Predicting Rectal Temperature of Broiler Chickens with Artificial Neural Network

Alison Zille Lopes¹, Tadayuki Yanagi Junior ², Wilian Soares Lacerda³, Giovanni Rabelo⁴

Abstract— Poultry production, facing modernization and increasing competitiveness, shows itself to be enterprising in the adoption of new technologies which enable increased productivity. Knowing that poultry productivity and rectal temperature (T_r) are affected by environmental conditions, this research was done with the objective of developing and evaluating artificial neural networks (ANNs) for the prediction of T_r in function of thermal conditions (air temperature, T_air; relative humidity, RH; and air velocity, V). The architecture chosen for this purpose was a single hidden layer Multilayer Perceptron (MLP), which was developed and trained under Scilab 4.1.1 aimed with ANN toolbox 0.4.2. The total data available, 139 data points obtained from literature, was divided into two sets, training (94) and validation (45). The selected MLP presented excellent results, providing estimates with an average error of 0.78% for the training set and 1.02% for the validation set. Thus, artificial neural networks constitute an appropriate and promising methodology to solve problems related to poultry production.

Index Term— Multilayer Perceptron, estimation, poultry, thermal comfort, heat stress

I. INTRODUCTION

Poultry production, holding more than one third of world meat market, has employed new technologies to enhance its competitiveness. The opening of new markets accentuated the search for productivity, involving both breeding program as well as the construction of high-tech poultry houses.

To get the most productivity in poultry production, it is essential that the thermal environment presents appropriate comfort levels, allowing broilers to express their maximum genetic potential. When thermal environment conditions inside a poultry house are out of the comfort limits, the environment becomes uncomfortable, requiring the animal body physiological adjustments to maintain homeothermy, be it to retain or dissipate heat [7]. As the thermal environment becomes increasingly stressful, the animal body perceives the risk to life and ceases to prioritize production and reproduction, focusing only on their survival [18].

The main effects of exposure of homeothermic animals to heat are changes in the normal standard of rectal temperature (T_r). Rectal temperature can be considered the best isolated criterion to judge heat tolerance [6] and it is an important efficiency indicator in the homeothermy maintenance facing the thermal environment. Rectal temperature can also be used to assess heat stress impacts [35]. The average rectal temperature of broiler chickens is around 41.5°C, ranging from 40.6 to 43.0°C, and the upper safety limit to maintain their survival is equal to 45°C [17].

Artificial neural networks (ANNs), a technique inspired by the operation and structure of biological neurons, are trained through the execution of standards across the network, enabling to identify relationships between variables independently of any prior knowledge [23]. Mathematically, the ANNs are universal approximators that carry out the mapping between two spaces of variables [10].

Currently, artificial neural networks have been applied in various areas of knowledge, and, in general, its use is linked to the search for patterns and techniques of temporal forecasts for making decisions. Moreover, the ANN is a technique that can be implemented in microcontrollers, producing systems with high performance and low cost [15, 32].

Specifically in poultry production, Roush et al. [23] used models based on artificial neural networks as a noninvasive way to identify broiler susceptibility to ascites. Similarly, ANN performance in detection of pulmonary hypertension syndrome suggests a new selection method for broilers not prone to this disease [24, 25].

Roush et al. [26], searching the modeling of broiler growth, verified the great predictive ability of neural networks, observing little or no overestimation of observed values. Additionally, there is still research related to analysis of feed intake and weight gain [38], detection of dirt in eggs [19], incubation process tracking [20, 29], breeding parameter estimates [28], broilers production management [22], among others.

In this context, this work aimed at to develop and evaluate the use of artificial neural networks for estimating broiler chicken rectal temperature, having air temperature (T_air), relative humidity (RH) and air velocity (V) as input variables.

II. MATERIAL AND METHODS

A. Neural network development

Artificial neural networks were implemented and evaluated in a microcomputer compatible to the standard IBM-PC, using the ANN Toolbox 0.4.2 in the Scilab 4.1.1 environment, both distributed free through the Internet. The Multilayer Perceptron (MLP) architecture was used with an input layer (3 inputs), a hidden layer (3 neurons) and an output layer (1 neuron). T_air, RH and V are the MLP’s inputs and T_r is the output (Fig. 1).
Broiler chickens, with more than 21 days of age, were randomized with values minimized by introduction of the amount important trends in data set. The development of artificial neural networks was possible valuable results were achieved in intervals of 16 to 40°C, 20 to 90% and 0 to 3 m s\(^{-1}\), respectively. Air velocity was not specified in 15 data pairs, considering, in these cases, V = 0 m s\(^{-1}\). In 7 data pairs, despite omission of information, it was known that there was a minimum air flow, adopting V = 0.2 m s\(^{-1}\).

