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Modeling of Biogas Production of Camel and Sheep Manure Using Tomato and Rumen as Co-Substrate via Kinetic Models

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ABSTRACT

The current study investigated anaerobic biodigestion (AD) of livestock manure, including camel dung (CD) and sheep manure (SM) mixed with tomato and rumen at different mixed ratios under mesophilic (24–34 °C) conditions. The study yielded successful results, as the process was able to produce sustainable bioenergy. Predicted biogas data was acquired through fundamental mathematical calculations using SPSS statistical analysis by non-linear regression. Three kinetic models, namely the modified Gompertz, Logistic, and Transference models, were used for simulating the daily biogas produced from the examinations, and model parameters were determined simultaneously. The three models performed well in AD simulations, with high correlation coefficient values (R-squared) and low root mean square error (RMSE), showing a significant link between experimental data and model parameters. However, modified Gompertz demonstrated an improved fit in the simulation of the measurements, as it could accurately represent the curves in the plots, with the highest R-squared of 0.987 compared to Logistics 0.981 and Transference models 0.933, and the lowest RMSE was 0.356 compared to 0.432, and 0.812, respectively. This work suggested that a modified Gompertz model is suitable for estimating the biogas yield potential. The findings also show that rumen, tomato, and control biodigesters operating in mesophilic environments are dependable choices for producing biogas.

Keywords: anaerobic biodigestion, manure, modified Gompertz, acidogenesis, lag phase.

INTRODUCTION

The usage of fossil fuels can negatively impact the environment by increasing greenhouse gas emissions and carbon accumulation, contributing to the global energy problem (Winquist et al., 2019). Organic material is becoming increasingly recognized as an abundant alternative energy resource, and its supply is not related to swings in global economic situations and politics (Kothari et al., 2010; Zhang et al., 2007). Organic matter has a high potential for producing vast amounts of clean energy (Scano et al., 2014), thus helping to solve the global energy concerns (Elsayed et al., 2016; Kothari et al., 2010; Zhang et al., 2007).

The majority of organic materials are usually used as substrates, such as animal manure (cattle, sheep, goat, pig, poultry, horse, etc.), agricultural wastes (paper, water hyacinth, etc.), wastewater, and solid waste. These substracts have demonstrated to be feasible for the generation of biogas (Umeghalu et al., 2012). One of the key benefits of using manure as a source of biogas generation is its widespread availability as a domestic resource in rural communities, which can minimize reliance on fossil fuels (Varma et al., 2017). Therefore, constructing biogas systems to be funneled into biogas stoves, especially in rural areas, will serve as an alternative energy source for generating electricity and cooking gas given the well-known biogas potential from livestock manure (Amogha, 2020; Anand et al., 2021). Although raising livestock is common in rural areas, where nearly all of the feedstock is found, it will be challenging to determine the exact amount of waste they produce. It also makes estimating the potential for biogas production challenging, particularly considering that animals often walk in search of nutrition. However, the process of anaerobic biodigestion (AD) has shown to be a viable and effective way of producing biogas. It has several benefits, including the ability to eradicate pathogens, reduce pollution, stabilize wastes, and decrease biomass. As a result, AD is regarded as a competitive source of clean energy.

The process of AD in biogas systems emits fewer pollutants and greenhouse gases than other treatment of waste methods, like incineration (Oliveira and Rosa, 2003), composting (Walker et al., 2009), and landfilling (Lou and Nair, 2009). It is generally used to break down organic wastes and produce energy as biogas (Lema and Omil, 2001). Four phases occur inside an anaerobic biodigester with absent oxygen, including hydrolysis, acidogenesis, acetogenesis, and methanogenesis. Anaerobic microbes, including fermentative, acetogenic, and methanogenic bacteria, convert biodegradable organic matter into high-energy biogas with methane (50–70%), carbon dioxide (30–40%), and trace amounts of H_2, N_2, H_2S, and O_2 (Li et al., 2011).

The anaerobic biodigestion technique for creating biogas can be performed through the batch, plug flow, fixed dome, and floating drum plants, each having advantages over the others. Batch plants have become extensively applied, primarily because they are simple and inexpensive to set up, work, and maintain (Hilkiah et al., 2008; Widodo et al., 2009). The digestate still contains sufficient nitrogen, ammonium, and other minerals to promote plant growth and is utilized as a conditioner for soil or fertilizer supplementation (Budiyono et al., 2010).

