Synergistic Applications of Machine Learning and Bioenergy for Environmental Sustainability: A Comprehensive Assessment

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Abstract

The increasing global demand for renewable energy and the pressing need for environmental sustainability have led to a growing interest in bioenergy production as a viable solution. Concurrently, advancements in machine learning (ML) techniques have opened up new opportunities for optimizing processes and improving efficiency across various sectors. Recognizing the potential of integrating ML with bioenergy, this study aims to explore the synergistic applications of these technologies to enhance environmental sustainability. Through a comprehensive assessment, which includes a systematic review and case study analysis, this research investigates the potential of ML algorithms and models in optimizing bioenergy processes and bioproduct production. By leveraging ML techniques, bioenergy processes can be refined and fine-tuned, leading to increased efficiency, reduced waste, and enhanced environmental performance. The systematic review component of this study critically examines existing literature on the integration of ML and bioenergy, identifying key trends, challenges, and opportunities. The case study component of this study provides a detailed analysis of the integration of ML and bioenergy in one case: the production of biomethane from municipal solid waste (MSW) in Mukono District, Uganda. Ultimately, this study's findings will provide valuable insights and recommendations for policymakers, researchers, and industry stakeholders. The insights gained will help harness the full potential of ML in advancing the field of bioenergy, while simultaneously achieving sustainable energy production. By identifying critical factors influencing the successful integration of ML and bioenergy, this research contributes to the broader objective of addressing environmental concerns and ensuring a sustainable future.

Keywords
Machine Learning, Biomass, Bioenergy, Renewable Energy Source

1. Introduction
In today's world, the growing global demand for renewable energy has led to a revived interest in using biomass as a sustainable and carbon-neutral alternative. Biomass, derived from organic materials like agricultural residues, forestry waste, and dedicated energy crops, possesses immense potential for energy production (Jungmeier 2017; Onu and Mbohwa 2021). However, traditional methods of biomass energy production often face challenges related to efficiency, cost-effectiveness, and environmental impact (Jungmeier 2017; OECD/IEA and IRENA 2017). In recent years, machine learning (ML) has emerged as a transformative technology capable of revolutionizing various industries (Wu et al. 2018). ML algorithms have the ability to analyze vast volumes of data, identify patterns, and make predictions or decisions without explicit programming. Applying ML techniques in biomass energy production opens up new possibilities for optimizing processes, enhancing efficiency, and improving overall system performance (Cinar et al. 2022). By harnessing the power of ML, we can unlock numerous potential benefits, including improved resource utilization, increased energy conversion efficiency, and enhanced operational decision-making. These advancements have the potential to expedite the adoption of biomass as a reliable and sustainable energy source, ultimately reducing greenhouse gas emissions and mitigating the adverse effects of climate change. To achieve this, modern technologies for bioenergy and bioproduct production offer promising avenues. Bioenergy involves producing energy from organic materials such as crops, agricultural residues, and organic waste, while bioproducts encompass a wide range of products derived from biomass, including bioplastics, biochemicals, and biofuels.

These modern technologies hold great potential to provide renewable and sustainable alternatives to conventional energy sources and petroleum-based products, thus reducing greenhouse gas emissions and dependence on fossil fuels. However, it is crucial to critically evaluate the environmental implications of these modern bioenergy and bioproduct technologies. While these technologies offer promising benefits, it is essential to conduct thorough assessments to ensure that they genuinely contribute to a greener and more sustainable future. By examining the integration of machine learning and bioenergy, this research aims to comprehensively assess the potential of ML algorithms and models in optimizing bioenergy processes and reducing environmental impacts. Moreover, it seeks to identify the key factors influencing the successful integration of ML and bioenergy for sustainable energy production. This study contributes to the broader objective of addressing environmental concerns and achieving a sustainable future. The findings and insights gained from this research will provide valuable recommendations for policymakers, researchers, and industry stakeholders, enabling them to harness the full potential of machine learning in advancing the field of bioenergy and promoting environmental sustainability. To facilitate a comprehensive understanding of the research topic, this paper will begin with an overview of bioenergy and its significance for environmental sustainability. It will then introduce machine learning and its potential applications in various sectors, highlighting its transformative capabilities.