**D. Comparison with mathematical models**

In order to do a comparative analysis with models proposed in the literature, MLP was confronted with equations adjusted by Medeiros [17] and Tao and Xin [36]. Medeiros [17], evaluating Avian Farm male broilers from 22 to 42 days of age, modeled (1) statistically. Equation (1), in which \(T_r\) is calculated in function of climatic variables (\(T_{air}, RH\) and V), was adjusted for intervals of 16 to 36 °C, 20 to 90% and 0 to 3 m s\(^{-1}\) for \(T_{air}, RH\) and V, respectively.

\[
T_r = 46.102818 - 0.425395T_{air} - 0.031012RH + 0.1189V + 0.009092T_{air}^2 + 0.00013RH^2 + 0.0263V^2 + 0.000893T_{air}RH -0.006944T_{air}V + 0.000661RHV
\]  

(1)

Studying the effect of intense heat stress on broiler chickens, Tao and Xin [36] developed a thermal comfort index: “temperature-humidity-velocity index” (THVI) (2). Based on THVI, (3) was developed to estimate the body temperature increase after 90-min exposure to the thermal conditions (\(T_{wb}\)). Equations (2) and (3) were developed through the combination of three \(T_{air}\) (35, 38 and 41 °C) values, two dew point temperature (\(T_{dw}\)) (19.4 and 26.1 °C) values and three V values (0.2, 0.6 and 1.2 m s\(^{-1}\)). These equations are only valid for the interval between inferior and superior limits of each considered variable. The wet bulb temperature (\(T_{wb}\), used in (2), is easily calculated in function of \(T_{air}\) and \(T_{dw}\) or RH through the methodology proposed by WILHELM [39].

\[
ITUV = (0.85T_{air} + 0.15T_{wb})V^{-0.058}
\]  

(2)

\[
\Delta T_{th} = 0.39\times THVI - 12.22
\]  

(3)
Tao and Xin [36] did not propose a model for the direct estimate of \( T_r \), so, \( \Delta t_{90} \) calculated by (3) was increased by 41.7 (midpoint of thermoneutral zone considered in the same study) in order to obtain the desired \( T_r \) value.

Finally, based on the training and validation data sets, \( T_r \) values estimated by MLP were confronted with those calculated by models proposed by Medeiros [17] and Tao and Xin [36], doing the comparative analysis through the mean square error (MSE), coefficient of determination \( (R^2) \), mean percent error with its standard deviation, and maximum percent error.

III. RESULTS AND DISCUSSION

The number of inputs and outputs of an artificial neural network is a characteristic of each studied problem, while the number of hidden layers and their neurons is dependent on the complexity, constituting a characteristic of the project [4]. A hidden layer with 3 neurons was sufficient for an efficient modeling of the problem. A superior number of neurons enhances the mapping capacity of neural networks. However, it is necessary to be aware of the possibility of incurring an over-adjustment. Besides, considering the computational cost, the increase of neuron numbers without over-adjustment does not reduce the error significantly.

Table I shows the results of the different training instances that originated five distinct artificial neural networks. The chosen model was the ANN 4 because it presented the lowest mean square error (MSE) and the highest coefficient of determination \( (R^2) \).

<table>
<thead>
<tr>
<th>ANN</th>
<th>Iterations</th>
<th>MSE</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>99,999</td>
<td>0.1862</td>
<td>0.8793</td>
</tr>
<tr>
<td>2</td>
<td>99,904</td>
<td>0.2101</td>
<td>0.8638</td>
</tr>
<tr>
<td>3</td>
<td>99,704</td>
<td>0.2078</td>
<td>0.8652</td>
</tr>
<tr>
<td>4</td>
<td>99,986</td>
<td>0.1758</td>
<td>0.8860</td>
</tr>
<tr>
<td>5</td>
<td>99,925</td>
<td>0.1998</td>
<td>0.87047</td>
</tr>
</tbody>
</table>

The learning rate and the momentum factor were selected according to the recommendation that these parameters should be comprised in the 0 to 1 interval [11] and that the momentum factor value is usually between 0.5 and 0.9 [27]. The learning rate and the momentum factor are the result of an empirical trial and error process, due to their values depending on the studied problem.

Knowing that the learning rate usually varies during the training process [4, 11, 21], tried to adjust it automatically through the bold driver technique [4]. However, the process showed to be quite slow and it did not reduce the error when applied to ANN 4.

Despite the variations, the training process presented fast convergence without affecting the solution process. Fig. 2 illustrates the training graph of ANN 4, which repeated 99,986 times to reach a training error (MSE) of 0.1758.

![Fig. 2. Evolution of mean square error (MSE) during the training process of the artificial neural network (ANN) 4.](image)

The final weights of the fourth training instance are shown in Table II, being possible to observe the bias and the weight vector represented by \( W \). In the hidden layer, \( W_1, W_2 \) and \( W_3 \) are the weights of the edges connected to \( T_{air}, V \) and RH inputs, respectively. In the output neuron, \( W_1, W_2 \) and \( W_3 \) are the weights of the edges that leave the neurons 1, 2 and 3, respectively.

| Resulting weights of the training process of the artificial neural network |
|-----------------------------|-----------------|-----------------|-----------------|
| neurons | bias | \( W_1 \) | \( W_2 \) | \( W_3 \) |
| 1         | -0.5827986 | 1.417465 | -3.8484132 | -6.5232177 |
| 2         | 1.7943517  | 1.1100434 | -4.0314207 | -7.666055  |
| 3         | -12.146503 | 11.924128 | -0.3432754 | 1.1697885  |
| output    | 1.5810874  | 5.2696701 | -1.4707425 | 6.3003672  |

