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Artificial neural networks for the management of poultry industry: a simulation based on the broiler production chain

Redes neurais artificiais para o gerenciamento da indústria avícola: uma simulação baseada na cadeia de produção de frangos de corte

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Abstract
The aim of this study was to predict production indicators and to determine their potential economic impact on a poultry integration system using artificial neural networks (ANN) models. Forty zootechnical and production parameters from broiler breeder farms, one hatchery, broiler production flocks, and one slaughterhouse were selected as variables. The ANN models were established for four output variables: “saleable hatching”, “weight at the end of week 5,” “partial condemnation,” and “total condemnation” and were analyzed in relation to the coefficient of multiple determination (R^2), correlation coefficient (R), mean error (E), mean squared error (MSE), and root mean square error (RMSE). The production scenarios were simulated and the economic impacts were estimated. The ANN models were suitable for simulating production scenarios after validation. For “saleable hatching”, incubator and egg storage period are likely to increase the financial gains. For “weight at the end of the week 5” the lineage (A) is important to increase revenues. However, broiler weight at the end of the first week may not have a significant influence. Flock sex (female) may influence the “partial condemnation” rates, while chick weight at first day may not. For “total condemnation”, flock sex and type of chick may not influence condemnation rates, but mortality rates and broiler weight may have a significant impact.
Keywords: artificial intelligence; data management; economic impact; poultry production

Resumo
O objetivo deste trabalho foi predizer os indicadores de produção e determinar o seu potencial impacto econômico em um sistema de integração utilizando as redes neurais artificiais (RNA). Quarenta parâmetros zootécnicos e de produção de granjas de matrizes e de frango de corte, um incubatório e um abatedouro foram selecionados como variáveis. Os modelos de RNA foram estabelecidos para quatro variáveis de saída (“eclosão vendável”, “peso ao final da quinta semana”, “condenações parciais” e “condenações totais”) e foram analisados em relação ao coeficiente de determinação múltipla (R^2), coeficiente de correlação (R), erro médio (E), erro quadrático médio (EQM) e raiz do erro quadrático médio (REQM). Os cenários produtivos foram simulados e os impactos foram estimados. Os modelos de RNA gerados foram adequados para simular diferentes cenários produtivos após o treinamento. Para “eclosão vendável”, o modelo de incubadora e o período de incubação aumentaram os ganhos financeiros. Para “peso ao final da quinta semana”, a linhagem também demonstrou influência no retorno financeiro, o que não aconteceu com o peso ao final da primeira semana. O sexo do lote possui influência nas taxas de “condenação parcial”, ao contrário do peso do frango no primeiro dia. As taxas de mortalidade e o peso do frango apresentaram influência na “condenação total”, mas o sexo do lote e o tipo de pinto não tiveram influência.
Palavras-chave: gerenciamento de dados; impacto econômico; inteligência artificial; produção avícola

1. Introduction

Despite improvements in broiler performance through genetics, nutrition, and management, there is still a gap between the potential and the performance achieved[(1)]. Chicken meat production is typically based on company guidelines and producer experience. However, the development of new technologies in the last decade has supported objective decision making in poultry farms[(2)]. In addition, epidemiological studies using an integrated approach to identify the different factors threatening broiler

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performance under field conditions are rare[1].

Artificial intelligence (AI) has been developed in tandem with the need to analyze big data using high-performance computing[3]. AI tools include artificial neural networks (ANN), which are computing systems inspired by biological neural networks that constitute animal brains[4]. ANN is a helpful tool for classification, clustering, pattern recognition, and prediction in several areas, including animal production[5]. The main advantage of ANN models is that they consider the nonlinearity of the relationship between input and output information[6]. Other interesting properties include self-learning, adaptivity, and fault tolerance[5].

Previous studies conducted by our research team showed that ANN can be used for performance parameter management in different areas of poultry production[3,7-10]. Furthermore, ANN has been used to evaluate lymphocyte depletion in the bursa of Fabricius and thymus[3, 11, 12]. Other mathematical models and intelligence systems have been developed to enable data management in several areas of the poultry production chain[13-16].

Productivity development increases the competitiveness of the poultry industry. Thus, it is imperative to determine the internal and external factors that may affect poultry production and increase the cost or reduce income. The identification of these factors may support the establishment of strategies to improve productivity[17]. The aim of this study was to evaluate the ability of ANN models to predict production indicators and to understand their potential economic impact on a poultry integration system.

2. Material and methods

2.1 Database

A historical series of data from broiler breeder farms, one hatchery, broiler production flocks, and one slaughterhouse of a single poultry company in Rio Grande do Sul (Brazil) was selected for this study. Data from 2,191 flocks and 2 million birds were collected over a period of seven months. Forty zootechnical and production parameters were selected as variables for this study (Tables 1). Descriptive analysis of the variables is described in Supplementary Material (Table S1).

2.2 Input and output variable selection

“Input variables” are those parameters selected to compose a predictive mathematical model; “output variables” refer to those indicators of interest to be estimated. For this study, output variables were defined based on the company’s interest and input variables used for each model were selected based on their influence, according to the literature. ANN models were established for four output variables: (1) saleable hatching; (2) weight at the end of week; (3) partial condemnation; and (4) total condemnation. The input variables included in each model are shown in Table 2.

2.3 Artificial neural networks (ANN)

The input and output variables were analyzed using NeuroShell Predictor[18]. The NeuroShell Predictor was used to forecast and estimate numeric amounts. The following settings were applied: (1) training strategy, genetic; (2) maximum number of hidden neurons, 80; (3) optimization goal, maximizing R-squared; (4) optimization method, gene hunter. For the ANN training, the genetic method was used, which is a genetic algorithm variation of the general regression neural network (GRNN), which is a cross-validation technique that combines a genetic algorithm with a statistical estimator. Individual data from 1,096 flocks (50% of the records) were randomly selected for training. The remaining data were used for validation.

