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Distributed Predictive Control for Building Temperature Regulation with Impact-Region Optimization ⋆

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Abstract: In multi-zones building temperature regulation systems whose subsystems are coupled with each other, how to improve the optimization performance of entire system with limited network information is a problem when distributed control framework or distributed model predictive control (DMPC) is employed. In this paper, a novel coordination strategy, where each subsystem-based model predictive control (MPC) added a quadratic function of the affection of the current subsystem's input to its down-stream neighbours into its optimization index, is proposed for improving the optimization performance of entire system. This method do not need any additional network connections comparing to the method without this coordination strategy. The simulation of applying the proposed DMPC to a four-zones building temperature regulation system shows the affectiveness of the proposed method.

1. INTRODUCTION

The multi-zones building temperature regulation systems are typical spatially distributed systems which are composed of many physically coupling subsystems (rooms or zones). The distributed control structure is usually used in this class of systems due to its good error tolerance and high flexibility. However, the performance of a distributed framework is, in most cases, not as good as that of a centralized control. How to improve the performance of entire system without any weakening of the characteristics of error tolerance and control flexibility is a problem in the control of multi-zones building temperature regulation systems.

The Distributed Model Predictive Control (DMPC) which controls each subsystem by a separate subsystem-based Model Predictive Control (MPC), has been more and more popular in the control of multi-zones building temperature regulation systems, See. Moroşan et al. [2010], since it not only inherits MPC's advantages of explicitly accommodating constraints and good dynamic performance, but also has the virtue of distributed framework (See Qin and Badgwell [2003], Maciejowski [2002], Sandell Jr et al. [1978], Scattolini [2009], Leirens et al. [2010], Christofides et al. [2012], Zheng et al. [2011b, 2013a]). Thus, this paper will proceed under the DMPC framework.

To improve the global performance of entire closed-loop system, several DMPC coordination strategies appeared in the literatures. The earliest and most adopted one is that each subsystem-based MPC uses the inputs sequence of its neighbors to estimate the interactions among subsystems Camponogara et al. [2002], and some design of stabilized DMPC with constraints is given by Dunbar [2007] and Farina and Scattolini [2012]. Since each subsystem-based MPC minimizes its own subsystem's cost in this method, some article call it as non-cooperative DMPC or local cost optimization based DMPC (LCO-DMPC). If iteration is used in this strategy, the *Nash Optimality* can be obtained, See Li et al. [2005]. In LCO-DMPC, each subsystem-based MPC requires to communicated with the MPCs for its downstream and upstream neighbors. Another very practically coordination strategy is that each subsystem-based MPC takes not only it's own performance but also that of the subsystems it directly impacts on into account in its optimization index, See Zheng et al. [2009, 2011a]. Experiments and numeric results improve that these strategy could significantly improve the performance of entire system. In this strategy, each subsystem-based control required to connected to the controllers of its upstream neighbours, downstream neighbors, and its downstream neighbors' upstream neighbours. The third commonly used strategy is that each subsystem-based MPC optimizes the cost over the entire system Zheng et al. [2013b], Venkat et al. [2007]. If iteration is used in this strategy, the *Pareto Optimality* can be obtained, See Venkat et al. [2007], Stewart et al. [2010]. In GCO-DMPC, each subsystem-based MPC requires the information of the whole system

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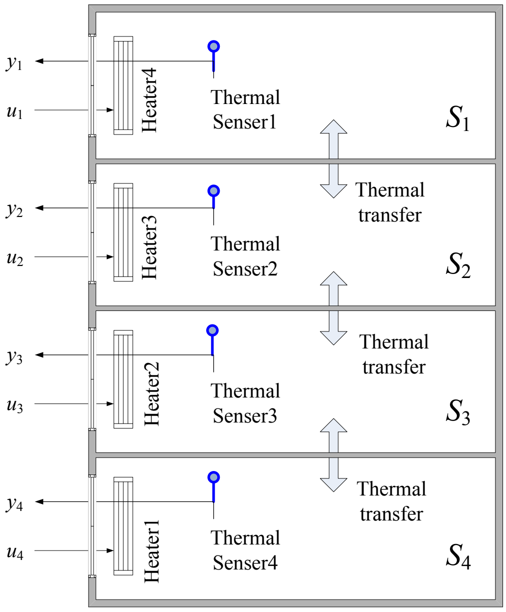

Fig. 1. Four-zones building configuration

and the full connected are required. It can be seen from above that, in the existing methods, with the increasing of the coordination degree, the performance of entire system becomes better and better, the network connectivity become more and more complicity, and consequently the error tolerance and high flexibility become weaker and weaker. To find a method which could improve the global performance or coordination degree without any increasing of network connectivity is still remain to be solved.

