Application of Nonlinear Adaptive PID Control in Temperature of Chinese Solar Greenhouses

Yonggang Wang¹, Yujin Lu¹, Yuhang Liu¹, Tan Liu¹, Nannan Zhang¹
1. College of Information and Electronic Engineering, Shenyang Agricultural University, Shenyang 110866
E-mail: a5588676@163.com

Abstract: The system of the Chinese solar greenhouses (CSGs) is required to ensure suitable environment for crops growth. However, the greenhouse system is described as complex dynamics characteristics, such as multi-disturbance, parameter uncertainty, and strong nonlinearity. Actually, the conventional PID control method is difficult to deal with above problem. To address above problem, a dynamic model of CSG is developed based on the energy conservation laws and a nonlinear adaptive control scheme, combining RBF neural network with incremental PID controllers, is applied to the temperature control. In this approach, parameters of PID controller are determined by the generalized minimum variance laws, and the unmodelled dynamics is estimated by RBF neural network. The control strategy is combined with a linear adaptive PID controller, a neural network nonlinear adaptive PID controller and switching mechanism. The simulation results show that the adopted method can achieve excellent control performance, which meets the actual requirements.

Keywords: Chinese Solar greenhouse, temperature control, Nonlinear adaptive control, RBF neural network, PID controllers

1 INTRODUCTION

Considerable attention has been given to the CSGs due to providing a proper environment for crops growth. It can supply pollution-free and high-quality vegetables although during the winter. For greenhouse plants, favorable microclimate means enough solar radiation, adequate temperature, suitable humidity and so on. However, in northeast China, the average temperatures are very low, even falling to below −10°C and the cold season generally lasts for four months due to the high latitude in some areas [1]. Such an arctic weather seriously affects normal production and bring great loss to the economic benefits [2]. Therefore, the inside temperature is a significant factor to restrict the greenhouse production of the northeast China. In this situation, the CSG must maintain a certain indoor temperature level to meet the needs of crops growth. Furthermore, determining automatic control strategies is the leading goal for obtaining higher-quantity greenhouse crops.

However, the control of inside temperature has generally confronted series of difficulties in actual greenhouse production due to its inherent complexity [3]. Firstly, the greenhouse is considered a nonlinear dynamic system with intensive multi-disturbance from surroundings, such as wind speed, external air temperature and humidity. Secondly, the control process is severely influenced by instable factors including global radiation, external weather and human activities. Finally, the relationship between crops and the environment is strong and interactive [4]. For example, the plants transpiration and photosynthesis similarly affected the greenhouse temperature that they depend on.

In order to solve these difficulties, many modeling methods have been proposed, such as mechanism, transfer function and black-box modeling [5]. A modeling approach was built using data gathered from a real greenhouse under closed-loop control [6]. An online identification technology was adopted to obtain more accurate greenhouse model [7]. A stochastic dynamic model was proposed by the maximum likelihood estimation method, which based on parameter identification [8].

During recent years, Many scholars have proposed advanced control strategies, such as adaptive control [9], fuzzy control [10], robust control [11], multiple neural control approaches [12] and so on. These control methods can maintain the inside temperature around desired temperature set point in some certain conditions. However, the problem caused by the instable factor and multi-disturbances still has difficulty dealing with. Furthermore, most of these climate control strategies are difficult to carry out in greenhouse production due to the theoretically complex.

This paper starts with the development of dynamic model of CSG and applies a nonlinear adaptive PID control scheme based on RBF neural networks to solve temperature control for CSG system. This control approach takes advantage of the simplicity of PID controllers and the powerful capability of learning and adaptability of RBF networks. In this paper, a linear adaptive PID controller, a neural network nonlinear adaptive PID controller and switching mechanism is combined to improve dynamic performance on the promise of guaranteeing the system stability. The parameter of PID controller is determined based on the generalized minimum variance control law. RBF neural networks is used to deal with the unmodeled dynamics of CSGs. The experimental results demonstrate that the applied control strategy shows quick setpoint tracking ability in the case of multi-disturbances and can achieve satisfactory control performances.

