Original Article

Artificial neural networks approach for predicting methionine requirement in broiler chickens

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Abstract

The objective of this research was to apply artificial neural networks (ANNs) for predicting the methionine requirement in broiler chickens at day 1-10 (starter period) and day 11-21 (grower period). A total of 28 data was obtained from five hundred and sixty male broiler chicks (Ross 308), which were divided into twenty-eight pens with twenty chickens in each. Body weight was determined at days 10 and 21. A bootstrapping method was used to multiply the observations to overcome the limited data for training. A total of 280 data was obtained and divided into a training set (n = 220) and a testing set (n = 60). The level of TSAA supplementation (%) was used as a variable in the input node, whereas the average daily gain (g) was used as a variable in the output node. The model evaluation was determined by R^2, mean absolute deviation (MAD), mean absolute percentage error (MAPE) and mean square error (MSE). Quadratic regression and ANNs with radial basis function were used to develop the model using Python programing. The results showed that no significant difference (P>0.05) was observed in means between the original data and the bootstrapping data. The ANNs showed greater accuracy of R^2 when compared with quadratic regression at the starter (0.7178 *vs*. 0.7294) and grower (0.8086 *vs*. 0.8097) periods. For error measurements, ANNs also resulted in lower MAD, MAPE and MSE when compared with quadratic regression at the starter and grower periods. In conclusion, the optimal level of methionine (as total sulphur amino acids) obtained by ANNs was 1.13 and 0.99% for starter and grower periods, respectively. Therefore, ANNs are an alternative method to predict methionine requirements of broiler chickens for improving poultry production.

Keywords: artificial neural networks, broiler chicken, methionine, prediction

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Introduction

Methionine has been widely accepted as a first limiting amino acid in poultry that is very important for growth performance, protein synthesis and cellular metabolic functions (Bunchasak, 2009). Dietary supplementation with methionine has a significant impact on growth performance and carcass quality in poultry (Kaewtapee and Bunchasak, 2018). For example, the greater methionine levels show lower body fat (Rostagno and Barbosa, 1995) and lower odor-related compounds in excreta (Chavez *et al*., 2004). Due to the sparing effect between methionine and cysteine, methionine can be supplemented in diets to meet the total sulfur amino acid (TSAA) requirement for poultry production (Bunchasak, 2009). As shown in previous research (NRC, 1994; Vázquez-Añón *et al*., 2004), regression analysis is commonly used to estimate nutrient requirements including TSAA intake. However, the predictive model obtained by traditional regression analysis requires a specific mathematical model (e.g. linear regression, quadratic regression or non-linear regression), which appears to be of more limited potential in obtaining the target value (Kaewtapee *et al*., 2011; Savegnago *et al*., 2011; Wang *et al*., 2012).

Currently, artificial intelligence (AI) is being applied to improve animal production and animal welfare (Liakos *et al*., 2018). Artificial neural networks (ANNs) are machines of learning in AI, which is based on the biological neuron of the human brain to respond to optimal predictive value (Sivanandam *et al*., 2006). The advantage of ANNs has been reported since it does not need mathematical models before prediction when compared with regression analysis (Kaewtapee *et al*., 2011). In addition, ANNs have been applied for the prediction of animal growth (Yee *et al*., 1993; Roush *et al*., 2006; Kaewtapee *et al*., 2011), the estimation of amino acid composition in feed ingredients (Roush and Cravener, 1997; Cravener and Roush, 2001), egg price forecasting (Ahmad *et al*., 2001) and nutrient requirements (Faridi *et al*., 2016). However, there is limited data for training the ANNs models as conducting experiments is costly, time-consuming and labor-intensive (Faridi *et al*., 2016). Alternatively, a bootstrapping method has been introduced to deal with this limitation. This method can generate a new dataset by replicating the original data (Faridi *et al*., 2014). As the amount of data in a training set affects the performance of the models, the data obtained from bootstrapping method can improve the accuracy and robustness of ANNs (Zhang, 1999).

Therefore, the objective of this study was to determine the potential of ANNs to predict TSAA requirements in broiler chickens at day 1-10 (starter period) and day 11-21 (grower period). A bootstrapping method was used to generate the data for developing ANNs models.

