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A kind of gas stove modeling method based on model free predictive control

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ABSTRACT

Model free method of nonlinear system predictive control is investigated in this paper. The universal model is taken as predictive model of a class of nonlinear system. Through the multi-layer hierarchical forecasting, feature vector in the universal model is predicted, so that predictive model based on universal model is worked out. Through the optimization of performance index, a kind of gas stove modeling method based on model free predictive control algorithm for nonlinear system is obtained. The simulation examples show the effectiveness of the algorithm, and through comparison of model free predictive control and model free control, it is concluded that model free predictive control with functional combination module has the same advantages with model free control.

KEYWORDS

Nonlinear system; Model free predictive control; Model free control.

INTRODUCTION

As is known to all, in the early 1960s, the modern control theory based on the state space model had gain huge success in aviation, aerospace and other fields[1,2]. Design theory and method based on the optimal performance index, uses state space analysis method to design control system, which not only improves the people inner understanding of controlled object, but also provides a means for the design of the control system at a higher level. But in the actual process, people find controlled object are often nonlinear, uncertain, and the actual control process also requires algorithm to have good real-time performance, which makes the modern control theory difficult to adapt to the requirement of practical production. In order to overcome a disharmony between theory and application, since the 1970s, in addition to strengthen the system identification, model simplification, adaptive control and robust control, people began to break the constraints of the traditional methods, trying to face the characteristics of the industrial process, looking for optimal control algorithm, which had low requirement for model, and has excellent comprehensive control quality, and convenient online calculation. Predictive control is a class of new computer optimization control algorithm, which developed from the industrial process control. After nearly 30 years of development, all kinds of predictive control algorithm emerge in endlessly, and show its great vitality, but no matter how different the algorithms form, they are based on model prediction, rolling optimization and feedback correction[3,4]. Predictive control is a control method based on but not confined by the model. Building prediction model is essential and critical to predictive control. Due to the lack of unified model, predictive control of various nonlinear systems is based on the model description of different nonlinear systems. Therefore, it is necessary to study modeling in nonlinear system predictive control.

Due to the structure identification and parameter identification problem of nonlinear objects, predictive control based on model is difficult to carry out[5,6]. Even if the dynamic model and output model are obtained by certain method, rolling optimization has some problems. Most of the nonlinear model turns up in the form of composite function, and is difficult to separate control and output. It is difficult to obtain analytic expression of optimal control. Although nonlinear predictive control has too many difficulties, a lot of research workers have done a lot of research. After nonlinear model is linearized, rolling optimal design method is used to design controller and at the same time keep nonlinear model as forecasting model for predictive control. In order to overcome model linearization error, online identification can be used to correct linear model. Nonlinear predictive control algorithm based on the linearized model is simple and has good real-time performance, but there are also disadvantages.

Model predictive control is a control algorithm based on system dynamic characteristic model, and this model is called a forecasting model[7,8]. Its function is to predict the future output of the system based on historical information and the future input of controlled object. Prediction model only emphasizes the function of the model and does not emphasize its structural form. Predictive control, therefore, has broken strict requirements of model structure in the traditional control. Under the background of MPC, model structure is flexible and varied in form. According to the model structure, predictive control can be divided into three categories. The first category is the predictive control algorithm based on the parametric model, such as MPHC, MAC, DMC, etc. The characteristics of this kind of predictive control method is that the impulse response and step response are easy to get in the industrial field, without complex system model. The online rolling optimization is on the basis of feedback correction to replace the traditional optimal control, which can overcome influence of various uncertainty and increase the control robustness. Online calculation is simple, therefore, this kind of algorithm is very suitable for actual industrial process control, and quickly caused widespread interest in control group and got a lot of successful application. The second category is the predictive control algorithm based on parametric model. In the early 80s, in the study of adaptive control, in order to overcome the shortcoming of minimum variance control, and enhance the adaptability and robustness of the algorithm, predictive control algorithm based on model identification turned up. By combining adaptive mechanism and predictive control, thus it could timely correct parameters, so as to improve the dynamic performance of system, such as the GPC and GPP. The third class is the predictive control algorithm based on structure. After the linearization of nonlinear model, linearization method uses rolling optimization to design controller. Retaining nonlinear model is used to predict, and in order to overcome model linearization error, online identification can be used to modify linear model. Peterson took nonlinear effect of the system as additive interference of a DMC model, estimated by online nonlinear valuator, so nonlinear DMC based on extended DMC model is discussed. Nonlinear compensator was introduced by Liu, so that the generalized system was transferred into a linear system.