2. Literature Review

Modern bioenergy and bioproduct technologies encompass various innovative approaches that utilize biomass resources to generate renewable energy and sustainable products (Carrillo-Nieves et al. 2019; Pattanaik et al. 2019). They offer significant potential as alternatives to conventional fossil fuels and petroleum-based products by utilizing biomass feedstocks derived from organic matter, which can be naturally replenished (Jungmeier 2017). Algae cultivation is a technology that utilizes microalgae to convert sunlight and carbon dioxide into biomass, which can be further processed to extract biofuels, bioplastics, and high-value biochemicals (Gjertsen et al. 2020; Iglina et al. 2022). Algae can be cultivated in diverse environments, including open ponds, closed photobioreactors, and wastewater treatment facilities (Iglina et al. 2022). Certain algae species, characterized by their rapid growth rate and high lipid content, are desirable for biofuel production (Osama et al. 2021). Another widely adopted technology is anaerobic digestion, which involves the decomposition of organic materials without oxygen, producing biogas primarily composed of methane and carbon dioxide (Onu et al. 2023). Anaerobic digestion provides a sustainable organic waste management solution while generating renewable energy (Onu and Mbohwa 2021). However, challenges related to feedstock availability, process stability, and effective waste segregation and pretreatment can impact the efficiency and scalability of anaerobic digestion systems (Grosser and Neczaj 2022; Şenol 2021). Biorefineries are integrated facilities that employ various conversion processes to transform biomass feedstocks into a wide range of valuable products (Jungmeier 2017). By utilizing approaches such as fermentation, enzymatic hydrolysis, and thermochemical conversion, biorefineries aim to maximize biomass utilization by extracting biofuels, biochemicals, bioplastics, and other high-value compounds (Onu and Mbohwa 2021). They play a crucial role in developing a bio-based economy by efficiently converting renewable resources into multiple products (Grosser and Neczaj 2022). Successful biorefinery operation depends on feedstock availability, process integration, and market demand for the derived products (Grosser and Neczaj 2022; Jungmeier 2017).

Machine learning, an integral part of artificial intelligence (AI), is a discipline that revolves around the development of algorithms and models. These innovative tools empower computers to learn from data, thereby enabling them to autonomously make predictions and decisions. autonomously (Bock et al. 2019; Peter et al. 2023). It eliminates the need for explicit programming by leveraging fundamental principles such as supervised, unsupervised, and reinforcement learning (shown in Figure 1). In supervised learning, algorithms learn from labeled data, using input-output pairs to recognize patterns and make predictions on new, unseen data. On the other hand, unsupervised learning involves training algorithms on unlabeled data to identify inherent patterns and structures. Reinforcement learning enables algorithms to make decisions based on feedback from interactions with an environment (Cinar et al. 2022), adjusting their behavior to optimize outcomes (Onu et al. 2023).

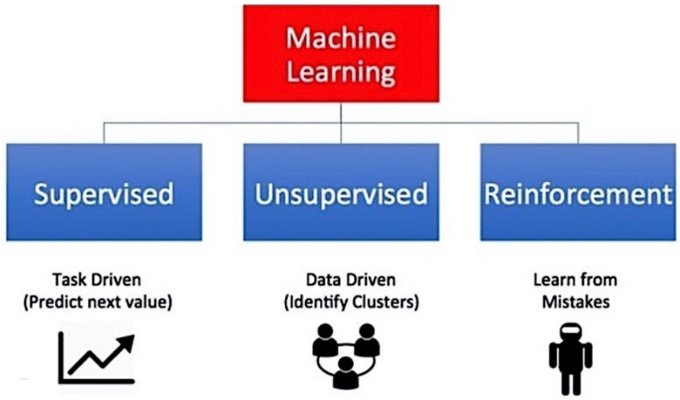

Figure 1. Supervised, Unsupervised, and Reinforcement Learning

Applying machine learning techniques to biomass energy production offers opportunities for optimization in various areas. ML algorithms can assist in feedstock selection and characterization, process optimization, resource management, and energy generation prediction (Long et al. 2021). By harnessing the power of ML, it becomes possible to identify the most suitable biomass feedstocks for efficient energy production, optimize conversion processes for improved performance, and develop predictive models for energy output and resource utilization (illustrated in table 1). Integrating machine learning into biomass energy production addresses process optimization, resource management, and decision support challenges. These algorithms analyze complex and dynamic data, identify patterns, and provide valuable insights to enhance overall system efficiency and sustainability (Liu et al. 2021; Onu and Mbohwa 2021).

