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Design of Intelligent Prediction and Self-Anti Disturbance Devices in Horizontal Dosing Control System for Paper Machine

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ABSTRACT

The lateral quantitative control of paper machine is the key to the quality control of paper machine. In this paper, the paper machine transverse quantitative control system is introduced, for the transverse quantitative control and the model exists of strong coupling, large time lag, multi-dimensional number of characteristics, combined with the predictive control theory, put forward based on the dynamic matrix control and Gram polynomials of the intelligent prediction method. Meanwhile, the speed chain control device of the paper machine control system is designed based on the self-immunity controller and simulated and analyzed. The simulation results show that the slope of the model size and computation in this paper's method is 1.97, which is smaller than that of the traditional MPC's 2.85, and has more computational efficiency without affecting the predictive control effect, which is more suitable for online operation. At the same time, the speed chain control system applying the self-resistant control algorithm is better than the traditional PID control in terms of steady state performance, dynamic performance and anti-disturbance performance. The method proposed in this paper facilitates the predictive control and speed chain anti-disturbance of the lateral dosing control system of paper machine and promotes the improvement of paper quality.

Keywords: gram polynomials, dynamic matrix control, self-resistant controller, speed chain, lateral dosing control system, paper machine

1. Introduction

In the context of economic growth, paper companies around the world on the optimization of the papermaking process are very important, have adopted a variety of advanced technical means to promote the development of the paper industry, it can be said that the world's most advanced

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control technology in the paper industry embodied in the best [1-3]. However, China's reform and opening up is less than forty years, the overall development of industry according to the western developed countries there is a big gap, the national paper industry is facing some serious problems, production efficiency is not high, the shortage of raw materials for papermaking, pollution is serious and energy consumption, etc. The most critical factor is the backwardness of papermaking technology, which is embodied in the, process technology, equipment technology and automation technology [4-6].

Therefore, it is very necessary to improve the quality quality of paper from the technical point of view, and the improvement of papermaking technology means the improvement of production efficiency, the reduction of energy consumption and the reduction of pollution, etc [7-8]. Paper quanlity, moisture and thickness are three important characteristics of paper. In fact, the three of them are coupled with each other, which brings great difficulties to the control of paper machine [9-10]. The change of moisture will cause the change of quantization and thickness, while the change of quantization will also cause the change of thickness and moisture. However, among these three variables, paper dosing is particularly important and is considered to be the main controlled variable in the paper control system [11-12].

In fact, the control of paper dosing is mainly carried out from two aspects, the control of horizontal dosing and the control of longitudinal dosing. Up to now, the control of longitudinal dosing has achieved good results. However, the control of transverse dosing has encountered a bottleneck, and there is still much to think about [13-14]. Since many paper machines in China still use lip-plate headboxes, i.e., the transverse dosing is controlled by changing the opening of the lip plate, but the sensitivity of this traditional control method is low and the error is large, and even the pulp consistency of the neighboring ranges can be greatly affected [15-16].

With the emergence of modern paper machine hydrodynamic headbox, it brings new life to the paper industry. It controls the dilution water valve through the dilution water actuator to quantitatively improve the localization of the paper web, and at the same time has the advantages of high sensitivity and small error. It is based on this situation, so that the paper machine speed increases, the paper width increases, to the lateral control puts forward new challenges. Papermaking lateral control is a hardware and software to cooperate with each other to complete the modern control process, the development of hardware has reached a certain level, this time the need for software on the entire lateral control system to further optimize and improve [17-18]. Due to the lateral paper width widening, so that the increase in lateral controller, in addition to the paper making process itself, the flow delay and the site of the many environmental factors, so that the lateral control system is a large time lag, strong coupling, the model is not sure of the pathological system, can not be through the conventional control methods for its effective control [19-20].

Time lag, multivariate and strong coupling are common phenomena in chemical process control systems such as pulp and paper. Time lag refers to the fact that when a signal is applied to a system, the output can be observed at the exit of the system after a certain period of time. It is one of the main factors that make the control system unstable [21-22]. As the intensity increases, the difficulty of controlling the system increases dramatically, and the requirements for controller design also increase gradually. Most of the current advanced control technologies are model-based control methods, however, any time-varying, nonlinear factors in process control may lead to changes in the control system model, which will deteriorate the control effect of the control system. Therefore all the above factors, if not handled properly, will directly affect the quality of industrial products. Therefore, parameter identification of process control systems, decoupling of multivariable strongly coupled systems and controller parameter tuning of time-lagged systems have been the research hotspots in the control community. The research for the above methods is conducive to enhancing the control effect of the controller, improving product quality and meeting the increasing requirements of consumers for product quality, while the optimization of the control system can reduce the loss of raw materials and improve the production efficiency [23-24].

This paper analyzes the components of the transverse dosing system of paper machine, in view of the characteristics of transverse dosing control system with many coupling dimensions, spanning the entire paper web and large spatial complexity, introduces Gram polynomials, and carries out accurate decoupling through model downgrading, and carries out single-loop control of the decoupled system by using the dynamic matrix control algorithm to realize intelligent predictive control of the transverse dosing system based on Gram polynomials and the DMC algorithm. The intelligent predictive control of the lateral quantitative system is realized based on Gram polynomials and DMC algorithm. Simulation experiments are set up to compare with the traditional MPC algorithm to explore the control efficiency and effect of the proposed method on the transverse quantitative control system by analyzing the computation time in the process of model size growth and the control effect of the model under a shock disturbance. Then the self-resistant controller technology is applied to the speed chain control of the paper machine system, and the speed chain control device based on ADRC is designed. Three motors are used to carry out experiments in the case of no disturbance and load disturbance, to analyze the tracking error and synchronization error of the system, and to verify the effect of the proposed self-immobilizing controller on the speed chain control.

2. Paper machine transverse dosing control system

Sheet lateral control and longitudinal control play an important role in the paper making process and are considered to be a central part of the paper industry. The pulp comes out of the headbox, passes through the web, press and dryer sections, including the scanner to monitor the properties of the sheet, and finally passes through the winding section to become the finished paper. This process is realized through the interaction of various equipment. The lateral dosing control system for paper is shown in Figure 1 and consists of the following three main parts: the measuring part (scanner frame), the control part and the field execution part.

