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Neural modeling of relative air humidity

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ABSTRACT

The objective of the present study was to use artificial neural networks for the estimation and prediction of relative air humidity. Neural modeling was carried out using MATLAB and STATISTICA software. Relative air humidity was predicted with a feedforward multi-layer perceptron artificial neural network with time delay. The backpropagation algorithm was used for ANN training in MATLAB. The forecasting horizon was one time interval (3 h). The forecast was extended to 48 h (16 measurements) by re-introducing a newly estimated value as an input. The mean relative prediction error for the horizon adopted was 2.1%, and the Pearson *r* correlation coefficient −0.972. Estimation was performed using a Generalized Regression Neural Network (GRNN) model. This model estimated relative air humidity at the highest value of the Pearson *r* correlation coefficient −1.000. The GRNN developed with MATLAB tools did not show overfitting, although 100% of the empirical data were used to generate its topology.

1. Introduction

The total cereal grain production in Poland in the years 2000–2002 was 21,954,000 tonnes (Anonymous, 2003). Fixed-bed grain whose moisture content does not exceed 12% is usually stored in concrete elevators or silos. Grain storage duration is from several to a dozen or so months. Adverse storage conditions (e.g. increased temperature and grain moisture content) may result in pest development, followed by grain quality deterioration or even unsuitability for consumption (Latif and Lissik, 1986; Alagusundaram et al., 1990; Sun and Woods, 1994). One of the measures taken to prevent grain quality deterioration is its periodical ventilation, aimed at removing moist gas from inter-grain spaces. To achieve the desirable effect of grain bed ventilation, relative humidity of air used for ventilation should be maintained at the proper level. Excessively high relative air humidity results in steam condensation on the grain surface, whereas excessively low humidity may cause grain overdrying; both of these effects are highly undesirable. Ventilation, being an additional unit process in the technological line, increases grain storage costs. To reduce these costs, unheated or slightly heated (several °C) air is used for grain ventilation. The best effects (i.e. high quality of stored grain and the lowest possible costs) are achieved for active ventilation systems. In such systems, control of air heating temperature and air humidity depends on the information on thermodynamic conditions in the grain bed (temperature and moisture content, and chemical composition of gas in inter-grain spaces), measured *online* at several selected points of the bed, and on the psychrometric properties of the atmospheric air (temperature and relative humidity) used for grain ventilation. In modern systems of stored grain quality management (Fleurat-Lessard, 2002), all decisions concerning the working parameters of a grain storage plant, including temperature and air humidity, are made on the basis of information on grain condition at each point of the bed. The information is acquired *online* by computer simulation, using a mathematical model of water and heat migration in the grain bed, and on the basis of the current and forecasted atmospheric state.

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Nomenclature

err	local absolute error of the estimation/prediction of RH (%)
n	number of time series prediction points
ψ	mean relative prediction error (%)
RH	relative air humidity (%)
std	standard deviation (%)
t	time (h)

Subscripts

e	empirical value
max	maximum value
mean	mean value
min	minimal value
p	model value

The estimation and prediction of changes in the thermodynamic air parameters are of significant importance, not only for grain storage. Regressive and predictive models of psychrometric air parameters may be applied, among others, to the optimization of agricultural produce drying and in the decision-making process concerning farm building ventilation.

The relationships between particular variables describing atmospheric air are difficult to present in the form of an applicable mathematical model. When it is too difficult or impossible to develop a formal mathematical model for estimation or prediction, artificial intelligence methods can be of great help. The group of these methods comprises artificial neural networks, and neural models are frequently used for agritechnical system analysis. Sablani and Rahman (2003) employed neural modeling for determining the correlations between thermal conductivity of some foodstuffs and their moisture content, temperature and porosity. Mittal and Zhang (2003) developed an artificial neural network for real-time prediction of psychrometric air parameters, achieving a relative error of relative humidity prediction below 5%. Raimundo and Narayanaswamy (2001) used an artificial neural network for the calibration of a chemical light pipe sensor measuring both relative air humidity and the ammonia content of the air. Farkas et al. (2000) created an artificial neural network for simulation of the grain drying process.

A prediction task is solved on the basis of analysis of a one-dimensional time series (e.g. Frank et al., 2001), where predicted values (the so-called forecasting horizon) are calculated on the basis of known preceding values (the so-called prediction order). In most cases, one (the next) value in a series is predicted. Trajer (2001) used this procedure for the prediction of ambient parameters while modeling the vegetable storage process. Many learning algorithms based on error back propagation can be used for prediction. Białobrzewski (2004) discussed the effects of network training algorithms offered by MATLAB on the accuracy of air temperature prediction. He found that one of the best algorithms is the BR (Bayesian regularization) algorithm, which was also used for network training in the present study.

