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Correlation Analysis Model of Environment Parameters Using IoT Framework in a Biogas Energy Generation Context

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Abstract: Recently, the significance and demand for biogas energy has dramatically increased. However, biogas operators lack automated and intelligent mechanisms to produce optimization. The Internet of Things (IoT) and Machine Learning (ML) have become key enablers for the real-time monitoring of biogas production environments. This paper aimed to implement an IoT framework to gather environmental parameters for biogas generation. In addition, data analysis was performed to assess the effect of environmental parameters on biogas production. The edge-based computing architecture was designed comprising sensors, microcontrollers, actuators, and data acquired for the cloud Mongo database via MQTT protocol. Data were captured at a home digester on a time-series basis for 30 days. Further, Pearson distribution and multiple linear regression models were explored to evaluate environmental parameter effects on biogas production. The constructed regression model was evaluated using R^2 metrics, and this was found to be 73.4% of the variability. From a correlation perspective, the experimental result shows a strong correlation of biogas production with an indoor temperature of 0.78 and a pH of 0.6. On the other hand, outdoor temperature presented a moderated correlation of 0.4. This implies that the model had a relatively good fit and could effectively predict the biogas production process.

Keywords: biogas energy; Internet of things; regression modeling; correlation analysis

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

Academic Editors: Panagiotis Papageorgas, Dimitrios Piromalis and Dionisis Kandris

Received: 9 June 2023
Revised: 12 July 2023
Accepted: 13 July 2023
Published: 9 August 2023

1. Introduction

The use of renewable energy is expanding globally due to resource availability and fluctuating energy prices, with efforts to mitigate the effects of climate change [1]. By 2015, its usage accounted for nearly 22% of the total energy consumed worldwide [2,3]. Developed nations are advancing their use of renewable energy; for example, renewable energy sources are anticipated to produce adequate electricity in several US states over the following two decades [4]. Further, Africa as a continent presents the highest potential to be the first continent to base a major amount of its industrial and economic growth on clean and renewable energy sources [5,6]. Unlikely other renewable energies, biogas is a promising solution since its characteristics are available and affordable to the local community. Biogas is a renewable gaseous fuel that is generated through the breakdown of organic materials without the presence of oxygen in a process called anaerobic digestion [7]. Domestic biogas is made from animal excrement from cow, or pig dung, coupled with food waste, agricultural waste, and occasionally human excreta. Biogas's major ingredients are methane (CH_4) and carbon dioxide (CO_2), representing 50–60% and 35–45%, respectively [8].

Rwanda's government has invested extreme efforts over recent years to encourage the adoption of biogas usage through various initiatives, including the construction of biogas digesters for local communities and the Girinka project (One Cow per Poor Family) [9], which has gradually increased cattle dung which is a major source of biogas in Rwanda. Figure 1 presents a report from the Rwanda Energy Group (REG) regarding the distribution of biogas plants in the local community until 2019.

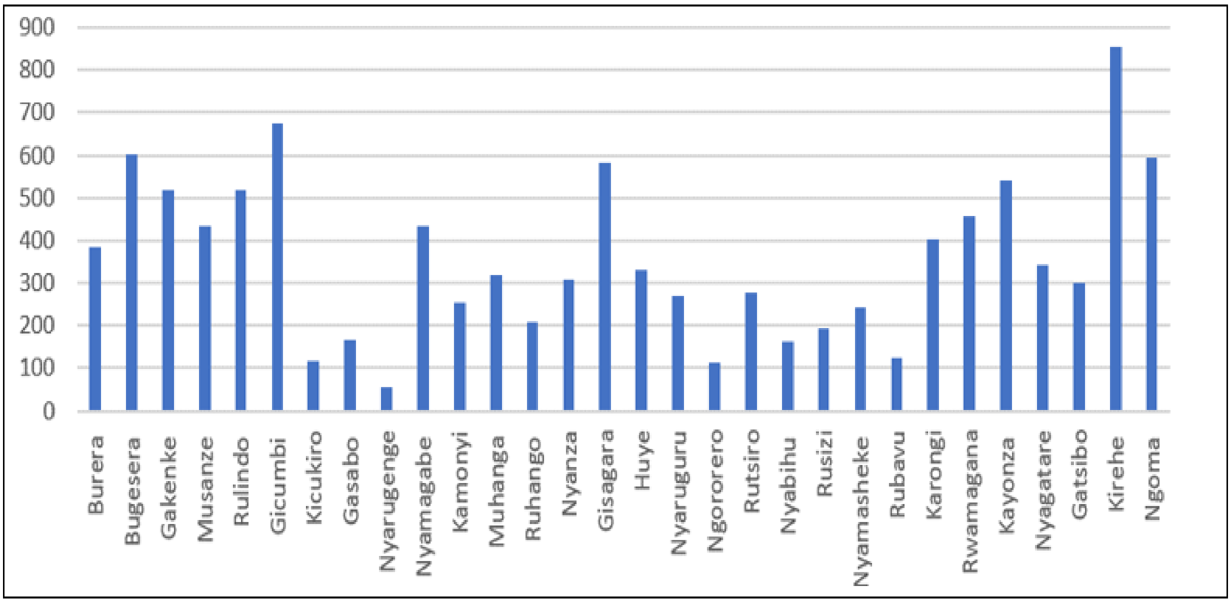


Figure 1. Biodigester distribution district-wise.

Despite various governments' support policies, these studies disclosed that the adoption and diffusion of biogas technology have been considerably low [10,11]. This is not isolated to Rwanda; the lower adoption of domestic biogas technology has been recognized globally [12,13]. These issues are not limited to technical challenges such as a lack of classification requirements, as well as insufficient raw materials, and a lack of precise technology for controlling the operating parameter.

