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Prediction of physiological responses of Holstein dairy cows

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Abstract. *The goal of the present study was to evaluate techniques for modeling the physiological responses, rectal temperature, and respiratory rate of black and white Holstein dairy cows. Data from the literature (792 data points) and obtained experimentally (5.884 data points) were used to fit and* *validate the models. Each datum included dry bulb air temperature, relative humidity, rectal temperature and respiratory rate. Three models based on artificial intelligence - fuzzy logic, artificial neural networks, and neuro-fuzzy networks - and one based on regression were evaluated for each response variable. The adjusted models predict rectal temperature and respiratory rate as a function of dry-bulb air temperature and relative humidity. The adjusted models were compared using statistical indices. The model based on artificial neural networks showed the best performance, followed by the models based on neuro-fuzzy networks, fuzzy logic, and regression; the last two performed similarly.*

Keywords. Physiological performance, computational models, dairy cattle.

Introduction

In 2009, Brazil was considered the fifth leading producer of milk in the world, with an annual production of 30.4 billion liters of milk, and the state of Minas Gerais led production for the country (EMBRAPA, 2011). The previously mentioned growth was accompanied by an increase in internal consumption *per capita* of approximately 1.59% annually and by an increase in exports (Gama, 2010). Brazil is located in an intertropical zone, with hot and humid climates, where the likelihood of animals suffering thermal stress is high, especially for bovines of European breeds (Souza et al., 2004).Therefore, there is great interest in the development of tools that can aid in decision making with regard to environmental conditions that directly or indirectly affect milk production, as is the case for thermal stress.

New models being developed for the livestock industry are characterized by the adoption of technologies based on principles of sustainable production, with an emphasis on animal comfort and well-being, considering that these animals were chosen for their ability to adapt to the soil and climate conditions (edaphoclimatic conditions) of each region (Pires and Campos, 2008). According to Silva et al. (2002), environmental conditions are directly related to the microclimate in facilities, thus influencing the thermal comfort of the animals that are housed there. The ideal temperature for milk production varies according to the breed of the cattle, its level of production, and its level of tolerance to heat or cold; Holsteins, in particular, reduce production beginning at 24°C.

The environment for dairy cattle plays a fundamental role in obtaining the proper climatic conditions for animal production, the limits of which bound the zone of thermoneutrality (Curtis, 1983). Within this zone, the animal reaches its maximum potential, and body temperature is maintained with minimal use of thermoregulatory mechanisms. When conditions are not within these proper limits, the environment becomes uncomfortable. Under conditions of heat stress, which are more frequent in Brazil and intertropical countries, dairy cows reduce their feed intake and consequently their milk production (Harner et al., 2009). Sweating and panting are some of the mechanisms these animals use to relieve thermal stress.

In addition to these consequences, the animals lose considerable amounts of sodium and potassium through sweat and urine (Pires and Campos, 2008) and suffer changes in rectal temperature (t_{rectal}) and in respiratory rate (RR) (Perissinotto and De Moura, 2007). Also, there is evidence that heat stress on cattle reduces future productivity, even if environment conditions are returned to acceptable levels (Curtis, 1983; Kazdere et al., 2002; West, 2003).

For these reasons, the development of models that assist dairy producers in making decisions to maintain the production environment within the zone of thermoneutrality for the animals, thus obtaining maximum production, is critical. The tools include empirical mathematical models, such as regression models (RMs), fuzzy models (FMs) (Perissinotto, 2007; Perissinotto et al. 2009), artificial neural networks (ANNs) and neuro-fuzzy networks (NFNs), and can assist in the control of ventilation and evaporative cooling systems.

Regression models

RMs use direct observation or the results of experiments concerning a particular phenomenon to demonstrate a correlation between input and output variables, without explaining the phenomena or processes involved (Baldwin, 1995). Thus, RMs consist of fitting statistical models to the data, with the goal of describing the behavior of dependent variables (output variables) as a function of a set of independent variables (input variables).

RMs have been applied in various studies, for example, to predict the growth of broilers (Ivey, 1999), thermal indices for the productivity of broilers (Medeiros et al., 2005), the surface area of broilers (Silva et al., 2009), t_{rectal} of broilers (Ponciano et al., 2012), and thermal comfort in cattle (Brown-Brandl et al., 2005).

Fuzzy models

FMs are based on fuzzy logic (FL), which is founded in the theory of fuzzy sets (Gomide and Gudwin, 1994) introduced by Zadeh (1965). FL works with approximate rather than exact information (Ferreira, 2009), similar to human reasoning (imprecise reasoning), to achieve precision in various applications to reduce the time needed for modeling. Having defined the study to be performed, it is necessary to define the input and output variables that will constitute the FM (Perissinotto, 2007; Pereira et al., 2008). For each variable, fuzzy sets are developed to characterize it, so that a pertinence function is created for each fuzzy set. These functions indicate to what degree of pertinence a particular element belongs to a fuzzy set. Next, rules are defined (system of rules or inference), through which a relationship exists between the input and output variables with their respective fuzzy sets. Software can be used to perform all of the procedures required to develop and construct an FM, and the computational evaluation of any FM consists of fuzzification, inference, and defuzzification (Oliveira et al., 2005).

