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Smart frost control in greenhouses by neural networks models

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ABSTRACT

Thermal comfort in greenhouses is a key fact to enhance productivity, due to the excess demand of energy for heating, ventilation and agroclimatic conditioning. Frost, in particular, represents a serious technological challenge if the crop sustainability is to be ensured. A Multi-Layer Perceptron artificial neural network, trained by a Levenberg-Marquardt backpropagation algorithm was designed and implemented for the smart frost control in greenhouses in the central region of Mexico, with the outside air temperature, outside air relative humidity, wind speed, global solar radiation flux, and inside air relative humidity as the input variables. The results showed a 95% confidence temperature prediction, with a coefficient of determination of 0.9549 and 0.9590, for summer and winter, respectively.

1. Introduction

The greenhouse cultivation is one of the main economic activities in the agricultural sector, in the agro-climate control greenhouses context; there are strategies that deal cold technology for better agriculture performance (e.g. Kumar et al., 2009; Zabeltitiz, 2011). Currently, precision agriculture for their monitoring and control is used by technology (e.g. Mesas et al., 2015; Ojha et al., 2015; Rehman et al., 2014; Simbeye et al., 2014; Srbinovska et al., 2015). But nature imposes limits as climate frost, that is, in agriculture plants as resistant or not to light frosts, let alone medium and heavy frosts (e.g. Cao et al., 2009; Kathke and Bruelheide, 2011; Savi et al., 2015). But several greenhouse crops are affected by the frost, because the low temperatures cause irreparable damage to crops (e.g. Kandula, 2011; Chávez et al., 2014). In recent years there has been a significant development and research projects aimed at increasing the heating and ventilation of greenhouses (e.g. Abdel and Al, 2011; Bennis et al., 2008; Körner and Van Stratenb, 2008; Mashonjowa et al., 2013; Molina et al., 2010; Pierre and Thierry, 2010; Sethi and Sharma, 2008; Sethi, 2009). But usually these systems already applied in the greenhouse uses heating means as turbines or pumps for heating water, among other methodologies heating involved directly with crop natural ventilation, the criticality of these methodologies is that the plant to these conditions CO_2 begins to perspire allowing low temperatures of frozen condensed water into plant, damaging the crop, which normally generates total loss of the crop, this process plant transpiration by heating the greenhouse which is affected by frost shown in Fig. 1, where the plant transpiration, which is water loss as vapor through stomata, cuticle and the periderm, this process heat from the air is used for passing liquid water on vegetation in water vapor, so that the low temperature in the vicinity of the leaves (e.g. Boulard et al., 2010; Chai et al., 2012). Of the total amount of water that is absorbed soil, carried on the stem and transpired to the atmosphere, only a very small fraction of 1% is incorporated into biomass, almost all the water lost by the blade makes through stomatal pores, which are more abundant on the underside of the leaf (e.g. Boulard et al., 2010; Chai et al., 2012; Teitel et al., 2010; Tong et al., 2010). The transpiration rate in the plant by heating that is affected by frost is influenced by such factors as the plant species and size, soil moisture, the amount of sunlight considering its duration and intensity, air temperature or wind speed, where climatic factors are temperature, solar radiation, rainfall, humidity, wind speed, through use of weather stations to monitor possible environmental conditions remotely on a greenhouse, where incorporating the use of embedded systems to embedded computing part for predicting natural events implementing statistical and artificial intelligence and knowledge engineering (e.g. Chevalier et al., 2012; Dombaycı and Gölcü, 2009; Hea and Ma, 2010; Higginsa et al., 2010; Huang et al., 2010; Li

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Nomenclature

$A(z)$	matrices
a_{ij}	model parameter (with i and j any natural number)
a_{na}, b_{nb}	model parameters
$B(z)$	matrices
b_{ij}	model parameter (with i and j any natural number)
C	classroom
C_c	control room
$D_{\bar{y}i}$	standard deviation
e	perturbation
$e(t)$	perturbation or any not-measurable input in the system (noise)
f	activation function of the ANN
H	humidity, %
H_0, H_1	hypothesis test
I_c	clothing insulation (clo), where 1 clo = 1.155 m^2 °CW^{-1}
M	metabolic rate (met), defined *met* as 58.2 Wm^{-2}
M_1	meeting room
N	number of data sets used for estimation
n	number of samples
n_a	number of pole
n_a, n_b	order of the respective polynomials (output, input)
$n_b - 1$	number the zeros
n_k	time delay
R_{hi}	inside air relative humidity, %
R_{ho}	outside air relative humidity, %
S_a	air speed, ms^{-1}
S_r	solar radiation, Wm^{-2}
T	transpose
t	domain (discrete) time interval
T_a	air temperature, °C
T_i	inside air temperature, °C
T_o	outside air temperature, °C
T_r	radiant temperature, °C
$u(t)$	input signal at (discrete) time t
$u(t-n_k)$	input signal at (discrete) time $t - n_k$
W	vector of synaptic weights of the ANN
W_s	wind speed, ms^{-1}
X	input vector of the ANN
X_{norm}	normalized value of X
$X_{\min}$	minimum values of X
$X_{\max}$	maximum value of X
X_r	real value in a parameter
y_i	actual value of the data set (observed output)
$\bar{y}_i$	mean value of the observed outputs of the prediction set
$\hat{y}_i$	predicted value of the data set (estimate output)
$y(t)$	output signal at (discrete) time t
$y(x)$	output of the ANN
z^{-1}	backward shift operator
α	number of the replicates or observation
δ_{ij}	kronecker symbol
θ	bias value

et al., 2015; Liu et al., 2015; Martí et al., 2013; Mohammadi et al., 2015; Prabha and Hoogenboom, 2008; Smith et al., 2009; Zhang et al., 2015). The light frosts are temperatures drop slightly below 0 °C exceptionally and temperatures rise again past few hours, this type of frost occurring in México central region, mainly it occurs with concurrency in the states of Mexico, Hidalgo, Tlaxcala. A particular type of soft ice is frozen by evaporation that occurs in plants due to the evaporation of water or mist that remains in the plant surfaces after rain or lowering the humidity. The phenomenon of evaporation of water causes the adsorption heat, which in turn produces heat loss to the plant and decrease in temperature may fall below the 0 °C level, this phenomenon can also occur in animals and can produce hypothermia or death. The stockings frost is temperatures drop below 0 °C during the nights and days of winter, temperatures remain very exceptional register below −10 °C. It is produced by the entrance of a mass of dry air and cold temperatures below 0 °C, accompanied by winds with speeds of 15 km/h. The action of the cold air, dehydrated plants and ending with the cellular fluids that serve as defense against frost (e.g. Cao et al., 2009; Ghielmi and Eccel, 2006). On the other hand, the high consumption of energy generated by the heating, ventilation and Agroclimatic Conditioning Systems (ACCS) is due to the use of inefficient methods; likewise, inadequate operation sequences and failure systems, rising production costs and lower profits generated by the crop, this becomes unprofitable to the farmer. Research shows that energy saving can be reached with the correct use of control systems regarding the models to predict the internal temperature at the greenhouses (e.g. Bennis et al., 2008; Körner and Van Stratenb, 2008). According to the models relied on both statistical and non-statistical methods, they are able to provide an important technique to raise the comfort heat level required by the greenhouses (e.g. Sethi and Sharma, 2008; Smith et al., 2009; Pierre and Thierry, 2010).