2.4 Analysis of ANN models

The ANN models were individually analyzed in relation to the coefficient of multiple determination (R^2), correlation coefficient (R), mean error (E), mean squared error (MSE), and root mean square error (RMSE). MSE is used in the regression analysis to show the closeness of a regression line to a set of points (the distance from the regression line), and RMSE is the standard deviation of the residuals (prediction errors). After ANN training, the most adjusted model for each variable was selected and validated. The performance of the generated model was analyzed based on the R^2, R, E, RMS, and RMSE values.

2.5 Scenario simulation

To estimate the impact of the input on the output variables selected for this study, different production scenarios were simulated (Table 3). For numeric variables (e.g. egg storage period, broiler weight, chick weight), the mean was obtained based on the historical series available, and was considered the standard or normal value. To simulate “increased” and “decreased” values, one standard deviation was added or subtracted, from the respective mean. By changing these parameter values, we simulated production scenarios whose results could represent an improvement or worsening of the performance.

Table 1. Zootechnical and production parameters (variables) selected for this study.

Variable	Unit	Total number
Farm	-	n=91
Birds lineage	-	A (n=1,821 flocks) B (n=305 flocks) Mixed flocks: A + B (n=64 flocks)
Average age of breeder flocks	week	-
Egg weight	g	-
Egg type	-	Clean nest egg (n=1,771) Dirty nest egg (n=335) Litter egg (n=84)
Egg storage period	h	-
Cracked eggs	%	-
Fertility	%	-
Hatching eggs	%	-
Incubator equipment	-	A (n=936) B (n=1,255)
Incubation time	min	-
Egg weight loss	g	-
Total hatch	%	-
Saleable eggs	%	-
Hatch basket	-	n=38
Total number of flocks in each hatch basket	-	-
Time at hatch basket	min	-
Hatch contamination (*Aspergillus* spp.)	CFU/10cm^2	-
Hatch contamination (*Escherichia coli*)	CFU/10cm^2	-
Hatch contamination (*Pseudomonas* spp.)	CFU/10cm^2	-
Hatch contamination (*Salmonella* spp.)	CFU/10cm^2	-
Chick weight	g	-
Use of chicks	%	-
Contamination during transfer	%	-
Type of chick		From breeder < 37 weeks old (n=1,145) From breeder 38-49 weeks old (n=766) From breeder >49 weeks old (n=279)
Flock sex		Male (n=983) Female (n=1,117) Mixed flocks (male and female) (n=4)
Producer		n=138
Professional		n=23
Broiler weight at the end of week 1	g	-
Broiler weight at the end of week 2	g	-
Broiler weight at the end of week 3	g	-
Broiler weight at the end of week 4	g	-
Broiler weight at the end of week 5	g	-
Mortality at the end of week 1	%	-
Mortality at the end of week 2	%	-
Mortality at the end of week 3	%	-
Mortality at the end of week 4	%	-
Mortality at the end of week 5	%	-
Partial condemnation	%	-
Total condemnation	%	-

Table 2. Input variables used for each output variable models (saleable eggs, broiler weight at the end of week 5, partial condemnation, and total condemnation) generated by artificial neural networks.

Input variables	Output variables[1]
Birds lineage	1, 2, 3, 4
Average age of breeder flocks	1, 2, 3, 4
Egg type	1, 2, 3, 4
Egg weight	1
Egg storage period	1
Cracked eggs	1
Incubator equipment	1
Incubation time	1
Total number of flocks in each hatch basket	1
Time at hatch basket	1
Hatches contamination (*Aspergillus* spp.)	1, 2, 3, 4
Hatches contamination (*Escherichia coli*)	1, 2, 3, 4
Hatches contamination (*Pseudomonas* spp.)	1, 2, 3, 4
Type of chick	2, 3, 4
Chick weight	2, 3, 4
Flock sex	2, 3, 4
Broiler weight at the end of week 1	2, 3, 4
Broiler weight at the end of week 2	2, 3, 4
Broiler weight at the end of week 3	2, 3, 4
Broiler weight at the end of week 4	2, 3, 4
Broiler weight at the end of week 5	3, 4
Mortality at the end of week 1	3, 4
Mortality at the end of week 2	3, 4
Mortality at the end of week 3	3, 4
Mortality at the end of week 4	3, 4
Mortality at the end of week 5	3, 4

[1]Saleable eggs (1), broiler weight at the end of week 5 (2), partial condemnation (3), and total condemnation (4).

Although some input categorical variables did not appear in the production scenarios described in this table, all variables were included in their respective models, as shown in Supplementary Material (Table S2). The inclusion of the variables in each scenario was based on the predominant group for each categorical variable. The inclusion of only one group per category was necessary because ANN models do not allow projections from two or more groups per categorical variable.

The measurement unit was defined as 1,000,000 birds (one day-old chicks or broilers) per production cycle for all economic estimation calculations. The reference indicators used in this study included the average meat yield per carcass (2.50 kg), average price paid to the producer (R$ 6.00/kg or $ 1.11/kg), average price of slaughtered chicken (R$ 7.08/kg or $ 1.31/kg), average partial condemnation of a carcass (20%), and broiler price (R$ 3.00/unit or $ 0.74/unit). Values in Brazilian Real (R$) were obtained from Avisite[19] and refer to June/2022. All values were converted to US Dollar ($).

The NeuroShell Run-Time Server[20] software was used to predict the simulated production scenarios, as it allows for the triggering of the ANN models generated with the NeuroShell Predictor. NeuroShell Fire[21] software was used to visualize the predicted values of the output variables.

3. Results and discussion

The use of monitoring systems and tools for data analysis usually increases a company's net income[2]. The use of intelligent systems for decision-making allows for the maximum index of market performance and competitiveness[13]. The properties of each ANN model generated, trained, and validated according to the output variables of interest are listed in Table 4.

The correlation between the predicted and actual values of each of the four output variables using ANN models can be found in Figure 1.

