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Fuzzy-genetic approaches to knowledge discovery and decision making: Estimation of the cloacal temperature of chicks exposed to different thermal conditions

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Behaviour and physiological responses (e.g. respiratory rate and cloacal temperature) could be an indication of the thermal comfort or discomfort of broilers chicks. This study aimed to estimate the cloacal temperature (CT) of chicks in response to different intensities and durations of thermal exposure during the first week of life using a fuzzy inference system (FIS) and a fuzzy genetic algorithm (Fuzzy-GA). The experiment was conducted in four temperature-controlled wind tunnels located at the environmental laboratory of the Federal University of Lavras (UFLA; Minas Gerais, Brazil). The experimental database is composed of 114 laboratory-based observations. The duration of thermal challenge (CD; days) and dry bulb temperature (t_{db}; °C) were used as input variables for FIS. This paper proposes a theoretical framework for the development of Fuzzy-GA systems via two different approaches: the Mogul approach and the Pittsburgh approach. According to our results, the predicted CT values for both models (FIS and Fuzzy-GA) were similar to the experimentally-observed CT values. However, we noted that the model based on Fuzzy-GA exhibited better statistical results than the manual FIS in terms of CT-predicting capability. Thus, the model based on Fuzzy-GA can be used to predict CT for chicks exposed to thermal challenges and can therefore aid in decision-making processes.

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Nomenclature

CT	Cloacal temperature (°C)
FIS	Fuzzy inference system
Fuzzy-GA	Fuzzy genetic algorithm
CD	Challenge duration (days)
t_{db}	Dry bulb temperature (°C)
RR	Respiratory rate
RH	Air relative humidity (%)
RM	Linear or non-linear regression models
ANN	Artificial neural networks
CI	Computational intelligence
NFN	Neuro-fuzzy networks
FL	Fuzzy logic
GA	Genetic algorithms
RMSE	Root mean square error
UI	User interface
E (Ci)	Evaluation function
NPC (Ci)	The number of patterns correctly classified by the MOGUL approach
KDB	Knowledge database
RB	Rule base
GFRBS	Genetic-fuzzy rule-based system

1. Introduction

Menegali, Tinoco, Carvalho, Souza, and Martins (2013) and Mujahid (2010) have stated that neonatal chicks, as poikilothermic animals, have difficulties retaining body heat because their thermoregulatory capacity is not well developed. Thus, young birds require a warm environment to keep their body temperature near constant (Cordeiro, Tinôco, Filho, & Sousa, 2011).

Physiological responses, such as respiratory rate (RR) and cloacal temperature (CT), and behaviours, such as huddling or spreading, may be indicators of the levels of comfort or discomfort of broilers. The evaluation of these responses provides a method by which to assess the effectiveness of breeding conditions and their impact on the welfare of the chicks. These physiological and behavioural responses are directly influenced by the environmental conditions inside broiler houses (Damasceno, Yanagi Junior, Lima, Gomes, & Moraes, 2010).

Broilers achieve the best performance when reared under thermoneutral conditions. Thermoneutral dry-bulb temperature (t_{db}) for chicks should range from 32 to 34 °C during the first week of life (Cony & Zocche, 2004; De Pauli et al., 2008; Oliveira et al., 2006). Air velocity should be maintained at less than 0.3 m s^{-1} until the birds are fully feathered in order to avoid chilling by draughts.

According to Abreu, Yanagi Junior, Campos, Bahuti, and Fassani (2017), when variation in CT occurs, broilers dissipate or retain heat, and part of the energy that should be allocated towards weight gain will be used for thermoregulatory processes, thereby reducing productivity. According to Silva et al. (2003), an increase in CT is a physiological response to high t_{db} and relative humidity (RH), resulting in the storage of metabolic heat. In order to maintain a relatively constant body temperature for the vital organs, body heat must be maintained or released in response to environmental changes (Funck & Fonseca, 2008). While the maintenance of body temperature is achieved by behavioural and physiological mechanisms (Furtado, Rocha, Nascimento, & Silva, 2010), internal temperatures will increase and may, in extreme cases, cause the animals to die of thermal stress if these mechanisms are not sufficient to maintain homeothermy.

Hence, the development of tools (models) that assist broiler producers in making decisions related to maintaining the production environment within the zone of thermoneutrality is crucial to achieving maximum production (Hernández-Julio, Yanagi Junior, Ávila Pires, Aurélio Lopes, & Ribeiro de Lima, 2015). These models include linear or non-linear regression models (RMs), models based on computational intelligence (e.g. artificial neural networks (ANNs) ((Hernández-Julio, Yanagi, de FátimaÁvila Pires, Aurélio Lopes, & Ribeiro de Lima, 2014), neuro-fuzzy networks (NFNs) (Ferraz et al., 2014), fuzzy logic (FL) (Ferreira, Yanagi Junior, Lacerda, & Rabelo, 2012; Hernández-Julio et al., 2015; Nascimento, Pereira, Nääs, & Rodrigues, 2011; Pereira, Bighi, Gabriel Filho, & Gabriel, 2008), genetic algorithms (GA), and fuzzy genetic algorithms (Fuzzy-GA) (Ferraz et al., 2018; Jha, Ahmad, & Crowley, 2018).

On the one hand, fuzzy models are based on FL, which is founded on the theory of the fuzzy sets introduced by (Zadeh, 1965). According to Hernández-Julio et al. (2015), FL works with approximate rather than exact information to achieve precision in various applications in a way that is similar to human reasoning, thereby reducing the time needed for modelling. These types of models have been used in a variety of fields, such as knowledge discovery and decision making (Mota, Damasceno, & Leite, 2018), medical diagnostics (Hernández-Julio et al., 2019a, 2019b; Pota, Esposito, & De Pietro, 2017), improving crop productivity and the efficient use of fertilisers (Prabakaran, Vaithiyanathan, & Ganesan, 2018), and the classification of wine quality (Petropoulos et al., 2017).

