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Experimental two-factor response surface optimisation of methane yield from pig manure co-digested with banana peel, cabbage and pumpkin waste

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Abstract: This study optimised methane yield from pig manure (PM) co-digested with banana peel, cabbage and pumpkin residues (BCP). A two-factor response surface methodology was used, with PM fraction and batch digestion time as factors. Blank-corrected biochemical methane potential (BMP) was the main response, with methane volume and energy yield as supporting responses. Design-Expert was used for quadratic modelling, while Python supported model checking and sensitivity analysis. BMP ranged from 191.48 to 468.23 N mL CH_4 g^{-1} VS. The PM fraction contributed 98.975% of the model sum of squares, compared with 0.855% for digestion time. The absolute maximum occurred at PM0:BCP100 after 60 days, but this was mono-digestion. The highest tested co-digestion BMP was 332.85 N mL CH_4 g^{-1} VS at PM50:BCP50 after 60 days. At 45 days, the same blend achieved 324.95 N mL CH_4 g^{-1} VS, retaining 97.6% of the 60-day yield. Feedstock composition affected methane yield more strongly than digestion time. PM50:BCP50 at 45 days is a time-efficient laboratory-scale condition requiring validation in continuous digesters.

Keywords: *Anaerobic digestion, Biochemical methane potential, Pig manure, Plant waste, Python sensitivity analysis, Response surface methodology.*

1. Introduction

Organic waste generation is increasing in many urban, peri-urban, and agricultural areas. Pig manure (PM) and plant-based food residues are common examples of wet organic wastes. If these wastes are poorly managed, they can cause odour, water pollution, and greenhouse gas emissions [1, 2]. However, they also contain biodegradable organic matter. This makes them useful feedstocks for renewable energy recovery. Anaerobic digestion is a suitable technology for treating wet organic wastes. It converts organic matter into biogas under oxygen-free conditions. Methane is the main energy component of biogas. It can be used for cooking, heating, electricity generation, or upgrading to biomethane. Anaerobic digestion, therefore, supports both waste treatment and renewable energy production [3, 4].

Pig manure is a useful anaerobic digestion feedstock. It contains moisture, nutrients, and microbial material. It can also provide buffering capacity during digestion [5, 6]. However, PM mono-digestion may give a limited methane yield. This is partly because some of its organic matter has already passed through animal digestion. The remaining organic fraction may therefore be less readily biodegradable [7]. Plant-based food residues can improve methane production when used as co-substrates. Banana peel, cabbage, and pumpkin residues (BCP) contain softer plant tissues and more readily degradable organic matter [8, 9]. These materials can provide a carbon-rich substrate for anaerobic microorganisms.

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However, plant residues can also degrade rapidly. This may increase acid formation if the system is not well-balanced [10, 11].

Co-digestion can help combine the advantages of different substrates. Manure can provide nutrients and buffering support. Plant residues can increase degradable carbon availability [12]. The final methane yield depends on the mixing ratio, digestion time, and substrate composition. Recent co-digestion studies have shown that the substrate ratio is an important factor in improving methane yield and process performance [13, 14]. Biochemical methane potential (BMP) testing is widely used to evaluate methane yield from organic substrates. BMP assays provide controlled batch data on substrate biodegradability and methane recovery [15]. However, BMP testing alone does not always show the best operating region. It gives useful experimental values, but it does not fully describe the combined effect of process factors. For this reason, statistical optimisation can be useful [16, 17].

Response surface methodology (RSM) is one of the most common tools for biogas process optimisation. It can model the relationship between selected factors and measured responses. It can also identify optimum regions using fewer experimental runs than a full factorial design [18]. RSM has been applied in recent biogas studies to optimise mixing ratio, pH, substrate concentration, inoculum-to-substrate ratio, carbon-to-nitrogen (C/N) ratio, and retention time [19, 20].

In this study, Design Expert was used as the main design of experiments (DoE) and RSM tool. The experimental data were obtained from batch digestion of PM and a composite plant-waste blend. The plant-waste blend consisted of banana peel, cabbage, and pumpkin residues. The two factors were the PM fraction and the selected batch digestion time. In the Design Expert model, the digestion time factor was labelled as HRT. The BCP fraction was complementary to the PM fraction. Therefore, increasing the PM fraction also meant reducing the BCP fraction. Blank-corrected BMP was used as the main response. Methane volume and energy yield were included as supporting engineering responses. This allowed the study to interpret both methane yield and energy recovery potential. Python was then used as a supporting tool. It was used to check the model equation, compare predicted and experimental values, assess sensitivity, and support practical optimum selection. Similar use of RSM and Python has been reported in biogas optimisation studies [21, 22].

Although recent studies have used response surface methodology to optimise biogas production, limited research has examined the combined influence of pig-manure fraction and batch digestion time when pig manure is co-digested with a composite blend of banana peel, cabbage and pumpkin residues [19, 20, 23]. Furthermore, few studies distinguish between the absolute mathematical optimum, the practical co-digestion optimum, and a tested, time-efficient operating condition. This distinction is important because the condition producing the highest predicted methane yield may represent mono-digestion rather than a practically relevant co-digestion mixture. The present study addresses this gap by combining Design-Expert response surface modelling with Python-supported model verification and sensitivity analysis to identify both maximum-yield and practically applicable operating conditions.

The study aimed to optimise methane yield from pig manure co-digested with banana peel, cabbage, and pumpkin waste using a two-factor RSM approach. The specific objectives were to develop a quadratic RSM model for BMP, evaluate the effects of substrate composition and digestion time, interpret methane volume and energy yield as supporting responses, identify absolute and practical optimum conditions, and use Python to support sensitivity analysis.

