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Economic Optimization Based on Control Redundancy for Zone Model Predictive Control

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Zone control is to augment the control target from one point to a convex set, and let the system take the shortest time to enter the control target. This paper proposes an optimization strategy based on redundant control variables to improve the economic benefits of zone control. When the system is outside the set target, the zone prediction control algorithm is used to preferentially drive the state to the inside of the set zone. When the system enters the set zone, it is directly optimized by using redundant control variables to achieve greater economic benefits. During the operation of the system, each variable is evaluated by the steady-state mapping model of the system, and variables satisfying certain conditions are marked as redundant variables. The controller and optimizer are coordinated based on this tag to achieve both system control and economic performance. Finally, the effectiveness and feasibility of the strategy are verified by a typical SHELL model.

1. Introduction

There are various performance indicators in process control. These performance metrics can be quantified as a mathematical expression, such as integrating the components of the product with the energy consumed during the reaction and the flow of the heat exchanger to obtain a comprehensive economic performance loss function. During the operation of the system, the controller will gradually minimize this performance loss. In this process, the system moves to the pre-designed optimal state. When the best advantage is reached, it means that the system can reach the state of least pollution and lowest energy consumption after this moment. The general optimization strategy does not take into account the dynamic losses during system operation. In addition, the optimal setting goal for continuous production equipment may be a zone rather than a point. Therefore, the relationship between coordinated control and optimization is also an important part of optimizing the energy conservation framework. Without loss of generality, these zone control targets can be quantified using ellipsoids in space. Researchers have abstracted this problem into zone control tasks (González and Odloak, 2009) and conducted related algorithm research (Ferramosca et al., 2010). Under the framework of zone control, it is generally possible to construct a new norm to quantify the distance from point to zone, and use this norm as the objective function to design the controller. However, when the system enters the interior of the set zone, there is still a certain degree of freedom that can balance economic optimization. Therefore, the coordination of control performance and economic optimization under the zone control framework has gradually become one of the research directions. In the literature (Xin et al., 2017), the similarities and differences between model predictive control (Mayne, 2014) and economic model predictive control (Ellis et al., 2014) are analysed. It is shown that the system trajectories in different gradient fields will advance in different directions. At the same time, researchers use Nash equilibrium theory to study multi-objective problems (Li et al., 2005). Starting from the means of realizing optimization, this paper proposes an optimization strategy based on redundant control variables. When the system is outside the set zone, it can be controlled by a set of zone prediction controllers targeting the zone, so that the system can quickly enter the set zone. When the controller enters the inside of the set zone, it means that the control target has been achieved. At this point, the economic performance of the system can be optimized, and the system is controlled by an optimizer. Although economic optimization is often incompatible with control performance, and the system may reach the boundary of the set point, it reaches both the critical region. In this case, the controller needs to be switched from the optimizer to the zone prediction controller. The entire system will be in this kind of dynamic balancing process. This paper first proposes the

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concept of redundant variables, and then uses a second-order system to illustrate the specific implementation mechanism. Then the related controller algorithm based on redundant variable control strategy is proposed. Finally, a simulation is used to illustrate the effectiveness of this strategy. At the same time, the performance index of the system can be guaranteed under the condition of increasing load.

2. Motivation

For zone control, there are two stages, the first is to enter the set zone, and the second is to optimize the economy. In order to achieve the above process, there are two ways to consider. The first is to build an EMPC (Economic Model Predictive Control) controller, but a single controller has only one objective function, and in order to reflect the priority of the zone, the objective function can only be the zone distance norm. However, the zone norm does not reflect the economic optimization of the second stage. Then consider the distance constraint as a global constraint and add a switch variable as a sign of whether this condition is active. This optimization problem with switching variables belongs to mixed integer nonlinear dynamic programming, and its solving efficiency is low, and the nonlinearity may cause the solution to fail. The second method is switching control, using zone control and conventional EMPC control to switch between different controllers at different stages. This method will control all control variables to an EMPC during optimization. When the optimization target is mutually exclusive with the control target, the system is driven by the optimizer and deviates from the control target. If the zone condition is added to the EMPC, it is similar to the first method. This paper propose an optimization strategy based on redundant control variables. Redundant variables represent control variables that have little effect on control performance. In this framework, the marked redundant variables are directly manipulated by the optimizer and the dynamic performance of the control system is improved by online dynamic optimization.

