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ARTIFICIAL NEURAL NETWORKS FOR PREDICTION OF PHYSIOLOGICAL AND PRODUCTIVE VARIABLES OF BROILERS

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KEYWORDS

poultry, thermal stress, artificial intelligence.

ABSTRACT

Due to a number of factors involving the thermal environment of a broiler cutting installation and its interaction with the physiological and productive responses of birds, artificial intelligence has been shown to be an interesting methodology to assist in the decision-making process. For this reason, the main aim of this work was to develop an artificial neural network (ANN) to predict feed conversion (FC), water consumption (C_{water}), and cloacal temperature (t_{clo}) of broilers submitted to different air dry-bulb temperatures (24, 27, 30, and 33ºC) and durations (1, 2, 3, and 4 days) of thermal stress in the second week of the production cycle. Relative humidity and wind speed were fixed at 60% and 0.2 ms^{-1}, respectively. The experimental data were used for the development of an ANN with supervised training using the Levenberg-Marquardt *backpropagation* algorithm. The ANN consisted of three input layers one hidden, and three output with sigmoidal tangent transfer functions with values between -1 and 1. The developed ANN has adequate predictive capacity, with coefficients of determination (R^2) for t_{clo}, FC, and C_{water} of 0.79, 0.87, and 0.97, respectively. In this way, the proposed ANN can be used as a support for decision-making to trigger poultry heating systems for broiler breeding.

INTRODUCTION

In the current poultry scenario, changes in management techniques are indispensable. Therefore, the use of intelligent systems for decision-making is necessary to obtain a maximum index of market performance and competitiveness (Pandorfi et al., 2012), in addition to mitigating or even eliminating the harmful effects of a thermal environment unsuitable for the physiological demands of birds (Nascimento et al., 2014).

Several studies have verified only the influence of different thermal stress intensities, without varying the duration of the thermal stress (Al-Zghoul et al., 2015; Cândido et al., 2016: Zhang et al., 2016). However, analyzing the intensity and duration together makes it possible to investigate possible occurrences of adaptation of the bird to the stressful environment, depending on the exposure time, or to verify how stressor intensity can aggravate productivity losses due to longer or shorter exposure times. Thus, the control of environmental variables becomes essential for the process of rearing broilers (Cassuce et al., 2013; Mirzaee-Ghaleh et al., 2015).

The evaluation of the thermal comfort of birds can be measured by cloacal temperature, which is altered when the bird is subjected to thermal stress (Yanagi Junior et al., 2012; Mayes et al., 2014). Also, discomfort influences water consumption (Lopes et al., 2015), feed intake, and weight gain, affecting feed conversion (Boiago et al., 2013).

Therefore, the importance of monitoring the thermal stress of broilers and the influence on behavioral parameters, physiological responses, and productive performance has been verified. Thus, through information generated by intelligent systems, the producer will be able to control his business more appropriately (Pandorfi et al., 2012; Ferraz et al., 2014).

Among these systems, we can include artificial neural networks (ANNs), which consist of computational models formed by simple processing units based on the structure of the human brain, thus called artificial neurons (Binoti et al., 2013). These units allow the system to

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simulate behaviors, such as learning, association ability, generalization, and abstraction, which are based on the logic of parameters (Ferreira et al., 2011).

The applicability of ANNs is associated with situations where input and output information are interconnected by a nonlinear relationship of dependent and independent variables. Thus, ANNs can be used for predicting and representing parameters not quantified from data evaluated by behavior patterns, thus allowing the development of techniques for solving complex problems (Pandorfi et al., 2011; Matin et al., 2012).

In this sense, mathematical modeling through ANNs is a critical methodology for the analysis of complex systems, such as the prediction of the thermal comfort of broilers. ANNs forecast different answers that quantify animal comfort, such as productive and physiological responses in the same network. Thus, there exist several studies that implement ANNs applied to predicting and managing environment and responses in animal production (Borges et al., 2018; Ribeiro et al., 2019; Santos et al., 2016).

Therefore, the main objective of this study was to develop an ANN to predict the cloacal temperature, water consumption, and feed conversion of broilers subjected to different intensities and durations of thermal stress during the second week of the production cycle.