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E-mail: a5588676@163.com
MODEL DESCRIPTION

Fig 1. Schematic diagram of energy balance of experimental greenhouse
(Note: 1. the greenhouse blanket 2. the north roof 3. the north wall 4. the soil 5. the greenhouse frame 6. crops)

Considering the characteristics of the unique structure in CSG, heat transfer quantity $Q_n(W/m^2)$ and $Q_m(W/m^2)$ are introduced from inside air to north wall and north roof, respectively. The greenhouse model developed in this paper according to energy balance (Fig.1). These differential equations are given by

$$\begin{align*}
\frac{dT_b}{dt} &= \frac{Q_{rad} + Q_{heat} - Q_c - Q_t - Q_s - Q_m - Q_b}{\rho C_p h}, \\
\frac{dH_r}{dt} &= E - C - \phi - \phi_r
\end{align*}$$
(1)

In the heat model of Eq.(1), where $\rho$ is the air density; $C_p$ is air specific heat capacity; and $h$ is the height of greenhouse. $Q_{rad}(W/m^2)$ is the intercepted solar radiant energy, $Q_{heat}(W/m^2)$ is the heat provided by greenhouse heaters, $Q_c(W/m^2)$ is the heat transferred from the envelop between the outside and the inside, $Q_t(W/m^2)$ is the heat absorbed by the crops through transpiration, $Q_s(W/m^2)$ is the sensible heat transferred from inside air to crops, $Q_m(W/m^2)$ is the heat transferred from inside air to the soil in the greenhouse, $Q_b(W/m^2)$ is the sensible heat transferred from north wall to indoor air, $Q_r(W/m^2)$ is the sensible heat transferred from north roof to inside air.

In the humidity model of Eq.(1), where $E$ is the transpiration rate of crops in g.m⁻².s⁻¹, $C$ is the water vapor condensation caused by the indoor and outdoor temperature difference in g.m⁻².s⁻¹, $\phi$ is the humidity taken away by the cold air penetrating the greenhouses in g.m⁻².s⁻¹, $\phi_r$ is the water condensation or evaporation when heating system is activated in g.m⁻².s⁻¹.

According to the well-known Penman-Monteith formula, $Q_r$ can be calculated by [13].

$$Q_r = C_i R_n + \left(\frac{e \beta}{\gamma}T_a - \frac{h_i P}{8.036}\right) H_{in}$$
(2)

where $C_i$ is the convective heat loss coefficient from indoor air to the cover, $R_n$ is the net radiative exchange between the canopy and the environment, $e$ is the air saturation vapor pressure, $\beta$ is the influence coefficient of temperature change on saturated water vapor pressure, $\gamma$ is the psychrometric constant, $h_i$ is the heat transfer constant between crops and inside air, and $P$ is the standard atmospheric pressure. $H_{in}$ indicates the absolute humidity of the indoor air.

Solar radiation, a significant factor affecting the indoor temperature, is defined as [14]:

$$Q_{rad} = c_r S_{out} A_p \sin I_p$$
(3)

where $c_r$ is the aging coefficient of lighting material, $\tau$ is the greenhouse global transmission, $S_{out}$ is the solar radiation, $A_p$ is surface area of greenhouse which absorbs solar radiation, $\sin I_p$ is the incidence angle of sunlight, and $V_a$ is the volume of the greenhouse.

In this study, $Q_{heat}$ is defined as [15]:

$$Q_{heat} = \eta Q_p$$
(4)

where, $\eta$ is the energy efficiency of heaters. $Q_p$ is the energy power of the heating equipment in W/m². $Q_c$ is defined as [16]:

$$Q_c = h_i (T_{in} - T_{out}) \frac{A_{in}}{A_p}$$
(5)

where, $T_{in}$ and $T_{out}$ are the inside and outside temperatures in °C respectively. $A_{in}$ is the superficial area of cover materials. The conversion relation between $t$ and $T$ is as follow:

$$t = T - 273.15$$
(6)

The overall energy loss coefficient $h_i$, increased with wind speed $v_{out}$ following the formula [17]:

$$h_i = A + Bv_{out}$$
(7)

where, the values of $A$ and $B$ are 6 and 0.5 respectively.

In Eq.(1) $Q_n$ and $Q_m$ are calculated as follows [3]:

$$Q_n = (T_a - T_s) \rho C_p / r_a$$
(8)

$$Q_m = (T_a - T_s) \rho C_p / r_s$$
(9)

where, $T_s$ is soil surface temperature, $T_l$ is the leaf temperature of crops.

The soil aerodynamic resistance $r_a$ is defined as [14]:

$$r_a = 305(D / v_{in})^{0.5}$$
(10)

where, $D$ is the leaf width, $v_{in}$ is indoor wind speed. Heat transfer quantity $Q_n$ is calculated as follow:

$$Q_n = A_{in} \alpha_n (T_{in} - T_l)$$
(11)

where, $A_{in}$ is north wall area, $T_l$ represents north wall temperature, $\alpha_n$ is the convective heat transfer coefficient between north wall and the inside air.

