

# Prediction and optimization of slaughter weight in meat-type quails using artificial neural network modeling

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**ABSTRACT** Carcass yield of meat-type quails is strongly correlated with the weight of the birds at slaughter (slaughter weight [SW]; body weight at 45 D of age). Moreover, prediction of superior animals for SW at the earlier stages of the rearing period is favorable for producers. Therefore, the aim of the present study was to predict and optimize SW of Japanese quails based on their early growth performances, sex, and egg weight as predictors through artificial neural network (ANN) modeling. To construct the ANN model a feed-forward multilayer perceptron neural network structure was used. Moreover, sensitivity analysis was used to arrange the predictors in the ANN model(s) according to their predictive importance too. In addition, the optimization process was conducted to determine the optimum values for the input variables to yield maximum SW. The best-fitted network on input data to predict SW in Japanese quails was determined with 7 neurons in the input layer, 11 neurons in the

hidden layer, and one neuron in the output layer. The coefficient of determination ( $R^2$ ) was 0.9404, 0.9359, and 0.9223 for training, validation, and testing phases, respectively. For the corresponding phases, SEM were also 51.8854, 52.2764, and 55.2572, respectively. According to sensitivity analysis, the most important input variable for prediction of SW was body weight at 20 D of age (BW20), whereas the less important input variables were weight of the birds at hatch and body weight at 5 D of age. The results of the neural network optimization indicated that all the input variables, except for BW20, were very similar but slightly higher than mean values ( $\mu$  for each input variable). The results of this study suggest that the ANN provides a practical approach to predict the final body weight (SW) of Japanese quails based on early performances. Moreover, phenotypic selection for higher values of early growth traits did not ensure the achievement of maximum SW, except for BW20.

**Key words:** correlation, sensitivity analysis, Japanese quail, artificial intelligence

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## INTRODUCTION

Body weight of quails (*Coturnix coturnix*) at slaughter (slaughter weight [SW]), its carcass yield (CY), and generally its global contribution to meat production are not comparable with broilers and turkeys; nevertheless, quail rearing for meat production is rising globally (Narinc et al., 2013; Silva et al., 2013; Barbieri et al., 2015). In comparison with other commercial poultry strains or breeds, quail production enterprises are at

earlier stages. Hence, appropriate information to manage meat-type quail-producing farms is scarce. Therefore, owing to a lack of information, quail producers sometimes take management guidelines of other poultry species into account, which might not be completely profitable in improving meat-type quail production systems (Anthony et al., 1991). Other difficulties also are associated with the ineffectiveness of management policies in quail production as a result of nonuniformity and higher variation in egg weight (EW), incubation period, hatch weight, body weights at different ages (Anthony et al., 1991; Hyankova et al., 2004), and CY. Thus, considering their highly variable performances, giving an overview of the quail-specific management system during the rearing period and slaughter might be inadequate. However, ununiformed carcasses resulted from higher variation in SW of the birds, which is not desirable. Although CY of

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meat-type quails has economic importance, direct selection to improve this trait is found to be challenging. Therefore, SW or other body weight traits at higher ages adjacent to SW were also included in the breeding programs as correlated traits rather than CY (Akbarnejad et al., 2015).

In common breeding programs, genetic correlations between traits assume major importance to improve correlated traits. However, the importance of phenotypic correlations should not be neglected (Silva et al., 2013; Barbieri et al., 2015; Mohammadi-Tighsiah et al., 2018). Nevertheless, despite the importance of the availability of records, pedigree information in particular, reliable pedigree information is indispensable to design a practical breeding program, but reliable pedigree information is not commonly available in quail production systems (Sari et al., 2011).

