Greenhouse Modeling Using Neural Networks

MARCOS ALBERTO BUSSAB
JOAO ISRAEL BERNARDO
ANDRE RIYUITI HIRAKAWA
Agricultural Automation Laboratory
Polytechnic School of Sao Paulo University
Sao Paulo
BRAZIL
http://www.pcs.usp.br/~laa

Abstract: - This paper presents an alternative process, based on Neural Networks, for modeling greenhouses. The proposed modeling process takes into account environmental variables and greenhouse features. The model composed by a Perceptron Multi-layer Network is applied to actual greenhouse. Simulation results are compared to experimental values. The results have shown a good approximation between neural network method and measured values.

Key-Words: - Neural Networks, Modeling, Precision Agricultural, Environmental Variables

1 Introduction

Artificial Intelligence (AI) is the field of Computer Science that attempts to give computers humanlike abilities. One of the primary means by which computers are endowed with humanlike abilities, is a Neural Network (NN). The human brain consists of a network of over a hundred billion interconnected neurons. Neurons are individual cells that can process small amounts of information and then activate other neurons to continue the process. Neural networks are often not suitable for problems where you must know exactly how the solution was derived. A NN can become very useful for solving the problem for which the neural network was trained [1].

The individual neurons that make up a NN are interconnected through the synapses. These connections allow the neurons to signal each other as information is processed. Not all connections are equal. Each connection is assigned a connection weight. If there is no connection between two neurons, then their connection weight is zero [2].

The neurons of a network can be connected in different ways, resulting in different architectures. One important NN architectures is the Multi-Layer model. The neurons are organized well-defined levels that are called layers. Each unit of a layer receives inputs comings from a preceding layer, and sends output signals for the following layer. These nets are known as nets feed-forward. Architecture of three layers - entered, occult layer and exit - are used in practical applications of the neural nets. Artificial the Neural Nets can be applied on different types of tasks, such as: pattern recognition (recognition of faces human beings), classification (recognition of characters OCR), transformation of data (compression of data), prediction (forecast of secular series in quotation of stock exchange or medical diagnosis), control of processes (applications in the robotics area), and so on [3].

Training is the process by which the connection weights of NN are assigned. Most training algorithms begin by assigning random numbers to the weight matrix. Then the validness of the NN is analyzed. Next, the weights are adjusted based on performance criteria. This process is repeated until the validation error is within an acceptable limit. NN training methods generally fall into the categories of supervised, unsupervised and various hybrid approaches [4]. Supervised training is accomplished by giving the NN a set of sample data along with the anticipated outputs from each of these samples. As supervised training proceeds, the NN is taken through several iterations, or epochs, until the actual output of the NN matches the anticipated output, with a reasonable error. Each epoch is one pass through the training steps [5].

Greenhouse is a dynamic system with distributed, non-linear and time varying parameters. Therefore, modeling involves a broader knowledge of biotic and non-biotic factors, whose mathematical representation is given by differential equations of complex resolution.

This work has as objectives the development of a computational model of greenhouses based on NN.

The text is organized in six sections. The second section presents a description of the analytical model and Fuzzy model for the control of the internal variable of a greenhouse. In section three, the NN model adopted in this paper is presented. The results from the NN are presented and analyzed in the following sections and, the last section, presents the general and specific conclusions.

2 Analytical and Fuzzy Modeling

It has presented the analytical model that describes the greenhouse microclimate behavior using the balance equations of mass and heat and considering natural ventilation as air renew [7]. External air humidity, solar radiation wind speed and physical constants were extracted from [6]. Equation (1) shows greenhouse energy balance.

$$Qr + Qm + Qso + Qsa + Qve = Qce + Qsp + Qsl + Qvs + Qft + Qtt \quad (1)$$

Where:
Qr - respiration sensible heat, W;
Qm - equipments, illumination and engines heat, W;
Qso- sun energy input, W;
Qsa- sensible heat from heating system, W;
Qve - entrance ventilation air sensible heat (naturally or forced), W;
Qce - structure conduction sensible heat, W;
Qsp - sensible heat transferred to the soil by perimeter, W;
Qsl - sensible heat converted to latent heat inside internal space (vase water evaporating, irrigation system or hydropony and evapotranspiration), W;
Qvs - Out ventilation air sensible heat (naturally or forced), W;
Qft - sensible heat used for photosynthesis, W, and
Qtt - thermal transmittance heat, W.

The values of the Qr, Qft and Qsp terms are hundred times small if compared to the other terms values and may usually dismissed. Besides, Qsl value is difficult to be measured [7], and may also be ignored.

