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Artificial Neural Network Modelling of Thermal Comfort Zone for Early Stage Broiler Chickens

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Abstract: *This study aims to develop an artificial neural network (ANN) model for predicting the thermal comfort zone (TCZ) of early stage broiler chickens. Environmental factors such as temperature and humidity play a crucial role in the growth and development of broiler chickens. The accurate prediction of TCZ can help to create a conducive environment for the chickens and improve their production. The study obtained data from 375 broiler chickens at the age of 0 to 21 days, and the data were used to train the ANN model. The ANN model was created using a multilayer perceptron (MLP) with back propagation algorithm and consisted of two hidden layers. The inputs were temperature and humidity, while the output was TCZ. The model accuracy was measured using root mean square error (3.83×10^{-3}).This study demonstrates the potential of ANN modeling in predicting the TCZ of broiler chickens and can be useful in optimizing the environmental conditions for their growth and development. The maximum R^2 (0.96498) with a hidden layer of 2 neuron results to be stable and optimum network.*

Keywords: *ANN, modelling, poultry, and thermal comfort.*

INTRODUCTION

Poultry production in Nigeria amounts up to 454 billion tons of meat and 3.8 million eggs per year. With a standing population of 180million birds (FAO, 2019). The enormous global and national growth in poultry farming was due mainly to developments in the areas of genetics, nutrition, management and health, as well as offering the most suitable environments to the thermal comfort of the animals (Ferraz, Andrade, Vlas Boas, Rezende, Yanagi Junior, & Barbari, 2022). Poultry plays an important economic, nutritional and socio-cultural role in the livelihood of poor rural households in many developing countries, including Nigeria. Poultry are birds that include fowl, turkey, duck, goose, ostrich, guinea fowl, etc. which render not only economic services but contribute significantly to human food as a primary supplier of meat, egg, raw materials to industries (feathers, waste products), source of income and employment to people compared to other domestic animals (Demeke, 2004). Poultry are efficient converters of feed to egg and meat within a short period of time. In terms of nutritive value, poultry egg rank second to cow milk. Agriculturists and nutritionists have generally agreed that developing the poultry industry of Nigeria is the fastest means of bridging the protein deficiency gap presently prevailing in the country (Amos, 2006).

One of the most essential factors in improving broiler production is providing an appropriate environment inside the broiler house (air temperature, relative humidity, air velocity, air quality, and gases) with lower possible costs (Fidaros, Baxevanou, Bartzanas, & Kittas, 2018). Microclimatic conditions in broiler rooms depend on the temperature and humidity of the air, lighting, ventilation, as well as concentration of harmful gases (Nawalany & Sokolowski, 2020). Several factors can influence broiler development, but thermal stress is one of the most responsible environmental factors influencing a wide range of broilers performances, including animal welfare and reduced feed intake, which in turn affect feed conversion ratio, growth rate, body weight, meat quality, and others (Vandana, Sejian, Lees, Silpa, & Malone, 2021). These negative influences on the poultry system may result in significant economic losses

In the first days of life, chicks are very sensitive to different comfort conditions, and air temperature can be considered the environmental factor with the greatest impact on broiler development because it affects homeothermy (Ferraz, Yanagi, Lima, & Xin, 2017). In the first's week of life, chicks present a fast metabolism and growth rate. These animals have a poor ability to adjust to the thermal environment fluctuations (Nawab, et al., 2018). Therefore, the thermal stress in the early development of broiler chickens exerts a very negative effect on the animals through physiological and behavioral mechanisms (Olfati, Mojtahedin, Sadeghi, Akbari, & Martinez-Pastor, 2018). The first days of broiler life are the most critical, and errors made in this phase cannot be satisfactorily corrected in the future, thus it can affect the final broiler development and performance (Cordeiro, Tinoco, Silva, Vigoderis, Pinto, & Cecon, 2010). Yearly chicks do not have sweat glands, and they are highly sensitive to heat stress (Nawab, et al., 2018), and due to their fast growth, commercial broiler chicks are particularly susceptible to climatic challenges.

The capability of the artificial neural network (ANN) to learn and at the same time generalize the

Relationship among data sets and give satisfactory and quick estimations has made in at more attractive for many engineering applications (Oumarou, Shodiya, Ngala, & Bashir, 2017). This modeling tool has found application in New empirical correlations for sizing adiabatic capillary tubes in refrigeration systems (Shodiya S, 2012), in health care organizational decision-making (Shahid, Rappon, & Berta, 2019), in control of domestic air-conditioning system for energy savings (Shodiya, Mukhtar, & Abdulrazaq, 2017). In modeling, carbon emission intensity (Acheampong & Boateng, 2019), as well as predicting energy content of municipal solid wastes (Oumarou, Shodiya, Ngala, & Bashir, 2017) etc. ANN methods provide a good alternative for modeling and evaluating the present problem and can be used to explore the physical relationships existing at the macroscopic level, in order to represent satisfactorily the dynamics of flows and their effects (Norton, Grant, Fallon, & Sun, 2010). Thus, the possibility of performing the modeling with ANN, mapping the animal husbandry thermal environment, of broiler facilities, and making use of natural ventilation, is an extremely important and pressing issue for animal production and the type of construction practiced in tropical and sub-tropical countries.

