UNIVERSIDADE FEDERAL DE LAVRAS

YAMID FABIÁN HERNÁNDEZ JULIO

DESENVOLVIMENTO DE MODELOS DE SUPORTE À DECISÃO PARA PREDIÇÃO DE RESPOSTAS FISIOLÓGICAS EM BOVINOS LEITEIROS

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Dissertação apresentada à Universidade Federal de Lavras, como parte das exigências do Programa de Pós-Graduação em Engenharia de Sistemas, área de concentração Avaliação e modelagem de sistemas biológicos, para obtenção do título de Mestre.

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LAVRAS-MG

2012

Ficha catalográfica preparada pela Divisão de Processos Técnicos da Biblioteca da UFLA

Hernández Julio, Yamid Fabián.
Desenvolvimento de modelos de suporte à decisão para predição de respostas fisiológicas em bovinos leiteiros / Yamid Fabián Hernández Julio. – Lavras: UFLA, 2012.
82 p. : il.

Dissertação (mestrado) – Universidade Federal de Lavras, 2012.
Orientador: Tadayuki Yanagi Junior.
Bibliografia.

1. Bovinocultura. 2. Freqüência respiratória. 3. Temperatura retal. 4. Modelos computacionais. 5. Inteligência artificial. I. Universidade Federal de Lavras. II. Título.

CDD – 620.00113

YAMID FABIÁN HERNÁNDEZ JULIO

DEVELOPMENT OF DECISION SUPPORT MODELS FOR PREDICTION OF PHYSIOLOGICAL RESPONSES IN DAIRY CATTLE (DESENVOLVIMENTO DE MODELOS DE SUPORTE À DECISÃO PARA PREDIÇÃO DE RESPOSTAS FISIOLÓGICAS EM BOVINOS LEITEIROS)

APROVADA em 27 de fevereiro de 2012

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Ao meu Deus todo poderoso, a minha esposa Martha e filhos (Jorge Enrique e Gabriella), pela paciência e colaboração com a causa. Aos meus pais e sogros, que desde Colômbia nos incentivaram a alcançar os nossos sonhos. A minha família paterna e materna pelo apoio incondicional e pelos ensinamentos desde criança.

DEDICO

AGRADECIMENTOS

O autor expressa seus mais sinceros agradecimentos:

À Universidade federal de Lavras (UFLA) e ao Departamento de Engenharia, por ter oferecido a oportunidade de estudar e completar com sucesso esta pesquisa através da sua infraestrutura física e dos recursos disponíveis para tal fim (humanos, financeiros, científicos e tecnológicos).

Ao Conselho Nacional de Desenvolvimento Científico e Tecnológico – CNPq, ao Ministério das Relações Exteriores e à Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – CAPES, pelo apoio via programa Estudante Convênio de Pós-Graduação – PEC-PG.

À Empresa Brasileira de Pesquisa Agropecuária – EMBRAPA, pelo apoio oferecido, cedendo os dados experimentais para que pudéssemos realizar com sucesso esta pesquisa.

Ao Professor Dr. TADAYUKI YANAGI JUNIOR, do Departamento de Engenharia – DEG, por ter acreditado em mim como aluno estrangeiro, pela paciência, ajuda e colaboração durante a sua orientação do trabalho de dissertação de Mestrado em Engenharia de Sistemas.

Ao Professor Dr. TARCÍSIO DE MORAES GONÇALVES, do Departamento de Zootecnia, pelo contato inicial com a EMBRAPA para a cessão dos dados experimentais.

Ao Professor Dr. RENATO RIBEIRO DE LIMA, do Departamento das Ciências Exatas – DCE, pela ajuda com a validação dos modelos através do *script* do *software* R.

À pesquisadora Dra. MARÍA DE FÁTIMA ÁVILA PIRES que, em nome da EMBRAPA Gado de Leite, cedeu os dados da sua pesquisa realizada nas instalações do centro experimental “Coronel Pacheco”.

À banca examinadora do exame de qualificação de Mestrado, composta pelos professores Sérgio Martins de Souza, Willian Soares Lacerda, Bruno Henrique Groenner Barbosa, pela participação, procedentes correções, sábias e oportunas sugestões.

À banca de defesa de mestrado, meu grande agradecimento pela participação, por todas as correções e sábias sugestões.

Aos meus colegas de estudo, pela convivência no meu estudo, a eles o meu carinho e gratidão.

Aos funcionários do Programa de Pós-Graduação em Engenharia de Sistemas, em especial à Secretária Greice Oliveira pela ajuda incondicional, pela paciência que teve comigo e com a minha esposa.

Muito obrigado a todos.

ABSTRACT

The objectives of this study were to develop and validate decision support systems using systems based on artificial intelligence: fuzzy logic, artificial neural networks, neuro-fuzzy networks, and regression models for the prediction of rectal temperature and respiratory frequency of dairy cows in confinement. All systems were developed based on two input variables: dry bulb air temperature (t_{db}) and relative humidity (RH), with rectal temperature (t_{rectal}) and respiratory rate (RR) as output variables. The fuzzy inference system was carried out using the Mamdani method, which consisted of elaborating 192 rules and defuzzification through the center of gravity. Data obtained from the literature and data observed in the field were used to manufacture the artificial neural network and the neuro-fuzzy network, where membership functions of the neuro-fuzzy system were of the triangular type. The regression models were developed in computing environment R. Experimental results were used to validate the models, and showed that the average standard deviations between the simulated and measured values of t_{rectal} for the regression model, the fuzzy system, the artificial neural network and the neuro-fuzzy network were 0.2 °C, 0.1 °C, 0.1 °C and 0.2 °C, respectively. For the values of RR, the average standard deviations were 5.0, 4.3, 3.2, and 3.5 breaths min^{-1} for the regression model, fuzzy model, artificial neural network and neuro-fuzzy network, respectively. Of the models developed, the artificial neural network and the neuro-fuzzy network showed the fewest prediction errors; therefore, these models are the most suitable for the prediction of rectal temperature and respiratory rate on the basis of the two climatic variables (t_{db} and RH), and can be used in decision support.

Keywords: Physiological performance. Computational models. Dairy cattle.

RESUMO

Os objetivos do presente estudo foram desenvolver e validar sistemas de suporte à decisão, utilizando os sistemas baseados na inteligência artificial: lógica *fuzzy*, as redes neurais artificiais, rede neuro-*fuzzy*, e, modelos de regressão, para a predição da temperatura retal e da frequência respiratória de bovinos leiteiros em confinamento. Todos os sistemas foram desenvolvidos com base em duas variáveis de entrada: temperatura de bulbo seco (t_{bs}) e a umidade relativa do ar (*UR*), tendo como variáveis de saída a temperatura retal (t_{retal}) e a frequência respiratória (*FR*). A inferência do sistema *fuzzy* foi realizada por meio do método tipo Mamdani, que consistiu na elaboração de 192 regras e a *defuzzificação* por meio do Centro de Gravidade. Para a confecção da rede neural artificial e da rede neuro-*fuzzy*, foram utilizados dados obtidos da literatura e dados observados em campo, sendo que as funções de pertinência para o sistema neuro-*fuzzy* foram do tipo triangular. Os modelos de regressão foram desenvolvidos no ambiente computacional R. Resultados experimentais usados para a validação dos modelos, mostraram que os desvios padrões médios entre os valores simulados e medidos da t_{retal} para o modelo de regressão, para o sistema *fuzzy,* para a rede neural artificial e para a rede neuro-*fuzzy* foram de 0·2°C, 0·1°C, 0·1°C e 0·2°C, respectivamente. Para os valores da *FR* os desvios padrões médios foram de 5·0, 4·3, 3·2 e 5·2 respirações min^{-1} para o modelo de regressão, sistema *fuzzy,* rede neural artificial e rede neuro-*fuzzy,* respectivamente. Dos modelos desenvolvidos, os que apresentaram menores erros de predição foram a rede neural artificial e a rede neuro-*fuzzy*, portanto, estes modelos são os mais indicados para a predição da temperatura retal e a frequência respiratória com base em duas variáveis climáticas (t_{bs} e *UR*), podendo ser utilizados como suporte à decisão.

Palavras Chave: Desempenho fisiológico. Modelos computacionais. Bovinocultura.

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SECOND PART

LISTA DE ABREVIATURAS, SIGLAS E SÍMBOLOS

AI	Artificial intelligence
ANN	Artificial neural network
fig.	Figure
FIS	Fuzzy inference system
FL	Fuzzy logic
FM	Fuzzy model
FRs	Functional relationships
LR	Linear regression
MLP	MultiLayer perceptron
MSE	Mean square error
NFN	Neuro-fuzzy network
R^2	Coefficient of determination
RH	Relative humidity of the air, %
RM	Regression model
RMSE	Root mean square error
RR	Respiratory rate, breaths .min^{-1}
t_{db}	Dry bulb temperature, ºC
t_{rectal}	Rectal temperature, ºC

SUMÁRIO

FIRST PART

1. INTRODUCTION

This work is divided into two parts; in the first, the reader can obtain information on the issues related to ambient conditions and their effects on the welfare of confined animals (theoretical reference), along with specific information about welfare, thermal comfort, comfort and discomfort for cattle, the implications of thermal discomfort on cattle, the classification of existing thermal comfort indices and those that are specific to cattle, and information about the models developed in this work. In the second part, the reader will find the article submitted to the Journal of Biosystems Engineering, belonging to the Engineering IV area – Modeling of biological systems. This article includes a short introduction to the topic, a theoretical summary about the subject, the purpose of the research, the material and methods used for its development, and the results, discussion, and conclusions.

The justification for the development of this research will be addressed in subsequent paragraphs at either a national or regional level.

Cattle are homeothermic animals; in other words, they are animals that maintain their body core temperature at an approximately constant level via control processes of heat dissipation when subjected to fluctuations occurring in the external environment (BAÊTA; SOUZA, 2010; NAVARINI et al., 2009; PERISSINOTTO, 2007).

Because of this, the production environment for the animal has a key role in ensuring appropriate climatic conditions for animal production, where the boundaries are characterized by the thermoneutral zone (CURTIS, 1983). In this zone, the animal reaches its maximum potential and the body temperature is maintained with minimal use of thermo-regulator mechanisms.

When environmental conditions are not within appropriate limits the environment becomes uncomfortable. In this situation, when the temperature exceeds the comfort range, cattle combat thermal stress having a lower feed intake, show sweating and panting (HOLTER; WEST; McGILLIARD, 1997), and lose too much sodium and potassium in the sweat and urine (PIRES; CAMPOS, 2008).

In this context, the goal of this work was to develop and validate models of regression (one) based on artificial intelligence (three: fuzzy logic, artificial neural networks and neuro-fuzzy networks) for the prediction of rectal temperature and respiratory rate of Holstein dairy cows.

2. THEORETICAL REFERENCE

2.1 Animal welfare

Among the various proposals for the definition of animal welfare, Broom (1991) defined welfare as the state of an individual in relation to its environment, being dependent on the body's ability to respond or adapt to the environment. Hurnik (1992) characterized the term welfare as optimal physiological and physical conditions and high quality of life of the animal. For Phillips (2002), the welfare of an animal mainly refers to its ability to deal with both its external environment, including housing, climate, and the presence of other animals, and its internal environment, such as specific pains, fever, and nutritional status.

The Farm Animal Welfare Council (FAWC, 2011) recognizes the term welfare through five freedoms inherent to animals: physiological freedom (absence of hunger and thirst), environmental freedom (adapted buildings), health freedom (absence of disease and fractures), behavioral freedom (ability to express normal behavior), and psychological freedom (absence of fear and anxiety).

