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Economic optimization of chemical processes based on zone predictive control with redundancy variables

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A R T I C L E I N F O

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A B S T R A C T

Zone control is to extend the control target from a point to a convex set. Additional degree of freedom can improve the control performance and optimize the economic performance.This additional degree of freedom has been proven to be expressed specifically by redundant control variables.This paper proposes an optimization control strategy based on redundant control variables to improve the economic benefits of zone control. When the system is outside the zone control target, the zone predictive control algorithm is used to preferentially drive the state to the interior of the zone control target. When the system enters the zone control target, it can be directly optimized by using redundant control variables to achieve greater economic benefits. During system operation, each variable is evaluated by the steady-state mapping model, and variables that meet certain conditions are marked as redundant variables. The controller and optimizer are coordinated based on this label for system control and economic performance. Finally, the effectiveness and feasibility of this strategy are verified by numerical simulation. The results show that this strategy can reduce the economic loss of the system.

1. Introduction

Model predictive control (MPC) has played a significant role in energy optimization and economic benefits. Many researchers have used the framework of predictive control in different application scenarios to make different attempts on energy conservation and economic optimization of the system [1]. designed a nonlinear model predictive controller (NMPC-controller), which uses following velocity, range deviation and energy consumption as cost functions to obtains better following performance and energy-saving behavior [2]. formulates the energy management problem as a multi-parameter quadratic programming problem to obtain the control law. In comparison, this method can significantly reduce the calculation elapsed time and can improve fuel economy [3]. uses the decoupling feature of MPC to decouple the demand side and the supply side so that large chillers can operate efficiently. The results show that the performance of chillers has improved in summer and winter conditions [4]. introduced load torque estimation and prediction into the MPC to reduce the negative impact of propulsion load fluctuations on the shipboard power network [5]. uses the MPC framework to optimize the electrical and thermal processes taking place in multi-building energy network. The strategy considers day-ahead and spot prices of electricity, resource prices and other factors as loss functions. The effectiveness of the strategy is verified by numerical simulation [6]. proposes a MPC control strategy based on multi-layer perception (MLP), which consists of MLP-based prediction model. Numerical experiments show that this strategy can significantly improve thermal power response [7]. proposes a tube-based explicit MPC control strategy, which can effectively reduce the computational time. The numerical simulation experiment of large wind turbines verified the effectiveness of the method [8]. has designed a nonlinear MPC control strategy with net power output as the control target. The strategy uses simplified gradients and quasi-sequential method for online optimization. The results show that this strategy can ensure the requirements of load tracking and can quickly improve the net power output. In order to reduce the negative impact of disturbance factors such as intermittent nature of renewable energy resources and randomness of load demands on island microgrids [9], proposes a control strategy based on two-stage robust MPC. Numerical simulations show that this method is more robust and economical than conventional methods. In the energy management system of the residential building [10], proposes an economic model predictive control (EMPC) strategy based on artificial neural

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networks. Compared with a conventional proportional-integral controller, this strategy can effectively improve flexibility indicators in experiments. In addition, based on the theoretical study of the stability of predictive control, a strict convergence criterion for closed-loop systems is established [11]. studies the influence of the predictive horizon on the average economic loss performance of EMPC under terminal loss function. And a strict proof of convergence is given. The closed-loop stability is analyzed using the constraints of the average of each input-output variable [12]. In addition, strict convergence usually depends on terminal constraints. This condition can ensure that the loss function of the system reaches the expected value [13]. gives an upper bound on the performance loss of MPC without terminal constraints, which simplifies the design of controllers for systems that do not have strict performance loss requirements.

In some chemical processes, the control objective is not a conventional set point, but a range. In this scenario, the set point should be extended to a set of points, which is also called zone control target. For example, in the petrochemical industry, the control target of a rectification column can be defined as a specific temperature, or a product yield. However, due to the particularity of chemical products, the components of similar products fluctuate within a small range. Therefore, this type of control problem can be abstracted using zone control [14]. Under the framework of zone control, the norm of performance indicators is different from the traditional set point control [15,16]. It is defined as the Euclidean distance from the point to the convex set, and this performance index is used as the objective function of the controller. The controller design should start from these points, with the goal of quickly reaching the zone control target. However, when the system enters the interior of the control target, the degrees of freedom will not be fully saturated. This means that it is possible to continue to operate the control variables without causing the system to deviate from the zone control target. This part of the degree of freedom is often ignored by engineers. In practical industrial processes, this part of the degree of freedom can be used to optimize energy or economic benefits. Therefore, the coordination of control performance and economic optimization under the zone control framework has gradually become one of the research directions [17].

In the design of economic performance indicators, additional indirect economic factors should be considered, such as reducing pollution, ensuring personnel safety, and rationally disposing of waste. These factors can usually be converted into more comprehensive system economic performance indicators using equivalent algorithms. However, in general, production and energy saving may be contradictory. Therefore, when designing the controller, excessive improvement of economic performance might reduce the control performance. In order to solve the above problems, some researchers use the Nash equilibrium theory to balance the control objectives and performance indicators [18]. coordinates the conflicting goals of each agent under the framework of MPC and makes the system reach a steady state.

[19] considered multiple influencing factors and designed a control problem for a heat exchanger network with scaling problems. This method treats disturbance parameters as time-varying parameters, constructs a robust MPC controller, and designs a control strategy that is superior to traditional proportional-integral-derivative (PID) controllers [20]. considers the thermal inertia existing in the house itself, adopts a predictive control framework, constructs an MPC controller based on mixed integer dynamic programming, and verifies the effectiveness of the control strategy [21]. improved the control object's hysteresis and the control performance of traditional control strategies. A simplified mechanism model was used to design the MPC control strategy, and stability and energy saving effects were obtained in the experiments [22]. adopted MPC control strategy to design a heating system combining solar energy and geothermal energy, and verified its operating cost and actual energy saving effect. Aiming at the uncertainty of the fuel cell model [23], designed a fuzzy generalized predictive controller. Under this control strategy, the output performance of the system and the energy efficiency of the system are improved. From the perspective of control strategy [24], proposed a predictive cruise control system. This control strategy uses a high-performance MPC controller to improve the tracking ability, that is, effectively reduce the time to reach the set trajectory. Therefore, fuel consumption can be reduced, and energy saving and emission reduction can be achieved.

For the purpose of energy and economic optimization, this paper proposes an optimization strategy based on input variables. This strategy utilizes input variables in the zone control framework that do not significantly affect the control target, that is, redundant variables. When the system is outside the control target, it is controlled by the zone MPC controller so that the system can quickly enter the control target. When the state enters the control target, it means that the control task has been achieved and the product quality has met the demand. At this time, the economic performance of the system can be optimized. Although economic optimization is generally contradictory with control performance, it is possible to use the potential degrees of freedom to coordinate these two performance indicators within the framework of zone control. In addition, external disturbance variables may also interfere with the state trajectory of the system. This will lead to the deviation from the control objectives that have been achieved, that is, the failure to produce products that meet the requirements. In this case, the control strategy should be switched in time to prevent the product quality from being affected. The entire system will be in this dynamic balancing process.

In order to explain the design process of this optimization strategy in detail, the structure of this paper is as follows: In Section 2, the design motivation of the optimization strategy proposed in this paper is discussed in detail. The standard zone control problem is modeled, and the existence of degrees of freedom under zone targets is analyzed. At the same time, some preliminary work related to economic optimization was also introduced. In Section 3, the properties of redundant variables are discussed in detail, and a search algorithm for redundant variables is given. In Section 4, the system optimization framework based on redundant variables is given, and the design method of the optimizer and controller for the response is also given. In Section 5, a typical chemical process is used to simulate the strategy proposed in this paper, which verifies the effectiveness and feasibility of the optimization strategy.