Riza, Bergmeir, Herrera, and Benítez Sánchez (2015) state that Fuzzy-GA is a combination approach of fuzzy and genetic algorithm (GA) methods, in which GA is used to optimise the parameters of the membership function and rules of the fuzzy inference system. Fuzzy-GA has also been used in various processes, such as in estimating microbial rock phosphate solubilisation in sandy clay loam-textured soil (Jha et al., 2018), asset allocation (Georgieva, 2016), large-scale regressions (Rodrêguez-Fdez, Mucientes, & Bugarên, 2016), and in forecasting problems (Koshiyama, Vellasco, & Tanscheit, 2015). Thus, Fuzzy-GA models can aid the implementation of embedded fuzzy logic controllers e.g. to help control the heating or cooling systems that maintain the thermoneutral zone for developing chicks.

Thus, this study aimed to estimate the cloacal temperature (CT) of chicks in response to different intensities and durations of thermal challenge during the first week of life by using a fuzzy inference system (FIS) and Fuzzy-GA.

2. Materials and methods

2.1. The experiment

The experiment was conducted in four identical temperature-controlled wind tunnels, which were installed in the environmental laboratory of the Federal University of Lavras (UFLA; Minas Gerais, Brazil). The procedure was approved by the Ethics Committee on Animal Use (CEUA) of the Federal University of Lavras (Minas Gerais, Brazil), according to Protocol 001/12.

The thermally and environmentally controlled wind tunnels were made of steel frames, sheets, and polyvinyl chloride (PVC) pipes. The target t_{db}, RH, and air velocity were well maintained in the wind tunnels throughout the experimental period, with a standard deviation of 0.3 °C, 0.5%, and 0.10 m s^{-1}, respectively.

Thirteen treatments were performed, combining four t_{db} conditions (27, 30, 33, and 36 °C) and four durations of exposure to thermal stress (1–4 days) (Table 1).

A total of 210 mixed-sex Cobb chicks (50% female and 50% male) were used for the experiment. The birds were randomly distributed among the treatments. Each trial consisted of four treatments, (60 birds, 50% female and 50% male, 15 per treatment) that were divided into three replicate groups of five birds each. Different numbers of replicates (unbalanced) were used for control treatments. Specifically, the ninth and eleventh treatments had one five-bird replicate group with five birds per treatment, whereas the tenth and twelfth treatments each had two five-bird replicate groups (Table 1). Because of this, the total number of birds for all the treatments was 210 instead of the expected 240.

During the experiment, water and commercial pre-starter feed were given to the chicks *ad libitum* to meet their nutritional requirements. A continuous lighting program was employed during the study period (Abreu et al., 2017). All experimental chicks had a similar initial body mass, came from the same hatchery, and received the same vaccines for Marek's disease, Gumboro disease, and fowl pox.

Table 1 – Dry-bulb temperature (t_{db}; °C), and duration of thermal stress (days) used in the study.

Treatments	Dry- bulb temperature (t_{db}, °C)	Stress duration (days)
1	27 ± 0.2	1
2	27 ± 0.3	2
3	27 ± 0.2	3
4	27 ± 0.3	4
5	30 ± 0.3	1
6	30 ± 0.3	2
7	30 ± 0.3	3
8	30 ± 0.2	4
9 (control)[a]	33 ± 0.2	0
10	36 ± 0.6	1
11	36 ± 0.5	2
12	36 ± 0.6	3
13	36 ± 0.5	4

[a] The optimal temperature (treatment 9) was 33 °C.

The chicks were placed inside the environmentally controlled wind tunnels on the day of hatching and remained there until eight days of age. At one day old, the chicks arriving from the incubator were housed inside the environmentally-controlled wind tunnels at the control temperature (33 °C) (Menegali et al., 2013). At two days old, each group of 15 chicks was subjected to one of the 13 treatments described in Table 1, with varying intensities and exposure times of t_{db}. After the allotted period of thermal exposure, chicks were returned to the comfort temperature for the rest of the first week (33 °C).

Every day, one chick from each replicate of each treatment was randomly captured, and CT was measured with the aid of a high-precision portable digital thermometer (INSTRUTHERM® São Paulo, SP, Brazil; ± 0.1% accuracy, + 0.2 °C), for a total of three animals from each treatment.

Matlab® 2017[a] (MathWorks, Inc, 2017) was used for the development of the FIS and the Fuzzy-GA toolbox.

2.2. Datasets

A database containing the raw data for thermal stress (t_{db}; °C), the duration of thermal challenge (CD; days), and cloacal temperature (CT) was generated for the Cobb chicks.

The experimental database was composed of 114 data points. To perform the necessary analyses, the subsets were randomly and iteratively distributed as follows: training (70%), validation (15%), and test (15%) using the "dividerand" Matlab software command. In addition to these subsets, data were further subdivided, and another subgroup was used for the total validation of the system performance, which was formed by the mean values of the measurements taken during the experiments. In total, there were 16 mean values, which were calculated using the observed replicates from the thirteen treatments.

2.3. Data preparation

First, it was necessary to define the input and output variables for modelling. To build the respective dataset, the data were transformed using extraction and transformation techniques. In this case, the objective was to arrange the input and output variables in matrix form (*m* x *n*), where *m* represents the number of instances and *n* represents the number of variables (Riza et al., 2015). In this case, the first two columns of the transformed dataset represent the input variables and the third column represents the output variable (Table 2).

2.4. Fuzzy model development

We developed an FIS to predict the CT of broiler chicks in response to different intensities and durations of thermal challenge. The duration of thermal challenge (CD; days) and dry bulb temperature (t_{db}; °C) were used as input variables (Table 3). Triangular membership function (MF) curves were chosen because these are the most commonly used and they represent the data profile that shows the best fit for the data of the developed model (Hernández-Julio et al., 2015; Ponciano, Yanagi Junior, Schiassi, Campos, & Nascimento, 2012a; Schiassi et al., 2012). In this case, the input variables were the exposure times (1–4 days) and four temperatures (27, 30, 33, and 36 °C), indicating that we wanted a maximum membership degree of (1.0) for each input variable. While developing the model, experts defined the ranges of each membership function. The experimental values that formed the basis for the definition of the inputs and outputs of the membership curves are shown in Table 3 and Fig. 1.

