World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(Research Article)

Check for updates

AI-driven optimization and IoT-enabled monitoring in adaptive automated biogas production systems

S. Kumarappa *

Department of Mechanical Engineering, Bapuji Institute of Engineering and Technology, Davanagere, Karnataka, India.

World Journal of Advanced Research and Reviews, 2026, 30(01), 283-294

Publication history: Received on 10 January 2026; revised on 31 March 2026; accepted on 02 April 2026

Article DOI: https://doi.org/10.30574/wjarr.2026.30.1.0129

Abstract

The rising global demand for renewable energy and sustainable waste management has intensified research into biogas generation from organic kitchen waste, which is rich in carbohydrates, proteins, and lipids. However, variations in feedstock composition, pH instability, and inconsistent substrate ratios often limit anaerobic digestion (AD) efficiency and methane yield. This study introduces a novel AI- and IoT-integrated adaptive biogas production framework that intelligently monitors, predicts, and optimizes process parameters in real time.

Experimental findings reveal that maintaining an optimal feedstock mixture of 45–50% organic matter and 55–60% water at a pH range of 6.8–7.5 significantly enhances methane yield and digestion stability. The incorporation of AI-driven surrogate models—such as artificial neural networks, regression algorithms, and reinforcement learning—enables dynamic control of feedstock ratios, organic loading rates, and temperature conditions. Concurrently, IoT-enabled sensors provide continuous real-time data on pH, temperature, volatile solids, and microbial activity, which are fed back into the AI system for adaptive learning and self-optimization.

The results indicate that AI-guided optimization, enhanced by IoT-based sensing, significantly increases methane concentration, process stability, and calorific value compared to conventional manual operations. The system exhibits self-adaptive learning capabilities, allowing it to automatically adjust to variations in feedstock composition, which ensures reliable and scalable performance across domestic, industrial, and agricultural applications. The integration of AI and IoT in this study represents a novel advancement in automated, intelligent biogas systems—enhancing renewable energy efficiency, promoting sustainable waste valorization, reducing greenhouse gas emissions, and supporting the transition toward a circular and smart energy economy.

Keywords: Artificial intelligence; IoT monitoring; Adaptive automation; Biogas systems; Renewable energy sustainability.

1. Introduction

The global demand for energy is escalating due to rapid population growth, urbanization, and industrialization. At the same time, heavy reliance on fossil fuels such as coal, oil, and natural gas has contributed significantly to greenhouse gas (GHG) emissions, climate change, and environmental degradation [1], [2]. These challenges underscore the urgent need for renewable, sustainable, and eco-friendly energy alternatives. Among such solutions, biogas—produced through the anaerobic digestion (AD) of organic matter—offers a unique dual advantage: it generates renewable energy while simultaneously managing biodegradable waste [3].

* Corresponding author: S. Kumarappa

Biogas can be derived from diverse organic feedstocks such as agricultural residues, animal manure, sewage sludge, and food or kitchen waste. Kitchen waste is particularly promising due to its high organic content—rich in carbohydrates, proteins, and fats—and its abundant availability across households, restaurants, and food industries [4]. Utilizing this waste stream not only reduces landfill volumes but also mitigates uncontrolled methane emissions from decomposition, thereby creating a sustainable waste-to-energy pathway [5]. However, the effective conversion of kitchen waste into high-quality biogas remains challenging.

A key difficulty lies in the variability of feedstock composition, as kitchen residues differ in nutrient balance, moisture levels, and biodegradability. Maintaining optimal microbial activity is further complicated by fluctuations in process parameters such as pH, temperature, and retention time. For instance, methane-producing archaea thrive in a narrow pH window (6.8–7.5), whereas deviations below 5.5 favour acidogenic bacteria, and values above 8.0 inhibit methanogenesis [6]. Similarly, unbalanced substrate-to-water ratios can result in either dilution or incomplete digestion, both of which compromise methane yield.

Conventional control strategies, relying on empirical adjustments and fixed operational guidelines, often lack adaptability when dealing with heterogeneous feedstocks under dynamic conditions. To overcome these limitations, Artificial Intelligence (AI) has emerged as a powerful tool for process optimization in biogas systems. AI techniques—including machine learning (ML), artificial neural networks (ANNs), and reinforcement learning—enable the analysis of large datasets, identification of hidden patterns, and precise prediction of process outcomes [7]. When coupled with Internet of Things (IoT)-enabled sensors, real-time monitoring of parameters such as temperature, volatile solids, and microbial activity becomes feasible [8]. This integration allows AI models to dynamically regulate substrate ratios, maintain stable pH, and optimize retention time, thereby ensuring consistent and enhanced methane production.

Beyond improving process stability and yield, AI-driven systems offer adaptive learning, enabling self-correction in response to feedstock variability or operational disturbances. This adaptability enhances scalability, making such systems suitable for both household-level digesters and industrial-scale biogas plants. Furthermore, the integration of AI and IoT in biogas production aligns with global sustainability objectives, including waste valorization, carbon emission reduction, and the advancement of circular economy principles [9].