Due to the inside temperature of the greenhouses seems to be affected by several inputs and output variables; along with the relevant control of the temperature predictions in standard rules and models concerned about the quantity of input variables for the purpose of getting the wanted precision, during the prediction of the concerned variables. On the other hand, there are some variables that affect directly the interior climate and those are proportionally related to specific variables such as the external climate conditions, outside and inside air temperature, outside and inside air relative humidity, wind speed, global solar radiation flux, and wind direction. In recent research several authors have dedicated time to find out mathematical models as a proficient tool to transform data into main information, in order to calculate and predict temperature (e.g. Frausto et al., 2003; González and Zamarreño, 2005) associated with the linear autoregressive models, physical models, as well as the artificial neural network models, allowing to give a better prediction and control in ACCS systems, generating more crop savings. Estimating the inside temperature in greenhouses is difficult and important to accomplish the main goal of this study. In this case, this data can be determined by two sorts of models either statistical or non-statistical, applied using mathematical models that is implemented in weather stations using embedded systems that capture data to be processed in real time (e.g. Chevalier et al., 2012).

A discrete model of the continuous climatic system in a greenhouse can be obtained in several ways, one of which is autoregressive relationships between the discrete output $y(t)$ and input $u(t)$. One of the most commonly used structures for the estimation of systems are the autoregressive models with external input (ARX) (e.g. Frausto et al., 2003; González and Zamarreño, 2005). On the other hand, the development of artificial neural network models (ANN) has proved those methods are capable of recognizing and learning the prediction of temperature with the advantage of being absolutely competent to solve complex problems during the time of requiring the greater precision of the new information (e.g. Smith et al., 2009). In this sense, ANN models can be handling as one of the non-linear or statistical methods with a multivariable

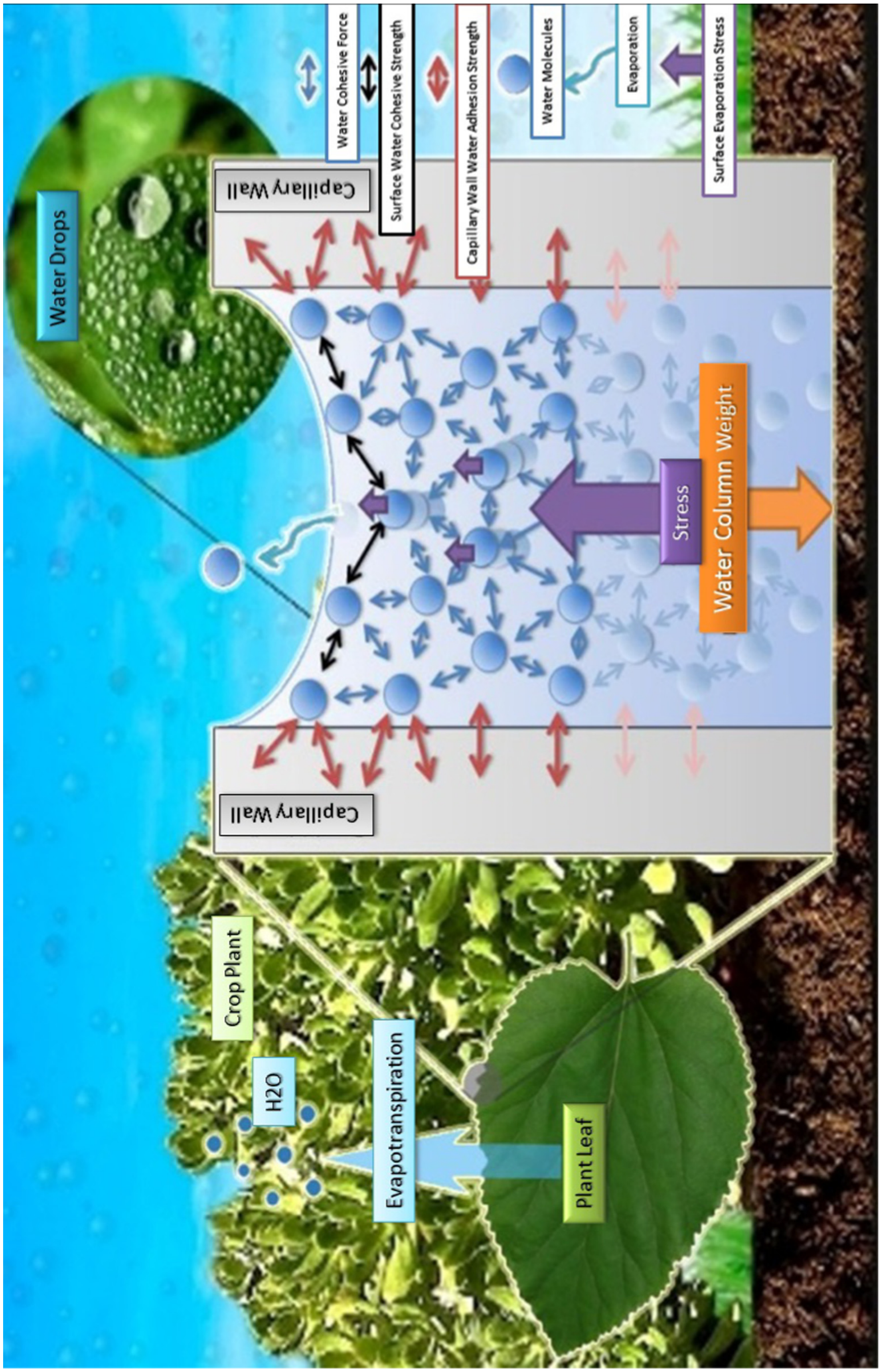

Fig. 1. Schematic transpiration by heating that damages the plant in a frost.

performance. In the last years, some researchers have tried to answer the strong demand of how to predict the thermal behavior and energy consumption in different areas to providing greater comfort to the occupants and potential power savings. Sinha's work suggests a modification to the ARX model in order to include the average mobile method as an efficient tool for the prediction of environmental temperature, solar radiation and thermal load (e.g. Sinha et al., 2001). The modification resulted in a very robust method, capable of predicting almost exact results. The advantage of this system is that they are viable in areas where meteorological data are not available or are uncertain. An autoregressive algorithm ARX was used to predict the temperature behavior in the interior of a greenhouse. The main purpose of this work is to determine the appropriate structure of the ARX and ANN models to predict the inside temperature of a greenhouse in an optimal manner. The procedure consists on using the external climate variables that are included in the models to accurately calculate the estimation of the prediction temperature. Thus, the dynamic model is turned into a practical alternative to obtain a more accurate estimation of the internal temperature of greenhouses, which allows increasing the thermal comfort for the occupants. This paper is organized as follows: in Section 2 the theoretical considerations for the identification of the ARX and ANN models are presented. Section 3 describes the materials and methods used for the prediction of the inside air temperature by means of field measurements and also presents the precision measurements to explain the variation of the temperature data. In Section 4 a discussion about the obtained results of the ARX and ANN models is carried out. Finally, the conclusions and future works are presented in Section 5.

2. Theoretical considerations

Today the importance of thermal comfort has been increasing because most of the occupants of agroclimatic applications, greenhouses and their activities are decreased due to the lack of an optimally ventilated work area. According to Smith in a closed atmosphere there are six main elements that determine the perception of the environmental quality from the thermal point of view: (1) metabolic rate (M), (2) clothing insulation (I_c), (3) air temperature (T_a), (4) radiant temperature (T_r), (5) air speed (S_a) and (6) humidity (H). Based on this, the proposed mathematical models to predict the temperature the interior of an intelligent greenhouse of classrooms in this study is based on the analysis of the following input variables: outside air temperature (T_o), outside air relative humidity (R_{ho}), wind speed (W_s), global solar radiation flux (S_r), inside air relative humidity (R_{hi}); being the inside air temperature the output variable (T_i) (Figs. 2 and 4).

