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Fault Diagnosis in Intelligent Greenhouse Control with Decomposed Neural Models

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Abstract-The novel approach to the intelligent greenhouse control is based on predictive thermal models and actuator action plans to increase control performance. As operating the actuators essentially changes the thermal dynamics, the overall thermal model is decomposed into sub-models based on the state of the actuators. For the intelligent control it is essential to know the actuator configuration to select the most appropriate sub-model, but unfortunately information available about actuator states is not reliable enough to be directly applicable. This paper proposes a method to detect the difference between the believed and the actual state of the greenhouse and to identify the most likely model for the actual state. The method can be used to support the intelligent control in case of actuator malfunction or other accidents and is also suitable to provide possible reasons of the malfunctions to support the greenhouse personnel to take the necessary repair actions.

I. Introduction

Greenhouses are widely used in agriculture to provide protected environment for plant growth. Solar radiation passing through the transparent walls is a cost efficient way to create a warmer and steadier environment inside the house compared to the external circumstances. This way greenhouses make plant cultivation possible in areas and in times of the year when otherwise outside weather would not be acceptable.

To avoid extreme high and low temperatures inside the house most greenhouses are equipped with actuators to regulate the internal parameters. The number of installed actuators heavily depends on the needs of the plants produced, e.g. the simplest greenhouse structures have only ventilation windows. If the plants have special requirements or the outside climate differs notably from the plants' natural environment, other actuators can be used: shading screens can reduce solar radiation inside the house; a heating system can increase inside temperature independently from the solar energy input; the humidity level can be controlled using misting sprinkles; the CO_2 concentration can be artificially increased by adding extra CO_2 (in most cases produced by the heating), etc.

A. Traditional greenhouse control

Most greenhouses are equipped with a control system to operate the actuators without the need of constant human presence. The majority of these so called traditional control systems is based on selecting operating temperatures, e.g. there is a temperature limit selected by the greenhouse operator to open the windows when the temperature gets higher. If the greenhouse contains sensitive plants and the number of actuators is high there might be a large number of such limits defining the desirable actuator configuration for each situation [1].

Traditional control solutions have an acceptable performance in practice, and are very well suited to substitute human operators in the greenhouse, but these control schemes have the following major disadvantages: (1) the configuration of the actuators must be determined by the human operators, and as the number of control parameters can be quite high, the parameter selection is suboptimal in most cases; (2) the traditional control is reactive as it only takes actions when the temperature level reaches the configured level, thus no avoiding actions are taken in advance; and (3) the actuators are not synchronised by the control, thus one actuator (e.g. opened windows) can easily repeal the effect of another actuator (e.g. the heating turned on), and avoiding such situations is left completely to the responsibility of the operator when selecting the control parameters.

B. The intelligent greenhouse control concept

The concept of intelligent greenhouse control is aimed to overcome the above mentioned limitations. To do so the intelligent control replaces the control parameters with control goals. The greenhouse operator has to specify only the (well-known) needs of the plants as control goals (e.g. preferred temperature and humidity regime for the day). The transformation from these goals and from the observed state of the greenhouse into particular actuator commands is a task of the control system. The control itself is based on predictive thermal models forecasting the future thermal state of the greenhouse in the coming hours. This way the intelligent control can take actions in advance based on the predicted future state without waiting for an unwanted situation to occur. The predictive models of the greenhouse can be used to form a basis for actuator control planning, and these control plans can be created for all actuators together, thus when the control system selects the most appealing control plan for execution the synchronisation of the actuators is ensured by design.

II. Greenhouse models for the intelligent control

The central component of an intelligent control is the predictive model forecasting the future state of the greenhouse and the accuracy of this model directly affects the performance of the control. Greenhouse thermal modelling has a large literature, and there are two main approaches of the problem: white-box models (based on thermodynamic equations), and black-box (mostly neural network based) models [2][3]. In this paper we focus on black-box models, as the effective model adaptation is essential in practice – the model has to follow the changes due to the changing seasons and the regularly replaced plants in the greenhouse [4][5].
Greenhouse actuators are quite special, as their different states heavily affect the thermal structure of the greenhouse. In the experimental greenhouse depicted in Figure 1. opening of the windows allows direct airflow between the external environment and the greenhouse while closed windows highly limit such interaction. Similarly when the shading screen is pulled over in 100% cover the external radiation is very limited at the plants level, while retracted screen with 0% cover allows almost all sunlight through.