The theory of fuzzy sets has been used as a viable and suitable option in various areas, such as in the study of thermal comfort or discomfort of birds and swine (Queiroz et al., 2005; Oliveira et al., 2005; Alves, 2006; Yanagi Junior et al., 2006; Owada et al., 2007; Pereira et al., 2008; Ferreira, 2009), cattle (Perissinotto, 2007; Perissinotto et al. 2009), and humans (Altrock et al., 1994). Fuzzy sets have also been used in the prediction of estrus in dairy cows (Ferreira et al., 2007), inspection systems for chickens (Yang et al., 2006), the prediction of cloacal temperature of broilers (Ferreira et al., 2011), statistics (Khashei et al., 2008; Liang-Hsuan and Chan-Ching, 2009), forensic science (Liao et al. , 2009), studies of pesticide pollution (Gil et al., 2008), industrial applications (Meier et al., 1994), and in data analysis, specialist systems, control, and optimization (Gomide and Gudwin, 1994; Ribacionka, 1999; Lopes, 1999; Cho et al., 2002; Weber and Klein, 2003; Castañeda-Miranda et al., 2006; Chao et al., 2000), among many other applications.

Artificial neural networks

According to Tsoukalas and Uhrig (1997), an ANN is a data processing system composed of a large number of highly interconnected simple processing elements (artificial neurons) in an architecture inspired by the structure of the cerebral cortex. Thus, ANNs are inspired by the functioning and structure of biological neurons and are trained by running patterns through the network, making it possible to identify the relationships between variables with no *a priori* knowledge (Roush et al., 1997). Mathematically, ANNs are universal approximators that perform mapping between two variable spaces (Hornik et al., 1990).

ANNs are currently being applied in various fields of knowledge, and their use is generally linked to searching for patterns and techniques for temporal forecasts for decision making. This approach is being used in fields such as aviculture (Lopes et al., 2008), applied geography (Spellman, 1999), thermal sciences and engineering (Yang, 2008), hydrology (Kurtulus and Razack, 2010), the study of thermal comfort in cattle (Brown-Brandl et al., 2005), growth performance in swine (Bridges et al., 1995) and in humans (Moustris et al., 2010). ANNs have been used to analyze the sensitivity of a mechanical system for poultry catching (Jaiswal et al., 2005), quantification of odours from piggery effluent ponds (Sohn et al., 2003), classify apples by their textural features (Kavdlr and Guyer, 2004), discriminating varieties of tea plant (Li and

He, 2008), daily stream flow prediction (Nayebi et al., 2006), simulate runoff and sediments yield (Agarwal et al., 2006), residual soil nitrate prediction (Gautam et al., 2012), discrimination of apricot cultivars by gas multisensor array (Parpinello et al., 2007), estimate leaf chlorophyll concentration in rice under stress from heavy metals (Liu et al., 2010), modelling total volume of dominant pine trees in reforestations (Diamantopoulou and Milios, 2010), in ortho-phosphate and total phosphorus removal prediction in horizontal subsurface flow constructed wetlands (Akratos et al., 2009), predicting the draught requirement of tillage implements in sandy clay loam soil (Roul et al., 2009), prediction of nitrate release from polymer-coated fertilizers (Du et al., 2008), and in near infrared spectral analysis (Wang and Paliwal, 2006). ANNs have also found to be useful in construction (Argiriou et al., 2000) and in demand analysis in the form of forecasting (Efendigil et al., 2009), among many other applications.

The MultiLayer perceptron (MLP) is the most commonly used architecture for developing an ANN (Barreto, 2002; Von Zuben, 2003) and contains input, hidden, and output layers.

Neuro-fuzzy networks

NFNs take advantage of the learning abilities of ANNs and use fuzzy systems to process knowledge in a clear way. The final solution of the NFN can be interpreted as a fuzzy inference system (FIS) of the Sugeno type. Various studies have been performed in different areas using these hybrids (ANNs and FL), including human thermal comfort (Chen et al., 2006), control and automation systems (Cheng-Hung et al., 2009), the decision support system for demand forecasting (Efendigil et al., 2009), thermal comfort for birds (Ferreira, 2009), the prediction of t_{rectal} of broilers (Ferreira et al., 2010), in statistics (Khashei et al., 2008), in hydrology (Kurtulus and Razack, 2010), to analyze livestock farm odour (Pan and Yang, 2007), and in robotics (Zacharia, 2010).

Given the above, the objective of this study was to develop and validate RMs and models based on artificial intelligence to predict the t_{rectal} and RR for black and white Holstein dairy cows kept in confinement as a function of the two meteorological variables dry bulb air temperature (t_{db}) and relative humidity (RH).

Material and methods

Datasets

A database was generated containing the raw data for t_{db}, RH, t_{rectal}, and RR for black and white Holstein dairy cows. These data were chosen because the authors quoted in table 1, worked in common with these four variables. Although some of these authors also measure wind speed, black globe temperature, black and white coat temperature and milk production, the amount of data wasn't enough to develop some of the proposal models.

To this work, the total dataset called as combined dataset (6,676 pieces of information) was conformed for data obtained from literature also called as Literature dataset (792 pieces of information) and data obtained in experiments conducted by EMBRAPA Dairy cattle, located in the city of *Coronel Pacheco,* state of *Minas Gerais*, Brazil, also called as Experimental dataset (5,884 pieces of information). In these experiments, 346 purebred Holstein cows, either primiparous or multiparous, in different stages of lactation, were used. The data from the literature were obtained from 128 Holstein dairy cows, for a total of 474 animals measured. The dataset included all seasons of the year, and all of the locations where data were collected in the Southeastern region of Brazil and fit the Köppen climatic classification of Cwa, with dry and cold winters and hot and humid summers (*table 1*). The data used in this study covered a total period of six (6) years.