We used a Mamdani-type FIS to predict CT. According to Leite, Fileti, and Silva (2010), this inference method yields a fuzzy set as answers by combining the input values with their relative degrees of membership using the minimum operator, and in sequence, the definitions of the rules by the maximum operator. The defuzzification method was the centre of gravity, which allowed for all output options, thereby converting the fuzzy set into a numerical value.

The fuzzy inference was manually structured and was composed of a set of 16 rules that stemmed from the multiplication of 4 MFs for t_{db} and 4 MFs for CD. Experimental data defined these basic rules and, with the help of experts in the field, are presented as if/then rules. A total of 16 rules were generated for each variable response, and a weighting factor of 1 was assigned to each sentence (Table 3). This assignment was made because the higher the rule weight, the larger the decision area of each rule (Ishibuchi & Nakashima, 2001), which can be also interpreted as the strength of each rule.

2.5. *Fuzzy-genetic approaches and framework*

The use of genetic algorithms has been shown to improve fuzzy inference models (Ferraz et al., 2018; Jha et al., 2018; Rodrêguez-Fdez et al., 2016). One of the biggest problems in executing this type of approach is in finding a methodology that helps with the implementation of the predicted models. For this reason, this section proposes a theoretical framework for the development of Fuzzy-GA systems. Our framework employs two different approaches: the Mogul approach (Cordón, del Jesús, Herrera, & Lozano, 1999; Herrera, 2008; Herrera, Lozano, & Verdegay, 1998) and the Pittsburgh approach (Herrera, 2008; Herrera & Magdalena, 1997; Smith, 1980, p. 220).

2.5.1. *MOGUL approach*

According to Herrera et al. (1998), this approach uses a genetic algorithm to determine the structure of the fuzzy rules and the parameters of the membership functions simultaneously

Table 2 – Example of Data Extraction and transformation (some illustrative values).

Original dataset					Extracted and transformed dataset		
Input 1	Input 2/Output				Inputs		Output
Days under stress	t_{db} (°C)/CT obs.				Days under stress	Stress Temp t_{db} (°C).	CT obs.
	27	30	33	36			
1	40.0	40.7	40.5	40.9	1	27.0	40.0
	40.4	41.3	40.7	40.1			40.4
	40.0	41.2	40.6	40.9			40.0
	40.1	40.8	40.6	40.8			40.1
	40.3	40.9	40.6	40.6			40.3
	39.6	40.6	40.3	40.4			39.6
	39.7	41.3		41.2			39.7
	40.6	41.0		41.0			40.6
	39.3	40.7		41.4			39.3
	39.7	40.9		40.9			39.7
	40.0	40.8		40.8			40.0
	40.5	41.0		40.6			40.5
2	40.5	41.0	40.9	41.2	1	30.0	40.7
	40.2	40.5	41.2	41.4			41.3
	40.3	40.8	41.2	40.4			41.2
	40.1	41.1	40.9	41.3			40.8
	40.4	41.2	41.3	40.9			40.9
	40.1	41.0	41.6	40.6			40.6
	40.5	41.3		41.5			41.3
	40.8	40.5		41.2			41.0
	40.2	40.7		41.1			40.7
3	40.2	40.9	41.1	40.9			40.9
	40.2	41.2	41.4	41.8			40.8
	40.4	41.3	41.5	41.0			41.0
	40.4	41.5	41.5	41.5	1	33.0	40.5
	40.9	41.9	41.2	41.4			40.7
	40.1	41.5	41.4	41.1			40.6
4	40.7	41.5	41.2	41.9			40.6
	41.0	41.9	41.3	42.1			40.6
	41.2	41.4	41.2	41.4			40.3

Values on the left side represent the original dataset, while the right side represents a portion of the extracted and transformed dataset. t_{db}, dry bulb temperature. CT Obs.: observed Cloacal temperature.

Table 3 – Fuzzy inference system developed by a fuzzy model.

[System]	Rules
Name = 'simulation triangular 11 curves'	If (CD = 1) and (Tdb = 1) then (CT = 3)
	If (CD = 1) and (Tdb = 2) then (CT = 5)
Type = 'mamdani'	If (CD = 1) and (Tdb = 3) then (CT = 11)
Version = 2.0	If (CD = 1) and (Tdb = 4) then (CT = 5)
NumInputs = 2	If (CD = 2) and (Tdb = 1) then (CT = 4)
NumOutputs = 1	If (CD = 2) and (Tdb = 2) then (CT = 5)
NumRules = 16	If (CD = 2) and (Tdb = 3) then (CT = 7)
AndMethod = 'min'	If (CD = 2) and (Tdb = 4) then (CT = 6)
OrMethod = 'max'	If (CD = 3) and (Tdb = 1) then (CT = 4)
ImpMethod = 'min'	If (CD = 3) and (Tdb = 2) then (CT = 8)
AggMethod = 'max'	If (CD = 3) and (Tdb = 3) then (CT = 7)
DefuzzMethod = 'centroid'	If (CD = 3) and (Tdb = 4) then (CT = 7)
	If (CD = 4) and (Tdb = 1) then (CT = 6)
	If (CD = 4) and (Tdb = 2) then (CT = 8)
	If (CD = 4) and (Tdb = 3) then (CT = 6)
	If (CD = 4) and (Tdb = 4) then (CT = 9)
	If (CD = 1) and (Tdb = 1) then (CT = 3)
	If (CD = 1) and (Tdb = 2) then (CT = 5)

Min: minimum. Max: Maximum. The weights of all rules were input as 1.0.

by using an approximate Mamdani-type fuzzy method. This method consists of three primary stages:

(i) The genetic generating process (to obtain desirable fuzzy rules that can include the complete knowledge base from the set of examples),
(ii) the genetic simplification process (to combine and eliminate redundant rules, and thereby select the most cooperative set of rules), and
(iii) the genetic tuning process (which fits the membership functions of the fuzzy rules that deal with the parameters of the membership functions, thereby minimising a square error function defined by means of an input–output data set for evaluation) (Cordón et al., 1999; Cordón & Herrera, 2001; Herrera, 2008; Herrera et al., 1998).

