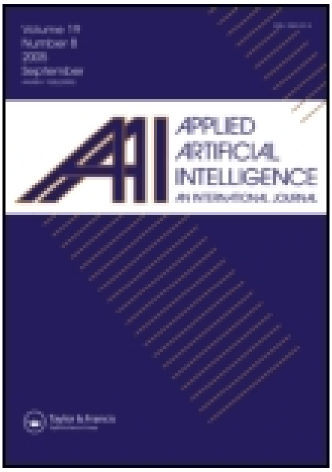

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MODELS FOR PREDICTION OF PHYSIOLOGICAL RESPONSES OF HOLSTEIN DAIRY COWS

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□ *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 (5884 data points) were used to fit and validate the models. Each datum included dry bulb air temperature, relative humidity, rectal temperature, and respiratory rate. Two models based on artificial intelligence—artificial neural networks and neurofuzzy 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. These models were compared using statistical indices. The model based on artificial neural networks showed the best performance, followed by the models based on neurofuzzy networks and regression; the last two performed similarly.*

INTRODUCTION

In 2010, Brazil was considered the fifth leading producer of milk in the world, with an annual production of 31.6 billion liters of milk, and the state of Minas Gerais led production for the country (EMBRAPA 2013). The growth was accompanied by an increase in internal consumption per capita of approximately 1.59% annually and by an increase in exports (Gama 2010).

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According to Souza et al. (2004), the likelihood of animals suffering thermal stress in countries such as Brazil, located in an intertropical zone (hot and humid climates), is high, especially for bovines of European breeds.

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 the 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 Da 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 at 24°C.

Within the thermoneutrality zone, the animal reaches its maximum potential, and body temperature is maintained with minimal use of thermoregulatory mechanisms playing a fundamental role in obtaining the proper climatic conditions for animal production (Curtis 1983). When conditions are not within these proper limits, the environment becomes uncomfortable. Under these conditions, dairy cows reduce their feed intake and consequently their milk production (Harner et al. 2009). In addition to these consequences, Sweating and panting are some of the mechanisms these animals use to relieve thermal stress, losing considerable amounts of sodium and potassium through sweat and urine (Pires and Campos 2008), suffering changes in rectal temperature (t_{rectal}) and in respiratory rate (RR) (Perissinotto and Moura 2007), compromising future productivity, even if environment conditions are returned to acceptable levels (Curtis 1983; Kazdere et al. 2002; West 2003; Hansen 2007).

For these reasons, it is critical that tools (models) be developed that assist dairy producers in making decisions to maintain the production environment within the zone of thermoneutrality for the animals in order to obtain maximum production. These models include empirical mathematical models, such as regression models (RMs), artificial neural networks (ANNs) and neurofuzzy networks (NFNs) that can assist in the control of ventilation and evaporative cooling systems. In this context, the aim of this study was to develop and validate RMs and models based on artificial intelligence to predict the t_{rectal} and RR as functions of the two meteorological variables dry bulb air temperature (t_{db}) and relative humidity (RH), for black and white Holstein dairy cows kept in confinement.

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 broiler chickens (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, Jones, and Woldt 2005).

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, Stinchcombe, and 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 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, Jones, and Woldt 2005), and growth performance in swine (Bridges et al. 1995) and in humans (Moustris et al. 2010). ANNs have been used in predicting leather handle (Wang et al. 2011), discriminating varieties of tea plant (Li and He 2008), classifying genera and identifying species in mosquitoes (Venkateswarlu, Kiran, and Eswari 2012), estimating leaf chlorophyll concentration in rice under stress from heavy metals (Liu et al. 2010), modeling total volume of dominant pine trees in reforestations (Diamantopoulou and Milios 2010), predicting the draught requirement of tillage implements in sandy clay loam soil (Roul et al. 2009), predicting nitrate release from polymer-coated fertilizers (Du et al. 2008), and analyzing thermodynamic properties of refrigerants (Şahin, Köse, and Selbaş 2012).

ANNs have also been found to be useful in construction (Argiriou, Bellas-Velidis, and Balaras 2000), in demand analysis in the form of forecasting (Efendigil, Önüt, and Kahraman 2009), in controlling drug delivery systems (Rafienia et al. 2010), and in predicting ph in seawater along a Gaza beach (Adel Zaqoot et al. 2010), among many other applications.

The multilayer perceptron (MLP) is the most commonly used architecture for developing an ANN (Fausett 1994; Barreto 2002; Von Zuben 2003) and contains input, hidden, and output layers.

Neurofuzzy 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 Fuzzy Logic [FL]), including human thermal comfort (Chen, Jiao, and Lee 2006), control and automation systems (Cheng-Hung, Cheng-Jian, and Chin-Teng 2009), the decision support system for demand forecasting (Efendigil, Önüt, and Kahraman 2009), thermal comfort for birds (Ferreira 2009), the prediction of t_{rectal} of broiler chickens (Ferreira et al. 2010), in statistics (Khashei, Reza Hejazi, and Bijari 2008), in hydrology (Kurtulus and Razack 2010), to analyze livestock farm odor (Pan and Yang 2007), in analysis of thermodynamic properties of refrigerants (Şahin, Köse, and Selbaş 2012) and in robotics (Zacharia 2010).

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 (Pires 1997; Pires and Campos 2003; Da Silva et al. 2002; Martello et al. 2004; Matarazzo 2004; Martello 2002; Perissinotto 2003) 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.

In this work, the total dataset, called the combined dataset (6676 pieces of information), was conformed for data obtained from literature, also called the 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 the experimental dataset (5884 pieces of information). In these experiments, 346 purebred multiparous Holstein cows, in different stages of lactation, were used. The data from the literature were obtained from 128 multiparous 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 fit the Köppen climatic classification of Cwa, with dry and cold winters and hot and humid summers. The data used in this study covered a total period of six (6) years.

To train, validate, and test the models based on ANN and NFN, the combined dataset was used. This dataset was randomly divided into three subsets (training, validation, and testing) through subroutines created for this purpose. These subsets were used to model the ANNs and NFN. The training set used 70% of the combined dataset (4674 independent data points); the sets for validation and testing each used 15% (1001 data points each), for a total of 2002 data points from the total set (combined dataset).

For the models based on regression, 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 the 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). These percentages of the subsets were chosen because they are the most common for mathematical modeling of systems (Brown-Brandl, Jones, and Woldt 2005).