Before discussing the specific optimization process, a simple second-order system is used to illustrate the existence of redundant control variables in the control system. The dynamic equation of the system can be expressed by Eq(1).

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

The steady-state mapping model of this system is of Eq(2).

$$x_s = (I - A)^{-1} B u_s \tag{2}$$

First assume that the input matrix B is an invertible matrix, thereby indicating the existence of control system redundancy.

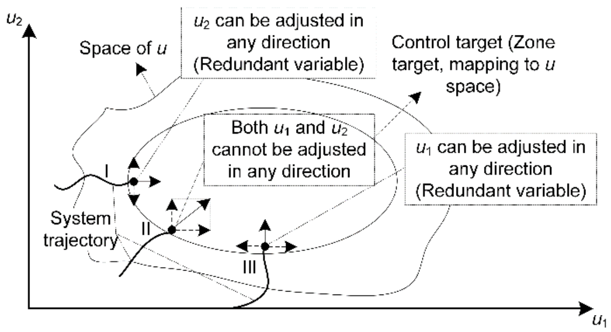

Figure 1: The diagram of system redundancy

If B is reversible, a steady-state mapping between system state x and control variable u can be found. In Figure 1, Assume that the system has stabilized within the control target for a limited time. At steady state, u_2 is changed within a certain small range, and the system is still stable under the action of the controller in trajectory I. After the system is stable, the entire system can still remain within the control target. In the trajectory III, the control variable u_1 has the same characteristics. However, in the trajectory I, u_1 cannot be arbitrarily adjusted. If u_1 is arbitrarily changed, it is possible to move the steady-state operating point of the system to the left. Therefore, the characteristics of u_1 and u_2 are different in this case. Mark u_2 in trajectory I as a redundant control variable, which means that any movement within a small range will not affect the control requirements. Similarly, u_2 in trajectory III cannot be arbitrarily adjusted, and u_1 is a redundant variable. A more special case is the trajectory

II. When the system is at the steady state point here, neither u_1 nor u_2 can be arbitrarily moved, so the system in this state has no redundant variables.
For more complex systems, redundancy still exists. Then, for a chemical process with zone control tasks, when the system enters the set target, the economic benefits and energy loss of the system can be optimized in a small range. In order to achieve an optimization algorithm that is different from the typical EMPC, the potential economic benefits can be improved by an optimizer that only considers economic factors.

3. Optimization operation based on redundant control variables

Implementing operations based on redundant control variables requires building a separate optimization layer as shown in Figure 2. This optimization layer needs to be able to directly manipulate the control variables and send the optimized control variable trajectory to the controller in the form of a feedforward variable. It is necessary to have a coordinator to monitor the status of the system in real time and dynamically label each variable accurately. The controller and optimizer need to be able to make corresponding structural changes based on this globally labelled information.

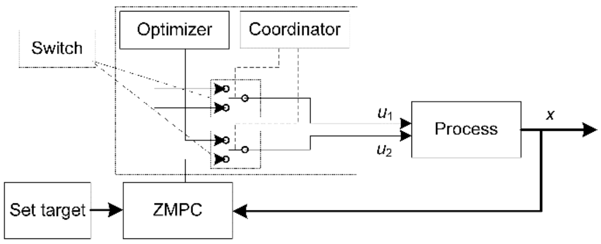

Figure 2: System structure based on an independent optimization layer

In the optimization process based on redundant variables, two points need to be noted. First, the redundant variables are relative to the control variables, and under certain conditions, the two variables can be transformed into each other. Second, the online system needs to have the ability to judge the current state of the current system in real time, and can convert control variables into redundant variables when appropriate, and can convert redundant variables into control variables in time.
The following will explain when it is possible to consider converting control variables into redundant variables in the control system.
Take a second-order system as an example. When the system enters the set zone, the control target can be switched. The problem is illustrated by a second-order system as shown in Figure 3.