2.5.2. *Pittsburgh approach*

This approach also works with Mamdani-type and genetic algorithms. Using this method, GA attempts to optimise the rule base of the fuzzy model to determine the best if/then rules without changing the knowledge database (membership functions). The first if/then rules are considered to be inside the initial population of the GA method, or more specifically, one chromosome encodes all if/then rules (entire rule base) (Herrera, 2008; Herrera & Magdalena, 1997; Smith, 1980, p. 220). According to the authors, crossover and mutation functions are implemented to obtain the new population of chromosomes. The root mean square error (RMSE) is used to evaluate the fitness of the original chromosomes, and is calculated between the observed output and the predicted output. The best set of chromosomes (rules) is obtained after several generations. The optimal set of rules could be used in the inference engine to achieve the linguistic output, and the actual output value is subsequently obtained using the defuzzification process (Jha et al., 2018; Smith, 1980, p. 220).

2.6. *Framework for the development of Fuzzy-GA systems*

2.6.1. *Front-end layer*

This layer is also called the user interface (UI) (Liu, Sha, Wang, Li, & Bureau, 2018). In this layer, we can validate and verify user authentication and employ the user interface to create or modify Fuzzy-GA systems. Furthermore, the user interface is displayed according to the role of the user. The main objective of this layer is to interact with the backend layer. The user who makes decisions about a given topic will interact with the user interface to enter the input variables and will show the result by choosing from one or more computational intelligence techniques (if possible). Moreover, each user will have a graphical user interface.

2.6.2. *Back-end layer*

This layer is composed of all individual application systems to be deployed. All applications must have a relationship with the core of an expert on fuzzy models. The focus of this section is to propose a framework of computational intelligence for the development of Fuzzy-GA systems.

2.6.3. *Data layer*

The data layer is part of the enterprise architecture data layer. Nieto Bernal and Luna Amaya (2015) state that this layer is composed of a set of models that displays the information integrated into the organisation infrastructure. This phase begins with conceptual models and ultimately encompasses the physical design of the database, data warehouses, and repositories of information. In this layer, the enterprise architect must identify and model objects to organise information (classes, objects, tables), describe them (relational data model objects), and design a database from the objects (physical database); integrate information using enterprise information integration (EEI); and design comprehensive databases, data repositories, and data warehouse design and repositories using the database management system (Nieto Bernal & Luna Amaya, 2015).

2.6.4. *Service infrastructure layer*

This layer is part of the enterprise architecture infrastructural layer. The primary role of this layer is to characterise the

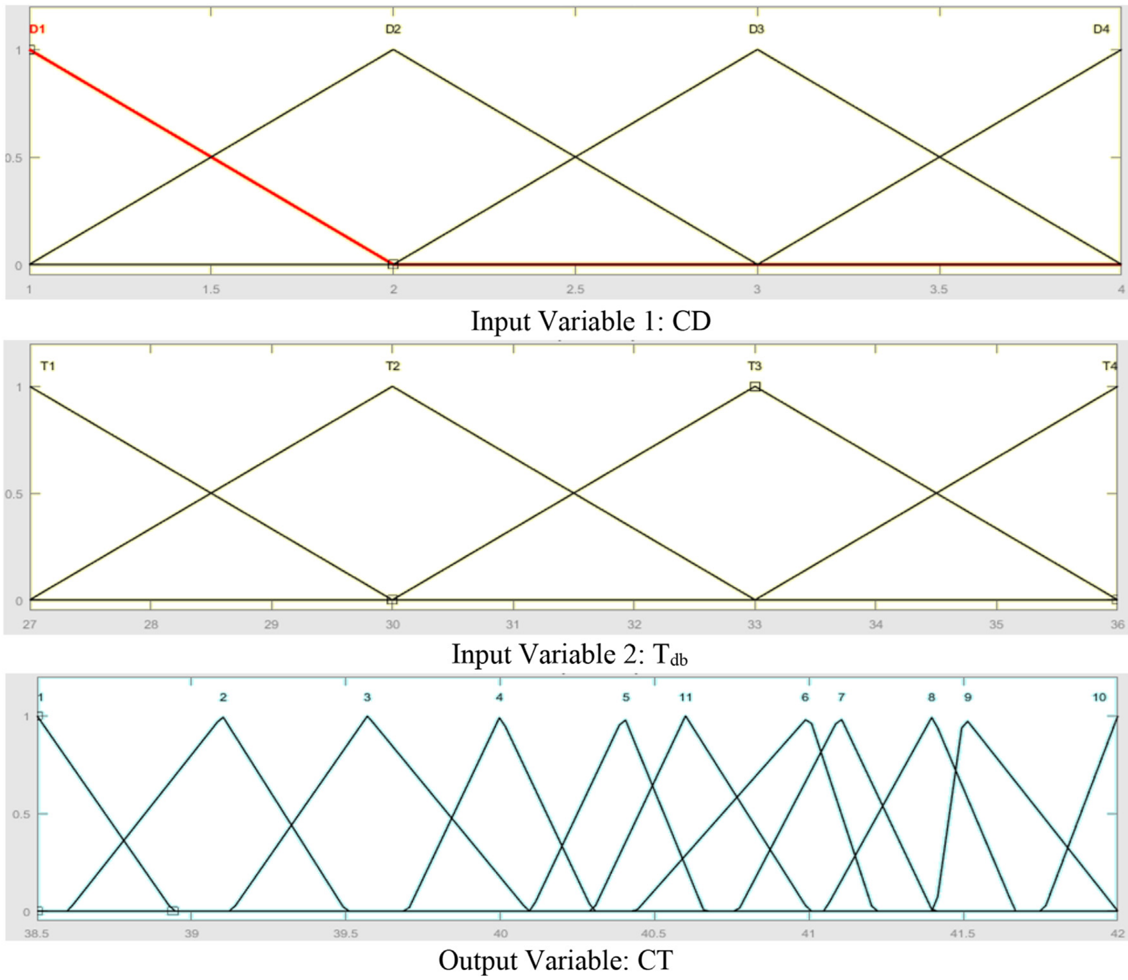


Fig. 1 – Membership functions for inputs and output variables.

business through modelling, design infrastructure architecture, model the physical distribution of the business, design the physical layout of the business, and to develop the physical distribution of the business (Lan, Man, Wan, Wireless, Pan) and the design of the extended physical distribution/business network (Nieto Bernal & Luna Amaya, 2015). The execution of this layer employs various operating systems (OS), web services (WS), open database connectivity (ODBC) drivers, and pre-processors.

