Shahid Bahonar University of Kerman

Biomechanism and Bioenergy Research

Online ISSN: 2821-1855
Homepage: https://bbr.uk.ac.ir

Iranian Society of Agricultural Machinery Engineering and Mechanization

Advancing Biogas Production Forecasting Using Artificial Intelligence: A Comprehensive Review of Models and Applications

Soha Sami[1], Jafar Massah[1]✉

[1] Mechanics of Biosystems Engineering Department, College of Aburaihan, University of Tehran, Tehran, Iran.

✉ Corresponding author: jmassah@ut.ac.ir

ARTICLE INFO

Article type:

Review Article

Article history:

Received 29 July 2025

Received in revised form 05 September 2025

Accepted 28 September 2025

Available Online 30 September 2025

Keywords:

Biogas Production, Artificial Intelligence, Machine Learning, Forecasting Models, Anaerobic Digestion, Random Forest.

ABSTRACT

Artificial intelligence (AI) plays a transformative role in improving the efficiency of biogas production by providing advanced tools for predicting and optimizing anaerobic digestion processes as a sustainable source of organic waste management and renewable energy supply. This study provides a systematic review of the applications of AI in biogas production prediction and, by reviewing recent studies, evaluates statistical, machine learning, and hybrid models and compares the performance of algorithms such as Random Forest and Artificial Neural Networks (ANN). These algorithms have shown outstanding performance in recent studies due to their ability to model nonlinear and dynamic behaviors. However, challenges such as inconsistent data quality, biochemical complexities, and generalizability limitations have limited the full exploitation of these technologies. Through a comprehensive literature review, this study identifies the strengths and weaknesses of existing models and proposes innovative solutions, including the integration of real-time data based on the Internet of Things (IoT), the development of hybrid models, and the utilization of transfer learning. The findings highlight the potential of artificial intelligence in improving the efficiency of biogas systems, reducing operating costs, and supporting sustainable energy planning, and provide directions for the development of intelligent and scalable forecasting tools.

Cite this article: Sami, S., & Massah, J., (2025). Advancing Biogas Production Forecasting Using Artificial Intelligence: A Comprehensive Review of Models and Applications. *Biomechanism and Bioenergy Research*, *4*(3), 29-41. https://doi.org/10.22103/bbr.2025.25660.1128

Publisher: Shahid Bahonar University of Kerman

DOI: https://doi.org/10.22103/bbr.2025.25660.1128

INTRODUCTION

Renewable energy sources have emerged as crucial solutions to address environmental crises and reduce global reliance on fossil fuels. Among these sources, biogas has gained considerable attention for its dual role in energy generation and organic waste management. Produced through the anaerobic digestion (AD) of organic matter, biogas stands out due to its ability to convert waste into a clean energy source, while simultaneously reducing greenhouse gas emissions (Angelidaki & Ellegaard, 2003; Raven & Gregersen, 2007; Rezaeifar et al., 2024).

Despite its significant advantages, the biogas production process is complex and inherently prone to significant fluctuations. These instabilities are mainly due to changes in feedstock composition, environmental conditions such as temperature and pH, and technical limitations or inefficiencies in reactor operation (Labatut et al., 2011). Such uncertainties can reduce production efficiency, increase operating costs, and thus pose significant obstacles to the development and widespread use of biogas technologies (Pilarski et al., 2025).

Predictive models powered by artificial intelligence (AI) play a vital role in optimizing biogas production and its integration into broader climate strategies. By accurately forecasting feedstock behavior, system efficiency, and emission outputs, AI supports smarter decision-making across biogas value chains. As shown in Figure 1, achieving significant CO_2 reductions by 2050 requires coordinated efforts across multiple sectors including renewable fuels like biogas (IEA)[1]. AI-driven forecasting ensures that biogas contributes efficiently and reliably to such long-term sustainable development scenarios (Tryhuba et al., 2024).