In this paper, an Impact region optimization based DMPC is proposed for multi-zones building temperature regulation system, where each subsystem-based MPC adds a quadratic function of the impact of current subsystem's input to its down stream neighbours into its optimization index to increase the coordination degree. It do not need any additional network connectivity comparing to the approach without this coordination strategy.

The remainder of this paper is organized as follows. Section 2 describes the problem to be solved in this paper. Section 3 presents the design of the ICO-DMPC. Section 4 presents the simulation results to demonstrate the effectiveness of the proposed ICO-DMPC algorithm. Finally, a brief conclusion to the paper is drawn in Section 5.

2. PROBLEM

2.1 Multi-zones Building Temperature Regulation System

The multi-zones building temperature regulation systems are a class of typical spatially distributed systems, as shown in (Fig. 1), which are composed of many physically interacted subsystems (rooms or zones) labeled with $\mathcal{S}_1, \mathcal{S}_2, \ldots, \mathcal{S}_m$, respectively. The thermal influences between rooms of the same building occur through internal walls (the internal walls isolation is weak) and/or door openings. A thermal-meter and a heater (or air condition) are installed in each zone, which is used to measure and adjust the temperature of the multi-zones building.

2.2 System Model

Assume that the coupling of each room is caused only between two adjacent zones through walls. And if zone $\mathcal{S}_i$ is affected by $\mathcal{S}_j$, for any $i, j \in \mathcal{P} = \{1, 2, \ldots, m\}$, and $i \neq j$, $\mathcal{S}_i$ is said to be a downstream neighbour of $\mathcal{S}_j$, and $\mathcal{S}_j$ is an upstream neighbour of $\mathcal{S}_j$. Let $\mathcal{P}_i^u$ denotes the set of the subscripts of the upstream neighbors of $\mathcal{S}_i$, and $\mathcal{P}_i^d$ denotes the set of the subscripts of the downstream neighbors of $\mathcal{S}_i$. Knowing that, for multi-zones building heating systems, the coupling element is the output of each subsystems (the measured temperatures), then as point by Moroşan et al. [2010, 2011], the subsystem model including this influence with the adjacent zones can be expressed in following state space formulation

$$\begin{cases} \mathbf{x}_{i,k+1} = \mathbf{A}_{ii}\mathbf{x}_{i,k} + \mathbf{B}_{ii}u_{i,k} + \sum_{i\in\mathcal{P}^u} \mathbf{B}_{ij}y_{j,k} \\ y_{i,k} = \mathbf{C}_{ii}\mathbf{x}_{i,k} \end{cases} \quad (1)$$

where, $u_{i,k}$ is input of the subsystem $\mathcal{S}_i$, refers to the given power to the heater i at time instant k; $y_{i,k}$ is the output of $\mathcal{S}_i$, refers to the temperature average in zone i at time instant k; $\mathbf{x}_{i,k}$ is the state vector of $\mathcal{S}_i$; $\mathbf{A}_{ii}$,$\mathbf{B}_{ii}$,$\mathbf{C}_{ii}$ and $\mathbf{B}_{ij}$ are the system coefficient matrices.

Consider that $y_{j,k} = \mathbf{C}_{jj}\mathbf{x}_{j,k}$ and let $\mathbf{A}_{ij} = \mathbf{B}_{ij}\mathbf{C}_{jj}$, then Equation 1 can be rewritten as following nominal state interacted model

$$\begin{cases} \mathbf{x}_{i,k+1} = \mathbf{A}_{ii}\mathbf{x}_{i,k} + \mathbf{B}_{ii}u_{i,k} + \sum_{i\in\mathcal{P}^u} \mathbf{A}_{ij}\mathbf{x}_{j,k} \\ y_{i,k} = \mathbf{C}_{ii}\mathbf{x}_{i,k} \end{cases} . \quad (2)$$

The control design and the discussion in this paper are all based on this model.

