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# Performance of Artificial Neural Networks Model under Various Structures and Algorithms to Prediction of Fat Tail Weight in Fat Tailed Breeds and Their Thin Tailed Crosses

Research Article

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## ABSTRACT

Today's large fat tail lost its importance because of rearing condition and consumers' demands. Therefore, recording fat tail weight on live animals is important to selecting animals for reduced fat tail weight. The study was conducted to predict the fat tail weight of five different genetic groups of lambs obtained from a mating system between fat-tailed and thin-tailed parents. An Artificial Neural Networks (ANN) procedure was used for prediction performance of different structures (40 levels) and algorithms (5 levels). Eight measurements, including birth type (2 levels), sex (2 levels), breed composition (5 levels), live body weight and four morphological assessments were used as ANN model's inputs. The results showed that ANN model with adequate structure and algorithm can accurately predict the tail weights and compositions of the studied breeds. Our results indicate that with increase of neurons in first hidden layers, the prediction accuracies were increase dramatically. Back propagation algorithm (BP) was the best algorithm with higher stable $R^2$ and lower stable root mean squire error (RMSE) in different structures. BP algorithm with 4 and 2 neurons in the first and second hidden layer, respectively, had more ability to predict fat-tail weight in different genetic groups. Best ANN model provided 0.962, 0.997 and 0.988 $R^2$ values and 338.156, 43.689 and 117.306 of RMSE for testing, training and the overall data sets, respectively. The study showed that, an ANN model based on the BP algorithm, have high potential to predict fat-tail weight as an important economic trait in sheep rearing systems.

KEY WORDS algorithms, ANN structure, Artificial Neural Network, Breeding, fat-tail, Prediction model, sheep.

## INTRODUCTION

Sheep form the most important group of ruminants in rural areas of Iran. Domestication had an essential role on human civilization around the world, the process of domestication caused significant change in variety of animals (Wright, 2015). Because, absence of fat tail in ancestors of domestic sheep living in similar condition with fat tailed sheep, it can be concluded that natural selection on presence of fat tail in domestic sheep breeds, is not the factor. The fat tail is result of response of the animal to harsh rearing condition during migration and winter (Kashan *et al*. 2005). High fat tail weight is a major factor for tropical climate condition during domestication of sheep, but it lost its importance because of losing market demand and efficient auxiliary feeding during drought.

It can be argued consequence of that adaption for local condition mainly because of its ability to deposit fat and adoption to grazing system, make fat tailed lamb to modest response to concentrate feeding (Atti *et al*. 2004). Energy expenditure to deposit fat is more than lean tissue (Moradi *et al*. 2012) and consequences of containing high saturated fatty acids on health, it's favorable to select to elimination of large fat-tails (Zamiri and Izadifard, 1997) for producers and consumers. This modification can be done with crossing fat tailed and thin tailed breeds or utilization of selection system to reduction of fat tail weight within the segregating populations (Kashan *et al*. 2005).The modification methods need to accurate prediction of fat tail weight in living animals.

Crossing thin tailed rams and fat tailed ewes can be an alternative for selection in the situation of positive phenotypic correlation between ultrasonic fat measurements and carcass traits (Atkins *et al*. 1991; Saatci *et al*. 1998). Increased carcass quality with decreased fat tail weight was reported in progeny of fat tailed breeds of Baluchi and Mehraban sheep crossed with Targhee and Corriedal (Farid, 1991).

Because of fat tailed breeds abundance in wide range of arid area of the world, especially in the Middle East and Iran (Davidson, 2006), it worth to facilitate selective breeding of this breeds. Zel is the only thin fat tailed breed of Iran that present on the Northern, Chal and Zandi are fat tailed breeds with presence in Ghazvin and Tehran provinces with highest fecundity within Iranian breeds, respectively.

To implementation of fat tail weight in selection strategies, measuring of tail weight is needed. Therefore measurement without slaughtering of the candidate animals are needed. To overcome this problem, *in vivo* fat tail morphological measurements were performed and used as a measure of tail weight in breeding programs (Vatankhah and Talebi, 2008). Estimation of fat tail weight on living individual using an accurate model with inputs of metric and morphologic measurements can be approved method to recording of the trait to genetic evaluation. The accurate estimated records can be applicable in young animals, enabling early selection of lambs with lower fat-tail weight and desirable carcass as breeding stock. The records can be used to obtain reliable estimates of genetic and phenotypic parameters in fat tail breeds of sheep.

Artificial Neural Network (ANN) is a powerful tool for modeling because of its multivariate non-linear non-parametric data driven self-adaptive feature. ANN technique is used to solve a wide range of problems in science and engineering, particularly for some areas where the mathematical modeling methods fail (Ghazanfari *et al*. 2011). Because of this feature of ANN, it can be used in complex studies of biological science. In this study, ANN modeling used to prediction of fat tail weight using easy *in vivo* measurements.