In most of the production systems, the slaughter age of meat-type quails was considered between 40 and 45 D of age (Sari et al., 2011; Silva et al., 2013). In addition, sexual maturity in females and egg laying simultaneously start at the same age. Moreover it should be taken into account that in spite of commercial broilers, 1-day-old chickens in meat-type quails are not usually obtained from line breeding. Therefore, in a quail population of the same age, some of the birds were assigned as slaughter animals, and the others remained as breeder birds in the production system. Accordingly, egg production parameters assumed major importance even in meat-type quails. Although genetic or phenotypic correlations between body weight and egg production traits are negative (Kranis et al., 2006; Silva et al., 2013), greater impact on body weights results in lower egg production and vice versa. Therefore, partitioning of the birds into egg- or meat-producing groups based on their capability of producing egg or meat at the earlier stages would be helpful for quail production enterprises. Nevertheless, genetic or phenotypic correlations between early body weights and SW are weak (Barbieri et al., 2015) may be owing to sigmoid nature of growth pattern in quails (Anthony et al., 1991; Ahmad, 2009). Therefore, genetic or phenotypic selection of the birds based on early growth performances (as correlated traits) does not lead to improvement in SW. This may be due to nonlinear nature of the growth pattern of the birds or presence of maternal effects, which are not inherited at older ages. Accordingly, to find superior animals at slaughter, application of alternative methods rather than selection based on correlated traits would be profitable.

Artificial neural networks (ANN) were frequently used in the poultry production sector. Powerful potential and flexibility of ANN models have been used for solving complex nonlinear problems, control problems, and prediction of economically important traits such as parameters of egg production curve (Faridi et al., 2013), growth curve parameters (Ahmad, 2009), reproductive performance (Mehri, 2013), and nutrient requirements (Ahmadi and Golian, 2010; Mehri, 2014). An ANN

refers to a mathematical model inspired by neural networks of the human brain that provides a nonlinear data mining computing scheme to model the complex relationships between input variables (predictors) and output variable(s). To the best of our knowledge, the same report is not available with regard to final economic weight (e.g., SW) based on early growth performance of poultry species using modeling approaches. Therefore, the aim of the present study was to predict body weight at 45 D of age as SW of a Japanese quail population based on early growth performances, sex, and EW using the ANN. Sex of the birds was also included in the ANN model owing to its impact on EW and SW as well as its strong correlation with the birds' early growth performances.

## MATERIALS AND METHODS

### *Birds and Data*

Data included to train the ANN have been recorded from a random bred population of Japanese quails reared at the Research Center of Special Domestic Animals, University of Zabol, Zabol, Iran. This population was primarily reared for meat production, and eggs were routinely delivered to the hatchery at the Research Center of Special Domestic Animals for regeneration. The study was conducted following the general ethical guidelines of the Animal Care and Use Committee of the Department of Veterinary, University of Zabol.

To develop an ANN for the prediction of the SW in this study, body weight records of 1,136 registered quails of both sexes were considered, which were obtained from a single hatch. In the present study, body weight at day 45 was considered SW. Generally, each chicken was identified using wing tags immediately after hatch. Traits were body weight at hatch (**HW**) and body weight at 5 D of age (**BW5**), body weight at 10 D of age (**BW10**), body weight at 15 D of age (**BW15**), and body weight at 20 D of age (**BW20**) as early growth performances in addition to the weight of eggs to incubation (**EW**). In addition to quantitative traits, sex of the birds was also considered as a discrete variable in neural network modeling.

During the rearing period, the birds were fed a standard diet containing 21% CP and 2,700 kcal of ME/kg. During the experiment, food and water were given *ad libitum*. A light regimen from hatch to the third week was 24 h/D, which decreased to 16 h/D from the fourth week and was then kept constant until the end of the experiment (day 45). Temperature of the birds' rearing house gradually decreased from 38°C in the first week to 22°C in the third week. Afterward, it was maintained between 18 and 20°C until the end of the rearing period. All the chickens were kept in group cages with 40 birds in each cage from 10 to 45 D of age. The chicks were not vaccinated during the experimental period. Descriptive statistics of data used in the present study are shown in Table 1.

**Table 1.** Descriptive statistics of data used for modeling of slaughter weight in Japanese quails ( $n = 1,136$ ).

Trait	Variables	Mean $\pm$ SD	Maximum	Minimum
EW	Input	12.76 $\pm$ 1.23	21.10	8.95
HW	Input	8.30 $\pm$ 1.00	11.10	5.25
BW5	Input	15.70 $\pm$ 2.85	24.60	8.20
BW10	Input	32.05 $\pm$ 7.70	54.40	11.30
BW15	Input	55.60 $\pm$ 14.20	97.45	18.90
BW20	Input	84.07 $\pm$ 19.82	136.40	28.75
SW	Output	211.08 $\pm$ 30.44	293.71	86.20

Abbreviations: BW5, body weight at day 5; BW10, body weight at day 10; BW15, body weight at day 15; BW20, body weight at day 20; EW, egg weight; HW, body weight at hatch; SW, body weight at day 45 as slaughter weight.

