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Research on Multivariable Fuzzy Dynamic Matrix Control Algorithm

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Abstract: To improve the control quality of distillation tower systems that suffer from issues such as coupling, delay, and nonlinearity, traditional control methods have been ineffective. Consequently, this paper proposes using a variable-domain fuzzy dynamic matrix control algorithm for control system optimization. The traditional dynamic matrix control algorithm is augmented with a fuzzy controller, which is utilized to compensate for predicted output. The concept of variable domain is introduced to address the problems of poor adaptive ability and low control accuracy in the Fuzzy-DMC algorithm. Scaling factors are designed to adjust the fuzzy domain, enabling the fuzzy controller to compensate for predicted output even in the event of a significant model mismatch, resulting in improved control performance. The experimental results indicate that the algorithm proposed in this paper is superior to both traditional DMC and Fuzzy-DMC algorithms in terms of rise time, overshoot, and steady-state rate. In addition, this algorithm possesses a simple structure and does not modify the conventional DMC algorithm structure, making it theoretically applicable in practice.

Keywords: The System of Distillation Column; Dynamic Matrix Control; Fuzzy Control; Variable Domain Fuzzy Control; Fuzzy Dynamic Matrix Control.

1. Introduction

Distillation columns are crucial apparatus for purification and separation processes, widely applied in industries such as petroleum and chemical engineering. Throughout the production process, the distillation tower is the primary energy-consuming device, accounting for approximately 50% of the total energy consumption. Moreover, a distillation column is a typical multivariable system with strong interconnections and coupling among variables, which poses a significant control challenge. Its control is also subject to high demands in practical applications, making it a subject of continuous research by scholars both domestically and internationally.

Wang Rui [1]used cascaded control to regulate the temperature of the ethylene distillation section. Simulation results show that this algorithm is effective to a certain extent. However, it ignores the coupling between other variables. Fuzzy control was introduced by Zhang, Han[2][3], and others into the decoupling stage of the control system, essentially eliminating the coupling between variables, and achieving good control performance in the temperature control system of the distillation column. Dulin et al[4]. introduced neural networks into the decoupling process, resulting in high learning accuracy. Fuzzy control heavily relies on human experience and knowledge. Completely decoupling the system is based on an accurate system model. However, in actual production processes, model mismatch and interference are unavoidable due to changes in the external environment and internal issues in the system. Ideal decoupling and good robustness are often difficult to achieve. Predictive control is a model-based optimization algorithm that has been developed in practical industrial processes. It possesses inherent decoupling features and doesn't require the system's exact model, making it highly potent for controlling complex industrial processes. Li and Zheng[5]-[6] applied predictive control in the temperature regulation of a distillation column. Simulation results indicate that the algorithm has good control effectiveness. However, it cannot meet the control requirements very well when the model mismatch is substantial. Although predictive control does not require an accurate controlled model and has the decoupling property, its control effect is comparatively poor when the controlled object model is significantly mismatched. This paper introduces a fuzzy controller on top of the original DMC controller to compensate for the poor control performance caused by severe model mismatch, relying on the long-term expertise of the fuzzy controller's experts. Subsequently, the concept of variable universe is introduced to address the issues of adaptive errors and low zero control accuracy in fuzzy dynamic matrix control, and a variable universe fuzzy dynamic matrix controller is designed. This algorithm uses more refined fuzzy compensation to mitigate the impact caused by model mismatch, thereby improving the robustness of the system.