Correct mathematical models explaining the process are necessary to create an excellent and very dependable design of a plant biodigester as well as analyze its effectiveness and productivity (Adamu and Aluyor, 2013). Numerous mathematical models have been described, including stoichiometry-based models for estimating the generation of biogas and responses, and kinetics-based models that account for substrate limitation, product inhibition, and other factors (Gerber and Span, 2008; Manjusha and Beevi, 2016). One of these models is the modified Gompertz model, which is a suitable choice for simulating batch anaerobic degradation of organic waste. This model shows the lag phase and greatest biogas generation rate (Syaichurrozi et al., 2018). The Logistic kinetic model explains a time-dependent process that begins with exponential growth and slows down to a plateau after saturation (Chan and Gareth, 2022a). Another model is the Transference model, which explains the relationship between biogas output and the activity of bacteria (Van et al., 2018) However, optimizing biogas yield from manure necessitates robust modeling of the digestion process (Jijai and Siripatana, 2017; Manjusha and Beevi, 2016). Despite the existing research on biogas production from animal manure, investigations into the specific combination of camel and sheep manure with tomato residue and rumen as co-substrates are limited. Furthermore, kinetic modeling of this unique co-digestion process remains relatively unexplored. In order to bridge the current gaps in this area of research, the current study aimed to evaluate the biogas production of this specific co-digestion mixture as well as examine kinetic model on batch anaerobic co-digestion of camel and sheep manure with tomato residue and rumen as co-substrates. The study sought to identify the most accurate model for fitting biogas yield curves, defining kinetic parameters by applying the Modified Gompertz, Logistic, and Transference Models, and apply the cross-validation technique to identify variability in models performance. The outcomes of this research hold the potential to contribute to the development of efficient and sustainable biogas production systems.

METHODOLOGY

Experimental set-up

Anaerobic biodigesters had six samples with a volume of 1000 mL. Six bio-digester samples were labeled as A1 and A2, B1 and B2, and C1 and C2. The bottles were fed by substrates containing sheep manure and camel manure, which were collected from a Bish farm situated in the Jazan region in Saudi Arabia. Tomatoes have been obtained from home kitchen waste that is used as co-substrate and the rumen fluid of sheep was sourced from the slaughtered livestock market. A1 and A2 contained a 100% manure mixture combined with 240 mL of seawater in a 1:1 volumetric ratio. B1 and B2 contained an 80% mixture of manure and 20% tomatoes mixed with 240 ml of seawater with a ratio of 1:1. C1 and C2 contained an 80% manure mixture and 20% rumen fluid, combined with 410 mL of seawater in a 1:2 ratio. These ratios are volumetric, indicating the volume proportions of substrate mixtures to seawater in each sample. The internal content of all biodigesters is shown in Table 1. The three samples were connected to Tedlar bags to collect the gas produced for 14 days, while the other three samples were monitored daily using glass graduated cylinders to determine the amount of gas produced. The biodigesters were operated twice previously, and it was observed that gas production decreased after 14 days. However, the duration may vary in other gas production operations, as the duration depends on many factors, including the type of feeding and the ratio (Khalid et al., 2011; Yadvika et al., 2004). The results of these experiments were published in authors' previous work (Alharbi et al., 2023).

Biogas production

The gas tests were carried out for A1, B1, and C1 using gas chromatography (GC) with GC-US17273025 serial number. On the other hand, the daily biogas produced from A2, B2, and C2 was determined via water displacement. Figure 1 shows the experimental set-up of samples.

Kinetic models

The kinetic model for anaerobic digestion is a fundamental tool used to predict various parameters and behaviors within the anaerobic digestion process. These models provide insights into the rates at which these biochemical reactions occur, enabling the optimization and control of anaerobic digestion systems. Anaerobic biodigester laboratory results were compared to three distinct models, namely the modified Gompertz model (Elsayed et al., 2022; Etuwe et al., 2016; Feng et al., 2018), the logistic model (Musingarimi et al., 2019; Pommier et al., 2007) and Transference model (Clarkson, 2023; Manu and Clarkson, 2022; Ugwu et al., 2018), in order to determine which model had the better fitting. Following are the types of the models that were utilized in the current study:

Table 1. Internal feeds of all biodigester

Samples	Substrate	Co-substrate	Water content (ml)	Ration (S:W)	Total volume content (g)
A1	Camel and sheep manure	-	240	(1:1)	480
B1		Tomato	240	(1:1)	540
C1		Rumen	410	(1:2)	700

Figure 1. The experimental set-up of anaerobic biodigester

The modified Gompertz model

This model was utilized by researchers to estimate volume biogas production. The modified Gompertz is expressed in Equation 1 (Chan and Gareth, 2022b)

$$P_{\circ} = P \cdot EXP^{\left(-EXP\left(\left(\frac{R \cdot e(L-t)}{P}+1\right)\right)\right)} \quad (1)$$

where: $P_{\circ}$ – represents maximum biogas yield at digestion time t (mL/g); P – maximum biogas production (mL/g); R – biogas production rate (day^{-1}); L – lag phase (day); e – equipment 2.718282 (logarithmic constant), t – hydraulic retention time (day).

The logistic model

One of the intricate models created especially for exploring the $P_{\circ}$ (Opurum, 2021). The logistic kinetic is presented in Equation 2 (Deepanraj et al., 2015)

$$P_{\circ} = \frac{P}{\left(1 + EXP^{\left(\frac{4R(t-L)}{P}+2\right)}\right)} \quad (2)$$

where: $P_{\circ}$ – represents maximum biogas yield at digestion time t (mL/g); P – maximum biogas production (mL/g); R – biogas production rate (day^{-1}); L – lag phase (day), t – hydraulic retention time (day).

The transference model

The transference function, which is usually included to fit both inputs and outcomes mathematically in either black box or curve-type models, is typically employed to evaluate the success rate of pretreatments (Y. Li et al., 2013). This model is given by Equation 3 (Gallipoli et al., 2020).

$$P_{\circ} = P\left(1 - EXP^{\frac{-R(t-L)}{P}}\right) \quad (3)$$

where: $P_{\circ}$– represents maximum biogas yield at digestion time t (mL/g); P – maximum biogas production (mL/g); R – biogas production rate (day^{-1}); L – lag phase (day), t – hydraulic retention time (day).