Heat transfer quantity $Q_m$ is calculated as follow:

$$Q_m = A_{in} \alpha_n (T_{in} - T_l)$$
(12)

in which $A_h$ is the area of north roof, $T_h$ represents north roof temperature, $\alpha_h$ is the convective heat transfer coefficient between the north roof and the inside air.

$$E = \frac{C_i R_n + (e \beta / \gamma)T_a - (h_i P / 8.036) H_{in}}{\lambda}$$
(13)

where $\lambda$ is latent heat of evaporation.
C = 0.00164(A / A_\text{c}) (T_\text{in}^3 - T_r^3) (H_\text{r} - H_\text{r, s}) \quad (14)

in which, \(A_r\) is the greenhouse covering area in \(\text{m}^2\). \(T_\text{in}\) is the virtual temperature of indoor air. Eq.(15) is the formula of \(T_\text{in}\) and \(T_r\), where \(e_\text{i}\) represents the actual water vapor pressure of indoor air.

\[
T_\text{in} = T_r (1 + 0.378 e_\text{i} / P) \quad (15)
\]

where, \(H_\text{r, s}\) is defined by:

\[
H_\text{r, s} = 2165 e_\text{i} / P \quad (16)
\]

In Eq.(1), \(\phi_r\) and \(\phi_p\) are calculated as follows:\[17\]

\[
\phi_r = \left(\frac{\eta A_t h_\text{r}}{A \gamma \lambda} \right) Q_r \quad (17)
\]

\[
\phi_p = \phi_r (H_\text{r} - H_\text{in}) \quad (18)
\]

The cold air infiltration \(\psi_a\) is calculated as follows:

\[
\psi_a = \frac{e\psi_a}{3600} \quad (19)
\]

The cold air infiltration \(\psi_a\) is influenced by the outdoor wind speed and the value of \(e\) lies between 0.2 and 0.5.

Make \(T_\text{in} = y_1, H_\text{in} = y_2, Q_r = u\), and Eqs.(2)-(12) are substituted into Eq.(1) to obtain the temperature dynamic model of the system, as shown in Eq.(20). Eqs.(13)-(19) are substituted into Eq.(1) to acquire the humidity dynamic model of the system, as shown in Eq.(21). The model parameters are provided in Table 1.

\[
y_1(t) = \frac{-h_\text{A}_t}{A_C/\rho C_\text{hu}} \left[ \psi_\text{a} 2 \right] + \frac{h P}{305(D/V_\text{in})^{1/3} \rho C_\text{hu}} + \frac{h P}{273.15} \left[ A_r h \psi_a \right] \frac{A_t}{A_\text{r} h} + \frac{e \beta}{\rho C_\text{hu}} \sin T_r \left[ V_a C_r h \right] \frac{A_r h}{\rho C_\text{hu}} + \frac{T_r}{305(D/V_\text{in})^{1/3} \rho C_\text{hu}} + \frac{T_r}{A_r h} A_t \frac{C_r}{\rho C_\text{hu}} + \frac{e \beta}{\rho C_\text{hu}} \sin T_r \left[ V_a C_r h \right] \frac{A_r h}{\rho C_\text{hu}} + \frac{T_r}{305(D/V_\text{in})^{1/3} \rho C_\text{hu}} + \frac{T_r}{A_r h} A_t \frac{C_r}{\rho C_\text{hu}} \left(1 + 0.378 e_i / P\right) \quad (20)
\]

\[
y_2(t) = \frac{h P}{8036 y_1^{1/3}} + \frac{h P}{273.15} \left[ A_r h \psi_a \right] \frac{A_t}{A_\text{r} h} + \frac{e \beta}{\rho C_\text{hu}} \sin T_r \left[ V_a C_r h \right] \frac{A_r h}{\rho C_\text{hu}} + \frac{T_r}{305(D/V_\text{in})^{1/3} \rho C_\text{hu}} + \frac{T_r}{A_r h} A_t \frac{C_r}{\rho C_\text{hu}} \left(1 + 0.378 e_i / P\right) \quad (21)
\]