2.1. Autoregressive models with external input (ARX)

The parameters' adjustment of a model used to represent a system is called System Identification. System Identification methods are often classified into two major categories: grey and black box models. Compared with direct modeling, which is governed by the system's physical laws, these models are well suited for greenhouse a mathematical model where the system's mechanism is not well understood or where its properties change in an unpredictable manner. The grey box method is a formulation of the model in which the parameters are traceable to actual physical principles. The black box method relates mathematically measured inputs to measured outputs in which the model parameters are transformed without any traditional physical significance. The black box models do not require previous knowledge of the system, which can be an advantage if the information on the system's dynamics is limited; however, it involves the problem of selecting an adequate structure for the model. Another advantage of this type of models is the possibility of obtaining a broad model with a relatively small set of measurements. The model can be improved as new data are entered. Compared with a grey box model, the black box approach requires less time and effort to be developed. Generally, in a black box model, non-statistical methods or statistical methods are used to formulate the relationship between inputs and outputs.

2.1.1. Autoregressive models with external input algorithm

The autoregressive models with external input (ARX) is a family of mathematical models commonly used to describe dynamical systems. A non-linear ARX model can be understood as an extension of a linear model; assuming a SISO linear time-invariant discrete-time ARX model (e.g. Arahal et al., 2005), the following expression can be used to describe this relationship in Eq. (1).

$$\begin{aligned} y(t) = &- a_1 y(t-1) - a_2 y(t-2) - \ldots - a_{na} y(t-n_a) \\ &+ b_1 u(t) + b_2 u(t-1) + \ldots + b_{nb} u(t-n_b+1) + e(t) \end{aligned} \tag{1}$$

where $y(t)$ is the output signal at (discrete) time t; $u(t-n_k)$ is the input signal at (discrete) time $t-n_k$; $e(t)$ is the perturbation or even any not-measurable input in the system (noise); a_{n_a} and b_{n_b} are the model parameters; n_a and n_b indicate the order of the respective polynomials (output, input); and n_k is time delay from input to output.The determination of all or some values of the parameters is done fitting the model to available data gathered from a real system using some estimation procedures (e.g. Rodríguez et al., 1999; Ramírez-Arias et al., 2005), that is, the coefficients enter as parameters to be determined; θ will be named as the vector that has all the parameters to estimate. The description of the model is the following modeling by Eq. (2).

$$y(t,\theta) = G(z,\theta)u(t) + H(z,\theta)e(t) \tag{2}$$

Because the white noise term enters as a direct error to the difference equations, the model of Eq. (1) is also known as the model or structure of error equation. In this case the parameters of adjustment will be Eq. (3).

$$\theta = [a_1 \quad a_2 \quad \cdots \quad a_{na} \quad b_1 \quad b_2 \quad \cdots \quad b_{nb}]^T \tag{3}$$

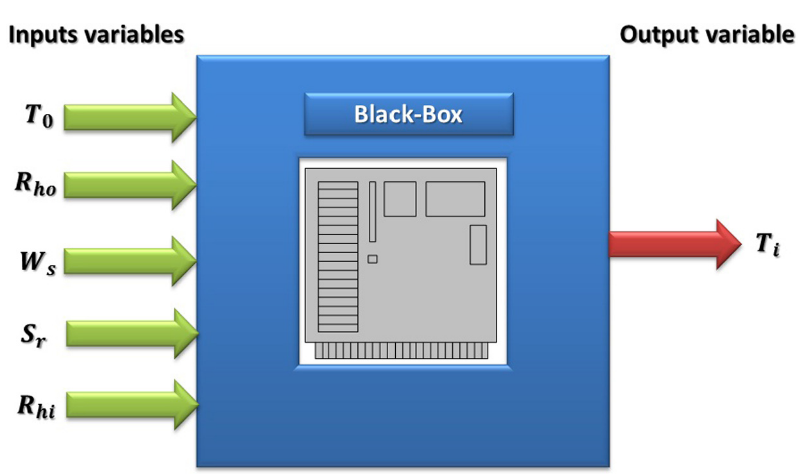

Fig. 2. Blocks diagram of the pattern of black box used to predict the temperature of the inside air in greenhouse.

The ARX models to predict the internal temperature with greater precision require more than one input, so a single-input single-output (SISO) ARX model in the multiple-input multiple-output (MIMO) ARX model should be adjusted. For ARX, Eq. (1) is often represented as Eq. (4), where the matrices $A(z)$ and $B(z)$ are giving by Eqs. (5), (6) and z^{-1} is the backward shift operator interpreted by Eq. (7).

$$y(t) = B(z)u(t - n_k)/A(z) + e(t)/A(z) \tag{4}$$

$$A(z) = 1 + a_1 z^{-1} + \ldots + a_{n_a} z^{-n_a} \tag{5}$$

$$B(z) = 1 + b_1 z^{-1} + \ldots + b_{nb} z^{-nb+1} \tag{6}$$

$$z^{-1}u(t) = u(t-1) \tag{7}$$

For a multivariable system in which the number of inputs is given by n_u and the number of output by n_y, $A(z)$ and $B(z)$ are n_y by n_y and n_u by n_u matrices, respectively, which elements are the polynomials in the shift operator z^{-m} (with m as any natural number). The entries $a_{ij}(z)$ and $b_{ij}(z)$ of the matrices $A(z)$ and $B(z)$, respectively, can then be expressed as Eqs. (8) and (9), where δ_{ij} represents the kronecker symbol.

$$a_{ij}(z) = \delta_{ij} + a_{1_{ij}} z^{-1} + \ldots + a_{na_{ij}} z^{-na_{ij}} \tag{8}$$

$$b_{ij}(z) = b_{1_{ij}} z^{-nk_{ij}} + \ldots + b_{n_{b_{ij}}} z^{-n_{k_{ij}} - n_{b_{ij}} + 1} \tag{9}$$

According to this, it is clear that the ARX structure has a system which can be defined by means of the number of poles n_a, the number of zeros $n_b - 1$, and the time delay n_k. It should be mentioned that these are also parameters of the model predictive control and must be estimated somehow (e.g. Sánchez et al., 2009; Yedra et al., 2014). The matrices $A(z)$ and $B(z)$ are determined by means of off-line parameter identification methods.

2.2. Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) have emerged as a technology for modeling and forecasting because of a flexible mathematical structure capable of describing complex non-linear relations between input and output datasets. ANNs have been successfully applied to prediction and pattern classification problems. An important property of neural networks is their ability to learn, where learning is often defined as a process which optimizes the performance of the network with respect to a given task. NNs can be thought of as algorithms for studying and modeling any given set of data. They are a non-standard tool of statistical analysis; by mean of which it is possible to study and make predictions on any set of data with NNs.

Although there are numerous types of ANNs, the most commonly used type of ANN is the Multi-Layer Perceptron (MLP). This is a feed-forward, fully-connected hierarchical network typically comprising three types of neuron layers each including one or several neurons. The first or the lowest layer is an input layer where external information is received. The last or the highest layer is an output layer where the problem solution is obtained. The input layer and output layer are separated by one or more inter mediate layers called the hidden layers, and only feed-forward connections are allowed. The nodes in adjacent layers are usually fully connected by acyclic arcs from a lower layer to a higher layer. The behavior of a neural network is determined by the transfer functions of its neurons, by the learning rule and by the architecture itself.

By virtue of their universal function approximation property, MLP play a fundamental role in neural computation, as they have been widely applied in many different areas including pattern recognition, image processing, intelligent control, time series prediction, etc. From the universal approximation theorem, a feed-forward network of a single hidden layer is sufficient to compute a uniform approximation for a given training set and its desired outputs.