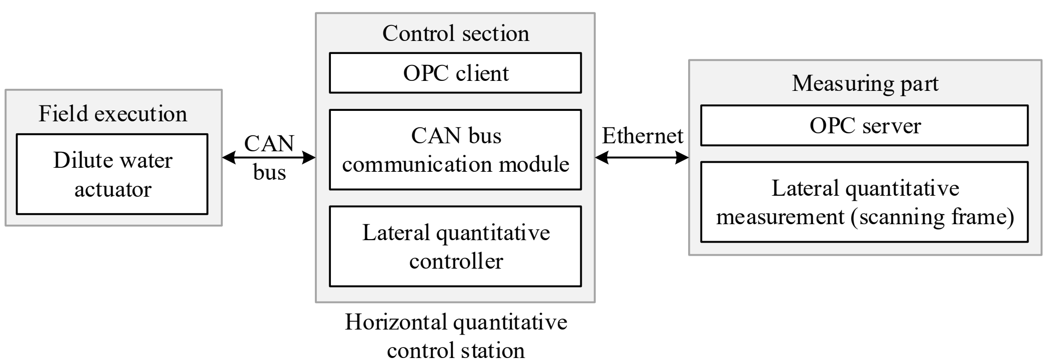


Fig. 1. Horizontal quantitative control system for paper

2.1. *Measurement component*

Transverse quantitative measurements are usually carried out by means of radiation penetration measurements such as infrared, beta and X-rays. The scanning sensor (radiation source) is usually fixed to the frame of the scanner, which is moved laterally to dynamically measure the data.

Typically, a paper machine has one or more scanning frames, which are installed before winding and before sizing, where the scanning frame before winding is used to measure the paper's medium weight. A scanning sensor detects the paper's weight at a certain speed, and collects data such as weight, moisture and ash. The scanner travels around scanning the sheet and converts the electrical signals measured by the scanning sensor into digital signals that are stored in the quality control system (QCS).

2.2. *Control section*

The horizontal dosing control part is the core of the whole horizontal dosing control system, and the control part exists in the form of control room in major paper mills, usually there are wet control room and cadre control room, and the distance between the two is generally in the range of 100-200 m. In the cadre control room and the wet control room there are a number of monitoring stations, which include all kinds of monitoring systems, including horizontal control system, and the main functions include real-time data monitoring, control status monitoring and control command issuance. The main functions of the monitoring station include monitoring of real-time data, monitoring of control status and issuance of control commands. The horizontal quantitative control center generally consists of several computer groups, integrating OPC clients, horizontal control algorithms and CAN bus communication modules. The lateral control framework is shown in Fig. 2. The OPC client obtains the original measurement data from the measurement server through the OPC protocol, and the original data need to be processed to compare with the set value of the lateral control system and obtain the deviation, and then the deviation signal is sent to the dilution water actuator through the designed lateral controller to realize the control of the lateral dosing through the adjustment of the actuator valve.

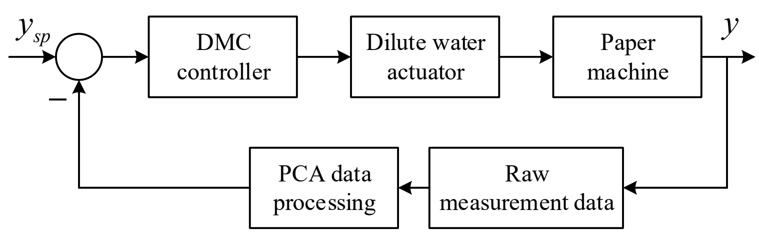


Fig. 2. Transverse control frame

2.3. *Field implementation component*

For the field execution part, the smart actuator is the core of the whole execution part, which is related to the accuracy of the horizontal quantitative control. The goodness of lateral quantitative control depends on the advantages and disadvantages of the control algorithm on the one hand, and on the smart actuator on the other hand. Generally, smart actuators are composed of controllers, actuators and sensors.

The smart actuator's ability to process data online is greatly enhanced by the integration of a digital signal processor with a CAN control module. The smart actuator is capable of processing data such as data pre-processing and gap compensation of valve positions by means of a digital signal processor (DSP) for the paper sheet quantitative data acquired by the sensing elements. The control information of the actuator reaches the CAN controller through the CAN bus communication protocol, and then is processed by the DSP processor and controlled by the DSP to rotate the stepping motor. The actuator through the feedback control, the feedback information will be transmitted to the lateral control system, lateral control center issued control commands, the input data obtained through the transmission device mapped to the stepping motor, the stepping motor and dilution water valve is connected to the dilution water valve to achieve the adjustment of the dilution water valve, so as to control the entire lateral process.

3. Intelligent forecasting methods for horizontal quantitative control

The transverse quantitative control system is one of the most complex control systems in paper making, with large spatial span, many dimensions, strong hysteresis and affected by many disturbances, which makes conventional PID control difficult to be effective. Therefore, this paper carries out the research of transverse quantitative control algorithm by introducing Gram polynomials in dynamic matrix control.

3.1. Modeling of transverse quantitative control systems

The lateral dosing control system is a high-dimensional, complex industrial process, so that a mathematical model reflecting its detailed characteristics is a prerequisite for good control results. For the quantitative control system equipped with n dilution water valve actuator and m lateral quantitative measurement points make the following assumptions:

1) In addition to the boundary effect, all the dilution water actuators on the corresponding downstream control area of the quantitative distribution of the impact is the same and centrally symmetric.

2) The coupling relationship between the dilution water valves can be treated statically.

3) The dynamic response of the entire longitudinal process from the dilution water valve to its corresponding downstream measurement position is independent of the lateral position.

