


# Predicting breeding value of body weight at 6-month age using Artificial Neural Networks in Kermani sheep breed

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**ABSTRACT.** The present study aimed to apply artificial neural networks to predict the breeding values of body weight in 6-month age of Kermani sheep. For this purpose, records of 867 lambs including lamb sex, dam age, birth weight, weaning weight, age at 3-month (3 months old), age at 6-month (6 months old) and body weight at 3 months of age were used. Firstly, genetic parameters of the animals were estimated using ASReml software. The data was then pre-processed for using in MATLAB software. After initial experiments on the appropriate neural network architecture for body weight at 6-month age, two networks were examined. A feed-forward back propagation multilayer perceptron (MLP) algorithm was used and 70% of all data used as training data, 15% as testing data and 15% as validating data, to prevent over-fitting of the artificial neural network. Results showed that the both networks capable to predict breeding values for body weight at 6 month-age in Kermani sheep. It can be concluded that artificial neural network has a good ability to predict growth traits in Kermani sheep with an acceptable speed and accuracy. Therefore, this network, instead of commonly-used procedures can be used to estimate the breeding values for productive and reproductive traits in domestic animals.

**Keywords:** estimate; genetic parameters; growth traits; lamb.

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## Introduction

There are 26 sheep breeds in Iran, each having been adapted to a certain region (Khodabakhshzadeh et al., 2016; Zamani, Akhondi, & Mohammadabadi, 2015). Kermani sheep is one of the most important breeds of Iran's native sheep. It is well adapted to the harsh and undesirable environmental conditions of the southeastern part of Iran which mainly has hot and dry climate, as well as poor pastures and low vegetation cover. This breed is a dual-purpose fat-tailed sheep (meat and wool) which is medium-sized and has white wool (Mohammadabadi & Sattayimokhtari, 2013). This sheep provides many needs of nomads and breeders in Kerman province. Therefore, attention to the breeding of this livestock improvement of its environmental condition and genetic parameters of Kermani sheep has contributed greatly to providing for part of needs to livestock (Kargar, Moradishahrababak, Moravej, & Rokuei, 2006).

One of the important economic values that can be measured in order to improve sheep breeding and to increase meat production are growth traits such as birth weight, weight at 3 months of age, weight at 6 months of age, weight at 9 months of age and weight at 12 months of age. The weight at 3 months of age in which weaning is often occurred is considered as one of the most important production traits in sheep. At this age, maternal effects are diminishing on the lamb and this trait can be considered as one of the selection criteria (Saatci, Dewi, & Ulutas, 1999). Measuring various body structures is a good criterion for judging meat qualities, and is also useful in developing appropriate selection criteria (Bote & Basu, 1984). The weight at 6 months of age is one of the most important economic values. If the selection response is to increase meat production at the period of fattening, this trait could be considered as a suitable criterion. Based on the available reports, different environmental factors such as year and month of birth, lamb sex and dam age have a significant effect on the weight at 6 months of age trait (Vaez, Nicolas, & Raadsma, 1996).

It is very important to know the sheep body weight for breeding (selection), nutritional reasons, health care (prescription of antibiotics, limnetic) and monitoring the growth pattern. On the other hand, live

weight can be predicted by means of body measurements. A weight prediction equation based on body measurements could be very useful for weighing animals in a farm with little facility (Bhattacharya, Ghosh, Duttgupta, & Maitra, 1984).

Few studies have applied artificial neural network (ANN) models in animal science research to predict milk yield, fat and protein (Salehi, Lacroix, & Wade, 1998), somatic cell count, fat and protein milk concentration and milk production (Pour Hamidi et al., 2017).

Pour Hamidi, Mohammadabadi, Asadi Foozi, and Nezamabadi-pour (2017) used ANN for predicting the breeding values for the milk production trait in Iranian Holstein dairy cattle (Pour Hamidi et al., 2017; Vassileva & Radev, 2001) applied ANN to evaluate the physiological status of cows such as estrus, calving and health and Wilkinson, Ming, Anderson, Bunch, and White (1996) also used ANN to perform laboratory analysis of fetal development. The usefulness of ANN has been examined properly for lactation prediction and test-day milk yield in Chios dairy sheep (Kominakis, Abas, Maltaris, & Rogdakis, 2002).

