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Estimation and Prediction of Metabolizable Energy Contents of Wheat Bran for Poultry

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ABSTRACT

The biological procedure used to determine the nitrogen-corrected True Metabolizable Energy (TMEn) value of feed ingredient is costly and time consuming. Therefore, it is necessary to find an alternative method to accurately estimate the TMEn content. In this study, 2 methods of Multiple Linear Regression (MLR) and Artificial Neural Network (ANN) were developed to describe the TMEn (Kcal kg^{-1} DM) value on a Dry Matter (DM) basis of Wheat Bran (WB) samples given their chemical composition of Ether Extract (EE), ash, Crude Protein (CP) and Crude Fiber (CF) contents (all used as % of DM). A data set containing 100 WB samples were used to determine chemical composition and TMEn. Accuracy and precision of the developed models were evaluated given their produced prediction values. The results revealed that the developed ANN model [R^2= 0.90; Root Mean Square Error (RMSE)= 64.07 Kcal kg^{-1} DM for training set; and R^2= 0.89; RMSE= 82.69 Kcal kg^{-1} DM for testing set] produced relatively better prediction values of TMEn in WB than those produced by conventional MLR [R^2= 0.81; RMSE= 86.76 Kcal kg^{-1} DM for training set; and R^2= 0.84; RMSE= 86.61 Kcal kg^{-1} DM for testing set]. The developed ANN model may be considered as a promising tool for modeling the relationship between chemical composition and energy of WB samples. To provide the users with an easy and rapid tool, an Excel® calculator, namely, ANN_WB_ME_Poultry, was created to predict the TMEn values in WB sample given its chemical composition and using the developed ANN model.

Keywords: Metabolizable energy, Prediction model, Wheat bran.

INTRODUCTION

During the processes of cleaning wheat and subsequent manufacture of flour, up to 40% by weight is classified as by-product material (Leeson and Summers, 2009). There is considerable variation in the classification and description of these by-products, and great care must be taken when formulating with wheat by-products in different countries. Traditionally there were four major by-products, namely Wheat Bran (WB), wheat shorts, wheat germs, and wheat middlings.

Wheat bran is one of the by-products from milling wheat into flour that could be used in poultry feed (Hemery *et al.*, 2007). The high costs of the conventional raw materials (such as corn) caused by the boom of the production of biofuels and by the global economic crisis (Aho, 2007; de Gorter *et al.*, 2013) has affected animal production, especially the poultry industry, where the feeds represent between 60 to 70% of the total production cost. Therefore, developing countries have had to seek alternative feeds for poultry, while maintaining product quality, to compensate the negative effects of its higher prices and lower consumption (Aho, 2007). The WB by-product may be an economical and nutritional alternative for animal feeding in many countries. It has adequate protein content for poultry and high crude fiber levels (106 to 136.3 g kg^{-1}), but lower metabolizable energy content than

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many ingredients such as corn, sorghum, and barley (National Research Council, 1994). Research studies have shown the positive effects of the use of WB and its by-products, combined or not with enzymes, on the growth performance, intestinal microflora, harmful lipids, egg production, and digestibility of some nutrients in poultry (Courtin *et al.*, 2008).

While WB is a by-product made by dry milling of wheat to produce flour, it may comprise of small amounts of wheat kernel, endosperm and the outer layers (Hoseney, 1994). It is important to note that WB is not a by-product with a universally accepted definition and clear boundaries. Though national regulations may contain mandatory requirements on bran composition, ingredients sold under that name encompass a wide range of wheat by-products. WB represents roughly 50% of wheat offals and about 10 to 19% of the kernel, depending on the variety and milling process (Hassan *et al.*, 2008).

WB nutritive value is highly variable irrespective of the origin. Like other animal feed ingredients, the variation in WB composition has been attributed to differences in variety, maturity, soil conditions and climate, management as well as processing factors (Safdar *et al.*, 2009). The WB is a proper source of protein, carbohydrate, minerals, vitamins and bioactive compounds such as betaine and choline (Slavin, 2007).

Metabolizable Energy (ME) is one of the most important parameters that have a large effect on animal performance and, consequently, on profitability. It is essential, therefore, for nutritionists to ensure that the ME content is considered in the selection of WB to meet the desired specifications. Direct determination of ME of the feedstuffs implies *in vivo* experiments (Mohamed *et al.*, 1984). These experiments require test animals, collection of samples and excreta, and determination of total energy content of used materials. Therefore, *in vivo* ME determination can be expensive and time consuming. Thus, it is important to develop fast laboratory methods for accurate and inexpensive prediction of ME (Zhang *et al.*, 1994). The alternative to *in vivo* experiments includes using the composition of feedstuffs and nutritional composition tables, and prediction equations based on the chemical composition of the feedstuffs. Traditionally, Multiple Linear Regression (MLR) models were used to predict the ME in feedstuffs. A more useful and innovative method is to use an Artificial Neural Network (ANN) model to estimate ME of Ingredient based on chemical composition (Sedghi *et al.*, 2011).