Values of R^2 near "1" indicate higher quality in the validation of the network. R^2 values above 0.70 in the ANN training processes indicate a good quality of networks for prediction[7]. After validation, all the output variables had an R^2 above 0.70. "Weight at the end of week 5," "partial condemnation," and "total condemnation" presented values higher than 0.96. The obtained values indicated that there was a strong association between the predicted and actual data, demonstrating that the four models were properly adjusted and, therefore, could be used for the simulations of productive scenarios. It is noteworthy that all variables can also be listed as output variables. This choice depends on the needs of the company[9, 10]. The variables selected as "output" data in this study were considered among the most important results to be predicted according to the poultry company evaluated. The relative importance of each input variable in the generated models for each output variable is shown in Supplementary Material (Table S2).

Table 3. Simulated productive scenarios for the output variables: “saleable hatching”, “weight at the end of week 5”, “partial condemnation”, and “total condemnation”.

Scenario	Manipulated input variables
	Output variable: saleable hatching
1	Lineage A x clean nest egg x incubator A
2	Lineage A x clean nest egg x incubator B
3	Lineage A x dirty nest egg x incubator A
4	Lineage A x dirty nest egg x incubator B
5	Lineage B x clean nest egg x incubator A
6	Lineage B x clean nest egg x incubator B
7	Lineage B x dirty nest egg x incubator A
8	Lineage B x dirty nest egg x incubator B
9	Egg storage period (mean)[1] – 113 h
10	Egg storage period (reduced)[1] – 74 h
11	Egg storage period (extended)[1] – 152 h
	Output variable: weight at the end of the week 5
Scenario	Manipulated input variables
12	Lineage A x male flocks
13	Lineage A x female flocks
14	Lineage B x male flocks
15	Lineage B x female flocks
16	Broiler weight at the end of the week 1 (mean)[2] – 184.84 g x male flocks
17	Broiler weight at the end of the week 1 (increased)[2] – 203.22 g x male flocks
18	Broiler weight at the end of the week 1 (decreased)[2] – 166.46 g x male flocks
19	Broiler weight at the end of the week 2 (decreased)[1] – 426.97 g x male flocks
20	Broiler weight at the end of the week 3 (decreased)[1] – 834.72 g x male flocks
21	Broiler weight at the end of the week 4 (decreased)[1] – 1,340.72 g x male flocks
22	Broiler weight at the end of the weeks 1, 2, and 3 (decreased)[1] – 166.46g | 426.97 g | 834.72 g x male flocks
	Output variable: partial condemnation
Scenario	Manipulated input variables
23	Lineage A or B x male flocks
24	Lineage A or B x female flocks
25	Chick weight (mean)[3] – 45.93 g x male flocks
26	Chick weight (increased)[3] – 49 g x male flocks
27	Chick weight (decreased)[3] – 42.85 g x male flocks
28	Chick weight (mean)[3] – 46.01 g x female flocks
29	Chick weight (increased)[3] – 49.61 g x female flocks
30	Chick weight (decreased)[3] – 42.41 g x female flocks
31	Chick weight (maximum)[3] – 50.2 g x female flocks
32	Chick weight (minimum)[3] – 33.1 g x female flocks
33	Broiler weight at the end of the week 2 (mean)[4] – 467.69 g x male flocks
34	Broiler weight at the end of the week 2 (increased)[4] – 508.41 g x male flocks
35	Broiler weight at the end of the week 2 (decreased)[4] – 426.97 g x male flocks
36	Broiler weight at the end of the week 3 (mean)[4] – 922.50 g x male flocks
37	Broiler weight at the end of the week 3 (increased)[4] – 1010.28 g x male flocks
38	Broiler weight at the end of the week 3 (decreased)[4] – 834.72 g x male flocks
39	Broiler weight at the end of the week 2 and 3 (decreased)[4] – 508.41 g | 1,010.28 g x male flocks
	Output variable: total condemnation
Scenario	Manipulated input variables
40	Lineage A or B x male flocks
41	Lineage A or B x female flocks
42	Type of chick (from breeder up to 37 weeks old) x male flocks
43	Type of chick (from breeder up to 37 weeks old) x female flocks
44	Type of chick (from breeder 38 to 49 weeks old) x male flocks
45	Type of chick (from breeder 38 to 49 weeks old) x female flocks
46	Type of chick (from breeder more than 49 weeks old) x male flocks
47	Type of chick (from breeder more than 49 weeks old) x female flocks
48	Mortality at the end of weeks 1, 2, and 3 (low: 0.09% | 0.62% | 0.97%)[5]
49	Mortality at the end of weeks 1, 2, and 3 (high: 1.39% | 1.70% | 2.45%)[5]
50	Mortality at the end of weeks 1, 2, and 3 (maximum: 2.16% | 4.45% | 4.06%)[5]
51	Broiler weight at the end of the week 2 (mean)[6] – 467.69 g x male flocks
52	Broiler weight at the end of the week 2 (increased)[6] – 508.41 g x male flocks
53	Broiler weight at the end of the week 2 (decreased)[6] – 426.97 g x male flocks

[1]Egg storage period, average: mean storage period; reduced: mean storage period minus one standard deviation; extended: mean storage period plus one standard deviation. [2]Broiler weight at the end of week 5– mean: mean weight; decreased: mean weight minus one standard deviation; increased: mean weight plus one standard deviation. [3]Chick weight – mean: mean weight; decreased: mean weight minus one standard deviation; increased: mean weight plus one standard deviation. [4]Broiler weight at the end of the week – mean: mean weight; decreased: mean weight minus one standard deviation; increased: mean weight plus one standard deviation. [5]Mortality at the end of weeks 1, 2, and 3 – low: average mortality at each week minus one standard deviation; high: average mortality plus one standard deviation; maximum: maximum mortality observed. [6]Broiler weight at the end of the week – mean: mean weight; decreased: mean weight minus one standard deviation; increased: mean weight plus one standard deviation.