Compared to regression analysis, ANNs do not require prior knowledge of the problem, and the adjustment and matching between the input and output variables are performed without any assumption, thus ANNs are more suitable tools for estimation, and are more accurate than multiple linear regression, especially when models are combined in a system (Njubi, Wakhungu, & Badamana, 2010).

The current study was conducted to apply artificial neural networks to predict the breeding values of body weight in 6-month age of Kermani sheep. Although ANNs have been widely used for prediction and categorization in various fields such as finance, medicine, geology, engineering, physics, and biology, but few studies have applied these networks in breeding and especially in the production of small ruminants (Grzesiak, Lacroix, Wójcik, & Błaszczyk, 2003; Sharma, Sharma, & Kasana, 2006, 2007). On the other hand, despite the fact that a lot of studies have been carried out on the quantitative and molecular genetics of Kermani sheep, no studies have been reported on the application of ANNs on this breed.

## Material and Methods

Data on 867 newborn lamb of Kermani sheep recorded from 1994 to 2004 were obtained from the Kermani sheep Breeding Center of Iran, after omitting the out-of-range and illogical data using the LINUX software. Breeding values for the body weight at 3 months and 6 months ages trait were estimated using the ASReml software via univariate animal model (1):

$$y = Xb + Zu + e \quad (1)$$

where,  $y$ ; is the observation vector,  $X$ ; matrix of design for fixed effects,  $b$ ; fixed effects vector,  $Z$ ; matrix of design for genetic effects,  $u$ ; genetic effects vector and  $e$ ; error random effects vector.

From all data, 70% data were used as training set, 15% as testing set and 15% as the validating set, to prevent over-fitting of artificial neural network. A feed-forward backpropagation multilayer perceptron (MLP herein) algorithm (Reed & Marks, 1998) was used in MATLAB v7.0 software (2005).

Backpropagation always seeks to minimize squared error. Therefore, each neural network follows an error function similar to Equation (1) (Moradi, Joka, & Forouzantabar, 2015).

$$\text{Equation (1)} \quad \varepsilon(t) = \frac{1}{2} e^2$$

In Equation (1),  $\varepsilon(t)$  indicates the instantaneous value of error at time  $t$  and  $e$  represents the value of observed error.

For designing a network, parameters such as network structure, type of training algorithm, learning rate, number of network layers, number of neurons per layer, and number of epochs for each pattern during training must be determined. MLP utilizes a supervised learning technique called back propagation for training, and its learning rule is generalized delta learning rule.

Prior to network training, inputs and targets were scaled so that they fall approximately in a specific range to improve network performance. There are several ways to normalize data. However, one of the common ways to scale network inputs is to use the maximum and minimum data. Equation (2) was used for this purpose (Moradi et al., 2015).

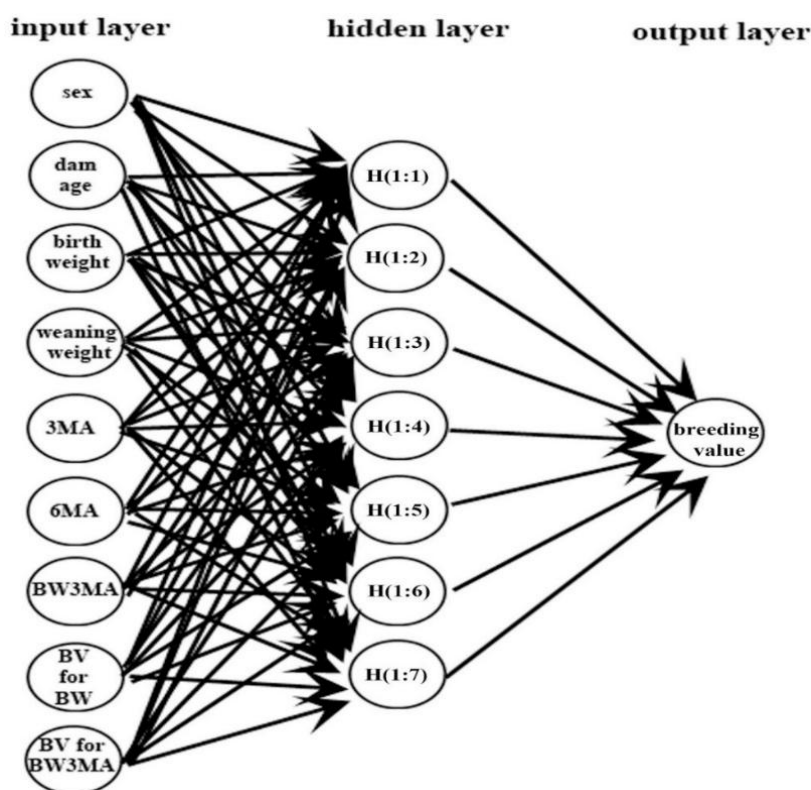
$$\text{Equation (2)} \quad xn = \frac{x - \min}{\max - \min}$$

