

Parallel Model Predictive Control for Input Constrained Linear Systems

Naoyuki Hara and Keiji Konishi
Osaka Prefecture University

Introduction

- Model Predictive Control (MPC)
 - Uses real-time optimization, requires a greater computational effort
 - This can be a drawback when applied to fast systems or available computational capabilities are not sufficient.
- Two approaches to overcome the drawback
 - Explicit MPC: replace on-line optimization with an explicit function
 - A. Bemporad, et al., *Automatica*, 2002
 - For relatively small systems
 - Implicit MPC: speed up on-line optimization
 - e.g. Y. Wang & S. Boyd, *IEEE Contr. Syst. Tech.*, 2010
 - For large systems

Introduction

- Parallel computation capabilities are becoming common
 - Advent of many-core CPUs and GPUs
 - Parallelizable algorithms should be designed.
- Use of parallel computation in MPC
 - Parallel move-blocking

S. Long, E.C. Kerrigan, K.V. Ling, and G.A. Constantinides, *CDC & ECC*, 2011
 - Tailored parallel optimization algorithms

S.D. Cairano, M. Brand, and S.A. Bortoff, *Int. J Control*, 2013,
I. Nielsen and D. Axehill, *CDC* 2015,
L. Ferranti and T. Keviczky, *CDC* 2015,
N. Hara, Y. Kagitani, and K. Konishi, *ICCAS*, 2014
- N. Hara, et al. (2014) uses the matrix splitting
 - An optimization problem is decomposed to several sub-problems.
 - Drawback: an excessive number of iterations is required.

Introduction

- In this paper,
 - Introduce a **reordering of dual optimization variables** for our method (N. Hara & K. Konishi, 2014).
 - Smaller sub-problems are obtained, and these can be solved in parallel.
 - The reordering is effective in improving the number of iterations.

MPC formulation

- Discrete-time LTI system

$$x(t+1) = Ax(t) + Bu(t), \quad t = 0, 1, 2, \dots,$$

$$Lu(t) \leq \bar{u},$$

$$x(t) \in \mathbb{R}^n : \text{state} \quad u(t) \in \mathbb{R}^m : \text{input}$$

$$L \in \mathbb{R}^{r \times m} \quad \bar{u} \in \mathbb{R}^r : \text{matrices for representing the input constraint}$$

$$\begin{aligned} \min_{U \in \mathbb{R}^{(n+m)N_p}} & \sum_{k=0}^{N_p-1} \{x_k^T Q x_k + u_k^T R u_k\} + x_{N_p}^T Q_f x_{N_p} \\ \text{s.t.} & \quad x_{k+1} = Ax_k + Bu_k, \quad x_0 = x(t) \\ & \quad Lu_k \leq \bar{u}, \quad k = 0, \dots, N_p - 1 \\ & \quad Q, R, Q_f > 0 \end{aligned} \quad U := \begin{bmatrix} u_0 \\ x_1 \\ u_1 \\ x_2 \\ \vdots \\ u_{N_p-1} \\ x_{N_p} \end{bmatrix}$$

MPC formulation

- Formulated as a QP-problem

$$\min_U \frac{1}{2} U^T H_{PP} U$$

$$\text{s.t. } VU \leq W$$

$$V_{eq}U = W_{eq}x_0, \quad x_0 = x(t),$$

$H_{PP}, V, W, V_{eq}, W_{eq}$
appropriate matrices

- MPC
 - We need to solve the QP-problem in real-time.
 - This motivates us to reduce the computational time.

Parallel formulation of MPC

- Dual of the QP problem

$$\begin{aligned} \min_z \quad & \frac{1}{2} z^T H_{DP} z + q_{DP}^T z & H_{DP} & := \begin{bmatrix} V \\ V_{eq} \end{bmatrix} H_{PP}^{-1} \begin{bmatrix} V \\ V_{eq} \end{bmatrix}^T, \\ \text{s.t.} \quad & z_a \geq 0_{rN_p} & q_{DP} & := \begin{bmatrix} W \\ W_{eq} x_0 \end{bmatrix} \in \mathbb{R}^{(r+n)N_p} \\ & z := \begin{bmatrix} z_a \\ z_b \end{bmatrix} \in \mathbb{R}^{(r+n)N_p} \end{aligned}$$

The optimal solution of the dual problem

The optimal solution of the original QP problem

$$z^* = \begin{bmatrix} z_a^* \\ z_b^* \end{bmatrix} \longrightarrow U^* = -H_{PP}^{-1} (V^T z_a^* + V_{eq}^T z_b^*)$$

Parallel formulation of MPC

Definition: Matrix splitting

H : symmetric matrix

(M, K) is a splitting of H if $H = M + K$.