Mehri (2013) found that the ANN based model had higher determination of coefficient and lower residual distribution for prediction of hatchability. The research showed that universal approximation capability of ANN made it a powerful tool to approximate complex functions.

Mehri (2012), showed that ANN model has higher accuracy to predict the bird performance compared with response surface methodology models. Takma *et al*. (2012) demonstrated that artificial neural networks predict305 day milk yield better than multiple linear regression.

Different modifications of backpropagation algorithm was used to compare with traditional one. Weights in resilient backpropagation (Rprop) algorithm change by the concept of resilient update-values, so, adaption cannot be shift by unpredictable gradient behavior. Advantages of the algorithm are fast convergence, no need to choose for parameters and equal distribution of learning all over the network independent on tendency to output or input layer. Rprop can be used with (Riedmiller, 1994) or without (Riedmiller and Braun, 1993) weight backtracking. Modified globally convergent version (GRPROP) that proposed because of its speed and stability compared to Rprop and general convergence property (Anastasiadis *et al*. 2005). Also, an algorithm of backpropagation learning with generalized weights introduced with Intrator and Intrator (1993) was used to comparison to traditional backpropagation algorithm.

In this study, our objective was to evaluate ability of different ANN algorithms, in a general ordinary least square context to predict the final weight of fat-tail in the deigned genetic groups of pure and cross-breed lambs.

## MATERIALS AND METHODS

This study was conducted at Golestan Agricultural and Natural Resources Research and Education Center, AREEO, from February 2018 to September 2019, to evaluate ability of different ANN algorithms, in the general ordinary least square context to predict the final weight of fat-tail in different genetic groups.

In this study three crossbred groups (i.e,) Za (Zandi), Ch (Chal), Za × Ch, Ze × Za and Ze × Ch lambs and two purebred group involves Ch × Ch and Za × Za were used. To obtain cross breed lambs the genotype of Za × Ch, 20 and 40 ewes of Zandi and Chal were crossed with 2 rams of each breed, respectively. Ze (Zel) × Za and Ze × Ch were produced from cross of 40 and 20 Zandi and Chal with 4 of Zel rams, respectively.

Identification number, genotype, sex and birth type of lambs were recorded at birth. Lambs weaned at range of 75 to 110 days of age. After weaning, lambs were maintained for 14 days for adaption to new environment and feeding status. At the adaption period lambs were fed 2 times a day using alfalfa (chopped in 1-2 mm) for 3 days, afterward barley added to the diet gradually. Then, diet balanced using alfalfa and barley on the basis of nutrient requirements (NRC) for daily weight gain of 200-250 g. Lambs were maintained for 3 months each with different component of ingredients (Table 1).

Mineral and vitamin premix and salt stone were freely available in fattening period. According to dry matter requirements of lambs, 10 percent more diet allowed, and residual feed were discarded each day. At the end of fattening period 8 lambs of each genotype were weighted and fat tail morphologies measured. Weight of fat tail was measured after slaughtering.

### *In vivo* measurements

Lambs were starved 24 h following the fattening period, and then their slaughtering live weight (LW) was measured. Eeight features, including upper fat tail width (UFTW), central fat tail width (CFTW), lower fat tail width (LFTW), fat tail length (FTL), genotype, sex, birth type of lambs and slaughter weight used as inputs of ANN model. As expected, the fat tail weight (FTW) was output of ANN model.

The ANN analysis was done with R project statistical system (the R Foundation for Statistical Computing, Vienna University of Economics and Business, Institute for Statistics and Mathematics, Austria).

### Comparison of learning algorithms and structures of ANN

Learning algorithm and structure of artificial neural network are essential factors affecting the performance of Artificial Neural Network Models. In this study, 5 different algorithms consist of backpropagation, Rprop$^-$ (without weight backtracking) (Riedmiller, 1994), Rprop$^+$ (with weight backtracking) (Riedmiller and Braun, 1993), GRPROP (modified globally convergent version) (Anastasiadis *et al.* 2005) and generalized weights (Intrator and Intrator, 1993) were comprised. Different combination of neurons in 1$^{st}$ and 2$^{nd}$ layers were considered (Table 2). Also, learning algorithm and ANN structure have significant impact on performance of ANN, size of the effect is application dependent. This paper presents a comparison of 5 algorithms and 35 different structure on adequacy parameters of ANN model. In total, 175 scenarios in combination of algorithms and structure levels were generated. Different scenarios performed using multilayer feed forward artificial neural network that use logistic function as transfer function.

### Development and training of ANN model

Each scenario was replicated for 200 times then best replicate, according to adequacy parameters, within converged ANN models was chosen as the result of the scenario. In each replicate of scenario, data set were randomly divided to two subset. The first subsetswas training data (75% of total data) which used to generate a model. The second subset was testing data (25% of total data) which used to evaluate adequacy parameters of the trained model.

