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Research Article

Research on Pressurizer Pressure Control Based on Adaptive Prediction Algorithm

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According to the high control quality requirements of nuclear power plants and the features of the pressurizer pressure with large inertia, time-varying, nonlinear, multi-interference, difficulty in obtaining accurate mathematical model, and open-loop unstable dynamic characteristic, the advanced control strategy is needed for pressurizer pressure control performance optimization. To tackle the problem, an adaptive predictive control method for pressurizer pressure is devised in this paper. Firstly, the non-self-regulating system is stabilized and the adaptive dynamic matrix controller is designed by identifying the controlled object online. In order to realize the engineering application for this controller, then the control signal output is obtained. Finally, the control system simulation platform is built. Simulation results reveal a superior control performance, disturbance rejection, and adaptability. Furthermore, it provides a solution for the application of dynamic matrix control algorithm in non-self-regulating system.

1. Introduction

Load changes or core reactivity disturbances may cause pressure changes in the primary circuit of a nuclear power plant. If the primary circuit pressure is too high, it may lead to equipment fatigue and pipeline rupture. If the pressure is too low, the risk of melting the fuel element may increase [1]. A pressurizer is a major component to control a system pressure in primary circuit for a nuclear power plant. Most of the existing pressurizer pressure control systems adopt the PID control strategy. Because of the high control quality requirements of nuclear power plants and the nonlinear characteristics of pressurizer pressure under different operating conditions, PID sometimes does not guarantee good control effect. Therefore, many studies have been done by scholars to optimize the pressurizer pressure control effect.

An internal model PID control system is applied to the pressurizer pressure control, which shows superior control performance compared with PID [2]. A fuzzy PID joint control system using logic judgment and switch shifting [3] is designed, which shows good control results. However, the selection of switching thresholds and the establishment of fuzzy controller came from experience, which is not conducive to learning and promotion. On the other hand, the pressurizer pressure has the features of large inertia, time-varying, nonlinear, multi-interference, difficulty in obtaining accurate mathematical model, and open-loop unstable dynamic characteristic. All these features lead to problem of choosing an appropriate method for control performance optimization.

Predictive control algorithm has lower requirements on model and has characteristics of rolling optimization and feedback correction. Dynamic Matrix Control (DMC) has been widely used in industrial process control, but it will produce truncation error when modeling non-self-regulating objects. The DMC algorithm is improved based on the objects' step response characteristics of an approximate straight line in the final stage [4]. A stable generalized predictive controller (SGPC) is designed by decomposing the non-self-regulating model [5], which theoretically solves the non-self-regulating system control problem. Rossiter et al. and Rossiter and Kouvaritakis [6, 7] make use of the particularity of SGPC

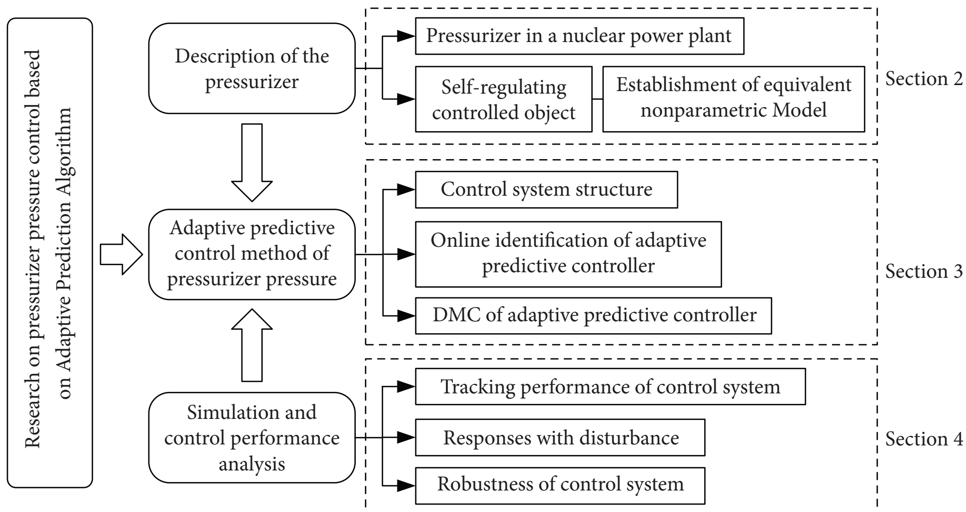

Figure 1: Article structure layout.

structure to carry on massive research to the constrained predictive control, which obtains better stability results. Constrained predictive control algorithm can improve the dynamic performance and the disturbance rejection ability to large-inertia, large-delay controlled objects, but it has poor adaptability to time-varying and nonlinear controlled objects.

Adaptive control can adapt to changes in the dynamic characteristics of objects and disturbances. Adaptive control and fuzzy control are combined and applied to the pressurizer pressure regulation of nuclear power plant with pressurized water reactor (PWR) [8] and vessel nuclear power plant [9], which can improve the robustness, rejection of disturbances, and adaptability of model changes. Model-free adaptive control is used to optimize the steam generator water level in nuclear power plant [10]. An adaptive output feedback structure is designed based on uncertain nonlinear system with time-varying delay [11]. Comparing the nonlinear model predictive control and the generalized predictive control [12], it shows that the former has a better control effect, but it requires more calculation time. In order to optimize operation speed, the offline calculation is converted to online optimization and the model predictive control (MPC) is improved [13]. However, few of the above methods have been applied to a pressurizer pressure control system, and few of them mentioned in the collection of engineering control signal output.