Table 1. Meanings of parameters of the greenhouse temperature model

| Parameter | Meaning and Value |
|-----------|------------------|
| \(P\)     | standard atmospheric pressure, 101kPa |
| \(\rho\)   | air density, 1.1691 kg/m³ |
| \(C_P\)   | the specific heat of air at constant pressure, 1.003 |
| \(e_s\)   | the specific heat of air at constant pressure, 3.167kPa |
| \(\gamma\) | the psychrometric constant, 660Pa/℃ |
| \(\lambda\) | the leaf temperature of crops, 6~15℃ |
| \(V_{\text{out}}\) | the area of north roof, 100m² |
| \(t_{\text{in}}\) | north wall temperature, 8~20℃ |
| \(a_w\) | convective heat transfer coefficient through north wall, 5~25 |
| \(h_i\) | the heat transfer constant between crops and inside air, 13.3 |
| \(D\) | leaf width, 0.15~0.25m |
| \(e\) | cold air permeability coefficient, 0.2~0.5m/s |
| \(\tau\) | the greenhouse global transmission, 0.6 |
| \(A_{\text{gr}}\) | surface area which absorbs solar radiation, 392m² |
| \(A_{\text{su}}\) | the superficial area of the cover materials, 815m² |
| \(h\) | the height of greenhouse, 2.5m |
| \(\alpha_h\) | the area of north roof, 100m² |
| \(t_{\text{roof}}\) | north roof temperature, 8~20℃ |
| \(c_\ell\) | the aging coefficient of lighting material, 0.82 |
| \(S_{\text{rad}}\) | solar radiation, 100~500W/m² |
| \(V_{\text{in}}\) | inside wind speed, 0~3m/s |
| \(t_s\) | soil surface temperature, 6~20℃ |
| \(t_i\) | the leaf temperature of crops, 6~15℃ |
| \(a_{\text{h}}\) | convective heat transfer coefficient through north roof, 5~25 |
| \(t_{\text{out}}\) | outside air temperature, 30~8℃ |
| \(e_u\) | the actual water vapor pressure of indoor air, 3.72kPa |

3 NONLINEAR ADAPTIVE PID CONTROL BASED ON SWITCHING MECHANISM

3.1 Controller Design Model

The dynamic model of northern greenhouse is shown in Eq.(20) and Eq.(21). The state variables are defined as \(x = [x_1, x_2]^T = [T_{\text{in}}, H_{\text{in}}]^T\), \(u = Q_r\), \(y = T_{\text{in}}\). Using this notation, the northern solar greenhouse model can be re-expressed as

\[
\dot{x}_1 = -a_0 x_1 + a_1 x_2 + a_2 u \quad (22)
\]

\[
\dot{x}_2 = a_3 x_1 - a_4 x_2 - a_5 u + a_6 (x_1 - 10)^{1/3} (x_1 + 273.15) \quad (23)
\]

where,

\[
a_0 = h_{A_{\text{r}} h} / A_{\text{r}}^2 C_{\text{ph}} + \frac{2}{305(D/V_{\text{in}})^{1/3}} + \frac{A_{\text{r}} h}{\rho C_{\text{hu}}} A_{\text{r}} h A_t C_r \rho C_{\text{hu}} \left(1 + 0.378 e_i / P\right) \quad (24)
\]

\[
a_1 = \frac{2 h_{A_{\text{r}} h}}{305(D/V_{\text{in}})^{1/3}} + \frac{2 h_{A_{\text{r}} h}}{305(D/V_{\text{in}})^{1/3}} A_{\text{r}} h A_t C_r \rho C_{\text{hu}} \left(1 + 0.378 e_i / P\right) \quad (25)
\]

\[
y(k) = \gamma (x(k)) \quad (26)
\]

where \(T\) is the sampling period, \(x_1(k), x_2(k)\) stand for corresponding state variables at sampling instants of continuous system.

Substitute Eq.(23) into Eq.(25), we obtain

\[
x_2(k) = x_1(k) + \frac{a_1 y(k)}{a_2 u(k)} \quad (27)
\]

\[
f_i(y(k-1), y(k), u(k))
\]

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Thus
\[ x_1(k-1) = f_1(y(k), y(k-1), u(k-1)) \]  
(28)

Furthermore, noticing Eq.(23), Eq.(25) and Eq.(28), we obtain

\[ x_1(k) = x_1(k-1) + \dot{x}_1(k-1)T \]
\[ = f_1(x_1(k), x_1(k-1), u(k-1)) + (a_0 x_1(k-1) \]
\[ -a_1 x_1(k-1) - a_2 u(k-1) - a_3(\dfrac{8053.8 x_1(k-1) - 101}{x_1(k-1) + 273.15}) \]
\[ -x_1(k-1))T = f_2(y(k), y(k-1), u(k-1)) \]

Noticing Eq.(24) and Eq.(26), we obtain

\[ y(k+1) = x_1(k+1) = x_1(k) + \dot{x}_1(k)T \]
\[ = x_1(k) + (-a_0 x_1(k) + a_1 f_1(y(k), y(k-1), u(k-1)) \]
\[ +a_2 u(k)T) = f_1(y(k), y(k-1), u(k), u(k-1)) \]

Applying the similar approach in [18], the greenhouse dynamical model can be expressed in the following formulation:

\[ A(z^{-1})y(k) = B(z^{-1})u(k-1) + v(k-1) \]  
(31)

where \( A(z^{-1}) = 1+az^{-1} \), \( B(z^{-1}) = 1+bz^{-1} \). \( a \) and \( b \) are polynomials about \( z^{-1} \). \( n_d \) and \( n_b \) are the system orders.