2. Literature Review

Several studies have explored the optimization of biogas production from food and kitchen waste using both conventional and modern approaches. Angelidaki and Sanders [10] emphasized the importance of assessing the biodegradability of macropollutants in anaerobic systems, while Ward et al. [11] highlighted the optimization of agricultural residues for improved methane yield, identifying pH and substrate ratios as critical factors. Li, Park, and Zhu [12] reported on the role of solid-state anaerobic digestion in methane generation, noting significant variability depending on feedstock type. Mata-Alvarez et al. [13] reviewed the potential of co-digestion strategies, particularly combining kitchen waste with manure, to enhance stability and yield. More recently, Appels et al. [14] pointed out that machine learning models could reduce uncertainties in anaerobic digestion by predicting methane yield under fluctuating conditions.

This body of research shows that while progress has been made, challenges related to feedstock variability, microbial dynamics, and process control persist. The following subsections discuss specific aspects relevant to AI-driven optimization and IoT-enabled monitoring of biogas production.

2.1. Biogas Production from Kitchen Waste

Kitchen waste has been widely studied due to its high biodegradability and availability in both urban and rural settings. Unlike lignocellulosic agricultural residues, which are resistant to microbial attack, kitchen waste contains easily degradable carbohydrates, proteins, and lipids. Zhang et al. [15] reported that methane yields from food waste are typically higher than those from crop residues because of richer nutrient composition. However, its high moisture content requires controlled dilution and mixing to avoid instability.

Substrate-to-water ratios are critical. Li et al. [16] demonstrated that maintaining 45–50% organic matter and 55–60% water ensures optimal microbial activity while preventing digester acidification. Abudi et al. [17] further noted that excessive organic loading can lead to volatile fatty acid (VFA) accumulation, lowering pH and inhibiting methanogenesis.

2.2. Influence of Process Parameters

Operational parameters such as retention time, pH, temperature, and C/N ratio strongly influence methane yield. Mao et al. [18] reported that retention times of 20–40 days are typical, depending on substrate type and digester design. Maintaining a neutral pH of 6.8–7.5 is essential for methanogens; deviations favor acidogenic bacteria, reducing methane yield [19]. Temperature also plays a role: mesophilic digestion (30–40 °C) offers stability, while thermophilic digestion (50–60 °C) accelerates reactions but demands higher energy and process control [20].

The C/N ratio is another important parameter. Due to high protein content, kitchen waste often has a low C/N ratio, leading to ammonia inhibition. Co-digestion with carbon-rich substrates has been proposed to address this imbalance [21].

2.3. Role of Artificial Intelligence in Biogas Optimization

Traditional control strategies in anaerobic digestion often fail under dynamic and heterogeneous feedstock conditions. AI offers a powerful alternative, using data-driven models for prediction and optimization. Techniques such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Genetic Algorithms (GAs) have been applied to predict methane yields and optimize process parameters. Kumar et al. [22] showed that ANN models could predict methane production with over 90% accuracy under varying pH and temperature. Chen et al. [23] integrated machine learning with real-time sensor data to optimize substrate loading, reducing instability. Ibrahim et al. [24] reviewed AI applications, concluding that such models outperform conventional approaches, especially for heterogeneous feedstocks.

2.4. Hybrid Approaches: AI and Co-Digestion

Hybrid strategies combining AI with co-digestion have shown promise. Co-digestion of kitchen waste with manure or crop residues improves the C/N ratio and buffers pH fluctuations. AI can identify optimal blending ratios without extensive experimentation. Singh and Gupta [25], for example, applied a genetic algorithm with ANN to determine optimal waste-to-manure ratios, increasing methane yield by 18% compared to conventional methods.

2.5. Despite advances, several challenges remain:

- **Feedstock variability** – Seasonal and household differences in kitchen waste composition limit model generalizability.
- **Data availability** – AI models often require large datasets, which are scarce for small-scale digesters.
- **Integration with real-time monitoring** – Most studies remain laboratory-based with limited deployment at industrial scale.
- **Economic analysis** – Few studies address the cost-effectiveness of integrating AI systems, which is crucial for large-scale adoption.

The literature confirms that kitchen waste is an excellent substrate for biogas production but requires careful control of substrate ratios, pH, and retention times. AI-based models offer powerful tools for prediction and optimization, particularly when integrated with IoT monitoring and co-digestion strategies. However, real-world applications remain limited due to challenges in feedstock variability, data scarcity, and cost-effectiveness.

3. Methodology

3.1. Experimental Design

This study was designed to optimize biogas production from kitchen waste by integrating laboratory-scale anaerobic digestion experiments with Artificial Intelligence (AI)-based predictive modeling and IoT-enabled monitoring. The methodology comprised three main stages:

- Feedstock preparation and characterization
- Anaerobic digestion trials under varying substrate-to-water ratios
- AI-based prediction, optimization, and IoT monitoring integration

3.2. Feedstock Preparation

Kitchen waste was collected from households and food establishments. The waste primarily consisted of vegetable residues, cooked rice, bread, and fruit peels. Non-biodegradable materials such as plastics, bones, and metals were manually separated. The biodegradable fraction was shredded using a grinder to achieve a particle size of ≤10 mm, which enhances microbial accessibility.