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

Equation (1) $\varepsilon(t)= 1/2\ e^2$

Where:

$\varepsilon(t)$: instantaneous value of error at time $t$.

$e$: value of observed error.

Four layers; input, output and two fully connected hidden layer, were used to generate ANN model. In each node logistic activation function used to transform the activation level of a unit (neuron) into an output signal. Logistic activation function is an S-shaped (sigmoid) curve, with output in the range (0, 1). Therefore, total data set were normalized between 0-1 using Equation 2.

Equation (2) $y_s= (y_i-y_{min}) / (y_{max}-y_{min})$

Where:

$y_s$: normalized values of the data.

$y_i$: Original values of the data.

$y_{min}$: minimum value.

$y_{max}$: maximum value.

### Adequacy parameters

To evaluation of ANN models of each replicate of scenario the $R^2$ and root mean squire error (RMSE) statistics were calculated as equations3 and 4 (Ghazanfari *et al.* 2011):

Equation (3) $$R^2 = \left[1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}\right]$$

Equation (4) $$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{n}}$$

Where:

$Y_i$: original fat tail weight of i$^{th}$ individual.

$\hat{Y}_i$: value of fat tail weight.

$\bar{Y}$: mean of original fat tail weight.

n: sample size.

**Table 1** Ingredients of balanced diet in different months of fattening period

| Month of fattening | Alfalfa (%) | Barley (%) |
|---|---|---|
| 1 | 80 | 20 |
| 2 | 70 | 30 |
| 3 | 60 | 40 |

**Table 2** Number of neurons in 1st and 2nd layer

| Neurons in 1st hidden layer | Neurons in 2nd hidden layer |
|---|---|
| 2 | 1 |
| 3 | 2 |
| 4 | 3 |
| 5 | 4 |
| 6 | 5 |
| 7 | - |
| 8 | - |

The adequacy parameters were calculated to each replicate of scenarios and parameters of a replication with best adequacy parameter was chosen as representative of the scenario's adequacy. The representative of each scenario were chosen based on two criterions, first one was highest overall $R^2$ with the lowest difference of $R^2$ between the train and test datasets.

Also, we present the RMSE of chosen ANN models that be show the performance of the criteriaof choosing best ANN model. To evaluate the ANN model choosing criterion we presented the plot of $R^2$ and RMSE the second criterion of lowest overall RMSE with lowest difference of test and train RMSE, across scenarios. Therefore, adequacy parameters were calculated for test, train and total datasets. The adequacy of models was calculated across scenarios and within learning algorithms.

## RESULTS AND DISCUSSION

Data characteristics of birth type, sex, weights and tail morphological measurements in each genotype were presented in Table 3.

$R^2$ and RMSE of best performed ANN models based on the criterion of highest overall $R^2$ with the lowest difference of $R^2$ between the train and test datasets, across scenarios were presented in Figure 1 and corresponding learning algorithm were presented in Table 4. Model performance across scenarios shows that $R^2$ increases with increasing number of first and second hidden layer. According the criterion of best performed ANN selection, RMSE decreases with increase of $R^2$.

In respect to the original data parameters, RMSE of the best performed ANN model in different structures was adequate.

Backpropagation algorithm was best performed in wide ranges of ANN structure. Best structure and algorithm across the study was backpropagation algorithm with 4 and 2 neurons in first and second hidden layer respectively. The model for test, train and overall datasets had $R^2$ of 0.962987, 0.9970592 and 0.9885411, also RMSE of 338.1565, 43.688974 and 117.30587, respectively.

Effect of different ANN structure on the $R^2$ of best performed ANN model within the learning algorithms based on the highest overall $R^2$ with the lowest difference of $R^2$ between the train and test datasets were presented in Figure 2. $R^2$ of backpropagation algorithm ANN model was stable and high in different datasets and wide range of ANN structure. In this study, neurons in first and second hidden layer for ANN with backpropagation algorithm should be more than 2 and 1, respectively. Effect of different ANN structure on the RMSE of best performed ANN model within the learning algorithms were presented in Figure 3.

The lowest RMSE found in the ANN structure that have backpropagation algorithm.

Plot of $R^2$ and RMSE of representative replicate of scenarios, based on the criterion of the lowest RMSE with the lowest difference between test and train data RMSE, across scenarios were presented in Figure 4. The results presented that criterion of $R^2$ difference of train and test dataset with stable $R^2$ and RMSE in different ANN structures is better than criterion of RMSE difference.

Table 5 shows the algorithms with the lowest RMSE with the lowest difference of test and train dataset's RMSE. Table 4 and 5 shows that backpropagation algorithm works better than other algorithms in range of different ANN structure.

Backpropagation algorithm was best performed in wide range of scenarios, in criterion of lowest difference between test and train data RMSE, across scenarios. Every modified version of traditional backpropagationhas some advantages, but to present experimental data, traditional backpropagation was the best learning algorithm in wide range of neural network structures.

