Neural Models for an Intelligent Greenhouse - The Heating

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Abstract—**High quality greenhouse control requires accurate modeling of the greenhouse as a thermal system along with all the influences affecting it. A decomposed model is the only way to tackle the complexity of such a system. A very important module of the decomposition is the heating system, due to its high impact on the overall financial cost of the greenhouse. This paper inspects the theoretical limits of heating modeling considering the stochastic circumstances present in the data measured in an industrial greenhouse. After that various models of different complexity and structure are examined. The best performance is produced by the usage of two neural networks separately for the warming and cooling heating pipe process.**

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. Experimenting with the set-points in case of a newly built greenhouse can take very long time and adversely affect the production.

(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 set-point based control depends on human intelligence and it is assumed that the greenhouse operator has the necessary know-how. The operator will in theory be able to choose optimal set-point combinations, if the dynamics of the greenhouse are well-known. 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 rather than on the unreliable set-point values. Instead of accepting set-points, an intelligent control system should expect global control goals, not influenced by imprecise assumptions made by human operators in the set-point selection. For a greenhouse the simple control goals could be expressed e.g. in the form of target parameter zones.

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 (e.g. the cost of running window opening motors or of activating the heating) 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 at any time. Setting the actuators that way is thus a rational decision based on the overall goals of the greenhouse operators.

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. Instead of examining fixed actuator configurations for the whole prediction length, control plans can be used to allow changes in the actuator states at any time. The quality of the plans (costs of the deviation from the goals and costs of the actuators adding up to the total cost value) can be evaluated by a straightforward extension of the ideas discussed above.

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. GREENHOUSE MODELING

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.

In the present research we have access to a well-equipped industrial greenhouse with a measurement and control system already deployed (see [3]). The system records temperature measurements from all 18 desks in the greenhouse. Additionally temperature and radiation is measured in 2 internal zones (under and above the shading screen), along with 1 external zone (outside the greenhouse) temperature measurements. In addition there is temperature data measured at the heating pipe of the greenhouse and some weather data is collected from online weather reports available for the geographical region of the greenhouse. The model must be able to predict future temperature values for all desks and the itnernal zones. Later these predictions will direct the planning algorithm to find the best way to set the actuators to minimize costs with maximizing plant comfort.

Because of the large number of input and output values (both over 20) the complexity of the modeling problem makes monolithic modeling of the whole system impossible. The decomposition of the model is unavoidable. Fig. 1 shows the proposed decomposition of the modeling problem (described in detail in [4]).

A. External Near-House Weather Model

Online weather forecasts have the advantage of providing directly full forecasts along with the current measurements. Unfortunately the forecast precision at the actual location of the greenhouse is usually not acceptable. Therefore Module-A is responsible for the prediction of the locally recorded external weather (temperature and radiation) based on the local measurements. To solve this problem we used time-series mining of the earlier measurements to produce reliable predictions for a few hours ahead [5]. The model is implicitly present in the recorded time series and the prediction is based on finding similar trends from the past.

B. Online Missing Data Restoration Model

Although online weather data from the internet is not accurate enough for local temperature modeling, online trends predictions are quite reliable, thus using them as a model input seems beneficial. On the other hand due to the internet connection this input has lower reliability than other locally measured data. Thus during normal operation Module-B is monitoring the weather forecast from the online source. If such data is available and trustworthy then it is forwarded to Module-D (Global Greenhouse Model). However in case of network outage or data corruption the data has to be restored from the local measurements, because Module-D cannot work without this input. This setup ensures that Module-D has always all the input values it needs.