2.2.1. Artificial neural networks algorithm

The architecture of ANN models is loosely based on the biological neural system. ANN allows the estimation of possibly non-linear models without the need of specifying a precise functional form. ANN's can be viewed as parallel and distributed processing systems that consist of a huge number of simple and massively connected processors called neurons. Each individual neuron consists of a set of synaptic inputs, through which the input signals are received; in this case five variables climatic are considered (see Eq. (16)). Then, the incoming activations are multiplied by the synaptic weights and summed up. The outgoing activation is determined by applying a threshold function to the summation. The threshold function can be a linear, or a nonlinear function that decides the output of the neuron. The structure of the neuron is shown in Fig. 3.In the Fig. 3 $x_1, x_2, \ldots, x_m$ represent the input of the neuron; $w_1, w_2, \ldots, w_m$ are their weights, θ is the threshold value and y represents the output. The input to output relationship is characterized by Eq. (10).

$$y(x) = f\left(\sum_{i=1}^{n} w_i x_i + \theta\right) = f(W^T X + \theta) \tag{10}$$

where W is the vector of synaptic weights, X is the input vector and θ is a constant called offset or bias, f is the activation function. The superscript T denotes the transpose operator and $y(x)$ is the output of the neuron. In this study, the activation function used is a sigmoid that has the following form modeling by Eq. (11).

$$f(x) = \frac{1}{1 + e^{-x}} \tag{11}$$

The training of an ANN is undertaken by a procedure called backpropagation (BP) based learning algorithm which is a supervised algorithm. This method requires a set of training patterns, and their corresponding desired outputs, and autonomously adjusts the connection weights among neurons. Correction of the weights is made according to imposed learning rules and thereby, obtains unique knowledge from the data.

To develop an adequate network it is necessary to work with several iterations even to solve problems with low complexity to collect a minor number of iteration along with the time reduction in the ANN learning. Although it is successfully used in many real world applications, the standard backpropagation algorithm (SBP) suffers from a number of shortcomings; one of these is the rate at which the algorithm converges. Reducing the number of iterations and speeding learning time of the neural networks are subjects of recent research; some improvements of the SBP algorithm are the conjugate gradient, variable metric methods and the Levenberg-Marquardt algorithms.

The model of neural network is determined by three factors: (1) the topological structure of the network; (2) the neuron characteristics; and (3) the raining algorithm. The ANN implemented in this study is a Multi-Layer Perceptron (MLP) that includes an input layer of 5 nodes, an hidden layer with variable number of hidden nodes and an output layer that has only one node. The input variables into the ANN are: outside air temperature (T_o), outside air relative humidity (R_{ho}), wind speed (W_s), global solar radiation flux (S_r), inside air relative humidity (R_{hi}); being the inside air temperature the output variable (T_i) (Fig. 4).

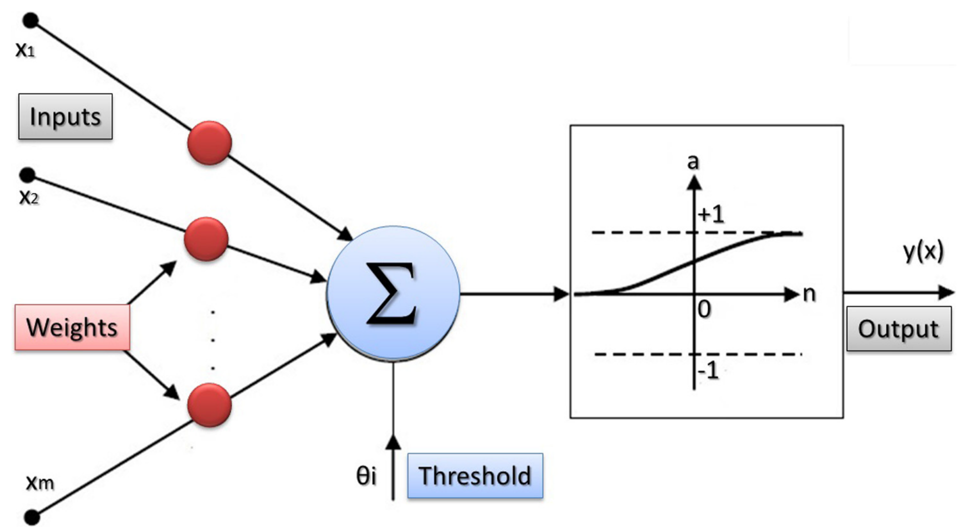

Fig. 3. Model of an artificial neural.

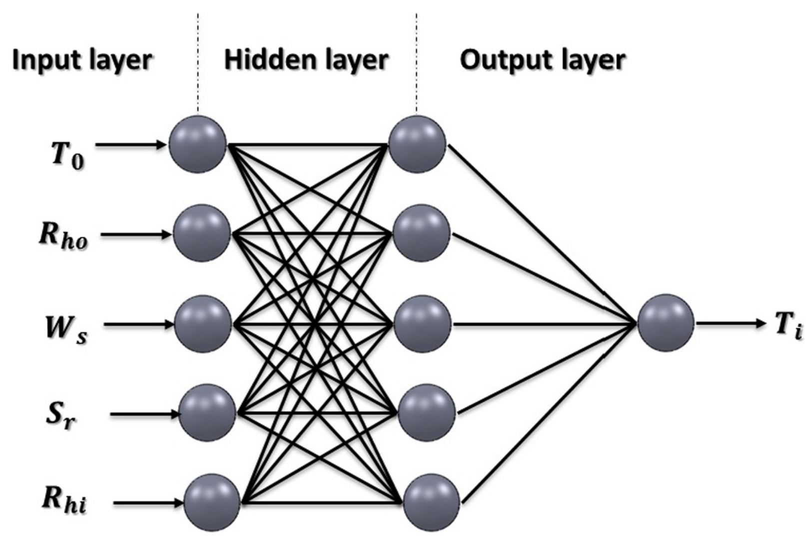

Fig. 4. Feed forward artificial neural network.

In order to avoid the saturation in neurons condition, data normalization is required. If neurons get saturated, changes in the input value will produce a negligible change, and not just one change of the output value. For this reason, data must be normalized before being presented to the artificial neural network. Data normalization compresses the range of the training data between 0 and 1. The normalization in this study was carried out by means of the following expression given by the Eq. (12).

$$X_{norm} = \frac{X_r - X_{\min}}{X_{\max} - X_{\min}} \tag{12}$$

where X_{norm} is the normalized value of a variable, X_r is a real value in a parameter $X_{\max}$ and $X_{\min}$ are the maximum and minimum values of X_r, respectively.

3. Materials and methods

3.1. Field measurements

The procedure was carried out in the Greenhouse. This greenhouse has one Section (C_1), a meeting section (M_1) and a control room (C_c); the total covering an area of 112.5 m^2. The height of the entire structure is 3 m. With respect to the use of sections, those were independent to each other, however; most of the time, those were used simultaneously and considered identical among them (Fig. 5).

