Application of Adaptive Fuzzy Logic System to Model for Greenhouse Climate*

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Abstract – **In this paper, the greenhouse climate model based on adaptive fuzzy logic system is presented. Greenhouse climate system is a non-linear system with the various climate factors being coupled. Due to its capability to handle both numerical data and linguistic information, it is feasible to apply adaptive fuzzy logic system to model for greenhouse climate, and then provide prediction for greenhouse climate control.**

Keywords – **Greenhouse, Fuzzy logic system, Model.**

I. INTRODUCTION

Greenhouse climate model is an essential tool for greenhouse climate control. The model must describe the responses of the greenhouse climate to the external influences such as solar radiation, outside air temperature, wind speed and outside humidity, and to the control actions performed over the actuators used in the greenhouse such as ventilators, heating systems etc.

The model can be computed in two ways. One method is based on the physical laws involved in the process and the other on the analysis of the input-output data of the process. In the first method the thermodynamic properties of the greenhouse system are employed. Businger(1963) proposed a greenhouse climate model which based on energy balance and provided detailed analysis. After that some dynamic models were presented (Takakura et al., 1971; Avissar, 1973; Mahrer, 1982; Van Bavel et al., 1985; Kimball, 1989). Bot(1991), Boulardand Baille(1993) described the greenhouse climate by energy and mass balance equations. However, the parameters of the equations are time-variant and weather-dependent, so it is difficult to obtain accurate mathematical models of the greenhouse climate.

The second approach is based on the theory of system identification. Because of parameter uncertainty and difficulty of linearization of the system, normal methods of system identification such as Least Square can't be applied to greenhouse climate system. Although three-layer BP neural network can fit a nonlinear map function by arbitrary accuracy, it can't utilize structured linguistic information, and its net weight values are random, which make algorithm converge slowly and the solution be immersed in local optimum. Normal fuzzy logic methods can make full use of linguistic knowledge, but they can't tune rules on-line, they don't adapt to process time-variant objects. We apply adaptive fuzzy logic system to model for the greenhouse system.

Adaptive fuzzy logic system is a class of fuzzy logic systems, which has the learning capability and can automatically modify fuzzy rules by learning. In addition, it can utilize both numerical data and linguistic information. So it can identify time-variant nonlinear systems. We call the fuzzy logic system fuzzy identifier, which has back propagation learning algorithm and is used to identify nonlinear dynamic systems. Compared with neural network identifier, fuzzy identifier has two essential advantages:

(1) The initial parameters of fuzzy identifier have physical meanings, we can select them in a good way. On the contrary, the initial parameters of neural network identifier are usually selected randomly. Because the back propagation learning algorithm adopted by two kinds of identifier belongs to gradient algorithm, the selection of initial parameters influences the convergence speed of algorithm to a great extent.

(2) Fuzzy identifier can handle linguistic information. Fuzzy identifier is based on fuzzy logic system, which is composed of a set of "if-then" rules, so it provides the path for utilizing linguistic information. Important information about the unknown nonlinear system is probably contained in the linguistic information. In brief, we utilize linguistic information to construct an initial identifier. The fuzzy identifier based on it tracks the real system faster.

II. PHYSICAL MODELING OF GREENHOUSE CLIMATE

A Physical Model of the Greenhouse Climate

Basing on the analysis of physical processes of greenhouse climate, we can obtain dynamic equation of greenhouse air temperature via energy balance. The general expression is:

$$V_g Cap_g \, dT_g / dt = E_s + E_{crad} + E_{heat} + E_{ga} + E_{cac} + E_{vent} + E_{soil} - E \tag{1}$$

