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Incremental Auto Regressive Prediction Models with External Variables of Greenhouse Air Temperature for Control Purposes

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Abstract

The impact of actuators should be considered in the prediction modeling of greenhouse air temperature. In this paper, the operating state of a greenhouse was divided into five sub-states based on the on-off characteristic of actuators. A group of novel incremental auto regressive models with external variables (IARX models) suitable for the five operating sub-states were deduced from the mechanistic modeling of greenhouse air temperature. The new IARX models have fewer coefficients than other known ARX models. In order to validate the IARX prediction models, the related environmental factors of a glass greenhouse were measured. The prediction results of the IARX models were compared with two typical ARX models. The maximum prediction errors and the mean square errors of the IARX models, under the three operating sub-states of passive state(all actuators are not working), mechanical ventilation and fan-pad cooling, are 0.1°C, 0.14°C, 0.7°C, and 0°C, 0.3°C, 0.4°C, respectively. The prediction results are much better than those of one compared model, while similar with the other.

Keywords*: Incremental ARX models, mechanistic model, system identification, temperature, prediction.*

1. Introduction

China has imported many modern greenhouses with automatic control systems from Western European countries in the past thirty years. However, most of these control systems do not work as expected. One major reason is that the climate in China is very different from that in Western European countries. In China, it is cold in winter and hot in summer and there is a big temperature difference between day and night in spring and autumn, which lead that the imported greenhouses are very energy-consuming. Therefore, the actuators are still mainly controlled manually over the years, which is very laborious. In some greenhouses, the ventilation fans can be controlled by using a simple Bang-Bang control method. However, the Bang-Bang control methods sometimes cause the actuators to switch too frequently or work too long because of improper set points. We found that if the greenhouse air temperature in the next about ten minutes can be predicted accurately, there are many advantages for making suitable control strategies, such as reducing the switching frequency and the operation time of actuators. So the accurate prediction models represent a cornerstone for the development of different model-based control strategies [1-3]. This paper will attempt to build new prediction models of greenhouse air temperature for control purposes.

Almost all the actuators in greenhouses in China use an on-off mechanism. The advantage of on-off actuators is that they are cheap and easy to operate and maintain, but the high nonlinearity of actuators makes the advanced control methods can't be used in greenhouses. It's well-known that the on-off actions of actuators

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have a strong impact on the greenhouse microclimate. Therefore, Linlin et al. took the on-off combinations of different actuators as various operating sub-states of a greenhouse, and then regarded the operating process of a greenhouse as a switching one between these operating sub-states [4, 5]. A prediction model of greenhouse air temperature suitable for each operating sub-state is required in the further research on switching control of different actuators in a greenhouse. The external environmental factors change continuously and they can only be measured but not controlled. So when the greenhouse switches back to one operating sub-state after a period of time, the prediction model of this sub-state may not work very well if the external environment has changed greatly, even if it predicted accurately before. Therefore, the prediction model of every operating sub-state should have as few coefficients as possible. When the models are unable to predict the greenhouse air temperature accurately, it can be quickly recovered by using very few sets of new measurement data of related environmental factors.

The mechanistic modeling based on energy balance [6, 7], auto regressive modeling with external variables (ARX modeling) [8, 9], artificial neural network modeling [10, 11], and their combinations [12, 13] are the main modeling methods of greenhouse air temperature. Compared with mechanistic models and artificial neural network models, ARX models own a much smaller computational load, and can be recursively identified online in real time to predict the greenhouse air temperature. However, the known ARX models are built without the full consideration of the impact of actuators, and they are also not compact enough because the external variables are selected empirically and subjectively. The factors, such as external air temperature, relative humidity, solar radiation, wind speed and cloudiness in the sky, all have been previously selected as external variables [8, 12, 14]. Additionally, the identification of ARX model structures is very tedious [13, 15].

The purpose of this paper is to deduce a group of new ARX prediction models of greenhouse air temperature suitable for various operating sub-states for control purposes. We aim to use as few coefficients as possible for the new models and use a simple and deterministic structure to avoid the tedious model structure identification. The rest of the paper is organized as follows. In section 2, the operating state of a greenhouse was divided into five sub-states based on the on-off characteristic of actuators. A group of novel incremental auto regressive models with external variables (IARX models) of greenhouse air temperature suitable for the five sub-states were deduced from the mechanistic modeling. In section 3, the new IARX models were identified and validated by using the data of related environmental factors measured in a glass greenhouse. Two typical ARX prediction models of greenhouse air temperature were also tested in order to compare the prediction accuracy with the new IARX models. The paper was concluded in the last section.

