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The Fuzzy Prediction Control Methods of Crop Growth Process

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Abstract

Today the huge demand for high-quality crops allowed the research on the improvement of crop quality and cultivation techniques to give increasing attention. Through effective variety selection and optimal control of the growth process, maintaining the long-term best growth environment is an important means to improve crop quality and yield. Due to the quality of the wheat crop ecological variability and complexity of the formation process, the effective forecasting and management under different conditions of wheat growth process becomes quite difficult. Aiming to the characteristics, such as nonlinear, time-varying, strong correlation, time-delay and more uncertainty, between the crop quality and various influencing factors, a modeling method of nonlinear dynamic multi-input multi-output system based on PLS and TS model is proposed. On this basis, a Generalized Predictive Controller (GPC) under implicit variable space is designed, which is provide a scientific basis for the realization of effective crop forecasting and control, to increase production, improve quality , regulating the growth cycle and increase economic efficiency purposes. The test results show that this method can effectively track the signal and meet the system demand.

Keywords: *crop quality, crop growth, PLS, TS, GPC*

1. Introduction

With the social catering, tourism development and people's living standards improvement, the demand and sales of high-quality special crops continue to show growth [1-2]. After joining the WTO, China's agricultural products, under the growing pressure from participating in international competition, is increasingly under attack similar foreign agricultural products in the domestic market, agricultural product quality issues stand out. Meanwhile, with the improvement of people's living standards, structural surplus food problems, especially the traditional staple food crops of wheat, the poor quality of special rice varieties, malting barley and other crops dependent on imports of industrial raw materials and other issues has restricted the processing enterprises and farmers Income bottleneck. According to the National Grain Quality census results released in September 2005, Chinese cultivar GB (GB /T 17891-1999) the achieved rate of three-level rice was 43.1%. If the high-quality rice standards promulgated by the Ministry of Agriculture (NY122-86) measure, the achieved rate is lower. This situation is clearly difficult to meet the urgent requirements of the domestic and foreign markets for the development of high-quality rice production and private consumption. According to statistics, the area of high-quality special wheat is accounted for only 38% of the national wheat harvest area of the country, ordinary wheat surplus, and the lack of high-quality wheat, especially high-quality bread wheat gluten and gluten quality wheat biscuit cake in short supply. From January to May in 2005, China imported a total of 2,459,800 tons of wheat (export only 61,300 tons), an increase of 65.9%, dependence on imports is difficult

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to reverse in the short term. Barley quality problems are more prominent, because of bad quality; most of malting barley into feed, resulting in China's beer industry used about 70% dependent on imports of barley from Australia and Canada. Therefore, the development of high-quality crops with high economic efficiency, to achieve high quality and efficiency of industrial production has become the highlight of crop production development in China, the effective way to improve plant efficiency and increase farmers' income. In addition to using conventional or biotechnological means to cultivate high-yielding varieties, the more need to monitor crop growth and cultivation of tuning to ensure the quality and stability of food.

In wheat, for example, the entire growth process is divided into several different stages, with winter wheat, for example, autumn sowing; the second in the summer of maturity, the whole growing season is generally from 190 to 210 days. From seed germination to produce seeds, wheat go through germination, seedling, tiller, winter, turning green, jointing, booting, heading, flowering, grouting, maturation of the growth process. After spring, Barley resumed growth into turning green. As temperatures rise, wheat seedling growth accelerated gradually elongate inter-nodes bottom-up, called jointing. At this time touching near-Earth straw, you can feel a clear projection of the section. After jointing, the differentiation between the wheat with the elongation gradually grow up, when the young panicle length to the uppermost leaf (Flag Leaf) the sheath, the sheath is gradually enlarged fusiform, called booting. When the last section between small straw elongate, extending from the top of the flag leaf sheathes of wheat, is heading. Wheat is generally heading in early April to early May 5 ten days, 2-6 days after heading, flowering, and fertilization after flowering wheat into the grain filling stage.

