CONTROLO
2004

Proceedings

SIXTH PORTUGUESE CONFERENCE ON AUTOMATIC CONTROL

Edited by A.E.RUANO

CONTROLO 2004

UNIVERSITY OF ALGARVE
FARO, PORTUGAL, JUNE 7-9, 2004

Organized by

APCA

Centre for Intelligent Systems

GREENHOUSE AIR TEMPERATURE MODELLING

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Abstract: This paper describes two implementation approaches for modelling the air temperature of an automated greenhouse located in the campus of the University of Trás-os-Montes e Alto Douro. Linear models, based in the discretization of the heat transfer physical laws, and non-linear neural networks models are used. These models are described as functions of the outside climate and the control actions performed for heating and cooling. Results are presented to illustrate the performance of each model in the simulation and prediction of the greenhouse air temperature. The data used to compute the simulation models was collected with a PC-based acquisition and control system using a sampling time interval of 1 minute.

Keywords: Greenhouse climate models, Neural networks, Parameter estimation, Temperature Control.

1. INTRODUCTION

Greenhouse crop production systems requires the use of complex management and control tools in order to maximise the grower profits. Several decisions must be performed at different hierarchical levels and time basis, such as crop planning and greenhouse climate control. Large time scales decisions, such as crop planning, are made manually, since there are practical limitations that makes this objective unachievable without the grower intervention (Challa, 1999; Van Straten *et al.,* 2000). However, the aerial and root environment control can be automated in order to achieve optimal solutions that provide the best balance between plant growth rate and the energy spend to regulate the climate.

In this way, proper software tools are needed to put into practice an adequate management strategy, namely greenhouse climate models. This paper addresses two approaches to design and implement inside air temperature dynamic models. One is based on the discretization of the physical laws involved in the heat fluxes between the air and components inside the greenhouse and the heat fluxes that take place between the inside and outside air. The second approach uses a neural network model.

The air temperature models simulations are computed for a greenhouse located in the University campus. The greenhouse has a floor area of $210m^2$, covered with a 200μm polyethylene film. Several actuators and sensors are installed and connected to an acquisition and control system (Boaventura J., Couto C., and A.E.B. Ruano, 1997) using a sampling interval of 1 minute.

The results achieved with these models, that are computed using 25 days of data (from 9 of January to 2 of February 1999) are presented for the simulation of the air temperatures over a validation data set from the 3rd of February to the 9th of February 1999.

In section two both the linear model derived using physical laws and the non-linear neural network modelling tool are described. In section three some preliminary research results are presented and in section four some conclusions are presented and future work outlined.

2. GREENHOUSE AIR TEMPERATURE MODEL

2.1 *Linear discrete model based on physical laws*

The greenhouse air temperature can be described by heat flow equations (Boulard *et al.*, 1993; Bot, 1991), which are generated by the differences in energy content between the inside and outside air and by the control or exogenous energy inputs,

$$\frac{dT_{ag}}{dt} = \frac{1}{C_{aph}}\left(q_{in,h} - q_{out,h} + p_h\right) \ [^{\circ}Cs^{-1}] \qquad (1)$$

where: T_{ag} is the air temperature, C_{aph} the thermal capacity, $q_{in,h}$ and $q_{out,h}$ the heat inflow and outflow and p_h the energy production per unit of time, which can occur by plant decomposition or other processes.

In the previous equation, the transport mechanisms for conduction, convection and radiation are implicit. For instance, the heat flux from inside to outside due to ventilation and losses, $q_{out,h}$, is described by the following equation:

$$q_{out,h} = \left(\Phi_{vent} C_{cap,h} + C_{c,h}\right).\left(T_{ag} - T_{out}\right) \qquad (2)$$

where: $C_{c,h}$ [W.m^{-2}.°C^{-1}] is the heat transfer coefficient related with the greenhouse cover losses, $C_{cap,h}$ [J.m^{-3}.°C^{-1}] is the air heat capacity per unit of volume air, $\Phi_{vent}=C_{vent}.u_{vent}+C_{losses}$ [m.s^{-1}] denotes the airflow generated by the ventilation system, $C_{vent}.u_{vent}$, due to the air exchange losses between the inside and outside the greenhouse, C_{losses} and T_{out} is the outside air temperature. The signal u_{vent} denotes a ventilation control signal that varies in the range 0 to 1, corresponding to delivered powers ranging from 0 to 100% of the actuator nominal power.