The ANN models have attracted growing interest in recent years as a supplement or alternative to standard statistical techniques to predict complex phenomena in medicine and biological studies (Jigneshkumar and Ramesh, 2007). A neural network is a non-linear mathematical-statistical data modeling tool that is able to capture and represent complex input/output relationships. Artificial neural network can be applied with different objectives, such as pattern recognition systems, data processing, function approximation and clustering. In poultry nutrition, Ahmadi *et al*. (2008) introduced an ANN model for predicting nitrogen-corrected True Metabolizable Energy (TMEn) of poultry by-products based on their chemical composition. Perai *et al*. (2010) reported an accurate prediction of TMEn using ANN for meat and bone meal.

The objective of this research was, therefore, to measure the chemical composition and TMEn of different WB samples. The second objective was to estimate and compare the performance of the MLR and ANN models in describing the relationship between TMEn (as model output) of WB and chemical composition (as model inputs).

MATERIALS AND METHODS

Data Collection

Thirty-five different WB samples were collected from commercial feed mills in Iran

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(from January to July 2017) and analyzed (with three replications) for EE (method 920.39; AOAC International, 2000), ash (method 942.05), CP (method 990.03) and CF (method 978.10). The 105 WB samples (35 separate samples with three replications each) were used to estimate TMEn values using precision-fed rooster assay (Sibbald, 1976) with some minor modifications. In bio-assay experiment, adult single intact roosters (65 weeks old) were fasted for 24 hours. Each sample was then force fed 30 g (as is basis) to each rooster. In addition, another 4 roosters were fasted for an additional 48 hours to obtain measurements of endogenous energy. The excreta of each bird were collected 48 hours after feeding, dried to constant weight at 65^{o}C, ground to pass through a 60-mesh screen, and stored in tightly covered jars. Gross energy contents of the WB and excreta samples were determined with a bomb calorimeter, and nitrogen contents were determined by the Kjeldahl method. Dry matter contents of the excreta were determined by re-drying subsamples at 65^{o}C for 24 hours to correct for moisture uptake during grinding. Nitrogen content of WB samples and excreta were also determined for nitrogen correction.

Model Development

Data preprocessing: The entire experimental data (105 data lines) obtained from bioassay and laboratory analyses were examined for outlier values. The five data lines were excluded from data due to inconsistency and large variations. The final analyses were done using a total of 100 data lines, which were randomly divided into 2 sets of training and testing, with 70 and 30 data lines, respectively. A data coding process using linear transformation was performed to normalize the values into the interval (-1, 1). The actual form of the coding operation for each value of a variable was as follows:

Coded value= (Original value−M)/S

Where, M is the average of the highest and lowest values for the variable in the design and S is half of their difference.

Regression: Data from training set was fitted into a MLR model. Basis model was defined as the following general equation,

$$\hat{y}_i = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + e_i\,,\ \ i = 1,2,\ldots n$$

Where, $\hat{y}_i$ is the TMEn (as Kcal kg^{-1} DM) in the ith sample, X_i is the value corresponding to input variables (EE, Ash, CP, and CF in WB, all used as % of DM) in the ith sample (assumed to be a known constant measured without error), β_0 is the overall intercept, β_i is the linear coefficient for input variables, and e_i is the residual error assumed to be normal [N ~ (0, σ2)]. The MLR and ANN processing was conducted using Statistica software (12.5.192.7 Enterprise).

ANN Model: An algorithm of the feed forward three-layer back propagation network was chosen and considered in constructing the ANN model. Hyperbolic tangent sigmoid (tansig) and linear (purelin) functions were used as the transfer function for the hidden and output layers, respectively (Demuth *et al.*, 2008). The input parameters of the implemented ANN were EE, Ash, CP and CF (all used as % of DM). The TMEn column was the values of desired output. A Genetic Algorithm (GA) was used to train the network. The GA required the parameters to be specified before running (Haupt *et al.*, 1998). These values were set as follow: the initial population of 50, generation number of 1000, mutation rate of 0.1, and crossover rate of 0.85. The Mean Squared Error (MSE) with level of 0.005 was used as the performance function, and training was terminated after 1,000 generations or iterations of the network. The process of training ANN with GA is based on the concept that the accuracy (i.e. MSE) of the network model may be adjusted by inclusion or exclusion of the neurons in the hidden layer. The GA attempts to define the optimal number of hidden layer neurons. The

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challenge for this optimization method is to find the optimal structure for ANN model (number of neurons in the hidden layer) that will accurately reproduce the data for a prediction while being able to generalize beyond the data set.