2. Deduction of the IARX Models

Actuators for controlling the greenhouse air temperature can be classified as either cooling actuators or heating ones. Roof windows, side windows, ventilation fans, and wet pads are the main cooling actuators, while air-fan heaters and hot-water pipelines are the main heating actuators. In China, a greenhouse control system usually contains several cooling actuators at the same time, but generally only one heating actuator, because heating actuators are very energy-consuming. Depending on the actual control situation, the operating state of a greenhouse is divided into five sub-states: passive state (all actuators are not working), natural ventilation, mechanical ventilation, fan-pad cooling and air-fan heating. The benefit of such a classification is that there are no interactions between these sub-states. Therefore, the following dynamic mechanistic model of greenhouse air based on the energy balance can be established:

$$\begin{cases} \rho_a C_a V_g \dfrac{dT_i(t)}{dt} = Q_{rad}(t) - x_1 Q_{nv}(t) - x_2 Q_{mv}(t) - x_3 Q_{pad}(t) + x_4 Q_h(t) - Q_{tran}(t) - Q_{exch}(t) - Q_{ca}(t) \\ \qquad\qquad - Q_{lw}(t) - Q_{other}(t) \\ s.t. \quad \sum x_j \le 1, \ \ x_j = 0, 1 \ (j = 1, \cdots, 4) \end{cases} \tag{1}$$

where ρ_a denotes the air density (g/m^3); C_a the air-specific heat capacity ($J/(g°C)$); V_g the volume of the greenhouse (m^3); $T_i(t)$ the internal air temperature ($°C$); t the time (s); $Q_{rad}(t)$ the power produced by solar radiation (W); $Q_{nv}(t)$ the power loss caused by natural ventilation (W); $Q_{mv}(t)$ the power loss caused by mechanical ventilation (W); $Q_{pad}(t)$ the power loss caused by fan-pad cooling (W); $Q_h(t)$ the power produced by the heating actuator (W); $Q_{tran}(t)$ the power absorbed by crop transpiration (W); $Q_{exch}(t)$ the power loss caused by the heat exchange between the internal air and external air through the cladding material of the greenhouse (W); $Q_{ca}(t)$ the power loss caused by the absorption of crop canopy (W); $Q_{lw}(t)$ the power loss caused by the long-wave radiation (W); $Q_{other}(t)$ the power loss caused by other factors, such as the absorption of soil and the energy leakage through gaps of the greenhouse (W); x_j (j=1,…,4) are the decision variables, and have two values of either 0 or 1 (0 denotes OFF and 1 denotes ON).

The crop transpiration has a close relationship with the solar radiation, and usually increases with the increase of solar radiation. Therefore, the power produced by the solar radiation and that absorbed by the crop transpiration can be combined together and expressed approximately as follows:

$$Q_{rad}(t) - Q_{tran}(t) \approx \eta Q_{rad}(t) \tag{2}$$

where η is the proportionality coefficient with a value between (0,1), dimensionless.

The solar radiation power has to be represented in the form of illuminance, since in the later experiment a luxometer will be used to measure it. However, the conversion coefficient varies with the wavelength of the light. A conversion coefficient of 555nm yellow-green light is adopted, which the human eye is most sensitive to. Eq.(2) can be rewritten as follows:

$$Q_{rad}(t) - Q_{tran}(t) \approx \mu \eta A_g I_o(t) \tag{3}$$

where μ is the coefficient of the conversion from illuminance to power ($W/(m^2 Lux)$); A_g the greenhouse area (m^2) and $I_o(t)$ the external illuminance (Lux).

According to related studies [6, 16, 17], the power losses due to heat exchange between the internal and external air through cladding material, natural ventilation and mechanical ventilation are closely related to the internal and external air temperature difference of the greenhouse; the power produced by an air-fan heater is closely related to the temperature difference between the heated air and the internal air; the power loss caused by the fan-pad cooling is closely related to the temperature difference between the pad surface and the internal air; the power absorbed by the crop canopy is closely related to the temperature difference between the canopy surface and the internal air; the long-wave radiation follows Stefan-Boltzmann law. Therefore, the terms described above can be expressed as follows:

$$Q_{exch}(t) = A_c \omega_c (T_i(t) - T_o(t)) \tag{4}$$

$$Q_{nv}(t) = \rho_a C_a \varphi_{nv} (T_i(t) - T_o(t)) \tag{5}$$

$$Q_{mv}(t) = \rho_a C_a \varphi_{mv} (T_i(t) - T_o(t)) \tag{6}$$

$$Q_{pad}(t) = \rho_a C_a \varphi_{pv} (T_i(t) - T_p(t)) \tag{7}$$

$$Q_h(t) = \rho_a C_a \varphi_{hv} (T_h(t) - T_i(t)) \tag{8}$$

$$Q_{ca}(t) = A_{ca}\omega_{ca}\left(T_i(t) - T_{ca}(t)\right) \tag{9}$$

$$Q_{lw}(t) = \varepsilon A_c \sigma\left(T_i^4(t) - T_o^4(t)\right) \tag{10}$$

where A_c denotes the cover area of the greenhouse (m^2); ω_c the heat transfer coefficient of the cladding material ($W/m^2{}^\circ C$); $T_o(t)$ the external air temperature ($^\circ C$); φ_{nv} the natural ventilation rate (m^3/s); φ_{mv} the mechanical ventilation rate (m^3/s); φ_{pv} the ventilation rate of fan-pad cooling (m^3/s); $T_p(t)$ the surface temperature of wet pad ($^\circ C$); φ_{hv} the ventilation rate of air-fan heater (m^3/s); $T_h(t)$ the heated air temperature ($^\circ C$); A_{ca} the crop canopy area (m^2); ω_{ca} the heat transfer coefficient of canopy surface ($W/(m^2{}^\circ C)$); T_{ca} the canopy surface temperature ($^\circ C$); ε the total emittance of the cover and crop, dimensionless; σ the Stefan-Boltzmann constant.

Although the crop canopy affects the greenhouse air temperature very differently at different stages of crop growth and the long-wave radiation considerably varies over a complete day-night cycle, their impacts on the greenhouse air temperature change continuously, and they change much more slowly compared with the sampling period of environmental factors during the real-time control process. This is also true for the energy losses due to the soil and gaps of greenhouse, etc. The recursive identification of prediction models in real time can effectively overcome the impact of the slow time-varying characteristics. Therefore, the long-wave radiation and the power losses due to the crop canopy, the soil and gaps of greenhouse, etc, can be treated as constant terms. The following definition is given:

$$M = Q_{ca}(t) + Q_{lw}(t) + Q_{other}(t) \tag{11}$$

Next we will deduce the new ARX prediction models of greenhouse air temperature based on the above known mechanistic models, suitable for the five operating sub-states. Substituting Eq.(3)~Eq.(11) into Eq.(1), we obtain the following dynamic equation after a simple merge of similar items:

$$\begin{cases} \rho_a C_a V_g \dfrac{dT_i(t)}{dt} = \mu\eta A_g I_o(t) - \left[A_c\omega_c + x_1\rho_a C_a\varphi_{nv} + x_2\rho_a C_a\varphi_{mv} + x_3\rho_a C_a\varphi_{pv} + x_4\rho_a C_a\varphi_{hv}\right]T_i(t) \\ \qquad + \left[A_c\omega_c + x_1\rho_a C_a\varphi_{nv} + x_2\rho_a C_a\varphi_{mv}\right]T_o(t) + x_3\rho_a C_a\varphi_{pv}T_p(t) + x_4\rho_a C_a\varphi_{hv}T_h(t) - M \\ s.t. \quad \sum x_j \le 1,\ x_j = 0,1\,(j = 1,\cdots,4) \end{cases} \tag{12}$$

In the passive sub-state, all the decision variables x_j (j=1,…,4) are 0. The dynamic equation Eq.(12) becomes much simpler:

$$\rho_a C_a V_g \frac{dT_i(t)}{dt} = A_c\omega_c\left[T_o(t) - T_i(t)\right] + \mu\eta A_g I_o(t) - M \tag{13}$$

In practice, the environmental factors are measured at discrete time intervals, so the differential equation can be rewritten as a difference one. $\Delta T_i(k+1)$ is used to represent the increment of greenhouse air temperature at the time instants $k+1$ and k, i.e. $\Delta T_i(k+1)=T_i(k+1)-T_i(k)$. $\Delta T_{oi}(k)$ is used to represent the difference value of the external and internal air temperature at the time instant k, i.e. $\Delta T_{oi}(k)=T_o(k)-T_i(k)$. Therefore, Eq.(13) can be rewritten as follows:

$$\Delta T_i(k+1) = \alpha_0\Delta T_{oi}(k) + \gamma I_o(k) + N \tag{14}$$

where $\alpha_0=A_c\omega_c\Delta t/(\rho_a C_a V_g)$; $\gamma=\mu\eta A_g\Delta t/(\rho_a C_a V_g)$; $N=-M\Delta t/(\rho_a C_a V_g)$; and Δt denotes the sampling period (s). Eq.(14) is the IARX prediction model of greenhouse air temperature for the passive operating sub-state.

The IARX prediction models for the other four sub-states of natural ventilation, mechanical ventilation, fan-pad cooling and air-fan heating can be deduced in the same way. For the natural ventilation sub-state, only the decision variable x_1 is 1 while the others are 0. The IARX prediction model of greenhouse air temperature can be deduced as follows:

$$\Delta T_i(k+1) = \alpha_1 \Delta T_{oi}(k) + \gamma I_o(k) + N \tag{15}$$

where $\alpha_1=(A_c\omega_c+\rho_a C_a \varphi_{nv})\Delta t/(\rho_a C_a V_g)$.