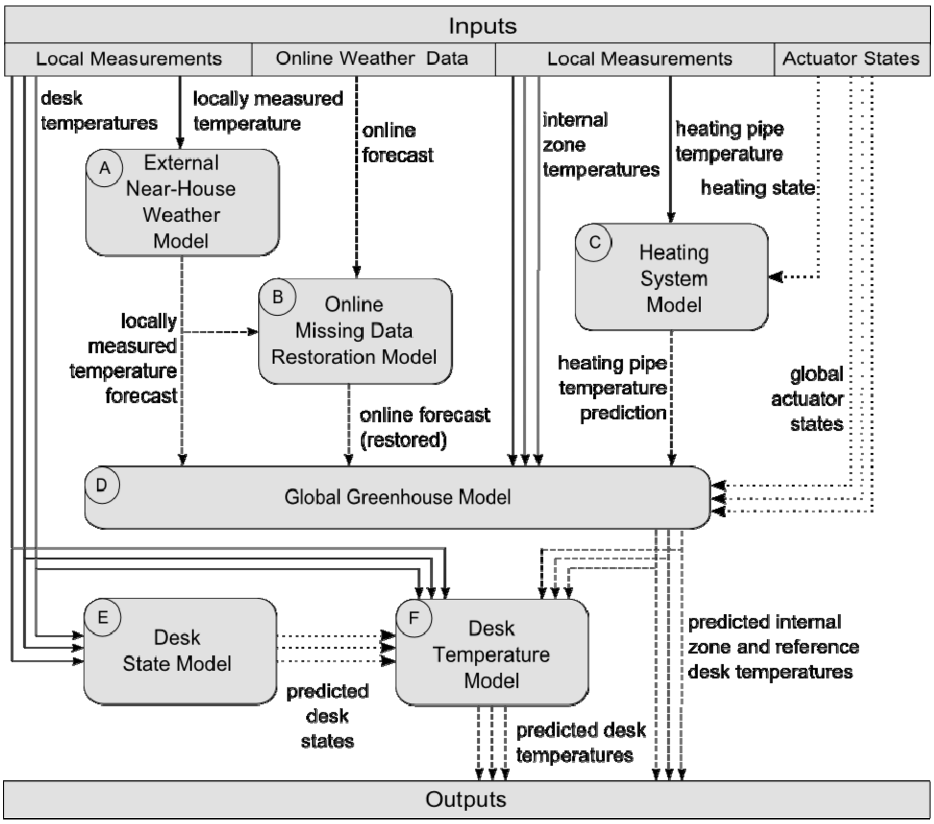

Figure 1. The decomposition of the global greenhouse model into 6 modules related to the thermal substructures of the greenhouse (solid lines: measurements; dotted lines: states; dashed lines: predictions)

C. Heating System Model

Module-C is the key topic of this paper. It predicts the heating pipe temperature, based on the current internal temperature, heat pipe temperature at its inlet and the heating control signal. This model can be easily separated from other modules, as the pipe temperature is mainly determined by its control signal.

D. Global Greenhouse Model

In the proposed decomposition Module-C and Module-D are responsible for all internal zones, except for the desks. At this level the desks are represented by a single reference desk, as this approach reduces the number of inputs significantly without notably affecting the modeling performance. The reference desk is used later to calculate the complete state of all desks. The application of the reference desk also makes the design flexible to handle less equipped greenhouses.

E. Desks State Model

As a special plant treatment the desks in the experimental greenhouse can be covered for the protection of sensitive plants. Unfortunately such state of the desks (covered or not) is not recorded in any way, although it heavily determinates the relation between the desk and its environment. This difficulty calls for the application of a separate Module-E to predict the cover state of each desk. Its inputs are the temperatures measured close to the plants on every desk (below the cover of covered desks) along with the recordings under the shading screen.

F. Desk Temperature Model

Module-F is responsible for predicting the temperature of the desks (air temperature close to the soil level) based on the current measurements; the predicted state of the desks; the predictions for the reference desk and the predictions for the zone under the shading screen. This is a quite simple model because of the underlying simple physical process. It has 20 temperature and 18 state inputs and 18 predicted outputs. The model could be further decomposed into 18 separate components for all the desks, but then the coupling between closely placed desks would be lost, therefore further decomposition of this model is not needed.

IV. MODELING THE HEATING

A. The Modeling Problem

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. Any optimization affecting heating performance results in high savings for the greenhouse owner. The problem can be easily separated from other modules of the decomposed model in Fig. 1 as the temperature of the heating pipe is mainly determined by its current value and the control signal of the heating. Fig. 2 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 on the one hand be easily separated from the modeling of 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 behaviour of the heating pipe temperature cannot be completely neglected. Fig. 3 shows 10 different graphs recorded in the greenhouse starting from 25 Celsius 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 heatpipe temperature were obtained. This means that the current values of the internal temperature of the house are important inputs to the heating model.

Furthermore all future internal temperature values are important factors in predicting the heating pipe temperature. In Fig. 1 Module-D is responsible for predicting the internal temperature of the house, so this information is available in the system. Unfortunately we must observe that Module-D requires the output of the Module-C, i.e. the predicted heating pipe temperature to work properly, thus this recursive dependence between the model modules makes it impossible to consider the internal zone predictions as inputs for the heating system.