Therefore, equation (2) is obtained from equation (1).

$$Q_{so} + Q_v = Q_{ce} + Q_{sp} + Q_{tt} \quad (2)$$

For a better comprehension of the relationship among the external variables (temperature, radiation and wind speed) and the internal temperature, equation (2) is modified and yields the equation (3).

$$F \cdot Ti^4 - (Vv \cdot B - G)Ti - (F\varepsilon_{ar} Te^4 - (Vv \cdot B - G)Te + I_c A) = 0 \quad (3)$$

Where:

$$A = \tau \cdot Ap$$
$$B = cp \cdot E \cdot Aa \cdot \rho$$
$$F = \varepsilon_{\sup} \cdot \gamma_t \cdot \sigma \cdot Ap$$
$$G = U \cdot Ac - F \cdot Per$$

τ: Cover Transmittance in relation to global radiation
I_e: External global radiation
cp: External air specific heat
E: Openings efficiency
Aa: Openings area
ρ: Air density
ε_{sup}: vegetation or floor emissive
γ_t: thermal transmittance of the plastic in the re-irradiation
σ: Stefan Boltzmann constant
Ap: Plastic greenhouse floor area
U: Global coefficient of transference of heat of the plastic
Ac: Plastic greenhouse contour area with open or closed lateral
F: Perimeter Factor
Per: Plastic greenhouse perimeter
I_e: External global radiation
Vν: Wind speed
Ti: Internal temperature
Te: External temperature

The average of the Internal Relative Humidity (URi) is obtained from the use of the average of Internal Temperature (Ti) within mass balance equation (Wi) as shown in equation (4) [8].

$$\overline{m} \cdot Wi = \overline{m} \cdot We + Map \quad (4)$$

where:
$\overline{m}$: dry air mass flow, kg s-1;
Wi: absolute internal humidity, kg kg-1 (H2O vapor kilogram by dry air kilogram);
We: external absolute humidity, kg kg-1 (H2O vapor kilogram by dry air kilogram);
Map: mass flow of the water produced by the plants, kg s-1.

Analytical modeling with large number of variables and equations, such as previously described, is difficult to be solved. In some cases, linearization and simplification are applied but it yields in error accumulation, compromising the model’s efficiency.
Considering that, [9] proposed the use of Fuzzy Logic to model the microclimate behavior inside a greenhouse, with the purpose of surpassing the

limitations imposed by the analytical model. This alternative method for modeling greenhouse was implemented and simulated. The use of Fuzzy Logic show advantages like the easy modeling without detailed known about actual modeled process, which is mandatory at the analytical modeling. The simulation results show good accuracy compared to measured values and to values obtained by analytical model, which proved the correctness of the proposed method.

3 Neural Network Modeling

A multilayer NN with 2 hidden layers was proposed for the greenhouse model, as shown Fig.1.
The first hidden layer has 40 neurons and second one has 20 neurons. A series of tests, from references, had been carried through until getting an acceptable configuration in what to refer it amount of hidden layers and the amount of neurons of those layers. The input of the NN is the values of External Temperature, External Global Radiation, External Relative Humidity and Wind Speed. The outputs are the values of Internal Temperature and Internal Relative Humidity. The hyperbolic tangent function, or TANH, was selected as activation method for input layer and for the first hidden layer. The linear function was selected as activation method for second hidden layer.

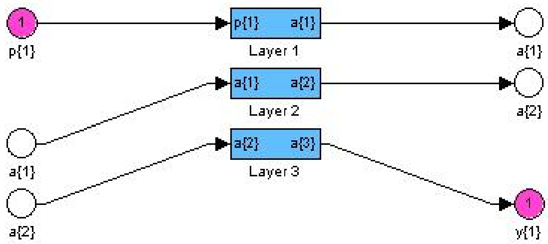

Fig 1. Greenhouse Multilayer Neural Network

The feed forward back propagation NN was chosen as the architectures. This NN architecture is very popular because it can be applied to many different tasks. “Feed forward" describes how this NN processes the pattern and recalls patterns. When using a "feed forward NN" neurons are only connected forward. Each layer of the NN contains connections to the next layer, but there are no connections back.
Back Propagation was the NN training method which is a supervised training. When using a supervised training method the network must be provided with sample inputs and anticipated outputs. Anticipated outputs will be compared against the anticipated outputs from the NN. Using anticipated outputs the "back propagation" training algorithm takes a calculated error and adjusts the weights of the various layers backwards from the output layer all the way back to the input layer.
Error calculation is an important aspect of any NN. The goal of the training algorithms is to minimize the error. There are some components to the error that must be considered. First, the error for each of the training sets must be calculated. Secondly, the average across each sample for the training set we must be taken. Finally, after all training sets have been processed, the root mean square (RMS) error is determined. In the present case, the goal was RMS equal 10E-8.