In the various stages of growth, the main factors affecting the quality of products in addition to grain varieties, but also influenced by cultural practices and ecological environment. Grow wheat, for example, in addition to grain varieties by genetic factors, but also by the entire growth process of climate, soil and cultivation environment management at the combined effects of extrinsic factors. This includes the yield and quality of wheat quality, yield parameters including spikes, grains, grain weight and yield. Quality parameters include grain protein and starch content, clearing the ball protamine content, straight amylopectin content. Regional environmental parameters include longitude region, latitude and altitude and other information. Climatic parameters includes growth to the highest daily temperature, minimum temperature, daily average temperature, sunshine hours (or radiation) and daily rainfall and so on. Soil environmental parameters include parameters reflecting the plow layer of soil properties such as soil type, the plow layer thickness, soil reflectance, pH, soil phosphorus and potassium, total nitrogen, ammonia nitrogen, nitrate, organic, slow-release potassium content soil saturated water content and soil physical clay content, soil layers of total nitrogen, ammonia nitrogen, nitrate nitrogen, organic matter, soil depth, soil bulk density, layers of clay content, each soil layer, field capacity, wilting water content. Variety parameters include the number of spring days varieties, basic earliness, light sensitivity factor, temperature sensitivity, filling factor of the total number of leaves, leaf area, leaf hot pitch, grain weight, harvest index, the number of the section between varieties tiller capacity, The maximum daily rate of nitrogen accumulation, starch daily maximum accumulation rate, varietal character protein content. Cultivation and management parameters include seeding (sowing, planting depth, seeding density, seeding mode) and cropping patterns (inter-cropping, relay inter-cropping), irrigation control (dry seed, intermittent irrigation, automatic irrigation), fertilizer logistics level (number of fertilizer, fertilizer, fertilizers, fertilizer use efficiency and nutrient content of manure, insect pest control level and so there is a very complex correlation between these parameters, such as: a positive correlation between gluten content and protein content between the settlement value of the protein content The positive correlation, correlation, cultivation and management and climatic factors, soil factors and so complex correlation between the falling number and starch content between highly significant negative correlation between climatic factors and soil factors.

Nonlinear of wheat different growth processes, uncertainty of external factors and operational personnel, the large data, the complex correlation of multi-variable, the time-delay with crop growth, and other characteristics, make it extremely difficult to describe the wheat growth process, and predict management control [3-4].

Based on this, combining TS fuzzy model and dynamic PLS model, a GPC control system is proposed, to deal with the dynamic non-linear characteristics during the greenhouse cultivation. This model has the ability to automatically decoupling and matching circuits similar as [5-6], and the ability of solving nonlinear similar as fuzzy model [7]. The hidden space GPC control strategy is simplified and ensured the tracking performance of the predictive control system [8-9]. This method has obvious advantages for strongly nonlinear Process Systems.

2. The GPC Control System Design Based on the TS-PLS Model

The system, using the dynamic PLS simplifies the multi-input multi-output system (MIMO) into a plurality of single-input single-output (SISO) system, resolved data processing complexity and multi-variety correlation. Using fuzzy modeling method resolved effectively the strong nonlinear of crop growth process, establishing a TS-PLS dynamic model. Finally, using the GPC method achieves the real-time monitoring of crop quality. Specific method is as follows.

2.1 The Nonlinear PLS Establish External Model

Crop cultivation process, various factors affect the quality of crops as an argument input data, referred to as $X=(x_{ij})_{l*m}$, crop quality parameters as the dependent variable output data, referred to as $Y=(y_{ij})_{l*n}$, where, *l*, *m*, *n* denote the number of observations systems, input and output variables of dimension. External model can be obtained by calculation, iteration and drawing main element from the input data *X* and output data *Y*:

$$\begin{aligned} X - E^* &= TP^T = \sum_{r=1}^{R} t_r p_r^T \\ Y - F^* &= UQ^T = TBQ^T = \sum_{r=1}^{R} t_r b_r q_r^T \end{aligned} \tag{1}$$

Where: R(R<max (m,n)) is the number of principal component selection, can be determined by cross-examination or other statistical methods; E^* *and* F^* represents respectively residual matrix of the input data X and output data Y; t_r *and* p_r denote the r-hidden variables and their input load vector; u_r and q_r represent the r-th output of hidden variables and load vector. Input and output of hidden variables t_r and u_r hidden variable algebraic relations constitutes the internal model of PLS algorithm.