## Artificial Neural Network

In brief, in the present study, the ANN structure determines the arrangement of neurons in 3 separate layers (input, hidden, and output layers). Hence, the input layer allocates data into the network, the hidden layer processes the data, and results are extracted in the output layer. To construct the ANN model in the present study, a feed-forward multilayer perceptron (MLP) neural network structure was used. The MLP neural network is very common for classification and prediction. This type of ANN is found to be effective for complex problems, which can be made use for supervised training (Haykin, 1999). The MLP ANN model consists of at least 3 layers of nodes (vectors), which include the input, hidden, and output layers. The input and output layers include predictors and predictive variable(s), respectively. To predict the SW of Japanese quails, the neural network was trained using the back-propagation algorithm. Backpropagation is a method to calculate the weight assigned to each neuron, which is used in the network (Bryson and Ho, 1969; Erb, 1993). The input vector included 7 variables: sex as a discrete variable and the other 6 continuous variables EW, early HW, BW5, BW10, BW15, and BW20, respectively. The input variables were assigned to the neural network to predict the output variable, which was SW in this study. There were no null fields in the data set for all the birds ( $n = 1,136$ ). Therefore, the data set included was an  $1,136 \times 8$  matrix with 9,088 elements. To train the neural network, randomly 70% (796 rows; 6,368 elements) of the input variables (for learning stage), 15% of the input variables (for validation phase) and 15% of the input variables (each 170 rows; 1,360 elements) (for testing stage) were assigned. Totally 5,000 different architectures (ANN models) with different neurons in the hidden layer (7 to 14 neurons) and different activation functions for the hidden and output layers (including each of identity, logistic, hyperbolic tangent, and exponential and sine functions) were assigned to the Automated Network Search (ANS) module of Statistica software version 8.0 (StatSoft Inc., Tulsa, OK, 2009). In fact, the main duty of the ANN is to find the most appropriate functions connecting the input and output layers. Therefore, the ANS module is used to

automatically find the best-fitted ANN models including the most appropriate connecting functions between 3 layers of MLP and the best number of hidden neurons, given that ANS provides a range of complexity to find the best-fitted model. Therefore, neurons' weighting function and their optimum network architecture were run automatically.

## Accuracy of the ANN

Accuracy of the ANN model prediction was evaluated using the coefficient of determination ( $R^2$ ). The  $R^2$  between actual and predicted values (obtained from the ANN) was separately calculated for the training, validation, and testing phases. Moreover, mean SE (MSE) was compared for the training, validation, and testing phases.

## Sensitivity Analysis

Owing to the nature of variables and/or the relationships between the input and output variables, a model may become very complex, and as a result, the relationships between inputs and output(s) may not be clear. In data mining and statistical model building or fitting, the sensitivity analysis ordinarily refers to the evaluation of the arrangement or importance of predictors in the ANN model(s) (Mehri, 2013, 2014). In Statistica Automated Neural Networks, the program will compute the residual sum of squares or misclassification rates for the model when the respective predictor is eliminated from the neural network. Moreover, ratios of the reduced model vs. the full model are reported, and the predictors can be arranged in terms of their importance to predict the output layer in a particular ANN. In the present study, the higher values reported as variable sensitivity ratio (VSR) indicate the more important predictor in relation to the prediction of SW in meat-type quails.

## Optimization of the ANN

In Statistica, optimization process refers to a search for the optimal values of input variables that will achieve a particular desired effect such as minimized or maximized values for output variables. In the present study, maximizing the SW was desired; therefore, the optimization process will determine the optimum values for input variables to yield maximum SW (293.71 g; Table 1). For this purpose, the "random search" optimization algorithm provided in the "response optimization" section of Statistica software was used (StatSoft Inc.).