2. Motivation

The revenue of a production process comprises many comprehensive factors, among which the sales of products occupy a major part. The sales of a product are related to the quality of the product, such as the proportion of each component in the product. Therefore, when designing a control strategy, each component or other variables that can characterize these components, such as pressure and temperature, are usually used as controlled variables. However, this simple consideration ignores additional costs, such as energy consumption and sewage treatment. At the same time, these additional costs are related to the input or output variables of the system. Therefore, this part should be considered when designing the optimization strategy of the system. This section mainly discusses the general problem description of zone control and the problems existing in its optimal control. The control target of zone control is different from set point control. In the chemical process, the controlled variables are usually temperature, pressure, flow and other variables. The composition of the product can be determined by these state variables, and the quality of the product is determined by the composition of the product. Therefore, the state variable can directly establish a connection with the quality of the product. When market factors are not considered, the product price and these state variables can be equivalently converted. There is a nonlinear mapping relationship between the product price . and the state variable x as shown in the following formula.

$$\text{price}(x) = \begin{cases} b_1 & x \in X_1 \\ b_2 & x \in X_2 \end{cases}$$

Where $X_i, i = 1,2$ is the set of state variables and $b_j, j = 1,2$ is the selling price of the unit product. In other words, for $\forall x \in X_i$, the selling price of the product is b_i. For this reason, such problems can be abstracted as zone control problems. Fig. 1 shows the basic elements of zone control. When the state enters the control target, its movement within the control target will not affect the price of the product. Therefore, it is possible to find a state that can reduce the cost of production or less pollution in this zone to achieve the improvement of economic benefits.

In the framework shown in Fig. 1, the molar composition of the chemical product is a continuous variable, while the sales of products corresponding to different components are discrete variables. This nonlinear mapping relationship is quite different from traditional tracking control. Therefore, from this perspective, this section first gives a more general definition of zone control targets, and then gives common optimization strategies based on zone control targets.

2.1. Zone control

A typical chemical process can be described abstractly using the dynamic equation as Equation (1).

$$x(k+1) = f(x(k), u(k)) \tag{1}$$

Where $x \in \mathbb{R}^n$ denote the system states; $u \in \mathbb{R}^m$ denote the input variables. In the classic control problem, the control target of the system is a set point target $x_{sp} \in \mathbb{R}^n$, and the evaluation of the control performance of the system depends on the Euclidean distance $d = x_{sp} - x(k) \in \mathbb{R}$ between the current state and the control target. This classic control framework is suitable for control scenarios that require precise targets and high level real-time performance. For zone control tasks, this type of control target will increase the difficulty of system control and increase the difficulty of system optimization. Therefore, the concept of zone control target is introduced so that the problem shown in Fig. 1 can be briefly described. In the zone control framework, the control target is expanded from a set point x_{sp} to a zone control target X_{sp} composed of specific limits. Among them, in order to simplify the design, we set the control target set as a convex set. It can be seen that the control target is a closed set, and the internal elements can be continuously changed within a certain range. At the same time, the control performance is reconstructed, and it is indicated by $d = \text{dist}(x(k), X_{sp}) \in \mathbb{R}$. $\text{dist}(x(k), X_{sp})$ represents the Euclidean distance between the set X_{sp} and current state $x(k)$, and satisfies the expression $\text{dist}(x(k), X_{sp}) = \inf\{d | d = \| x(k) - x \|, x \in X_{sp}\}$.

Fig. 2(a) and Fig. 2(c) represent classic control methods, where the goal is to gradually minimize the error between the system state and the set point value in order to make the system run to the specified state. In the case of zone targets, as shown in Fig. 2(b) and (d), the system state trajectory is different from set point control. When the states enters the control target zone, it means that the product at the current moment has reached a certain level, as shown in Fig. 1. However, on the premise of ensuring that the zone control target are achieved, the state variables can be moved within a small range. In other words, the state of the system can move freely without negatively affecting the price of the product. This phenomenon is determined by the characteristics of zone control, so the zone control system has some degrees of freedom after achieving the zone control target. Therefore, we can use this part of the degree of freedom to design the optimization strategy of the system, in order to obtain a more efficient, more energy-efficient, more economical optimization control strategy.

2.2. Economic optimization based on redundancy

In this section, our framework relies on the prerequisites mentioned in Section 2.1, When the zone control target is achieved, there are still degrees of freedom. This section shows the idea of

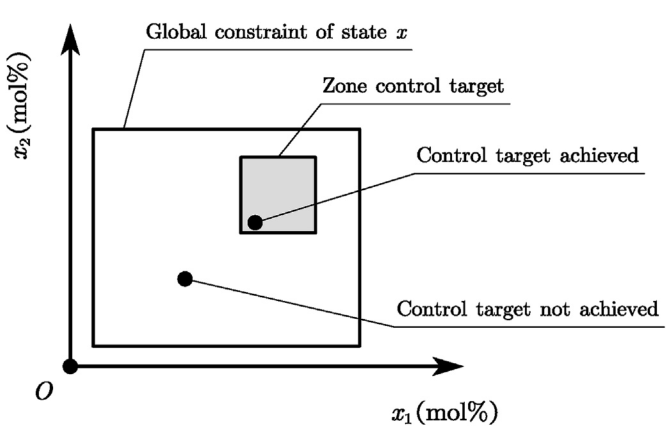

Fig. 1. Schematic diagram of zone setting target (Control requirements are met when the state is inside the zone control target; Product quality is unqualified when the state is outside the zone control target).

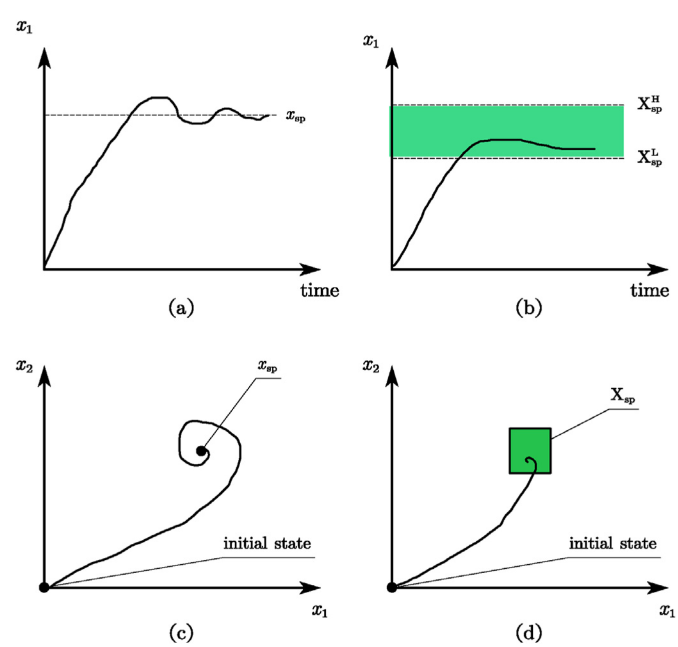

Fig. 2. Diagram of the difference between set point control and zone control. (a: Set point control state x_1 v.s. time. b: Zone control state x_1 v.s. time. c: Set point control system state trajectory. d: State trajectory of the zone control system.)

how to achieve economic optimization within the control targets. According to Equation (1), we can find its steady-state mapping model. For complex nonlinear links, we can use model simplification techniques such as piecewise linearization to give the steady-state mapping relationship in affine form. To facilitate subsequent derivation, we use $S(\cdot):\mathbb{R}^m\rightarrow\mathbb{R}^n$ to represent the mapping relationship between input and state. Therefore, the input space and the state space can be transformed into each other. Take a two-input two-output fully observable and controllable system as an example to illustrate this feature.The general transformation is shown in Fig. 3.