2. Materials and Methods

2.1. Study Approach

This study used experimental methane-yield data to optimise anaerobic co-digestion of PM and composite plant waste. The composite plant-waste blend consisted of banana peel, cabbage, and pumpkin residues. The work followed an experimental-data-based response-surface approach. Design-Expert was used as the main DoE and RSM tool. Python was used as a supporting tool. It was used to check the fitted equation, assess factor sensitivity, and support practical optimum interpretation.

2.2. Experimental Data Source and Substrate Combination

The experimental BMP data used in this RSM study were obtained from a companion experimental dataset generated by the authors. The dataset is reported in a separate manuscript submitted for publication. The companion study focused on the AMPTS batch digestion performance of pig manure and a composite plant-waste blend. The present study uses the experimental dataset for response surface optimisation and Python-supported sensitivity analysis. Fresh pig manure, banana peel, cabbage, and pumpkin waste were collected from Johannesburg, South Africa. The plant wastes were chopped into smaller pieces and homogenised to improve sample uniformity. Pig manure was mixed thoroughly before subsampling. Anaerobic sludge from an active digester was used as inoculum and was mixed before use. The composite plant-waste blend consisted of banana peel, cabbage, and pumpkin residues. The BCP blend was prepared using volatile-solids contributions rather than equal wet masses. This was done because the plant residues had different moisture and solids contents. Therefore, the wet masses loaded into the reactors were calculated from the measured volatile-solids values.

The original batch experiment included PM100, PM75:BCP25, PM50:BCP50, and BCP100 treatments. For the present two-factor RSM model, three substrate levels were used. These were PM100, PM50:BCP50, and BCP100. The PM fraction was treated as the main mixture factor. The BCP fraction was calculated as the complementary fraction. Therefore, an increase in PM fraction also represented a decrease in BCP fraction. The BMP assays were conducted using an Automatic Methane Potential Test System under mesophilic conditions. The digestion temperature was set at 37 °C. Each reactor had a working volume of 400 mL and a headspace volume of 200 mL. The inoculum-to-substrate ratio was maintained at 2:1 on a volatile-solids basis. The reactors were sealed and flushed with nitrogen gas before incubation to establish anaerobic conditions. Methane production was recorded automatically in normal millilitres. Carbon dioxide was removed in the gas-cleaning unit before methane volume measurement.

The digestion was continued for 60 days. For the RSM analysis, BMP values at 30, 45, and 60 days were used as selected digestion-time points. These time points were labelled as HRT in the Design Expert model. However, they represent batch digestion time and not hydraulic retention time under continuous feeding. The experimental data were blank-corrected before use. Methane produced by inoculum-only blank reactors was subtracted from the substrate reactors after scaling for inoculum volatile solids. This helped isolate methane produced from the test substrate. The blank-corrected BMP values were then normalised to substrate volatile solids and reported as N mL CH_4 g^{-1} VS. The RSM model used the corresponding mean BMP values for the selected substrate levels and digestion-time points.

2.3. Factors and Responses

Two independent factors were considered in the RSM model. These were the PM fraction and HRT. The HRT values represented selected digestion time points from the batch BMP profile. The main response was blank-corrected BMP. BMP was selected because it expresses methane yield on a volatile-solids basis. This makes it suitable for comparing substrates and treatment conditions. Methane volume and energy yield were also included. These were treated as supporting engineering responses. Methane volume shows the total methane output on a reactor basis. Energy yield translates methane production into an energy-related value. The factors and responses used in the study are shown in Table 1.

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Table 1.
Condensed experimental RSM design matrix and response values.

Run group	Sample	PM (%)	BCP (%)	HRT (days)	A coded	B coded	Replicate count	VS loading (gVS)	BMP (N mL CH_4 g^{-1} VS)	Methane volume (N mL CH_4)	Energy yield (MJ kg^{-1} VS)
1	BCP100	0	100	30	−1	−1	1	5.38	441.16	2373.44	15.79
2	BCP100	0	100	45	−1	0	1	5.38	458.44	2466.41	16.41
3	BCP100	0	100	60	−1	+1	1	5.38	468.23	2519.08	16.76
4	PM50:BCP50	50	50	30	0	−1	1	5.73	309.42	1772.98	11.08
5	PM50:BCP50	50	50	45	0	0	5	5.73	324.95	1861.96	11.63
6	PM50:BCP50	50	50	60	0	+1	1	5.73	332.85	1907.24	11.92
7	PM100	100	0	30	+1	−1	1	6.08	191.48	1164.20	6.86
8	PM100	100	0	45	+1	0	1	6.08	204.03	1240.50	7.30
9	PM100	100	0	60	+1	+1	1	6.08	211.66	1286.89	7.58

Note: The table presents the nine unique factor combinations. The centre-point condition, PM50:BCP50 at 45 days, was performed in five independent runs, giving a total Design-Expert design size of 13 runs.

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2.4. Design-Expert RSM Design

Design-Expert 13 was used for response surface modelling. A two-factor central composite design was used. The design included 13 runs, with five centre points. The centre points supported model fitting and assessment of pure error. The centre-point condition was replicated five times in the Design Expert design. The two coded factors were PM fraction and HRT. The coded PM fraction was represented as A, while the coded HRT was represented as B. Factor coding was done following Equations (1) and (2).

$$A = \frac{PM - 50}{50} \quad (1)$$

$$B = \frac{HRT - 45}{15} \quad (2)$$

where PM is the pig manure fraction in percent, and

HRT is the digestion time in days.

The corresponding BCP fraction was calculated using Equation (3).

$$BCP = 100 - PM \quad (3)$$

This means that the model can be read in two ways: an increase in PM fraction means a decrease in BCP fraction, while a decrease in PM fraction means an increase in BCP fraction.

2.5. RSM Model Development

A quadratic response surface model was fitted to each response. The general model form is shown in Equation (4).

$$Y = \beta_0 + \beta_1 A + \beta_2 B + \beta_{12} AB + \beta_{11} A^2 + \beta_{22} B^2 \quad (4)$$

where (Y) is the predicted response,

β_0 is the intercept,

β_1 and β_2 are linear coefficients.

