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Technical Note

Artificial Neural Networks to Predict Egg-Production Traits in Commercial Laying Breeder Hens

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ABSTRACT

In recent years, egg production has had an intense growth in Brazil, and Brazilian egg consumption *per capita* has significantly increased in the last decade. To reduce sanitary and financial risks, decisions regarding the production and health status of the flock must be made based on objective criteria. Our aim was to determine the main "input" variables for the prediction of egg production performance in commercial laying breeder flocks using an ANN model. The software NeuroShellClassifier and NeuroShell Predictor were used to build the ANN. A total of 26 egg-production traits were selected as input variables and eight as output variables. A database of 44,120 Excel cells was generated. For the training and validation of the models, 74.9% and 25.1% of the data were used, respectively. The accuracy of the ANN models was calculated and compared using the analysis of coefficient of multiple determination (R2), mean squared error (MSE), and an assessment of uniform scatter in the residual plots. The models for the outputs "weekly egg production," "weekly incubated egg,", "accumulated commercial egg," and "viability" showed an R2 greater than 0.8. Other models yielded R2 values lower than 0.8. The ANN predicts adequately eight egg-production traits in the breeders of commercial laying hens. The method is an option for data management analysis in the egg industry, providing estimates of the relative contribution of each input variable to the outputs.

INTRODUCTION

Over the years, technological improvement in genetics, handling, and facilities has guaranteed increased production and positioned Brazil as the world's third largest producer of chicken meat, with over 13 million tons per year of this protein. Thus, the Brazilian industry has provided a healthy and low-cost protein source for consumers in all five continents. Similarly, egg production in Brazil has shown intense growth in recent years. Brazilian egg consumption *per capita* increased from 148 in 2010 to 212 eggs in 2018 (ABPA, 2021).

Although distant from the largest consuming countries, the significant increase in egg consumption presents a challenge for the commercial laying hen chain, which has shown a larger number of housed birds and data for management in recent years. According to the Brazilian Institute of Geography and Statistics (IBGE), the number of laying hens in the country in 2017 increased by more than 11% compared to 2016 (IBGE, 2010). To reduce sanitary and financial risks, decisions regarding the production and health status of the flock must be made based on objective criteria (Salle *et al.*, 2018).

In the case of poultry production processes, it is desirable to obtain accurate information reflecting the reality of the company and develop tools that assist in decision making. In this context, artificial intelligence (AI) has been developed in tandem with the need to analyze big data using high-performance computing (Tedeschi, 2019). An artificial neural network (ANN) is a computing system inspired by biological neural networks that constitute animal brains (Pinto, 2006; Vanneschi & Castelli, 2018). ANNs have the ability to learn the patterns of a dataset during the training process, thereby being able to provide consistent predictions or generalization capabilities over test sets considering the relationship between the input and output information (Savegnago *et al.*, 2011).

In the past five years, AI technologies have grown by 300% per year, and it is estimated that they will increase civilization's productivity by 40% by 2035 (Salle *et al*., 2018). Several studies in different segments of the poultry chain have been conducted over the years using ANNs (Salle *et al.*, 2003; Moraes *et al*., 2010; Spohr 2011; Savegnano *et al*., 2011; Carvalho *et al.*, 2016; Ramírez-Morales *et al.,* 2017; van der Klein *et al.*, 2020; You *et al.*, 2021). However, the evaluation of the use of this tool in the commercial laying hen chain is still limited. In this context, the aim of this study was to determine the main "input" variables for the prediction of egg production performance in commercial laying breeder flocks using an ANN model.

MATERIALS AND METHODS

Flock productive data

Data on the egg production traits of 51 flocks of layer breeders (Isa Brown and Bovans White) from a multiplier company located in the state of Rio Grande do Sul, southern Brazil, were selected for the study. The collected data refer to flocks housed between 2010 and 2018, representing a total of 405,511 breeders. The birds were housed under an all-in all-out system, and data were analyzed from 1 to 75 weeks of age.

Production systems and the sanitary management

For this study, only commercial laying breeder flocks (Isa Brown and Bovans White) data were selected. All flocks were raised in conventional production systems and all farms adopt strict bio-security systems that include, among other measures, installation of a disinfection arch at the farm entrance, a cleaning and disinfection process prior to flock arrival, fumigation, isolation fences, restroom for shower and clothes changing before entering the clean area. Egg management includes collection in the nests, selection, fumigation, and storage in an air-conditioned room.