All these parameters are called kinetic parameters, except $P_{\circ}$ and t. For large-scale anaerobic reactors to operate at their best and for the development of digestion systems, kinetic parameters are crucial (Paritosh et al., 2018).

Statistical analysis

The result analysis was performed using SPSS statistics software. The statistical significance of the models was estimated by the analysis of variance (ANOVA). The most popular statistical method for determining, assessing, and examining the link between both independent and dependent variables is regression analysis (Sarstedt and Mooi, 2014). Furthermore, non-linear regression was used for calculating the kinetic parameters. The choice of the best kinetic model for analysis in fields like biogas production often depends on metrics that assess the accuracy and predictive power of the model. Two key metrics commonly used for this purpose are the coefficient of determination R-squared and Root Mean Square Error (RMSE) (Chicco et al., 2021). In the current study, the highest of the definition coefficients (R^2) and the smallest root mean square error (*RMSE*) were calculated, proving the accuracy of this approach (Zahan et al., 2018). *RMSE* is a measure of the differences between values predicted by a model and the actual values. It is calculated by taking the square root of the average of the squared differences between the predicted and actual values (Chai and Draxler, 2014).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{P_{i,exp} - P_{i,pre}}{P_{i,exp}}\right)^2} \quad (4)$$

where: N – represents the number of experimental runs; $P_{i,\exp}$ – denotes the experimental values for the i-th experiment; and $P_{i,\,\mathrm{pre}}$ – refers to the model predictions for the i-th experiment (Onu et al., 2022).

Leave-one-out cross-validation (LOOCV) technique

The purpose of LOOCV is a cross-validation technique used to estimate how well a predictive model will perform on unseen data. It provides a robust method for assessing model generalization. Each observation is used once as a validation set, while the rest of the data is used as the training set. This process is repeated for every observation in the dataset. It gives a detailed measure of the model's accuracy across the entire dataset, providing a more comprehensive assessment of model performance (Yates et al., 2023). LOOCV results in a series of metrics as R-squared, RMSE, and mean absolute error (MAE) calculated for each iteration (Somogyi, 2021). The average of these metrics gives an overall measure of the model's performance and generalization.

RESULTS AND DISCUSSION

Biogas production measured experiment

The biogas was collected at mesophilic temperature for 14 days. The anaerobic biodigester system was stabilized better under mesophilic conditions (Nges and Liu, 2010).

Table 2. The daily biogas yield of biodigesters

Days	A2 (ml/Day)	B2 (ml/Day)	C2 (ml/Day)
1	0.00	0.00	0.00
2	0.00	0.00	1.30
3	0.00	0.05	1.90
4	0.00	1.09	2.69
5	0.70	2.25	3.60
6	1.65	3.00	3.88
7	2.20	3.35	4.65
8	2.98	4.90	5.00
9	3.72	5.10	6.81
10	5.41	7.50	9.34
11	5.33	8.45	10.22
12	6.94	11.20	14.87
13	7.68	11.95	16.11
14	9.84	11.99	16.97

The growth rate of methanogenic bacteria in a batch biodigester system is shown in Table 2. Due to the delayed growth of methanogenic bacteria, often known as the lag phase parameter, gas generation started a few days later than expected. The gas realization started quickly after two to four days because of the biological exponential growth system. However, after roughly 12 to 14 days, gas generation appears to be decreasing. It is possible to anticipate that at this point the microbial growth is in the stationary phase, meaning that the rates of death and growth are equal. The yield of gases in certain systems decreased and eventually stopped after around 14 days of incubation. This could be explained by the methanogen growth declining as a result of the limiting nutrient drop or total exhaustion. Figure 2 shows daily biogas production from all biodigesters.

The lag phase lasted for 4 days in A2, 2 days in B2, and only one day in the C2 sample. Therefore, A2 recorded the lowest gas production during 14 days. The highest gas production was on the 14th day in C2 (16.97 mL), whereas after the 14th day, reduced gas productivity in C1 was observed. According to the test, the gas became flammable on the 14th day in C2.

In the A2 plant, biogas generation started quickly on the second day. The maximum yield was determined in digester C2, reaching 16.97 ml, whereas the minimum volume biogas value was observed in digester A2, reaching 9.84 ml. Each sample of gas was tested using Gas