2.6.5. *Back-end explanation*

The methodology used to perform this is represented by three components (fuzzy logic, genetic algorithms, and the genetic-fuzzy component). The first component is responsible for the manual development of the fuzzy system. The second component applies the genetic operators (selection, crossover, and mutation) to the initial population and the other populations resulting from the interactions between the operators. Finally, the third component is the conjunction of the first two components. The result is the best rule base configuration without modification of the database (Pittsburgh approach) or the best database configuration with or without modification of the rule base (MOGUL approach). The first two components are not presented here in detail because they belong to well-known methods of computational intelligence. However, the third component is presented here in more detail, as to the best of our knowledge, there are no studies that address the specific methodology required to perform a hybridisation of the two techniques.

2.6.6. *Evaluation function*

According to Pires (2004, p. 128), the same evaluation function is used for both approaches (i.e. Pittsburgh and MOGUL).

The evaluation function E (Ci) is based on the parameter values of the rules-based performance or membership functions that were generated from the information contained in the chromosomes (population) and calculated by the number of patterns correctly classified using the fuzzy reasoning method. The evaluation function is expressed by equation (1):

$$E(Ci) = NPC(Ci) \tag{1}$$

where $NPC(Ci)$ is the number of patterns correctly classified using the MOGUL approach (database and rule base) or Pittsburgh approach (rule base), generated by the chromosome Ci. The evalfis function (software command) was used to calculate this value.

3. Results and discussion

The parameters of the genetic algorithm (i.e. the maximum number of generations, population size, the probabilities of mutation and crossing, and the percentage of elitism) were defined empirically and are listed in Table 4 (Pires, 2004, p. 128). It is worth noting that all of these values can be changed at any time during the creation of Fuzzy-GA systems.

The main aim of a Fuzzy-GA is to adjust the parameters of the input and/or output variables of the determined fuzzy model in order to improve or modify the performance (accuracy) of predicting the value(s) of the output variable(s) (CT) and to reduce the prediction error (RMSE) (Georgieva, 2016). In this study, the parameters of the input and output variables had been manually defined in the FIS. In the elaborated toolbox (Fuzzy-GA), input and output variables and rule base were selected to optimise the parameters. The Fuzzy-GA acted by changing the ranges of the membership functions of the output variable (MOGUL approach) and the rule base (Pittsburgh approach), thereby optimising the model.

The input, output, and rules of the original FIS are listed in Table 3 and Fig. 1. Table 5 is a comparison of the intervals of the membership function curves (knowledge database: MOGUL approach) for the output and the rule base (RB: Pittsburgh approach) for FIS and the Fuzzy-GA system.

Descriptive statistical indices (i.e. absolute and standard deviation, percentage error, the coefficient of determination [R^2; Fig. 2], histograms, standard error, RMSE, regression coefficients [slopes], and intercepts) were computed to evaluate the effectiveness of Fuzzy-GA in improving the proposed FIS for predicting CT in chicks. The results of the performance of FIS and Fuzzy-GA for the subset of the test data (means datasets) are listed in Table 6.

In addition to the descriptive statistical indices, the functional relationships between the CT values predicted by FIS (Eq. (2) and Fig. 3a) and Fuzzy-GA, (Eq. (3) and Fig. 3b), and the actual values observed during the experiment period were analysed, and the following respective equations were found:

$$CT_{simulated\ by\ FIS} = 0.91032*CT_{Observed} - 3.6449,\ (Standard\ error = \pm 0.0900) \quad (2)$$

$$CT_{simulated\ by\ Fuzzy-GA} = 0.95936*CT_{Observed} - 1.6243,\ (Standard\ error = \pm 0.0611) \quad (3)$$

As can be observed, the intercept values are not close to zero (0), for that reason, we wanted to show is whether there is a significant difference in the centre of mass of the predicted CT values, for doing that, we adjusted the formula and calculated again the intercepts and slopes values with the following equation:

$$CT_{simulated\ by\ FIS\ or\ Fuzzy-GA} - 41^{\circ}C = m \cdot (CT_{Observed} - 41^{\circ}C) + c, \quad (4)$$

where the 41 °C represents the median of the observed values of the cloacal temperature. m and c represent the slope and the intercepts of the formulae.

With the new formulae, the obtained values for slopes and intercepts were:

$$CT_{simulated\ by\ FIS} - 41^{\circ}C = 1.06315^{S} \cdot (CT_{Observed} - 41^{\circ}C) + 0.035^{NS},\ (Standard\ error = \pm 0.0973) \quad (5)$$

$$CT_{simulated\ by\ Fuzzy-GA} - 41^{\circ}C = 1.0269^{S} \cdot (CT_{Observed} - 41^{\circ}C) + 0.0433^{S},\ (Standard\ error = \pm 0.063) \quad (6)$$

where s means a significant difference at a 95% confidence interval.

According to Tedeschi (2006), accuracy increases as the intercept approaches 0, and the slope approaches 1. For both equations, the values of the slopes are close to 1, with Eq. (6) more accurate than Eq. (5). The intercept values of both are close to 0, which indicates a more accurate prediction of the output (Tedeschi, 2006).