A nonlinear predictive control algorithm based on the linear model is simple, has good implementation, but also has shortcomings. Because of online model change, it is difficult to guarantee the feasibility of optimization problem of each sampling time. Nonlinear predictive control based on the special model is an important research direction. The so-called special model, also known as empirical model, generally means that the model structure is certain and parameters must be identified. Commonly used special nonlinear models of nonlinear predictive control[9] are Wiener model, Volterra model, Hammerstein model, Laguerre model, Bilinear model, etc. These special nonlinear models can generally describe nonlinear characteristic of many chemical equipment or process, so researching this kind of nonlinear predictive control is very meaningful to the practical application. Nonlinear systems were also described by intelligent model. The predictive control algorithm based on intelligent technology turned up, such as neural network model[10-15], fuzzy model[16-19], genetic algorithm optimization model, the model based on particle swarm optimization[20-25], etc. Predictive control system designed by intelligent method can avoid the difficulties brought about by the traditional control method. Although fuzzy model and neural network model have good effect on description of the nonlinear process, which accords with the requirement of predictive control function of the model. But also they have shortcomings, and they lack of effective method in the multi-step prediction control. Network training time is long, and it is difficult to implement. Multi-model method is a kind of commonly used method to deal with nonlinear systems, and its characteristic is using multiple linear model to approximate the nonlinear process. Xi Yu Geng combined predictive control and multiple model method, so nonlinear system was transfer into multi model. In the early 1990s, model free control method was put forward, also known as the model free adaptive control, which solved the integration of controlled object modeling and had very satisfying results in practical application. The outline of the paper is as follows. Section II introduces model free control law. In section III, derivation of model free predictive control law, the feature vector prediction of universal model and model free predictive control algorithm are investigated. Section IV performance analysis of model free predictive control is given. In order to test the performance of the proposed algorithm, two experiments are carried out. Section V concludes the papers and gives some remarks.

MODEL FREE CONTROL LAW

Basic form of model free control law

Model free control is a control method combining modeling and control. For nonlinear model,

$$y(k) = f[Y_{k-1}^{k-n}, u(k-1), U_{k-2}^{k-m}, k] \tag{1}$$

It can be described as (2) combing with control law.

$$y(k) - y(k-1) = \phi(k-1)^{\tau}[u(k-1) - u(k-2)] \tag{2}$$

$y(k)$ is one dimension output, $u(k)$ is system input and k is discrete time.

$Y_{k-1}^{k-n} = \{y(k-1), y(k-2), \dots y(k-n)\}$, n is positive integer.

$U_{k-2}^{k-n} = \{u(k-2), y(k-3), \dots u(k-m)\}$, m is positive integer.

$\phi(k)$ is function of Y_{k-1}^{k-n} and U_{k-2}^{k-n}. If system S is described as (3).

$$y(k+1)-y(k)=\phi(k)^{\tau}[u(k)-u(k-1)] \quad \textbf{(3)}$$

$\hat{\phi}(k)$ is known and is the optimal estimation of $\phi(k)$, (3) can be described as (4).

$$y(k+1)-y(k)=\hat{\phi}(k)^{\tau}[u(k)-u(k-1)] \quad \textbf{(4)}$$

When designing control law, $y(k+1)$ is replaced by $y_0(k+1)$.

$$y_0(k+1)-y(k)=\hat{\phi}(k)^{\tau}[u(k)-u(k-1)] \quad \textbf{(5)}$$

$u(k)=u(k-1)+\frac{1}{\left\|\hat{\phi}(k)\right\|^2}\hat{\phi}(k)\{y_0(k+1)-y(k)\}$ is obtained, which is control law of system S. In order to avoid $\left\|\hat{\phi}(k)\right\|^2=0$, $a+\left\|\hat{\phi}(k)\right\|^2$ is used to replace $\left\|\hat{\phi}(k)\right\|^2$, and a is a suitable small integer. Then basic
form of model free control law is (6).

$$u(k)=u(k-1)+\frac{\lambda_k}{a+\left\|\hat{\phi}(k)\right\|^2}\hat{\phi}(k)\{y_0-y(k)\} \quad \textbf{(6)}$$

Functional module combination form of model free controller

In the design of model free controller, functional module combination is used. Controller design pays attention to various functional modules of controller. According to different object, choose different functional modules. Form of model control law which is suitable for theoretical analysis is (7).

$$u(k)=u(k-1)+\frac{\lambda_k}{a+\left\|\phi(k)\right\|^2}\phi(k)\cdot \quad \textbf{(7)}$$
$$\{A+D(Y_{k-1}^{k-n},U_{k-1}^{k-m},\theta,k)\}(y_0-y(k))$$

$D(\cdot)$ is a suitable function, which represents functional combination of control law. A and θ are configuration parameters of model free control law. A is bigger than 0 and θ is nonnegative vector.

