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INTEGRATING MACHINE LEARNING AND REINFORCEMENT LEARNING FOR SMART BIOGAS SYSTEMS

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Abstract

Urban areas face escalating challenges in waste management and energy security amidst rapid population growth. While renewable energy technologies exist, integrated systems optimizing waste-to-energy conversion using artificial intelligence remain underexplored. This study proposes an Advanced Urban Smart Biogas Generator (AUSBG) framework integrating biogas, solar panels, and microalgae modules optimized by Machine Learning (ML) and Reinforcement Learning (RL). Using a Systematic Literature Review (SLR) approach, relevant scientific articles were analyzed to identify key parameters and optimization strategies. The results indicate that ML enhances predictive accuracy for biogas production and solar output, while RL enables dynamic operational control for multi-objective optimization. The findings suggest that the AUSBG concept significantly improves energy efficiency and reduces carbon emissions, supporting circular economy principles. However, challenges regarding data scarcity and model interpretability persist. This study provides a conceptual architecture for smart urban energy systems.

INTRODUCTION

Modern cities are increasingly confronting complex environmental and energy challenges driven by rapid population growth and urbanization. Accelerated economic development and rising household numbers have led to a significant increase in waste generation globally (Avarand et al., 2023). It is estimated that annual solid waste production will surge significantly by 2050, contributing to resource loss and environmental pollution if not managed properly (Elsheekh et al., 2021). Currently, more than half of global waste ends up in landfills without adequate processing, contributing to greenhouse gas (GHG) emissions. In the energy context, reliance on fossil fuels remains a primary contributor to climate change, necessitating a shift toward renewable sources (Al-Maamary et al., 2017). Consequently, the transition to renewable energy and circular economy solutions has become crucial for climate change mitigation.

The Advanced Urban Smart Biogas Generator (AUSBG) offers an integrated solution by utilizing waste as a source of renewable energy, producing biogas for electricity and heating. Integrating solar panels as an additional energy source strengthens this system, making it more efficient and environmentally friendly (Kamarudin & Ismail, 2021). By reducing dependence on fossil fuels and lowering GHG emissions, AUSBG supports the circular economy and the transition toward cleaner energy. However, existing systems often lack intelligent control mechanisms to optimize the complex interactions between waste composition, environmental conditions, and energy demand (Ahmad et al., 2022).

Despite the potential of hybrid renewable systems, there is a research gap in the comprehensive integration of Artificial Intelligence (AI) within urban waste-to-energy frameworks. Most studies focus on isolated components, such as digester optimization or photovoltaic efficiency, without considering a holistic smart system approach (Rao & Kumar, 2022). Furthermore, the application of Machine Learning (ML) and Reinforcement Learning (RL) in managing the dynamic parameters of biogas-solar hybrid systems in dense urban environments remains limited (Khan & Islam, 2022). This study aims to address these gaps by proposing a conceptual framework for AUSBG integrated with AI technologies. The objective is to analyze how AI can optimize the performance of hybrid systems combining solar panels and biogas, identify key implementation challenges in urban settings, and propose technological solutions to overcome these barriers. This research is urgent as it provides a theoretical foundation for developing scalable, smart renewable energy systems that align with Sustainable Development Goals (SDGs).

LITERATURE REVIEW

The theoretical foundation of this study rests on three primary components: anaerobic digestion for biogas production, photovoltaic energy systems, and air quality enhancement modules, all integrated within a smart control architecture. Understanding the parameters influencing each component is essential for effective system optimization.

Anaerobic Digestion and Biogas Production

The success of anaerobic digestion heavily depends on feedstock characteristics. A balanced carbon-to-nitrogen (C/N) ratio is required for optimal microbial development. Zhang et al. (2022) highlighted the links between C/N ratios, synergy, and microbial characteristics in long-term co-digestion. Szyba and Mikulik (2023) found that co-digestion of kitchen waste with green silage in optimal C/N ratios at a 1 MW facility could produce approximately 4.1 million m³ of biogas annually. This underscores the importance of benchmarking input composition. Temperature is another critical operational parameter, divided into mesophilic (35°C) and thermophilic (55°C) ranges. Wu (2014) noted that temperature directly affects methanogen metabolic pathways; a drop of 10°C below optimum can reduce bacterial growth rates significantly. Conversely, temperatures above 50°C increase reaction rates but risk reducing microbial populations if exceeding 60°C. Therefore, temperature control is vital, and solar energy integration can assist in maintaining slurry temperature in colder regions (Issahaku et al., 2024).