Therefore, an advanced control strategy for non-self-regulating system and its practical value of engineering are two main problems of pressurizer pressure control performance optimization. In this paper, the pressurizer pressure adaptive predictive control method based on DMC algorithm is designed. Firstly, a feedback structure is used to self-stabilize the non-self-regulating system and the adaptive predictive controller is designed by identifying the controlled object online. Then, the control signal output is solved to make this controller easy to be implemented in engineering. Finally, the feasibility of the controller design is verified by simulation comparison and disturbance test.

In Section 2, the pressurizer of a nuclear power plant and the equivalent nonparametric model of pressurizer pressure are illustrated. Section 3 presents the control method and the adaptive predictive controller. Section 4 analyzes the performance of the proposed control method. Finally, conclusions are made in Section 5. Figure 1 shows an article structure layout of the main content of this paper.

2. Description of the Pressurizer

2.1. Pressurizer in a Nuclear Power Plant. The pressurizer is an important equipment in primary circuit for a nuclear power plant. The basic functions of the pressurizer are pressure control, pressure protection, and compensation of primary circuit coolant volume change. According to the different structure and operating principles, the pressurizer can be divided into gas tank pressurizer and electrothermal pressurizer. The structure of the gas tank pressurizer is simple, but there are certain nuclear safety issues in the process of compressing air or high-pressure inert gas. Therefore, the electrothermal pressurizer is often used in modern nuclear power plants.

The structure of the electrothermal pressurizer is shown in Figure 2. The upper part is the steam space, the lower part is the water space, and the bottom is connected to the primary circuit heat pipe section through the surge line. The conventional PWRs adopt a saturated steam pressure regulation method to achieve pressure control by electric heating and spraying. More specifically, the pressurizer is made up of the spray system, the electric heater unit, the safety valve group, and the measuring instrument. The spray system, which is primarily composed of spray valves, is used to spray the coolant with a low temperature to reduce the pressure of primary circuit. The electric heater unit, which consists of electric heating rods, is used to heat the coolant in pressurizer to raise the pressure of primary circuit.

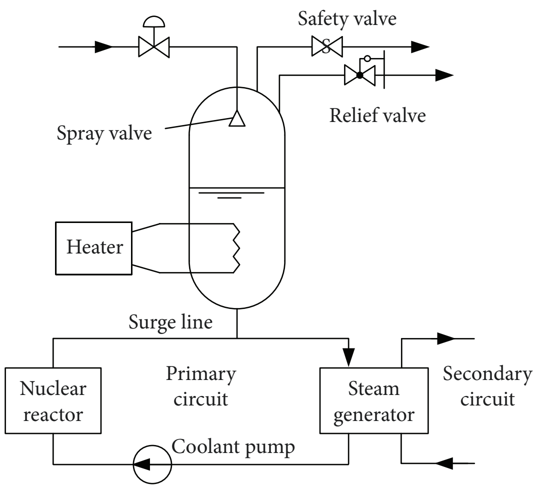

FIGURE 2: Structure of the electrothermal pressurizer.

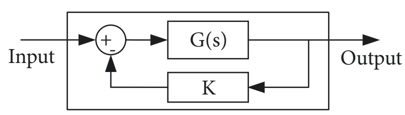

FIGURE 3: Structure of controlled object with feedback.

2.2. Establishment of Pressurizer Pressure Equivalent Nonparametric Model. In order to obtain an equivalent nonparametric model, it is necessary to self-stabilize the non-self-regulating controlled object. The model of non-self-regulating controlled object can be described as

$$G(s) = \frac{k_o}{s(Ts+1)} e^{-\tau s}. \tag{1}$$

Given the feedback channel gain K, the structure of the controlled object with feedback is shown in Figure 3.

The model in Figure 3 can be expressed as follows:

$$G_1(s) = \frac{G(s)}{1 + K \times G(s)} = \frac{k_o}{Ts^2 + s + Kk_o e^{-\tau s}} e^{-\tau s}. \tag{2}$$

The stability of $G_1(s)$ in (2) is related to the value of K. When K is smaller than the reciprocal of the product of k_o and τ, $G_1(s)$ is stable [14]. It can be seen that the pure delay link in the denominator is too complex to be directly used as a predictive controller internal model and needs to be simplified. According to the differential deflection linearization method of a univariate nonlinear system, the pure delay link in denominator can be expanded to the Taylor series near the steady-state point, and the high-order term is omitted. The simplification is shown in

$$e^{-\tau s} \approx 1 - \tau s + \tau^2 s^2. \tag{3}$$

Substituting (3) into (2) results in an equivalent model.

$$G_2(s) = \frac{k_o}{(T + Kk_o\tau^2)s^2 + (1 - Kk_o\tau)s + Kk_o} e^{-\tau s}. \tag{4}$$

If $G_1(s)$ is stable, the equivalent model $G_2(s)$ in (4) can be considered as a self-regulating controlled object to design the initialization parameters of dynamic matrix controller. Taking the opening of spray valve to adjust the pressurizer pressure as an example, this paper obtains experimental data from the nuclear power plant simulator and identifies the transfer function $G(s)$ in (1) under different operating conditions. The full scope simulator has a 1 : 1 fidelity with the nuclear power plant; hence, it is equivalent to the actual data source of the nuclear power plant. $G(s)$ that shows the dynamic characteristics between the spray valve opening and the pressurizer pressure is shown in Table 1.