Furthermore, several approaches have been used to determine levels of animal welfare, in which all of the criteria are based on some demonstrated evidence of a change in physical (growth and health), mental (pleasure or pain) or naturalness attributes that reflect the proximity or distance of the natural environment (APPLEY; WEARY, 2000). Another factor that influences the assessment of welfare is the environmental factor, which, according to Baldwin (1979), can be divided into social, physical, and management aspects. According to the Handbook of Fundamentals of American Society of Heating and Refrigeration and Air-conditioning Engineers – ASHRAE (2009) – the physical environment covers meteorological elements that affect the mechanisms of heat transfer, regulation and the balance between the animal and the environment, which exerts a strong influence on the performance and health of animals.

According to Baêta and Souza (2010), the external environment of an animal comprises all physical (space, light, sound, and equipment), chemical (gases present in the atmosphere), biological (nature of feed material), social (number of animals per area, behavior and hierarchy), and climate (temperature, relative humidity, the movement of air, and radiation) factors that interact with the animal.

Welfare is assessed through behavioral and physiological indicators. An animal that is not maintained under optimal welfare conditions will not develop its full reproductive potential, even if health and nutritional conditions are apparently satisfied. The goal of confinement systems is to reduce energy loss and animal work and to gain space and environmental control; however, according to Machado Filho (1998), such systems can generate inappropriate conditions such as, for example, limited space, a high stocking density, the presence of microorganisms, inadequate temperature and lighting conditions, noise, and worsening behavioral problems, preventing an animal from behaving naturally.

The assessment of animal welfare in agricultural production may involve aspects relating to the facilities, management and the environment, such as the distribution of water and food, the existence of beds, possibilities of movement, rest, contact between animals and reproduction, temperature, ventilation, light, and available space or pavement type, among others.

2.1.1 Thermal comfort

Thermal comfort can be defined as being the state of the spirit that reflects satisfaction with the thermal environment that surrounds the animal (RODRIGUEZ, 2003).

Heat stress is caused by a combination of environmental conditions that result in a larger effective temperature of the environment than an animal's thermo-neutral zone (PIRES; CAMPOS, 2008). According to Nääs (2000), four factors influence increases in the effective temperature of the environment: dry bulb temperature, relative humidity, radiation, and wind speed.

According to Navarini et al. (2009), factors such as the availability of water and shade, the animal's body temperature, and behavior under different temperature conditions, which directly affect the sensitivity of thermal heat exchange (conduction, skin convection and radiation) and latent heat losses (cutaneous evaporation) to the environment, can cause thermal stress in animals, which can cause serious problems in both animal production and breeding.

2.1.2 Ranges of comfort and discomfort for cattle

According to Müller (1989) and Rodriguez (2003), defining the temperature limits of the comfort zone is a difficult task because they depend on several variables such as air temperature, relative humidity, wind, and solar radiation, which vary according to the location, time of year, and time of the day. In addition, they also depend on the animal's age, the housing density, the breed, nutritional conditions, management, and the conditions of installations and equipment.

Great variation exists in the literature regarding the temperatures that denote the thermo-neutral zone of dairy cattle (ARAÚJO, 2002). According to the results of an experiment by Baêta (1985), for European bovine animals under conditions of relative humidity of 50% and a wind speed of 0.5 m s^{-1}, the thermal comfort zone ranges from 11 °C to 25 ºC.

Youlsef, (1985), Roenfeldt, (1998), stated that the thermoneutral zone for dairy cattle varies from 5 and 25ºC. Silva (1998) stated that for dairy cattle the comfort zone varies from 18 to 21 °C, while heat and cold stress occur at 4 °C and 28 °C, respectively. For beef cattle, the comfort zone varies from 22 ºC to 26 °C, while heat and cold stress occur at 4 °C and 30 °C, respectively. In turn, Fuquay (1981), considered that the upper critical temperature for dairy cattle is between 25 and 27ºC. For Baêta and Souza (2010), they stated that thermal comfort zone for dairy cattle (adult European) is -1 and 16ºC.

For the case of thermal comfort through physiological responses (t_{rectal} and *RR*), was founded the works of Perissinotto (2007, p. 66) and Perissinotto et al. (2009), where they proposed a linguistic characterization (table 1) of the thermal comfort sensation of Holstein dairy cows as a functionality of t_{rectal} and *RR* based on a wide literature review.

Table 1. Linguistic characterization of thermal comfort sensation as a function of t_{rectal} (ºC) and *RR* (breaths.min^{-1}).

Rectal temperature (t_{rectal} - ºC)	Respiratory rate (RR – breaths.min^{-1})		
	High comfort (≤ 56)	Medium comfort (> 56 – ≤ 64)	Low comfort (> 64)
High comfort (≤ 38,8)	Very good	Good	Regular
Medium comfort (> 38,8 - ≤39,2)	Good	Regular	Bad
Low comfort (> 39,2)	Regular	Bad	Bad

Font: Perissinotto et al. (2009).

2.1.3 Implications of thermal discomfort in dairy cattle

When environmental conditions are not within appropriate limits, the animal becomes uncomfortable. According to Harner et al. (2009), in this situation, when the temperature exceeds the recommended range, dairy cattle combat thermal stress having a lower feed intake (HOLTER et al., 1997) and show sweating and panting. These mechanisms increase the energy costs of livestock, resulting in up to 35% more food being required for their maintenance (NRC, 1981). When the consumption of dry matter decreases during thermal stress, milk production also decreases. A dairy cow in an environment of 37.7 °C shows milk production reduction of 50% or more when compared with thermoneutral conditions (COLLIER, 1985), which can result in a loss of production. In addition, animals under thermal stress conditions also suffer from changes in rectal temperature and respiratory rate (PERISSINOTTO; MOURA, 2007). According to Silva et al. (2002), the Holstein breed shows a decrease in milk production above 24 ºC, although Swiss and Jersey breeds have a somewhat greater tolerance because they show good performance in temperatures up to 27 ºC.

2.2 Thermal comfort indices

In view of these factors, some authors have developed so-called thermal comfort indices, which can be classified according to Nääs (1998) depending on the way that they were developed: biophysical indices (their development is based on the exchange of heat between the body and the environment, correlating elements of comfort with the heat exchange that originate); physiological indices (based on physiological relationships caused by known conditions of air temperature, average radiant temperature, air humidity, and wind speed), and subjective indices (based on subjective sensations of comfort obtained under experimental conditions where the elements of thermal comfort vary). In the case of dairy cattle, some of the indices used are temperature and humidity indices (THI), as proposed by Thom (1959); the effective temperature index, adjusted by Bianca (1963); the black globe temperature and humidity index (BGTHI) developed by Buffington et al. (1981); the enthalpy index, described by Villa Nova (1999, cited by FURLAN, 2001) and the equivalent temperature index (ETI), proposed by Baêta (1985).

2.3 Mathematical modeling

According to Bassanezzi (2006), mathematical modeling is a dynamic process used to create and validate mathematical models, as well as a form of abstraction and generalization with the purpose of predicting tendencies. For the author, a mathematical model is a set of symbols and mathematical relationships that in some way represent the object being studied. For McLone (1976, cited by BASSANESSI, 2006) a mathematical model is a “simplified abstract mathematical construct that represents a portion of reality with some particular goal”. In turn, for Tedeschi (2005), “Models are mathematical representations of mechanisms that govern natural phenomena that are not fully recognized, controlled, or understood.”

Models can be formulated in accordance with the nature of the phenomena or situations to be analyzed and they can be classified into linear or non-linear (depending on the basic equations) (BASSANEZZI, 2006), static (representing the shape of the object) or dynamic (simulates variations in the stages of the phenomenon) (BALDWIN, 1995; BASSANEZI, 2006), educational (based on small numbers or simple assumptions), applicable (based on realistic assumptions involving a large number of variables) (BASSANEZI, 2006), stochastic (describes the dynamic system in probabilistic terms) or deterministic (assumes that if there is enough information about a system at a given instant of the process then the whole future of the system can be precisely predicted) (BALDWIN, 1995; BASSANEZI, 2006), empirical (based only on correlations or associations between two or more variables, without taking into account the mechanisms that control the phenomenon) or mechanistic (attempts to explain or describe the mechanisms involved, based on the laws of physics, chemistry, and biochemistry etc.) (BALDWIN, 1995).

In addition to these are computational models. Among these models are fuzzy systems (linguistic - fuzzy rules) (GOMIDE; GUDWIN, 1994), artificial neural networks (YAMAKAWA, 1993), and hybrid systems, such as neuro-fuzzy networks.

2.3.1 Empirical models – simple and multiple linear regressions

The Greek *Empeirikos* means experience. These models use direct observations or the results of experiments on a particular phenomenon. In these types of models the correspondence between input and output variables is tested regardless of the phenomenon or process (BALDWIN, 1995).

According to Rondon et al. (2002), the difficulty in defining the mechanisms involved in biological phenomena means that the majority of the proposed animal models are empirical. These models are created from data collected in experiments and are used for certain functions, such as predicting the growth of broilers (IVEY, 1999) or the thermal indices of productivity for broilers (MEDEIROS et al., 2005), or calculating the superficial area of broilers (SILVA et al., 2009), among other applications.

2.3.2 Fuzzy models

Aspects related to the difficulties encountered in analyzing large amounts of information and its complexity are found in the production of agricultural systems. Therefore there is a need to seek mathematical methodologies that incorporate specialist, subjective knowledge, enabling the simulation of situations for decision support (AMENDOLA; SOUZA; BARROS, 2005).

Basically, these models are divided into two types: the Mandani (MANDANI; ASSILIAN, 1975) and Sugeno types (TAKAGI; SUGENO, 1985). The Mandani type model is a kind of fuzzy relational model, where each rule is represented by the relationship IF-THEN. It is also called a linguistic model because both the antecedent and consequent are fuzzy propositions (BABUSKA, 1998). Its structure is developed manually. The output of the

Mandani type model is a fuzzy membership function based on the rules created during the modeling process. Mathematically and linguistically, it can behave as follows:

$$\text{If } x \text{ is } A \text{ and } y \text{ is } B \text{ then } z \text{ is } C \tag{1}$$

where x and y are the system input variables, z is the system output variable, A and B are antecedent membership functions, and C is a consequent membership function.

Generally, software programs for the implementation of this type of models use the Centroid method for defuzzification, which can be considered a weighted average where the weights are represented by μ_A (xi), which indicates the degree of membership of the value x_i with the concept modeled by the fuzzy output set A, and which, in its compound shape, is calculated by:

$$Z= \frac{\mu_c(z)z\delta z}{\mu_c(z)\delta z} \tag{2}$$

where Z is the consequent variable and $\mu_c(z)$ is the function of the composed shape. The result of the defuzzification process Z can be continuous or discrete (BARROS; BASSANEZI, 2006; TANAKA, 1997).

The Sugeno type model (TAKAGI; SUGENO, 1985): for a system with two input variables and one output variable, the system is as follows:

$$\text{If } x \text{ is } A \text{ and } y \text{ is } B \text{ then } z = f(x, y) \tag{3}$$

where x and y are the input variables, z is the output variable, A and B are antecedent membership functions, and f $(x,\ y)$ is a crisp function in the consequent. Usually, this function is a polynomial of the input variables x and y. As an example it can be cited the case of the first-order polynomial, which is expressed as follows:

$$Z = p_1x + q_1y + r_1 \tag{4}$$

Defuzzification is expressed as a weighted average Z of the consequent functions:

$$Z = \frac{\Sigma wz}{\Sigma w} \tag{5}$$

Where W is the rule firing strength and z is a consequent function output.

2.3.3 Artificial neural networks

Neural networks are highly sophisticated pattern recognition systems capable of learning relationships in patterns of information (data) (BROWN-BRANDL; JONES; WOLDT, 2005). These neural networks are sets of mathematical algorithms used in processing elements (PEs) arranged to imitate the complexity of non-linear and parallel mechanisms involved in the interpretation of information by biological neural networks (BATCHELOR et al., 1997).