2.2 TS-PLS Model

TS fuzzy model is in each fuzzy rule uses a linear function to represent a local feature, then the membership function of these local model outputs are combined to form an approximate output of the entire model. TS fuzzy model contains a former piece part and the consequent parts, and its identification contains structure identification and parameter identification. The structure identification contains input/output variables selection, fuzzy sets, the type of membership function, the number of fuzzy rules, *etc.* Parameter identification includes parameter identification and the consequent membership function model. Wherein, after the member model uses ARX models.

In the PLS outer model, MIMO model identification problem is reduced to a plurality of SISO models, here we only need to consider each one separately hidden space SISO dynamic fuzzy inference system. In the *i*-th hidden variable space, using TS fuzzy model to regress score vector t_i and u_i. The following with t and u represent a hidden space dimension of input and output. Definition:

$$q^{-1}y(k)=y(k-1), A_l=a_{l0}+a_{l1}q^{-1}+\ldots+a_{\ln}q^{-n}, B_l=b_{l0}+b_{l1}q^{-1}+\ldots+b_{lm}q^{-m}$$

The *l*-th rule expressed as ARX form:

$$u_l(k)=A_l u(k-1)+B_l t(k-1) \tag{2}$$

Define:

$$\varphi(k)=[u(k-1),u(k-2),\ldots,u(k-1-n),t(k-1),t(k-2),\ldots,t(k-1-m)]$$
$$\theta_l=[a_{l0},a_{l1},\ldots,a_{\ln},b_{l0},b_{l1},\ldots,b_{lm}]$$

Where, n, m is the order of input and output variables. Equation (2) can be expressed as:

$$u_l(k)=A_l u(k-1)+B_l t(k-1)=\varphi(k)\theta_l^T \tag{3}$$

Then, the TS fuzzy model can be expressed as:

$$R_l : if\ \varphi(k)\in\Omega_l$$
$$then\, u_l(k)=\varphi(k)\theta_l^T \quad l=1,2,\ldots,L$$

Where, L defines the number of rules, Ω_l is fuzzy sets, the hidden space output of k time is:

$$u(k)=\frac{\sum_{l=1}^{L}\omega_l(\varphi_k)u_l(k)}{\sum_{l=1}^{L}\omega_l(\varphi_k)} \tag{4}$$

The φ_k $\varphi(k)$ is equivalent, $\omega_l(\varphi_k)$is $\varphi(k)$ is the membership functions belonging to the l rule. The membership function solved by GK clustering algorithm, equation (4) can be rewritten as:

$$u(k)=\sum_{l=1}^{L}w_l(\varphi_k)u_l(k)$$
$$w_l(\varphi_k)=\frac{\omega_l(\varphi_k)}{\sum_{l=1}^{L}\omega_l(\varphi_k)} \tag{5}$$

Equation (5) is hidden space TS fuzzy model, membership functions' identification and parameter identification of ARX model is to be carried out.

In this paper, using GK clustering algorithm, the membership function is to be solved. Is assumed to be clustering data set, N is the number of samples, the number of clusters is set to c ($c = L$). GK clustering algorithm to calculate the fuzzy partition matrix $U=(\mu_{ij})_{c*N}$, cluster center vectors $V=[v_1,v_2,\ldots,v_c]$ and covariance matrix $F=[F_1,F_2,\ldots,F_c]$, where, F_i is the *i*-th cluster of fuzzy covariance matrix, is a positive definite matrix, $\mu_{ij}\in[0,1]$ is membership between the data points z_j and relative cluster centers of v_i. Define the distance square between data point z_j and cluster center v_i as follows:

$$D_{ij}^2=(z_j-v_i)^T A_i(z_j-v_i), A_i=[\det(F_i)]^{1/(n+m)}\cdot F_i^{-1} \tag{6}$$

The GK clustering algorithm's step is as follows:

Step 1: For a given data set to be cluster Z, select the number of clusters c, fuzzy index r>1, the convergence error ε>0, random initialization fuzzy partition matrix U;

Step 2: Calculate the cluster centers:

$$v_i = \frac{\sum_{j=1}^{N} (\mu_{ij})^r z_j}{\sum_{j=1}^{N} (\mu_{ij})^r} \tag{7}$$