The equivalent nonparametric model of DMC is easily obtained from $G_2(s)$. Assuming the equivalent nonparametric model is $A_1 = [a_1, a_2, \dots, a_N]^T$, N is the modeling time domain. The sampling period is selected as 100 s. It is easy to get the equivalent nonparametric model A_{1-100}

$$\begin{aligned} A_{1-100} = [&-0.0445, -0.0870, -0.1277, -0.1665, -0.2036, \\ &-0.2390, -0.2729, -0.3053, -0.3362, -0.3657, \dots, \\ &-0.9999, -0.9999, -0.9999, -0.9999, -0.9999]^T. \end{aligned} \tag{5}$$

where A_{1-100} is a 200-dimensional column vector and the subscript of A represents A_1 under 100% operating condition. The equivalent nonparametric model A_{1-90} is as follows:

$$\begin{aligned} A_{1-90} = [&-0.0975, -0.1855, -0.2650, -0.3366, -0.4013, \\ &-0.4597, -0.5124, -0.5600, -0.6029, -0.6416, \dots, \\ &-0.9999, -1.0000, -1.0000, -1.0000, -1.0000]^T, \end{aligned} \tag{6}$$

where A_{1-90} is a 100-dimensional column vector, and the subscript of A represents A_1 under 90% operating condition. The equivalent nonparametric model A_{1-80} is as follows:

$$\begin{aligned} A_{1-80} = [&-0.1154, -0.2175, -0.3078, -0.3876, -0.4583, \\ &-0.5208, -0.5761, -0.6250, -0.6683, -0.7066, \dots, \\ &-1.0000, -1.0000, -1.0000, -1.0000, -1.0000]^T, \end{aligned} \tag{7}$$

where A_{1-80} is a 100-dimensional column vector and the subscript of A represents A_1 under 80% operating condition.

3. Adaptive Predictive Control Method of Pressurizer Pressure

3.1. Control System Structure. The structure of the pressurizer pressure control system based on adaptive prediction algorithm is shown in Figure 4. The self-regulating controlled

Table 1: Mathematical model of the controlled object.

Operating condition	100%	90%	80%
Transfer function (MPa/%)	$-4.553 \times 10^{-4}/s$	$-1.0261 \times 10^{-3}/s$	$-1.2261 \times 10^{-3}/s$

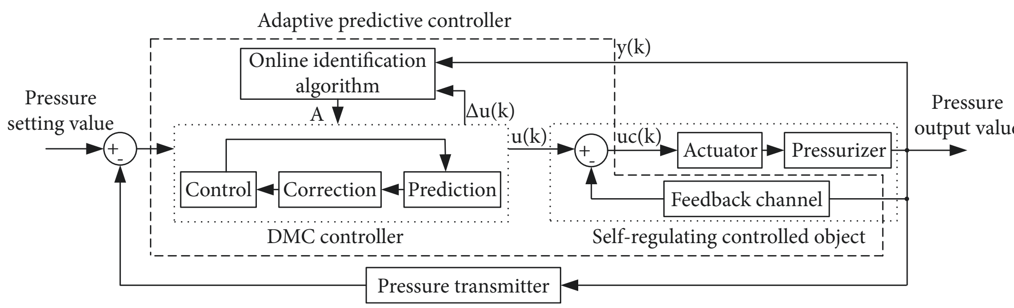

Figure 4: Structure of control system based on adaptive predictive algorithm.

object consists of feedback channel, actuator, and pressurizer controlled object. Then, the control signal output $u_C(k)$ of adaptive predictive controller is obtained by (8). And the pressurizer pressure adaptive predictive controller that directly acts on non-self-regulating system is established.

$$u_C(k) = u(k) - Ky(k), \tag{8}$$

where k represents the time of simulation, $u(k)$ is the controller output at step k, K is the feedback channel gain, and $y(k)$ is the pressure output at step k.

The adaptive predictive controller is composed of online identification algorithm module, DMC controller module, and feedback channel module. The online identification algorithm module is an online identification layer. The DMC controller module and the feedback channel module are control layer. The online identification layer and the control layer work in parallel. The online identification algorithm uses the current and the historical values of control increment $\Delta u(k)$ and pressure output $y(k)$ to calculate the dynamic matrix A of DMC controller online, which achieves the purpose of self-adaptation of the controller. A consists of the element values in A_1, which can be obtained by (9). The DMC algorithm is a predictive control algorithm based on device step response and applicable to progressively stable linear device [15]. Its predictive model is easy to obtain from engineering, and it has less computations and strong robustness. The online cyclic operation with prediction, correction, and control achieves prediction and optimization.

$$A_1 = \Delta U_2(k) \times Y_2(k), \tag{9}$$

where $\Delta U_2(k)$ consists of the element values in $\Delta U_1(k)$ to form an N-dimensional matrix, $\Delta U_1(k)$ is a sequence of N control incremental historical values, $Y_2(k)$ consists of the element values in $Y_1(k)$ to form an N-dimensional column vector, and $Y_1(k)$ is a sequence of $N+1$ pressure output historical values.