The pH level of the digester mixture influences microorganism communities, particularly methanogenic bacteria sensitive to acidity. The optimal pH range is approximately 6.5 to 8.0 (Prasad & Meher, 2016). Outside this range, performance declines drastically. If pH is too acidic (<6.5), methanogen activity is inhibited due to volatile acid accumulation (Sun et al., 2023), while overly basic pH (>8) can cause excess ammonia inhibition (Akindele, 2016; Zhang et al., 2017). Practical operations maintain pH by adding alkalinity buffers or adjusting input C/N ratios. Hydraulic Retention Time (HRT) refers to the average time material remains in the digester. Balancing HRT with urban land availability and desired output targets is crucial. Issahaku et al. (2024) identified design challenges in small-scale digesters, noting that HRT variability makes performance comparison difficult. Biogas output typically contains 60% CH_4 and 40% CO_2 (Jameel et al., 2024). The methane content determines the calorific value; for energy purposes, biogas can be used in micro-turbines or gensets. Nassereddine et al. (2024) demonstrated hybrid scenarios where biogas systems support supply when solar panels are insufficient, ensuring continuous electricity supply at night.

Solar Panel Integration

Photovoltaic (PV) components in AUSBG provide environmentally friendly electricity for system needs or grid distribution. Integrating PV with biogas creates a complementary hybrid system: PV generates electricity during the day, while biogas acts as a buffer at night or during poor weather (Nassereddine et al., 2024). Key optimization parameters include irradiance intensity, panel angle and orientation, module efficiency, installed capacity, and power output profiles. PV energy output depends heavily on solar irradiance, influenced by weather and shading from buildings or trees in urban environments. Although irradiance cannot be controlled, Machine Learning-based weather prediction technology can project daily PV power production (Homayounzadeh et al., 2024). With this information, the system can optimize energy distribution and ensure biogas supply compensates for solar energy shortages.

Panel tilt angle and orientation also affect absorption efficiency. In equatorial regions, the optimal panel angle is near horizontal, around 10 - 15° (Siregar, 2023). In urban areas, panels are often mounted on roofs with fixed angles, although solar tracker systems optimized with Reinforcement Learning (RL) can adjust panel orientation in real-time to ensure maximum energy absorption. Module efficiency is also influenced by temperature, which can decrease when module temperatures rise, especially in urban environments with high roof temperatures. Smart systems can incorporate temperature data to correct PV output estimates. As part of hybrid system integration, solar panels need to be adjusted to biogas production capacity to maximize renewable energy contribution (Mohan & Reddy, 2020).

Air Quality Enhancement Module

A key feature of AUSBG is the air quality enhancement module using microalgae or plants to absorb CO_2 and pollutants like NO_x and SO_x, releasing O_2 through photosynthesis. In the AUSBG context, this module is placed near the biogas genset unit to immediately utilize exhaust CO_2 as photosynthesis input. Microalgae, such as Chlorella and Spirulina, are selected for their rapid growth rates and efficient CO_2 absorption capabilities (Shabani et al., 2016). This module functions dualistically as a pollution filter and a biomass source that can be reused in the system's closed cycle

(Chen et al., 2023). Harvested algae biomass can be used as raw material for biogas digesters or by-products like fertilizer and fish feed. Relevant parameters include air flow rate, light intensity for photosynthesis, and microalgae species used. Gas sensors can monitor CO_2 and O_2 concentrations before and after passing through this module. The integration of these three main components waste-biogas, solar panels, and algae modules forms a symbiosis that supports each other, creating a system approaching zero waste and zero emission.

METHODS

This study employs a Systematic Literature Review (SLR) approach to comprehensively examine the optimization of hybrid systems combining solar panels and biogas, along with the implementation of Artificial Intelligence (AI) in enhancing renewable energy efficiency, particularly in urban areas. The SLR method was chosen to explore how AI can optimize renewable energy system performance and identify emerging trends from related studies (Carrera-Rivera et al., 2022). The research design follows a structured protocol to ensure reproducibility and rigor.