First, the output response of a single dilution water valve to the measurement point directly downstream of it is as follows:

$$y(s) = g(s)u(s) \tag{1}$$

where, $y(s)$ - the quantitative measurement of the measurement point, $u(s)$ - the dilution of the water valve actuator output, $g(s)$ - the dynamic response transfer function between the two.
where: $g(s)$ transfer function form for industrial process control commonly used in the first-order inertia plus pure hysteresis link, that is, there:

$$\mathrm{g}(s) = \frac{k\mathrm{e}^{-\tau s}}{Ts+1} \tag{2}$$

With n measurement point and m dilution valves on the entire paper web transverse, a correlation matrix of $n \times m$ is introduced with the following relationship:

$$Y(s) = Gg(s)U(s) \tag{3}$$

In the formula:

$$Y(s) = \begin{bmatrix} y_1(s) \\ y_2(s) \\ \vdots \\ y_n(s) \end{bmatrix} \tag{4}$$

$$U(s) = \begin{bmatrix} u_1(s) \\ u_2(s) \\ \vdots \\ u_m(s) \end{bmatrix} \tag{5}$$

$$G = \begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1m} \\ g_{21} & g_{22} & \ddots & \vdots \\ \vdots & \ddots & \ddots & \vdots \\ g_{n1} & \cdots & \cdots & g_{nm} \end{bmatrix} \tag{6}$$

$y_i(s)$ refers to the quantitative measurement value of the $i(i = 1, 2, \ldots, n)$ nd measurement point along the paper traverse, $u_j(s)$ refers to the output value of the $j(j = 1, 2, \ldots, m)$ th actuator, and g_{ij}

refers to the influence coefficient between the i th measurement point and the j th actuator, i.e., G is the associated coupling matrix of the whole system.

3.2. Predictive Control Theory

Predictive control, is an algorithm that uses a dynamic model of the controlled object to predict its future outputs, and calculates the optimal sequence of control inputs by optimizing the outputs of the process in the future time domain. Its control strategy basically consists of predictive modeling, rolling optimization and feedback correction.

3.2.1. Predictive modeling. Predictive control is an algorithm based on an object model, but does not focus on the specific form of the model, but rather on the model function, i.e., the prediction of the future output of an object based on its historical information and future inputs. The predictive model has the function of expressing the future dynamic behavior of the system, so that the predictive model can be used to provide a priori knowledge for predictive control to carry out optimization operations, and then to obtain a certain sequence of control inputs, so that the change of the output of the object to be controlled will reach the desired goal at a future moment.

3.2.2. Rolling Optimization. Predictive control also has an on-line optimization function, which determines the future control role by optimizing some performance metric. Instead of using a static global optimization objective, predictive control optimization uses a finite time domain rolling optimization strategy. At any sampling moment, the optimized performance metric contains only the finite time domain from that moment to the future, while at the next sampling moment, the optimized time domain is synchronously shifted forward.

3.2.3. Feedback correction. In the rolling optimization of predictive control algorithms, since the predictive model is only a rough description of the dynamic characteristics of the object, ignoring the existence of time-varying, model mismatch, nonlinearities, disturbances, and other factors in the actual system, and thus the model predicted output may not match the actual situation, which requires compensatory measures, or on-line corrections to the underlying model. Predictive control, after determining the sequence of future control actions through the optimization operation, does not implement all of these control actions, but only the control actions of the current moment, to the next moment, the first detection of the output value of the object, and the use of this real-time information to correct the predicted output, and then re-open the new optimization operation.

3.2.4. Mathematical description of predictive control. For the following systems:

$$\begin{cases} x[k+1] = f(x[k], u[k], k) \\ y[k] = h(x[k], k) \\ x[0] = x_0 \sim P(x_0) \end{cases} \tag{7}$$

At each sampling moment, predictive control solves online the finite time-domain open-loop optimal control problem as:

$$\min_{U(k)} V_k = \min_{U(k)} \sum_{i=1}^{P} L_i(x[k+i \mid k], u[k+i-1 \mid k]) \tag{8}$$

Or:

$$\min_{U(k)} V_k = \min_{U(k)} \sum_{i=1}^{P} L_i(y[k+i \mid k], u[k+i \mid k]) \tag{9}$$

Satisfaction:

$$\begin{cases} x[k+1]-f(x[k],u[k],k)=0 \\ y[k]-h(x[k],k)=0 \\ l(x[k],u[k])=0 \\ c(x[k],u[k])\geq 0 \end{cases} \tag{10}$$

where V_k is the optimization objective function, f is the prediction model, the estimated state trajectory $x[k]$, h is the computed prediction output, l,c is the equation and inequality constraints at the sampling moment, P is the prediction time domain, and the control time domain is M, and $U(k)$ is the computed control sequence of the optimization problem at the k moment.

At k moments only the first control quantity of $U(k)$ is implemented on the controlled object in time domain $[k,k+1]$, and at the next moment, the prediction time domain and the control time domain are shifted one step forward to re-solve the above optimization problem with state $x[k+1]$ as the initial condition, forming a rolling optimization.

3.3. Gram polynomials

Has the following definition: for a family of functions $\{P_i(x)\}$ in a discrete set of points $x(i)$ with respect to the weight function $w(x)$ if any:

$$\sum_{i=0}^{N-1} w(x(i))P_j(x(i))P_k(x(i)) = \begin{cases} 0 & (j\neq k) \\ \lambda_i & (j=k) \end{cases} (j,k=0,1,\cdots,m) \tag{11}$$

Then the function family $\{P_i(x)\}$ is said to be orthogonal. For equally spaced data points, a discrete orthogonal polynomial is called a Gram polynomial system when $w(x(i))=1$.

3.4. Intelligent Predictive Design of Controller

The mathematical model of the transverse quantitative control system has been given in Chapter 3.1, it can be seen that the mathematical model of the control object consists of two parts, one part is the sparse coupling matrix throughout the entire banner, and the other part is the longitudinal transfer function of the paper machine from the dilution of the water method of the actuator to the corresponding measurement point. To control the quantization of the whole banner well, corresponding control strategies should be adopted for these two parts respectively. The overall decoupling is achieved by a rational transformation of the Gram polynomials, which transforms the non-square coupling matrix into a square matrix of principal diagonal elements, thus solving the inverse decoupling. The decoupled system can finally achieve a satisfactory control effect of transverse quantization with the help of the model predictive control which does not require high model accuracy and can be effectively constrained.