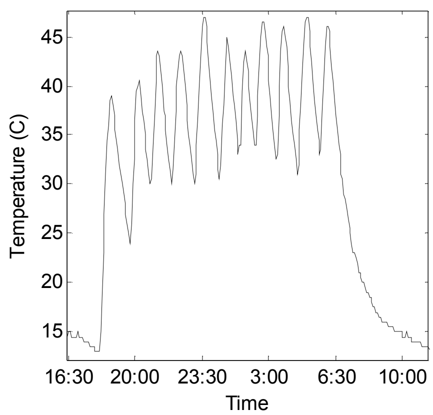

Figure 2. The recorded heating pipe temperature on 11-02-2009 from 16:30 to 10:00 the next day. The heating was turned on 11 times that night

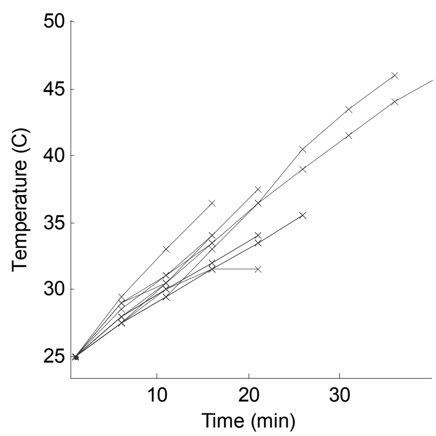

Figure 3. Different graphs of the heating pipe temperature both starting from 25 °C . Differences are caused by the influence of the internal temperature of the greenhouse (as an indirect result of external weather and/or temperature changes during the measurements)

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 at most 100 states determined by its temperature. This relatively small state space makes it possible to inspect all states separately and store the prediction from each state in a table for easy retrieval later.

In practice two tables are needed: one for the warming state of the pipe (heating turned on) and another for the cooling state (heating turned off). Examining the data recorded in the greenhouse for the former case it is evident, that after activating the heating, it was almost always operating for at least 20 minutes before being turned off. The time resolution of the measurement system is 5 minutes which means that we have many training data with at least 4 temperature steps. In the later case (heating turned off) we have much more training data (since the heating is off most time of the day and most days of the year), but most of the time the heating pipe temperature just passively follows the internal temperature of the house. Accordingly we require the heating pipe to be warmer by at least 10 °C than the internal air to use these data as training examples for the system – otherwise the model would have to create predictions for the internal air turbulences as well.

Both tables can be filled in with data generated by the following simple algorithm described here for the warming case: the algorithm looks for any t time points in the measurement data when the heating was active. If the heating was not turned off between t and t + 20, then t can serve as the beginning of a training 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 t) in the first column. After finding it, the T(t+5), T(t+10), T(t+15) and T(t+20) values are inserted into the 2-5 columns of the table. If there are values already in these cells, then weighted averages of these and the new values are stored. The temperatures close to T(t) (in the current implementation temperatures within 2 °C range) are also updated with smaller weight factors to smooth out the prediction.

Fig. 4 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: the tables can be quickly generated and predictions can be created by simply reading them. Because of the simplicity the precision of this solution is also limited. This method cannot handle other inputs (such as internal greenhouse temperature) because increasing the number of inputs would exponentially scale up the necessary size of table. It is unacceptable with limited number of training examples available.

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 is especially important. The need for two separate networks (just like for two separate tables in the previous section) can be eliminated if the future control signal values for the heating system are also considered as inputs.

To handle all 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 (5-20 minutes) ahead. In this case the training and validation sets contain both examples with heating turned on and off (and also mixed examples when the heating control changed during the example). The only requirement for a data record to be considered as an example was that the heating pipe temperature is at least 10 °C higher than the internal air temperature.

Fig. 5 shows graphs for the monolith neural network method. The curves are much smoother compared to Fig. 4 because of the good interpolation property of the network. Comparing the figures large differences can only be observed close to the Y axis. This is caused by smaller number of examples covering lower temperatures on the X axis and different interpolation capabilities of the methods. We also have to note here, that this single neural network is able to predict the cooling regime also, while there were two separate tables needed with the former method.