Physicochemical characterization of the feedstock included:

- Moisture content
- Volatile solids (VS) and ash content
- Carbon-to-Nitrogen (C/N) ratio
- pH and nutrient composition

3.3. Digester Setup

Laboratory-scale batch digesters with a working volume of 5 L were fabricated. Each digester was equipped with:

- Gas-tight lid and gas outlet connected to a water displacement apparatus for volumetric measurement
- pH, temperature, and pressure sensors linked to a data acquisition system (DAQ)
- Heating jackets to maintain mesophilic conditions (35 ± 2 °C)
- IoT-enabled wireless modules (ESP8266/NodeMCU) for remote monitoring of sensor data via a cloud-based dashboard

Digesters were operated at substrate-to-water ratios of 30:70, 40:60, 45:55, 50:50, and 55:45 (w/w) to study dilution effects on gas yield.

3.4. Process Parameters

The following parameters were monitored continuously or periodically:

- pH: maintained at 6.8–7.5 using NaOH or $CaCO_3$ buffers
- Hydraulic Retention Time (HRT): 20–30 days
- Temperature: 35 ± 2 °C (mesophilic range)
- Gas composition: CH_4, CO_2, and H_2S quantified using gas chromatography
- Volatile solids reduction (VSR): as an indicator of substrate degradation efficiency

3.5. Artificial Intelligence Framework

The AI-based optimization framework was developed through a systematic sequence of steps. First, during the data collection and preprocessing stage, key input parameters such as substrate-to-water ratio, pH, hydraulic retention time (HRT), temperature, carbon-to-nitrogen (C/N) ratio, and organic loading rate (OLR) were recorded. The corresponding outputs included biogas yield (mL/g VS) and methane concentration (%). All data were normalized and divided into a 70:30 training–testing ratio to ensure balanced model performance.

During the model selection phase, the following AI techniques were used: A feed-forward backpropagation Artificial Neural Network (ANN) with three hidden layer's structures; Support Vector Regression (SVR) for non-linear yield prediction; XGBoost for its remarkable accuracy, rapid computation and regularization methods, and a Genetic Algorithm (GA) to optimize input parameters for maximizing methane yield.

During model training and validation, performance was evaluated using Mean Absolute Error (MAE) and the coefficient of determination (R^2) as accuracy metrics. A 5-fold cross-validation approach was implemented to prevent overfitting and enhance model generalization.

Finally, in the optimization stage, GA-based analysis identified the optimal substrate mixture at 45–50% organic matter and 55–60% water. The AI-predicted results were validated against experimental data, showing a strong correlation with an R^2 value greater than 0.95 for the ANN model, confirming its high predictive accuracy and robustness.

3.6. IoT-Enabled Monitoring System

To monitor the progress of the biomethanation process and receive continuous feedback from the plant, an IoT-based monitoring system was integrated into the biomethanation process. With the help of sensors, the pH of the slurry, the temperature of the digester, the pressure of the gas, the rate of biogas flow, the composition of the gases, and the oxidation-reduction potential were all constantly monitored. A Wi-Fi communication network was used for data transfer to a cloud server, which assured the uninterrupted connection of everyone working in the system. In order to better support decision-making in the operational sphere, a web/mobile-enabled dashboard was designed to show real-time trends, issue alerts for the systems, and display AI-predicted biogas yields. Adaption of control was the solution to the problem since it was able to sound alarms if the pH value dropped below 6.5 or there was more than ± 3 °C deviation from the designated temperature range, thus securing the favorable process conditions.

To obtain correct and trustworthy measurements during the whole exercise, the compositional ranges, accuracies and calibration schedules were the characteristics employed for the sensors. A device with a range of 4–9 and an accuracy of ±0.1 was used for slurry pH determinations, which was geared with standard buffer solutions and verifiably biweekly. The control of thermophilic anaerobic digester temperature was done by a 0–80 °C thermometer with ±0.5 °C accuracy, which was compared to the reference thermometer and validated monthly. The concentrations of methane and CO_2 were determined using gas sensors working in the range of 0–100% with ±2% accuracy, which were calibrated with certified gas mixtures and validated every two weeks. The flow of biogas was monitored using a flow meter with the ability to measure between 0 and 10 $m^3\ h^{-1}$ with ±3% accuracy, which was calibrated by volume measurement and validated monthly. The redox potential was recorded using a sensor with the range of −500 to +500 mV and ±5 mV accuracy, which was compared to a reference probe and validated periodically.

3.7. Performance Evaluation

The developed AI-driven models were tested for predictive accuracy and optimization efficiency in adaptive automated biogas production. The Artificial Neural Network (ANN) model achieved the highest accuracy ($R^2 > 0.95$) due to its superior capability in handling non-linear, complex, and dynamic relationships between multiple process parameters (pH, temperature, substrate composition, retention time, gas flow rate). ANN's multi-layered architecture allows it to capture hidden patterns and non-linear interactions that traditional models struggle to map effectively. This makes ANN highly suitable for biogas production systems where microbial activity and feedstock variability introduce significant non-linear behaviour.