Where V_g is the volume of the greenhouse (m^3), Cap_g is the

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heat capacity of the greenhouse($Jm^{-3}k^{-1}$), T_g and T_a the in-and exterior temperature respectively (k or ${}^0c$). E_s is the solar radiation, $E_s = Q_s \times s$; E_{crad} is the long-wave radiation between the cover and outside air, $E_{crad} = -\varepsilon_{ca}F_c\sigma(T_g^4 - T_a^4)$. E_{heat} is the heat transfer between the heating system and greenhouse air, $E_{heat} = Q_{heat} \times s_p$; E_{ga} is the heat conduction between the greenhouse and outside by the cover, $E_{ga} = Q_{ga} \times s_c$; E_{cac} is the convective heat transfer between the cover and outside air, $E_{cac} = \alpha_c s_c(T_a - T_g)$; E_{vent} is the ventilation heat exchange, $E_{vent} = \Phi_v Cap_g(T_g - T_a)$; E_{soil} is the heat exchange with soil, $E_{soil} = -l(dT_s/dt)s$; E is the heat for transpiration, $E = Hr_{tot}^{-1}(c_1 - c_g)$.

This leads to the detailed expression:

$$\begin{aligned} V_g Cap_g\, dT_g/dt &= \alpha_s I\tau\cos\theta\, s - \varepsilon_{ca}F_c\sigma(T_g^4 - T_a^4) \\ &+ \alpha_p s_p(T_p - T_g) - k_c s_c(T_g - T_a)/d \\ &+ \alpha_c s_c(T_a - T_g) + \Phi_v Cap_g(T_g - T_a) \\ &- l(dT_s/dt)s - Hr_{tot}^{-1}(c_1 - c_g) \end{aligned} \quad (2)$$

Where s is the ground area of greenhouse (m^2), s_c is the cover area (m^2), s_p is the outside area of the heating pipes (m^2).

B Analysis of the Physical Model

1) Parameter Analysis The model shows that the greenhouse climate system is a time-variant nonlinear system. For a given greenhouse, some coefficients such as α_s、τ、ε_{ca}、V_g、F_c、s、s_p、s_c、d are fixed, which are determined by the structure and physical property of greenhouse. Others are difficult to fix on. At first, convection is a complex process. Newton cooling law doesn't post the essence of convection, and just concentrates on the heat transfer coefficients which involve all factors affecting the convection such as air flow speed, temperature difference etc. Convective heat transfer between the heating system and the greenhouse is natural convection. Due to relative steady airflow, heat transfer coefficient α_p can be fixed. α_c is time-variant and nonlinear because of outside weather uncertainty. Secondly, ventilation exchange relates to fluid dynamics, its accurate analysis and computation are difficult. Even if empirical formulas are used, we must do many experiments to determine the coefficients. Thirdly, due to the complexity of soil component, it is hard to compute the heat transfer with soil, which is a function of exterior and interior temperature. Finally, transpiration resistance r_{tot} is related to the boundary layer resistance and stomata resistance etc. While the stomata resistance is related to the stomata openings which depends on crop photosynthesis, respiration, outside temperature, humidity as well as illumination. These result in that transpiration resistance is a time-variant nonlinear function of various factors.

2) Input Analysis Some parameters of the model can be measured by sensors, which are considered as the disturbances, for example T_a、T_g、T_s、c_1、c_a、c_g、I、θ、u. While heating pipe temperature T_p and opening of ventilator β are regarded as the control inputs. T_p is controlled via water flow of pipe. According to the types of the inputs, we can rearrange the equation:

$$\begin{aligned} V_g Cap_g\, dT_g/dt &= \alpha_s\tau sI\cos\theta + \varepsilon_{ca}F_c\sigma T_a^4 + (k_c/d + \alpha_c)s_c T_a \\ &- l_s\, dT_s/dt - Hr_{tot}^{-1}(c_1 - c_g) - \varepsilon_{ca}F_c\sigma T_g^4 \\ &- [\alpha_p s_p + (k_c/d + \alpha_c)s_c]T_g + \alpha_p s_p T_p \\ &+ (ku + \lambda\sqrt{|T_g - T_a|})A_w Cap_g(T_g - T_a) \end{aligned} \quad (3)$$

If overlooking the non-linearity of some coefficients, it is linear for T_p and nonlinear for A_w (effective ventilation area) because of many coupled factors. For various disturbances, it is nonlinear.