Serological monitoring was carried out every two months for infectious anemia, Gumboro disease, pneumovirus, infectious bronchitis, and avian mycoplasmosis. Bacteriological tests were also carried out for the detection of *Salmonella* spp.

Selected egg-production traits

The egg production traits used for the mathematical models were classified as the "input" data, and the measures to be predicted were classified as the "output" data. The variables selected as "output" data are considered to be among the most important results to be predicted, according to the multiplier company. A total of 26 egg-production traits were selected as "input" data.

Variables included flocks characteristics such as age (weeks), number identification (identification code), number of breeders (total number), number of males (total number), lineage (Isa Brown or Bovans White), and number of eggs per hen (egg/hen). General performance data included absolute number of discarded breeders (total number), breeders sold vs. housed birds, viability (100% – mortality rate, %), flock uniformity [determined based on the mean weight (± 10%) of the flock], weekly hatching eggs (weekly total number), weekly incubated eggs (weekly total number), weekly commercial eggs (weekly total number), egg weight (grams), daily feed consumption per hen (grams/hen), and weekly total feed consumption (kilograms). Weekly means data included weekly mortality of breeders (weekly total number), weekly mortality of males (weekly total number), absolute number of breeders in the flock (weekly total number), weekly weight (grams), weekly egg production (weekly total number), weekly cracked eggs (weekly total number), weekly floor eggs (weekly total number), and weekly discarded eggs (weekly total number). Finally, weekly accumulated variables included accumulated egg production (total number) and accumulated commercial eggs (total number).

A total of eight egg production traits were considered as variables to be predicted: weekly egg production (%), weekly total feed consumption (kilograms), number of eggs per hen (egg/hen), weekly commercial eggs (weekly total number), weekly incubated eggs (weekly total number), egg weight (grams), accumulated egg production (total number), and viability (100% – mortality rate, %).

Artificial neural networks (ANN)

The input and output variables were analyzed using NeuroShell Classifier and NeuroShell Predictor software (Ward Systems Group, Frederick, USA), version 4.0TM. Back-propagation architecture (Ward Network) with supervised feed-forward networks with three hidden layers and different activation functions was used in these software. NeuroShell Predictor is used for forecasting and estimating numeric amounts, and the following settings were applied: (1) training strategy: genetic; (2) maximum number of hidden neurons: 80; (3) optimization goal: maximize R-squared; (4) optimization method: gene hunter. Data inclusion and software use procedures followed the developer's guideline.

The genetic method was used for ANN training, a genetic algorithm variation of the General Regression Neural Network (GRNN), which is a cross validation technique combining a genetic algorithm with a statistical estimator. A database of 44,120 Excel cells was generated according to the selected variables. Individual data from 33,046 flocks (74.9% of records) were randomly selected for training. After ANN training and the selection of the most adjusted network model for each variable of interest, ANN models were validated. Individual data from the flocks that were not used for training (11,074 flocks, 25.1% of records) were used to verify the predictive capacity (degree of generalization) of ANN models.

Analysis of ANN models

ANN models were individually analyzed in relation to the coefficient of multiple determination (R^2) and mean squared error (MSE). MSE is used in regression analysis to show how close a regression line is to a set of points (the distance from the regression line). An assessment of uniform scatter in the residual plots was also used (Salle *et al.*, 2003; Almeida *et al.*, 2020). These statistical parameters were obtained in the training stage, when the predicted values were compared to the actual values of the respective output variables.

R² was calculated using the following equation:

$R^2 = 1 – (SSE / SSyy)$

Where:

$SSE = (\text{real value} – \text{predicted value})^2$

$SSyy = (\text{real value} – \text{mean of values})^2$

The MSE was calculated using the following equation:

$MSE = \text{mean} \times (\text{real value} – \text{predicted value})^2$

RESULTS AND DISCUSSION

Traditionally, poultry are monitored based on the producer's experience and expertise in managing and evaluating the production process. However, there is a current tendency of using monitoring systems and tools for data analysis as a complement to human observations (Frost *et al.*, 1997; Ramírez-Morales *et al.*, 2017, Singh, 2021). An expert system to support decision-making is fundamental because it allows the identification of anomalies in production by specifying important differences among the production indices (De Vries & Reneau, 2010; Abreu *et al.*, 2020). Poultry companies in the world market depend on constant decision making. When made improperly or without criteria, these decisions may lead to incorrect and unfounded diagnoses (Salle, 2018; Salle *et al.*, 2018; Abreu *et al.*, 2020). The poultry production chain faces several challenges related to industrial-level production, and intelligence systems may help in addressing these issues. Today, the majority of the farms are collecting data manually, but in 30 years, it is probable that data will be automatically generated by several sensors and other devices (Singh, 2021).