In the case of strong nonlinearity, a piecewise linearization method should be used to obtain a linearized description model near each stable state. When the mapping matrix of a linear system is not directly invertible, consider finding a generalized inverse in order to find the inverse mapping of the system. In general, the steady-state mapping models of ordinary linear systems meet the reversible conditions. Based on the steady-state mapping, the set goals of the system can be mapped to the state space as shown in Fig. 3(b). Without loss of generality, we also give a schematic diagram for the case of constant value control as a comparison, as shown in Fig. 4.

In Fig. 4, the zone control target can be reflected in the input space through the mapping relationship in Fig. 3(b). At the same time, combined with the input constraints in the input space, the final steady-state input feasible region can be obtained. When the control target is a set point, the steady-state map feasible region obtained through the above mapping operation has only one point. There are degrees of freedom in the feasible region of the system under the zone target, while the set point control target has only one steady-state feasible solution when it works in steady-state. By comparison, under the zone target framework, the system can perform steady-state optimization within a certain range. When the system enters the set zone, the feasible region obtained by projecting the state of the system into the input space can intuitively reflect the degree of freedom that the system has under the control performance requirements. In the steady-state feasible region of the system, actively adjusting the control input variables of the system within a small range can cause the system to move the steady-state operating point within the control target within a local range. This small-scale movement needs to meet two

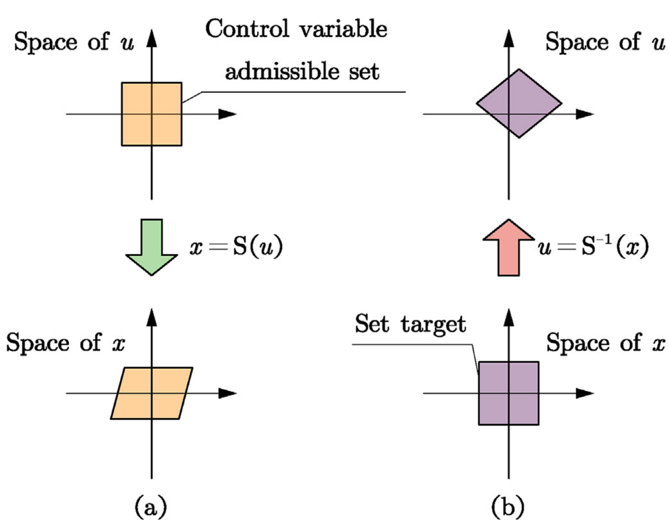

Fig. 3. System steady-state mapping diagram. (a: Map the control variable admissible set of the input space to the state space. b: Map the control target of the state space to the input space).

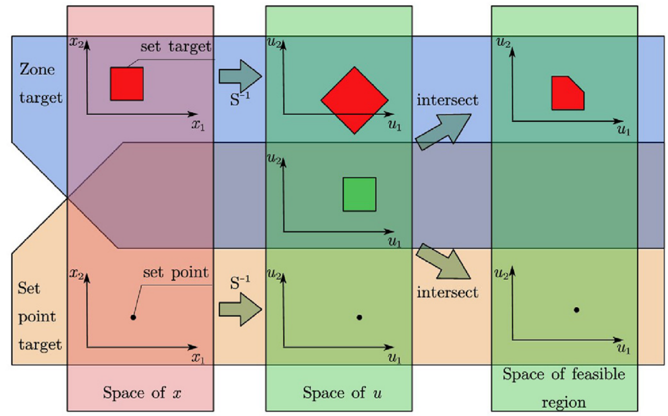

Fig. 4. Schematic diagram of steady-state feasible region evolution under different control targets (The upper part adopts zone control; the lower part adopts set point control).

requirements: the first is which input variable can change in a small range, and the second is how to define the specific boundaries of the small range. We use Fig. 5 to illustrate these two requirements.

Fig. 5 shows some typical system optimization scenarios. First assume that all steady-state feasible regions are obtained by setting targets through steady-state mapping, and the operation of taking intersections with the input constraints of the system has been completed. In Fig. 5(a), in order to meet the specifications and boundary conditions, it is necessary to focus on the boundary situation. The movable direction (dotted line) indicates that the system can only move to a limited direction to meet the control performance when it is at the boundary. When the current state is inside and at the same time there is a certain distance between each direction and the boundary, the system can move in any direction to obtain better economic performance. In Fig. 5(b), the shape of the feasible region of the system is a thin strip. In this case, the degree of freedom of the system is very limited. In order to ensure that the system is always within the feasible region, the system can only run in one direction. Similarly, in Fig. 5(c), the initial state of the system determines the direction in which the system can move. The moving direction of the system can be determined by a linear combination of the two input variables. Therefore, we can define this kind of movability in the zone control target as redundancy.

System redundancy exists in the framework of zone control. The specific manifestation is that the steady state of the system is mapped to a region rather than a point. The contribution of this paper is to propose an economic optimization strategy based on redundancy. This paper analyzes a simulation case and uses the optimization strategy we have proposed to obtain better economic performance.

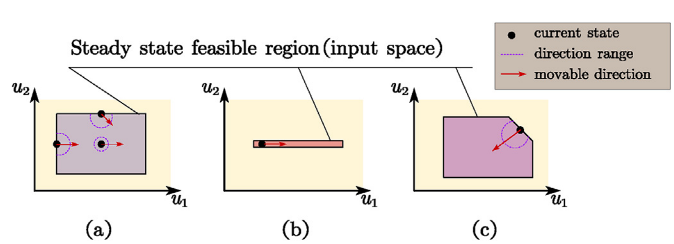

Fig. 5. Schematic of steady state optimizability. (a: Rectangular steady-state feasible region. b: Thin-band steady-state feasible region. c: Trapezoidal steady-state feasible region).

2.3. Related work

Designing optimization strategies in control systems to obtain better economic benefits is often considered an important part in recent research. According to the characteristics of the control system, different economic optimization strategies can be designed in different scenarios. In a typical set point control task, according to the cost of the control input variable, different trajectories can be designed to minimize the economic loss of the system. In complex large-scale systems, it is usually impossible to obtain global optimality through the optimality of each subsystem. In other words, the minimum economic loss operating state of each subsystem may not necessarily cause the entire system to obtain the minimum economic loss. At the same time, mutual coupling factors will cause mutual interference, which will cause the optimization effect of the optimal control strategy of each subsystem to be abnormal. For this reason, energy loss must be considered from the integrity of the system, rather than simply maximizing the benefits of each subsystem [25].

At the same time, when the control target of the system is a zone control target, how to obtain a higher economic optimization effect from the perspective of the system control strategy is discussed in Ref. [14,26]. Under the zone control framework, the trajectory of the system is divided into two parts, a control part and an optimization part. In the control phase, we do not consider economic optimization. Before considering economic loss, the system state should be driven into the zone control target. However, at this stage, the control time should be minimized, that is, the time period with the greatest economic loss is minimized. When the system enters the control target, a control algorithm is designed under a strong constraint environment, so that the system can find the best working point inside the control target. The working point needs to meet the global optimum within which economic factors such as economic loss can be achieved.