In the previous equation, $C_{cap,h}$ has a physical meaning,

$$C_{cap,h}=\rho_{air}.C_{cap,h,p} \qquad (3)$$

where: $C_{cap,h,p}$=1000Jm^{-3}°C^{-1} is the heat capacity of the air at constant pressure and ρ_{air}=1,29kgm^{-3} is the air density.

The greenhouse heat input flow, $q_{in,h}$, has two major components, one is generated by the heating system and the other by the solar radiation. The heat flow component of the heating system is computed by:

$$q_{heat} = C_H\left(T_{pipe} - T_{ag}\right)\cdot u_{heat} \qquad (4)$$

in which C_H [W.m^{-2}.°C^{-1}] is the actuator heat transfer coefficient, T_{pipe} is the water temperature of the heating pipes and u_{heat} is the heating control signal in the range 0 to 1.

The short wave radiation coming from the Sun generates the principal heating source during the day periods. This heat flow, q_{rad} [W.m^{-2}] is related with the solar radiation that passes trough the cover, Rad [W.m^{-2}], by the following equation,

$$q_{rad} = C_{rad} Rad \qquad (5)$$

in which C_{rad} is a coefficient that reflects the optical and geometrical properties of the greenhouse cover.

Besides these heat fluxes there are radiative exchanges, long wave radiation, governed by the Stefan-Boltzmann laws and heat fluxes between the inside air and soil. However, since normally these components have much lower weight than the previous ones, they are not taken in account in the air temperature model.

The model described in (1) was discretized using difference equations leading to:

$$q_{total} = q_{heat}(k-1) + q_{rad}(k-1) - q_{out,h}(k-1) \qquad (6.1)$$

$$\hat{T}_{ag}(k) = \frac{q_{total}}{C_{aph}} \times T + \hat{T}_{ag}(k-1) \qquad (6.2)$$

in which k denotes the sample at the time kT with T representing the sampling time of 60s.

Some of the model parameters are physical constants and were obtained from the work of De Jong (1990). The remaining parameters were computed using an optimisation algorithm to minimise a cost function proportional to the sum of the squared errors between the simulated and measured temperatures using a data estimation set from 9 of January to 2 of February 1999. The estimated parameters and the simulation results are showed in section 3.

2.2 *Neural network model*

Artificial neural networks are collections of mathematical models that reproduce some of the observed properties of biological nervous systems. The key element of the ANN is the structure of the information processing system. This system is composed of a large number of highly interconnected processing elements that are analogous to neurons and are coupled together with weighted connections that are analogous to synapses. Non-linear autoregressive models are potentially more powerful than linear ones because they can model more complex underlying characteristics of the data.

There are a broad number of ANNs topologies. Among the most widespread are feedforward networks. In this paper, a multilayer perceptrons (MLP) network, using a hyperbolic tangent as the activation function of the hidden processing units. These type of structures have proved to be an universal approximator (Hornik *et al.*, 1989). This means that they can approximate any reasonable function f with a subjective accuracy given by:

$$f(u)=\left(\sum_{j=1}^{k} v_{jl}\tau\left(\sum_{i=1}^{n} w_{ij}\cdot u_i-\theta_j\right)-\theta_l\right), l=1...m \qquad (7)$$

where: τ is the activation function, k is the number of hidden units, v_{jl} and w_{ij} are weights, θ_i are biases and u is the data vector.