β_{12} is the interaction coefficient, and

β_{11} and β_{22} are quadratic coefficients.

The quadratic model was selected because it can capture linear effects, interaction effects, and curvature. This is useful in anaerobic digestion studies because methane yield may not respond linearly to process variables [20, 23]. The coded BMP model obtained from Design-Expert is shown in Equation (5).

$$BMP = 324.85 - 126.78A + 11.78B - 1.72AB + 6.63A^2 - 3.47B^2 \quad (5)$$

This equation was used to interpret how the PM fraction and HRT affected BMP. A negative coefficient of (A) indicates that increasing the PM fraction reduced BMP. Since BCP is complementary to PM, this also means that increasing the BCP fraction increases BMP.

2.6. ANOVA and Model Adequacy Assessment

Analysis of variance was used to test the significance of the fitted model and its terms. A p-value below 0.05 was considered statistically significant. The F-value was used to assess the strength of each model term. Model adequacy was evaluated using R^2, adjusted R^2, predicted R^2, standard deviation, and Predicted Residual Error Sum of Squares (PRESS). The predicted-versus-actual plot was used to assess agreement between experimental and predicted BMP values. The residual plot was used to check whether the fitted model showed any obvious pattern or deviation. The quadratic model was used as the main BMP model because it showed strong prediction performance and was recommended by the Design-Expert output.

2.7. Response Surface and Contour Analysis

Contour plots and 3D response surface plots were generated in Design-Expert. These plots were used to show the combined effect of PM fraction and HRT on BMP. The BMP contour and surface plots were treated as the main RSM figures. The methane volume and energy-yield contour plots were treated as supporting figures. They were used to show the engineering meaning of the methane-yield response. All response surfaces were interpreted only within the studied design space. The model was not used to predict beyond 0 to 100% PM and 30 to 60 days.

2.8. Numerical Optimisation

Numerical optimisation was carried out to identify the best response conditions. The first optimisation targeted maximum BMP across the full design space. This provided the absolute maximum methane-yield condition. However, the absolute maximum may not represent co-digestion if it contains only BCP and no PM. Therefore, a second interpretation was included. This was the practical co-digestion optimum. It focused on conditions that retained both PM and BCP in the mixture. A time-efficient practical condition was also identified. This was based on a tested condition that retained most of the 60-day co-digestion BMP while reducing digestion time. This approach helps separate the highest mathematical yield from the most practical co-digestion option.

2.9. Python-Supported Sensitivity Analysis

Python was used to support the Design Expert results. It was not used as the main modelling tool. The Design-Expert BMP equation was first implemented in Python. The predicted values were then compared with the experimental values to check that the equation had been transferred correctly. Python was also used for sensitivity analysis. Two approaches were applied. The first was ANOVA-based contribution analysis. This used the model sum of squares to show the relative contribution of each term. The second was one-factor-at-a-time sensitivity analysis.

For the one-factor-at-a-time analysis, PM fraction was varied from 0 to 100% while HRT was fixed at 45 days. HRT was then varied from 30 to 60 days while the PM fraction was fixed at 50%. This made it possible to compare the effect of changing substrate composition with the effect of extending digestion time. Python was further used to generate a prediction grid over the design space. The grid was used to visualise the absolute optimum, the practical co-digestion optimum, and the time-efficient practical region. The use of Python as a supporting tool improves transparency. It also allows independent checking of the RSM equation and sensitivity trends [21].

2.10. Methodological Limitation

The RSM was based on batch BMP data. Therefore, the optimisation results were interpreted as laboratory-scale methane-yield optimisation and not as direct continuous-digester design results. In addition, the HRT values used in the model represent selected digestion time points from a batch profile. They do not represent hydraulic retention time under continuous feeding. Future studies should validate the selected optimum conditions using semi-continuous or continuous digestion.

3. Results and Discussion

3.1. Experimental RSM Design and Response Range

The experimental RSM design matrix and response values are shown in Table 1. The two factors were PM fraction and HRT. The BCP fraction was complementary to the PM fraction. Therefore, an increase in PM fraction also represented a decrease in BCP fraction. BMP was used as the main response. Methane volume and energy yield were included as supporting responses. BMP gives a clearer substrate-based comparison. Methane volume and energy yield show the practical energy implications. As shown in Table 1, BMP ranged from 191.48 to 468.23 N mL CH_4 g^{-1} VS. The lowest BMP was obtained from PM100 at 30 days. The highest BMP was obtained from BCP100 at 60 days. Methane volume ranged from 1164.20 to 2519.08 N mL CH_4. Energy yield ranged from 6.86 to 16.76 MJ kg^{-1} VS. The trend was clear. BCP-rich conditions gave higher BMP, methane volume, and energy yield than PM-rich conditions. Longer digestion time also improved the responses.

However, the effect of substrate composition was much stronger than the effect of digestion time. This agrees with the general understanding of BMP testing. BMP assays are used to compare the methane potential of substrates under controlled batch conditions [16, 24]. Therefore, the response range in Table 1 provides the experimental basis for the RSM optimisation.

3.2. BMP Model Selection and Adequacy

The BMP model selection and adequacy statistics are presented in Table 2. The quadratic model was selected because it fitted the experimental BMP data better than the linear and 2FI models. It also showed stronger predictive ability, as indicated by the low standard deviation, high predicted R^2, and lowest PRESS value. These results show that the quadratic model was suitable for describing the BMP response within the studied design space.

Table 2.
Model selection and adequacy statistics for BMP.