To train, validate and test the models based on artificial neural networks (ANN and NFN) the total dataset (Combined dataset) was used. This dataset was randomly divided into three subsets through sub-routines created for this purpose. These subsets were used to model the ANNs and NFN (training, validation, and testing). The training set used 70% of the combined dataset (4,674 independent data points); the sets for validation and testing each used 15% (1,001 data points each), for a total of 2,002 data points from the total set (combined dataset).

For the models based on Regression and fuzzy logic, the dataset used were the means of the combined dataset. This dataset had a total of 427 means (216 means of the Literature dataset and 211 means of the Experimental dataset). For RM these means of combined dataset were randomly divided into two subsets, one containing 70% of the data for fit (299 pieces of information) and one containing 30% for validation (128 pieces of information). For fuzzy logic model, whole dataset of means (427 data points), was used to validate the model.

These percentages of the subsets were chosen because they are the most common for mathematical modeling of systems (Brown-Brandl et al., 2005).

Mathematical modeling

To develop the models based on artificial neural networks (ANN and NFN) were used the dataset previously mentioned (Combined dataset), while for RM and fuzzy logic were used the means of the combined dataset.

Once developed, the models were tested using the minimum, mean, median, and maximum values; standard deviations; patterns; and percentage errors. Also calculated were standard errors, coefficients of determination (R^2), the root mean square error (RMSE), the coefficients of regression (slopes), and intercepts for each of the variables studied (t_{rectal} and RR) (*table 3*). In addition, histograms (*figs. 9* and *10*) and graphs of the functional relationships - FRs between (with line of linear trend) predicted and observed variables (means of the combined dataset) (*figs. 3, 4, 5, 6, 7,* and *8*) were used to compare the performance of the proposed models.

Regression models

Eighteen multiple RMs were fit using the regression procedure of the statistical software R (R Development Core Team, 2011). All of the models used the climatic variables (t_{db} and RH) as input data, and the output variables were the physiological parameters t_{rectal} and RR. The significance of the models and regression coefficients was tested using the F and t tests ($P<0.05$), respectively. The model that exhibited the best fit was selected (smallest sum of squared deviations).

Table 1. Characteristics related to the data obtained from the literature and obtained through observations (Southeastern region of Brazil).

Authors	[1]	[2]	[3]	[4]		[5]			[6]	[7]	[Observed]	
City.	Juiz de fora,	Nova Odessa	Pirassununga	São Pedro		Pirassununga			Pirassununga	São Pedro	Juiz de Fora	
State	MG	SP	SP	SP		SP			SP	SP	MG	
Altitude (mts).	790	550	630	580		630			630	580	790	
Latitude (S).	21°38'	22°42'	21°57'	22°33'		21°57'			21°57'	22°33'	21°38'	
Longitude (W).	43°19'	47° 18'	47°27'	47°38'		47°27'			47°27'	47°38'	43°19'	
Köppen Climate	Cwa	Cwa	Cwa	Cwa		Cwa			Cwa	Cwa	Cwa	
Number of livestock	346 (1)	12 (2)	27 (3)	12 (4)	15 (4)	18 (5a)	18 (5b)	19 (5c)	27 (6)	20 (7)	346 (8)	
Season study.	Sum. – Winter	Sum.	Sum.	Sum.	Spring	Spring	Sum.	Winter	Sum.	Spring	Sum.	Winter
t_{db} min. obs. (°C)	12.3	N/A	N/A.	17.5	16.0	16.0	16.0	5.0	21.0	21.2	17.0	9.0
t_{db} Max. obs. (°C)	30.7	N/A	N/A	33.6	34.4	38.0	37.0	35.0	35.0	34.1	37.0	33.4
RH min. obs. (%)	N/A	N/A	N/A	N/A	N/A	24.0	28.0	24.0	40.0	26.2	57.0	58.0
RH Max. obs. (%)	N/A	N/A	N/A	N/A	N/A	95.0	99.0	95.0	93.0	74.8	97.0	98.0

N/A, Not available. **SP** - São Paulo. **MG** - Minas Gerais. **Sum**, Summer. **[1]** (Pires, 1997, in Pires and Campos, 2003). **[2]** Silva et al., (2002). **[3]** Martello et al., (2004). **[4]** (Matarazzo, 2004). **[5]** Matarazzo, (2004). **[6]** Martello, (2002). **[7]** Perissinotto, (2003). **(1)**, 258 cows and 88 heifers. **(2)**, N/A. (3) , 7 multíparous (mult.) and 10 primiparous (prim.) between the 2nd and 8th month of lactation. **(4)**, mult. in lactation. **(5a)**, 15 mult. and 3 prim. **(5b)**, 14 mult. and 4 prim. **(5c)**, 18 mult. and 1 prim. **(6)**, stage of lactation between the 2nd and 7th month. (17 mult. and 10prim.). **(7)**, mult. in lactation average of180 days. **(8)**, 346 multiparous cows and primiparous in different stage of lactation.

Fuzzy inference system

This model consists of two input variables (t_{db} and *RH*) and two output variables (t_{rectal} and *RR*). The inference method was of the Mandani type (Mandani and Assilian, 1975). In this type of FM, a large amount of intervention is required on the part of the modeler because the FM can be generated with no experimental data; therefore, data were not used either for training, the total of means of the combined dataset were used for validation of the model. Because of the intervention of the modeler, a spreadsheet was used to organize the data (in this case, the means of the combined dataset – 427 independent data point) to attempt to establish the set of rules that might explain the behavior of the input and output variables studied.