MATERIAL AND METHODS

The research was developed in four air-conditioned wind tunnels (0.8 x 5.0 m) installed in an animal ambiance laboratory. All procedures performed during this experiment were approved by the Ethics Committee for the Use of Animals (CEUA) of the Federal University of Lavras (UFLA), Minas Gerais, protocol Nº 008/12. The air-conditioned wind tunnels were constructed of steel plates and PVC pipes; each tunnel was equipped with two electric heaters and two humidifiers operating in two stages of the drive.

Ventilation inside each tunnel was performed by employing an exhaust with a diameter of 40 cm, and the speed adjusted using a potentiometer. Inside the tunnels, cages of 0.24 m^2 (0.40 x 0.60 m) were allocated, which were divided into three equal parts and equipped with independent feeders and drinking fountains in each repetition. To control the temperature inside the room, two air conditioning systems with 18,000 BTUs of power were used.

The control of the thermal environment within the air-conditioned wind tunnels was carried out by the combination of a data logger (CR1000, Campbell Scientific), a relay controller (SDM-CD16AC, Campbell Scientific), a channel multiplexer (AM16/32B, Campbell Scientific), and air dry-bulb temperature sensors (t_{db}) and relative air humidity (RH) (HMP45c, Vaisala, accuracy ± 0.3ºC for t_{db} and ± 2 % for RH).

During the entire experimental period, Cobb 500® males and females from the same hatchery were used, where they were vaccinated against the avian diseases Marek's, Gumboro, and avian pox. The birds arrived at the experiment shortly after birth and remained until they had completed twenty-two days of life. During this period, water and ad libitum feed was supplied to birds to meet their nutritional requirements according to Rostagno et al. (2011). The feed used was the same for all chicks throughout the experimental period, with no variation in its formulation.

The experiment was carried out in four stages, in order to evaluate sixty birds in each stage, totaling two hundred and forty animals. Thus, in each distribution of the cage, five birds were allocated, characterizing fifteen birds per air-conditioned wind tunnel in the first week of life. However, to maintain the ideal density of comfort, in the second and third week of life, four and three birds were kept, respectively, according to the Cobb manual (2013), because the high density harmfully affects physiological parameters (Castilho et al., 2015). Hygienic maintenance of the breeding environment was carried out daily to avoid the formation of gases and to provide a pleasant environment for the development of broilers (Sousa et al., 2016).

The experiment was carried out for twenty-one days, in which the birds were submitted to thermal challenges only in the second week of life—from the eighth day of life. During the first and third weeks of life, temperatures were maintained in the thermoneutrality zone, with air dry-bulb temperatures (t_{db}) of 33ºC and 27ºC, respectively (Cassuce et al., 2013; Ferraz et al., 2018). In the second week, a difference between treatments was established by the intensity and duration of thermal stress. The stress intensities were 24, 27, and, 33ºC for each stage, in addition to 30ºC for t_{db}, which was considered as comfort for the second week of life (Cassuce et al., 2013; Ferraz et al., 2017).

Thermal stress was applied at four levels of duration (1, 2, 3, and 4 days) in the first four days that make up the second week (8th, 9th, 10th, and 11th days of life); shortly after this period, the temperatures returned to the thermal comfort zone (30ºC). The experimental stage submitted to a temperature of 30°C was considered the control (comfort), and the others were maintained in order to provide thermal challenges both by low (24ºC and 27ºC) and high (33ºC) temperatures (Curtis, 1983; Cassuce et al., 2013).

The luminosity was fixed inside each tunnel with the aid of an analog dimmer and measured using a lux meter (LDR-380, accuracy ± 3%). The established values were 25, 10, and 5 lux, for the first, second, and third week, respectively (Cobb, 2013), to provide the maximum efficiency in development that adequate lighting can generate on broilers (Lima et al., 2014). In turn, relative air humidity (RH) was set at 60% and airspeed at $0.2 \pm 0,1 \text{ m s}^{-1}$.

Cloacal temperature (t_{clo}) was measured daily using a digital thermometer (±0.01ºC accuracy) in a bird by distribution of the cage, totaling twelve birds per day or forty-eight in each of the four stages.

The experiment was conducted by adopting a completely randomized design (CRD) with three replicates in a factorial scheme (4 x 4), four t_{db} in the second week of birdlife (24, 27, 30, and 33°C), and four durations of thermal stress (1, 2, 3, 4, and 5 days).

After the experiment, a database containing the primary information of t_{db}, duration of stress (DS), days after stress (DAS), cloacal temperature (t_{clo}), feed conversion (FC), and water consumption (C_{water}) was generated.