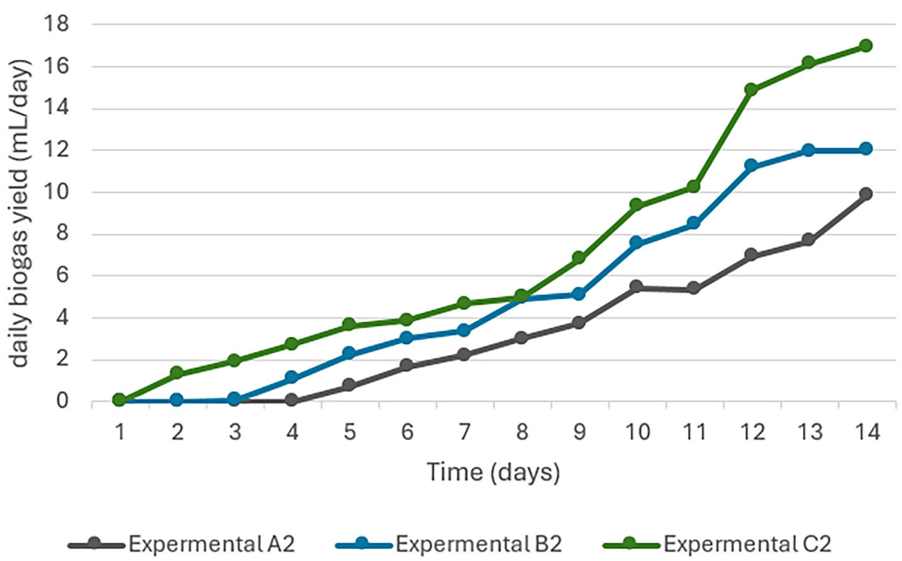

Figure 2. Plot of daily biogas yield from biodigesters

Chromatography (GC). The concentration of biogas for the various biodigesters observed had disparate yields. The A1, B1, and C1 biodigesters yielded 58.98%, 59.08%, and 69.30% methane concentrations, respectively. Overall, the outcome of the three samples of biodigester suggests that C1 produces the greatest amount of methane yield when compared to A1 and B1. The experimental data were examined to determine the best model for predicting the produced biogas. The Transference Model, Logistic Model, and Modified Gompertz Model are the three kinetic models that were fitted with the experimental data on the three samples.

Modified Gompertz modeling of biodigester reactors

The predicted biogas yields of A2, B2, and C2 based on the modified Gompertz model started from 0.05–9.32, 0.11–12.67, and 0.78–17.93 ml/day. This model was used to simulate the kinetic process. Non-linear regression was applied to determine the kinetic parameters of P, R, and L. Table 3 contained a comprehensive representation of the established kinetic parameters. For samples A2, B2, and C2 the estimated value of maximum biogas production P was 19.66, 2.981, and 129.050 ml respectively. Additionally, the biogas production rate R of A2, B2, and C2 was 1.153, 1.386, and 3.470 ml/day respectively. In turn, the lag phase that represented L of samples A2, B2, and C2 was 5.887, 4.620, and 9.621 DAY^{-1}, respectively. The graph in Figure 3 was created to show experimental data and simulate a modified Gompertz model.

Table 3. Kinetic parameters of modified Gompertz model

Parameter estimates	*P* (ml)	*R* (ml/day)	*L* (day^{-1})
A2	19.660	1.153	5.887
B2	20.981	1.386	4.620
C2	129.050	3.470	9.621

Table 4. Kinetic parameters of the Logistic model

Parameter estimates	P (ml)	R (ml/day)	L (day^{-1})
A2	12.274	1.221	6.157
B2	14.713	1.550	5.171
C2	29.997	2.216	5.984

Logistic modeling of biodigester reactor operation

The predicted biogas yields of A2, B2, and C2 based on the Logistic model started from 0.21–9.26, 0.34–12.48, and 0.90–17.74 ml/day. The logistic model was utilized to create a kinetic simulation of the generation of biogas based on experimental results gathered from volume biogas yield production. The kinetic parameters of P, R, and L were determined by applying Non-linear regression analysis. Table 4 contains a comprehensive representation of the established Logistic kinetic parameters.

For samples A2, B2, and C2, the estimated value of maximum biogas production P was 12.274, 14.713, and 29.997 ml, respectively. Additionally, the biogas production rate R of A2, B2, and C2 was 1.221, 1.550, and 2.216 ml/day while the lag phase that represented the L of samples

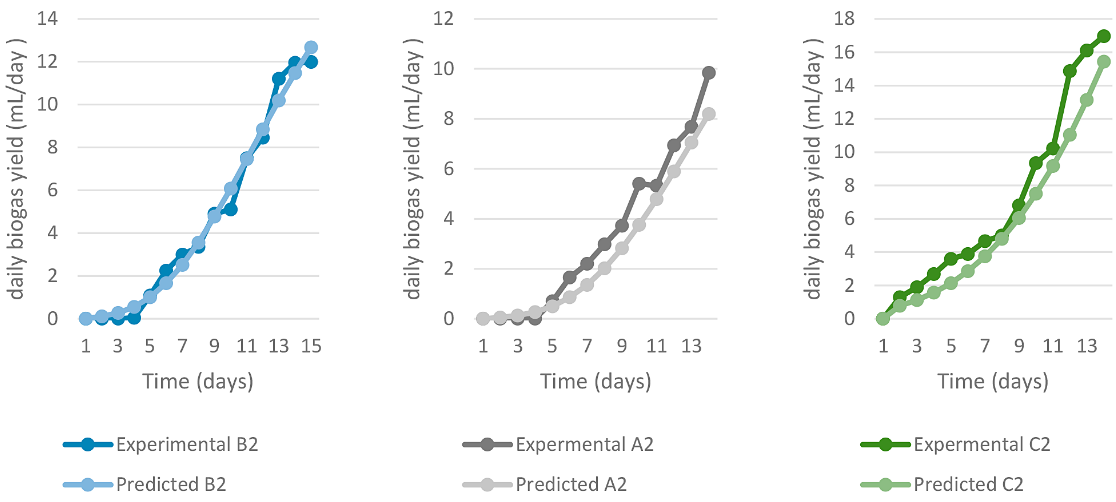

Figure 3. Comparison of experimental data and predicted outcomes modified Gompertz model

A2, B2, and C2 was 6.157, 5.171, and 5.984 DAY-1, respectively. The graph in Figure 4 was created to show experimental data and simulate the prediction of the Logistic model.

