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Research Article

The PVC Stripping Process Predictive Control Based on the Implicit Algorithm

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According to the nonlinear and parameters time-varying characteristics of stripper temperature control system, the PVC stripping process Generalized Predictive Control based on implicit algorithm is proposed. Firstly, supporting vector machine is adopted to dynamically modelize for the stripper temperature; Secondly, combining with real-time model linearized of nonlinear model, a predictive model is linearized for real-time online correction. Then, the implicit algorithm is used for optimal control law. Finally, the simulation results show that the algorithm has excellent validity and robustness of temperature control of the stripper.

1. Introduction

Polyvinyl chloride (PVC) resin is a kind of bulk basis chemical raw material, one of the five common plastics. It is generated by the polymerization of vinyl chloride monomer PVC. Since vinyl chloride monomer has some toxicity, so the residual chloride in the PVC resin must be controlled within a certain range, which requires high precision of stripper temperature control. The removal of vinyl chloride monomer in PVC commonly uses stripping process, which is a typical complex industrial process with characteristics of highly nonlinear, time-varying and coupling. Domestic PVC stripper temperature control system usually uses cascade control scheme as common [1, 2], which is difficult to achieve highly precise control result. Therefore, it can improve the PVC product quality, reduce production costs and protect the environment to use advanced intelligent control technology in the stripping process.

Generalized Predictive Control (GPC), a computer control method developed with the Adaptive Control, has been successfully used in industrial process control. In recent years, for nonlinear predictive control system, many foreign scholars have proposed model predictive control method based on piecewise linear [3–6]. But domestic scholars use linear method or hierarchical optimization method, or directly use Hammersteina model, Wiener model, Volterra model, fuzzy reasoning and neural network as a predictive model for nonlinear model predictive control. And based on structural risk minimization support vector machine (SVM) regression, solved the small sample, nonlinearity, high dimension and local minima problems, and it has strong generalization ability. The researches of support vector machine used in Generalized Predictive Control are gradually increased, and there are some non-linear support vector machine based predictive control method [7, 8]. Literature [9] for nonlinear predictive control process ant colony algorithm is proposed rolling optimization least squares support vector machine (LS-SVM) predictive controller. Literature [10], in the process of treatment of sewage biochemical reaction, generalized the fuzzy adaptive predictive control method to achieve water quality indicators ammonia concentration and nitrate concentration of effective control.

The article puts forward the implicit algorithm PVC stripping process generalized predictive control based on high accuracy of PVC stripper temperature control. It builds models adopting support vector machine model as a predictive model after linearization, real-time online correction. And it adopts the implicit algorithm to solve for optimal control law. Simulation results show that the algorithm based on the implicit generalized predictive control for stripper temperature control with a good validity and robustness.

2. Modeling Method of Supporting Vector Machine Regression

2.1. Principle of Support Vector Machine Regression. PVC stripping process is a complex industrial process with strong nonlinear characteristics. For non-linear support vector regression, the basic idea is to map the data into a high dimensional feature space through a nonlinear mapping, and then linear regression in this space. Thus, linear regression of the high dimensional feature space corresponds to the low dimensional input space nonlinear regression. The specific method is implemented by the kernel function $K(x_i, x_j) = \Phi(x_i)\Phi(x_j)$. Finally it gets global optimal solution by solving the following quadratic programming problem:

$$\begin{aligned} W(\alpha,\alpha^*) = \max & \left\{ -\frac{1}{2}\sum_{i,j=1}^{n}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)k(x_i,x_j) \right. \\ & \left. +\sum_{i=1}^{n}(\alpha_i-\alpha_i^*)y_i-\sum_{i=1}^{n}(\alpha_i+\alpha_i^*)\varepsilon \right\} \\ \text{s.t.} \quad & \sum_{i=1}^{n}(\alpha_i-\alpha_i^*)=0, \\ & 0\le\alpha_i, \quad \alpha_i^*\le C, \quad i=1,\dots,n. \end{aligned} \tag{1}$$