For the preparation of the ANN, the data set consisted of three input variables: t_{db} (24, 27, 30, and 33ºC), DS (1, 2, 3, 4 days), and DAS (0, 1, 2, 3, 4 and 5 days). The t_{clo} (ºC), FC (g g^{-1}) and C_{water} (mL day^{-1}) were used as output variables. To train, validate, and test ANN-based models, the total dataset formed by 360 data pairs was used. The data were randomly divided using the random sampling function, and 70% (252 data pairs) of the data were used for training, 15% (54 data pairs) for validation, and 15% (54 data pairs) for testing. These percentages for the subsets were chosen because they are those most commonly used for mathematical modeling (Brown-Brandl et al., 2005; Hernández-Julio et al., 2014). Thus, 3000 ANN-based models were developed (modifying the number of neurons in the hidden layer from 1 to 300 with 10 replications each) with the objective of predicting the three output variables (t_{clo}, FC, and C_{water}), and the architecture that presented the highest correlation coefficient (R^2) and the lowest mean square error (MSE) was selected.

According to Kiran & Rajput (2011), the formation layer is transmitted to the ANN model with the aid of a set known as data patterns, causing the network to continually "learn," adapting its weights and deviations through an activation function.

Activation functions can be sigmoid, tangent-sigmoid, linear, or other types. Thus, the network is formed until the error is reduced enough to provide an accurate output to the input dataset. Model parameters include the number of hidden layers, transfer functions in each hidden layer, the number of neurons in the hidden layer, the learning rate, the moment rate, and the weights of neurons.

To develop the ANN-based models, Matlab® software, version 7.13.0.564 (R2011b), was used with the application of the neural adjustment tool (Mathworks, 2013). These models were trained using 70% of randomly divided experimental data, with different numbers of hidden neurons (from 1 to 20, ranging from 1 to 1; from 25 to 200, ranging from 5 to 5; and from 210 to 300, varying from 10 to 10) for the test.

In this study, of all trained network architectures (3000) using the mentioned methodology, the tested architecture that presented the best performance for prediction of t_{clo}, FC, and C_{water} was the multi-layer network (multi-layer perceptron; MLP) with 50 neurons in the hidden layer. This MLP architecture has been widely used for the development of ANN (Rocha Neto et al., 2015; Rigo Júnior et al., 2016; Borges et al., 2017; Felix et al., 2017).

Three feedforward layers (input, hidden layer, and output layer) and supervised training were employed with the Levenberg-Marquardt backpropagation training algorithm, which is considered the fastest method for networking (Barbosa et al., 2005). MSE was used for the performance function of the model, in which, for the output of the neuron, the sigmoidal tangent activation function was selected (Ferraz et al., 2014; Oliveira et al., 2015).

Initial network parameters were configured as follows: hidden layer (1, default value), number of times (1000), error tolerance (<0.099), learning rate (0.7), and time rate ($1x10^{-3}$) (Hernández-Julio et al., 2014). These values, as well as neuron weights, were used as the standard configuration by the software for network training. The software optimized these values automatically. This model was developed to allow the user to train and test ANN independently. In turn, for the significance analysis of the ANN coefficients, f- and t-tests ($p<0.05$) were used.

RESULTS AND DISCUSSION

For the output variables cloacal temperature (t_{clo}), feed conversion (FC), and water consumption (C_{water}), the ANN architectures with the best performance were chosen using the criterion of the lowest mean square error (MSE) of prediction. The MSE values in the training, validation, and testing processes were 59.16, 102.27, and 67.23, respectively. The variables chosen contributed to the learning of the network, increasing accuracy in pattern recognition (Pandorfi et al., 2011).

Adjustment of the values of the errors of the desired output versus predicted output was carried out using the Levenberg-Marquardt *backpropagation* algorithm (Hernández-Julio et al., 2014), in which the system made changes in the values of synaptic weights and bias values until it reached the least error. Table 1 lists synaptic and bias weights resulting from the ANN training process that achieved the best performance.

TABLE 1. Bias and synaptic weights of input and output variables.