Previous studies conducted by our research team have shown that ANNs can be used for performance parameter management in broiler breeders, poultry flocks, hatcheries, and poultry slaughterhouses (Reali, 2004; Salle, 2005; Salle *et al.*, 2013; Spohr, 2011; Tedeschi, 2019). Spohr (2011) successfully simulated the zootechnical performance of an entire poultry production chain using AI. Furthermore, ANNs were used by our team to predict the antimicrobial resistance of *Escherichia coli* strains (Rocha, 2012) and to evaluate lymphocyte depletion in the bursa of Fabricius and thymus (Moraes *et al.*, 2010, Carvalho *et al.*, 2016). Other research groups have also developed mathematical models and intelligence systems that allow for the data management of several areas of the poultry production chain (Lourençoni *et al.* 2019; Abreu *et al.*, 2020; van der Klein *et al.*, 2020; You *et al.* 2021). In this study, a database of more than 21 million birds from a poultry industry in Rio Grande do Sul state was evaluated for seven months.

The significant increase in egg production, leading to a large number of housed birds and consequently of data for management, motivated the development of the first studies on the use of ANNs in the commercial laying chain by our research team. Recently, Almeida *et al.* (2020) showed that ANN was capable of managing six parameters selected as "output" data in a commercial egg production facility. The current study evaluated the use of ANNs in the initial and fundamental stages of the commercial laying hen chain, and the results obtained may reflect the entire performance of a company. Certain earlier studies evaluated the use of ANNs as a prediction tool in commercial laying hen chain. However, only one or more parameters (such as egg production and egg abnormalities) were estimated. Moreover, a smaller number of egg-production traits were selected as input variables (Ahmad, 2011; Savegnago *et al.*, 2011; Ramírez-Morales *et al.*, 2017), and no study specifically analyzed commercial laying breeders.

In this study, it was possible to build models for eight different outputs by selecting a variable number of egg production traits as input variables. However, it is important to emphasize that all egg production traits may be selected as output variables, depending on companies' interests (Almeida *et al.*, 2020). R^2 and MSE were used to evaluate the fit of the models, and their values for each model (training and validation) are listed in Tables 1 and 2. R^2 is an indicator of how efficiently the model fits the data (Salle *et al.*, 2003; Savegnago *et al.*, 2011). Values of R^2 near "1" indicate a higher quality in the validation of the network, whereas those that are more distant present a lower quality (Salle *et al.*, 2003; Almeida *et al.*, 2020). Previous studies in the same area have already shown that R^2 values above 0.70, in the ANN training processes, indicate a good quality of networks for prediction (Salle *et al.*, 2003; Reali, 2004; Salle, 2005; Spohr, 2011; Tedeschi, 2019; Almeida *et al.*, 2020). Furthermore, MSE values indicate the error in the prediction of a specific variable, and smaller values indicate better fitting of the models (Savegnago *et al.*, 2011). Since the output variables are a subset of the input variables, they were removed from the model fitting stage. The selection of the best model for each output was based on the largest R^2, lowest MSE, and an assessment of uniform scatter in the residual plots. Fig. 1 depicts an example of the scatter plot and fitting performance with the analysis of the network prediction versus the actual value of the output; in this case, "weekly incubated eggs." Figures for the other outputs are available in the Supplementary Material (Fig. S1 to S7).

Table 1 – Coefficient of multiple determination, mean squared error, and total of input variables selected for training of each output variable.