Figure 1 shows the feedforward neural network topology used, considering as inputs the indicated variables, a single hidden layer with four neurons and a single output predicting the inside greenhouse temperature one step-ahead. The activation function for the last neuron is linear.

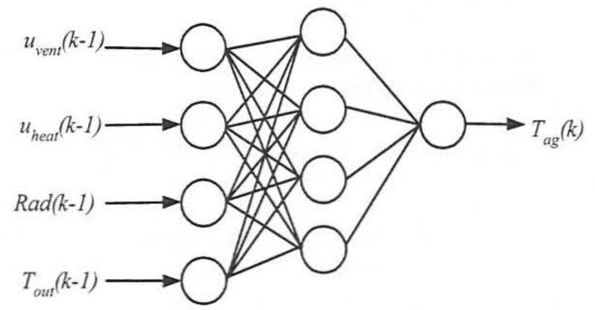

Fig. 1. Feedforward neural network topology used.

The non-linear function f is estimated based on data samples using the Lavenberg-Marquardt optimisation technique. The Lavenberg-Marquardt is the standard method for minimization of mean square error criteria, due to its rapid convergence properties and robustness (Marquardt, 1963).

Weight initialisation is performed following the Nguyen and Widrow (1990) technique and a simple weight decay technique is used in order to force their magnitude to small values by adding to the mean square error expression an extra regularisation term (Principe *et al.*, 2000). The natural neural network limitation, regarding the number of samples available to train the network is not a problem in this case due to the considerable amount of measured greenhouse data (three weeks for training and one week for model validation). Standard data normalization was performed and no pre/post processing techniques involving data filtering were used.

3. SIMULATION RESULTS

The computed parameters of the linear model (eq. 6.2) are showed in table 1.

Table 1 Parameters of the linear model

parameter	*value*
C_{aph}	$31977\ J\ m^{-2}\ °C^{-1}$
C_H	$1.206\ W\ m^{-2}\ °C^{-1}$
C_{rad}	0.61
$C_{cap,h}$	$1290\ J\ m^{-3}\ °C^{-1}$
$C_{c,h}$	$3.80\ W\ m^{-2}\ °C^{-1}$
C_{vent}	$11.33\times10^{-3}\ m\ s^{-1}$
C_{losses}	$1.5\times10^{-4}\ m\ s^{-1}$

The performances of the linear and neural network models are presented in table 2 using the *MSE* index criteria in the estimation and validation data sets,

$$MSE=\frac{1}{N}\sum_{k=1}^{N}\left(T_{ag}(k)-\hat{T}_{ag}(k)\right)^2 \qquad (8)$$

in which N is the number of data samples and $\hat{T}_{ag}$ denotes the simulated air temperature.

Table 2 Model performances for the estimation and validation data periods

Model	*MSE* (9/1 to 2/2/99)	*MSE* (3/2 to 9/2/99)
Linear	3.74	6.87
Neural Network	1.95	3.78

Figure 2 shows the models responses and the measured air temperature for 2 days of the validation data set. From this plot it can be seen that the dynamics of the air temperature is adequately described. Notice that this simulation results are computed in open-loop and so, no feedback information about the real air temperature is feed into the model.

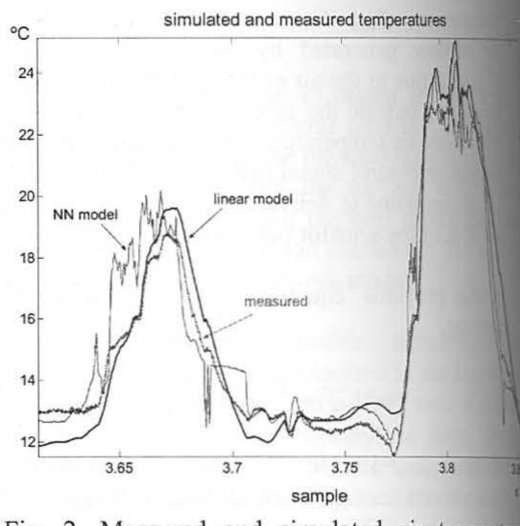

Fig. 2. Measured and simulated air temperatures computed for 2 days of the validation data set.