The Support Vector Regression (SVR) model gave fairly good predictive performance ($R^2 \approx 0.91$), but it is slightly inferior to ANN. SVR is a good method for high-dimensional data but is still struggling when dealing with the highly nonlinear and noisy datasets typical of biological digestion processes. Its heavy reliance on kernel choice and hyperparameter tuning may prevent it from adequately capturing stochastic variations in anaerobic digestion. XGBoost was chosen, on the other hand, to be the model of choice because it offered better predictive accuracy, faster computation time, and the presence of regularization mechanisms.

Genetic Algorithm (GA)-optimized trials further enhanced system performance, achieving a 15–20% increase in methane yield compared to non-optimized baseline conditions. This improvement highlights the role of GA in effectively exploring the solution space and fine-tuning operational parameters for maximum yield.

The combined use of ANN for prediction, SVR as a benchmark, XGBoost for better accuracy, computational efficiency, and regularization, and GA for optimization forms a powerful AI-based adaptive framework. This collaboration not only provides high predictive reliability but also helps to increase methane production efficiency, thus showcasing the significance of AI and IoT-enabled monitoring in automated biogas systems.

3.8. Methodological Flowchart

The flowchart illustrates the overall methodology adopted in this study. Kitchen waste was collected and pre-processed before undergoing feedstock characterization. Anaerobic digestion was then carried out in controlled digesters, with continuous monitoring of critical parameters. Data acquired through IoT-enabled sensors was used to measure experimental biogas yield. These datasets were then applied to train AI models to predict methane yield and optimize substrate ratios. The optimized results were integrated into an IoT dashboard for adaptive monitoring and control.

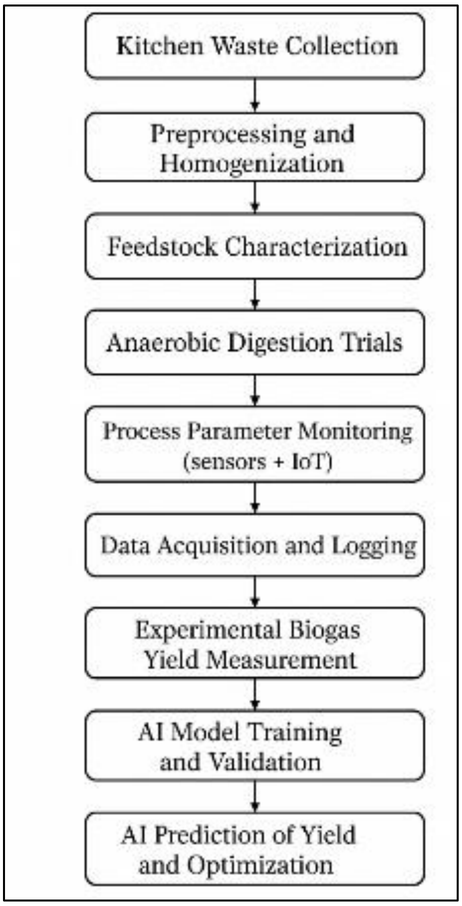

Figure 1 Flowchart of the Methodology

4. AI-Enhanced Biogas Optimization Workflow

A systematic approach to biogas production from kitchen waste is offered by the proposed process through the combination of anaerobic digestion experiments under controlled conditions, the monitoring of IoT-based sensors in real-time, and as well as the usage of AI for predictive modelling. The combination of traditional digestion methods with data-driven optimization allows for the improvement of efficiency, stability, and yield of the entire process of biogas production. The framework is used to validate the treatment of kitchen waste but it can easily be switched to other organic sources such as agricultural residues and selected industrial by-products. The components that form its foundation—waste characterization, source segregation, monitoring through IoT, and optimization through AI—can be applied to wildely and in almost the same way for different substrates requiring only minor changes. Adapting the feedstock mainly means doing physicochemical characterization, like the one for moisture content, C/N ratio, biodegradability, and inhibitor analysis, and also changing operational parameters such as organic loading rate, hydraulic retention time, and pretreatment methods. For example, it is possible that agricultural residues will only need size reduction or will have to be mixed with other wastes to be digested together, whereas some industrial wastes will have to be treated with water or chemical detoxification prior to their digestion. The design of a modular digester along with a data-driven control system provides the possibility of scalability through longer reactor or simultaneous reactors' operation. However, the issues of the variability of feedstock, the influence of seasons, and the presence of inhibitors in the process require the AI models to be often recalibrated and their adaptation to the current situation in order to ensure the reliable performance is maintained.