where,  $x_n$ , max and min represent the normalized data, maximum data and minimum data, respectively, and  $x$  indicates the data before normalization. After the application of raw and normalized data in this research, it was observed that normalized data improves the network performance, especially its generalizability. Therefore, this study used normalized data.

Neural networks can have different structures, but the most common one is multilayer structure which is also utilized in this study. The structure used in this study has one input layer, one to several intermediate or hidden layers, and one output layer. As shown in Figure 1, each layer has a number of nodes or neurons (in biological terms).

After normalizing the input data, the network architecture was selected. After creating the models, prediction accuracy was used as the criterion for models' performance in order to investigate the research hypotheses. Prediction accuracy is the correlation between the predicted value and the actual value estimated by MATLAB itself. It indicates the degree in which the estimated outputs are close to the actual outputs.

In this study, the number of neurons in the input layer of the first network for body weight at 6-month age was seven neurons, and in the second network for body weight at 6-month age was 9 neurons. Determining the number of neurons in the intermediate (hidden) layer is not an easy task, and is more done using trial and error in a way that the overall performance of the network is improved. In fact, if the number of neurons in the intermediate layer is too large, the network will memorize rather than learn. Therefore, a balance must be established between the two in order to improve the overall performance of the network. 70% of all data used as training data, 15% as testing data and 15% as validating data, to prevent over-fitting of the artificial neural network. During the learning process, network learning rate was regularly measured by objective functions, and eventually the network that had the least error was accepted. In the artificial neural network used in this research, data was analyzed via various training functions such as `traingd` (Gradient Descent) and `trainlm` (Levenberg-Marquardt Backpropagation) (Beale, Hagan, & H.B., 2004). Based on the correlation coefficient and mean squared error (MSE), `trainlm` had the best results than other training functions as it had the highest correlation coefficient and lowest MSE.



**Figure 1.** Variables and layers used in the training data sets for artificial neural networks in Kermani sheep. 3 MA: 3 months of age, 6MA: 6 months of age, BW3MA; body weight at 3 months of age, BV for BW: breeding value for birth weight, BV for BW3MA: breeding value for body weight at 3 months of age.