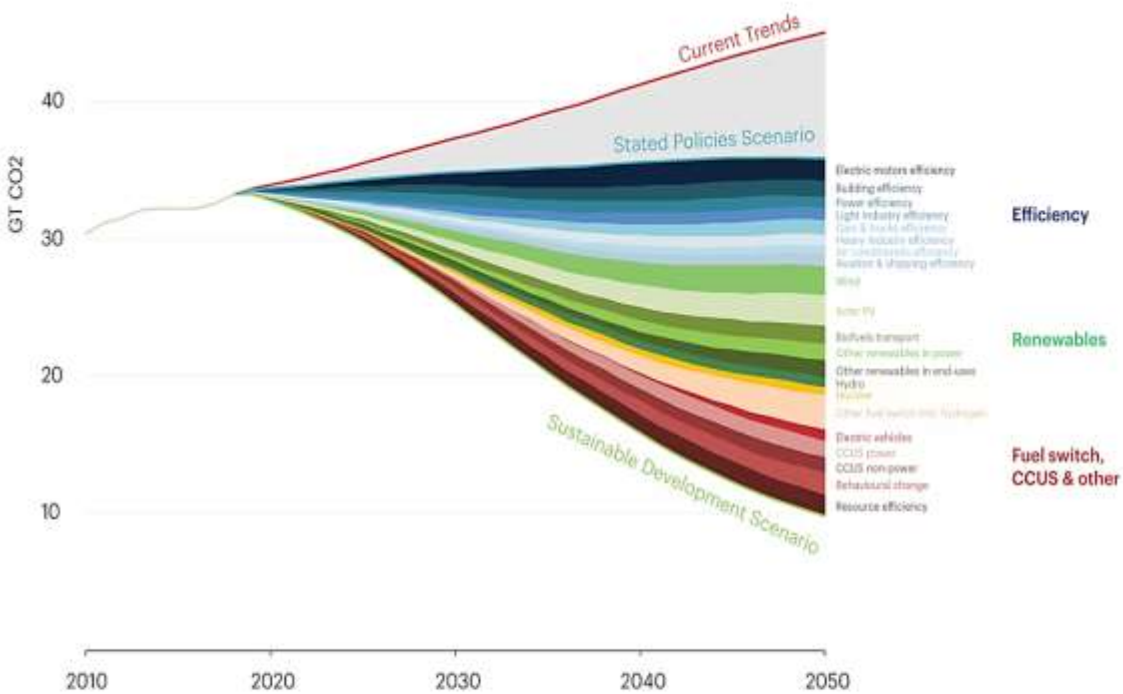

Figure1. Global CO_2 Emissions Trajectories under Different Policy Scenarios (2010–2050).

Accurate forecasting of these fluctuations is essential for enhancing system stability, minimizing disruptions, and optimizing overall performance. Predictive models enable early

[1] https://www.iea.org/

identification of potential issues, allowing timely intervention and prevention of production losses (Theuerl et al., 2019; Tisocco et al., 2024). As shown in Figure 2, the projected global use of biogas—particularly in the industrial sector and for biomethane upgrading—is expected to grow significantly by 2040, highlighting the urgent need for robust and scalable predictive tools (IRENA)[2].

Beyond improving stability, predictive modeling plays a crucial role in operational cost reduction. By analyzing historical data and detecting complex patterns, machine learning (ML) techniques facilitate process optimization and more efficient use of resources. For instance, models such as Random Forest (RF) and Artificial Neural Networks (ANNs) have demonstrated high accuracy in forecasting biogas output, thereby reducing the risks and expenses associated with operational errors (Mukasine et al., 2024).

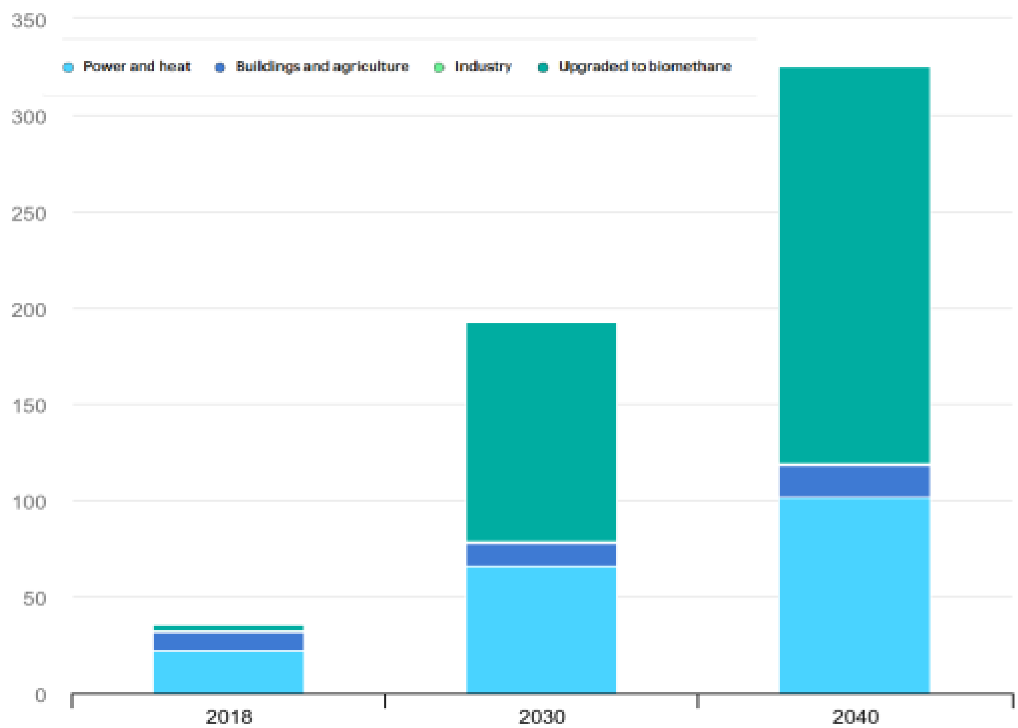

Figure 2. Forecast of global biogas consumption.

Impact on long-term biogas planning and energy forecasting: Accurate forecasting greatly assists strategic engineering decisions in long-term biogas planning, especially in managing input variability and process disturbances (Tisocco et al., 2024). Full-scale applications have benefited from hybrid computational models to improve energy efficiency and resource allocation in both bioreactor and biogas upgrading environments (Isenkul et al., 2025). The systematic use of computational and machine learning-based models in resource recovery and waste-to-energy pathways has been valuable in maximizing efficiency, reducing inefficiencies, and informing sustainable engineering design (Drudi et al., 2024).

As illustrated in Figure 2, fluctuations in biogas production are influenced by multiple interconnected factors including feedstock variability, environmental and operational challenges, and technical limitations. Predictive modeling addresses these factors by enabling early issue detection, improving efficiency, lowering operational risks, and guiding informed

[2] https://www.irena.org/publications

decision-making. Advanced techniques such as deep learning (DL) and big data analytics further enhance the predictive capabilities of these models, supporting both technical optimization and high-level energy policy development (Dittmer et al., 2021).

This growing intersection between AI and biogas production creates a transformative potential for renewable energy systems, where intelligent forecasting can lead to cleaner, more efficient, and economically viable energy solutions.