\( v[x(k)] = v[y(k-1), ... , y(k - n_d), u(k - 1), ..., u(k-n_b - 1)] \) is the higher order nonlinear item.

### 3.2 Nonlinear PID Controller

In order to effectively control the nonlinear plant (31), the PID controller is adopted as follow [19]:

\[ H(z^{-1})u(k) = K_p[e(k) - e(k-1)] + K_i e(k) \]
\[ +K_d[e(k) - 2e(k-1) + e(k-2)] - \bar{K}(z^{-1}) v(k-1) \]  
(32)

where \( e(k) = y(k) - y(k) \), \( K_p, K_i, K_d \) denote proportional gain, integral gain and derivative gain, respectively. \( H(z^{-1}) \) and \( \bar{K}(z^{-1}) \) are polynomial about \( z^{-1} \).

The linear PID controller can be obtained from (32) without considering the nonlinear term:

\[ H(z^{-1})u(k) = K_p[e(k) - e(k-1)] + K_i e(k) \]
\[ +K_d[e(k) - 2e(k-1) + e(k-2)] \]  
(33)

By substituting Eq. (32) into Eq. (31), the closed-loop equation of (33) on \( y(t) \) is obtained:

\[ [H(z^{-1})A(z^{-1}) + z^{-1} B(z^{-1}) \bar{G}(z^{-1})]y(k+1) = B(z^{-1}) \bar{G}(z^{-1})u(k) + [H(z^{-1}) - B(z^{-1}) \bar{K}(z^{-1})]v(t-1) \]  
(34)

where \( \bar{G}(z^{-1}) = \bar{G}_0 + \bar{G}_1 z^{-1} + \bar{G}_2 z^{-2} \), \( \bar{G}_0 = K_p + K_i + K_d \), \( \bar{G}_1 = -K_p - 2K_d \), and \( \bar{G}_2 = K_d \).

According to Eq.(34), the closed-loop characteristic polynomial of the system is as follow:

\[ T(z^{-1}) = H(z^{-1})A(z^{-1}) + z^{-1} B(z^{-1}) \bar{G}(z^{-1}) \]  
(35)

According to Eq.(35), in order to eliminate the influence of nonlinear term, the following conditions. \( \bar{K}(z^{-1}) \) are selected to meet the following requirements

\[ H(z^{-1}) = B(z^{-1}) \bar{K}(z^{-1}) \]  
(36)

### 3.3 Parameters Selection

To choose \( K_p, K_i, K_d \), and \( \bar{K}(z^{-1}) \) in Eq.(32), the following performance index is introduced based on generalized predictive control law:

\[ \psi = \| y(k+1) - G(z^{-1})u(k) + Q(z^{-1})u(k) + K(z^{-1})v(k-1) \| \]  
(37)

where \( G(z^{-1}) \), \( Q(z^{-1}) \), \( K(z^{-1}) \) are polynomial about \( z^{-1} \). \( v(k) \) is known as bounded reference input.

The following Diophantine equation is introduced:

\[ 1=F A(z^{-1}) + z^{-1} G(z^{-1}) \]  
(38)

where \( F \) is a constant. \( G(z^{-1}) = g_0 + g_1 z^{-1} + g_2 z^{-2} \).

A constant \( \lambda \) is introduced, we select \( \lambda \) which satisfy the performance index of Eq.(38):

\[ \bar{G}(z^{-1}) = \lambda G(z^{-1}) \]  
(39)

\[ Q(z^{-1}) = \lambda^{-1} H(z^{-1}) - FB(z^{-1}) \]  
(40)

\[ K(z^{-1}) = \lambda^{-1} H(z^{-1}) B(z^{-1}) - F \]  
(41)

\[ \det \{ H(z^{-1}) A(z^{-1}) + z^{-1} \lambda B(z^{-1}) G(z^{-1}) \} \neq 0, |\lambda| < 1 \]  
(42)

Select the \( K_p, K_i, K_d \), and \( \bar{K}(z^{-1}) \) of Eq.(32)

\[ K_p = -\lambda(2g_2 + g_1) \]  
(43)

\[ K_i = \lambda(g_0 + g_1 + g_2) \]  
(44)

\[ K_d = \lambda g_2 \]  
(45)

\[ \bar{K}(z^{-1}) = \lambda \bar{F} + K(z^{-1}) \]  
(46)

