NEURAL MODELS FOR AN INTELLIGENT GREENHOUSE - THE HEATING

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I. Introduction

Greenhouses are building structures widely used in vegetable production and for growing ornamental plants or flowers. Solar radiation passing through the transparent walls and roofs is essential for the photosynthesis, and supplements heating in the cold season. In hot weather other actuators, like roof vents, shading systems, exhaust fans or evaporative cooling may be used to avoid overheating. In most modern greenhouses these automated actuators are operated by some kind of control system.

Control systems for greenhouses available on the market have not changed much in the last years: actuators are individually controlled based on set-points and actual measurements [1]. This traditional control design has three major drawbacks: (1) The adjustment of set-points depends strongly on the expertise of the greenhouse operator. (2) The control system is reactive: without predicting the future state of the greenhouse, it is impossible to control effectively for a long time horizon. (3) The actuator operations are unsynchronized (all are set independently from each other), resulting in possible oscillations in the control and poor maintenance of the internal climate.

The solution overcoming these limitations is to increase the level of intelligence of the system by applying an intelligent control solution [2].

II. Intelligent Control

The primary objective of greenhouse control solutions is to provide suitable environmental conditions for the plants. The traditional form of control depends on human intelligence. The operator will in theory be able to choose optimal set-point combinations. Unfortunately with several actuators finding the optimal control configuration intuitively, without serious theoretical modeling and computing, is impossible. Consequently optimal control in this case is neither possible. Yet the greenhouse operator is fully aware of the physiology of the plants and their physical and chemical needs. The control system therefore should operate on this available information. Instead of accepting set-points, an intelligent control system should expect global control goals.

The concept of control goal as the direct control information makes the human interaction easier, but the knowledge intensive transformation from the goals to the control actions is left to the control system. This transformation can be implemented with predictive modeling, which also solves the second problem of traditional control, namely its reactiveness. Predictive modeling means in this case making assumptions about the actuator settings, and predicting the future thermal states of the greenhouse. These thermal states reported over a given time span can be then evaluated with respect to the control goals. The costs of the actuator setting and the deviation from the goals can be fused together into a numerical cost function. By computing the minimal value of this cost, e.g. by trying all different actuator configurations, makes it possible to find the most appropriate actuator settings.

Predictive modeling solves in part the missing synchronization of the actuators, but the common problem of traditional control, i.e. swinging controlled variable, still remains. The possible control loops, repeatedly setting and resetting the actuators cannot be avoided this way. All such problems can be however handled by (AI) planning. We expect that the concept of intelligent control will provide solutions to all principal limitations of the traditional greenhouse control, with better environmental conditions for the plants and lower costs for the owners.

III. Modeling the Heating

A The Modeling Problem

The necessary basis of the intelligent control is the prediction of the future thermal state of the greenhouse, thus the first step is modeling. The greenhouse model must be able to predict all important internal and external parameters of the house for a reasonable span of the time. This paper focuses on the modeling of the heating system. This subsystem within the greenhouse is very important because it is the main financial cost factor of the greenhouse during the cold period of the year. Fig. 1. (A) shows an example of the heating pipe temperature recorded on 11-02-2009 with the heating turned on 11 times. The modeling of the heating system can be easily separated from the whole greenhouse because the involved quantities are relatively independent from other quantities affecting the greenhouse. On the other hand the influence of the internal and external temperature on the heating pipe temperature cannot be completely neglected. Fig. 1. (B) shows 10 different graphs recorded in the greenhouse all starting from 25 °C heating pipe temperature when the heating was turned on. Depending on the actual internal temperature and the changes in both internal and external temperatures (even weather changes) different graphs of the heating pipe temperature were obtained.