The two final models for predicting CT were compared using different methods. According to these results, the predicted CT values for both models (FIS and Fuzzy-GA) were similar to those that were observed experimentally. However, it should be noted that the model based on Fuzzy-GA exhibited both higher and statistically significant outcomes in its capacity to predict CT in comparison to the manual FIS, as can be seen in Table 6, Fig. 2, and Fig.3. The statistical indices indicate that predictions using Fuzzy-GA concentrated errors (88%) over a smaller range of absolute deviations (from 0 to 0.1 °C), while the remaining 12% of the absolute deviations were between 0.15 and 0.2 (Fig. 2). The percent prediction accuracy for Fuzzy-GA was significantly higher than for FIS (higher R^2, Fig. 3b) when the means dataset was used as the test dataset. The difference between the maximum value of absolute deviations in both models (0.065) was statistically significant ($p > 0.01$). These results indicate an improvement in the previously functional predictive capacity of the FIS model. In consideration of the two approaches to genetic algorithms (i.e. MOGUL and Pittsburgh), it should be noted that both approaches played a role in the improved predictive capacity observed in the present study. While the MOGUL approach recognises the structure (knowledge database) and estimates the parameters of the models simultaneously (Herrera, 2008; Herrera & Magdalena, 1997; Herrera et al., 1998; Riza et al., 2015; Smith, 1980, p. 220), the Pittsburgh approach also changed the original FIS rule-based configuration in this case (Table 6), showing that in some cases, attempting to change the rule database can be helpful. Furthermore, it can be observed that modifying a single parameter in the original FIS can influence the performance of the developed model (Ferraz et al., 2018). For example, the maximum values of the statistical deviations (absolute and standard deviations, and percentage errors) exhibited notable differences in the present

Table 4 – Fuzzy-GA parameters.

Parameters	Values
Generation maximum number	100
Population size	4 chromosomes
Mutation probability	0.02
Crossover probability	0.01
Selection method	Tournament
Crossover method	Uniform
Percentage of elitism	5%
Number of repetitions	100

Table 5 – Comparison between the knowledge and rule base of the two systems.

Cloacal Temperature (CT, °C)				
Membership functions	Membership function curves (KDB Parameters)			RB
	A	B	C	Rules
[a]MF1	**38.06**	38.50	38.94	If (CD = 1) and (Tdb = 1) then (CT = 3)
	38.50	38.50	38.94	If (CD = 1) and (Tdb = 1) then (CT = 4)
MF2	39.13	39.57	**40.01**	If (CD = 1) and (Tdb = 2) then (CT = 5)
	39.13	39.57	**40.09**	If (CD = 1) and (Tdb = 2) then (CT = 6)
MF3	39.70	40.00	40.30	If (CD = 1) and (Tdb = 3) then (CT = 11)
	39.70	40.00	40.30	If (CD = 1) and (Tdb = 3) then (CT = 11)
MF4	40.10	40.40	40.66	If (CD = 1) and (Tdb = 4) then (CT = 5)
	40.10	40.40	40.66	If (CD = 1) and (Tdb = 4) then (CT = 6)
MF5	**40.40**	**40.90**	**41.00**	If (CD = 2) and (Tdb = 1) then (CT = 4)
	40.44	**41.00**	**41.21**	If (CD = 2) and (Tdb = 1) then (CT = 5)
MF6	40.77	41.10	41.40	If (CD = 2) and (Tdb = 2) then (CT = 5)
	40.77	41.10	41.40	If (CD = 2) and (Tdb = 2) then (CT = 6)
MF7	41.05	41.40	**41.60**	If (CD = 2) and (Tdb = 3) then (CT = 7)
	41.05	41.40	**41.67**	If (CD = 2) and (Tdb = 3) then (CT = 8)
MF8	41.41	41.50	42.00	If (CD = 2) and (Tdb = 4) then (CT = 6)
	41.41	41.50	42.00	If (CD = 2) and (Tdb = 4) then (CT = 7)
MF9	41.76	42.00	**42.40**	If (CD = 3) and (Tdb = 1) then (CT = 4)
	41.76	42.00	**42.00**	If (CD = 3) and (Tdb = 1) then (CT = 5)
MF10	38.60	39.10	39.50	If (CD = 3) and (Tdb = 2) then (CT = 8)
	38.60	39.10	39.50	If (CD = 3) and (Tdb = 2) then (CT = 8)
MF11	40.30	40.60	41.00	If (CD = 3) and (Tdb = 3) then (CT = 7)
	40.30	40.60	41.00	If (CD = 3) and (Tdb = 3) then (CT = 8)
				If (CD = 3) and (Tdb = 4) then (CT = 7)
				If (CD = 3) and (Tdb = 4) then (CT = 8)
				If (CD = 4) and (Tdb = 1) then (CT = 6)
				If (CD = 4) and (Tdb = 1) then (CT = 7)
				If (CD = 4) and (Tdb = 2) then (CT = 8)
				If (CD = 4) and (Tdb = 2) then (CT = 9)
				If (CD = 4) and (Tdb = 3) then (CT = 6)
				If (CD = 4) and (Tdb = 3) then (CT = 7)
				If (CD = 4) and (Tdb = 4) then (CT = 9)
				If (CD = 4) and (Tdb = 4) then (CT = 10)

[a] The first row in every Membership Function (MF) and every rule represents the FIS values, while the second row represents the Fuzzy-GA. Bold values indicate the difference between the original Fuzzy Inference System (FIS) and the value modified by Fuzzy-GA. A, B, and C represent the parameters of the triangular memberships function of the fuzzy sets. KDB: knowledge data base. RB: Rule Base.

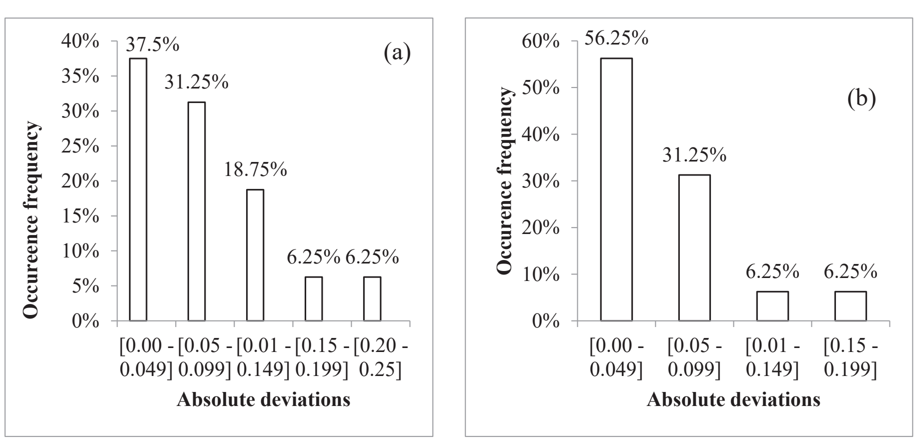


Fig. 2 – The occurrence frequency of absolute deviations between the data for cloacal temperature as simulated by (a) the fuzzy inference system and (b) the Fuzzy-GA system and the means datasets.