Artificial neural net model

The models based on ANNs were developed using the subsets of data previously mentioned. The ANN developed possessed two feed-forward layers that were trained using the back-propagation algorithm. The parameters of the model include the number of hidden layers (1, the standard value used in various applications), transference functions in each hidden layer (sigmoidal tangent "tansig" for hidden layers, the standard value in various applications), the number of neurons in the hidden layer(s) (a user-modifiable parameter), the rate of learning, the instantaneous rate, and the weights of the neurons (these parameters are taken as standard and automatically modified during training of the network). The model was developed such that the user can train and test the network independently. The two resulting ANNs predict the t_{rectal} and *RR* from the input variables (t_{db} and *RH*), and each neural net has one output.

Neuro-fuzzy adaptive inference system

The model was also developed using the subsets of data mentioned above. The application used to develop this model was the fuzzy logic toolbox of Matlab (MathWorks, Inc, 2009a). This toolbox uses input and output datasets (sets for training, validation, and testing, each with input and output data), and the main function of this toolbox is to construct a fuzzy inference system (FIS), the parameters of which are fit for the pertinence function using two types of methods (the back-propagation algorithm, either alone or in a hybrid form combined with the least squares method). This fit allows FMs to learn from the data being modeled. Similar to the model based on ANNs, the parameters for fitting the network can be modified according to the percentage of the dataset used for training, validation, and testing, as well as in other ways, such as the generation of the FIS, the training method (back-propagation or hybrid), error tolerance, or the number of stages. Finally, the possibility exists of testing the result of the model generated by training the network. The result of this model is an FIS of the Sugeno type, with only one output.

Results

For this study, we work with two output physiological variables; these variables are rectal temperature (t_{rectal}) and respiratory rate (*RR*). The physical units of these variables are Celsius degree (°C) and breaths per minute (breaths.min^{-1}), respectively. The balance between gain and heat loss from the body can be inferred by the t_{rectal}. The measurement of rectal temperature is often used as an index of physiological adaptability to hot environments, because its increase shows that the heat loss mechanisms become insufficient (Martello, 2002). In turn, in defense against heat stress, cattle resort to adaptive physiological mechanisms of heat loss to try to prevent hyperthermia. Thus, increase the respiratory rate (*RR*), with tachypnea, in addition to the increase of the sweat production rate (sweat rate) is an important means to lose heat by evaporation (respiratory and cutaneous evaporative heat loss). Tachypnea is the first visible sign in response to heat stress, although situated in third place in the sequence of the mechanisms of physiological adaptation, because the increase in peripheral vasodilatation and sweating occur previously (Baccari, 2001).

Regression models

Of the 18 RMs fit to predict the t_{rectal} and RR, the models represented by Eq. (1) and Eq. (2) had the highest coefficients of determination (R^2), and all of the coefficients of the equations were significant ($P<0.05$). For the model estimating t_{rectal} (ºC), Eq. (1), 21.6% of the variation in t_{rectal} can be explained by the variation in t_{db} (ºC) and RH (%) when testing 70% of the data (4,673 observations) used for fitting; the values were 20.7% when testing 30% of the data (2,003 observations) used for validation and 44.4% when testing 100% of the data (*table 3*).

$$t_{rectal} = 37.08 - 0.02\ t_{db} + 0.02146\ RH + 0.0014\ t_{db}^{\ 2} - 0.000055\ RH^2 \tag{1}$$

In turn, 26.4% of the variation in the RR can be explained by the variation in t_{db} (ºC) and RH (%) when testing the 70% of the data used for fitting; the values were 25.8% when testing 30% of the data used for validation and 44.5% when testing 100% of the data (*table 3*).

$$RR = 7.8 + 0.992287\ t_{db} + 0.142209\ RH + 0.013354\ t_{db}^{\ 2} \tag{2}$$

Fuzzy inference system

The result of this fuzzy inference system can be described as a set of membership functions constructed based on linguistic descriptors of the input variables (*fig. 1*). Initially, this model was based on the research developed by Perissinotto (2007, p.120; Perissinotto et al., 2009), which has 120 rules (t_{db} = 15 MFs and RH = 8 MFs), but these values of MFs were fit to reduce deviations, because the model proposed by Perissinotto did not have values lower than 22ºC, thus, the model with these configuration (set), had absolute deviations higher than 1.0 ºC. The linguistic expressions established in this model are an interpretation dependent on the previously organized data

The fuzzy sets of input and output variables are graphically represented by triangular membership curves (*fig. 1*) because these are the most common used and represent the profile of the data, as observed by several authors (Amendola et al., 2005; Yanagi Junior et al., 2006; Ferreira et al., 2007; Schiassi et al., 2008).

The fuzzy inference was composed of a set of 192 rules, stemming from the factorial combination of 24 MFs for t_{db} and 8 MFs for RH. Each rule was composed of logical connectors (if, and, or, then) and the antecedent and consequent parts. For example, IF x is A AND y is B, THEN z is C, in which A, B, and C are fuzzy sets; x and y are input variables; and z is the output variable. Thus, "IF x is A AND y is B" is the antecedent part, and "THEN z is C" is the consequent part.