A splitting (M, K) is a regular splitting if $M - K > 0$.

$$\begin{array}{l} \min_z \frac{1}{2} z^T H_{DPC} z + q_{DPC}^T z \\ \text{s.t. } z_a \geq 0_{rN_p} \end{array} \quad \longrightarrow \quad \begin{array}{l} H_{DPC} = M + K \\ \text{regular splitting} \end{array}$$

Theorem 1: (E. Yamakawa & M. Fukushima, 1997; Z.Q. Luo & P. Tseng, 1992)

$z^{(j)}$ ($j = 0, 1, 2, \dots$) converges to the optimal solution.

$$\begin{array}{l} z^{(j+1)} := \arg \min_{z \in \mathbb{R}^{(r+n)N_p}} \frac{1}{2} z^T M z + (K z^{(j)} + q_{DPC})^T z \\ \text{s.t. } z_a \geq 0_{rN_p} \end{array}$$

Parallel formulation of MPC

- Main idea of parallelization based on Theorem 1 lies in **choosing a block diagonal matrix M** in the splitting.

$$H_{DP} = M + K$$

$$\begin{bmatrix} \boxed{} & & & & 0 \\ & \boxed{} & & & \\ & & \boxed{} & & \\ & & & \ddots & \\ 0 & & & & \boxed{} \end{bmatrix}$$

QP-problem

$$\begin{aligned} \min_{z \in \mathbb{R}^{(r+n)N_p}} \quad & \frac{1}{2} z^T M z + (K z^{(j)} + q_{DP})^T z \\ \text{s.t.} \quad & z_a \geq 0_{rN_p} \end{aligned}$$

↓
Independent sub-problems

- If H_{DP} has a structure close to a block diagonal matrix, the above problem approximates the dual problem effectively.
 - However, actual H_{DP} has not: excessive number of iterations (N. Hara & K. Konishi, 2014)

1. Choose parallelization degree: $d \geq 1$ (divisor of N_p)
2. Extract a block diagonal matrix and build a splitting of H

e.g. $N_p = 4, d = 2$

$$H = \begin{bmatrix} \text{Block} & & & 0 \\ & \text{Block} & & \\ & & \text{Block} & \\ 0 & & & \text{Block} \end{bmatrix}$$

$$= \begin{bmatrix} \text{Block} & & & 0 \\ & \text{Block} & & \\ & & \text{Block} & \\ 0 & & & \text{Block} \end{bmatrix} + \begin{bmatrix} 0 & & & 0 \\ & \text{Block} & & \\ & & \text{Block} & \\ 0 & & & 0 \end{bmatrix}$$

M K

3. Obtain a regular splitting

$$(M_{\epsilon+}, K_{\epsilon-})$$

$$M_{\epsilon+} := M + \epsilon I_{(r+n)N_p} \quad K_{\epsilon-} := K - \epsilon I_{(r+n)N_p}$$

$$\epsilon : \epsilon > \frac{\epsilon_0}{2}, \quad \epsilon_0 := |\min(\lambda_{\min}(M - K), 0)|,$$

4. Iterative equation involving d sub-QP problems:

$$\theta_i^{(j+1)} := \arg \min_{\theta_i \in \mathbb{R}^{(r+n)b_s}} \frac{1}{2} \theta_i^T (M_{\epsilon+})_i \theta_i + ((K_{\epsilon-})_i \theta^{(j)} + q_i)^T \theta_i$$

$$\text{s.t.} \quad \bar{\theta}_i \geq 0_{rb_s}$$

$$i = 1, 2, \dots, d,$$

$$j = 0, 1, 2, \dots,$$

- ✓ The problem size reduced to $1/d$
- ✓ The regular splitting ensures the convergence.