Based on the above inference, we found that economic optimization can still be achieved from the perspective of system redundancy. From this point of view, this paper uses a pre-solved steady-state mapping model to design the optimization strategy of the system. The specific redundancy analysis and modeling of the research objects are given in detail in Section 3.

3. Redundancy identification algorithm

3.1. Characteristics of redundant control variables

There will be additional degrees of freedom within the framework of the zone control system proposed in Section 2.1. According to Section 2.2, when the system reaches the set zone, the input variable can be actively adjusted within a certain range. This adjustment process does not affect the control performance of the system. Therefore, it is necessary to determine whether all variables can be freely adjusted. When designing the relevant redundant variable identification algorithm, the following prerequisites must be met: the control target has been achieved, that is, the state of the system has been driven into the control target. Based on this, we design an online redundant variable identification algorithm.

Redundant input variables should have the following properties in specific performance:

1. The variable must belong to a bounded feasible field.
2. The sampling period of the optimized operation in this zone control target should be greater than the sampling period of the zone controller.
3. The redundant variable will not affect the control performance of the system, that is, the influence of the change of the variable on the steady-state operating point of the system can be judged by the steady-state mapping matrix.

According to Equation (1) the steady state mapping is known and satisfies $x_s = f(x_s, u_s)$. If the setting target of each state variable of a given system is $x = [x_1, \ldots, x_n]^T \in X_{sp}$, each component satisfies $x_i \in X_{sp,(i)}, i \in I_{[1,n]}$ and the input constraint of each input variable of the system is $u = [u_1, \ldots, u_m]^T \in U$, each component satisfies $u_i \in U_{(i)}, i \in I_{[1,m]}$, then the steady-state feasible region of the system can be expressed by Equation (2).

$$X_s = \{x | x = X_{sp} \cap \{\tilde{x} | \tilde{x} = f(\tilde{x}, u), u \in U\}\} \tag{2}$$

Equation (2) is different from Fig. 4. Equation (2) expresses the constraint of input space to the state space. The elements in X_s are candidate steady-state operating points of the control system. In other words, the redundant variable u_d should satisfy the condition that the steady state mapping of the system is in X_s under the condition of arbitrary values in its domain.

During the design of the search algorithm, the steady-state mapping equations may not be given explicitly. For general application scenarios, under the condition of low error accuracy requirements, a linearized model can be used as shown in Equation (3).

$$x(k+1) = Ax(k) + Bu(k) \tag{3}$$

In the case of linearization, the steady-state feasible region X_s of the system can be given by Equation (4).

$$X_s = \left\{ x \middle| x = X_{sp} \cap \{\tilde{x} | \tilde{x} = (I - A)^{-1} Bu, u \in U\} \right\} \tag{4}$$

To simplify the derivation, we assume a candidate redundant variable u_d whose index number in the input channel of the original system is $d_{index} \in I_{[1,m]}$. Next, we define the domain of the redundant variable as U_d , and satisfy the relationship $U_d \subseteq U_{(d_{index})}$ between the input space U of the original system.

Without loss of generality, in this case, the steady state mapping of the system is rewritten as Equation (5).

$$x_s = f(x_s, u_c, u_d) \tag{5}$$

In Equation (5), u_d is a candidate redundant control variable, and u_c is the remaining input variable of the system, which is controlled by the controller and satisfies the constraint $u_c \in U_c$. U_c is a set of domains of the remaining control variables. If the candidate redundant variable u_d is a real redundant input variable, according to the above definition, the entire control system should satisfy Equation (6).

$$\forall u_d \in U_d, \exists u_c \in U_c, \{x | x = f(x, u_c, u_d)\} \in X_{sp} \tag{6}$$

Equation (6) belongs to a direct heuristic method, which needs to traverse every element inside the set u_d. This formula can intuitively express the characteristics of redundant control variables, but iterating through all the elements will take a huge computational cost. In comparison, a gridding method was utilized to reduce the search burden. We give a division interval u_{delat} and use the equal interval division method to divide the control target into a point set $U_d^{delta} = \{u_d | u_d = \min\{U_d\} + iu_{delta}, i \in I\} \cap U_d$ consisting of a limited number of points. The value of u_{delat} can be chosen based on the ratio of this value to the length of the interval. If the ratio is too small, the search burden will increase, and if the ratio is too large, the accuracy of the search interval will decrease. For different control problems, the setting zone and the constraint range of the input variables are different. Similarly, the search interval of redundant variables should change as the control problem changes, which brings additional costs to the actual operation. Therefore, it is necessary to design a search algorithm that can meet the following conditions:

(1) As few parameters as possible need to be determined.
(2) Minimal computational burden.

3.2. Redundancy search algorithm

According to the discussion in the previous section, the interval of the redundant variable candidate interval to be searched can be divided by the interval segmentation method to reduce the computational burden. However, in the actual implementation process, too many parameters need to be defined, so that there is still a lot of uncertainty. To facilitate analysis and derivation, we define the domain of candidate redundant variables as belonging to a convex connected region. In other words, there are upper and lower bounds on the domain of the candidate redundant variable.

Therefore, the interval of the candidate redundant variable u_d can be written as $u_d \in [u_{d,low}, u_{d,high}]$. Therefore, the algorithm mentioned in Section 3.1 can be further simplified to obtain a lower computational burden. From the mapping theory of convex set, we know that the convex set after affine transformation is still convex set. Therefore, we can directly determine the two elements of the u_d boundary $\{u_{d,low}, u_{d,high}\}$ to represent the change of the entire u_d in the entire interval. Under this premise, Equation (6) can be rewritten as Equation (7).

$$\forall u_d \in \left\{u_{d,low}, u_{d,high}\right\}, \exists u_c \in U_c, \\ \{x | x = f(x, u_c, u_d)\} \in X_{sp} \tag{7}$$

Compared with Equation (6), Equation (7) reduces the elements to be checked to two. As a result, a significant computational burden is reduced. At the same time, low computational burden can make the program design more flexible, and can realize the automatic search function for the domain of redundant variable.

Before giving a specific search algorithm, we first define a redundant variable test method. Without loss of generality, in order to be applicable to non-linear situations, we construct an optimization problem such as Equation (8).

$$\begin{aligned} \min J(u_d, X_{sp}, U_c) &= ||x_s - x_v|| \\ \text{s.t.}\, x_v &\in X_{sp} \\ u_c &\in U_c \\ x_s &= f(x_s, u_c, u_d) \end{aligned} \tag{8}$$

In Equation (8), u_d, X_{sp}, U_c are given as parameters, x_s is the solution of the steady-state equation, and x_v can be regarded as an auxiliary variable. The intuitive meaning of this optimization problem is to find a control variable u_c that satisfies the control constraint set U_c and drive the steady-state operating point of the system as close as possible to the control target X_{sp}. When x_s is inside the control target, the auxiliary variable x_v can coincide with x_s, and the value of the optimization objective function is 0. When x_s is outside the control target, the two points cannot be completely overlapped due to the constraint of x_v, the objective function of the optimization problem is numerically expressed as the shortest distance between x_s and the control target. The redundancy search algorithm for a given interval is shown in Fig. 6.