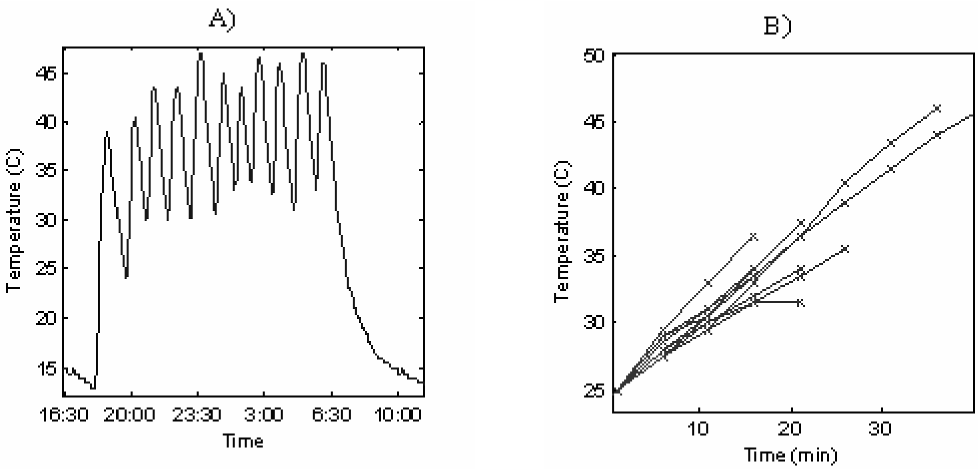

Figure 1: A) The recorded heating pipe temperature on 11-02-2009; B) Different graphs of the heating pipe temperature both starting from 25 °C

B Using Prediction Tables

In the given greenhouse the temperature of the heating pipe is always in the range of 0-50 °C. The resolution of the measurement system is 0.5 °C, which means that the heating pipe has 100 states determined by its temperature. This small state space makes it possible to inspect all states separately and store the prediction from each state in a table for easy retrieval. In practice two tables are needed: one for the warming state of the pipe and another for the cooling state. Examining the data from the greenhouse for the former case it is evident, that after activating the heating, it was almost always operating for at least 20 minutes. The time resolution of the measurement system is 5 minutes thus we have many training data with at least 4 steps. In the later case we have more training data, but most of the time the pipe temperature passively follows the internal temperature. Accordingly we require the pipe to be warmer by 10 °C than the internal air to use these data as training examples.

Both tables can be filled in with data generated by the following algorithm described here for the warming case: the algorithm looks for any t time points in the measurements when the heating was on. If the heating was not turned off before t + 20, then t can serve as the beginning of an example. The prediction table has 5 columns and 100 rows. The first column is the starting temperature, so the algorithm looks for the T(t) (heating pipe temperature at time t) in the first column. After finding it, the T(t+5), T(t+10), T(t+15) and T(t+20) temperature values are inserted into column 2-5. If there are values in these cells, then weighted averages are stored. Other temperatures close to T(t) are also updated with small weight factors to smooth out the prediction. Fig. 2. (A) visualizes the values in the warming state table. Axis X is the starting temperature (T(t) in the algorithm) while axis Y shows the predicted value. The dashed line represents no change, other curves above each other are the predicted changes for 5/10/15/20 minutes ahead accordingly.

The main advantage of using the tables is simplicity: tables can be quickly generated and used. Because of the simplicity the precision of this solution is limited. This method can not handle other inputs (such as internal greenhouse temperature) as increasing the number of inputs would exponentially scale up the size of table. It is unacceptable with limited number of training examples.

C Using Monolith Neural Network

In order to gain more accurate predictions more inputs have to be considered than the current pipe temperature alone. The actual internal air temperature seems especially important, therefore it is also used as input in this method. The need for two separate networks can be eliminated if the control signal for the heating system is also considered as input. To handle these different inputs a neural network (MLP) was built from 20 neurons. The inputs are as specified above, while the outputs are the predicted pipe temperature values for 1-4 steps ahead. The only requirement for the example data records was that the heating pipe temperature is at least 10 °C higher than the internal air temperature. Fig. 2. (B) shows graphs for this method, where the curves are smoother because of the interpolation property of the network. Comparing the figures large differences can only be observed close to the Y axis caused by smaller number of examples covering the X axis here.