A NEW KIND OF MODEL FREE PREDICTIVE CONTROL BASED ON UNIVERSAL MODEL

Derivation of model free predictive control law

In the derivation of model free control law, feature vector of universal model is identified. The estimated value of feature vector is used to replace its true value. $y(k+1)$ is replaced by given value, so that model free control law is obtained.

Universal model is taken as predictive model, which is shown in (4). Predictive form of universal model is (8) to (10).

$$y(k+2)-y(k+1)=\hat{\phi}(k+1)^{\tau}[u(k+1)-u(k)] \quad \textbf{(8)}$$

$$y(k+3)-y(k+2)=\hat{\phi}(k+2)^{\tau}[u(k+2)-u(k+1)] \quad \textbf{(9)}$$

…

$$y(k+N_y)-y(k+N_y-1)=\hat{\phi}(k+N_y-1)^{\tau}\cdot [u(k+N_y-1)-u(k+N_y-2)] \quad \textbf{(10)}$$

$$y(k+N_y)=y(k+N_y-1)+\hat{\phi}(k+N_y-1)^{\tau}\cdot [u(k+N_y-1)-u(k+N_y-2)]$$

$$\begin{aligned}
&=\hat{\phi}(k+N_y-1)^{\tau}[u(k+N_y-1)-u(k+N_y-2)]\\
&+\hat{\phi}(k+N_y-2)^{\tau}[u(k+N_y-2)-u(k+N_y-3)]\\
&+\ldots+\hat{\phi}(k)^{\tau}[u(k)-u(k-1)]+y(k)\\
&=\hat{\phi}(k+N_u)^{\tau}[u(k+N_u)-u(k+N_u-1)]\\
&+\ldots+\hat{\phi}(k)^{\tau}[u(k)-u(k-1)]+y(k)\\
&=y(k+N_u)
\end{aligned}$$

(8) to (10) can be described in vector form.

$$\begin{bmatrix} y(k+1)\\ y(k+2)\\ \vdots \\ y(k+N_u)\end{bmatrix}=\begin{bmatrix}\hat{\phi}(k) & & & \\ \hat{\phi}(k) & \hat{\phi}(k+1) & & \\ \ldots & & & \\ \hat{\phi}(k) & \hat{\phi}(k+1) & \ldots & \hat{\phi}(k+N_u-1)\end{bmatrix} \cdot \begin{bmatrix}\Delta u(k)\\ \Delta u(k+1)\\ \vdots \\ \Delta u(k+N_u)\end{bmatrix}+\begin{bmatrix}1\\1\\ \vdots\\1\end{bmatrix}y(k) \quad \textbf{(11)}$$

$$Y^{\tau}=[y(k+1),y(k+2),\ldots y(k+N_u)].$$

$$U^{\tau}=[\Delta u(k),\Delta u(k+1),\ldots \Delta u(k+N_u)].$$

$$G=\begin{bmatrix}\hat{\phi}(k) & & & \\ \hat{\phi}(k) & \hat{\phi}(k+1) & & \\ \ldots & & & \\ \hat{\phi}(k) & \hat{\phi}(k+1) & \ldots & \hat{\phi}(k+N_u-1)\end{bmatrix}.$$

$F=\begin{bmatrix}1\\1\\ \vdots\\1\end{bmatrix}$. (11) can be described as (12).

$$Y = GU + Fy(k) \tag{12}$$

When sequence is $y_r(k)$, predictive step length is N_y, and control step length is N_u. Quadratic performance index is (13).

$$J = \sum_{i=1}^{N_y}[y_r(k+i) - \hat{y}(k+i)]^2 + \sum_{j=1}^{N_u}\lambda_j[\Delta u(k+j-1)]^2 \tag{13}$$

$Y_r^\tau = [y_r(k+1), y_r(k+2), \ldots, y_r(k+N_u)]$, so J can be described as (14).

$$J = [Y - Y_r]^\tau[Y - Y_r] + \lambda U^\tau U \tag{14}$$

$\frac{\partial J}{\partial U} = 0$, the optimal control law is

$$U = (G^\tau G + \lambda I)^{-1} G^\tau (Y_r - Fy(k)) \tag{15}$$

$p^\tau = (G^\tau G + \lambda I)^{-1} G^\tau$.