In figure 3 it is possible to view the heat fluxes computed with the linear temperature sub-models (eqs. 2, 4 and 5) for the same time period used to simulate the air temperatures in Fig. 2.

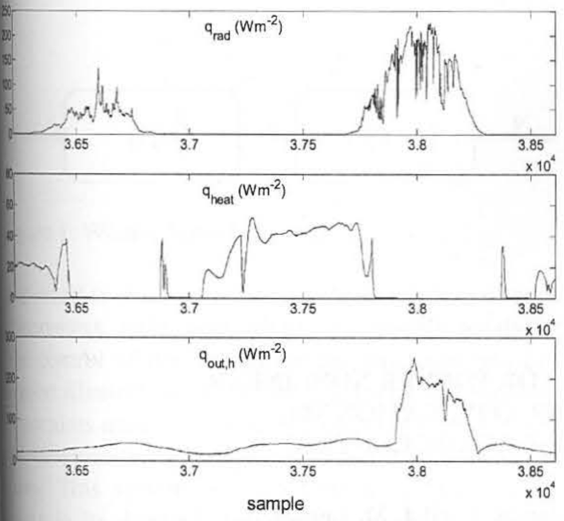

Fig. 3. Heat fluxes from solar radiation (top), heating system (middle) and ventilation/cover losses (bottom).

Next figure shows the variables of the outside climate and the control signals used to compute the simulation results for the same time period used in the previous figures.

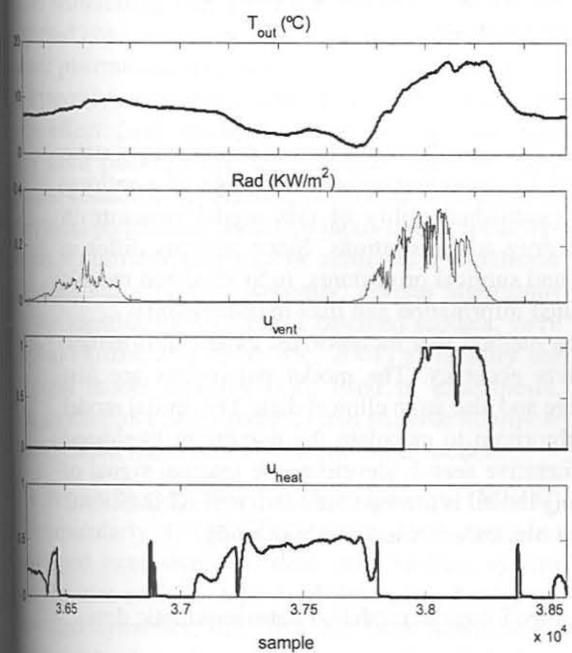

Fig. 4. Input signals used in the air temperature models.

4. CONCLUSION AND FURTHER WORK

This study has drawn a comparison between a linear model, based in physical laws, and a non-linear neural network model applied to the simulation of the air temperature inside a greenhouse. The preliminary results presented here show that the non recursive linear based physical model give worst results in terms of the mean square error cost function used. However, with the linear model is possible to compute the heat fluxes and explain physically the energy exchanges that occur in this process, which is an advantage in relation to the black box neural network identifier used.

Some future work research points are:

1. to use other combination variables as the neural network inputs and consider the use of more available measurements which while available were not used in this study, such as the greenhouse soil temperature, relative humidity inside and outside the greenhouse, among others.
2. to consider the feedback of the simulated output delayed one sample to the neural network input.
3. to consider different models for the day and night periods.

ACNOWLEDGEMENTS

The authors appreciate the support of the Portuguese Foundation for Science and Technology (FCT) through the project MGS/33906/2000.

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