Mathematical Modeling

To develop the models based on ANN and NFN, the combined dataset was used, whereas for RM, the means of the combined dataset were used.

Once developed, the models were tested using the minimum, mean, median, and maximum values; standard deviations 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 2). In addition, histograms (Figures 8 and 9) and graphs of the functional relationships (FRs) between (with line of linear trend) predicted and observed variables (means of the combined dataset) (Figures 2, 3, 4, 5, 6 and 7) were used to compare the performance of the proposed models.

Regression Models

Eighteen multiple RMs (Appendix A) were fit using the regression procedure of the statistical software R (R Development Core Team 2012). 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).

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 Levenberg–Marquardt backpropagation algorithm (MathWorks, Inc 2013). 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 learning rate, the momentum rate, and the neurons' weights (these parameters were chosen as standard and were 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 (one per output variable) predict the t_{rectal} and RR based in the input variables (t_{db} and RH). Each neural net has one output.

Neurofuzzy 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 2011). 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 backpropagation 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 (backpropagation 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

Regression Models

Of the 18 RMs fit to predict the t_{rectal} and RR (Appendix A), the models represented by Equation (1) and Equation (2) (models number 15 and 14 of Appendix A, respectively) 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} (°C), Equation (1), 21.6% of the variation in t_{rectal} can be explained by the variation in t_{db} (°C) and RH (%) when testing 70% of the data (299 pieces of information) used for fitting; the values were 20.7% when testing 30% of the data (128 pieces of information) used for validation and 44.4% when testing 100% of the data (Appendix A, Table 2).

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

In turn, 26.4% of the variation in the RR can be explained by the variation in t_{db} (°C) 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 2).

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

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 2a, 3a, 4a and Figures 5a, 6a, and 7a, respectively.

Artificial Neural Network System

The architectures of the best-performing final ANN models for predicting t_{rectal} and RR were multilayer networks (MLP) with two feed-forward layers and supervised training (with knowledge of the desired output) using the Levenberg–Marquardt backpropagation 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 with the fewest prediction errors were 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 hidden 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 2b, 3b, and 4b and Figures 5b, 6b, and 7b, respectively.

Adaptive Neurofuzzy Inference System

Various NFN models were developed and simulated using different configurations, such as the type of pertinence function (Gaussian, triangular or trapezoidal, etc.), the number of epochs, 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 1. The hybrid training (optimization) method was selected based on a tolerance to error of 0.0 and number of stages of 1000. Training was interrupted when the training error stabilized. The pertinence function with the best performance for the input variables was the triangular function, and the best output function for the output variables was constant. 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 1).

Figure 1 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.

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} (Figure 1a) and RR (Figure 1b). 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

TABLE 1 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				
(a)	**[Input 1]**	**[Output]**	**tdb**	**RH**	**Out**	**W**	**Con.**
<Name>fuzzy sets t_{rectal} – FIS	<Name>t_{db}	<Name>t_{rectal}					
<type>TS	<Range>9 - 37	<Range>37·5 – 40·4	1	1	1	1	1*
<SNorm>max	<Number MFs>3	<Number MFs>6					
<SNormPar>0	<Function>trimf	<Function>constant	1	2	2	1	1
<TNorm>min	<NameMF1><in1MF1>	<NameMF1><out1MF1>					
<TNormPar>0	−5.0 10.3 24.0	38.3	2	1	3	1	1
<Comp>sugeno	<NameMF2><in1MF2>	<NameMF2><out1MF2>					
<CompPar>0	7.9 25.6 36.9	38.4	2	2	4	1	1
<ImpMethod>prod	<NameMF3><in1MF3>	<NameMF3><out1MF3>					
<AggMethod>max	22.3 7.8 51.0	37.9	3	1	5	1	1
<defuzzMethod>waver	**[Input 2]**	<NameMF4><out1MF4>					
	<Name>RH	39.2	3	2	6	1	1
	<Range>26.2 – 99	<NameMF5><out1MF5>					
	<Number MFs>2	39.1	*It means: If t_{db} MF1 and RH MF1 then t_{rectal} MF1.				
	<Function>trimf	<NameMF6><out1MF6>					
	<NameMF1><in2MF1>	39.8					
	−46.6 26.3 98.9						
	<NameMF2><in2MF2>						
	26.1 99.1 171.8						
(b)	**[Input 1]**	**[Output]**	**tdb**	**RH**	**Out**	**W**	**Con.**
<Name>fuzzy sets RR-FIS	<Name>	<Name>RR					
<type>TS	<Range>9 – 37	<Range>20 – 116	1	1	1	1	1*
<SNorm>max	<Number MFs>3	<Number MFs>6	1	2	2	1	1
<SNormPar>0	<Function>trimf	<Function>constant	2	1	3	1	1
<TNorm>min	<NameMF1><in1MF1>	<NameMF1><out1MF1>	2	2	4	1	1

<TNormPar>0	−5.0 16.4 22.0	48.6	3	1	5	1	1
<Comp>sugeno	<NameMF2 t_{db}><in1MF2>	<NameMF2><out1MF2>	3	2	6	1	1
<CompPar>0	7.4 26.0 37.0	28.8					
<ImpMethod>prod	<NameMF3><in1MF3>	<NameMF3><out1MF3>	* It means: If t_{db} MF1 and RHMF1 then RRMF1.				
<AggMethod>max	22.9 38.8 51.0	33.1					
<defuzzMethod>waver	**[Input 2]**	<NameMF4><out1MF4>					
	<Name>RH	57.1					
	<Range>26·2 − 99	<NameMF5><out1MF5>					
	<Number MFs>2	73.1					
	<Function>trimf	<NameMF6><out1MF6>					
	<NameMF1><in2MF1>	70.7					
	−46.6 26.8 98.4						
	<NameMF2><in2MF2>						
	25.6 99.6 171.8						

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.