2. Multivariable Dynamic Matrix Control

2.1. Prediction Model

For a linear system with multiple inputs and outputs, each output is inevitably influenced by multiple inputs. According to the proportionality and superposition principles of a linear multivariate system, the predicted output of the system can be obtained by adding up the predictions of each individual variable. Assuming that the controlled system is a multivariable system with m inputs and n outputs; and that there are M consecutive changes in the control increments $\Delta u(k)$, $\Delta u(k+1)$, $\Delta u(k+2)$, … $\Delta u(k+M-1)$ at any time k, the predicted outputs of the system can be obtained:

$$y_{PM}(k) = y_{P0}(k) + A\Delta u_M(k) \tag{1}$$

Among them,

$$y_{PM}(k)=\begin{bmatrix} y_{1,PM}(k) \\ \vdots \\ y_{n,PM}(k) \end{bmatrix}, y_{P0}(k)=\begin{bmatrix} y_{1,P0}(k) \\ \vdots \\ y_{n,P0}(k) \end{bmatrix}$$

$$A=\begin{bmatrix} A_{11} & \cdots & A_{1m} \\ & \ddots & \\ A_{n1} & \cdots & A_{nm} \end{bmatrix}, \Delta u_M(k)=\begin{bmatrix} \Delta u_{1,M}(k) \\ \vdots \\ \Delta u_{m,M}(k) \end{bmatrix}$$

In the equation, $y_{PM}(k)$ represents the predicted output of the system; $y_{P0}(k)$ represents the initial predicted value; $\boldsymbol{A}$ represents the dynamic matrix.

2.2. Rolling Optimization

In the multivariable dynamic matrix control algorithm, besides the requirement of well-tracking the given reference values at any instance k, it is also necessary to prevent sudden fluctuations of the control variable[7]. Therefore, the performance metric selected at time k for optimization is:

$$\min J = \| w(k) - y_{PM}(k) \|^2_Q + \| \Delta u_M(k) \|^2_R \quad (2)$$

In the equation, *w(k)* represents the set value, *Q* is the weight matrix for errors, and *R* is the control weight matrix.

By optimizing the performance indicator to a minimum, we can obtain the optimal control increments at time *k*:

$$\Delta u_M(k) = (A^T QA + R)^{-1} A^T Q[w(k) - y_{P0}(k)] \quad (3)$$

2.3. Feedback Correction

Due to the existence of unknown factors such as model mismatch and external environmental interference in the actual production process, the predicted value given by formula (1) may deviate from the actual value. If feedback correction is not adopted in time, the next optimization will be based on inaccurate model predictions, and as the process progresses, the predicted output may deviate more and more from the actual value. To prevent the occurrence of such situations, it is necessary to promptly compensate and correct the predicted output using the actual output error at the current time, using an error-weighted approach to compensate for the predicted output. The corrected predicted output is shown in the following equation.

$$y_{cor}(k+1) = y_{N1}(k+1) + He(k+1) \quad (4)$$

At the next time step, the correction predicted output at time k can be used as the initial predicted value for time k+1 by shifting the time base from k to k+1.

$$y_{No}(k+1) = S_0 y_{cor}(k+1) \quad (5)$$

In the formula, $y_{cor}(k+1)$ represents the calibrated predicted output, H represents the error correction matrix, and S_0 represents the displacement matrix.

The entire control process is repeatedly performed online using the rolling optimization method combined with feedback correction.

3. Principle of Variable Domain Fuzzy Control

3.1. Principles of Fuzzy Control

Fuzzy control is an intelligent control method based on fuzzy language, with its core being fuzzy reasoning[8]. The most significant feature of fuzzy control is converting the experience and expertise of operators and experts into fuzzy rules, which are then used to control the system. Figure 1 illustrates the typical two-dimensional fuzzy control structure used in fuzzy control.