For the mechanical ventilation sub-state, only the decision variable x_2 is 1. The IARX prediction model of greenhouse air temperature can be deduced as follows:

$$\Delta T_i(k+1) = \alpha_2 \Delta T_{oi}(k) + \gamma I_o(k) + N \tag{16}$$

where $\alpha_2=(A_c\omega_c+\rho_a C_a \varphi_{mv})\Delta t/(\rho_a C_a V_g)$.

For the fan-pad cooling sub-state, only the decision variable x_3 is 1. The IARX prediction model of greenhouse air temperature can be deduced as follows:

$$\Delta T_i(k+1) = \alpha_3 \Delta T_{oi}(k) + \beta_3 \Delta T_{pi}(k) + \gamma I_o(k) + N \tag{17}$$

where $\alpha_3=\alpha_0$; $\beta_3=\varphi_{pv}\Delta t/V_g$; $\Delta T_{pi}(k)=T_p(k)$-$T_i(k)$.

For the air-fan heating sub-state, only the decision variable x_4 is 1. The IARX prediction model of greenhouse air temperature can be deduced as follows:

$$\Delta T_i(k+1) = \alpha_4 \Delta T_{oi}(k) + \beta_4 \Delta T_{hi}(k) + \gamma I_o(k) + N \tag{18}$$

where $\alpha_4=\alpha_0$; $\beta_4=\varphi_{hv}\Delta t/V_g$; $\Delta T_{hi}(k)$; $\Delta T_{hi}(k)=T_h(k)$-$T_i(k)$.

Therefore, the IARX prediction models of greenhouse air temperature for the five operating sub-states can be compiled into the following single equation:

$$\begin{cases} \Delta T_i(k+1) = \sum_{j=0}^{4} x_j \left(\alpha_j \Delta T_{oi}(k) + \beta_j \Delta T_{phi}(k) \right) + \gamma I_o(k) + N \\ s.t. \quad \sum_{j=0}^{4} x_j = 1,\ \ x_j = 0,1\,(j=0,\cdots,4); \quad \beta_j = 0\,(j=0,1,2) \end{cases} \tag{19}$$

where $\Delta T_{phi}(k)$ denotes $\Delta T_{pi}(k)$ and $\Delta T_{hi}(k)$. The subscript j = 0 corresponds to the passive sub-state.

It can be easily seen that the IARX prediction models have fewer coefficients than the previously ARX models. Only two external variables are involved for the three sub-states: passive state, natural ventilation and mechanical ventilation; while for the other two sub-states, just three external variables are involved. The number of model coefficients and the selection of external variables are both optimized theoretically. It also can be seen that α_j, β_j and γ are relevant with these factors, such as the sampling period, the volume and cover area of greenhouse, the heat transfer coefficient of cladding material and the different ventilation rates, etc. In addition, the term N depends on the factors including the greenhouse volume and the energy exchange between the internal air and the crop, soil, etc. Therefore, the greenhouse parameters and the actuators only affect the values of the model coefficients, but not the model structure. Before these new IARX prediction models are used in practice, the environmental factors in each operating sub-state should firstly be measured and then used to identify the model coefficients. Therefore, it is not necessary to measure the greenhouse parameters, the natural ventilation rate and the mechanical ventilation rate, etc. During the future control process of greenhouse air temperature, the model coefficients can be recursively identified in real time as the environmental factors are measured periodically, which can effectively overcome the impact of the slow time-varying characteristics mentioned above. The deduction process has determined the first order structure of the IARX models, so the tedious identification of model structure can be avoided.

3. Measurement of Greenhouse Environmental Data

In order to validate the new IARX prediction models, the relevant environmental factors of a glass greenhouse were measured. The greenhouse is near Nanjing city and is 60 meters long and 30 meters wide. An ornamental butterfly orchid plant was planted inside. Three ventilation fans have been installed on one side wall and a wet pad has been installed on the opposite. Therefore, the relevant environmental factors can be measured for the three operating sub-states: passive state, mechanical ventilation and fan-pad cooling. Two temperature-humidity recorders (RC-4HA type) were adopted to measure the air temperature and relative humidity both inside and outside the greenhouse. The measurement accuracy of temperature is ±0.4*°C*, and that of relative humidity is ±3*%*. A luxometer (HS1010A type) was adopted to measure the external solar radiation, which had a measurement range of 0~200 *kLux*, and a measurement accuracy of ±4*%* (<10 *kLux*) and ±5*%* (>10 *kLux*).