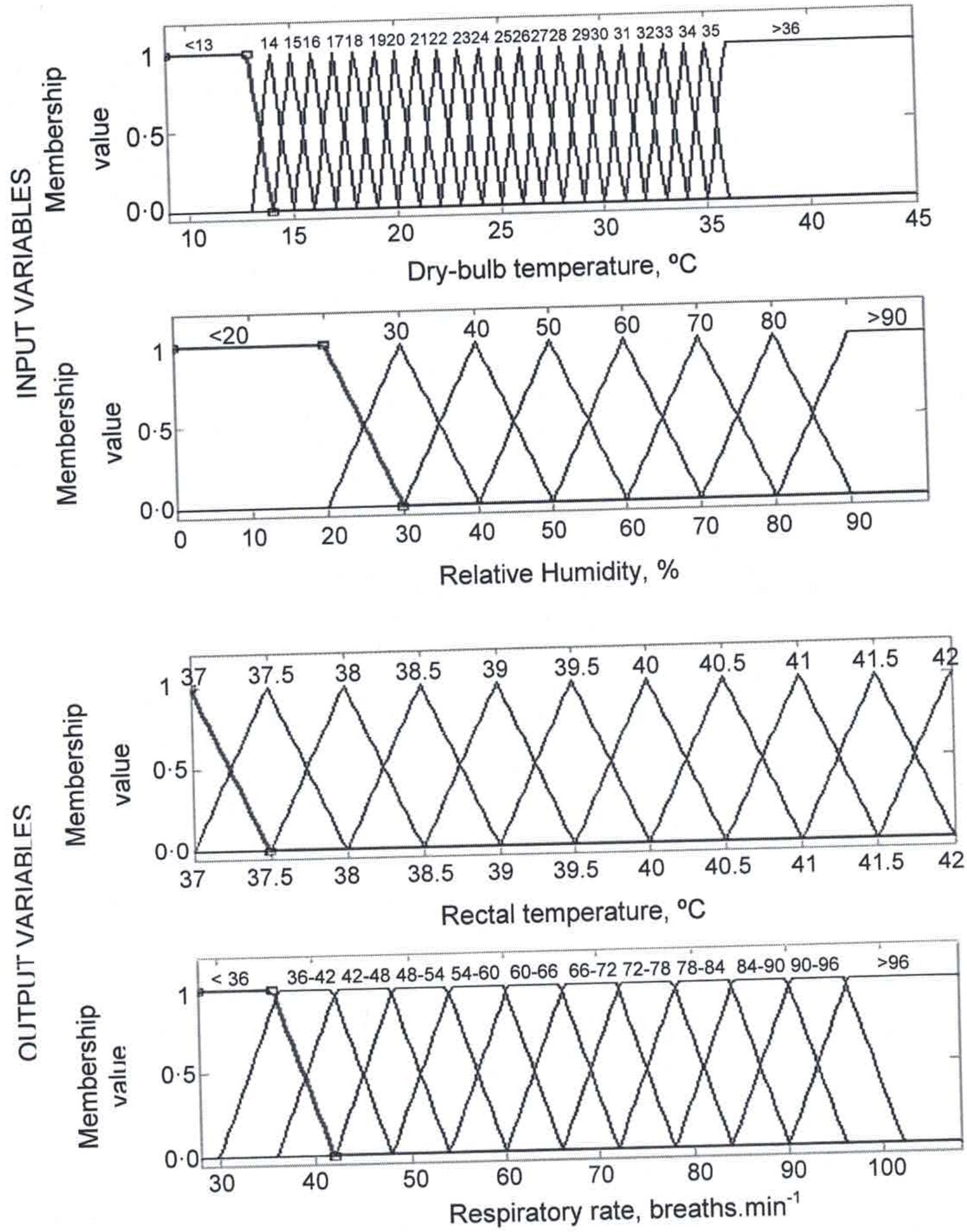

Figure 1. The membership function structure developed for the fuzzy inference system.

Artificial neural network system

The architectures of the best-performing final ANN models for predicting t_{rectal} and *RR* were multilayer networks (MultiLayer perceptron; MLP) with two feed-forward layers and supervised training (with awareness of the desired outcome) using the back-propagation training algorithm; the performance function was the mean square error (MSE), and the activation function for neuron output was the sigmoidal tangent "tansig."

The architectures with the best performance obtained through the training and validation process and had the fewest prediction error was as follows: training error = 0.13, validation error = 0.14, testing error = 0.145 for t_{rectal}, training error = 116.9, validation error =117.9 and testing error =118.9 for *RR*. The input layer had two variables, t_{db} and *RH*. The intermediate layer was composed of 90 neurons for t_{rectal} and 100 for *RR*. In each ANN, the output layer was composed of only one neuron, that is, t_{rectal} or *RR*. The initial parameters of the networks were configured as follows: number of epochs: 1.000; error tolerance: 0.0; learning rate: 0.7; and momentum rate: 0.5; these values were automatically optimized.

Adaptive neuro-fuzzy inference system

Various NFN models were developed and simulated using different configurations, such as the type of pertinence function (gaussian, triangular or trapezoidal), the number of stages, and the type of optimization method, resulting in 18 models. The architectures of the best-performing final NFN models for predicting t_{rectal} and *RR* are listed in *table* 2. The hybrid training (optimization) method chosen was selected based on a tolerance to error of 0.0 and number of stages of 1.000. Training was interrupted when the training error stabilized. The pertinence function chosen for the input variables was the triangular function, and the constant function was chosen for the output variables. The model with the least training error and no internal errors in its fuzzy sets (amplitude outside of the normal range or sets with values of 0 for the variables studied; t_{rectal} and *RR*) was selected.