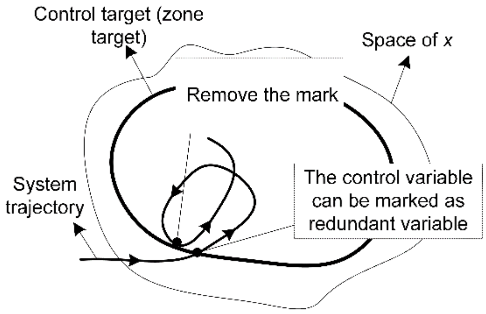

Figure 3: Second-order system trajectory based on redundant variable optimization operations

The field of view is returned to the x space, and under the action of the zone prediction controller, the system gradually advances to the set zone. When the system trajectory runs inside the set target (zone target), the coordinator marks a certain control variable as a redundant variable. At this point, the optimizer begins to directly manipulate the control target, and uses the dynamic optimization algorithm to obtain the optimal trajectory of the redundant variable. At the same time, state variables move along a track dominated by the optimizer. When the system breaks through the control target under the action of the optimizer, the coordinator will clear the flag of the redundant variable in time. The control of the redundant variables is taken back by the controller. Then, under the action of the zone prediction controller, the state of the system is re-stabilized at the boundary of the set zone. When the coordinator detects that the system is re-stabilized, a control variable is again marked as a redundant variable and is subject to direct control by the optimizer. By repeating the above process, the system economic performance under the framework of the zone control target can be improved.

4. Control and optimization algorithm

First consider a typical predictive control algorithm in Eq(3).

$$\min\ J = \sum_{k=0}^{N-1} l(x(k), u(k)) \tag{3.a}$$

$$\text{s.t. } x(k) \in \mathrm{X},\ u(k) \in \mathrm{U} \tag{3.b}$$

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

After augmenting the control target into a set of points, a new norm is needed to measure control performance. The distance metric function is first introduced to calculate the spatial distance between the current state x and the set zone δ as shown in Eq(4).

$$d_x^{\delta} = dist(x, \delta) \tag{4}$$

Considering this distance metric function, the zone prediction control algorithm is obtained as shown in Eq(5).

$$\begin{aligned} &\min\ J = \sum_{k=0}^{N-1} d_{x(k)}^{\delta} \\ &\text{s.t. Eq(3.b)-Eq(3.c)} \end{aligned} \tag{5}$$

The above algorithm can ensure that the system trajectory can reach the set zone preferentially and quickly reach the control target. When the system enters the zone, the coordinator will calibrate the redundant control variables based on the steady-state mapping model. The system represented by Eq(1) undergoes a structural change as shown in Eq(6).

$$x(k+1) = Ax(k) + B_{\mathrm{c}} u_{\mathrm{c}}(k) + B_{\mathrm{d}} u_{\mathrm{d}}(k) \tag{6}$$

At this time, the redundant control variable u_{d} is directly operated by the optimizer, and the controller can only operate the unlabeled control variable. In the zone prediction control algorithm, the marked redundant variable is used as a feedforward variable to participate in the calculation. At this time, the zone prediction control has the structure shown in Eq(7).

$$\begin{aligned} &\min\ J = \sum_{k=0}^{N-1} d_{x(k)}^{\delta} \\ &\text{s.t. Eq(6),Eq(3.b)} \end{aligned} \tag{7}$$

The feedforward variable u_{d} in Eq(7) needs to be provided by the optimizer. Next, an optimizer function based on redundant control variables is given as Eq(8).

$$\begin{aligned} &\min\ J = \sum_{k=0}^{N-1} l_{\mathrm{e}}(x(k), u_{\mathrm{d}}(k)) \\ &\text{s.t. Eq(6),Eq(3.b)} \end{aligned} \tag{8}$$

The objective function of Eq(8) is different from the Eq(3). Usually when designing the objective function of Eq(3), it is necessary to balance the stability of the system, and it is necessary to make the whole objective function be regarded as the Lyapunov function of the system. However, such a design will result in loss of economic performance, and there will be mutual exclusion factors when designing the controller. Therefore, the optimizer represented by Eq(8) is proposed. The variable to be determined only has the marked redundant variable u_{d}, and the variable u_{c} controlled by the controller is used as a parameter to participate in the calculation. In the design of the objective function of Eq(8), only economic optimization can be considered, and the stability of the entire system is not considered for the time being. Only considering economic optimization can relax the restriction on the objective function, and the economic objective function of the positive quadratic form is not necessary.