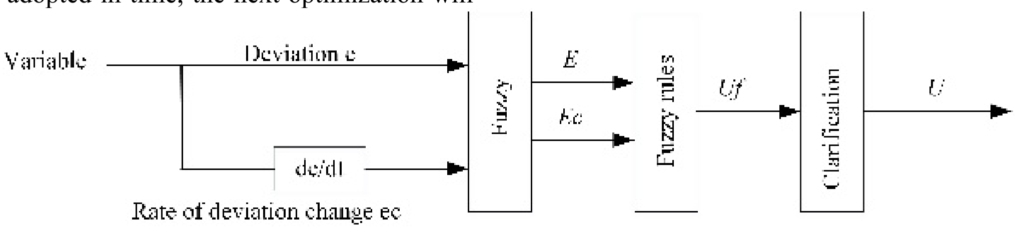

Figure 1. Two-Dimensional Fuzzy Controller

From Figure 1, it can be observed that the error e and the rate of change of error ec are the inputs of the fuzzy controller, while U is its output. To be utilized as input for the fuzzy controller, e and ec should be fuzzified into fuzzy signals E and EC. The fuzzy signals E and Ec are then combined with fuzzy rules to obtain the fuzzy control amount Uf through fuzzy reasoning. Finally, after refining the fuzzy control variable Uf into the precise control variable U, it is then sent to the control structure to control the target object.

3.2. Principle of Variable Domain Fuzzy Control

In traditional fuzzy control, once the structure of the fuzzy controller is determined, it cannot be changed, meaning that fuzzy rules and fuzzy domains are immutable, leading to poor system adaptability and limited control accuracy. To address these issues, this paper introduces the theory of variable domain, which involves the use of scaling factors. The size of the scaling factor is determined based on the error and the rate of error change. That is to say, when a large error occurs, the domain expansion is controlled by the fuzzy rule; when a small error occurs, the domain contraction refines the fuzzy rule, thus improving the control accuracy[9]. The principle of variable domain is shown in Figure 1.

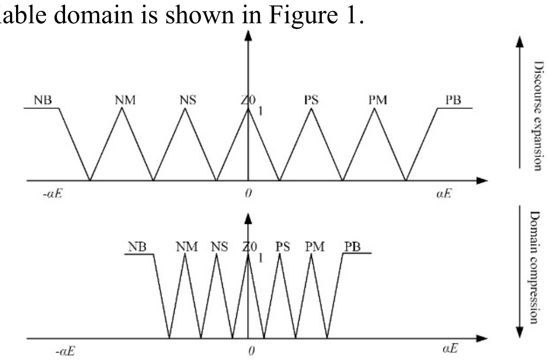

Figure 2. Principle of Variable Domain

As shown in Figure 2, when the domain stretches and shrinks with the change in error, the number of fuzzy rules remains constant, but the peaks of the fuzzy rules shift, thereby enhancing the precision of the controller.

Calculating the appropriate scaling factor is crucial in designing a variable domain fuzzy controller and plays a decisive role in controlling quality. Currently, the two commonly used methods for constructing scaling factors are function-based and fuzzy rule-based scaling factors. However, function-based scaling factors present several issues, including multiple function forms, complex selection of function parameters and difficulty representing scaling factor variation using a fixed formula. Therefore, this paper proposes the use of a fuzzy rule-based approach to determine scaling factors by describing their variation with expert knowledge and experience designed as fuzzy rules. Fuzzy reasoning has the advantage of easy-to-understand design and effectively addresses the complicated problem of determining scaling factor function parameters.

4. Designing a Dynamic Matrix Controller with Variable-Domain Fuzzy Logic

In traditional dynamic matrix control algorithms, model mismatch may occur because the predicted outputs obtained from the prediction model cannot be completely consistent with the actual outputs due to external disturbances and the characteristics of the controlled object. When the model mismatch is small, relying on the feedback correction process of the dynamic matrix control algorithm can achieve good control performance. However, when the model significantly misaligns, the predicted output deviates considerably from the actual values. Correcting for future output using only present error information will inevitably result in bias. After introducing fuzzy control, the fuzzy controller output is used to compensate for the error value. The fuzzy controller can compensate well when the error value is large, but its fixed and unchanging fuzzy rules gradually become unsuitable for fine control as the error value decreases or approaches zero, resulting in reduced control accuracy. Therefore, this paper proposes a variable domain fuzzy dynamic matrix control algorithm, as shown in Figure 3.