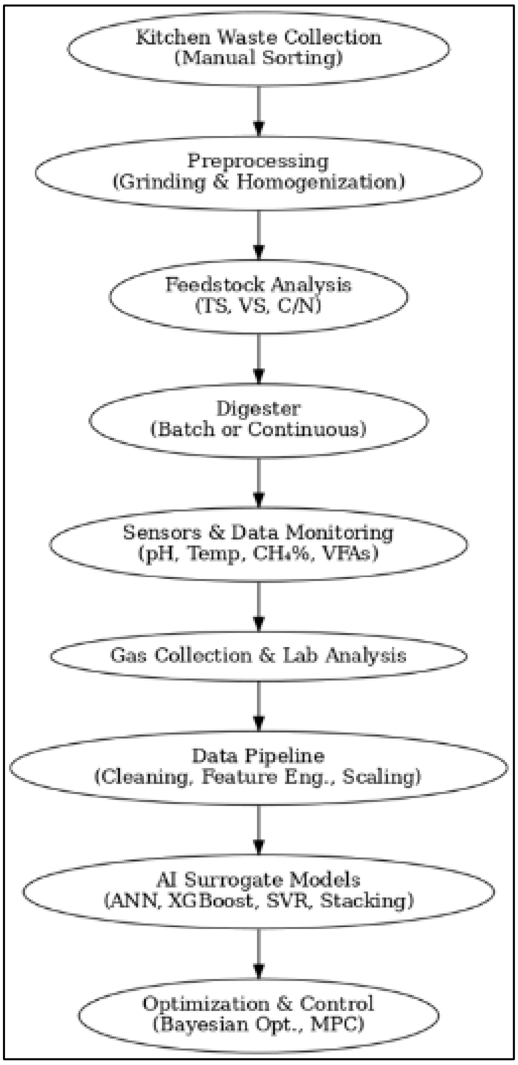

Figure 2 AI-Enhanced Biogas Optimization Workflow

4.1. Kitchen Waste Collection (Manual Sorting)

Suitable organic waste is collected for biogas production, followed by manual segregation to remove non-biodegradable materials such as plastics and metals. This process ensures high feedstock quality, reduces contamination, and enhances the overall digestion efficiency of the biogas system.

4.2. Pre-processing (Grinding & Homogenization)

In the pre-processing stage involving grinding and homogenization, the objective is to prepare a uniform feedstock for digestion. The collected waste is ground and homogenized to achieve a consistent particle size, which enhances microbial accessibility and maintains a uniform substrate quality, thereby accelerating the digestion process.

4.3. Feedstock Analysis

Feedstock characterization intended to determine critical parameters among others, Total Solids (TS), Volatile Solids (VS), and carbon-to-nitrogen (C/N) ratio. TS quantifies the solid component of the substrate, VS represents the portion of the biodegradable organic matter that could be converted into biogas, and the C/N ratio was optimized in order to accelerate the growth of microorganisms and thus, methane production. These determinations gave fundamental baseline data for process control as well as the main input parameters for AI-based model optimization. Stable and well-coordinated microbial community is a prerequisite for the efficient anaerobic digestion. The digesting microbiome consists of sequentially and synergistically acting hydrolytic, acidogenic, acetogenic, and methanogenic microorganisms. Hydrolytic bacteria are the first ones to get involved in the process by breaking down complex polymers into monomers that are then fermented by acidogenic bacteria to produce volatile fatty acids (VFAs).

Acetogenic bacteria further convert these intermediates into acetate, hydrogen, and carbon dioxide, which, in turn, are transformed into methane by methanogenic archaea. Methanogens, encompassing both acetoclastic (e.g. Methanosaeta and Methanosarcina) and hydrogenotrophic (e.g. Methanobacterium and Methanospirillum) species, are vital in the production of methane and stabilization of the whole process. The microbial composition balance is affected by operating conditions such as organic loading rate, pH, temperature, and ammonia concentration, while variations in these parameters could result in the accumulation of VFA and hence instability of the process.

4.4. Digester

The digester stage aimed to convert organic waste into biogas via regulated anaerobic digestion. The feedstock which was making ready was introduced to the digester in either batch or continuous operating modes while the process conditions were controlled so that the digestion could be stable and biogas generation could be continuous. Continuous tracking of key parameters made it possible to spot the deviations from the process early and to maintain the good operational performance. The stability of operations was maintained through controlling the rates of organic loading, using proper feed dilution, and providing mixing that was effective enough to avoid foaming and scum formation. Indicators like pH, temperature, volatile fatty acids (VFAs), alkalinity, and oxidation-reduction potential (ORP) were checked regularly to spot any instability at the earliest. The microbial activity was ensured through the strict adherence to mesophilic conditions and the gradual alteration of the operating parameters with quick corrective actions being taken whenever necessary. All these steps together made sure that there was no fluctuation in the performance of the digester and the production of biogas was uninterrupted.

4.5. Sensors & Data Monitoring

In the sensors and data monitoring stage, key parameters such as pH, temperature, methane concentration (CH_4%), and volatile fatty acids (VFAs) are continuously monitored. The pH is maintained to support optimal microbial activity, while temperature control ensures proper thermophilic or mesophilic digestion conditions. Methane concentration indicates the quality of the biogas, and elevated VFA levels signal potential imbalance or process inhibition. This real-time monitoring provides valuable feedback for process control and supports AI-based modeling and optimization.