	Synaptic input weights				Synaptic output weights					
Number of neurons	**Bias**	**t_{db}**	**DS**	**DAS**	**t_{clo}**	**Bias**	**FC**	**Bias**	**C_{water}**	**Bias**
1	5.6730	-3.7309	-2.1988	-2.5360	-0.8105		-1.0462		0.5961	
2	5.4965	-1.6594	-2.9090	-2.6028	-0.0417		0.6430		-0.2194	
3	4.5551	-4.8295	-1.1604	3.2698	0.5774		-0.3427		0.3309	
4	4.2253	-3.7410	-3.2180	1.5039	0.2993		-0.0691		0.6132	
5	3.7633	-1.5908	-5.6054	2.0938	0.1191		0.7127		-0.6062	
6	3.7993	-5.1288	-0.8997	-0.9806	0.0360		0.1020		0.7392	
7	3.9382	-4.2414	-2.7975	0.8227	-0.1431		0.4602		-0.9695	
8	-3.7455	3.2583	-3.0143	-1.4687	-0.3335		0.1747		0.0806	
9	3.8952	-3.9638	-2.6769	-1.4269	0.2714		0.8014		0.0097	
10	-2.4731	0.8126	5.4852	-0.7459	0.1950		0.5199		-0.4965	
11	3.4339	-1.5757	-4.5601	-0.7468	0.4251		-0.0822		-0.0410	
12	2.9459	-4.4153	0.8536	2.9175	-0.9589		0.7146		-0.1023	
13	-2.8741	0.0841	-0.3531	4.8561	0.3627		-0.2947		0.2444	
14	-2.4693	3.0516	-4.2634	0.3784	-0.1241		-0.4582		-0.0999	
15	3.4082	-3.9547	1.5403	-1.2257	0.0288		0.3433		0.2909	
16	-1.9316	5.2635	-0.7620	0.9752	0.5126		0.1848		-0.0303	
17	1.2329	-2.2100	1.3950	-2.8426	-0.2358		0.4321		-1.1778	
18	2.1046	-2.7346	1.7043	-4.0373	-0.0693		-0.3800		0.7716	
19	-2.0332	4.0696	3.2312	4.2627	-0.9403		0.1424		0.0399	
20	-3.3880	3.3955	-1.1837	3.3351	-0.6707		-0.0018		0.2229	
21	-0.1774	-1.9272	3.2974	2.3974	-0.6174		-0.1925		-0.2343	
22	-0.1527	-4.3510	-3.1714	0.8211	0.2560		-0.5563		0.0761	
23	-0.5192	-0.7998	-2.2317	-2.5793	-0.9796		-0.5854		-0.0632	
24	-0.6838	4.0195	-0.0300	4.0795	-0.2690		0.2154		-0.3345	
25	0.2941	3.8122	3.5383	-2.2838	1.1548	-1.9518	-1.1709	-1.1428	0.2044	-1.0346
26	0.1135	4.6109	1.7382	-4.5512	-0.1423		0.5313		-0.0620	
27	-0.6931	4.1909	1.9806	4.1861	0.6677		-0.0362		0.4297	
28	-0.5459	-3.3901	3.1203	0.2114	-0.4230		0.8781		-0.2626	
29	-1.4810	-3.9807	-4.5295	2.5876	1.1113		-0.9750		0.2020	
30	-0.9797	3.0255	-3.5221	-3.9337	-0.2520		0.1789		-0.2063	
31	-1.3851	-4.7913	2.3962	-1.9010	0.7647		-1.2764		0.2495	
32	-2.3812	-1.3094	3.5509	2.1522	0.0825		-0.6756		0.1143	
33	2.5705	3.6264	3.3295	1.4181	-1.0652		0.0338		-0.0028	
34	1.4169	3.9074	3.4495	0.8445	0.5382		-0.4481		0.4072	
35	-2.2387	-4.8972	1.3467	0.4737	0.1076		-0.4438		-0.1736	
36	-2.3037	-1.5509	5.0220	0.3295	0.5899		-0.0982		0.2742	
37	-3.5870	-2.2083	3.8040	2.1091	-0.5302		1.1806		-0.6557	
38	2.4058	3.2096	-0.6839	-3.0771	-0.2512		0.3810		0.0444	
39	-2.7776	-2.8914	-1.7215	1.9028	-0.3326		-0.2601		-0.2765	
40	-1.2673	-5.8171	-0.0245	-2.2488	-0.0350		-0.0270		0.0273	
41	5.3834	0.3080	-1.4606	4.3778	-0.4368		-0.5450		0.5777	
42	2.3525	2.0842	3.2726	4.9933	-0.5924		-0.2983		-0.1340	
43	4.3052	2.5841	2.6182	4.2024	-0.2405		0.9707		0.0420	
44	-4.1299	-4.3737	-1.7779	1.4595	-0.7133		1.4519		0.0956	
45	5.5556	0.3355	-0.4018	4.4813	1.7529		0.8221		-0.2202	
46	-5.6530	-3.7297	1.2921	3.8807	0.4996		-0.3991		0.8200	
47	4.2032	2.4936	-2.0691	6.1808	0.2713		-0.1002		0.1937	
48	-5.4270	-2.8866	0.2158	4.0836	-0.3463		-0.2538		-0.7294	
49	4.4499	5.5281	-1.7889	-0.6415	0.2831		-0.3974		-0.4044	
50	5.3942	2.5977	3.8161	4.0788	0.8404		-0.7622		0.0342	