Parallel formulation of MPC

- The negative effective of the approximation is small when
 1. $K_{\epsilon-}$ is relatively small
 2. The 'guess solution' $\theta^{(j)}$ is close to the optimal solution

Lemma 2:

$$\|K_{\epsilon-}\|_F^2 = \frac{d-1}{2} \|AQ^{-1}\|_F^2 + (r+n)N_p\epsilon^2$$

$\|\cdot\|_F$: Frobenius norm

- A quantitative measure for evaluating the effective of splitting

$$\frac{\|K_{\epsilon-}\|_F}{\|H\|_F}$$

Illustrative Examples

- Plant

- Distillation column model created by mkoilfr.m (J.M. Maciejowski, Chapter 9, *Predictive Control with Constraints*, 2002)

- 22 states, 3 inputs

- Input constraint:
$$-0.1 \cdot \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \leq u(t) \leq +0.1 \cdot \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

- Design parameters

$$N_p = 100, \quad Q = I_{20}, \quad R = 0.1I_3$$

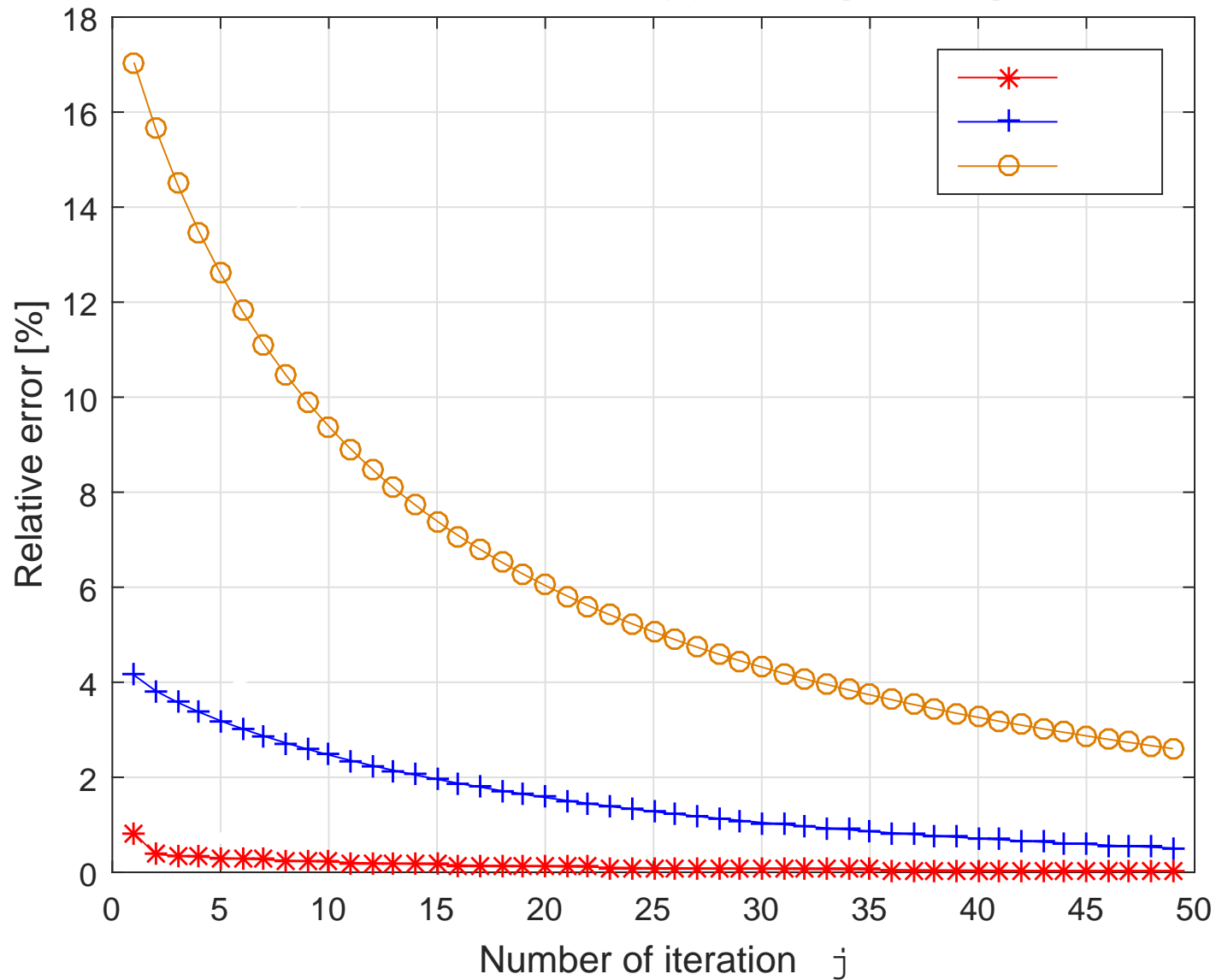
Q_f : solution of the Riccati equation

- Optimization

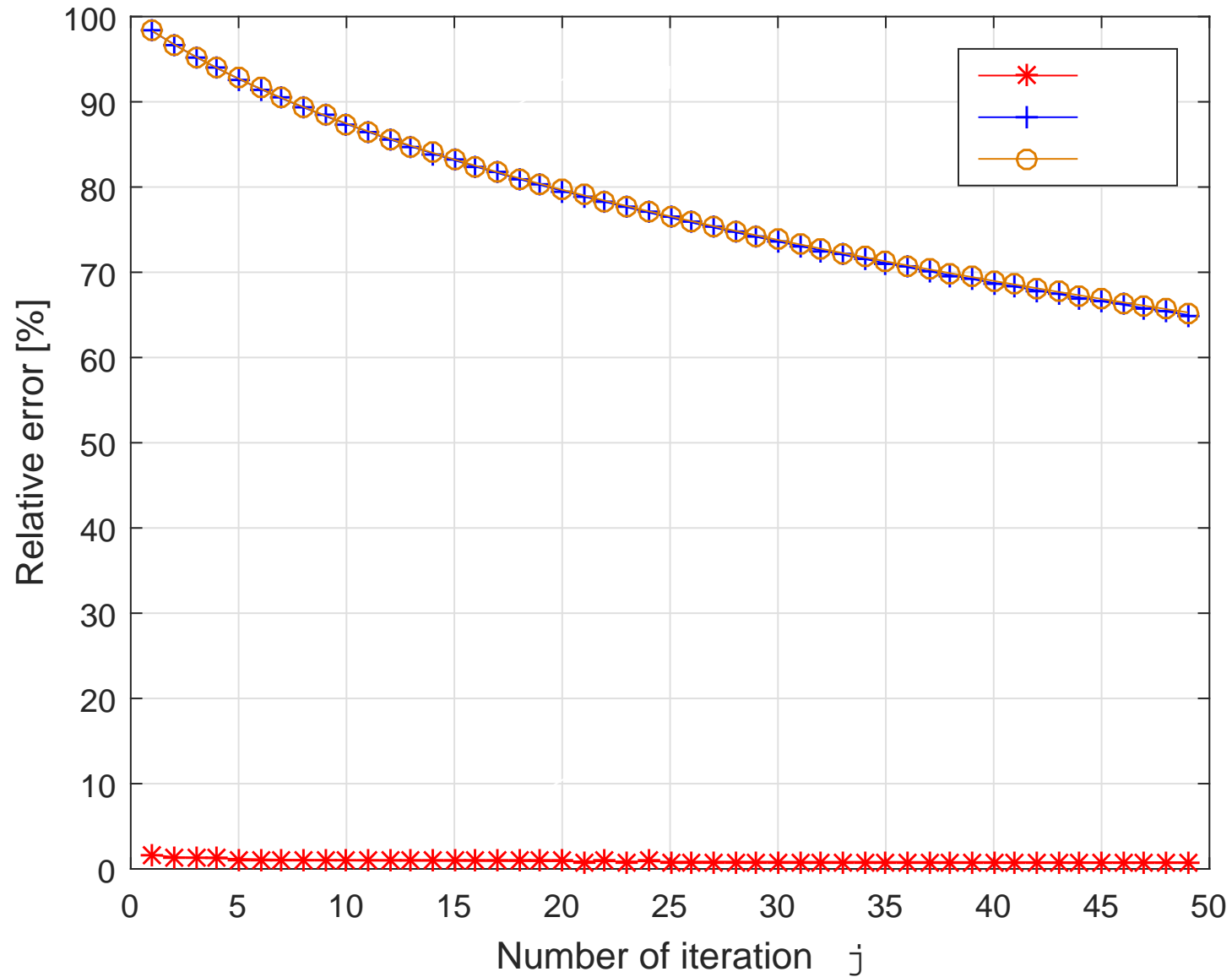
- quadprog with default algorithm (interior-point-convex) and parameters
- Sub-problems are solved sequentially

