improved forecast accuracy by 25 to 40%, alongside optimized resource allocation and grid resilience. The findings from this paper benchmarks interdisciplinary coordination, suitable data infrastructures and regulatory support as driving forces to scaling Artificial Intelligent applications in bioenergy sectors. While reconstructing conventional supply systems using intelligent automation, Artificial Intelligence has been confirmed one foundation stone upon which to scale clean energy agendas around the world.

Keywords: Artificial Intelligence; Bioenergy Supply Chain; Machine Learning; Sustainable Energy; Feedstock Optimization.

1. Introduction

The global energy sector is undergoing a significant transformation, propelled by escalating concerns over climate change, dwindling fossil fuel reserves, increasing energy demand, and a growing commitment to sustainable development. Renewable energy has taken center stage as a reliable and clean alternative to conventional fossil fuels [1, 2, 3]. Within the renewable energy portfolio, bioenergy holds distinctive promise due to its versatility, storability, and compatibility with existing infrastructure. Derived from biological materials such as crop residues, forest biomass, energy crops, and organic waste, bioenergy can be used to produce heat, electricity, and transportation fuels. Unlike

* Corresponding author: Ifeanyi Kingsley Egbuna.

intermittent sources like solar and wind, bioenergy can be harnessed continuously, offering a dispatchable renewable energy option [4]. However, despite its potential, bioenergy systems are often hindered by supply chain inefficiencies, geographical dispersion of feedstocks, seasonal availability, variability in feedstock quality, and high transportation costs [5, 6, 7]. The Bioenergy Supply Chain (BESC) includes numerous interconnected stages: feedstock identification, harvesting or collection, transportation, storage, preprocessing, conversion (through biochemical or thermochemical methods), and power generation. Each phase introduces operational challenges and uncertainties that can significantly affect the overall efficiency, economic viability, and sustainability of the bioenergy system [8, 9].

1.1. The Role of Artificial Intelligence in Energy Systems

To overcome these challenges, modern energy systems are increasingly integrating digital technologies, and at the forefront of this shift is Artificial Intelligence (AI). AI encompasses a broad set of computational techniques, including machine learning (ML), deep learning (DL), reinforcement learning (RL), natural language processing (NLP), and intelligent optimization algorithms. These tools enable machines to learn from data, identify patterns, and make informed decisions with minimal human intervention [10, 11, 12]. AI has already demonstrated considerable success in optimizing complex systems in various industries, including finance, healthcare, manufacturing, and, more recently, energy [13, 14]. In the context of energy systems, AI is being used to enhance demand forecasting, optimize grid operations, manage energy storage, enable predictive maintenance, and support decentralized energy generation. These capabilities are now being explored in the context of bioenergy to optimize resource allocation, reduce environmental impact, and enhance system reliability and responsiveness [15, 13, 16].