The relative importance of each variable in the developed MLR and ANN models was determined using sensitivity analysis. For the sensitivity analysis in the MLR model, input factors were ranked based on the calculated absolute value of t value |t-value| appeared in the table of analysis of variance for the MLR model. The higher |t-value| indicates the higher importance of that factor. In the ANN model, the variables are ranked with determination of Variable Sensitivity Ratio (VSR) as described by Hunter *et al.* (2000) and Ahmadi and Golian (2010). A more important variable has a higher VSR value.

Evaluation of the model performance was based on the accuracy of their predictions in the training and testing set. The measures used in this process were as follows (Ahmadi, 2017): Coefficient of determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE).

Commercially available software, Matlab® R2016a (Version, 2016), was used to write the mathematical code for developing and evaluating the ANN model. The developed program is actually a modified source code of an ANN algorithm that was previously applied by Ahmadi and Golian (2010) and Arab *et al*. (2018). Finally, using the developed ANN model, an Excel® TMEn calculator, namely, ANN_WB_ME_Poultry, was created.

RESULTS

The present data demonstrated that the TMEn of WB varied widely, ranging from 1273.85 to 2496.09 Kcal kg^{-1} DM. Descriptive statistics for observed and predicted values of TMEn from the MLR and ANN model are shown in Table 1. The calculated MLR model on the 100 data set was obtained as follows:

TMEn=2364+19 CP+46.1 EE-63 CF-51.1 Ash

Table 1. Descriptive statistics for the entire data set representing the observed and predicted response of nitrogen-corrected True Metabolizable Energy (TMEn) (Kcal kg^{-1} DM) of Wheat Bran (WB) samples (n= 100) provided through Ether Extract (EE), Ash, Crude Protein (CP) and Crude Fiber (CF) (all used as % of DM).

Training data set (n= 70)							
	Inputs (%)				TMEn (Kcal kg^{-1} DM)		
	EE	Ash	CP	CF	Observed	MLR model predicted values	ANN model predicted values
Average	4.92	5.83	16.20	8.74	2051.54	2051.54	2053.23
Maximum	8.57	12.33	20.65	12.40	2377.13	2298.12	2328.05
Minimum	2.66	3.21	11.42	4.75	1367.61	1404.18	1350.94
SD [a]	1.26	1.65	1.85	1.55	196.50	177.23	186.76

[a] Standard Deviation of 70 WB samples.

	Inputs (%)				TMEn (Kcal kg^{-1} DM)		
	EE	Ash	CP	CF	Observed	MLR model predicted values	ANN model predicted values
Average	4.52	5.32	16.30	8.26	2086.87	2086.87	2096.64
Maximum	6.43	10.59	18.21	12.62	2496.09	2420.52	2349.74
Minimum	3.25	2.67	12.84	5.64	1273.85	1364.61	1473.58
SD [b]	0.95	1.45	1.42	1.36	207.57	190.69	156.17

[b] Standard Deviation of 30 WB samples.

