Design and Simulation of Main Steam Pressure Control System Based on Dynamic Matrix Control

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Abstract. Main steam pressure is a typical controlled process with complex modeling and serious delay. Traditional control schemes are difficult to implement effective control. This paper designs the main steam pressure control system based on the dynamic matrix control algorithm and gives the simulation results under MATLAB adopting multi-step prediction, rolling optimization and feedback correction and other control strategies. Compared with the traditional control scheme, dynamic matrix control has a strong ability to adapt, showing a strong robustness.

1. Introduction

The main steam pressure is an important indicator of the stability of the boiler combustion. There are many factors that cause changes in the steam pressure, such as the amount of fuel, air supply, water supply, steam flow, and the operation mode of the boiler and steam turbine. Moreover, the actual combustion process is extremely complex and often has multivariable, nonlinear, time-varying, and uncertainties, and it is difficult to establish an accurate mathematical model. Even if a mathematical model can be established, its structure is often very complex and it is difficult to design and implement effective control. Such complex controlled processes usually have large delays and large lags. Although some compensation methods have been implemented such as the Smith predictor and the Dahlin algorithm, these methods need to establish an accurate mathematical model, thus limiting the use of compensation control methods [1, 2].

In this context, a new type of control method—predictive control—is produced, and multi-step prediction, rolling optimization, and feedback correction are applied to control strategies that are suitable for industrial processes that are not easy to establish precise mathematical models. The dynamic matrix control algorithm plays an vital role in the predictive control algorithm. It has the characteristics of simple algorithm, small amount of calculation and strong robustness. It has been widely used in industrial process control in recent years. This paper presents a design of main steam pressure control system based on dynamic matrix control algorithm, and gives the simulation results under MATLAB. By comparing different control methods, the advantages and disadvantages of various control schemes are analyzed to improve the main steam pressure control level.
2. Principle of dynamic matrix control algorithm

Dynamic matrix control algorithm is mainly based on step response prediction model of the object, rolling implementation and combined with feedback correction optimization control algorithm. This method is also the essence of predictive control. The principle of its block diagram is shown in figure 1.

![Block Diagram](image)

**Figure 1.** Predictive control functional block diagram

The DMC algorithm is applicable to non-minimum phase systems with pure delay and open-loop asymptotic stability. It adopts the step response model of the controlled object that is easy to measure in engineering, describes the system in a non-parametric model, and is suitable for asymptotically stable linear stationary systems. For weak nonlinear objects, it can be linearized at the working point first; for unstable objects, it can be stabilized by conventional PID control first, and then the dynamic matrix control algorithm is used.

The DMC control algorithm includes the following three parts: [3]

2.1. Forecast model

In DMC, it is preferred to determine the sampled value of the step response of the object \( a_i = a(iT), i = 1, 2, \ldots \), where \( T \) is the sampling period. For asymptotically stable objects, the step response will tend to plateau after \( t_N = NT \), which \( a_N \) is approximately equal to the steady-state value of the step response \( a_\infty = a(\infty) \). In this way, the dynamic information of the object can be described approximately by a finite set of \( \{a_1, a_2, \ldots, a_N\} \). The parameters of this set form the model parameters of the DMC. \( a = [a_1, a_2, \ldots, a_N]^T \) is called model vector and \( N \) is called modeling time domains.

The output values at each of the following moments under the effect of successive control increments \( \Delta u(k), \ldots, \Delta u(k + M - 1) \) are:

\[
\hat{y}_M(k + | k) = \hat{y}_0(k + | k) + \sum_{j=1}^{\min(M,i)} a_{i-j+1} \times \Delta u(k + j - 1), i = 1, 2, \ldots, N
\]

2.2. Rolling optimization

DMC is an algorithm that determines the control strategy with optimization, and it is a rolling optimization strategy that replaces global optimization with local optimization. At any time \( k \), the control increments \( \Delta u(k), \ldots, \Delta u(k + M - 1) \) from this moment are to be determined so that the predicted output \( \hat{y}_M(k + | k) \) of the controlled object under its effect at the next \( P \) moments is as close as possible to the given expected value \( w(k + | k), i = 1, 2, \ldots, P \). Here, \( M, P \) are called control time domain and optimization time domain, respectively \( M \leq P \leq N \).

In the control process, it is often not expected that the control increment \( \Delta u(k) \) will change too drastically. This factor can be considered by adding soft constraints to the optimization performance indicator. Therefore, the optimal performance indicator at the moment of \( k \) is:
\[ \min J(k) = \sum_{i=1}^{p} q_i \left[ w(k + i) - \tilde{y}_M(k + i | k) \right]^2 + \sum_{j=1}^{M} r_j \Delta u^2(k + j - 1) \]

2.3. Feedback correction

When \( u(k) \) is actually applied to an object at time of \( k \), it is equivalent to adding \( \Delta u(k) \) to the input of the object. Using the prediction model, the predicted output value at the future time under its effect can be calculated:

\[ \tilde{y}_{N1}(k) = \tilde{y}_{N0}(k) + a \Delta u(k) \]

After shifting, they can be used as the initial predictor of \( k + 1 \) time for new optimization calculations. However, due to unknown factors such as model mismatch and environmental interference, the predicted value may deviate from the actual value. Therefore, if the feedback correction is not performed in time using real-time information, further optimization will be based on a false basis. At the next sampling time, the actual output \( y(k + 1) \) of the object must first be detected and compared with the predicted output \( \tilde{y}_{i}(k + 1 | k) \) of the model to constitute the output error:

\[ e(k + 1) = y(k + 1) - \tilde{y}_{i}(k + 1 | k) \]