1.2. Artificial Intelligence in Bioenergy Supply Chain Management (BESCM)

The integration of AI into the Bioenergy Supply Chain Management (BESCM) provides a compelling opportunity to revolutionize how biomass resources are identified, processed, transported, and converted into usable energy. The application of AI within the bioenergy context spans across the entire value chain viz a viz, Feedstock Identification and Collection - One of the major bottlenecks in bioenergy supply chains is the identification and quantification of feedstock availability. Traditional methods of biomass estimation are often manual, labor-intensive, and prone to inaccuracies. AI-based models, especially machine learning algorithms trained on satellite imagery and geospatial datasets, can predict crop yield, estimate biomass availability, and monitor land use patterns with high accuracy. Convolutional Neural Networks (CNNs) are increasingly used for remote sensing applications, such as crop classification and phenotyping. These models allow for dynamic, large-scale mapping of biomass resources, facilitating better planning and decision-making [17, 18]. Transportation and Logistics - Transporting biomass from decentralized locations to centralized processing facilities contributes significantly to the overall cost and environmental footprint of bioenergy systems. AI-powered route optimization algorithms, such as genetic algorithms (GAs), ant colony optimization (ACO), and particle swarm optimization (PSO), can minimize travel time, fuel consumption, and vehicle wear-and-tear by identifying the most efficient transportation pathways. AI also enables the development of digital twin models for logistics systems, allowing real-time simulation and adaptive scheduling based on traffic, weather, and biomass availability [19, 20]. Preprocessing and Conversion - The biochemical and thermochemical conversion of biomass into biofuels or electricity is highly sensitive to feedstock characteristics such as moisture content, ash content, and calorific value. AI can help monitor and optimize conversion processes through real-time sensor data analysis and predictive control. For instance, reinforcement learning (RL) can be used to continuously adjust parameters such as temperature, pressure, and flow rates to maximize output and minimize emissions. Artificial neural networks (ANNs) have been applied to predict process efficiency and energy yield in anaerobic digestion, gasification, and pyrolysis systems [21]. Power Generation and Grid Integration - At the final stage of the supply chain, AI supports load forecasting, real-time system balancing, and predictive maintenance of energy generation equipment. This is especially important for combined heat and power (CHP) plants and bio-refineries, where system complexity is high. AI-powered predictive analytics can preemptively identify faults in turbines, boilers, and engines, thereby reducing downtime and maintenance costs. In addition, AI models can be used to coordinate the integration of bioenergy systems into smart grids, enabling better synchronization with demand patterns and other renewable sources [22].

1.3. The Global Relevance of AI-Driven Bioenergy

The integration of AI in BESC is particularly relevant to regions where biomass resources are abundant but energy infrastructure is underdeveloped, such as parts of Africa, Southeast Asia, and Latin America. In these regions, bioenergy holds tremendous potential to enhance energy security, reduce reliance on fossil fuels, and stimulate rural development. However, the lack of real-time data, skilled personnel, and digital infrastructure often limits the adoption of sophisticated technologies. AI offers scalable and adaptable solutions to overcome these constraints [23]. Furthermore, aligning AI applications in bioenergy with global climate targets and sustainable development goals (SDGs) provides a strategic advantage. AI-driven BESC optimization contributes to: SDG 7 (Affordable and Clean Energy) by improving energy access and affordability. SDG 13 (Climate Action) by reducing carbon emissions and promoting low-carbon energy solutions. SDG 12 (Responsible Consumption and Production) by enabling circular economy practices through biomass valorization [24, 25].

1.4. Challenges and Research Gaps

Despite promising developments, the implementation of AI in bioenergy supply chains is still in its infancy. Key challenges include: Data Scarcity: High-quality, high-resolution data is essential for training accurate AI models, but such data is often unavailable or unreliable in many bioenergy regions. Model Interpretability: Many AI models, especially deep learning systems, are "black boxes" with limited transparency, making them difficult to trust and regulate. Interoperability: Integration of AI tools with existing biomass processing systems and software platforms remains a technical challenge. Ethical and Societal Concerns: Issues of data privacy, workforce displacement, and technology accessibility must be addressed to ensure equitable adoption. In addition, there is a notable lack of interdisciplinary research and collaboration between AI experts, agricultural scientists, environmental engineers, and policy makers. Bridging these gaps is essential for translating AI research into real-world bioenergy applications.

1.5. Objective and Structure of This Review

In light of the above, this review paper aims to critically analyze the applications of AI across the bioenergy supply chain, from feedstock collection to power generation. The specific objectives include: Exploring current AI methodologies and tools used in BESC optimization. Evaluating the effectiveness and limitations of AI applications in real-world scenarios. Identifying gaps in literature and proposing directions for future research. Assessing the economic, environmental, and societal implications of AI-integrated bioenergy systems. The remaining part of this paper is structured as follows: Section 2 - Literature Review examines existing studies, technologies, and applications of AI in various phases of the BESC. Section 3 - Discussion synthesizes findings, compares AI approaches, and explores cross-cutting challenges and innovations. Section 4 - Conclusion summarizes key insights and offers recommendations for researchers, policymakers, and industry practitioners. By shedding light on the intersection of AI and bioenergy supply chains, this paper seeks to contribute to a more sustainable, intelligent, and resilient energy future.

