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Coordinated Non-Cooperative Distributed Model Predictive Control for Decoupled Systems Using Graphs ⋆

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Abstract: This paper proposes a novel strategy for Non-Cooperative Distributed Model Predictive Control (Non-Coop. DMPC) of Networked Control Systems (NCS) consisting of dynamically decoupled agents where the coupling is achieved in the objective function or in the constraints. Moreover, the coupling is considered to be time-variant. We call this strategy Priority-Based Non-Coop. DMPC (PB-Non-Coop. DMPC). It is based on assigning priorities to the agents and the use of the coupling graph. Each PB-Non-Coop. DMPC is associated with a different agent and computes the local control inputs based only on its states and that of its neighbors. PB-Non-Coop. DMPC satisfies the prediction consistency property and reduces the overall computation time in comparison with existing Non-Coop. DMPC strategies in literature, thereby improves the overall behavior of NCS. We compare PB-Non-Coop. DMPC with centralized MPC as well as with another Non-Coop. DMPC strategy from literature.

Keywords: Non-Cooperative Distributed Model Predictive Control, Decoupled Agents, Prediction Consistency, Priority, Time-variant Coupling Graph

In the following is a list of the used abbreviations in this paper and their meanings.

Abbreviations	**Meanings**
NCS	Networked Control Systems
MPC	Model Predictive Control
CMPC	Centralized MPC
DMPC	Distributed MPC
Coop. DMPC	Cooperative DMPC
Non-Coop. DMPC	Non-Cooperative DMPC
PB-Non-Coop. DMPC	Priority-Based Non-Coop. DMPC
DAG	Directed Acyclic Graph

1. INTRODUCTION

Networked Control Systems (NCS) consist of interacting dynamic subsystems. Hereafter, we will use the term agent for dynamic subsystem. The agents of NCS communicate and interact over a communications network. Generally, the network topology is time-variant. Each agent has its own controller which aims to track its reference trajectory with the smallest possible change in its inputs while satisfying constraints on its states and inputs, and further coordinating with other agents in the NCS. This problem can be solved using Distributed Model Predictive Control (DMPC) as it can deal with the action of other agents with respect to their future intention and while making decisions of the agent's own control actions. In DMPC, an optimization problem is formulated and solved at each sample time to compute the optimal inputs. Formulations of a networked control problem as an optimization problem using DMPC can be found in Maestre and Negenborn (2013) and Scattolini (2009).

The focus of this paper lies on studying the distribution of the control problem of NCS, where the agents are dynamically decoupled and the coupling is achieved in the objective function or in the constraints using DMPC. Furthermore, we consider the coupling topology as time-variant. Nonetheless, we assume the set of neighbors to be constant over the prediction horizon. Additionally, we assume that data exchange is only allowed before and after the decision making process and that the time needed for the decision of control actions is not affected by communications issues such as network delays and data losses. We propose a novel DMPC strategy called Priority-Based Non-Cooperative DMPC (PB-Non-Coop. DMPC) and compare it with another Non-Coop. DMPC strategy from literature.

Let $\mathcal{V}$ indicate the set of agents and $\mathcal{V}^i \subset \mathcal{V}$ the set of neighbors of an agent $v_i \in \mathcal{V}$. An important property that needs to be satisfied in any DMPC strategy is the prediction consistency. It is defined as follows:

Definition 1.1. Prediction consistency means that the predictions used or computed in the optimization problem of an agent $v_i \in \mathcal{V}$ at time t for an agent $v_j \in \mathcal{V}^i$ coincide with the predictions computed by agent v_j itself at time t.

Without the satisfaction of the prediction consistency property, even if we assume an infinite prediction horizon, no DMPC can guarantee that solutions computed locally in the agents are NCS-stable and -feasible. Furthermore, if this property is not satisfied in NCS, it is not possible

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to study the effects of external disturbances and noises separately, see Lunze (2014).

In Non-Coop. DMPC, the predictions used by an agent $v_i \in \mathcal{V}$ for its neighbors $\mathcal{V}^i$ differ from the predictions computed by agents $\mathcal{V}^i$. The reason is that the obtained predictions of agents $\mathcal{V}^i$ in agent v_i are time delayed. As a result, the prediction consistency property is not satisfied in Non-Coop. DMPC.

This problem of Non-Coop. DMPC was also discussed in literature and different solutions were presented. The main two solutions are reviewed in the following:

- One strategy is that agents solve their optimization problems in sequence and iterate until they converge to a solution. For the order of sequence, there are different suggestions. In Kuwata and How (2011) and Richards and How (2007), the order of sequence is assumed to be fixed. In Chaloulos et al. (2010), the agents solve either with a fixed or a random order at each sample time. Another approach in Chao et al. (2011) suggests the order to be based on the deviation of agents from their reference trajectories and other missions of agents.
- Another strategy is to add a constraint on the predicted control inputs that limits its deviation from the control inputs sent to other agents, see Trodden and Richards (2013), Farina and Scattolini (2012), Zheng et al. (2011), Defoort et al. (2009), and Dunbar and Murray (2006).