Table 1. Application of Machine learning Model in Anaerobic Digestion Process

	Xu et al. (2021)	Park et al. (2021)	Long et al. (2021)	Wang et al. (2020)	Yi-Fan et al. (2017)	Alejo et al. (2018)
Inputs	Total solid (TS), Volatile solid (VS), COD, pH, temperature and zero-valent iron (ZVI) dosage, and particle size	pH, alkalinity (ALK), COD removal efficiency, VFA	VFAs, temperature, Organic load rate, Hydraulic retention time, and waste types	Feedstock composition and temperature	COD, hydraulic retention time (HRT), ALK, pH, VFA, oxidation-reduction potential	Total ammonium nitrogen (TAN), VS, COD, and TS
Outputs	Methane production	Methane yield	Methane yield	Methane yield	COD	TAN
ML model	XGBoost, RF, and FNN	RF, XGBOOST, SVM and RNN	Generalized linear model network, RF, k-NN, XGBOOST FNN, and SVM	k-NN, RF, GLMNET and C-SVM	-	SVM, ANN
Best model	XGBoost	RNN	RF	k-NN	FNN	SVM

Several research works have explored the use of machine learning techniques in optimizing various aspects of bioenergy production, such as feedstock selection, process optimization, energy conversion, and resource management (Abu Qdais et al. 2010; Fakharudin et al. 2013; Gueguim Kana et al. 2012). These studies have demonstrated the potential of machine learning to improve the efficiency, sustainability, and economic viability of bioenergy systems. However, despite the progress made in this field, there are still several research gaps that need to be addressed. Firstly, the majority of existing studies have focused on specific aspects or subdomains of bioenergy production, leaving room for a more comprehensive assessment of the entire value chain. A holistic approach that considers the integration of machine learning across different stages of bioenergy production, from feedstock preprocessing to energy distribution, is needed to fully understand its potential impact. Secondly, there is a need for more in-depth investigations into the scalability and generalizability of machine learning models in the bioenergy context. Many studies have been conducted on a small scale or with limited datasets, which may not accurately reflect real-world scenarios. It is crucial to evaluate the performance and reliability of machine learning algorithms when applied to large-scale bioenergy systems and diverse geographical regions. Furthermore, while the technical aspects of machine learning integration have been extensively studied, there is a lack of research on the social, economic, and policy implications of this approach. Understanding the potential social and economic impacts, as well as the regulatory and policy frameworks required for successful implementation, is essential for the widespread adoption of machine learning in bioenergy.

In light of these research gaps, a comprehensive assessment is needed to bridge the knowledge divide and provide a holistic understanding of the integration of machine learning and bioenergy. Such an assessment would not only identify the potential benefits and challenges but also inform the development of best practices, guidelines, and policy recommendations for realizing the full potential of machine learning in advancing the bioenergy sector. By addressing these research gaps and conducting a comprehensive assessment, this study aims to contribute to the existing body of knowledge and provide valuable insights into the integration of machine learning and bioenergy.

3. Methodology

This study employs a research design that combines qualitative and quantitative approaches to conduct a thorough analysis of the integration of machine learning in biomass energy production. The qualitative component involves a systematic literature review, utilizing Systematic Literature Network Analysis (SLNA), to identify and examine existing studies in this field. Reputable databases such as Scopus, IEEE Xplore, and Web of Science were searched using relevant keywords, limited to English articles published within the past 20 years. Inclusion criteria for the studies encompassed peer-reviewed journal publications focusing on biomass energy production and comparing the productivity of machine learning-enabled methods with traditional biogas production approaches. Non-English publications, conference abstracts, and duplicates were excluded. Two independent reviewers screened titles and abstracts, and full-text articles meeting the criteria were reviewed using a standardized form to extract key information.

Additionally, an exploratory case study was conducted to gain preliminary insights into the impact of machine learning advancements on sustainable and clean energy solutions in biomass energy production. This case study employed an exploratory-descriptive approach, ensuring comprehensive understanding. A specific case study was chosen in Mukono District, where an operator implemented an anaerobic digester equipped with state-of-the-art technologies (shown in figure 2). This advanced digester system generated comprehensive data encompassing biomass characteristics, process parameters, the machine learning algorithms employed, and the resulting performance outcomes. Data collection involved gathering information from various sources, including published literature, technical reports, operational data, and stakeholder interviews. Thematic analysis was employed to analyze interview transcripts and extract patterns, themes, and key insights. Through this research design, the study aims to comprehensively assess the integration of machine learning in biomass energy production. The combination of qualitative and quantitative approaches, along with the systematic literature review and case studies, will yield valuable knowledge and insights regarding the potential benefits, challenges, and implications of employing machine learning in this domain.