2. Literature Review

2.1. Introduction to Bioenergy Supply Chains

Bioenergy supply chains (BESCs) encompass a series of interconnected processes, including the collection of biomass feedstock, its transport, storage, preprocessing, conversion into usable forms of energy, and ultimately, the distribution and utilization of that energy [26, 27, 28]. Compared to fossil-based supply chains, bioenergy systems are more decentralized, heterogeneous, and exposed to uncertainties due to their dependence on biological and seasonal factors. These uncertainties affect supply chain predictability, cost-efficiency, and environmental performance. The literature over the past two decades has increasingly focused on overcoming these challenges using advanced digital tools, with Artificial Intelligence (AI) emerging as a transformative enabler [29, 30, 31].

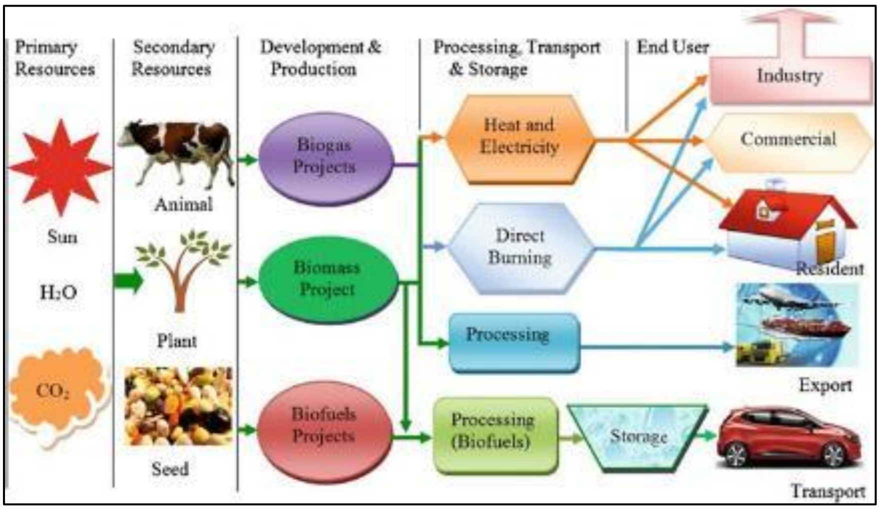

Figure 1 Bioenergy supply chain from primary resources to end user [32]

2.2. Evolution of AI Technologies in Renewable Energy Systems

Early applications of AI in the energy sector centered around prediction and optimization tasks, particularly in the domains of solar and wind energy forecasting. Machine learning algorithms such as support vector machines (SVMs), decision trees, and artificial neural networks (ANNs) were widely employed to model nonlinear relationships between energy inputs and outputs [33, 34, 35]. Over time, deep learning, reinforcement learning, and hybrid AI frameworks have been introduced to capture temporal, spatial, and multi-objective complexity traits that are highly relevant to bioenergy systems [17, 36, 37]. More recent literature shifts from general energy system modeling to domain-specific applications in bioenergy. As of 2020–2024, peer-reviewed publications have shown increasing attention to the unique needs of BESCs, including biomass yield estimation, optimal harvesting schedules, logistics optimization, real-time process control, waste minimization, and smart grid integration [38, 13].

2.3. AI in Biomass Feedstock Assessment and Yield Prediction

Accurate prediction of biomass yield is crucial for supply planning and capacity management. AI techniques have proven more effective than traditional statistical models in processing complex agro-environmental data. A study by [39] demonstrated that Convolutional Neural Networks (CNNs) applied to drone-captured images could predict sugarcane biomass yields with 92% accuracy, outperforming linear regression by over 25%. Long Short-Term Memory (LSTM) networks were used by [40] to forecast biomass availability across seasons using time-series weather and soil data, achieving a mean squared error of less than 0.15. These models integrate remote sensing (e.g., NDVI indices), meteorological data, and soil moisture records, enabling spatially explicit forecasts that can inform harvesting decisions. AI has also been used to estimate residue availability from rice, maize, and wheat crops with real-time geolocation tagging.