3.4.1. Decoupling control based on Gram polynomials. There are a large number of dilution valves and measuring points across the paper machine width. At each control cycle, the control quantities of all dilution water valves of the entire banner are sequentially lined up and viewed as a profile, and similarly, the measurement signals of all quantitative measurement points of the entire banner are sequentially lined up and viewed as a profile. Both of these profiles, consisting of discrete sets of points, can be rationalized with discrete Gram polynomials, thus re-transforming the mathematical model established earlier.

First define a matrix x_0 which contains the first m orthogonal polynomials of the Gram polynomial system, each with N discrete points:

$$x_0 = \begin{bmatrix} P_1(0) & P_2(0) & \cdots & P_m(0) \\ P_1(1) & P_2(1) & \cdots & P_m(1) \\ \vdots & \vdots & \cdots & \vdots \\ P_1(N-1) & P_2(N-1) & \cdots & P_m(N-1) \end{bmatrix}^T = \begin{bmatrix} P_1 & P_2 & \cdots & P_m \end{bmatrix}^T \tag{12}$$

Regarding the orthogonal basis function system x_0, the transverse quantitative profile Y can be written:

$$Y = x_0^T y_c + \varepsilon \tag{13}$$

where y_c is the parameter of the orthogonal polynomial and ε contains information about polynomials of order $m+1$ and higher. A $N-1$th order polynomial will exactly match the data from the N measurements. The least squares estimate of the y_c vector is:

$$\hat{y}_c = (x_0 x_0^T)^{-1} x_0 Y \tag{14}$$

Matrix $x_0 x_0^T$ is a diagonal matrix, and since it consists of orthogonal vectors, its inverse matrix is easy to solve. Least squares estimation can be written:

$$\hat{y}_c = \begin{bmatrix} \frac{1}{P_1^T P_1} & 0 & \cdots & 0 \\ 0 & \frac{1}{P_2^T P_2} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \frac{1}{P_m^T P_m} \end{bmatrix} \times \begin{bmatrix} P_1 & P_2 & \cdots & P_m \end{bmatrix}^T Y = \begin{bmatrix} \frac{1}{P_1^T P_1} P_1^T Y \\ \frac{1}{P_2^T P_2} P_2^T Y \\ \vdots \\ \frac{1}{P_m^T P_m} P_m^T Y \end{bmatrix} \tag{15}$$

From the above equation, it can be seen that each element of the $\hat{y}_c$ vector can be calculated separately. If more parameters are required, the $m+1$nd parameter can be calculated by the following equation:

$$\hat{y}_c(m+1) = \frac{1}{P_{m+1}^T P_{m+1}} P_{m+1}^T Y \tag{16}$$

The control volume profile of the dilution valve for each control cycle can also be transformed from a set of Gram polynomial parameters. Assuming that there is N_a actuator and the Gram polynomial order used is m_a, the control volume profile can be written:

$$U = x_a^T u_c \tag{17}$$

Paper machine transverse quantitative mathematical mode $Y(s) = Gg(s)U(s)$, then there is type for:

$$\hat{y}_c(s) = (x_0 x_0^T)^{-} x_0 G g(s) x_a^T u_c(s) \tag{18}$$

Since only the coupling relation is dealt with here, not $g(s)$. After removing it and converting back to the time domain, there is:

$$\hat{y}_c(t) = (x_0 x_0^T)^{-1} x_0 G x_a^T u_c(t-\tau) \tag{19}$$

Order:

$$G_x = (x_0 x_0^T)^{-1} x_0 G x_a^T = \begin{bmatrix} \frac{P_1^T G P_{1a}}{P_1^T P_1} & \frac{P_1^T G P_{2a}}{P_1^T P_1} & \cdots & \frac{P_1^T G P_{ma}}{P_1^T P_1} \\ \frac{P_2^T G P_{1a}}{P_2^T P_2} & \frac{P_2^T G P_{2a}}{P_2^T P_2} & \cdots & \frac{P_2^T G P_{ma}}{P_2^T P_2} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{P_m^T G P_{1a}}{P_m^T P_m} & \frac{P_m^T G P_{2a}}{P_m^T P_m} & \cdots & \frac{P_m^T G P_{ma}}{P_m^T P_m} \end{bmatrix} \tag{20}$$

G_x is a matrix of $m \times m_a$. When the Gram polynomials used for the two conversions are of equal order, i.e., $m = m_a$, then G_x is a square matrix and it is easy to find its inverse matrix.

3.4.2. DMC-based single-loop control. The DMC controller design for SISO system is mainly through the reasonable selection and adjustment of a number of control parameters, so that the system has a better closed-loop performance as well as stability. For the first-order inertia plus pure hysteresis control object in this paper, its parameter selection and adjustment are analyzed as follows:

1) Sampling period T_0. Sampling period T_0 and prediction time domain N are interrelated and affect prediction time domain P. For the lateral quantitative control system T_0 is selected to be greater than the scanning time of the scanning frame from one end to the other to ensure that the measured quantitative values have been updated.

2) Prediction time domain P. The selection of the prediction time domain P depends on the sampling period, by increasing the prediction time domain P will not significantly improve the performance of the controller, but the stability of the closed-loop system will be better. For first order inertia plus pure hysteresis systems often need to be satisfied:

$$P \geq \left(\frac{5T}{T_0} + k \right) \tag{21}$$

3) Control time domain M. In DMC controller design, the control time domain is adjustable and as M increases, the degrees of freedom for controller optimization increase and the control system performance improves accordingly, homogenizing the control objective. For the first order model, it should be ensured that the product of M and T_0 is greater than the response time for the system model to reach 60% of the steady state value.

4) Controlled variable weights λ. Changing the weights of the controlled variables means changing the weight of the optimization indexes of the controlled variables in the total optimization indexes, so as to recalibrate the measurement of the controlled variables and determine their importance. This value is not used as the main adjustment parameter in this paper.

5) Control increment weight w. This parameter affects the closed-loop response of the system, and the absence of this parameter may lead to oscillations in the response of the object. If this value increases, it will cause the system response to become slow.

6) Constraints. In the actual horizontal quantitative control system, the dilution of water actuator constraints exist, which mainly stems from its own mechanical structure and service life considerations. Each actuator adjustment range there are upper and lower limits, for which the constraints on the control volume can be described as:

$$u_{\min} \le u_i \le u_{\max} \quad (i = 1, 2, \ldots, m) \tag{22}$$

where: $u_{\min}$ - lower control output limit, $u_{\max}$ - upper control output limit.