Then substitute the obtained parameters α_i, α_i^* into the following formula:

$$\omega = \sum_{i=1}^{n}(\alpha_i-\alpha_i^*)\Phi(x_i). \tag{2}$$

Regression function can be derived:

$$\begin{aligned} f(x) &= \sum_{i=1}^{n}(\alpha_i-\alpha_i^*)(\Phi(x_i)\cdot\Phi(x))+b \\ &= \sum_{i=1}^{n}(\alpha_i-\alpha_i^*)K(x_i,x_j)+b. \end{aligned} \tag{3}$$

When $\alpha_i - \alpha_i^*$ is not equal to zero, the corresponding sample data is the support vector. When b is taken on the boundary point, the mean value, that is,:

$$b = \text{average}_k\left[\sigma_k + y_k - \sum_{i=1}^{n}(\alpha_i-\alpha_i^*)K(x_i,x_k)\right] \tag{4}$$

σ_k is the prediction error, which varies different loss functions for different values.

2.2. Construction of Stripper Model. PVC stripping process has the characteristic of nonlinear, and the object model is difficult to be accurately established. First of all, to establish the procedure for support vector regression model, the following nonlinear system model is introduced:

$$\begin{aligned} Y(k) = f(&y(k-1),\dots,y(k-n),u(k-1),\dots, \\ &u(k-m),w(k-1)) \quad y\in R^n,\ u\in R^n,\ m\le n. \end{aligned} \tag{5}$$

Among them, $u(k)$, $y(k)$ and $w(k)$ represent the input, output, and disturbance of the controlled object, take input $U(k) = (u_{k-m}, u_{k-m+1}, \dots, u_k)$ and output $Y(k) = (y_{k-n}, y_{k-n+1}, \dots, y_{k-1})$ to form the input vector of SVM form: $X(K) = [y(k-1), \dots, y(k-n), u(k), \dots, u(k-m)]$, the form of the training samples: $(X(k), Y(k))$, ignoring the disturbance $w(k)$, by support vector regression we can get the following model:

$$y_M(k) = \sum_{i=1}^{l}(\alpha_i-\alpha_i^*)K(X_i,X_k)+b. \tag{6}$$

In the formula, X_i is the support vector, l is the number of support vectors. According to the process of PVC stripping analysis, it is known that stripper top temperature accuracy must be strictly controlled to remove vinyl chloride monomer content in PVC. Therefore, this paper selects the stripper top temperature as the output vector of the model $y(k)$. In the slurry flow and steam flow uniformity conditions, the slurry flow and steam flow input vectors that comprise the model $u(k)$, that is to say, SVM input vectors $X(k)$ is constituted by the stripper top temperature $y(k)$, composed vector of Slurry flow and steam flow $u(k)$, the value of n and m is 2 and 4.

According to the site of the 106 group field data collection, to be normalized, of which 53 groups are used SVM training sample, with the other 53 group as the test samples. In the simulation, selecting the polynomial kernel function $q = 2$, the insensitive coefficient $\varepsilon = 0.2$, capacity control $C = 40$, 53 training sample get obtained SVM 39, then the established model can be expressed as:

$$y(k) = \sum_{i=1}^{39}(\alpha_i-\alpha_i^*)[(X_i\cdot X_k+1)]^2+b. \tag{7}$$

In the formula, X_i is the support vector b is the threshold value, in this experiment $b = 0.5322$, $[(X_i \cdot X_k) + 1]^2$ is the polynomial kernel function.

The parameters of support vector machine model that supports vector coefficients is shown in Table 1, As can be seen from Table 1, when parameter $\alpha_i - \alpha_i^*$ is zero, it means that the vector is non-support vector, otherwise $\alpha_i - \alpha_i^*$ is the support vector.

The formula (7) with a non-linear model is transformed into a form with characteristic of quadratic programming, quadratic programming algorithm in Matlab support vector machine regression. Figures 1 and 2 are output model and the real value of the contrast of the output curve obtained in the training and testing samples under the input.

Meanwhile, introducing the variance as the evaluation indexes: $(1/(n-1))\sum_{i=1}^{n}(Y_m - Y_r)^2$. Y_m is the output of the support vector model, Y_r is the actual output value. Training

Table 1: The parameter of SVM model.