Despite significant advancements in predictive modeling for biogas systems, notable gaps remain in the comprehensive evaluation of model accuracy, generalizability across diverse operating conditions, and the systematic analysis of their practical strengths and limitations. Much of the existing literature tends to focus on isolated models or limited datasets, with insufficient comparative studies that assess multiple predictive approaches within a unified analytical framework. Moreover, the practical applicability of these models in real-world, large-scale biogas operations remains underexplored, particularly regarding their integration into industrial process control and strategic energy planning.

The objective of this study is to assess the accuracy of implemented predictive models and to provide a critical, analytical perspective on their advantages and limitations within the context of biogas production. By addressing these gaps, the study aims to support the development of more robust forecasting tools and inform smarter decision-making in the design, operation, and scaling of biogas technologies.

Methods and Predictive Models in Biogas Production

Accurate prediction of biogas production is a critical factor in optimizing AD processes and enhancing system efficiency. A variety of predictive models have been employed for this purpose, generally categorized into statistical/mathematical models, AI models, and hybrid approaches.

Statistical and Mathematical Models

Statistical and mathematical modeling techniques, such as linear regression, Autoregressive Integrated Moving Average (ARIMA), and time series analysis, have been widely used due to their capacity to analyze historical data and identify underlying patterns. ARIMA models, in particular, have shown effective performance in handling non-stationary data for biogas yield forecasting (Colak & Özhan, 2025; Nazmi et al., 2023). Similarly, extended variants like Seasonal ARIMA (SARIMA) have demonstrated success in capturing seasonal variations in biogas production, offering improved prediction reliability in long-term forecasting scenarios (Dittmer et al., 2021; Sakib et al., 2025)

Artificial Intelligence Models

AI-based approaches, including ANNs and ML algorithms, have gained significant attention for their ability to process large volumes of complex and nonlinear data. These models utilize learning algorithms to identify intricate patterns in multidimensional datasets, thereby enhancing the accuracy of biogas production forecasting. Studies have shown that ANNs can effectively optimize biological processes by accurately modeling the relationships between operational parameters and gas yield (Mukasine et al., 2023). In addition to ANNs, other ML algorithms like RF and Support Vector Machines (SVM) have also been successfully applied. RF has been utilized to identify the most significant input variables, while SVM has proven capable of managing nonlinear fluctuations and delivering high accuracy in biogas forecasting (de Lima Pacheco et al., 2025).

Hybrid Models

Hybrid models, which integrate the strengths of both statistical and AI-based techniques, have emerged as robust tools for biogas prediction. These models aim to overcome the limitations of individual modeling approaches by combining their complementary advantages. For instance, the integration of the Gompertz growth model with ML has resulted in a 53% reduction in forecasting error (Arumugham et al., 2023; Olatunji et al., 2024). Furthermore, hybrid frameworks incorporating ANN with time series models have achieved significant improvements in prediction accuracy (Chen et al., 2025; Wang et al., 2021). Such models are particularly effective when addressing nonlinear, dynamic, and multivariate characteristics of AD systems.

Model Evaluation Criteria

Evaluating the performance of predictive models is essential for selecting the most suitable approach for a given biogas system. Standard evaluation metrics include the Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R^2). These metrics quantify the model's ability to replicate observed data and reliably forecast future outputs accurately. For instance, in a comparative study, a hybrid model assessed using RMSE and MAPE outperformed other methods in terms of biogas prediction accuracy (Drudi et al., 2024). Similarly, RMSE and R^2 have been widely adopted to benchmark the predictive quality of AI and hybrid models, with several studies reporting superior performance using these indicators (Rutland et al., 2023).

COMPARATIVE ASSESSMENT OF ML MODELS FOR BIOGAS PRODUCTION

With the expansion of research in the field of biogas production prediction, the use of machine learning algorithms has become a primary focus of studies. In recent years, a variety of models have been employed, ranging from random forests and reinforcement learning algorithms to deep neural networks and hybrid models. This section reviews and compares the studies conducted to identify the strengths, limitations, and main trends of previous research while examining the performance of the models.

Performance of Machine Learning Algorithms for Industrial-Scale Biogas Prediction

Industrial-scale biogas production through anaerobic digestion (AD) is a key pillar of sustainable energy systems. Accurate prediction of biogas yield plays an important role in optimizing operational efficiency, reducing costs, and increasing energy recovery, but the nonlinear and dynamic nature of AD processes has posed serious challenges for traditional modeling (Ellacuriaga et al., 2021). In the meantime, ML using advanced algorithms has been able to identify complex relationships between operational parameters and has become a transformative tool for increasing prediction accuracy. The most widely used algorithms include regression models (such as linear regression and Ridge regression), clustering methods (such as Random Forest and Gradient Boosting), SVM, and ANN. Aggregate methods, especially RF, typically offer the best balance between accuracy, robustness, and computational efficiency, and have consistently outperformed other models in numerous studies (Isenkul et al., 2025; Tryhuba et al., 2024; Yildirim & Ozkaya, 2023).

Industrial-scale case studies have also confirmed this; for example, RF has the highest accuracy in modeling nonlinear relationships between operating parameters and biogas production (Yildirim & Ozkaya, 2023), while XGBoost and SVR have also provided acceptable performance in some applications, such as wastewater treatment plants (De Clercq et al., 2019; Isenkul et al., 2025). Although the k-NN algorithm is interpretable and straightforward, it has low accuracy in high-dimensional datasets (De Clercq et al., 2020). In contrast, ANN has a high ability to recognize complex patterns but requires substantial computational resources and a long training time. Combining multiple algorithms in Ensemble frameworks, such as Stacking, can increase the prediction accuracy more than single models (Mukasine et al., 2024; Sun et al., 2023).