2.3 Problem

A distributed or decentralized control structure is employed in the multi-zones building temperature regulation system, where an individual controller is installed in each zone and each controller independently controls the average temperature of corresponding zone through adjusting the corresponding heater.

The control objective is make the global performance index of closed-loop system as small as possible, in the same time, do not violate the characteristics of good error tolerance and the high control flexibility. The optimization index of entire system is

$$J(k) = \sum_{i\in\mathcal{P}} J_i(k) \quad (3)$$

where

$$J_i(k) = \sum_{l=1}^{N}\left(\left\| \mathbf{C}_{ii}\mathbf{x}_{i,k+l|k} - y_i^{sp} \right\|_{q_{i,l}}^2 + \left\| \Delta u_{i,k+l-1|k} \right\|_{r_{i,l}}^2 \right), (4)$$

y_i^{sp} is the set point of the i^{th} zone's temperature and $\Delta u_{i,k+l|k} = u_{i,k+l|k} - u_{i,k+l-1|k}$ is the increment of heater power of the i^{th} zone at the time instant k. Constant $q_{i,l}, r_{i,l} > 0$, $l = 1, 2, \ldots, N$, is weighting coefficients for the i^{th} zone, and let the weighting matrices for $\mathcal{S}_i$ be

$$\mathbf{Q}_i = \text{block} - \text{diag}\{q_{i,1}, q_{i,2}, \ldots, q_{i,N}\} > 0$$

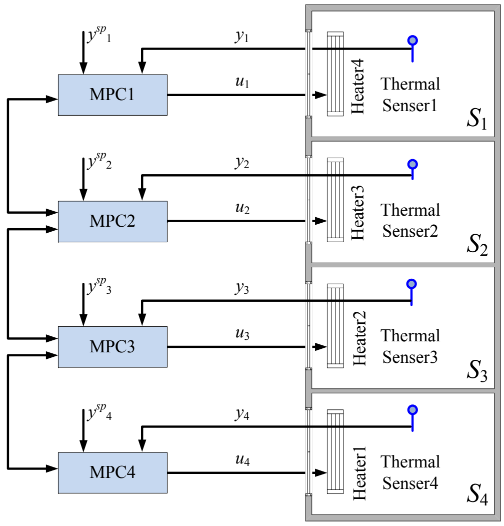

Fig. 2. Distributed MPC configuration

$$\mathbf{R}_i = \text{block} - \text{diag}\{r_{i,1}, r_{i,2}, \ldots, r_{i,N}\} > 0.$$

It seems that the DMPC is very suitable for control this system. However as is well known that the performance of the DMPC is not as good as that of centralized MPC when coupling among subsystems exists. In the existing coordination methods, the increasing of the network connectivity degree is always companied with the to improving of the global performance or the increasing of the coordination degree (the range of the subsystems included in each subsystem-based controller's cost function). It is unexpected in the multi-zones building temperature regulation system since it causes the decreasing of the degree of error tolerance and control flexibility of control system.

Can we find a method which could increase the coordination degree of the whole control system without any increasing of the network connectivity requirements? It stimulates this study.

3. DISTRIBUTED MODEL PREDICTIVE CONTROL

3.1 Control Structure

The configuration of DMPC for multi-zones building temperature regulation is shown in (Fig. 2). The temperature of each zone is controlled by and individual MPC due to its good dynamic performance. The temperature $y_{i,k}$ is measured by thermal sensors and feeds into the i^{th} MPC through cables. Then MPC i calculated the control law $u_{i,k}$ according to the temperature set point y_i^{sp}. The heater acts according to the control law $u_{i,k}$ to regulate the temperature of $\mathcal{S}_i$. These subsystem-based MPCs are able to communicate with its neighbours and the exchanged information can be used to coordinate these subsystem-based MPCs.

