PRODUCTION, MODELING, AND EDUCATION

A comparison of artificial neural networks with other statistical approaches for the prediction of true metabolizable energy of meat and bone meal

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ABSTRACT There has been a considerable and continuous interest to develop equations for rapid and accurate prediction of the ME of meat and bone meal. In this study, an artificial neural network (ANN), a partial least squares (PLS), and a multiple linear regression (MLR) statistical method were used to predict the TME_n of meat and bone meal based on its CP, ether extract, and ash content. The accuracy of the models was calculated by R^2 value, MS error, mean absolute percentage error, mean absolute deviation, bias, and Theil's U. The predictive ability of an ANN was compared with a PLS and a MLR model using the same training data sets. The squared regression coefficients of prediction for the MLR, PLS, and ANN models were 0.38, 0.36, and 0.94, respectively. The results revealed that ANN produced more accurate predictions of TME_n as compared with PLS and MLR methods. Based on the results of this study, ANN could be used as a promising approach for rapid prediction of nutritive value of meat and bone meal.

Key words: meat and bone meal, metabolizable energy, neural network model, partial least squares model, multiple linear regression model

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INTRODUCTION

Meat and bone meal (**MBM**) is a co-product of the meat industry obtained by the rendering, drying, and grinding of tissues and bones from beef, sheep, and pork either as individual or a mixture of these animal species. In general, hair, wool, hide, and blood are not present in this product. It is an effective and economic way to recycle inedible animal ingredients, which prevents additional environmental pollution and other associated problems. Liu (2000) reported that the production of every tonne of meat for human consumption could produce about 1/3 tonne of the raw material as animal waste. Considering a total world meat production of 269.1 million tonnes in 2007 (FAO, 2007), the estimated total inedible animal residues would be about 89.7 million tonnes. Meat and bone meal has been considered as an excellent source of protein for providing essential amino acids, especially lysine and threonine, minerals, and B vitamins as well as a valuable source of energy for all classes of poultry. Because of the nature of raw materials, composition ratio, and processing conditions such as time and temperature, the quality of available MBM samples varies markedly, making it difficult to accurately determine the nutritive value of commercially prepared MBM for feed formulation. For example, the nutrient content of 32 MBM samples obtained from different commercial plants varied considerably: protein from 40 to 60%, ash from 20 to 47%, and the TME_n values were 2,310 to 3,400 for pork meal, 2,250 to 2,850 kcal/kg for beef meal, and 1,940 to 3,240 kcal/kg for meal mixtures (Wang and Parsons, 1998). Proper utilization of MBM requires accurate ME values. The ME determination of feedstuffs requires the use of live animals, appropriate sample collection, ME assay trial, and determination of energy content of feed ingredients and collected excreta. It can be expensive in terms of time and resources and is therefore a continuous interest for rapid, inexpensive, and accurate methods for assessing ME of MBM samples, so that manufacturers and nutritionists can more consistently monitor quality contents of this animal by-product meal. Several studies showed that ME content of MBM correlated with its chemical composition and developed equations

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to estimate TME_n values by using the multiple linear regression (**MLR**) technique (Dolz and De Blas, 1992; NRC, 1994; Robbins and Firman, 2005).

Artificial neural networks (**ANN**) are inspired by the neurological structures and processing function in the brain. The increased using of ANN is derived from several advantages they possess, namely i) they can model complex, possibly nonlinear, relationships between variables without requiring a priori knowledge of a model; ii) noise tolerance; and iii) the ability to generalize from the input data. Regarding their use in poultry science, Roush and Cravener (1997) have compared 2 types of ANN models (a 3-layer backpropagation neural network and a general regression neural network) with a linear regression model in the prediction of amino acids levels of corn, wheat, soybean meal, and MBM based on CP or proximate analysis and concluded that the general regression neural network model (proximate analysis input) outperformed either the 3-layer backpropagation neural network or linear regression model. A group method of data handling-type neural network could accurately predict the TME_n values of feather and poultry offal meals from their chemical composition (Ahmadi et al., 2008).

The objective of this study is to compare performance of ANN, partial least squares (**PLS**), and MLR methods for rapid prediction of TME_n values of MBM samples based on their chemical composition.