## RESULTS

### Artificial Neural Network

Comparing results through running 5,000 different neural network structures using ANS and based on  $R^2$  and mean standard error (MSE) of the networks at

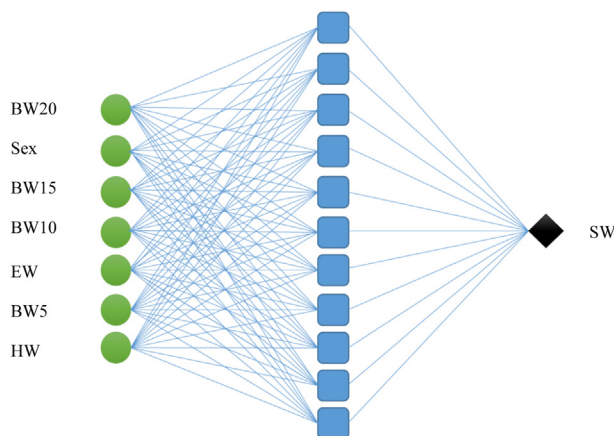
training, validation, and testing phases, the best-fitted network on input data to predict SW in meat-type quails was determined, with 7 neurons in the input layer, 11 neurons in the hidden layer, and one neuron in the output layer (SW). The connecting function between the input and hidden layer was hyperbolic tangent (tanh) and between the hidden and output layer was identity function. The topology of the network is shown in Figure 1.

The  $R^2$  values were 0.9404, 0.9359, and 0.9223 for the training, validation, and testing phases, respectively. Moreover, the MSE for the corresponding phases were 51.8854, 52.2764, and 55.2572, respectively. In other words, based on the  $R^2$  values, the ANN model was appropriately able to predict SW of meat-type quails based on EW, sex, HW, BW5, BW10, BW15, and BW20 (Figure 2).