Also, emerging tools and methods such as automated machine learning (AutoML) frameworks including TPOT and AutoGluon have automated the process of model selection, hyperparameter tuning, and feature engineering, and facilitated the development of accurate and scalable models (Nguyen et al., 2019; Wang et al., 2021). In addition, interpretability tools such as SHAP have identified the contribution of features to prediction and helped improve operational strategies and model reliability (Sun et al., 2023). Finally, new trends are moving towards integrating ML models with adaptive and real-time control systems that can make the anaerobic digestion process dynamic and optimized. Despite challenges such as poor data quality, limited model generalizability, high computational resource requirements in complex models, and difficulty in integrating with operational systems, the findings show that RF and ensemble methods combined with interpretability tools are the best options for biogas prediction on an industrial scale and can help improve the efficiency and sustainability of bioenergy systems (Chen et al., 2025; Paleyes et al., 2022; Rutland et al., 2023; Zhu et al., 2023).

Comparative Analysis of Machine Learning Models for Biogas Production Prediction

Recent advancements in ML have significantly improved predictive modeling for biogas production, enabling better optimization of AD processes. A critical analysis of commonly applied models reveals distinct advantages and limitations in terms of accuracy, computational efficiency, and adaptability to real-time environments.

ANNs demonstrate strong capability in capturing nonlinear and complex patterns within large datasets, making them suitable for biogas prediction when extensive data are available. However, their reliance on high-quality data, sensitivity to noise, and long training times limit their practical deployment (Tryhuba et al., 2024). Similarly, CNN models have been successfully applied for predicting microbial activity and optimizing pretreatment strategies in AD (Kasulla et al., 2025). Despite their superior performance in handling complex data, CNN models are computationally expensive and less suited for real-time applications.

Tree-based models, particularly RF, offer robustness to noisy and incomplete data while maintaining high predictive accuracy under practical conditions (Tryhuba et al., 2024). Their main drawback lies in increased computational demand with large ensembles. In contrast, SVM models excel in small datasets with high-dimensional features, but their performance deteriorates with scale, and they require precise kernel tuning (Isenkul et al., 2025).

Boosting algorithms, especially XGBoost, have gained prominence due to their fast training speed and excellent accuracy in multidimensional datasets (Gaikwad et al., 2025). Nevertheless, their sensitivity to noisy inputs and risk of overfitting when hyperparameters are not optimized remain notable concerns. Similarly, Gradient Boosting achieves high predictive accuracy but is computationally intensive and prone to overfitting without careful parameter adjustment (Tryhuba et al., 2024). The k-NN algorithm, although conceptually simple, is only suitable for small, uniformly distributed datasets and performs poorly on large or complex data (Mukasine et al., 2024).

Table 1 provides a comparative overview of machine learning models for biogas production prediction, including their performance metrics, computational complexity, real-time suitability, and relevant studies.

A visual comparison of these models in terms of predictive accuracy, computational complexity, and real-time suitability is presented in Figure 2, which illustrates their relative performance across key evaluation dimensions.

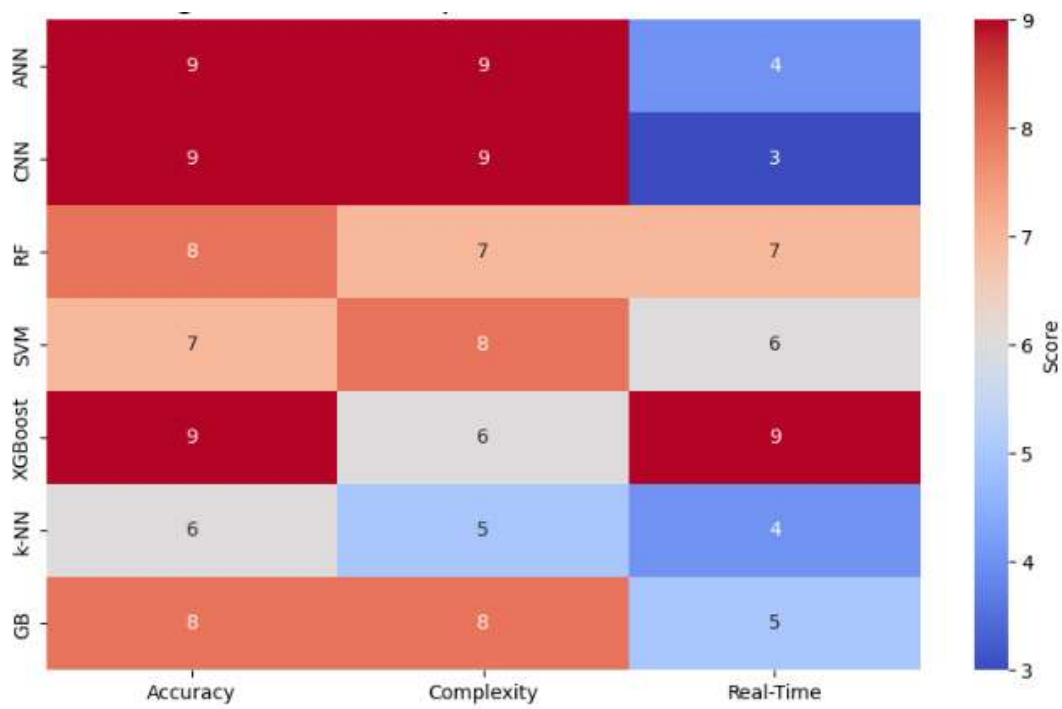

Figure3. Relative evaluation of algorithms in three key performance metrics.