Output variable	R^{2*}	*MSE	Total of entries (input variables)
Weekly egg production (weekly total number)	0.9832	2,0E+06	11
Weekly total feed consumption (Kg)	0.7666	283,79	15
Number of eggs per hen (egg/hen)	0.9666	1,27E+11	11
Weekly commercial eggs (weekly total number)	0.9389	2,12E+06	6
Weekly incubated eggs (weekly total number)	0.9973	158375,1	7
Egg weight (g)	0.7153	7.439	13
Accumulated commercial eggs (total number)	0.8772	49.234	6
Viability (100 – mortality %)	0.9729	23.2146	15

*Coefficient of multiple determination (R^2) and mean squared error (MSE).

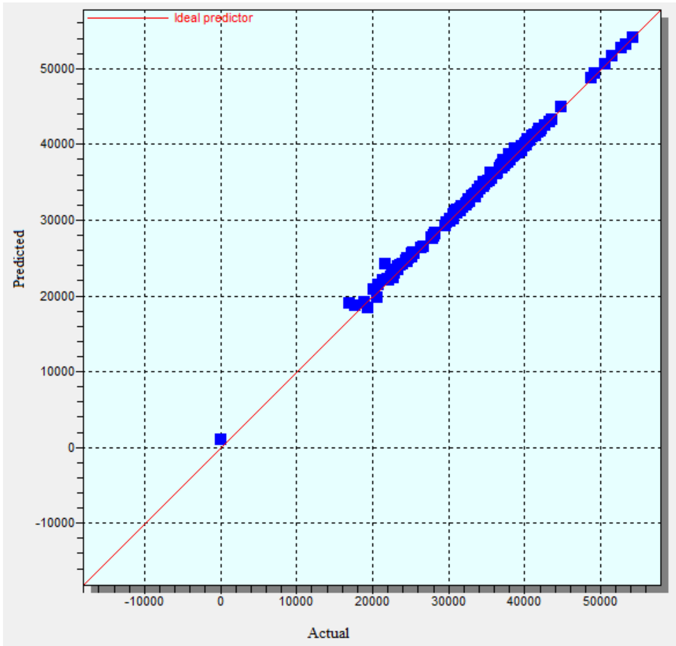

Figure 1 – Scatter plot of weekly incubated eggs (weekly total number). Predicted values (y) and actual values (x) of 51 flocks of layer breeders.

The relative contributions (%) of the egg production traits selected as input variables for the ANN models are presented in Tables 3, 4, 5, 6, 7, 8, 9 and 10.

The models for the outputs "weekly egg production," "weekly incubated eggs," "accumulated commercial eggs," and "viability" showed an R^2 greater than 0.8 (Table 1 and 2). Despite the higher MSE, justified by the variable number of birds housed in each flock, the models related to these variables showed a high capacity to predict the results (Fig. 1, S1, S6, and S7). The use of mathematical models to estimate egg production curves is of great importance to estimate the financial loss caused by a decline in egg production, as evidenced by a deviation from the expected curve (Forsström & Dalton, 1995; Savegnago *et al.*, 2011). The input variables "flock age," "accumulated egg production," and "weekly egg production" were the most important for prediction of "weekly total egg production" (Table 3) and "weekly commercial eggs" (Table 6) with a relative contribution

Table 2 – Coefficient of multiple determination, mean squared error, and total of input variables selected for validation of each output variable.

Output variable	R^{2*}	*MSE	Total of entries (input variables)
Weekly egg production (weekly total number)	0.9551	4.92E+06	11
Weekly total feed consumption (Kg)	0.7707	260.0547	15
Number of eggs per hen (egg/hen)	0.7249	7.96E+11	11
Weekly commercial eggs (weekly total number)	0.7725	8.07+E	6
Weekly incubated eggs (weekly total number)	0.9978	144896.4	7
Egg weight (g)	0.7179	4.6412	13
Accumulated commercial eggs (total number)	0.8210	58.348	6
Viability (100 – mortality %)	0.9674	25.6912	15

*Coefficient of multiple determination (R^2) and mean squared error (MSE).

Table 3 – Relative contribution of each input variable for the output variable "Weekly egg production (weekly total number)".

Input Variable	Relative contribution of the variable (%)
Accumulated eggs production (total number)	22.9
Weekly incubated eggs (weekly total number)	22.8
Flock age, weeks	22.6
Weekly commercial eggs (weekly total number)	17.1
Number of animals (total number of breeders)	6.6
Other variables	8

Table 4 – Relative contribution of each input variable for the output variable "Weekly total feed consumption (kilograms)".