3.5. Simulation Analysis

In this section, the effectiveness of the intelligent prediction algorithm of this paper will be illustrated through simulation examples. The control effect and the computation time consumed by this paper's algorithm are compared with the traditional MPC algorithm. Considering that the traditional MPC algorithm is more difficult for more complex systems, a simpler simulation model (simple dynamics, no measurement noise, no model mismatch) is chosen, which is also to make the comparison results more intuitive. To facilitate the simulation study, it is assumed that there are n=100 CD actuators and measurement points in the transverse quantitative control model. Due to the simplicity of the model's dynamics, the sampling time is taken to be 1.5 s, the output time domain P = 8 and the control time domain M = 4. Fig. 3 shows the computational time results of the different algorithms, demonstrating the time curves of the traditional MPC algorithm and the algorithms in this paper for solving this problem as a function of model size when the model size is taken to different values. The time shown in the figure is the average of the time consumed to compute the control action for 10 simulations on the same machine.

The change in the computational effort of the algorithm as the model size grows can be estimated using the slope of the straight line in the figure. The slope of the traditional MPC algorithm is 2.85, while the slope of the straight line of this paper's algorithm is 1.97. From this point of view, the intelligent prediction algorithm for lateral quantitative control of paper machines in this paper has a great advantage over the traditional MPC algorithm.

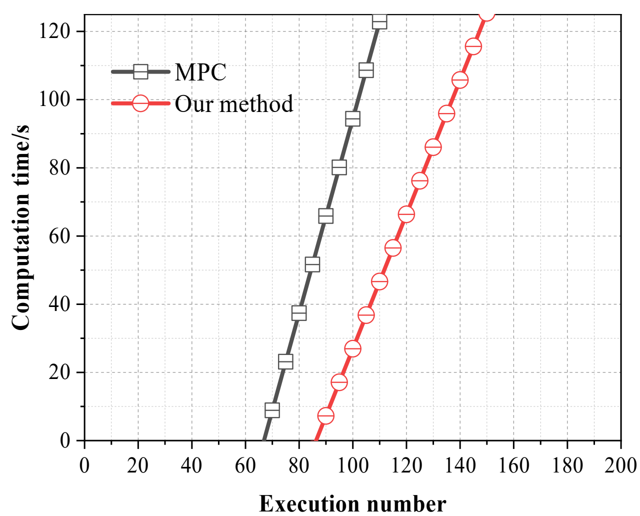
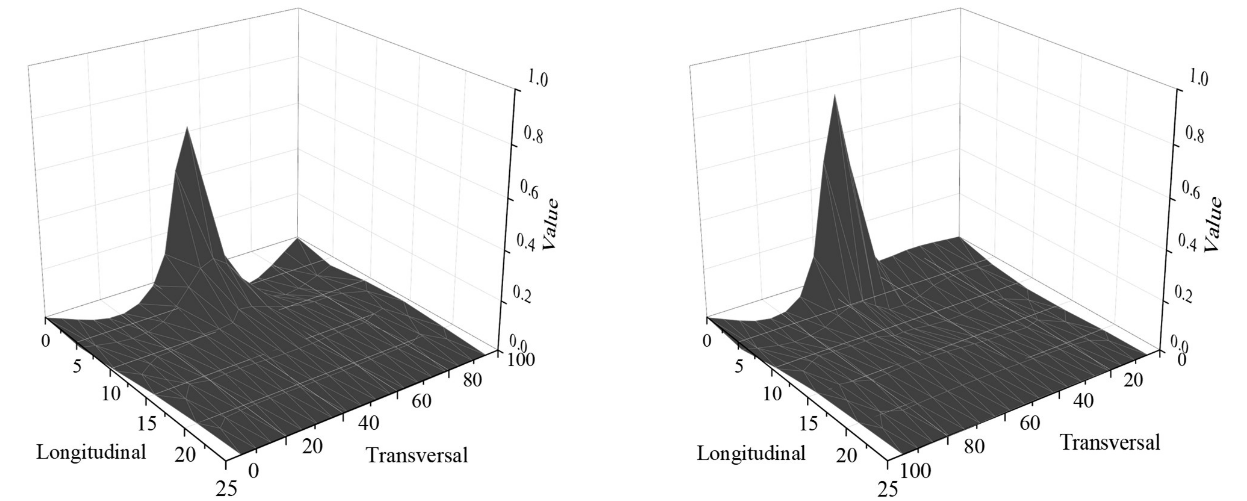


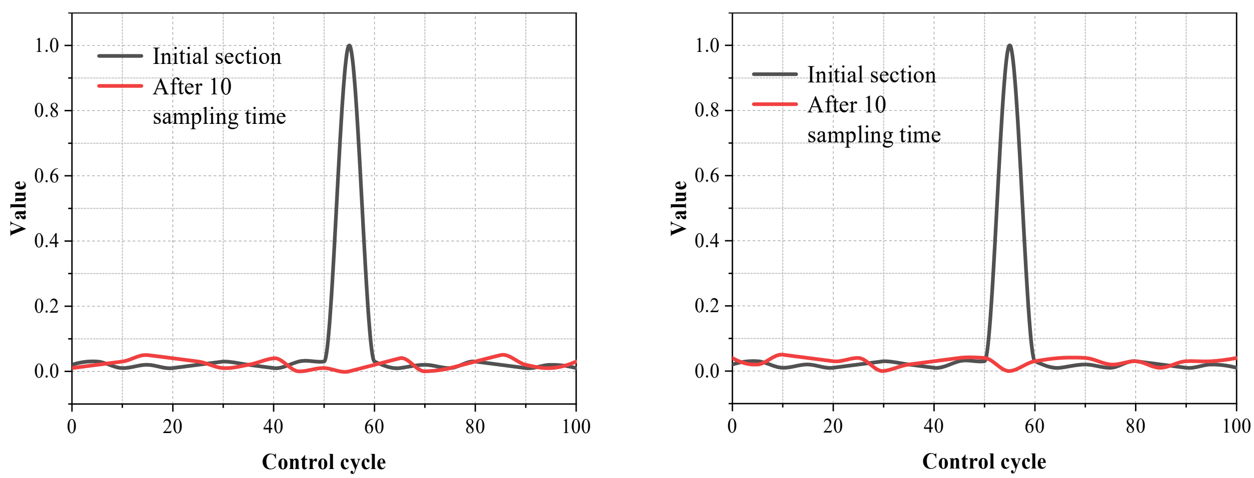
Fig. 3. Calculation time of different algorithms