Number of group	$\alpha_i - \alpha_i^*$
1	−0.6541
2	0.0000
3	0.7959
4	0.0000
5	−0.6588
6	0.3045
7	0.9018
8	−0.5018
9	1.0000
10	1.0001
11	0.9666
12	1.0001
13	1.0000
14	−0.4135
15	−0.0000
16	−0.0000
17	−0.2612
18	−0.0609
19	−1.0118
20	−0.6405
21	1.0000
22	−1.0000
23	−1.0000
24	1.0000
25	−1.0000
26	−1.0000
27	1.0000
28	−0.5313
29	0.0000
30	−0.0000
31	−0.0000
32	0.0000
33	0.5482
34	0.3102
35	0.0000
36	1.0000
37	0.3309
38	−1.0000
39	−1.0000
40	−0.0008
41	0.0000
42	0.0000
43	0.0000
44	0.2357
45	0.5109
46	−1.0000
47	−0.0000
48	0.6334
49	1.0000
50	1.0005
51	1.0000
52	−0.0725
53	−0.0000

error is calculated as $1.5937 * 10^{-3}$, test error is 0.0194. It uses support vector regression model to meet the requirements of the stripping process modeling.

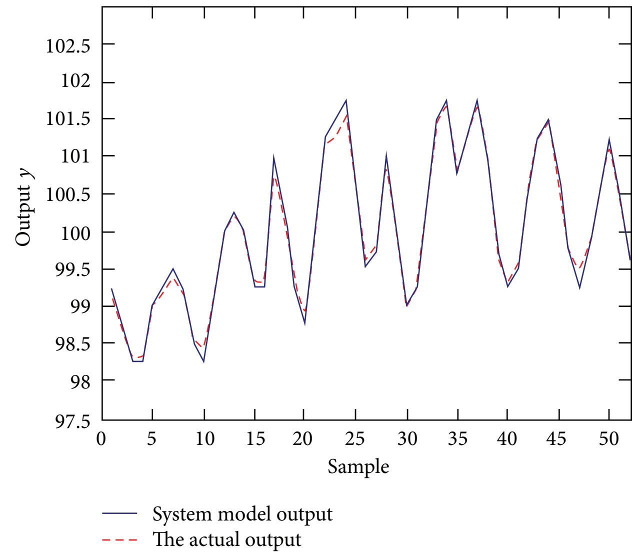

Figure 1: The simulation of modeling on SVR (Training sample).

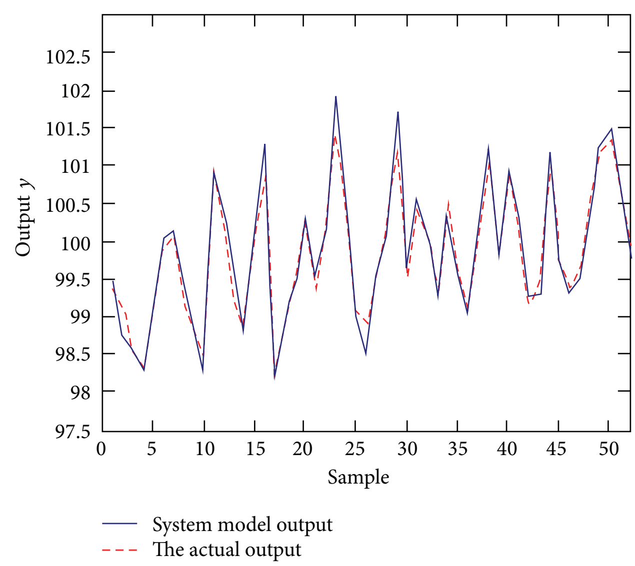

Figure 2: The simulation of modeling on SVR (Testing sample).