Materials and Methods

Animal Data: The data of our previous work (Nukreaw *et al*., 2011) was used to develop the models and animal care and use committee approval was not necessary for this study. A total of 28 data was obtained from five hundred and sixty male broiler chicks (Ross 308), which were divided into twenty-eight pens with twenty chickens in each. The experimental diets were provided as shown in Table 1 to meet the recommendations ((Aviagen, 2020). For day 1-10, the basal diet was supplemented with methionine (Sumitomo Chemical Co., Ltd, Tokyo, Japan) to meet the level of TSAA at 0.78, 1.25, 1.30 and 1.36%. For day 11-21, the basal diet was supplemented with methionine (Sumitomo Chemical Co., Ltd, Tokyo, Japan) to meet the level of TSAA at 0.54, 0.90, 0.95 and 1.00%. Water and feed were offered *ad libitum* throughout the experimental period. The chicks were weighed, and average daily gain (ADG) was averaged per pen at the end of each period.

Table 1 The feed formulation and nutrient compositions in the basal diet (g/kg, as fed-basis)

Ingredient	Day 1-10	Day 11 to 21
Corn	623.40	629.31
Rice bran oil	10.01	32.77
Soybean meal	285.93	265.71
Full-fat soybean meal	20.00	20.00
Monodicalcium phosphate (Phophorus 21%)	23.85	21.14
Lime stone	13.30	11.96
Salt	2.09	2.13
L-lysine	-	-
DL-methionine	-	-
L-threonine	2.13	1.18
Vitamin and trace mineral premix[1]	5.00	5.00
Sacox	0.50	0.50
Antioxidant	0.50	0.50
Cornstarch	13.29	9.80
Total	1000.00	1000.00
Chemical composition (g/kg, as dry matter basis)		
Metabolizable energy (kcal/kg) kcal/kg	3,010	3,175
Crude protein (g/kg)	190.0	180.0
L-Lysine (mg/g)	10.2	9.6
Total sulfur amino acid (mg/g)	6.2	5.9

[1]Vitamin and mineral premix content (per kg of diet): retinyl acetate 4.13 mg, cholecalciferol 75 µg, α-tocopherol acetate 13.5 mg, vitamin K_3 1.5 mg, vitamin B_1 1.5 mg, vitamin B_2 5 mg, vitamin B_6 2 mg, vitamin B_{12} 0.05 mg, niacin 25 mg, Ca-D-panthothenate 8 mg, folic acid 3 mg, biotin 0.12 mg, choline chloride 0.16 mg, antioxidant 30 mg, manganese 80 mg, zinc 60 mg, iron 40 mg, copper 8 mg, iodine 0.05 mg, cobalt 0.10 mg, selenium 0.10 mg.

[2]Calculated metabolizable energy (g/kg, as dry matter basis)

A bootstrapping method was used to multiply the observations to overcome the limited data for training (Faridi *et al.*, 2014). The original data (n=28) was randomly divided into two groups of 22 data and 6 data and the resample scikit-learn library was performed in the bootstrapping method using Python 3.7 (Brownlee, 2018) to generate 220 data and 60 data, respectively. Mean, standard deviation (SD) and 95% confident interval were calculated, whereas a paired t-test was used to compare the mean of two groups using the data analysis function in Microsoft Excel. Probability values of <0.05 were considered significant.

Model development: *Quadratic regression* was used to study TSAA requirements. The model is shown below:

$$y = \beta_0 + \beta_1 x + \beta_2 x^2$$

where y is the ADG (g), x is a level of TSAA supplementation (%), and β is a rate constant.

The radial basis function (RBF) is a feed-forward, which is classified as ANNs that can be used to develop the predictive model (Kaewtapee *et al.*, 2011). The network is designed to perform as a local mapping to provide a simple topological structure for solving the complexity of problems (Bishop, 1991). The RBF has 3 layers including an input layer, hidden layer and output layer. The hidden nodes were chosen based on the number of nodes (parameters) in the input layer using the function as follows (Xiong and Dai, 2020):

$$\text{Hidden nodes} = (2 \times \text{number of input node}) + 1$$

Therefore, a 1-3-1 of ANNs was used and referred to one input layer of one node, one hidden layer of three nodes and the output layer of one node (Figure 1). The level of TSAA supplementation (%) was used as a variable in the input node, whereas the ADG (g) was used as a variable in the output node.