The control effects of the two algorithms are compared in the case of initial profiles both with one shock disturbance. The control effects of the two algorithms are shown in Fig. 4, where (a) shows the surface plot of the conventional MPC algorithm and (b) shows the surface plot of the algorithm in this paper. Fig. 5 shows the comparison of the two control algorithm profiles, demonstrating the effect of the two algorithms acting on the same uneven initial profile after 10 sampling cycles, where (a) is the traditional MPC algorithm profile and (b) is the algorithm profile in this paper. Both the traditional MPC algorithm and the algorithm in this paper can achieve a more satisfactory control effect, and the profiles can be flattened after about 13 sampling times. The control method based on DMC and Gram polynomials proposed in this paper has good predictive control effect.



(a)Traditional MPC (b)Our method

Fig. 4. Comparison of the performance of the two algorithms control



(a)Traditional MPC (b)Our method

Fig. 5. Comparison of the two control algorithm profiles

4. Self-immunity design for lateral dosing control systems

According to the requirements of the papermaking process, the paper machine transmission between the various divisions of the linear speed is not the same, it changes with the paper copying speed, paper moisture content and other factors. Between the various divisions required to achieve linear speed ratio coordination between the two neighboring divisions of the linear speed ratio should be kept constant, forming a speed chain, high precision, reliable maintenance of this ratio coefficient is to ensure product quality, the production of normal operation of the important conditions, for any reason to destroy this ratio coordination, it will reduce product quality. Based on this, this chapter proposes the design of a self-immunity device based on the speed chain control in the control system of paper machine.

4.1. Self-immunity controller design

Auto-Disturbance Control is abbreviated as ADRC.The theory of Auto-Disturbance Control is evolved from the PID control theory, which adopts the core idea of error feedback control in the traditional PID control, and uses the transition process to realize the smooth control of the initial error, so as to reduce or even eliminate the amount of overshoot. The autodisturbance controller (ADRC) is mainly composed of three parts: tracking differentiator (TD), expanded state observer (ESO) and nonlinear state error feedback control law (NLSEF).

The role of the tracking differentiator is to arrange the transition process according to the limitations of the reference input v and the controlled object to obtain a smooth input signal, where v_1 is the tracking signal of the reference input v and v_2 is the differentiation of v_1. The expanded state observer (ESO) is the core aspect of the self-resilient controller design, by which the expanded state observer (ESO) not only estimates the individual state variables, but also estimates the real-time amount of the uncertain model and the external perturbation, and finally makes this uncertainty of the object compensated in the feedback, so as to reconstruct the object.The expanded state observer (ESO) is composed of the system Output y produces three signals: z_1, z_2, z_3, where z_1 is the tracking signal for y, z_2 is the differential signal for z_1, and z_3 is an estimate of the system model and external perturbations (total perturbations). The nonlinear state error feedback control law refers to the error nonlinear combination between the derivatives of each order generated by the tracking differentiator (TD) and the state variable estimates generated by the expanded state observer (ESO). The final control quantity consists of the nonlinear combination output together with the compensation of the perturbations by the state observer.

As an example of second-order ADRC controlling a second-order object, a discrete form algorithm utilizing Euler's method with a spacing step of h is given below. The specific self-resistant controller algorithm is as follows:

1) Arrange the transition process:

$$TD:\begin{cases} fh = fhan(v_1(k)-v(k), v_2(k), r_0, h) \\ v_1(k+1) = v_1(k) + h\times v_2(k) \\ v_2(k+1) = v_2(k) + h\times fh \end{cases} \tag{23}$$

For a given reference input signal $v(k)$, two signals are generated after TD: one is the tracking signal $v_1(k)$ of the reference input signal $v(k)$ and the other is the differential signal $v_2(k)$ of the reference input signal $v(k)$.

2) Estimation of state and total perturbation:

$$ESO:\begin{cases} e(k) = z_1(k) - y(k) \\ fe = fal(e(k), 0.5, h) \\ fe_1 = fal(e(k), 0.25, h) \\ z_1(k+1) = z_1(k) + h(z_2(k) - b_{01}\times e(k)) \\ z_2(k+1) = z_2(k) + h\times(z_3(k) - b_{02}\times fe + b_0\times u \\ z_3(k+1) = z_3(k) - h\times b_{03}\times fe_1 \end{cases} \tag{24}$$

In the output signal of ESO, $z_1(k), z_2(k)$ is the estimated state variable of signal $y(k)$, respectively, and $z_3^{(k)}$ is the estimated signal of the total disturbance to the controlled object. A reasonable selection of parameters $\beta_{01}, \beta_{02}, \beta_{03}$, ESO gives a satisfactory estimated signal, and thus ESO is an observer independent of the controlled object and the effect of external disturbances.

3) Formation of the control quantity:

$$NLSEF:\begin{cases} e_1(k)=v_1(k)-z_1(k) \\ e_2(k)=v_2(k)-z_2(k) \\ u_0=\beta\cdot fal(e_1(k),a_1,\delta_1) \\ +\beta_2\cdot fal(e_2(k),a_2,\delta_2) \\ u=u_0-z_3(k)/b_0 \end{cases} \tag{25}$$

The tracking signal $v_1(k)$ and the differential signal $v_2(k)$ generated by TD form $e_1(k)$ and $e_2(k)$ with the state estimation signals $z_1(k)$ and $z_2(k)$. The appropriate nonlinear function $fal(e,a,\delta)$ is chosen to generate $u_0(k)$ based on these two error quantities, and finally the control quantity $u(k)$ can be obtained from the estimation signals $z_3(k)$ and b_0 of the total disturbance.