Generally, an artificial neural network is composed of multiple processing units called neurons, which have a fairly simple function. The neurons are connected by communications channels that are associated with a particular weight (W); in turn, these only can make operations with local data: entries that are received by their connections. This type of model is adaptive and trainable; it can work with complex domains (non-linear problem cases), it does not need to have complete information to perform its process of generalization, and it is robust and has a great parallelism; thus, this type of model also has a fast processing speed (VON ZUBEN, 2003).

In order to build models with this type of technology, sets of pairs of data (input (s) and output (s)) in the form of vectors or matrices should be used in order to train them to select the transfer function applied to each interconnection between two neurons and to define the rules of learning through training. The artificial neural network produces its own output vectors, which are compared with the training output vectors (supervised training). If the degree of accuracy between the neural network output and training output vectors is not satisfactory, the neural network applies learning rules to adjust the weights of interconnections and subsequently repeats the comparison until the accuracy criterion proposed by the user between two vectors is satisfied.

There is a variety of strategies for the training of neural networks, but the most frequently used is the back-propagation training algorithm. Mathematically, it can be expressed as the answer *O* of each neuron *i* to input signals of *I* from the connecting neurons *j* using equation 6:

$$O_i = f\left(\sum I_j W_{ij} + B_i\right) \tag{6}$$

The transfer function *f* can be linear or non-linear. The most commonly used functions are sigmoidal and hyperbolic tangents. The learning process starts with randomly initialized weights. Errors associated with output neurons are transmitted from the output layer to the input layer through hidden layers using the back-propagation algorithm; therefore, in order to minimize errors, weights are adjusted at the end of each back-propagation cycle (BRARATH; DROSEN, 1994). In order to prevent overfitting or overtraining, a strategy must be implemented that stops training at the time the network has the lowest global error, avoiding increasing the error rate again, which is included in order to enhance the ability of networks to generalize (good performance on new data or unknown) (ANDERSON et al., 1999).

2.3.4 Neuro-fuzzy networks

Neuro-fuzzy networks take advantage of the learning ability of neural networks and use fuzzy systems to process the knowledge clearly. The final solution of a neuro-fuzzy network can be interpreted as a Sugeno-type fuzzy inference system (Section 2.3.2). Basically, the operation of this type of system, is the same as that of neural networks, except that when a neural network “learns”, it modifies the sets and rules of the fuzzy inference system (membership functions); this way, the system reaches the slightest possible error taking advantage of the learning ability of networks through pattern recognition (JANG, 1993; JANG; SUN, 1995).

A neuro-fuzzy network based on the LOLIMOT algorithm (local linear model tree) works with the decomposition of input space in subspaces. Each subspace corresponds to a local linear model. The network output is calculated by adding the results of each local linear model, with its validation function, which can be obtained through a weight function. Each linear model, with its validation function, corresponds to a fuzzy neuron (NELLES; ISERMANN, 1996).

3. GENERAL CONSIDERATIONS

The final considerations of this work are as follows:

1. The prediction of t_{rectal} and *RR* of Holstein dairy cows provides primordial information for decision making related to the handling and care of animals because they are direct measures that help in the classification of thermal comfort conditions.

2. A comparison between models based on regression and artificial intelligence enables the choice of which has the best performance, making predictions more realistic.

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SECOND PART- ARTICLE BIOSYSTEMS ENGINEERING JOURNAL

ARTICLE 1 MODELS FOR THE 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.

RESUMO

Objetivou-se, com o presente trabalho, avaliar técnicas de modelagem para predição de respostas fisiológicas, temperatura retal e frequência respiratória, de vacas leiteiras de raça holandesa branca e preta. Dados oriundos da literatura (792 dados) e obtidos experimentalmente (5.884 dados) foram usados no ajuste e validação dos modelos. Cada dado foi composto por valores de temperatura de bulbo seco do ar, umidade relativa, temperatura retal e frequência respiratória. Três modelos baseados em inteligência artificial (lógica *fuzzy*, redes neurais artificiais e redes neuro-*fuzzy*) e um de regressão foram avaliados para cada variável resposta. Os modelos ajustados predizem a temperatura retal e frequência respiratória em função da temperatura de bulbo seco do ar e da umidade relativa do ar. Os modelos ajustados foram comparados entre si por meio de índices estatísticos. O modelo baseado em redes neurais artificiais apresentou o melhor desempenho, seguido pelos modelos baseados em rede neuro-*fuzzy*, lógica *fuzzy* e o modelo de regressão; os dois últimos apresentaram desempenhos similares.

Palavras Chave: Desempenho fisiológico. Modelos computacionais. Bovinocultura.

1. 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, Nääs, Marcheto, Salgado, 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 & Campos, 2008). According to Silva, Pandorfi, Piedade, and Moura (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 24ºC.

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, Smith, Bradford, Overton, Dhuyvetter, 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 & Campos, 2008) and suffer changes in rectal temperature (t_{rectal}) and in respiratory rate (RR) (Perissinotto & 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, Murphy, Silanikove, Maltz, 2002; West, 2003; Hansen, 2007).

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.

1.1 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; Yanagi Junior, Schiassi, Lima, Texeira, 2012), and thermal comfort in cattle (Brown-Brandl, Jones, Woldt, 2005).

1.2 Fuzzy models

FMs are based on fuzzy logic (FL), which is founded in the theory of fuzzy sets (Gomide & 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, Bighi, Gabriel Filho, Gabriel, 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, Amendola, Nääs, 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, Nääs, Sampaio, 2005; Oliveira, Amendola, Nääs, 2005; Alves, 2006; Yanagi Junior, Xin, Gates, Ferreira, 2006; Owada, Nääs, Moura, Baracho, 2007; Pereira et al. 2008; Ferreira, 2009), cattle (Perissinotto, 2007; Perissinotto et al. 2009), and humans (Altrock, Arend, Krause, Steffens, Behrens-Römmler, 1994). Fuzzy sets have also been used in the prediction of estrus in dairy cows (Ferreira, Yanagi Junior, Nääs, Lopes, 2007), inspection systems for chickens (Yang, Chao, Chen, Kim, Chan, 2006), the prediction of cloacal temperature of broilers (Ferreira, Yanagi Junior, Lacerda, Rabelo, 2011), statistics (Khashei, Reza Hejazi, Bijari, 2008; Liang-Hsuan & Chan-Ching, 2009), forensic science (Liao, Tian, Wang, 2009), studies of pesticide pollution (Gil, Sinfort, Guillaume, Brunet, Palagos, 2008), industrial applications (Meier, Weber, Zimmermann, 1994), and in data analysis, specialist systems, control, and optimization (Gomide & Gudwin, 1994; Ribacionka, 1999; Lopes, 1999; Cho, Chang, Kim, An, 2002; Weber and Klein, 2003, Castañeda-Miranda, Ventura-Ramos, Del RocíoPeniche-Vera, Herrera-Ruiz, 2006; Chao, Gates, Sigrimis, 2000), among many other applications.

1.3 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, Cravener, Kochera Kirby, Wideman, 1997). Mathematically, ANNs are universal approximators that perform mapping between two variable spaces (Hornik, Stinchcombe, White, 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, Ferreira, Yanagi Junior, Lacerda, 2008), applied geography (Spellman, 1999), thermal sciences and engineering (Yang, 2008), hydrology (Kurtulus & Razack, 2010), the study of thermal comfort in cattle (Brown-Brandl, Jones, Woldt, 2005), growth performance in swine (Bridges, Gates, Chao, Turner, Minagawa, 1995) and in humans (Moustris, Tsiros, Ziomas, Paliatsos, 2010). ANNs have been used to analyze the sensitivity of a mechanical system for poultry catching (Jaiswal, Benson, Bernard, Van Wicklen, 2005), quantification of odours from piggery effluent ponds (Sohn, Smith, Yoong, Leis, Galvin, 2003), classify apples by their textural features (KavdIr & Guyer, 2004), discriminating varieties of tea plant (Li & He, 2008), daily stream flow prediction (Nayebi, Khalili, Amin, Zand-Parsa, 2006), simulate runoff and sediments yield (Agarwal, Mishra, Ram, Singh, 2006), residual soil nitrate prediction (Gautam, Panigrahi, Franzen, Sims, 2012), discrimination of apricot cultivars by gas multisensor array (Parpinello, Fabbri, Domenichelli, Mesisca, Cavicchi, Versari, 2007), estimate leaf chlorophyll concentration in rice under stress from heavy metals (Liu, Liu, Li, Fang, Chi, 2010), modelling total volume of dominant pine trees in reforestations (Diamantopoulou & Milios, 2010), in ortho-phosphate and total phosphorus removal prediction in horizontal subsurface flow constructed wetlands (Akratos, Papaspyros, Tsihrintzis, 2009), predicting the draught requirement of tillage implements in sandy clay loam soil (Roul, Raheman, Pansare, Machavaram, 2009), prediction of nitrate release from polymer-coated fertilizers (Du, Tang, Zhou, Wang, Shaviv, 2008), and in near infrared spectral analysis (Wang &

Paliwal, 2006). ANNs have also found to be useful in construction (Argiriou, Bellas-Velidis, Balaras, 2000) and in demand analysis in the form of forecasting (Efendigil, Önüt, Kahraman, 2009), among many other applications.

The MultiLayer perceptron (MLP) is the most commonly used architecture for developing an ANN (Fausset, 1994; Barreto, 2002; Von Zuben, 2011) and contains input, hidden, and output layers.

1.4 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, Jiao, Lee, 2006), control and automation systems (Cheng-Hung, Cheg-Jian, Ching-Teng, 2009), the decision support system for demand forecasting (Efendigil, Önüt, Kahraman, 2009), thermal comfort for birds (Ferreira, 2009), the prediction of t_{rectal} of broilers (Ferreira,Yanagi Junior, Lopes, Lacerda, 2010), in statistics (Khashei, Reza Hejazi, Bijari, 2008), in hydrology (Kurtulus & Razack, 2010), to analyze livestock farm odour (Pan & Yang, 2007), and in robotics (Zacharia, 2010).

2. Objective

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*).

3. Material and methods

3.1. 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).

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).	21º38’	22º42’	21º57’	22º33’		21º57’			21º57’	22º33’	21º38’	
Longitude (W).	43º19’	47º 18’	47º27’	47º38’		47º27’			47º27’	47º38’	43º19’	
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. (ºC)	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. (ºC)	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, em Pires & Campos, 2003). **[2]** Silva, Pandorfi, Júnior, Piedade and Moura, (2002). **[3]** Martello, Savastano Júnior, Silva and Titto, (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.

3.2 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 5*). 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.

3.2.1. *Regression models*

Eighteen multiple RMs (*Appendix A*) 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).

3.2.2. *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 & 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.

3.2.3. *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.

3.2.4. *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.

4.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 (ºC) 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).

4.1. *Regression models*

Of the 18 RMs fit to predict the t_{rectal} and *RR* (*Appendix A*), 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 (*Appendix A, table 5*).

$$t_{rectal} = 37.08\ (\pm 0.12) - 0.02\ (\pm 0.008)\ t_{db} + 0.02146\ (\pm 0.003)\ RH + 0.0014\ (\pm 0.00018)\ t_{db}^{\,2} - 0.000055\ (\pm 0.0000021)\ RH^2 \quad (1)$$

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 (*Appendix A, table 5*).

(2)

$$RR = 7.8\ (\pm\ 2.93) + 0.992287\ (\pm\ 0.251)\ t_{db} + 0.142209\ (\pm\ 0.02)\ RH + 0.013354\ (\pm\ 0.006)\ t_{db}^{\ 2}$$

The FRs between the values for t_{rectal} and *RR* predicted by the RMs and the means of the literature dataset, means of the experimental dataset, and the means of combined dataset (means of experimental and literature datasets) are illustrated in figures *3a, 4a, 5a* and figures *6a, 7a,* and *8a,* respectively.

4.2. *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 structural characteristics of which are listed in *table 2.*

Table 2. Characteristics of the fuzzy inference system.