Table 4. Mathematical characteristics of the models generated for the output variables: after training and after validation.

Data after training					
Output variable	**R^2**	**R**	**E**	**MSE**	**RMSE**
saleable hatching	0.8214	0.9066	1.9299	9.9593	3.1558
weight at the end of the week 5	0.9998	0.9999	0.1577	2.8144	1.6776
partial condemnation	0.9837	0.9918	0.0183	0.0171	0.1306
total condemnation	0.9961	0.9880	0.0027	0.0004	0.0201

Data after validation					
Output variable	**R^2**	**R**	**E**	**MSE**	**RMSE**
saleable hatching	0.8236	0.9066	1.8801	10.1390	3.1842
weight at the end of the week 5	0.9623	0.9999	3.5230	502.1338	22.4083
partial condemnation	0.9677	0.9918	0.0261	0.0323	0.1798
total condemnation	0.9761	0.9880	0.0049	0.0027	0.0524

Legend: Coefficient of multiple determination (R^2), correlation coefficient (R), mean error mean squared error (MSE), and root mean squared error (RMSE).

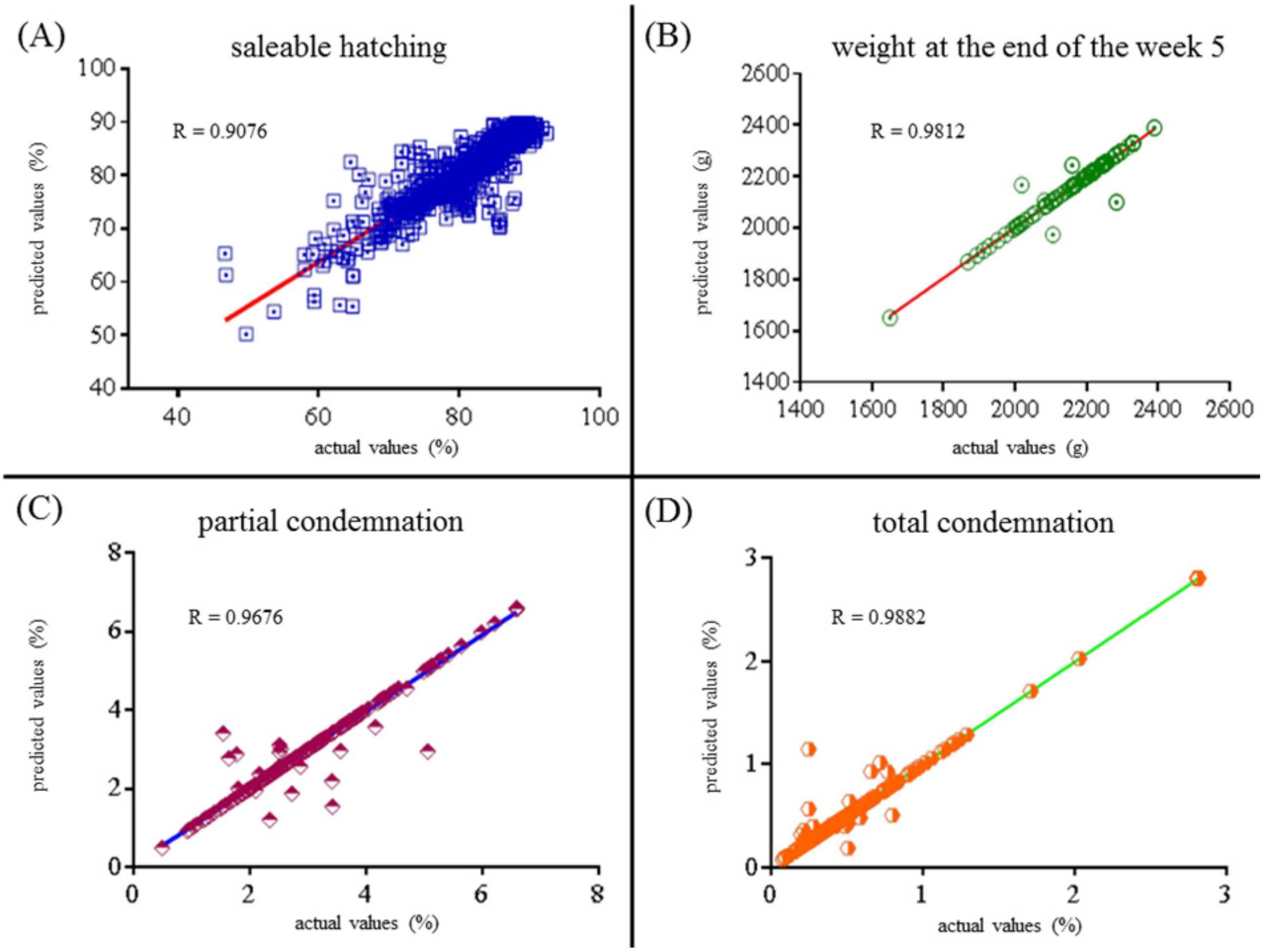
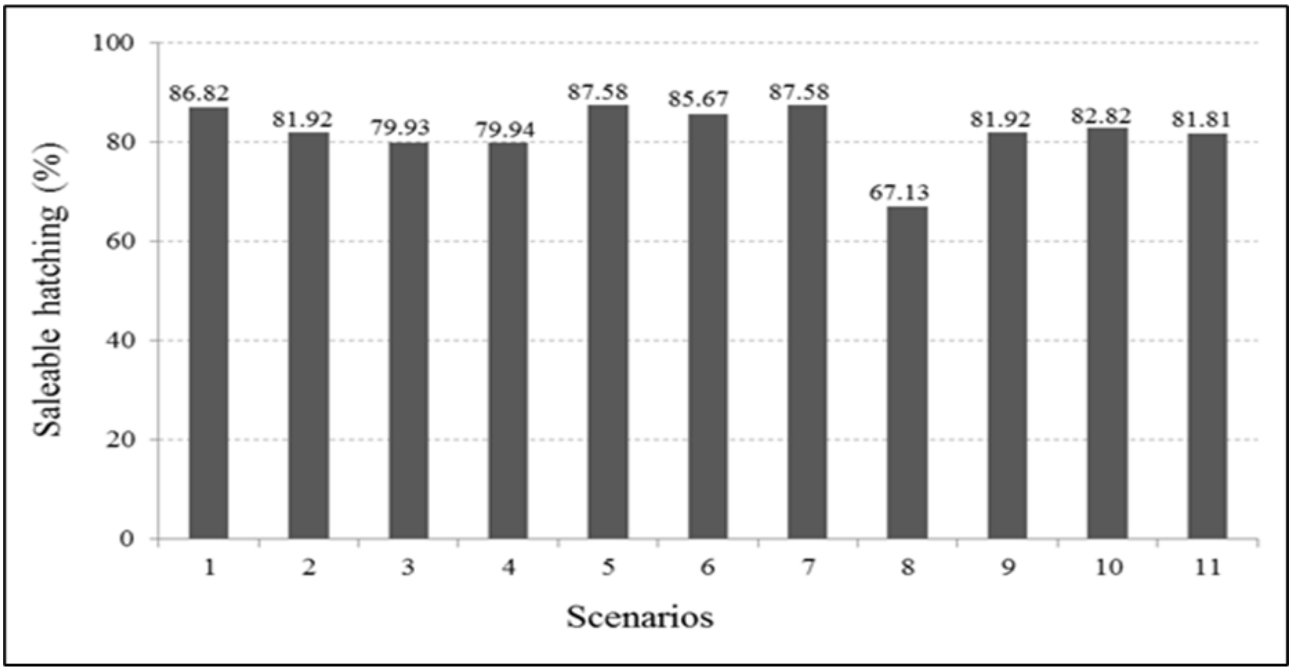