Thus, the best models for the prediction of t_{rectal} and *RR* were composed of six rules that govern the behavior of the input variables (t_{db} and *RH*) and the respective outputs (t_{rectal} or *RR*) (*table 2*).

Figure 2 (*fig.*2) shows the interactive interface of the FIS, with each line in the figure representing a rule and each column representing an input. The pertinence functions are shown in the first two columns. The position of the vertical line represents the input value entered by the user. The value predicted by the NFN appears in the third column.

Table 2. Characteristics of the Sugeno type or data-dependent fuzzy inference system – NFN - for rectal temperature (a) and respiratory rate (b).

Fuzzy systems' characteristics	Inputs	Outputs	Rules				
			t_{db}	*RH*	Out	W	Con.
(a) <Name> fuzzy sets t_{rectal} - FIS <type>TS <SNorm>max <SNormPar>0 <TNorm>min <TNormPar>0 <Comp>sugeno <CompPar>0 <ImpMethod>prod <AggMethod>max <defuzzMethod>waver	**[Input 1]** <Name>t_{db} <Range>9 - 37 <Number MFs>3 <Function>trimf <NameMF1><in1MF1> -5.0 10.3 24.0 <NameMF2><in1MF2> 7.9 25.6 36.9 <NameMF3><in1MF3> 22.3 7.8 51.0 **[Input 2]** <Name>*RH* <Range>26·2 - 99 <Number MFs>2 <Function>trimf <NameMF1><in2MF1> -46.6 26.3 98.9 <NameMF2><in2MF2> 26.1 99.1 171.8	**[Output]** <Name>t_{rectal} <Range>37·5 – 40·4 <Number MFs>6 <Function>constant <NameMF1><out1MF1> 38.3 <NameMF2><out1MF2> 38.4 <NameMF3><out1MF3> 37.9 <NameMF4><out1MF4> 39.2 <NameMF5><out1MF5> 39.1 <NameMF6><out1MF6> 39.8	1	1	1	1	1*
			1	2	2	1	1
			2	1	3	1	1
			2	2	4	1	1
			3	1	5	1	1
			3	2	6	1	1
			*It means: If t_{db} MF1 *and RH* MF1 *then* t_{rectal} MF1.				
			t_{db}	*RH*	Out	W	Con.
(b) <Name> fuzzy sets *RR*-FIS <type>TS <SNorm>max <SNormPar>0 <TNorm>min <TNormPar>0 <Comp>sugeno <CompPar>0 <ImpMethod>prod <AggMethod>max <defuzzMethod>waver	**[Input 1]** <Name>t_{db} <Range>9 - 37 <Number MFs>3 <Function>trimf <NameMF1><in1MF1> -5.0 16.4 22.0 <NameMF2><in1MF2> 7.4 26.0 37.0 <NameMF3><in1MF3> 22.9 38.8 51.0 **[Input 2]** <Name>*RH* <Range>26·2 - 99 <Number MFs>2 <Function>trimf <NameMF1><in2MF1> -46.6 26.8 98.4 <NameMF2><in2MF2> 25.6 99.6 171.8	**[Output]** <Name>*RR* <Range>20 – 116 <Number MFs>6 <Function>constant <NameMF1><out1MF1> 48.6 <NameMF2><out1MF2> 28.8 <NameMF3><out1MF3> 33.1 <NameMF4><out1MF4> 57.1 <NameMF5><out1MF5> 73.1 <NameMF6><out1MF6>70.7	1	1	1	1	1*
			1	2	2	1	1
			2	1	3	1	1
			2	2	4	1	1
			3	1	5	1	1
			3	2	6	1	1
			* It means: If t_{db}MF1 and *RH*MF1 *then RR* MF1.				

TS, Takagi-Sugeno. tdb, dry bulb temperature. Out, output. Con., connector. W, weight of the rule. trimf., triangular membership function. MF., membership function. waver, weighted average. max, maximum. min, minimum.

