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The prediction of the inside temperature and relative humidity of a greenhouse using ANN method with limited environmental and meteorological data

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Abstract. In this paper, the prediction of the internal temperature (Tin) and relative humidity (Rhin) of a greenhouse located near Agadir, Morocco using artificial neural net-work (ANN) as machine learning method. First, an analyze of correlations be-tween inputs and outputs is studied in order to select the adequate input parameters. External temperature, relative humidity and solar radiations were the parameters that have the highest correlation coefficient with the outputs. They are thus selected as the only input parameters. The prediction of Tin and Rhin with the previously cited inputs gives a perfect coefficient of correlation (R=0.996). The aim of this study is to use only one measured input parameter (external temperature) and eliminate the two environmental parameters (relative humidity and solar radiation), by introducing the factor of time as input of the ANN model. Results were very satisfying and 20 neurons was sufficient to reach a correlation of about 0.98.

1 Introduction

Greenhouse cultivation systems is a prominent agricultural technique that has numerous advantages over the field production namely proper maintenance and careful monitoring of the growth. This technique allows production for off-season year-round. Its production outperforms 15 times the under field conditions [1]. Thus, the management of the interior microclimate of the greenhouse has become a major concern. The prediction of internal temperature and relative humidity could be of great importance. Artificial neuron network method is a relevant solution that has been widely used in different field of research: Nema et al.[2] has compared the efficiency of different ANN models, to improve the prediction of monthly evaporation in a study station, in the region of Dehradun, India. Best results were shown by An ANN model with nine neurons in a single hidden layer. Based on ANN method as well, Hernández-Pérez et al.[3] presented a predictive model for temperature and moisture kinetics on-line predictions during the drying of cassava and mango. Two separate ANN models were studied, based on one hidden layer. Best results were reached using 3 neurons in the hidden layer. Ferreira et al.[4] studied the adequacy of RBF neural networks to model the inside air temperature of a greenhouse using solar radiation, outside air temperature, and the inside relative humidity as input parameters. According to results, the algorithm based on a Levenberg– Marquardt method has achieved the best results.

In this paper, the prediction of the inside temperature and relative humidity with limited meteorological data is studied, using artificial neuron networks. The case study is a greenhouse located near the Atlantic Moroccan coast for which experimental data of the month of March were collected.

2 Methodology

2.1 Greenhouse description and data set acquisition

The studied commercial greenhouse is located in Agadir region, Morocco. It's composed with three arched roof chapels (9 m * 35 m * 4 m) and contains roof and side openings in different places (Figure 1).

Fig. 1. View of the greenhouse.

This study requires the measurement of:

- The outside and inside relative humidities (Rhout, Rhin), and air temperatures (Tout, Tin): A thermo−hygrometers probes is used for measurement, with an accuracy of ±1% for relative humidity and ± 0.2 °C for temperature.
- The outside wind direction (WD) and speed (WS): Measurements are conducted with cup anemometer and a wind vane with an accuracy of ± 1° for wind direction and ± 0.1 m s^{-1} for wind speed.

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- The outside solar radiation (G) is measured with a pyranometer with an accuracy of ± 5 $W.m^{-2}$

2.2 Feature's selection

The aim of this part is to study correlations (defined by equation 1) between the in-puts and the outputs in order to select the adequate features. Five inputs are used name-ly: wind direction (WD) , wind speed (WS) , external temperature (Tout), external rela-tive humidity (Rhout) and global radiation (G), The matrix of correlations between the inputs and the outputs is presented in table 1.

$$R = cov(x,y)/(\sigma_x \sigma_y) \tag{1}$$

where x and y are the predicted and the target value respectively.

Table 1. Correlation between the inputs and outputs.

	W_S	W_D	G	T_{out}	Rh_{out}	T_{in}	Rh_{in}
W_S	1	0.04	0.44	0.45	-0.5	0.43	-0.5
W_D	0.04	1	0.08	-0.03	0.03	-0.005	0.02
G	0.44	0.08	1	0.89	-0.7	0.92	-0.8
T_{out}	0.45	-0.03	0.9	1	-0.86	0.97	-0.9
Rh_{out}	-0.5	0.04	-0.7	-0.87	1	-0.8	0.98
T_{in}	0.43	0.0053	0.93	0.97	-0.8	1	-0.9
Rh_{in}	-0.5	0.02	-0.8	-0.9	0.98	-0.9	1

According to the matrix of correlations above, W_S and W_D do not correlate with the two outputs. Thus, they are omitted from the inputs list. It can be remarked that Tout and Rhout and G correlate well with the considered outputs.