MATERIALS AND METHODS

Data Source

Four separate data sets from MBM that consisted of 34 raw data lines were used to train the ANN model. The data of MBM were described previously (Dale, 1997; Parsons et al., 1997; Johnson et al., 1998; Robbins and Firman, 2005). Each data line consisted of CP, ether extract (**EE**), and ash percentages and a calculated TME_n of an individual sample.

Model Development

Neural Network Model Development. The fundamentals, functioning, and application of ANN have been adequately described by Basheer and Hajmeer (2000). A 3-layer feedforward ANN was used in this study and the network was trained using an error backpropagation training algorithm. When a multi-layer ANN with a backpropagation training algorithm was used, the signals were transferred from the input neurons through the hidden layer to the output neuron. The difference between the predicted output and the actual training output was calculated. The error propagated backward through the hidden layer to the input layer to iteratively adjust weights and biased to minimize the error in prediction. To avoid overtraining and consequence deterioration of its generalization ability, the predictive performance of the ANN after each weight adjustment was checked on validation data. The input, hidden, and output layers consisted of 1, 6, and 1 neurons, respectively. The learning rate and momentum for network training were set, respectively, to 0.5 and 0.1.

The input parameters in this multi-input signal output that affect TME_n were CP, EE, and ash content of samples. The raw data set was randomly partitioned into training (28 raw data sets) and validation sets (6 raw data sets) to train and validate the ANN. The neural network toolbox of MATLAB (version 7.5, Mathworks Inc., Natick, MA) was used for constructing the ANN model.

MLR and PLS Models Development. The MLR statistical approach is used to investigate the relative effect of several independent predictors on a particular output. It minimizes differences between observed and predicted values. Multiple linear regression is the most used statistical technique for prediction of nutritive value of feedstuffs in poultry nutrition. The collinearity problem of the MLR method has been overcome through the development of the PLS method known as a linear modeling technique, which has been shown to be an efficient approach in monitoring many complex processes, reducing the high-dimensional strongly cross-correlated data to a much smaller and interpretable set of principal components or latent variables. The MLR and PLS models were generated by using the same applied training data set for ANN model development. The program used for MLR analysis was written in SPSS (SPSS 11, SPSS Inc., Chicago, IL). The modeling by the PLS method was performed in the MATLAB (version 7.5, Mathworks Inc.) using PLS Toolbox (PLS_Toolbox, version 2.1, Eigenvector Research Inc., Wenatchee, WA).

Comparison of performance of models was made using error-measured indices, which commonly are used to investigate forecasting models. The following parameters were computed to evaluate the performance and accuracy of the models: R^2 value (correlation coefficient between predicted and observed values), MS error (**MSE**), mean absolute percentage error (MAPE), mean absolute deviation (MAD), bias, and Theil's U (Bolzan et al., 2008). These parameters are calculated by the following equations:

$$MAD = \frac{\sum_{t=1}^{n} \left| y_t - \hat{y}_t \right|}{n}$$

$$MAPE = \frac{\sum_{t=1}^{n} \left| \frac{y_t - \hat{y}_t}{y_t} \right|}{n} \times 100, (y_t \neq 0)$$

$$MSE = \frac{\sum_{t=1}^{n} \left| y_t - \hat{y}_t \right|^2}{n}$$

$$Bias = \frac{\sum_{t=1}^{n} y_t - \hat{y}_t}{n},$$

where y_t is the observed value, $\hat{y}_t$ is the estimated value, and n is the number of observations and

$$Difference\ Coefficient\ (Theil's\ U)\ \ \mathrm{r} = \frac{\sqrt{\sum_i \left(\hat{y}_i^1 - y_i\right)^2}}{\sqrt{\sum_i \left(\hat{y}_i^2 - y_i\right)^2}},$$

where $\hat{y}_i^1$ is the estimated value by the first model, y_i is the observed value, and $\hat{y}_i^2$ is the estimated value by the second model.

The ratio r is known as Theil's U or difference coefficient and is calculated to determine the relative efficiency of a prediction model.