In this section, a DMPC called *Impacted-Region Optimization based DMPC* (ICO-DMPC) is proposed for improving the performance of the entire system, yet remaining the error tolerance and flexibility characteristics of closed-loop system. With this strategy, each subsystem-based MPC only exchanges information with its adjacent MPCs. The ICO-DMPC for multi-zones building temperature regulation is detailed in the following context.

3.2 The Coordination Strategy

Consider that the control law of current subsystem $\mathcal{S}_i$ effects the performance of its downstream neighboring subsystems $\mathcal{S}_j, j \in \mathcal{P}_i^d$, in the ICO-DMPC, the performance of $\mathcal{S}_j$ is added into the performance index of the MPC which control $\mathcal{S}_i$ based on a approximation of the updated state sequence of $\mathcal{S}_j$. The approximated state sequence equals the assumed state sequence of $\mathcal{S}_j$ pluses the impact caused by the change of control law of $\mathcal{S}_i$ to the state sequence of $\mathcal{S}_j$. In this way, the coordination degree is expanded without any increasing of the required network connectivity in solving each subsystem-based MPC.

Define that $\mathbf{f}_{i,k+l|k}$ be the matching from $u_{i,k:k+l-1|k}$ to $\mathbf{x}_{i,k+l|k}$, and it can be deduced from equation (2) as

$$\begin{aligned}\mathbf{f}_{i,k+l|k} =& \mathbf{x}_{i,k+l|k}\\ =& \mathbf{A}_{ii}^{l}\mathbf{x}_{i,k} + \sum_{h=1}^{l}\mathbf{A}_{ii}^{l-h}\mathbf{B}_{ii}u_{i,k+h-1|k}\\ &+ \sum_{j\in\mathcal{P}_i^u}\sum_{h=1}^{l}\mathbf{A}_{ii}^{l-h}\mathbf{A}_{ij}\mathbf{x}_{j,k+h-1|k} \qquad (5)\end{aligned}$$

Then, it have

$$\frac{\partial \mathbf{f}_{i,k+l|k}}{\partial \mathbf{x}_{j,k+h-1|k}} = \mathbf{A}_{ii}^{l-h}\mathbf{A}_{ij} \qquad (6)$$

$$\frac{\partial \mathbf{x}_{i,k+l|k}}{\partial u_{i,k+h-1|k}} = \mathbf{A}_{ii}^{l-h}\mathbf{B}_{ii} \qquad (7)$$

The $\mathbf{f}_{i,k+l|k}$ derivation of the $u_{j,k+h-1|k}$ becomes

$$\begin{aligned}\frac{\partial \mathbf{f}_{i,k+l|k}}{\partial u_{j,k+h-1|k}} &= \sum_{p=h+1}^{l}\frac{\partial \mathbf{f}_{i,k+l|k}}{\partial \mathbf{x}_{j,k+p-1|k}}\frac{\partial \mathbf{x}_{j,k+p-1|k}}{\partial u_{j,k+h-1|k}}\\ &= \sum_{p=h+1}^{l}\mathbf{A}_{ii}^{l-p}\mathbf{A}_{ij}\mathbf{A}_{jj}^{p-h}\mathbf{B}_{jj}. \qquad (8)\end{aligned}$$

Since the state and input sequences of downstream and upstream neighbors of $\mathcal{S}_i$ is unknown to the controller of $\mathcal{S}_i$, assume the state and input sequences define that $\hat{\mathbf{x}}_{i,k+l|k}$, $\hat{u}_{i,k+l|k}$ and $\Delta\hat{u}_{i,k+l|k}$ be the assumed states, the assumed input and the assumed input increment which are calculated in the previous calculation, respectively. Add the estimation of the performance of the $\mathcal{S}_j$, $j \in \mathcal{P}_i^d$ to the cost function of the MPC for $\mathcal{S}_i$, then the optimization index of $\mathcal{S}_i$ becomes