Input Variable	Relative contribution of the variable (%)
Weekly commercial eggs (weekly total number)	11.3
Flock age, weeks	11
Number of eggs per hen, egg/hen	9.3
Accumulated egg production (total number)	7.2
Weekly discarded eggs (weekly total number)	5.8
Weekly incubated eggs (weekly total number)	4.8
Weekly cracked eggs (weekly total number)	3.5
Other variables	47.1

of 68.3% and 92.3%, respectively, to the models. These results were expected because these egg production traits are directly related to egg production (Almeida et al. 2020). The effect of age on hatchability and egg production is well known (Ahmad, 2011; Abudabos *et al.*, 2017, Nasri *et al.*, 2020), and it is also an important input variable for the prediction of "weekly incubated eggs" (Table 7). Other variables may also influence the prediction of egg production traits related to egg production, including temperature and variations in the period of natural and artificial light or the season in which the laying period begins (Tumová & Gous, 2012; Almeida *et al.,* 2020), which are not regularly collected by companies.

Table 5 – Relative contribution of each input variable for the output variable "Number of eggs per hen (egg/hen)".

Input Variable	Relative contribution of the variable (%)
Number of males (total number)	30.8
Weekly cracked eggs (weekly total number)	18.3
Number of breeders (total number)	16
Weekly egg production (weekly total number)	12.5
Accumulated egg production (total number)	11.6
Flock age, weeks	3.8
Absolute number of discarded breeders (total number)	3.1
Other variables	3.9

Table 6 – Relative contribution of each input variable for the output variable "Weekly commercial eggs (weekly total number)".

Input Variable	Relative contribution of the variable (%)
Flock age, weeks	32.4
Accumulated egg production (total number)	32.1
Weekly egg production (weekly total number)	27.8
Weekly incubated eggs (weekly total number)	3.9
Breeders sold X X housed birds	2.9
Number of animals (total number of males)	0.9

Table 7 – Relative contribution of each input variable for the output variable "Weekly incubated eggs (weekly total number)".

Input Variable	Relative contribution of the variable (%)
Flock age, weeks	34
Accumulated egg production (total number)	33.9
Weekly egg production (weekly total number)	14.1
Number of males (total number)	8.7
Weekly commercial eggs (weekly total number)	4.6
Number of breeders (total number)	3.9
Other variables	0.8

Table 8 – Relative contribution of each input variable for the output variable "Egg weight (grams)".

Input Variable	Relative contribution of the variable (%)
Number of breeders (total number)	17
Weekly incubated eggs (weekly total number)	16.7
Weekly commercial eggs (weekly total number)	13.5
Accumulated egg production (total number)	13.3
Number of males (total number)	9.3
Weekly mortality of breeders (weekly total number)	8.9
Weekly weight, grams	8.4
Other variables	12.9

Besides "flock age," the "number of males" and "number of breeders" were the input variables that most contributed to the prediction of "viability" (Table 10). The importance of these variables was expected because they directly reflect the zootechnical parameter calculation. However, it must be highlighted that the structure of the aviaries and management conditions, which were not available in the database of the company, are factors that could have influenced the "viability." These potential input variables were shown to be relevant in the prediction of mortality in commercial laying flocks in an earlier study (Almeida *et al.*, 2020). Moreover, serological monitoring records were not available in the current database and should be considered for the prediction of "viability" in the future (Salle *et al.*, 2003). Although the values of R^2 and MSE indicate an adequate network for the prediction of "viability" (Savegnago *et al.*, 2011), the addition of these or other input variables would provide an even higher ANN quality for all models built in this study.

Table 9 – Relative contribution of each input variable for the output variable "Accumulated commercial eggs (total number)".