RESULTS AND DISCUSSION

Table 1 shows the chemical composition of MBM samples and the observed and predicted TME_n values from training and validation sets for MLR, PLS, and ANN models. A summary of statistical results for the models is shown in Table 2. These results indicated forecasting error measurement based on difference between the observed and predicted values. The statistical test (in terms of R^2, MSE, mean absolute percentage error, and mean absolute deviation) revealed that the ANN model produced a more efficient prediction of TME_n as compared with MLR and PLS models. There was only a slight difference in these forecasting error measurements between the MLR and PLS models. The R^2 and MSE of the MLR model for training data set was 0.38 and 91,335.2, respectively. The R^2 and MSE of the PLS model for training data set was 0.36 and 94,359.7, respectively. The ANN model for the same training data set produced a much improved result with $R^2 = 0.94$ and MSE = 2,338.19. The ANN model improved the R^2 value of MLR and PLS models by 147.37 and 161.11%, respectively. The ANN model reduced the MSE value of MLR and PLS models by 97.44 and 97.5%, respectively. However, the lowest bias was seen with the MLR model. As measured by bias, the MLR and PLS models produced very little underestimation and overestimation of the observed TME_n values, respectively. The ANN gave little overestimation of the actual TME_n values. Plots of observed versus predicted TME_n values for training and validation data sets and distribution of the residual values about zero mean (observed TME_n − predicted TME_n), obtained by MLR, PLS, and ANN, were shown in Figure 1a, b, and c and Figure 2a, b, and c, respectively. The agreement between observed and predicted values and the randomized distribution of residual about zero mean demonstrated the higher predictive capacity of the ANN model than MLR and PLS models.

To determine which model obtained the best prediction, the measure of the r ratio, described in the text, was used. According to Bolzan et al. (2008), prediction models with Theil's U values equal or lower than 0.55 are considered reliable. The values of r ratio for the ANN model relative to MLR and PLS were 0.16 and 0.15, respectively.

Our results with the MLR technique agreed with Robbins and Firman (2005), who reported that a developed MLR equation via proximate analysis was not able to predict the TME_n values of MBM samples accurately for broilers and turkeys. The coefficient of determination (R^2) of PLS and MLR methods is considerably lower than that ($R^2 = 0.978$) reported by Dolz and De Blas (1992) for a developed equation with 2 input variables (EE and CP). Several studies have been conducted to examine and compare the predictive ability of statistical techniques of regression and ANN for many areas. Bolzan et al. (2008) compared an ANN model with a MLR model to predict hatchability of broiler breeder eggs in an artificial incubation process. The results demonstrated that ANN gave a more accurate prediction as compared with the MLR. Sargent et al. (2001) reviewed 28 published medical studies in which both ANN and regression (linear or Cox) approaches were used and reported that ANN outperformed regression in 10 cases (36%), was outperformed by regression in 4 cases (14%), and both methods gave similar results in the remaining 14 cases (50%). The author concluded that none of the methods produce appropriate performance and ANN should not replace the traditional regression methods. As mentioned, previous predicting models for ME of MBM samples have been based on the linear regression approach. In this study, 28 raw data sets were used to set up the models and the remaining data sets were used to test the developed models. Several factors can affect the accuracy of predictive models for determining ME content of feed ingredients. They are the number of samples, sample selection manner, variation of sample's chemical composition, ME content of feed ingredients, and number of independent variables. For example, in large data sets, 2 methods (ANN and linear regression) produced very similar outputs and in the more moderate data sets, the ANN gave equal or more efficient performance (Sargent et al., 2001). True ME obtained in this study with ANN for sample 3, which had approximately similar EE and CP percentage, was higher than that in the NRC (1994). This result supported the findings of previous studies (Martosiswoyo and Jensen, 1988; Dolz and De Blas, 1992; Liu, 2000; Janmohammadi, 2005) that the ME of MBM was higher than that reported by the NRC (1994).

In this study, the relationship between MBM chemical composition (EE, ash, and CP) and TME_n values

Table 1. The composition of meat and bone meal (MBM) samples and observed TME_n values used to train and validate multiple linear regression, partial least squares, and artificial neural network models for the TME_n prediction