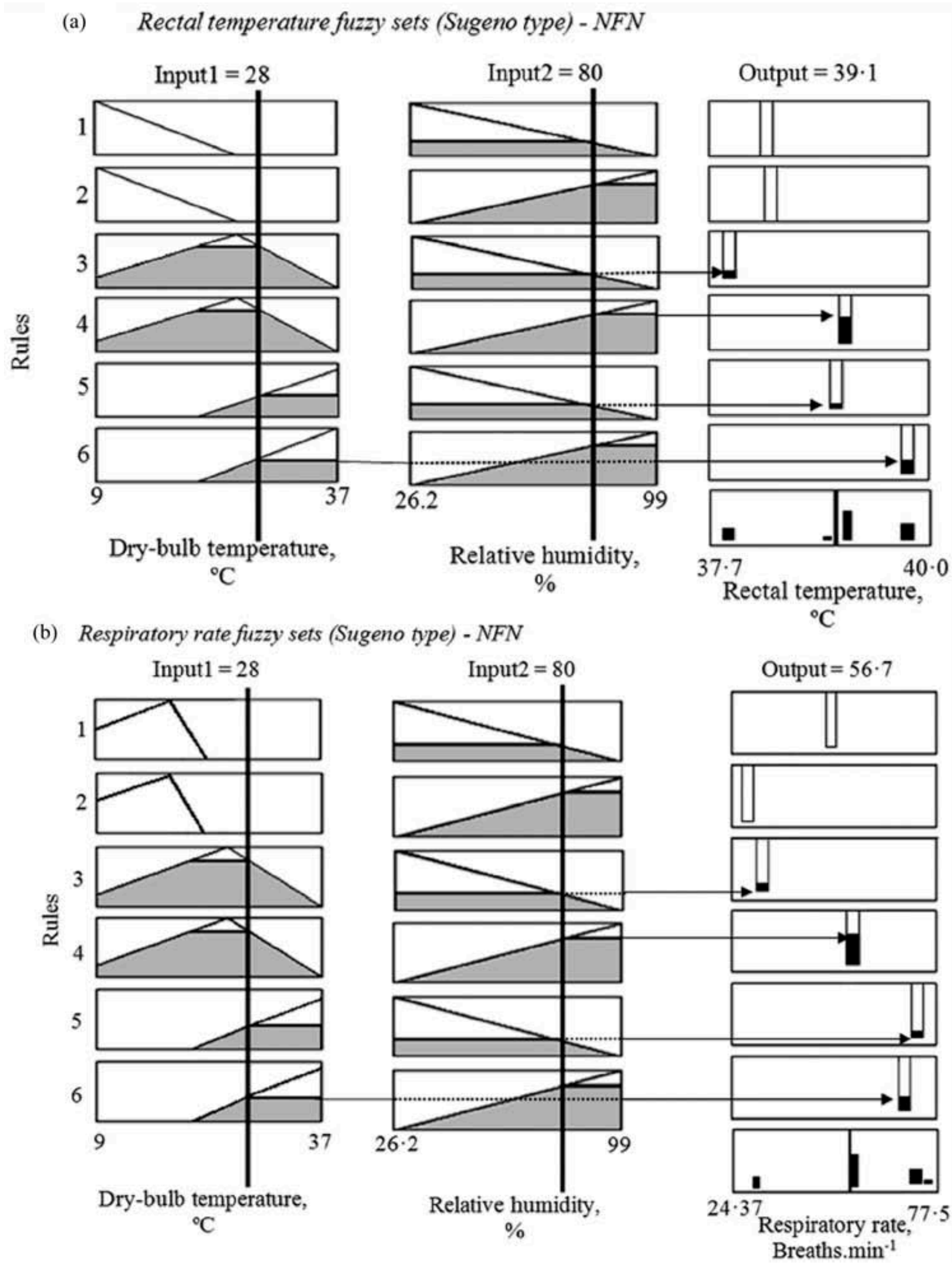

FIGURE 1 An example of the interactive interface generated by the fuzzy logic toolbox, describing the data-dependent fuzzy inference system.

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 Figures 1a and 1b 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 (Brown-Brandl, Jones, and Woldt 2005).

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, the means of the experimental dataset, and the means of the combined dataset (the means of experimental and literature datasets) are shown in Figures 2c, 3c, and 4c and Figures 5c, 6c, and 7c, 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} (Figure 8) and RR (Figure 9) are presented, in addition to the statistical results shown in Table 2. 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 NFN and RMs performed similarly.

DISCUSSION

Three 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 Figures 8 and 9; scatter plots with trend line/linear regression (LR) shown in Figures 2, 3, 4, 5, 6, and 7; and the statistical indices shown in Table 2). 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} (Figures 2, 3, 4, and 8) and RR (Figures 5, 6, and 9) for dairy cows. Although the majority of statistical indices for RR were better for RM than for NFN (Table 2), the predictions of the NFN concentrated errors over a smaller range of absolute deviation, from 0.0 to 9.9 breaths min^{-1} (Figures 8a and 8c). 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.

TABLE 2 Statistical Results of the Models

Output variables			Regression Model (RM)	Artificial Neural Network (ANN)	Neurofuzzy Network (NFN)
			Model Type		
Rectal temperature (t_{rectal})	Absolute deviations	Minimum	0.0	0.0	0.0
		Mean	0.2	0.1	0.2
		Median	0.2	0.1	0.2
		Maximum	0.9	1.1	0.9
	Standard deviation	Minimum	0.0	0.0	0.0
		Mean	0.2	0.1	0.2
		Median	0.1	0.1	0.1
		Maximum	0.6	0.8	0.6
	Percentage error	Minimum	0.0	0.0	0.0
		Mean	0.6	0.4	0.6
		Median	0.5	0.3	0.5
		Maximum	2.2	2.9	2.2
	R^2		0.44	0.67	0.44
	Standard error		0.28	0.21	0.28
	RMSE		0.28	0.21	0.28
	Regression coefficients (Slopes)		1.16*	0.93*	1.19*
			($\pm$ 0.06)	($\pm$ 0.03)	($\pm$ 0.06)
	Intercepts		−6.36*	2.84*	−7.46*
			($\pm$ 2.46)	($\pm$ 1.21)	($\pm$ 2.52)
Respiratory rate (*RR*)	Absolute deviations	Minimum	0.0	0.0	0.0
		Mean	7.1	4.6	7.3
		Median	5.9	3.0	6.3
		Maximum	30.6	28.5	30.8
	Standard deviation	Minimum	0.0	0.0	0.0
		Mean	5.0	3.2	5.2
		Median	4.2	2.1	4.5
		Maximum	21.7	20.2	21.8

Percentage error	Minimum	0.0	0.0	0.1
	Mean	13.8	8.7	14.0
	Median	11.5	5.6	12.9
	Maximum	62.3	62.0	53.5
R^2		0.44	0.71	0.44
Standard error		8.96	6.49	8.99
RMSE		8.98	6.67	9.12
Regression coefficients (Slopes)		1.05*	7.20*	1.15*
		(± 0.06)	(± 1.43)	(± 0.06)
Intercepts		−1.65	0.87*	−6.25
		(± 2.95)	(± 0.027)	(± 3.22)

R^2, determination coefficients. RMSE, root mean square error. *, coefficients are significant (p <0.05), simultaneously if the intercept is close to 0 and slope is close to 1, then the accuracy is higher.