The condition for judging whether a variable is a redundant control variable is given by Eq(9) below.

Given an optimization tolerance $\Delta u_{\mathrm{d,max}}>0$, if the following proposition is true, the variable is considered to be a redundant variable.

$$\begin{aligned} &\forall u_{\mathrm{d}} \in \left\{ u_{\mathrm{d0}} + \Delta u_{\mathrm{d}} \mid \left|\Delta u_{\mathrm{d}}\right| \le \Delta u_{\mathrm{d,max}} \right\} \\ &\exists u_{\mathrm{c}} \in U_{\mathrm{c}},\ x = (\mathrm{I} - A)^{-1} B \left[u_{\mathrm{c}} \mid u_{\mathrm{d}} \right]^{\mathrm{T}} \in \delta \end{aligned} \tag{9}$$

According to the system steady-state mapping model given by Eq(2), the following conclusion can be obtained. When a redundant control variable changes within a given small range, the un-marked control variable is fixed, and a new steady-state set can be obtained. It is necessary to determine the spatial relationship between the original set zone and the set. If the new set is included in the original set target, the control variable can be marked as redundant. At this point, the control of the tagged variable has been given to the optimizer and the economic benefits are improved. In order to ensure the control performance of the system in the optimized operation, it is required to dynamically detect whether the system can still be within the set target within a certain prediction time domain. Once the set zone is detected within the predicted trajectory of the zone prediction controller, the flag of the redundant variable needs to be cleared so that the zone controller can regain control of these variables. The entire control system can only be in one of two states of control or optimization. Therefore, the above dynamic monitoring process can refer to the finite state machine principle, as shown in Figure 4.

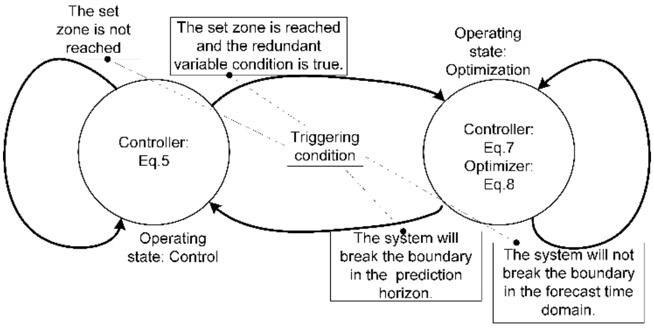

Figure 4: Schematic diagram of working condition switching

5. Case study

In order to verify the feasibility of the proposed control strategy, the classic SHELL heavy oil preliminary distillation tower model (Vlachos et al., 2002) was adopted. The variables of the system and their constraints are shown in Table 1. The mathematical model of the system is as shown in Eq(10), and a dimensionless operation has been performed. The initial operating point of the system is $y = [1.1052\ 1.6521\ 1.4756]^T$, and the system is first driven into the control target under the initial conditions by the zone prediction controller. Without loss of generality, the control target can be an ellipsoid in a space with a center of $[0\ 0\ 0]^T$ and the radius r = diagonal matrix ([0.5 0.5 0.5]). The economic loss function is $e_{loss}(k)=(y(k)-R)^T\mathrm{diag}([0.5\ 0.9\ 0.3])(y(k)-R)$, where $R=[1\ 2\ 1]^T$. The control loss function is the distance from the current state $y(k)$ to control target.