Table1. Comparison Table of Machine Learning Models for Biogas Production Prediction

Model	(R^2)	RMSE	Suitable for Real-Time	Strengths	Weaknesses	Studies Conducted
ANN	0.92	0.15	No	High capability in capturing complex patterns	Requires high-quality data, long training time	(Mukasine et al., 2023; Nazmi et al., 2023)
Random Forest	0.94	0.12	Yes	Robust to noisy data	High computational demand with large ensembles	(Tryhuba et al., 2024; Yildirim & Ozkaya, 2023)
SVM	0.89	0.18	No	Suitable for small, high-dimensional datasets	Requires precise kernel tuning, poor scalability	(Isenkul et al., 2025; Wang et al., 2020)
XGBoost	0.93	0.13	No	Fast training, high accuracy	Sensitive to noise, risk of overfitting	(Gaikwad et al., 2025; Tryhuba et al., 2024)
k-NN	0.85	0.22	No	Simple and interpretable	Poor performance on large, complex datasets	(De Clercq et al., 2019; Mukasine et al., 2024)

RESPONSE TO THE CHALLENGES IN BIOGAS PRODUCTION FORECASTING

Improving Data Quality

Improving data quality is essential for accurate predictions. Preprocessing methods such as outlier detection, data imputation, and sensor calibration can significantly improve model inputs. Additionally, the use of IoT-based monitoring systems enables the collection of real-time, high-resolution data on parameters like temperature and organic content, enhancing overall model reliability (Dewi et al., 2024; Gouiza et al., 2024).

Managing Biochemical Complexity

To address the nonlinear and dynamic nature of AD systems, AI-based methods—such as ANNs and genetic algorithms (GAs)—have shown strong capabilities in identifying hidden patterns in complex datasets and optimizing biogas output (Aguida et al., 2021).

Enhancing Generalizability

To improve model generalizability across different facilities, hybrid approaches that combine data-driven ML with process-based domain knowledge have been recommended (Pilarski et al., 2025). Establishing standardized data protocols can further enhance transferability and enable benchmarking.

Enabling Real-Time Modeling

Real-time forecasting can be realized by integrating deep learning algorithms such as LSTM into IoT-enabled infrastructures, allowing continuous data collection and adaptive prediction (Aguida et al., 2021; Dewi et al., 2024).

Infrastructure and Policy Support

Policy interventions—such as forming biogas cooperatives and implementing supportive regulatory frameworks—can facilitate the widespread adoption of intelligent forecasting systems (Mittal et al., 2018).

Technological Innovations

Advanced pretreatment methods like ultrasonic and thermal processes have proven effective in increasing the digestibility of lignin-rich substrates and boosting methane yield in industrial-scale systems (Janke et al., 2015).

Stakeholder Collaboration

Collaborative frameworks that include researchers, plant operators, technology developers, and policymakers are essential for practical implementation. These partnerships support knowledge exchange and the co-development of locally appropriate forecasting solutions (Mittal et al., 2018).

Table 2 shows a summary of the challenges.

Table2. Key Challenges in Biogas Prediction and Suggested Solutions

Challenge	Cause	Effect on Prediction	Proposed Solution
Incomplete or noisy data	Sensor errors, data gaps	Lower accuracy, unstable outputs	Data cleaning, imputation, sensor calibration
Nonlinear process behavior	Complex biochemical reactions	Poor model fit, misprediction	Use of ANN, LSTM, or hybrid AI models
Low substrate degradability	Lignocellulosic or fatty feedstocks	Fluctuating biogas yield	Pre-treatment (thermal, chemical, ultrasonic)
Lack of real-time data	No integrated monitoring	Delayed or outdated forecasts	IoT-based monitoring, real-time LSTM models
Poor model generalization	Plant-specific training data	Limited transferability	Transfer learning, hybrid modeling
Infrastructure limitations	Technical or financial constraints	Low adoption of prediction tools	Policy support, funding schemes
Weak collaboration	Gaps between sectors	Redundant efforts, limited impact	Shared platforms, research-industry linkages

CRITICAL REVIEW OF EXISTING STUDIES

Recent studies have demonstrated significant progress in predicting biogas production using advanced machine learning algorithms, including ANN, LSTM, and SVR. These algorithms provide high accuracy in biogas yield prediction due to their ability to model nonlinear and time-dependent behaviors in anaerobic digestion systems. For example, a study using a combination of ANN and genetic algorithm, using real-time data from environmental and process sensors, reported a correlation coefficient of 0.85 and an operational efficiency of 78.2% (Gouiza et al., 2024). Also, hybrid models that integrate artificial intelligence with physics-based knowledge or statistical methods have improved the robustness and interpretability of the models. For example, Mathur et al. used a combination of Random Forest and ANN models to predict chemical oxygen demand (COD) of wastewater, achieving a coefficient of determination (R^2) of 0.96, which is significantly superior to traditional methods (Mathur et al., 2024).