As both mechanical ventilation and fan-pad cooling require very high energy consumption, the once operating time of the both operating sub-states is very short, usually no more than ten minutes. In order to obtain enough data of environmental factors, the once operating time was set to fifteen minutes. For consistency, the measuring time in the passive sub-state was also set to fifteen minutes. The measurement interval for the three sub-states was all set to one minute.

The measurement experiment was done on April 15 2014. In the early morning, the internal and external air temperature and the solar radiation were all lower. The greenhouse was in the passive sub-state. The relevant environmental factors were measured from 8:00 am to 8:15 am and were plotted in Figure 1, including the air temperature and relative humidity both inside and outside, and the solar radiation.

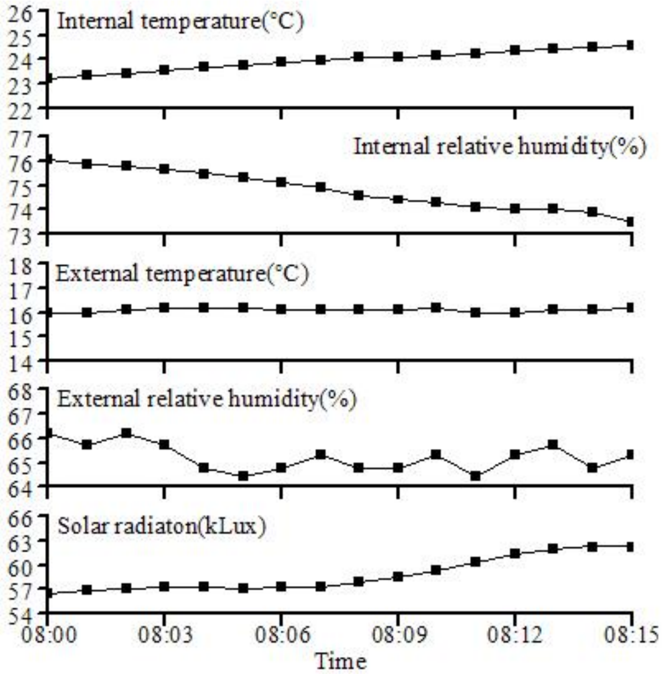

Figure 1. Relevant Environmental Factors from 8:00 am to 8:15 am

The external air temperature rose and the solar radiation also became stronger gradually with time. The internal air temperature rose accordingly and reached 34*°C* at 10:15 am. At this time, the three ventilation fans were started for mechanical ventilation. After fifteen minutes, they were turned off and the internal air temperature had reduced to 25.6°*C*. The relevant environmental factor data measured during this time period have been plotted in Figure 2.