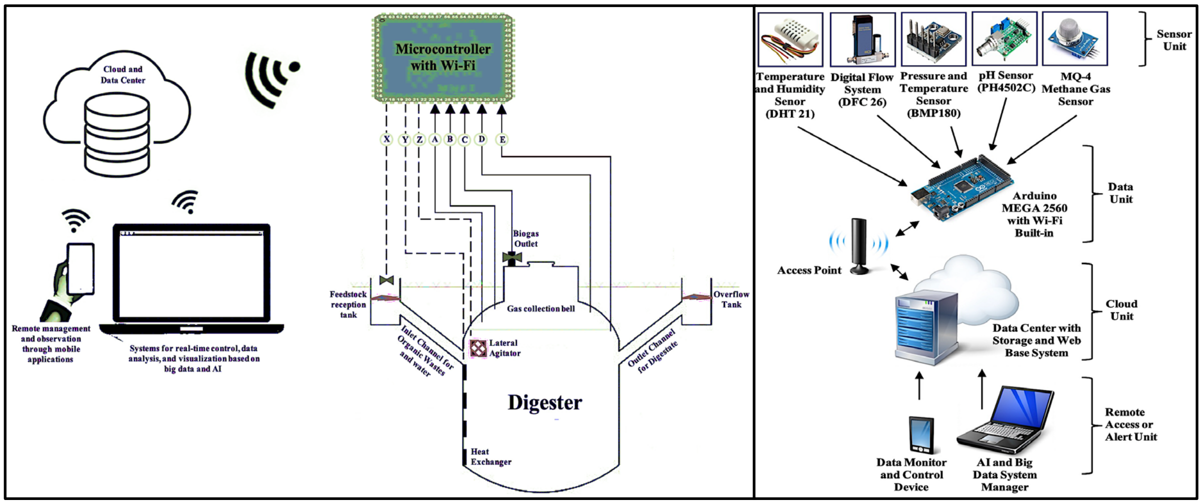

Figure 2. IoT – AI based Anaerobic Digester (Onu et al. 2023)

4. Synergistic Applications of Machine Learning and Bioenergy

4.1 Summary of Relevant Studies on Machine Learning in Biomass Energy Production

This section provides a comprehensive overview of relevant studies identified through a systematic literature review, focusing on the application of machine learning in biomass energy production. These studies encompass various aspects, including biomass feedstock characterization, process optimization, predictive modeling, and real-time monitoring and control.

The bioenergy sector encompasses various promising pathways, each with its own potential, advantages, and challenges. Machine learning can significantly enhance these pathways by providing valuable insights and optimization opportunities. For example, in biomass feedstock characterization, machine learning techniques have successfully predicted properties such as composition, moisture content, and calorific value.

Furthermore, machine learning has proven to be a valuable tool in optimizing different stages of biomass energy production processes. Studies have employed machine learning algorithms to identify optimal operating conditions, optimize resource allocation, and improve overall process efficiency.

Predictive modeling using machine learning techniques has also shown promise in estimating energy yield and performance indicators in biomass energy systems. These models utilize historical data on biomass feedstock characteristics, process parameters, and energy output to make accurate predictions. Various machine learning techniques, including regression models, support vector regression, and ensemble methods, have been employed to develop predictive models that support decision-making and resource planning in biomass energy production.

In addition, machine learning algorithms have played a vital role in the real-time monitoring and control of biomass energy systems. By integrating machine learning techniques with sensor networks and data-driven control strategies, these algorithms ensure optimal performance and efficient resource utilization. They analyze sensor data in real-time, detect anomalies, and make control decisions to maintain system stability and optimize energy production.

4.2 Successful Integration of Machine Learning and Bioenergy

The case study component of this study presents a comprehensive analysis of the integration of machine learning (ML) and bioenergy in the production of biomethane from municipal solid waste (MSW) in Mukono District, Uganda. This study serves as an exemplar, showcasing the diverse ways in which machine learning techniques have been applied to various aspects of bioenergy production, including biomass characterization, process monitoring, and operational decision-making. The present case illustration discusses the monitoring, and operational decision-making process.