The best structure for the algorithm across the study was ANN with 2 hidden layer. Many studies on ANN modeling in animal science showed that backpropagation algorithm can be chosen for learning ANN. Results of the study was in agreement with many other researches that used ANN model with backpropagation algorithms in comparison to statistical models in wide range of animal science research (Bishop, 2006; Perai *et al*. 2010; Grzesiak and Zaborski, 2012; Ali *et al*. 2015; Atil and Akilli, 2015; Ehret *et al*. 2015; Norouzian and Vakili-Alavijeh, 2016; Akkol *et al*. 2017).

The study showed that ANN modeling with adequate accuracy and precision parameters can be fit for prediction of fat tail weight using fat tail dimensions on live animals.

**Table 3** Characteristics of *in vivo* and after slaughtering measurements

| Genotype | Chal (Ch) | | Zandi (Za) | | Za♂ × Ch♀ | | Zel (Ze)♂ × Za♀ | | Ze♂ × Ch♀ | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD[a] | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| LW[1] | 38.28 | 6.11 | 41.01 | 4.74 | 35.75 | 2.94 | 31.95 | 4.53 | 28.69 | 4.45 |
| UFTW[2] | 15.10 | 2.65 | 16.85 | 1.56 | 16.36 | 3.26 | 14.11 | 2.08 | 13.14 | 2.11 |
| CFTW[3] | 24.63 | 2.63 | 29.325 | 3.64 | 25.26 | 3.63 | 21.65 | 3.99 | 18.54 | 2.02 |
| LFTW[4] | 19.58 | 3.76 | 23.05 | 2.53 | 19.99 | 3.60 | 17.48 | 3.28 | 13.65 | 2.41 |
| FTL[5] | 21.45 | 4.53 | 25.45 | 3.53 | 19.93 | 2.21 | 20.46 | 2.50 | 18.19 | 2.29 |
| FTW[6] | 2500 | 493.53 | 2768.75 | 402.61 | 2250 | 312.82 | 1306.25 | 400.39 | 922.5 | 286.69 |
| **Number of** | | | | | | | | | | |
| Male | 5 | | 5 | | 4 | | 4 | | 4 | |
| Female | 3 | | 3 | | 4 | | 4 | | 4 | |
| Mono | 6 | | 4 | | 3 | | 3 | | 4 | |
| Twin | 2 | | 4 | | 5 | | 5 | | 4 | |

LW: live Weight; UFTW: upper fat tail width; CFTW: central fat tail width; LFTW: lower fat tail width; FTL: fat tail length and FTW: fat tail weight.
SD: standard deviation.

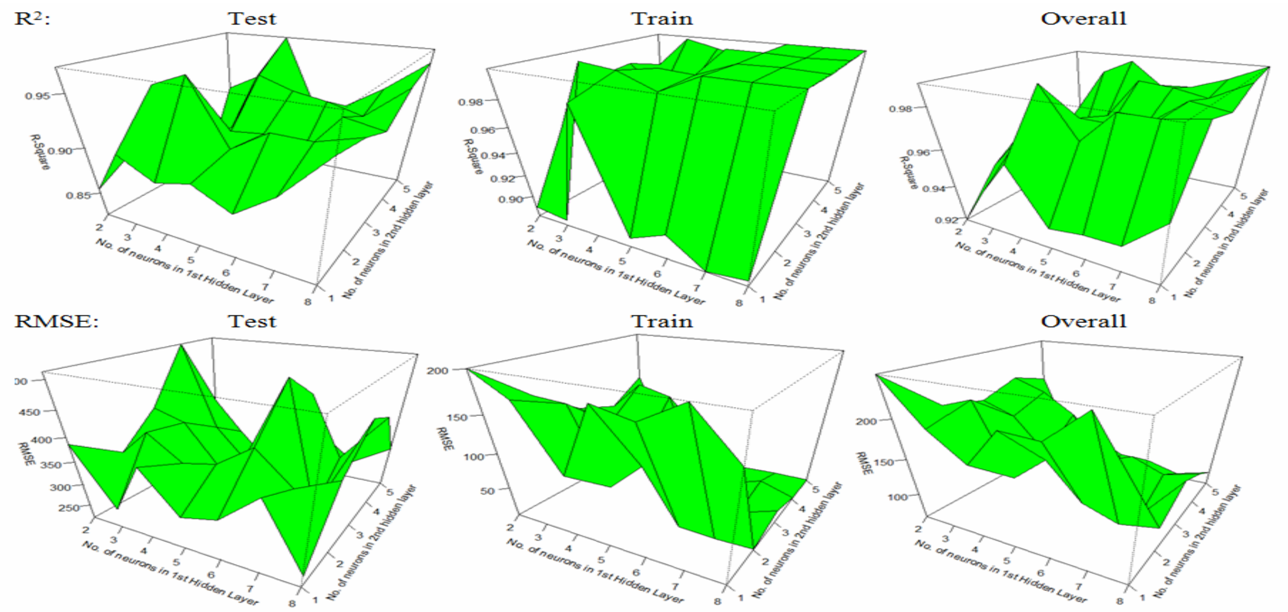


**Figure 1** $R^2$ and RMSE of best performed ANN models base on the criterion of highest overall $R^2$ with the lowest difference of $R^2$ between the train and test datasets