It is difficult to develop a regression model for relative air humidity estimation on the basis of a continuous function, because the value modeled is a nonlinear stochastic variable. Markowski and Siejkowski (2000) proposed a continuous model of daily changes in relative air humidity disregarding non-periodic and random variations in air parameters. A neural network enabling the analysis of such a problem is the Generalized Regression Neural Network (GRNN). Such networks most often have two hidden layers: a Radial Basis Function (RBF) layer and a linear layer. GRNNs usually have more neurons than standard feedforward networks with backpropagation algorithms (Demuth and Beale, 2001). Chtioui et al. (1999) compared the GRNN model and the standard multiple regression model describing changes in the moisture content of spring wheat leaves, and proved the higher accuracy of the former.

The objective of the present study was to compare artificial neural networks developed with MATLAB and STATISTICA, applied for the estimation and prediction of relative air humidity. In the prediction task with a given time horizon, a feedforward multilayer perceptron neural network with time delay and the backpropagation algorithm was used. Estimation was performed with a GRNN model.

2. Material and methods

Experimental data were the results of 823 relative air humidity measurements taken during 100 days in the year 1988 at the Meteorological Station in the city of Olsztyn (NE Poland). The measurements were recorded every 3 h. Neural modeling was carried out with MATLAB and STATISTICA 6.1.

Relative air humidity was predicted with a feedforward multilayer perceptron artificial neural network with time delay. Eight hundred and seven measurements were included in the training set, and the last 16 were used for model evaluation. The forecasting horizon was one time interval (3 h). The forecast was extended to 48 h (16 measurements) by reintroducing a newly estimated value as an input. The effects of the prediction order (6–18 measurements) and network architecture (2–12 neurons in the first nonlinear hidden layer and 1 neuron in the second linear output layer) on prediction accuracy were determined (Demuth and Beale, 2001; Świąć and Bilski, 2000). The BR algorithm and 807 measurements were used for the purpose of network training with Toolbox Neural Networks (MATLAB). Empirical data were scaled to the range [−1,1]. Four STATISTICA models were chosen. Two were built with Intelligent Problem Solver implemented in Neural Network (STATISTICA); the range of changes in the prediction order and network architecture was the same as in the network developed with MATLAB tools, whereas the inputs of the training process differed only in the training set size, which contained 100% (807 measurements) and approximately 50% (402 measurements) of the empirical data, respectively. Another two models were developed using Custom Network Designer; the network architecture was the same as for the best model created with MATLAB; again, the inputs of the training process differed only in the training set size, which contained 100% (807 measurements) and approximately 50% (402 measurements) of the empirical data, respectively. Each time, 500 networks were tested in both modules, using sets of automatic options of relevant STATISTICA modules, including the criterion determining the most appropriate network.

The regression models describing the values of relative humidity of air versus time were developed using Generalized Regression Neural Network models. Three models were created: one model using MATLAB (model ME) and two models using STATISTICA (SEP100 and SEP50). The GRNN was developed and trained employing the newgrnn function of MATLAB. In the ME model 100% (823 points) of the measurement data was used in the training process (Demuth and Beale, 2001). Two other networks were created with Custom Network Designer, STATISTICA. The first one (SEP100), in which 100% of the measurement data was used in the training process, was developed applying all option combinations (STATISTICA 6.1, 2007; Krzyżak and Rafajłowicz, 2000):

- with and without a choice of the option, *Set number of hidden units to equal number of training cases*;
- with assignment of radial centers by *Random sampling* and *K-Means clustering*;
- for different values of the *Smoothing factor* in the range [0.00001,10];
- with and without a choice of the option, *Prune inputs with low sensitivity after training*; the threshold value of the sensitivity ratio was 1.0.

The second network (SEP50) was created using all set options of Custom Network Designer, STATISTICA.