Process monitoring is a critical aspect of bioenergy production, and machine learning techniques offer significant advantages in this regard. By leveraging real-time sensor data, operators are able to monitor and analyze key process variables, such as temperature, pH levels, and gas composition. The data is collected through an IoT system, analyzed using an artificial intelligence (AI) model with a genetic algorithm (GA), and transmitted to a feedback system for remote access or alerts. The study results showed that the proposed artificial intelligence-based and IoT-enabled biogas production system achieved high efficiency in biomethane production. The artificial neural network model with backpropagation (BP) training and the genetic algorithm captured biogas production patterns effectively.

Operational decision-making in bioenergy production can greatly benefit from the application of machine learning techniques. ML models can analyze vast amounts of data, including historical records, sensor data, and environmental factors, to identify correlations and patterns that are not easily discernible through traditional methods. Through additional operational and decision-making protocol in the system, the controlled feeding strategy in a biogas plant facilitated the substrate's physicochemical properties and improved the fermentation process's efficiency. Maintaining a consistent and appropriate organic load and chemical composition of the substrate led to a more predictable and stable fermentation process, which led to a more accurate estimation of biogas production and improved process control.

In summary, the analysis indicates that leveraging machine learning models to optimize control parameters in anaerobic digester systems has proven highly beneficial for biomass energy production. The case study demonstrates enhanced process efficiency and increased biogas yield by fine-tuning key parameters, such as temperature, pH level, and retention time. The ML algorithms adaptively optimize the system's performance based on real-time data, improving resource utilization and reducing operational costs. This application enables efficient biogas production from biomass feedstock, contributing to renewable energy generation and waste management.

4.3 Key Factors Influencing the Integration of Machine Learning and Bioenergy

The successful integration of machine learning (ML) techniques in the bioenergy sector depends on various key factors. This section aims to identify the critical success factors for ML adoption in bioenergy production, analyze the challenges and limitations associated with implementing ML techniques, and provide recommendations for overcoming barriers and promoting the synergistic applications of ML and bioenergy.

Literature posits one of the crucial factors influencing the integration of ML in bioenergy is the availability and quality of data. ML algorithms rely on large volumes of high-quality data for effective training and accurate predictions. Therefore, ensuring access to comprehensive and reliable datasets related to biomass characteristics, process parameters, and energy output is essential. This may involve establishing robust data collection systems, leveraging IoT technologies, and fostering data sharing collaborations within the bioenergy industry.

Another key factor according to the study review analyses is the development and customization of ML algorithms and models specifically tailored to the bioenergy domain. Bioenergy production involves unique challenges and complexities that necessitate ML solutions designed to address them. Therefore, investing in research and development efforts to create specialized ML algorithms for biomass characterization, process optimization, and predictive maintenance is crucial.

Computational resources and expertise to handle the complex ML algorithms effectively, while the implementation of ML techniques in bioenergy production also pose a barrier. Addressing this challenge requires investments in computational infrastructure, training programs, and collaborations between ML experts and bioenergy professionals.

Additionally, the interpretability and explainability of ML models pose challenges in the bioenergy sector. Stakeholders, including policymakers, industry regulators, and end-users, need to understand and trust the decisions made by ML models. Promoting transparency and developing explainable ML models can help overcome this challenge and enhance the adoption of ML techniques in bioenergy.

To overcome these barriers and promote the synergistic applications of ML and bioenergy, several recommendations can be considered. Firstly, fostering interdisciplinary collaborations between ML experts, bioenergy researchers, and industry stakeholders can facilitate knowledge exchange, innovation, and the development of tailored ML solutions. Secondly, policymakers should provide support through funding initiatives and regulatory frameworks that incentivize the adoption of ML in the bioenergy sector. Thirdly, investing in research and development efforts to advance ML techniques specifically for bioenergy production can drive technological advancements and address sector-specific challenges.

4.4 Insight and Outlook

In conclusion, this study has explored the synergistic applications of machine learning (ML) and bioenergy, shedding light on their integration and potential for environmental sustainability. The findings highlight the transformative capabilities of ML in optimizing bioenergy processes, enhancing efficiency, and improving overall system performance. According to the literature and through an overview of the case of Mukono, we have demonstrated the successful integration of ML in various aspects of bioenergy production, including biomass characterization, process monitoring, and operational decision-making. The integration of ML techniques has led to significant improvements in bioenergy production, such as real-time anomaly detection, the prediction of equipment failures, and the optimization of operating conditions. These advancements offer opportunities for process optimization, efficiency improvements, and enhanced environmental sustainability in the bioenergy industry. The study has identified critical success factors for ML adoption in the bioenergy sector, including data availability and quality, development of specialized ML algorithms, computational resources, and interpretability of ML models. By addressing these factors and overcoming challenges, policymakers, researchers, and industry stakeholders can unlock the full potential of ML in advancing bioenergy production and achieving sustainable energy goals.