Convergence Property

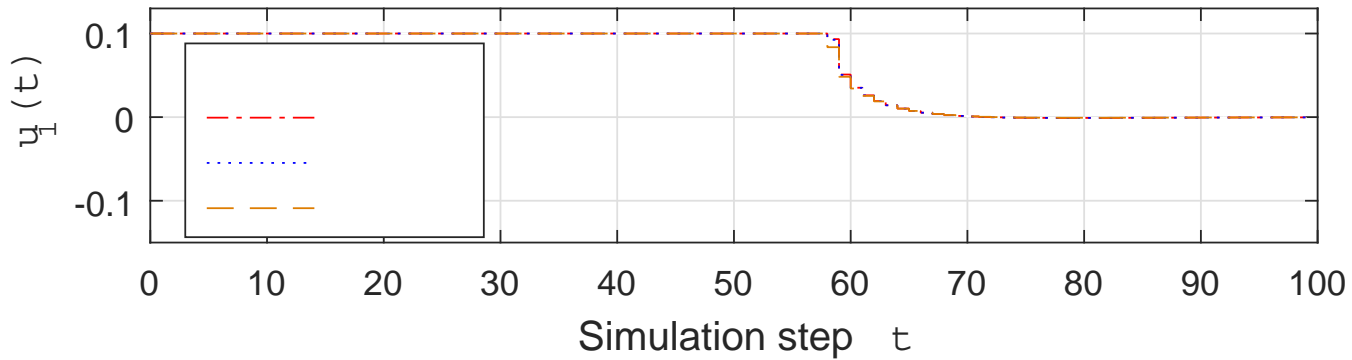
Initial condition: $x(0) = 200[1, \dots, 1]^T$



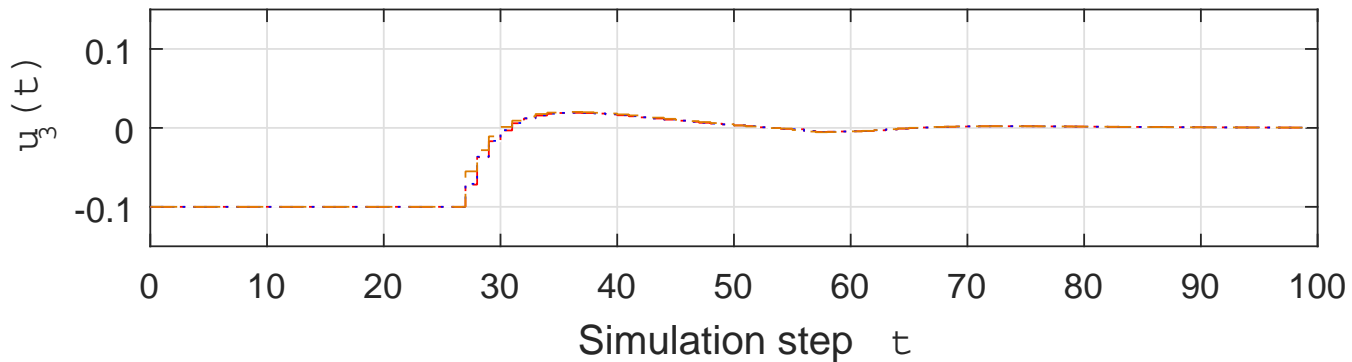
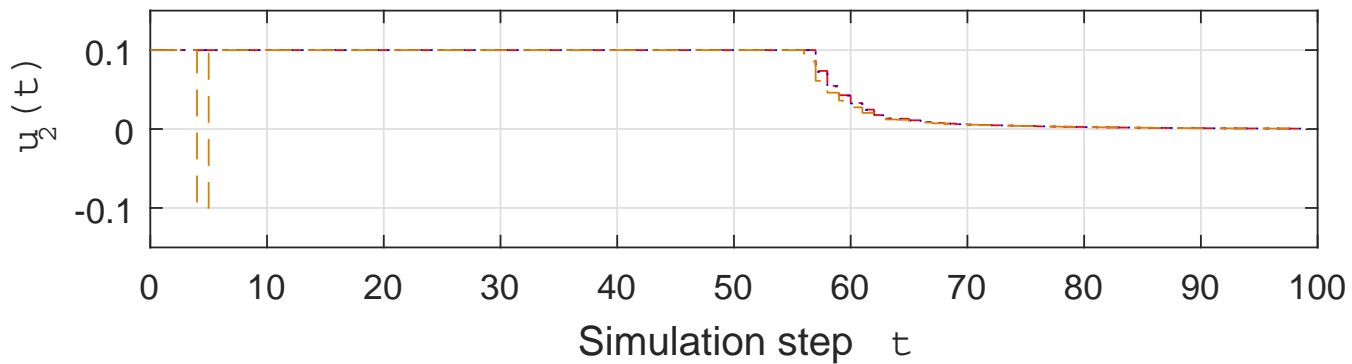
Convergence Property (previous method)