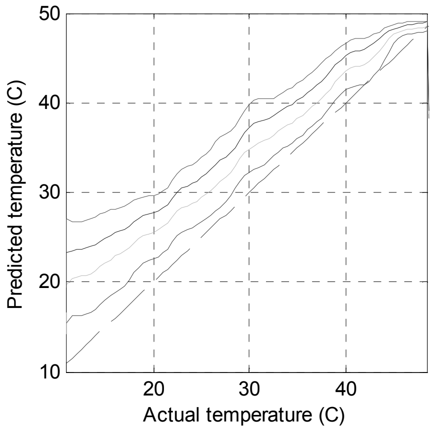

Figure 4. Visualization of the transfer function of the prediction table. The dashed line is the constant reference, graphs above are the predictions for 5/10/15/20 minutes ahead

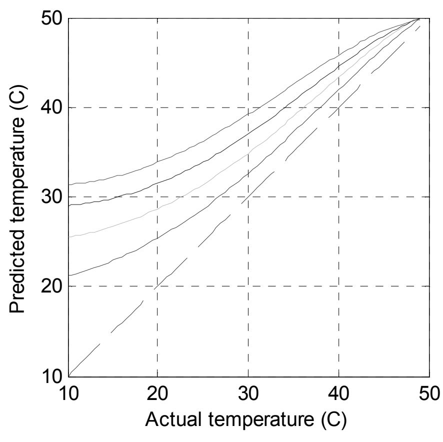

Figure 5. Visualization of the transfer function of the monolith neural network method. The dashed line is the constant reference, graphs above are the predictions for 5/10/15/20 minutes ahead

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. It results in a higher accuracy with the same or even lower model complexity due to the diverse character of the modeled processes.

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 kept on. This model has a very similar transfer function to Fig. 5. It means that the same accuracy is guaranteed for the warming pipe problem with only 7 neurons. 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 proved to be a useful extension. 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. Fig. 6 shows an example of combining the outputs of the applied neural networks based on the heating control signal.

V. 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. 6 for the decomposed neural method. Table I. shows the average absolute errors of each 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. To ensure maximal accuracy the longest possible prediction was used (4 steps = 20 minutes in this case) every time when the heating control signal made it possible. In case of the monolithic model it was always possible to use 4 steps except the last prediction step if the length of the whole validation example was not divisible by 4.

TABLE I.
Average Absolute Error of the Methods for 5-20 Minutes Predictions

Method	**Average absolute error**			
	5 min	***10 min***	***15 min***	***20 min***
Prediction Tables	0.818	0.725	0.952	1.307
Monolith Neural Network	0.688	0.895	1.0336	1.094
Neural Network Decomposition	0.436	0.453	0.452	0.473

The table method on the validation example set had the lowest accuracy. This is not a surprise after comparing Fig. 4 and Fig. 5. 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 of the applied neural network. 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 (using a sum of 15 hidden neurons in the two networks) 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 (at least 10 degrees) warmer than its environment. This 12 hours long prediction is shown in Fig. 7.

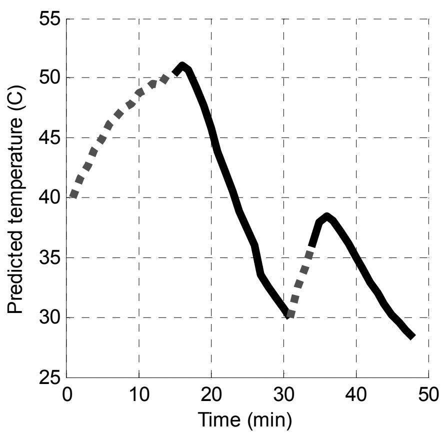

Figure 6. Predicting the heating pipe temperature for 50 minutes ahead with two active heating session (0-15 and 30-35 minutes on the X axis) with model switching (dotted line = warming pipe model; solid line = cooling pipe model)

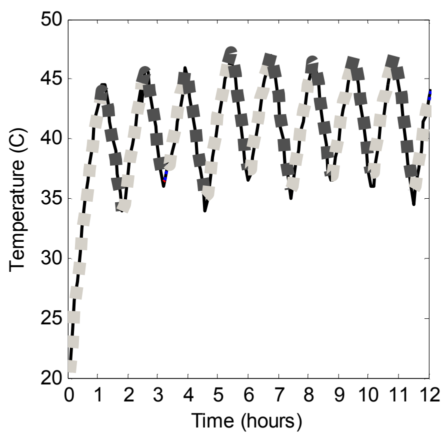

Figure 7. Predicted and measured heating pipe temperature for 12 hours ahead (solid line = measured temperature; light dots = prediction of the warming pipe model; dark dots = prediction of the cooling pipe model)

VI. CONCLUSION

Accurate temperature predictions for the heating pipe are very important for high quality predictive greenhouse control, because of the high impact of the heating on the greenhouse operation costs. Three methods were examined from low complexity tables to high complexity neural network composition. The best solution was provided by a composition of two neural networks: one for the warming process and a separate one for the cooling pipe situation. The combination of these models with relatively low number of hidden neuron was able to create reliable predictions (with errors in 1 °C range) for the heating pipe temperature up to 12 hours ahead.

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