$$\begin{aligned}
\Delta U_1(k) &= [\Delta u(k-N), \cdots, \Delta u(k-2), \Delta u(k-1)]^{\mathrm{T}}, \\
Y_1(k) &= [y(k-N), \cdots, y(k-1), y(k)]^{\mathrm{T}}, \\
\Delta U_2(k) &= \begin{bmatrix} \Delta u(k-N) & 0 & \cdots & 0 \\ \Delta u(k-N+1) & \Delta u(k-N) & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ \Delta u(k-2) & \Delta u(k-3) & \cdots & 0 \\ \Delta u(k-1) & \Delta u(k-2) & \cdots & \Delta u(k-N) \end{bmatrix}^{-1}, \\
Y_2(k) &= \begin{bmatrix} y(k-N+1) - y(k-N) \\ y(k-N+2) - y(k-N) \\ \cdots \\ y(k-1) - y(k-N) \\ y(k) - y(k-N) \end{bmatrix}.
\end{aligned} \tag{10}$$

3.2. Online Identification of Adaptive Predictive Controller

3.2.1. Online Identification Algorithm Structure. The online identification algorithm continuously detects the instantaneous $\Delta u(k)$ and the current $y(k)$ and updates the vectors $\Delta U_1(k)$, $Y_1(k)$, and $Y_2(k)$ and the matrix $\Delta U_2(k)$ in real time. Then, A_1 of the controlled object is calculated, and finally, the dynamic matrix A is obtained for adaptive predictive control, which completes online identification of the controlled object model. The algorithm flowchart is shown in Figure 5.

At each time k, the control increments of first $k-1$ times in $\Delta U_1(k)$ are shifted up by one, then the online identification module detects the current $\Delta u(k)$ to replace the original

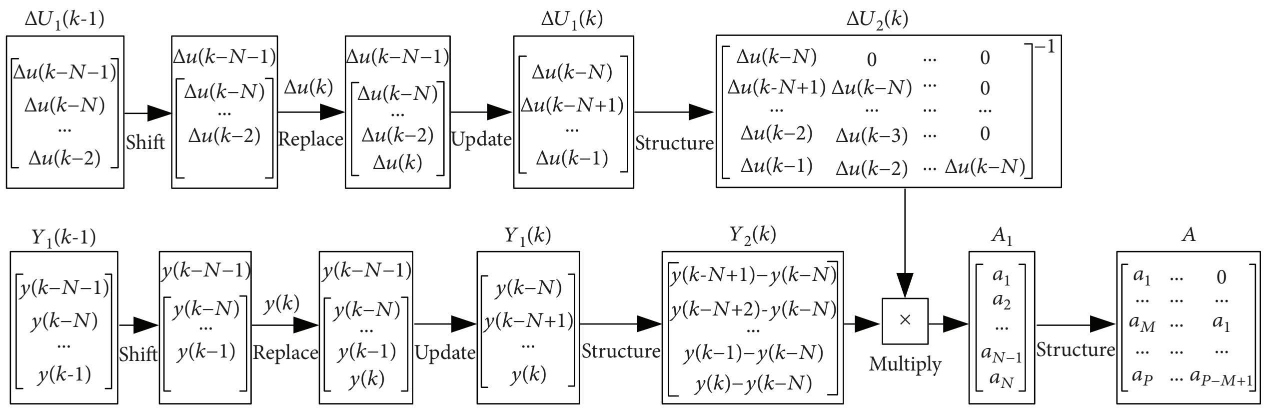

Figure 5: Flowchart of online identification algorithm.

$\Delta u(k\text{-}1)$. And the new vector $\Delta U_1(k)$ at that moment is obtained that can be used to construct a new matrix $\Delta U_2(k)$. In the same way, the new vectors $Y_1(k)$ and $Y_2(k)$ at this moment are obtained. Multiply $\Delta U_2(k)$ and $Y_2(k)$ to get A_1, then A is obtained.

3.2.2. Online Solution of Dynamic Matrix. In every moment, the relationships between control increment, pressure output, and nonparametric model elements are shown in (11).

$$\begin{aligned} y(k-N+1) &= y(k-N) + a_1 \times \Delta u(k-N), \\ y(k-N+2) &= y(k-N) + a_1 \times \Delta u(k-N+1) + a_2 \times \Delta u(k-N), \\ &\vdots \\ y(k) &= y(k-N) + a_1 \times \Delta u(k-1) + a_2 \times \Delta u(k-2) \\ &\quad + \cdots + a_N \times \Delta u(k-N). \end{aligned} \tag{11}$$

Equation (11) can be rewritten as

$$y(k-N+i) = y(k-N) + \sum_{j=1}^{N} a_j \times \Delta u(k-N+(i-j)), \quad i = 1, 2, \ldots, N, \ j \le i. \tag{12}$$

The matrix form of (12) can be written as

$$\begin{bmatrix} y(k-N+1) \\ y(k-N+2) \\ \cdots \\ y(k-1) \\ y(k) \end{bmatrix} = \begin{bmatrix} y(k-N) \\ y(k-N) \\ \cdots \\ y(k-N) \\ y(k-N) \end{bmatrix} + \begin{bmatrix} \Delta u(k-N) & 0 & \cdots & 0 \\ \Delta u(k-N+1) & \Delta u(k-N) & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ \Delta u(k-2) & \Delta u(k-3) & \cdots & 0 \\ \Delta u(k-1) & \Delta u(k-2) & \cdots & \Delta u(k-N) \end{bmatrix} \times \begin{bmatrix} a_1 \\ a_2 \\ \cdots \\ a_{N-1} \\ a_N \end{bmatrix}. \tag{13}$$