Then predictive control law based on universal model is

$$\begin{cases} \Delta u(k) = p^\tau [Y_r - Fy(k)] \\ u(k) = u(k-1) + \Delta u(k) \end{cases} \tag{16}$$

The feature vector prediction of universal model

In above proposed model free predictive control law, an important parameter is G, which includes feature vector of universal model and predictive value of feature vector of universal model. The calculation of feature vector of universal model is the key point.

For $y(k) - y(k-1) = \phi(k-1)^\tau [u(k-1) - u(k-2)]$, recursive least square method can be used to calculate estimated value of $\phi(k-1)$.

$$\hat{\phi}(k-1) = \hat{\phi}(k-2) + M(k)(\Delta y(k) - \Delta u(k-1)\hat{\phi}(k-2))$$

$$M(k) = \frac{p(k-1)\Delta u(k-1)}{I + \Delta u^\tau (k-1) p(k-1) \Delta u(k-1)} \tag{17}$$

$$p(k) = (I - M(k)\Delta u^\tau (k-1)) p(k-1)$$

At time k, $\hat{\phi}(1), \hat{\phi}(2), \ldots, \hat{\phi}(k-1)$ can be got, which are used to predict $\hat{\phi}(k), \hat{\phi}(k+1), \ldots, \hat{\phi}(k+N_u-1)$ based on AR model.

$$\begin{aligned} \hat{\phi}(k) &= \theta_1(k)\hat{\phi}(k-1) + \theta_2(k)\hat{\phi}(k-2) + \ldots + \theta_r(k)\hat{\phi}(k-r) \\ &= \Phi^\tau \theta \end{aligned} \tag{18}$$

$\Phi^{\tau}(k)=(\hat{\phi}(k-1),\hat{\phi}(k-2),\ldots,\hat{\phi}(k-r))$.

$\theta(k)$ is coefficient, r is suitable order, and parameter estimation can be obtained by using generalized recursive gradient algorithm.

$$\hat{\theta}(k)=\hat{\theta}(k-1)+\frac{\Phi(k)}{\|\Phi(k)\|^{2}}\{y(k)-\Phi^{\tau}(k)\hat{\theta}(k-1)\} \quad \textbf{(19)}$$

If the parameter is time-invariant, predictive formula of $\hat{\phi}(k+i)$ is

$$\hat{\phi}(k+i)=\theta_1(k)\hat{\phi}(k+i-1)+\theta_2(k)\hat{\phi}(k+i-2)+\ldots+\theta_r(k)\hat{\phi}(k+i-r) \quad \textbf{(20)}$$

If the parameter is time-varying, for each component, set its corresponding AR model, as is shown in (21).

$$\hat{\theta}_i(k+1)=\hat{\alpha}_0\hat{\theta}_i(k)+\hat{\alpha}_1\hat{\theta}_i(k-1)+\ldots+\hat{\alpha}_{n_i}\hat{\theta}_i(k-n_i) \quad \textbf{(21)}$$

n_i is order of the i-th model. Unknown parameters can be identified using least square method. If the results of the identification are time-invariant, (18) can be used as prediction formula.

$$\hat{\theta}_i(k+2)=\hat{\alpha}_0\hat{\theta}_i(k+1)+\hat{\alpha}_1\hat{\theta}_i(k)+\ldots+\hat{\alpha}_{n_i}\hat{\theta}_i(k-n_i+1) \quad \textbf{(22)}$$

$$\hat{\theta}_i(k+N_u-1)=\hat{\alpha}_0\hat{\theta}_i(k+N_u-2)+\hat{\alpha}_1\hat{\theta}_i(k+N_u-3)+\ldots+\hat{\alpha}_{n_i}\hat{\theta}_i(k+N_u-n_i) \quad \textbf{(23)}$$

The prediction formula is (24).

$$\hat{\phi}(k+i)=\theta_1(k+i)\hat{\phi}(k+i-1)+\theta_2(k+i)\hat{\phi}(k+i-2)+\ldots+\theta_r(k+i)\hat{\phi}(k+i-r) \quad \textbf{(24)}$$

$i=0,1,2\ldots N_u-1$.

The process of new model free predictive control algorithm

The process of model free predictive control algorithm is as follows.

Step1. Calculate $\hat{\phi}(k-1)$ and $\hat{\theta}(k)$.

Step2. Calculate $\hat{\phi}(k+i)$, $i=0,1,2\ldots N_u-1$.

Step3. $G = \begin{bmatrix} \hat{\phi}(k) & & & \\ \hat{\phi}(k) & \hat{\phi}(k+1) & & \\ \cdots & & & \\ \hat{\phi}(k) & \hat{\phi}(k+1) & \cdots & \hat{\phi}(k+N_u-1) \end{bmatrix}$.