Fig. 6 implements the redundancy search algorithm for a given redundant variable interval. However, there is no detailed search method for the setting target of candidate redundant variables, so we propose a method for determining the interval of candidate redundant variables.

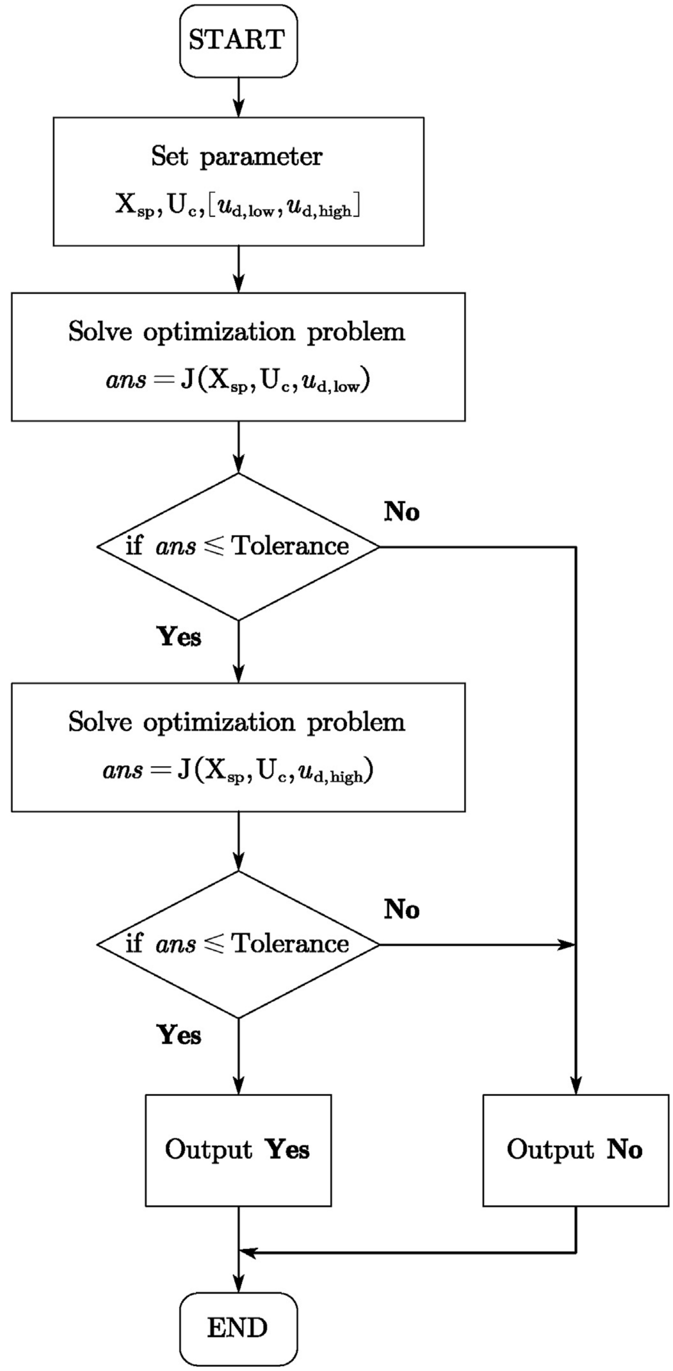

Fig. 6. Flow chart of redundancy search algorithm (Tolerance: depends on the calculation accuracy of the optimization algorithm solver).

When the system is inside the control target, the actual value of the candidate redundant variable u_d at the current moment can be obtained. The largest redundant variable interval is generated based on this expansion, so we use the original single-step operation range of the redundant variable delta(u_d) as the step size to perform a two-way search. The search process is shown in Fig. 7.

In Fig. 7, the interval of candidate redundant variables can gradually increase until the algorithm shown in Fig. 6 is not satisfied. In the specific implementation process, a search algorithm can be designed to step through each input variable step by step. While determining the redundant variable, the maximum domain of the

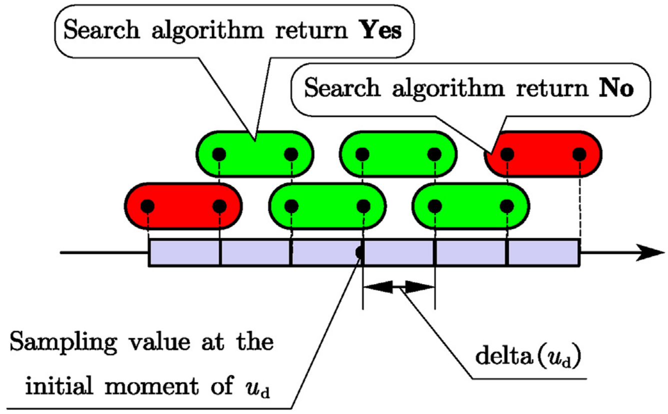

Fig. 7. Schematic diagram of interval boundary search method for candidate redundant variables.

redundant variable can also be determined.

This section mainly proposes search methods for redundant variables. Firstly, some characteristics of redundant variables are analyzed, and then a specific algorithm for examining redundant variables and a method for determining the domain of redundant variables are proposed.

4. Optimization strategy design based on redundant variables

The optimization strategy based on redundant variables needs to meet two prerequisites. First assume that the necessary preparation conditions have been met, that is, the control target is a zone target. Second, ensure that the system has redundant control variables and that its domain has been acquired.

4.1. Optimal control strategy of parallel structure

When controlling for a continuous production process, the entire control system could have two working states. Control mode and optimization mode. It is worth noting that a system operating in optimized mode will not completely shut down the controller. In the framework proposed in this paper, optimization is based on redundant control variables, which means that there is an optimizer to adjust the redundant variables, while the remaining variables are still under the regulation of the zone controller. In the optimization process, the optimizer and the controller are of equal importance to the overall stability of the control system. The design of the optimizer needs to consider both optimization and control performance. In Section 3, the domain of redundant variables can be obtained according to the redundant variable search algorithm and interval search method. The change of the redundant variables in the definition domain will not affect the steady-state performance of the system, so the need for ensuring the control performance of the system can be reduced in the process of designing the optimizer. In the design process of the controller, two different stages need to be considered. The emphasis is on the design of the controller when the system is operating in an optimized state. Because the optimizer directly operates on the redundant variables, the value of the redundant variables can be regarded as a measurable disturbance variable relative to the controller. Therefore, the design of the controller should consider the existence of measurable disturbances.

When the system is in control mode, the optimizer is suspended. All control variables of the system are directly operated by the zone controller. In this case, economic optimization is not considered, and the system states are driven into the control target as the only requirement.

During the operation of the above strategy, the switching process of the above two operation modes also needs to be considered. We design a coordinator to switch the controller adopted by the system by real-time monitoring whether the current state is within the control target. When the state variables of the system are outside the control target of the system, the zone controller is used to control all the control variables. When it is detected that the state variable of the system is in the control target, the optimization strategy of the parallel structure described above is adopted to improve the economics of the process system. The structure of the entire control system is shown in Fig. 8. The switching process of the system between two operating states is shown in Fig. 9.

The coordinator in Fig. 8 monitors the value of the operating state variable x of the system in real time, and switches the operating state of the system as shown in Fig. 9 according to different zone where the state x is located. The specific implementation formula of the zone controller and the formula of the optimizer are described in detail in Section 4.1 and Section 4.2.