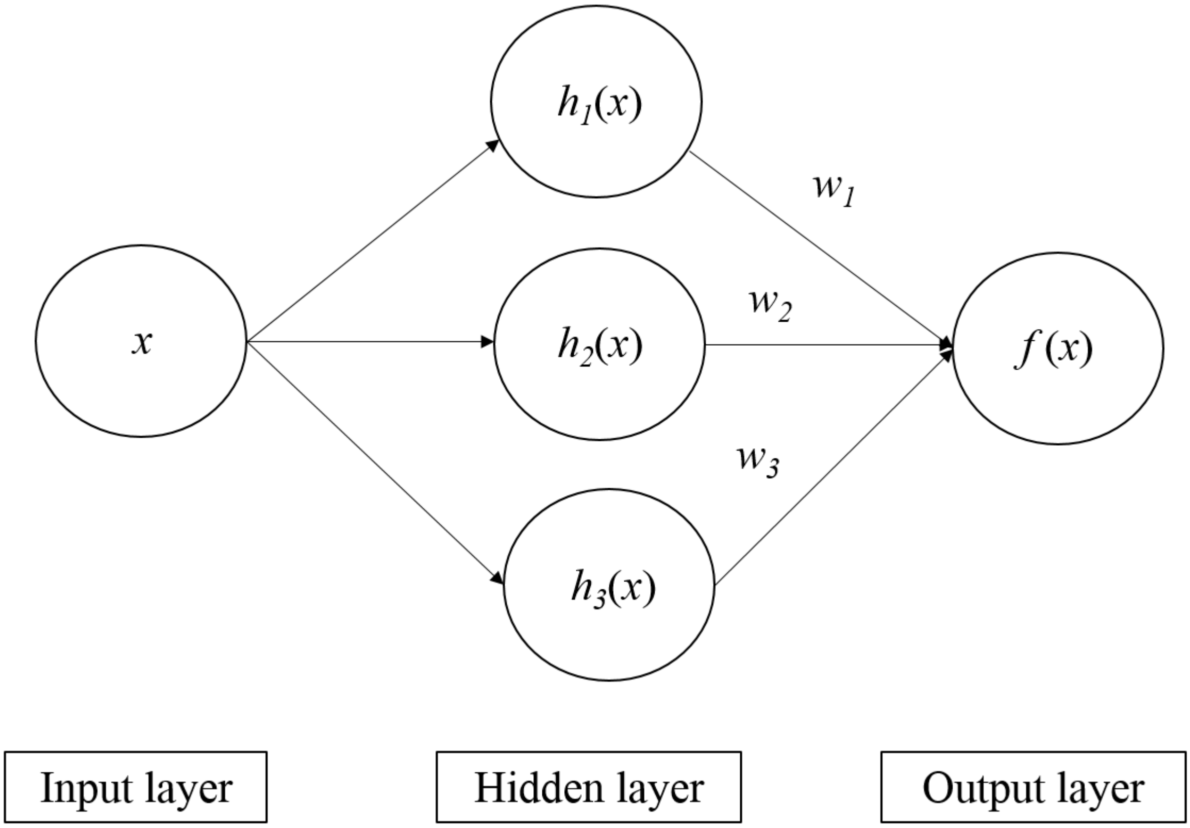

Figure 1 The radial basis function network. One node in the input layer feeds forward to three nodes with radial basis function of $h(x)$ in the hidden layer and the three nodes are combined with each weight (w_1, w_2, w_3) into the network output node with a linear function of $f(x)$.

The learning rate is set at 0.01 and initialized with a population of random particles and the algorithm searches. The maximum R^2 and minimum error measurement are used as the optimization technique to obtain the predictive model. The K-means clustering was used to determined unit centers according to the method described by Yuqing *et al*., (2016) as follows:

Step 1: the k samples were randomly selected as initial cluster centers from the total samples.

Step 2: the Euclidean distance between samples and the clustering centers were calculated, and each sample was allocated to the neighboring clustering in accordance with the minimum distance.

Step 3: the mean of each cluster was used as a new clustering center.

Step 2 and 3 were repeated until the clustering center was no longer changed. Finally, the k clustering centers were obtained and then were fully connected to each node in the hidden layer. A typical radial basis function is the Gaussian function (Orr, 1996) which is used as the activation functions in the hidden layer. The Gaussian function is shown as follows:

$$h(x) = \exp(-\frac{(x-c)^2}{2\sigma^2})$$

where x is a level of TSAA supplementation (%) of input layer and c is a unit center. The σ^2 is variance, which is calculated as follows:

$$\sigma^2 = \frac{\sum (x-\bar{x})}{n-1}$$

where $\bar{x}$ is the mean of all observations and n is the number of observations. The linear function used in the output layer is shown as follows:

$$f(x) = \sum_{i=1}^{3} w_i h_i(x)$$

where w_i is the weight for the linear combination at the hidden node i, and h_i is radial basis function at the hidden node i. Therefore, $f(x)$ is a function of output (y) which can be expressed as

$$y = \sum_{i=1}^{3} w_i \exp(-\frac{(x-c_i)^2}{2\sigma_i^2})$$

where σ_i^2 is variance at the hidden node i.