Model	Std. dev.	R^2	Adjusted R^2	Predicted R^2	PRESS	Decision
Linear	3.70	0.9986	0.9983	0.9973	262.79	Not selected
2FI	3.73	0.9987	0.9983	0.9969	306.72	Not selected
Quadratic	0.3612	1.0000	1.0000	0.9999	8.12	Selected

The predicted versus actual BMP plot is shown in Figure 1(a). The points were close to the diagonal line. This shows that the predicted BMP values agreed well with the experimental values. Figure 1(b) shows that most residuals were close to zero. However, one externally studentised residual was large. This is likely linked to the treatment of repeated centre-point values and the resulting low pure error. Therefore, the residual diagnostics were interpreted with caution, and the model was further supported using predicted versus actual agreement and Python-based sensitivity checks.

The ANOVA results for the BMP model are shown in Table 3. The model was significant, with $p < 0.0001$. The main effects, interaction term, and quadratic terms were also significant. This shows that the model captured the response pattern within the studied design space. The use of RSM for biogas optimisation is well supported in the literature. RSM has been used to study the effects of process variables and to identify optimum biogas production conditions [20, 21]. In this study, the same approach was used to identify how PM fraction and HRT affected BMP.

Table 3.
ANOVA for the quadratic BMP model.

Source	Sum of squares	df	Mean square	F-value	p-value	Significance
Model	97402.67	5	19480.53	1.493E+05	<0.0001	Significant
A, PM fraction	96433.94	1	96433.94	7.392E+05	<0.0001	Significant
B, HRT	832.61	1	832.61	6382.31	<0.0001	Significant
AB	11.87	1	11.87	90.97	<0.0001	Significant
A^2	121.37	1	121.37	930.33	<0.0001	Significant
B^2	33.28	1	33.28	255.07	<0.0001	Significant
Residual	0.9132	7	0.1305			
Lack of fit	0.9132	3	0.3044			
Pure error	0.0000	4	0.0000			
Corrected total	97403.59	12				

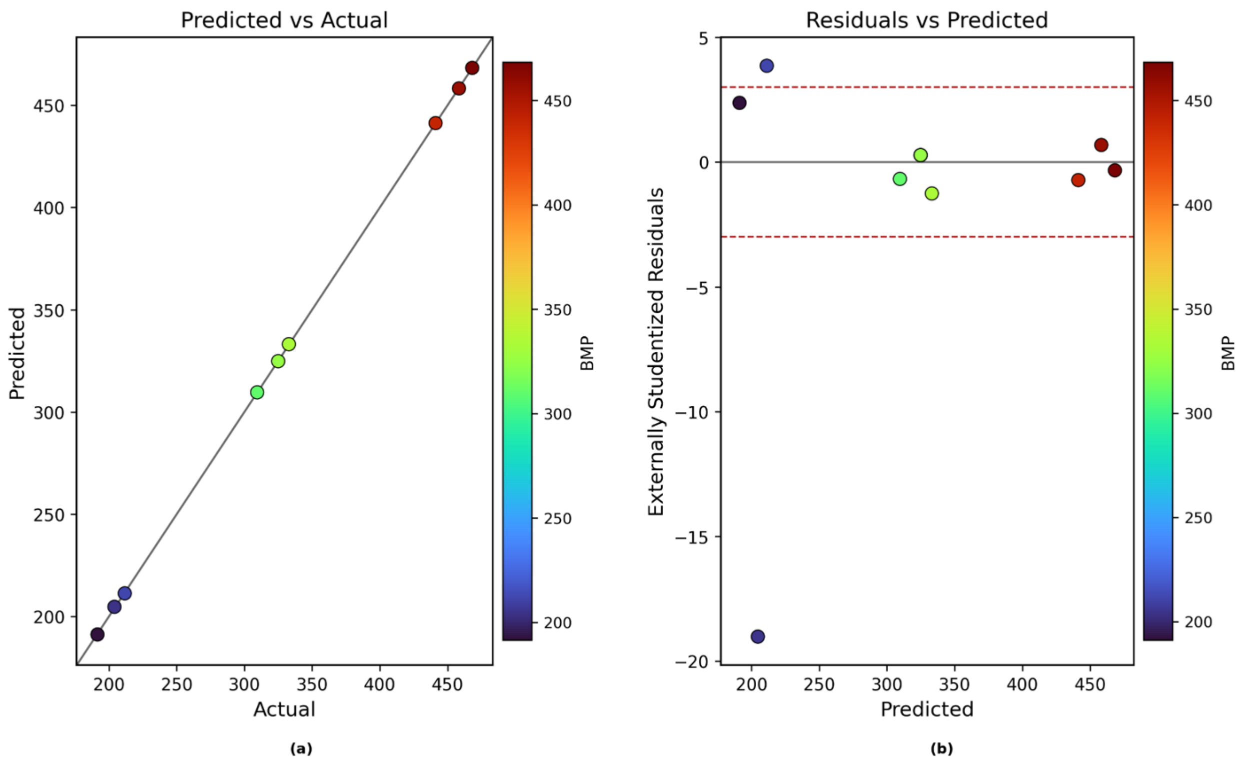

Figure 1.
BMP model diagnostic plots: (a) predicted versus experimental BMP and (b) externally studentised residuals versus predicted BMP.

3.3. Regression Coefficients and Model Interpretation

The coded regression coefficients for BMP are presented in Table 4. The coded BMP equation is presented in Equation (5). The coefficient of the PM fraction was negative. This means that BMP decreased as the PM fraction increased. Since BCP was complementary to PM, the result also means that BMP increased as the BCP fraction increased. The coefficient of HRT was positive. This shows that a longer digestion time improved BMP. However, the HRT effect was much smaller than the PM fraction effect. The negative coefficient of (B^2) also suggests that methane gains became smaller at longer digestion times. The interaction coefficient was negative and small. This means that the combined effect of the PM fraction and HRT existed, but it was not the main driver of BMP. The main interpretation remains simple. Substrate composition controlled the methane response more strongly than digestion time.