4.2. Implementation of the zone controller

For multi-variable strongly coupled control systems, traditional PID control strategies may not be able to achieve the aforementioned zone control tasks. Therefore, in the framework of this paper, predictive control theory is used to achieve zone target control. The zone prediction controller needs to work in two operating states, and the two states have different numbers of operable input variables for the controller. Therefore, the controller formula of the system working in the control mode is given first.

$$\begin{aligned}
&\min J = \sum_{k=1}^{N} \mathrm{dist}(x(k), X_{sp}) + \sum_{k=1}^{N-1} l(\Delta u(k), \Delta x(k)) \\
&\mathrm{s.t.}\, x(k+1) = f(x(k), u(k)), k = 1, \ldots, N \\
&u(k) \in U, k = 1, \ldots, N \\
&x(k) \in X, k = 1, \ldots, N \\
&\Delta u(k) = u(k+1) - u(k), k = 1, \ldots, N-1 \\
&\Delta x(k) = x(k+1) - x(k), k = 1, \ldots, N-1
\end{aligned} \tag{9}$$

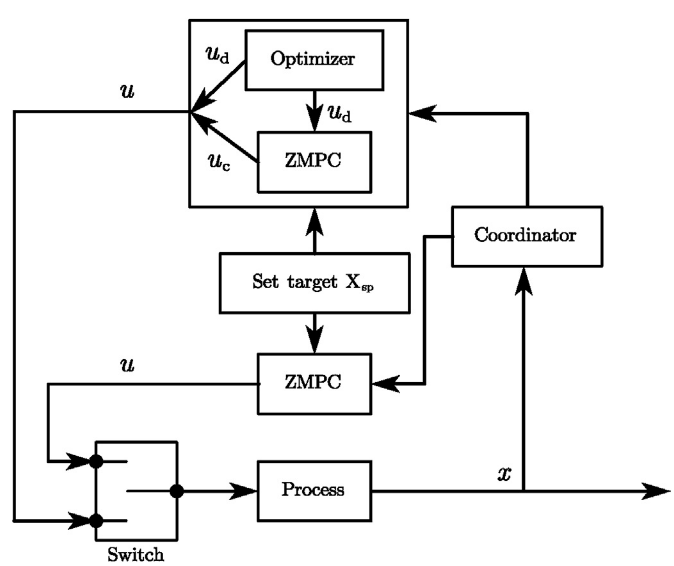

Fig. 8. Control system structure diagram (Coordinator transmits activation signal and state measurement value at the current moment).

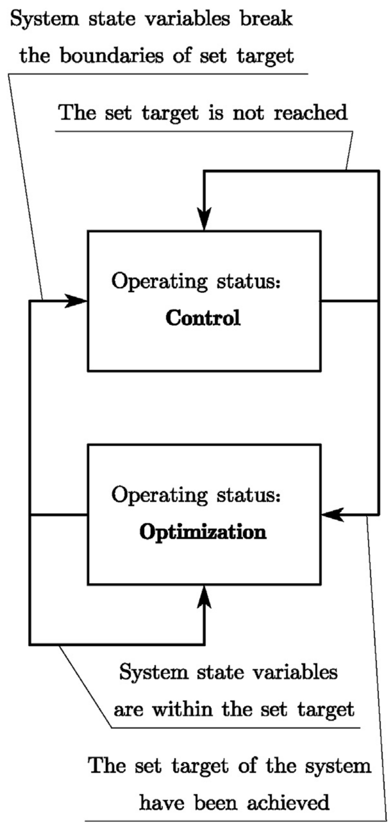

Fig. 9. Schematic diagram of system operating state switching (When the directional line switching conditions are met, the system operating state will be changed).

In Equation (9), the objective function of the optimization problem is composed of two parts, one of which is the distance function $\mathrm{dist}(x(k), X_{sp})$ mentioned in Section 2.1, and the other is an additional part $l(\Delta u(k), \Delta x(k)) \in R$ that stabilizes the system. This function satisfies $l(\Delta u(k), \Delta x(k)) \geq 0$, and the equality sign holds if and only if $\Delta u(k) = 0, \Delta x(k) = 0$. When the system is outside the control target . the first term of the objective function predominates, which will drive the system to move toward the control target. When the system state variable is within the control target, the $\mathrm{dist}(x(k), X_{sp})$ part of the objective function is always 0, and $l(\Delta u(k), \Delta x(k))$ dominates.

When it is detected that the state variable of the system is in the control target, the optimization strategy of the parallel structure is adopted to improve the economy of the process system. The control formula is shown in Equation (10).

$$
\begin{aligned}
&\min J = \sum_{k=1}^{N} \mathrm{dist}(x(k), X_{sp}) + \sum_{k=1}^{N-1} l(\Delta u_c(k), \Delta x(k)) \\
&\mathrm{s.t.}\, x(k+1) = f(x(k), u_c(k), u_d), k = 1, \ldots, N \\
&u_c(k) \in U_c, k = 1, \ldots, N \\
&x(k) \in X, k = 1, \ldots, N \\
&\Delta u_c(k) = u_c(k+1) - u_c(k), k = 1, \ldots, N-1 \\
&\Delta x(k) = x(k+1) - x(k), k = 1, \ldots, N-1
\end{aligned}
\tag{10}
$$

In Equation (10), the basic form is the same as Equation (9). However, because of the existence of redundant control variables, the system is in an operating state with insufficient degrees of freedom, so there are two processing methods for processing uncontrolled redundant input variables. The first method is to treat it as an unmeasurable disturbance, which does not consider its modeling inside the controller, and only uses feedback control to reduce its impact on the system. The second method is to process the redundant input variable by using a measurable feedforward variable. During the design of the controller, the modeling of redundant channels is retained and treated as a constant value disturbance. In order to ensure the validity of constant value processing, we need to make the operating cycle of the optimizer greater than the operating cycle of the controller. The specific implementation form is explained in section 4.3.

4.3. Implementation of the optimizer

The design of the optimizer is divided into two parts. First, when the system is detected to be inside the control target, the coordinator marks the redundant input variables and sends the information to the optimizer. The optimizer calculates the best steady-state operating value for redundant input channels. Second, the optimizer should implement this optimization effect in a special way. In the actual chemical production process, rapid adjustment of input variables is not allowed in some cases. Therefore, segmentation is needed to achieve optimal adjustment of redundant input variables. For this reason, we propose the concept of optimization cycle ratio to implement the segmentation optimization in detail.

The formula of the optimizer is shown in Equation (11).

$$
\begin{aligned}
&\min J = l_e(x, u_c, u_d) \\
&\mathrm{s.t.}\, x = f(x, u_c, u_d) \\
&x \in X \\
&u_c \in U_c \\
&u_d \in U_d
\end{aligned}
\tag{11}
$$

In Equation (11), $l_e(x, u_c, u_d) \in R$ represents the economic cost of the system, and energy saving, economic optimization and other indicators should be fully considered in the design process. The economic indicator function should also satisfy semi-positive definiteness, that is, $l_e(x, u_c, u_d) \geq 0$.

The u_d^* calculated by Equation (11) can be regarded as the optimal steady state value of the redundant input channel. In the optimization mode, the redundant input channel needs to be set to the optimal value. However, the change rate of the redundant channel will affect the stability of the system, because the excessive change of the redundant variable will cause the system to temporarily leave the zone control target. Therefore, we introduced the optimization cycle ratio to achieve the entire optimization process, as shown in Equation (12).

$$
\gamma = \frac{T_o}{T_c}
\tag{12}
$$

In Equation (12), T_c represents the operating cycle of the controller, and T_o represents the operating cycle of the optimizer. In general, choose $\gamma \geq 1$ to determine the execution cycle of the optimizer. Fig. 10 shows the implementation of parallel optimization based on the optimization cycle ratio.