Step4. Calculate $\Delta u(k)$.

$$\Delta u(k) = [1,0,\ldots,0](G^{\tau}G + \lambda I)^{-1}G^{\tau}(Y_r - Fy(k)).$$

Step5. Under the condition of $u(k) = u(k-1) + \Delta u(k)$, calculate $y(k+1)$.

Step6. $k = k+1$ and go to step1.

In the predictive algorithm, when $N_u = 1$, the predictive control based on universal model is called model free control.

PERFORMANCE ANALYSIS AND SIMULATION

Performance analysis

When $N_u = 1$, the predictive control based on universal model is called model free control. When control time domain is bigger than 1, $\Delta u(k)$ and its final expression is as follows.

$$\Delta u(k) = [1,0,\ldots,0](G^{\tau}G + \lambda I)^{-1}G^{\tau}(Y_r - Fy(k))$$

$$u(k) = u(k-1) + \Delta u(k).$$
$$H = (G^{\tau}G + \lambda I)^{-1}.$$

$$H = \begin{bmatrix} h_{11} & h_{12} & \cdots & h_{1N_u} \\ h_{21} & h_{22} & \cdots & h_{2N_u} \\ \cdots & & & \\ h_{N_u 1} & h_{N_u 2} & \cdots & h_{N_u N_u} \end{bmatrix}$$

$$G^{\tau} = \begin{bmatrix} \hat{\phi}(k) & \hat{\phi}(k) & \cdots & \hat{\phi}(k) \\ & \hat{\phi}(k+1) & \cdots & \hat{\phi}(k+1) \\ & & & \vdots \\ & & & \hat{\phi}(k+N_u-1) \end{bmatrix}$$

$$\begin{aligned} \Delta u(k) &= [1,0,\ldots,0](G^{\tau}G + \lambda I)^{-1}G^{\tau}(Y_r - Fy(k)) \\ &= h_{11}\hat{\phi}(k)(y_r(k+1) - y(k)) + (h_{11}\hat{\phi}(k) + h_{12}\hat{\phi}(k+1)) \\ &\cdot(y_r(k+2) - y(k)) + \cdots + (h_{11}\hat{\phi}(k) + h_{12}\hat{\phi}(k+1) + \cdots \\ &+ h_{1N_u}\hat{\phi}(k+N_u))(y_r(k+N_u) - y(k)) \end{aligned}$$

When $y_r(k+1) = y_r(k+2) = \ldots y_r(k+N_u) = y_0$,

$$\Delta u(k)=[1,0,\ldots,0](G^{\tau}G+\lambda I)^{-1}G^{\tau}(Y_r-Fy(k))$$
$$=(N_u h_{11}\hat{\phi}(k)+(N_u-1)h_{12}\hat{\phi}(k+1)+$$
$$h_{1N_u}\hat{\phi}(k+N_u-1))\cdot(y_0-y(k))$$

Model free predictive control law can be written as the following form.

$$u(k)=u(k-1)+(N_u h_{11}\hat{\phi}(k)+(N_u-1)h_{12}\hat{\phi}(k+1)$$
$$+h_{1N_u}\hat{\phi}(k+N_u-1))\cdot(y_0-y(k))$$

$h_{11},h_{12},\ldots,h_{1N_u}$ are functions related to $\hat{\phi}(k)$. If $f_1(\hat{\phi}(k))=N_u h_{11}\hat{\phi}(k)+(N_u-1)h_{12}\hat{\phi}(k+1)$ $+h_{1N_u}\hat{\phi}(k+N_u-1)$, model free predictive control law can be expressed as $u(k)=u(k-1)+f_1(\hat{\phi}(k))(y_0-y(k))$. For (5), $f_2(\hat{\phi}(k))=\dfrac{\lambda_k}{a+\left\|\hat{\phi}(k)\right\|^2}\hat{\phi}(k)$, model free predictive law is $u(k)=u(k-1)+f_2(\hat{\phi}(k))(y_0-y(k))$. It can be seen that model free predictive law and model free predictive control law have similar forms. But $f_1(\hat{\phi}(k))$ of model free predictive control should predict $\hat{\phi}(k)$ and calculate matrix inversion.