Step 3: Calculate the cluster co-variance matrix:

$$F_i = \frac{\sum_{j=1}^{N} (\mu_{ij})^r (z_j - v_i)(z_j - v_i)^T}{\sum_{j=1}^{N} (\mu_{ij})^r} \tag{8}$$

Step 4: Calculate the distance between data point z_j and cluster center v_i:

$$D_{ij}^2 = (z_j - v_i)^T [\det(F_i)]^{1/(n+m)} \cdot F_i^{-1} (z_j - v_i) \tag{9}$$

Step 5: Update fuzzy partition matrix:

$$\mu_{ij} = \left[\sum_{k=1}^{c} (D_{ij} / D_{kj}) \right]^{-2/(r-1)} \tag{10}$$

Repeat step 2 to 5, until the two iterations U is less than convergence error ε.

Obtained U, F and V, at time k can be implicit spatial output $u(k)$ is expressed as:

$$\begin{aligned} u(k) &= \sum_{l=1}^{L} w_l(\varphi_k) u_l(k) = \sum_{l=1}^{L} w_l(\varphi_k) \varphi(k) \theta_l^T \\ &= [w_1(\varphi_k)\varphi(k), w_2(\varphi_k)\varphi(k), \ldots, w_L(\varphi_k)\varphi(k)] \cdot [\theta_1, \theta_2, \ldots, \theta_L]^T \end{aligned} \tag{11}$$

Set

$$\psi = [w_1(\varphi_k)\varphi(k), w_2(\varphi_k)\varphi(k), \ldots, w_L(\varphi_k)\varphi(k)]$$
$$\theta = [\theta_1, \theta_2, \ldots, \theta_L]$$

Equation (11) can be expressed as:

$$u(k) = \psi \cdot \theta^T \tag{12}$$

$u(k)$ and ψ is known, unknown parameters are determined by the least squares method, the identification of the entire TS-PLS model is completed.

2.3 The Hidden Space GPC Fuzzy Control Strategy

The fuzzy GPC Hidden Space Control Strategy is established based on TS-PLS model. In the hidden variable space, the following CARIMA model are established for each group $t_i(k)$, $u_i(k)$:

$$\begin{cases} a_1(q^{-1}) u_1(k) = b_1(q^{-1}) t_1(k-1) + \dfrac{e_1(k)}{\Delta} \\ \vdots \\ a_a(q^{-1}) u_a(k) = b_a(q^{-1}) t_a(k-1) + \dfrac{e_a(k)}{\Delta} \end{cases} \tag{13}$$

Where,

$$a_i(q^{-1}) = 1 + a_{i,1} q^{-1} + \ldots + a_{i,n_a} q^{-n_a}$$
$$b_i(q^{-1}) = b_{i,0} + b_{i,1} q^{-1} + \ldots + b_{i,n_b} q^{-n_b}, i = 1,2,..a$$
$$\Delta = 1 - q^{-1}$$

a is the principal component number, q^{-1} is the backward shift operator, $e_i(k)$ is non-related random sequence shows the effect of a class of random noise. Each model can be combined into a hidden space below the diagonal form:

$$\begin{bmatrix} a_1(q^{-1}) & & \\ & \ddots & \\ & & a_a(q^{-1}) \end{bmatrix}\begin{bmatrix} u_1(k) \\ \vdots \\ u_a(k) \end{bmatrix}=\begin{bmatrix} b_1(q^{-1}) & & \\ & \ddots & \\ & & b_a(q^{-1}) \end{bmatrix}\begin{bmatrix} t_1(k-1) \\ \vdots \\ t_a(k-1) \end{bmatrix}+\begin{bmatrix} e_1(q^{-1})/\Delta & & \\ & \ddots & \\ & & e_a(q^{-1})/\Delta \end{bmatrix} \tag{14}$$

Abbreviated as:

$$a(q^{-1})u(k)=b(q^{-1})t(k-1)+e(k)/\Delta \tag{15}$$

Due to each model of hidden variables structure is the same, take *i*-th latent variable space for example, illustrate the derivation of PLS Hidden Space GPC control rate. GPC is a multi-step ahead predictive control technology, usually with Diophantine equations to derive *j*-step ahead forecasting model.