Several works of research on the parameters affecting the production of biogas in the anaerobic digestion (AD) process have increased in importance over the past few years. Feedstock characteristics, digester structures, continuous processing, operating, and environmental conditions present importance in biogas production [14]. Concerning environmental conditions, parameters including temperature, pH, moisture content, humidity, and pH presented a high impact during biogas generation [15,16]. For example, Toutian et al. [17] discussed a lab-based experiment on the effect of temperature on biogas production during the hydrolysis stage. It presented the efficiency of production in the mesophilic environment [18]. Abudi et al. [19] detailed the contribution of pH for optimum biogas generation. Optimal biogas production was obtained at a pH range between 6.8 and 7.4 [20]. Furthermore, the moisture content in the substrate allowed for the free and relaxing movement of microorganisms, resulting in high biogas production [21]. Therefore, to ensure the consistent and effective generation of biogas, it is essential to maintain proper continuous control over the environmental parameters. This research aimed to assess the impact of environmental parameters on biogas production using a combination of IoT technology and ML techniques.

In recent years, the global renewable energy robot market has been predicted to reach USD 75.82 Billion by 2030, with a growth rate of 27.9% during 2022–2030 [22]. Recent researchers have demonstrated the impressive contributions of artificial intelligence (AI) and the IoT on renewable energy economies and how these can be implemented in the entire process from energy generation to transmission and use [23–25]. The most recent IoT trends indicate the potential application of the IoT in energy, including energy utilization monitoring in smart cities, solar plant health monitoring, and more [26,27].

This has been commonly applied in other industries, where IoT technology has been adapted for designing and optimizing the anaerobic digestion process [28]. For example, research on the IoT performance of anaerobic digestion was performed, where an operating condition monitoring tool was developed; however, this article lacked intelligent control mechanisms to regulate the optimum condition [29]. In [30], technologies covering the IoT architecture, and data analytics modeling, were leveraged to explore the existing works in biogas supply chain management. It experienced limitations when implementing the proposed architecture in a specific case study. Additionally, the authors of [31] proposed an IoT-based biogas measurement monitoring system that was capable of classifying various gases. However, the authors did not consider monitoring environmental conditions and behaviors that could affect production. Furthermore, in [32], the security mechanism for IoT applications in biogas generation was proposed focusing on cyber-physical systems. Among these related works, the works in [33,34] investigated the integration of the IoT and data analytics models approach for anaerobic digestion performance. The main emphasis of these two publications was primarily on the algorithms used for analysis. Overall, based on the state-of-the-art IoT in AD automation, IoT technology has already been integrated by proposing various applications to support people. However, there is still a lack of applications in the community with the available validated dataset to support the AI modeling process.

The main contribution of this paper was to design and implement an IoT framework for gathering data, monitoring, and controlling operating conditions in the biogas generation process while addressing some of these existing limitations. This paper also proposed the application of data validation algorithms to avail datasets for further prediction purposes and support the production control of biogas in the Rwanda context. This work proposed the use of multi-linear regression and Pearson distribution models to perform a correlation analysis of biogas production by considering multivariant environmental parameters in the biogas generation context. These models were validated using data gathered by the implemented IoT framework.

Figure 2 presents an overview of the proposed IoT framework for acquiring the biogas digester's environmental parameters, such as indoor temperature, ambient temperature, humidity, Ph, and the moisture content of the subtract. The proposed IoT framework comprised three main components: (1) the edge layer with sensors, microcontrollers, and actuators; (2) the network layer was made by an IoT Wi-Fi gateway; and (3) the cloud layer was made of a web-based platform with persistent data management hosted on the cloud server. In this study, edge computing architecture was chosen since it enabled a flexible framework through the early decision provision paradigm. Each layer was independent; hence the decision could be made at any layer [35].

The purpose of this research was to provide environmental data control using the IoT technology and to investigate the effect of environmental parameters in the biogas generation context.

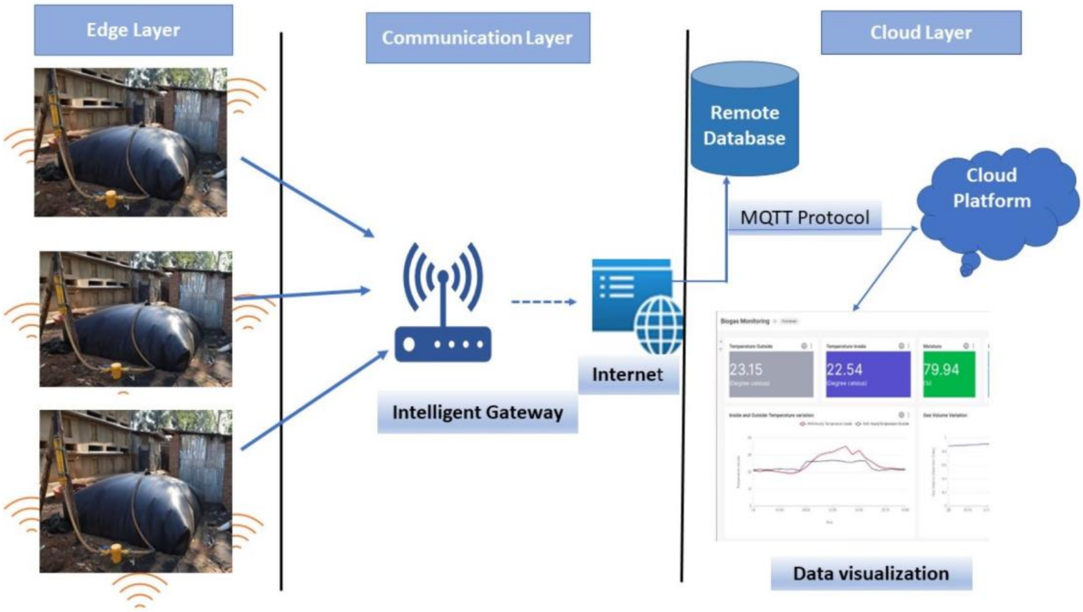


Figure 2. The proposed IoT framework applied in the biogas generation context.