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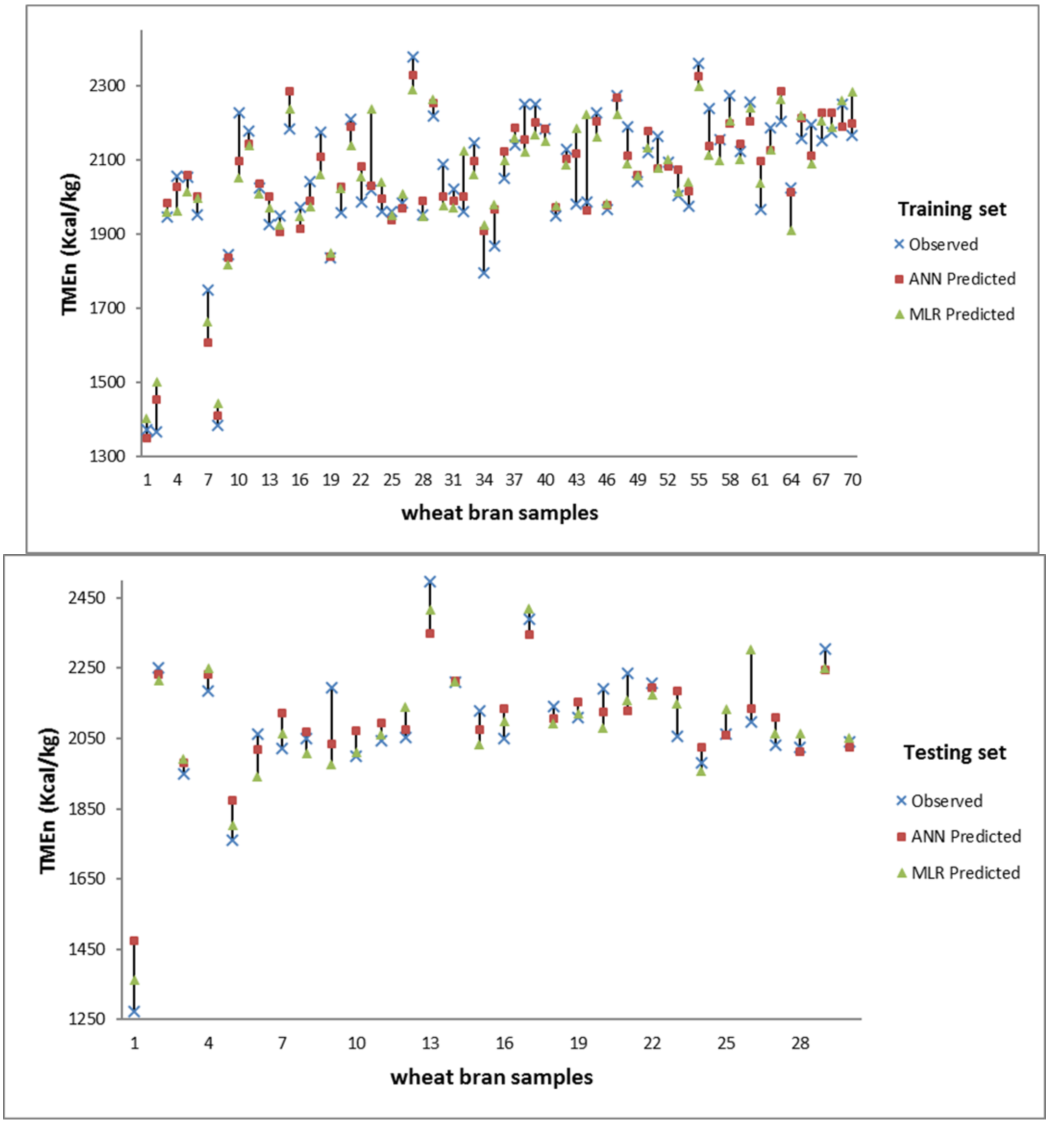

Figure 1. Comparison of observed and model-predicted values for nitrogen-corrected true metabolizable energy (TMEn; Kcal kg^{-1} DM) of wheat bran samples (n= 100) obtained by Multiple Linear Regression (MLR) and Artificial Neural Network (ANN) models from training (n= 70) and testing (n= 30) data sets.

All the parameter estimates were found to be significant ($P< 0.05$). The plots of observed versus predicted values of TMEn from the MLR and ANN models are shown in Figure 1. The comparison of observed and predicted TMEn describes the behavior of the MLR and ANN models from investigating inputs. The results revealed a good agreement between the observed and predicted TMEn (Kcal kg^{-1} DM) value for MLR and ANN models. Therefore, the TME may be predicted very well by the chemical composition such as EE, Ash, CP and CF (all used as % of DM) in WB samples. The prediction efficiency and some statistics of the chosen MLR and ANN model are shown in Table 2. The goodness of fit in terms of R^2 values corresponding to ANN model showed a higher accuracy of prediction than the equation established by MLR model for training (R^2: 0.90 for ANN model and R^2: 0.81 for MLR model) and testing (R^2: 0.89 for ANN model and R^2: 0.84 for MLR model). In terms of RMSE (%) error, the

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ANN model showed lower residuals distribution than the MLR model for training (RMSE: 64.07 Kcal kg^{-1} DM for ANN model and RMSE: 86.76 Kcal kg^{-1} DM for MLR model) and testing (RMSE: 82.69 Kcal kg^{-1} DM for ANN model and RMSE: 86.61 Kcal kg^{-1} DM for MLR model). The ANN model had lower values of MAD and MAPE than the MLR model, both training and testing dataset (Table 2).