Although the previous approaches succeeded in their applications, they have some drawbacks. Regarding the sequential iterative approach, it requires a high computation time as the number of agents becomes large, which reduces the performance of NCS. The approach with an additional constraint on the predicted control inputs has the drawback that limiting the control inputs to some extent prevents the states from changing according to new constraints or disturbances. This can lead to undesired behavior or constraints violation, which corresponds to instability or infeasibility of NCS.

This paper proposes a novel Non-Coop. DMPC strategy that deals with the problem of loss of the prediction consistency property while reducing the computation time as well. First, it introduces the idea of priority and the related optimization problem in section 2. Then, it investigates the coupling graph of this strategy in section 3. Subsequently, section 4 discusses the stability and feasibility of this strategy. Section 5 presents numerical results. Finally, section 6 concludes with a summary and an outlook for future research.

2. PRIORITY IDEA AND OPTIMIZATION PROBLEM

Similar to Non-Coop. DMPC, in PB-Non-Coop. DMPC each agent solves only its own optimization problem. However, in order to solve the problem of loss of the prediction consistency property, we introduce the concept of priority. Each agent v_i in the NCS is assigned a distinct priority $p(v_i)$ using a priority assignment function $p : \mathcal{V} \rightarrow \mathbb{N}_{>0}$, where $\mathcal{V}$ is the set of agents. If $p(v_i) < p(v_j)$ then agent v_i has a higher priority than agent v_j. Every agent considers its own objective function, constraints, and only the coupling objectives and constraints with agents assigned a higher priority. Consider the example shown in Fig. 1, where the communications graph (black edges) and coupling graph (red edges) of a PB-Non-Coop. DMPC are illustrated. The set of vertices is equivalent to the set of agents $\mathcal{V}$. Note that the communications and coupling graphs are different, since the coupling graph is directed. Each agent in PB-Non-Coop. DMPC considers only the coupling edges with its higher priority neighbors. In Fig. 1, agent v_1 has the highest priority and does not consider any coupling edges. Agent v_2 has the second highest priority and considers the coupling edge e_{12}. Agent v_3 has the third highest priority and needs to consider the coupling with agents v_1 and v_2, but since it does not have a common coupling edge with agent v_1, it considers only agent v_2, i.e., the coupling edge e_{23}. Agent v_4 has the lowest priority and needs to consider the coupling with all other agents, i.e., the coupling edges $\{e_{14}, e_{24}, e_{34}\}$. Thus, each agent considers only the incoming edges of the coupling graph. Fig. 2 shows the principle design of PB-Non-Coop. DMPC.

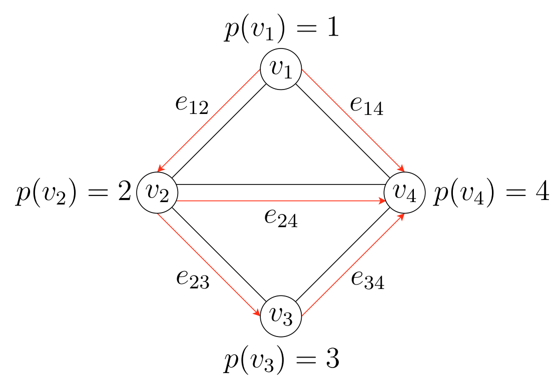

Fig. 1. Graphs of PB-Non-Coop. DMPC. Black edges correspond to the communications graph and red edges to the coupling graph

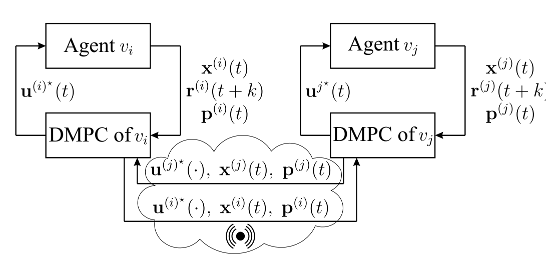

Fig. 2. Principle design of PB-Non-Coop. DMPC

Let $\hat{\mathcal{V}}^i = \{v_{i_1}, v_{i_2}, \ldots, v_{i_{\hat{N}^i}}\}$ denote the set of higher priority neighbors of agent v_i and $\hat{N}^i = |\hat{\mathcal{V}}^i| \in \mathbb{N}$ its number. Formally, $\hat{\mathcal{V}}^i$ is defined as follows:

$$\hat{\mathcal{V}}^i = \{v_j | \forall v_j \in \mathcal{V}^i, p(j) < p(i)\}. \quad (1)$$

Based on this, the optimization problem of an agent $v_i \in \mathcal{V}$ at time t is formulated as follows: