Iranian Society of Animal Science

Journal of Livestock Science and Technologies

Shahid Bahonar University of Kerman

ISSN: 2322-3553 (Print) ISSN: 2322-374X (Online)

Paper type: **Original Research**

Accuracy of non-linear kinetic models for predicting ruminal fermentation of agro-industrial by-products

Khalil Zaboli, Saeed Moradi, Mostafa Malecky*

Department of Animal Science, Faculty of Agriculture, Bu-Ali Sina University, Hamedan, Iran

*Corresponding author,
E-mail address:
zaboli@basu.ac.ir

Received: 30 Jun 2025,
Received in revised form: 27 Aug 2025,
Accepted: 08 Sep 2025,
Published online: 09 Sep 2025,

ORCID
Khalil Zaboli
0000-0001-9887-2736
Saeid Moradi
0009-0001-1920-0411
Mostafa Malecky
0000-0002-9949-2724

Abstract Gas production kinetics is considered as one of the key indicators for assessing the nutritional value of feeds; therefore, precise prediction of kinetic parameters can provide reliable estimates of the nutritive value of feedstuffs. The objective of this study was to assess the accuracy of various nonlinear models in predicting ruminal fermentation parameters using the *in vitro* gas production (IVGP) technique. The fermentation substrates used in this study were agro-industrial by-products, including sugar beet pulp, lemon pulp, tomato pomace, grape pomace, sesame meal, rapeseed meal, bakery waste, and saffron flower waste. Rumen fluid was collected from three adult ruminally-fistulated Mehraban rams, then filtered and buffered. Each of the feed samples (in 3 replicates and 3 separate runs) was incubated with buffered rumen fluid for 144 hours. The gas production data were fitted to five nonlinear models, including Exponential (EXP), Gompertz (GOM), Logistic (LOG), Mitscherling (MCH), and Weibull (WEB). The goodness of fit of these models was evaluated using metrics such as mean square error (MSE), coefficient of determination (R^2), residual mean absolute deviation (RMAD), and mean percentage error (MPE). Additionally, the Akaike's information criterion (AIC), Bayesian information criterion (BIC), accuracy factor (AF), run test, and linear regression analysis were employed to assess the accuracy of the models. Based on MSE and R^2 statistics, the EXP model demonstrated the lowest accuracy (37.30 and 0.958, respectively), while the MCH (8.15 and 0.991, respectively) and WEB (4.02 and 0.996, respectively) models exhibited the highest accuracy (P<0.05). Additionally, the AIC, BIC, and AF statistics were lowest for the WEB and MCH models, and highest for the EXP model. The results of the run test and linear regression analysis corroborated these findings. Overall, these findings indicated that the WEB model was the most accurate among the evaluated models for predicting the rumen fermentation kinetics, offering a reliable estimate of the nutritional value of new feedstuffs, such as agro-industrial by-products.

Keywords: exponential model, gas production kinetics, goodness of fit, prediction

Introduction

The *in vitro* gas production (IVGP) technique is a widely used method to determine the nutritional value of feedstuffs in ruminant diets. The kinetic data from IVGP are generally fitted to non-linear models to obtain certain parameters that provide important information on the nutritional value, particularly the ruminal digestibility of the diets (France et al., 2000; Wang et al., 2025). The exponential (EXP) model, first utilized by Menke et al. (1979), is widely recognized as the predominant nonlinear model in this context. However, subsequent research indicated that the EXP model may not yield accurate predictions of fermentation parameters across different feedstuffs (Cabral et al., 2019; Wang et al., 2025). Hence, alternative nonlinear models such as Logistic (LOG) and Gompertz (GOM) models suggested to improve the precision in predicting the ruminal fermentation kinetic parameters (Lopez et al., 1999; Sahin et al., 2011). The LOG and GOM models were utilized as growth functions with a sigmoidal structure to characterize the kinetics of IVGP for the first time (Schofield et al., 1994). The Mitscherling (MCH) and Weibull (WEB) models were also proposed by some researchers to predict IVGP parameters and ruminal fermentation kinetics (Huhtanen et al., 2008; Peripolli et al., 2014). Peripolli et al. (2014) utilized the EXP, GOM, and LOG models to evaluate the ruminal fermentation kinetics of various dietary compositions and concluded that the EXP model exhibits lower accuracy compared to the GOM and LOG models. In another experiment, Ucardes and Efe (2014) found that the EXP model has lower accuracy in predicting the ruminal fermentation kinetics of various clover varieties compared to the LOG, WEB, and MIT models. It is important to notice that nonlinear models exhibit distinct mathematical structures. Consequently, evaluating differences in predictive performance among these models is crucial to determine the most suitable model for IVGP parameters. For this purpose, a range of specific statistical measures are employed (Peripolli et al., 2014; Zornitta et al., 2021). Some of these measures are derived from the analysis of variance of the projected data from each model. Additionally, others are calculated through diverse assessments, including the run test, accuracy factor (AF), and linear regression analysis comparing the observed versus the predicted values from each model (Wang et al., 2011).

With frequent droughts highlighting the challenge of feed shortages in many regions of the world, wastes and by-products from the agro-alimentary industry have gained increasing attention as alternative sources of feeds for the animal production sector in recent decades. Numerous by-product feedstuffs have been the subject of *in vitro* studies, with their nutritional values assessed through *in vitro* gas production (IVGP) and the use of the EXP model. However, the other nonlinear models with higher accuracy have rarely been used in these experiments (Paya et al., 2012; García-Rodríguez et al., 2019).

Regarding the fact the EXP model has a non-sigmoid structure, whereas the rumen microbial growth and have a sigmoidal curve, thus employing the EXP model to describe rumen functions such as gas production may results in unreliable outcomes. Therefore, in this experiment, other models with higher complexity and sigmoidal structure were used to compare the accuracy of rumen fermentation parameters prediction with the EXP model.

Moreover, Small ruminants, particularly native breeds, play a crucial role in the livelihoods of a significant portion of the human population in tropical regions from socio-economic perspectives (Hajalizadeh et al., 2019). These animals are well-adapted to harsh environmental conditions. So, effective management strategies need to be focused on them (Amirteymoori et al., 2021). One of these strategies is the use of alternative and inexpensive feed sources. By integrating these approaches, small ruminant breeders can improve flock productivity, ensure food security, and contribute to the economic well-being of rural populations. Hence, the objective of this study was to assess the nutritional value of some agricultural by-products through the application of the IVGP technique, and to calculate the ruminal kinetic parameters using more precise nonlinear models.

Materials and methods

Feed samples and preparation

Eight by-product feeds from the agro-alimentary sector, including sugar beet pulp, lemon pulp, tomato pomace, grape pomace, sesame meal, rapeseed meal, saffron flower and bakery waste were used as fermentation substrates in this experiment (Table 1).

Table 1. Chemical composition of the experimental feedstuffs (% of DM)

Feed-stuffs	DM	OM	CP	NDF	ADF
Sugar beet pulp	91.02	94.14	9.06	40.03	27.16
Lemon pulp	23.44	94.53	8.66	23.11	16.98
Tomato pulp	14.95	93.74	21.59	53.01	39.04
Grape pulp	17.94	93.50	9.11	51.75	48.30
Sesame meal	93.08	90.76	39.84	21.31	7.00
Rapeseed meal	90.87	92.86	33.33	56.92	28.00
Saffron flower	94.00	85.91	8.01	45.90	38.00
Bakery wastes	90.90	94.73	11.26	14.98	11.00

Dry matter (DM), organic matter (OM), crude protein (CP), neutral detergent fiber (NDF), and acid detergent fiber (ADF).

The samples were ground to pass through a 1-mm sieve (Wiley mill; Thomas Scientific, Gloucester, NJ) and subjected to approximate chemical analysis. The dry matter (DM), organic matter (OM), crude protein (CP), neutral detergent fiber (NDF) and acid detergent fiber (ADF) contents of the samples were determined using standard methods (Vansoest et al., 1991; AOAC, 1995).