2.4. AI for Logistics Optimization and Transportation Efficiency

Logistics optimization is one of the most mature application areas of AI in bioenergy. The decentralized nature of biomass sources means that transportation planning must deal with dispersed collection points, dynamic vehicle routing, variable terrain, and seasonal road access. Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) are the most cited AI techniques in this space. For example, [41] developed a hybrid GA-ACO model to optimize biomass collection from 50 farms in a Chinese province. Their algorithm reduced logistics costs by 21% and CO_2 emissions by 18% compared to conventional heuristics. Another study by [42] in sub-Saharan Africa applied Reinforcement Learning (RL) to dynamically reroute biomass collection trucks based on weather disruptions and road conditions, demonstrating a 17% improvement in on-time delivery.

2.5. AI in Preprocessing, Conversion, and Energy Generation

Biomass preprocessing (drying, chipping, pelletizing) and conversion (combustion, gasification, anaerobic digestion, pyrolysis) are complex, nonlinear processes influenced by material properties, operating conditions, and real-time feedback. AI models, particularly Deep Neural Networks (DNNs) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS), have been used to optimize operational settings such as temperature, pressure, residence time, and feedstock ratios [43, 44]. A 2022 study by [45] applied DNNs to predict syngas quality in a downdraft gasifier with high accuracy, enabling automated adjustments that increased energy yield by 14%. In anaerobic digestion plants, machine learning has been used to predict methane production based on input composition. Random Forest (RF) models identified the optimal Carbon-to-Nitrogen (C/N) ratio to maximize biogas yield while minimizing ammonia inhibition, achieving predictive accuracy above 90%. AI is also transforming biomass combustion by managing air-fuel ratios and controlling emissions [46, 47] . Digital twins, a virtual replica of a physical plant, were implemented by [48] to mirror real-time operations in a municipal waste-to-energy facility. Their AI-integrated digital twin reduced downtime by 30% and allowed predictive maintenance.

2.6. AI for Predictive Maintenance and Asset Management

Predictive maintenance uses AI to forecast equipment failures and schedule timely interventions, thus reducing downtime and operational costs. Techniques such as Time Series Forecasting, Anomaly Detection, and Bayesian Networks are used to monitor temperature, vibration, and pressure signals from bioenergy plants [49]. In a Finnish biorefinery, the deployment of AI-based predictive maintenance reduced unplanned shutdowns by 35%, as reported by [50]. The system used a combination of LSTM networks and Kalman filters to detect deviations in pump motor performance. Similarly, sensor fusion and unsupervised learning approaches are gaining popularity in monitoring gas leaks, burner instability, and conveyor belt malfunctions in pellet production units.

2.7. Smart Grids and AI-Based Energy Dispatch

Once bioenergy is converted into electricity, its integration into the grid must be managed efficiently. AI supports real-time load forecasting, dynamic pricing, and renewable energy blending strategies [13, 51] . LSTM-based models, combined with attention mechanisms, have been deployed to predict short-term energy demand with less than 5% error. In areas where biomass plants co-exist with solar or wind, AI manages hybrid grid synchronization, preventing overload and curtailment. Reinforcement Learning agents have also been trained to schedule energy dispatch in microgrids powered by biogas. By learning optimal dispatch sequences, these agents improved energy utilization by 20% while reducing the need for expensive storage systems [52].