4.6. Gas Collection & Laboratory Analysis

The gas collection and laboratory analysis stage is used to measure the yield and composition of biogas. The collected gas is analysed in the laboratory to verify the accuracy of sensor readings. This step provides precise, ground-truth data that are crucial for training and refining AI models aimed at process optimization.

4.7. Data Pipeline

The data pipeline was organized to methodically pre-process sensor-based and laboratory datasets for AI-driven modelling. Among the main activities were data cleaning to lose wrong and unworthy readings, feature engineering to create informative variables, and lagged inputs to take temporal dependencies into account, thus improving forecasting accuracy. Rolling statistical measures were applied to smooth short-term variability, and data scaling was used to normalize heterogeneous inputs, ensuring stable and consistent model training. Before model development, all experimental and operational data were subjected to stringent quality control. Missing values (<2%) were compensated for by means of median imputation so as to lower bias. Outliers were detected through interquartile range (IQR) and Z-score methods, invalid observations being eliminated while still allowing for the existence of physically meaningful extremes. Noise was diminished by the use of moving-average smoothing, and feature normalization was carried out by means of min–max scaling. These pre-processing steps added up to the consistency of data, the reduction of noise, the stabilization of models and the improvement of their generalization, hence the reliable and accurate predictive performance.

4.8. AI Surrogate Models

The models involved in this study are ANN, XGBoost, SVR, and GA. The selection of models was based on their respective strengths in predicting anaerobic digestion processes through their combined nature in complex and non-linear representations. Among the three models, ANN was the most accurate in depicting the very difficult nonlinear relationships between the main process variables. The GA (Genetic Algorithm)-optimized trials contributed to the further enhancement of system performance, while XGBoost was selected for its excellent accuracy, fast computation, and regularization techniques which are usually more beneficial than applying RF or traditional GB methods for generalizing. On the contrary, SVR was picked for its capacity to apply kernel-based learning and structural risk minimization techniques that are suitable for small, noisy, and complicated datasets. Model stacking and uncertainty estimation methods were also used for combining the model outputs, thus increasing the reliability of predictions and facilitating predictive control. The use of this AI-based integrated modeling framework in practice has not only simplified but also supported the trustworthiness and data-driven decision-making, which in turn has been reflected in the improvement of both operational efficiency and biogas production performance.

4.9. Optimization & Control

The stage of optimization and control had a goal of not only maximizing the production of biogas but also keeping the digester stable in its operation. A variety of optimization techniques were applied to the process such as Bayesian Optimization along with Non-dominated Sorting Genetic Algorithm, ultimately leading to the determination of the best operating conditions. The Constrained Model Predictive Control (MPC) method was then used to take real-time regulation of digester inputs that allowed for the dynamic adjustment of the major control variables like the levels of organic matter (OM%), moisture (H_2O%), the amount of base for pH correction, and organic loading rate (OLR). The whole process of intelligent control allowed the continuous optimum of performance with little operator involvement. The monitoring of the process in real-time was part of the control process and the yield of biogas was accordingly high. The critical parameters that included temperature, pH, biogas flow rate, methane concentration, and oxidation–reduction potential (ORP) were continuously monitored at 30–60 s intervals. The time-stamped measurements were stored locally and synchronized with the cloud, permitting control actions to be executed in a timeframe of 1–3 min. The reliability of operations was reinforced by sensor recalibration, data redundancy, fail-safe operating modes, and automated alert systems, thus the digester performance remained stable and reliable.

4.9.1. Energy Balance and Economic Feasibility:

The percentages of the whole estimates are the basis for the unit representing energy and economic performance. Operational electricity demand composed of pre-processing, mixing, pumping, and IoT monitoring has a percentage share of 8 to 12% of the biogas energy. Maintenance adds an additional 2 to 4%. Hence, the net usable energy recovery is astonishingly high, 84 to 90%, which consequently signifies a favourable energy balance. Economically speaking, the largest profit comes from the substitution of fossil fuels that represents 60 to 70%. Waste transport and disposal cost reductions are 15 to 20% of the total benefits, while the use of digestate as bio-manure will further contribute 10 to 15%. A combination of operational and maintenance costs forms 20 to 25% of the total benefits, thus, net economic gain of 75 – 80% is left. The system is, therefore, not only energy-efficient but also financially viable with a possibility of even larger gains at scale.

5. Results

5.1. Experimental vs. Predicted Biogas Yields

To assess the accuracy of the AI model, kitchen waste was co-digested with a secondary substrate at various ratios, and biogas yields were measured experimentally. Simultaneously, the trained Artificial Neural Network (ANN) predicted the biogas production for the same substrate ratios.