The two nonlinear functions $fhan(x_1,x_2,r_0,h)$ and $fal(e,a,\delta)$ are defined as follows:

$$fal(e,a,\delta)=\begin{cases} e\cdot\delta^{a-1},|e|\le\delta \\ |e|^a\cdot sign(e),|e|>\delta \end{cases} \tag{26}$$

$$\begin{cases} \delta=r_0\cdot h \\ \delta_0=\delta\cdot h \\ y=x_1-u+h\cdot x_2 \\ a_0=\sqrt{\delta^2+8r_0|y|} \\ a=\begin{cases} x_2+y/h,|y|\le\delta_0 \\ x_2+0.5(a_0-\delta)sign(y),|y|>\delta_0 \end{cases} \\ fhan=\begin{cases} -ra/\delta,|a|\le\delta \\ -rsign(a),|a|>\delta \end{cases} \end{cases} \tag{27}$$

The design of the self-immunity controller involves three parts, which can be divided into three independent parts of the design, that is, according to their respective engineering significance of the design of each component separately and independently, and then combined into a complete self-immunity controller.

4.2. ADRC-based speed chain control

The speed control of the inverter, which is commonly used in modern AC speed control, still uses conventional PID control, which makes the motor less resistant to perturbations occurring during the working process, and the robustness of the system is not good. The synchronization control structure based on ADRC is shown in Fig. 6, in this paper, we try to improve this link with a self-resistant controller device, and then apply the improved motor control scheme in the speed chain to improve the synchronization performance of the system.

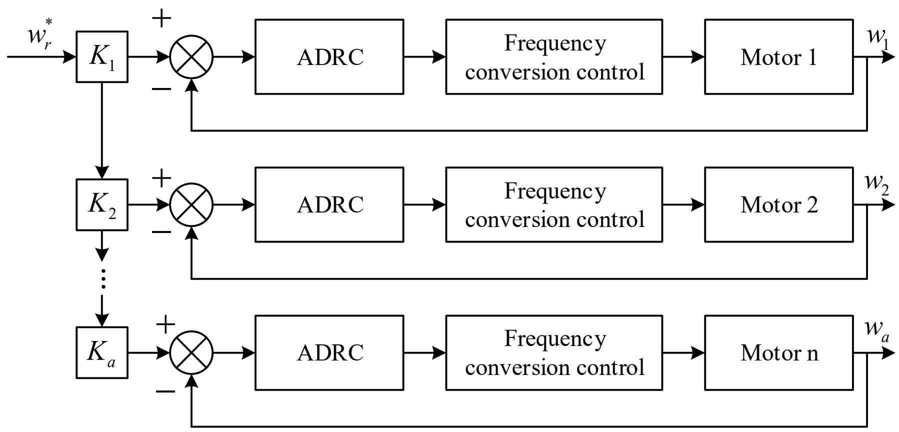


Fig. 6. The synchronous control structure of ADRC

4.3. Simulation Analysis

In order to verify the effectiveness of the above self-immunity control design, Matlab/Simulink is used to simulate the speed chain synchronization system composed of three axes, with Asynchronous Machine pu Units for the motor module, vector control scheme for the inverter speed control, speed synchronization ratio coefficient between each motor and the previous one being 0.01, and spindle speed is set to 110 rad/s.

A total of the following four sets of experiments are done:

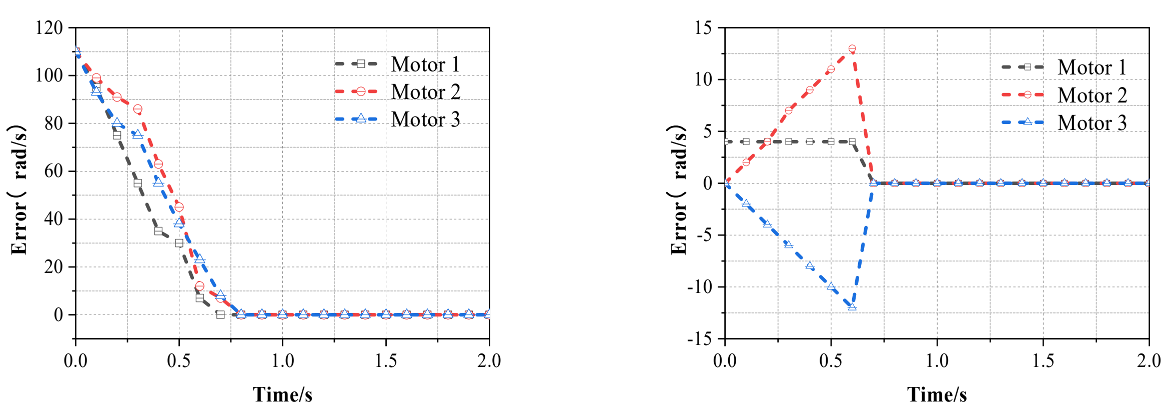
1) When there is no disturbance, the tracking error and synchronization error of the three motors under PID control are shown in Fig. 7.

2) When there is no disturbance, the tracking error and synchronization error of the three motors under the control of the self-resistant controller are shown in Fig. 8.

3) When load perturbation is added, the tracking error and synchronization error of the three motors under PID control are shown in Fig. 9.

4) The tracking error and synchronization error of the three motors under the self-immobilizing control when the load perturbation is added are shown in Fig. 10.