To determine the relative importance of input variables in MLR model, the entire 100 data sets were used to calculate the t value. The obtained absolute value of t value for dietary EE, Ash, CP and CF (all used as % of DM) in MLR model are shown in Table 3. Based on t values, input factor were ranked according to their importance of effect on TMEn (Kcal kg^{-1} DM). Among the input variables, CF has the highest values of t value (9.35). It is followed by the Ash, EE and CP (7.43, 6.15, and 3.25, respectively). This indicates that the dietary CF is the most important variable in the MLR model, followed by Ash, CF and CP contents.

The relative importance of input variables in ANN model was determined using the entire 100 lines of data (training and testing) to calculate the overall VSR. The VSR obtained for the ANN model output (TMEn), with respect to CP, CF, EE and Ash (all used as % of DM) is shown in Table 3. Among the input variables, dietary Ash (%DM) has the highest values of VSR (3.14). It is followed by the dietary CF% (2.85), EE% and CP% (2.23 and 1.36, respectively). This indicates that the dietary Ash (%DM) is the most important variable

Table 2. The statistic values derived from Multiple Linear Regression (MLR) and Artificial Neural Network (ANN) models to estimate the nitrogen-corrected true metabolizable energy (TMEn) (Kcal kg^{-1} DM) of Wheat Bran (WB) provided through Ether Extract (EE), ash, Crude Protein (CP) and Crude Fiber (CF) (all used as % of DM).

	ANN model		MLR model	
Item[a]	Training set	Testing set	Training set	Testing set
R^2	0.90	0.89	0.81	0.84
RMSE (Kcal kg^{-1})	64.07	82.69	86.76	86.61
MAD	51.28	61.92	66.96	63.18
MAPE (%)	2.53	3.04	3.31	3.07
Type of activation function in hidden neurons	Exponential tangent			
Type of network	3 Layers perceptron			
Optimized number of hidden neurons found by genetic algorithm	5			

[a] RMSE= Root Mean Square Error; MAD= Mean Absolute Deviation, MAPE= Mean Absolute Percentage Error.

Table 3. The sensitivity analysis of input variables including Ether Extract (EE), ash, Crude Protein (CP) and Crude Fiber (CF) (all used as % of DM) in the Multiple Linear Regression (MLR) and Artificial Neural Network (ANN) models.

	Input Variable			
ANN Model	EE	Ash	CP	CF (%)
VSR[a]	2.23	3.14	1.36	2.85
Rank	3	1	4	2

[a] Variable sensitivity ratio.

	Input Variable			
MLR model	EE (%)	Ash (%)	CP (%)	CF (%)
Absolute *t* value	6.15	7.43	3.25	9.35
Rank	3	2	4	1

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in the ANN model, followed by dietary EE, CF and CP contents.

As mentioned, ANN model was more accurate to predict WB TMEn. For this reason, this model was used to draw a 3D response surface graph (Figure 2). The graphs are useful for understanding the effect of EE, Ash, CP and CF on TMEn. One of the graphs shows factors that have a positive effect (EE and CP) on TMEn and the other indicates factors that have a negative effect (Ash and CF) on TMEn. Due to the slope of the lines, EE (%DM) has a greater positive impact on TMEn than CP (%DM) (Figure 2). It is also observed that Ash (%DM) has greater negative impact on TMEn (Kcal kg^{-1} DM) than CF (Figure 2). It may be seen that, with increase of EE (%DM) and CP (%DM) content of WB, TMEn increased, while increasing the Ash and CF decreased the TMEn content.

DISCUSSION

The TMEn (Kcal kg^{-1} DM) values in this experiment were approximately similar to previously reported data (Dale, 1996; Nadeem, 2005). Dale (1996) found a range of 1663 to 3,178 Kcal kg^{-1} of DM by determining the TMEn (Kcal kg^{-1}) of wheat by-product samples. Nadeem *et al*. (2005) showed the TME (Kcal kg^{-1}) content of WB sample as 2,274 Kcal kg^{-1}. Hill *et al*. (1960) showed that WB contained low ME of 6.72 MJ kg^{-1} and later experiments reported that WB ME was lower with values varying from 5.26 to 5.44 MJ kg^{-1} (Allen, 1990; National Research Council, 1994).

The variations in TMEn (Kcal kg^{-1} DM) content among different WB may be due to the different values of EE, Ash, CP and CF contents (all used as % of DM). The energy content of WB has a positive correlation with the CP (%DM) and EE (%DM) content and negative correlation with the Ash (%DM) and CF (%DM) content.