Transference modeling of biodigester reactor operation

The predicted biogas yields of A2, B2, and C2 based on the Transference model started from -1.58–8.21, -1.70–11.82, and -1.49–15.39 ml/day. This model was used to simulate three kinetic parameters. Non-linear regression analysis was applied to determine the kinetic parameters of P, R, and L. Table 5 contains a comprehensive representation of the established Transference kinetic parameters.

For samples A2, B2, and C2, the estimated value of maximum biogas production P was 68423.945, 66703.774, and 90417.190 ml respectively, and the biogas production rate R of A2, B2, and C2 was 1.221, 1.550, and 2.216 ml/day. Also, the lag phase, represented as the L of samples A2, B2, and C2 was 6.157, 5.171, and 5.984 day^{-1} respectively. The graph in Figure 4 was created to show experimental data and simulate the prediction of the Logistic model. The fitting model is shown in Figure 5.

Comparison of predicted valued and experimental data

The authors of the current research compared the observed biogas yield to the estimated biogas yield derived from the modified Gompertz, Logistic, and Transference models as illustrated in Figure 6, Figure 7 and Figure 8. The daily biogas production yield in this study proved to generally follow a comparable shape as noted by (Musa Abubakar et al., 2022)

In Figure 6, Figure 7, and Figure 8, the C2 biodigesters exhibited the highest kinetic parameter of R compared to the A2 and B2 biodigesters. This indicates that the growth rate of rumen waste was the fastest in the C2 biodigesters so the predicted values agree with the experimental values. Moreover, the B2 biodigesters had a higher growth rate than A2 biodigesters, implying that the growth rate of C2 and B2 as a co-biodigester was optimal for B2 as a single biodigester. The R-squared values for the three kinetic models used in this study by SPSS statistics are presented in Table 6.

The R-squared values obtained were considered good for all nine biodigesters, but modified Gompertz demonstrated to be an improved fit for the simulation of the measurements, as it could accurately represent the curves in the plots, with the highest correlation coefficient R^2 (0.987, 0.985 and 0.980) than Logistics (0.981, 0.985 and 0.982) and Transference models (0.933, 0.955, and 0.920). The research by Moharir et al. (2020) found that the modified Gompertz model had higher R-squared values (0.98, 0.83, and 0.99) compared

Table 5. Kinetic parameters of the Transference model

Parameter estimates	*P* (ml)	*R* (ml/day)	*L* (day^{-1})
A2	68423.945	0.753	3.095
B2	66703.774	1.040	2.636
C2	90417.190	1.299	2.145

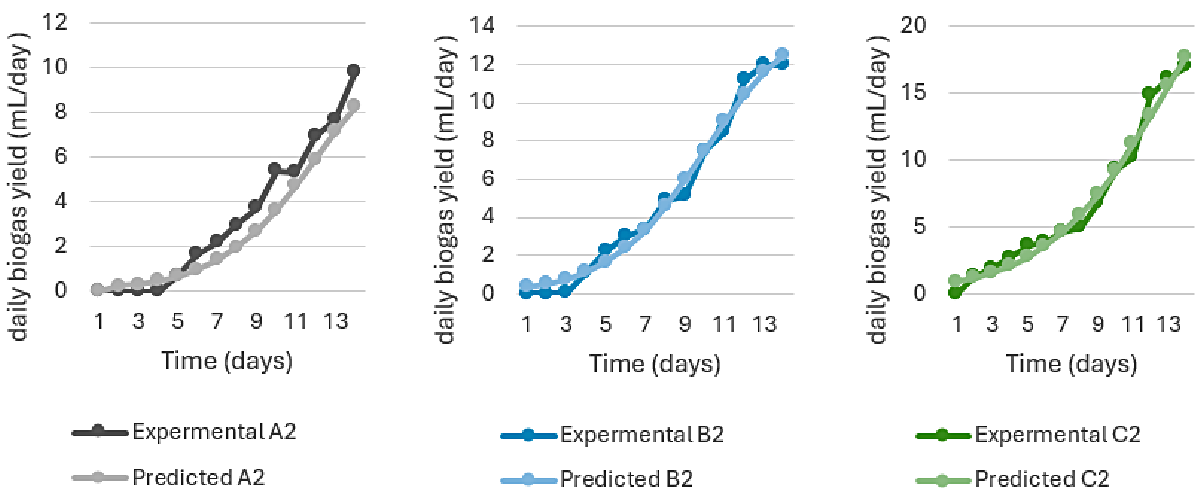

Figure 4. Comparison of experimental data and predicted outcomes of the Logistic model

to the Logistic model (0.97, 0.83, and 0.99) in a kinetic model of biogas generation from cow manure, horse waste, and industrial culture over 14 days. According to Ejimofor et al. (2020), the logistic model's regression coefficient (R-squared = 0.997) was greater than that of the modified Gompertz model (R-squared = 0.64) for biogas production kinetics from paint wastewater. They suggested that the logistic model is suitable for simulating cumulative biogas production. Similarly, research