Data Collection and Search Strategy

Relevant scientific articles regarding the use of AI in renewable energy systems (biogas and solar panels) were collected and analyzed. The search was conducted across major academic databases, including Scopus, Web of Science, and IEEE Xplore. Keywords used in the search string included combinations of "Biogas," "Solar Panel," "Machine Learning," "Reinforcement Learning," "Urban Energy," and "Optimization." The search was limited to publications from the last 10 years to ensure relevance to current technological advancements.

Inclusion and Exclusion Criteria

Articles were selected based on inclusion criteria such as topic relevance, research quality, and publication type. Priority was given to peer-reviewed journal articles published in international reputable journals. Conference proceedings were included if they presented significant novel findings. Articles were excluded if they lacked empirical data, were not available in English, or focused solely on theoretical aspects without practical application implications. The initial search yielded a broad range of papers, which were subsequently screened based on titles and abstracts.

Data Analysis

Selected articles were analyzed to answer the core research questions: How can AI technology be used to optimize the performance of hybrid systems combining solar panels and biogas? What are the main challenges in implementing AI-based biogas-solar hybrid systems in dense urban environments? And how can technology-based solutions overcome these problems? The analysis focused on identifying relationships between ML integration and AUSBG optimization from the parameters intended to be built. Data extraction involved categorizing findings based on system components, AI algorithms used, performance metrics, and identified challenges. The synthesis of this data forms the basis for the conceptual architecture proposed in this study.

To ensure the reliability of the synthesized data, a quality assessment was conducted on the selected articles. Each study was evaluated based on criteria such as methodological rigor, clarity of AI model description, and relevance to urban contexts. Studies lacking empirical validation or clear performance metrics were excluded from the final synthesis. This step ensured that only high-quality evidence contributed to the proposed AUSBG framework, minimizing bias from preliminary or theoretical-only studies.

RESULTS AND DISCUSSION

Role of Machine Learning and Reinforcement Learning

The AUSBG system involves various biological, chemical, and physical processes requiring intelligent approaches to manage interrelated parameters. Machine Learning (ML) and Reinforcement Learning (RL) play critical roles in optimization and adaptive decision-making. ML can be used to model complex relationships between parameters and predict system outputs, such as biogas production and solar energy, based on input data like waste volume, temperature, and solar radiation (Abdullah et al., 2021). With the ability to predict and handle complex data, ML helps the system plan and optimize energy distribution in the biogas-PV hybrid system (Rutland et al., 2023).

Reinforcement Learning (RL), on the other hand, focuses on dynamic control aimed at maximizing clean energy output and minimizing emissions. Gao et al. (2024) demonstrated that RL can regulate operational variables such as waste feeding rate to the digester, biogas genset usage, and temperature or air flow adjustment to the photobioreactor to ensure efficient system operation. The RL system learns autonomously from received feedback, adapting operations based on changing conditions like waste supply fluctuations or weather changes (Devi & Kumar, 2021). The combination of ML and RL provides complementary solutions: ML provides predictions based on historical data, while RL optimizes decisions in real-time to achieve system goals more dynamically (Amin et al., 2020). Together, these technologies enable AUSBG to function automatically, learning from data to improve efficiency and system stability.

System Architecture Integration

The AUSBG architecture is designed to integrate physical, digital, and control components into one optimal smart system. This model is divided into three main layers: the physical layer, the supervision and network layer, and the intelligent digital layer. The physical layer consists of devices operating directly in the field, including biogas digesters, gensets, solar panels, and algae modules. These components are equipped with various sensors to monitor important variables such as temperature, pH, light intensity, and gas levels. Data from these sensors is transmitted via sensor networks (IoT) to the supervision and network layer for further processing (Ahmad et al., 2022).

The supervision and network layer is responsible for connecting physical devices with control and communication systems. Here, the Energy Management Unit (EMU) regulates energy flow between solar panels, biogas gensets, and loads, and receives sensor data for basic control. This system is also connected to an IoT Gateway for real-time data collection. In this layer, local controls such as PID and fuzzy logic are used for fast control, ensuring operational stability even in emergency conditions or disturbances. The intelligent digital layer is the brain of the AUSBG system, where ML and RL technologies play a major role in optimization and decision-making. Digital Twins are used to model the system virtually, allowing simulation and predictive analysis without disturbing physical operations (Hernandez & Martinez, 2022).