One of the most important parameters of feed quality is its energy, since it is needed for execution of metabolic processes and animal activity. Not all energy of the feed (gross energy) will be utilized by the animal, but only a bio-available portion called Metabolizable Energy (ME). This parameter serves as an accurate indicator of feed quality, can be reliably used for feed quality control, and is crucial for diet formulation (Farrell, 1999). Several different equations to predict ME have been derived based on chemical characteristics of a feedstuff.

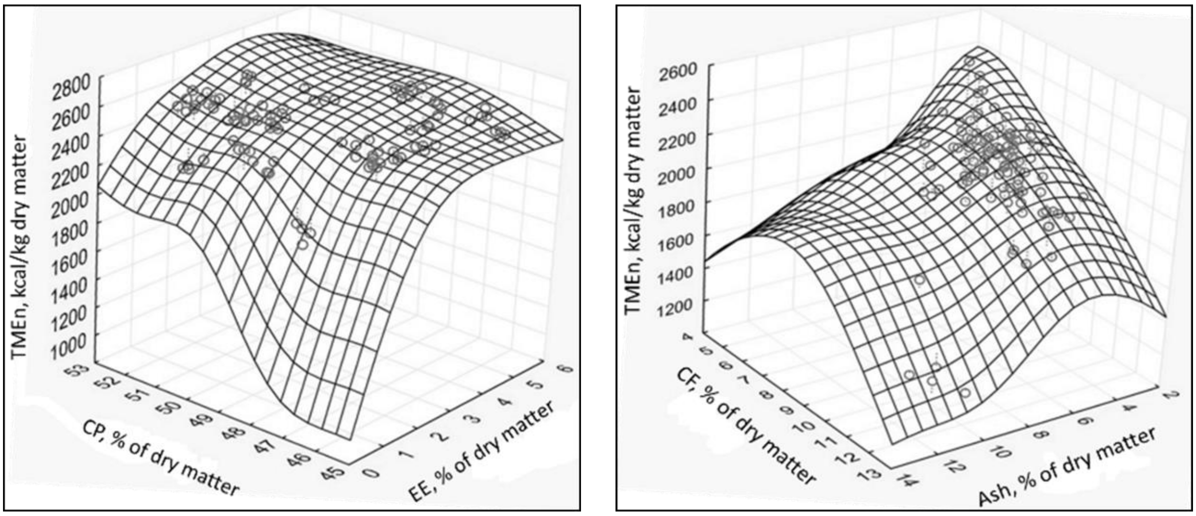

Figure 2. Variation of Artificial Neural Network (ANN) model predicted values of nitrogen-corrected True Metabolizable Energy (TMEn; Kcal kg^{-1}) of wheat bran given chemical compositions of Ether Extract (EE), ash, Crude Protein (CP) and Crude Fiber (CF) (all standardized as % of dry matter).

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Metayer *et al.*(1993) found that there is a noticeable correlation between starch (%), CF (%) and ME in oat. Losada *et al.* (2009) used regression equations to estimate ME of some grains using DM (%), EE (%), Ash (%), total sugars and CF (%). Ravindran *et al*. (2014) showed that the Apparent Metabolizable Energy (AME) (Kcal kg^{-1}) was positively influenced by EE (%) and sucrose (%), and negatively influenced by CF (%) and Ash (%) in SBM. Wan *et al.* (2009) used stepwise regression analysis to estimate TME values of wheat milling by-products for ducks using chemical composition, and demonstrated that NDF is the best predictor for TME, whereas the accuracy of prediction could be improved by the use of EE and CP rather than NDF alone.

As shown in this experiment, there is a good relationship between the TMEn and the chemical composition (EE, Ash, CP and CF, all used as % of DM) of WB. Of course, the EE, Ash, CP and CF (all used as % of DM) have a different effect on metabolism. As can be seen in the results, the increase in the EE (%DM) and CP (%DM) increases the TMEn (Kcal kg^{-1} DM) of the WB. The EE (%DM) can be considered an important variable responsible for the energetic variability of the feedstuffs (Zhang *et al*., 1994). This result can be linked to the high energy content of the EE (%DM) compared to the other contents of the feedstuffs.

As the Ash (%DM) and CF (%DM) rises, TMEn (Kcal kg^{-1} DM) decreases. Rodrigues *et al*. (2002) reported that the Ash (% DM) is also important in the energetic estimation of the feedstuffs because it represents, in the inverse form, the organic fraction of feedstuff. Some studies suggested that the fiber fraction should be considered when the chemical composition is used to establish a regression equation for predicting the ME (Kcal kg^{-1}) of feedstuffs (Noblet and Perez, 1993; Nascimento *et al.*, 2011). Svihus and Gullord (2002) determined that CF (%) content was negatively correlated to AME (Kcal kg^{-1}). CF (%) implies an incomplete degradation of feedstuff in the digestive system of birds and increases the transit time of feed through the gastrointestinal tract. This result corresponds well to the finding in the present study indicating that there is a negative correlation between CF (%DM) and TMEn (Kcal kg^{-1} DM) of WB samples.