In vitro gas production

Rumen fluid was collected from three adult ruminally-fistulated Mehraban rams before morning feeding.

These rams were fed twice daily a maintenance diet composed of (per kg DM): 700 g alfalfa hay and 300 g barley, providing137.4 g crude protein (CP) and 9.58 MJ metabolizable energy (ME). The rumen fluid samples were pooled and transferred to a pre-warmed (39ºC) insulated flask and transported to the laboratory under anaerobic conditions. The rumen fluid was filtered through four layers of cheesecloth and then continuously mixed with CO_2 and maintained at 39ºC prior to use. The rumen fluid was then mixed with the buffer solution in a 1:2 (v/v) ratio to obtain the rumen buffered inoculum (Menke and Steingass, 1988). The composition of the buffer used included 400 mL of distilled water, 0.1 mL of micro solution (13.2 g $CaCl_2.2H2O$, 10 g $MnCl_2.4H_2O$, 1 g $CoCl_2.6H_2O$, 8 g $FeCl_3.6H_2O$ dissolved in 100 mL of distilled water), 200 mL of bicarbonate buffer solution (35 g $NaHCO_3$ and 4 g $(NH_4)HCO_3$ in 1 liter of distilled water), 200 mL of macro solution (5.7 g Na_2HPO_4, 2.6 g KH_2PO_4 and 0.6 g $MgSO_4.7H_2O$ in 1 liter of distilled water), 1 mL of resazurin solution (100 mg of resazurin in 100 mL of distilled water) and 40 mL of reducing solution (4 mL of NaOH 1N and 625 mg of $Na_2S.9H_2O$ added to 95 mL of distilled water). The samples (200 mg, DM basis) were incubated in triplicate with 30 mL of buffered rumen inoculum in 100 mL glass syringes (Fortuna, Häberle Labortechnik, Lonsee-Ettlenschieb, Germany). Three syringes without fermentation substrate were used as blank. The syringes were incubated in a water bath at 39°C for 144 hours and the volume of gas produced was recorded at 2, 4, 6, 8, 10, 12, 16, 20, 24, 36, 48, 72, 96, 120 and 144 hours of incubation. The gas production technique and all incubations were repeated in 3 runs.

Models and goodness of fit

The gas production kinetic data (72 curves) were analyzed by 5 non-linear models, using the non-linear regression procedure of SPSS (SPSS16.0 Inc., 2007). The mathematical structure of 5 candidate non-linear models used in this study has been presented in equations 1-5:

(1) Exponential model: $G = A.(1 - e^{-c.t})$ Domain: t ≥ 0
(2) Gompertz model: $G = (A.\ e^{-be^{(-c.t)}})$ Domain: t ≥ 0
(3) Logistic model: $G = A.(1 + e^{(b-c.t)})^{-1}$ Domain: t ≥ 0
(4) Mitscherling model: $G = A.(1 - b.e^{-ct})$ Domain: t ≥ 0
(5) Weibull model: $G = A.(1 - e^{-ct})^{b}$ Domain: t ≥ 0

where, G: volume of gas at time t, A: asymptotic gas volume, c: rate parameter, b: adjustable (shape) parameter, t: incubation time, and e: Napier's constant (2.718218284…)

The mean square error (MSE), coefficient of determination (R^2), residual mean absolute deviation (RMAD) and mean percentage error (MPE) values were used to check the accuracy of the models (match between the observed and predicted values). These statistics were calculated using equations 6 - 10.

(6) $RSS = \Sigma(y_i - \hat{y})^2$

(7) $MSE = \frac{RSS}{(n-p)}$

(8) $R^2 = 1 - \frac{MSE}{S_y^2}$

(9) $RMAD = \sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{n}$

(10) $MPE = \frac{1}{n}\Sigma\frac{(y_i - \hat{y}).100}{y_i}$

where, y_i is the observed value, ŷ is the predicted value, RSS is the residual sum of square sum, n is the number of data (number of time points measured), p is the number of parameters in each model and S_y^2 is the total variance of the observed values.