Model free control law with function combination is

$$u(k)=u(k-1)+f_2(\hat{\phi}(k))\{A+D(Y_{k-1}^{k-n},U_{k-1}^{k-m},\theta,k)\}(y_0-y(k))\cdot$$

Model free predictive control law with function combination is

$$u(k)=u(k-1)+f_1(\hat{\phi}(k))\{A+D(Y_{k-1}^{k-n},U_{k-1}^{k-m},\theta,k)\}(y_0-y(k))\cdot$$

$D(Y_{k-1}^{k-n},U_{k-1}^{k-m},\theta,k)$ meets the following conditions.

(1) $\theta=0$, $D(Y_{k-1}^{k-n},U_{k-1}^{k-m},\theta,k)=0$.

(2) $D(Y_{k-1}^{k-n},U_{k-1}^{k-m},\theta,k)$ is continuous function of θ.

For $\beta>0$, there exists a constant vector $\theta_0>0$, when θ meets $0\le\theta<\theta_0$, $D(Y_{k-1}^{k-n},U_{k-1}^{k-m},\theta,k)$ meets $B>|D(Y_{k-1}^{k-n},U_{k-1}^{k-m},\theta,k)|$. In fact, $\lim_{\theta\to 0}D[Y_{k-1}^{k-n},U_{k-1}^{k-m},\theta,k]=0$. For $\beta>0$, there must exist $\eta>0$, when $\|\theta\|<\eta$, $B>|D(Y_{k-1}^{k-n},U_{k-1}^{k-m},\theta,k)|$. So θ_0 must meet the condition of $\|\theta_0\|<\eta$. When θ is available, function combination model has the same function for model free control and model free predictive control. Model free controller has various performances, such as convergence, anti-interference, decoupling. Model free predictive control also has these performances.

Simulation

The following system is chosen as controlled object.

$$y(k+1)=\frac{5y(k)y(k-1)}{1+y(k)^2+y(k-1)^2+y(k-2)^2}$$
$$+u(k)+1.1u(k-1)$$

In the predictive control, predictive time domain is $N_y = 3$, control time domain is $N_u = 3$, $\lambda = 0.09$. $y_r(k) = 75\sin(2k\pi/100)$, $y(1) = 0.1$, $y(2) = 0.2$, $y(3) = 0.1$, $u(1) = 0.3$, $u(2) = 0.5$, $u(3) = 0.6$. The least square method is used to get $\hat{\phi}(k-1)$ and the autoregressive model is set up.

$$\hat{\phi}(k) = \theta_1(k)\hat{\phi}(k-1) + \theta_2(k)\hat{\phi}(k-2)$$
$$+ \ldots + \theta_r(k)\hat{\phi}(k-r)$$

In the simulation $r = 3$, that is $\hat{\phi}(k) = \theta_1(k)\hat{\phi}(k-1) + \theta_2(k)\hat{\phi}(k-2) + \theta_3(k)\hat{\phi}(k-3)$.

The method of generalized recursion is used to get $\hat{\theta}(k)$. And then set up autoregressive model for $\hat{\theta}_1(k)$, $\hat{\theta}_2(k)$ and $\hat{\theta}_3(k)$. Then identify parameters by least square method, $\hat{\theta}_1(k+1)$, $\hat{\theta}_2(k+1)$ $\hat{\theta}_3(k+1)$, $\hat{\theta}_1(k+2)$, $\hat{\theta}_2(k+2)$ and $\hat{\theta}_3(k+2)$ are got.

$$\hat{\phi}(k) = \hat{\theta}_1(k)\hat{\phi}(k-1) + \hat{\theta}_2(k)\hat{\phi}(k-2) + \hat{\theta}_3(k)\hat{\phi}(k-3)$$

$$\hat{\phi}(k+1) = \hat{\theta}_1(k+1)\hat{\phi}(k) + \hat{\theta}_2(k+1)\hat{\phi}(k-1)$$
$$+ \hat{\theta}_3(k+1)\hat{\phi}(k-2)$$

$$\hat{\phi}(k+2) = \hat{\theta}_1(k+2)\hat{\phi}(k+1) + \hat{\theta}_2(k+2)\hat{\phi}(k)$$
$$+ \hat{\theta}_3(k+2)\hat{\phi}(k-1)$$

Control result in the above example is shown in Figure 1, Control error in the above example is shown in Figure 2, and control variable in the above example is shown in Figure 3. In Figure 1, the blue line represents set value curve and the green line represents system output curve. Then we do another example, and the controlled object is

$$y(k+1) = \frac{y(k)y(k-1) + u(k) - 0.2u(k-1)}{1 + y(k)^2 + y(k-1)^2 + y(k-2)^2}$$
$$+ u^2(k) - \sin(y(k-2)u(k-1))$$

In the predictive control, predictive time domain is $N_y = 4$, control time domain is $N_u = 4$, $\lambda = 0.2$.

$$y_r(k) = \begin{cases} 5 & 0 \le k < 10, 200 \le k < 300, 400 \le k < 500 \\ 10 & 100 \le k < 200, 300 \le k < 400 \end{cases}$$

$y(1) = 5$, $y(2) = 6$, $y(3) = 4$, $u(1) = 0.3$, $u(2) = 0.5$, $u(3) = 0.6$.