2. Materials and Methods

This section details the materials and methods that were adopted for implementing IoT framework, data preprocessing, and data analysis used in this study.

Figure 3 describes the flow of the methodology, which was used to validate the proposed architecture as well as the data correlation modeling process. From a material perspective, the IoT framework was developed and deployed on physical digesters to collect time series data. From a method perspective, a series of data pre-processing, such as missing values, the high peak value records removal, and datatype conversion, was performed before data validation analysis was conducted and validated.

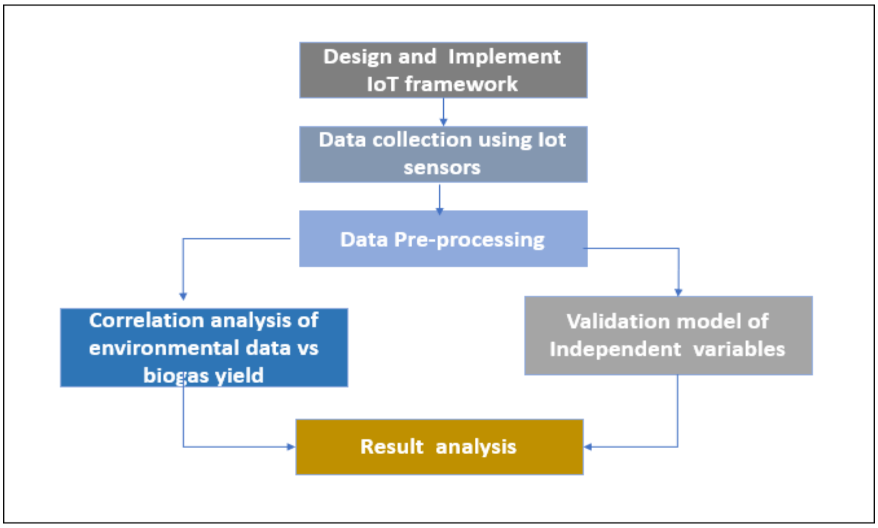


Figure 3. Research study methodology.

2.1. IoT Framework Design and System Setup

During this research, a single-stage low-cost polyethylene tube digester of 4000 L was experimented on, and cow manure and home wastes were considered as input materials. This research was conducted in the eastern province of Rwanda, specifically in the Rwamagana district. The reason for choosing this case study area was that it was recognized as a hub for agriculture and animal husbandry [36]. Therefore, it is held a promising supply of biogas from crop residues and animal manure. Furthermore, the selected district often experiences a high average temperature, which is a crucial factor in biogas production [37].

The proposed IoT framework was composed of ground-based nodes mounted on a digester to periodically collect related environmental data. Table 1 presents the detailed role of each layer during the system's implementation.

Table 1. Description of proposed architecture.

Component	Description
Edger layer	Comprises sensors, the actuator and microcontroller Perform local data analysis for controlling actuators Ensure data security through authentication Perform local data analysis
Network layer	Comprises the Wi-Fi module Perform data routing and transmission
Cloud layer	Allow permanent data storage Allow public data access High data performance analysis

The detailed system design and implementation of the edge and cloud node are discussed in the next subsections.

2.1.1. Edge Lyer

The designed sensor kit comprised various sensors to acquire data such as moisture content, pH level, pressure, and temperature, respectively. Sensing devices were connected to a customized Raspberry Pi 3 B+ microcontroller with a built-in Wi-Fi module and were used as an IoT gateway where captured data from these sensors could easily be sent to the database. Each node was connected to a solar panel power supply. Table 2 describes all the devices required to design the kit.

Table 2. Components of designed sensor kit.

Device	Description
DS18b20	Indoor Temperature, Humidity
OAT-M-24	Ambient Temperature
700KPGPN	Gas pressure
DIY Ph	pH
Capacitive Moisture	Moisture
Solderless breadboard	Breadboard
Raspberry Pi.3	Microcontroller

Figure 4 presents the IoT kit design setup, which was implemented to connect and control the IoT sensing devices.

In addition, a set of activation tools were implemented to provide environmental control mechanisms. Table 3 presents a set of actuator devices, such as sprinklers, thermostatics, and thermal electric actuators, which were implemented.

Table 3. The actuators implemented in smart biodigester.

Components	Description
Sprinkler	Discharge water when the effect of low moisture is detected
A thermostatic	Provide heating in the environment when the system notifies
Thermal electric	Provide cooling in the environment when the system notifies