3. Generalized Predictive Control Based on SVM

3.1. Prediction Model. Using a support vector machine method to create predictive models, it turns the nonlinear systems into linear time-varying systems, and thus adopts the generalized predictive algorithm based on linear model, and realizes the generalized predictive control of nonlinear systems [11]. The stripping process SVM model of PVC is shown as the following formula:

$$y(k) = \sum_{i=1}^{39} (\alpha_i - \alpha_i^*) \left[(X_i \cdot X_k) + 1 \right]^2 + b. \tag{8}$$

Then linearize the following formula (8) at the sampling time using Taylor equation, the parameters of generalized predictive control model is obtained:

$$a_j(k) = -\sum_{i=1}^{39} (\alpha_i - \alpha_i^*) 2 [(X_i \cdot X_k) + 1] X_i(j), \quad j = 1, 2, 3,$$
$$b_j(k) = \sum_{i=1}^{39} (\alpha_i - \alpha_i^*) 2 [(X_i \cdot X_k) + 1] \times X_i(j+4), \quad j = 0, 1, 2, 3. \tag{9}$$

The linearized model is:

$$\begin{aligned} y(k) &+ a_1(k) y(k-1) + a_2(k) y(k-2) + a_3(k) y(k-3) \\ &= b_0(k) u(k-1) + b_1(k) u(k-2) + b_2(k) u(k-3) \\ &\quad + b_3(k) u(k-4) + Y_c(k-1). \end{aligned} \tag{10}$$

In the formula, parameters a_j and b_j are related to support vector machines. Number of support vectors is also decided by the number of data input and output, after the linearization, CARIMA generalized predictive control model based on linear control algorithms for predictive control of nonlinear systems can be used.

3.2. Design of the Predictive Controllers. The article begins with the stripping process of PVC for support vector machine modeling, with model online correction, and then linearized as Generalized Predictive Control prediction model and solves the optimal control law when using implicit algorithm, avoiding online solving Diophantine equations, thereby reducing the amount of computation.

PVC stripping process is a typical nonlinear system. When input is $u(k)$, output is $y(k)$, the system output $y_m(k)$ can be obtained by the SVM predict model through the past input and output data of systems and the amount of current control input $u(k)$. Then the deviation between the actual system output and predicted output is:

$$e(k) = y(k) - y_m(k). \tag{11}$$

Predict model is:

$$y_p(k+i) = y_m(k+i) + e(k). \tag{12}$$

In the feedback correction, the use of SVM modeling can be corrected online, but in order to reduce the amount of computation repeated correction model, the following correction strategies can be used:

(1) When the error e between the actual output value and predicted output is bigger than the allowable error (take SVM insensitive loss function ε), re-establishment of the model.

(2) When the error e between the actual output value and predicted output is smaller than the allowable error, in order to reduce the computational model reconstruction, the general error model for feedback correction should be used.

Reference trajectory chooses one-order filter equations yields:

$$y_r(k+i) = \alpha y(k) + (1-\alpha) y_r, \quad i = 1, 2, \ldots, n. \tag{13}$$

In the formula, y_r, $y(k)$ and $y_r(k+i)$ are Set value, the system output and the reference trajectory respectively; α is the soften modulus, $0 < \alpha < 1$.

Performance index function select:

$$J = \sum_{i=1}^{n} [y(k+i) - y_r(k+i)]^2 + \sum_{i=1}^{m} \lambda_i [\Delta u(k+i-1)]^2. \tag{14}$$

Written in vector form as follows:

$$J = (Y - Y_r)^T (Y - Y_r) + \lambda \Delta U^T \Delta U. \tag{15}$$

Derivation of future control increment, that is

$$\frac{\partial J}{\partial \Delta U} = 0. \tag{16}$$

The optimal control law is:

$$\Delta U = \left(G^T G + \lambda I\right)^{-1} \left(G^T (Y_r - f)\right). \tag{17}$$

Expand the above equation, the control increment sequence of the open-loop control from time k to time $k+m-1$, $\Delta u(k)$, $\Delta u(k+1), \ldots, \Delta u(k+m-1)$ can be get:

$$\Delta u(k+i-1) = d_i^T (Y_r - f). \tag{18}$$

In the formula, d_i^T is the i row vector of $(G^T G + \lambda I)^{-1} G^T$, and $d_i^T = [d_{i1} \ \ d_{i2} \ \ \cdots \ \ d_{in}]$.