Legend: t_{db}: air dry-bulb temperature; DS: duration of stress; DAS: days after stress; t_{clo}: cloacal temperature; FC: feed conversion; and C_{water}: water consumption.

The model with the lowest values of MSE (59.16, 102.27, and 67.23) in the training, validation, and test data was obtained with a hidden layer consisting of 50 neurons; the highest values of MSE among all the tested architectures were 145.54, 1,935.04, and 2,140.02 for the training, validation, and test data, respectively. The number of neurons in the hidden layer for the architecture with the highest values of MSE was 230 and it obtained an R^2 of 0.875. Figure 1 illustrates that the lowest value was obtained on the tenth cycle. The maximum number of seasons was 15, and the final momentum rate was 0.1. The function used to stop training was "minimum gradient reached." The output layer was composed of three neurons (t_{clo}, FC, and C_{water}).

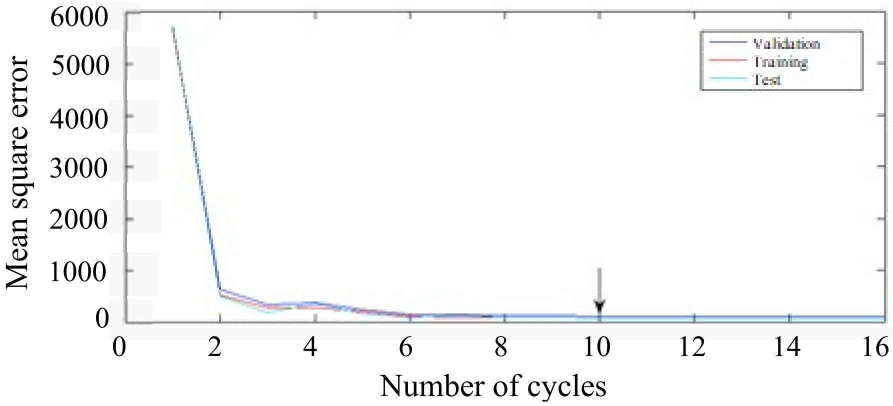

FIGURE 1. ANN training curve for the renewal of synaptic weights.

As the number of neurons in the hidden layer increases, performance improves and reaches satisfactory levels; however, if the number of neurons in the hidden layer is excessive, performance can be compromised, because many weights and the bias of neurons could have values equal to zero and would increase the processing of output value calculations (spatial and temporal complexity). In this case, the methodology proposed by Ferraz et al. (2014) recommends using the model with the best performance, using the highest coefficient of determination (R^2) and the lowest MSE. Thus, these values were obtained with values of intermediate neurons.

The efficiency of the model presented in this study corroborates the studies conducted by Klassen et al. (2009), who used ANN to model the cooling process of chicken carcasses in immersion tanks, in which artificial neural networks were adequate for the modeling of the researched system.

In this work, the simulation of the model was performed according to the combination of the input variables t_{db}, DS, and DAS, to predict t_{clo}, FC, and C_{water}. The simulated values were compared with the experimental data obtained in the air-conditioned wind tunnels, and the means, medians, and minimum and maximum values for mean deviation, standard deviation, and percentage error were determined (Table 2).

TABLE 2. Descriptive statistics comparing the values obtained experimentally and simulated by the model for cloacal temperature, feed conversion, and water consumption of broilers.