$$1=E_j(q^{-1})a_i(q^{-1})\Delta+q^{-j}F_j(q^{-1}) \tag{16}$$

Where, E_j and F_j is a polynomial determined by the prediction step j and a_i. Using this equation to obtain the value of u_i of time $k+j$:

$$u_i(k+j)=F_j(q^{-1})u_i(k)+E_j(q^{-1})b_i(q^{-1})\Delta t_i(k+j-1)+E_j(q^{-1})e_i(k+j) \tag{17}$$

The last one is unknown noise, so $u_i(k+j)$ of the predicted value can be represented by the following formula:

$$\hat{u}_i(k+j)=F_j(q^{-1})u_i(k)+E_j(q^{-1})b_i(q^{-1})\Delta t_i(k+j-1) \tag{18}$$

Introduced equation

$$E_j(q^{-1})b_i(q^{-1})=\tilde{G}_j(q^{-1})+q^{-j}\overline{G}_j(q^{-1}) \tag{19}$$

Equation (18) can be expressed as:

$$\hat{u}_i(k+j)=\tilde{G}_j(q^{-1})\Delta t_i(k+j-1)+\overline{G}_j(q^{-1})\Delta t_i(k-1)+F_j(q^{-1})u_i(k) \tag{20}$$

The set value of each SISO controller is initially set values of the projection of hidden space. For each latent variable space GPC, its performance index function is:

$$J^i(k)=\sum_{j=1}^{N_p}\left\|u_{spi}(k+j)-\hat{u}_i(k+j)\right\|^2+\lambda\sum_{j=1}^{N_c}\left\|\Delta t_i(k+j-1)\right\|^2 \tag{21}$$

Where, N_p is the prediction horizon, N_c is the time control domain. Plug the formula (20) into (21), and calculate the optimal solution to minimize the time it can control rate was as follows:

$$\begin{bmatrix} \Delta t_i(k) \\ \Delta t_i(k+1) \\ \vdots \\ \Delta t_i(k+N_C-1) \end{bmatrix}=(G^TG+\lambda I)^{-1}G^T\begin{bmatrix} u_{spi}(k)-\overline{G}_{N_1}(q^{-1})\Delta t_i(k-1)-F_{N_1}(q^{-1})u_i(k) \\ u_{spi}(k)-\overline{G}_{N_1+1}(q^{-1})\Delta t_i(k-1)-F_{N_1+1}(q^{-1})u_i(k) \\ \vdots \\ u_{spi}(k)-\overline{G}_{N_2}(q^{-1})\Delta t_i(k-1)-F_{N_2}(q^{-1})u_i(k) \end{bmatrix} \tag{22}$$

$$G=\begin{bmatrix} \tilde{g}_{N_1-1} \cdots 0 & 0 & \\ \tilde{g}_{N_1-1} & \tilde{g}_{N_1-1} \cdots 0 & \\ \vdots & \ddots & \vdots \\ \tilde{g}_{N_2-1} & \tilde{g}_{N_2-2} & \tilde{g}_{N_2-N_C} \end{bmatrix}$$

GPC as a time-domain approach scroll, only the current control action $\Delta t_i(k)$ applied to the system:

$$\Delta t_i(k)=[h_{N_1},h_{N_1+1},\ldots,h_{N_2}]\begin{bmatrix} u_{spi}(k)-\overline{G}_{N_1}(q^{-1})\Delta t_i(k-1)-F_{N_1}(q^{-1})u_i(k) \\ u_{spi}(k)-\overline{G}_{N_1+1}(q^{-1})\Delta t_i(k-1)-F_{N_1+1}(q^{-1})u_i(k) \\ \vdots \\ u_{spi}(k)-\overline{G}_{N_2}(q^{-1})\Delta t_i(k-1)-F_{N_2}(q^{-1})u_i(k) \end{bmatrix} \tag{23}$$