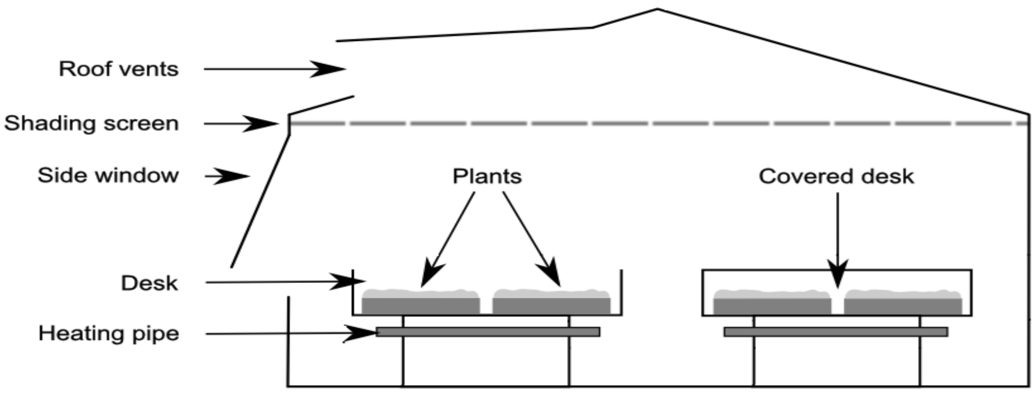

Figure 1. The structure of the experimental greenhouse located in Western Hungary

Such effects can be incorporated into the greenhouse model in two ways: the first approach is using a monolith model (where actuator states serve as model inputs) thus leaving the learning of the actuator effects completely to the modelling [6]. The other approach is using a decomposed model built from separate sub-models for all possible actuator configurations. Such approach is feasible as usually there is a limited number of actuators, all of them controlling a limited number of settings. In this case the actuator states are used only to select the sub-model to be used, in consequence the complexity of the modelling is lower at the expense of using more independent sub-models. In this paper we focus on decomposed greenhouse models where model inputs are the temperature and radiation values measured in the greenhouse and the actuator states are used to select the appropriate sub-model.
The experimental greenhouse of Figure 1. has 4 actuators and 18 allowed actuator state configurations, as some configurations (e.g. activating heating with windows opened) are contradicting and should be never allowed. Each state is identified by a state code listed it Table I.

Heating	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Shading screen	0	2	0	0	0	0	0	0	1	1	1	1	1	1	2	2	2	2
Upper windows	0	0	0	0	1	1	2	2	0	0	1	1	2	2	0	0	1	1
Side windows	0	0	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
State code	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18

Table I. State code definitions based on heating (0/1 = off/on), shading (0/1/2 = 0%/90%/100% cover), upper windows (0/1/2 = closed/33% open/100% open), and side windows (0/1 = closed/open).

The 18 allowed actuator configuration of Table I. means that the control system has to create and maintain 18 independent forecasting models. To this aim previous measurements are needed to support the model learning process. A special problem not elaborated here is the fact that states specified in Table I. happen in the real life with different frequency, resulting in the situation when for some neural models we have an abundance of data to learn, yet for other neural models data is rare or even not existing (these states did not happen during the collection of the measurement data). To initialize such models data from closely related states is used and such models are continuously updated when particular state data becomes available.

III. Fault diagnosis in intelligent control

Using a decomposed greenhouse model built from independent sub-models for all allowed actuator configurations is an appealing choice, however this model architecture is very sensitive to the reliability of the information available about the actuator configurations as e.g. using the model for state #3 when the greenhouse is in state #15 results in very high prediction errors.

A. Sensing the current state of the actuators

The control system obtains information about the current state of the greenhouse from 3 sources. The first is the list of actuator commands issued in the past. Under normal operation regime commands are executed within a few minutes and the house follows the trajectory selected by the control logic. The second source represents direct sensors connected to some actuators. The last source of information are values deduced from the measurements, e.g. the state of the shading screen can be deduced based on the difference between the measurements of the external and internal light sensors.

Unfortunately neither of the above sources is fully reliable. Actuators can malfunction or maintenance can prevent control commands to be executed, direct actuator sensors are rarely connected to the control system, and deducing values also has several limitations (e.g. the shading screen prediction method does not work during night-time). Furthermore accidents affecting the greenhouse (e.g. breaking the fragile glass walls) can also heavily influence the thermal behaviour of the greenhouse, and no direct sensor can measure such effects.

This means that there is a considerable chance that the greenhouse state assumed by the intelligent control is not the actual state of the greenhouse, and such an error (and using the inappropriate model for prediction) results in bad control performance. It is important to note, that the most possible malfunctions mean that the greenhouse is not in the state assumed by the control system, but in most cases the house will be just in another allowed state (e.g. the broken glass walls have similar effects as opening the side windows).