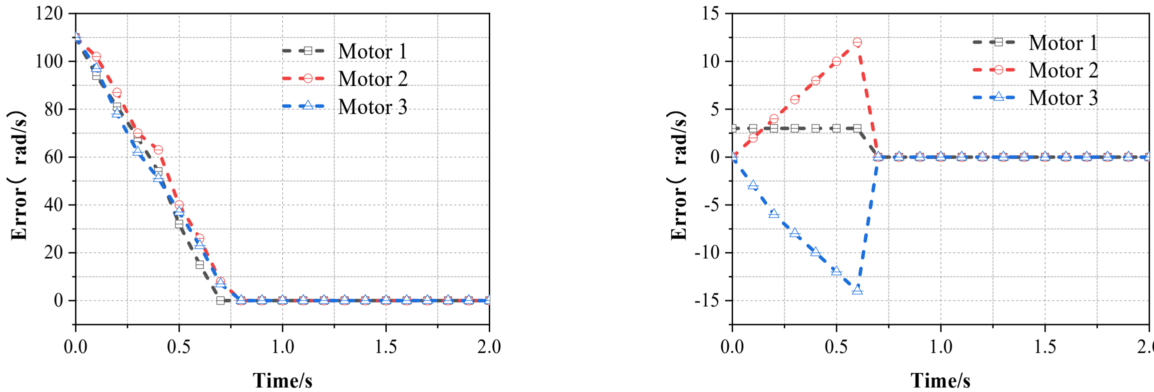
From the experimental results, it can be seen that under the ideal situation without perturbation, both the PID controller and the self-resistant controller can make each motor achieve the ideal synchronization performance in the speed chain, and the tracking error and synchronization error converge to 0 after about 0.8s. However, when there is a disturbance in the load, the synchronization performance of each motor in the speed chain under the control of the self-immobilizing controller is significantly better than that of the PID controller, indicating that the self-immobilizing controller has a strong robustness.



(a)Tracking error

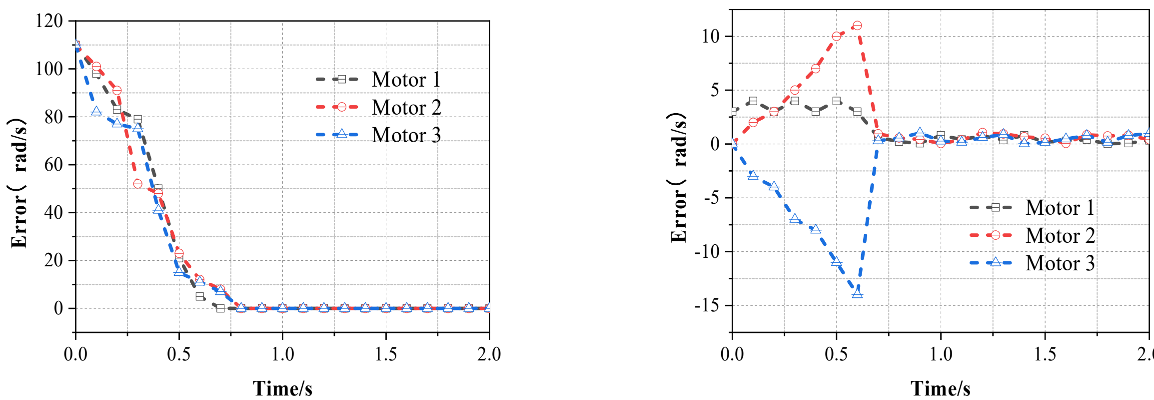
(b)Synchronization error

Fig. 7. The tracking error and synchronization error of experiment 1



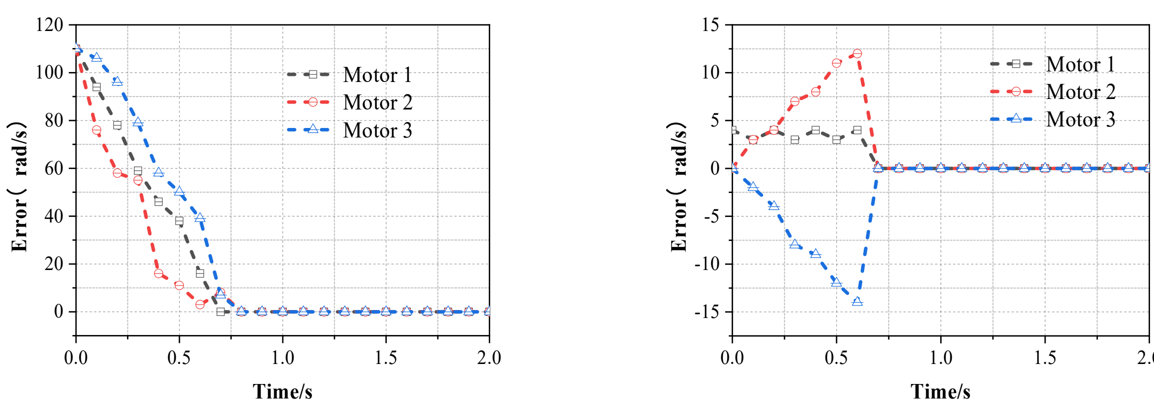
(a)Tracking error (b)Synchronization error

Fig. 8. The tracking error and synchronization error of experiment 2



(a)Tracking error (b)Synchronization error

Fig. 9. The tracking error and synchronization error of experiment 3



(a)Tracking error (b)Synchronization error

Fig. 10. The tracking error and synchronization error of experiment 4

5. Conclusion

In this paper, the paper machine lateral quantitative control system is modeled, the predictive control theory is introduced, and an intelligent predictive control method for the paper machine lateral qualitative control system is designed by Gram polynomials and dynamic matrix control algorithm. In addition, a self-resistant controller device is designed for the speed chain control of the paper machine system. Simulation experiments are carried out and it is found that the predictive control method based on Gram polynomials and DMC algorithm in this paper significantly reduces the computation amount than the traditional MPC algorithm with almost no influence on the control effect, and the slopes of the computation amount and the model size of the two are 1.97 and 2.85, respectively.Therefore, the algorithms in this paper are more conducive to the on-line operation, and they can satisfy the real-time requirements of the practical applications. In the motor disturbance experiment of the paper machine control system, the traditional PID control and this paper's self-immunity controller are about 0.8s to realize the synchronous control of the speed chain, when adding load disturbance, this paper's method has a more stable anti-jamming effect than the traditional PID controller, the experimental results proved that this paper's design of the self-immunity controller can help to solve the problem of the disturbance of the speed chain of the paper machine system.

With the continuous development of the paper industry, people have higher and higher requirements for paper quality, simple longitudinal quantitative control can not meet the quality control requirements, there are still many problems for the horizontal quantitative control need to do further research. Paper machine's horizontal quantitative control system space span, the number of dimensions, affected by many disturbing factors, is one of the most complex control system in papermaking, this thesis is designed to intelligent prediction and self-anti-interference device solutions, to a greater extent, the theoretical approach, software integration and system stability, but also need to be further modified and optimized.

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