The nonparametric model A_1 can be deduced in (13).

$$A_1 = \begin{bmatrix} \Delta u(k-N) & 0 & \cdots & 0 \\ \Delta u(k-N+1) & \Delta u(k-N) & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ \Delta u(k-2) & \Delta u(k-3) & \cdots & 0 \\ \Delta u(k-1) & \Delta u(k-2) & \cdots & \Delta u(k-N) \end{bmatrix}^{-1} \times \begin{bmatrix} y(k-N+1) - y(k-N) \\ y(k-N+2) - y(k-N) \\ \cdots \\ y(k-1) - y(k-N) \\ y(k) - y(k-N) \end{bmatrix}. \tag{14}$$

Equation (14) can also be expressed as (9), and the elements in A_1 are shown as follows:

$$a_i = \begin{cases} \dfrac{y(k-N+1)-y(k-N)}{\Delta u(k-N)}, & i=1, \\ \dfrac{1}{\Delta u(k-N)} \times \left\{ y(k-N+j)-y(k-N) - \left[\sum_{j=1}^{i-1} a_j \times \Delta u(k-N+i-j) \right] \right\}, & i=2,3,\dots,N. \end{cases} \tag{15}$$

It is easy to get a new dynamic matrix A at this moment from the nonparametric model A_1 of the controlled object. Then, the original A of prediction algorithm is replaced to complete the online model identification.

3.3. DMC of Adaptive Predictive Controller

3.3.1. Self-Regulating Controlled Object Prediction Model. The prediction time domain P and the control time domain M are selected, usually $M \le P \le N$. Assume that the initial predictive value of pressure at time k is $\hat{y}_0(k+i \mid k)$, $i=1, 2, \dots, N$, where the subscript of y represents the number of control action changes and $k+i|k$ represents the prediction of time $k+i$ at time k. When the opening of the spray valve has an increment $\Delta u(k)$, the pressure predictor at the next moment is

$$\hat{y}_1(k+i \mid k) = \hat{y}_0(k+i \mid k) + a_i \Delta u(k), \tag{16}$$

where a_i is the value of the element in the nonparametric model A_1, $i=1,2,\dots,N$. When M continuous spray valve opening changes $\Delta u(k), \dots, \Delta u(k+M-1)$ occur, the predicted value of pressurizer pressure is

$$\hat{y}_M(k+i \mid k) = \hat{y}_0(k+i \mid k) + \sum_{j=1}^{\min(M,i)} a_{i-j+1} \Delta u(k+j-1), \tag{17}$$

where $i=1,2,\dots,N$. Equation (17) is the predictive model of the output under the effect of continuous control increment.

3.3.2. Scroll Optimization and Solution of Control Signal Output. M changes of spray valve opening from each time k are needed, which can make the pressure predictor value $\hat{y}_M(k+i \mid k)$ for the next P moments as close as possible to the expected pressure value $\omega(k+i)$, $i=1,2,\dots,P$. The drastic change of $\Delta u(k)$ is usually undesirable during control. So a soft constraint can be added to the performance optimization index.

$$\min J(k) = \sum_{i=1}^{P} q_i [\omega(k+i) - \hat{y}_M(k+i \mid k)]^2 + \sum_{j=1}^{M} r_j \Delta u^2(k+j-1), \tag{18}$$

where q_i is the error weighting coefficient and r_i is the control weighting coefficient, which, respectively, represents the restraint on tracking error and control variation.

The vector form of (17) can be written as

$$\hat{y}_{PM}(k) = \hat{y}_{P0}(k) + A\Delta U_M(k), \tag{19}$$

where A is called the dynamic matrix.

$$\hat{y}_{PM}(k) = \begin{bmatrix} \hat{y}_M(k+1 \mid k) \\ \vdots \\ \hat{y}_M(k+P \mid k) \end{bmatrix},$$
$$\hat{y}_{P0}(k) = \begin{bmatrix} \hat{y}_0(k+1 \mid k) \\ \vdots \\ \hat{y}_0(k+P \mid k) \end{bmatrix}, \tag{20}$$
$$A = \begin{bmatrix} a_1 & \cdots & 0 \\ \cdots & \cdots & \cdots \\ a_M & \cdots & a_1 \\ \cdots & \cdots & \cdots \\ a_P & \cdots & a_{P-M+1} \end{bmatrix}.$$

The vector form of (18) can be written as

$$\min J(k) = \| \omega_P(k) - \hat{y}_{PM}(k) \|_Q^2 + \| \Delta U_M(k) \|_R^2, \tag{21}$$

where $\omega_P(k) = [\omega(k+1), \cdots, \omega(k+P)]^{\mathrm{T}}$, $\Delta U_M(k) = [\Delta u(k), \cdots, \Delta u(k+M-1)]^{\mathrm{T}}$, the error weight matrix $Q = \mathrm{diag}\,(q_1, \cdots, q_P)$, and $R = \mathrm{diag}\,(r_1, \cdots, r_M)$ is the control weight matrix.