$$\begin{aligned}\bar{J}_i(k) =& \sum_{l=1}^{N}\left(\left\|\mathbf{C}_{ii}\mathbf{x}_{i,k+l|k} - y_i^{sp}\right\|_{q_{i,l}}^2 + \left\|\Delta u_{i,k+l-1|k}\right\|_{r_{i,l}}^2\right)\\ &+ \sum_{j\in\mathcal{P}_i^d}\sum_{l=1}^{N}\left\|\mathbf{C}_{jj}\left(\hat{\mathbf{x}}_{j,k+l|k} + \omega_i\mathbf{S}_{ji,k+l|k}\right) - y_j^{sp}\right\|_{q_{j,l}}^2\\ &+ \sum_{j\in\mathcal{P}_i^d}\sum_{l=1}^{N}\left\|\Delta\hat{u}_{i,k+l-1|k}\right\|_{r_{j,l}}^2 \qquad (9)\end{aligned}$$

where ω_i is the weighting coefficients for improving the convergence when using iterative algorithm, and

$$\mathbf{S}_{ji,k+l|k} = \sum_{h=1}^{l} \sum_{p=h+1}^{l} \mathbf{A}_{jj}^{l-p} \mathbf{A}_{ji} \cdot \mathbf{A}_{ii}^{p-h} \mathbf{B}_{ii} (u_{i,k+h-1|k} - \hat{u}_{i,k+h-1|k}) \quad (h = 1, 2, \ldots, l). \tag{10}$$

The predictive model can be expressed as

$$\mathbf{y}_{i,k+l|k} = \mathbf{C}_{ii}\mathbf{A}_{ii}^{l}\mathbf{x}_{i,k} + \sum_{h=1}^{l} \mathbf{C}_{ii}\mathbf{A}_{ii}^{l-h}\mathbf{B}_{ii}u_{i,k+h-1|k} + \sum_{j\in\mathcal{P}_i^u} \sum_{h=1}^{l} \mathbf{C}_{ii}\mathbf{A}_{ii}^{l-h}\mathbf{A}_{ij}\hat{\mathbf{x}}_{j,k+h-1|k} \tag{11}$$

Consider the physical limitations on the heater's capability and the zone temperature, the output, the input and the input increment constraints are added into each subsystem-based MPC. Then we get following optimization problem for $\mathcal{S}_i$ in each control period.

Problem 1. For all subsystem $\mathcal{S}_i$, provided that $\mathbf{x}_{i,k}$, $\hat{\mathbf{x}}_{j,k+l|k}$, $j \in \mathcal{P}_i^u \bigcup \mathcal{P}_i^d$ and $\Delta\hat{u}_{i,k+l-1|k-1}$,$j \in \mathcal{P}_i^d$, $l = 1, 2, \ldots, N$, find the control sequence $\Delta u_{i,k:k+N-1|k}$, which minimize the performance index

$$\min_{u_{i,k:k+N-1|k}} \bar{J}_i(k)$$

Subject to the constraints:

$$\begin{aligned}
&\text{Equation(11)}, \\
&y_{i,L} \le y_{i,k+l|k} \le y_{i,U}, && (12)\\
&y_{j,L} \le y_{j,k+l|k} + \mathbf{C}_{ji}\omega_i\mathbf{S}_{ji,k+l|k} \le y_{j,U}, && (13)\\
&u_{i,L} \le u_{i,k+l-1|k} \le u_{i,U}, && (14)\\
&\Delta u_{i,L} \le \Delta u_{i,k+l-1|k} \le \Delta u_{i,U}, && (15)\\
&l = 1, 2, ..., N; \\
&||y_{i,k+N|k} - y_i^{sp}||_{q_{i,N}}^2 < \varepsilon^2. && (16)
\end{aligned}$$

where, $[y_{i,L}, y_{i,U}]$, $[u_{i,L}, u_{i,U}]$ and $[\Delta u_{i,L}, \Delta u_{i,U}]$ are the bounds of the average temperature, the bounds of the capability of heater and the bounds of the charge rate of the heater in zone $\mathcal{S}_i$. Equation (16) is a final constraint for improve the stability of each subsystem-based MPC, and $\varepsilon > 0$.

To solve problem (1) efficiently, following ICO-DMPC algorithm is given for $\forall\mathcal{S}_i$, $i \in \mathcal{P}$.

Algorithm 1. (GCO-DMPC Algorithm).

Step 1: Initialization.