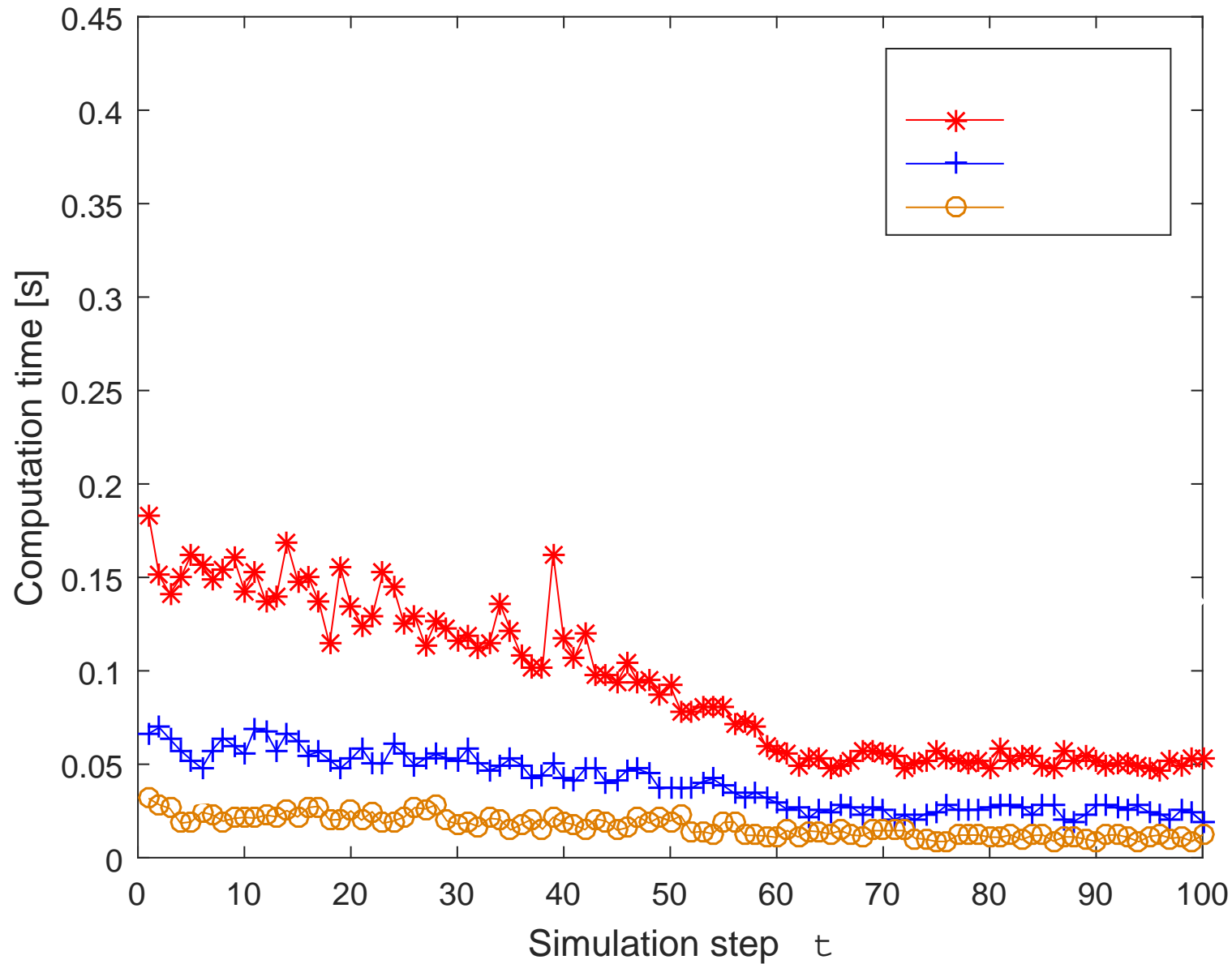
Closed-loop response (control inputs)



Only one iteration
(without warm starting)



Maximum computation time at each time step



Concluding Remarks

- Parallel MPC using the matrix splitting
 - A reordering of the dual optimization variables is effective
 - One iteration gives sufficiently accurate control inputs
 - Warm starting improves the convergence significantly.

- Future research topics
 - a. Actual parallel implementation and evaluate the communication overhead of parallelization
 - b. State constraint: possible but need some modification
 - c. Guarantee for constraint satisfaction and stability in use of intermediate solutions: tightening constraint?

Acknowledgements:

We gratefully acknowledge the support of the Hara Research Foundation, Japan. We thank the anonymous reviewers for their careful reading and constructive comments.