III. DESIGN OF FUZZY IDENTIFIER

In order to find out the functional relation between the greenhouse temperature and various disturbances, it is assumed that the discrete nonlinear system has the following form:

$$T_g(k) = f(T_g(k-1), T_a(k), u(k), Rad(k), RH_g(k)) \quad (4)$$

Where f is the function that will be identified, $T_g(k-1)$ is the (k-1)th sampled greenhouse temperature(${}^0c$), $T_a(k)$ is the kth sampled outside temperature(${}^0c$), $u(k)$ is the kth sampled wind speed(cm/sec), $Rad(k)$ is the solar radiation(w/m^2), $RH_g(k)$ is the relative humidity of greenhouse, $T_g(k)$ is output .i.e. the kth outside temperature(${}^0c$).

The model that is applied to identify is a serial-parallel model as figure 1.

$$\hat{T}_g(k) = \hat{f}(T_g(k-1), T_a(k), u(k), Rad(k), RH_g(k)) \quad (5)$$

The design includes two parts:
(1) construction of initial fuzzy logic system;

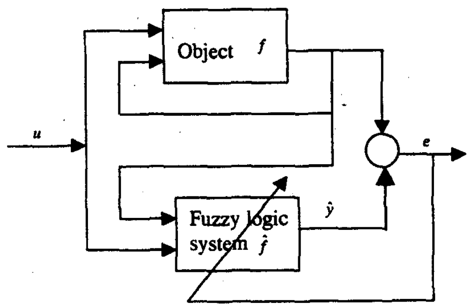

Figure 1. The serial-parallel identification model based on fuzzy logic system

(2) on-line self-tuning. During the construction, we should make full use of all initial information to approach the function. On-line self-tuning of parameters aims at minimize the error e between the system output and identifier output. The fuzzy logic system which is composed of central mean fuzzy eliminator, product inference rule, single-value fuzzy generator and gaussian membership function has the form as the following:

$$f(x)=\frac{\sum_{l=1}^{M}\bar{y}^{l}[\prod_{i=1}^{n}a_i^l\exp(-(\frac{x_i-\bar{x}_i^l}{\sigma_i^l})^2)]}{\sum_{l=1}^{M}[\prod_{i=1}^{n}a_i^l\exp(-(\frac{x_i-\bar{x}_i^l}{\sigma_i^l})^2)]} \quad (6)$$

Where $\bar{y}^l$ is the center of output fuzzy set, $\bar{x}_i^l$ and σ_i^l the center and width of input fuzzy set respectively, x_i is the ith input. Constructing a reasonable initial fuzzy logic system is to select the initial parameters($\bar{y}^l$, $\bar{x}_i^l$ and σ_i^l)properly. For the function that will be identified, it is described by the equation,

$$T_g(k)=\frac{H}{G} \quad (7)$$

With

$$H=\sum_{l=1}^{15}T_g{}^l(k)*[a_1^l\exp(-(\frac{T_a(k)-T_a^l(k)}{\sigma_1^l})^2)] *[a_2^l\exp(-(\frac{Rad(k)-Rad^l(k)}{\sigma_2^l})^2)] *[a_3^l\exp(-(\frac{u(k)-u^l(k)}{\sigma_3^l})^2)] *[a_4^l\exp(-(\frac{RH(k)-RH^l(k)}{\sigma_4^l})^2)] *[a_5^l\exp(-(\frac{T_g(k-1)-T_g{}^l(k-1)}{\sigma_4^l})^2)] \quad (8)$$

$$G=\sum_{l=1}^{15}[a_1^l\exp(-(\frac{T_a(k)-T_a^l(k)}{\sigma_1^l})^2)] *[a_2^l\exp(-(\frac{Rad(k)-Rad^l(k)}{\sigma_2^l})^2)] *[a_3^l\exp(-(\frac{u(k)-u^l(k)}{\sigma_3^l})^2)] *[a_4^l\exp(-(\frac{RH(k)-RH^l(k)}{\sigma_4^l})^2)] *[a_5^l\exp(-(\frac{T_g(k-1)-T_g{}^l(k-1)}{\sigma_4^l})^2)] \quad (9)$$