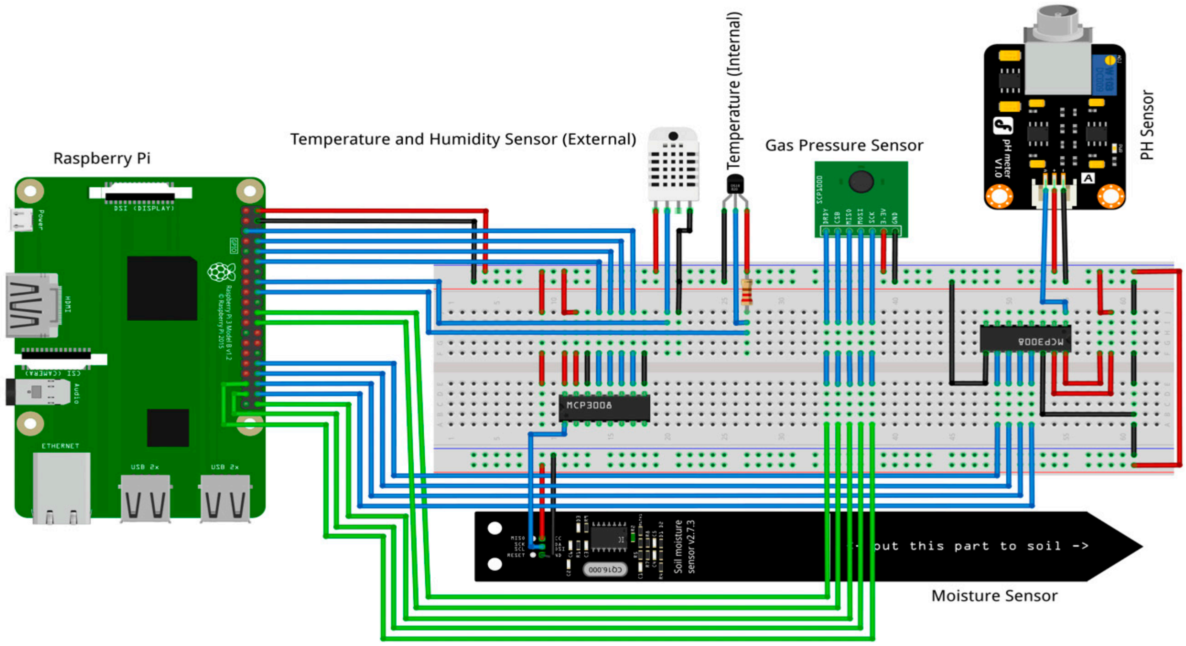


Figure 4. IoT kit design.

2.1.2. Cloud Layer

Data Storage

The sensor data were pushed to the MongoDB database hosted on the cloud server. MongoDB is an open-source that is used to store semi-structured data (NoSQL): a database that saves and retrieves documents in either JavaScript Object Notification (JSON) or extensive Markup Language (XML). Mongo is recommended to be adapted to big data management due to its characteristics [38]. In this research, MongoDB was chosen due to its capability to store and process data in real time. The application implemented with Mango had capabilities such as scalability and a high processing speed [39].

MQTT Protocol

The MQTT (Message Queueing Telemetry Transfer) is a communication protocol that can be adapted at the application layer. MQTT Serving, as a client-server, publishes/subscribes to the messaging protocol designed for machine-to-machine communications in a low bandwidth environment [40]. MQTT has been adopted in many IoT-based applications, such as manufacturing process management and healthcare [41,42], energy generation and trading [43], and agricultural environmental monitoring [26]. Developing an IoT system involves IoT data transmission and thus requires IoT communication protocols. MQTT presents a remarkable contribution to IoT applications due to low power consumption, a small bandwidth, and less memory, which are common in IoT systems [44].

Figure 5 displays the sensor node publishing data to the Mongo database. These data were sent to the MQTT broker, followed by the MQTT client subscriber, as shown in Figure 6.

Cloud Web Platform

The web application is a major part of the IoT system; it enables intended users to view and understand the status of the biogas station in real time. ReactJS Programming language was adapted to develop the front-end and the back-end web services, which were developed using the Laravel PHP framework. The web application is currently running on the cloud server. Table 4 presents the summarized functionalities of the application.

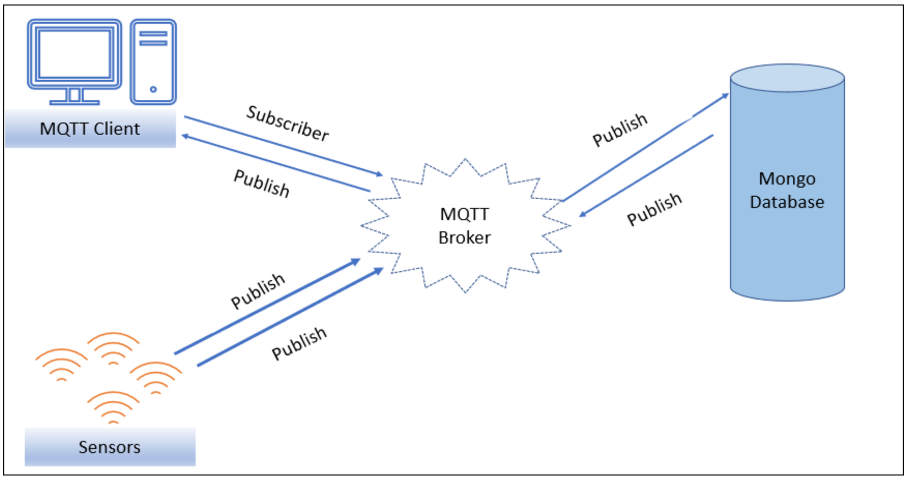


Figure 5. MQTT communication pathway.