Indices	Cloacal Temperature (ºC)				Feed Conversion				Water consumption (mL day^{-1})			
	Min.	Mea.	Medi.	Max.	Min.	Mea.	Medi.	Max.	Min.	Mea.	Medi.	Max.
Mean deviation	0.00	0.13	0.07	0.81	0.00	0.07	0.05	0.34	0.00	2.24	1.20	11.52
Standard Deviation	0.00	0.09	0.05	0.57	0.00	0.05	0.04	0.24	0.00	1.59	0.85	8.14
Error (%)	0.00	0.30	0.18	1.95	0.10	4.85	3.43	21.7	0.00	2.05	1.10	9.98

Min.= Minimum; Mea.= Mean; Medi.= Median; Max.= Maximum.

The ANN trained in this work for prediction of t_{clo} presented an average deviation of 0.13ºC (Table 2) that is, close to the value obtained by Ferreira et al. (2010). In this work, the authors developed a neuro-fuzzy model to predict the t_{clo} of broilers as a function of RH, t_{db}, and air velocity, and the compared results between the neuro-fuzzy network and those experimentally measured obtained a mean deviation of 0.11ºC.

The mean percentage error found between the simulated and observed values of FC was 4.85%. In turn, Schiassi et al. (2015) obtained an average percentage error of 1.94% for FC. It is noteworthy that while in this study the data were evaluated daily, in work developed by Schiassi et al. (2015) the analyses were weekly; this study is characterized by lower variation resulting in lower error values.

When using ANN to predict the body mass of broilers, Ferraz et al. (2014) found mean values for absolute deviation, standard deviation, and percentage error of 3.3, 2.3, and 1.2%, respectively. For the ANN developed, considering the same statistical analyses, it can be verified that the values are modified according to the output variable; however, the mean values found in this study were close to the values published by the cited authors.

Vieira et al. (2011) developed an ANN to predict pre-slaughter losses through the mortality of broilers, and the results were not satisfactory due to low accuracy. Table

3 shows that the MSEs have variation between output neurons; this reflects the actual behavior of the variable (t_{clo}, FC, and C_{water}) instead of the absence of information. Also, when adjusting the linear regression models to confer the accuracy of an ANN developed with the observed values, it can be observed that the slope values closer to 1 indicate a better accuracy in the model (Tedeschi, 2006).

The values of the standard error and mean quadratic error associated with C_{water} are 3.29 and 3.40%, respectively (Table 3). These values were higher than those of the other variables studied, and were influenced by oscillation in daily consumption that was influenced by factors such as age, rise in room temperature, and feed consumption (Gama et al., 2008).

TABLE 3. Standard error, square root of the mean square error (RMSE), regression coefficient, and intercept for cloacal temperature (t_{clo}), feed conversion (FC) and water consumption (C_{water}) obtained experimentally and simulated by the model.

Variable	Standard Error	RMSE	Regression Coefficients
Cloacal Temperature	0.17	0.19	0.8431 ± 0.0379[1]
Feed Conversion	0.09	0.10	0.8683 ± 0.0517[1]
Water Consumption	3.29	3.40	0.9648 ± 0.0176[1]

[1] The coefficients are significant according to the t-test (p<0.05). All regressions were significant according to the F-test (p<0.05).