While in actual practice, each time only the first component added to the system, while the control increment moments later recalculated each step, closed-loop control measure is achieved, then we only need to calculate the first row d_1^T of $(G^T G + \lambda I)^{-1} G^T$.

Now, the actual implementation is:

$$u(k) = u(k-1) + d_1^T (Y_r - f). \tag{19}$$

According to the actual input and output data of the Stripper, directly identify the matrix G and vector predictive of open loop f, and then get the control increment ΔU.

The best predictive value can be drawn from projections theory:

$$\widehat{Y} = G \Delta U + f. \tag{20}$$

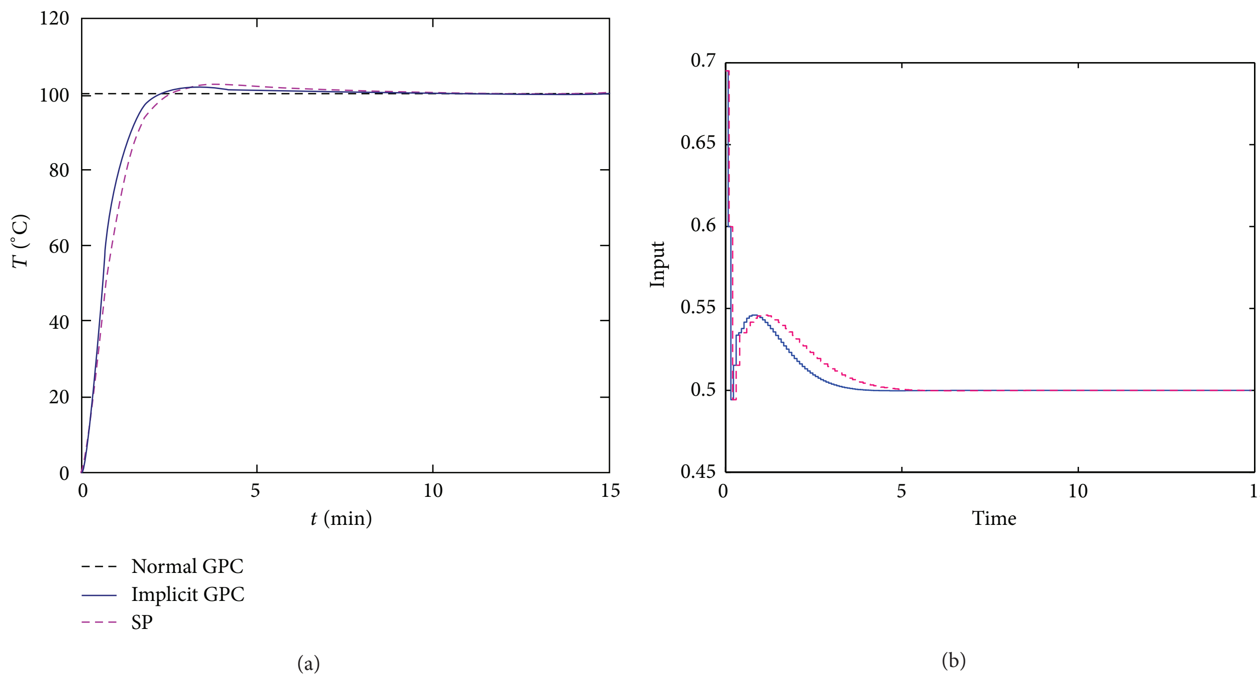

FIGURE 3: The control result of PVC stripping process in proper operation.

3.3. Generalized Predictive Control Implicit Algorithm Steps. The generalized predictive algorithm strikes the optimal control law algorithms with identification of the controller parameters directly from the input and output data. It avoids the online solving Diophantine equations and inverse matrix to improve the speed of operation and save computing time.

Step 1. Algorithm Initialization: The length of time domain $nn = 7$, Forecast length $n = 6$, Controlling length $m = 2$, the weighting coefficients of controlling parameter $t_0 = 1.8$, soften coefficient $\alpha = 0.85$ and forgetting factor $K_1 = 1$.