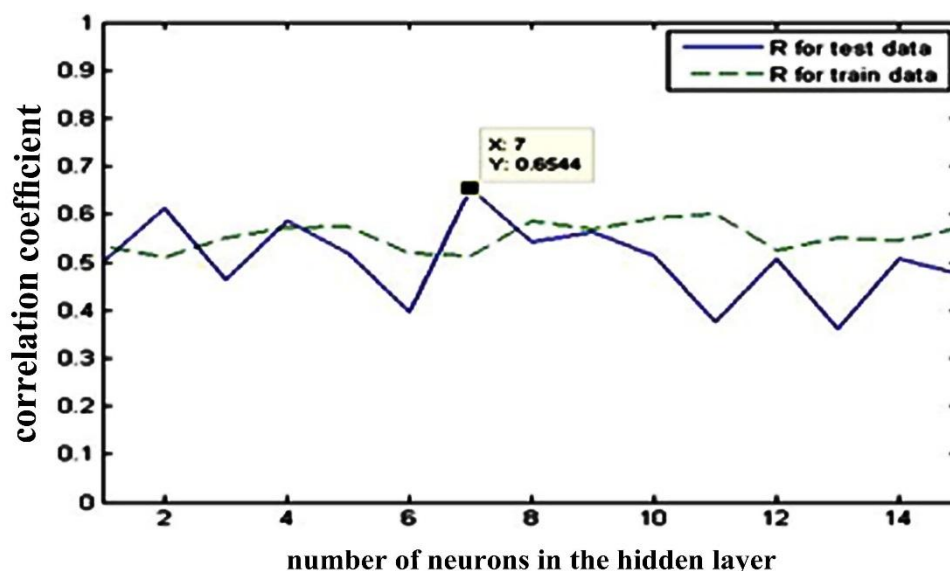
## Results

### The First Neural Network to Predict the Breeding Values for body weight at 6 months of age

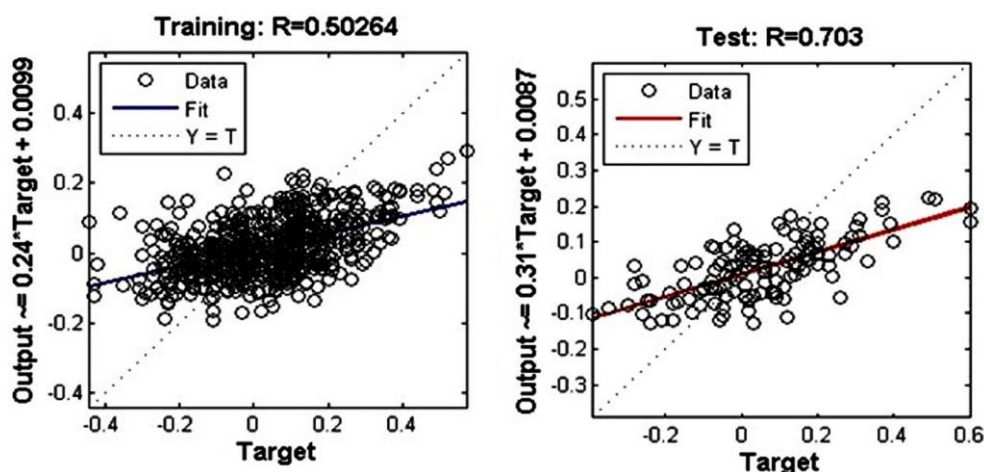
After determining the number of neurons in the input layer, the number of neurons in the hidden layer was investigated. The neural network was trained using `trainlm` training function. This network consisted of seven input variables including sex, dam age, birth weight, body weight at 3 months of age, 3 months of age, body weight at 6 months of age and 6 months of age, as well as an output which was the breeding values for body weight at 6 months of age. The network was trained with 1 to 15 neurons in the hidden layer along 27 epochs. Based on the results obtained, as shown in Figure 2, seven neurons were selected as the optimum number of neurons for the hidden layer.

Based on the number of neurons in the hidden layer, the correlation coefficient (R) was drawn with up to 15 neurons (Table 1). The highest correlation coefficient belongs to the point that contains seven neurons in the hidden layer.

After determining the number of neurons in the hidden layer, the training was restarted by the software with seven neurons. The best network to predict the breeding values for body weight at 6 months of age consisted of seven neurons, i.e., sex, dam age, birth weight, body weight at 3 months of age, 3 months of age, body weight at 6 months of age and 6 months of age in the input layer as well as seven neurons in the hidden layer which occurred at the sixth epoch from a total of 16 epochs while using `trainlm` training function. As shown in Figure 3, this network has a correlation coefficient of 70% for test dataset and 50% for training dataset.



**Figure 2.** Correlation coefficients of the testing and training data sets related to the number of neurons in the first hidden layer of the first network for predicting the breeding value for the body weight at 6 month-age of Kermani sheep.



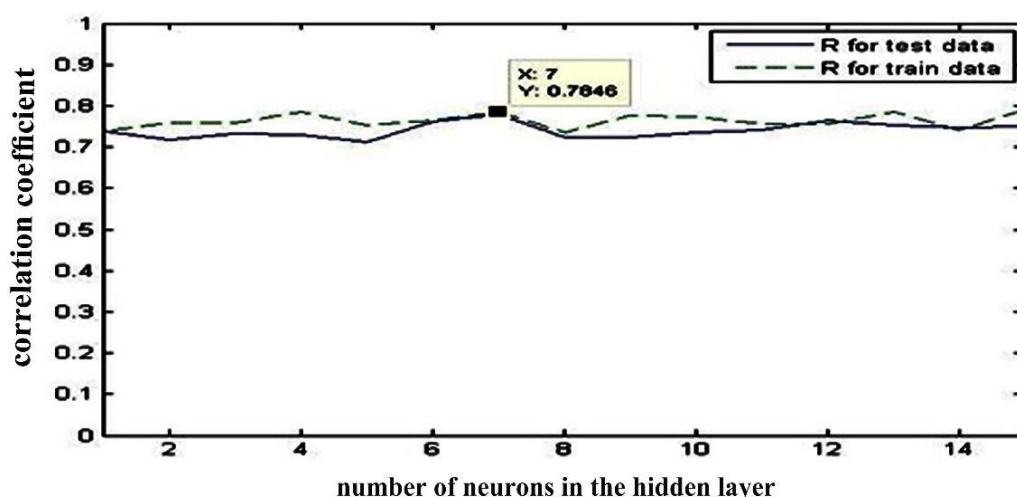
**Figure 3.** Regression lines and correlation coefficients of the first network for the body weight at 6 month-age of Kermani sheep.