Substituting (19) into (21),

$$\min J(k) = \| \omega_P(k) - \hat{y}_{P0}(k) - A\Delta U_M(k) \|_Q^2 + \| \Delta U_M(k) \|_R^2. \tag{22}$$

The optimal control increment $\Delta U_M(k)$ in (22) can be deduced by the extremum requirement $dJ(k)/d\Delta U_M(k) = 0$,

$$\Delta U_M(k) = \left(A^T Q A + R \right)^{-1} A^T Q [\omega_P(k) - \hat{y}_{P0}(k)]. \tag{23}$$

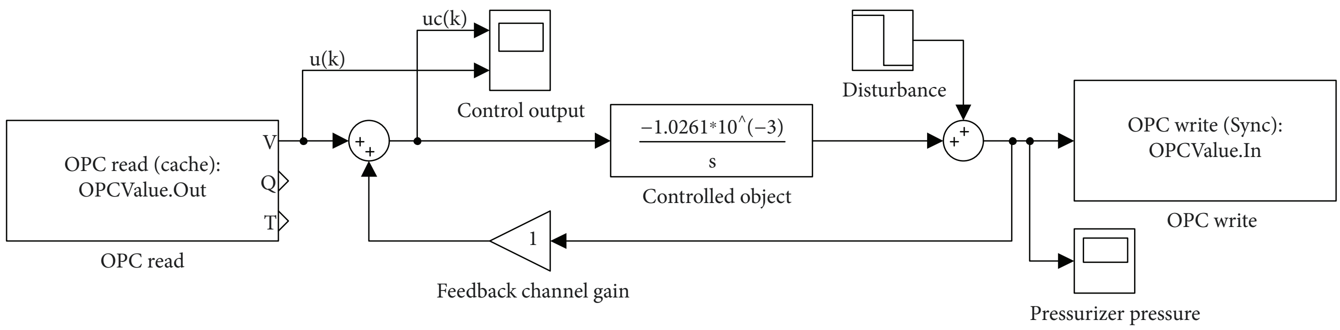

Figure 6: Simulation model based on pressurizer pressure adaptive predictive control.

The "rolling optimization" strategy means that the DMC only takes the immediate control increment $\Delta u(k)$ of $\Delta U_M(k)$ to form a controller output $u(k) = u(k-1) + \Delta u(k)$, and the next time, the same method is used to obtain the instantaneous control increment $\Delta u(k+1)$ to complete a rolling optimization.

Since $u(k)$ is the output acting on the self-regulating model, which theoretically realizes the non-self-regulating system predictive control. In order to solve the engineering problem, the control signal output $u_C(k)$ directly acting on spray device is required by (8). Equation (8) represents the structural relationship of self-regulating process of controlled object. Then, the structural relationship can be expressed as

$$u_C(k) = u(k-1) + \Delta u(k) - Ky(k), \tag{24}$$

where $\Delta u(k) = d^T[\omega_P(k) - \hat{y}_{P0}(k)]$, the control vector $d^T = C^T(A^TQA + R)^{-1}A^TQ$, and the M-dimensional column vector $C^T = [1, 0, \cdots, 0]$ which means to get the first element, $i = 1, 2, \ldots, M$.

3.3.3. Feedback Correction. Model mismatch, environmental disturbances (such as load changes or core reactivity disturbances) and other factors, may cause the output error $e(k+1) = y(k+1) - \hat{y}_1(k+1 \mid k)$. The weighting method can be used to correct the error by introducing the correction vector $h_{cor} = [h_1, \cdots, h_N]^{\mathrm{T}}$. The corrected output prediction vector is shown in

$$\hat{y}_{cor}(k+1) = \hat{y}_{N1}(k) + h_{cor}e(k+1), \tag{25}$$

where

$$\hat{y}_{cor}(k+1) = \begin{bmatrix} \hat{y}_{cor}(k+1 \mid k+1) \\ \vdots \\ \hat{y}_{cor}(k+N \mid k+1) \end{bmatrix},$$
$$\hat{y}_{N1}(k) = \begin{bmatrix} \hat{y}_1(k+1 \mid k) \\ \vdots \\ \hat{y}_1(k+N \mid k) \end{bmatrix}. \tag{26}$$

The initial prediction value at time $k+1$ is obtained by shifting, which can be expressed in vector form as follows:

$$\hat{y}_{N0}(k+1) = S\hat{y}_{cor}(k+1), \tag{27}$$

where S is the shift matrix

$$S = \begin{bmatrix} 0 & 1 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & 0 & 1 \\ 0 & \cdots & 0 & 1 \end{bmatrix}. \tag{28}$$

4. Simulation

The simulation test platform is based on Visual Studio2010 and MATLAB/Simulink. The function of adaptive DMC controller of pressurizer pressure control system in nuclear power plant is realized in Visual Studio2010. It is connected with MATLAB/Simulink through OLE for Process Control (OPC) interface. MATLAB/Simulink simulation model is shown in Figure 6. The controller output calculated by adaptive DMC controller is transmitted to the OPC Read module through OPC interface, and the control signal output acts on the controlled object. The pressure output will be returned by the OPC Write module to adaptive DMC controller for controller output calculation via the OPC interface. Finally, the tracking of pressure output value to set value is realized. Compared with DMC and PID, the improvement of control performance is verified by the proposed non-self-regulating system adaptive predictive control method.