A total of 220 data was used for the training set, whereas a total of 60 data was used for testing set. In addition, the training set was split at 0.1 for a validation set to demonstrate the generalizability of the models. Quadratic regression and ANNs were used to develop the predictive model. The optimal level of TSAA (%) for maximum ADG (g) was determined as follows:

Optimal level = argmax(F(x))

where F is the quadratic function and ANNs model. The model evaluation was determined as follows: 1) R^2, computed as

$$R^2 = 1 - \frac{\sum_{t=1}^{n}(y_t - \hat{y})^2}{\sum_{t=1}^{n}(y_t - \bar{y})^2}$$

where y_t is the observed value at time t, $\bar{y}$ is the mean of y_t and $\hat{y}_t$ is the estimated value; 2) the mean absolute deviation (MAD), computed as

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

3) mean absolute percentage error (MAPE), computed as

$$\text{MAPE} = \frac{1}{n}\frac{\sum_{t=1}^{n}|y_t - \hat{y}_t|}{y_t} \times 100$$

4) mean square error (MSE), computed as

$$\text{MSE} = \frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{n}$$

The python libraries including numpy, pandas, matplotlib and scikit-learn were used to determined quadratic regression and the accuracy of the predictive model, whereas Visual C# program was used to perform ANNs to develop the predictive model. The pipeline of data processing is shown in Figure 2.

Results

The data of the bootstrapping method is shown in Figure 3 and Figure 4 for starter and grower periods, respectively. The means of the original data and bootstrapping data were 17.21 g and 17.25 g for the starter period and 50.88 g and 50.99 g for the grower period (Table 2). Furthermore, there was no significant difference (P=0.85) in ADG between the original data and the bootstrapping data at the starter and grower periods.

Table 2 The pairwise comparison between original data and bootstrapping data of average daily gain in broiler chickens

Item	Original data (*n=28*)			Bootstrapping data (*n=280*)			*P*-value
	Mean ± SD	95% confident interval		Mean ± SD	95% confident interval		
		Lower	Upper		Lower	Upper	
Day 1-10	17.21 ± 1.08	16.79	17.63	17.25 ± 1.09	17.12	17.38	0.85
Day 11-21	50.88 ± 3.13	49.66	52.09	50.99 ± 3.11	50.63	51.36	0.85

n = number of data; SD = standard deviation

The scatter plots and curves of the models are shown in Figure 5. The quadratic regression was fit for the data at the starter period as y = -1.74 + 32.87x - 13.72x^2 (R^2=0.7178), and for the data at the grower period as y = 17.35 + 73.11x -37.85x^2 (R^2=0.8086). In comparison, ANNs models were a better fit than quadratic regressions as the higher R^2 of ANNs are 0.7294 and 0.8097 at the starter and grower periods, respectively. In addition, ANNs also showed lower MAD, MAPE and MSE when compared to quadratic regressions at the starter and grower periods (Table 3).

The optimal level of TSAA (%) in broiler chickens is shown in Table 4. The optimal level of TSAA obtained from ANNs model and quadratic regression was 1.13 and 1.20% at the starter period, and 0.99 and 0.97% at the grower period, respectively. Furthermore, the predicted ADGs were greater in ANNs model than quadratic regression, amounting to 18.21 and 17.95 g at the starter period, and 52.73 and 52.65 g at the grower period, respectively.

Table 3 The model evaluation of quadratic regression and artificial neural networks (ANNs)

Item	Day 1-10		Day 11-21	
	Quadratic regression	ANNs	Quadratic regression	ANNs
R^2	0.7178	0.7294	0.8086	0.8097
MAD	0.1260	0.0964	0.2555	0.2470
MAPE	0.7309	0.5634	0.4906	0.4768
MSE	0.0229	0.0150	0.1257	0.1087

MAD = mean absolute deviation; MAPE = mean absolute percentage error; MSE = mean square error

Table 4 Optimal level of total sulphur amino acid requirement in broiler chicken

Item	Optimal level of total sulphur amino acid requirement (%)		Predicted average daily gain (g)	
	Quadratic regression	ANNs	Quadratic regression	ANNs
Day 1-10	1.20	1.13	17.95	18.21
Day 11-21	0.97	0.99	52.65	52.73