During network training, the error of the training, test, and validation datasets is measured regularly, and when the MSE for validation dataset no longer drops after ten epochs, the training stops. If this process is not carried out, the network memorizes the data instead of learning them, and as a result, predicts with low accuracy. The MSE for validation dataset was dropping until the sixth epoch, but bottomed out from the sixth epoch and started to increase. The MSE of the validation dataset was 0.02% (0.0210) at the sixth epoch.

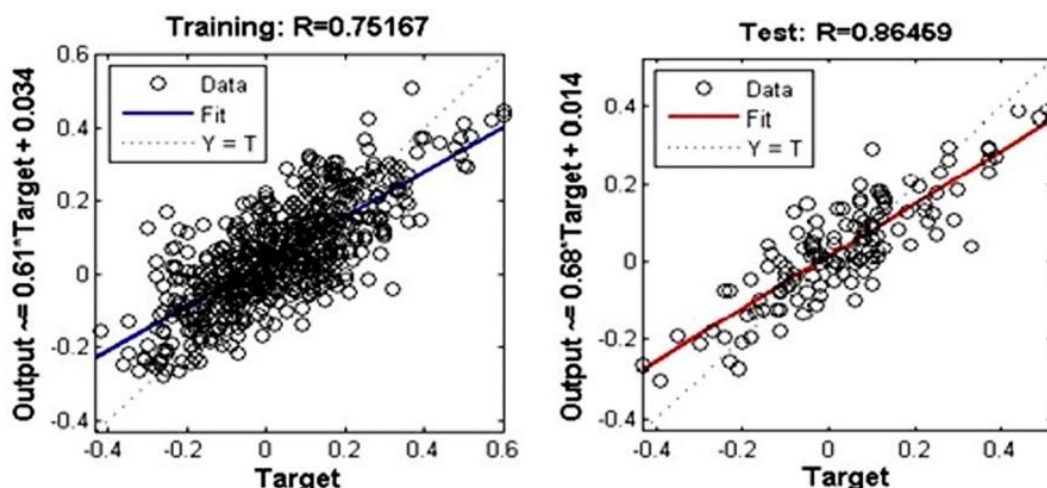
### The Second Neural Network to Predict the Breeding Values for body weight at 6 months of age

To predict the breeding values for body weight at 6 months of age, a network comprised of nine inputs including sex, dam age, birth weight, body weight at 3 months of age, age at 3-month (3 months old), body weight at 6 months of age, age at 6-month (6 months old), breeding values for birth weight and breeding values for body weight at 3 months of age was applied. Next, in order to obtain the optimum number of neurons in the hidden layer, the network was trained using trainlm training function with 9 neurons in the input layer and 17 epochs. According to Figure 4 (Table 1), seven neurons were determined as the optimum number of neurons for the hidden layer.

After determining the number of neurons in the hidden layer, a network with nine neurons in the input layer, seven neurons in the hidden layer, and one neuron in the output layer was trained using trainlm training function, along 17 epochs. The network was stopped at the 17<sup>th</sup> epoch and the obtained correlation coefficient for the training dataset was 0.751, and the correlation coefficient for the test dataset was 0.864, which is acceptable for predicting the breeding values shown in Figure 5.



**Figure 4.** Correlation coefficients of the testing and training data sets related to the number of neurons in the first hidden layer of the second network for predicting the breeding value for the body weight at 6 month-age of Kermani sheep.