- Initialize $\mathbf{x}_{i,k_0}$, $\mathbf{x}_{i,k_0+l|k_0}$, $l = 1, 2, \ldots, N$, which satisfy the constraints of Problem 1.

Step 2: Update control law at time $k > k_0$.

- Step 2.1
  Set iteration $t = 1$, and set $\hat{\mathbf{x}}_{i,k+l|k} = \mathbf{x}_{i,k+l|k-1}$.
- Step 2.2
  Measure $x_i(k)$, transmit $\hat{\mathbf{x}}_{i,k+l|k}$ to its down stream neighbors and upstream neighbors; And receive $\hat{\mathbf{x}}_{j,k+l|k}$ from its down stream neighbors and upstream neighbors.
- Step 2.3
  Solving Problem 1 to obtain the optimal solution $\Delta u_{i,k+l|k}^t$, and predict the future state $\mathbf{x}_{i,k+l|k}$ based on the solution $\Delta u_{i,k+l|k}^t$.
- Step 2.4
  If
  $$||\Delta u_{i,k+l-1|k}^t - \Delta u_{i,k+l-1|k}^{t-1}||_2^2 \le \varepsilon_0 \text{ or } t > t_{max}$$
  then set
  $$u_{i,k}^* = u_{i,k-1} + \Delta u_{i,k+l-1|k}^*,$$
  and goto Step 3; Else set
  $$\hat{\mathbf{x}}_{i,k+l|k} = \mathbf{x}_{i,k+l|k}, t = t + 1,$$
  and goto Step 2.2.

Step 3: Update control at time $k + 1$.

- Let $k + 1 \to k$, repeat Step 2.

It should be notice that although an iterative Algorithm is a present, the Problem 1 can also be solved by a non-iterative algorithm through setting $t_{max} = 1$. Since the communication burden will increase with the increasing of iteration, t_{max} should not be set too large in practice. So far the ICO-DMPC for multi-zones building temperature regulation system is introduced, some simulation results will be presented in the next section to show the effectiveness of the proposed method.

4. SIMULATION

For simplicity, the 4-zones building shown in Fig. 1 is taken as example. The relationship among these four zones is also shown in Fig. 1, where zone $\mathcal{S}_1$ is impacted by zone $\mathcal{S}_2$, zone $\mathcal{S}_2$ is impacted by zone $\mathcal{S}_1$ and zone $\mathcal{S}_3$, zone $\mathcal{S}_3$ is impacted by zone $\mathcal{S}_2$ and zone $\mathcal{S}_4$, zone $\mathcal{S}_4$ is impacted by zone $\mathcal{S}_3$, The models of these four zones are respectively given by

$$\mathcal{S}_1 : \begin{cases} x_{1,k+1} = 0.64x_{1,k} + 0.32u_{1,k} + 0.13x_{2,k} \\ y_{1,k} = x_{1,k}, \end{cases} \tag{17}$$

$$\mathcal{S}_2 : \begin{cases} x_{2,k+1} = 0.61x_{2,k} + 0.31u_{2,k} + 0.12x_{1,k} \\ \qquad +0.12x_{3,k} \\ y_{2,k} = x_{2,k}, \end{cases} \tag{18}$$

$$\mathcal{S}_3 : \begin{cases} x_{3,k+1} = 0.62x_{3,k} + 0.33u_{3,k} + 0.12x_{2,k} \\ \qquad +0.12x_{4,k} \\ y_{3,k} = x_{3,k}, \end{cases} \tag{19}$$

$$\mathcal{S}_4 : \begin{cases} x_{4,k+1} = 0.67x_{4,k} + 0.33u_{4,k} + 0.13x_{3,k} \\ y_{4,k} = x_{4,k}, \end{cases} \tag{20}$$

For the purpose of comparison, the centralized MPC, LCO-MPC and the ICO-DMPC are all applied to this system. Let the constraint on the input be $[u_{i,\mathrm{L}}, u_{i,\mathrm{U}}] = [-2, 2]$ and the constraint on the increment of input be $[\Delta u_{i,\mathrm{L}}, \Delta u_{i,\mathrm{U}}] = [-1.5, 1.5]$. Set the all controllers' (Centrialized MPC, ICO-DMPC, LCO-DMPC) parameters of control horizon be $N = 10$, $\mathbf{Q}_i = [1, 1, 1, 1, 1, 1, 1, 1, 1, 5]$, $\mathbf{R}_i = [1, 1, 1, 1, 1, 1, 1, 1, 1, 1]$ and $\omega_i = 0.8$, where $i \in \{1, 2, 3, 4\}$. In order to reduce the communication resource, non-iterative algorithm is used in both ICO-DMPC and LCO-DMPC.