Although MLR model has been used to predict the ME (Kcal kg^{-1} DM) in several feed ingredients, ANN is another candidate that can be successfully used to estimate the ME content of ingredient. The ANN is a modeling technique that is especially useful to address problems where solutions are not clearly formulated or where the relationships between inputs and outputs are not sufficiently known (Roush and Cravener, 1997).

Several studies have been conducted to evaluate the predictive ability of MLR models and ANN models in poultry. Ahmadi and Rodehutscord (2017) used MLR, ANN and Support Vector Machines (SVM) models to predict ME content of compound feeds for pigs based on the German energy evaluation system from analyzed contents of CP (%), EE (%), CF (%), and starch (%). Their results showed that ANN and SVM models were a more accurate prediction tool compared with the MLR model. Ahmadi *et al*. (2008) proposed an ANN model to predict the TMEn (Kcal kg^{-1}) of poultry by-products using 3 variables of CP (%), EE (%), and Ash (%). They reported that the ANN model may be used to accurately estimate the nutritive value of feedstuffs from their corresponding chemical composition, and the ANN model may show a higher efficiency of prediction compared with regression models. Similarly, Perai *et al*. (2010) examined the relationship between chemical composition of meat and bone meal (EE%, Ash%, and CP%) and TMEn (Kcal kg^{-1}) values by MLR, partial least squares, and ANN models. The results showed that the ANN model was a more accurate method for TMEn (Kcal kg^{-1}) estimation of meat and bone meal for poultry. MLR and AAN models were previously used to describe the correlation between chemical compositions and TMEn value of sorghum grain in poultry (Sedghi *et*

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al., 2011). The results of this study showed that the ANN model may more accurately estimate TMEn of feed ingredients than those using the MLR model.

The main advantages of ANN compared to MLR are: (1) The ANN models do not require a prior specification of suitable fitting function, and (2) ANN model have a universal approximation capability and it can approximate almost all kinds of non-linear functions including quadratic functions, whereas MLR is useful only for linear approximations (Desai *et al*., 2008). However, there are some limitations for the ANN modeling techniques. In this technique, standardized coefficients corresponding to each variable may not be easily calculated and presented as they are in MLR models. The ANN analyses produce matrix of weights, which are difficult to interpret as they usually are affected by the program used to generate them (Ahmadi and Rodehutscord, 2017). Thus, they actually use a “black box” approach, which does not offer complete insight into the internal workings of the model or information for evaluating the interaction of inputs (Dayhoff and DeLeo, 2001). In addition, there are some difficulties in sharing the developed ANN model with other researchers. In MLR model, one needs only to know the coefficients of the generated model and to perform simple calculations to predict an output (e.g. TMEn in our case). To share the developed ANN model, one needs to provide either a copy of the trained model or the connection weight matrices, which might be extremely large and complex, while to run ANN model one also needs some especial program or software. In this study, we export the developed ANN models as a C++ code and ANN_WB_ME_Poultry Excel® ME calculator to share them with the readers who might be interested to duplicate the results or to predict a new output based on WB chemical components. This spreadsheet is accessible via Supplementary Material. The ANN_WB_ME_Poultry (Figure 3) provides the nutritionist with an efficient and user-friendly tool to predict the TMEn in WB for poultry using ANN model. The only required information to obtain a given TMEn (Kcal kg^{-1}) is the chemical contents of EE, Ash, CP and CF (acceptable as % of DM) in a given WB sample.

