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Comprehensive study of decomposition effects on distributed output tracking of an integrated process over a wide operating range

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ABSTRACT

A comprehensive study of plant decomposition effects is presented for distributed model predictive control (DMPC) of an integrated process system. Different decompositions are obtained via community detection and other methods. The closed-loop performance and computational efficiency of employing various decompositions for DMPC design are evaluated through tracking outputs in different tracking zones corresponding to desired operating conditions. Different levels of communication and cooperation between local controllers, levels of system uncertainty, and dynamic optimization platforms are considered. The results are analyzed to determine the most suitable method for decomposition of the studied integrated process.

1. Introduction

Model predictive control (MPC) is a well-established advanced multivariable control strategy, inherently tailored to account for performance optimality and constraints (Rawlings and Mayne, 2009). MPC implements an open-loop optimal control policy iteratively, by solving a constrained dynamic optimization problem at each iteration to obtain a sequence of future manipulated inputs (Morari and Lee, 1999). The applicability of MPC depends on the solvability of the underlying optimization problem in real time. Therefore, applying centralized model predictive control (CMPC) to industrial scale process networks is challenging as it requires solving a large-scale constrained nonlinear dynamic optimization problem in real time (Lopez-Negrete et al., 2013; Biegler, 2017). Some attempts have been made to speed up the dynamic optimization and accelerate the CMPC computations (Biegler, 2017; Griffith et al., 2017; Muller et al., 2017). However, the real time CMPC of large-scale process networks is still a challenge.

An alternative strategy is to decompose the large-scale optimization-based control problem into smaller problems. Following this idea, we can replace the CMPC with a distributed model predictive control (DMPC) architecture consisting of local controllers with some level of communication (Camponogara et al., 2002; Mayne, 2014; Patel et al., 2016; Scattolini, 2009). The system decomposition, *i.e.* identifying the optimal number of subsystems and deciding how the output variables and the manipulated inputs must distribute among the network of local controllers, is a key factor for applying DMPC. Research on DMPC in the last decade has focused mostly on feasibility, optimality, and closed-loop stability for a given decomposition (Christofides et al., 2011, 2013; Doan et al., 2011; Dunbar, 2007; Dunbar and Murray, 2006; Franco et al., 2008; Liu et al., 2010; Stewart et al., 2011; Tippett and Bao, 2013; Yin and Liu, 2017; Rawlings et al., 2017) which is usually obtained following the layout of the physical units

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(Stewart et al., 2011; Tippett and Bao, 2013), or according to material/energy balance subsystems (Christofides et al., 2011). Until recently, there had been only a few attempts to find on optimal decomposition, *e.g.* by solving a multi-objective mixed integer nonlinear program to optimize performance (Al-Gherwi et al., 2010), or by employing an open-loop performance metric (Motee and Sayyar-Rodsari, 2003).

The system decomposition problem can be viewed in the context of network theory as the one of identifying weakly connected subsystems whereby the variables of each subsystem are strongly connected (Fortunato, 2010; Girvan and Newman, 2002). Inspired by this perspective, a clustering approach based on input/output connectivity has been employed to derive hierarchies of system decompositions (Heo and Daoutidis, 2016; Heo et al., 2015). Maximization of the modularity of a suitable graph has also been adopted to identify optimal distributed architectures (Jogwar and Daoutidis, 2017; Tang and Daoutidis, 2018; Tang et al., 2018a,b). A limited number of community-based decompositions was evaluated through closed-loop simulations for *state regulation* by employing sequential DMPC (Pourkargar et al., 2017a). The impact of information sharing between the local controllers of an iterative DMPC scheme on the state regulation performance was also examined (Pourkargar et al., 2017b). These studies in Pourkargar et al. (2017a,b) documented the importance of the decomposition in achievable closed-loop performance and computational cost of DMPC. They also established that community detection based on a system digraph provides a good compromise between closed-loop performance and cost of computation. However, the studies were limited in scope, in that they focused on state regulation around a single operating point, compared only a limited number of decompositions, and all computations were based on the use of sequential quadratic programming (SQP) for the solution of the optimization problem.