Step 2. Set square P to a diagonal matrix; Set the initial value of the input output sequence $X(K) = [y(k-1), \ldots, y(k-n), u(k), \ldots, u(k-m)]$, Produce a given value the signal Y_r.

Step 3. According to formula (7), calculate the output values $y_m(k)$ of time k, conserve n output values before time k to modelize calculation; when error $e > \varepsilon$, rebuild the model; when error $e < \varepsilon$, use the error to correct the model.

Step 4. According to the recursive least squares equation, $y(k)$ calculate the element of G $g_0, g_1, \ldots, g_{n-1}$, get the matrix G.

Step 5. According to the vector Y_0 latter time, calculate the forecast vector f; the output $y(k)$ of time k and set value Y_r, get the reference trajectory after time k.

Step 6. Calculate and reserve m control increments after time k; draw the given value, the output value.

4. PVC Stripping Process Control Simulation

In the control system of PVC stripping process, the support vector machine modeling and Generalized Predictive Control Implicit algorithm are combined with online correction of the model and error models feedback correction, and PVC stripping process is studied according to the actual situation to simulation. PVC stripping process according to the actual process, the stripper top temperature optimum temperature of 100°C, so the simulation signal is a given value 100°C.

Using support vector machine model obtained by the linearized expression:

$$y(k) = 2.5y(k-1) - 2.2y(k-2) + 0.7y(k-3) + 0.08u(k-1) + 0.12u(k-2). \tag{21}$$

Compare the Simulation curve of the normal algorithm GPC and implicit algorithm GPC. Simulation predicted length $n = 6$, controllable length $m = 2$, the weighting coefficients of the control parameter $t_0 = 1.8$, soften coefficient $\alpha = 0.85$ and forgetting factor $K_1 = 1$. According to the actual situation may arise during the stripping process, four main cases are considered in the simulation.

(1) Good condition during operation, shown in Figure 3.

Curve can be seen from Figure 3. The system can track a smooth change of the reference signal output. Figure 3 also shows the general algorithm for GPC, Implicit algorithm for GPC effect curves, it can be seen that the implicit algorithm by reducing the amount of computation, control effect can be improved.

(2) Set value temperature changes because of the different grades of polyvinyl chloride resin, or process requirements,