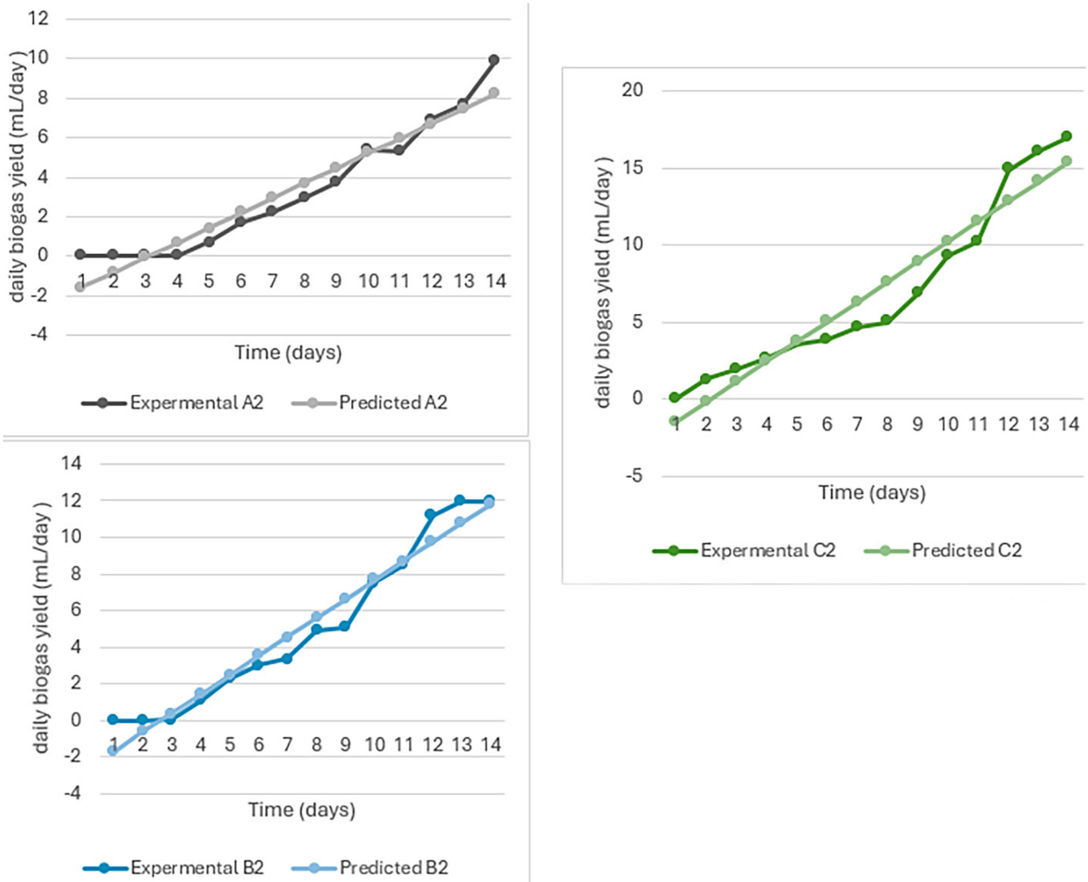

Figure 5. Comparison of experimental data and predicted outcomes Transference model

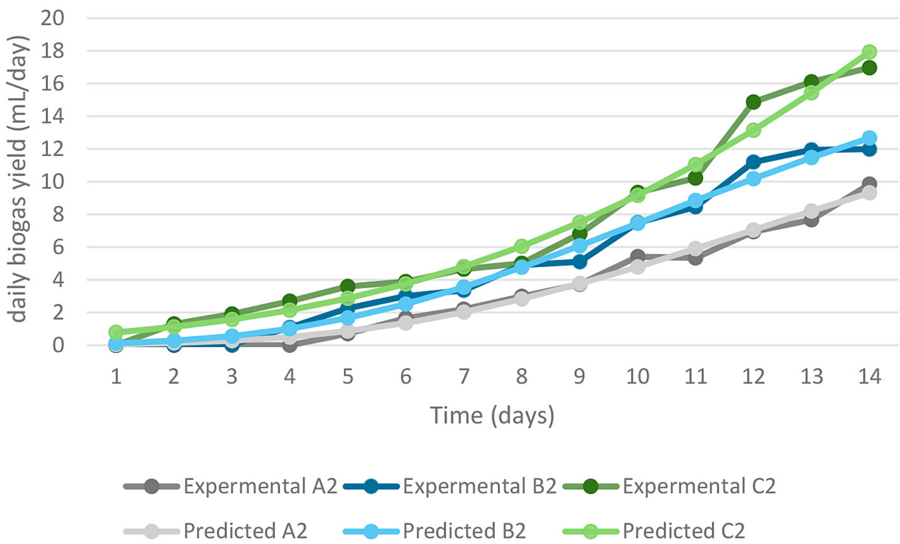

Figure 6. Comparison of experimental values and predicted values by the modified Gompertz model