The evaluation criterion for selected prediction and regression models was the value of the Pearson *r* correlation coefficient, the minimal, maximal and mean values of relative air humidity, and sample standard deviation. The difference between these values and experimental results was determined. Local absolute errors of estimation and prediction of relative air humidity were also calculated, including the minimal, maximal and mean absolute value, and sample standard deviation; local absolute errors of prediction and estimation were defined according to the following formula:

$$\mathrm{err}(t) = \mathrm{RH}_e(t) - \mathrm{RH}_p(t). \qquad (1)$$

Another criterion of prediction accuracy was mean relative prediction error, ψ (Dittmann after Trajer, 2001)

$$\psi = \frac{1}{n}\sum_{i=1}^{n}\frac{|\mathrm{RH}_{ei} - \mathrm{RH}_{pi}|}{\mathrm{RH}_{ei}} \times 100\%. \qquad (2)$$

The above criteria were established with MATLAB procedures. In order to do that, solutions of neural models built with STATISTICA tools were generated in the source code of the C language (with Code Generator, STATISTICA). The source code was then implemented in MATLAB. The GRNNs were tested for overfitting by analysis of the descriptive statistics of model estimated values of relative air humidity, obtained for a 1-h time step, and measured values obtained for a 3-h time step. The minimal, maximal and mean values of relative air humidity, and sample standard deviation were compared. The differences between model estimated values and corresponding linearly interpolated values between measuring points were also determined.

3. Results and discussion

Fig. 1 presents the architecture of the best neural network, developed and trained using MATLAB procedures. For the criteria adopted, the best predictive ability was recorded for the network architecture (*a*:*b*-*c*-*d*-*e*:*f*)—a = 1: number of input variables; b = 10: steps used to predict; c = 3: number of neurons in the first nonlinear hidden layer (transition function: tan-sigmoid); d = 1: number of neurons in the second linear hidden layer; e = 1: number of outputs; f = 1: number of output variables, with the BR algorithm, i.e. a modified Levenberg–Marquardt algorithm developed for constructing a

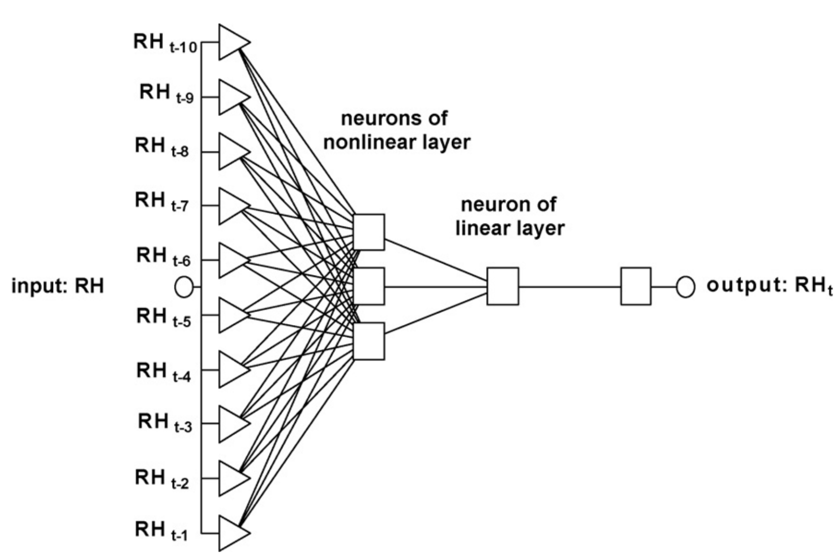

Fig. 1 – Topology of a multilayer perceptron (1:10-3-1-1:1) for predicting relative air humidity.

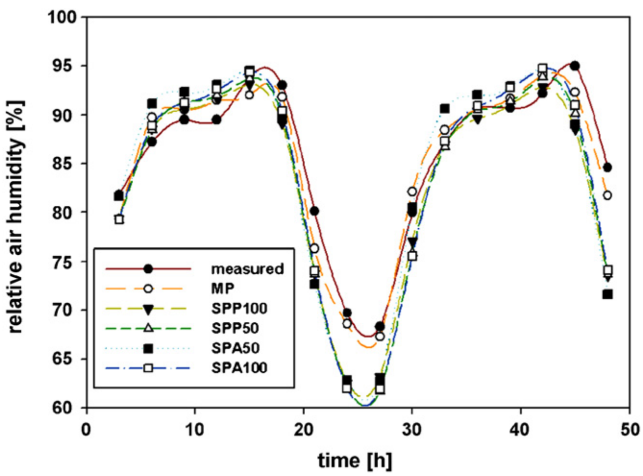

Fig. 2 – Changes in empirical and predicted values of relative air humidity for a forecasting horizon of 48 h.