ANNs = artificial neural networks

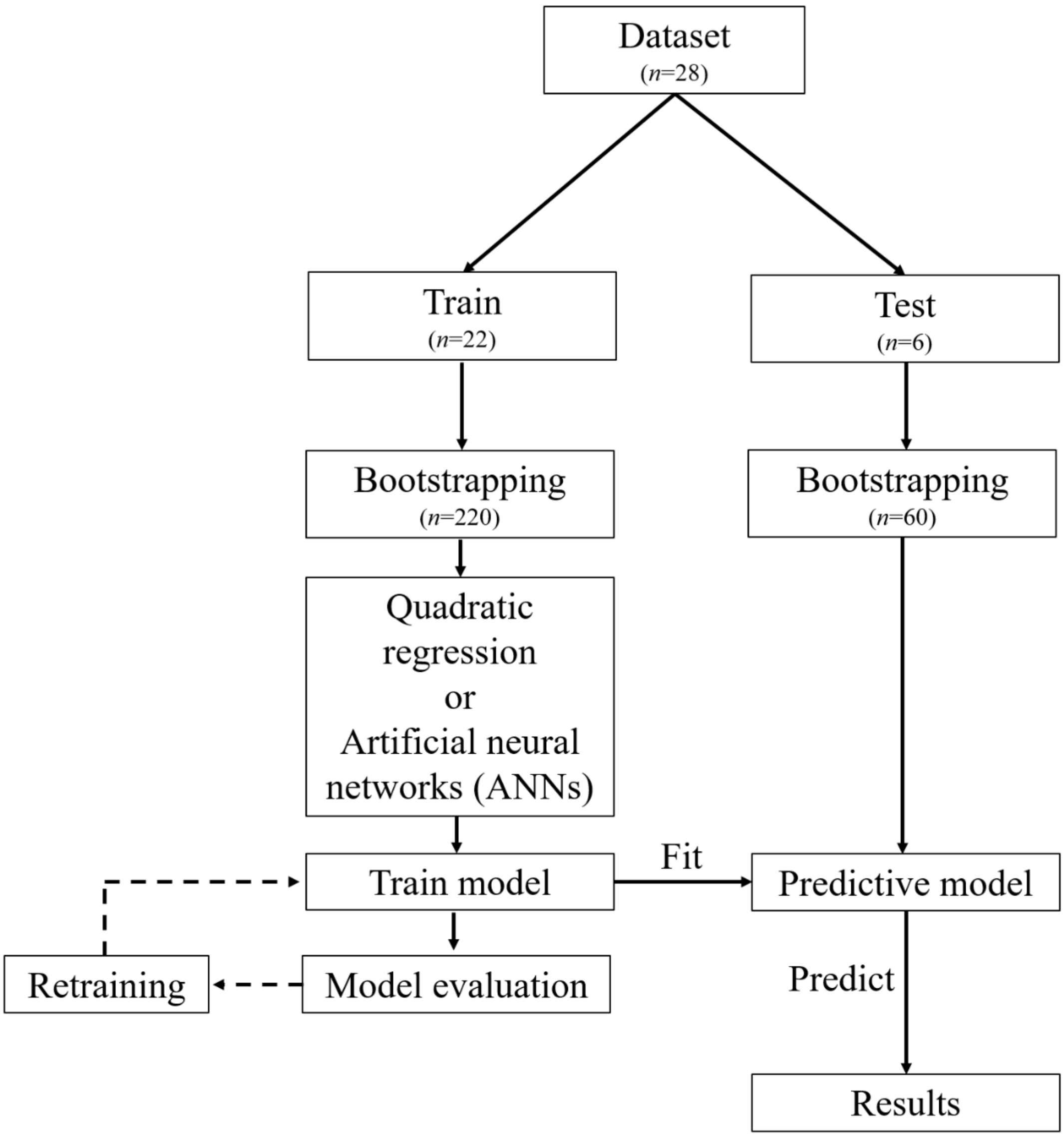

Figure 2 The pipeline of data processing to develop the predictive model of quadratic regression and artificial neural networks.