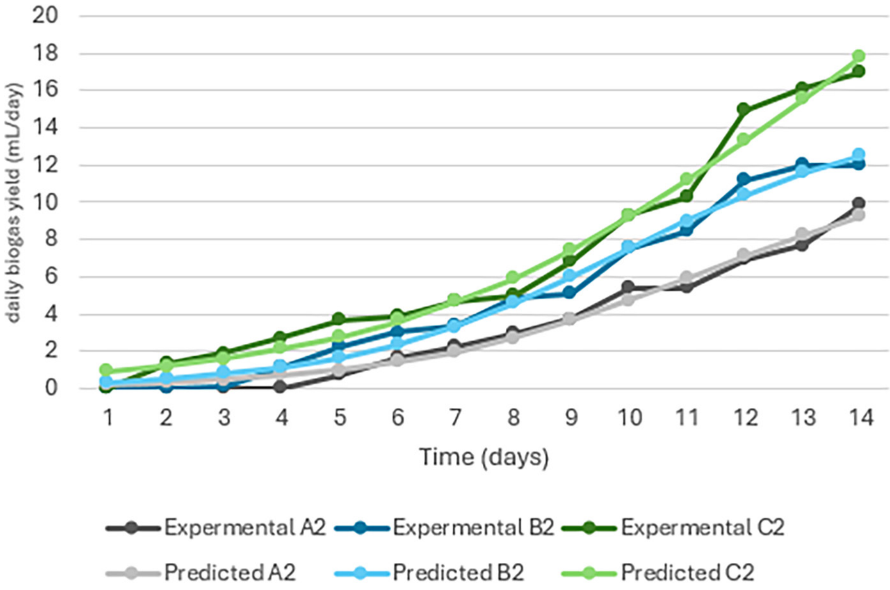

Figure 7. Comparison of experimental values and predicted values by the Logistic model

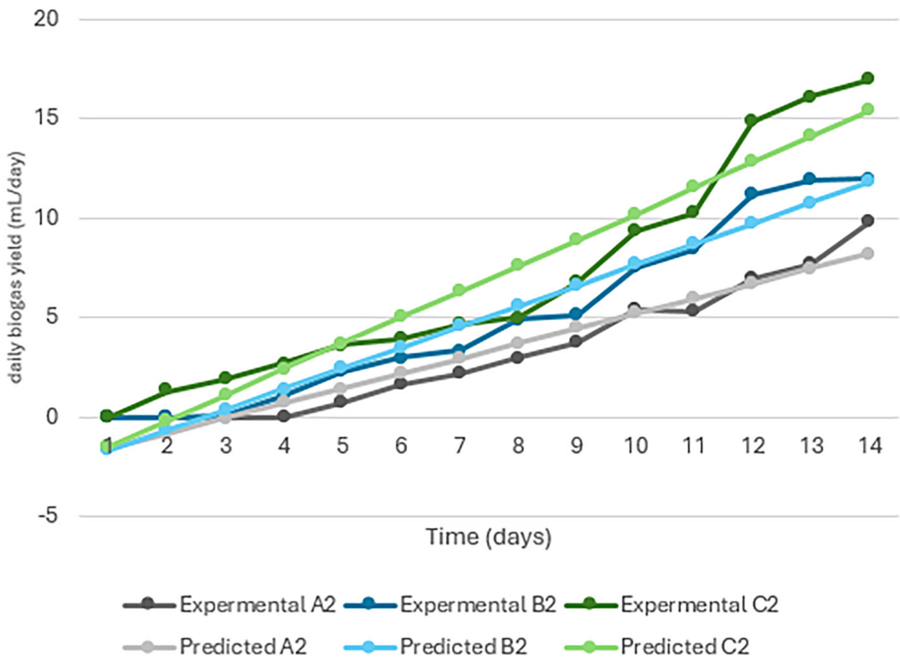

Figure 8. Comparison of experimental values and predicted values by the Transference model

by Elkawnie et al. (2021) found that the logistic model had a higher R-squared value (0.9951) compared to the modified Gompertz model (R-squared = 0.9817) for simulating cumulative biogas production from tofu liquid waste.

Furthermore, These models were analyzed to compare their RMSE across different samples, i.e. A2, B2, and C2. Table 7 shows the RMSE values obtained from Excel. For the Modified Gompertz model, the RMSE values were 5.9562 for A2, 5.8918 for B2, and 3.2651 for C2. This trend indicates that C2 is the most accurate configuration among the three, with lower RMSE values representing more accurate predictions. In the Logistic model, the RMSE values were lower compared to the Modified Gompertz model. The RMSE for the Logistic model was 3.5276 for A2, 3.3660 for B2, and 2.8870 for C2, indicating that again, C2 is the most accurate configuration. The Transference model could not be evaluated due to an error, suggesting potential issues with this model. In a recent study (Shitophyta et al., 2023) They suggested

Table 6. Results of coefficient of determination value using SPSS

Types of models	R^2		
	A2	B2	C2
Modified Gompertz	0.987	0.985	0.980
Logistics	0.981	0.985	0.982
Transference	0.933	0.955	0.920

Table 7. Results of RMSE value using Excel

Types of models	RMSE		
	A2	B2	C2
Modified Gompertz	5.9562	5.8918	3.2651
Logistics	3.5276	3.3660	2.8870
Transference	Error		

employing the logistic model for the kinetic modeling of the anaerobic digestion of pretreated maize stover since its RMSE was lower (RMSE = 2.3029) and its R-squared value was higher (R-squared = 0.9452) than that of the modified Gompertz model (RMSE = 4.4800) and (R-squared = 0.9416).