The state responses and the inputs of the closed-loop system under the control of the centralized MPC, ICO-DMPC and LCO-DMPC are shown in Figs. 3 and 4, respectively. The shape of the state response curves under the control of ICO-DMPC are similar to those under the centralized MPC. Under the ICO-DMPC control design, when set point changed, there is no significant overshooting, but some fluctuation exists in the trajectories of states of the interacting subsystems. Under the LCO-DMPC control design, the states of all subsystems could converge to set point, but there exists much larger overshooting and larger amplitude in the state fluctuation comparing to those under the control of ICO-DMPC and centralized MPC.

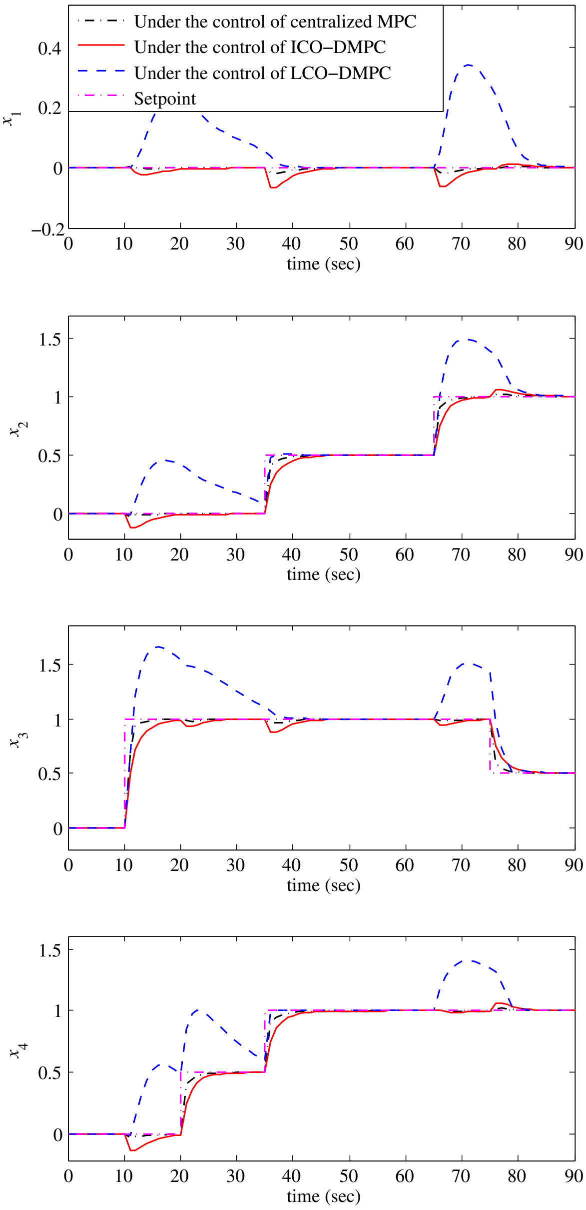

Fig. 3. The evolution of the states under the centralized MPC, LCO-DMPC and ICO-DMPC.

Table 2 shows the state square errors of the closed-loop system under the control of the centralized MPC, the ICO-DMPC and the local cost optimization based DMPC, respectively. The total errors under the ICO-DMPC is 3.04 (28.83%) larger than that under the centralized MPC. The total errors resulting from LCO-DMPC is 71.45 (679.89%) larger than that resulting from the centralized MPC. The performance of the ICO-DMPC is significantly better than that of LCO-DMPC.