Control result in the above example is shown in Figure 4, Control error in the above example is shown in Figure 5, and control variable in the above example is shown in Figure 6. In Figure 4, the blue line represents set value curve and the green line represents system output curve. It can be seen from the two examples, when using model free predictive control algorithm for nonlinear system control, it can get good control effect, which proves the effectiveness of the proposed algorithm.

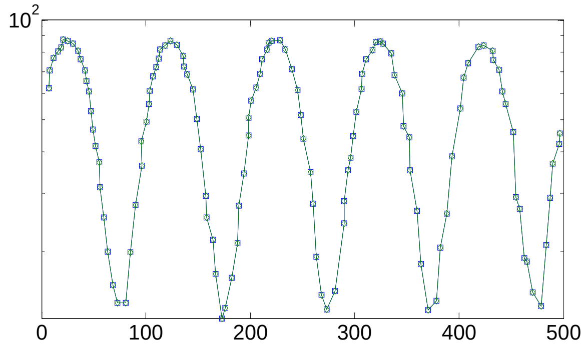

Figure 1 : Control result in example 1

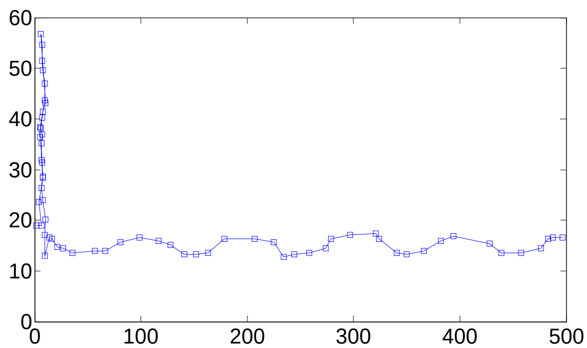

Figure 2 : Control error in example 1

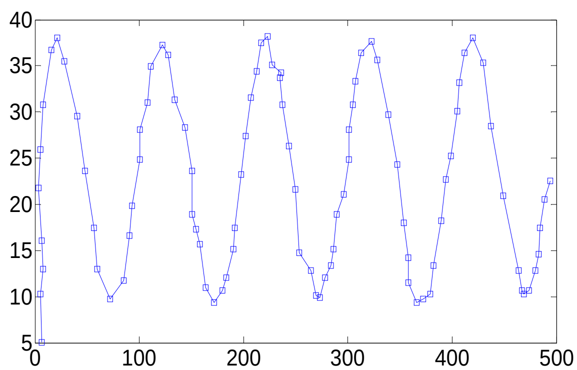

Figure 3 : Control variable in example 1

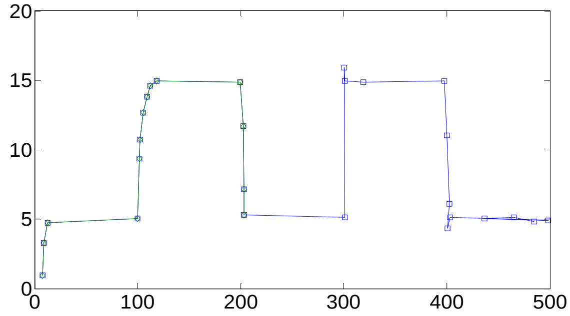

Figure 4 : Control error in example 2

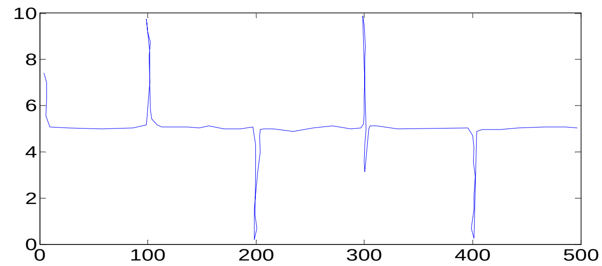

Figure 5 : Control error in example 2

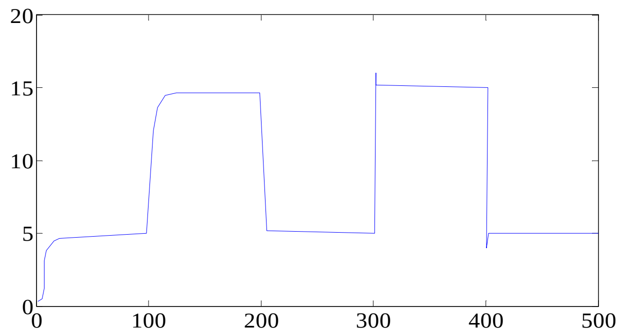

Figure : 6 Control variable in example

The 296 pairs of data of Box-Jenkins gas stove are used for simulation. The range of input data $v(k)$ is [-3, 3] and the range of output data $x(k)$ is [46, 61].

$$u(k)=\frac{v(k)+3}{3+3}.$$

$$y(k)=\frac{x(k)-46}{61-46}.$$

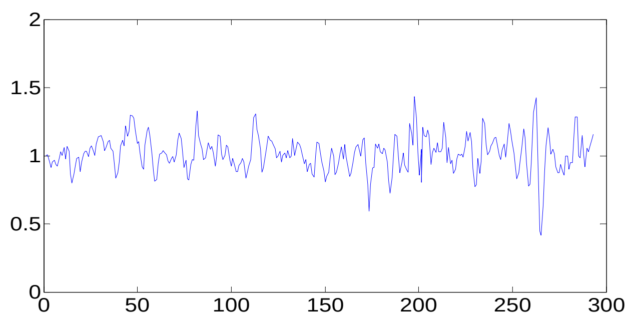

Figure7 : modeling error

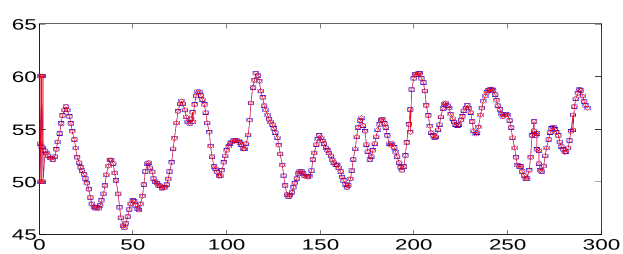

Figure 8 : Model output and fact output

Modeling error is shown in Figure 7 and model output and fact output is shown in Figure 8. The horizon axis represents time. Comparison of modeling for Box-Jenkins gas stove is shown in TABLE I. It can be seen the mean square error of our proposed algorithm is 0.098, which is smaller than other algorithms.

TABLE 1 : Comparison of modeling for Box-Jenkins gas stove

Model	The number of input	The number of rule	Mean square error
Tong(1977)	2	19	0.684
Pedrycz(1984)	2	81	0.565
Xu(1987)	2	25	0.572
Peng(1988)	2	49	0.548
Sugeno(1991)	6	2	0.261
Wang(1996)	2	5	0.397
Li(2003)	2	2	0.426
Lin jinxing（2006）	2	2	0.401
This paper			0.098

CONCLUSIONS