In this paper, we present a comprehensive case study which analyzes the system decomposition impact on *output tracking* of an integrated process network over a wide range of operating conditions. Our goal is to assess and identify the most efficient distributed optimization-based control strategy, in terms of utilizing the best system decomposition, the most efficient levels of information sharing and cooperation between local controllers, and the most effective dynamic optimization solver. To this end, we apply the iterative DMPC structure introduced in Pourkargar et al. (2017b) to the benchmark reactor-separator system containing two continuous stirred tank reactors (CSTRs) and a vapor–liquid separator. Five system decompositions are obtained through various methods (decomposition based on the relative time-average gain and sensitivity array Tang et al., 2018a; Yin and Liu, 2017, decomposition using a weighted input–output bipartite graph Tang and Daoutidis, 2018, and decomposition based on an unweighted digraph Jogwar and Daoutidis, 2017) or by intuition (based on the layout of the physical units, and material/energy balance subsystems). We employ two classes of optimization methods, namely SQP and interior point optimization (IPOPT) to ensure that the comparison of the DMPC performance using different decompositions is not limited to a specific optimization platform. Both these platforms are suitable to solve nonlinear dynamic optimization problems, while IPOPT is computationally faster compared to SQP. Also, we considered different tracking zones to examine the closed-loop performance of DMPC using the proposed decompositions, where the term tracking zones refers to different setpoint values for setpoint tracking. In these zones, the controllers track desired steady state values of the system which indicate low, moderate, and high overall conversion of the feed into the product. The output tracking errors, the required control actions, and the computation time for the different architectures are compared over the tracking zones with and without considering measurement noise effects. The results are analyzed and evaluated by comparing them to those obtained by CMPC to identify the most efficient distributed control architecture.

The rest of the paper is organized as follows. Section 2 presents the mathematical description of the studied class of nonlinear systems, the CMPC formulation for output tracking, and the system representation in the form of decomposed subsystems for distributed control. In this section, we also develop an iterative DMPC formulation for output tracking and review recent community-based methods for the control-oriented optimal decomposition of large-scale systems. We then evaluate the impact of the resulting system decomposition on the computational demand and closed-loop performance of iterative DMPC for the benchmark reactor-separator process network in Section 3.

2. Model predictive control

We consider a general class of nonlinear input-affine process systems defined by the following state space model

$$\begin{aligned} \dot{x}(t) &= f(x(t)) + g(x(t))\, u(t) \\ y(t) &= h(x(t)) \end{aligned} \tag{1}$$

where $x(t) = [x_1(t) \;\; x_2(t) \;\; \cdots \;\; x_n(t)]^T \in \mathbb{R}^n$ denotes the vector of state variables of the system, $y(t) = [y_1(t) \;\; y_2(t) \;\; \cdots \;\; y_r(t)]^T \in \mathbb{R}^r$ the vector of outputs, $u(t) = [u_1(t) \;\; u_2(t) \;\; \cdots \;\; u_m(t)]^T \in \mathbb{R}^m$ the vector of manipulated inputs, and t is the time. The terms $f : \mathbb{R}^n \to \mathbb{R}^n$, $g : \mathbb{R}^n \to \mathbb{R}^{n\times m}$, and $h : \mathbb{R}^n \to \mathbb{R}^r$ denote smooth nonlinear locally Lipschitz functions. The states of the system are assumed to be measured at periodic sampling times.

A CMPC architecture can be synthesized to track the outputs, by solving a single constrained nonlinear dynamic optimization problem over a predetermined prediction horizon. The underlying optimization problem is formulated based on the process model of (1) subject to constraints and input bounds

$$\begin{aligned} \min_{u} \quad & \int_{t_k}^{t_{k+N}} \left[(y - y^{ref})^T P\, (y - y^{ref}) + (u - u^{ss})^T W\, (u - u^{ss}) \right] dt \\ \text{s.t.} \quad & \dot{x} = f(x) + g(x)\, u \\ & y(t) = h(x(t)) \\ & u^{\min} \le u \le u^{\max} \\ & \mathcal{F}(x, u, t) \le 0 \\ & \mathcal{G}(x, u, t) = 0 \end{aligned} \tag{2}$$

where t_k denotes the kth sampling time and N indicates the number of sampling times in the prediction horizon. By considering a constant sampling period, $\Delta = t_{k+1} - t_k$, for the entire closed-loop operation, the prediction horizon for solving the optimization problem at each sampling time is equal to $N\Delta$. The vectors of $y^{ref}(t) = [y_1^{ref}(t) \;\; y_2^{ref}(t) \;\; \cdots \;\; y_r^{ref}(t)]^T \in \mathbb{R}^r$, and $u^{ss}(t) = [u_1^{ss}(t) \;\; u_2^{ss}(t) \;\; \cdots \;\; u_m^{ss}(t)]^T \in \mathbb{R}^m$ are the outputs of the system and their corresponding steady state manipulated