Research on fast self-learning improvement of ADRC control algorithm for film thickness control system

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Abstract. In the biaxially stretched film (BOPP) thickness control system, the traditional PID and Active-Disturbance Rejection Controller (ADRC) can't achieve the ideal control effect. The Smith prediction method is used in the essay to establish a discretization model for the BOPP thickness control system. Combining with BP self-learning algorithm, a fast self-learning improved ADRC control algorithm (FSADRC) is proposed. By means of the additional momentum term and the adaptive learning rate method, the nonlinear combination of the ADRC system is adjusted in real time, the optimal control parameters are found, and the parameters are self-tuned. As a consequence, the improved algorithm is applied to the biaxial tensile film thickness control model. The simulation results show that the method has the advantages of high response speed and strong self-adaptive ability, which can effectively improve the control performance of the BOPP thickness control system.

1. Introduction
The thickness uniformity of the Biaxially-oriented polypropylene (BOPP) is one of the important criteria for its quality. If the film's thickness uniformity is not good, the relative deviation will occur at a certain position of the film. If the deviation position remains constant, the film may have some defects such as grooves, hoops or ribs after thousands of layers accumulating, and then cause permanent deformation. So the measurement and control of the film thickness are very important because it directly affects the mechanical properties and performance quality of the film product [1]. And film thickness control is a complex system with the characters of nonlinear, multivariable coupling, time-varying and large lag [2].

Since the film thickness control model cannot be accurately established, the existing control method mainly aims to eliminate errors based on system errors. The representative method is the PID controller, its structure is simple, mature and reliable, and so it is widely used in industrial control. However, for the film thickness high-precision control system, the PID controller has a contradiction between rapidity and overshoot and its anti-interference is poor. The active disturbance rejection control (ADRC) technology [3] is an improved method for PID, it can treat the internal and external interference of the system as the total disturbance so as to proceed observation compensation although the disturbance rejection controller proposed in [4] and [5] can theoretically handle complex control systems, it not only has many parameters but also is difficult to adjust a set of relatively ideal control
parameters. The neural network [6] has the strong nonlinear fitting ability and self-learning ability and has a positive effect on parameter optimization, so it is widely used in the control field.

In this paper, combined with the neural network the self-learning method, by means of improving self-learning method, the control parameter of optimal nonlinear combination in the ADRC model can been adjusted more fastly. The control method has be applied to the BOPP film thickness control system, and the Smith predicts method is used to compensate for the large delay in film thickness control. The traditional PID controller, ADRC, self-learning ADRC (SADRC) and the improving method has been realized in MATLAB simulation, the four methods simulation results show that the improved fast self-learning ADRC (FSADRC) algorithm has many advantages such as fast response, short transition process and strong adaptability.

2. Modeling the controlled object

The BOPP production process is as follows: first the raw material is melted by the extruder, then cooled and shaped into the casting film by the cooling roller, then the casting film is stretched vertically and horizontally into the thin film, finally winded up into a film roll by the winder material. According to the production process, a detection feedback link is needed to control the film thickness in a closed loop, and the film thickness value \( y \) after the biaxial stretching is fed back to the thickness \( v \) of the original open-loop control model to form a closed-loop control system. The flow chart of BOPP production is shown in figure 1.

![Flow chart of BOPP production.](image)

In this paper, the BOPP thickness control system is simulated by MATLAB. From the BOPP production line, the transfer function of the identified film thickness model is [7]:

\[
G(s) = \frac{2.45}{(10.5s + 1)(2.5s + 1)} \ \ \ \ \ \ \ \ \ \ \ (1)
\]

In response to this large delay control problem, Smith proposed a pure lag compensation model, which is based on a compensation link parallel connection with the controller [8]. This compensation link is called the Smith predictor.

Taking the sampling period as 1s, combined with the Smith prediction method, the transfer function formula in equation (1) is transformed into a discrete form, and the form of the BOPP thickness control model is obtained as follows:

\[
\begin{align*}
   y(k) &= 1.5795y(k-1) - 0.6094y(k-2) + 0.0397u(k-9) + 0.0337u(k-10) \\
   x_m(k) &= 1.582x_m(k-1) - 0.6094x_m(k-2) + 0.03972u(k-1) + 0.03368u(k-2) \\
   y_m(k) &= 1.582y_m(k-1) - 0.6094y_m(k-2) + 0.03972u(k-9) + 0.03368u(k-10)
\end{align*}
\]

The above discretization equation (2) is the controlled plant model for the subsequent fast self-learning ADRC control model.