					Multiple linear regression		Partial least squares		Artificial neural network	
MBM no.	CP (%)	Ash (%)	Ether extract (%)	Observed TME_n	Predicted TME_n	Residuals	Predicted TME_n	Residuals	Predicted TME_n	Residuals
Training sets										
1	53.82	27.27	10.8	2,240	2,641.58	−401.58	2,596.8	−356.8	2,228.3	11.7
2	50.44	28.89	10.27	2,469	2,410.51	58.49	2,412.7	56.3	2,565	−96
3	50.88	31.06	9.65	3,026	2,398.55	627.45	2,367.8	658.2	2,907	119
4	58.97	23.85	8.37	3,329	2,915.05	413.95	2,864.8	464.2	3,325.1	3.9
5	51.94	27.01	12.44	3,356	2,576.98	779.02	2,546.1	809.9	3,323.4	32.6
6	51.1	26.8	11.5	2,685	2,503.61	181.39	2,506.9	178.1	2,702.8	−17.8
7	48.32	27.32	8.17	1,703	2,242.93	−539.93	2,343.4	−640.4	1,686.8	16.2
8	52.44	23.62	12.12	2,282	2,631.21	−349.21	2,649.6	−367.6	2,392.5	−110.5
9	50.07	34.2	8.57	2,267	2,290.33	−23.33	2,242.4	24.6	2,302.3	−35.3
10	58.94	25.71	9.41	2,858	2,923.29	−65.29	2,827.8	30.2	2,853	5
11	48.7	30.3	8.7	2,215	2,250.69	−35.69	2,288.4	−73.4	2,160.4	54.6
12	50.2	25.7	11.9	2,599	2,471.78	127.22	2,503.3	95.7	2,605.4	−6.4
13	52.1	22	11.3	2,841	2,604.62	236.38	2,668	173	2,830.1	10.9
14	57.8	19.8	10.6	2,922	2,945.8	−23.8	2,946.7	−24.7	2,876	46
15	50.4	22.4	11.9	2,991	2,516	475	2,595.9	395.1	2,939	52
16	47.8	28.2	10	2,211	2,253.11	−42.11	2,320.7	−109.7	2,141.2	69.8
17	49.7	24.6	14.7	2,625	2,528.9	96.1	2,543.1	81.9	2,635.4	−10.4
18	56	18.3	15.1	2,822	2,975.77	−153.77	2,963.6	−141.6	2,795.2	26.8
19	51.3	22.2	13.1	2,477	2,604.02	−127.02	2,651.1	−174.1	2,496.4	−19.4
20	51.6	23.4	14.3	2,656	2,642.67	13.33	2,646.1	9.9	2,615.7	40.3
21	56.3	16.5	10.9	2,650	2,897.17	−247.17	2,974.1	−324.1	2,661	−11
22	48.6	31.7	10.3	2,138	2,274.48	−136.48	2,266.7	−128.7	2,216.2	−78.2
23	50.7	28.9	8.8	2,336	2,385.94	−49.94	2,406.2	−70.2	2,342.6	−6.6
24	49.8	30.7	9.7	2,224	2,339.27	−115.27	2,334	−110	2,264	−40
25	60	21.7	9.6	2,966	3,030.72	−64.72	2,975.5	−9.5	3,020.1	−54.1
26	49	35.3	16	2,020	2,417.76	−397.76	2,255.4	−235.4	2,025.3	−5.3
27	55	24.1	10	2,345	2,721.02	−376.02	2,716.6	−371.6	2,349	−4
28	50	28.1	13	2,607	2,466.25	140.75	2,446.2	160.8	2,589.5	17.5
Validation sets										
29	58.5	23.33	12.26	2,547	2,997.87	−450.87	2,903.4	−356.4	2,497.6	49.4
30	45.69	37.73	9	2,106	2,007.2	98.8	1,979.9	126.1	2,197	−91
31	48.2	25.3	11.9	2,667	2,356.89	310.11	2,432.8	234.2	2,619.8	47.2
32	48.8	23.5	13.6	2,583	2,456.34	126.66	2,522.4	60.6	2,538.2	44.8
33	53.3	17.3	14.3	3,068	2,803.44	264.56	2,871.1	196.9	3,166.5	−98.5
34	49	32.5	10	2,357	2,282.25	74.75	2,259	98	2,294.9	62.1