2.3 Artificial neuron network (ANN):

Artificial neuron network is a machine learning method that mimics the learning process of a human brain [5]. In literature various neural network types can be found namely: Hopfield, feed-forward, Elman, self-organizing maps, and radial basis networks [6]. In this paper, forecasting T_{in} and Rh_{in} of the studied greenhouse is done using a feed-forward neural network. The Levenberg-Marquardt backpropagation is chosen as training algorithm. The ANN model of our case study is composed with one hidden layer with various numbers n of neurons (Figure 2):

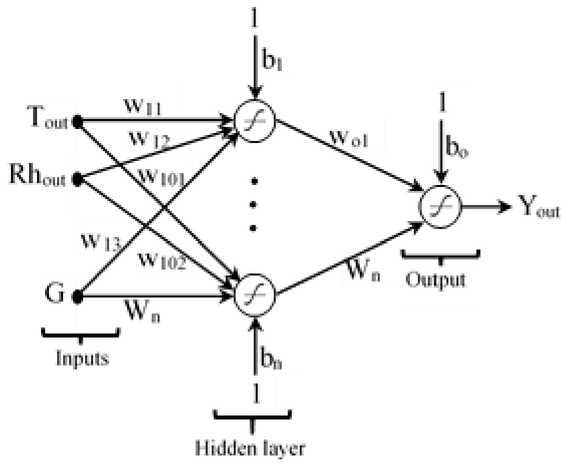
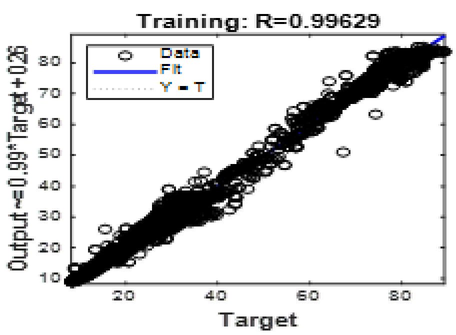


Fig. 2. ANN architecture.

3 Prediction of the greenhouse inside temperature and relative humidity using ANN method and limited meteorological data

3.1. Tin and Rhin forecasting using three measured inputs:

In this part, three measured inputs are taken into account: T_{out}, Rh_{out} and G. The parameters and features of the ANN model are presented in part 2.3. the number of neurons is chosen equal to 10 in the hidden layer. The simulation results are presented in figures 3 , 4 and 5.



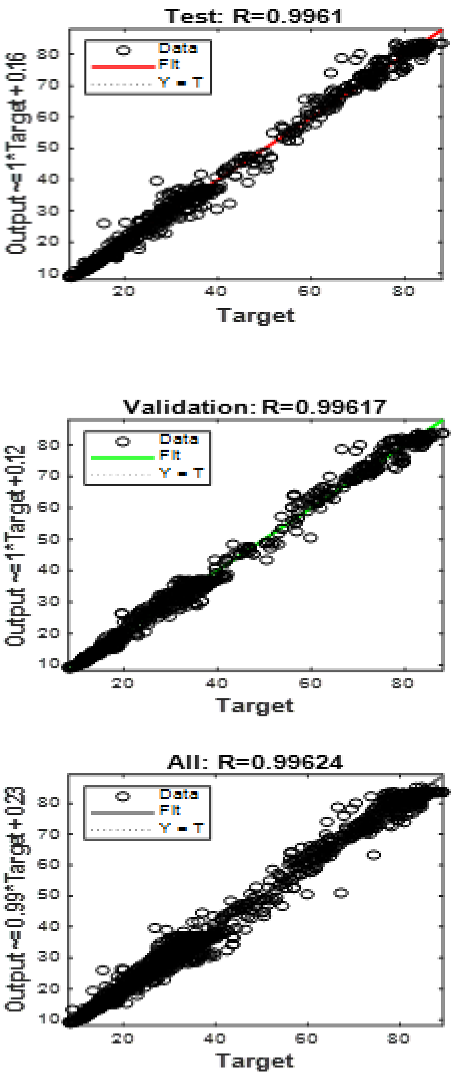


Fig. 3. Graphs of correlations.