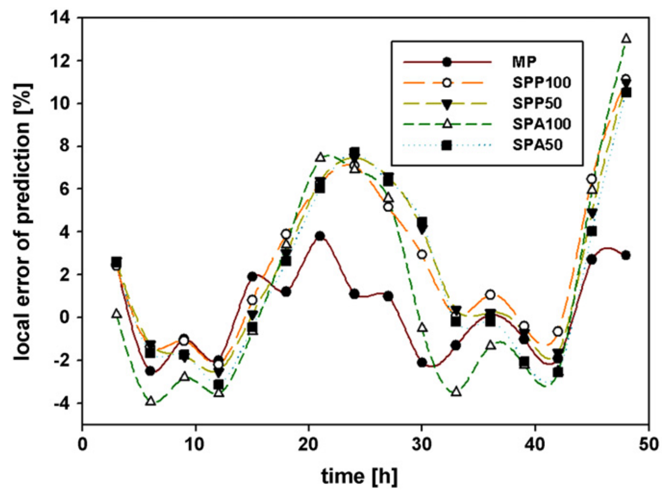

Fig. 3 – Changes in local absolute error of relative air humidity prediction for a forecasting horizon of 48 h.

network with better generalization properties. Fig. 2 shows changes in empirical and predicted values of relative air humidity for models obtained with MATLAB and STATISTICA. Analysis of the shapes of these curves indicates the highest similarity between the courses of the empirical curve and the curve plotted for a model developed with Neural Toolbox, MATLAB. All simulated courses generated with Neural Networks, STATISTICA are similar and less fitted to experimental data. The similarities are confirmed by the descriptive statistics of relative air humidity included in Table 1, such as: minimal, maximal and mean values, and standard deviation. The statistics of the MP model are the closest to the experimental data. This agreement suggests that the neural model built with MATLAB tools can accurately predict relative air humidity for the forecasting horizon of 48 h. This agreement is also proven by the values of local absolute prediction error (Fig. 3), which vary from −3% to 4% for the best model, reaching a maximum of 11–13% for the following models: SPP50, SPP100, SPA50, SPA100 generated with STATISTICA. The values of this parameter for the best model (MP) are only two-fold higher than those recorded with most sensors measuring relative air humidity. The mean relative prediction error, ψ, for the forecasting horizon adopted was 2.1% for the MP model, which was approximately two-fold lower than in the case of SPP50, SPP100, SPA50, SPA100. All values of the Pearson r coefficient given in Table 1 show a significant correlation (at significance level $p<0.01$) between the predicted values obtained for all of the models analyzed and the empirical data. The highest value of the coefficient r (0.972) was obtained for the MP model. Both values of these parameters (r and ψ) and a graphic interpretation (Fig. 4) of linear regression analysis of the MP model confirm that a feedforward multilayer perceptron artificial neural network with time delay may be successfully applied to the prediction of relative air humidity. It seems that similar or higher prediction accuracy may be achieved for a wider forecasting horizon, using a larger training set.

Fig. 5 presents the topology of a GRNN. The first hidden layer consists of 413 or 823 neurons with Radial Basis Functions (RBF), and the second—of 2 neurons with a linear transit function. Table 2 presents descriptive statistics for empirical data estimated with the GRNN model developed with Neural Network modules offered by MATLAB and STATISTICA, and the results of neural network verification. The Pearson r correlation coefficient = 1.000 was achieved for the models ME and SEP100, for the smoothing factor = 0.001 (at accuracy $r=\pm0.01$, this model did not show sensitivity to a choice of all other Custom Network Designer options). Although for both these models $r=1.000$, the model developed with STATISTICA tools estimates relative air humidity with much lower accuracy. The reduced accuracy is substantiated by the other values of descriptive statistics given in Table 2. The curve representing the SEP100 model is “flattened” (lower value std) and shifted downwards (lower values RH_{min}, RH_{max}, RH_{mean}). In the SEP50 model, created using all set options of Custom Network Designer, data are automatically divided into three subsets: training (approximately 50% measuring points),

Table 1 – Descriptive statistics for measured and predicted relative air humidity for a forecasting horizon of 48 h