The goodness of fit of each model was evaluated by the Akaike's information criterion (AIC), Bayesian information criterion (BIC), accuracy factor (AF) and run test (Wang et al., 2011; Uckardes and Efe, 2014).

The linear regression between observed and predicted values of the gas volume at different incubation times was calculated using the REG procedure of SAS (SAS/STAT 9.1 user's guide, 1999). The significant (P<0.05) difference of the intercept and slope (regression parameters) of the models from 0 and 1, respectively, were analyzed according to Wang et al. (2011).

Statistical analysis

The estimated parameters of the models studied (A and c) and the goodness of fit parameters (RMSE, R^2, RMAD and MPE) were analyzed using the GLM procedure of SAS (SAS/STAT 9.1 user's guide, 1999) according to the following model:

$Y_{ij} = \mu + M_i + R_j + e_i$

where, Y_{ij} is the dependent variable, µ is the overall mean, M_i is the model effect, R_j is the run effect and e_{ij} is the residual error. When the model effect was significant (P<0.05), the difference between the means was compared using the Tukey test at the 5% significance level.

Results

The kinetic parameters estimated from the models are presented in Table 2. According to the data in Table 2, the calculated asymptotic gas production (A) varied from 107.86 (in the EXP model) to 113.07 (in the WEB model). Nevertheless, there was no statistically significant difference between the models in their estimation of the parameter 'A'. The gas production rate (c) estimated by the models exhibited significant variation (P<0.05), with the highest (0.099 mL/h) and lowest (0.039 mL/h) values estimated by the LOG and WEB models, respectively. The structural parameter (b) was only derived from the GOM, LOG, MCH and WEB models (the EXP model had no 'b' parameter).

The results on the goodness of fit parameters are outlined in Table 3. The EXP model had the highest mean squared error (MSE) value of 37.30, while the MIT and WEB models had the lowest values of 8.15 and 4.02 (P<0.05). The MIT and WEB models achieved the highest R^2 values of 0.991 and 0.996, while the EXP model, consistent to its MSE, had the lowest R^2 value of 0.958 (P<0.05). The WEB and EXP models exhibited the lowest and highest RMAD values (1.34 and 4.72, respectively). In addition, the EXP and GOM models had the highest and lowest MPE values (4.08 and -1.32, respectively).

Table 2. Comparison of the ruminal fermentation kinetics parameters estimated by several models

Parameters	EXP	GOM	LOG	MIT	WEB	P-value
A	107.86	109.94	109.11	112.03	113.07	0.1691
c	0.081^{b}	0.077^{b}	0.099^{a}	0.055^{c}	0.039^{d}	<.0001
b	-	-1.425	0.946	0.823	-0.221	-

Models were EXP: Exponential, GOM: Gompertz, LOG: Logistic, MIT: Mitscherling, and WEB: Weibull

A: asymptotic gas volume (mL/200 mg DM), b: shape parameter, c: rate parameter ($mL.h^{-1}$)

$^{a, b}$: Within rows, means followed by common superscript(s) are not different (P>0.05; Tukey's test)

Table 3. Comparison of the models for their goodness of fit parameters

Statistical criteria*	EXP	GOM	LOG	MIT	WEB	p-value
MSE	37.30^{a}	16.68^{c}	25.59^{b}	8.15^{d}	4.02^{d}	<.0001
R^2	0.958^{d}	0.982^{b}	0.973^{c}	0.991^{a}	0.996^{a}	<.0001
RMAD	4.72^{a}	2.88^{c}	4.11^{b}	1.92^{d}	1.34^{e}	<.0001
MPE	4.08^{a}	-1.32^{d}	0.32^{b}	-0.51^{c}	-0.22^{bc}	<.0001

Models were EXP: Exponential, GOM: Gompertz, LOG: Logistic, MIT: Mitscherling and WEB: Weibull

*MSE: mean squares errors, R^2: coefficient of determination, RMAD: residual mean absolute deviation, MPE: mean prediction error

$^{a, b}$: Within rows, means followed by common superscript(s) are not different (P>0.05; Tukey's test)

The Bayesian information criterion (BIC), Akaike information criterion (AIC), and accuracy factor (AF) criteria are displayed in Table 4. The EXP and WEB models exhibited the highest and lowest values for these criteria, respectively.