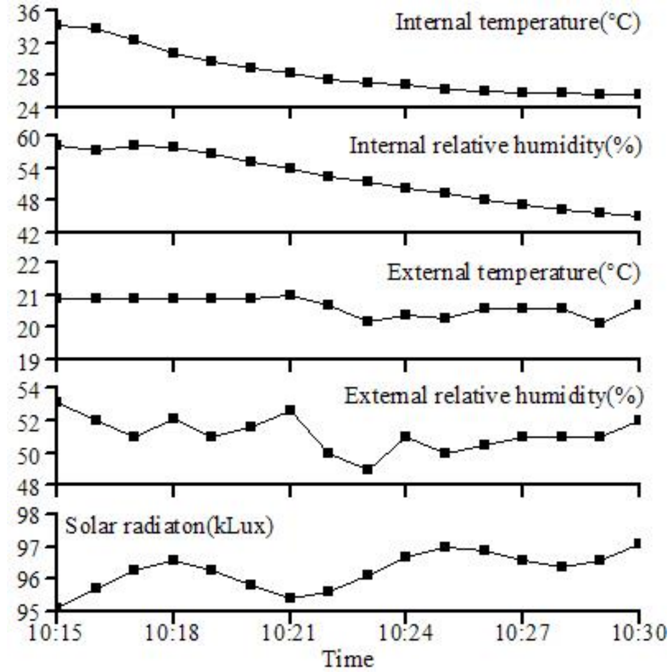

Figure 2. Relevant Environmental Factors from 10:15 am to 10:30 am

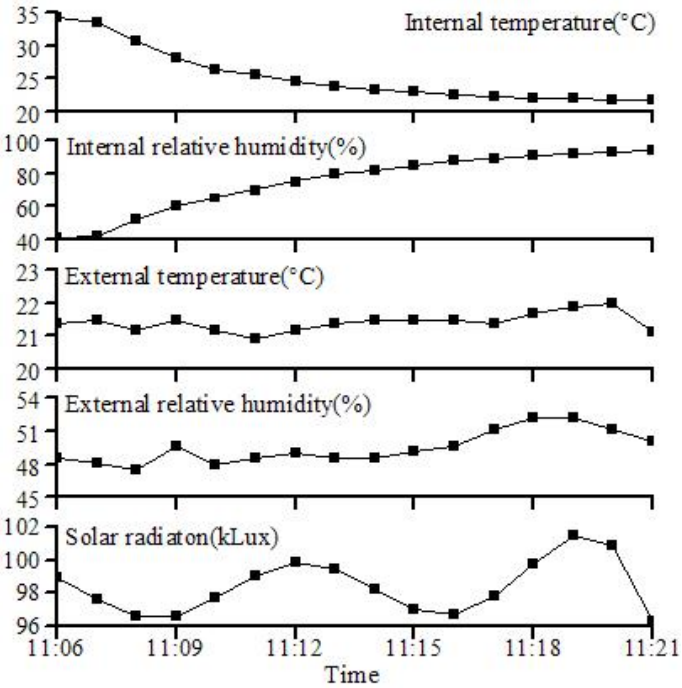

Figure 3. Relevant Environmental Factors from 11:06 am to 11:21 am

After the ventilation fans were turned off, the greenhouse returned to the passive operating sub-state again and the internal air temperature also rose accordingly. At 11:06 am, the internal air temperature exceeded 34°*C*. The three ventilation fans and the wet pad were then started simultaneously, and the greenhouse entered the fan-pad cooling sub-state. After fifteen minutes, they were all turned off and the internal air temperature had reduced to 21.7°*C*. During the cooling process, the temperature of the water poured on the pad was about 12°C without obvious variation. The relevant environmental factor data measured during this time period has been plotted in Figure 3.

4. Model Validation and Result Analysis

4.1. Two Compared Models

In this section, two typical ARX prediction models of greenhouse air temperature have been selected to compare their prediction accuracy with the new IARX models. Although ARX models have been studied in details in [8, 13], the impact of different actuators was not considered, because their greenhouses were always in the operating state of natural ventilation. In fact, actuators have rarely been considered in many ARX prediction models, so it's difficult to take these models to compare with the new IARX models. In earlier research [18], the on-off characteristic of actuators was taken into account and all the possible operating state combinations of actuators were regarded as the operating sub-states of greenhouse. For each sub-state, a first-order ARX prediction model of internal air temperature and relative humidity was established as follows:

$$\begin{bmatrix} T_i(k+1) \\ RH_i(k+1) \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} T_i(k) \\ RH_i(k) \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \end{bmatrix} \begin{bmatrix} T_o(k) \\ RH_o(k) \\ Q_{rad}(k) \end{bmatrix} \tag{20}$$

where $RH_i(k)$ and $RH_o(k)$ denoted the internal and external relative humidity of the air, respectively, at the time instant k; a_{11}, a_{12}, a_{21}, a_{22}, b_{11}, b_{12}, b_{13}, b_{21}, b_{22}, b_{23} the identification coefficients.

The establishment of these ARX models is easy to understand, because it is easy to know that the internal air temperature is affected by the external air temperature, relative humidity and solar radiation from experience and intuition. This was the reason why the model was chosen for comparison. Since in this paper only the internal air temperature prediction was studied, the relative humidity prediction component was removed and Eq.(20) was rewritten as follows:

$$T_i(k+1) = \begin{bmatrix} a_{11} & a_{12} \end{bmatrix} \begin{bmatrix} T_i(k) & RH_i(k) \end{bmatrix}^T + \begin{bmatrix} b_{11} & b_{12} & b_{13} \end{bmatrix} \begin{bmatrix} T_o(k) & RH_o(k) & Q_{rad}(k) \end{bmatrix}^T \tag{21}$$

The second compared model was given directly in the literature [19] and was similar to the new IARX models:

$$T_i(k) = \frac{[b_1 q^{-1}\ b_2 q^{-1}\ b_3 q^{-1}\ b_4 q^{-1}\ b_5]}{1 + a q^{-1}} \begin{bmatrix} \Delta T_{io}(k) & Q_{rad}(k) & \Delta T_{hi}(k) \cdot H(k) & \Delta T_{io}(k) \cdot V(k) & 1 \end{bmatrix}^T \tag{22}$$

where a denoted the transfer function denominator parameter; b_j (j=1,…,4) the coefficients of the delay operator in the numerator; b_5 the coefficient of the offset component; q^{-1} the backward shift operator; $H(k)$ and $V(k)$ the heating and ventilation control input signals, respectively.