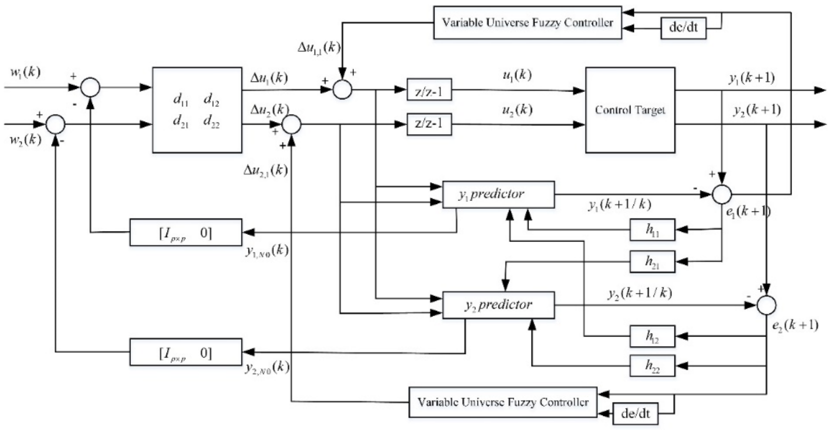

Figure 3. Shows the structure of the variable domain fuzzy dynamic matrix control

In the fuzzy control of variable domain dynamic matrix control, $\Delta u_1(k)$ and $\Delta u_2(k)$ represent the control increments calculated by the dynamic matrix control algorithm for the current input variables $w_1(k)$ and $w_2(k)$. The prediction output and the actual output's error values and error rate of each variable's predictive model serve as inputs for both the fuzzy controller and the variable domain fuzzy controller. This can be observed from Figure 3. The scaling factor of the fuzzy controller is calculated by the variable domain, to adjust the domain of the fuzzy controller to obtain the control increments $\Delta u_{1,1}(k)$ and $\Delta u_{2,1}(k)$ of each compensated variable. The control increments $w_1(k)$ and $w_2(k)$ of the input variables $\Delta u_1(k)$ and $\Delta u_2(k)$ are then applied together with their compensating control increments $\Delta u_{1,1}(k)$ and $\Delta u_{2,1}(k)$ and the control increments of the previous moment to the controlled object. Due to the integration of variable universe fuzzy control, traditional dynamic matrix control has become more flexible, resulting in more precise control performance and effectively enhancing the system's anti-interference ability and robustness.

4.1. Controller Parameter Design

4.1.1. Design of DMC Parameters

The size of predicted time domain P has a significant impact on the stability and speed of control systems. Proper selection of P is necessary to achieve the desired control effects. If the system speed is insufficient, P can be appropriately reduced; if the stability is insufficient, P can be appropriately increased.

The size of the time domain M indicates the number of future control changes to be determined. As system optimization is carried out within the predicted time domain P, theoretically, M is less than or equal to P. As M decreases, the number of controlled variables also reduces, making it difficult to ensure that the output closely tracks the reference value at each sampling point. This leads to poorer control performance. On the other hand, a larger value of M implies that there are more controlled variables, allowing greater control flexibility and the ability to change the dynamic performance of the system. However, the flexibility of control often conflicts with the stability and robustness of the control system, therefore the control time-domain M must be chosen based on the control requirements.

The role of control weighting matrix R is to moderately suppress changes in control increments, but increasing R does not necessarily improve system performance. When R is too large, the system can be stable but will slow down the response speed. The main function of R is to suppress the drastic changes in the control increment. Therefore, during the tuning process, R can be initially set to zero. If the system is stable but the control quantity changes drastically, R can be increased appropriately. The error weight matrix Q represents the degree of importance placed on the error information at different time points. For the time lag and reverse components of the sampling object, the weight coefficient qi can be taken as 0, while for the remaining parts of the sampling object step response, it is taken as qi=1.