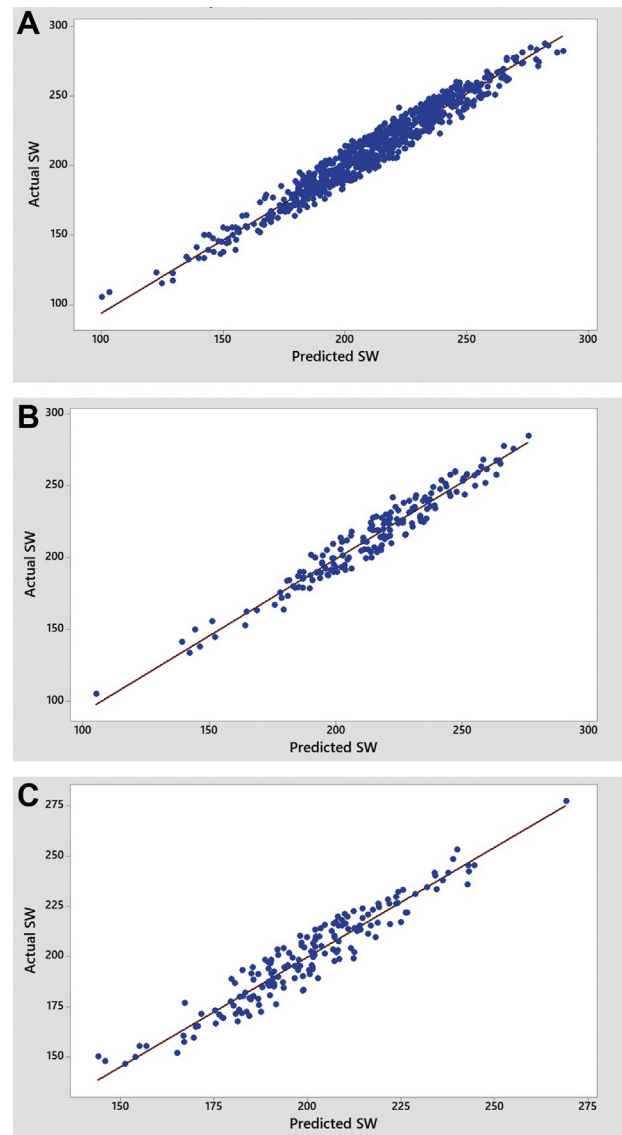
### Sensitivity Analysis

In this study, the importance of EW, sex, and early growth performances of meat-type quails to SW prediction was analyzed through sensitivity analysis (Table 2). According to VSR, the most important input variable in the prediction of SW was BW20 (VSR = 4.73). However, the less important input variables were HW and BW5, with VSR equal to 1.52 and 1.53, respectively. Considering only early body weights as the predictor of SW, the adjacent body weights to SW were BW20 (less interval between BW20 and SW), which resulted in higher VSR for BW20. Accordingly, the body weights from the highest VSR to the lowest were as follows: BW15, BW10, BW5, and HW, as expected. Indeed, with the increase of the interval between SW and early body weights (predictors), the importance of those predictors decreased.

Sex of the birds as a discontinuous variable was the second important predictor of SW (VSR = 2.04). However, between 7 input variables to predict SW in the



**Figure 1.** Artificial neural network topology (input layer sorted based on VSR). BW5, body weight at day 5; BW10, body weight at day 10; BW15, body weight at day 15; BW20, body weight at day 20; EW, egg weight; HW, body weight at hatch; SW, body weight at day 45 as slaughter weight; VSR, variable sensitivity ratio.



**Figure 2.** Correlation between actual and predicted SW at training (A), validation (B), and testing (C) phases. SW, body weight at day 45 as slaughter weight.

present study, EW was the fifth important predictor. Egg weight was more important than HW and BW5. Correlation between EW and HW is high. Moreover, EW could be a marker for chicken healthfulness and survivability, at least at earlier stages of life.

### Optimization of the ANN

To obtain the maximum value for SW in the present study (271.93 g), input variables were assigned to the “random search” optimization algorithm of Statistica software. The optimized values for input variables compared with mean and maximum values (derived from descriptive statistics, Table 1) are shown in Table 3.

The results of the neural network optimization showed that all the input variables, except for BW20, were very similar but slightly higher than mean values. However,

**Table 2.** Sensitivity of input variables (predictors) for prediction of slaughter weight (SW) in Japanese quails.

Input variable	BW20	Sex	BW15	BW10	EW	BW5	HW
Variable sensitivity ratio	4.73	2.04	1.79	1.73	1.71	1.52	1.53
Importance of input variables to predict SW	1	2	3	4	5	6	7

Abbreviations: BW5, body weight at day 5; BW10, body weight at day 10; BW15, body weight at day 15; BW20, body weight at day 20; EW, egg weight; HW, body weight at hatch; SW, body weight at day 45 as slaughter weight.

differences between optimal values and mean values for EW, HW, BW5, BW10, and BW15 were 1.10, 4.94, 6.37, 1.84, and 4.10%, respectively. However, the difference between the optimal value of BW20 and the mean value was higher than other differences (22.28%). The higher difference of BW20 with the optimal value refers to higher importance of this input variable to the prediction of SW as was suggested by sensitivity analysis. However, the differences between optimal and maximum values were 38.89, 21.74, 32.20, 40.01, 40.63, and 24.63% for EW, HW, BW5, BW10, BW15, and BW20 input variables, respectively, which indicate 20–40% differences between optimal values and maximum values for all the input variables.

## DISCUSSION

Breeding programs have been made to enhance meat production in quails (Lotfi et al., 2011; Narinc et al., 2013; Barbieri et al., 2015). However, selecting birds for SW based on early growth performance is not common owing to weak correlation between early and late body weights. Several studies have confirmed positive and high estimates of phenotypic or genetic correlation for body weights at adjacent ages, while there was a significant decrease of estimates as the interval between ages has increased (Silva et al., 2013; Barbieri et al., 2015; Mohammadi-Tighsiah et al., 2018). In the present study, the importance of later body weight traits to prediction of SW was explained with higher VSR value of BW20, whereas the earlier body weight traits are weak predictors for SW, as suggested in other studies. In the study of body weights in a meat-type quail, phenotypic correlation for BW28–BW42 (with less interval between 2 traits) was 0.67, whereas phenotypic correlation for BW0–BW42 (with high interval between 2 traits) was 0.17