	Structure of model	RH_{min} (%)	RH_{max} (%)	RH_{mean} (%)	std(RH) (%)	r	ψ (%)
Measured		68.3	95.0	85.8	8.0		
MP	1:10-3-1-1:1	67.3	94.1	85.5	8.6	0.972	2.1
SPP50	1:10-3-1-1:1	62.6	93.1	83.2	10.3	0.945	4.1
SPP100	1:10-3-1-1:1	61.7	93.8	83.4	10.9	0.955	4.2
SPA50	1:12-5-1-1:1	61.9	94.8	83.8	11.1	0.957	4.3
SPA100	1:14-9-1-1:1	62.7	94.7	84.5	11.2	0.912	4.8

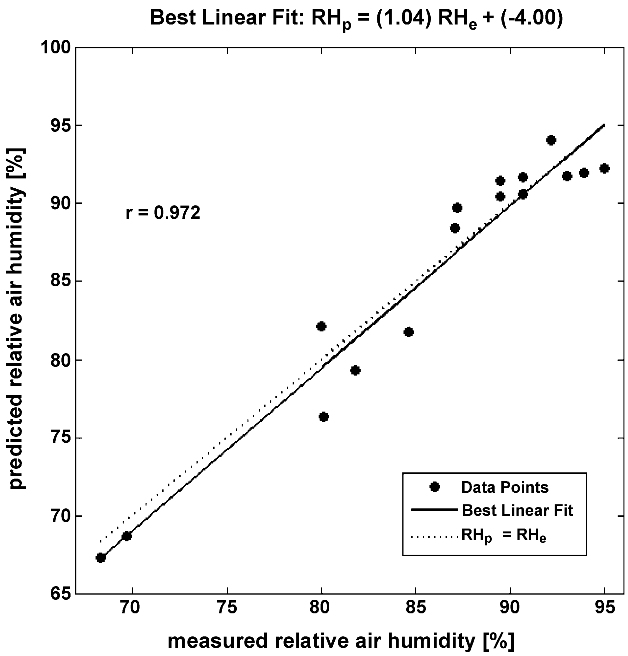

Fig. 4 – Relationships measured against predicted values of relative air humidity.

validation (approximately 25% measuring points) and testing (approximately 25% measuring points), and the value of the *smoothing factor* is 0.2. In the GRNN, each point of the training set is mapped in the first hidden layer, which determines estimation accuracy. In the case of set options in STATISTICA, about 50% of the data was used for GRNN training. This reduced amount of data probably means that with strongly nonlinear variables, this network would estimate values with lower accuracy than a network containing 100% of empirical data. The descriptive statistics (Table 2) show that the SEP50 model, based on set options in STATISTICA, provided the lowest accuracy of relative air humidity estimation among the models tested. If a validation set is not distinguished from the measurement data set during neural network development, another way of checking whether overfitting is likely to occur must be found. In this paper, descriptive statistics of model estimated values were examined, obtained for a time step of 1 h (the time step for empirical values was 3 h). It was found that the values of the above statistics achieved for the MATLAB model were similar to empirical values (Table 2). This suggests that the network proposed is not prone to overfitting. The problem of overfitting was observed in the case of the SSP100 model, based on set options in STATISTICA. A graphic interpretation of verification is shown in Fig. 6. In this figure, the time interval is limited to 48 h, but the courses are representative of the entire measurement range. The graphic presentation of the values analyzed for the whole measurement range would be illegible. The curve in Fig. 6 representing verification of the results of estimation with the MS model oscillates around the line connecting the measured values. The difference between model estimated values and corresponding linearly interpolated values between measuring points did not exceed ±1.4% over the entire time interval. Models SSP100 and SSP50, built with STATISTICA tools, were much less accurate: the SSP100

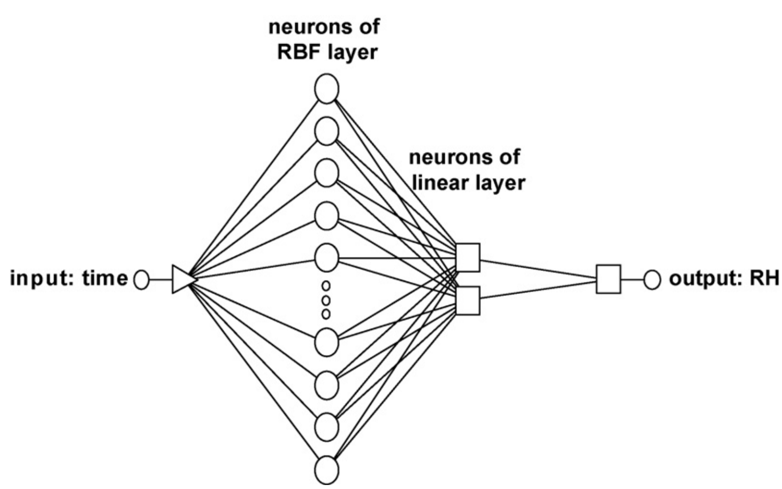

Fig. 5 – Topology of GRNN (1:1-823-2-1:1) for the estimation of relative air humidity.