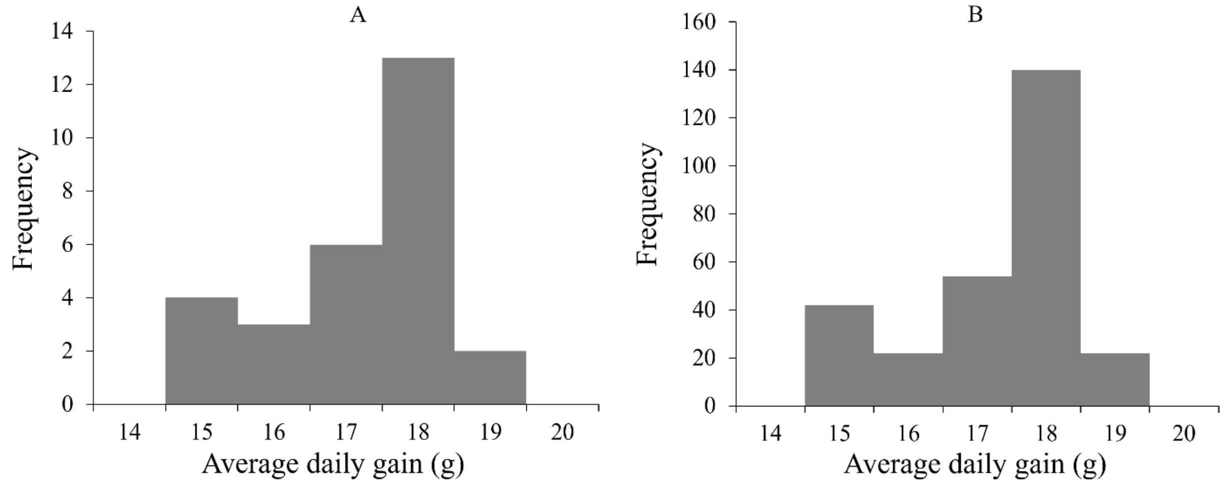

Figure 3 The histogram of frequency of average daily gain of broiler chickens on day 1-10: A) original data, and B) bootstrapping data.

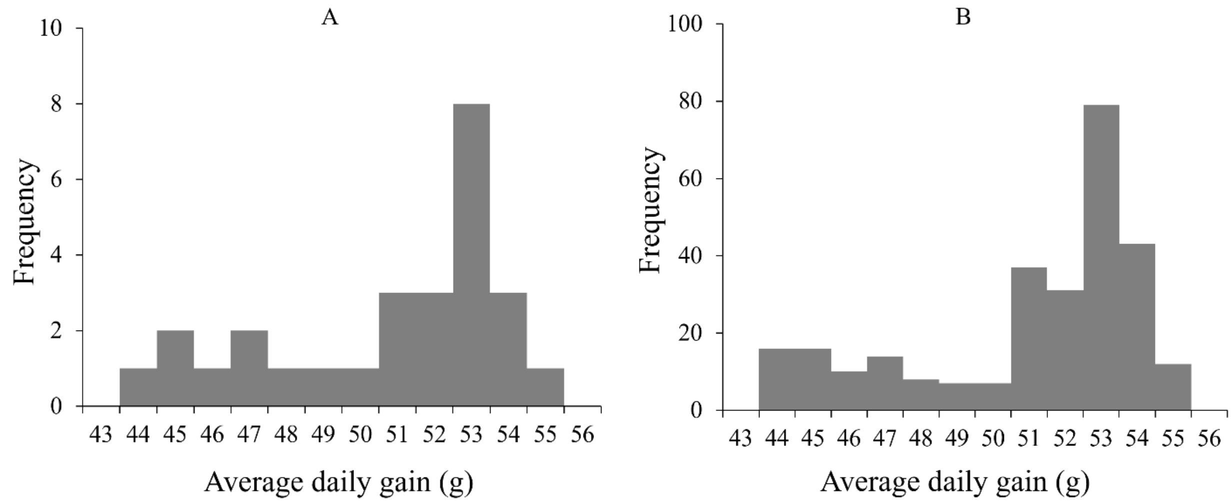

Figure 4 The histogram of frequency of average daily gain of broiler chickens on day 11-21: A) original data, and B) bootstrapping data.

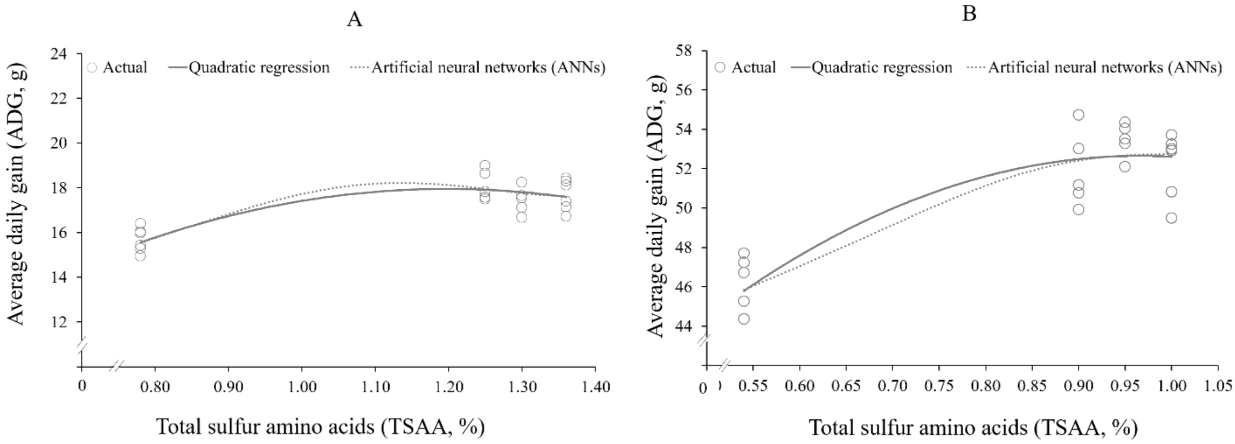

Figure 5 The scatter plots and the curves of the quadratic regression and ANNs between TSAA level (%) and ADG (g): A) day 1-10, and B) day 11-21.