**Table 3.** Optimal values of input variables (predictors) in comparison with mean and maximum values (from Table 1).

Input variable	Sex	EW	HW	BW5	BW10	BW15	BW20
Optimal	Female	12.90	8.71	16.70	32.64	57.88	102.80
Mean	-	12.76	8.30	15.70	32.05	55.60	84.07
Maximum	-	21.11	11.13	24.63	54.41	97.49	136.40

Abbreviations: BW5, body weight at day 5; BW10, body weight at day 10; BW15, body weight at day 15; BW20, body weight at day 20; EW, egg weight; HW, body weight at hatch; SW, body weight at day 45 as slaughter weight.

(Barbieri et al., 2015). Early growth traits assumed less importance in prediction of final body weights in quail. This may be due to the S-shaped pattern of the growth curve in this bird. In fact, the growth rate of the birds at early stages is very slow, and after 15–20 D of age, the growth rate accelerates to the inflection point (Hyankova et al., 2001; Faraji-Arough et al., 2018). Selection for body weight at week 4 (28 D) was recommended in the study of Barbieri et al. (2015) to maximize body weight at week 6 (42 D) as a correlated trait (phenotypic correlation for BW28–BW45 = 0.67). However, selection for body weight at 28 D of age may adversely lead to increase in the abdominal fat (Murata et al., 2013).

Sex of birds has been found to have a significant fixed effect on body weights of quails in different statistical analyses (Silva et al., 2013; Mohammadi-Tighsiah et al., 2018). Although the effect of sex on initial body weights has assumed a lower importance, it should be taken into account at higher rates as suggested by the sensitivity analysis of this study. In our study, the importance of sex to the prediction of SW was lower than BW20 but higher than other predictors (EW, HW, BW5, BW10, and BW15). In Japanese quails, bird sexing becomes possible at 3 wk of age based on the plumage pattern. Differences between male and female body weights usually refer to their differentially expressed sex-specific genes and reproductive activities (Caetano-Anolles et al., 2015). In quails, before sexual maturity, females become heavier than males. Aggrey et al. (2003) reported that body weight of female quails at 28 D was higher than males but was not statistically significant; however, after 28 D of age, body weights of all females became significantly higher than males. In dual-purpose and even in the meat-type quails despite higher body weight of females at the end of the production period, they were not slaughtered. Rather, they were transferred to the laying phase. Moreover, in the breeder rearing system, each male quail is usually assigned to 2 to 3 females. Therefore, at the end of the growing period, at least half of the males would be slaughtered. Consequently, although higher body weight of female quails is inevitable (as shown in this study), it is not desirable from an economical point of view.

Several reports have demonstrated that maternal effects at the earlier stages of the birds' life should be considered to study the early body weight traits (Hartmann et al., 2003; Ghorbani et al., 2013; Barbieri et al., 2015). In fact, maternal effects were transmitted to the chicken through egg composition, and for later body weights, the influence of maternal effects decreased. Being highly correlated with early growth performance, the egg size and composition directly reflected the maternal ability. However, the results of our study suggest that the importance of EW is less than BW20, BW15, BW10, and sex of the birds for the prediction of SW. In fact, assigning higher EW to incubation necessarily did not result in higher SW.

To confirm the sensitivity analysis output, the ANN optimization revealed that higher values of EW or early

body weights (especially HW and BW5) of quails would not lead to higher SW. Karami et al. (2017) studied weekly body weights of Japanese quails using the random regression model. They suggest that earlier body weights of quails (especially HW) are naturally different from body weights at older ages. Therefore, they imply that to improve SW, HW could not be used as a selection criterion. This finding was in agreement with our results.

In conclusion, lack of pedigree information makes the selection for correlated traits difficult. However, the ANN provides a powerful approach to predict the response variable only based on phenotypic records. We developed a practical approach to predict SW in meat-type quails based on early body weights, sex, and EW. However, owing to the lower importance of HW and BW5, these 2 traits may be ignored in the commercial scale to predict SW. Moreover, considering higher values of early body weights and EW (except for BW20) did not ensure to improve SW.

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