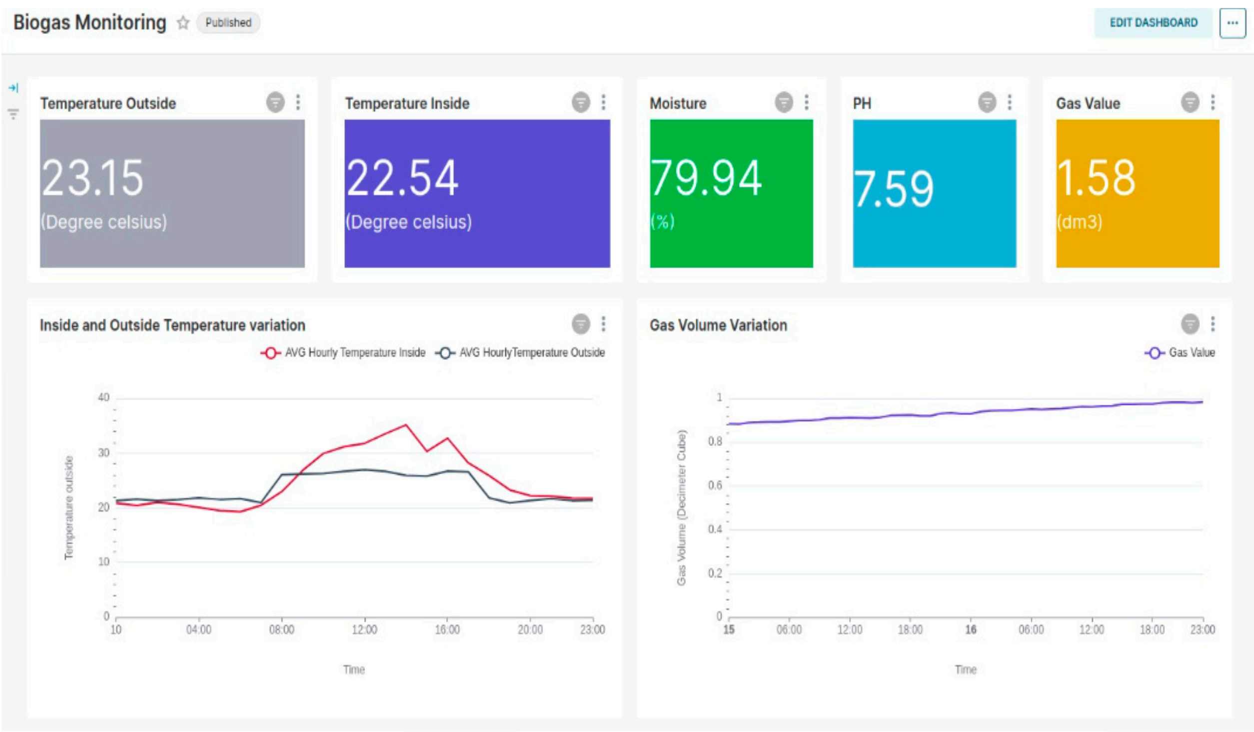


Figure 6. Sample of captured data appearing on the web user interface.

Table 4. Web application features.

Non-Function	Functional
Scalable design enables fast response	Dashboard for data visualization
Security via user authentication	Instant Notification
Responsiveness across multiple devices	Data Export capabilities

2.2. Data Acquisition

As discussed in previous sections, a novel contribution of this paper is the implementation and integration of an IoT framework that could automate environmental data collection and data analysis. Data acquisition is a fundamental and essential task when conducting data analysis. The IoT kit was placed for a period of 30 days to collect data in 16 min.

Figure 6 presents the sensor data observations acquired on the on-cloud Mongo database and visualized on the web dashboard. This dashboard presents the last sensor records in widget form, such as temperatures, moisture, pH, and biogas variation for a specified period. The developed web application is intended to facilitate the biogas operators in decision-making processes.

During the data collection period, a dataset of 3000 records was acquired on the Mongo database, and each record had 6 variables.

Table 5 presents the sample of the first five rows, The description of variables within the dataset is as follows: (1) the moisture content of substances (moisture), presenting the moisture content level of substances within a biogas digester in its percentage (%). (2) the outdoor temperature (Temp_out), which presents the outdoor temperature of the digester in degrees Celsius (°C). (3) The temperature of substances within the digester (Temp_in) is presented as the indoor temperature in Celsius. (4) The pH level of the substances (pH) represents the acidity level of the substances, which ranged from 0 to 14. (5) The gas generated (gaz_change), which presents the gas yield from the biogas generation process in a decimeter cube (dm^3), and (6) acquisition time (time_occur), presenting the timestamp when the data were captured.

Table 5. Dataset sample.

Moisture	Temp_out	Temp_in	pH	Gaz Value	Time-Occur
85.24	20.32	36.90	6.86	0.08	3 January 2023 0:01
85.95	19.59	36.60	7.62	0.07	3 January 2023 0:16
86.04	20.96	37.77	6.27	0.08	3 January 2023 0:31
83.31	19.67	35.00	7.31	0.06	3 January 2023 0:46
85.18	20.33	36.50	6.24	0.08	3 January 2023 1:01

2.3. Data Pre-Processing

The data acquired from the experiment were extracted in the CSV file format to be used in the machine learning model as input data. Data preprocessing was performed using the Anaconda Python programming environment. Before preprocessing, a set of Python libraries, such as Matplotlib, Pandas, Scikit-learn library, and NumPy, were imported for data preprocessing. The dataset was imported using the read_csv () function of Panda's library. The CSV file contained certain extra columns and rows with missing values and high peak values that were impractical. The rows with missing and high peak values were replaced with the mean values of the entire available values via the Imputer class of the sklearn preprocessing library. In addition, timestamp values were converted from the 12 h system to 24 h using the strftime () function from the datetime library to easily employ time in our model. The many targets here tacked days onto an hourly basis since this could impact the variability of some parameters. Table 6 shows the sample of the dataset after pre-processing.

Table 6. Dataset after preprocessing.