Where

$T_g(k-1), T_a(k), u(k), Rad(k), RH_g(k)$: Input variables;

$T_g(k)$: Output variable;

$T_g^l(k)$, $T_a^l(k)$, $Rad^l(k)$, $u^l(k)$, $RH^l(k)$, $T_g^l(k-1)$: The center of various fuzzy set.

σ_i^l : The width of various fuzzy set.

The descriptive rules in relation to the unknown nonlinear function:

IF $T_a(k)$ is moderate and $Rad(k)$ is weak and $u(k)$ is larger and $RH_g(k)$ is larger and $T_g(k-1)$ is lower, THEN $T_g(k)$ is lower.

IF $T_a(k)$ is moderate and $Rad(k)$ is weak and $u(k)$ is moderate and $RH_g(k)$ is moderate and $T_g(k-1)$ is lower, THEN $T_g(k)$ is lower.

IF $T_a(k)$ is moderate and $Rad(k)$ is weak and $u(k)$ is larger and $RH_g(k)$ is low and $T_g(k-1)$ is lower, THEN $T_g(k)$ is moderate.

IF $T_a(k)$ is moderate and $Rad(k)$ is weaker and $u(k)$ is larger and $RH_g(k)$ is moderate and $T_g(k-1)$ is moderate, THEN $T_g(k)$ is moderate.

IF $T_a(k)$ is higher and $Rad(k)$ is weaker and $u(k)$ is moderate and $RH_g(k)$ is moderate and $T_g(k-1)$ is moderate, THEN $T_g(k)$ is moderate.

IF $T_a(k)$ is higher and $Rad(k)$ is weaker and $u(k)$ is larger and $RH_g(k)$ is moderate and $T_g(k-1)$ is moderate, THEN $T_g(k)$ is high.

IF $T_a(k)$ is high and $Rad(k)$ is moderate and $u(k)$ is large and $RH_g(k)$ is large and $T_g(k-1)$ is high, THEN $T_g(k)$ is high.

IF $T_a(k)$ is high and $Rad(k)$ is powerful and $u(k)$ is large and $RH_g(k)$ is large and $T_g(k-1)$ is high,

THEN $T_g(k)$ is high.

IF $T_a(k)$ is high and $Rad(k)$ is more powerful and $u(k)$ is large and $RH_g(k)$ is large and $T_g(k-1)$ is high,

THEN $T_g(k)$ is higher.

IF $T_a(k)$ is high and $Rad(k)$ is moderate and $u(k)$ is larger and $RH_g(k)$ is large and $T_g(k-1)$ is higher,

THEN $T_g(k)$ is high.

IF $T_a(k)$ is moderate and $Rad(k)$ is weak and $u(k)$ is larger and $RH_g(k)$ is large and $T_g(k-1)$ is lower,

THEN $T_g(k)$ lower.

IF $T_a(k)$ is lower and $Rad(k)$ is weak and $u(k)$ is moderate and $RH_g(k)$ is large and $T_g(k-1)$ is lower,

THEN $T_g(k)$ is lower.

IF $T_a(k)$ is lower and $Rad(k)$ is weak and $u(k)$ is small and $RH_g(k)$ is large and $T_g(k-1)$ is lower,

THEN $T_g(k)$ is low.

IF $T_a(k)$ is lower and $Rad(k)$ is weak and $u(k)$ is smaller and $RH_g(k)$ is large and $T_g(k-1)$ is low,

THEN $T_g(k)$ is low.

IF $T_a(k)$ is low and $Rad(k)$ is weak and $u(k)$ is small and $RH_g(k)$ is small and $T_g(k-1)$ is low,

THEN $T_g(k)$ is low.