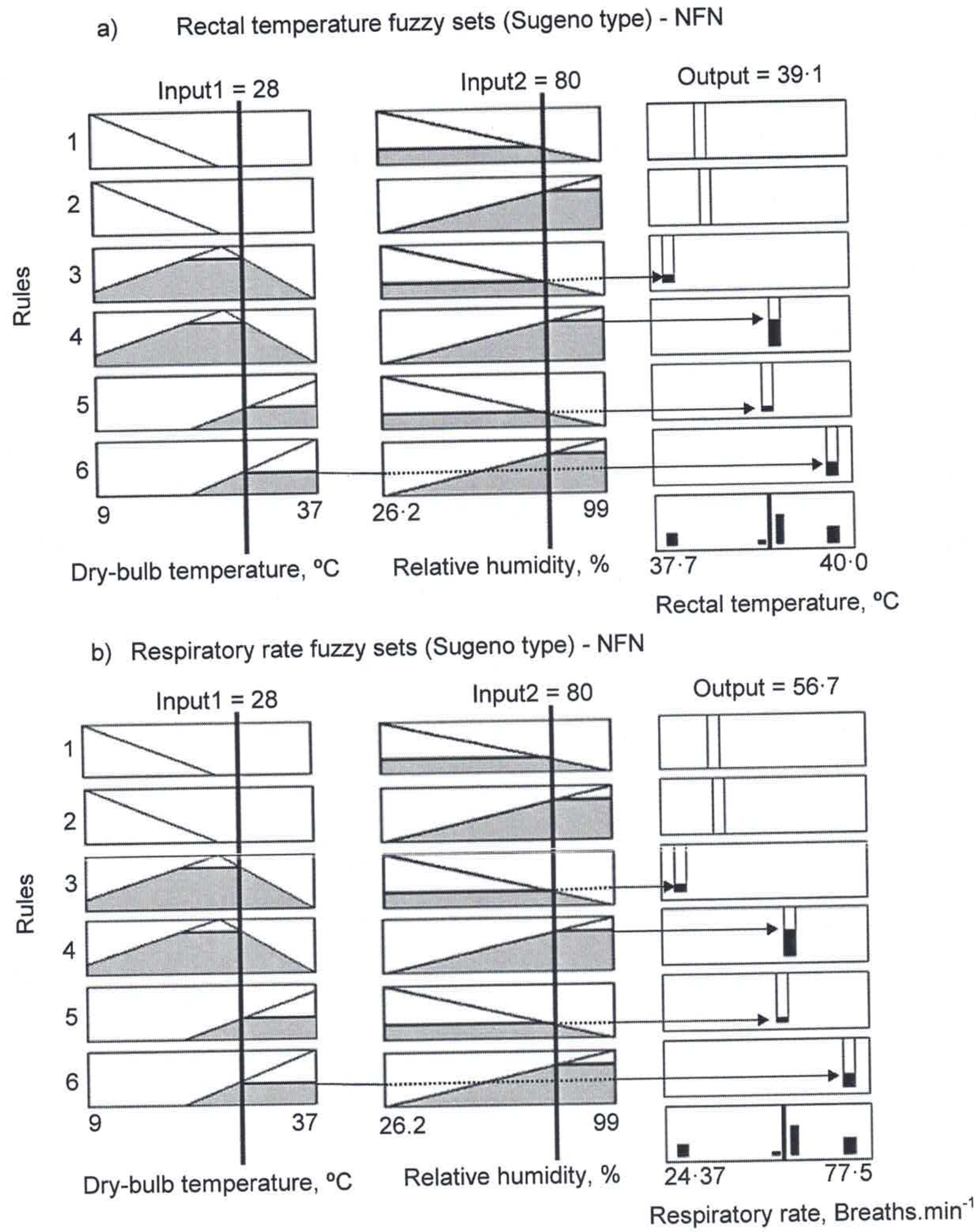

Figure 2. Example of the interactive interface generated by the fuzzy logic toolbox.

In the example presented, the t_{db} was 28°C, and the *RH* was 80%. For each individual pertinence function, the amplitude of the input values is represented by the X-axis, and the pertinence value is represented by the Y-axis. The shaded region is a visual representation of the pertinence resulting from the input value. The final column represents the output for t_{rectal} (*fig. 2a*) and *RR* (*fig. 2b*). The black portion of the bar represents the weight factor for this rule in particular and is determined by the minimum pertinence value for each rule. The horizontal line with an arrow indicates which input function determines the weight factor. A simple output is the result of an average of the output weights for each one of the six rules and is shown on the upper right. The larger the black area, the greater is the contribution of the associated rule (rule four (4) in both *figs.2a* and *2b* in this example).

This model was developed using the triangular type of pertinence function and uses the logical connector "AND" to combine spaces of data in fuzzy sets. The degree of pertinence of an input vector to a particular cluster determines the contribution of the associated rules. The final output is a weighted average of each contributed rule.

Statistical results are shown in *table 3.* For t_{rectal}, the frequency of occurrence of absolute deviations in the range from 0 °C to 0.39 °C varied from 83.6% to 97.7%, and the model based on ANNs showed the highest frequency of occurrence of errors over this range. Likewise, values of 72.1% and 93.4% were observed for *RR*, and the ANNs again performed best. The RMs and FMs performed the worst.

Table 3. Statistical results of the models.

Output variables (a)			Regression model (RM) (b)	Fuzzy model (FM)	Artificial Neural Network (ANN)	Neuro-Fuzzy Network (NFN)
			Model type			
Rectal temperature (t_{rectal})	Absolute deviations	Minimum	0·0	0·0	0·0	0·0
		Mean	0·2	0·2	0·1	0·2
		Median	0·2	0·2	0·1	0·2
		Maximum	0·9	0·9	1·1	0·9
	Standard deviation	Minimum	0·0	0·0	0·0	0·0
		Mean	0·2	0·1	0·1	0·2
		Median	0·1	0·1	0·1	0·1
		Maximum	0·6	0·6	0·8	0·6
	Percentage error	Minimum	0·0	0·0	0·0	0·0
		Mean	0·6	0·5	0·4	0·6
		Median	0·5	0·5	0·3	0·5
		Maximum	2·2	2·4	2·9	2·2
	R^2		0·44	0·49	0·67	0·44
	Standard error		0·28	0·27	0·21	0·28
	RMSE		0·28	0·27	0·21	0·28
	Regression coefficients (Slopes)		1·16* (± 0.06)	0·92* (± 0.05)	0·93* (± 0.03)	1·19* (± 0.06)
	Intercepts		-6·36* (± 2.46)	2·87 (± 1.8)	2·84* (± 1.21)	-7·46* (± 2.52)
Respiratory rate (RR) (c)	Absolute deviations	Minimum	0·0	0·0	0·0	0·0
		Mean	7·1	6·0	4·6	7·3
		Median	5·9	4·8	3·0	6·3
		Maximum	30·6 (d)	27·4	28·5	30·8
	Standard deviation	Minimum	0·0	0·0	0·0	0·0
		Mean	5·0	4·3	3·2	5·2
		Median	4·2	3·4	2·1	4·5
		Maximum	21·7	19·4	20·2	21·8
	Percentage error	Minimum	0·0	0·0	0·0	0·1
		Mean	13·8	12·0	8·7	14·0
		Median	11·5	9·1	5·6	12·9
		Maximum	62·3	67·9	62·0	53·5
	R^2		0·44	0·58	0·71	0·44
	Standard error		8·96	7·73	6·49	8·99
	RMSE		8·98	7·73	6·67	9·12
	Regression coefficients (Slopes)		1·05* (± 0.06)	1·01* (± 0.04)	7·20* (± 1.43)	1·15* (± 0.06)
	Intercepts		-1·65 (± 2.95)	-0·56 (± 2.18)	0·87* (± 0.027)	-6·25 (± 3.22)