TABLE 3 Performance of Models for Predicting the Physiological Variables Cited in Literature

Author(s)	Physiologic Response Modeled	Model Type					
		RM		FM		ANN	NFN
Ferreira, Yanagi-Junior, Lopes, Lacerda, (2010).	t_{rectal} in broilers chicken. (°C)	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 chicken broilers.	R^2 RM1~RM4 = 0.73 Mean standard deviation: RM1: 0.32°C RM2: 0.35°C RM3: 0.69°C RM4: 0.38°C	Mean percentage error: RM1: 0.79% RM2: 0.86% RM3: 1.68% RM4: 0.94%	Standard deviation: RM1: 0.22°C RM 2: 0.25°C RM 3: 0.49°C RM 4: 0.27°C	N/A	N/A	N/A
Ferreira, Yanagi-Junior, Lacerda, Rabelo, (2011).	Cloacal temperature in chicken broilers	N/A			R^2: 0.9318 Mean error: 0.13°C 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 and HT in Holstein cattle.	$R^2{}_{RR} = 0.62$ $R^2{}_{CT} = 0.31$			N/A	N/A	N/A

N/A, not available. RM, regression models. FM, fuzzy model. ANN, artificial neural networks. NFN, neurofuzzy network. C*T*, coat temperature. *RR*, respiratory rate. R2, determination coefficient. trectal, rectal temperature.

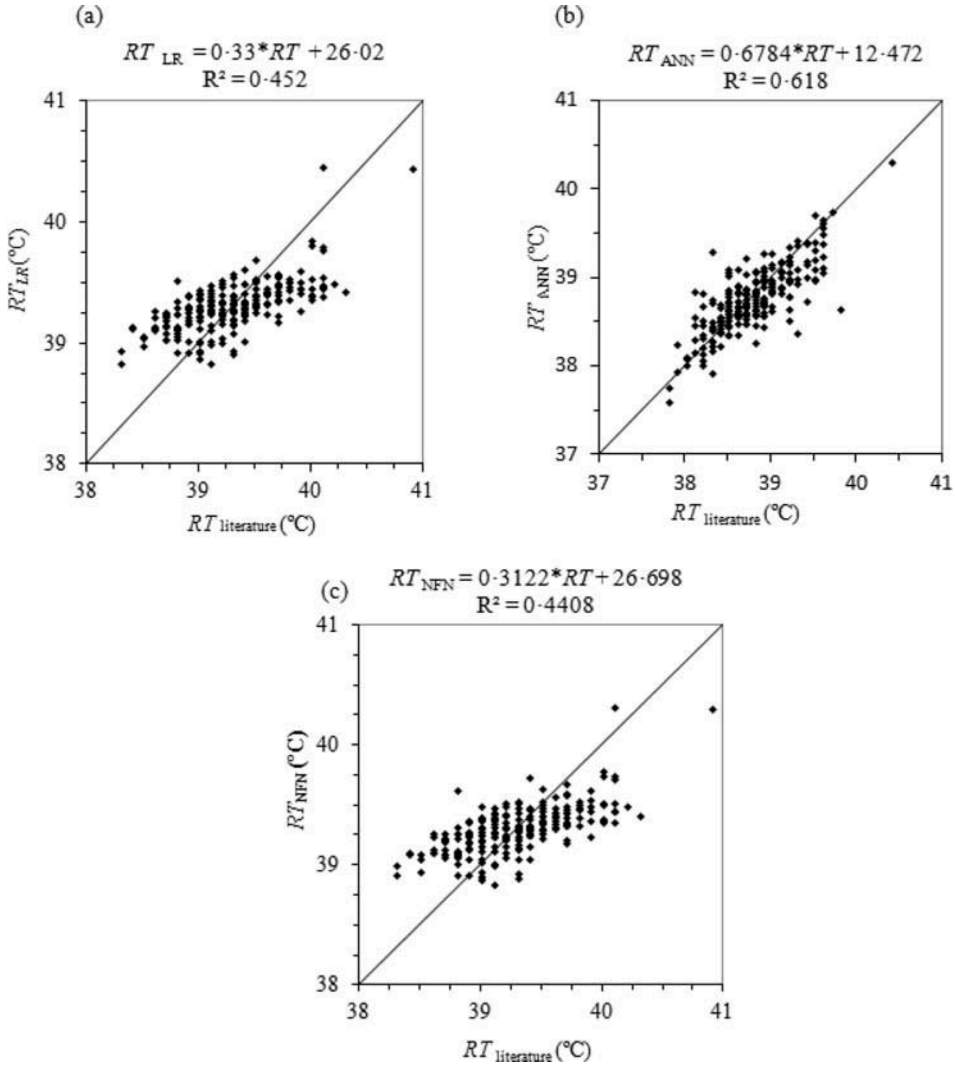

FIGURE 2 Functional relationship between the values for rectal temperature (t_{rectal}) simulated by the models: regression model (a), artificial neural network (b), neurofuzzy network (c) and the means of the literature dataset.