B. Detecting possible failures

Model failures can be detected based on the prediction error of the forecasting model used by the intelligent control: large prediction errors make it likely that there is state discrepancy. No hard constraint can be specified for the prediction error indicating state differences as the quickly changing external weather can also produce large prediction errors even during normal operations, but 2-3 times increase in prediction error value can already be a possible indicator.

Identifying the reason of the large error is crucial for two reasons: firstly the intelligent control formulates actuator plans depending on the predictions of the sub-model selected by the current state of the greenhouse, thus if the believed greenhouse state differs from the real one, all actuator plans will be at most suboptimal. Secondly in case of any accident and in case of most actuator failures it is very important to alert the greenhouse operators in the shortest possible time, as the sensitive plants inside the greenhouse can suffer serious damage already within a few hours. For both problems the key issue is to identify the real state of the greenhouse based on the latest measurements if a state difference is suspected.

C. Identifying the real state of the greenhouse

The proposed method of identifying the real state of the greenhouse depends on the assumption that the intelligent control maintains sub-models for all allowed states of the greenhouse. If a state discrepancy is suspected these sub-models can be reviewed to find the most likely sub-model to be used by the intelligent control. The forecasting model providing the lowest MAE (Mean Avaerage Error) value is the most likely sub-model, thus the system can expect the greenhouse to be in the state defining the most likely sub-model. It is important to note that the lack of the compact mathematical formulism describing the state-to-measurement mapping makes it difficult to derive some specific analytic error criteria. MAE criteria was chosen among other heuristic possibilities due to its widely accepted usage.

The difference between the believed state by the control system and the most likely state of the greenhouse can be even used to estimate the reason of such difference. If the two states differ only in a single actuator state then the malfunction of this actuator can be suspected, or other external disturbances can be present having similar effect. These findings can be used to alert the greenhouse operators and to provide them with possible issues to investigate, thus troubleshooting can be much faster. For the intelligent control itself the reason behind the state difference is not important, the main concern is to use the model based on the most likely state of the greenhouse for the actuator planning.

It is important to note that in some cases the real state of the greenhouse cannot be identified even if all necessary information is available. In some cases the intelligent control might not posess a sub-model for the actual state of the house (e.g. there is no sub-model maintained for the state of active heating with windows open), and in such cases the proposed method is only able to identify the most similar state. This state might still be useful to provide troubleshooting tips for the operators (in the previous example the state of the heating and the windows are obviously incompatible), and for control planning this state is still the best that can be used. In other cases the analysis can provide more than one likely state. This is no surprise as e.g. the effects of opening the side windows are very similar to the effects of opening the top windows to 33%, thus the analysis will find more states equally probable. In this case the control will use the most likely state which can describe the actual situation with the highest precision and this is the optimal choice in such a situation. For the troubleshooting personnel all likely states can be presented to help them identify the source of the problem.

IV. Results

To demonstrate the proposed method real data was used measured in the experimental greenhouse between January and May 2008. Figure 2. below demonstrates the situation when the greenhouse control believes the house to be in State-15 (see Table I.), but the house is in fact in State-3, thus data from State-3 was provided for the predictive models. Figure 2. shows that the error of Model-3 is in almost all cases significantly lower than the error of Model-15: Model-3 has a mean average error of 1.84 °C for the 31 weeks long observations while Model-15 has much higher mean average error of 5.7°C. Based on this the proposed method can be used to identify the most likely state of the greenhouse.