**Table 4** Best performed learning algorithms in different structures

| | | Number of neurons in 2nd hidden layer | | | | |
|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 |
| Number of neurons in 1st Hidden layer | 2 | nnBP | nnBP | nnBP | nnBP | nnBP |
| | 3 | nnrpropw | nnsag | nnBP | nnrpropw | nnBP |
| | 4 | nnBP | nnBP | nnBP | nnBP | nnBP |
| | 5 | nnrprop | nnBP | nnBP | nnBP | nnBP |
| | 6 | nnrprop | nnBP | nnBP | nnBP | nnBP |
| | 7 | nnrpropw | nnBP | nnBP | nnBP | nnBP |
| | 8 | nnsag | nnBP | nnBP | nnBP | nnBP |

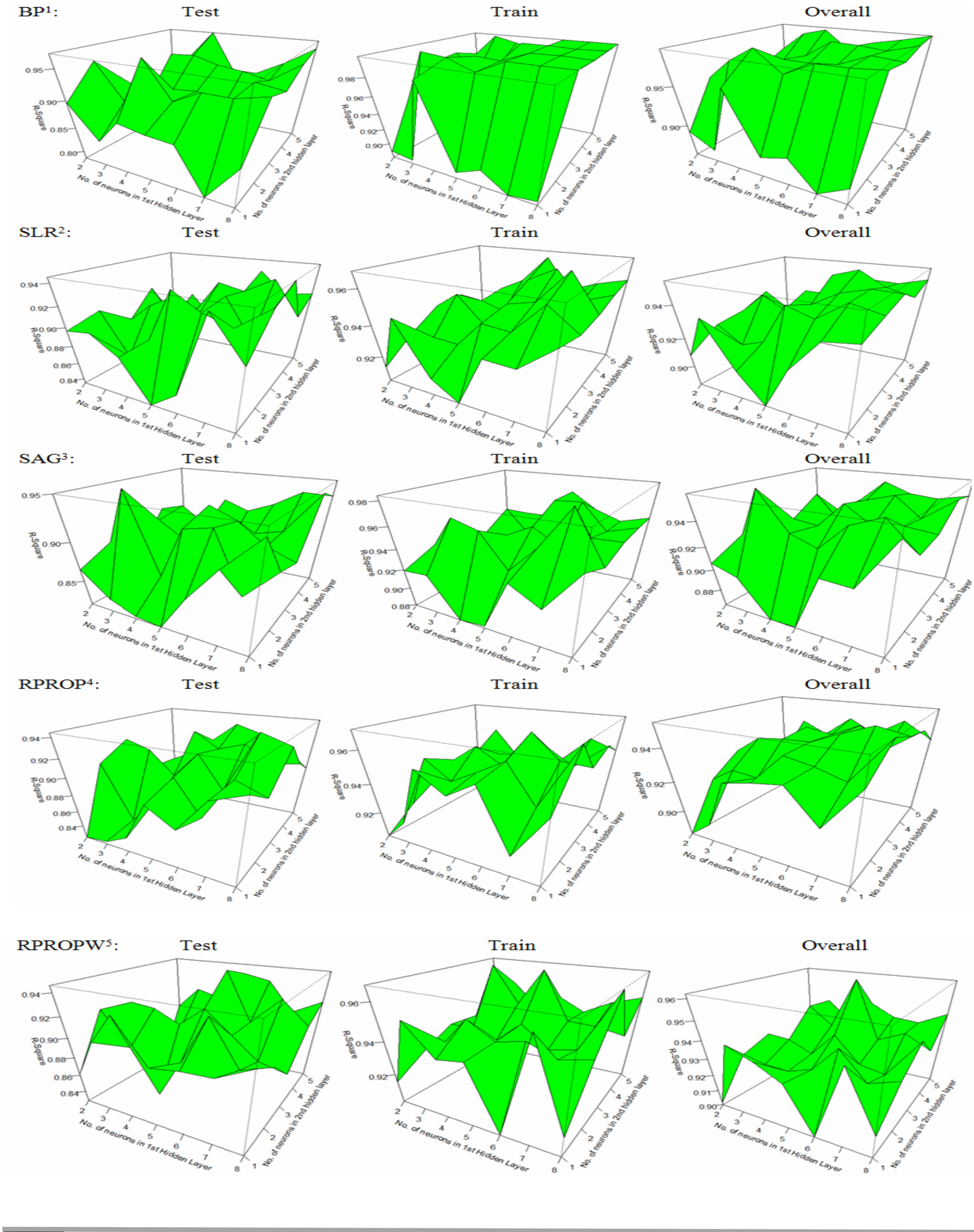


**Figure 2** Effect of different ANN structure on the $R^2$ of best performed ANN model within the learning algorithms
[1] Backpropagation; [2] Without weight backtracking; [3] With weight backtracking; [4] Modified globally convergent version and [5] Generalized weight