However, a critical review of the existing studies reveals several key limitations. First, heterogeneity in the selection of input variables, such as pH, temperature, or organic loading rate (OLR), and differences in data resolution (e.g., hourly versus daily data) make it difficult to compare models directly. For example, Tryhuba et al. used Random Forest and Gradient Boosting to predict biogas from household waste, reporting a mean absolute error of 0.088 with optimal feature selection and dimensionality reduction (Tryhuba et al., 2024). However, this study focused on household data and may not be generalizable to industrial wastewater. Second, the risk of overfitting in complex models such as ANNs is a serious challenge, especially in small datasets (fewer than 1000 samples). Mukasine et al. demonstrated that ANNs perform well on high-dimensional data ($R^2 = 0.92$) (Mukasine et al., 2023). However, without fine-tuning of hyperparameters (e.g., number of layers), the risk of overfitting increases, especially in industrial settings with noisy data. Third, the lack of validation at an industrial scale, as seen in Isenkul et al. limits the transferability of models to real power plants. In addition to technical challenges, environmental and ethical issues related to the application of AI in biogas forecasting have received less attention (Isenkul et al., 2025). One of the main concerns is the carbon footprint resulting from the heavy computation required by deep learning models, such as convolutional networks (CNNs) or LSTMs. For example, Kasulla et al. used CNNs to predict microbial activity, but these models require high-power computing infrastructure (e.g., GPUs with more than 1000 W of power), which can conflict with biogas sustainability goals. One study estimated that training a deep learning model can produce several tons of CO_2, which poses an environmental paradox in the context of biogas, which aims to reduce greenhouse gas emissions (Kasulla et al., 2025). It is suggested that lighter models, such as LightGBM or TinyML, that run on low-power devices, be investigated to reduce the carbon footprint. From an ethical perspective, IoT systems that are used to collect real-time data (e.g., temperature and pH) pose data privacy risks (Aguida et al., 2021; Dewi et al., 2024). This data, which includes operational information from biogas plants, can be vulnerable to misuse if not adequately protected. Utilizing blockchain technology to securely and transparently store data can help mitigate this problem. Equal access to AI technologies is also a significant challenge. Advanced models such as ANN and AutoML may be inaccessible to small plants or developing countries due to high infrastructure costs, which can exacerbate regional inequalities. The development of open-source frameworks and low-cost models, such as Edge AI, can make these technologies accessible to resource-poor communities.

In summary, advanced AI algorithms, such as ANN, LSTM, and hybrid models, have great potential for modeling the complex behavior of biogas systems. However, limitations such as data heterogeneity, overfitting, and lack of industrial validation prevent the full exploitation of these technologies. Environmental (carbon footprint) and ethical (privacy, equitable access) issues also require further attention. Future directions should focus on developing sustainable and accessible models, standardizing data, and integrating physics-based knowledge with machine learning to provide more accurate and equitable predictions for biogas production.

RESEARCH GAPS AND FUTURE DIRECTIONS

Despite significant advances in AI-driven biogas prediction, several critical research gaps continue to limit the scalability, generalizability, and operational value of current forecasting models.

1. **Limited Robustness Under Dynamic Conditions**

Although models such as ANN and RF have shown high accuracy, their performance often degrades under fluctuating feedstock characteristics and operational variability. Improving model resilience in dynamic environments remains a key challenge (Isenkul et al., 2025).

2. **Challenges in Multisource Data Integration**

Biogas production depends on variables such as pH, temperature, hydraulic retention time, and substrate composition—often collected from heterogeneous sources. The lack of standardized frameworks for integrating this multisource data reduces model efficiency and accuracy (Adeoba et al., 2025; Clifford et al., 2025).

3. **Underutilization of Hybrid Optimization Techniques**

Although hybrid approaches using optimization algorithms like PSO show promise, their application in real-time process optimization is still underdeveloped. Future research should explore how to better combine neural networks and evolutionary algorithms to enhance biogas yield (Kasulla et al., 2025).

4. **Lack of Uncertainty Quantification**

Most AI models provide only point predictions, which limits their usefulness in operational planning. Methods such as Box-Cox transformation and LUBE offer probabilistic forecasting and should be integrated to support decision-making under uncertainty (Dittmer et al., 2021).

5. **Limited Industrial-Scale Validation**

Many models are trained and validated on lab-scale datasets, which reduces their reliability when deployed in full-scale biogas plants. Industrial validation under real-world conditions is critical for model generalizability and long-term adoption (Gaikwad et al., 2025; Isenkul et al., 2025).

CONCLUSIONS

This review found that AI has great potential to optimize anaerobic digestion processes and enhance biogas as a sustainable source of renewable energy by providing advanced tools for predicting biogas production. A recent literature review suggests that machine learning models such as Random Forest and ANN are superior in modeling nonlinear and dynamic behaviors of biogas systems. Hybrid models, by combining the advantages of statistical methods and AI, have improved prediction accuracy and paved the way for reducing operational costs and increasing sustainability. However, obstacles such as inadequate data quality, biochemical complexities, and limitations in model generalizability remain challenging. By identifying these shortcomings, this research proposes innovative solutions, including leveraging real-time data from the Internet of Things (IoT), developing hybrid models, and utilizing transfer learning. Future directions should focus on industrial validation of models, strengthening interdisciplinary collaborations, and integrating with environmental policymaking to make AI a key tool for achieving sustainable energy goals and a greener future.

REFRENCES

Adeoba, M., Pandelani, T., Ngwangwa, H., & Masebe, T. (2025). The Role of Artificial Intelligence Technology in the Fulfilment of Sustainable Development Goals in Biogas Production. CONECT. International Scientific Conference of Environmental and Climate

Technologies. https://doi.org/10.7250/CONECT.2025.040

Aguida, M. A., Ouchani, S., & Benmalek, M. (2021). An IoT-based framework for an optimal monitoring and control of cyber-physical systems: application on biogas production system. Proceedings of the 11th International Conference on the Internet of Things (pp. 143-149). https://doi.org/10.1145/3494322.3494341

Angelidaki, I., & Ellegaard, L. (2003). Codigestion of manure and organic wastes in centralized biogas plants: status and future trends. *Applied biochemistry and biotechnology*, *109*(1), 95-105. https://doi.org/10.1385/ABAB:109:1-3:95

Arumugham, V., Ghanimi, H. M., Pustokhin, D. A., Pustokhina, I. V., Ponnam, V. S., Alharbi, M., Krishnamoorthy, P., & Sengan, S. (2023). An artificial-intelligence-based renewable energy prediction program for demand-side management in smart grids. *Sustainability*, *15*(6), 5453. https://doi.org/10.3390/su15065453