Table 4.
Coded regression coefficients for the BMP model.

Term	Coefficient estimate	Standard error	95% CI low	95% CI high	VIF
Intercept	324.85	0.1500	324.50	325.21	
A, PM fraction	−126.78	0.1475	−127.13	−126.43	1.00
B, HRT	11.78	0.1475	11.43	12.13	1.00
AB	−1.72	0.1806	−2.15	−1.30	1.00
A^2	6.63	0.2173	6.12	7.14	1.17
B^2	−3.47	0.2173	−3.98	−2.96	1.17

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3.4. Effect of Substrate Composition On BMP

Substrate composition had the strongest effect on BMP. This is shown in Tables 1 and 3 and Figure 2. At 60 days, BCP100 gave 468.23 N mL CH_4 g^{-1} VS. PM50:BCP50 gave 332.85 N mL CH_4 g^{-1} VS. PM100 gave 211.66 N mL CH_4 g^{-1} VS. Figure 2(a) shows the BMP contour plot. The highest BMP region occurred at a low PM fraction and a high BCP fraction. Figure 2(b) shows the same trend in the 3D response surface. The surface was steep along the PM fraction axis. This confirms that the substrate ratio strongly influenced methane yield.

The higher BMP under BCP-rich conditions may be linked to the degradability of the plant-waste fraction. The BCP blend contains soft plant tissues and readily degradable organic matter. Pig manure contains useful nutrients and buffering capacity. However, part of its organic matter has already passed through animal digestion. This may reduce its remaining methane potential. Similar trends have been reported in manure and food-waste co-digestion studies, where the substrate ratio strongly influenced methane yield and process stability [12, 13]. Therefore, the higher BMP of BCP-rich treatments is reasonable.

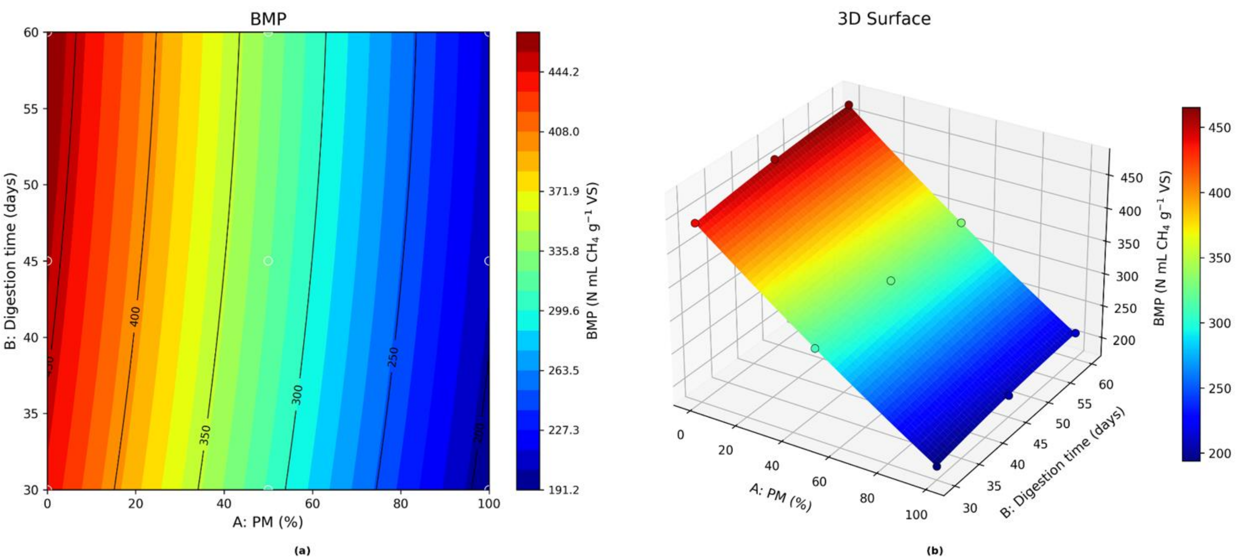

Figure 2.
Response surfaces for BMP showing the combined effects of pig-manure fraction and batch digestion time: (a) contour plot and (b) three-dimensional response surface.

3.5. Effect of HRT on BMP

HRT also affected BMP, although its effect was smaller than that of substrate composition. As shown in Table 1, BMP increased as the digestion time increased from 30 to 60 days. For BCP100, BMP increased from 441.16 N mL CH_4 g^{-1} VS at 30 days to 468.23 N mL CH_4 g^{-1} VS at 60 days. For PM50:BCP50, BMP increased from 309.42 to 332.85 N mL CH_4 g^{-1} VS. For PM100, BMP increased from 191.48 to 211.66 N mL CH_4 g^{-1} VS.

The positive coefficient for HRT in Table 4 supports this trend. A longer digestion time allowed more organic matter to be converted into methane. However, the increase was not large compared with the effect of changing the substrate ratio. This result has practical value. It suggests that increasing the BCP fraction has a stronger effect than extending the digestion time. Therefore, substrate blending should be prioritised during process optimisation. Similar behaviour has been reported in anaerobic digestion

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studies, in which a longer digestion time improved methane recovery, but the additional gain became smaller as digestion progressed [17, 25].

3.6. Interaction and Curvature Effects

The ANOVA results in Table 3 show that the interaction and quadratic terms were significant. This supports the use of a quadratic RSM model. The fitted surface was not purely linear. However, the interaction term had a small contribution compared with the PM fraction. The quadratic terms also had smaller effects than the main PM fraction term. This means that curvature improved the model fit, but it did not change the main response pattern. Figure 2(a) and Figure 2(b) support this interpretation. The contour and surface plots show a strong gradient from low PM fraction to high PM fraction. The response changed more gently along the HRT axis. Therefore, the interaction and curvature effects are useful for model accuracy. However, they remain secondary to the main substrate composition effect.