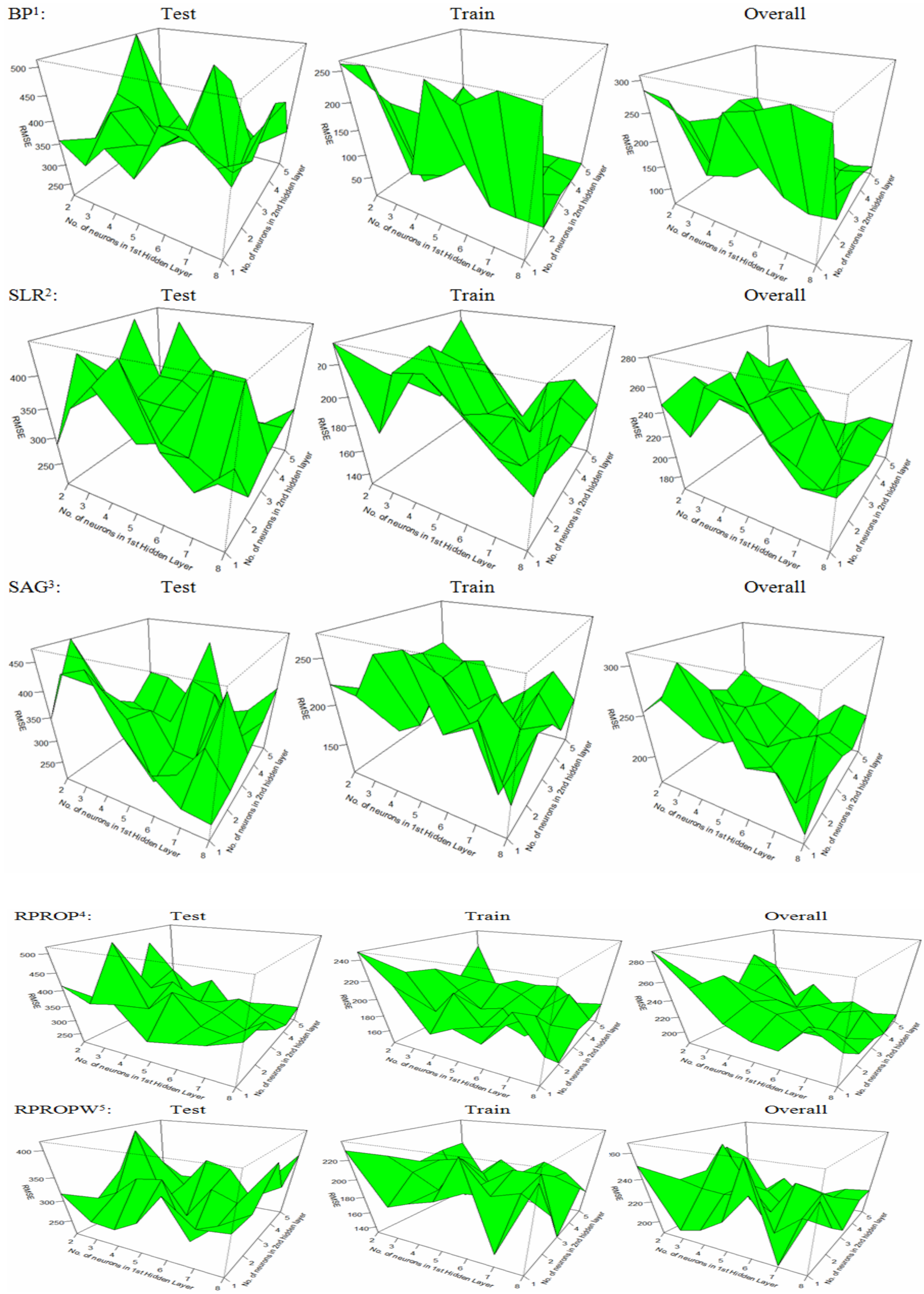


**Figure 3** Effect of different ANN structure on the RMSE of best performed ANN model within the learning algorithms

[1] Backpropagation; [2] Without weight backtracking; [3] With weight backtracking; [4] Modified globally convergent version and [5] Generalized weight