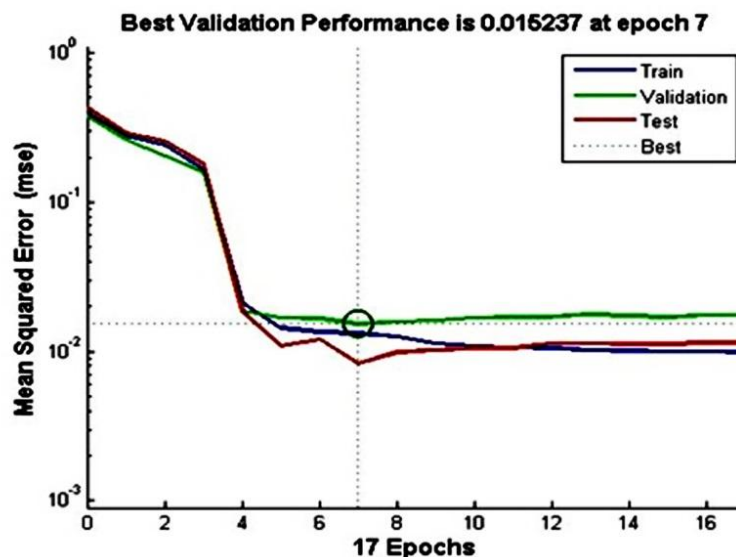


**Figure 5.** Regression lines and correlation coefficients of the second network for the body weight at 6 month-age of Kermani sheep.

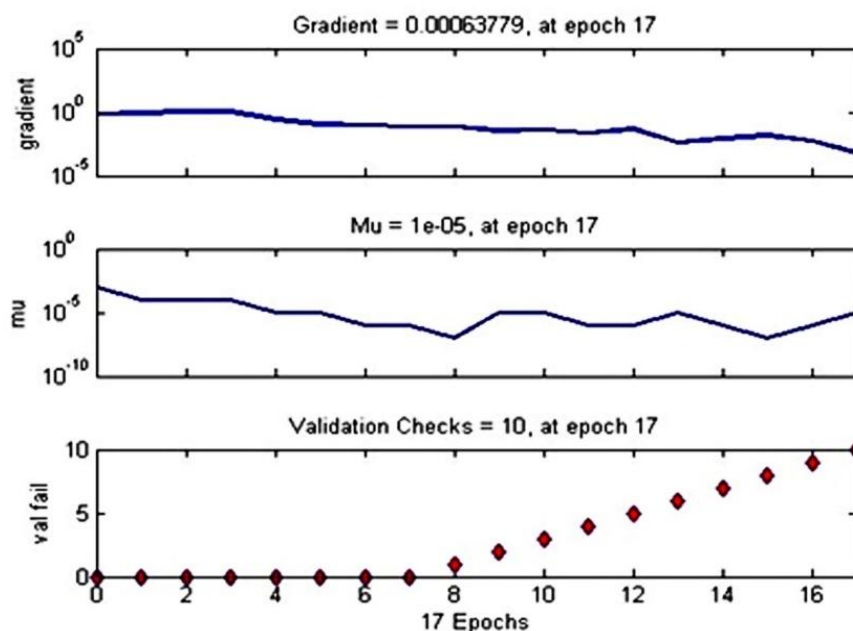
As shown in Figure 6, the MSE of test dataset was decreasing up to the seventh epoch, but no longer decreased after this epoch. Hence, the learning process was stopped at this stage and weights were frozen.

The gradient error for this network was in the range of  $1e/05$  and, as shown in Figure 7, the validation failed in the 17<sup>th</sup> epoch for 10 consecutive times due to excessive repetition of errors. Hence, the learning process was stopped at this stage and weights were frozen, and the validation failed for 10 consecutive times.

As shown, the first neural network for body weight at 6-month age has a correlation coefficient of about 0.70 for the test dataset. This means that the estimated breeding values were acceptable. The second network for body weight at 6-month age has a correlation coefficient of 0.864.



**Figure 6.** Performance curve of the validation data for the first hidden layer in the second network. The best validation performance is at epoch 7 (MSE=0.015237).



**Figure 7.** The validation error gradient and evaluation curve of the second network for the body weight at 6 month-age of Kermani sheep.

**Table 1.** Number of input and output layers and correlation coefficient of training and testing data for predicting breeding value of body weight at 6-month age using 2 networks in Kermani sheep.