The initial values of $T_g^l(k), T_a^l(k), Rad^l(k), u^l(k), RH^l(k), T_g^l(k-1)$ and σ_i^l are determined via these fuzzy rules. Basing on the two-day actual observation records to a certain greenhouse, the simulation values are listed in the following. Iteration number for the error back propagation computation is 500 times.

$\bar{y}^l = T_g^l(k)$ =[27.3280 27.4092 29.7113 29.9971 29.0652 34.0541 34.2582 34.2961 32.0686 30.7187 27.3279 27.8259 25.7208 25.5886 24.7859]

$\bar{x}_1^l = T_a^l(k)$ =[27.2001 26.8605 27.1689 26.9033 28.4435 28.1140 29.8989 29.8996 29.9655 29.7776 27.2002 25.3787 25.4839 25.7233 23.5217]

σ_1^l =[1.0985 0.6643 0.3196 0.5048 0.5035 0.0373 0.4986 0.4999 0.5061 0.5112 1.0985 0.4906 0.5788 0.8084 0.9541]

$\bar{x}_2^l = Rad^l(k)$ =[110.9959 110.9963 111.0026 280.0001 279.9915 280.0032 448.9999 787.0000 617.9992 449.0094 110.9959 111.0002 110.9988 110.9962 110.9868]

σ_2^l = [201.0032 201.0033 200.9977 200.9999 201.0045 200.9976 200.9999 201.0000 201.0003 201.0037 201.0032 200.9998 201.0012 201.0039 201.0127]

$\bar{x}_3^l = u^l(k)$ =[737.9969 551.0014 738.0014 738.0000 551.0215 738.0039 924.0003 924.0000 923.9956 737.9792 37.9969 551.0001 178.0008 364.0000 177.9976]

σ_3^l = [241.0028 241.0017 240.9991 241.0000 241.0254 240.9971 240.9994 241.0000 241.0076 241.0153 241.0028 241.0000 241.0007 241.0022 241.0044]

$\bar{x}_4^l = RH^l(k)$ =[99.3001 98.9001 97.9998 98.9000 98.9004 98.8999 99.7000 99.7000 99.7000 99.7001 99.7000 99.7000 99.7000 99.7000 98.0005]

σ_4^l = [0.6000 0.6000 0.6000 0.6000 0.6000 0.6000 0.6000 0.6000 0.6000 0.6000 0.6000 0.6000 0.6000 0.6000 0.6000]

$\bar{x}_5^l = T_g^l(k-1)$ =[27.9024 27.9005 27.9002 30 30.0044 30.0008 34.2999 34.3000 34.3000 32.1907 27.8961 27.9007 27.9009 25.7966 25.8107]

σ_5^l = [2.9000 2.9000 2.9000 2.9000 2.9000 2.9000 2.9000 2.9000 2.9000 2.9002 2.9001 2.9000 2.9000 2.9001 2.9001]

The learning and prediction results are showed in Fig 2.

IV.CONCLUSION

It is rather difficult to model completely for greenhouse climate only basing on the physical laws involved in the process. Combing physical modeling with adaptive fuzzy logic system is a way to obtain the nonlinear functional relation between the greenhouse temperature and various climate factors. The simulation shows that this method can track the real system.

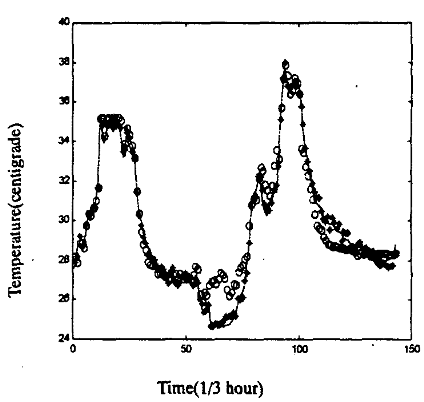

Fig.2 Learning and prediction results of greenhouse temperature

V.ACKNOWLEDGMENS

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