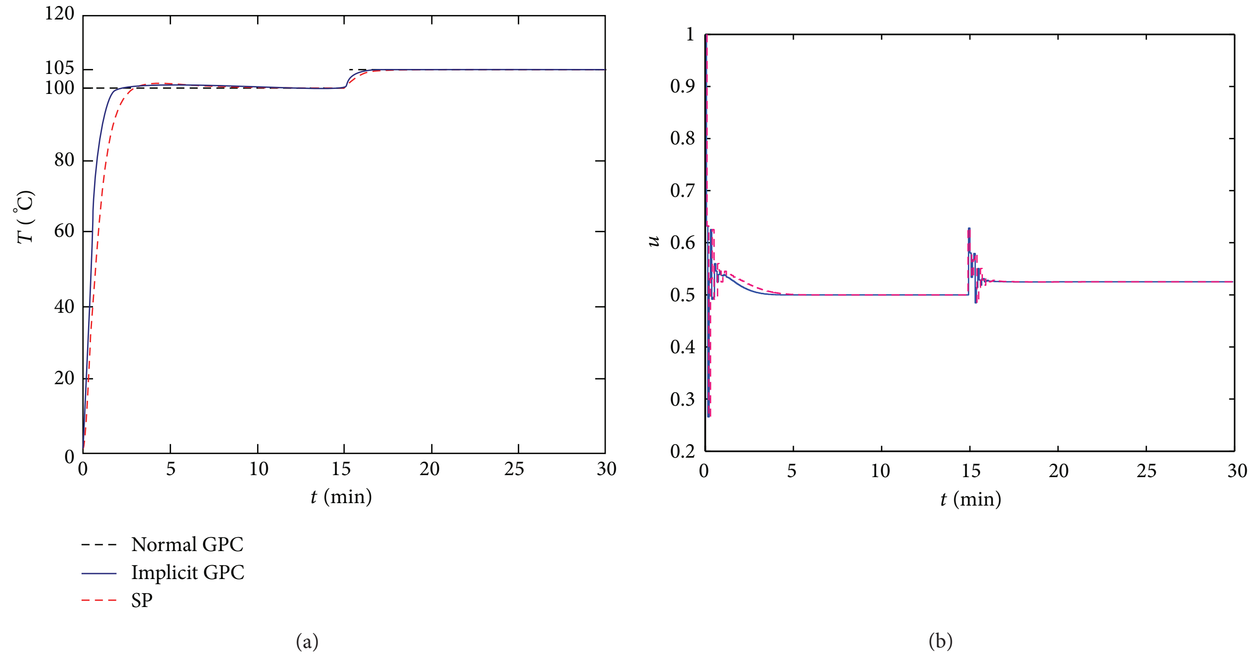

Figure 4: The control result of PVC stripping process when set value changed.

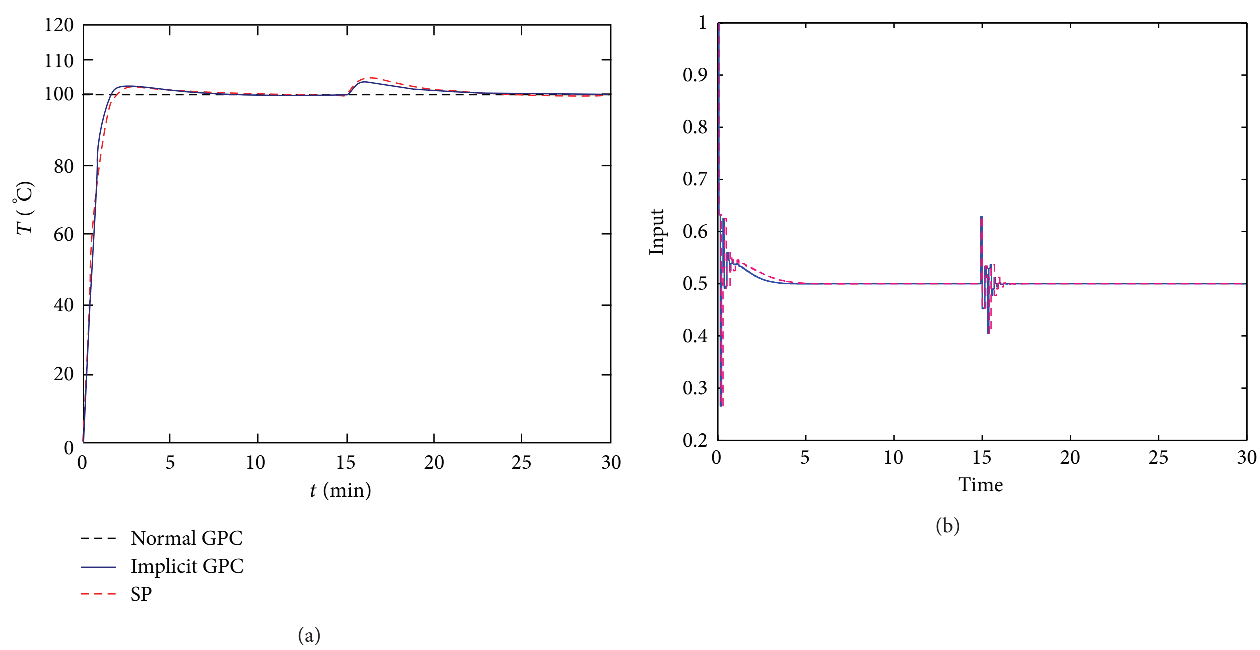

Figure 5: The control result of PVC stripping process by a sudden noise.

the optimum temperature of the stripping column top is different. The simulation is given the first 15 minutes 100°C, in 15 minutes changing the resin grades; the optimum temperature was changed to 105°C, as the obtained control effect curve shows in Figure 4.

As can be seen from Figure 4, when the given value is changed, the system can quickly respond to and track new set value. In addition, the use of implicit algorithm generalized predictive has faster response speed.