Table 6 – Statistical indices applied to cloacal temperature (CT) as predicted by the fuzzy inference system (FIS) and the fuzzy genetic algorithm (Fuzzy-GA) and experimental observations.

Input variables		Fuzzy-GA					FIS			
Duration of stress (days)	Dry bulb temperature (°C)	Output CT	Fuzzy-GA	Absolute deviation	Standard deviation	Percentage error	FIS	Absolute deviation	Standard deviation	Percent error
1	27	40.00	40.00	0.000	0.000	0.000	40.00	0.000	0.000	0.000
1	30	40.90	40.88	0.017	0.012	0.042	40.77	0.133	0.094	0.326
1	33	40.60	40.63	0.033	0.024	0.082	40.63	0.033	0.024	0.082
1	36	40.80	40.88	0.083	0.059	0.203	40.77	0.033	0.024	0.082
2	27	40.30	40.39	0.087	0.061	0.215	40.39	0.088	0.062	0.217
2	30	40.90	40.88	0.017	0.012	0.042	40.77	0.133	0.094	0.326
2	33	41.20	41.37	0.173	0.122	0.420	41.35	0.150	0.106	0.365
2	36	41.10	41.09	0.010	0.007	0.024	41.09	0.010	0.006	0.021
3	27	40.40	40.39	0.013	0.010	0.033	40.39	0.012	0.009	0.031
3	30	41.40	41.37	0.027	0.019	0.065	41.64	0.238	0.168	0.575
3	33	41.40	41.37	0.027	0.019	0.065	41.35	0.050	0.035	0.120
3	36	41.30	41.37	0.073	0.052	0.177	41.35	0.050	0.036	0.122
4	27	41.00	41.09	0.090	0.064	0.219	41.09	0.091	0.065	0.223
4	30	41.60	41.64	0.037	0.026	0.089	41.64	0.038	0.027	0.091
4	33	41.00	41.09	0.090	0.064	0.219	41.09	0.091	0.065	0.223
4	36	41.80	41.93	0.131	0.093	0.314	41.93	0.130	0.092	0.311
Mean				**0.057****	**0.040****	**0.138****		0.080	0.057	0.195
Minimum				0.000	0.000	0.000		0.000	0.000	0.000
Median				**0.035****	**0.025****	**0.085****		0.069	0.049	0.170
Maximum				**0.173****	**0.122****	**0.420****		0.238	0.168	0.575
Standard error				**0.061****				0.090		
Root Mean Squared Error				**0.074****				0.101		

Bold values in performance metrics (max, min, mean, etc.) represent the best performance for the fuzzy genetic algorithm. ** indicates a significant difference with a level of significance of 0.01.

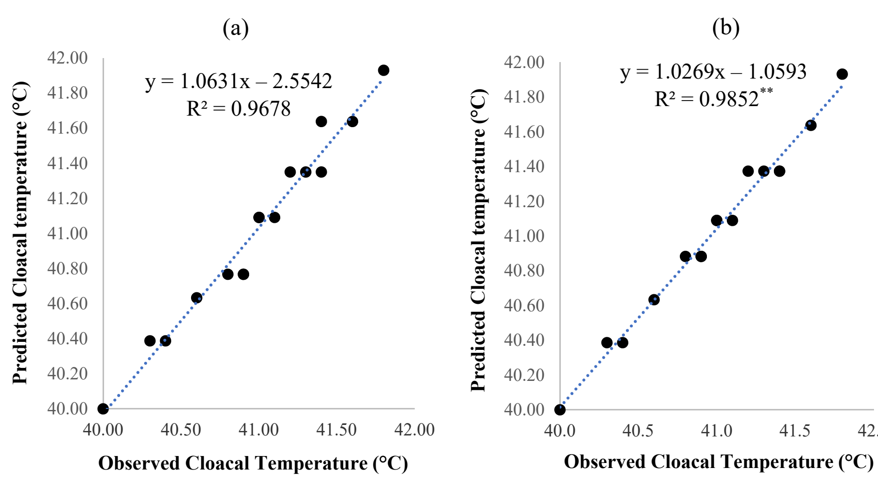
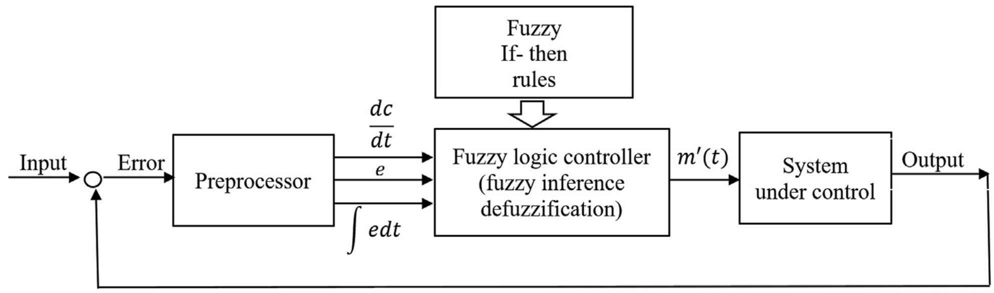


Fig. 3 – The functional relationship between the observed values for cloacal temperature and the means dataset simulated by the models: (a) fuzzy inference system and (b) fuzzy genetic algorithm. ** indicates a significant difference with a level of significance of 0.01.

study. The FIS exhibited a standard error of 0.090, while the standard error for the genetic fuzzy rule-based system (GFRBS) was 0.061, indicating an improvement in the predictive accuracy of CT when using the Fuzzy-GA tool (Table 6).