The implications of this research are far-reaching. For policymakers, the study provides insights into the benefits and challenges associated with integrating ML in the bioenergy sector. It highlights the need for supportive funding initiatives and regulatory frameworks that incentivize ML adoption while ensuring transparency and accountability. Researchers can leverage the findings to guide further investigations into ML techniques tailored to the bioenergy domain and to explore additional areas for ML integration, such as supply chain optimization and market forecasting. Industry stakeholders can gain valuable insights into the potential of ML to enhance operational efficiency, reduce costs, and contribute to a greener and more sustainable future. Future research directions should focus on expanding the application of ML in bioenergy production and addressing emerging challenges. Further studies can explore advanced ML algorithms, such as deep learning and reinforcement learning, to tackle complex bioenergy optimization problems. Additionally, investigating the socio-economic and policy implications of ML integration in bioenergy can provide a holistic understanding of its broader impact.

5. Conclusions

This study contributes to the growing body of knowledge on ML and bioenergy integration. By harnessing the power of ML, the bioenergy sector can advance towards a more sustainable and efficient future, reducing greenhouse gas emissions, mitigating climate change, and promoting environmental sustainability. Through collaboration, innovation, and continued research, the synergies between ML and bioenergy can pave the way for a cleaner and greener energy landscape.

References

Abu Qdais, H., Bani Hani, K., & Shatnawi, N., Modeling and optimization of biogas production from a waste digester using artificial neural network and genetic algorithm. *Resources, Conservation and Recycling*, 2010, https://doi.org/10.1016/j.resconrec.2009.08.012.

Alejo, L., Atkinson, J., Guzmán-Fierro, V., & Roeckel, M., Effluent composition prediction of a two-stage anaerobic digestion process: machine learning and stoichiometry techniques. *Environmental Science and Pollution Research*, 2018, https://doi.org/10.1007/s11356-018-2224-7.

Bock, F. E., Aydin, R. C., Cyron, C. J., Huber, N., Kalidindi, S. R., & Klusemann, B., A review of the application of machine learning and data mining approaches in continuum materials mechanics. In *Frontiers in Materials*, 2019, https://doi.org/10.3389/fmats.2019.00110.

Carrillo-Nieves, D., Rostro Alanís, M. J., de la Cruz Quiroz, R., Ruiz, H. A., Iqbal, H. M. N., & Parra-Saldívar, R., Current status and future trends of bioethanol production from agro-industrial wastes in Mexico. In *Renewable and Sustainable Energy Reviews*, 2019, https://doi.org/10.1016/j.rser.2018.11.031.

Cinar, S. Ö., Cinar, S., & Kuchta, K., Machine Learning Algorithms for Temperature Management in the Anaerobic Digestion Process. *Fermentation*, 2022, https://doi.org/10.3390/fermentation8020065.

Fakharudin, A. S., Sulaiman, M. N., Salihon, J., & Zainol, N., Implementing Artificial Neural Networks and Genetic Algorithms To SolveModeling and Optimisation of Biogas Production. *Computing & Informatics, 4Th International Conference,* 2013.

Gjertsen, A., Bay-Larsen, I., Bjørkhaug, H., & Vangelsten, B. V., Access to areas for algae cultivation in Norway. *Marine Policy*, 2020, https://doi.org/10.1016/j.marpol.2020.103853.

Grosser, A., & Neczaj, E., Anaerobic digestion. In *Biodegradable Waste Management in the Circular Economy: Challenges and Opportunities*, 2022, https://doi.org/10.1002/9781119679523.ch8.

Grosser, A., & Neczaj, E., Biorefineries. In *Biodegradable Waste Management in the Circular Economy: Challenges and Opportunities*, 2022, https://doi.org/10.1002/9781119679523.ch10.

Gueguim Kana, E. B., Oloke, J. K., Lateef, A., & Adesiyan, M. O., Modeling and optimization of biogas production on saw dust and other co-substrates using Artificial Neural network and Genetic Algorithm. *Renewable Energy*, 2012, https://doi.org/10.1016/j.renene.2012.03.027.