Moisture	Temp_out	Temp_in	pH	Gaz Value	Date	Time (12 h)	Time (24 h)	Day_Hour
85.24	20.32	36.90	6.86	0.08	3 January 2023	12:01 a.m.	0:01	12.0
85.95	19.59	36.60	7.62	0.07	3 January 2023	12:16 a.m.	0:16	12.2
86.04	20.96	37.77	6.27	0.08	3 January 2023	12:31 a.m.	0:31	12.3
83.31	19.67	35.00	7.31	0.06	3 January 2023	12:46 a.m.	0:46	12.5
85.18	20.33	36.50	6.24	0.08	3 January 2023	1:01 a.m.	1:01	1.0

2.4. Data Analysis

A major objective of the IoT framework was to improve the quality monitoring of environmental parameters in the biogas generation context using sensors and data analytic tools. In this regard, the multiple linear regression model was adopted to assess the fitness of environmental parameters, and subsequently, the Pearson correlation analysis was utilized to examine the relationship between environmental parameters and biogas production.

2.4.1. Multiple Linear Regression Model

Multiple linear regression is a supervised machine learning model that employs two or more independent variables to forecast the outcome of a dependent variable [45]. This paper was adapted in (Equation (1)) to validate the contribution of digester environmental parameters in biogas generation. The Ordinary Least Squares (OLS) regression analysis technique was employed to find the best fitting. In essence, the OLS entailed leveraging the parameter estimation from linear regression and considered the sum of squared discrepancies between the real sample value and the OLS estimation as the main point of reference for parameter estimation [46]. In this context, Y represents the dependent variable, and βs are the regression coefficients. Additionally, a set of X's presents the independent variable.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon \tag{1}$$

The multiple linear regression model could be evaluated by several metrics, including the mean squared error (RMSE), mean absolute error (MAE), and R Squared (R^2). This study explored R^2 to validate the model since it was very informative compared to others [47].

2.4.2. Pearson Correlation Coefficient

The Pearson correlation coefficient, indicated in (Equation (2)), is a measure of linear correlation that could analyze the relationship between two or more variables [48]. In this context, the Pearson correlation was adopted to express the degree of linear correlation between environmental parameters and biogas production.

$$r_{xy} = \frac{\sum (x - \overline{x})(y - \overline{y})}{\mathrm{N} \cdot S_x S_y} \tag{2}$$

The formula given defines the correlation coefficient of the two variables. In the formula, N represents the total number of data samples, while x and y represent the mean values of the two sets of variable data. S_x and S_y represent the standard deviations of the respective variable data samples.

3. Result

3.1. Model Validation Results

The validation of the models was assessed using R^2 metrics. The model was constructed by taking the indoor temperature, ambient temperature value, the moisture content as independent variables and the biogas production value as the dependent variable.

Table 7 presents the OLS model result, while R-squared indicates 73.4% of the variability in the biogas production, which was explained by the environment parameters explored in the regression model. This implies that the model had a relatively good fit and could effectively predict the biogas production process.

Table 7. OLS Multiple Regression Model Results.

Dep. Variable	Gaz-value	**R-squared**	0.734		
Model	OLS	Adj. R-squared:	0.734		
Method	Least Squares	F-statistic:	2066		
	Coef	std err	T	P > ∣t∣	[0.025, 0.975]
Const	−0.3942	0.000	42.463	0.040	−0.376
Ph	0.6021	0.000	19.186	0.021	0.002
Temp_in	0.843	0.000	25.460	0.012	0.005
Temp_out	0.526	0.000	17.903	0.032	0.003
Moisture	0.0129	0.000	20.974	0.040	0.003

3.2. Correlation Analysis

The relationship between biogas production (y-variable) and environmental parameters (x-variables) was calculated by the Pearson correlation coefficient r. The relationship between environmental variables and biogas yields was constructed using the Seaborn heatmap Python data visualization library, which revealed the correlation between temperature, moisture, pH, and biogas yield.

Figure 7 presents how the inter-variables correlation matrix was constructed. The value of r fell within the range of −1 to +1. When r > 0, it indicated a positive correlation between the two variables, meaning that as one variable increased, the other variable tended to increase as well. Conversely, when r < 0, it indicated a negative correlation, whereas when one variable increased, the other variable tended to decrease, and the larger the absolute value of r, the stronger the correlation. It was important to note that this correlation did not imply causation. When r = 0, it indicated no linear correlation between the two variables.