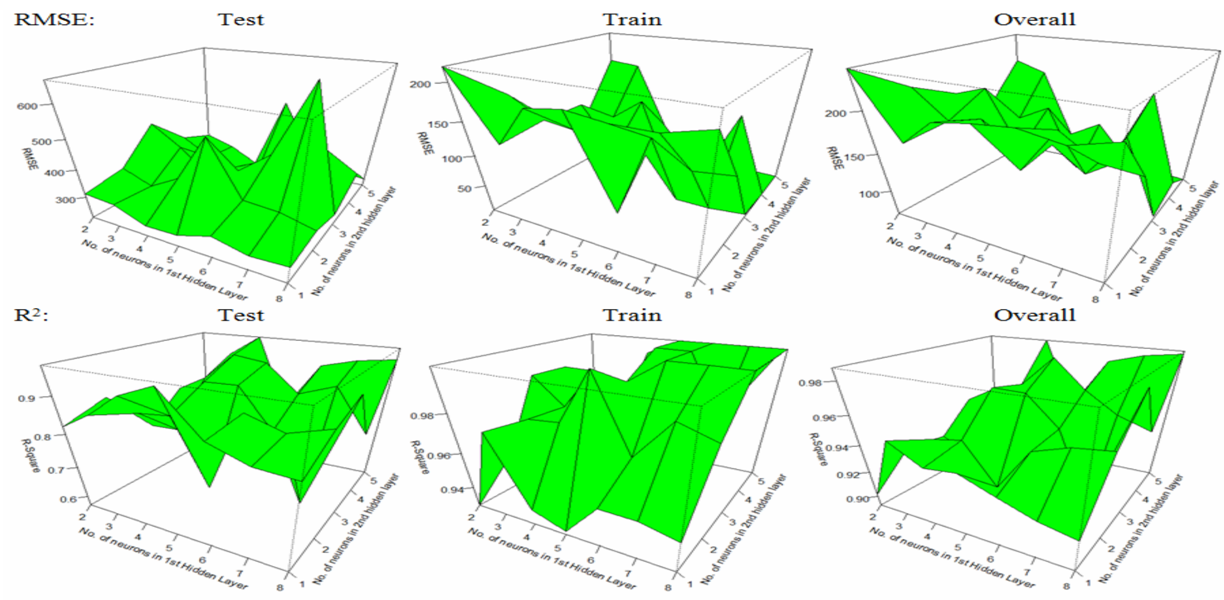


**Figure 4** Plot of $R^2$ and RMSE of representative replicate of scenarios, based on the criterion of the lowest RMSE

**Table 5** Algorithms with the lowest root mean squire error (RMSE)

| | | Number of neurons in 2nd hidden layer | | | | |
|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 |
| Number of neurons in 1st Hidden layer | 2 | nnrpropw | nnBP | nnBP | nnBP | nnBP |
| | 3 | nnBP | nnBP | nnrpropw | nnBP | nnrpropw |
| | 4 | nnrpropw | nnBP | nnBP | nnBP | nnBP |
| | 5 | nnrprop | nnBP | nnBP | nnBP | nnBP |
| | 6 | nnrprop | nnBP | nnBP | nnBP | nnBP |
| | 7 | nnsag | nnsag | nnBP | nnsag | nnBP |
| | 8 | nnsag | nnBP | nnBP | nnBP | nnBP |

In this study, discovered that backpropagation algorithm and 2 hidden layer structure is the best for ANN modeling to prediction of fat tail weight on live lamb. The results can be critical for predicted records of fat tail weight trait for using in sheep breeding programs, and the obtained best algorithm and structure are helpful to accurate prediction the trait using ANN modeling.

## CONCLUSION

Criterion of highest overall $R^2$ with the lowest difference of $R^2$ between the train and test datasets with lower stable RMSE in the testing dataset was better than alternative. Backpropagation algorithm with the better adequacy parameters across scenarios was the best learning algorithm of ANN model in wide range of ANN structure.

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## REFERENCES


Akkol S., Akilli A. and Cemal İ. (2017). Comparison of Artificial Neural Network and Multiple Linear Regression for prediction of live weight in hair goats. *Yuzuncu Yil Univ. J. Agric. Sci.* **27(1),** 21-29.

Ali M., Eyduran E., Tariq M.M., Tirink Abbas C.F., Bajwa M.A., Baloch M.H., Nizamani A.H., Waheed A., Awan M.A., Shah S.H., Ahmad Z. and Jan S. (2015). Comparison of artificial neural network and decision tree algorithms used for predicting live weight at post weaning period from some biometrical characteristics in Harnai sheep. *Pakistan J. Zool.* **47,** 1579-1585.

Anastasiadis D.A., Magoulas G.D. and vrahatis M.N. (2005). New globally convergent training scheme based on the resilient propagation algorithm. *Neurocomputing*. **64,** 253-270.

Atil H. and Akilli A. (2015). Investigation of dairy cattle traits by using artificial neural networks and cluster analysis. Pp. 23-27 in Proc. 7th Int. Conf. Inform. Commun. Technol. Agric. Food Environ., Kavala, Greece.