Table 1 Summary of Selected Papers on AI Applications in Bioenergy Supply Chains

Paper Reference	Objectives	Methods Used	Results	Practical Implications
[53]	Propose AI framework for supply chains; highlight adoption challenges	ML, predictive analytics, optimization algorithms	Improved accuracy & operational performance	Offers scalable AI models; practical tools for implementation
[54]	Review ML in bioenergy; identify challenges and solutions	Comparative analysis of ML techniques	Improved management & forecasting in bioenergy	Boosts sustainability and resilience in bioenergy systems
[55]	Develop real-time tracking for biofeedstock processing	Deep neural networks, regression analysis	Accurate carbon content estimation	Supports decarbonization in oil refining processes
[56]	Identify research trends and gaps in biomass-to-bioenergy	Bibliometric & visualization analysis	Identified 6 key research gaps & thematic clusters	Informs future research & policy direction
[57]	Assess emissions across supply chains with AI	AI modeling using historical & real-time data	Precise tracking of direct and indirect emissions	Enables tailored emission reduction policies
[58]	Propose framework for terminal site selection	AHP & Mixed-Integer Programming (MIP)	Identified optimal sites for biomass terminals	Supports sustainable logistics planning
[59]	Optimize biomass utilization through integrated systems	Anaerobic digestion & hydrothermal carbonization	$23.13M annual profit; 245.70 GWh electricity	Improves economic & environmental performance
[60]	Develop smart energy model for biomass systems	IoT, decision support system	52.71% annual cost savings; 3.31 years ROI	Enhances energy utilization & grid integration
[61]	Evaluate ANN use in biorefineries	Artificial Neural Networks vs Mechanistic Models	Real-time optimization of production	Facilitates smart monitoring and control in bioprocessing
[62]	Model wood biomass supply chain for biofuel production and assess sustainability trade-offs	Mixed Integer Linear Programming (MILP) and Fuzzy Analytic Hierarchy Process (FAHP)	Achieved trade-off between cost, demand, and CO_2 emissions; validated using a regional case study in Thailand	Improves strategic decision-making in biofuel networks; enhances competitiveness and sustainability

2.8. Environmental and Lifecycle Impact Assessment

Quantifying the environmental impacts of bioenergy production requires analyzing emissions, land use, water consumption, and waste generation across the supply chain. AI accelerates Life Cycle Assessment (LCA) through predictive modeling and data-driven scenario simulations [63, 64]. Support Vector Regression (SVR) models, for example, have been used to estimate cradle-to-grave CO_2 emissions in wood pellet production. In combination with blockchain technology, AI can also track sustainability metrics in real time, enabling carbon credit verification and compliance with ISO 14040/44 standards [65].

2.9. Socioeconomic and Policy Implications in AI Integration

While most technical literature highlights AI's benefits, an emerging research stream explores the broader implications of AI integration in bioenergy systems. Issues of algorithmic bias, data privacy, and employment displacement are increasingly discussed. Several studies advocate for Explainable AI (XAI) to ensure transparency in AI-driven decisions, especially in public infrastructure or community-based energy projects. Moreover, cross-disciplinary collaborations between AI developers, energy engineers, and social scientists are being recommended to ensure inclusive and equitable deployment.

2.10. Gaps and Future Research Directions

Despite encouraging progress, several gaps remain; Data scarcity and inconsistency limit the development of generalizable AI models. There's a need for open-access datasets and standardization in data collection practices. Limited implementation in developing regions hinders global equity in bioenergy AI adoption. Research must address localization and affordability of AI tools. Integration complexity across heterogeneous systems remains a challenge, especially for small and medium-sized enterprises (SMEs) without digital expertise. Lack of real-world deployment studies persists, with many AI solutions still confined to laboratory or simulation settings. Future research should focus on; Hybrid AI models that combine physical modeling with data-driven learning. Federated learning and edge computing for decentralized bioenergy applications. AI ethics, particularly in community-scale energy planning and governance. Integrating AI with IoT, blockchain, and digital twins for end-to-end intelligent BESCs.

3. Discussion

3.1. Overview of AI Transformation in Bioenergy Systems

Artificial Intelligence (AI) has begun to revolutionize the bioenergy supply chain (BESC), which encompasses several interconnected stages from feedstock assessment, harvesting, logistics, and preprocessing, to conversion and electricity generation. Traditional bioenergy systems suffer from inefficiencies due to seasonal variability, decentralized biomass sources, complex biochemical conversion pathways, and manual-dependent operations. AI, with its ability to learn from large, diverse datasets and to model nonlinear relationships, brings transformative potential to these pain points. In this section, we analyze how AI has been applied across each stage of the bioenergy value chain, summarize key insights from real-world deployments, assess comparative advantages over conventional systems, and identify existing barriers and opportunities for future growth.