Input Variable	Relative contribution of the variable (%)
Flock age, weeks	32.9
Number of breeders (total number)	32.8
Number of males (total number)	19
Weekly mortality of breeders (weekly total number)	11.7
Absolute number of discarded breeders (total number)	2.1
Weekly mortality of males (weekly total number)	1.5

The other four models showed R^2 values lower than 0.8 (Table 1 and 2). The model for the output "weekly total feed consumption" presented an R^2 of 0.7707 (Fig. S2), and certain factors interfered with the obtained value. The feed consumption of laying breeders could vary from 9 g to 123 g, depending on the production stage. Moreover, all evaluated flocks were housed in conventional aviaries, where thermal amplitude could affect feed consumption. Several studies have demonstrated the influence of temperature in production traits (Osti *et al.*, 2017; Blanco *et al.*,2022). Bordas & Minvielle (1997) observed a reduction of up to 16% in the feed intake of laying breeders housed in environments with a temperature of 35 °C compared to that of birds of the same lineage housed in aviaries at 21 °C. The model for the "egg weight" output also presented a lower prediction (Fig. S5), which was influenced by the low uniformity of certain flocks during peak production, in addition to the occurrence of dietary alterations in seasonal periods (Hudson et al., 2001; Ekmay *et al.*, 2012).

Table 10 – Relative contribution of each input variable for the output variable "Viability (100% − − mortality rate, %)".

Input Variable	Relative contribution of the variable (%)
Number of animals (total number of males)	18.5
Number of animals (total number of breeders)	18.5
Flock age, weeks	15.3
Weekly cracked eggs (weekly total number)	13
Weekly incubated eggs (weekly total number)	8.6
Number of eggs per hen, egg/hen	7
Other variables	19.1

It is impossible to compare different ANNs or use datasets from other populations when considering the synaptic weights of neural networks (Hocking & Bernard, 2000). The eight built models are specific to the company of the present study, and they do not provide parameters that may be useful for comparative purposes (Savegnago *et al.*, 2011; Salle, 2018). Thus, the use of ANNs in a hen production type, characterized by the presence of several small companies in southern Brazil, may be limited. Another restriction of ANNs is the inability to explain, in a comprehensible way, the process by which a given decision or answer was made by the model, which is considered a "black box" (Roush *et al.*, 2006, Almeida *et al.*, 2020). A small database also represents a limitation in building ANNs because of the impossibility of partitioning the database into fairly sized subsets for training and validation (Ekmay *et al.*, 2012). For instance, approximately 75% of the data were used for training and validation of the models in the present study. In addition to the size, ANNs depends on the quality of the database, as has been observed in any conventional statistical model (Roush *et al.*, 2006; Savegnago *et al.*, 2011; Almeida *et al.*, 2020). The existence of outliers justified by the bias in the annotation of data sheets and in the incorrect use of equations negatively interfered in the prediction of the models for the outputs "number of eggs per hen" and "weekly commercial eggs" (Fig. S3 and S4). Errors in managing the production of commercial eggs were particularly more frequent, which is partly justified by farmers only being remunerated for incubated eggs produced.

Despite this, an ANN would be more appropriate for generalizing the predictions using the input information of the neural network for a commercial dataset with a large amount of environmental noise

(Savegnago *et al.*, 2011). The advantage of using neural networks is that they can be fitted to any type of dataset and do not require model assumptions, such as those required in the nonlinear methodology (Almeida *et al.*, 2020). Neural networks, as observed in the model built in this study, can be fitted to any type of dataset and are characterized by a high tolerance to data containing measurement errors (Wasserman & Schwartz, 1988; Almeida *et al.*, 2020).

Moreover, the contributions of the different inputs used to estimate the outputs, as presented in Tables 3 to 10, allow us to understand what interferes with the variable to be predicted. This method is a tool for process management, and poultry professionals can evaluate the data, propose pertinent corrections, and focus on the most important interfering variables (Salle *et al.*, 2003; Salle, 2018). It is clear that certain inputs cannot be modified by the industry, and others are unchangeable, such as the season of the year (Salle *et al.*, 2003).

The ANN models were capable of predicting eight egg-production traits in breeders of commercial laying hens: weekly egg production, weekly total feed consumption, number of eggs per hen, weekly commercial eggs, weekly incubated eggs, egg weight, accumulated egg production, and viability. The relative contribution of each input variable was different for different output variables. Thus, ANN provides predetermined criteria to measure and ensure the optimal outcome in a specific topic in a decision-making process. The results demonstrated that ANNs are an option for data management analysis in the egg industry.

CONFLICT OF INTEREST STATEMENT

The authors have no competing interests.