Table 2 – Descriptive statistics for empirical data and values estimated with GRNNs models developed with MATLAB and STATISTICA, and neural network verification

	Structure of model	Time step (h)	RH_{min} (%)	RH_{max} (%)	RH_{mean} (%)	std(RH) (%)	r
Measured		3	45.4	98.0	79.5	13.8	
ME	1:1-823-2-1:1	3	45.4	98.0	79.5	13.8	1.000
SEP100	1:1-823-2-1:1	3	42.1	90.1	73.2	12.6	1.000
SEP50	1:1-413-2-1:1	3	76.5	83.9	79.4	2.6	0.254
MS	1:1-823-2-1:1	1	45.4	98.0	79.5	13.6	
SSP100	1:1-823-2-1:1	1	7.0	90.1	29.1	31.9	
SSP50	1:1-413-2-1:1	1	76.4	83.9	79.4	2.6	

Table 3 – Descriptive statistics of local absolute error of relative air humidity estimation with GRNNs models developed with MATLAB and STATISTICA

	Structure of model	err_{min} (%)	err_{max} (%)	Mean(|err|) (%)	std(err) (%)
ME	1:1-823-2-1:1	−0.1	0.1	0.0	0.0
SEP100	1:1-823-2-1:1	3.3	85.3	6.6	5.2
SEP50	1:1-413-2-1:1	−34.1	19.6	11.9	13.4

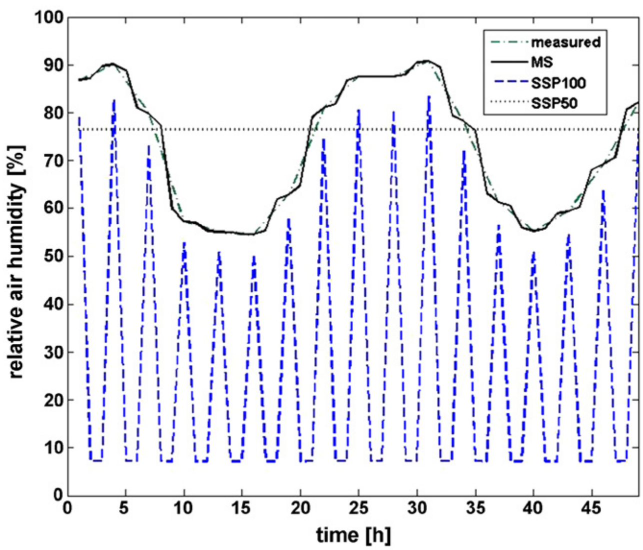

Fig. 6 – Changes in relative air humidity, measured (time step 3 h) and estimated (time step 1 h) with GRNN models generated with MATLAB and STATISTICA.

model clearly demonstrates overfitting (RH differences reaching approximately 80% between points corresponding to the measurement time step and additional points being a consequence of time step reduction), whereas the SSP50 model can be represented by a plane curve (std = 2.6%), which is a straight line in the figure discussed. Such a shape of the curve describing the SSP50 model was affected by the assumed value of the *smoothing factor*: 0.2. Table 3 presents descriptive statistics of local absolute estimation error: the minimal, maximal and mean values of relative air humidity, and sample standard deviation. Analysis of these data indicated that the model built with MATLAB procedures provided the highest accuracy of relative air humidity estimation.

4. Conclusions

The results obtained show that the neural models built with MATLAB estimated and predicted relative air humidity with higher accuracy than those created with STATISTICA. Mean relative prediction error, ψ, for the horizon adopted was 2.1%, and the Pearson r correlation coefficient −0.972 were for the feedforward multilayer perceptron artificial neural network with time delay, based on the Bayesian regularization backpropagation algorithm developed with used MATLAB.

When 100% of the empirical data was introduced to the Generalized Regression Neural Network models, these models estimated relative air humidity at the Pearson r correlation coefficient of 1.000, both for MATLAB and STATISTICA. The GRNN developed with MATLAB tools did not show overfitting, although 100% of the empirical data was used to generate its topology.

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