Table 4. The Bayesian and Akaike's information criterions, accuracy factor values after fitting models

Statistical criteria*	EXP	GOM	LOG	MIT	WEB
BIC	54.43	44.07	51.92	28.99	20.04
AIC	56.20	47.95	53.47	33.02	24.62
AF	477.57	55.33	135.31	14.47	5.29

Models were EXP: Exponential, GOM: Gompertz, LOG: Logistic, MIT: Mitscherling, and WEB: Weibull

* BIC (Bayesian Information Criterion), AIC (Akaike's Information Criterion), and AF (Accuracy Factor) were calculated according to the formula proposed by Uckardes and Efe (2014), Wang et al. (2011) and Uckardes and Efe (2014), respectively

The results of the run test are shown in Table 5. The 72 curves for each fitted model were divided into 5 groups based on the number of runs (<4, 4-5, 6-7, 8-9, >9 runs). Among the models tested, the EXP model had the highest percentage of curves (94%) clustered in the first group with <4 runs. In contrast, The WEB model had the largest number of curves (60%) regrouped in the third group with 8-9 runs. The run test for the EXP, GOM and LOG models were significant (P<0.05) but for the MCH and WEB models were not significant.

Table 5. Distribution of gas production curves according to the number of runs (based on percentage)

Number of runs	EXP	GOM	LOG	MIT	WEB
< 4	94	0	0	0	0
4-5	6	97	100	70	39
6-7	0	3	0	18	52
8-9	0	0	0	8	8
> 9	0	0	0	4	1
P-value	0.008	0.027	0.020	0.154	0.191
Distribution of the curves according to the significant (P<0.05) and non-significant (P>0.05) of the run test (total curve=72)					
Significant	68	70	72	41	25
Non-significant	4	2	0	31	47

Models were EXP: Exponential, GOM: Gompertz, LOG: Logistic, MIT: Mitscherling, and WEB: Weibull

The result of linear regression between observed (X-axis) and predicted (Y-axis) gas volume of the 72 curves for each model is shown in Table 6. In all examined models, the regression coefficients (intercept and slope) were found to be statistically significant from zero and 1, respectively (P<0.05). Notably, the EXP and WEB models exhibited the most distant and closest proximity to an intercept of 0 and a slope of 1, respectively. The MSE and R^2 obtained from the regression analysis showed that the EXP model had the highest MSE (28.52) and lowest R^2 (0.974) compared to the other examined models. Conversely, the WEB model was the most accurate of the models with the lowest MSE (3.20) and highest R^2 (0.996).

Table 6. Regression parameters between observed (in X-axis) and predicted (in Y-axis) gas volumes

Parameters	EXP	GOM	LOG	MIT	WEB
Intercept	-5.21*	1.619*	2.678*	0.538*	0.361*
Slope	1.053*	0.980*	0.967*	0.993*	0.995*
MSE	28.52	12.99	19.47	6.51	3.20
R^2	0.974	0.986	0.979	0.993	0.996

Models were EXP: Exponential, GOM: Gompertz, LOG: Logistic, MIT: Mitscherling, and WEB: Weibull

* Intercept and slope significantly (P<0.05) different from 0 and 1, respectively