MATERIALS AND METHOD

The Experimental data of the artificial neural network modeling of thermal comfort zone for early stage broiler chicken were obtained from (Márcia, Tinôco, Pinto, Santos, & Roberti, 2016).

In developing the ANN model, the available data from literature is used. The temperatures ranging from 15°C-33°C as the Inputs and the outputs are feed consumption at 7 days, body weight at 14 days and 21 days and weight gain at 21 days in gram. The table 1 shows the experimental data used in this study.

Table 1: Experimental Data (Márcia, Tinôco, Pinto, Santos, & Roberti, 2016)

Environmental Temperature (⁰C)	Feed conversion at day 7 (g)	Body weight at day 14 (g)	Body weight at day 21 (g)	Weight gain at day 21 (g)
15	_	_	1105.4	550.49
18	_	554.91	1142.32	570.83
21	1.03	571.49	1208.12	604.48
24	0.97	603.64	1165.28	581.56
27	0.9	583.72	1118.36	553.78
30	0.95	564.58	_	_
33	1.09	_	_	_

2.3 Artificial Neural Network (ANN) Modeling

ANN is an attempt at modeling the information processing capabilities of the brain and nervous systems. The brain consists of large number (approximately 10^{11}) of highly connected elements (approximately 10^4 connections per element) called neuron. Each neuron consists of three components –dendrite, cell body and axon. The dendrite (input unit) receive electric signal and pass it to cell body (processing unit) that process the signal and pass the processed signal to other neuron through the axon (output unit). The ANN is similar to the biological neural network whereby the network is trained by some set of input and the associated output data. Once trained, another set of input data are used to predict the output with the hope that during the training, the neurons has learned the relationship between the input and output data (error between the output and target is minimal). A typical example of an architectural neural network that consists of the three major layers (input, hidden and output) is shown in Figure 1. The number of hidden layer may be varied which can improve the predictive capability of the network.

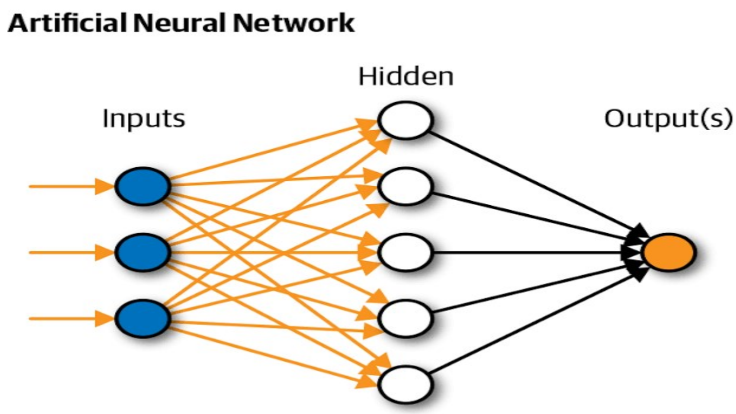

Fig 1: schematic diagram of a multi-layered ANN

The number of input parameter must be equal to the number of input layer. Likewise, the output parameter must also be equal to the output layer. The inputs (X) into a neuron are multiplied by their corresponding connection weights (W), summed together and a threshold (θ), acting at a bias, is added to the sum. This sum is transformed through a transfer function (f) to produce a single output (h), which may be passed, on to other neurons. The function of a neuron can be mathematically expressed as

$$h = f(\sum W\,\mathrm{X} - \theta) \quad (1)$$

Where the transfer function (f) of the neuron is the sigmoid activation function, being in the present work given as

$$\text{F(x) = 1/1+e-x } f(x) = \frac{1}{1+e^{-x}} \quad (2)$$

In this study, back propagation (BP) algorithm is used to train the network because it has been proven that BP with appropriate number of hidden layer, can successfully model any nonlinear relation to high level of accuracy (Pacheco-Vega et al., 2001). The purpose of BP is to reduce the error between the output and the target to higher level. The proposed algorithm in this study was developed using MATLAB 7.12.0.635 (R2013a).