All of the models fitted to predict the t_{rectal} performed better than those fitted to predict the RR (Table 2 and Figures 8 and 9). 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 (Figures 2 and 3, 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 researcher's experiments. The inclusion of air velocity and

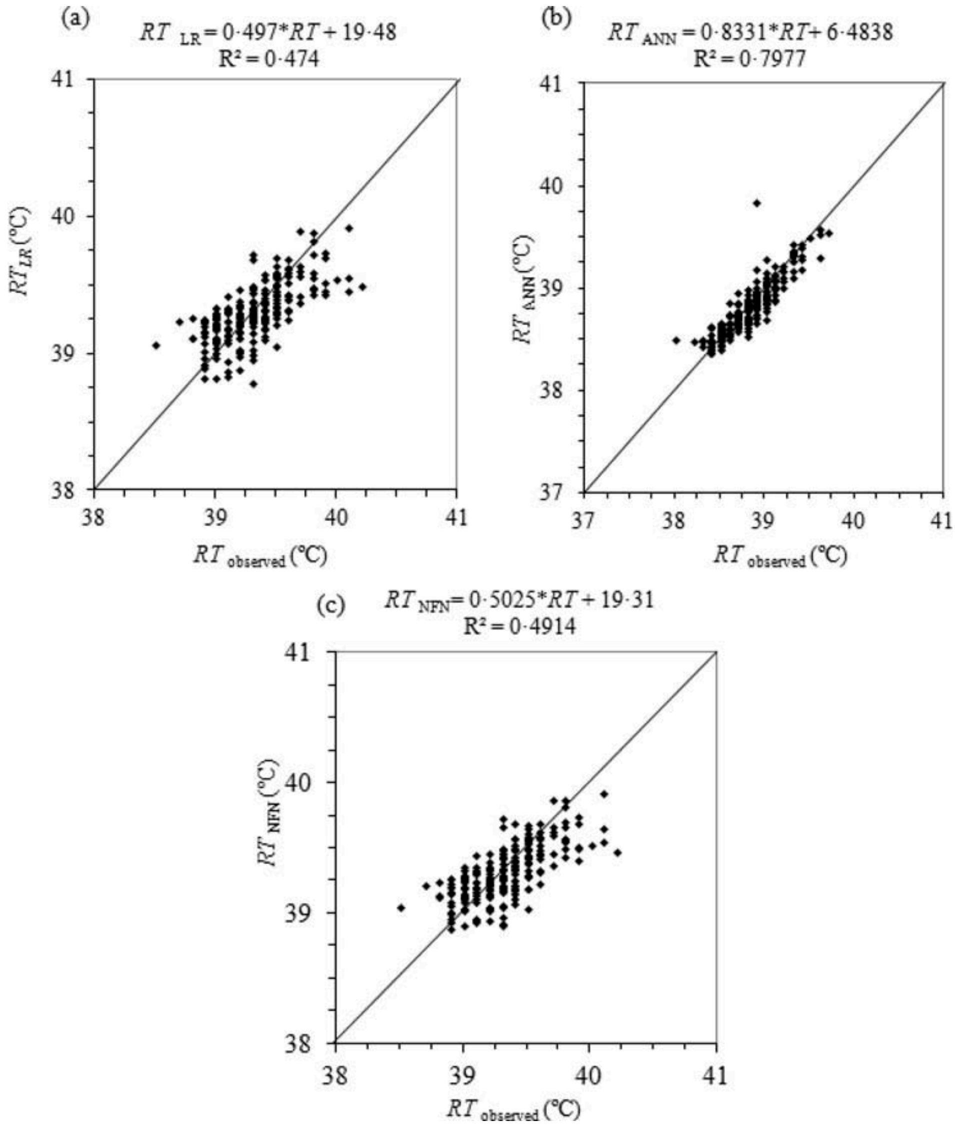

FIGURE 3 Functional relationship between the values for rectal temperature (t_{rectal}) simulated by the models: regression models (a), artificial neural network (b), neurofuzzy network (c) and the means of the experimental dataset.

radioactive 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.

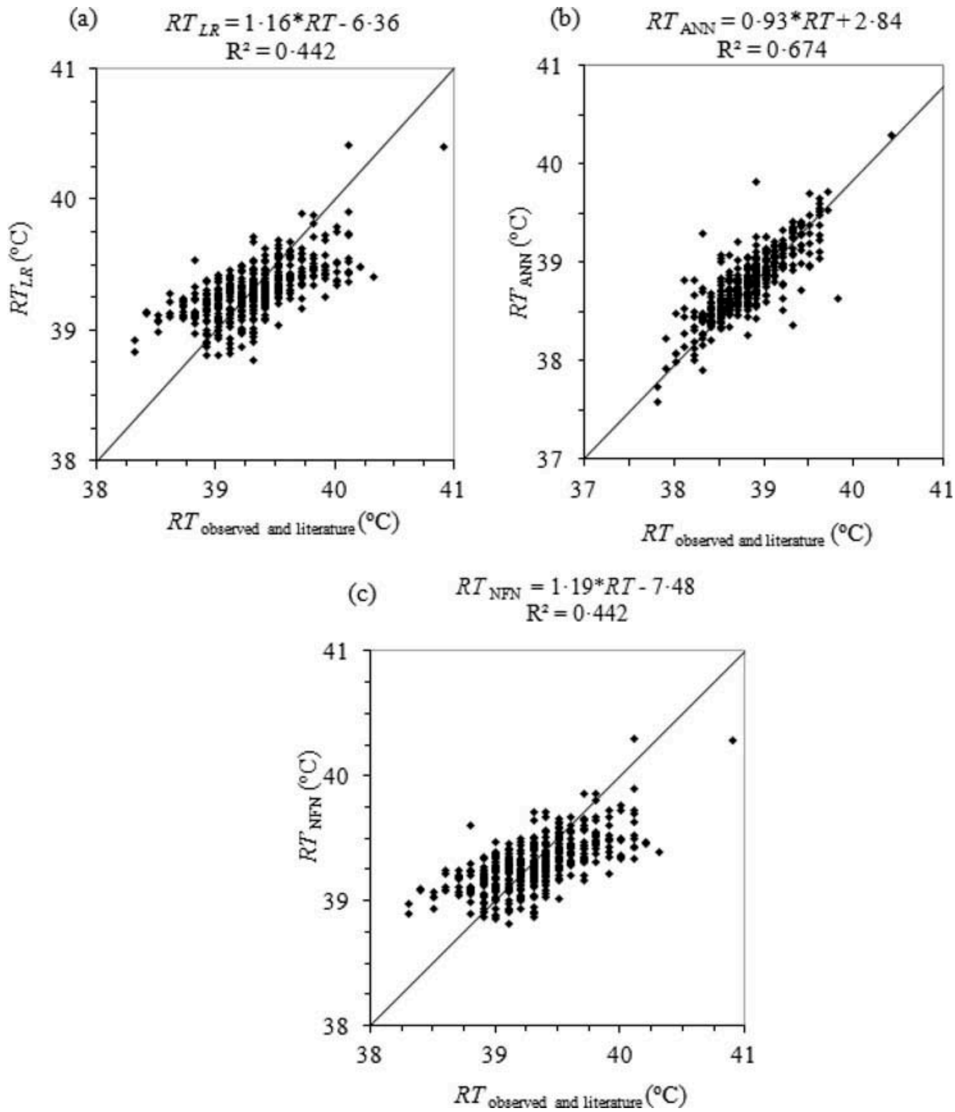

FIGURE 4 Functional relationship between the values for rectal temperatures (t_{rectal}) simulated by the models: regression models (a), artificial neural network (b), neurofuzzy network (c) and the means of the combined dataset.