(3) When the controlled object was disturbed, such as the uneven heating of the slurry and other factors led to sudden abrupt changes in temperature.

The simulation time of 15 minutes, adding the amplitude of a sudden disturbance 5°C, as control effect curve shown in Figure 5, and it can be seen that the system is disturbed suddenly, the system can quickly overcome the disturbance, the control to a given values, control of implicit algorithm has better control effect.

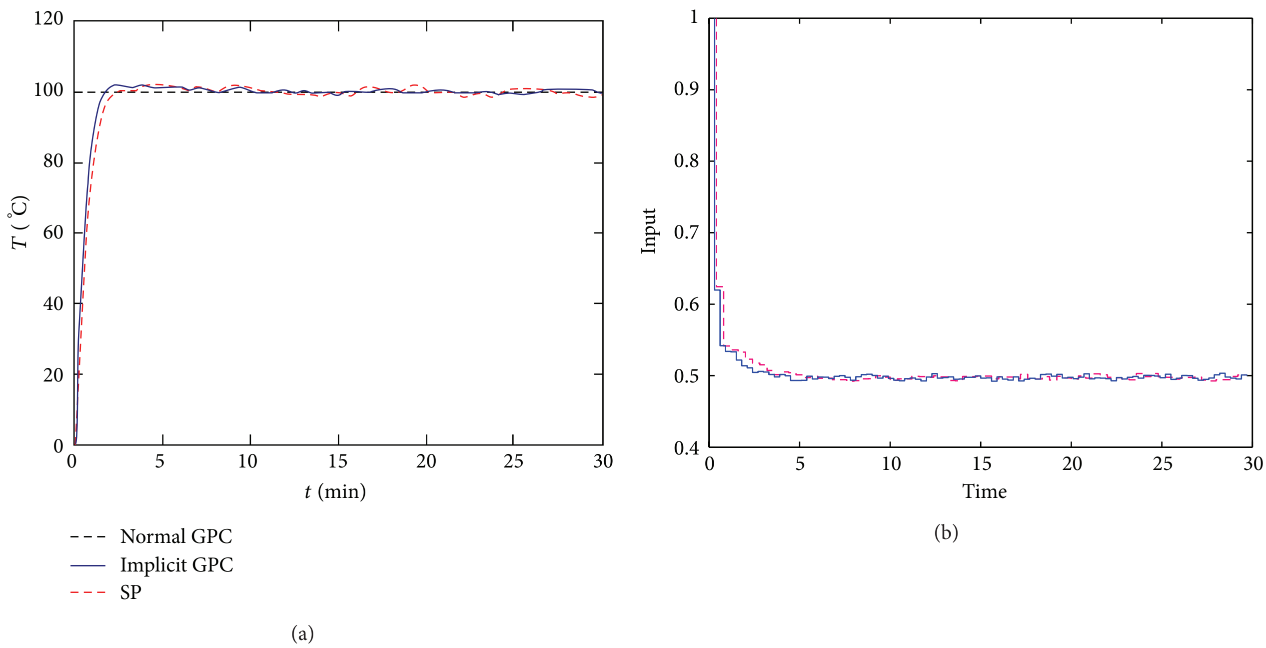

Figure 6: The control result of PVC stripping process by random noise.

(4) In simulation, during operation subject to the random disturbance of uncertainties factor is added, the value at −5~+5°C, for controlling the effect of the curve in Figure 6, can be seen in systems are known in the case of random disturbance. The system has better robustness. Controlled temperature value is near the set value and the deviation is small, it can be seen from Figure 6 that the rate of change of the implicit algorithm control effect is small with better robustness.

Above four cases can be seen from the simulation curve, using the implicit algorithm for GPC was better than general for GPC control effect.

5. Conclusion

The dynamic modeling is adopted based on the principle of support vector machines and the field data of PVC stripping process. Meanwhile, it combines the model online correction and error feedback correction with the real-time linear and nonlinear model. And the Generalized Predictive Control is adopted by using implicit algorithm with stripping process of PVC. Simulation results verify the validity of the model and the feasibility and robustness of the algorithm.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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