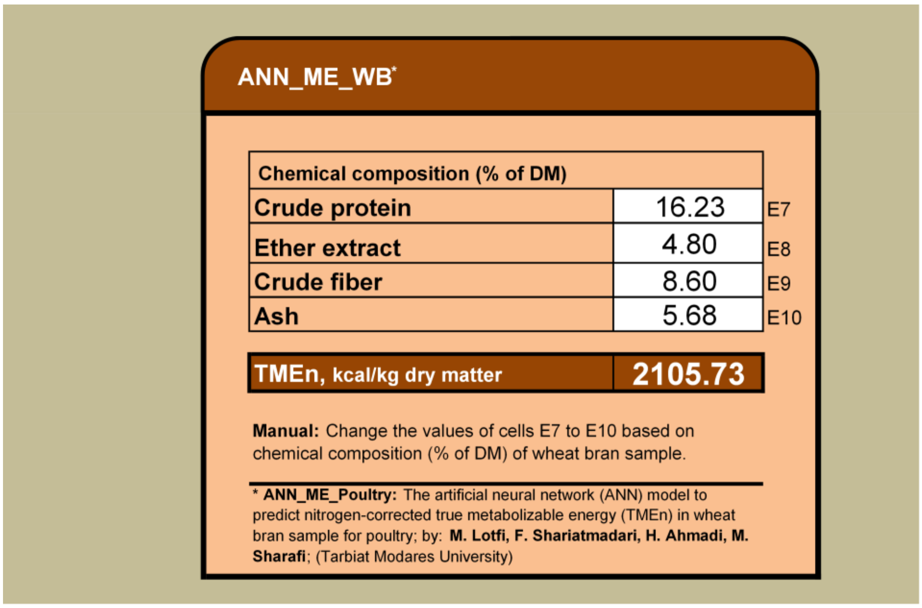

Figure 3. The ANN_ME_Poultry: An Excel® calculator to predict the nitrogen-corrected True Metabolizable Energy (TMEn) values of Wheat Bran (WB) samples for poultry, using Artificial Neural Network (ANN) model.

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CONCLUSIONS

The present study proposes the two methods of MLR and ANN approaches to predict TMEn of WB samples for poultry with given levels of chemical compositions. The developed ANN model produces relatively better prediction values in estimating TMEn in WB than those produced by MLR model. The results suggest that ANN methods may be able to enhance our ability to accurately predict energy contents of WB in order to achieve optimal situation in poultry nutrition. The developed and presented Excel® calculator, namely, ANN_WB_ME_Poultry, provides for the nutritionist an efficient and user-friendly tool to predict the TMEn values in WB for poultry, using ANN model.

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برآورد و پیش‌بینی انرژی قابل متابولیسم سبوس گندم برای طیور

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چکیده

روش بیولوژیکی مورد استفاده برای تعیین انرژی قابل متابولیسم حقیقی تصحیح شده برای ازت (TMEn)در مواد اولیه خوراکِ طیور پرهزینه و وقت‌گیر است. بنابراین یافتن یک روش جایگزین برای محاسبه دقیق میزانTMEn در مواد اولیه خوراک ضروری به نظر می‌رسد. در این مطالعه ۲ مدل رگرسیون خطی چندگانه و مدل شبکه عصبی مصنوعی برای پیش‌بینی مقدار TMEn (کیلو کالری/کیلوگرم ماده خشک) در نمونه‌های سبوس گندم با توجه به ترکیب شیمیایی آن (شامل: عصاره اتری، خاکستر، پروتئین خام و فیبر خام) به کار گرفته شد. برای تعیین ترکیب شیمیایی و TMEn ، یک مجموعه داده حاوی ۱۰۰ نمونه سبوس گندم مورد استفاده قرار گرفت. دقت پیش‌بینی هر یک از مدل‌ها در این آزمایش مورد بررسی قرار گرفت. نتایج این آزمایش نشان داد که مدل شبکه عصبی مصنوعی (ضریب تعیین: ۰.۹۰ و جذر میانگین مربعات خطا: ۶۴.۰۷ کیلو کالری/کیلوگرم برای داده‌های آموزش و ضریب تعیین: ۰.۸۹ و جذر میانگین مربعات خطا: ۸۲.۶۹ کیلو کالری/کیلوگرم برای داده‌های تست) توانسته است مقدار TMEn خوراک را با دقت بالاتری نسبت به مدل رگرسیون خطی چندگانه (ضریب تعیین: ۰.۸۱ و جذر میانگین مربعات خطا: ۸۷.۷۶ کیلو کالری/کیلوگرم برای داده‌های آموزش و ضریب تعیین: ۰.۸۴ و جذر میانگین مربعات خطا: ۸۶.۶۱ کیلو کالری/کیلوگرم برای داده‌های تست) پیش‌بینی نماید. به همین علت مدل شبکه عصبی معرفی شده می‌تواند به عنوان یک ابزار مفید برای مدل‌سازی رابطه بین ترکیب شیمیایی و انرژی نمونه‌های سبوس گندم مورد استفاده قرار گیرد. برای فراهم آوردن یک ابزار کاربردی و سریع برای کاربران یک فایل اکسل با نام ANN_WB_ME_Poultry، برای پیش‌بینی مقدار TMEn در نمونه‌های سبوس گندم با توجه به ترکیب شیمیایی آن تهیه و معرفی گردید.

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