Chen, L., He, P., Zou, J., Zhang, H., Peng, W., & Lü, F. (2025). Scalable and interpretable automated machine learning framework for biogas prediction, optimization, and stability monitoring in industrial-scale dry anaerobic digestion. *Chemical Engineering Journal*, *519*, 165482. https://doi.org/10.1016/j.cej.2025.165482

Clifford, J. L., Chan, Y. J., Yusof, M. A. B. M., Tiong, T. J., Lim, S. S., Lee, C. S., & Tong, W.-Y. (2025). Predictive Modelling of H2S Removal from Biogas Generated from Palm Oil Mill Effluent (POME) Using a Biological Scrubber in an Industrial Biogas Plant: Integration of Artificial Neural Network (ANN) and Process Simulation §. *Food Technology and Biotechnology*, *63*(2), 124-133. https://doi.org/10.17113/ftb.63.02.25.8792

Colak, M. B., & Özhan, E. (2025). Renewable Energy Forecasting in Turkey: Analytical Approaches. *Journal of Intelligent Systems: Theory and Applications*, *8*(1), 25-34. https://doi.org/10.38016/jista.1447980

De Clercq, D., Jalota, D., Shang, R., Ni, K., Zhang, Z., Khan, A., Wen, Z., Caicedo, L., & Yuan, K. (2019). Machine learning powered software for accurate prediction of biogas production: A case study on industrial-scale Chinese production data. *Journal of cleaner production*, *218*, 390-399. https://doi.org/10.1016/j.jclepro.2019.01.031

De Clercq, D., Wen, Z., Fei, F., Caicedo, L., Yuan, K., & Shang, R. (2020). Interpretable machine learning for predicting biomethane production in industrial-scale anaerobic co-digestion. *Science of the Total Environment*, *712*, 134574. https://doi.org/10.1016/j.scitotenv.2019.134574

de Lima Pacheco, M., Ramos, R. C., & Fernando, J. S. (2025). Artificial Intelligence in Developing Countries: Challenges and Opportunities_An African view and its Application in Angola. *Revista Gênero e Interdisciplinaridade*, *6*(2), 60-82. https://doi.org/10.51249/gei.v6i02.2455

Dewi, E. P., Sumarsono, J., Amuddin, A., & Kompyang, I. G. M. (2024). Development of data acquisition biogas monitoring system based on IoT. *Jurnal Agrotek Ummat*, *11*(1), 1-15. https://doi.org/10.31764/jau.v11i1.20574

Dittmer, C., Krümpel, J., & Lemmer, A. (2021). Power demand forecasting for demand-driven energy production with biogas plants. *Renewable Energy*, *163*, 1871-1877. https://doi.org/10.1016/j.renene.2020.10.099

Drudi, R., Drudi, K. C. R., dos Anjos Silva, Í., Antonio, G. C., & de Campos Leite, J. T. (2024). Mathematical Modeling of Biogas Production in Sanitary Landfills. *Revista de Gestão Social e Ambiental*, *18*(11), 1-17. https://doi.org/10.24857/rgsa.v18n11-010

Ellacuriaga, M., García-Cascallana, J., & Gómez, X. (2021). Biogas production from organic wastes: Integrating concepts of circular economy. *Fuels*, *2*(2), 144-167. https://doi.org/10.3390/fuels2020009

Gaikwad, P., Chavan, A., Ghodekar, S., Marale, D., & Karne, H. (2025). Predictive Modeling of Biogas Production Using Machine Learning. *International Journal of Latest Technology in Engineering, Management & Applied Science*, *14*(5), 54-61. https://doi.org/10.51583/IJLTEMAS.2025.140500009

Gouiza, N., Jebari, H., & Reklaoui, K. (2024). Integration of iot-enabled technologies and artificial intelligence in diverse domains: Recent advancements and future trends. *Journal of Theoretical and Applied Information Technology*, *102*(5), 1975-2029.

Isenkul, M. E., Güneş-Durak, S., Kocak, Y. P., Pir, İ., Tüfekci, M., Demirkol, G. T., Sevgen, S., Çığgın, A. S., & Tüfekci, N. (2025). Predicting biogas production in real scale anaerobic digester under dynamic conditions with machine learning approach. *Environmental Research Communications*, *7*(6), 065016. https://doi.org/10.1088/2515-7620/ade03b

Janke, L., Leite, A., Nikolausz, M., Schmidt, T., Liebetrau, J., Nelles, M., & Stinner, W. (2015). Biogas production from sugarcane waste: assessment on kinetic challenges for process designing. *International journal of molecular sciences*, *16*(9), 20685-20703. https://doi.org/10.3390/ijms160920685

Kasulla, S., Malik, S., Yadav, A., Kathpal, G., & Zafar, S. (2025). Harnessing Convolutional Neural Networks for The Optimization of Anaerobic Digestion of Sugarcane Bagasse: A Novel Approach to Pretreatment Strategies and Microbial Activity Prediction. *African Journal of Biomedical Research*, *28*, 601-618. https://doi.org/10.53555/8fp4dq69

Labatut, R. A., Angenent, L. T., & Scott, N. R. (2011). Biochemical methane potential and biodegradability of complex organic substrates. *Bioresource technology*, *102*(3), 2255-2264. https://doi.org/10.1016/j.biortech.2010.10.035

Mathur, R., Sharma, M. K., Loganathan, K., Abbas, M., Hussain, S., Kataria, G., Alqahtani, M. S., & Srinivas Rao, K. (2024). Modeling of two-stage anaerobic onsite wastewater sanitation system to predict effluent soluble chemical oxygen demand through machine learning. *Scientific Reports*, *14*(1), 1835. https://doi.org/10.1038/s41598-023-50805-x

Mittal, S., Ahlgren, E. O., & Shukla, P. (2018). Barriers to biogas dissemination in India: A review. *Energy Policy*, *112*, 361-370.