Discussion

The *in vitro* gas production technique is a simple and cost-effective method with the potential to evaluate large numbers of samples for assessing the nutritional value of feedstuffs (Zaboli and Maleki, 2016). Kinetic parameters obtained from long-term gas production incubations (144 hours) can provide valuable information on the extent and rate of ruminal degradability and energetic value of feedstuffs, and ultimately their nutritional value for farm animals. Depending on their structure and flexibility, non-linear models applied to gas production can yield varying estimated parameters. Consequently, the precision of the estimated kinetic parameters is crucial for reliably assessing the nutritional value of feedstuffs. In this research, five non-linear models were used to estimate kinetic parameters for gas production. The EXP model included only the A and c parameters, while the other models incorporated an additional parameter b, into their equations. It is important to notice that the parameter b is a shape parameter in these models and lacks direct biological significance. As a result, its values cannot be statistically compared across different models (Huhtanen et al., 2008). However, including this parameter in advanced non-linear models such as the GOM, LOG, MIT, and WEB, improves their flexibility and, consequently, their precision compared to simpler models like the EXP model (Huhtanen et al., 2008). Furthermore, differences in model structure can alter the shape of the gas production curve, thereby affecting the slope represented by the gas production rate parameter (c). Table 2 indicates that the estimated values of parameter c differed across the models. Similar to our results, Zaboli (2016) in a study evaluating ruminal fermentation kinetics of alfalfa hay reported no significant differences in the predicted values of the asymptotic gas volume (A) among the EXP, MCH and WEB models. However, the gas production rate (c) estimated by the WEB model differed significantly from that of the EXP model. In contrast, Wang et al. (2011) reported that the EXP model produced significantly higher the A values compared to the GOM and LOG models during a 48-hour incubation period involving 23 forage samples. This disparity likely arises from differences in feed composition and the duration of incubation (144 hours versus 48 hours).

The predicted ruminal fermentation kinetic parameters (A and c) are influenced by several factors, including the chemical composition of the feed, rumen microbial communities, incubation time, feed particle size the and the type of the model used. Consequently, the values of these parameters may vary between different research studies (Gatachew et al., 2004).

As stated in the results section, the R^2 and MSE values obtained from the models were significantly different (P<0.05). It is well known that low R^2 values and high MSE values, respectively, indicate poor model performance (Korkmaz and Uckades, 2014). Therefore, the EXP model demonstrates significantly lower accuracy, while the WEB model exhibits the highest accuracy. Similar to our results, in a study investigating the gas production kinetics of diets containing 60% alfalfa hay with different levels of maize and glycerol, a higher MSE and lower R^2 values were observed for the EXP model, indicating a poor goodness of fit of the EXP model (Peripolli et al., 2014). Also, other researchers have observed that the EXP model is generally less accurate than the LOG and GOM models (Beuvink and Kogut, 1993; Wang et al., 2011).

The RMAD is another criterion of the goodness of fit of models, with a lower value indicating greater model accuracy (Peripolli et al., 2014). Based on RMAD values, the WEB model as well as the other models were more accurate than the EXP model. Mean percentage error (MPE) is a measure indicating whether the model overestimates (negative MPE) or underestimates (positive MPE) the predicted values. In other words, a value of MPE closer to zero indicates greater model accuracy (Peripolli et al., 2014). According to the MPE values, the EXP model underestimated, while the GOM model overestimated gas production. The WEB model has an MPE value of -0.22, which is fairly close to zero. Similar to our findings, a study by Zaboli (2016) comparing different nonlinear models for predicting ruminal fermentation kinetics of alfalfa hay reported the highest RMAD for the EXP model and the lowest for the WEB model. This indicates that the EXP model was the least and the WEB model the most accurate model. In this study, the MPE values for the EXP, MCH and WEB models were 2.79, -1.39 and -1.28 respectively, with the EXP model having the lowest accuracy (Zaboli, 2016). In a study of gas production kinetics for diets containing 60% alfalfa with different levels of corn and glycerol, the RMAD and MPE values in the EXP model were 4.03 and 15.4, respectively, which were significantly higher than the LOG and GOM models and indicated poor goodness of fit for the EXP model (Peripolli et al., 2014).

The BIC, AIC and AF statistics provide a good index of the relative quality of a model in terms of goodness of fit, as models with a lower value of these statistics have a better goodness of fit (Wang et al., 2011; Uckardes and Efe, 2014). Based on data in Table 4, these statistics were highest for EXP and lowest for WEB models. Similar to our results, Zaboli (2016) found that the BIC, AIC and AF statistics were significantly higher in the EXP compared to the other models, indicating its poor goodness of fit. In another study evaluating the gas production kinetics of corn silage, the AIC statistic was 18.686 and 15.53, in the EXP and WEB models, respectively, demonstrating a higher goodness of fit of the WEB than the EXP model (Zaboli and Maleki, 2016).