3. Improve the ADRC control model

3.1. Self-learning ADRC

Although the NLSEF of ADRC has a fixed structure, it has many parameters and is difficult to analyze and understand. The neural network self-learning technology has strong robustness, memory ability,
nonlinear fitting ability, and powerful self-learning ability [9]. In this paper, the self-learning method is applied to the NLSEF. This control method improves the response speed, tracking accuracy and anti-interference ability. A self-learning nonlinear ADRC model (SADRC) is designed as shown in figure 2, in which the nonlinear error feedback (NLSEF) part adds an \( e_0 \) input parameter.

![Figure 2. Self-learning nonlinear auto disturbance rejection control system model.](image)

For the second-order controlled object of the thickness control model, the discretization of the nonlinear differential tracker is:

\[
v_1(k + 1) = v_1(k) + h v_2(k), \quad v_2(k + 1) = v_2(k) + hfst(v_1(k) - v(k), v_2(k), \delta, h_0)
\]

Make:

\[
\begin{aligned}
\lambda_i &= v_1(k) - v(k), \quad d = \delta h, d_0 = d h, \quad \tau = \lambda_i + h v_2, \quad a_0 = \sqrt{d_2 + 8\delta} \\
a &= \begin{cases} 
 v_2 + \left[\left(a_0 - d\right)/2\right] \text{sign}(\tau) & \text{if } |\tau| > d \\
 v_2 + \tau/h & \text{if } |\tau| \leq d 
\end{cases}
\end{aligned}
\]

In the above formula \( h \) is the sampling period. The system optimal control function \( fst(\cdot) \) has the form:

\[
fst(\lambda_i, v_2, \delta, h) = \begin{cases} 
-\delta \text{sign}(a) & \text{if } |a| > d \\
-\delta (a/d) & \text{if } |a| \leq d 
\end{cases}
\]

Using the system output \( y \) and input \( u \), the third-order extended state observer is constructed as follows:

\[
e = z_1 - y, \quad \dot{z}_1 = z_2 - \beta_1 e, \quad \dot{z}_2 = z_3 - \beta_2 fal(e, \alpha_1, \delta) + bu, \quad \dot{z}_3 = -\beta_3 fal(e, \alpha_2, \delta)
\]

Where \( z_1, z_2, \) and \( z_3 \) are the states of the observer; \( \beta_1, \beta_2, \) and \( \beta_3 \) are observer gain coefficients (greater than zero). The nonlinear combined power function \( fal(e, \alpha, \delta) \) is designed as:

\[
fal(e, \alpha, \delta) = \begin{cases} 
\frac{e}{\delta - \alpha} & \text{if } |e| \leq \delta \\
|e|^\alpha \text{sgn}(e) & \text{if } |e| > \delta 
\end{cases}
\]

The nonlinear control law obtained from figure 2 is:

\[
\begin{aligned}
u_0 &= k_p fal(e_1(k), \alpha_1, \delta) + k_1 fal(e_1(k), \alpha_0, \delta) + k_2 fal(e_2(k), \alpha_2, \delta) \\
u &= u_0 - z_3/b_0
\end{aligned}
\]

Where \( k_p, k_1, k_2 \) are adjustable parameters and let:

\[
\begin{aligned}
e_0(k) &= e_1(k - 1) + e_1(k), \quad e_1(k) = v_1(k) - z_1(k) - x_m + y_m, \quad e_2(k) = v_2(k) - z_2(k) \\
b_0(k) &= fal(e_1(k), \alpha_1, \delta), \quad b_1(k) = fal(e_1(k), \alpha_0, \delta), \quad b_2(k) = fal(e_2(k), \alpha_2, \delta)
\end{aligned}
\]

In neural network self-learning system, \( e_0, e_1, e_2 \) are used as input, and \( u_0 \) are used as output. \( b_1(k), b_2(k), b_3(k) \) are used as the excitation function of the neural network is hidden layer neurons, with \( k_p, k_1, k_D \) as the neural network weight, and the structure of the neural network is shown in
The nonlinear control model has a simple structure, and the three weights $k_p$, $k_I$, $k_D$ can be dynamic regulated, so that it has a good nonlinear control effect.