Correct the forecast for future output by weighting \( e(k + 1) \), so

\[ \tilde{y}_{corr}(k + 1) = \tilde{y}_{N1}(k) + he(k + 1) \]

3. Control system design

3.1. Dynamic characteristics of controlled object

Taking the combustion process of an ALSTON 1000MW ultra-supercritical unit in a power plant as an example. Under the 80% load condition of the power plant, the particle swarm optimization algorithm is used to perform parameter optimization. After the identification, the transfer function from fuel quantity to main stream pressure is:

\[ G(s) = \frac{0.0439}{(83.62s + 1)^2} e^{-48s} \]

Its step response curve is shown in figure 2.
3.2. Algorithm application process
Because DMC is a model-based control method and applies the principle of online optimization. Compared with conventional PID control algorithm, it is clear that more offline preparations are needed. These tasks include the following three aspects:

1) $a_1, a_2, \cdots, a_N$ is obtained through the step response of the controlled object;
2) $d_1, d_2, \cdots, d_P$ is calculated using the optimization strategy by the simulation program;
3) $h_1, h_2, \cdots, h_N$ is determined.

After the above three sets of coefficients are determined, they are loaded into the storage space for the real-time module to call.

The online calculation of DMC consists of an initialization module and a real-time control module. The first step is to detect the actual output $y(k)$ of the object and set it to the predicted initial value $y_0(k+i|k), i = 1, \cdots, N$. The second step begins to transfer to the real-time control module. The online calculation process at each sampling time is shown in Figure 3, in which only one N-dimensional array $y(i)$ is required for the predicted value of the future output $[4]$.

![Figure 3. DMC algorithm online calculation flow chart](image)

3.3. Controller parameter selection
The parameters that the DMC controller needs to set by the user mainly include: $T, P, M, Q, R, \text{ and } h$. Under the premise of covering the time lag and the main dynamic part of the step response of the object, the smaller the optimized time domain $P$ is selected, the faster the control system responds. The smaller the control time domain $M$, the worse the tracking performance; the larger the system, the lower the stability and robustness of the system. Therefore, the choice should balance the speed and
stability. There is no direct analytical relationship between these design parameters and the fastness, stability, robustness, and anti-interference of the control effect. For common controlled objects, the DMC algorithm usually uses the method of trial and error combined with simulation to design parameters [5].

3.4. Simulation results and analysis

In the actual industrial process, the physical quantity in the system cannot be infinitely valued. For example, when the actuator is a valve, there is a certain dead zone to a certain extent, and the value of the opening degree can only be changed within a certain range. Therefore, in the realization of the actual control system, we must take into account the actual problems, the control of the amount and output constraints within a certain range.

The controlled object adopts the PID control algorithm, and the controller parameters adopt the engineering setting method. The proportional coefficient is 25.3, the integral time is 105.8, and the differential time is 17.6. The control effect is shown in figure 4.

![Figure 4. Simulation curve of traditional PID control algorithm](image)

3.4.1. Nominal system simulation results. When the prediction model exactly matches the actual model, it is a nominal system. Since the unit-step response steady-state value of the fuel quantity to the main steam pressure system is 0.0439, the steady-state signal sent to the actuator by the controller is 22.779. Therefore, in this simulation, the controller output signal is limited to between 0 and 50. The predictive control simulation results with constraints are shown in curve 1 of figure 5.

In this simulation, under the constraint of the control quantity constraint, the actuator action is more frequent at the beginning stage. Fortunately, the controller output is constrained and the dynamic control quality is ideal. Compared with the conventional PID control effect, under the DMC control mode, the system overshoot is small and the actuator motion is gentle, which is beneficial to the protection of the on-site actuator [6].

3.4.2. Robust verification simulation results. Because it is not accurate enough to identify the step response of the object, or the perturbation of the object parameter, or due to the existence of non-linear factors, it will cause the deviation between the prediction model and the actual model [7]. The stability of the model mismatch is so-called robustness. If the actual process steady-state gain perturbs 20% from 0.0439 to 0.0527, the simulation analysis results are shown in curve 2 of figure 5.

From the simulation curve, it can be seen that after the parameter perturbation in the production process, the system response effect is still relatively satisfactory, and there is no large fluctuation in the adjusted amount, but this is at the cost of drastic control of the control amount. Fortunately, we used the
dynamic matrix control scheme with a constraint, and the control volume is limited to 0 to 50. From the simulation curve, it can also be seen that in the initial stage of the adjustment, the control amount has already reached the high (low) limit set because of large deviations. In the subsequent adjustment process, the controller output is gradually stable. From the above analysis, it is known that the DMC algorithm is based on the closed-loop mechanism of feedback correction, so that even if the model is mismatched, it can guarantee the static no difference. As long as the control quantity magnitude is effectively constrained, the constrained dynamic matrix control method will show good robust performance.

![DMC Response y](image)

**Figure 5.** DMC algorithm simulation experiment results

4. Summary and outlook
This article uses the DMC algorithm to control the complex main steam pressure object, and uses the MATLAB simulation, whose results, compared with the conventional PID control, show that the DMC control algorithm has the advantage of a simple algorithm, a small amount of calculation, real-time, and easy computer implementation, less adjustment parameters, simple adjustment rules, good control effects and so on. The algorithm’s advanced predictability and constant error feedback correction make it highly adaptable to large delays and inertial objects. And because of its strong robustness, it has wide application prospects in process control.

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