Atkins K.D., Murray J.J., Gilmour A.R. and Luff A.L. (1991). Genetic variation of live weight and ultrasonic fat depth in Australian pool Dorset sheep. *Australian J. Agric. Res.* **42,** 629-640.

Atti N., Bocquier F. and Khaldi G. (2004). Performance of the fat-tailed Barbarine sheep in its environment: Adaptive capacity to alternation of underfeeding and re-feeding periods. *Anim. Res.* **53(3),** 165-176.

Bishop C.M. (2006). Pattern Recognition and Machine Learning. Springer, New York, USA.

Davidson A. (2006). The Oxford Companion to Food. Oxford University Press, Oxford, United Kingdom.

Ehret A., Hochstuhl D., Gianola D. and Thaller G. (2015). Application of neural networks with back-propagation to genome-enabled prediction of complex traits in Holstein-Friesian and German Fleckvieh cattle. *Genet. Sel. Evol.* **47,** 22-31.

Farid A. (1991). Slaughter and carcass characteristics of three fat-tailed sheep breed and their crosses with Corriedal and Targhee rams. *Small Rumin. Res.* **5(3),** 255-271.

Ghazanfari S., Nobari K. and Tahmoorespur M. (2011). Prediction of egg production using Artificial Neural Network. *Iranian J. Anim. Sci.* **1(1),** 11-16.

Grzesiak W. and Zaborski D. (2012). Examples of the use of data mining methods in animal breeding. Pp. 303-324 in: Data Mining Applications in Engineering and Medicine. A. Karahoca, Ed. InTech, Rijeka, Croatia.

Intrator O. and Intrator N. (1993). Using Neural Nets for Interpretation of Nonlinear Models. Pp. 244-249 in Proc. Stat. Comput. Section, San Francisco, USA.

Kashan N.E.J., Manafi-Azar G.H., Afzalzadeh A. and Salehi A. (2005). Growth performance and carcass quality of fattening lambs from fat-tailed and tailed sheep breeds. *Small Rumin. Res.* **60,** 267-271.

Mehri M. (2012). Development of artificial neural network models based on experimental data of response surface methodology to establish the nutritional requirements of digestible lysine, methionine, and threonine in broiler chicks. *Poult. Sci.* **91,** 3280-3285.

Mehri M. (2013). Comparison of neural network models, fuzzy logic, and multiple linear regression for prediction of hatchability. *Poult. Sci.* **92,** 1138-1142.

Moradi M.H., Nejati-Javaremi A., Moradi-Shahrbabak M., Dodds K.G. and McEwan J.C. (2012). Genomic scan of selective sweeps in thin and fat tail sheep breeds for identifying of candidate regions associated with fat deposition. *BMC Genet.* **13,** 10-12.

Norouzian M.A. and Vakili-Alavijeh M. (2016). Comparison of Artificial Neural Network and multiple regression analysis for prediction of fat tail weight of sheep. *Iranian J. Appl. Anim. Sci.* **6(4),** 895-900.

Perai A.H., Nassiri-Moghaddam H., Asadpour S., Bahrampour J. and Mansoori G. (2010). A comparison of artificial neural networks with other statistical approaches for the prediction of true metabolizable energy of meat and bone meal. *Poult. Sci.* **89,** 1562-1568.

Riedmiller M. (1994). Rprop-Description and Implementation Details. Technical Report, University of Karlsruhe, USA.

Riedmiller M. and Braun H. (1993). A direct adaptive method for faster backpropagation learning: The RPROP algorithm. Pp. 48-52 in Proc. IEEE Int. Conf. Neural Networks (ICNN), San Francisco, USA.

Saatci M., Appewi I., Jones H.E. and Ulutas Z. (1998). Genetic parameter and estimated breeding value of live weight, fat and muscle depth in Welsh Mountain rams. Pp. 238-240 in Proc. 6th World Congr. Gen. Appl. Livest. Prod., Armidale, Australia.

Takma Ç., Atil H. and Aksakal V. (2012). Comparison of Multiple Linear Regression and Artificial Neural Network models goodness of fit to lactation milk yields. *Kafkas Univ. Vet. Fak. Derg.* **18(6),** 941-644.

Vatankhah M. and Talebi M.A. (2008). Heritability estimates and correlations between production and reproductive traits in Lori-Bakhtiari sheep in Iran. *South African J. Anim. Sci.* **38(2),** 110-118.

Wright D. (2015). The genetic architecture of domestication in animals. *Bioinform. Biol. Insight.* **9(4),** 11-20.

Zamiri M.J. and Izadifard J. (1997). Relationships of fat-tail weight with fat-tail measurements and carcass characteristics of Mehraban and Ghezel rams. *Small Rumin. Res.* **15,** 261-266.