Neural network	Number of input layers	Number of hidden layers	Correlation coefficient of training data	Correlation coefficient of test data
First	7	7	0.502	0.703
Second	9	7	0.751	0.864



## Discussion

This study used multilayer perceptron to estimate the breeding values for body weight at 6-month age trait of Kermani sheep. The results showed that the multilayer perceptron with seven input variables and seven neurons in the hidden layer, and a correlation coefficient of 0.703, as well as the multilayer perceptron with nine input variables and seven neurons in the hidden layer, and a correlation coefficient of 0.864 are both capable of predicting the breeding values for body weight at 6-month age in Kermani sheep.

Regarding the selection methods in statistical genetics, some methodology categories are significant and have been widely used. They include the selection index (Verardi, Oliveira, Silva, Gouvêa, & Gonçalves, 2014), the combined selection method (Ribeiro, Mambrin, Storck, Prigol, & Nogueira, 2013; Verardi et al., 2014), and the REML/BLUP (Restricted Maximum Likelihood/Best Linear Unbiased Prediction) method (Ferreira, Viana, Barroso, Resende, & Amaral Júnior, 2012). However, a new paradigm can be employed in genetic breeding for selection purposes which does not involve stochastic modeling. Gorgulu (2012), using artificial neural networks for prediction of 305-day milk yield in Brown Swiss cows, showed that predicted 305-d mean milk production was very close to the observed values, with correlation coefficient ( $R$ ) values between 0.74 and 0.82 for the artificial neural networks. However, 305-d milk yield prediction by multiple linear regression was lower than the observed 305-d milk yield. He proposed that artificial neural network module provided a better prediction for the 305-d milk yield than conventional regression models. Roush, Dozier, and Branton (2006) compared the Gompertz non-linear regression model and neural network modeling for prediction of body weight in broilers and showed that neural network modeling resulted in the lowest bias. Behzadi and Aslaminejad (2010) compared six nonlinear regression forms as counterparts to artificial neural network in order to predict Baluchi sheep growth traits. They concluded that artificial neural network creates a better descriptive sheep growth curve than nonlinear models and makes the most accurate prediction. They reported an MSE of 0.06 for the artificial neural network, which is similar to our research results. Grzesiak et al. (2003) compared multiple regression and artificial neural network to estimate 305-day lactation yield. They reported a correlation coefficient and MSE of 0.88 and 0.08 for the artificial neural network, which confirms our results. In a further research, Ehret et al. (2015) tested various nonlinear architectures as network inputs to assess their ability to predict lactation traits in dairy cows using large-scale SNP data. For training, they employed a regularized back propagation algorithm and used the average correlation between the observed and predicted phenotypes to assess predictive ability. They concluded that artificial neural networks are powerful machines for non-linear genome-enabled predictions in animal breeding. The results of various studies indicate that MLP can be applied to calculate the breeding values of Iranian Holstein dairy cows with a correlation of 0.92, can excellently predict the breeding values for the milk production trait (Pour Hamidi et al., 2017), to predict lactation yield, milk fat and protein (Ruhil, Raja, & Gandhi, 2013), to predict and determine the value of carcass of meat cattle using pre-slaughter information (Brethour, 1994; Salehi et al., 1998), to estimate lactation based on the records of the first 5 months with a confidence level of 80% (Ruhil et al., 2013) and to estimate milk yield in Indian Karan Fries dairy cattle with an accuracy rate of 92% (Kominakis et al., 2002). The present study also indicated that MLP (or artificial neural network) has the potential for predicting the breeding values for growth traits in Kermani sheep. Furthermore, the results obtained in this study are consistent with the results of other researches in terms of ANN application in animal science (Brethour, 1994; Craninx, Fievez, Vlaeminck, & De Baets, 2008; Kominakis et al., 2002; Salehi et al., 1998).

## Conclusion

Our results demonstrated that for predicting the breeding values for the growth traits in Iranian Kermani sheep artificial neural networks are replaceable with multiple regression models, because they had higher  $R^2$  and Pearson's correlation coefficients and lower standard deviation and mean square error. Although both artificial neural networks and multiple regression models can excellently predict the breeding values for the growth traits, but artificial neural network provides more precise estimates, and may be used as an alternative technique for predicting the breeding values for growth traits.

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