From Eqs.(38)-(46), Eq.(32) and Eq.(33) can be expressed as:

\[ H(z^{-1})u(k) = \bar{G}(z^{-1})u(k) - \bar{G}(z^{-1})y(k) \]  
(47)

\[ H(z^{-1})u(k) = \bar{G}(z^{-1})u(k) - \bar{G}(z^{-1})y(k) \]  
(48)

### 3.4 Adaptive PID Switching Control

Actually, the parameters of greenhouse model always vary with the external environment changing. These situations directly lead to the occurrence of parameters uncertainties. Therefore, it is necessary to update model parameters of CGS in real time. According to Eq.(32), the identification equation of system parameters is: \( y(k) = \theta^T X(k-1) + v(k-1) \). \( \theta \) is identified by the following algorithm:

\[ y(k) = -[a_1, ..., a_{n_a}, b_0, ..., b_{n_b}]^T \]
\[ X(k-1) = [y(t), ..., y(t-n_a+1), u(t), ..., u(t-n_b)]^T \]

In this paper, two estimation models are used to predict output of system. The first one is the linear estimation model:

\[ \hat{\theta}(k) = \hat{\theta}(k-1) X(k-1) \]  
(49)

where, \( \hat{\theta}(k-1) \) is an estimation of \( \theta \) at instant \( k-1 \). The parameter \( \theta \) is identified by the following algorithm:

\[ \hat{\theta}(k) = \hat{\theta}(k-1) + \mu_1(k) X(k-1) \]  
(50)

\[ \mu_1(k) = \begin{cases} 1 & \text{if } |\varepsilon(k)| \geq 4\Delta \\ 0 & \text{else} \end{cases} \]  
(51)

where, \( \Delta > 0 \) is the upper bound of the nonlinear term \( v(k-1) \). \( e_1(k) \) is the linear model error, i.e.
The second one is the neural network nonlinear estimation model given by:

\[ \hat{y}_2(k) = \hat{\Theta}_2(k-1)X(k-1) + \hat{\upsilon}(k-1) \]  

(53)

where \( \hat{\upsilon}(k-1) \) can be estimated by RBF neural networks and \( \hat{\Theta}_2(k-1) \) is another estimation of \( \Theta \) at instant \( k-1 \). The parameter is identified by the following algorithm:

\[ \hat{\Theta}_2(k) = \hat{\Theta}_2(k-1) + \frac{\beta(k)X(k-1)e_2^T(k)}{1 + \lambda X(k-1)\lambda^T} \]  

(54)

\[ \beta(k) = \begin{cases} 1 & \text{if } ||e_2(k)|| > 4\xi \\ 0 & \text{else} \end{cases} \]  

(55)

where \( ||v(k-1) - \hat{y}(k-1)|| \leq \xi \), \( \xi < 0 \) is a pre-specified small positive number and \( e_2(k) \) is the nonlinear model error, i.e.

\[ e_2(k) = y(k) - \hat{y}_2(k) = y(k) - \hat{\Theta}_2^T(k-1)X(k-1) - \hat{\upsilon}(k-1) \]  

(56)

If nonlinear item \( \hat{\upsilon}(k-1) \) is not considered, the linear adaptive PID control law based on the linear estimation model is obtained as:

\[ H(z^{-1})u(k) = \hat{\Theta}_2^T(k)w(k) - \hat{\Theta}_1^T \hat{y}(k) \]  

(57)

From Eq. (33), the nonlinear adaptive PID control law based on the neural network nonlinear estimation model is obtained as and the structure can be seen Fig. 3.

\[ H(z^{-1})u(k) = \hat{\Theta}_2^T(z^{-1})w(k) - \hat{\Theta}_2^T(z^{-1})y(k) - \hat{\Theta}_1^T(z^{-1})\hat{y}(k) \]  

(58)

In order to improve performance of control system and ensure the stability for the closed-loop system, a switching mechanism is introduced in Fig.4. The switching criterion is defined as:

\[ J_i(k) = \sum_{i=k-N+1}^{k} \mu_i(k)||e_i(k)||^2 + \lambda \sum_{i=k-N+1}^{k} ||e_i(k)||^2 \]  

(59)

\[ + \alpha \sum_{i=k-N+1}^{k} (1 - \mu_i(k)) ||e_i(k)||^2 \]  

(60)

where \( N \) is an integer and \( \alpha \geq 0 \) is a predefined constant. \( i=1 \) stands for the linear model, \( i=2 \) denotes the nonlinear models. At each time instant \( k \), the linear estimation model and the nonlinear model predict the system output, and the parameters of models are updated through the input-output data. At the same time, we calculate \( J_1(k) \), \( J_2(k) \) and choose the control law \( u'(t) \) corresponding to the smaller \( J' \) to be applied to the system.