The ML module is used to predict system output based on historical data, such as biogas production and solar energy, and to identify potential problems like temperature or pH mismatches in the digester (Liu et al., 2021). On the other hand, RL is tasked with regulating operational decisions adaptively, such as controlling the waste feeding rate to the digester or temperature adjustments to maintain efficiency. This entire architecture enables AUSBG to operate autonomously with data-based optimization to improve efficiency and system stability. RL plays a role in controlling and adjusting operational parameters dynamically, while ML supports more accurate predictions regarding energy output and biogas quality. The system can adapt to changing conditions, such as waste supply fluctuations or weather affecting energy production.

Challenges and Future Potential

Although the AUSBG concept integrated with ML and RL offers significant potential, several research gaps need to be addressed to optimize its development. One major constraint is the lack of integrative studies and field data. Currently, most research focuses on separate parts of the system, such as digester optimization or PV-biogas hybrid studies without considering air quality. Consequently, empirical data needed to validate AI models is very limited (Nguyen & Tran, 2022). Another challenge faced is multi-objective optimization, where AUSBG must balance several sometimes conflicting goals. For instance, maximizing energy production might require burning all biogas immediately, but to reduce CO_2 emissions, it is better to store gas longer for microalgae absorption.

Beyond technical performance, the economic viability of integrating AI into biogas systems remains a critical factor for widespread adoption. While ML and RL optimize efficiency, the initial investment for sensors, IoT infrastructure, and computational resources can be substantial. However, long-term operational cost savings from reduced energy waste and predictive maintenance often offset these costs. Future implementations should consider techno-economic analyses to determine the return on investment (ROI) for different city scales, ensuring that smart biogas solutions are not only environmentally sound but also financially sustainable for municipal budgets. Future research needs to utilize multi-objective optimization algorithms, such as Pareto optimization or multi-objective RL, to find the optimal balance point between energy production, waste reduction, and emissions (Li et al., 2023). Additionally, while AI technologies like ML and RL have great potential in system optimization, issues of interpretability limitations and trust in AI decisions remain obstacles, especially in critical applications like waste processing. Upcoming research must integrate Explainable AI (XAI) elements so operators can understand decisions made by the system (Alzubaidi et al., 2024). This will increase transparency and trust, allowing operators to intervene if necessary.

Scalability and system replication also need consideration. Given different conditions between cities, the biggest challenge is adapting AUSBG design to larger scales. Further research could focus on modular designs allowing this system to be adjusted to different capacity needs, as well as examining the impact of integrating multiple AUSBG units on the city electricity grid (Mukhtar et al., 2023). Finally, it is important to conduct holistic environmental impact studies through Life Cycle Assessment (LCA), which is currently rarely done due to complexity (Kusuma & Pratama, 2023). LCA research will help evaluate the environmental impact of the entire system, from component production to long-term operation. With clear comparisons between cities using AUSBG and those that do not, this research can provide strong evidence regarding the environmental benefits obtainable from this system (Wijaya & Santoso, 2024).

Furthermore, the successful deployment of AUSBG relies heavily on supportive policy and regulatory frameworks. Current urban energy policies often treat waste management and energy generation as separate sectors. Integrated systems like AUSBG require cross-sectoral regulations that incentivize waste-to-energy projects and facilitate grid integration for decentralized power. Governments should consider subsidies for AI-driven renewable technologies and establish data-sharing protocols to foster innovation. Aligning technological advancements with policy incentives will accelerate the transition toward smart, sustainable urban energy ecosystems.

CONCLUSION

This study presents an innovative solution to address major challenges faced by modern cities in waste management and energy. The concept of the Advanced Urban Smart Biogas Generator (AUSBG) combined with renewable energy technologies, such as solar panels and biogas-based waste processing systems, shows great potential in reducing carbon emissions, improving energy efficiency, and mitigating negative waste impacts. The integration of components, such as microalgae for air quality improvement and the utilization of Machine Learning (ML) and Reinforcement Learning (RL) technologies for further operational optimization, enhances the effectiveness of this system.

The implications of this research suggest that smart integration can significantly boost urban sustainability. However, limitations exist regarding data availability for model training and the complexity of multi-objective control in real-world settings. Future research is suggested to focus on empirical validation through pilot projects, development of explainable AI models for operator trust, and comprehensive Life Cycle Assessments to quantify environmental benefits. By addressing these gaps, AUSBG can be brought closer to reality, creating a cleaner and more efficient future for urban environments.

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