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SUPPLEMENTARY MATERIAL

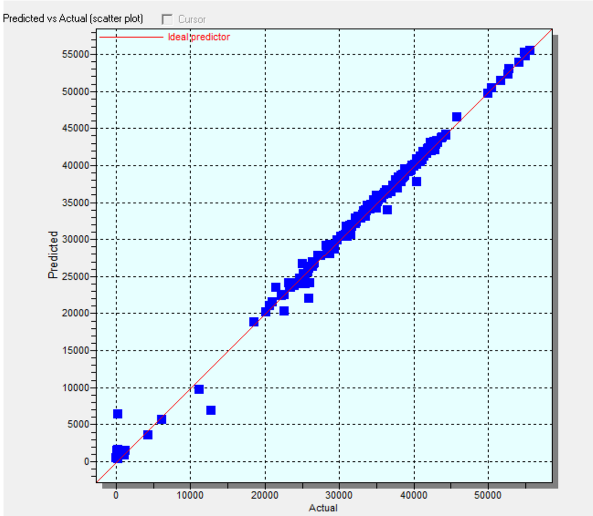

Figure S1 – Scatter plot of weekly egg production, %. Predicted values (y) x actual values (x) of 51 flocks of layer breeders.

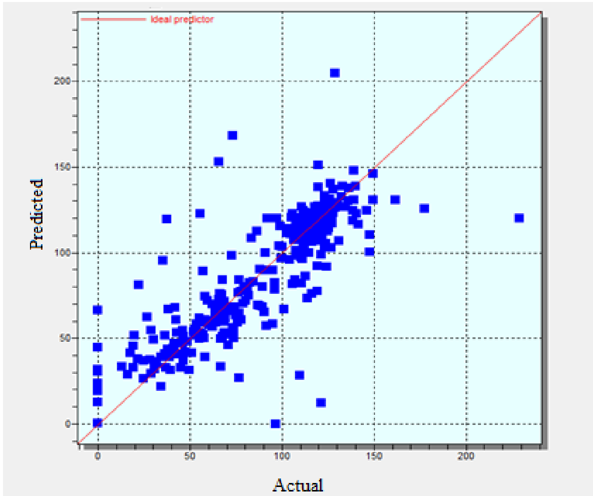

Figure S2 – Scatter plot of weekly total feed consumption, kg. Predicted values (y) x actual values (x) of 51 flocks of layer breeders.

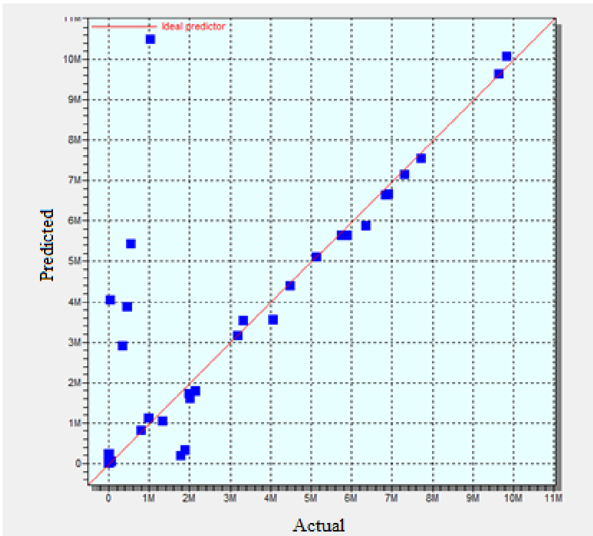

Figure S3 – Scatter plot of number of eggs per hen, egg/hen. Predicted values (y) x actual values (x) of 51 flocks of layer breeders.

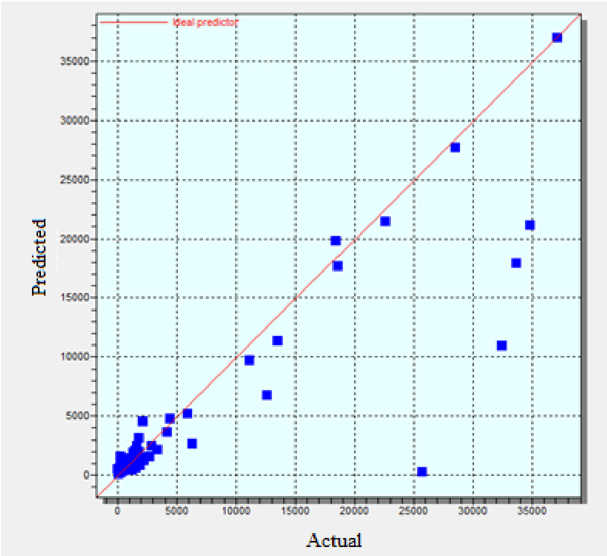

Figure S4 – Scatter plot of weekly commercial eggs (weekly total number). Predicted values (y) x actual values (x) of 51 flocks of layer breeders.