### 3.5 RBF Neural Network for Unmodeled Dynamics

RBF neural network herein has three layers, the input layer which connects the input vector to the network, the hidden layer is unique, and the output layer which as a linear transformation relationship[20]. The activation function of RBF neural network is Gaussian function, which is defined as[21]:

\[ F(x) = \exp \left( \frac{||x-c||^2}{2\sigma^2} \right) \]  

(61)

where \( x \) is the \( n \)-dimensional input vector, and \( c \) is the center vector, which is the same as the \( x \)-dimension, \( \sigma \) is the width of the basis function around the center point.

In this paper, the output of the neural network input layer is \( \hat{v}[x(k)] \), the input vector is \( x(k) = [y(k)^T, y(k-1)^T, \hat{y}(k)^T, u(k-1)^T]^T \), and the output layer network nonlinear output is as follow:

\[ \hat{v}[x(k)] = \sum_{m=1}^{q} w_{pm}F_m(X) \]  

(62)

where, \( m=1,2,...,l \) and \( q \) is the number of nodes in the hidden layer, \( l \) is the number of nodes in the output layer, \( w_{pm} \) is the connection weight between the neuron \( P \) in the hidden layer and the neuron \( m \) in the output layer, and \( F_m(x) \) is the excitation function of the neuron \( P \) in the hidden layer.

### 4 SIMULATION RESULTS

The research is designed to prove the effective of the control method for CSG in terms of the tracking performance with strong multi-disturbance. There exits internal conditions as follow: solar radiation \( S_{in} = 350 \text{W/m}^2 \), outside air temperature \( T_{out} = 5 \text{°C} \), outside humidity \( H_{out} = 16 \% \), outside wind speed \( v_{out} = 2 \text{m/s} \), inside temperature \( T_{in} = 17 \text{°C} \), inside humidity \( H_{in} = 18 \% \). After using Euler method, the initial design model can be obtained around the nominal operating point as follows:

\[ A(z^{-1}) = 1 - 1.992 z^{-1} + 0.9851 z^{-2}, B(z^{-2}) = 0.004321 - 0.4223 z^{-1} \]  

where the system order are \( n_e = 2, n_l = 1 \). In this case \( \lambda = 0.2 \) are selected, and the parameters of the switching criterion are chosen to be \( \alpha = 1, N = 2, \Delta = 0.015 \). The initial weights of RBF neural network can be obtained by training the input and output data in a small range of working points. The hidden layer is equal to 8 and relevant parameters are chosen to be \( q = 6, \sigma = 0.65, \alpha = 0.05, \eta_{RBF} = 0.3 \).

In order to study the tracking performance of the nonlinear adaptive PID controller, the setpoint of inside temperature is changed in a wide range. At the same time, the outside weather conditions, such as outside temperature, outside wind speed, outside solar radiation, fluctuate in a large scope. The experiments design as follows. The inside temperature is change from 17°C to 28°C at \( t = 0-500 \)s. Effects of the external disturbances are simulated in this process. The outside temperature is changed from 5°C to -3°C at \( t = 150 \)s. The solar radiation is changed from the 350 W/m² to 150 W/m² at \( t = 350 \)s. The inside temperature is changed from 28°C to 24°C at \( t = 500 \)s and the outside solar radiation simultaneously becomes zero. The outside wind speed is changed from 2m/s to 6 m/s at \( t = 700 \)s and the outside temperature is changed from -3°C to -12°C at \( t = 850 \)s. In the end, the inside temperature is changed from 24°C to 19°C at \( t = 1000 \)s. Effect of the extreme outside temperature is simulated during this period. The outside temperature is changed from -16°C to -27°C at \( t = 1200 \)s.
The results of the setpoint tracking experiment are demonstrated in Fig.2-3. The inside temperature can quickly track the setpoint and the control method can reduce the influence of uncertain factors. What’s more, although in face of strong external disturbance such as stiff wind weather and coldest weather, the inside temperature still tracks the setpoint quickly.

CONCLUSION

In this paper, the CSG was described as a nonlinear, uncertain and multi-disturbance dynamic system. A nonlinear dynamic model for CSGs, based on the energy conservation laws, was constructed by equations and the corresponding control model was proposed. We adopted a nonlinear adaptive control strategy for CSGs production by combining RBF neural network with increment PID controllers. The main objective is to meet normal requirements of the temperature control based on generalized predictive control. IET Control Theory & Applications, Vol.15, No.4, 1241-1255, 2016.