The self-learning process of parameters $k_p$, $k_I$, and $k_D$ is as follows:

Let $E(k) = v_1(k) - z_1(k)$, and the neural network output layer error (loss function) are defined as:

$$J = 1/2 E^2(k + 1)$$

In order to minimize the output error, the steepest gradient descent method is used to adjust the neural network weights [10]:

$$k_i(k+1) = k_i(k) + \eta \frac{\partial J}{\partial k_i}, \quad i \in \{P, I, D\}$$

In the above formula, $\frac{\partial J}{\partial k_i}(i = P, I, D)$ is:

$$\frac{\partial J}{\partial k_i}(k) = -E(k+1) b_j(k) z_{u_0}(k), \quad i \in \{P, I, D\} \text{ and } j = 1, 2, 3$$

Among them:

$$z_{u_0}(k) = \frac{\partial z_i(k + 1)}{\partial u_0(k)}$$

From equation (11), both $E(k + 1)$ and $z_{u_0}(k)$ are related to the system’s future state [11], which makes it difficult to train neural network weights. If the algorithm is convergent, then there must be $|E(k + 1)| < |E(k)|$, so you can get:

$$|E(k + 1)| = \lambda E(k), \quad 0 < \lambda < 1$$

Since $\lambda$ can be compensated by the learning rate $\eta$, $E(k)$ can be used instead of $E(k + 1)$. In addition, because $z_{u_0}(k)$ is unknown, it can be approximated by a symbol function, namely:

$$z_{u_0}(k) = \text{sign}(z_i(k + 1) - z_i(k))$$

Comprehensive (11)-(24) are available:

$$k_p(k + 1) = k_p(k) - \eta E(k) b_1(k) z_{u_0}(k), \quad i \in \{P, I, D\} \text{ and } j = 1, 2, 3$$

In order to avoid excessive power, causing oscillations in the neural network training process, normalizing the weights [12] as follows:

$$k_i(k+1) = \frac{k_i(k+1)}{\sum_{a=1}^{3} |k_a(k+1)|}, \quad (i = 1, 2, 3)$$

3.2. Fast Self-learning ADRC

In the above, the neural network uses the steepest gradient descent method to adjust the weight. In order to further improve the response speed, tracking accuracy and anti-interference ability, the method of additional momentum term is adopted to design the adaptive mechanism for learning rate, so as to improves the original SADRC algorithm. In this section, the fast self-learning ADRC (FSADRC) algorithm based on dynamic adaptive learning rate is implemented.

3.2.1. Additional momentum term. The additional momentum term is an optimization method widely used to accelerate the convergence of the gradient descent method. The core idea is that during the gradient descent searching process, if the current gradient descent is the same as the previous’ one, the search is accelerated, and vice versa. The parameter update items of the neural network standard BP algorithm are:

$$\Delta w(k) = \eta g(k)$$

Where $\Delta w(k)$ is the parameter adjustment amount of the $k$th iteration, $\eta$ is the learning rate, and $g(k)$ is the gradient calculated by the $k$th iteration.

After adding the momentum term, the parameter update based on the gradient descent is:
\[ \Delta w(k) = \eta[(1 - \mu) g(k) + \mu g(k - 1)] \]  
(18)

Where \( \mu \) is a momentum factor (value 0~1). The above formula is also equivalent to

\[ \Delta w(k) = \alpha \Delta w(k - 1) + \eta g(k) \]  
(19)

Where \( \alpha \) is called the “forgetting factor”, and \( \alpha \Delta w(k - 1) \) represents the adjustment effect of the direction and size information of the previous gradient dropping on the current gradient.