The greenhouse has a 1 cm thick plastic layer on top. The data selected for the development of this research were: Outside air temperature °C (S_3), outside air relative humidity % (S_4), wind speed m/s (S_5), global solar radiation flux W/m^2 (S_6), time and the specific day, this meteorological station is configured to analyze the sampling information every 10 min the variables plotted are: external temperature, external humidity, wind speed, solar radiation, internal temperature and internal humidity (Fig. 6).In order to obtain the coefficients for both the ARX and ANN mathematical models several measures were done to predict the inside air temperature in the greenhouse C_1. This research is based on the analysis of the input variables, which are: T_o, R_{ho}, W_s, S_r, R_{hi}, being the inside air temperature the output variable T_i. The measures of the foregoing variables were done by sampling every 10 min during a period of 365 days. Those were divided into four groups, which represents the four seasons of the year, though only

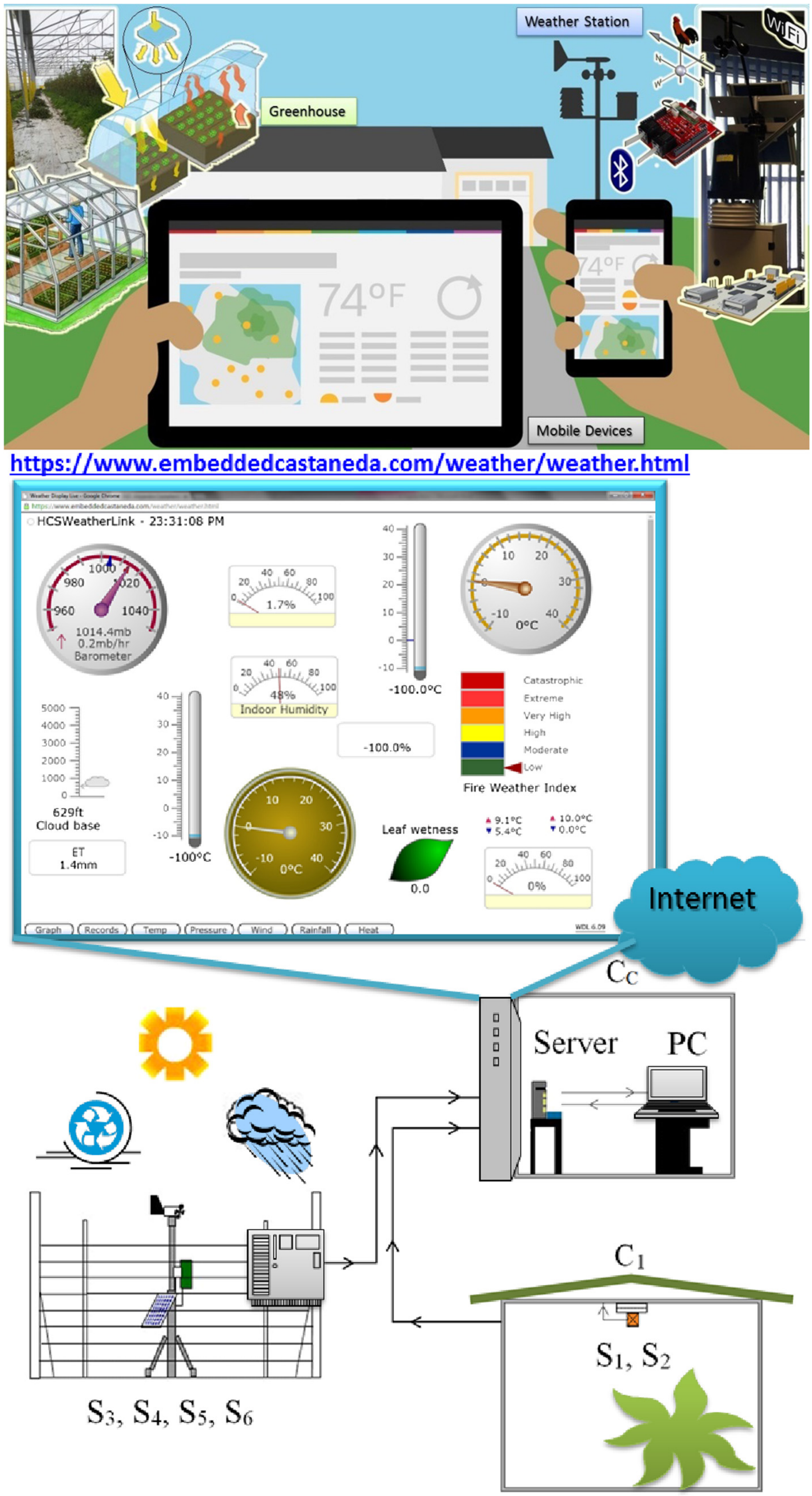

Fig. 5. Data acquisition of the weather station.

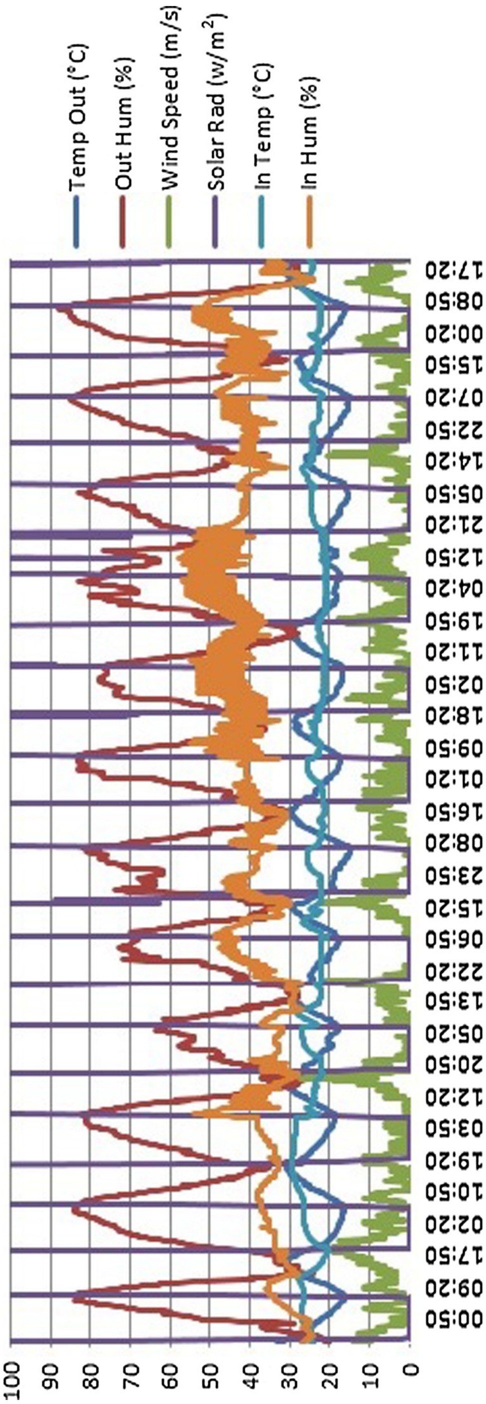

Fig. 6. Results of the weather station.

two seasons were used as data for this project: summer and winter seasons. Thinking about the Input-output values registered along with the performance of experimental identification, it could be all input signals and the desired restrictions needed during the procedure. Taking into consideration a group of ARX and ANN models, the correct candidate to make the best predictions in the summer and winter seasons is chosen, making a comparison to select the best model to predict the internal temperature among the real data provided with ARX and ANN models. In case of ARX models, once the data have been recorded, the first two thirds or so of the data record were used in order to determine the model coefficients and the remaining data for validation.

3.2. Structure and configuration ANN models

A neural network algorithm for prediction the inside temperature of a greenhouse of classrooms was proposed. First, the mean absolute percentage error (*MAPE*) was used to select the best network architecture ANN-MLP. Then, the best network was compared with actual and ARX models data using *MAPE*. Finally, analysis of variance (ANOVA) and Duncan's multiple range test (DMRT) procedures were used to compare, verify and validate the models. The description of the algorithm is follows:

- Determine input-output variables of the model.
- A group of data (B), of the input and output variables for past times describing the input/output relationship is collected.
- The group of data (B) is divided into two subsets: training ($B-1$) and testing ($B-2$). This procedure requires independent validation data to be used in order to test the neuronal network capability for generalizing non-predicted data. Representative testing (validating) data are taken from the training data. It is necessary to find a balance between the size of training and validation data. Were used to train the network, 70%, and the remaining 30% was employed for testing and validation of the network.
- Once the ($B-1$) and ($B-2$) data subsets are correctly defined, a conventional regression model of the data training was performed. Then, the interior air temperature for the testing periods was predicted.
- Finally, the ANN method is used to estimate the inputs/outputs relationship. In order to find an appropriate number of hidden nodes, the aforementioned steps are repeated using different architecture and training parameters for the network, with a single hidden layer of (n) nodes and employing sigmoid transfer functions. If the (n) value is optional, it can be modified. If after applying the above steps the minimum relative error is not obtained, the following procedures have to be performed: (a) Choose the architecture and the training parameters; (b) Train the model using the learning data ($B-1$); (c) Evaluate the model using the testing data ($B-2$); (d) Select the best network architecture ANN for the testing data with the desired error; (e) Apply ANOVA procedures to the formal testing data for verification and validation of the ANN results.