Nonlinear predictive control is an important research aspect in predictive control. Since most practical industrial processes have strong nonlinear characteristics, the research of nonlinear predictive control attracts more and more attention. In recent years, there have been many scholars committed to the research of nonlinear model predictive control, and they have achieved gratifying results. The basic principle of nonlinear predictive control is similar to the principle of linear predictive control, characterized by three mechanisms, model prediction, rolling optimization and feedback correction. Because of the nonlinear system is very complex, different nonlinear systems can be described by a specific form of nonlinear model.

As a category of control algorithm adopting online receding horizon optimization, model predictive control (MPC) attracts much attention of industrial and theoretical researchers due to its good control performance and capability of handling constraints explicitly. Over the past decades, qualitative synthesis of model predictive control rapidly develops and many important results are proposed. Predictive control is a control method based on but not confined by the model. Building prediction model is essential and critical to predictive control. Model predictive control (MPC) is nowadays arguably the most widely accepted control design technique in control of industrial processes. After more than thirty years research, many synthesis of model predictive control and many important results have been proposed. However, there is still a great gap between theories and applications because of some open problems, such as control performance, online computation burden and so on. Due to the lack of unified model description, predictive control of various nonlinear systems is based on the model description of different nonlinear systems. Therefore, it is necessary to study modeling in nonlinear system predictive control.

For a class of nonlinear system, a gas stove modeling method based on model free predictive control is presented. This method does not need modeling in the predictive control. The eigenvector of universal model is identified and predicted by multi-layer recursive method. With function combinations, the model free predictive control law has the same advantages as model free control does.

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