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 (Figure 8b), thus

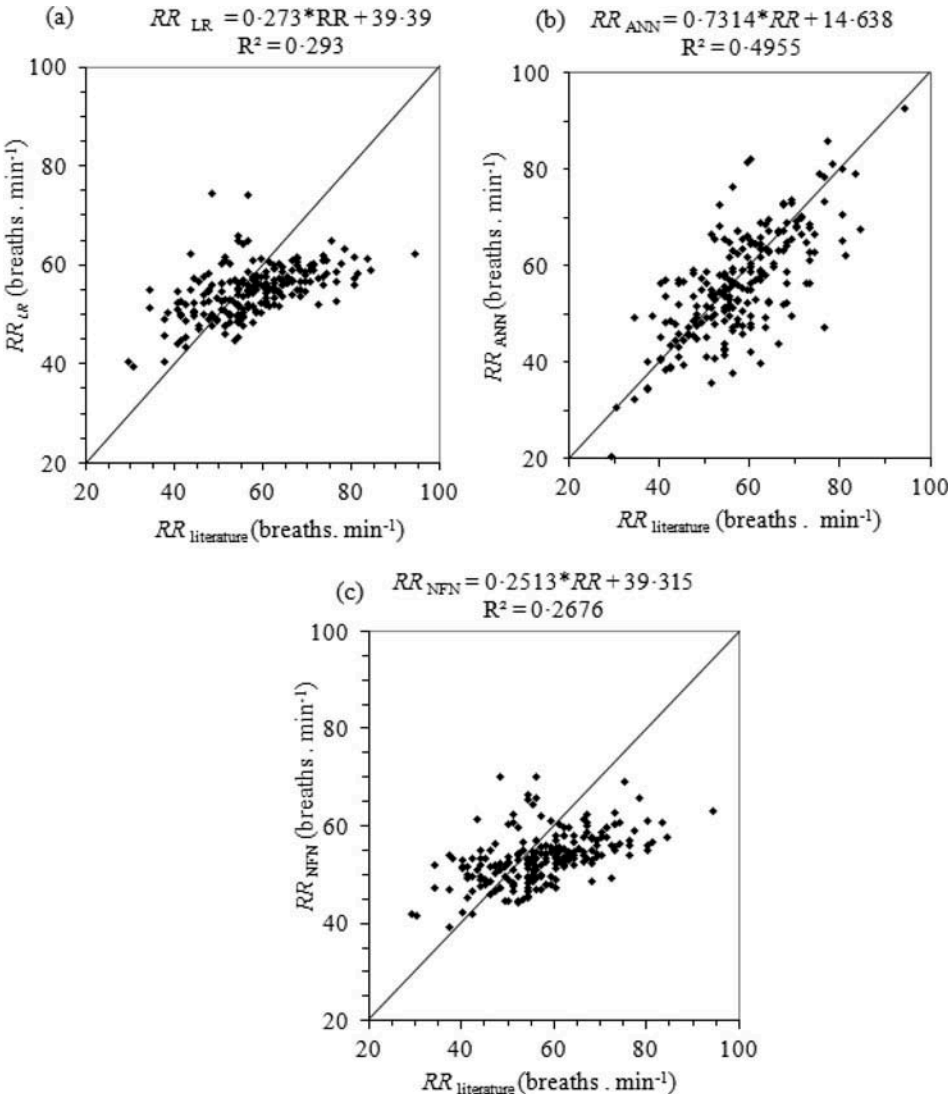

FIGURE 5 Functional relationship between the values for respiratory rate (RR) simulated by the models: regression models (a), artificial neural network (b), neurofuzzy network (c) and the means of the literature dataset.

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 (Figure 8c). The RM performed similarly, for which 84.6% of the absolute deviations were found in the interval from 0.0 °C to 0.39 °C, and the remaining 15.4%