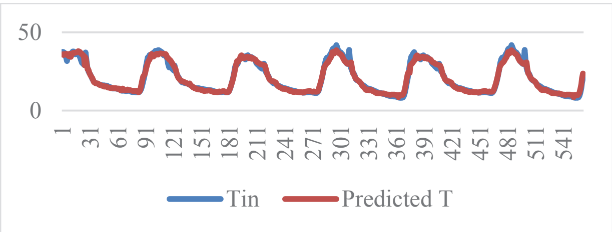


Fig. 4. Comparison between measured and predicted inside temperature.

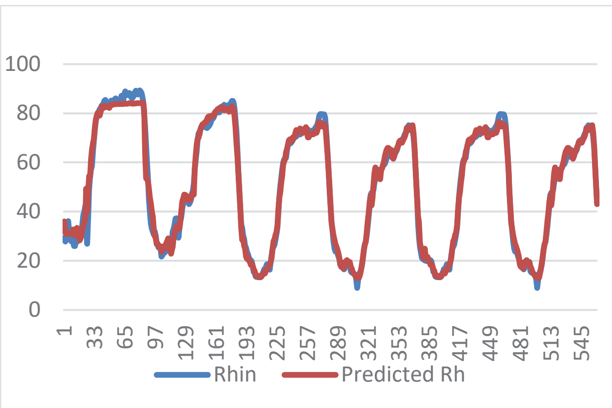


Fig. 5. Predicted and target Rhin.

According to figure 3, there is a perfect correlation between measured and predict-ed parameters: the correlation coefficient R>0.996 for all phases of training, validation and testing. This perfect accuracy is shown clearly in figures 5 and 6, where predicted values approached perfectly the measured ones.

3.2 T_{in} and Rh_{in} forecasting using one measured input:

In this section, the factor of time is introduced as input parameter. Only one measured parameter will be considered which is external temperature. Results of the simulations are presented in table 2.and figure 6 .

Table 2. Correlation coefficients according to number of neurons.

Number of neurons	R
5	0.966
10	0.971
15	0.973
20	0.979
25	0.979
30	0.981
35	0.981
40	0.980
45	0.981
50	0.982

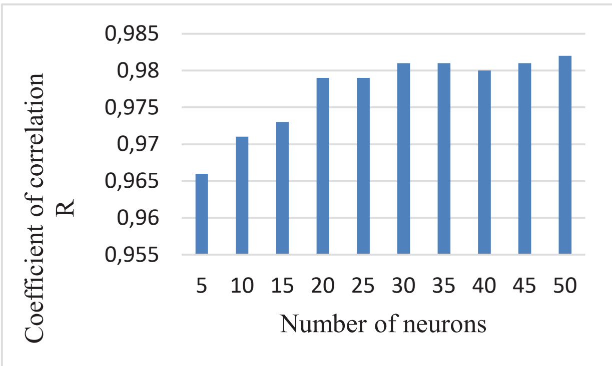


Fig. 6. Graphs of correlations according to number of neurons.

According to table 2 and figure 6, very good correlation coefficients are observed when predicting the greenhouse microclimate parameters using just external tempera-ture as measured parameter. It can be remarqued that from 20 neurons, correlation coefficient reached 0.979.

3.3 Discussion

Results presented in part 3.1 show that forecasting $\mathbf{T_{in}}$ and $\mathbf{Rh_{in}}$ using three measured inputs: $\mathbf{T_{out}}$, $\mathbf{Rh_{out}}$ and G , gives excellent results according to the coefficients of correlation presented in figure 3. In fact, for the three steps: training, validation and testing, the correlation coefficient is equal to 0.996. The aim of this study is to predict the same parameters using less measured inputs. Thus, the factor of time was introduced. The measurements were recorded each 15 minuts for 24 hours-a day for the hole month of March. Each 15 min a day was given a number. External temperature was the only measured input parameter used in section 3.2. The ANN model performance was tested for various number of neurons in the hidden layer. Table 2 and figure 6 show that results were very satisfying due to the coefficients of correlation that reaches 0.96 at least for all number of neurons cases. It can be remarqued that 20 neurons in the hidden layer are sufficient to have a correlation of about 0.98.

4 Conclusion

The main problem faced during the prediction of energetic parameters is the need to have a carefully recorded experimental database. The prediction of inside temperature and relative humidity of a greenhouse with limited meteorological data is presented. The introduction of the factor of time was a very good solution that makes it possible to reach a very good coefficient of correlation without using other environ-mental parameters such as solar radiations and external relative humidity.

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