Mukasine, A., Sibomana, L., Jayavel, K., Nkurikiyeyezu, K., & Hitimana, E. (2023). Correlation Analysis Model of Environment Parameters Using IoT Framework in a Biogas Energy Generation Context. *Future Internet*, *15*(8), 265. https://doi.org/10.3390/fi15080265

Mukasine, A., Sibomana, L., Jayavel, K., Nkurikiyeyezu, K., & Hitimana, E. (2024). Maximizing biogas yield using an optimized stacking ensemble machine learning approach. *Energies*, *17*(2), 364. https://doi.org/10.3390/en17020364

Nazmi, H., Siau, N. Z., Bramantoro, A., & Suhaili, W. S. (2023). Predictive modeling of marine fish production in brunei darussalam's aquaculture sector: A comparative analysis of machine learning and statistical techniques. *International Journal of Advanced and Applied Sciences*, *10*(7), 109-126. https://doi.org/10.21833/ijaas.2023.07.013

Nguyen, G., Dlugolinsky, S., Bobák, M., Tran, V., Lopez Garcia, A., Heredia, I., Malík, P., & Hluchý, L. (2019). Machine learning and deep learning frameworks and libraries for large-scale data mining: a survey. *Artificial Intelligence Review*, *52*(1), 77-124. https://doi.org/10.1007/s10462-018-09679-z

Olatunji, O. O., Adedeji, P. A., Madushele, N., Rasmeni, Z. Z., & van Rensburg, N. J. (2024). Evolutionary optimization of biogas production from food, fruit, and vegetable (FFV) waste. *Biomass Conversion and Biorefinery*, *14*(11), 12113-12125. https://doi.org/10.1007/s13399-023-04506-0

Paleyes, A., Urma, R.-G., & Lawrence, N. D. (2022). Challenges in deploying machine learning: a survey of case studies. *ACM computing surveys*, *55*(6), 1-29. https://doi.org/10.1145/3533378

Pilarski, K., Pilarska, A. A., & Dach, J. (2025). Biogas as renewable energy source: A brief overview. *Journal of Ecological Engineering*, *26*(7), 408–416. https://doi.org/10.12911/22998993/203376

Raven, R. P., & Gregersen, K. H. (2007). Biogas plants in Denmark: successes and setbacks. *Renewable and sustainable energy reviews*, *11*(1), 116-132. https://doi.org/10.1016/j.rser.2004.12.002

Rezaeifar, J., Rohani, A., & Ebrahimi-Nik, M. (2024). Unleashing Dairy Manure's Biogas Potential: A Michaelis-Menten Modeling Approach. *Biomechanism and Bioenergy Research*, *3*(1), 46-55. https://doi.org/10.22103/bbr.2024.22854.1076

Rutland, H., You, J., Liu, H., Bull, L., & Reynolds, D. (2023). A systematic review of machine-learning solutions in anaerobic digestion.

Bioengineering, *10*(12), 1410. https://doi.org/10.3390/bioengineering10121410

Sun, J., Xu, Y., Nairat, S., Zhou, J., & He, Z. (2023). Prediction of biogas production in anaerobic digestion of a full-scale wastewater treatment plant using ensembled machine learning models. *Water Environment Research*, *95*(6), e10893. https://doi.org/10.1002/wer.10893

Theuerl, S., Klang, J., & Prochnow, A. (2019). Process disturbances in agricultural biogas production—Causes, mechanisms and effects on the biogas microbiome: A review. *Energies*, *12*(3), 365. https://doi.org/10.3390/en12030365

Tisocco, S., Weinrich, S., Lyons, G., Wills, M., Zhan, X., & Crosson, P. (2024). Application of a simplified ADM1 for full-scale anaerobic co-digestion of cattle slurry and grass silage: assessment of input variability. *Frontiers of Environmental Science & Engineering*, *18*(4), 50. https://doi.org/10.1007/s11783-024-1810-9

Tryhuba, I., Tryhuba, A., Hutsol, T., Cieszewska, A., Andrushkiv, O., Glowacki, S., Bryś, A., Slobodian, S., Tulej, W., & Sojak, M. (2024). Prediction of Biogas Production Volumes from Household Organic Waste Based on Machine Learning. *Energies*, *17*(7), 1786. https://doi.org/10.3390/en17071786

Wang, T., Wang, X., Ma, R., Li, X., Hu, X., Chan, F. T., & Ruan, J. (2020). Random forest-bayesian optimization for product quality prediction with large-scale dimensions in process industrial cyber–physical systems. *IEEE Internet of Things Journal*, *7*(9), 8641-8653.

Wang, Y., Huntington, T., & Scown, C. D. (2021). Tree-based automated machine learning to predict biogas production for anaerobic co-digestion of organic waste. *ACS Sustainable Chemistry & Engineering*, *9*(38), 12990-13000. https://doi.org/10.1101/2021.07.12.452124

Yildirim, O., & Ozkaya, B. (2023). Prediction of biogas production of industrial scale anaerobic digestion plant by machine learning algorithms. *Chemosphere*, *335*, 138976. https://doi.org/10.1016/j.chemosphere.2023.138976

Zhu, J.-J., Yang, M., & Ren, Z. J. (2023). Machine learning in environmental research: common pitfalls and best practices. *Environmental Science & Technology*, *57*(46), 17671-17689. https://doi.org/10.1021/acs.est.3c00026