3.7. Methane Volume and Energy Yield Responses

Methane volume and energy yield followed the same trend as BMP. This is shown in Table 1 and Figure 3. BCP-rich treatments produced higher methane volumes and energy yields. Figure 3(a) shows the methane volume contour plot. The highest methane volume occurred at a low PM fraction and a longer digestion time. Figure 3(b) shows the energy-yield contour plot. It followed almost the same pattern as BMP. BCP100 at 60 days gave the highest methane volume of 2519.08 N mL CH_4. It also gave the highest energy yield of 16.76 MJ kg^{-1} VS. PM100 at 30 days gave the lowest methane volume of 1164.20 N mL CH_4 and the lowest energy yield of 6.86 MJ kg^{-1} VS.

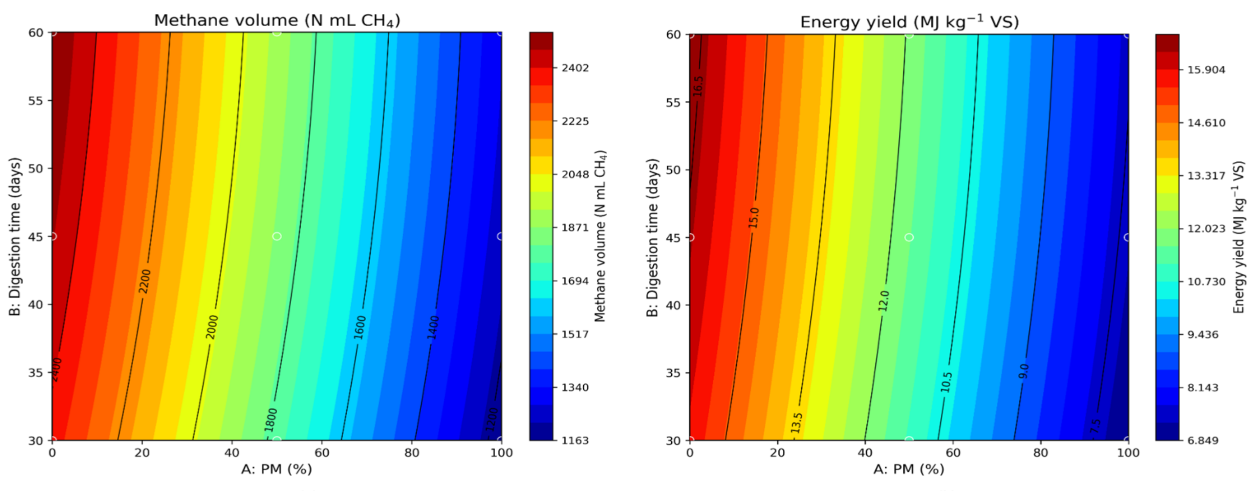

Figure 3.
Supporting engineering response contours showing the combined effects of pig-manure fraction and batch digestion time on: (a) methane volume and (b) energy yield.

These results confirm that BCP addition improved the energy value of the digestion process. However, methane volume and energy yield should be interpreted as supporting engineering responses. They are linked to methane production and are not fully independent biological responses. The engineering value of these responses is still important. BMP is useful for scientific comparison. Methane volume and energy yield are useful for process interpretation and energy recovery assessment. This approach is consistent with waste-to-energy studies, where methane yield is translated into energy terms to support process-level interpretation and practical energy recovery assessment [3, 26].

3.8. Numerical Optimisation

The optimisation results are summarised in Table 5. The absolute maximum BMP was obtained at PM0:BCP100 and 60 days. The predicted BMP under this condition was 468.29 N mL CH_4 g^{-1} VS. This was very close to the experimental value of 468.23 N mL CH_4 g^{-1} VS. This condition represents the maximum methane-yield point within the design space. However, it is not a co-digestion condition because it contains no PM. It should therefore be treated as the absolute maximum BMP condition.

Table 5.
Optimisation summary for BMP and energy yield.

Optimum type	**PM (%)**	**BCP (%)**	**HRT (days)**	**BMP (N mL CH_4 g^{-1} VS)**	**Energy yield (MJ kg^{-1} VS)**	**Interpretation**
Absolute maximum BMP	0	100	60	468.29	16.76	Highest modelled BMP, but not co-digestion
Model prediction at the highest tested co-digestion condition	50	50	60	333.16	11.93	The highest modelled condition within the tested co-digestion region
Model-derived time-efficient point	50	50	36	316.53	11.33	Indicative 95% threshold, not experimentally tested
Best tested co-digestion condition	50	50	60	332.85	11.92	Highest experimentally tested co-digestion BMP
Tested time-efficient condition	50	50	45	324.95	11.63	Safer practical recommendation

The highest tested co-digestion condition was also evaluated using the fitted model. As shown in Table 5, PM50:BCP50 at 60 days gave the highest tested co-digestion condition within the experimentally supported region. The predicted BMP was 333.16 N mL CH_4 g^{-1} VS. The experimental BMP was 332.85 N mL CH_4 g^{-1} VS. This close agreement supports the reliability of the model in the co-digestion region. Figure 4 shows the optimum regions. It separates the absolute maximum BMP from the highest tested co-digestion condition. This is important. The highest mathematical yield is not always the most practical co-digestion condition.