3.3. Accuracy measurements

Then, a comparison between the best ARX and the best ANN models was made introducing the base of the coefficient of determination (R^2), which is a measurement of the correlation between the observed and predicted data (Sinha et al., 2001). Some measures of variances are the percent standard error of the prediction (*% SEP*) (Smith et al., 2009) and the mean absolute percentage error (*MAPE*) (Srbinovska et al., 2015). There are used to determine how the model is able to explain the total variance of the data. The mean absolute percent error is defined accord Eq. (13).

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|y_i - \hat{y}_i|}{\hat{y}_i} \times 100 \tag{13}$$

The coefficient of determination (R^2) and the percent standard error of the prediction (*% SEP*) are indicated according to the Eqs. (14) and (15) respectively. For a perfect match, the coefficient of determination (R^2) should be close to 1 and the value of the percent standard error of the prediction (*% SEP*) close to 0.

$$R^2 = 1 - \frac{SSE}{SSTO} = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2} \tag{14}$$

where *SSE* is a measurement of the relationship between the predicted and observed values; *SSTO* a measurement of the variability of mean observed values. The % *SEP* is defined according to the Eq. (15).

$$\%SEP = \frac{100}{\bar{y}_i}\sqrt{\frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{N}} \tag{15}$$

where N is the total number of data sets used for estimation; y_i is the actual value of temperature of the data set (observed output); $\hat{y}_i$ is the predicted value of the temperature of the data set (estimate output) and $\bar{y}_i$ is the mean value of the observed outputs of the prediction set.

4. Results and discussion

4.1. Models selection

Model structures ARX and typical parameter identification results for the seasonal models giving the inside air temperature (T_i) as a function of outside air temperature (T_o), outside air relative humidity (R_{ho}), wind speed (W_s), global solar radiation flux (S_r), inside air relative humidity (R_{hi}), and perturbation (e), in the discrete time (t) domain, using the z-transform operator (z^{-1}); a_1 to a_5 and b_{11} to b_{55} are regressive coefficients as defined in the model structure; all the ARX selected models included the five variables climatic (Eq. (16)).

$$T_i(t) = \left\{\frac{[\,T_o(t) \quad R_{ho}(t) \quad W_s(t) \quad S_r(t) \quad R_{hi}(t)\,]}{1 + a_1z^{-1} + a_2z^{-2} + a_zz^{-3} + a_4z^{-4} + a_5z^{-5}}\right\} \times \begin{bmatrix} b_{11}z^{-1} + b_{12}z^{-2} + b_{13}z^{-3} + b_{14}z^{-4} + b_{15}z^{-5} \\ b_{21}z^{-1} + b_{22}z^{-2} + b_{23}z^{-3} + b_{24}z^{-4} + b_{25}z^{-5} \\ b_{31}z^{-1} + b_{32}z^{-2} + b_{33}z^{-3} + b_{34}z^{-4} + b_{35}z^{-5} \\ b_{41}z^{-1} + b_{42}z^{-2} + b_{43}z^{-3} + b_{44}z^{-4} + b_{45}z^{-5} \\ b_{51}z^{-1} + b_{52}z^{-2} + b_{53}z^{-3} + b_{54}z^{-4} + b_{55}z^{-5} \end{bmatrix} + \frac{e(t)}{1 + a_1z^{-1} + a_2z^{-2} + a_zz^{-3} + a_4z^{-4} + a_5z^{-5}} \tag{16}$$

Several ARX and ANN models were performed and tested according to their capacity of inside temperature prediction the greenhouse. The data was divided into four groups related to the seasons of the year, involving just two seasons: summer and winter for this research. The 144 samples are considered as equivalent to one day.

The external climate variables used to validate the behavior of the measured data and for the estimated data of the ARX and ANN models, these consider 2880 samples from summer and winter seasons. The coefficient of determination (R^2), the percent standard error of the prediction (% *SEP*) and the mean absolute percentage error (*MAPE*) were used to compare the error and capacity of prediction of ARX and ANN models with the purpose of determine the best models.

Table 1 shows the results from the best models corresponding to the summer season, also the reliability of the model and the model with the best performance. Thus, the ARX model (4,3,0) corresponding to the summer season was better compared to the other ARX models from that season, obtaining a coefficient of determination (R^2 = 0.9130), with a percent standard error of the prediction (% *SEP* = 9.05) and a mean absolute percentage error (*MAPE* = 0.5337). The ANN model (6,4,1) responding to the same summer season reached better estimation of the internal temperature, holding a coefficient of determination (R^2 = 0.9549), with a percent standard error of the prediction (% *SEP* = 2.98) and a mean absolute percentage error (*MAPE* = 0.2284).

Table 1
Comparing the estimated error for the different ARX and ANN models in the summer season.

Models summer season	Validation		
	R^2	MAPE	% SEP
ARX			
4,6,0	0.9081	0.6078	10.15
4,5,0	0.9040	0.6356	10.53
4,4,0	0.9026	0.6398	10.65
4,3,0	0.9130	0.5337	9.05
4,2,0	0.9071	0.6114	10.32
ANN			
6,6,1	0.9412	0.2371	3.32
6,5,1	0.9406	0.2403	3.51
6,4,1	0.9549	0.2284	2.98
6,3,1	0.9459	0.2317	3.25
6,2,1	0.9511	0.2291	3.17

ARX: auto regressive model with external input; ANN: artificial neural networks.

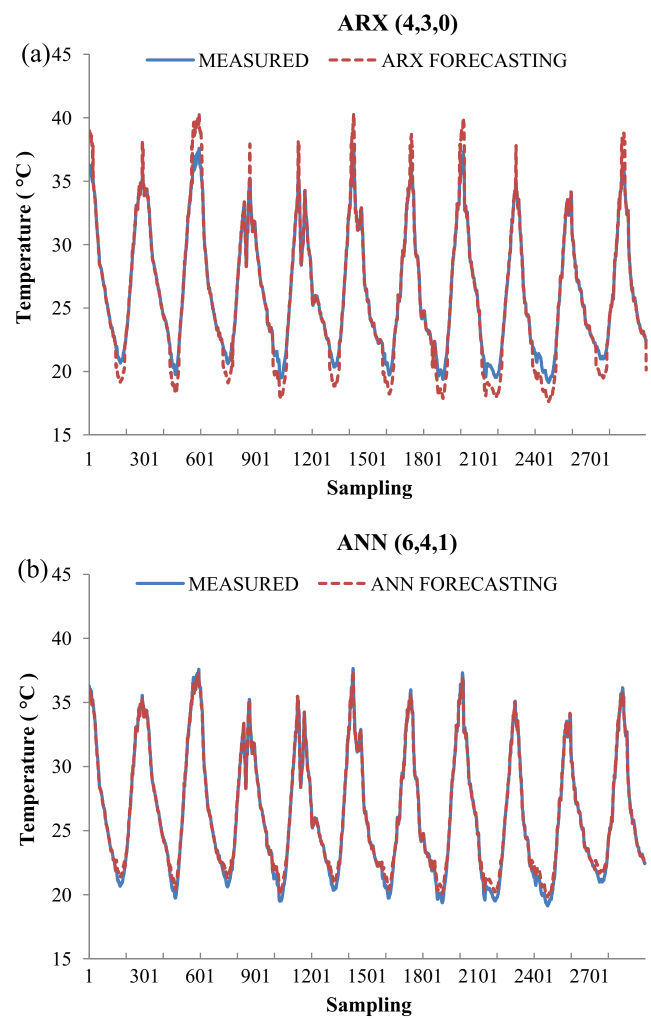

Fig. 7. Original data versus results of the (a) autoregressive model with external input and the (b) artificial neural network and the difference between both models for the summer season of sampling; —— measured; - - - forecasting.