Figure 1. Correlation between predicted and actual values in the artificial neural network (ANN) models, according to each output variable: saleable hatching (A), weight at the end of week 5 (B), partial condemnation (C), and total condemnation (D).

The ability of ANN models to predict production indicators and the potential economic impact generated from the relations of the variables of a poultry integration system were evaluated. Thus, productive scenarios that combined different variables were simulated. The elaboration of the models was based on a database that included a historical series of records of the production parameters of the poultry production chain. Table S3 (Supplementary Material) summarizes the main simulated scenarios and their economic impact. The output variable results obtained from the simulation of the production scenarios are shown in Figures 2–5.

Figure 2. Saleable hatching values (%) predicted from simulated production scenarios.



Legend: (1) lineage A × clean nest egg × incubator A; (2) lineage A × clean nest egg × incubator B; (3) lineage A × dirty nest egg × incubator A; (4) lineage A × dirty nest egg × incubator B; (5) lineage B × clean nest egg × incubator A; (6) lineage B × clean nest egg × incubator B; (7) lineage B × dirty nest egg × incubator A; (8) lineage B × dirty nest egg × incubator B; (9) egg storage period (average: 113 h); (10) egg storage period (reduced: 74 h); (11) egg storage period (extended: 152 h).

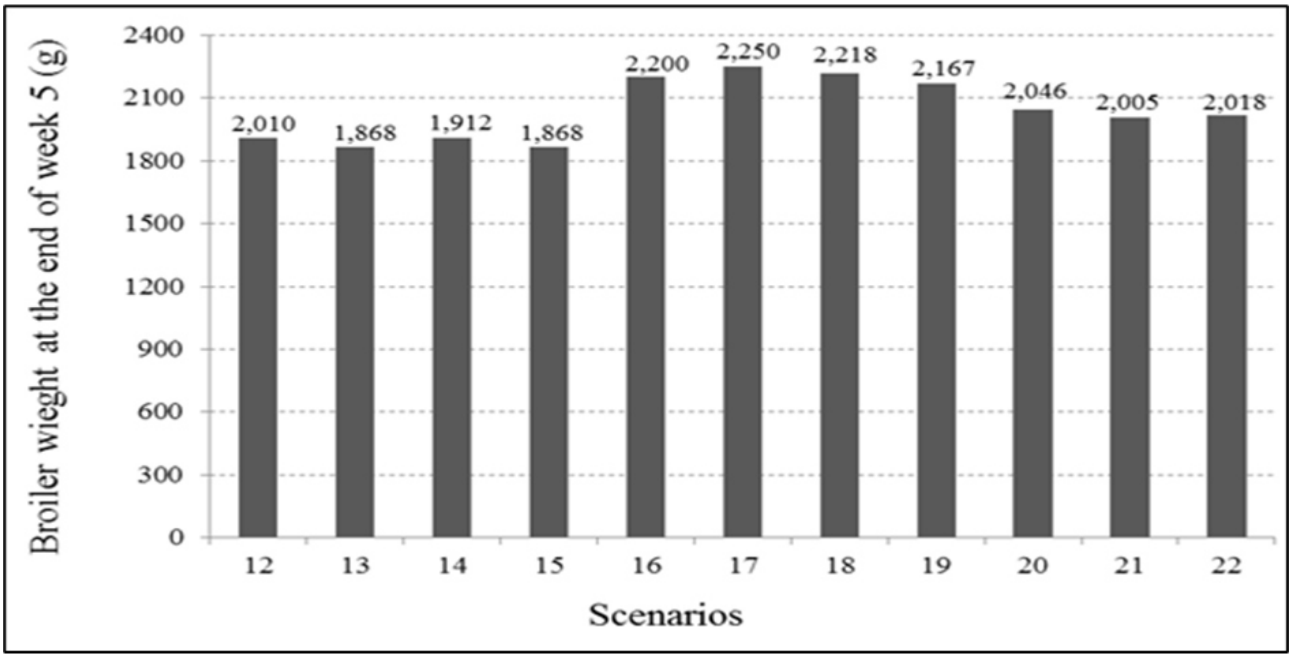