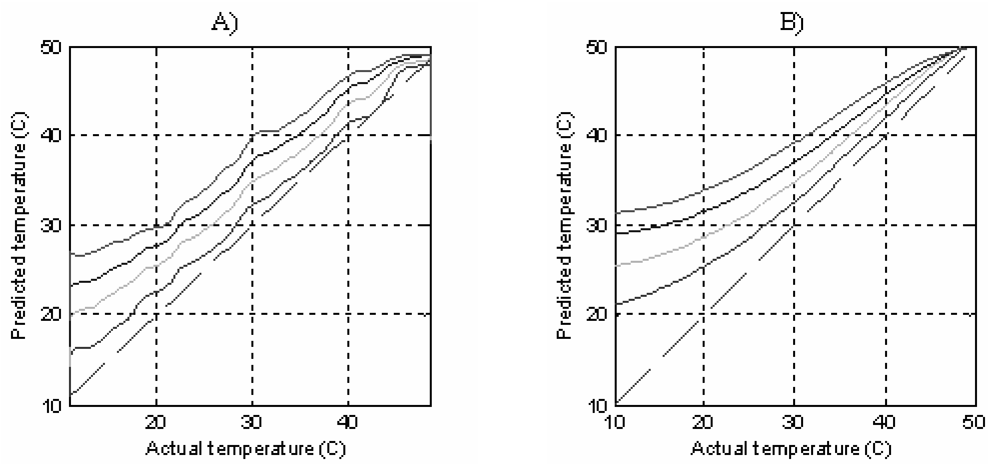

Figure 2: Visualization of the transfer function of the prediction table (A) and the monolith neural network method (B). The dashed line is the constant reference, graphs above are the predictions for 5/10/15/20 minutes ahead

D Neural Network Decomposition

The monolithic neural network solution has the advantage of modeling the whole process (both the warming and the cooling regime) with a single neural network, but the complexity of the network had to be increased to obtain good results. It seems reasonable to decompose it into separate neural models. The warming pipe model is realized by a neural network with 7 neurons in the hidden layer. The inputs and outputs are identical to the monolithic network discussed earlier, but the training samples were selected only from examples where the heating was on. This model has a very similar transfer function to Fig. 2. (B). The cooling pipe model has 8 neurons in the hidden layer and it has an additional input: the number of minutes since the heating was turned off. This network was trained with examples where the heating was off for the whole training sample therefore the heating control inputs could be omitted from both models. To create predictions the models are coupled with a simple control logic. Based on the planned heating control signal this logic switches from one model to the other.

IV. Results

The accuracy of the methods introduced in the previous section was compared by testing them on randomly selected validation heating sequences. Such a sequence is shown in Fig. 3. (A) for the decomposed neural method.

The table and the decomposed neural network method were applied repeatedly as many times as it was necessary. In both cases the switching between tables or models had to be explicitly implemented. The monolith neural network solution was able to handle changes of the heating signal on its own, thus it was easier to experiment with. In all three cases the models served predictions for 1-4 steps ahead. The table method on the validation example set had the lowest accuracy. The table method has a very noisy transfer function which means that it was unable to extract the smooth changes of the heating pipe temperature. We have to note on the other hand, that this method has the lowest computing complexity and in some environments (e.g. in embedded applications) it might be an important factor. The monolith neural network had better performance than the table method by the price of its higher complexity. This model is compact, but modeling the notably different warming and cooling processes together is not the optimal solution. The best accuracy was obtained by the decomposed neural network model. This solution had a lower complexity than the previous and it provided the best predictions. Using this method a test prediction for 12 hours was created and the predicted value was never out of the 1 degree proximity of the measured value while the heating pipe was notably warmer than its environment. This 12 hours long prediction is shown in Fig. 3. (B).

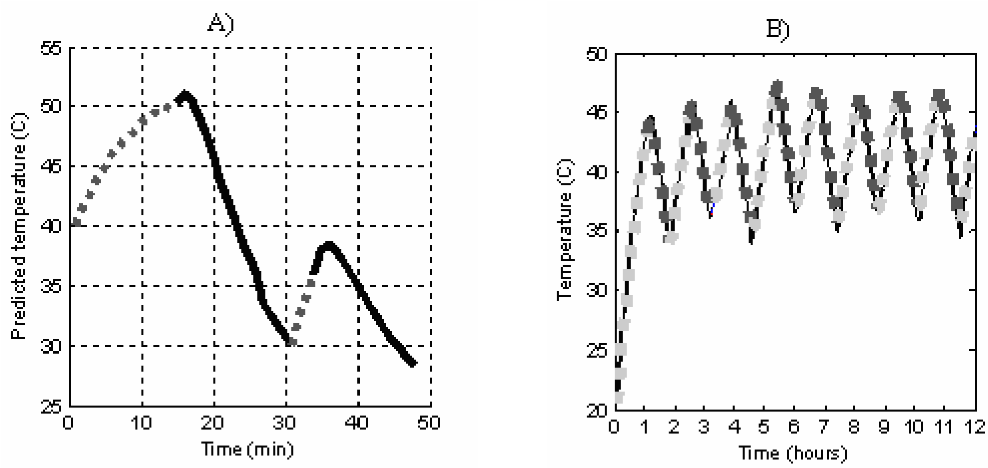

Figure 3: Predicting the heating pipe temperature for A) 50 minutes ahead with two active heating sessions (0-15 and 30-35 minutes on the X axis) with model switching and for B) 12 hours ahead

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References

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