As described in section 3, there is no air-fan heater in the greenhouse, but there is a wet pad. The heating control input signal $H(k)$ was regarded as that of the fan-pad cooling, and $\Delta T_{hi}(k)$ was replaced by $\Delta T_{pi}(k)$ accordingly. As the actuators are all on-off types, the values of $H(k)$ and $V(k)$ are just 0 or 1. Eq.(22) was rewritten in the following forms, corresponding to the three sub-states: passive state, mechanical ventilation and fan-pad cooling, respectively:

$$T_i(k) = \frac{[b_1 q^{-1}\ b_2 q^{-1}\ b_5]}{1+aq^{-1}} \left[\Delta T_{io}(k)\ \ Q_{rad}(k)\ \ 1\right]^T \tag{23}$$

$$T_i(k) = \frac{[(b_1+b_4) q^{-1}\ b_2 q^{-1}\ b_5]}{1+aq^{-1}} \left[\Delta T_{io}(k)\ \ Q_{rad}(k)\ \ 1\right]^T \tag{24}$$

$$T_i(k) = \frac{[b_1 q^{-1}\ b_2 q^{-1}\ b_3 q^{-1}\ b_5]}{1+aq^{-1}} \left[\Delta T_{io}(k)\ \ Q_{rad}(k)\ \ \Delta T_{pi}(k)\ \ 1\right]^T \tag{25}$$

The reason why we chose this model for comparison was that Eq.(23)~Eq.(25) had the same structure as the new IARX models, with only one additional coefficient a. Therefore, the new IARX models for the three sub-states: passive state, mechanical ventilation and fan-pad cooling, are the particular cases of Eq.(23)~Eq.(25) when coefficient a is -1. The effect on the prediction of greenhouse air temperature by this specific value -1 and other different values of the coefficient a can be found naturally.

4.2. Model Identification and Validation

For the three models, the numbers of coefficients were listed in Table 1 for each of the three sub-states: passive state, mechanical ventilation and fan-pad cooling. It's easy to see that the maximum number of coefficients was five. Based on the structure of the models, at least six sets of measured data were required to identify five coefficients. In section 3.1, sixteen sets of environmental factors were acquired in each operating sub-state. In order to reduce the impact of measurement noise, we would use the first seven sets of measured data to identify the coefficients of the three models for each sub-state. Then the identified models would be used to predict the greenhouse air temperature at the future sampling instants.

Table 1. The Numbers of Coefficients of the Three Models

Models \ Sub-states	Passive state	Mechanical ventilation	fan-pad cooling
New IARX models	3	3	4
Compared model 1	5	5	5
Compared model 2	4	4	5

The letter k was used to denote the current time instant. In order to predict the greenhouse air temperature at a future time instant $k+i$ ($i>1$), the relevant external environmental factors at the future time instant $k+i-1$ ($i>1$) are required. The lazy man weather prediction method was adopted here to predict these external environmental factors at the future sampling instants [20], i.e. the external environmental factors were assumed the same as the latest measured data. Good prediction result could be obtained when the prediction horizon was not too long. In order to reduce the impact on the identification accuracy caused by the large numerical differences of different environmental factors, the measured data was normalized. The normalization processing rules were shown in Table 2.

Table 2. Normalization Processing Rules

Environmental factors	Measurement ranges	Normalization ranges
Internal and external air temp (°*C*)	-10~50	0~100
Internal and external air RH (%)	0~100	0~100
External solar radiation (*kLux*)	0~200	0~100

4.2.1 Passive Sub-State: The seven sets of measured data from 8:00 am to 8:06 am were used to identify the coefficients of the three models, and then the models were used to predict the greenhouse air temperature at the next time instants from 8:07 am to 8:15 am. The measurement and prediction results of the three models were shown in Figure 4. The maximum prediction errors of the IARX model and the two compared models are 0.1°C, 0.4°C, and 0.1°C, and the mean square errors are 0°C, 0.2°C, and 0°C respectively.

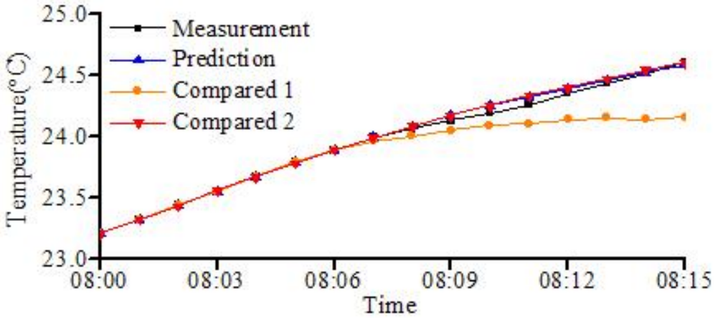

Figure 4. Prediction of Greenhouse Air Temperature in the Passive Sub-State

4.2.2 Mechanical Ventilation Sub-State: The ventilation fans were started for mechanical ventilation at 10:15 am. The fans require about ten seconds to reach the full-speed operation, so in order to guarantee high identification accuracy, the data measured at 10:15 am was not used for the identification of model coefficients, while the seven sets of measured data from 10:16 am to 10:22 am were taken. The models were then used to predict the greenhouse air temperature at the next time instants from 10:23 am to 10:30 am. The measurement and prediction results of the three models were shown in Figure 5. The maximum prediction errors of the IARX model and the two compared models are 0.4°C, 5.2°C, and 0.4°C, and the mean square errors are 0.3°C, 2.4°C, and 0.3°C, respectively.