$$G(s)=\begin{bmatrix} \frac{4.05e^{-27s}}{50s+1} & \frac{1.77e^{-28s}}{60s+1} & \frac{5.88e^{-27s}}{50s+1} \\ \frac{5.39e^{-18s}}{50s+1} & \frac{5.72e^{-14s}}{60s+1} & \frac{6.9e^{-15s}}{40s+1} \\ \frac{4.38e^{-20s}}{33s+1} & \frac{4.42e^{-22s}}{44s+1} & \frac{7.2}{50s+1} \end{bmatrix} \tag{10}$$

Table 1: The description and constraint of each variable

Input	Constraints	Description	Output	Constraints	Description
u_1	[-1,1]	Top draw	y_1	[-2,2]	Top end point
u_2	[-1,1]	Side draw	y_2	[-2,2]	Side end point
u_3	[-1,1]	Bottoms reflux duty	y_3	[-2,2]	Bottoms reflux temperature

The system trajectory and the comparison of system control and economic loss was shown in Figure 5. The system is first driven to the inside of the control target. When the system detects that the control target has been implemented, it searches for redundant control variables. In this experiment, the control variable u_1 is marked as a redundant variable, at which point it is directly operated by an optimizer, while u_2 and u_3 continue to be controlled by the zone prediction controller. The system simulation curve points out the feasibility and effectiveness of this optimization strategy. The only economic performance index penalty function in the constituency quantifies the economics of the entire process. During the optimization process, the value of the economic index penalty function is gradually decreasing in stage II.

As the system is running, the optimization may drive the state of the system out of the set zone. In stage III, the tag of the redundant variable will be cleared, and the zone prediction controller will continue to control all variables. From the experimental results, the system will continue to drive back to the inside of the set zone. On the premise that the system product quality can be expressed by the performance index. The optimization strategy proposed in this paper can make the system economic loss gradually decrease within a certain time range. In other words, it is optimized by using the system's redundant control variables. Control. The control performance of the system is still guaranteed while economic optimization.

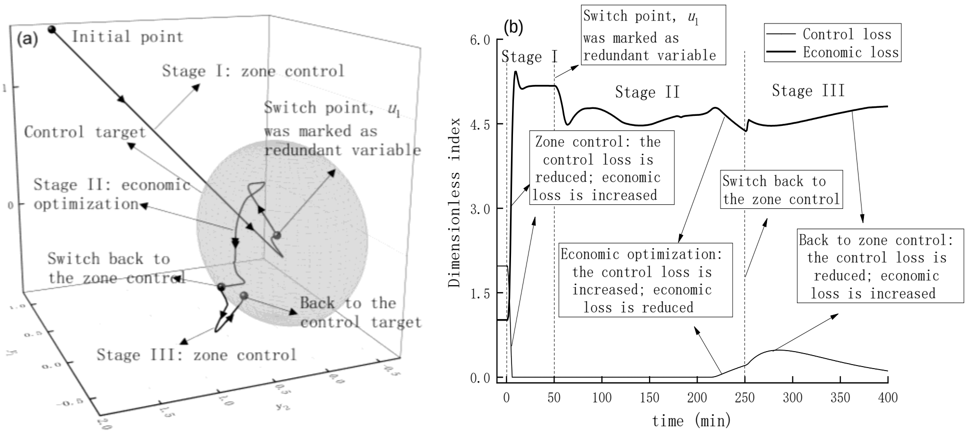

Figure 5: System state variable simulation trajectory and the comparison of system control and economic loss (stage I: zone control; stage II: economic optimization; stage III: zone control), (a) Schematic diagram of the system operation trajectory, (b) System dimensionless loss index (control loss index and economic loss index)

6. Conclusions

This paper proposes an optimization strategy based on predictive control, which directly utilizes two parallel controllers and optimizers to achieve economic optimization. The state of the current system is evaluated by a steady-state mapping model, and redundant variables that can be used for optimization are searched and marked. Controllers and optimizers control these variables separately for optimal economics. At the same time, the system also has the ability to stop optimization in time to ensure control performance. This paper uses the classical SHELL model to verify the proposed algorithm. The experimental results show that for the interval control task, the optimization strategy proposed in this paper can guarantee additional economic optimization under the premise of certain control performance. The stability and feasibility of the strategy have also been verified.

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