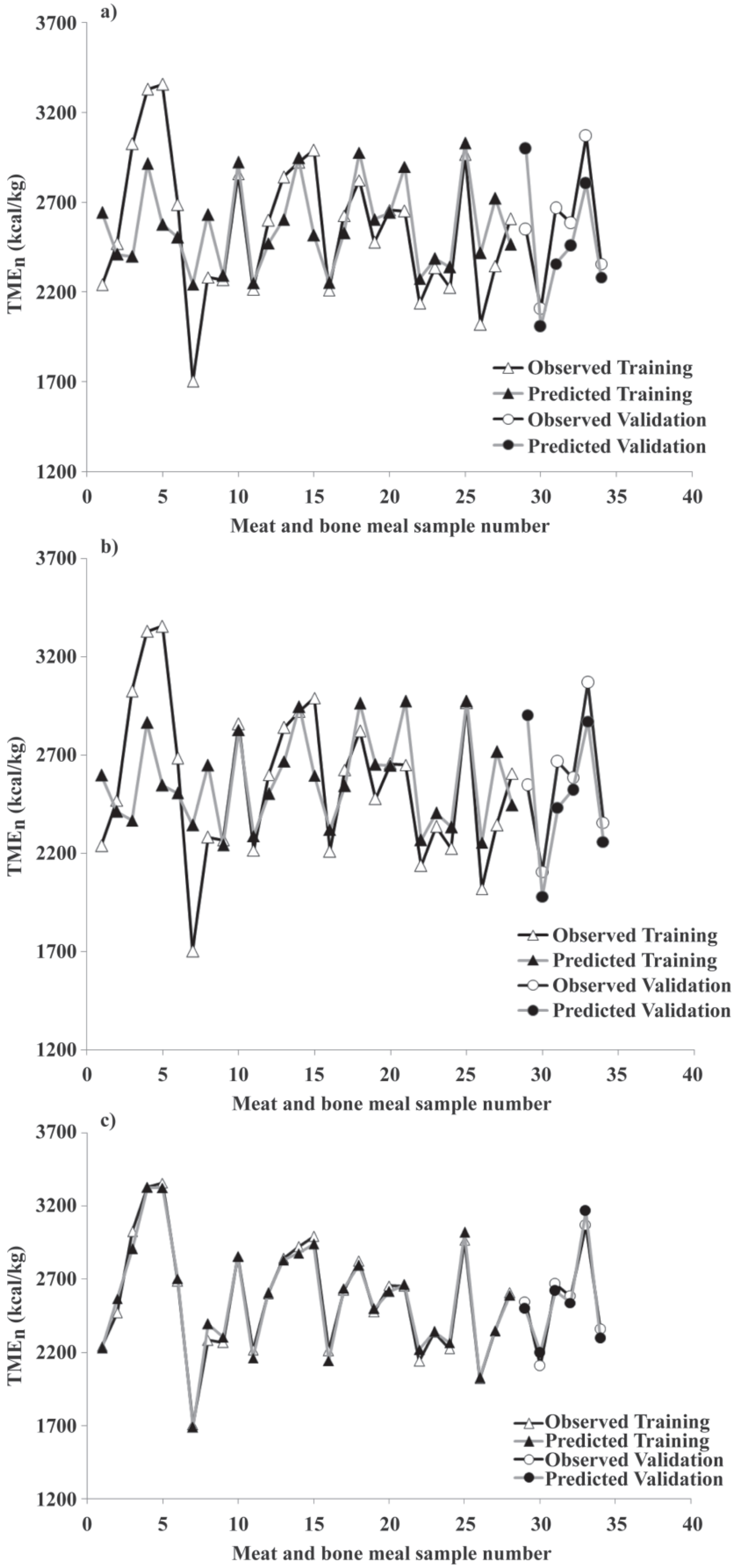

Figure 1. (a) The comparison of observed and multiple linear regression predicted TME_n values obtained from training (1 to 28) and validation (29 to 34) sets. (b) The comparison of observed and partial least squares predicted TME_n values obtained from training (1 to 28) and validation (29 to 34) sets. (c) The comparison of observed and artificial neural network predicted TME_n values obtained from training (1 to 28) and validation (29 to 34) sets.