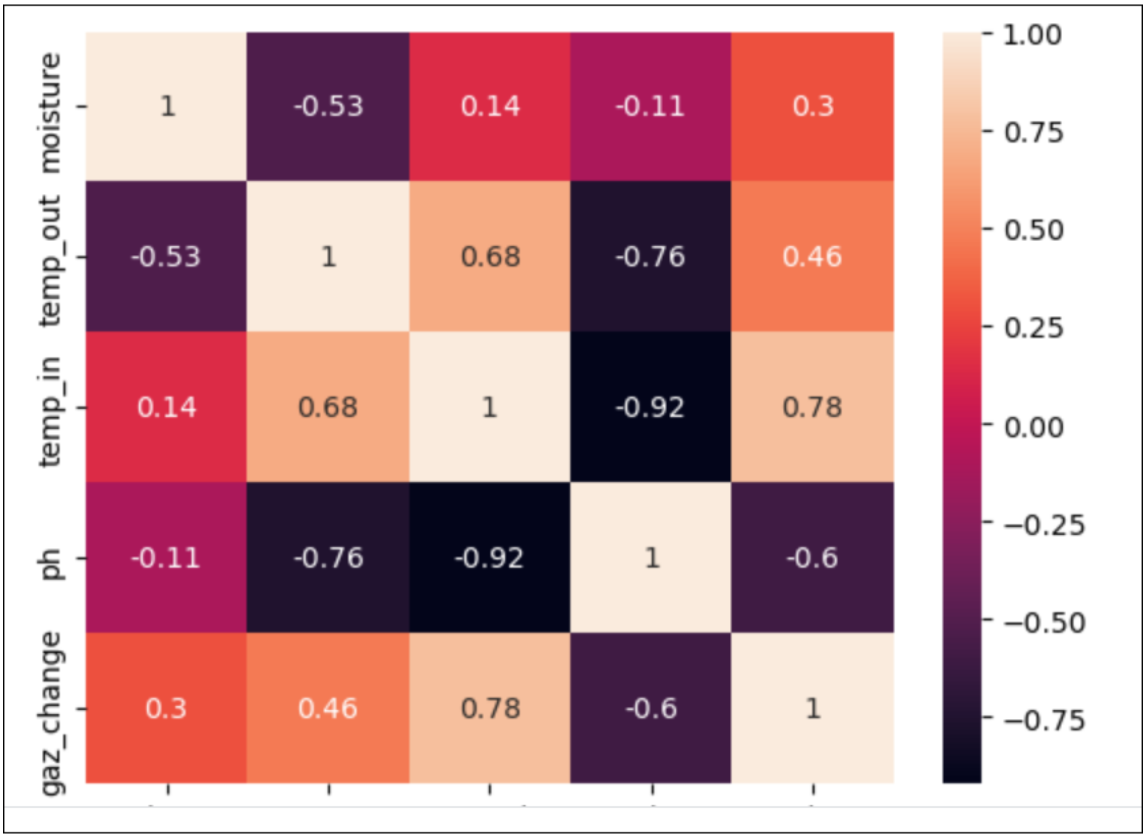
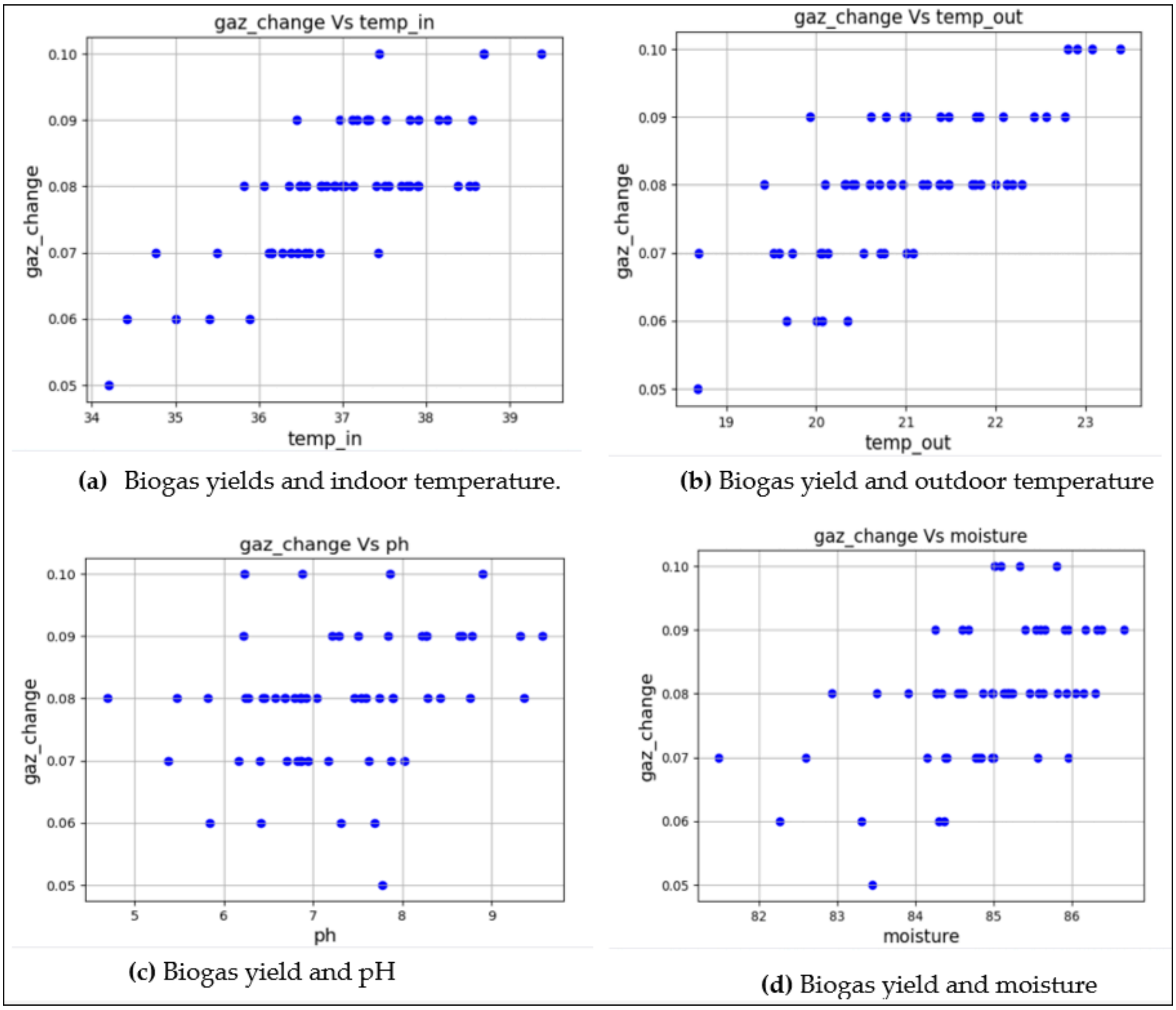


Figure 7. Inter-correlation matrix.

The Pearson correlation result showed that the indoor temperature and pH had a strong correlation of 0.77 and −0.6, while the outdoor temperature and moisture presented a moderate correlation of 0.46 and 0.3, respectively.