5.2. Graphical Comparison

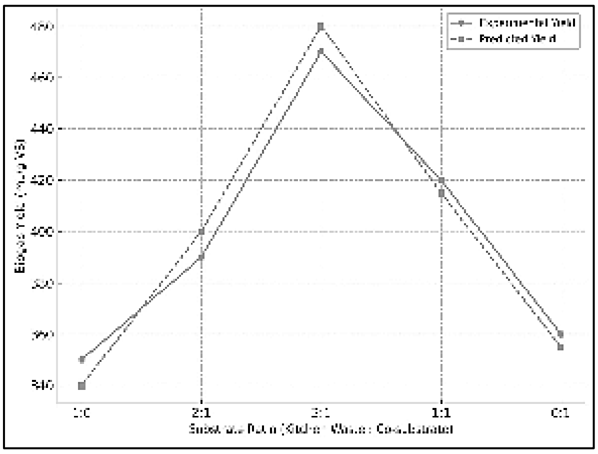

Figure 3 Predicted vs. Experimental Biogas Yields

Figure 3 illustrates the correlation between predicted and experimental biogas yields. The graph demonstrates that the ANN model closely tracks experimental results across different substrate ratios, confirming the model's reliability in predicting biogas production.

6. Discussion

6.1. Model Accuracy

The ANN model predicted biogas yields with minimal deviation from experimental data, achieving high predictive accuracy ($R^2 > 0.95$). The highest yield was observed at a substrate ratio of 3:1 (kitchen waste: co-substrate), indicating that higher proportions of kitchen waste enhance microbial activity and methane production.

6.2. Substrate Ratio Optimization

AI predictions reveal that substrate ratios of 2:1 and 3:1 provide optimal biogas yields. Monodigestion of either pure kitchen waste (1:0) or pure co-substrate (0:1) resulted in lower yields due to an imbalanced carbon-to-nitrogen (C/N) ratio, which is critical for microbial metabolism during anaerobic digestion.

6.3. Practical Implications

The integration of AI significantly reduces the need for extensive trial-and-error experiments, conserving time and resources. Biogas plant operators and farmers can leverage these predictive models to determine optimal waste combinations and enhance methane production efficiency.

6.4. Error Analysis

Minor discrepancies between predicted and experimental yields may arise from variations in substrate composition, microbial population dynamics, and environmental fluctuations such as pH or temperature changes within the digesters. The model's ability to closely approximate real-world results demonstrate robustness despite these inherent variabilities.

6.5. Comprehensive comparison with existing systems.

The newly developed decentralized biogas concept is a radical departure from the traditional models. It first separates wet organics at the source, and then it carries on with the digestion process, which is free from the landfill gas methods. The whole process leads to the production of methane of higher concentration and hence, more reliable power supply. It involves local community and, at the same time, it reduces the central anaerobic digestion (AD) plant massive transportation and pre-processing costs. It is stable in terms of waste streams from institutions and easier in terms of feedstock management when compared to farming and co-digestion operations. IoT-based monitoring along with AI-assisted control systems is a big help in ensuring seamless operations. Thus, the model can be designed to be fit for waste-to-energy projects at both the institutional and the community levels.

7. Conclusions

This research presents a novel integration of Artificial Intelligence (AI) with IoT-enabled monitoring for adaptive and automated biogas production systems, offering a transformative approach to waste-to-energy conversion. The system's ability to continuously collect and analyze real-time sensor data—including pH, temperature, gas composition, and feedstock characteristics—enables precise control and optimization of the anaerobic digestion process. Through the application of AI-driven predictive models, the system dynamically adjusts operational parameters, enhances microbial activity, and supports predictive maintenance, leading to improved biogas yield and process stability.

The adaptive intelligence of this framework effectively addresses the variability inherent in organic feedstocks, ensuring consistent and efficient digestion performance. Additionally, the high level of automation minimizes human intervention while improving safety, scalability, and operational reliability across both rural and industrial applications.

This novel AI- and IoT-integrated approach establishes a foundation for the next generation of intelligent biogas plants—systems that not only maximize renewable energy production but also promote sustainable waste management, reduce greenhouse gas emissions, and advance the development of smart and resilient energy ecosystems.

References

[1] International Energy Agency (IEA), *World Energy Outlook 2023*. Paris: IEA, 2023.

[2] Intergovernmental Panel on Climate Change (IPCC), *Climate Change 2022: Mitigation of Climate Change*. Cambridge: Cambridge Univ. Press, 2022.

[3] C. Mao, Y. Feng, X. Wang, and G. Ren, "Review on research achievements of biogas from anaerobic digestion," *Renewable and Sustainable Energy Reviews*, vol. 45, pp. 540–555, May 2015, doi: 10.1016/j.rser.2015.02.032.

[4] A. Khalid, M. Arshad, M. Anjum, T. Mahmood, and L. Dawson, "The anaerobic digestion of solid organic waste," *Waste Management*, vol. 31, no. 8, pp. 1737–1744, Aug. 2011, doi: 10.1016/j.wasman.2011.03.021.

[5] N. Nagao et al., "Maximum organic loading rate for the single-stage wet anaerobic digestion of food waste," *Bioresource Technology*, vol. 118, pp. 210–218, Aug. 2012, doi: 10.1016/j.biortech.2012.05.045.