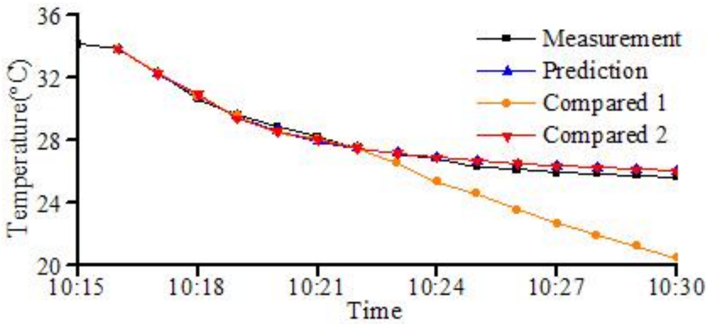

Figure 5. Prediction of Greenhouse Air Temperature in the Mechanical Ventilation Sub-State

4.2.3 Fan-pad Cooling Sub-state

The ventilation fans and the wet pad were started for fan-pad cooling at 11:06 am. The data measured at 11:06 am was not used to identify the model coefficients for the same reason of mechanical ventilation sub-state. The seven sets of measured data from 11:07 am to 11:13 am were taken for the identification of the model coefficients. The models were then used to predict the greenhouse air temperature at the next time instants from 11:14 am to 11:21 am. The measurement and prediction results of the three models were shown in Figure 6. The maximum prediction errors of the IARX model and the two compared models are 0.7°*C*, 1.8°*C*, and 0.5°*C*, and the mean square errors are 0.4°*C*, 1.0°*C*, and 0.3°*C*, respectively.

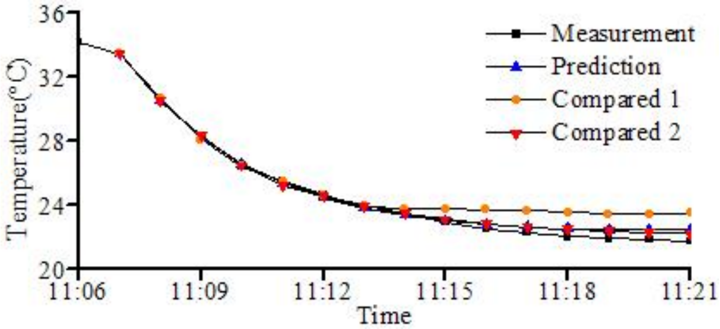

Figure 6. Prediction of Greenhouse Air Temperature in the Fan-Pad Cooling Sub-State

4.3. Analysis of Results

It can be seen that the IARX models obviously have better prediction results than the first compared model for all the three operating sub-states, which demonstrates that the IARX models deduced from the mechanistic model are much more suitable for predicting greenhouse air temperature than those established by other methods, such as based on experience. The prediction curves of the IARX models and those of the second compared model almost overlap with each other completely in Figure 4~6, which demonstrates than the IARX models with fewer coefficients can predict as well as the second compared model. The validation results demonstrate that the IARX models are more suitable for researching model-based switching control strategies of different operating sub-states.

5. Conclusion

The impact of actuators on greenhouse air temperature has been considered when the new prediction models are built. Based on the on-off characteristic of actuators, the operating state of a greenhouse is divided into five sub-states and the new IARX prediction model has been built for each sub-state based on the mechanistic modelling. It’s well-known that the actuators in different greenhouses have much difference and a greenhouse does not necessarily have all the five operating sub-states, due to their local climates and construction costs, etc. The five sub-states considered in this paper include all the possible sub-states of most greenhouses in China, so the IARX prediction models are suitable for different types of greenhouse with various actuators.

In our experimental greenhouse, the IARX prediction models for three operating sub-states have been validated with very good results, as the greenhouse just has the three sub-states. We will validate the IARX models for the other two sub-states in other greenhouses in future. The IARX prediction models have very few identification coefficients and a simple structure. In future real-time control processes, the model coefficients will be recursively identified to predict the greenhouse air temperature with a very small calculation, which can be easily realized. With the sufficient consideration of ON-OFF actuators in greenhouses, we will next research the switching control strategies of different operating sub-states based on the new IARX prediction models.

Acknowledgments

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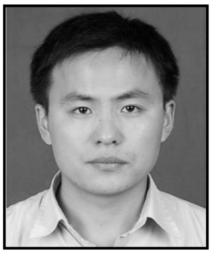

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