The optimal value u_d^* of the redundant input variables is realized in multiple stages due to the existence of the optimization cycle ratio during the tracking process. In each step of the change process, the zone predictive controller has a certain adjustment time so as to be able to generate a corresponding control effect to suppress the disturbance caused by redundant variables. However, under the framework of zone control, the control target is set as a set, and the control performance of the system can still be guaranteed.

In order to quantitatively analyze this control strategy, we designed a specific numerical simulation experiment in Section 5 to illustrate the effectiveness and feasibility of the method.

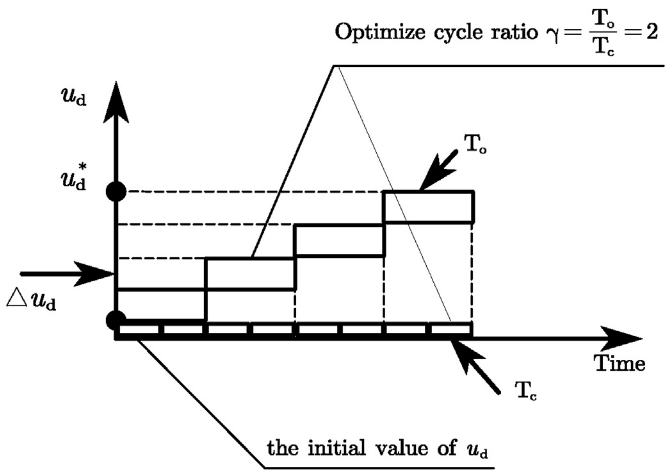

Fig. 10. Schematic of optimization strategy based on optimization cycle ratio.

Table 1
Description of each variable of Shell model.

Variable name	Description
u_1	Top draw flow rate
u_2	Side draw flow rate
u_3	Bottom reflux head transfer rate
x_1	Top end point
x_2	Side end point
x_3	Top temperature
x_4	Upper reflux temperature
x_5	Side draw temperature
x_6	Intermediate reflux temperature
x_7	Bottom reflux temperature

Table 2
The control constraints of Shell model.

Variable name	Limitation
x_1	[-0.5 1]
x_7	[-0.5 -]
u_1, u_2, u_3	[-0.5 0.5]
$\Delta u_1, \Delta u_2, \Delta u_3$	[-0.05 0.05]

5. Method verification and results analysis

The SHELL model [27] is used to verify the control optimization strategy proposed in this paper. The Process flowsheet drawing of this system is shown in Fig. 11.

The SHELL model is given by the form of a transfer function, so it is a coupled linear model with time delay. All of the state variables are dimensionless. The description of each variable of the model and the constraints of each variable are shown in Table 1 and Table 2 [28].

Numerical simulation is mainly used to verify the feasibility and effectiveness of the strategy proposed in this paper. Before giving the simulation results, we verified two problems. The first is whether the zone control system must have redundancy. The second is whether a system with redundancy can be optimized based on redundant variables. In the first problem, we take the zone control target and the constraints of each variable as an application scenario. Simulation shows that for each random application scenario, redundancy does not necessarily exist. But for some application scenarios, this constraint can be obtained by reducing the constraints of some variables. For example, narrowing the control limitation of the flow can make the flow a redundant control variable. Based on the above facts, we believe that redundancy exists as a property of zone control systems. In the second problem, we found that each application scenario with redundant control variables can be economically optimized using the strategy proposed in this paper. Simulation experiments show that the optimization strategy can indeed reduce the economic loss index. Therefore, it can be verified that the optimization strategy in this paper can indeed be applied to the zone control system with redundancy. We chose a representative simulation example to verify the feasibility and effectiveness of the optimization strategy proposed in this paper.

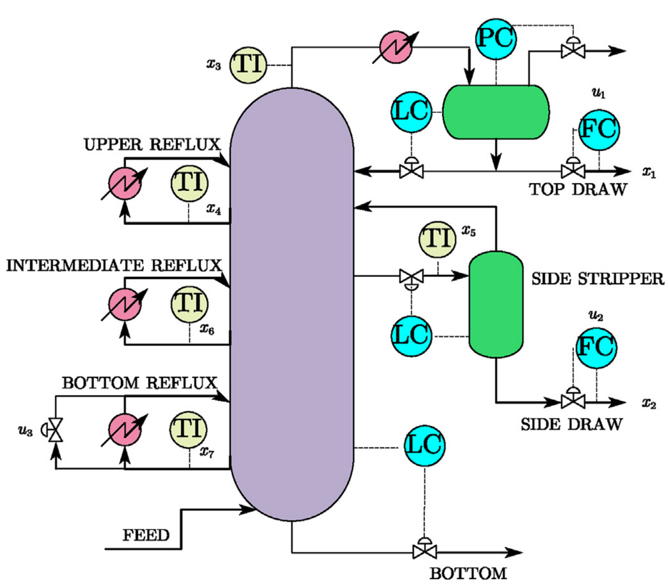

Fig. 11. Diagram of Shell control problem.

We give the following zone control target: $x_1^{sp} \in [0.13, 0.67]$, $x_2^{sp} \in [0.23, 0.86]$, $x_7^{sp} \in [0.35, 0.68]$.In the MPC framework, each variable can be guaranteed to be within constraints. When the main concern variable is under control, the remaining variables are free to change within an acceptable range, so additional attention to this part is omitted. According to the redundant variable search algorithm mentioned in Section 3.2, we judge each control variable separately, and finally obtain the redundant definition domain of each variable as: $u_1 \in [-0.17, 0.13]$, $u_2 \in [-0.07, 0.02]$, $u_3 \in [-0.3, 0.4]$. In the process of optimization, since u_3 has a greater impact on the system, the controller needs to always have control over it. Therefore, even if u_3 has a large redundancy interval, we still do not consider it as a redundant variable. At the same time, we perform offline simulation inside a given target to obtain the steady-state value of u_3 when u_1 and u_2 change, and the time required to reach the steady state.

Fig. 12 shows the steady state values of u_1 and u_2 corresponding to different u_3 when the zone control target is achieved, and the time required to reach the steady state. We choose 1 min as the sampling period of the zone prediction controller. If u_1 is selected as a redundant control variable and its optimization range is limited to [0.05 0.15], $\gamma = 46$ can be selected so that the system can ensure that the system has sufficient response time. In this numerical simulation experiment, we select the performance index function $l_e = \| u - [0.08, -0.03, -0.02]^T \| + \| x - [0.4, 0.545, 0.515]^T \|$. We use u_1 as a redundant input channel, and the simulation results of the system is shown in Fig. 13.

Fig. 13 shows the entire numerical simulation process, which is

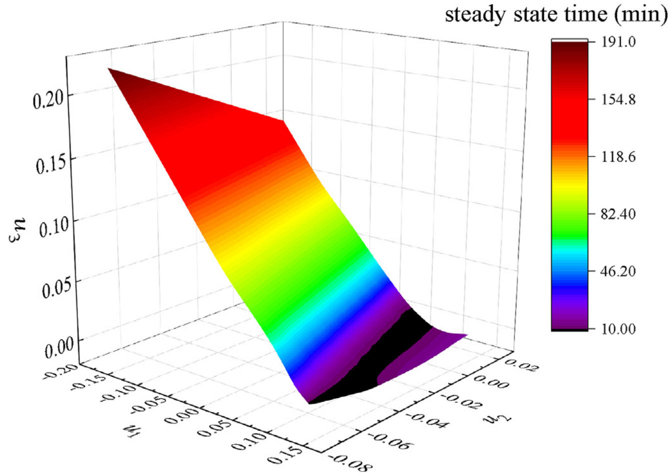

Fig. 12. System offline simulation diagram (Each point is the steady-state operating point, and the time from the initial moment to the steady-state operating point).