Figure 3. Broiler weight at the end of week 5 (g) predicted from simulated production scenarios. Legend: (12) lineage A × male flocks; (13) lineage A × female flocks; (14) lineage B × male flocks; (15) lineage B × female flocks; (16) broiler weight at the end of week 1 (mean: 184.84 g) × male flocks; (17) broiler weight at the end of week 1 (increased: 203.22 g) × male flocks; (18) broiler weight at the end of week 1 (decreased: 166.46 g) × male flocks; (19) broiler weight at the end of week 2 (decreased: 426.97 g) × male flocks; (20) broiler weight at the end of week 3 (decreased: 834.72 g) × male flocks; (21) broiler weight at the end of week 4 (decreased: 1,340.72 g) × male flocks; (22) broiler weight at the end of weeks 1, 2, and 3 (decreased: 166.46 g, 426.97 g, and, 834.72 g, respectively) × male flocks

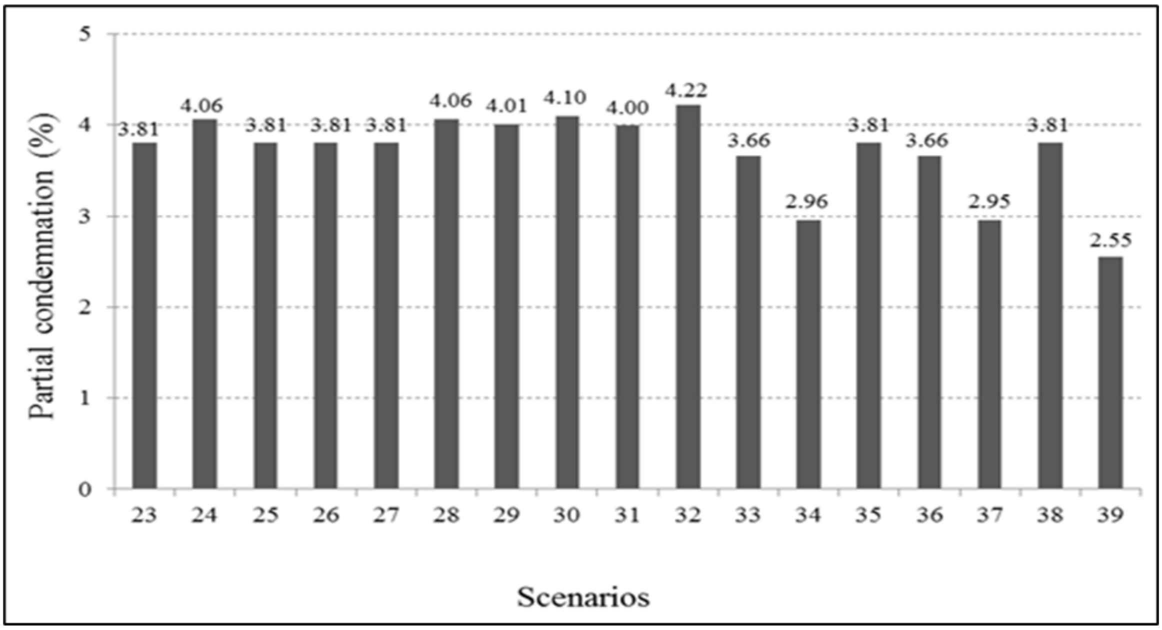


Figure 4. Partial condemnation (%) predicted from simulated production scenarios.

Legend: (23) lineage A or lineage B × male flocks; (24) lineage A or lineage B × female flocks; (25) chick weight (mean: 45.93 g) × male flocks; (26) chick weight (increased: 49 g) × male flocks; (27) chick weight (decreased: 42.85 g) × male flocks; (28) chick weight (mean: 46.01 g) × female flocks; (29) chick weight (increased: 49.61 g) × female flocks; (30) chick weight (decreased: 42.41 g) × female flocks; (31) chick weight (maximum: 50.2 g) × female flocks; (32) chick weight (minimum: 33.1 g) × female flocks; (33) broiler weight at the end of week 2 (mean: 467.69 g) × male flocks; (34) broiler weight at the end of week 2 (increased: 508.41 g) × male flocks; (35) broiler weight at the end of week 2 (decreased: 426.97 g) × male flocks; (36) broiler weight at the end of week 3 (mean: 922.50 g) × male flocks; (37) broiler weight at the end of week 3 (increased: 1,010.28 g) × male flocks; (38) broiler weight at the end of week 3 (decreased: 834.72 g) × male flocks; (39) broiler weight at the end of weeks 2 and 3 (decreased: 508.41 g and 1,010.28 g, respectively) × male flocks.