System's characteristics	Inputs	Outputs
<Name> fuzzy dataset RT RR		
<Type>m	**[Input 1]**	**[Output 1]**
<Number Rules>192	<Name>t_{db}	<Name>t_{rectal}
<SNorm>max	<Range>9 - 45	<Range>37 - 42
<SNormPar>0.0	<Number MFs>24	<Number MFs>11
<TNorm>min		
<TNormPar>0.0	**[Input 2]**	**[Output 2]**
<Comp>one	<Name>*RH*	<Name>*RR*
<CompPar>0.0	<Range>0 - 100	<Range>28 -108
<ImpMétodo>min	<Number MFs>8	<Number MFs>12
<AggMétodo>max		
<DefuzzMethod>Centroid		

m, Mandani type. tdb, dry-bulb temperature. *RH*, relative humidity.MFs, membership functions.*trectal*, rectal temperature. *RR*, respiratory rate.max, maximum. min, minimum.

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, Souza, Barros, 2005; Yanagi Junior, Xin, Gates, Ferreira, 2006; Ferreira, Yanagi Junior, Nääs, Lopes, 2007; Schiassi, Yanagi Junior, Ferreira, Damasceno, Yanagi, 2008).

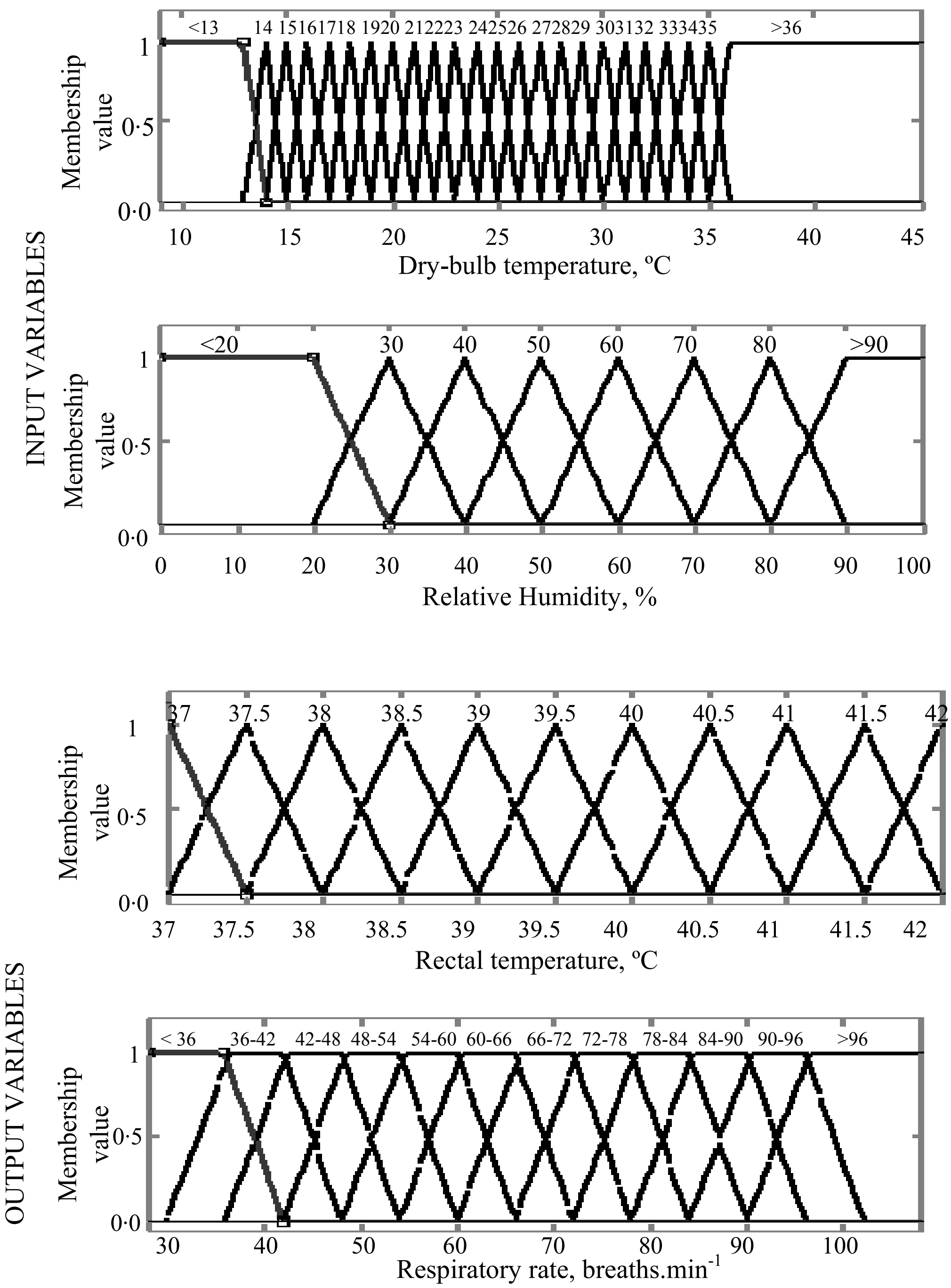


Fig. 1.The membership function structure developed for the fuzzy inference system.

The fuzzy inference was composed of a set of 192 rules (*table 3*), 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.

The FRs between the values for t_{rectal} and *RR* predicted by the FMs and the means of the literature dataset, means of experimental dataset, and the means of the combined dataset (means of experimental and literature datasets) are shown in *figures 3b, 4b,* and*5b* and *figures 6b, 7b,* and *8b,* respectively.

4.3. 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.

The FRs between the values of t_{rectal} and *RR* predicted by the ANNs and the means of the literature dataset, means of the experimental dataset, and the means of the combined dataset (means of experimental and literature datasets) are shown in *figures 3c, 4c,* and *5c* and *figures 6c, 7c,* and *8c,* respectively.

Table 3. Set of rules for the fuzzy inference system.

1 1 1 1 1 1.0	5 1 2 1 1 1.0	10 2 3 3 1 1.0	15 3 4 4 1 1.0	20 4 5 7 1 1.0
1 2 1 1 1 1.0	6 8 5 2 1 1.0	10 1 3 3 1 1.0	15 2 4 4 1 1.0	20 3 5 6 1 1.0
1 3 2 1 1 1.0	6 7 4 2 1 1.0	11 8 5 5 1 1.0	15 1 4 4 1 1.0	20 2 4 4 1 1.0
1 4 2 1 1 1.0	6 6 5 2 1 1.0	11 7 4 2 1 1.0	16 8 5 6 1 1.0	20 1 4 4 1 1.0
1 5 3 1 1 1.0	6 5 4 4 1 1.0	11 6 4 2 1 1.0	16 7 5 6 1 1.0	21 8 6 7 1 1.0
1 6 3 1 1 1.0	6 4 4 2 1 1.0	11 5 4 2 1 1.0	16 6 5 6 1 1.0	21 7 6 6 1 1.0
1 7 4 1 1 1.0	6 3 3 2 1 1.0	11 4 4 2 1 1.0	16 5 4 4 1 1.0	21 6 5 4 1 1.0
1 8 5 2 1 1.0	6 2 3 2 1 1.0	11 3 4 2 1 1.0	16 4 3 4 1 1.0	21 5 5 4 1 1.0
2 8 4 2 1 1.0	6 1 2 2 1 1.0	11 2 3 2 1 1.0	16 3 4 5 1 1.0	21 4 5 7 1 1.0
2 7 4 3 1 1.0	7 8 4 3 1 1.0	11 1 3 2 1 1.0	16 2 4 4 1 1.0	21 3 5 6 1 1.0
2 6 3 2 1 1.0	7 7 4 2 1 1.0	12 8 6 5 1 1.0	16 1 4 4 1 1.0	21 2 5 5 1 1.0
2 5 3 2 1 1.0	7 6 3 1 1 1.0	12 7 5 5 1 1.0	17 8 5 6 1 1.0	21 1 5 4 1 1.0
2 4 2 2 1 1.0	7 5 3 1 1 1.0	12 6 5 4 1 1.0	17 7 5 6 1 1.0	22 8 6 7 1 1.0
2 3 2 2 1 1.0	7 4 3 1 1 1.0	12 5 5 5 1 1.0	17 6 5 4 1 1.0	22 7 6 7 1 1.0
2 2 1 2 1 1.0	7 3 3 1 1 1.0	12 4 5 5 1 1.0	17 5 4 5 1 1.0	22 6 6 6 1 1.0
2 1 1 2 1 1.0	7 2 2 1 1 1.0	12 3 4 5 1 1.0	17 4 5 5 1 1.0	22 5 6 5 1 1.0
3 8 4 1 1 1.0	7 1 2 1 1 1.0	12 2 4 5 1 1.0	17 3 4 6 1 1.0	22 4 6 11 1 1.0
3 7 4 3 1 1.0	8 8 5 4 1 1.0	12 1 4 4 1 1.0	17 2 4 6 1 1.0	22 3 5 7 1 1.0
3 6 4 1 1 1.0	8 7 4 3 1 1.0	13 8 5 5 1 1.0	17 1 4 5 1 1.0	22 2 4 5 1 1.0
3 5 3 1 1 1.0	8 6 5 5 1 1.0	13 7 5 4 1 1.0	18 8 6 8 1 1.0	22 1 4 5 1 1.0
3 4 3 1 1 1.0	8 5 4 4 1 1.0	13 6 4 3 1 1.0	18 7 6 8 1 1.0	23 8 7 7 1 1.0
3 3 2 1 1 1.0	8 4 4 4 1 1.0	13 5 4 4 1 1.0	18 6 6 8 1 1.0	23 7 7 7 1 1.0
3 2 2 1 1 1.0	8 3 3 3 1 1.0	13 4 4 4 1 1.0	18 5 6 6 1 1.0	23 6 7 6 1 1.0
3 1 1 1 1 1.0	8 2 3 3 1 1.0	13 3 4 4 1 1.0	18 4 4 6 1 1.0	23 5 6 5 1 1.0
4 8 5 2 1 1.0	8 1 3 2 1 1.0	13 2 4 3 1 1.0	18 3 4 4 1 1.0	23 4 5 5 1 1.0
4 7 4 1 1 1.0	9 8 5 3 1 1.0	13 1 4 3 1 1.0	18 2 4 4 1 1.0	23 3 4 8 1 1.0
4 6 3 1 1 1.0	9 7 4 3 1 1.0	14 8 5 5 1 1.0	18 1 4 4 1 1.0	23 2 5 6 1 1.0
4 5 3 1 1 1.0	9 6 4 3 1 1.0	14 7 5 4 1 1.0	19 8 6 8 1 1.0	23 1 4 6 1 1.0
4 4 2 1 1 1.0	9 5 4 3 1 1.0	14 6 5 4 1 1.0	19 7 5 5 1 1.0	24 8 7 4 1 1.0
4 3 2 1 1 1.0	9 4 4 3 1 1.0	14 5 4 4 1 1.0	19 6 5 3 1 1.0	24 7 8 7 1 1.0
4 2 2 1 1 1.0	9 3 3 3 1 1.0	14 4 4 3 1 1.0	19 5 5 7 1 1.0	24 6 7 7 1 1.0
4 1 1 1 1 1.0	9 2 3 3 1 1.0	14 3 4 4 1 1.0	19 4 5 6 1 1.0	24 5 6 9 1 1.0
5 8 4 2 1 1.0	9 1 3 3 1 1.0	14 2 4 3 1 1.0	19 3 4 5 1 1.0	24 4 6 9 1 1.0
5 7 4 2 1 1.0	10 8 5 5 1 1.0	14 1 4 3 1 1.0	19 2 4 4 1 1.0	24 3 6 8 1 1.0
5 6 4 2 1 1.0	10 7 5 4 1 1.0	15 8 5 6 1 1.0	19 1 4 4 1 1.0	24 2 6 8 1 1.0
5 5 4 4 1 1.0	10 6 3 3 1 1.0	15 7 5 6 1 1.0	20 8 5 6 1 1.0	24 1 6 7 1 1.0.
5 4 3 2 1 1.0	10 5 5 3 1 1.0	15 6 5 5 1 1.0	20 7 5 6 1 1.0	
5 3 3 2 1 1.0	10 4 4 3 1 1.0	15 5 5 4 1 1.0	20 6 5 6 1 1.0	
5 2 2 1 1 1.0…	10 3 4 3 1 1.0…	15 4 5 1 1 1.0…	20 5 5 6 1 1.0…	

* The fisrt two numbers for each column represent the fuzzy input sets (*tdb* and *RH*), the next two represent the two fuzzy output sets (*trectal andRR*), the following number represents the weights of the rules and the final number represents the connector of the rule (0 signifies OR, 1.0 signifies AND). Example: (1 1 1 1 1 1.0) – signifies: If MF *tdb*1 (< 13ºC) *and* MF*RH* 1 (< 20 breaths. min-1) *then* MF *trectal* 1 (37ºC) *and* MF*RR* 1 (< 36 breaths . min-1). MF, membership functions.