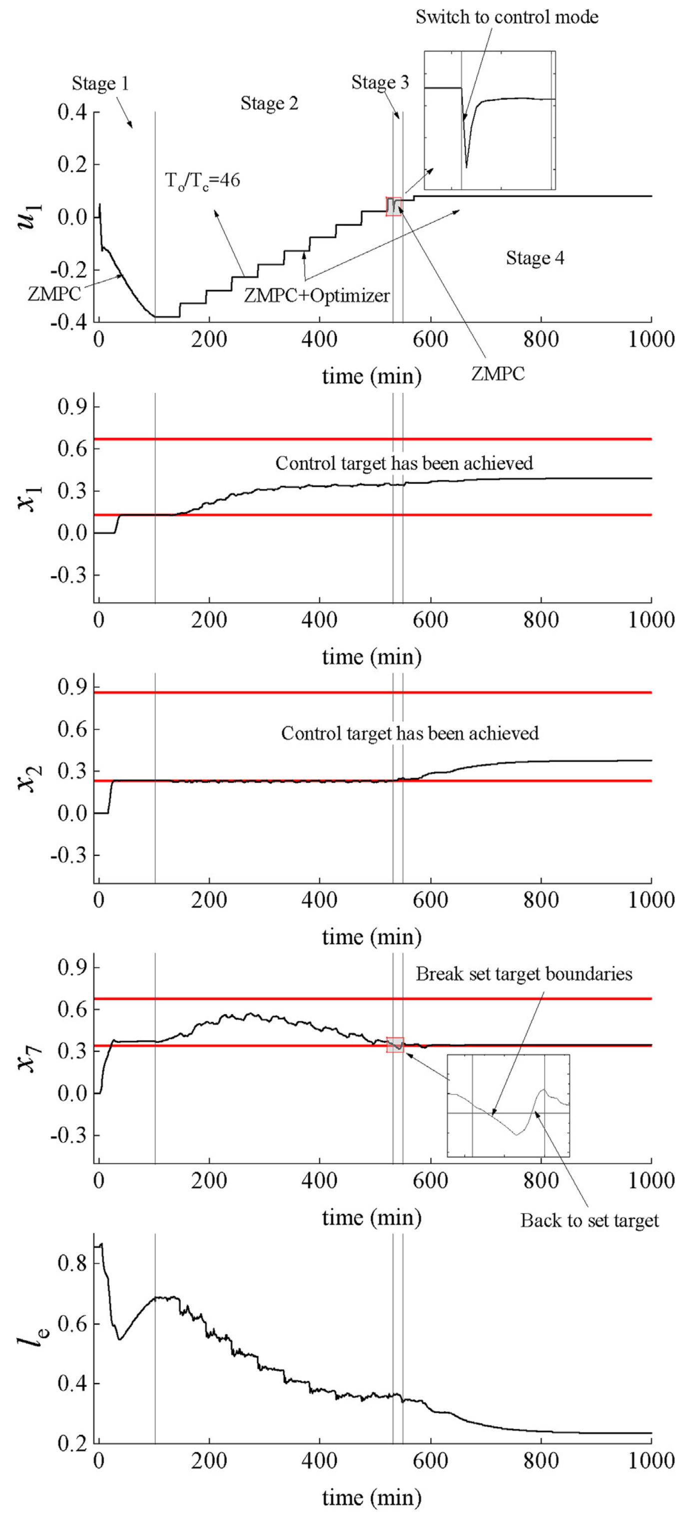

Fig. 13. Schematic diagram of simulation (Stage 1: ZMPC, Stage 2: ZMPC + Optimizer (redundant variable u_1), Stage 3: ZMPC, Stage 4: ZMPC + Optimizer (redundant variable u_1). Zone control target: $x_1^{sp} \in [0.13, 0.67]$, $x_2^{sp} \in [0.23, 0.86]$, $x_7^{sp} \in [0.35, 0.68]$).

divided into four stages. In the first stage, the system is in control mode, and all input variables are controlled by the controller. When the state variable of the system enters the zone control target, the system switches to the optimization mode and enters the second stage. At the same time, the coordinator uses u_1 as a redundant variable to start the optimization operation. The optimizer performs an optimization operation with a sampling period of $T_o = 46$ min. Increasing u_1 means increasing the output flow at the top of the column, but it is still necessary to monitor the temperature at the bottom of the column to avoid x_7 being too low. In the second stage, the temperature at the bottom of the column rises first and then drops. At the last moment of this stage, x_7 moves out of the zone control target. Therefore, the coordinator switches the system working state back to the control mode, that is, the third stage starts. The main task of the third stage is to re-achieve the control target. According to the numerical simulation results, it can be seen that x_7 was quickly re-driven to the zone control target. In the fourth stage, we manually lowered the upper limit of the redundancy interval of u_1, so the system can maintain stability under the largest possible state of u_1. At the same time, the bottom temperature x_7 still meets the control target.Through the economic index function l_e, we can intuitively obtain the real-time economic index of the system when it is running at different stages. In the optimization stage, the index gradually decreases and eventually stabilizes to the lowest point, indicating that the simulation optimization results are consistent with the original design of the optimization strategy.

Numerical experiments show that the parallel structure optimization strategy proposed in this paper is feasible. In practical applications, attention should be paid to the selection of the optimizer's sampling period and redundancy interval. In this experiment, because the redundancy interval was too large, the state of the system exceeded the control goal in the second stage. Therefore, when designing the redundancy interval, it can be appropriately reduced to obtain more stable control performance.

6. Conclusion

A two-layer parallel structure optimization strategy based on predictive control is proposed in this paper. Firstly, a redundant variable search algorithm based on a steady-state mapping model and a method for identifying redundant variable optimization intervals are proposed. Secondly, two different operating modes are proposed. A coordinator detects the current state in real time through a steady-state mapping model to switch between different modes. The controller and optimizer play different roles in different working modes, and control these variables separately to achieve the best economic benefits. To ensure the timeliness and accuracy during the handover process, additional monitoring procedures are designed. When the system state variables are outside the control target or are about to break the control target boundary and move outside, the control of all control variables will be obtained by the zone predictive controller. This ensures that the system state is driven into the control target when the system state is outside the zone control target. When the system state variable is inside the zone control target, the coordinator will start an optimization operation to ensure potential economic benefits. This result verifies the feasibility and effectiveness of this optimization strategy through simulation.

Author contributions section

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. The manuscript was written through contributions of Xin Wan and Xiong-Lin Luo. All authors have given approval to the final version of the manuscript. These authors contributed equally. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

We understand that the Corresponding Author is the sole contact for the Editorial process (including Editorial Manager and direct communications with the office). He/she is responsible for communicating with the other authors about progress, submissions of revisions and final approval of proofs. We confirm that we have provided a current, correct email address which is accessible by the Corresponding Author and which has been configured to accept email from the email luoxl@cup.edu.cn (Xiong-Lin Luo).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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