The run test is a simple technique used to assess the dispersion of residual values in a model (the difference between observed and predicted gas volume at various incubation times) along the gas production curve. Its purpose is to determine the serial randomness of these residual values. A higher number of observed runs in a model indicate a better fit, as a run is defined as a sequence of consecutive numbers with the same sign. Therefore, a greater number of runs suggest that the predicted values in the model align more closely with the observed values, resulting in a more random distribution of residual values along the gas production curve and a higher goodness of fit (Korkmaz and Uckades, 2014). Based on data in Table 5, the EXP model exhibited a poor goodness of fit due to a lower number of runs, while the WEB model demonstrated a better fit. It has been noted that a lower number of runs in a model may indicate an over or underestimation of predicted values, whereas a higher number of runs signifies a more random dispersion of residual values and greater accuracy of the model (Dhanoa et al., 2000). Regarding data in table 5, the run test was statistically significant in the EXP, GOM, and LOG models ($P<0.05$). The significance of the run test in these models suggests that the arrangement of residual values along the gas production curve does not follow a random distribution, indicating the presence of systematic error in the models (Wang et al., 2011). In other words, these results indicate that the EXP, GOM, and LOG models are not highly accurate in predicting gas production kinetics, while the MCH and WEB models demonstrate relatively better accuracy. These results are consistent with those of previous study on alfalfa hay, which indicated that the EXP model exhibited the lowest performance, with the WEB model outperforming the MCH and EXP models (Zaboli, 2016). In research examining a range of feedstuffs, Danoa et al. (2000) found that 90% of curves in the EXP, GOM, and LOG models exhibited weak performance, as indicated by 5 or less runs. Similarly, Wang et al. (2011) analyzed 23 gas production curves from various forage sources and observed that 15, 9, and 20 curves in the EXP, GOM, and LOG models, respectively, displayed poor performance with 4 or less runs.

Based on the linear regression analysis, Intercepts and regression coefficients closer to 0 and 1 respectively, indicate greater regression model accuracy (Wang et al., 2011; Peripolli et al., 2014). In Table 6, the intercept and regression coefficient showed statistically significant deviations from 0 and 1, respectively, for all models ($P<0.05$). However, the EXP and WEB models with the highest (-5.21) and lowest (0.361) intercepts were the worst and best models respectively. Similarly, the estimated regression lines by the EXP and WEB models were farther and closer to the 1:1 line, respectively, indicating a lower and higher accuracy of the EXP and WEB models, respectively, compared to the other models. These results were in line with those of MSE and R^2 (table 6), as the EXP model had the highest and lowest MSE and R^2, respectively, among the tested models, confirming its poor accuracy in predicting the gas production kinetics (Korkmaz and Uckardes, 2014).

Generally, choosing an appropriate model will allow for more accurate prediction of rumen fermentation parameters. The accuracy of these parameters and their knowledge provide important information about the process of digestion and absorption of nutrients in the rumen. This information can be used to design appropriate nutritional strategies and improve the efficiency of feed consumption in animals. Among these strategies, we can mention the selection of suitable feed sources, management of feeding time, use of additives, prevention of metabolic disorders, and finally increasing livestock performance.

Conclusion

The results indicated that the estimated kinetic parameters differed depending on the structure and complexity of the nonlinear models. Models with a shape parameter and greater flexibility provided more accurate predictions of gas production kinetics compared to the simpler EXP model, which lacked a shape parameter. Among the models featuring shape parameters, the WEB model demonstrated the best performance in predicting gas production kinetics. Therefore, the WEB model can be considered as a reliable tool for describing ruminal degradability and fermentation characteristics of new feedstuffs, ultimately aiding in assessing their nutritional value.

Declaration of interest

The authors declare that they have no competing interests.

Acknowledgment

This research was financially supported by Bu-Ali Sina University as an MSc thesis program funding.

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