4 Simulation Results

For the training of the NN, 14 inputs and output data sets had been selected, from the values gotten in an experiment lead in the College of Agricultural Engineering of State University of Campinas, as described in [10]. Others 13 data sets of the same experience had been used for the validation of the training of the network.
The NN reached the goal after 22 epochs in the training, as shown in Fig. 2.

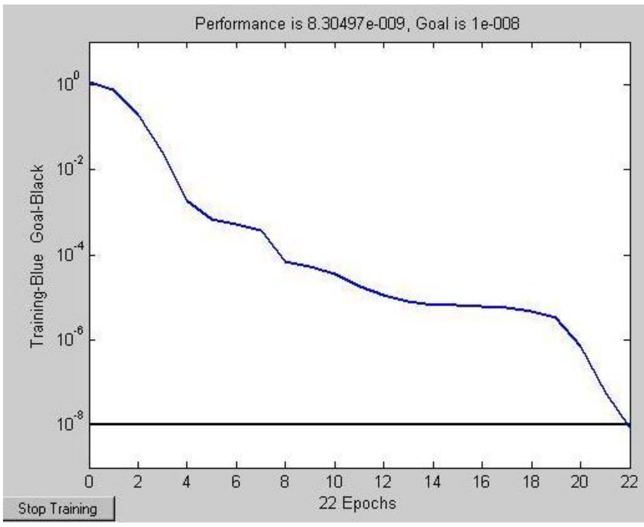

Fig 2. Network Performance for error 1E-08

The NN training was repeated for 200 epochs, considering goal at zero, in order to verify that the result reached after 22 epochs was not a local minimum, as shown in Fig. 3. Fig.4 and fig. 5 show the temperature and humidity error calculated between analytical and NN technique. Table 1 shows the comparison between experimental and simulation results using analytical and proposed NN method. Each line of the Table 1 represents the average values in one day. It is possible to observe that in 10 dataset results the internal relative humidity has a better performance than analytical approach. As can be seen in Table 1, the simulation results from NN technique have been more precise when compare to analytical method in 81% cases.

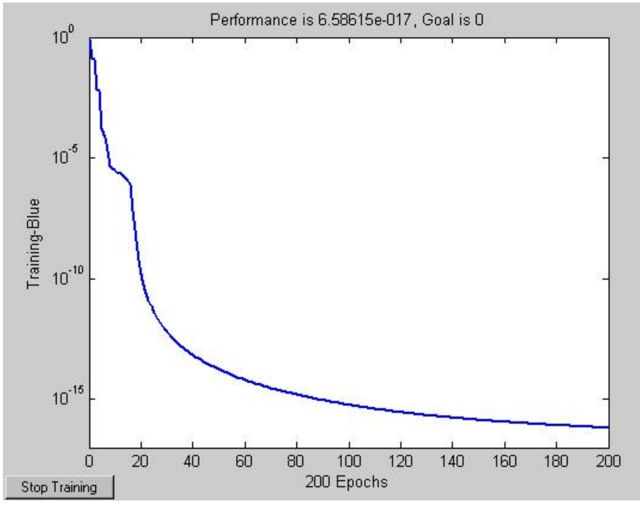

Fig 3. Network Performance for 200 epochs

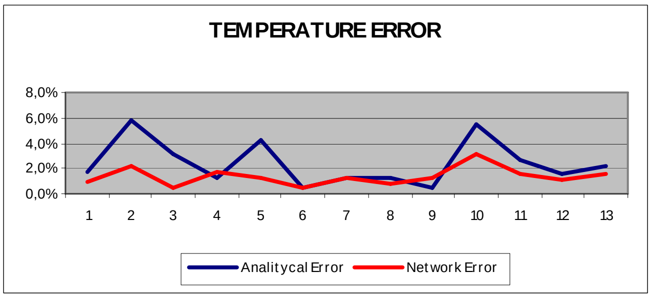

Fig 4. Temperature Error

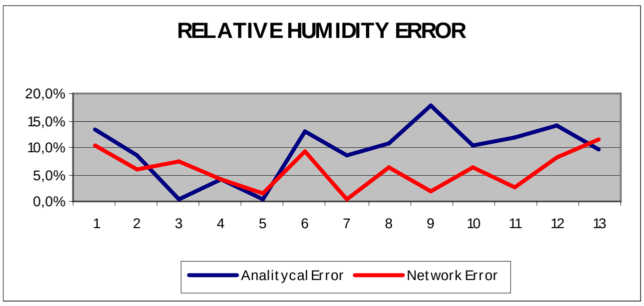

Fig 5. Relative Humidity

Besides, it can be noted that NN has also better results for the internal temperature. In this situation, the NN method had a good approximation in 77% cases. In 62% cases it can be observed that NN has been more efficient than analytical method.