4.4. 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 4*. 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.

Table 4.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 2 2 3 3	1 2 1 2 1 2	1 2 3 4 5 6	1 1 1 1 1 1	1* 1 1 1 1 1

*It means: If t_{db} MF1 *and* *RH* MF1 *then* t_{rectal} MF1.

Table 4. Continue.

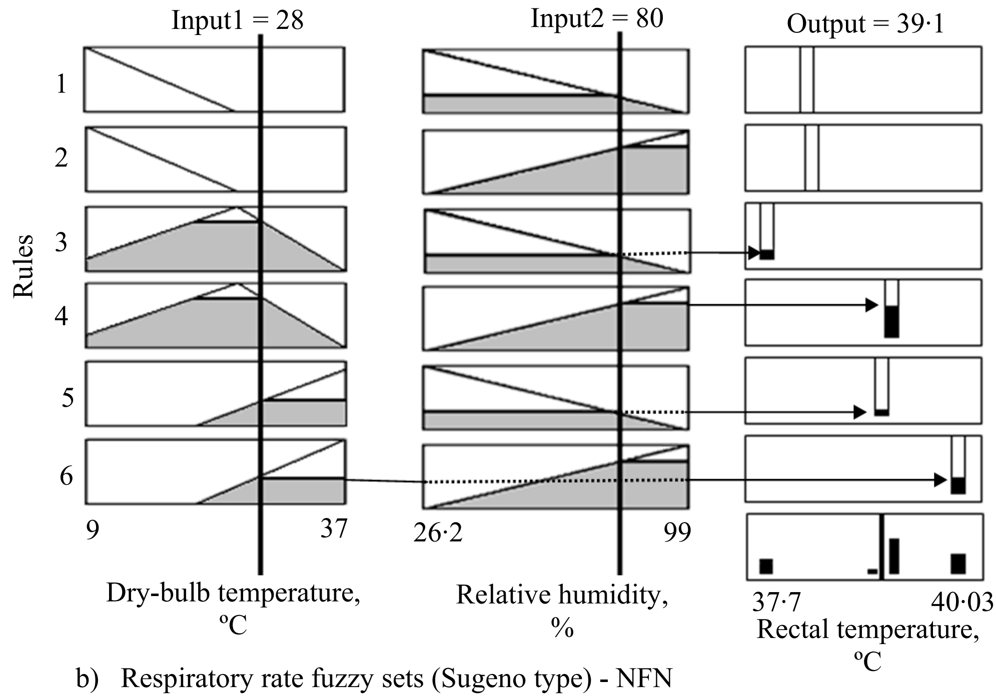
Fuzzy systems' characteristics	Inputs	Outputs	Rules
(b) <Name> fuzzy sets *RR*-FIS <type>TS <SNorm>max <SNormPar>0 <TNorm>min <TNormPar>0 <Comp>sugeno <CompPar>0 <ImpMethod>prod <AggMethod>max <defuzzMethod>waver	**[Input 1]** <Name>t_{db} <Range>9 - 37 <Number MFs>3 <Function>trimf <NameMF1><in1MF1> -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	t_{db} *RH* Out W Con. 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.

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 4*).

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.

a) Rectal temperature fuzzy sets (Sugeno type) - NFN



b) Respiratory rate fuzzy sets (Sugeno type) - NFN

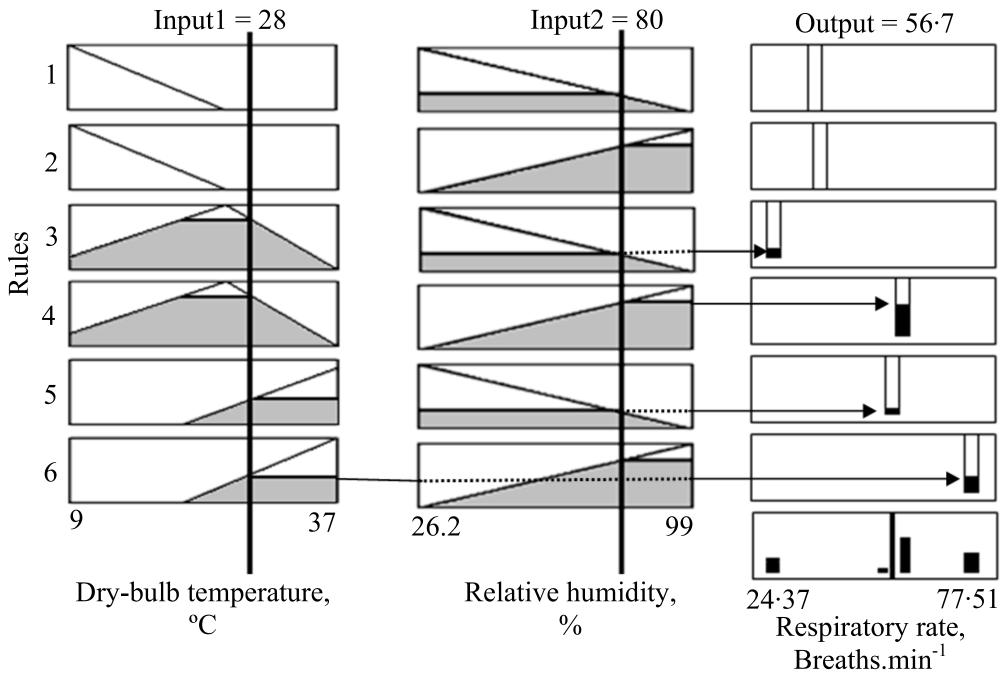


Fig. 2. Example of the interactive interface generated by the fuzzy logic toolbox.

In the example presented, the t_{db} was 28ºC, 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.

Similar to the other models, the FRs between the values for t_{rectal} and *RR* predicted by the NFNs and the means of the literature dataset, means of the experimental dataset, and the means of the combined dataset (means of experimental and literature datasets) are shown in *figures 3d, 4d,* and *5d* and *figures 6d, 7d,* and *8d,* respectively.

In addition to the graphs that illustrate the FRs previously described for the various fitted models, histograms for the frequency of occurrence of absolute deviations for t_{rectal} (*fig. 9*) and *RR* (*fig. 10*) are presented, in addition to the statistical results shown in *table 5*. For t_{rectal}, the frequency of occurrence of absolute deviations in the range from 0 ºC to 0.39 ºC 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.

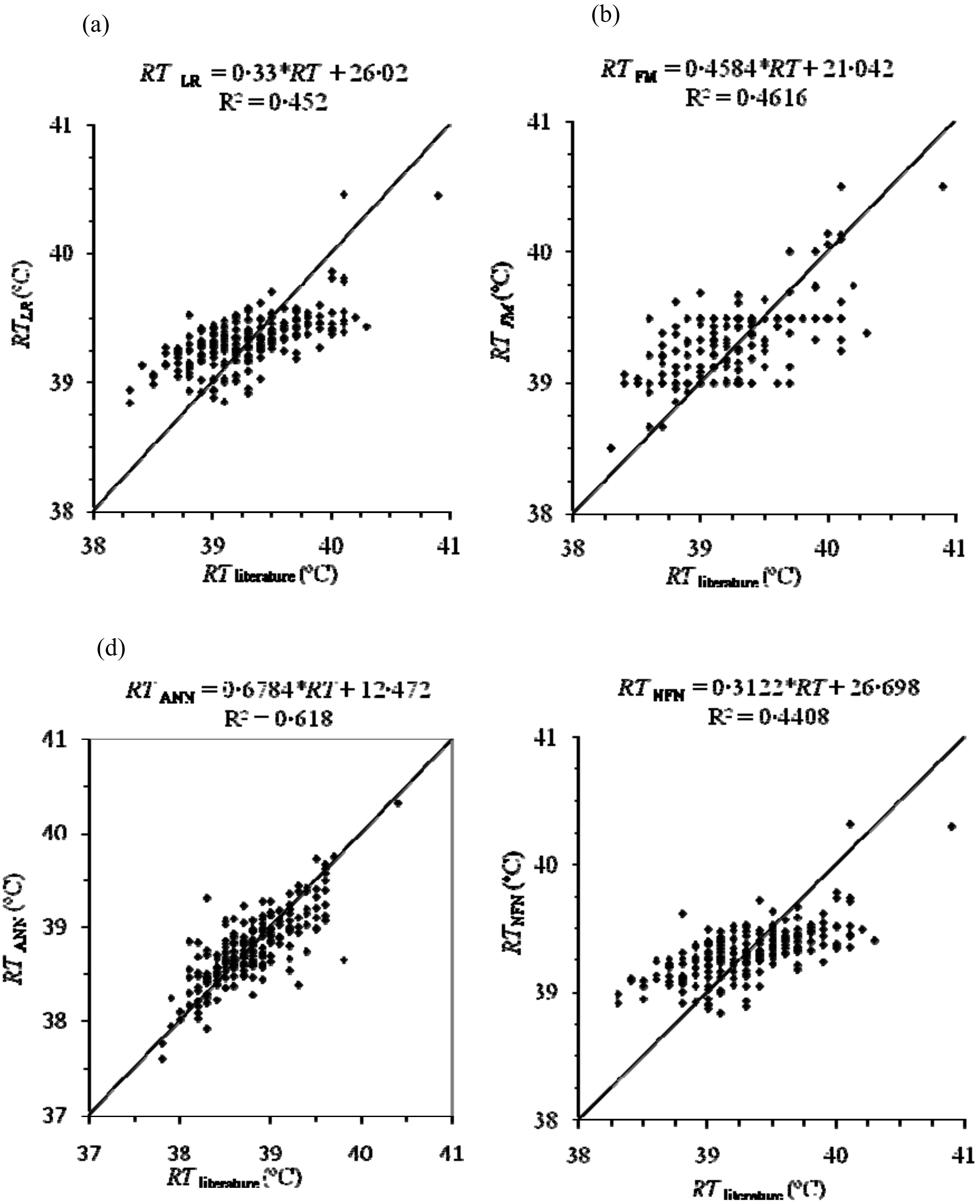


Fig.3.Functional relationship between the values for rectal temperature (t_{rectal}) simulated by the models: regression models (a), fuzzy model (b), artificial neural network (c), neuro-fuzzy network (d) and the means of the literature dataset.