In order to facilitate the comparisons between predicted values and experimental values, an error analysis, has been done using Mean Square Error (MSE) and the absolute fraction of variance (R2). The MSE is given by:

$$\text{MSE} = \frac{1}{n}\sum_j (tj - oj)^2 \quad (3)$$

And the R^2 is given by

$$R^2 = 1 - \frac{\sum_j (tj-oj)2}{\sum_j (oj)2} \quad (4)$$

Where t_j is actual values, o_j is the predicted (output) values and n is the number of the data.

Table 2 shows the description of thermal treatment performed during the 1st, 2nd and 3rd weeks of broiler chick rearing as reported by (Márcia, Tinôco, Pinto, Santos, & Roberti, 2016).

Table 2: Description of the thermal treatments performed during the 1st, 2nd and 3rd weeks of broiler chick rearing, respectively.

Treatment	Description	T(ºC) 1st week	T(ºC) 2nd week	T(ºC) 3rd week
TCL	Thermal comfort recommended in literature	33	30	27
TCC	Thermal comfort updated by (Cassuce, Tinoco, Baeta, Zolnier, Cecon, & Vieira, 2013)	30	27	24
MiC	Mild cold stress	27	24	21
MoC	Moderate cold stress	24	21	18
SeC	Severe cold stress	21	18	15

TCL: Thermal comfort range set by international literature (Curtis, 1983; Cheng et al., 1997);
TCC: Thermal comfort range updated by (Cassuce, Tinoco, Baeta, Zolnier, Cecon, & Vieira, 2013)
MiC: Apparent thermal range of mild cold stress;
MoC: Apparent thermal range of moderate cold stress;
SeC: Apparent thermal range of severe cold stress; all given for each of the three first weeks of broiler rearing.

3.0 RESULTS AND DISCUSSION

First Week Statistics

An Artificial Neural Network analysis indicated that the animal weight was not significantly influenced by the environmental temperature, even though the birds were given more foods. Figure 2 displays the mean feed conversion rate for each treatment during the initial week of rearing and also presents an adjusted model through ANN analysis.

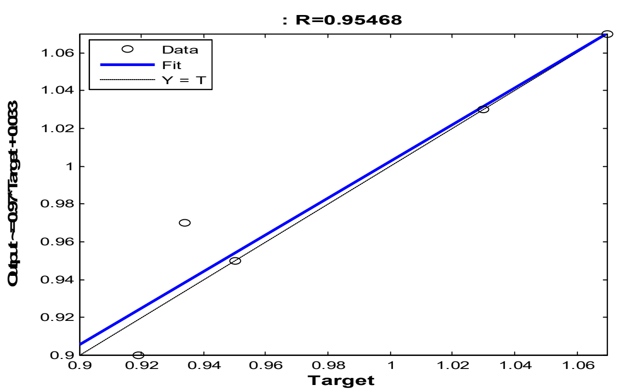

Fig 2: Feed conversion ratio at different environmental temperature levels during the first rearing week of broiler chicks by ANN

During this time, the temperature in the surrounding environment that improved the conversion of feed was 27^{0}C (MiC) and the prediction by ANN model was more accurate

compared to the experimental and polynomial models. This model shows that ANN is very good at predicting the thermal comfort zone of early stage broiler chicken.
The polynomial formula used to calculate the feed conversion ratio at different temperature level is given below:

$$FC = 3.6386-0.2037t + 0.0038t^2 \quad (5)$$

Table 3: Comparison of data from ANN, experiment and polynomial showing better prediction by ANN.

Temperature (^{0}C)	ANN	Experimental	Polynomial
21	1.0300	1.0300	1.0367
24	0.9413	0.9700	0.9386
27	0.9263	0.9000	0.9089
30	0.9500	0.9500	0.9476
33	1.0700	1.0900	1.0547
Mean square error	3.83×10^{-3}		

Second Week Statistics

Figure 3 displays the mean body weight for different conditions during the second week of rearing broiler chickens, along with the adjusted model calculated through ANN analysis. Artificial Neural Network model was validated, when the temperature that maximizes body weights was recorded as 24^{o}C.

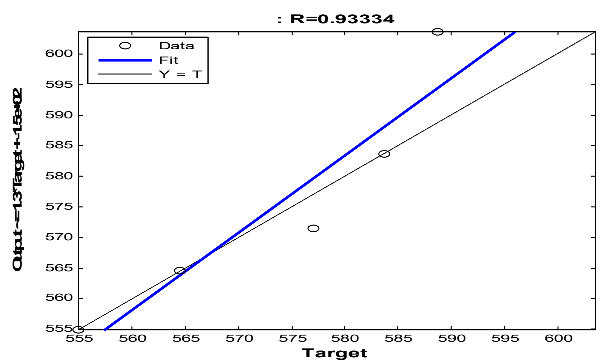

Fig 3: broiler body weight at different environment temperature levels during the second rearing week of broiler chicks by ANN