Abreu et al. (2017) estimated an R^2 of CT as a function of t_{db} of 0.75, while Ponciano, Yanagi Junior, de Lima, Schiassi, and Teixeira (2012b) observed that the R^2 for four model equations was 0.73 with a mean absolute error of 0.32, 0.35, 0.69, and 0.38 °C for the four equations and average percentage errors of 0.79, 0.86, 1.68, and 0.94%, respectively. The standard deviations were 0.22, 0.25. 0.49 and 0.27, respectively, for each regression model. Ferreira et al. (2012), obtained a mean deviation of 0.13 °C and a mean percentage error (MPE) of 0.31% when comparing the elaborated fuzzy system and data measured experimentally (R^2 = 0.9318), indicating that the fuzzy system satisfactorily simulates the CT of broiler



$$m'(t) = f\left\{e, \int edt, \frac{de}{dt}\right\}$$

Fig. 4 – Block diagram of the feedback of a fuzzy logic controller (Yamakawa, 2011).

chickens. Ferraz et al. (2018) used a fuzzy-GA system to predict the RR of chicks exposed to thermal challenges. In addition, the fuzzy genetic system resulted in an improvement in the predictive accuracy of RR, yielding an R^2 value of 0.9837 for FIS and 0.9864 for the fuzzy genetic system, with maximum absolute deviation values of 4 and 3.10, respectively (a difference of 0.9).

As is evidenced by this study, both models used here (FIS and Fuzzy-GA) demonstrated better predictive performances than other previously published models.

The values obtained during the experimental period showed that the CT always presented lower values for animals exposed to 27 °C in comparison to the other temperatures evaluated (i.e. 30, 33, and 36 °C) (Table 6). The low CT values indicate that the experimental chicks experienced discomfort in response to the cold, although the CT values observed here were greater than those found in the literature (Elson, 1995). Moreover, the physiological responses of the chicks to temperature change occurred even when the exposure time was only one day. According to Cordeiro et al. (2011), when young chicks are subjected to low temperatures in the first days of life, development can be delayed and animals may not adequately recover.

High t_{db} is known to increase CT (Chowdhury, Tomonaga, Nishimura, Tabata, & Furuse, 2012) and may cause heat stress in broiler chickens (Singh, Ghosh, Creswell, & Haldar, 2015). Furthermore, increases in CT have been shown to be proportional to age (Marchini, Silva, Nascimento, and Tavares (2007), while the stress caused by high CT results in decreases in mass gain (Costa, Saraiva, & dos Santos, 2012).

However, the present study shows that t_{db} of 36 °C did not cause heat stress in broiler chicks, and that the CTs of these animals were very similar to the those of animals subjected to 33 °C, except on day 4 of exposure to 36 °C. In this case, CT increased when the chicks were exposed to higher temperatures, demonstrating the influence of the thermal environment on the physiological response of broiler chicks.

As the thermoregulatory system of chicks is not completely developed in the first days of life, chicks need to be raised in thermoneutral temperatures. According to Funck and Fonseca (2008), developing chicks need to absorb all the nutrients and antibodies necessary for healthy development in the embryonic sac. This absorption will only happen if chickens are maintained at a thermoneutral temperature and ingest ample amounts of food and water. On the one hand, if t_{db} is too low, chickens will remain huddled and may go to the feeders and drinkers less frequently. On the other hand, when the t_{db} is too high, part of the feed energy intake that could be used for growth or production is diverted to thermoregulation in order to maintain homeostasis. Furthermore, a higher formation rate of vital organs such as heart, lungs, immune, and digestive systems occur during the first seven days of the broiler chick's life. Thus, a thermoneutral temperature is essential early in life to both meet the requirements of thermal comfort for chicks and for healthy development (Tinôco, 2001).

Although this study was undertaken in a laboratory environment, the results can be used to drive decision-making processes aimed at creating satisfactory environmental conditions for chicks. Furthermore, it is essential to emphasise that submitting young chicks to thermal challenge, even for a small period, may affect their growth, development, welfare, and they may not be able to recover adequately. For this reason, the proposed FIS could be embedded in environmental control systems to maintain an adequate microclimate inside the broiler houses and to ultimately improve production. In this case, the model could be embedded in a fuzzy logic controller as proposed by Yamakawa (2011) (Fig. 4) or Kobersi, Finaev, Almasani, and Abdo (2013) for turning on/off the heating or cooling systems to maintain the thermoneutral zone for the birds ($T_{db} = 33$ °C).

In order to do this, we can use the Simulink toolbox in Matlab. To implement to the fuzzy logic controller system, any dry bulb temperature sensor can be used to obtain the T_{db}. The other input variables can be calculated based on the date format of the system (calculating the number of days that the same dry bulb temperature has been observed). The output of the fuzzy logic controller would be CT. If the output (CT) is stressful (below or above 41 °C), then the system would turn on/off the heating or cooling system until CT attains the recommended temperature (41 °C).

4. Conclusions

This paper presented a detailed framework for the development of Fuzzy-GA systems using two different approaches: The Mogul and the Pittsburgh approaches. The main contribution of this study is two-fold. First, the proposed methodology was successfully employed to improve manually developed fuzzy models, allowing a reduction in predictive errors and the generation of more realistic estimates. We further improved the fuzzy models by using genetic algorithms. Most importantly, this computational technique enables an improvement in the membership–function curves using the MOGUL approach, as well as an improvement in the rule base using the Pittsburgh approach, which depends directly on the behaviour of the data and the experience of experts.

Secondly, the Fuzzy-GA tool exhibited a good interaction with the FIS, which has been previously modelled by specialists, and demonstrated an improvement in the precision of CT predictions. Thus, the model based on Fuzzy-GA can be used to predict CT for chicks subjected to thermal challenges and can be embedded in a fuzzy-logic controller to assist in decision-making processes related to turning on/off heating or cooling systems in order to maintain the thermoneutral zone of the chicks.

Declaration of Competing Interest

The authors declare no conflict of interest in the work presented in this paper.

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