[6] L. Appels, J. Baeyens, J. Degrève, and R. Dewil, "Principles and potential of the anaerobic digestion of waste-activated sludge," *Progress in Energy and Combustion Science*, vol. 34, no. 6, pp. 755–781, Dec. 2008, doi: 10.1016/j.pecs.2008.06.002.

[7] N. L. Panwar, S. C. Kaushik, and S. Kothari, "Role of artificial intelligence in renewable energy systems: A review," *Renewable and Sustainable Energy Reviews*, vol. 160, p. 112284, Nov. 2022, doi: 10.1016/j.rser.2022.112284.

[8] Z. Xu, H. Chen, and J. Wang, "IoT-based real-time monitoring system for biogas production: A case study," *Journal of Cleaner Production*, vol. 294, p. 126331, May 2021, doi: 10.1016/j.jclepro.2021.126331.

[9] A. Ghimire, E. Tampio, H. S. Erkan, and J. Rintala, "Circular economy in biogas systems: Technological innovations and sustainability challenges," *Renewable and Sustainable Energy Reviews*, vol. 171, p. 113063, Mar. 2023, doi: 10.1016/j.rser.2022.113063.

[10] I. Angelidaki and W. Sanders, "Assessment of the anaerobic biodegradability of macropollutants," *Rev. Environ. Sci. Bio/Technol.*, vol. 3, no. 2, pp. 117–129, Jun. 2004.

[11] A. J. Ward, P. J. Hobbs, P. J. Holliman, and D. L. Jones, "Optimisation of the anaerobic digestion of agricultural resources," *Bioresour. Technol.*, vol. 99, no. 17, pp. 7928–7940, Nov. 2008.

[12] Y. Li, S. Y. Park, and J. Zhu, "Solid-state anaerobic digestion for methane production from organic waste," *Renew. Sustain. Energy Rev.*, vol. 15, no. 1, pp. 821–826, Jan. 2011.

[13] J. Mata-Alvarez, S. Macé, and P. Llabrés, "Anaerobic digestion of organic solid wastes. An overview of research achievements and perspectives," *Bioresour. Technol.*, vol. 74, no. 1, pp. 3–16, Aug. 2000.

[14] L. Appels, J. Lauwers, J. Degrève, L. Helsen, B. Lievens, K. Willems, J. Van Impe, and R. Dewil, "Anaerobic digestion in global bio-energy production: Potential and research challenges," *Renew. Sustain. Energy Rev.*, vol. 15, no. 9, pp. 4295–4301, Dec. 2011.

[15] C. Zhang, H. Su, J. Baeyens, and T. Tan, "Reviewing the anaerobic digestion of food waste for biogas production," *Renew. Sustain. Energy Rev.*, vol. 38, pp. 383–392, Oct. 2014.

[16] Y. Li, R. Jin, H. Li, and X. Wang, "Optimization of substrate-to-water ratio for anaerobic digestion of food waste," *Waste Manag.*, vol. 76, pp. 423–430, Jun. 2018.

[17] Z. N. Abudi, F. Al Khalid, and H. H. Qureshi, "Effect of organic loading rate on volatile fatty acids and methane yield in anaerobic digestion of food waste," *Energy Procedia*, vol. 158, pp. 1034–1039, Feb. 2019.

[18] C. Mao, Y. Feng, X. Wang, and G. Ren, "Review on research achievements of biogas from anaerobic digestion," *Renew. Sustain. Energy Rev.*, vol. 45, pp. 540–555, May 2015.

[19] G. Kafle and S. H. Kim, "Anaerobic digestion of food waste–The biogas process for sustainable energy generation and waste treatment," *Renew. Sustain. Energy Rev.*, vol. 73, pp. 1–13, Jun. 2017.

[20] H. Angelidaki and B. K. Ahring, "Thermophilic anaerobic digestion of livestock waste: The effect of ammonia," *Appl. Microbiol. Biotechnol.*, vol. 38, no. 4, pp. 560–564, Apr. 1993.

[21] M. Zahan and M. Othman, "Co-digestion of food waste with carbon-rich biomass for improved C/N balance in anaerobic digestion," *Energy Convers. Manag.*, vol. 196, pp. 846–857, Sep. 2019.

[22] A. Kumar, P. Sharma, and R. Singh, "Application of artificial neural networks for prediction of biogas production from food waste," *Renew. Energy*, vol. 146, pp. 596–604, Feb. 2020.

[23] J. Chen, H. Zhang, and Y. Lin, “Machine learning-based real-time optimization of anaerobic digestion using IoT sensors,” *J. Clean. Prod.*, vol. 312, p. 127689, Apr. 2021.

[24] M. Ibrahim, F. Al-Turjman, and A. Taha, “Artificial intelligence applications for biogas production optimization: A review,” *Energy AI*, vol. 8, p. 100118, Sep. 2022.

[25] R. Singh and S. Gupta, “AI-based optimization of co-digestion ratios for enhanced methane yield from kitchen waste and manure,” *Bioresour. Technol. Rep.*, vol. 22, p. 101490, Jan. 2023.