4.1.2. Fuzzy Controller Parameter Design

(1) Fuzzy membership function determination

The adjustment rules of the range of the top temperature loop are analyzed as an example. To account for practical working conditions, the deviation e, deviation change rate ec and output $\Delta u_{1,1}(k)$ were subjected to fuzzification processing. The fuzzy subsets were defined as {NB (negative large), NM (negative medium), NS (negative small), ZO (zero), PS (positive large), PM (positive medium), PB (positive small)}. The range is quantified to {-3, 3}, with the basic discourse domain of the error e being {-6, 6}, the basic discourse domain of the error variation rate ec being {-0.3, 0.3}, and the basic discourse domain of the output $\Delta u_{1,1}(k)$ being {-1, 1}. At the same time, highly sensitive triangular membership functions are selected, as shown in Figure 4.

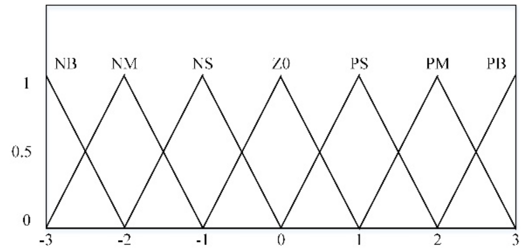

Figure 4. The triangular membership functions

(2) Developing fuzzy rules

In fuzzy control, the key is to establish fuzzy rules. This paper formulates the following fuzzy rule table (as shown in Table 1) based on factory operational experience and relevant professional knowledge [10].

Table 1. Fuzzy rule table

ec \ e	PB	PM	PS	Z0	NS	NM	NB
PB	NB	NB	NM	NM	NS	NS	Z0
PM	NB	NB	NM	NS	NS	Z0	Z0
PS	NM	NM	NM	NS	Z0	Z0	PS
Z0	NM	NS	NS	Z0	PS	PS	PM
NS	NS	Z0	Z0	PS	PS	PS	PM
NM	Z0	Z0	PS	PS	PS	PM	PM
NB	Z0	PS	PS	PM	PM	PB	PB

(3) Clarification

The actual output U is obtained by the membership function of the output fuzzy quantity Uf. It is multiplied by the proportional factor to derive the actual control increment $\Delta u_{1,1}(k)$.

4.1.3. Design of Institutions for Adjusting Domains of Discourse

Taking the example of a tower top temperature control loop, three fuzzy controllers were designed to adjust the scaling factors of quantization and proportionality to achieve the goal of tuning the input-output domain. The input and output domains of the stretch factor fuzzy controller were set to {-0.6, 0.6} based on the actual situation, and the fuzzy subset was set to {NB (negative big), NM (negative medium), NS (negative small), ZO (zero), PS (positive big), PM (positive medium), PB (positive small)}. In the control mechanism for regulating the quantification factor, the output range of the fuzzy controller for adjustment is set at {0, 1.5}, with the fuzzy subset set as {CM (medium compression), CS (slight compression), Z (basically unchanged), DS (medium expansion)}. As for the fuzzy controller for regulating the proportion factor, its output range is set at {0, 1}, with the fuzzy subsets set as {CB (heavy compression), CM (medium compression), CS (slight compression), Z (basically unchanged), DS (slight expansion), DM (medium expansion), DB (heavy expansion)}.

Table 2. Quantification factors Fuzzy Rule Table

e \ ec	NB	NM	NS	Z0	PS	PM	PB
NB	DS/DS	DS/DS	CM/CM	CS/CS	CM/CM	CM/CM	DS/DS
NM	DS/DS	DS/CM	CM/CS	CS/CS	CS/CS	CM/CM	DS/DS
NS	CM/CM	CM/CS	Z/CS	Z/Z	Z/Z	CM/CM	CM/CM
Z0	CM/CM	Z/CS	Z/Z	Z/Z	Z/Z	CS/CS	CM/CM
PS	CM/CM	CM/CM	CM/CM	Z/Z	CS/CS	CM/CM	CM/CM
PM	DS/DS	CM/CM	CM/CM	CS/CS	CS/CS	CM/CM	DS/DS
PB	DS/DS	DS/DS	CM/CS	CS/CS	CS/CM	DS/DS	DS/DS