4.1. Tracking Performance of Control System. The feedback channel gain $K = 1$ meets the stability of $G_1(s)$ in (2). The disturbance is set to zero, which temporarily ignores the effects of disturbances. The initialization parameters of pressurizer pressure dynamic matrix controller are designed by A_{1-90} under 90% operating condition (as shown in Table 1). The set point of the pressure steps from 0 to 1 MPa at $t = 0$ s, and the control characteristics of pressure adaptive predictive control, pressure dynamic matrix control, and pressure PID control are shown in Figure 7. Figure 7 shows that the rise time of ordinary DMC is 2.8 s, and the adjustment time of

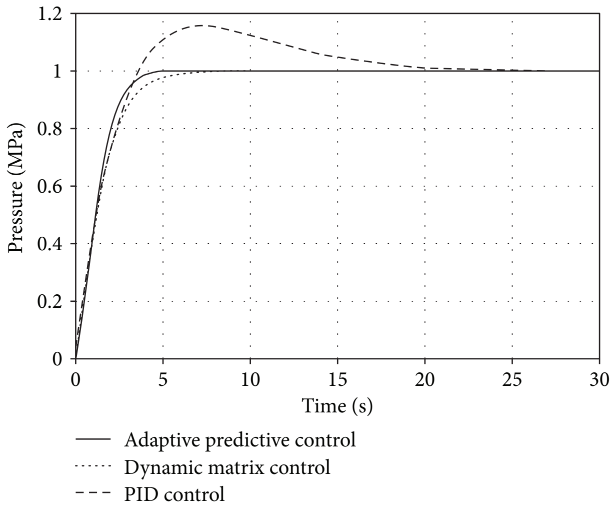

Figure 7: Response curves with different control systems.

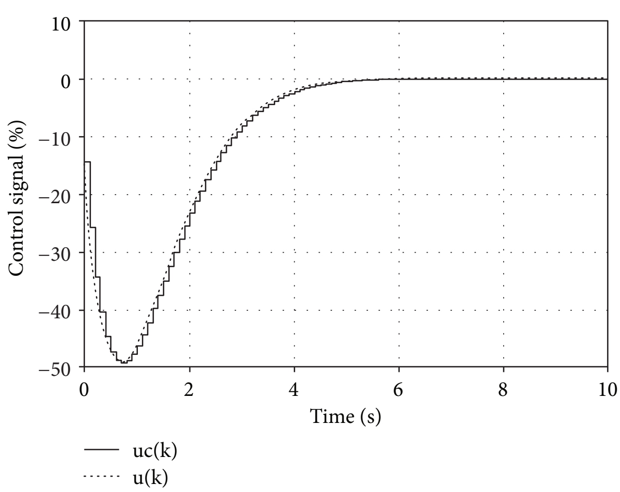

Figure 8: Control output curves.

DMC is 5 s (error is ±2%). It is observed that the rise time of adaptive prediction control is 2.3 s and the adjustment time of adaptive prediction control is 3.8 s (error is ±2%), which is, respectively, 18% and 24% lower than DMC, and the integral absolute error (IAE) is reduced by 13% compared with DMC. PID control response curve can also achieve an approximate rise time at the cost of overshoot adjustment time. The rise time of PID is 2.7 s, the peak time of PID is 7.2 s, the overshoot of PID is 15.6%, and the adjustment time of PID is 18.2 s (error is ±2%). The results show that the adaptive prediction control has faster response and better static stability. The adaptive predictive control signal output curve directly acting on spray device and the controller output curve are shown in Figure 8 (from 0 to 10 s in an interval of 30 s). It is obvious that this pressurizer pressure adaptive prediction controller can be realized in engineering, and it can also be applied to solve the same kind of non-self-regulating system predictive control problems.

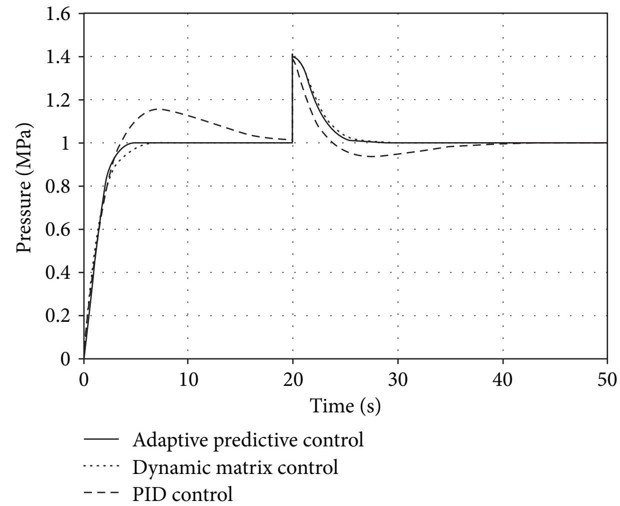

Figure 9: Response curves with different control systems under disturbance.

4.2. Responses with Disturbance. Disturbance is inevitable in an industrial process. Load changes and core reactivity disturbances are ultimately reflected in changes of pressure. It is necessary to test the disturbance rejection ability of the adaptive predictive controller with a pressure disturbance. The feedback channel gain K is set to 1. The initialization parameters of pressurizer pressure dynamic matrix controller are designed by A_{1-90} under 90% operating condition (as shown in Table 1). In an interval of 50 s, a step pressure disturbance of 0.4 MPa is added at $t = 20$ s after the system is stable. The response curves with different control systems under disturbance are shown in Figure 9. It is observed that the adjustment time of ordinary DMC is 5.5 s (error is ±2%) and the adjustment time of adaptive predictive control is 4.8 s (error is ±2%). The latter is 13% shorter than the former. And the adjustment time of PID is 15 s (error is ±2%), which is about three times than that of adaptive predictive control and DMC. The results show that the disturbance rejection ability of adaptive predictive controller is better than that of ordinary dynamic matrix controller and PID controller, and it can achieve a faster and more stable control effect.