The vector $[h_{N1},h_{N1+1},...,h_{N2}]$ is the first line of $(G^TG+\lambda I)^{-1}G^T$. For closed-loop analysis, the equation (23) re-organized into the following classic RST general linear form:

$$T_i\left(q^{-1}\right)\Delta t_i(k) = R_i\left(q^{-1}\right)u_{sp_i}(k) - S_i\left(q^{-1}\right)u_i(k) \tag{24}$$

$$\begin{aligned} T_i\left(q^{-1}\right) &= 1 + q^{-1}\sum_{j=N_1}^{N_2} h_j \overline{G}_j\left(q^{-1}\right) \\ R_i\left(q^{-1}\right) &= \sum_{j=N_1}^{N_2} h_j \\ S_i\left(q^{-1}\right) &= \sum_{j=N_1}^{N_2} h_j F_j\left(q^{-1}\right) \end{aligned} \tag{25}$$

The control rate similar as formula (24) can be deduced for each latent variable space, they are combined to obtain the control rate of all latent variables space. Since the decouple characteristics of PLS hidden space variables, the control rate has a special diagonal form. In order to facilitate said, it will be referred to as:

$$T\left(q^{-1}\right)\Delta t(k) = R\left(q^{-1}\right)u_{sp}(k) - S\left(q^{-1}\right)u(k) \tag{26}$$

$$\Delta t(k) = T^{-1}\left(q^{-1}\right)\left[R\left(q^{-1}\right)u_{sp}(k) - S\left(q^{-1}\right)u(k)\right] \tag{27}$$

According to the mapping relationship of PLS, the hidden variables t, u can be back projection to the original variable space, and obtained the control rate under the original variable space:

$$N\cdot\Delta x(k) = T^{-1}\left(q^{-1}\right)\left[R\left(q^{-1}\right)M\cdot y_{sp}(k) - S\left(q^{-1}\right)M\cdot y(k)\right] \tag{28}$$

The conversion matrix N, M satisfies the following formula:

$$\begin{aligned} t(k) &= \left(W_x\cdot p\right)^{-1}x(k) \overset{\Delta}{=} N\cdot x(k) \\ u(k) &= Q^{+}W_y^{-1}y(k) \overset{\Delta}{=} M\cdot y(k) \end{aligned} \tag{29}$$

3. Simulation Results and Analysis

Different varieties of wheat, for example, protein and gluten content as the system dependent variables, and the temperature, humidity and nitrogen fertilizer of growing conditions as the independent variables, getting sample data. Comparing the output data through T-S fuzzy model and the original output data shown in Figure1, we can see that, the T-S fuzzy modeling method can effectively fit the nonlinear characteristic based on sample data. And then, the T-S model data is sent to GPC controller, after many times adjusted, the system can effectively tracking and prediction signal.

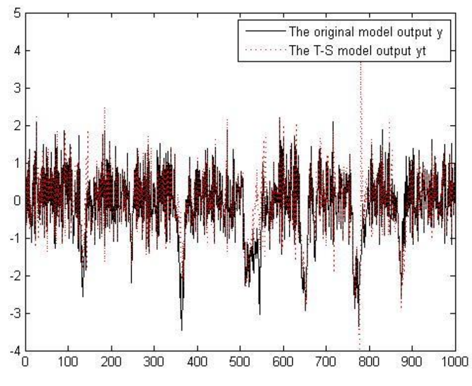

Figure 1. The Test of T-S Model

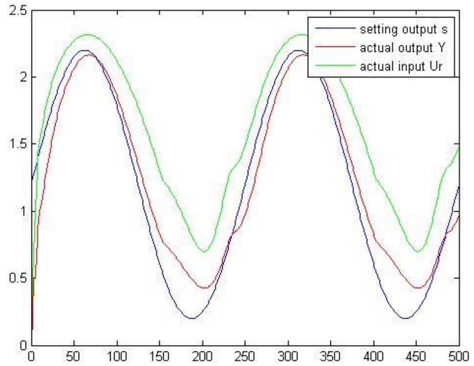

Figure 2. The Test of GPC

4. Conclusion

The fuzzy predictive control method studied in this paper, using the dynamic PLS simplifies the multi-input multi-output system (MIMO) into a plurality of single-input single-output (SISO) system, resolved data processing complexity and multi-variety correlation. Using fuzzy modeling method resolved effectively the strong nonlinear of crop growth process. Finally using the GPC method predicts crop growth trend and controlling. The simulation results show that this method can be a good forecasting and tracking.

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