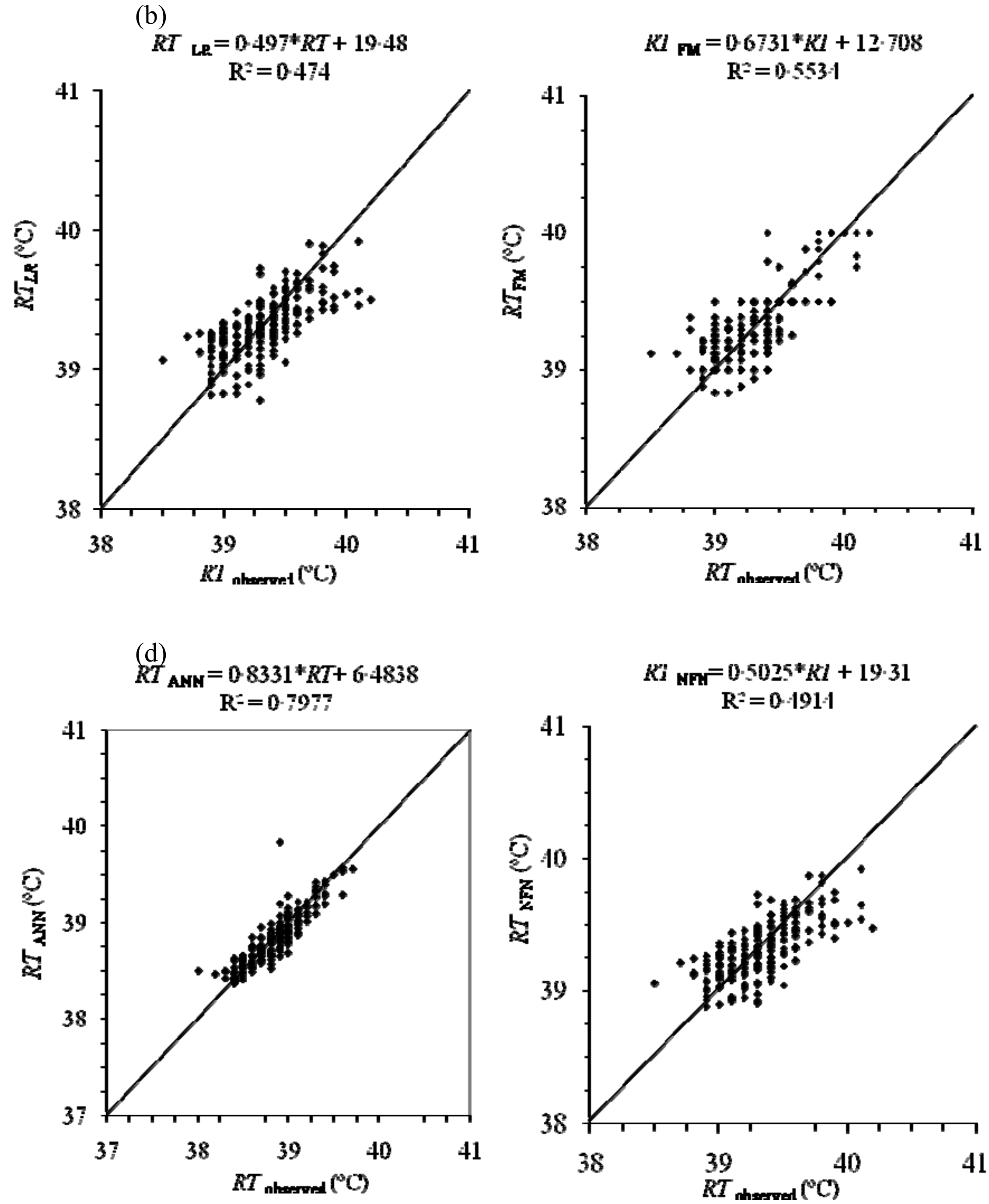


Fig.4.Functional relationship between the values for rectal temperature (t_{rectal}) simulated by the models: regression models (a), fuzzy model (b), artificial neural network (c), neuro-fuzzy network (d) and the means of the experimental dataset

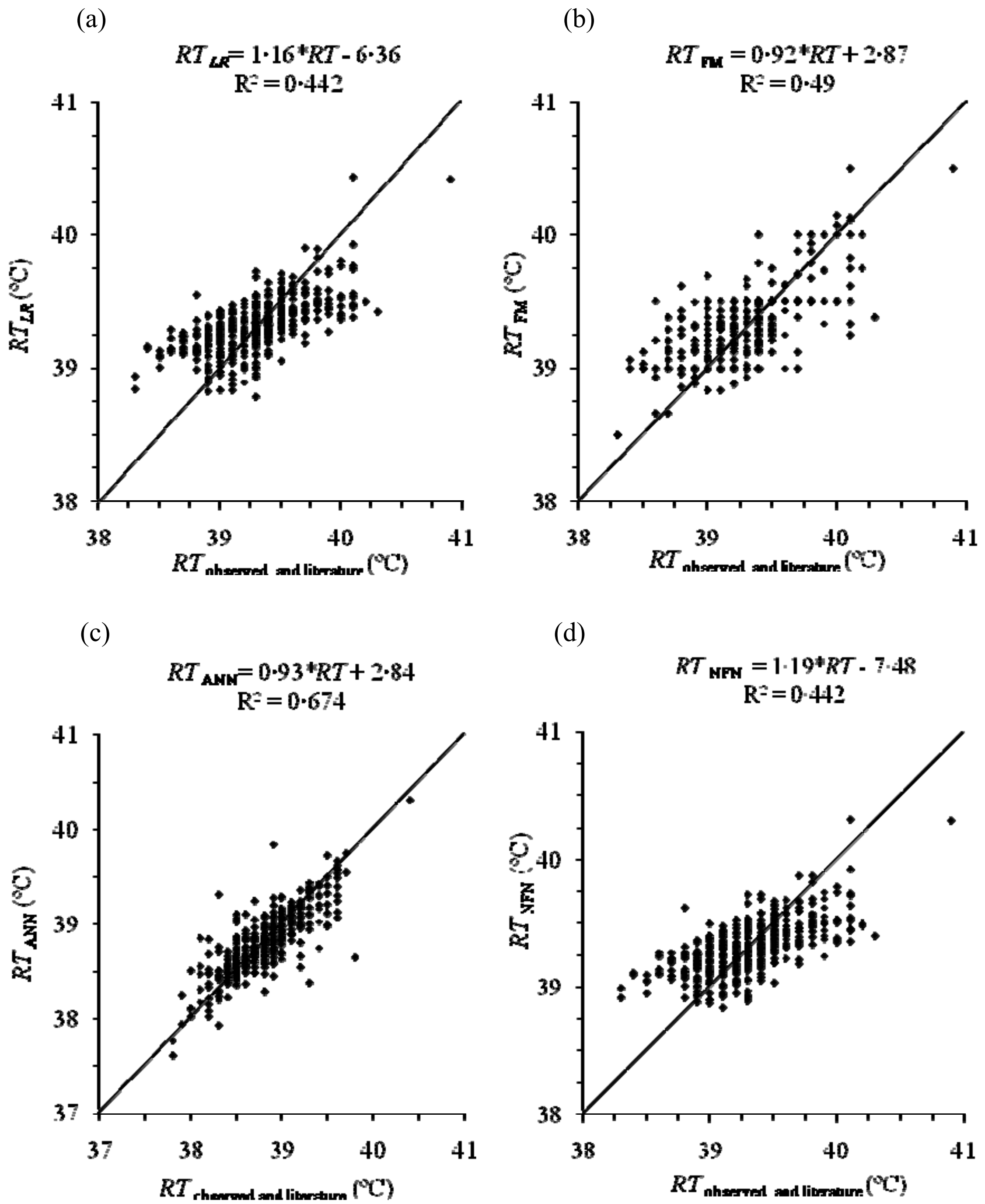


Fig.5. Functional relationship between the values for rectal temperatures (t_{rectal}) simulated by the models: regression models (a), fuzzy model (b), artificial neural network (c), neuro-fuzzy network (d) and the means of the combined dataset.

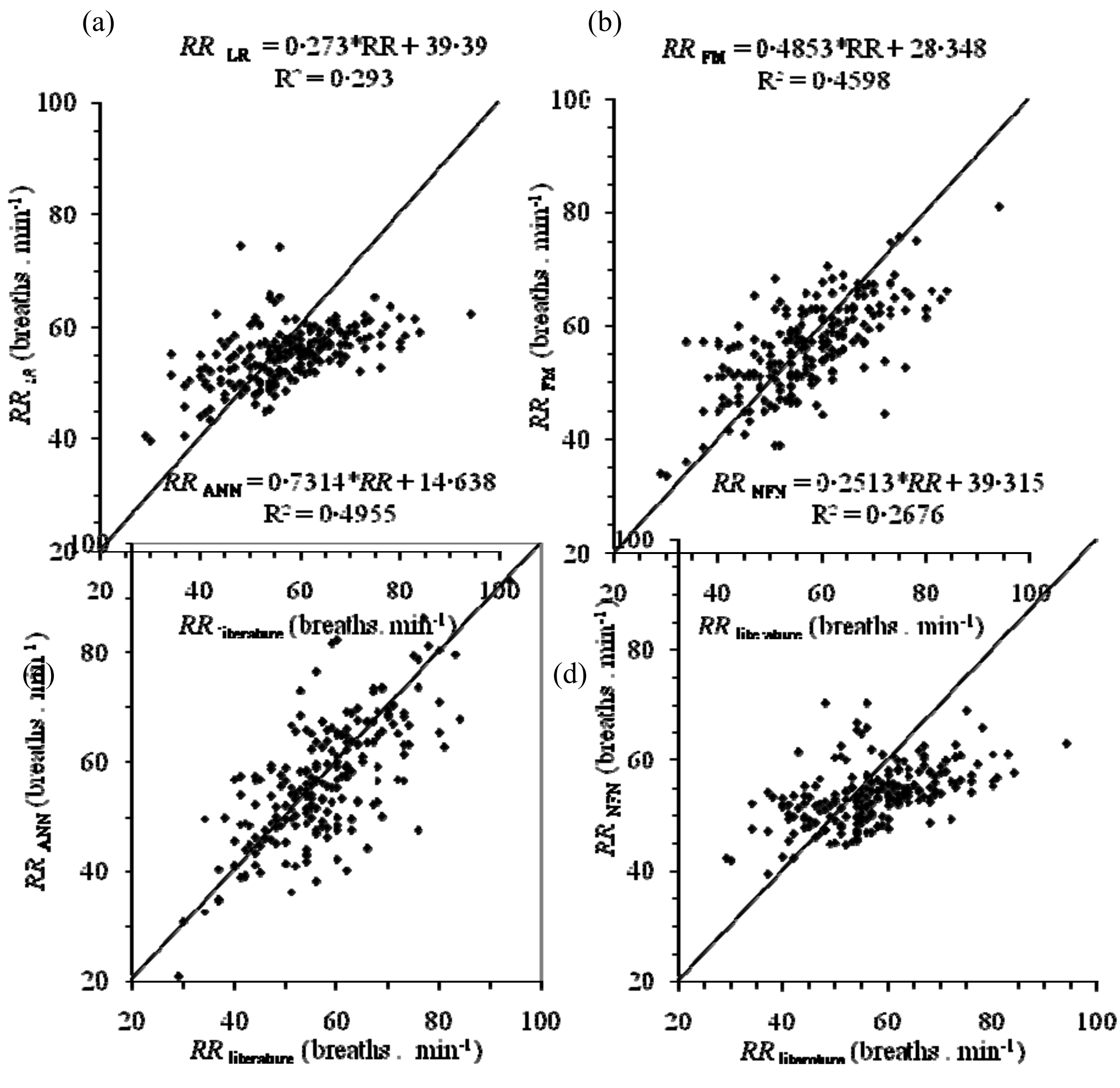


Fig.6. Functional relationship between the values for respiratory rate (RR) simulated by the models: regression models (a), fuzzy model (b), artificial neural network (c), neuro-fuzzy network (d) and the means of the literature dataset.