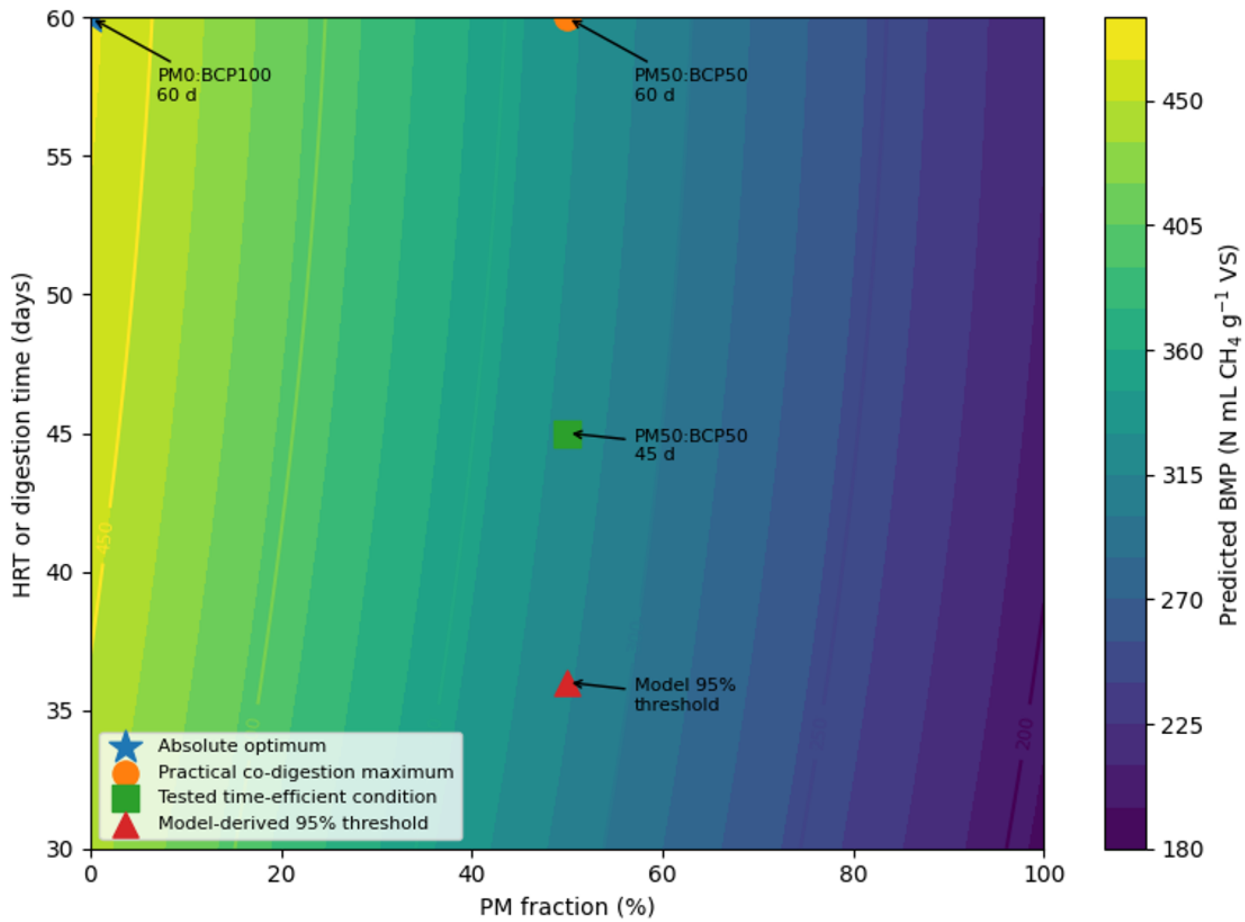

Figure 4.
Predicted BMP within the studied design space showing the absolute maximum at PM0:BCP100 and 60 days, the highest tested co-digestion condition at PM50:BCP50 and 60 days, the tested time-efficient condition at PM50:BCP50 and 45 days, and the model-derived 95% threshold near 36 days.

3.9. Time-Efficient Practical Condition

The highest tested co-digestion BMP was obtained at PM50:BCP50 and 60 days. However, PM50:BCP50 at 45 days also performed well. It produced 324.95 N mL CH_4 g^{-1} VS. This represents about 97.6% of the 60-day BMP. The time-efficient tested condition is shown in Table 5 and Figure 4. It retained most of the methane yield while reducing digestion time by 15 days. This suggests potential for reducing batch digestion time, subject to continuous-digester validation. The Python model also suggested that 95% of the practical co-digestion maximum could be reached at approximately 36 days. This point is also shown in Table 5 and Figure 4. However, it was model-derived and was not directly tested. For a conservative recommendation, PM50:BCP50 at 45 days is safer. It is based on an actual, tested condition. It also provides a good balance between methane recovery and digestion time.

3.10. Python-Supported Sensitivity Analysis

Python was used to support the Design-Expert RSM results. It was not used as the main model. The Python analysis helped check the model equation and interpret factor sensitivity. The one-factor-at-a-time sensitivity results are presented in Table 6 and Figure 5(b). Changing the PM fraction from 0 to

100% at 45 days changed BMP by 253.56 N mL CH_4 g^{-1} VS. Changing HRT from 30 to 60 days at 50% PM changed BMP by only 23.56 N mL CH_4 g^{-1} VS.

Table 6.
Python-supported one-factor-at-a-time sensitivity summary.

Sensitivity output	Fixed condition	Lower factor level	Model-predicted BMP at a lower level	Higher factor level	Model-predicted BMP at a higher level	Absolute BMP change	Interpretation
PM fraction	HRT fixed at 45 days	0 % PM	458.26	100 % PM	204.70	253.56	Dominant effect
HRT	PM fixed at 50%	30 days	309.60	60 days	333.16	23.56	Secondary effect

Note: HRT refers to the selected batch digestion time in this study, as defined in the Methods. All BMP values reported in this table are model-predicted values from the fitted quadratic RSM model and are not experimental observations.

The ANOVA-based contribution of model terms is shown in Table 7 and Figure 5(a). PM fraction contributed 98.975% of the model sum of squares. HRT contributed 0.855%. The combined curvature and interaction terms contributed only a small fraction. This confirms the main RSM interpretation. Substrate composition was the dominant factor controlling BMP. HRT improved BMP, but its effect was secondary. The Python analysis independently confirmed the fitted-model predictions and sensitivity trends. This approach is consistent with previous biogas optimisation studies [21].