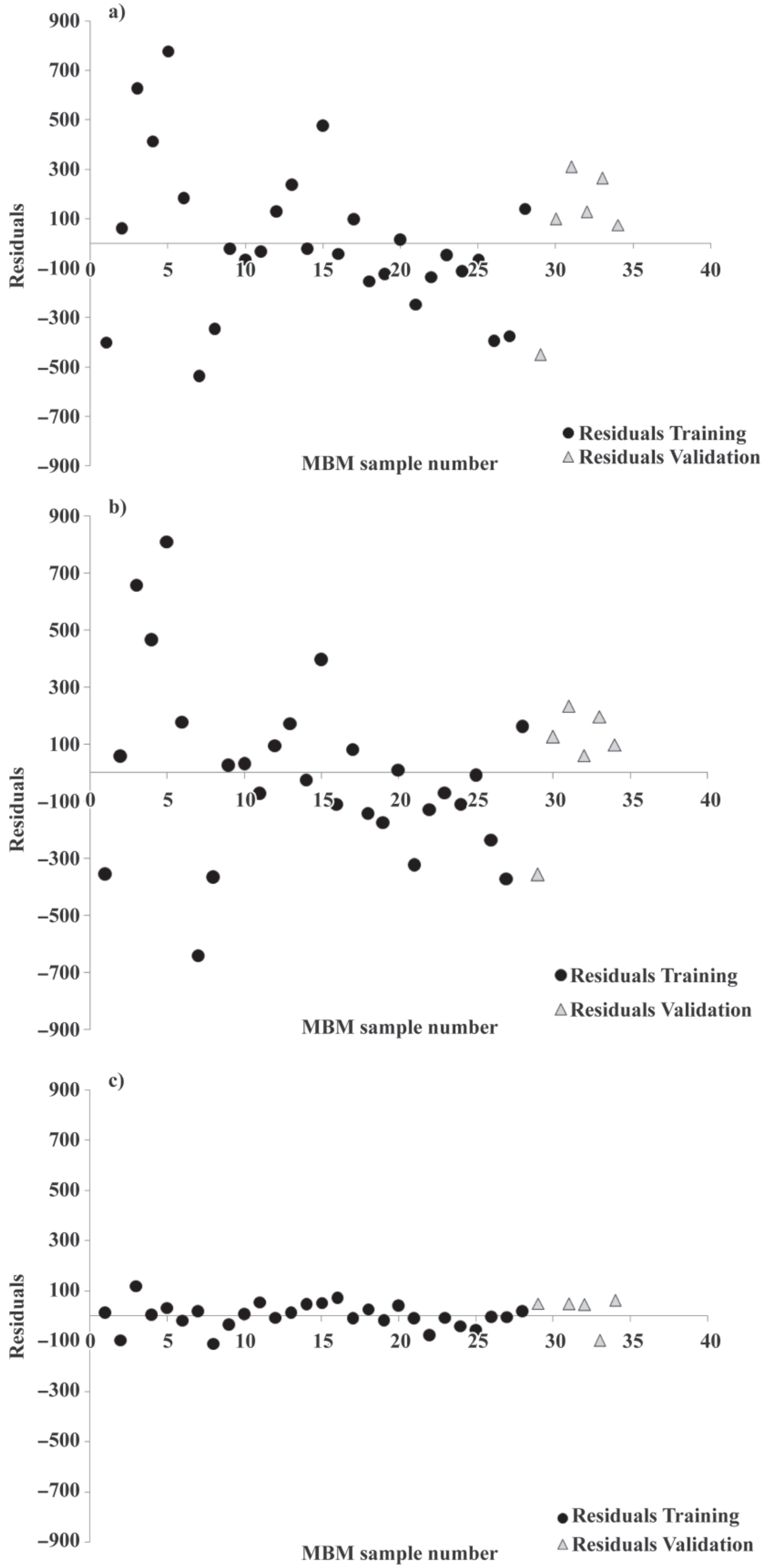

Figure 2. (a) Residual versus meat and bone meal (MBM) sample number for both training and validation sets in multiple linear regression model. (b) Residual versus MBM sample number for both training and validation sets in partial least squares model. (c) Residual versus MBM sample number for both training and validation sets in artificial neural network model.

Table 2. Statistical information of the multiple linear regression, partial least squares, and artificial neural network models for TME_n prediction

Parameter[1]	Multiple linear regression	Partial least squares	Artificial neural network
MAD	224.94	224.13	35.76
MAPE	1.43	1.489	0.06
MSE	91,335.17	94,359.68	2,338.1875
Bias	−0.000357	0.00357	0.4035714
R^2	0.38	0.36	0.94

[1]MAD = mean absolute deviation; MAPE = mean absolute percentage error; MSE = MS error.

was evaluated by MLR, PLS, and ANN models. The results demonstrated that the ANN model outperformed the PLS and MLR models. It is concluded that the ANN model may be a promising method for rapid and accurate estimation of TME_n values of MBM.

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