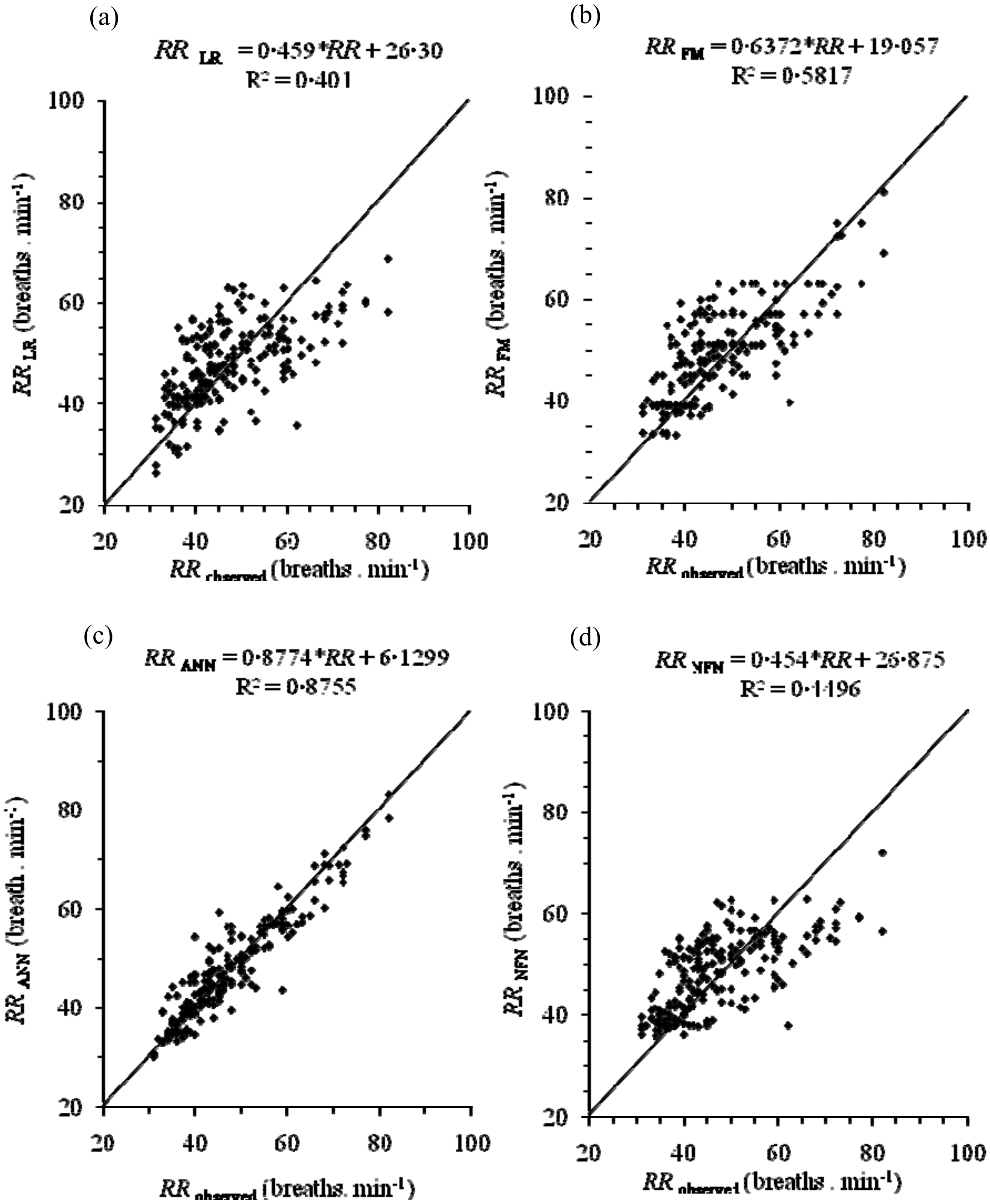


Fig.7.Functional relationship between the values for respiratory rate (RR) simulated by the models: regression models (a), fuzzy model (b), artificial neural network (c), neuro-fuzzy network (d) and the means of the experimental dataset.

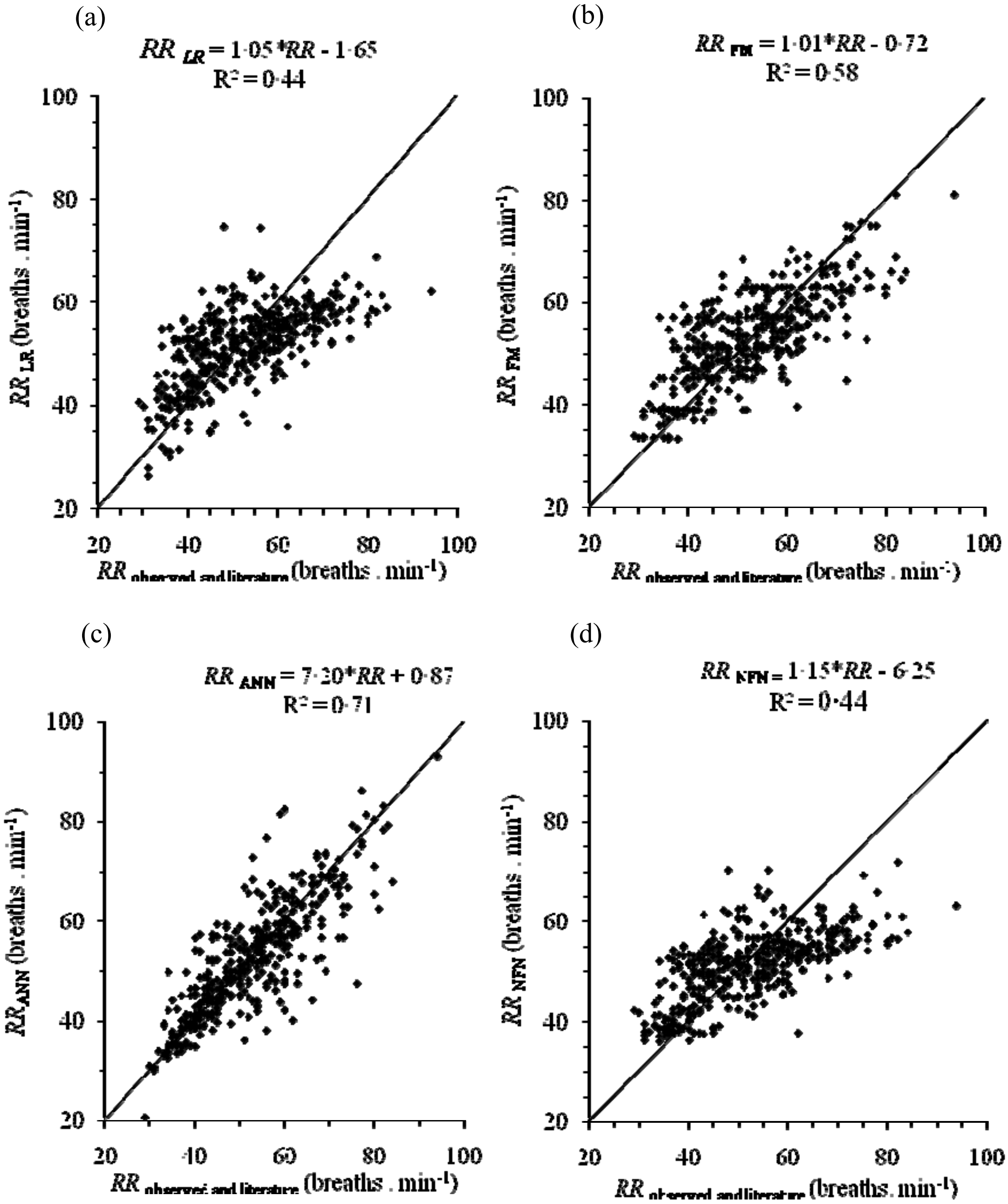


Fig. 8.Functional relationship between the values for respiratory rates (RR) simulated by the models: regression models (a), fuzzy model (b), artificial neural network (c), neuro-fuzzy network (d) and the means of combined dataset.

(a) (b)

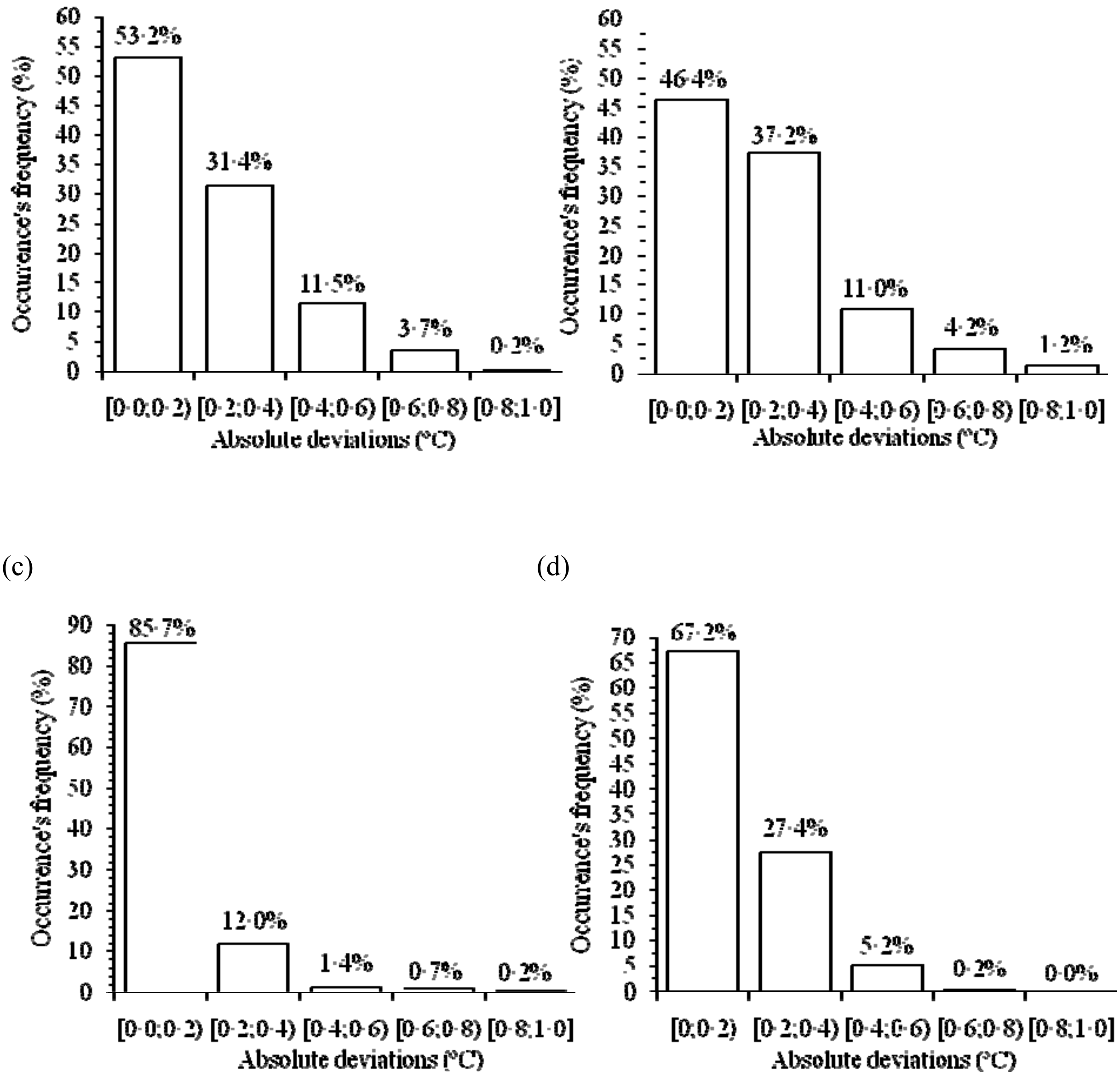


Fig. 9. Frequency of occurrence of absolute deviations (ºC) between the data for rectal temperature simulated by the models: regression models (a), fuzzy model (b), artificial neural network (c), neuro-fuzzy network (d) and the means of the combined dataset.