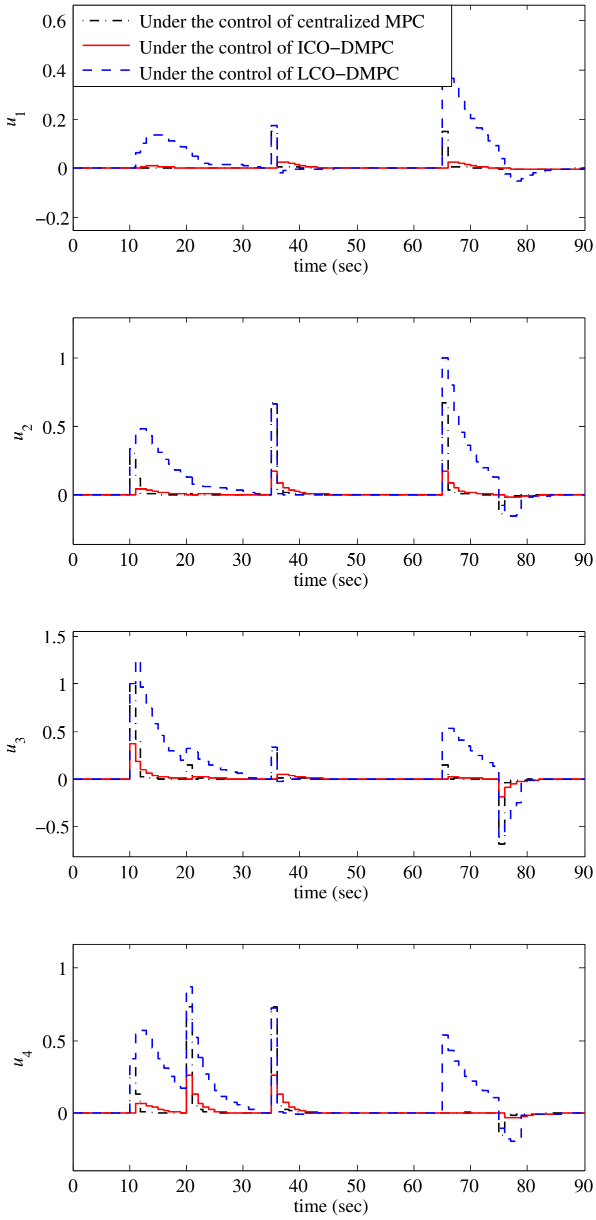

Fig. 4. The evolution of the inputs under the centralized MPC, LCO-DMPC and ICO-DMPC.

Table 1. State square errors of the closed-loop system under the control of the centralized MPC (CMPC), the LCO-DMPC and the ICO-DMPC

Items	CMPC	ICO-DMPC	LCO-DMPC
$\mathcal{S}_1$	0.0190	0.1219	6.1832
$\mathcal{S}_2$	2.3190	3.0572	18.9352
$\mathcal{S}_3$	5.8060	7.2366	35.5856
$\mathcal{S}_4$	2.3648	3.1232	21.2535
Total	10.5088	13.5390	81.9575

Table 1 shows the required network connectivity under the control of the centralized MPC, the ICO-DMPC and the LCO-DMPC, respectively. The required network connectivity under the control of ICO-DMPC equals to that under the control of LCO-DMPC and is much less than that under the control of centralized MPC.

Table 2. Required network connectivity under the control of the centralized MPC (CMPC), the LCO-DMPC and the ICO-DMPC

Items	CMPC	ICO-DMPC	LCO-DMPC
$\mathcal{S}_1$	All	2	2
$\mathcal{S}_2$	All	1, 3	1, 3
$\mathcal{S}_3$	All	2, 4	2, 4
$\mathcal{S}_4$	All	3	3

From these simulation results, it can be seen that the proposed ICO-DMPC could obtain a better global performance than LCO-DMPC when the same network connectivity provided. The global performance of entire closed-loop system is improved without any weakening of the characteristics of good error tolerance and high flexibility of the whole control system.

5. CONCLUSION

In this paper, a Impact-Region Optimization based DMPC is proposed for 4-zones building temperature regulation system. The proposed method could improve the global performance of entire closed-loop system without any increasing of network connectivity. The stabilizing implementation of proposed DMPC subject to decoupled constraints maybe a extension of this work and will be done in the near future.

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