5. Conclusion

In this work the NN was applied in order to predict some parameters in a greenhouse. A multiplayer perceptron NN has been trained using backpropagation algorithm.

Despite the good results obtained, it is possible to improve the NN performance by using more dataset of the main system parameters. From the simulation results, the neural architecture can be a good alternative for another existing technique in this kind of application.

References:

[1] Barrera, J.; Terada, R.; Jr R. H.; Hirata, N. S. T.Automatic programming of morphological machines by pac learning. Fundamenta Informaticae. 2000, 41(1-2): pp. 229-258.

[2] Baldi, P.; Hornik, K. Neural networks and principal components analysis: learning from examples without local minima Neural Networks, 1989, pp. 53-58.

[3] Fausett, L. Fundamentals of neural networks architectures, algorithms and applications, Prentice Hall, 1994.

[4] Haykin, S. Neural networks – a comprehensive foundation, Prentice-Hall, 1994.

[5] Hassoun, M. H. Fundamentals of artificial neural networks, MIT Press, Cambridge, M.A., 1995.

[6] Albright, L.D. Environment control for animals and plants. St. Joseph: ASAE, 1990, p. 453.

[7] Ashrae. Environment control for animals and plants. In: ASHRAE Handbook of Applications. USA: ASHRAE, Chapter 22, 1978, p.22.1-22.20.

[8] Hellickso, M.A. Ventilation of agricultural structures, St.Joseph: ASAE, 1983, p. 372.

[9] Silvério M.; Bernardo J.I.; Amancio S.M.; Hirakawa A.R.; Atarassi R.T. Greenhouse analytical modeling with spatial variability identification, 8th International Precision Agricultural Conference, 2006.

[10] Costa, E., Leal, P. A. M., Carmo Junior, R. R. 2004. Modelo de Simulação da temperatura e umidade relativa no interior de estufa plastica, Journal of the Brazilian Association of Agricultural Engineering, v. 24, n. 1, p. 57-67, jan./abr. 2004.

Input				*Output*									
				Relative Humidity					**Temperature**				
Ie	**Vve**	**Ure**	**Te**	**Sensor**	**Analitycal**	**Network**	**Analitycal Error**	**Network Error**	**Sensor**	**Analitycal**	**Network**	**Analitycal Error**	**Network Error**
292,94	0,95	80,1	19,93	81,9	71,1	73,5	13,2%	10,3%	22,3	21,9	22,1	1,8%	0,9%
354,07	1,24	76,8	19,28	62,7	68,1	59,1	8,6%	5,7%	22,5	21,2	22,0	5,8%	2,2%
782,34	2,09	65,5	18,94	54,2	54,5	50,1	0,6%	7,6%	22,6	21,9	22,5	3,1%	0,4%
398,01	1,52	83,1	20,65	77,2	74,1	74,0	4,0%	4,1%	22,8	22,5	22,4	1,3%	1,8%
623,88	1,88	69,0	19,73	59,2	58,9	60,1	0,5%	1,5%	23,3	22,3	23,0	4,3%	1,3%
513,95	1,17	76,2	20,98	72,4	62,9	65,7	13,1%	9,3%	24,2	24,1	24,3	0,4%	0,4%
763,33	1,36	64,8	20,60	54,6	49,9	54,9	8,6%	0,5%	24,6	24,9	24,9	1,2%	1,2%
571,84	1,33	79,1	21,33	72,8	65,1	68,3	10,6%	6,2%	24,8	24,5	24,6	1,2%	0,8%
637,73	1,22	80,8	21,66	77,7	63,9	79,0	17,8%	1,7%	25,5	25,6	25,8	0,4%	1,2%
739,54	2,39	53,9	21,73	51,7	46,3	48,5	10,4%	6,2%	25,6	24,2	24,8	5,5%	3,1%
722,44	1,45	64,5	22,46	58,3	51,3	59,8	12,0%	2,6%	25,6	26,3	25,2	2,7%	1,6%
440,72	1,05	69,5	22,50	67,9	58,3	62,3	14,1%	8,2%	25,8	25,4	25,5	1,6%	1,2%
759,16	1,24	65,5	22,49	54,8	49,6	61,0	9,5%	11,3%	26,6	27,2	26,2	2,3%	1,5%

Table 1. Validation Results