REFERENCES

[1] G. Tong, D.M. Christopher, B. Li. Numerical modelling of temperature variations in a Chinese solar greenhouse. Computers and Electronics in Agriculture, Vol.68, No.1, 129-139, 2009.

[2] L. Wang, H. Zhang. An adaptive fuzzy hierarchical control for maintaining solar greenhouse temperature. Computers and Electronics in Agriculture, Vol.155, 251-256, 2018.

[3] Y. Su, L. Xu, E. D. Goodman. Greenhouse climate fuzzy adaptive control considering energy saving. International Journal of Control, Automation and Systems, Vol.13, No.4, 1936-1948, 2017.

[4] Y. Guo, H. Zhao, S. Zhang, Y. Wang, C. David. Modeling and optimization of environment in agricultural greenhouses for improving cleaner and sustainable crop production. Journal of Cleaner Production, 124843, 2020.

[5] Y. He, M. Liang, L. Chen, X. Qiao, S. Du. Greenhouse modelling and control based on T-S model. IFAC PapersOnLine, Vol.51, No.17, 2-806, 2018.

[6] J. del Sagrado, J.A. Sánchez, F. Rodríguez, M. Berenguel. Bayesian networks for greenhouse temperature control. Journal of Applied Logistic, Vol.17, 25-35, 2016.

[7] A. Pérez-González, O. Begovich-Mendoza, J. Ruiz-León. Modeling of a greenhouse prototype using PSO and differential evolution algorithms based on a real-time LabView™ application. Applied Soft Computing, Vol.62, 86-100, 2018.

[8] H. Yang, Q. Liu, H. Yang. Deterministic and stochastic modeling of greenhouse microclimate. Systems Science & Control Engineering, Vol.7, No.3, 65-72, 2019.

[9] L. Chen, S. Du, M. Liang, Y. He. Adaptive Feedback Linearization-based Predictive Control for Greenhouse Temperature. IFAC PapersOnLine, Vol.31, No.17, 786-789, 2018.

[10] S. Revathi, N. Sivakumaran. Fuzzy Based Temperature Control of Greenhouse. IFAC PapersOnLine, Vol.49, No.1, 1549-1554, 2016.

[11] L. Chen, S. Du, Y. He, M. Liang, D. Xu. Robust model predictive control for greenhouse temperature based on particle swarm optimization. Information Processing in Agriculture, Vol.5, No.3, 329-338, 2018.

[12] F. Fathi. Multiple neural control of a greenhouse. Neurocomputing, Vol.139, 138-144, 2014.

[13] D. Xu, S. Du, L. G.V. Willigenburg. Optimal control of Chinese solar greenhouse cultivation. Biosystems Engineering, Vol.171, 205-219, 2018.

[14] T. Boulard, S. Wang. Greenhouse crop transpiration simulation from external climate conditions. Agricultural and Forest Meteorology, Vol.170, No.1, 25-34, 2000.

[15] T. Boulard, A. Baule. A simple greenhouse climate control model incorporating effects of ventilation and evaporative cooling. Agricultural and Forest Meteorology, 1993, Vol.65, No.3-4, 145-157, 1993.

[16] P. Thirumal, K.S. Amirthagadeswaran, S. Jayabal. Optimization of IAQ characteristics of an air-conditioned car using GRA and RSM. Journal of Mechanical Science and Technology, Vol.28, No.5, 1899-1907, 2014.

[17] N. Atyah, H. Afif. Modeling of greenhouse with PCM energy storage. Energy Conversion and Management, Vol.49, No.11, 3338-3342, 2008.

[18] M. Azaza, K. Echaieb, E. Fabrizio, I. Afif, M. Abdelkader. An intelligent system for the climate control and energy savings in agricultural greenhouses. Energy Efficiency, Vol.9, No.6, 1241-1255, 2016.

[19] L. Zhai, T. Chai. Nonlinear decoupling PID control using neural network works and multiple models. Journal of Control Theory and Applications, Vol.4, No.1, 62-69, 2006.

[20] Y. Wang, T. Chai, J. Fu, Y. Zhang, Y. Fu. Adaptive decoupling swiching control based on generalized predictive control. IET Control Theory & Applications, Vol.6, No.12, 1828-1841, 2012.

[21] Y. Zhou, A. Wang, P. Zhou, H. Wang, T. Chai. Dynamic performance enhancement for nonlinear stochastic systems using RBF driven nonlinear compensation with extended Kalman filter. Automatica, Vol.112, 108693, 2020.