4.3. Robustness of Control System. In order to further verify the adaptability of adaptive predictive controller to the change of controlled object model, take 90% operating condition (as shown in Table 1) as initial condition, 100% and 80% (as shown in Table 1) as comparison conditions to compare the adaptive predictive control effect with DMC and PID.

The feedback channel gain K is set to 1, and the disturbance is set to zero. The initialization parameters of pressurizer pressure dynamic matrix controller are designed by A_{1-90} under 90% operating condition (as shown in Table 1). The operating condition is changed from 90% to 100% at $t = 0$ s, and the characteristic curves of control systems are shown in Figure 10. It is observed that the rise time of DMC is 2.5 s, the peak time of DMC is 5.3 s, the overshoot of DMC is 9.3%, and the adjustment time of DMC is 8 s (error

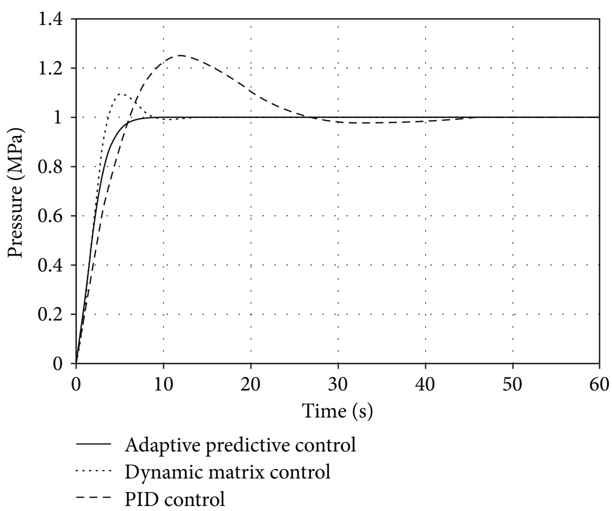

Figure 10: Response curves with different systems under 100% operating condition.

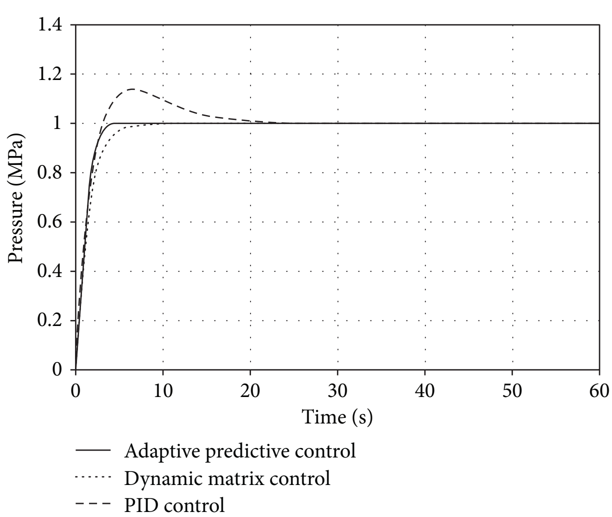

Figure 11: Response curves with different systems under 80% operating condition.

is ±2%). The rise time of adaptive predictive control is 3.5 s, the adjustment time of adaptive predictive control is 6 s (error is ±2%) which is 25% shorter than DMC, and the IAE is reduced by 2% compared with DMC. The rise time of PID is 4.7 s, the peak time of PID is 12.2 s, the overshoot of PID is 25%, and the adjustment time of PID is 24.8 s (error is ±2%). It is clear that the adaptive predictive control characteristic curve changes more smoothly and there is no overshoot.

The operating condition is changed from 90% to 80% at $t = 0$ s, and the characteristic curves of control systems are shown in Figure 11. It shows that the rise time of ordinary DMC is 3 s, the adjustment time of DMC is 5.3 s (error is ±2%), the rise time of adaptive prediction control is 2 s which is 33% shorter than DMC, the adjustment time of adaptive prediction control is 3.3 s (error is ±2%) which is 38% shorter than DMC, and the IAE is reduced by 21% compared with DMC. Similar to the performance in Figure 10, the adaptability of PID controller to the change of controlled object model is relatively poor. It can be seen that adopting adaptive predictive controller not only makes the control characteristic curve more stable but also has better tracking ability and adaptability.

5. Conclusion

Stimulated by the control performance optimization of pressurizer pressure, the adaptive predictive control method based on DMC algorithm is proposed in this paper. Some conclusions could be drawn as follows.

(1) The pressurizer pressure adaptive predictive controller has good control performance and dynamic characteristic. It is characterized by rapid response, small overshoot, strong disturbance rejection ability, and guaranteed robustness.

(2) The stabilization of non-self-regulating system overcomes the disadvantages of DMC in modeling non-self-regulating object.

(3) The acquisition of control signal output shows the adaptive predictive controller is effective and practical value of engineering application.

(4) The online identification of models helps to improve the ability of predictive controller to adapt to changes in controlled objects.

(5) The physical constraints of valve have been ignored for the time being, and further research and improvement are needed.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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