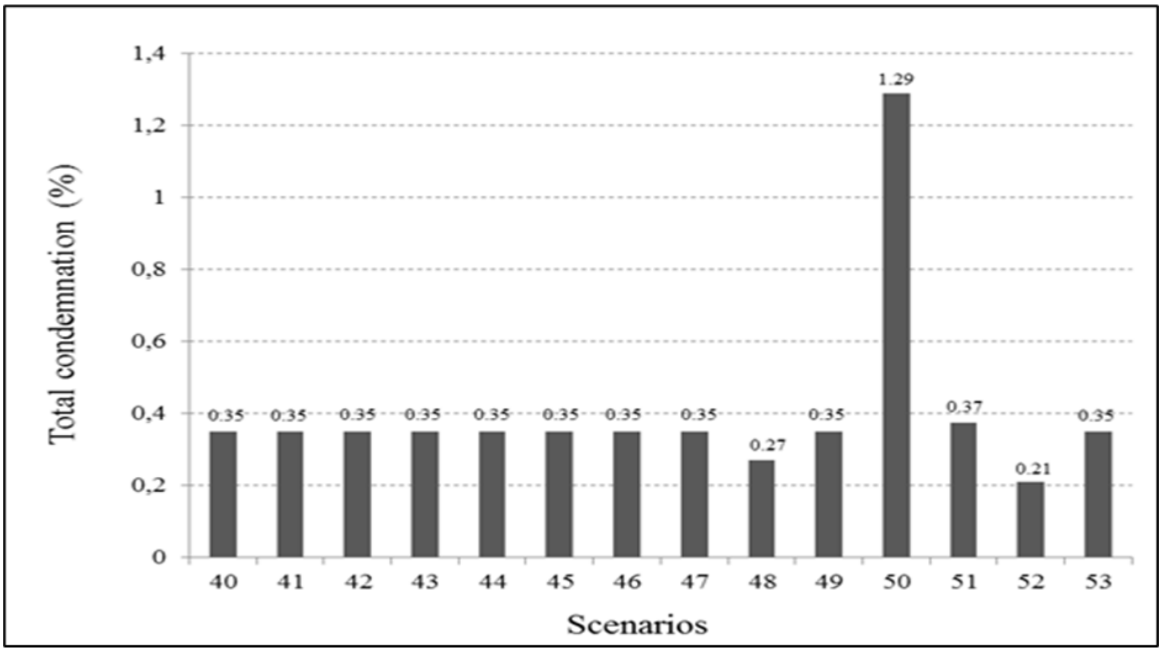


Figure 5. Total condemnation (%) predicted from simulated production scenarios.

Legend: (40) lineage A or lineage B × male flocks; (41) lineage A or lineage B × female flocks; (42) type of chick (from breeder up to 37 weeks old) × male flocks; (43) type of chick (from breeder up to 37 weeks old) × female flocks; (44) type of chick (from breeder up to 38 to 49 weeks old) × male flocks; (45) type of chick (from breeder up to 38 to 49 weeks old) × female flocks; (46) type of chick (from breeder to more than 49 weeks old) × male flocks; (47) type of chick (from breeder to more than 49 weeks old) × female flocks; (48) mortality at the end of weeks 1, 2, and 3 (low: 0.09%, 0.62%, and 0.97%, respectively); (49) mortality at the end of weeks 1, 2, and 3 (high: 1.39%, 1.70%, and 2.45%, respectively); (50) mortality at the end of weeks 1, 2, and 3 (maximum: 2.16%, 4.45%, and 4.06%, respectively); (51) broiler weight at the end of week 2 (mean: 467.69 g) × male flocks; (52) broiler weight at the end of week 2 (increased: 508.41 g) × male flocks; (53) broiler weight at the end of week 2 (decreased: 426.97 g) × male flocks.

The creation of adjusted mathematical models depends on the correct recording of data, which requires the continuous training of the people involved in this process. It is also noteworthy that the models created from the database shared by the company for this study cannot be used in other establishments because each company has a unique production context. Each company must build its own ANN model, looking for those that best fit the context[7].

The training of the four models in this study was performed using a genetic method. The main limitation of this method is that projections can only be made from values that are within the range between the maximum and minimum of each variable that constitutes the historical series under analysis.

3.1 Output variable: saleable hatching (scenarios 1 to 11)

From a total of 1,000,000 incubated eggs, each 0.1% increase in the salable hatch rate means an increase of 1,000 chicks for commercialization, or $ 740.00 in income. Thus, all gains and losses result in a great financial impact.

Influence of incubator (scenarios 1 to 8). The predicted saleable hatching rates showed that incubator A had a better performance than incubator B. The difference in saleable hatching rates among incubators was 4.9% when lineage A and clean nest eggs are incubated (scenarios 1 and 2). Therefore, the difference in revenue between incubators was approximately $ 36,260.00, considering the incubation of one million eggs under the same conditions. The hatch difference observed in the incubation of lineage B and clean nest eggs (scenarios 5 and 6) was 1.91%, which may represent an increase of approximately $ 14,134.00 when using incubator A. Superior performance of incubator A was verified when of lineage B and dirty nest eggs are incubated (scenarios 7 and 8), with a difference of 20.45% between the hatch rates.

Influence of egg storage period (scenarios 9 to 11). By reducing the storage period of embryonated eggs from 113 h (scenario 9) to 74 h (scenario 10), there was a gain of 0.9% in the saleable hatching rate. This projected result can serve as an argument to the hatchery manager for future changes in procedures, aiming to reduce the waiting time of embryonated eggs in the egg room. Embryos of lineages A and B had differential growth trajectories owing to differences in physiological parameters. Lineage A has a faster development in the first 4–5 days, but lineage B develops faster in the second incubation week. Thus, the incubation conditions can be improved for each lineage[23].

3.2 Output variable: broiler weight at the end of the week 5 (scenarios 12 to 22)

Influence of lineage (scenarios 12 to 15). The predictions of broiler weight at the end of week 5 showed that the lineages presented differences in performance. Male lineage A broilers weighed approximately 4.88% (98 g) higher than male lineage B broilers. A difference of 98 g can represent an increase of $ 0.13 per chicken slaughtered. The income from a production cycle with one million birds, all of which are male, may increase by $ 130,000.00. Some Brazilian poultry companies slaughter more than one million birds per day. Thus, the estimated economic impact is evident and may justify the policy adopted by the company for the predominant use (83.11%) of lineage A. Broiler sex is a factor that may have significant effects on production parameters, and male birds usually present higher production indices than female birds[1]. There was no difference in performance when comparing female flocks between the lineages. Although previous studies have already shown that broilers of lineage A usually present higher weight than those of lineage B[24,25], this is the first report that describes the possible income differences in Brazilian companies.