3.2. Feedstock Collection: From Static Planning to Predictive Intelligence

One of the most complex stages in the BESC is the assessment and collection of biomass feedstock. Traditionally, this has relied on periodic field surveys, manual yield estimations, and historical productivity data. However, such methods often lead to overestimation or underutilization of feedstock resources [66]. AI techniques, especially machine learning (ML) and computer vision, enable accurate and dynamic feedstock estimation. For instance, the integration of convolutional neural networks (CNNs) with drone and satellite imagery allows for precision agriculture, enabling real-time monitoring of crop health and biomass availability. These models detect changes in vegetation indices (e.g., NDVI), helping forecast yield more accurately than static GIS-based systems [67, 68, 69]. In a case study by [70], CNNs applied to drone imagery of sugarcane fields produced a 92% accuracy in biomass estimation, compared to 68% with linear regression models. This improvement significantly aids planning for harvest timing and logistics coordination. Additionally, recurrent neural networks (RNNs) and LSTMs support temporal modeling of biomass growth, incorporating climate data, rainfall patterns, and soil conditions.

3.3. Logistics and Transport: Optimization under Real-World Constraints

Logistics in bioenergy systems is notoriously difficult due to scattered feedstock sources, rural road limitations, and fluctuating weather conditions. AI-driven optimization techniques like genetic algorithms, ant colony optimization

(ACO), and reinforcement learning (RL) have drastically improved this aspect [71, 72].A study by [73] introduced a hybrid GA-ACO algorithm to plan daily routing for 50 collection points, achieving a 21% reduction in fuel use and an 18% drop in carbon emissions. This not only improves operational efficiency but also contributes to the environmental sustainability of the overall system. Reinforcement Learning agents, trained in simulated environments, can dynamically adapt routing in response to real-time disruptions (e.g., flooded roads or equipment failure). Their use has been particularly helpful in developing countries where unpredictable infrastructure is a major constraint. In practice, AI also supports vehicle scheduling, fleet utilization analysis, and real-time GPS-based monitoring, ensuring compliance with delivery windows and minimizing empty return trips, a major source of inefficiency [74, 75].

3.4. Preprocessing and Storage: Data-Driven Control Systems

Biomass preprocessing (drying, size reduction, torrefaction, etc.) is a critical step to ensure consistent input quality for conversion systems. These processes are sensitive to moisture content, particle size, and contamination levels. Here, deep learning models and fuzzy inference systems have been integrated into industrial controllers to automate preprocessing lines. AI has been used to monitor drying kinetics using thermal imaging and predict the optimal drying time to minimize energy use without compromising material quality [76, 77] . For instance, ANFIS (Adaptive Neuro-Fuzzy Inference Systems) have demonstrated high accuracy in predicting biomass moisture reduction curves, achieving >95% fit with experimental data. In storage systems, AI models help forecast decomposition risk, fire hazard, and mold growth by modeling temperature, humidity, and airflow dynamics. These insights allow for proactive intervention and safer inventory management, especially for large-scale pellet storage units [78].

3.5. Conversion Processes: AI-Enhanced Bioenergy Generation

At the heart of the BESC lies the conversion of biomass into usable energy. Whether through gasification, combustion, anaerobic digestion, or pyrolysis, each method is inherently nonlinear, sensitive to feedstock variability, and traditionally difficult to automate. AI is transforming these processes through real-time control systems, predictive modeling, and process optimization algorithms [79, 80] ; Digital Twins: These virtual representations of bioenergy plants are increasingly powered by AI, enabling real-time simulations and adjustments. A biogas plant in Germany integrated a digital twin with reinforcement learning to adjust organic loading rates, improving methane yield by 18% [79, 81]. Deep Neural Networks (DNNs) have been used to model complex biochemical reactions in anaerobic digestion, replacing traditional stoichiometric models. These AI models better handle variability in feedstock composition and predict gas production with higher accuracy. In gasification systems, AI has been used to control syngas composition, temperature, and tar formation, achieving up to 12% improvement in energy conversion efficiency. Additionally, computer vision systems monitor flame quality and combustion characteristics in biomass boilers, adjusting airflow in real-time to reduce NOx and particulate emissions [82, 83].