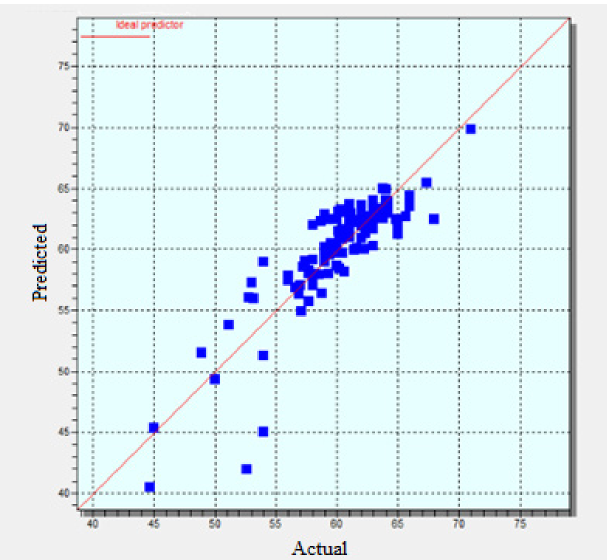

Figure S5 – Scatter plot of egg weight, g. Predicted values (y) x actual values (x) of 51 flocks of layer breeders.

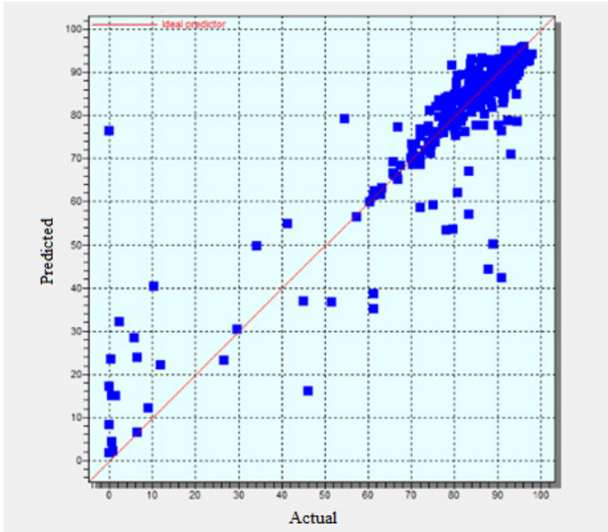

Figure S6 – Scatter plot of accumulated egg production (total number). Predicted values (y) x actual values (x) of 51 flocks of layer breeders.

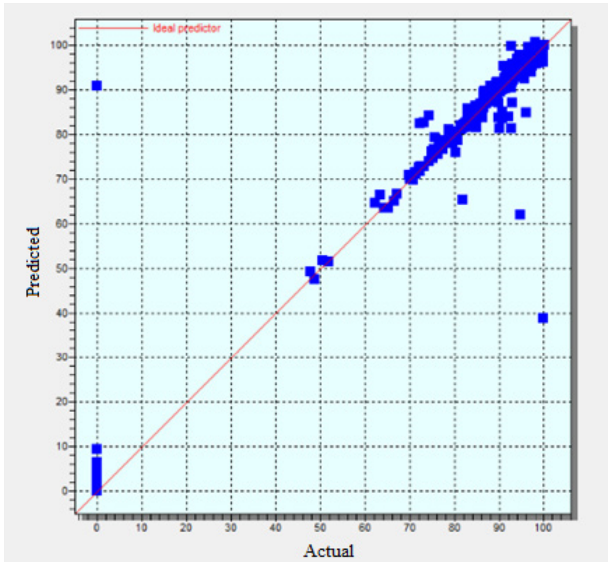

Figure S7 – Scatter plot of viability (100% – mortality), %. Predicted values (y) x actual values (x) of 51 flocks of layer breeders.