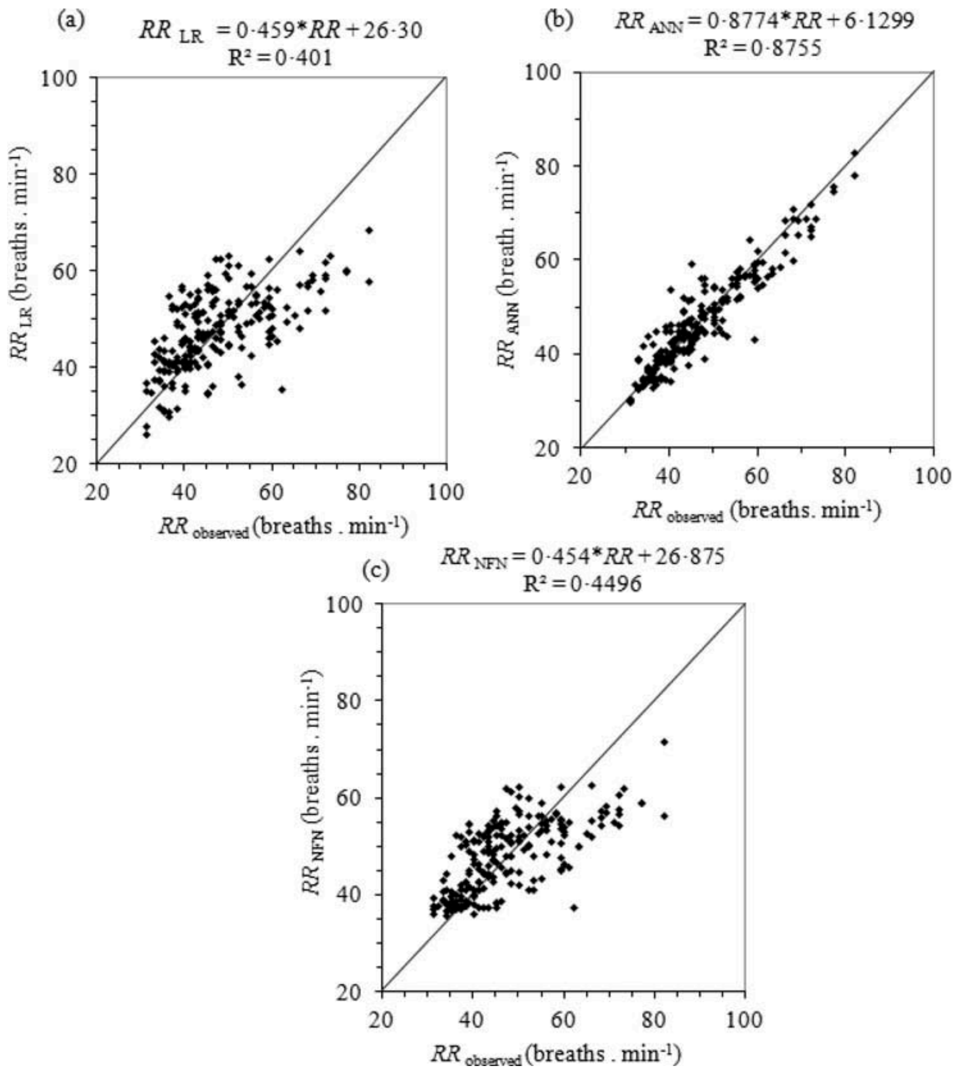

FIGURE 6 Functional relationship between the values for respiratory rate (RR) simulated by the models: regression models (a), artificial neural network (b), neurofuzzy network (c) and the means of the experimental dataset.

of the absolute deviations were between the values of 0.4 °C and 1.0 °C (Figure 8).

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 breaths min^{-1}; the remaining 6.6% of the deviations were between the values of 10.0 and 30.0 breaths min^{-1} (Figure 9b). For the NFN, the model that showed the second best performance, 90.2% of the absolute

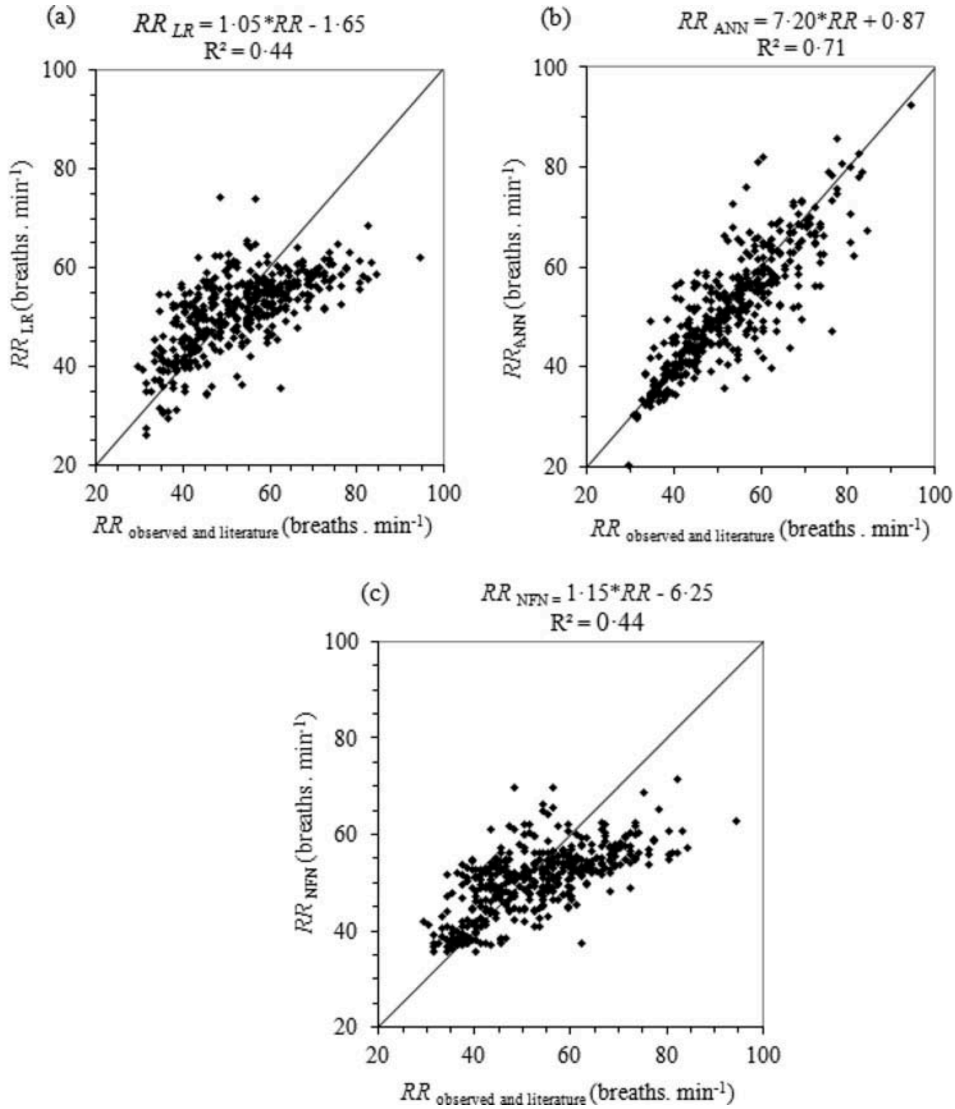

FIGURE 7 Functional relationship between the values for respiratory rates (RR) simulated by the models: regression models (a), artificial neural network (b), neurofuzzy network (c) and the means of combined dataset.

deviations were between the values of 0.0 and 9.9 breaths min^{-1}, and the remaining 9.8% of the deviations were between the values of 10.0 and 30.0 breaths min^{-1} (Figure 9c). For the RMs, 72.1% of the absolute deviations were observed between the values of 0.0 and 9.9 breaths min^{-1}, and the remaining 27.9% were between the values of 10.0 and 30.0 breaths min^{-1}, respectively (Figure 9a).