Influence of broiler weight at the end of the week 1, 2, 3, and 4 (scenarios 16 to 22). Previous studies have shown that the heaviest broilers at slaughter usually presented the heaviest initial weights in the first week. Thus, initial chick weight is described as a determinant factor in final broiler performance. In addition, during this period, approximately 80% of chick energy is used for growth[26]. However, in this study, ANN models demonstrated that broiler weight at the end of the first week (scenarios 16–18) may not have a significant influence on the weight of the chicken at the end of week 5 for this company. It is possible that chicks with decreased weight in the first week may have time to overcome losses and have a compensatory weight gain in weeks 2, 3, and 4, when favorable management and nutrition conditions are available. It is likely that there is a minimum weight limit to avoid variations at the end of week 5[27]. Thus, it has been suggested that genetic selection should focus on increasing egg production instead of egg weight[28]. Broilers that reached the end of weeks 2, 3, or 4 (scenarios 19 to 22) with a weight below their average potential will have a lower weight at the end of week 5, indicating that there is not enough time to recover their weight after the second week. For example, in scenario 20, broiler weight at the end of week 3 (834.72 g) was lower than that expected by the company (922.5 g). The potential for income loss for the producer in this scenario is approximately $ 100,000.00. These predictions are important for preventing potential negative impacts on broiler final weight by adopting measures to avoid the occurrence of such scenarios.

3.3 Output variable: partial condemnation (scenarios 23 to 39)

Influence of flock sex (scenario 23 to 32). The results show that female flocks, regardless of lineage, have a higher rate of partial condemnation of carcasses than male flocks. This difference, calculated as 0.25% (scenarios 23 and 24), represents 2,500 carcasses and 1,250 kg of chicken meat discarded in one million slaughtered broilers. The final economic loss is estimated to be approximately $ 1,637.00 per million of slaughtered broilers. For a company that slaughters one million birds per day, after one month, the amount may be up to $ 49,125.00, when considering 50% of the female flocks. However, it should be noted that there are still no data in the literature that explain the difference in carcass condemnation associated with the sex of the flock.

Chick weight (scenarios 25 to 32). No effect of one-day-old chick weight on the partial condemnation rate was observed. Previous studies have shown that increased daily growth in broilers is associated with higher condemnation rates[1].

Broiler weight (scenarios 33 to 39). Although the chick weight did not influence in the condemnation rates, the results of this study showed that a higher weight at the end of weeks 2 and 3 resulted in a lower rate of the partial condemnation of carcasses. Thus, the adoption of breeding and management strategies that favor greater weight gain in these weeks can guarantee great contributions in the company revenue.

3.4 Output variable: total condemnation (scenarios 40 to 53)

Influence of flock sex (scenario 40 to 47). Although female flocks showed a higher partial condemnation rate than that by male flocks, this was not observed in the total condemnation rate.

Influence of type of chick (scenario 42 to 47). The prediction model demonstrated that the type of chick (breeder age) did not influence the total condemnation rates, regardless of flock sex. These findings indicate that the effects of sex and broiler weight in the first weeks on partial condemnation are not linear and may not be explained by a direct association.

Influence of mortality at the end of weeks 1, 2, and 3 (scenarios 48 to 50). The effect of accumulated mortality (low or high) on total carcass condemnation was also evaluated. By reducing mortality rates at weeks 1, 2, and 3 by at least one standard deviation, there was a decrease in the predicted value of the total carcass condemnation rate. The difference between the expected average rate and high mortality (scenario 48) was approximately -0.0795%. In a production cycle with one million birds, this difference represents a reduction in condemnation of at least 795 carcasses, approximately $ 2,603.00. The projection with the occurrence of maximum combined mortality in the first three weeks (scenario 50) resulted in an increase of 0.9405% in the total condemnation rate, which means a loss of approximately $ 30,785.00 for every one million birds slaughtered. The mortality rates simulated in this study (2–5%) can be attributed to several factors. The first week is a sensitive period in which many chicken systems and organs are still immature. Individual-dependent characteristics, such as breeder age, chick gender, and lineage, as well as external factors, including the type of broiler house, egg storage, and season, are related to chick mortality in the first week[29]. High mortality rates in the later weeks can be an indication of management problems or diseases that are common in poultry farming, and broilers that do not die may have compromised productive performance, which leads to greater nonuniformity in the flocks. Abnormal flock uniformity results in a higher condemnation rate[1], owing to the automatic eventration at the slaughterhouse, which may cause rupture of the viscera and leakage of intestinal contents[30]. Thus, our findings support the idea that flocks with higher mortality rates may have a higher rate of partial and total carcass condemnation.

Influence of broiler weight at the end of the week 2 (scenarios 51 to 53). Regarding the effect of broiler weight at the end of week 2 on the total condemnation rate, it was observed that both a reduction and increase in broiler weight can result in a decrease in the condemnation rate. In these cases, the predicted results are difficult to understand because they lack a logical explanation (linear relationship). On the other hand, predictive models have great assertive capacity, as verified in the validation stage.

4. Conclusion

The ANN models generated in this study were suitable for simulations of production scenarios and enabled the prediction of important production parameters for the poultry production chain. The results obtained in this study demonstrate that companies can use predictive models to adopt strategies that minimize the negative impact of certain scenarios. The company can also manage its resources better because the effects of different scenarios can be predicted by the models.

Supplementary material

Available on line from: https://revistas.ufg.br/vet/article/view/75400/39888

Conflict of interest statement

The authors have no competing interests.

Authors contributions

Conceptualization: C.T.P. Salle, H.L.S. Moraes, V.P. do Nascimento and E. Camilotti. *Data curation*: E. Camilotti. *Formal analysis*: E. Camilotti. *Investigation*: E. Camilotti, T.Q. Furian, K.A. Borges and D.T. da Rocha. *Methodology*: E. Camilotti and D.T. da Rocha. *Project management*: C.T.P. Salle, H.L.S. Moraes and V.P. do Nascimento. *Software*: C.T.P. Salle, E. Camilotti and D.T. da Rocha. *Supervisão*: C.T.P. Salle, H.L.S. Moraes and V.P. do Nascimento. *Validation*: E. Camilotti, T.Q. Furian and K.A. Borges. *Writing (original draft):* E. Camilotti, K.A. Borges and T.Q. Furian. *Writing (review & editing):* K.A. Borges and T.Q. Furian.

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