Table 3. Fuzzy rules table for the scaling factor

e \ ec	**NB**	**NM**	**NS**	**Z0**	**PS**	**PM**	**PB**
NB	DB	DB	DS	CS	CM	CM	CB
NM	DB	DS	DS	Z	CS	CS	CS
NS	DB	DM	DS	DS	CM	CS	Z
Z0	DS	DM	DB	CB	DB	DM	DS
PS	Z	DS	CM	DS	DS	DM	DB
PM	CS	CS	CS	Z	DS	DS	DB
PB	CS	CM	CM	CS	DS	DB	DB

After studying the input and output variables and identifying the fuzzy relationships between error, rate of error change, and scaling factor through multiple experiments, we summarized the relevant experience and derived the fuzzy rule table for the quantitative factors and proportional factors, as shown in Tables 2 and 3. We have used the highly sensitive triangle membership function.

5. Simulation Study

This article focuses on an approximate distillation tower model, which is shown below:

$$\begin{bmatrix} T_t \\ T_d \end{bmatrix} = \begin{bmatrix} \dfrac{7.5}{(150s+1)^2}e^{-7s} & \dfrac{4}{(130s+1)^2}e^{-8s} \\ \dfrac{5}{(225s+1)^2}e^{-2s} & \dfrac{6.5}{(115s+1)^2}e^{-6s} \end{bmatrix} \begin{bmatrix} u_L \\ u_Q \end{bmatrix}$$

In the equation: T_t represents the top temperature of the tower, T_d represents the bottom temperature of the tower, u_L represents the reflux rate and u_Q represents the steam quantity of the bottom reboiler.

According to the controller parameter design requirements stated in section 4.1, the specific DMC parameter design is shown in Table 4.

Table 4. Design of DMC parameters

P	M	***Q***	***R***
14	4	0.006*eye(P)	5*eye(M)

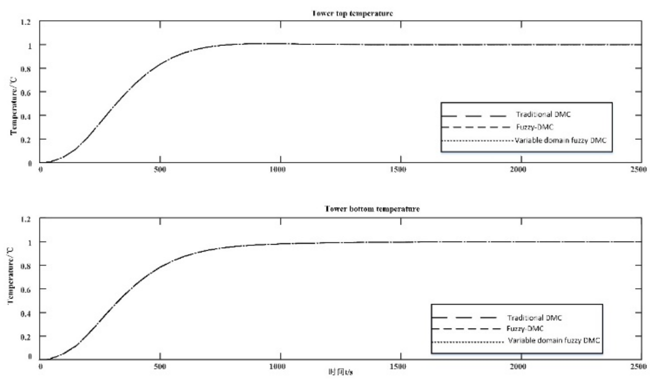

Figure 5. Simulation results during model matching

To verify the effectiveness of the researched algorithms, experiments were conducted on the traditional DMC algorithm, Fuzzy-DMC algorithm, and variable universe Fuzzy-DMC algorithm through simulation. A step test was conducted on each algorithm with a sampling time of Ts=40s and a simulation time of T=2500s. The control results are shown in Figure 5 when the model is matched.

It can be observed from Figure 5 that there is no error between the predicted output and actual output when the model is matched. The simulation curves for three algorithms are consistent, and the fuzzy controller and variable universe fuzzy controller are inactive. All three algorithms exhibit fast response times, short tuning times, and achieve satisfactory control.

To test the system's ability to resist interference, a disturbance with an amplitude of 0.1 was introduced at T=1300s when the system was stable, as shown in Figure 6.