Table 7.
ANOVA-based contribution of BMP model terms.

Model term	Sum of squares	Contribution (%)	Interpretation
PM fraction	96433.94	98.975	Dominant factor
HRT	832.61	0.855	Secondary factor
PM^2	121.37	0.125	Minor curvature effect
HRT^2	33.28	0.034	Minor curvature effect
PM × HRT	11.87	0.012	Very small interaction contribution

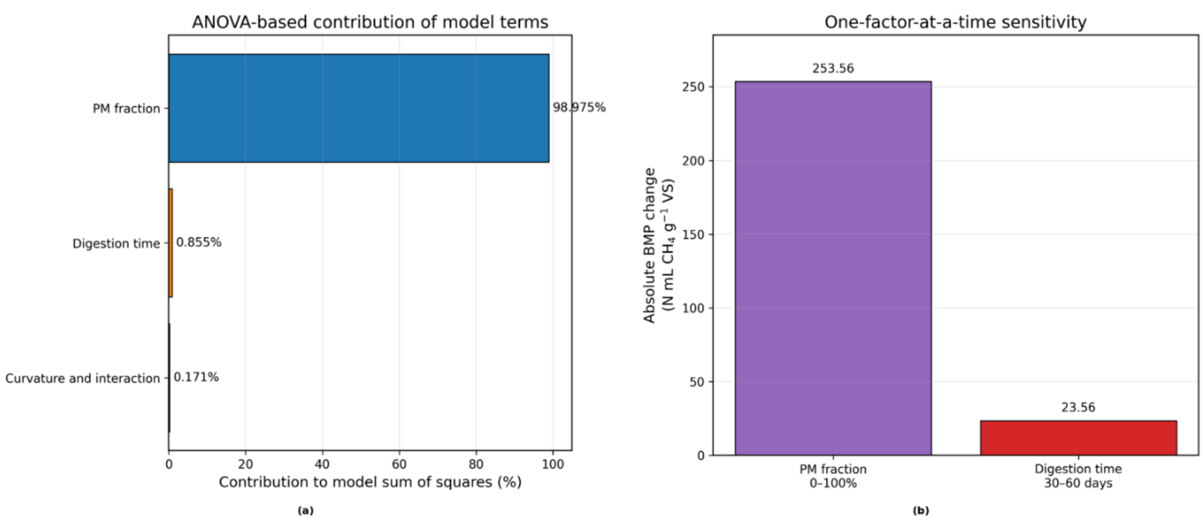

Figure 5.
Python-supported sensitivity analysis showing: (a) the percentage contribution of model terms to the model sum of squares and (b) the absolute BMP change obtained from one-factor-at-a-time sensitivity analysis.

3.11. Practical Interpretation

The combined Design Expert and Python results show that optimisation should not be interpreted using only the absolute maximum BMP. BCP100 at 60 days gave the highest BMP. However, it is a mono-digestion condition. For PM–BCP co-digestion, PM50:BCP50 represented the best-performing tested co-digestion condition. At 60 days, it gave the highest tested co-digestion BMP. At 45 days, it retained most of the 60-day BMP while reducing digestion time. Therefore, PM50:BCP50 at 60 days can be selected when maximum co-digestion BMP is required. PM50:BCP50 at 45 days can be selected when a shorter digestion time is important. The results also show that feedstock blending was more important than simply extending digestion time. This is useful for small-scale systems where feedstock availability, reactor size, and operating time matter.

3.12. Limitations of the RSM Interpretation

The RSM model should only be interpreted within the studied design space. The model covered PM fractions from 0 to 100% and digestion times from 30 to 60 days. Predictions outside this range require further validation. The study was based on batch BMP data. Therefore, the results should not be treated as direct continuous-digester optimisation. Semi-continuous or continuous digestion may give different responses. The methane volume and energy yield responses were useful engineering indicators. However, they were linked to methane production. They are therefore being discussed as supporting responses rather than independent biological responses. Despite these limitations, the model provided useful insight. It showed that the BCP fraction strongly improved BMP. It also identified a practical co-digestion region. Python sensitivity analysis supported the same conclusion.

4. Conclusion

This study used experimental BMP data to optimise methane yield from PM and composite plant-waste anaerobic digestion. Design Expert was used as the main RSM tool, while Python was used to support model checking, sensitivity analysis, and practical optimum selection. The composite plant-waste fraction consisted of banana peel, cabbage, and pumpkin residues. The results showed that substrate composition was the main factor controlling BMP. Increasing the BCP fraction improved methane yield, while increasing the PM fraction reduced BMP. HRT also improved BMP, but its effect was much smaller than that of substrate composition. This was confirmed by the Python sensitivity analysis, in which the PM fraction contributed about 98.98% of the model sum of squares, while HRT contributed about 0.86%.

The absolute optimum was obtained at PM0:BCP100 and 60 days, with a predicted BMP of 468.29 N mL CH_4 g^{-1} VS. However, this condition represents BCP mono-digestion and not PM–BCP co-digestion. Therefore, it should be interpreted as the maximum methane-yield reference within the design space. For practical co-digestion, PM50:BCP50 at 60 days gave the highest tested co-digestion BMP of 332.85 N mL CH_4 g^{-1} VS. However, PM50:BCP50 at 45 days produced 324.95 N mL CH_4 g^{-1} VS, which was about 97.6% of the 60-day value. This condition reduced digestion time by 15 days while retaining most of the methane yield. It was therefore identified as the more practical, time-efficient condition.

The findings show that feedstock blending is more important than simply extending digestion time. A balanced PM50:BCP50 blend can provide a useful co-digestion option where both pig manure and plant residues are available. However, the model was developed from batch BMP data. Further validation under semi-continuous or continuous digestion is required before field-scale application.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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