Comparison of kinetic models using Cross-validation technique

While LOOCV, R-square, and RMSE are related, since they all evaluate model performance, they are not the same and often produce different results. The primary advantage of LOOCV is that it evaluates models in a more robust, generalized context. In contrast, R-square and RMSE calculated without cross-validation are more limited, focusing on a single dataset or set of predictions. However, LOOCV may lead to higher computational costs, it often yields more reliable insights for model comparison and validation. On the basis of the provided data, LOOCV technical can be made to determine which model performs best based on RMSE, MAE, and R-squared. The Gompertz model was analyzed across three samples, with the following results, the A2 samples emerged as the best-performing sample, with RMSE of 0.3559, MAE of 0.2943, and a high R-squared value of 0.9872. This indicates low prediction errors and strong fit to the data. The B2 sample, showed slightly less accuracy compared to A2. It had an RMSE of 0.5223, MAE of 0.4264, and R-squared value of 0.9852. Although this sample performed well, it was outperformed by A2. The C2 sample, displayed the highest errors among the Gompertz model variations, with RMSE of 0.7707 and MAE of 0.6414. Additionally, its R-squared value of 0.9801 was the lowest, indicating a less accurate fit. In the analysis of the Logistic model, A2 sample was the best performer, with RMSE of 0.4320, MAE of 0.3871, and R-squared value of 0.9811. The performance of this sample was relatively strong and reliable. The B2 sample, while competitive, showed a slightly higher RMSE of 0.5245, MAE of 0.4507, and R-squared value of 0.9851. Although it had a similar R-squared value to A2, its higher errors indicated a slightly reduced accuracy. The C2 sample had the highest RMSE among the Logistic model variations, at 0.7320, with MAE of 0.6107 and R-squared value of 0.9820. This suggests that this sample is less reliable in terms of prediction accuracy. For the Transference model, the A2 sample was the best-performing, but with noticeably higher errors than the other models. It had an RMSE of 0.8120, MAE of 0.6793, and R-squared value of 0.9332, indicating a lesser fit and higher prediction errors compared to the other models. The B2 sample showed a moderate drop in performance compared to A2, with RMSE of 0.9120, MAE of 0.7379, and R-squared value of 0.9548. While these metrics were better than C2, they reflected a decline compared to A2. The C2 sample had the highest errors and the lowest R-squared among all Transference model samples. With RMSE of 1.5474, MAE of 1.3886, and R-squared value of 0.9196, it demonstrated the lowest predictive accuracy, indicating this sample was the least suitable for reliable model predictions. The RMSE, MAE, and R-squared values were summarized for

Table 8. The output result for the three models using LOOCV

Models	Samples	RMSE	MAE	R-squared
Modified Gompertz	A2	0.3559	0.2943	0.9872
	B2	0.5223	0.4264	0.9852
	C2	0.7707	0.6414	0.9801
Logistic	A2	0.4320	0.3871	0.9811
	B2	0.5254	0.4507	0.9851
	C2	0.7320	0.6107	0.9820
Transference	A2	0.8120	0.6793	0.9332
	B2	0.9120	0.7379	0.9548
	C2	1.5474	1.3886	0.9196

the Modified Gompert, Logistic, and Transference Model using LOOCV, as shown in Table 8.

On the basis of the given metrics, the Gompertz model with an A2 sample appears to be the most accurate and predictive, with the lowest RMSE and MAE and the highest R-square. The Logistic model with A2 sample also performs reasonably well, but has slightly higher errors. The Transference model has the highest errors and lower R-square, indicating it is less suitable for the given data. These findings align with those published in a previous study by Moharir et al. (2020). However, other authors, such as Shitophyta et al. (2023b), have indicated that the logistic model is the most accurate for estimating cumulative yields and modeling kinetic processes in the anaerobic digestion of pretreated corn stoves.

CONCLUSIONS

Results show that the mesophilic condition is suitable for biogas production. Furthermore, co-digestion in C2 and B2 increased biogas production. The selection of an optimal kinetic model for biogas production analysis typically hinges on metrics the coefficient of determination (R-squared) and Root Mean Square Error (RMSE) that evaluate model accuracy and predictive power. LOOCV provided accurate results from SPSS and Excel. However, the outcome of the kinetics analysis demonstrated that modified Gompertez with high R-squared (0.9872) showed a significant link between experimental data and lowest RMSE (0.3559). Thus, it is evident that the modified Gompertz model equation is optimal for the prediction of maximum daily biogas production rate and provides a better fit for biogas yield curves. The technology of anaerobic digestion and biogas production has shown to be the way to advance environmentally acceptable and sustainable agricultural and industrial waste management pathways that are rich in biomass. While the authors suggest future investigations in AD utilizing the multiple kinetic models, the preliminary results in this study might prove useful for arranging for the anaerobic fermentation of animal manure for large-scale biogas production.

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