Discussion

The bootstrapping method can increase the limited number of data for the training model without reshaping the distribution. It is confirmed by the present study that there were no significant differences between the original data and bootstrapping data at the starter and grower periods (Figure 3 and Figure 4). The mean and SD are very close between the original data and bootstrapping data. In general, the data is randomly divided into training and testing sets (8:2 ratio). The small amount of data also affected the learning process, which may interrupt the potential of the model as it was dependent on the available data in the training set (Maier and Dandy, 2000). To overcome this problem, the bootstrapping method has been widely accepted to multiply the data for training and testing the model (Faridi *et al*., 2013). As shown in a previous study (Faridi *et al*., 2016), the bootstrapping method showed the advantage of re-sampling data in poultry nutrition where the conducting experiments are expensive and time-consuming. Therefore, the bootstrapping method is one technique to overcome the limited data for ANNs.

Artificial neuron networks are a mathematical method, which can be used to solve complex problems and improve predictability value (Ahmad *et al*., 2001; Cravener and Roush, 2001; Faridi *et al*., 2016). The methods have great flexibility and do not require model assumption (Savegnago *et al*., 2011). In the present study, ANNs showed higher accuracy and lower error measurement, which indicates that ANNs can provide a better fit than quadratic regression. Notably, the optimal level of TSAA requirement obtained from ANNs was very close to strain recommendation (Aviagen, 2020). This result is in line with our previous research (Kaewtapee *et al*., 2011), where ANNs using radial basis function produced more accurate predictions for the body weights of Cherry Valley ducks. The power of prediction may lie in the fact that a learning algorithm corresponds to solve rapidly with radial basis function and the network performs based on the cluster data, which is usually concentrated in a local area centered at the weight vector (Bishop, 1991).

Furthermore, the number of ANNs research in animal science has been increased in recent decades. The previous research in broiler chickens (Roush *et al*., 2006) suggested that ANNs resulted in lower MAD, MAPE, MSE and bias when compared to Gompertz non-linear regression. The ANNs also produced little or no overestimation of the observed body weight responses. Likewise, Wang *et al*., (2012) reported that ANNs is more accurate than regression analysis for predicting egg production. For pig production, Pandorfi *et al*., (2011) evaluated the performance of pregnant sows based on environmental and physiological variables using ANNs. The prediction of the response parameters presents few cases of over- or underestimating values. Overall, the results suggested that ANNs are a powerful technique for data analysis as they can be fitted to any kind of dataset by learning the process and adjusting weight, resulting in more accurate prediction based on input data (Kaewtapee *et al*., 2011; Savegnago *et al*., 2011).

In conclusion, it is likely that ANNs has more accurate prediction for methionine requirement in broiler chickens since the results indicated a better fit than quadratic regression. The bootstrapping method is one technique, which can be used to increase the data for training the ANNs models. The optimal level of TSAA obtained by ANNs was 1.13 and 0.99%, resulting in maximum ADG (18.21 and 52.73 g at starter and grower periods, respectively). Therefore, ANNs are an alternative method to predict methionine requirement for improving the ADG of broiler chickens.

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References

Ahmad HA, Dozier GV and Roland Sr DA 2001. Egg price forecasting using neural networks. J Appl Poult Res. 10: 162–171.

Bishop C 1991. Improving the generalization properties of radial basis function neural networks. Neu Comp. 3: 579–588.

Brownlee J 2018. "A gentle introduction to the bootstrap method." [Online]. Available: https://machinelearningmastery.com/a-gentle-introduction-to-the-bootstrap-method/. Accessed January 31, 2020.

Bunchasak, C 2009. Role of dietary methionine in poultry production. J Poult Sci. 46: 169–179.

Chavez C, Coufal CD, Lacey RE, and Carey JB 2004. The impact of methionine source on poultry fecal matter odor volatiles. Poult Sci. 83: 359–364.

Cravener TL and Roush WB 2001. Prediction of amino acid profiles in feed ingredients: Genetic algorithm calibration of artificial neural networks. *Anim Feed Sci Technol*. 90: 131–141.

Faridi A, Golian A, France J and Heravi H 2013. Study of broiler chicken responses to dietary protein and lysine using neural network and response surface models. Bri Poult Sci. 54: 524–530.