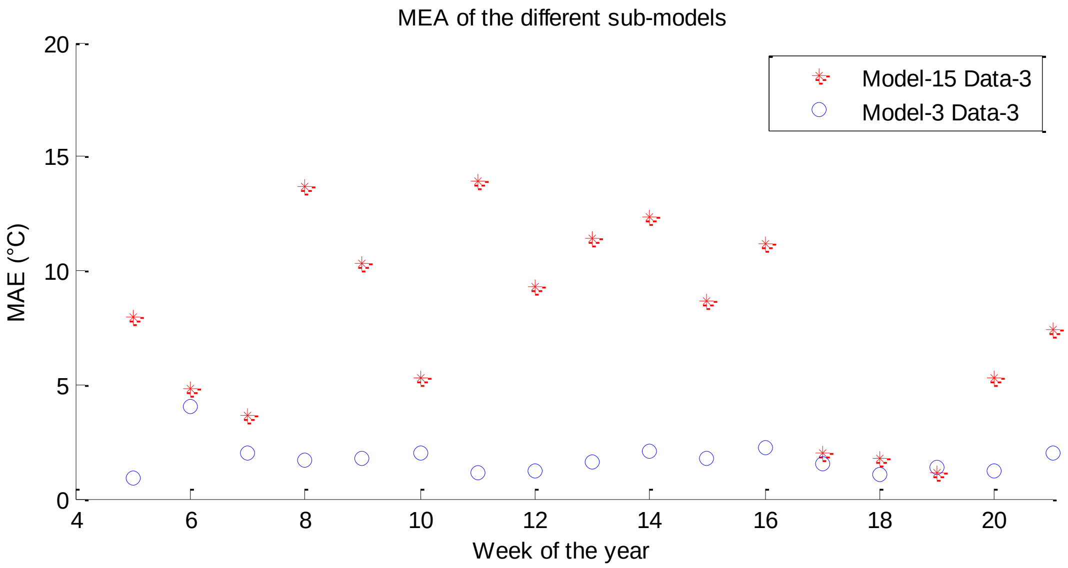

Figure 2. Comparing the mean average error of the believed states (Model-15 and Model-3) with the measurements from the real state (State-3)

Figure 3. below shows the results of selecting the most likely state of the greenhouse for 21th week based on measurement data from weeks 15-20. The X axis shows the sub-models used while on the Y axis the mean average error of the provided prediction is shown.

The results in Figure 3. show that the greenhouse is more likely to be in State-3 or State-5 than in the believed State-15. Decoding the meaning of the state codes (see Table I.) the interpretation is that the shading screen is most likely fully retracted (0% cover) and there is a 50% chance that the upper windows are partially open. As the data was provided by State-3 the conclusion about the shading screen is correct, thus the greenhouse operators have to repair the shading screen. As for the upper windows the 50% alarm is false in the current case, and after repairing the shading screen the warning should disappear.

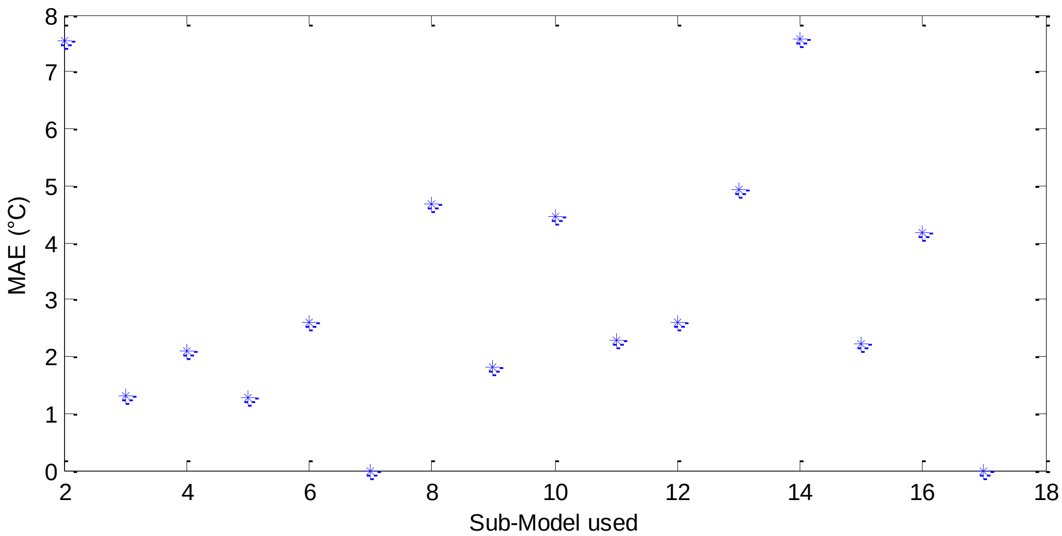

Figure 3. Identifying the most likely state for week 21 based on measurements from weeks 15-20

V. Conclusions

Knowing the actual state of the greenhouse is the key question when using decomposed predictive models to implement an intelligent greenhouse control. As information available about the actuator states of the greenhouse is unreliable detecting state differences and determining the most likely state is essential. The method proposed in this paper was to use the sub-models maintained by the intelligent control, and to identify the most likely states of the house by selecting the sub-model with the lowest prediction error. Results show that the method can help the intelligent control in case of actuator malfunctions and is also able to provide troubleshooting tips to the greenhouse operators even in case of accidents like glass walls broken or other unexpected disturbances.

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