As presented in Figure 8, throughout the experiment, the matplotlib python library was imported to create graphs representing the correlation between variables. According to its constraints, the premise of the correlation analysis was that the distribution of environmental parameters conformed to a normal distribution. Figure 8a–d provides information regarding our findings.



(a) Biogas yields and indoor temperature.

(b) Biogas yield and outdoor temperature

(c) Biogas yield and pH

(d) Biogas yield and moisture

Figure 8. Relationship between biogas yield and environmental parameters.

In Figure 8a, a correlation between the biogas yield and indoor temperature indicated an indoor temperature range between 37 and 39 °C, which was induced to a maximum production of about 0.10 dm^3. In Figure 8b, the correlation between the biogas yield and outdoor temperature showed the maximum outdoor temperature of (23–24) °C, which resulted in a maximum biogas generation of about 0.10 dm^3. In Figure 8c, the correlation between the biogas yield and pH showed a maximum biogas production of 0.10 dm^3 for a pH range (6–9). In Figure 8d, a correlation between the biogas yield and moisture indicated a moisture range of 85–86, which presented the maximum biogas production. These results indicate that the environmental parameters had a high impact on biogas production. Moreover, the temperature increased both outdoors and inside during the daytime while it decreased at night. Thus, it could be concluded that the daytime period also had a significant impact on biogas prediction.

4. Discussion

The main aim of this research was to contribute to the Rwanda biogas industry by designing and implementing a testable solution for the biogas community to collect and manage the data and Biogas functionality statuses. This research paper implemented an approach for an IoT-based framework to gather multivariate time-series data of biogas digester environmental parameters. The prototyping was conducted in a home environment with a series of activities, such as data acquisitions using one designed sensor node (with five mounted sensors to capture environmental parameters). Each sensor node was assigned to a unique identifier and as well as assigning it to a specific biogas owner. This setup helped contribute to mapping Biogas owners in Rwanda and could help the decision makers to know in real-time the status of the biogas setup in general. The backend configuration of the proposed framework was made in such a way that apart from the biogas owner receiving notifications, all data from different deployed sensor nodes owned could be controlled and managed under a secure and authenticated user interface.

The developed IoT framework comprised a Raspberry Pi sensor kit and is equipped with several sensors, such as an indoor and outdoor temperature sensor, pH sensor, moisture sensor, and actuators, which are shown in Figure 4 and explained in Tables 2 and 3. These data were then uploaded to a central gateway database using the MQTT protocol, as depicted in Figure 2. The MQTT protocol was configured to allow real-time communication at a low bandwidth. The platform was designed in the publish-subscribe paradigm, and the parameters sent were considered topics, while the time series data sent were messages. As disputed in Figure 5, the edge node was configured as the MQTT-client publisher to the MQTT broker. The edge node published data to the MQTT broker. The Mongo database was configured as an MQTT-client subscriber. The messages captured from the edge node were gathered to the Mongo server database, as presented in Figure 5 and, in this research, an unstructured database management system called MongoDB was adopted. From a web perspective, the Laravel PHP framework was explored to develop the back-end web services which read data from the database to display them to the web interface, as shown in Figure 6. The system setup was placed in the production environment and tested for a period of 30 days.

Further, the collected data were subsequently analyzed by a statical and supervised machine learning model to analyze the effect of the environmental parameters, including indoor temperature, outdoor temperature, Ph, and moisture, on biogas production. The data sets acquired from the IoT platform were analyzed using both the Pearson correlation coefficient and the multiple linear regression OSL model with a Python programming environment. Through the multiple linear regression analysis, the performance of the model was evaluated using the R-squared metric. Therefore, the OLS model result presented an R-squared value of 0.734, indicating that approximately 73.4% of the variability in biogas production presented a good fit and could effectively predict the biogas production process, as shown in Table 6. From Pearson's correlation perspective, the variables were correlated in a way that provided insight, while the indoor temperature and pH presented a strong correlation with a correlation coefficient of 0.78 and -0.6, respectively. The outdoor temperature presented a moderate correlation of 0.46, as shown in Figure 7.

While implementing the abovementioned architecture, the following were found as limitations: a lack of benchmarks for sensor calibrations, the need for industrial sensors for precise accuracy, and sensor power harvesting during prototype deployment.

The future research direction is to figure out the best model for gas production forecasting after a comparative analysis of various machine learning techniques using the correlated data presented in this paper. Furthermore, the best model should integrate into the real system. The next step is to investigate different mechanisms for supporting energy harvesting, as most biogas deployment is conducted outdoors. The framework should be stressed to ensure it can support multi-concurrent high volumes of data.

Author Contributions: Conceptualization, A.M., L.S., K.J., K.N. and E.H.; methodology, A.M., L.S., K.J., K.N. and E.H.; software, A.M., L.S. and E.H.; validation, A.M., L.S., K.J. and K.N.; formal analysis, A.M., L.S., K.J. and K.N.; investigation, L.S. and K.J.; resources, A.M., L.S., K.J. and E.H.; data curation, A.M., L.S. and K.J.; writing—original draft preparation, A.M.; writing—review and editing, L.S., K.J., K.N. and E.H.; visualization, A.M. and E.H.; supervision, L.S., K.J. and K.N.; project administration, L.S.; funding acquisition, A.M. and L.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the African Centre of Excellence on the Internet of Things (ACEIoT) under the University of Rwanda, College of Science and Technology (UR-CST).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: All data used to achieve the research objectives are available online (ACEIoT portal at the University of Rwanda).

Conflicts of Interest: The authors declare no conflict of interest.

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