Faridi A, Golian A, Heravi H and France J 2014. Bootstrapped neural network models for analyzing the responses of broiler chicks to dietary protein and branched chain amino acids. Can J Anim Sci. 94: 79–85.

Faridi A, Gitoee A, Sakomura NK, Donato DCZ, Angelica Gonsalves C, Feire Sarcinelli M, Bernardino de Lima M and France J 2016. Broiler responses to digestible total sulphur amino acids at different ages: a neural network approach. J Appl Anim Res. 44: 315–322.

Kaewtapee C, Khetchaturat C and Bunchasak C 2011. Comparison of growth models between artificial neural networks and nonlinear regression analysis in Cherry Valley ducks. J Appl Poult Res. 20: 421–428.

Kaewtapee, C and Bunchasak C 2018. Comparative effect of DL-methionine and DL-methionine hydroxy analogue supplemented diet on productive performance, fat accumulation and lipid profile in blood of meat-type ducks. Thai J Vet Med. 48(4): 645–653.

Liakos KG, Busato P, Moshou D, Pearson S and Bochtis D 2018. Machine learning in agriculture: a review. Sensors. 18: 2674.

Maier HR and Dandy GC 2000. Neural networks for the prediction and forecasting of water resources variables: a review of modeling issues and applications. Environ Model Soft. 15: 101–124.

NRC 1994. Nutrient Requirements of Poultry. 9th rev. ed. Washington, DC: National Academy Press. 176 pp.

Nukreaw R, Bunchasak C, Markvichitr K, Choothesa A, Prasanpanich S and Loongyai W 2011. Effects of methionine supplementation in low-protein diets and subsequent re-feeding on growth performance, liver and serum lipid profile, body composition and carcass quality of broiler chickens at 42 days of age. J Poult Sci. 48: 229–238.

Orr MJL 1996. Introduction to radial basis function. Centre for Cognitive Science, University of Edinburgh, Scotland. 67 pp.

Pandorfi P, Silva IJO, Sarnighausen VCR, Vieira FMC, Nascimento ST and Guiselini C 2011. Use of artificial neural networks on the prediction of zootechnical indexes on gestation and farrowing stages of swine. Rev Bras Zootecn 40(3): 676–681.

Rostagno, HS and Barbosa WA 1995. Biological efficacy and absorption of DL-methionine hydroxyl analogue free acid compared to DL-methionine in chickens as affected by heat stress. Bri Poult Sci. 36: 303–312.

Roush WB and Cravener TL 1997. Artificial neural network prediction of amino acid levels in feed ingredients. Poult Sci. 76: 721–727.

Roush WB, Dozier WA and Branton SL 2006. Comparison of Gompertz and neural network models of broiler growth. Poult Sci. 85: 794–797.

Xiong M and Dai K 2020. The optimization algorithm based on neural networks in post-processing ensemble forecast. In: Signal and Information Processing, Networking and Computers: Proceedings of the 6th International Conference on Signal and Information Processing, Networking and Computers (ICSINC). Y Wang, M Fu, L Xu and J Zou (Eds). Singapore: Springer Nature.772–780.

Savegnago RP, Nunes BN, Caetano SL, Ferraudo AS, *Schmidt GS*, *Ledur MC* and *Munari DP 2011*. *Comparison* of *logistic* and *neural network models* to *fit* to the *egg production curve* of *White Leghorn hens*. Poult Sci. 90: 705–711.

Sivanandam SN, Sumathi S and Deepa SN 2006. Introduction to neural networks using matlab 6.0. Tata McGraw-Hill Publishing Company Limited, New Delhi, India. 656 pp.

Vázquez-Añón MD, Kratzer R, Gonzalez-Esquerra GF Yi and Knight CD 2004 A comprehensive summary of experiments to define factors that may affect the gain response to 2-hydroxy-4 methylthio butanoic acid (HMTBA) and DL-methionine (DLM) in broilers. Poult Sci. 83(Suppl 1): 432.

Wang BY, Chen SA and Roan SW 2012. Comparison of regression and artificial neural network models of egg production. J Anim Vet Adv. 11(14): 2503–2508.

Yee D, Prior MG and Florence LZ 1993. Development of predictive models of laboratory animal growth using artificial neural networks. Comput Appl Biosci. 9: 517–522.

Yuqing, S., Q. Junfei and H. Honggui. 2016. Structure design for RBF neural network based on improved K-means algorithm. *In: Chinese Control and Decision Conference (CCDC)*, Yinchuan, China, May 28-30. 7035-7040.

Zhang J, 1999. Inferential estimation of polymer quality using bootstrap aggregated neural networks. Neural Netw. 12: 927–938.