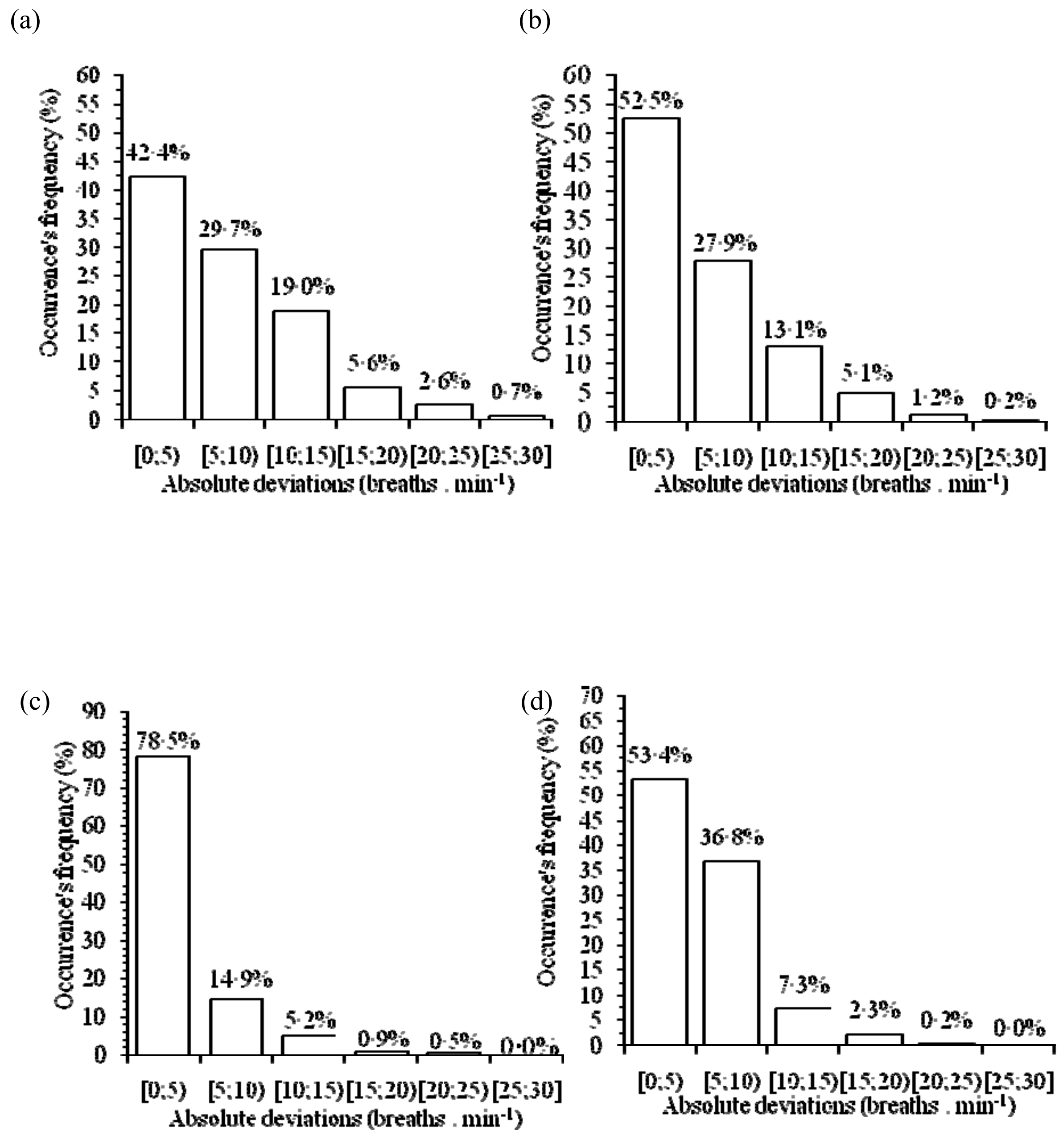


Fig. 10.Frequency of occurrence of absolute deviations (breaths . min^{-1}) between the data for respiratory rate simulated by the models for the regression models (a), fuzzy model (b), artificial neural network (c), neuro-fuzzy network (d) and the means of the combined dataset.

Table 5.Statistical results of the models.

Output variables			Model type			
			Regression model (RM)	Fuzzy model (FM)	Artificial Neural Network (ANN)	Neuro-Fuzzy Network (NFN)
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)	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	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 ($P<0.05$).

Table 6.Performance of models for predicting the physiological variables cited in literature.

Author(s)	Physiologic response.	Model type: RM	FM	ANN	NFN
Ferreira, Yanagi-Junior, Lopes, Lacerda, (2010).	t_{rectal} in broilers chicken. (ºC)	N/A	N/A	N/A	Mean standard deviation: 0.11
Brown-Brandl, Jones, Woldt, (2005)	*RR* in different breeds' cattle. (breaths.min^{-1}).	Linear regression: R^2: 0.59, mean error: 1.14 Quadratic Regression: R^2: 0.62, mean error: 0.91	Mandani: R^2: 0.27, Mean error: 8.0 Sugeno: R^2: 0.66, Mean error: 0.92	R^2: 0.68 Mean error: 1.04	N/A
Ponciano, Yanagi Junior, Schiassi, Lima, Texeira, (2012).	t_{rectal} in broilers chicken.	R^2 RM1~RM4 = 0.73 Mean standard deviation: RM1: 0.32ºC RM2: 0.35ºC RM3: 0.69ºC RM4: 0.38ºC Mean percentage error: RM1: 0.79% RM2: 0.86% RM3: 1.68% RM4: 0.94% Standard deviation: RM1: 0.22ºC RM 2: 0.25ºC RM 3: 0.49ºC RM 4: 0.27ºC	N/A	N/A	N/A
Ferreira, Yanagi-Junior, Lacerda, Rabelo, (2011).	Cloacal temperature in broilers chicken.	N/A	R^2: 0.9318 Mean error: 0.13ºC Percentage error: 0.31%	N/A	N/A
Martello, (2006).	*RR* in Holstein cattle.	R^2: 0.43	N/A	N/A	N/A
Azevedo et al., (2005).	*RR*,t_{rectal} and *CT* in Holstein cattle.	$R^2_{RR} = 0.62$ $R^2_{CT} = 0.31$ $R^2 t_{rectal} = 0.43$	N/A	N/A	N/A

N/A, not available. RM, regression models. FM, fuzzy model. ANN, artificial neural networks. NFN, neuro-fuzzy network. *CT*, coat temperature. *RR*, respiratory rate. R2, determination coefficient. t_{rectal}, rectal temperature.

5. 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 (graphs representing the histograms of frequency of occurrence of absolute deviations shown in *figs. 9* and*10;* scatter plots with trend line/linear regression (LR) shown in *figs. 3, 4, 5, 6, 7,* and *8;* and the statistical indices shown in *table 5*). 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} (*figs. 3, 4, 5,*and *9*) and *RR* (*figs.6, 7,* and *8*) for dairy cows. Although the majority of statistical indices for RR were better for FM than for NFN (*table 5*), the predictions of the NFN concentrated errors over a smaller range of absolute deviation, from 0.0 to 9.9 respirations min^{-1} (*figs.10b* and *10d*). 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 5* and *figs.9* and *10*). 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 (*figs. 3* and *4*, respectively). 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 ºC and 0.39 ºC, and the remaining 2.3% of the deviations were between the values 0.4 ºC and 1.0 ºC (*fig. 9c*), 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 ºC and 0.39 ºC, and the remaining 5.4% of the deviations were between the values of 0.4 ºC and1.0 ºC (*fig. 9d*). 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 ºC to 0.39 ºC, and the remaining 15.4% and

16.4% of the absolute deviations were between the values of 0.4 ºC and 1.0 ºC (*figs. 9a* and *9b*), 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} (*fig. 10c*). 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} (*fig. 10d*). 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 (*figs. 10b* and *10a*).

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 (*table 6*), 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 (*table 6*). 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}.

6. Conclusions

Of the models developed, those based on ANNs and NFN showed, in that order, the fewest prediction errors, and the average standard deviations were 0.1ºC and 0.2ºC 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 ºC to 0.39 ºC 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.

FUNDING SOURCES

The authors express their deep thanks to the National Council for Scientific and Technological Development – CNPq, the Ministry of Foreign Relations, and the Co-ordination for Improvement of Higher Level Personnel – CAPES for the study fellowship for master's candidate Yamid Fabián Hernández Julio through the Graduate Student Agreement program – PEC-PG. The authors would also like to thank CNPq for a research grant (PQ2) to the second author.

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APPENDIXES

APPENDIX A

Appendix A. Developed regression models.

Developed regression models.	Coefficients of Determination (R^2). 70% Analysis data 4·673 obs.		30% validation data. 2·003 obs.		100% test data. 427 means.	
	t_{rectal}	RR	t_{rectal}	RR	t_{rectal}	RR
1) $y = a + b \cdot t_{db} + c \cdot R_H$	0·211	0·274	0·185	0·237	0·404*	0.443
2) $y = a + b \cdot t_{db} \cdot R_H$	0·200	0·158	0·182	0·127	0·330*	0·056*
3) $y = a + b \cdot t_{db} + c \cdot R_H + d \cdot (t_{db} \cdot R_H)$	0·211	0·276	0·188	0·237	0·403	0·430
4) $y = a + b \cdot t^2_{db} + c \cdot R^2_H$	0·215	0·272	0·183	0·238	0·410*	0·437*
5) $y = a + b \cdot t_{db} + c \cdot R_H + d \cdot (t_{db} \cdot R_H)^2$	0·214	0·283	0·194	0·245	0·389*	0·382*
6) $y = a + b \cdot t^2_{db} + c \cdot R_H$	0·218	0·271	0·192	0·236	0·436*	0·438*
7) $y = a + b \cdot t_{db} + c \cdot R^2_H$	0·209	0·275	0·178	0·239	0·389*	0·443*
8) $y = a + b \cdot t_{db} \cdot R_H + c \cdot (t_{db} \cdot R_H)^2$	0·208	0·173	0·185	0·149	0·324	0·043*
9) $y = a + b \cdot t_{db} + c \cdot t^2_{db}$	0·110	0·263	0·095	0·226	0·113	0·437
10) $y = a + b \cdot t_{db} + c \cdot t^2_{db} + d \cdot t^3_{db}$	0·110	0·263	0·095	0·226	0·113	0·437
11) $y = a + b \cdot t_{db} + c \cdot R_H + d \cdot R^2_H$	0·211	0·275	0·187	0·242	0·403	0·442*
12) $y = a + b \cdot t_{db} + c \cdot R_H + d \cdot R^2_H + e \cdot R^3_H$	0·217	0·276	0·193	0·242	0·386*	0·436*
13) $y = a + b \cdot t_{db}$	0·096	0·258	0·123	0·234	0·115*	0·437*
14) $y = a + b \cdot t_{db} + c \cdot R_H + d \cdot t^2_{db}$	0·217	0·264	0·195	0·258	0·440	**0·445***
15) $y = a + b \cdot t_{db} + c \cdot R_H + d \cdot t^2_{db} + e \cdot R^2_H$	0·216	0·276	0·207	0·242	**0·444***	0·443
16) $y = a + b \cdot t^2_{db} + c \cdot R_H + d \cdot R^2_H$	0·218	0·260	0·203	0·263	0·438	0·437
17) $y = a + b \cdot t_{db} + c \cdot R_H + d \cdot t^2_{db} + R^2_H + f \cdot (t_{db} \cdot R_H)$	0·224	0·284	0·211	0·291	0·420*	0·366*
18) $y = a + b \cdot R_H + c \cdot t^2_{db} + d \cdot R^2_H + e \cdot (t_{db} \cdot R_H)$	0·220	0·276	0·191	0·274	0·433	0·420

t_{db}, drybulb temperature. *RH,* relative humidity. t_{rectal}, rectal temperature. *RR*, respiratory rate. (a,b,c,d), variables coefficients. obs, observed. *, all coefficients are significant (P<0.05).