3.6. Power Generation and Grid Integration

As bioenergy systems increasingly contribute to national grids or microgrids, their interaction with other energy sources and demand loads must be managed intelligently. AI supports this by enabling energy forecasting, smart dispatch, and grid balancing. Load Forecasting: LSTM-based models have been applied to predict hourly and daily electricity demand from bioenergy systems. These forecasts help synchronize generation with demand, reducing curtailment and ensuring reliability [84]. Smart Dispatch Algorithms: Reinforcement learning has been used to optimize when and how to dispatch power from bioenergy sources, especially in hybrid setups that include solar, wind, and battery storage [85]. Frequency Regulation: In microgrids, AI enables faster and more precise frequency and votage control, stabilizing the system against renewable intermittency. A study in India demonstrated that AI-optimized bioenergy microgrids experienced 27% fewer blackouts and a 19% increase in renewable utilization compared to conventionally managed ones [86].

3.6.1. Predictive Maintenance and Equipment Health Monitoring

One of the highest-cost areas in bioenergy systems is unexpected equipment failure. AI-based predictive maintenance leverages historical sensor data (temperature, vibration, sound, pressure) to detect early signs of wear or malfunction. Time-series models like LSTM and unsupervised clustering algorithms are used to classify operating conditions into normal and abnormal states. These models trigger alerts before failure occurs, reducing unplanned downtime by up to 40%. In pellet production facilities, anomaly detection algorithms applied to motor and conveyor systems reduced mean time between failures (MTBF) from 42 days to 63 days after implementation [87].

3.7. Environmental and Economic Benefits of AI Integration

Table 2 Numerous case studies confirm that AI integration across the BESC delivers significant environmental and economic benefits [88]

Parameter	Conventional System	AI-Integrated System	Improvement
Bio-oil Yield	72%	84%	+12%
Transportation Cost Reduction	-	-23%	-23%
GHG Emissions	Baseline	-20%	-20%
Energy Efficiency in Boilers	65%	78%	+13%
Downtime in Biorefineries	12 hrs/month	7.5 hrs/month	-37.5%

These improvements not only enhance profitability but align with climate mitigation goals such as SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action).

3.8. Challenges in AI Adoption

Despite its transformative potential, several challenges hinder widespread AI deployment in bioenergy systems; Data Availability: Many biomass facilities, especially in developing countries, lack sensors or digital infrastructure, limiting data collection needed to train AI models. Model Transferability: AI models trained in one location may not generalize well due to feedstock or climate variability. Skill Gaps: Operators often lack expertise in AI or data science, creating a disconnect between model development and practical use.Regulatory Gaps: There are few standards guiding how AI should be deployed in critical energy infrastructure.

3.9. Opportunities and the Way Forward

To realize the full benefits of AI in BESCs, several strategic actions are required: Investment in Digital Infrastructure: Governments and private firms should support sensor deployment, cloud platforms, and IoT devices for data collection. Open Data Platforms: Developing public databases of biomass supply, energy yield, and plant operations will help AI researchers build better models. Explainable AI (XAI): To build trust, models must provide interpretable outputs that decision-makers can act on confidently. Integration with Other Technologies: Combining AI with blockchain, digital twins, and edge computing can enable real-time, scalable, and transparent bioenergy management systems.