Iglina, T., Iglin, P., & Pashchenko, D., Industrial CO2 Capture by Algae: A Review and Recent Advances. In *Sustainability (Switzerland)*, 2022, https://doi.org/10.3390/su14073801.

Jungmeier, G., The Biorefinery Fact Sheet. *The International Journal of Life Cycle Assessment*, 2017.

Liu, Y., Esan, O. C., Pan, Z., & An, L., Machine learning for advanced energy materials. In *Energy and AI*, 2021, https://doi.org/10.1016/j.egyai.2021.100049.

Long, F., Wang, L., Cai, W., Lesnik, K., & Liu, H., Predicting the performance of anaerobic digestion using machine learning algorithms and genomic data. *Water Research*, 2021, https://doi.org/10.1016/j.watres.2021.117182.

OECD/IEA, & IRENA., Perspectives for the Energy Transition: Investment Needs for a Low-Carbon Energy System. In *International Energy Agency*, 2017.

Onu, P., & Mbohwa, C., Agricultural Waste Diversity and Sustainability Issues: Sub-Saharan Africa as a Case Study. In *Agricultural Waste Diversity and Sustainability Issues: Sub-Saharan Africa as a Case Study*, 2021, https://doi.org/10.1016/B978-0-323-85402-3.01001-9.

Onu, P., & Mbohwa, C., Industry 4.0 opportunities in manufacturing SMEs: Sustainability outlook. *Materials Today: Proceedings*, 2021, https://doi.org/10.1016/j.matpr.2020.12.095.

Onu, P., Mbohwa, C., & Pradhan, A., An analysis of the application of machine learning techniques in anaerobic digestion. *IEEE- 2023 International Conference on Control, Automation and Diagnosis, ICCAD'23*, 2023.

Onu, P., Mbohwa, C., & Pradhan, A., Artificial intelligence-based IoT-enabled biogas production. *IEEE- 2023 International Conference on Control, Automation and Diagnosis, ICCAD'23*, 2023.

Osama, A., Hosney, H., & Moussa, M. S., Potential of household photobioreactor for algae cultivation. *Journal of Water and Climate Change*. https://doi.org/10.2166/wcc.2021.261, 2021.

Park, J. G., Jun, H. B., & Heo, T. Y., Retraining prior state performances of anaerobic digestion improves prediction accuracy of methane yield in various machine learning models. *Applied Energy*, 2021, https://doi.org/10.1016/j.apenergy.2021.117250.

Pattanaik, L., Pattnaik, F., Saxena, D. K., & Naik, S. N., Biofuels from agricultural wastes. In *Second and Third Generation of Feedstocks*, 2019, https://doi.org/10.1016/b978-0-12-815162-4.00005-7.

Peter, O., Pradhan, A., & Mbohwa, C., Industrial internet of things (IIoT): opportunities, challenges, and requirements in manufacturing businesses in emerging economies. *Procedia Computer Science*, *217*, 856–865, 2023, https://doi.org/10.1016/j.procs.2022.12.282.

Şenol, H., Methane yield prediction of ultrasonic pretreated sewage sludge by means of an artificial neural network. *Energy*, 2021, https://doi.org/10.1016/j.energy.2020.119173.

Wang, L., Long, F., Liao, W., & Liu, H., Prediction of anaerobic digestion performance and identification of critical operational parameters using machine learning algorithms. *Bioresource Technology*, 2020, https://doi.org/10.1016/j.biortech.2019.122495.

Wu, Y., Tan, H., Qin, L., Ran, B., & Jiang, Z., A hybrid deep learning based traffic flow prediction method and its understanding. *Transportation Research Part C: Emerging Technologies*, 2018, https://doi.org/10.1016/j.trc.2018.03.001.

Xu, W., Long, F., Zhao, H., Zhang, Y., Liang, D., Wang, L., Lesnik, K. L., Cao, H., Zhang, Y., & Liu, H., Performance prediction of ZVI-based anaerobic digestion reactor using machine learning algorithms. *Waste Management*, 2021, https://doi.org/10.1016/j.wasman.2020.12.003.

Yi-Fan, H., Chang-Zhu, Y., Jin-Feng, D., Wen-Hong, P., & Jia-Kuang, Y., Modeling of expanded granular sludge bed reactor using artificial neural network. *Journal of Environmental Chemical Engineering*, 2017, https://doi.org/10.1016/j.jece.2017.04.007.

Biographies

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