The estimation of the temperature and the error of the models from that summer season were analyzed Fig. 7(a) and (b), show the accuracy of the ARX model as well as the ANN model respect to the internal temperature of the greenhouse. The results of the estimate data are compared to the measured data; it was observed that the ARX model (4,3,0) has a greater error compared to ANN model

(6,4,1). The result of the best models implemented for the prediction of the inside temperature of the greenhouse of the summer season, it was observed that the ARX models has a greater error compared to ANN models, the result of the best models implemented for the prediction of the inside temperature of the greenhouse; namely, the ANN models reach better results of the internal temperature prediction referring to ARX models.

The results of the error of the best models ARX (4,3,0) and ANN (6,4,1) for the summer season were compared; it was done with respect to coefficient of determination (R^2), the percent standard error of the prediction (*% SEP*) and the mean absolute percentage error (*MAPE*). Such results show that the prediction models of the internal temperature with ANN obtain a smaller error in comparison with ARX models (Fig. 8).

Table 2 shows the results from the best models corresponding to the winter season, also shows the reliability and better performance, corresponding to winter season. The ARX model (4,4,0) reached the best estimation of the internal temperature with a coefficient of determination ($R^2 = 0.9294$), a percent standard error of the prediction (*% SEP* = 7.74) and a mean absolute percentage error (*MAPE* = 0.4546); meanwhile the ANN model (6,4,1) corresponding to the same winter season was the ANN model obtained the best estimate of the temperature with a coefficient of determination ($R^2 = 0.9590$), a percent standard error of the prediction (*% SEP* = 2.89) and a mean absolute percentage error (*MAPE* = 0.2249). This shows that ANN models improve the performance of ARX models, getting less percent standard error of the prediction (*% SEP*) and mean absolute percentage error (*MAPE*) than ARX models and ANN models get a higher coefficient of determination (R^2) with respect to ARX models.

The estimation of the temperature and the error of the models from that summer season were analyzed too Fig. 9(a) and (b) show the accuracy of the ARX model as well as the ANN model to predict the internal temperature at the greenhouses. The results of the estimate data are compared to the measured data; newly it was observed that the ARX model (4,4,0) has a greater error compared to ANN model (6,4,1). The result of the best models implemented for the prediction of the inside temperature of the greenhouse of the winter season, it was observed that the ARX models has a greater error compared to ANN models, the result of the best models implemented for the prediction of the inside temperature of the greenhouse; namely, the ANN models reach better results of the internal temperature prediction referring to ARX models.

The results of the error of the best models ARX (4,4,0) and ANN (6,4,1) for the winter season were compared; it was done with respect to coefficient of determination (R^2), percent standard error of the prediction (*% SEP*) and the mean absolute percentage error (*MAPE*). Such results show that the prediction models of the internal temperature with ANN obtain a smaller error in comparison with ARX models (Fig. 10). So, the best models that estimate the internal temperature in the greenhouse ANN models were compared with ARX models.

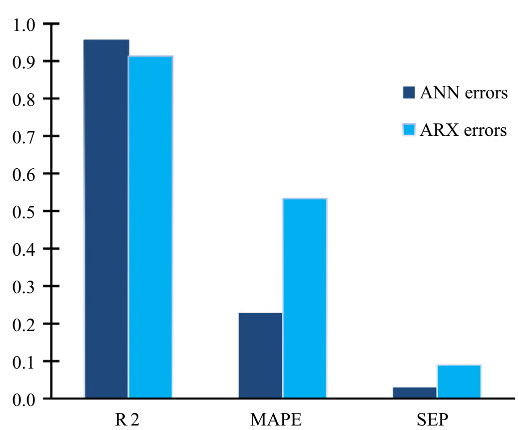

Fig. 8. Comparing the error of the ARX and ANN models of the summer season.

Table 2
Comparing the estimated error for the different ARX and ANN models in the winter season.

Models winter season	Validation		
	R^2	MAPE	% SEP
ARX			
4,5,0	0.9188	0.5112	8.65
4,5,1	0.9119	0.5478	9.12
4,4,0	0.9294	0.4546	7.74
4,4,1	0.9175	0.5321	8.95
4,3,1	0.9281	0.5216	8.70
ANN			
6,6,1	0.9585	0.2252	2.94
6,5,1	0.9465	0.2295	3.23
6,4,1	0.9590	0.2249	2.89
6,3,1	0.9425	0.2299	3.28
6,2,1	0.9533	0.2287	3.04

ARX: auto regressive model with external input; ANN: artificial neural networks.

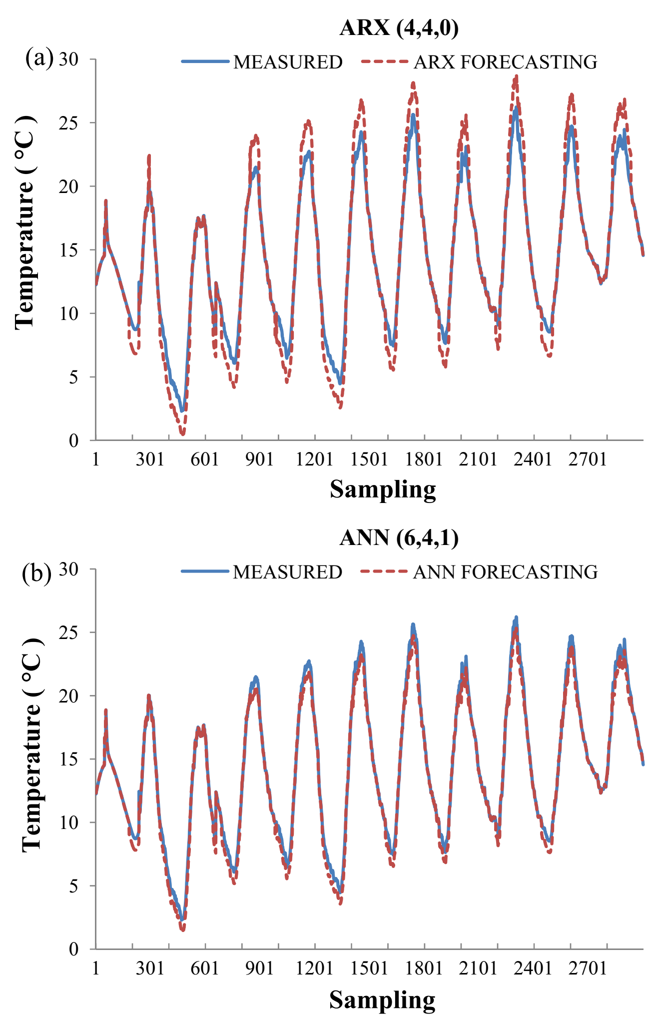

Fig. 9. Original data versus results of the (a) autoregressive model with external input and the (b) artificial neural network and the difference between both models for the winter season of sampling; —— measured; - - - forecasting.