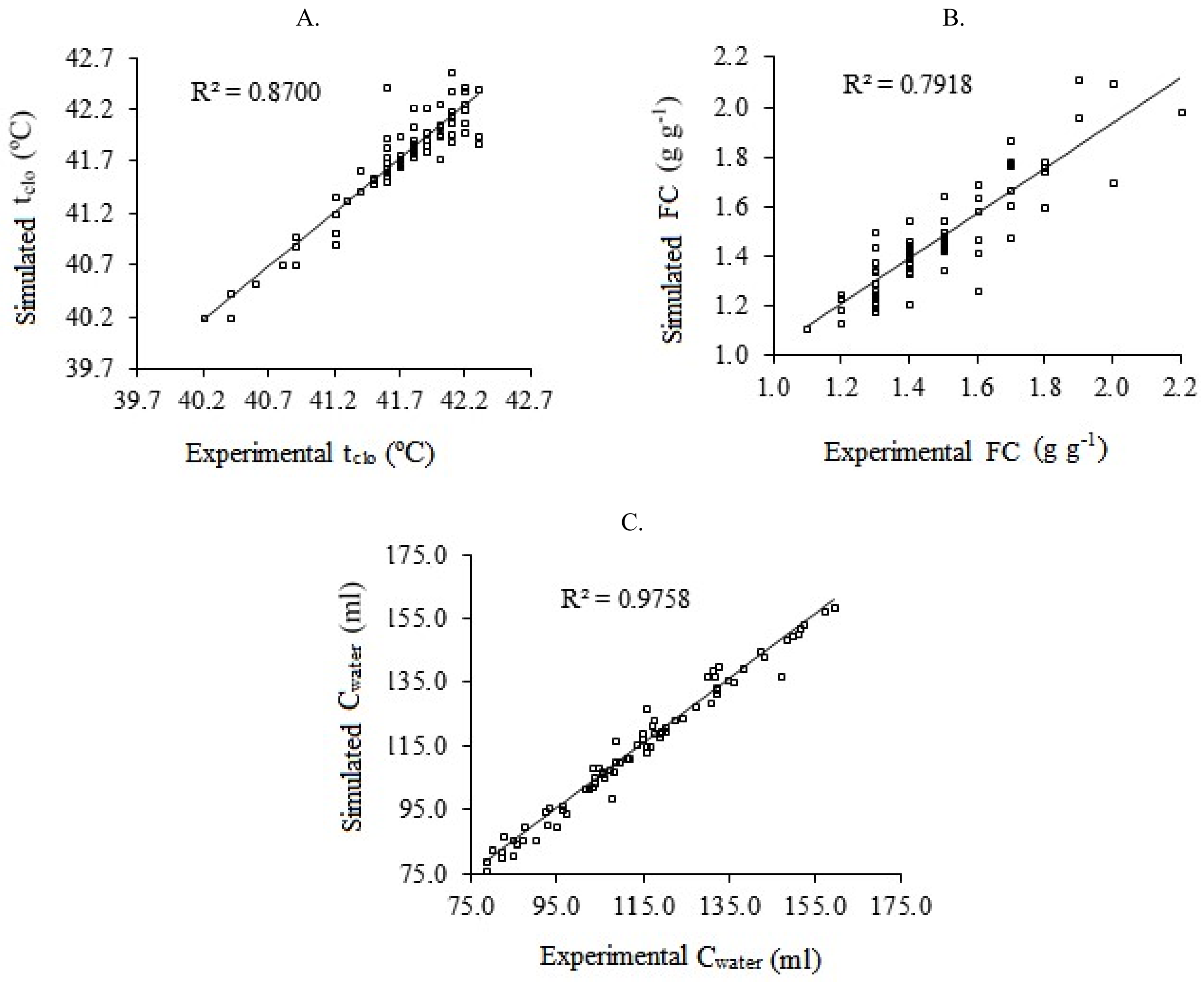

FIGURE 2. Linear regressions of cloacal temperature (t_{clo} - A), feed conversion (FC - B), and water consumption (C_{water} - C) of broilers obtained experimentally and simulated by the ANN model, in the second week of life.

Simple linear regressions of the values obtained experimentally and simulated by ANN are illustrated in Figure 2, in which the values of R^2 for t_{clo}, FC, and C_{water} were 0.87, 0.79, and 0.97, respectively.

According to the mentioned results, the ANN with the best architecture performed well, because 87% of the predicted values for the t_{clo} were achieved with absolute deviations ranging from 0 to 0.8. For the case of FC, the ANN obtained satisfactory performance, because 79% of the predicted values were reached with absolute deviations ranging from 0 to 0.34. For C_{water}, the performance was higher than the others, and 97% of the predicted values for the variable were reached with absolute minimum deviations of zero (0) and maximum sums of 1.20.

Therefore, choosing an architecture with the lowest EQM and with the highest R^2 indicates that the predicted values will have the best results and, consequently, a better performing system for management aid in the second week of the production cycle.

According to the data obtained from the literature, Medeiros et al. (2001) developed an empirical model to predict FC and found a coefficient of determination (R^2) of 0.72 for the same variable under study; the R^2 for the adjusted model in this study was 0.79.

CONCLUSIONS

The methodology used in this work allowed us to obtain different models based on ANN. Thus, it can be verified that the application of repetitions (in this case, 10) for each number of neurons in the hidden layer (from 1 to 300), made it possible to obtain different random combinations of the training, validation, and testing data, allowing the ANN architectures to capture an appropriate combination for predicting output variables.

Thus, the proposed multilayer perceptron artificial neural network obtained adequate performance for the prediction of cloacal temperature, feed conversion, and water consumption of Cobb 500® strain broilers subjected to thermal challenges in the second week of the production cycle.

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