The experimental outcomes surpass the findings obtained by ANN and that of the polynomial model. This aspect can be gauged by the increased humidity levels observed in the environment examined by (Ponciano, Junior, & Schiassi, 2012). However ANN predict more accurate than the polynomial. From the table starting from 18^{0}C – 30^{0}C at 14 days, ANN is leading in prediction than polynomial, thus it shows that better results are obtained.
The polynomial formula used to calculate the body weight at 14 days ratio of different temperature level is given below:

$$BW = 3.4391 + 48.104t – 0.9802t^2 \quad (6)$$

Table 4: comprising of results by ANN, experiment and polynomial

Temperature (^{0}C)	ANN	Experiment	Polynomial
18	576.45	554.91	551.726
21	589.88	571.49	581.354
24	591.59	603.64	593.359
27	592.97	583.72	587.681
30	603.53	564.58	564.379
Mean square error	510.0062		

Third week statistics:

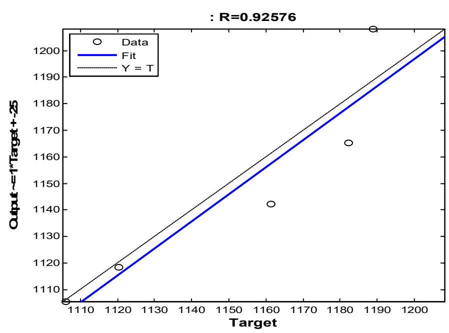

Fig 4: The mean body weight at 21 days for various temperatures during the third week of breeding alongside ANN corresponding adjusted model.

Broiler body weight at different environment temperature, Better prediction achieved with Artificial Neural Network as seen in the table and the polynomial formula used to calculate the body weight ratio at 21 days at different temperature level is given below:

$$BW \text{ at } 21 \text{ days} = 186.03 + 93.736t - 2.193t^2 \quad (7)$$

Table 5: Comparison of results by ANN, experiment and polynomial

Temperature (^{0}C)	ANN	Experiment	Polynomial
15	1187.0	1105.4	1098.645
18	1189.6	1142.32	1162.746
21	1189.9	1208.12	1187.373
24	1188.8	1165.28	1172.526
27	1179.9	1118.36	1118.205
Mean square error	2713.258		

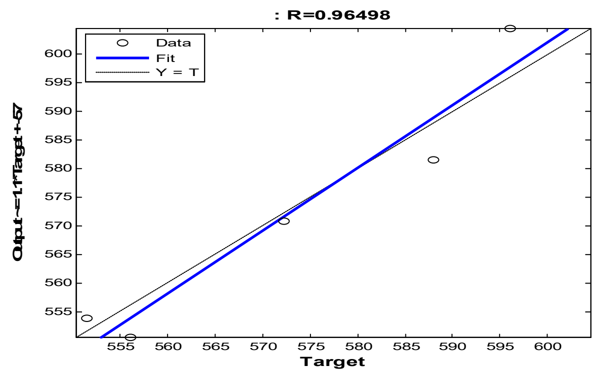

Fig 5: The mean weight gain at 21 days for every temperature and the corresponding ANN model.

During the third week, the chicks exposed to MiC gained a significantly greater amount of weight than those given TLC which had been previously considered the best method for the initial stage of breeding broiler chickens.

The polynomial formula used to calculate the weight gain ratio at different temperature level is given below:

$$WG = -299.319 + 81.894t - 1.867t^2 \quad (8)$$

Table 6: comparison of ANN, Experiment and Polynomial

Temperature (^{0}C)	ANN	Experiment	Polynomial
15	544.22	550.49	509.016
18	568.63	570.83	569.865
21	604.48	597.100	571.53
24	570.28	581.56	590.745
27	558.84	553.78	550.776
Mean square error	50.292		

These findings are consistent with those discovered by (Cassuce, Tinoco, Baeta, Zolnier, Cecon, & Vieira, 2013), who determined that the optimal temperature for chickens during the third week is 21.8^{0}C. Consequently, the experiment, polynomial and Artificial Neural Network models estimates are close to this figure. Moreover the ANN supersedes both the experimental data and the polynomial from 15-27^{0}C and thus ANN gives better results compared to the others.

CONCLUSION

During this modeling, data was obtained from literature and ANN was used to model the thermal comfort zone of broiler chicks. The best suitable interval during the first, second and third week of broiler existence was between (27, 24, and 21 ^{0}C) whereas artificial neural network gives better prediction than other models compared. The following conclusions can be drawn:

i. The artificial neural network was used to successfully model the thermal comfort zones for broiler chickens at different stage.
ii. The model developed can be used to predict the thermal comfort zone of early-stage broiler bird chickens at a given temperature and humidity.
iii. The predicting capability of the ANN model is better than that of the polynomial correlation in literature.

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