3.2.2. Adaptive learning rate. The additional momentum method faces the difficulty of the learning rate selecting, which leads to a contradiction between convergence speed and convergence. Then the learning rate adaptive adjustment method is introduced, namely:

\[ \eta(k) = \sigma(k) \eta(k - 1) \]  
(20)

Where \( \sigma(k) \) is the adaptive learning rate factor at the \( k \)th iteration, and an expression of \( \sigma(k) \) is defined as follows:

\[ \sigma(k) = 2^{k} \]  
(21)

Where \( \lambda \) is the gradient direction, and the expression is:

\[ \lambda = \text{sign}(g(k) g(k - 1)) \]  
(22)

Combined with the above method of adding momentum terms and adaptive learning rate, equations (19) and (20) can be obtained:

\[ \Delta w(k) = \alpha \Delta w(k - 1) + \sigma(k) \eta(k - 1) g(k) \]  
(23)

We substitute equation (22) into equation (15), then:

\[ k_p(k + 1) = k_p(k) - \Delta w_p(k), \quad i \in \{P, I, D\} \]  
(24)

Among them, P, I, D parameter update items are obtained by:

\[ g_i(k) = E_{ij} b_{kj}(k) z_{ui}(k) \]

\[ \eta_i(k) = 2^{\text{sign}(g_i(k)) g_i(k - 1) \eta_i(k - 1)}, \quad i \in \{P, I, D\} \text{ and } j = 1, 2, 3 \]

\[ \Delta w_i(k) = \alpha \Delta w_i(k - 1) + \eta_i(k) g_i(k) \]  
(25)

4. Comparative analysis of experiments

In order to verify the performance of the above control algorithm, the simulation experiment was carried out using the MATLAB simulation platform. The controlled plant model experimentally tested in this paper is the delay model described in equation (2). According to the actual situation of the BOPP production line, the input signal \( v \) is taken as

\[ v(k) = \begin{cases} 0.01k, & k < 500 \\ 5, & k \geq 500 \end{cases} \]  
(26)

And in order to test the anti-interference ability of the FSADRC controller, the interference signal \( d(k) = 0.2 \) is added at the 800th sampling time point of the input signal \( v(k) \). The four controlled models of PID, ADRC, SADRC, and FSADRC are used to control the plant object.

Figure 4 is a comparative analysis of the experimental simulation results of the four control algorithms. Figure 4(a) is a general comparative diagram of the simulation of the system adjustment process of the four control algorithms, figure 4(b) is the end stage details of the system setpoint changing and figure 4(c) is the interference stage details of the system set value Table 1 is the adjustment process’s performance indicators comparison between four control algorithms.
Figure 4. Comparison of system adjustment processes for four control algorithms.

It can be seen from figure 4(b) that in the end stage of the system setpoint changing, the adjustment of PID controller takes the longest time, and the FSADRC adjustment completion time is the least, it’s adjustment speed is the fastest. It can be seen from figure 4(c) that, in the interference stage, the has obvious forward and negative overshoot, The ADRC and SADRC controller has the smaller overshoot, but the adjustment time is also long. While the FSADRC has the shortest adjustment time, only relatively small forward overshoot, and zero steady-state error, and its comprehensive adjustment performance is optimal. The interference is highly anti-interference and robust by FSACRC.

Table 1. Control performance indicators comparison of the four algorithm.

| Control algorithm | Start stage | Interference stage |
|-------------------|-------------|--------------------|
|                   | Adjustment time (s) | Overshoot (%) | Steady-state error (%) | Adjustment time (s) |
| PID               | 103         | 56.15             | 0.909               | 83                 |
| ADRC              | 85          | 34.30             | 0                   | 61                 |
| SADRC             | 58          | 28.45             | 0                   | 56                 |
| FSADRC            | 42          | 49.55             | 0                   | 15                 |

5. Conclusions

In this paper, the improved self-learning algorithm is combined with the ADRC control algorithm. By means of the self-learning ability of the neural network and the nonlinear function approximation ability, the ADRC parameters can be dynamically adjusted in real-time, and the BOPP thickness can be effectively controlled. The simulation results show that comparing with other control methods, the proposed FSADRC method has the advantages of fast response, no overshoot and undershoot, good adaptability and strong anti-interference, which can meet the requirements of many large delay control systems. The performance of the BOPP thickness control system can be effectively improved.

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