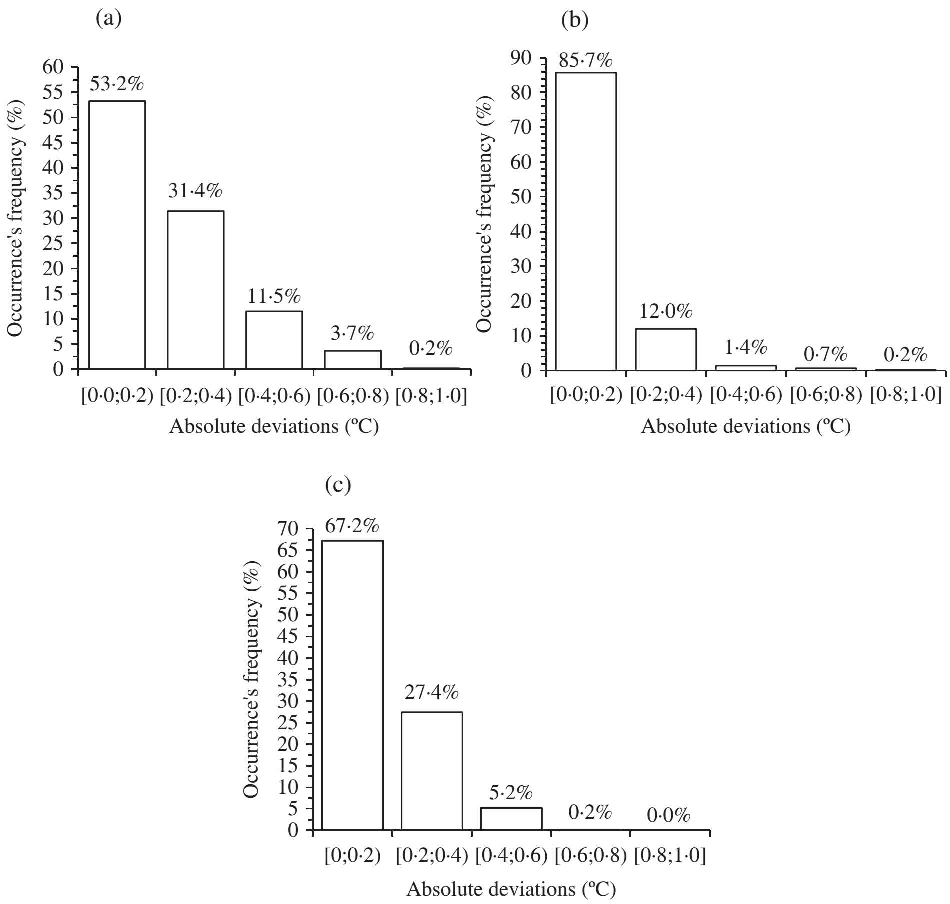

FIGURE 8 Frequency of occurrence of absolute deviations (°C) between the data for rectal temperature simulated by the models: regression models (a), artificial neural network (b), neurofuzzy network (c) and the means of the combined dataset.

The capacity for the prediction of t_{rectal} by the ANN-based model developed in this study was similar to or greater than found in the literature (Table 3), 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-Brand, Jones, and Woldt 2005); however, the average absolute deviation was less than that of the best models obtained by the previously quoted authors (Table 3). 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}.

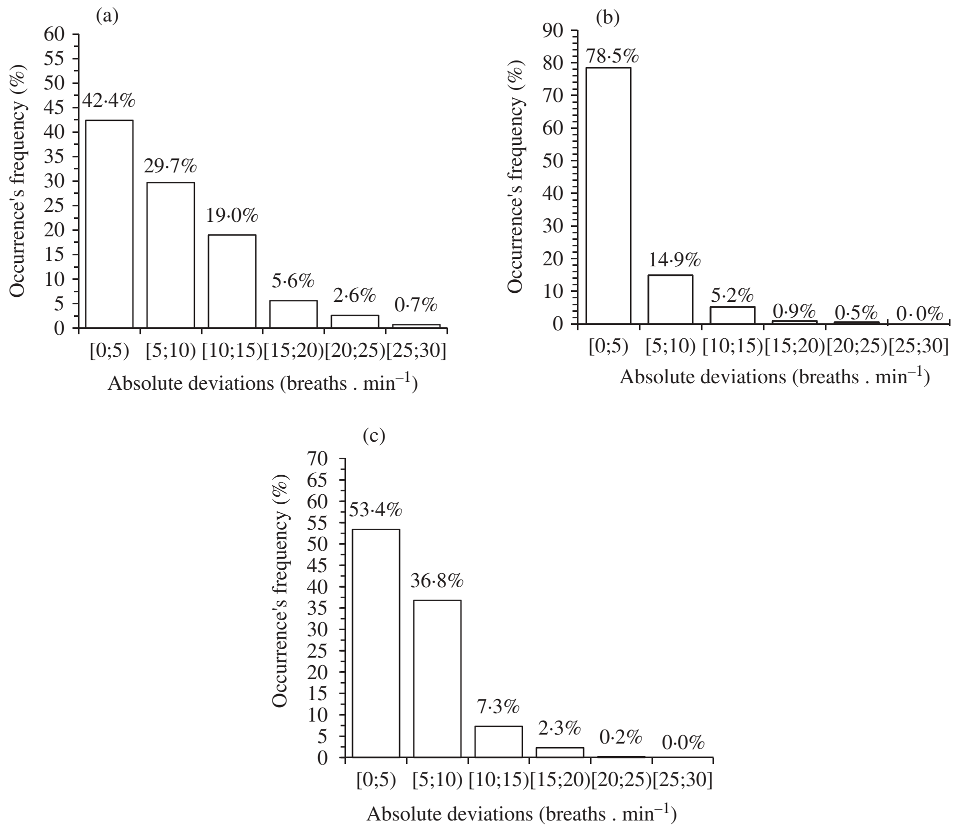

FIGURE 9 Frequency of occurrence of absolute deviations (breaths.min^{-1}) between the data for respiratory rate simulated by the models for the regression models (a), artificial neural network (b), neurofuzzy network (c) and the means of the combined dataset.

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 0.1°C and 0.2°C for the t_{rectal}, and 3.2 breaths min^{-1} and 5.2 breaths 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 breaths 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 aid in the decision-making process.

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APPENDIX A

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	
Developed Regression Models	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

tdb,drybulb temperature. RH, relative humidity.trectal, rectal temperature. RR, respiratory rate. (a,b,c,d), variables coefficients. obs, observed.
*, all coefficients are significant ($p < 0.05$).