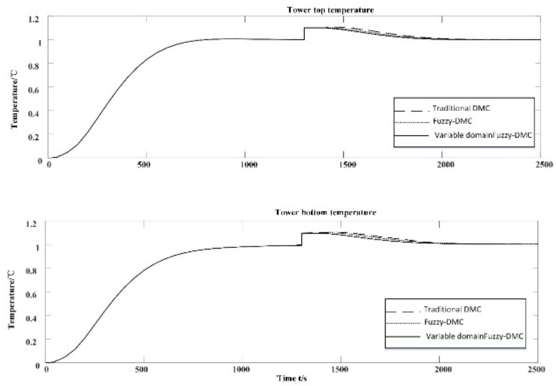

Figure 6. Simulation results when interference is introduced

Figure 6 shows that when disturbances are introduced to the stable system under model matching conditions, all three algorithms can rapidly reach a stable state without overshooting. In terms of response time and steady-state time when facing disturbances, the variable universe fuzzy-DMC algorithm demonstrates superior anti-interference capability compared to the other two algorithms.

When there is a change in external conditions that causes model mismatch, the simulation results are illustrated in Figure 7.

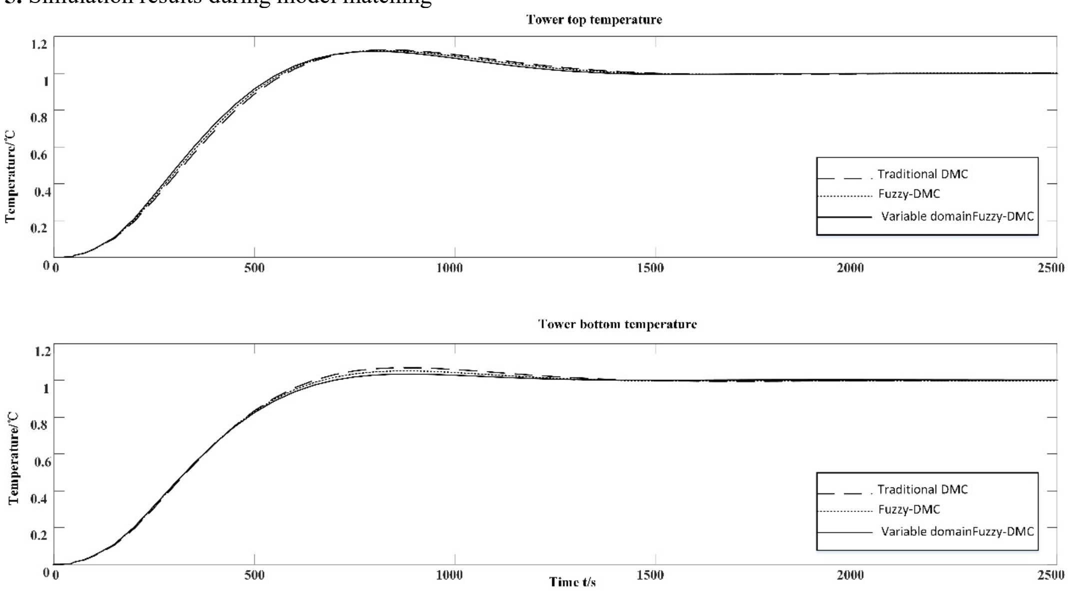

Figure 7. Simulation results when the model is mismatched

According to the simulation results, when model mismatch occurs, both the top and bottom temperatures of the tower exhibit significant overshoot, long rise time, and slow settling time under the control of both traditional DMC algorithm and Fuzzy-DMC algorithm, resulting in poor control performance and low robustness. The proposed algorithm in this paper outperforms the other two algorithms in terms of overshoot, rise time and settling time, resulting in a satisfactory control effect and demonstrating strong robustness.

6. Conclusion

This paper introduces a fuzzy controller onto the conventional DMC algorithm. Although it can reduce the impact of model mismatch to some extent, the control performance is not ideal when the model mismatch is severe. Therefore, this paper introduces the variable domain concept to improve the control precision of the system. The experimental results demonstrate that the algorithm proposed in this paper has better dynamic and static performance compared to traditional DMC and Fuzzy-DMC algorithms, leading to improved control quality for the system. Furthermore, the algorithm utilizes a conventional DMC algorithm structure without adding complexity, therefore, it has a certain level of feasibility.

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