Fig. 3 displays the functional relation among observed values (training data – Fig. 3a and validation data – Fig. 3b) and data estimated by the selected MLP. The points are very close to tendency line, suggesting that ANN is able to represent observed data efficiently, which is also confirmed through the high value of the coefficient of determination \( (R^2) \).
The neural network training adjustment presented mean percent error equal to 0.78\% with standard deviation of 0.6, observing a maximum value of 2.81\%. Validation process got excellent results: R² of 0.8205 and MSE of 0.2682. Mean percent error of validation process was equal to 1.02\% with standard deviation of 0.68, verifying a maximum value of 3.61\%.

The contours shown in Fig. 4 were plotted, based on the relationship between the inputs and MLP estimated $T_r$, through the Scilab function contour2D. Fig. 4a exhibits $T_r$ values estimated by neural network in function of $T_{air}$ ranging from 10 to 40 °C, RH ranging from 20 to 90\% and V equal to 1.5 m s⁻¹. Likewise, Fig. 4b shows the behavior of the rectal temperature estimate, fixing RH at 55\% and varying $T_{air}$ between 10 and 40 °C and V between 0 and 4 m s⁻¹. Fig. 4c shows $T_r$ values estimated in function of RH ranging from 20 to 90\%, V ranging from 0 to 4 m s⁻¹ and $T_{air}$ equal to 26 °C. Behavior observed in Fig. 4 are according to the expected physiological responses of broiler chickens, and they agree with results observed in other studies, such as Medeiros [17] and Tao and Xin [36].
Table III shows the comparative analysis between MLP and the method proposed by Medeiros [17]. The comparisons were accomplished based on data of training and validation, extrapolating as well as respecting the limits of the model proposed by Medeiros [17]. Comparisons using just the average data presented in Medeiros [17] were also done.

<table>
<thead>
<tr>
<th>Table III</th>
<th>Comparative analysis between the model developed by Medeiros [17] and the artificial neural network (ANN)</th>
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</thead>
<tbody>
<tr>
<td>MSE</td>
<td>ANN*</td>
</tr>
<tr>
<td>R²</td>
<td>0.2328</td>
</tr>
<tr>
<td>Emean (%)</td>
<td>0.2149</td>
</tr>
<tr>
<td>Emax (%)</td>
<td>2.0243</td>
</tr>
<tr>
<td>Meaks [17]</td>
<td>ANN*</td>
</tr>
<tr>
<td>Validation</td>
<td>(1)</td>
</tr>
<tr>
<td>Emean (%)</td>
<td>0.2701</td>
</tr>
<tr>
<td>Emax (%)</td>
<td>1.2579</td>
</tr>
</tbody>
</table>

Emean and Emax are, respectively, percentages of mean and maximum error. * indicates the extrapolation of the considered interval in (1).

The artificial neural network presented better results than (1), besides being a model of more ample scope. Even for the average values used for the (1) adjustment, ANN provided better results. In spite of coefficient of determination value being superior for (1) (0.8675 against 0.7679), MLP presented smaller MSE values, mean and maximum percent errors.

Table IV shows the comparative analysis between artificial neural networks and the mathematical model developed by Tao and Xin [36]. So, ΔTm was increased by 41.7. It is important to observe that there is an application limitation of this model when V is equal to 0 m s⁻¹, due to the occurrence of a division by zero in the calculation of THV1. Thus, the comparisons were accomplished based on both training and validation data, excluding the data pairs in which V is equal to 0 m s⁻¹. Besides these, there are comparisons using, from the total data, only those which belong within the scope of (3) and only present in the work done by Tao and Xin [36].

<table>
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<tr>
<th>Table IV</th>
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</tr>
</thead>
<tbody>
<tr>
<td>MSE</td>
<td>ANN</td>
</tr>
<tr>
<td>R²</td>
<td>(3)</td>
</tr>
<tr>
<td>Emean (%)</td>
<td>0.2325</td>
</tr>
<tr>
<td>Emax (%)</td>
<td>(3)</td>
</tr>
<tr>
<td>Scope</td>
<td>ANN</td>
</tr>
<tr>
<td>(3)</td>
<td>0.4890</td>
</tr>
<tr>
<td>Means [36]</td>
<td>ANN</td>
</tr>
<tr>
<td>(3)</td>
<td>0.2563</td>
</tr>
</tbody>
</table>

Emean and Emax are, respectively, percentages of mean and maximum error.

Again, ANN furnished better results than the mathematical model, in spite of being a more encompassing model, even for the data used in the fitting of Tao and Xin [36] model.

IV. CONCLUSION

Artificial neural networks adjusted for prediction of broiler chicken rectal temperature in function of air temperature, relative humidity and air velocity were trained and validated, presenting statistical indexes adequate to applications related to poultry production.

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REFERENCES