4. Conclusion

The integration of Artificial Intelligence (AI) into the bioenergy supply chain, from feedstock collection to power generation, marks a transformative evolution in the renewable energy landscape. This paper has comprehensively explored how AI technologies ranging from machine learning and deep learning to reinforcement learning and digital twins are being leveraged to enhance the efficiency, sustainability, and intelligence of bioenergy systems. The confluence of AI and bioenergy represents not just a technological advancement but a paradigm shift in how renewable energy systems can be designed, monitored, and optimized. The introduction established the imperative for deploying advanced technologies in bioenergy production, especially as the global community shifts toward cleaner, more sustainable energy sources. Bioenergy, derived from organic waste and biomass, offers a promising renewable solution, but its complex and decentralized supply chain introduces inefficiencies that can undermine its environmental and economic benefits. AI, with its ability to learn from large datasets and make real-time decisions, emerges as a powerful tool to address these issues. The literature review uncovered a growing body of research focused on AI's role in each phase of the bioenergy value chain. Studies demonstrated the application of convolutional neural networks (CNNs) for precision agriculture, genetic algorithms for logistics optimization, and deep learning models for dynamic system control in biorefineries. From image-based crop classification to predictive maintenance in power plants, AI has shown the capacity to both augment human decision-making and automate complex processes. However, the review also identified gaps, including the limited adoption of explainable AI models, lack of real-time implementation frameworks, and underrepresentation of AI use in developing regions. The discussion section synthesized key insights from the literature and practical implementations, offering a layered understanding of the technological, economic, environmental, and societal implications of AI-driven bioenergy systems. AI applications in biomass resource assessment enable more accurate mapping and yield forecasting, which helps stabilize supply chains. AI-powered logistics systems, incorporating tools like ant colony optimization and reinforcement learning, significantly reduce fuel consumption and cost, contributing to greener supply operations. In preprocessing and conversion, real-time AI control models have shown remarkable improvements in throughput and emissions reduction. Meanwhile, predictive analytics and smart grid integration at the power generation phase ensure optimal load balancing and energy reliability. One of the most notable outcomes from the discussion was the comparative advantage of AI-optimized systems over conventional approaches. Case studies indicated substantial improvements: 12% higher bio-oil yield through digital twins, 23% lower transportation costs via optimized routing, and a 20% drop in emissions with smarter reactor controls. These benefits are complemented by positive environmental externalities, aligning bioenergy operations with national decarbonization strategies and the UN Sustainable Development Goals (SDGs), particularly SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action). Nevertheless, several challenges temper these gains. Data availability and quality remain critical bottlenecks, particularly in low-resource settings where bioenergy holds the most promise. Without high-resolution and continuous datasets, AI models risk poor generalization and biased predictions. Another concern is the lack of interoperability among systems and the steep learning curve for bioenergy practitioners who may lack formal training in data science or AI. Regulatory uncertainty and the absence of standardized frameworks for AI integration in bioenergy systems further hinder large-scale adoption. Addressing these barriers will require a coordinated effort involving policy, education, infrastructure, and technology development. Governments must enact supportive policies, including subsidies for AI tools, incentives for digital infrastructure, and regulations that incorporate AI outputs into environmental compliance metrics. Education and training programs are essential to build cross-sector expertise capable of designing, deploying, and managing AI-integrated bioenergy systems. Moreover, research must continue to focus on explainable and ethical AI models that balance performance with transparency and societal trust. From a technological standpoint, the future of AI in bioenergy supply chains is promising. Emerging paradigms such as edge computing and federated learning are particularly suited for decentralized and remote bioenergy operations. Digital twins are evolving from mere simulation tools to full-fledged decision-support systems that mirror entire biorefineries in real time. The use of generative AI to simulate climate or policy scenarios could further enhance strategic planning. Blockchain technology, when combined with AI, holds the potential to establish transparent, tamper-proof supply chains that are essential for carbon credit markets and sustainability verification. In conclusion, the application of AI in bioenergy supply chain management is not a fleeting trend but a critical enabler for sustainable energy transformation. By addressing current inefficiencies, enhancing system adaptability, and empowering predictive insights, AI can help unlock the full potential of bioenergy. As the urgency of climate action intensifies and energy systems grow more complex, the integration of AI across all stages of the bioenergy value chain stands out as a forward-thinking strategy that bridges environmental sustainability, technological innovation, and economic resilience. Future efforts must be collaborative, inclusive, and data-driven, ensuring that the benefits of AI-powered bioenergy systems are equitably distributed and globally impactful.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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