R^2, determination coefficients.RMSE, root mean square error. *, Coefficients are significant ($P<0.05$).

Discussion

Four final models for predicting the t_{rectal} and *RR* in black and white Holstein dairy cows that are kept in confinement systems were compared side by side using different methods with the means of the combined dataset as validation of the models (*table 3*). The models based on ANNs and NFNs, listed in decreasing order of performance, generally exhibited the best statistical indices related to capacity for predicting the t_{rectal} and *RR* for dairy cows. Although the majority of statistical indices for RR were better for FM than for NFN (*table 3*), the predictions of the NFN concentrated errors over a smaller range of absolute deviation, from 0.0 to 9.9 respirations min^{-1}. This finding was probably attributable to the small difference between the values of the statistical indices used, which can be observed only through analysis of the frequency of occurrence of *RR*.

All of the models fitted to predict the t_{rectal} performed better than those fitted to predict the *RR* (*table 3*). In addition, it is evident that all of the models developed had higher percentages of prediction accuracy (higher R^2) when using the observed dataset compared to the literature dataset. This result is attributable to the features of the management used, the type of thermal isolation in the installation, and the adoption of ventilation and evaporative cooling systems intrinsic to each experiment (*table 1*). The inclusion of air velocity and radiative heat load as input variables may increase the performance of the models because t_{db} affects the loss of sensible heat through conduction and convection, *RH* affects the quantity of latent heat lost, and air velocity affects the rate of loss of sensible and latent heat (Dikmen and Hansen, 2009), thereby reducing the prediction errors.

A more detailed analysis of the graphs of the frequency of occurrence of absolute deviations reveals that for the means of the combined dataset of t_{rectal} predicted by the model based on ANNs, 97.7% of the absolute deviations were between the values of 0.0 °C and 0.39 °C, and the remaining 2.3% of the deviations were between the values 0.4 °C and 1.0 °C, thus indicating the good predictive capacity of the model. The second best model (lowest amplitude of deviations) was the NFN, for which 94.6% of the absolute deviations were between 0.0 °C and 0.39 °C, and the remaining 5.4% of the deviations were between the values of 0.4 °C and1.0 °C. The RMs and FMs performed similarly, for which 84.6% and 83.6% of the absolute deviations were found in the interval from 0.0 °C to 0.39 °C, and the remaining 15.4% and 16.4% of the absolute deviations were between the values of 0.4 °C and 1.0 °C, respectively.

Similarly, the model predicting the means of the combined dataset of *RR* based on ANNs had 93.4% of absolute deviations between the values of 0.0 and 9.9 respirations min^{-1}; the remaining 6.6% of the deviations were between the values of 10.0 and 30.0 respirations min^{-1}. For the NFN, the model that showed the second best performance, 90.2% of the absolute deviations were between the values of 0.0 and 9.9 respirations min^{-1}, and the remaining 9.8% of the deviations were between the values of 10.0 and 30.0 respirations min^{-1}. For the FMs and RMs, 80.4% and 72.1% of the absolute deviations were observed between the values of 0.0 and 9.9 respirations min^{-1}, and the remaining 19.6% and 27.9% were between the values of 10.0 and 30.0 respirations min^{-1}, respectively.

The capacity for the prediction of t_{rectal} by the ANN-based model developed in this study was similar to or greater than that in the literature, emphasizing that the published studies used fewer statistical resources for the evaluation of the proposed models. For the *RR*, the fitted ANN presented an R^2 similar to or greater than the models reported in the literature (Brown-Brandl et al., 2005); however, the average absolute deviation was less than that of the best models obtained by the previously quoted authors. This finding was attributable to the greater quantity of variables used by these authors, such as air velocity and radiation, which directly affect the physiological responses of the animals, particularly the RR, which naturally has greater variability than t_{rectal}.

Conclusion

Of the models developed, those based on ANNs and NFN showed, in that order, the fewest prediction errors, and the average standard deviations were 0.1°C and 0.2°C for the t_{rectal} and 3.2 respirations min^{-1} and 5.2 respirations min^{-1} for the *RR*, respectively. These values correspond, respectively, to average percentage errors of 0.4% and 0.6% for the t_{rectal} and 8.7% and 14% for the *RR*. The frequencies of occurrence of the standard deviations for the t_{rectal} for ANN and for NFN for the range from 0 °C to 0.39 °C were 97.7% and 94.6%, respectively. For the *RR*, we observed values of 93.4% and 90.2% for the range from 0 to 10 respirations min^{-1}, respectively. Thus, the models based on ANNs and NFNs can be used to predict the t_{rectal} and *RR* for Holstein dairy cows and can thus aid in the decision-making process.

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