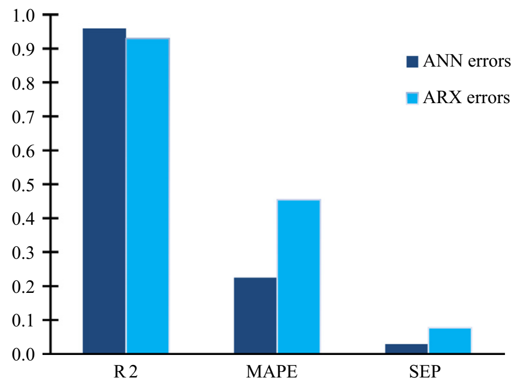

Fig. 10. Comparing the error of the ARX and ANN models of the winter season.

4.2. Validation and verification

4.2.1. Analysis of variance

The results of ARX and ANN models selected and measured data corresponding to the summer and winter seasons were compared by using ANOVA procedures. The experiment was designed in such way that variability was derived from external systematically controlled sources. Time is the common external source of variability in the experiment and can be systematically controlled by blocking (Teitel et al., 2010). Therefore, one-way ANOVA was used. The results are shown in Tables 3 and 4.Some proposals were realized on the determined values of the models, in order to make a decision between accepting or rejecting them, by means of a data analysis tool called hypothesis test. The hypothesis test was defined as follow:

$$H_0 : \mu_1 = \mu_2 = \mu_3 \quad H_1 : \mu_i \neq \mu_j \quad i,j = 1, 2, 3, \quad i \neq j \tag{17}$$

where μ_1, μ_2 and μ_3 are average values obtained from the measurement data, ARX and the ANN models. From Table 3 (summer season), it is possible to concluded that the null-hypothesis is rejected with a significant level $\alpha = 0.025$, since $f_{0.025,(2,198)} = 3.76$, $f_{0.05,(2,198)} = 3.04$, $f_{0.1,(2,198)} = 2.33$ and $7.10 > 3.76, 3.04, 2.33$. From Table 4 (winter season), it is possible also concluded that the null-hypothesis is rejected with a significant level $\alpha = 0.025$, since $f_{0.025,(2,198)} = 3.76$, $f_{0.05,(2,198)} = 3.04$, $f_{0.1,(2,198)} = 2.33$ and $7.7 > 3.76, 3.04, 2.33$.

4.2.2. Duncan's multiple range test

In order to find out which treatment means (measured data, ARX and ANN) are closer to the real data, applies the test of Duncan's Multiple Range Test (DMRT). Before the DMRT is performed, the standard deviation for each treatment has to be calculated as:

$$D_{\bar{y}i} = \sqrt{\frac{MS(error)}{\alpha}} \tag{18}$$

where α is the number of the replicates or observation for the three treatments (measured data, ARX and ANN). Then, the states values for R_p are calculated accord Eq. (19).

$$R_p = r\alpha(p,f)D_{\bar{y}i} \tag{19}$$

R_p can be understood as the minimum difference that must exist - between the mean largest and the smallest of a set of size. On the other hand $r\alpha(p,f)$ is obtained from the DMRT tables. Then means treatment classification, each treatment can be compared as follow:

- *Summer season:*

$D_{\bar{y}i} = 0.657$
$r_{0.05}(2, 198) = 3.042$
$r_{0.05}(99, 198) = 1.322$
$R_2 = r_{0.05}(2, 198)D_{\bar{y}i} = (3.042)(0.657) = 1.998$

Table 3
ANOVA comparison between data measured, ARX and ANN models corresponding to summer season.

Summary summer season						
Groups		Count	Sum (T °C)			Average (T °C)
Measured		100	2861.44			28.61
ANN		100	2781.56			27.82
ARX		100	3116.53			31.17
Source of variation	Sum square	Degree of freedom	Mean square	F_0	$F_{0.025(2,198)}$	$F_{0.1(2,198)}$
Between groups	612.19	2	306.09	7.10	3.76	2.33
Blocks	134.42	99	1.36			
Within groups	8542.08	198	43.14			
Total	9288.68					

Table 4
ANOVA comparison between data measured, ARX and ANN models corresponding to winter season.

Summary winter season						
Groups		Count	Sum (T °C)			Average (T °C)
Measured		100	1365.89			13.66
ANN		100	1327.43			13.27
ARX		100	1503.85			15.04
Source of variation	Sum square	Degree of freedom	Mean square	F_0	$F_{0.025(2,198)}$	$F_{0.1(2,198)}$
Between groups	172.11	2	86.06	7.67	3.76	2.33
Blocks	56.61	99	0.57			
Within groups	2222.23	198	11.02			
Total	2450.95					

$R_{99} = r_{0.05}(99, 198)D_{\bar{y}i} = (1.322)(0.657) = 0.869$
Comparing treatments 2 and 3 $= |(27.816) - (31.165)| = 3.349 > 1.998$
$\rightarrow \mu_1 \neq \mu_2$
Comparing treatments 1 and 3 $= |(28.614) - (31.165)| = 2.551 > 0.869$
$\rightarrow \mu_1 \neq \mu_3$
Comparing treatments 1 and 2 $= |(28.614) - (27.816)| = 0.798 < 1.998$
$\rightarrow \mu_1 = \mu_2$

- *Winter season:*
$D_{\bar{y}i} = 0.335$
$r_{0.05}(2, 198) = 3.042$
$r_{0.05}(99, 198) = 1.322$
$R_2 = r_{0.05}(2, 198)D_{\bar{y}i} = (3.042)(0.335) = 1.019$
$R_{99} = r_{0.05}(99, 198)D_{\bar{y}i} = (1.322)(0.335) = 0.443$
Comparing treatments 2 and 3 $= |(13.274) - (15.038)| = 1.764 > 1.019$
$\rightarrow \mu_1 \neq \mu_2$
Comparing treatments 1 and 3 $= |(13.659) - (15.038)| = 1.379 > 0.443$
$\rightarrow \mu_1 \neq \mu_3$
Comparing treatments 1 and 2 $= |(13.659) - (13.274)| = 0.385 < 1.019$
$\rightarrow \mu_1 = \mu_2$

From the above results of both seasons (summer and winter), it can be observed that only one third of the mean (measured data) and the third treatment (the selected ANN) equals to $\alpha = 0.05$ this indicates that the average of temperature estimated values for the selected ANN and the real data were approximately similar with a 95% confidence level. Therefore, results from the ANN models are significantly better than those obtained by ARX models.

5. Conclusions

We have used the extent linear autoregressive models with external input (ARX) and the artificial neural network models (ANN) were employed to predict the dynamic behavior of the temperature air in the interior of a greenhouse. The temperature predictor uses a Multi-Layer Perceptron (MLP) artificial neural network, which is trained by Levenberg-Marquardt backpropagation (BP) algorithm, and the data validity was done by means of analysis of variance (ANOVA) method also compared with the ARX model. For this, measurements of outside air temperature, outside air relative humidity, wind speed, global solar radiation flux, inside air relative humidity were used as the input variables to the system, and different structures of ARX and ANN models were tested. The external climate variables provided by the meteorological station were divided into two main sections corresponding to summer and winter seasons, in order to develop and evaluate the ARX and ANN models. By means of programming, the acting indexes were calculated for each one of the structures, selecting those models with better prediction of the real conditions of interior temperature. The ANOVA statistical method was used to analyze the variation of the two seasons comparing the neuronal network and the ARX models results versus real data. In addition, it was observed that using $\alpha = 0.05$, there was significant difference among treatments. Therefore, the DMRT was used to find the closest model to the real data. The best results of indoor temperature prediction were obtained by the structures of ANN models; with a 95% of confidence level, so the best models are given by the ANN (6,4,1) with a coefficient of determination of 0.9549 and 0.9590, corresponding to the summer and winter season respectively.

The performance and focus presented in this work for the prediction of the internal temperature at intelligent greenhouses could be used as a complement for an intelligent control strategy in ACCS equipment's; where, based on the model of the controlled greenhouse will determine the best control sequence in order to get the desired reference with a minimum expense of energy.

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