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A robust distributed model predictive control algorithm

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ABSTRACT

Although distributed model predictive control (DMPC) has received significant attention in the literature, the robustness of DMPC with respect to model errors has not been explicitly addressed. In this paper, a novel online algorithm that deals explicitly with model errors for DMPC is proposed. The algorithm requires decomposing the entire system into N subsystems and solving N convex optimization problems to minimize an upper bound on a robust performance objective by using a time-varying state-feedback controller for each subsystem. Simulations examples were considered to illustrate the application of the proposed method.

1. Introduction

Distributed model predictive control (DMPC) has received significant attention in the literature in recent years. The key potential advantages of DMPC over centralized MPC strategies are: (i) it can provide better performance than fully decentralized control especially when the interactions ignored in the latter approach are strong, and (ii) it can maintain flexibility with respect to equipment failure and partial plant shutdowns that may jeopardize the successful operation of centralized MPC. The basic idea of DMPC is to partition the total system of states, controlled and manipulated variables into smaller subsystems and to assign an MPC controller to each subsystem. For the reported DMPC strategies their design is composed of three parts: (1) *Modeling*: each controller has access to a local dynamic model of the corresponding subsystem along with an interaction dynamic model that accounts for the influence of the other subsystems. These models can be obtained by directly decomposing a centralized model of the process [20]. (2) *Optimization*: each MPC solves a local optimization problem. Some reported strategies use modified objective functions that take into account the goals of other controllers to achieve full coordination [23,25] whereas some others use strictly local objectives [14], e.g. a Nash-equilibrium objective. (3) *Communication*: at every control time interval all the controllers exchange their respective solutions. These three steps are executed at each time interval in an iterative manner until convergence among the controllers is reached. Venkat [23] showed that increasing the iterations allows the DMPC strategy to reach the optimal centralized solution while the termination at any intermediate iteration maintains system-wide feasibility. Zhang and Li [25] analyzed the optimality of the iterative DMPC scheme and derived the closed-form solution for an unconstrained DMPC Motee and Sayyar-Rodsari [17] proposed an algorithm for optimal partitioning of the process model into subsystems to be used with distributed MPC. In that work an unconstrained distributed MPC framework is used and then a weighting matrix is defined to convert the distributed system into a directed graph. Al-Gherwi et al. [1] proposed a methodology for selecting the control structure in the context of distributed model predictive control that achieves a trade-off between closed-loop performance in the presence of model uncertainty and structure simplicity by solving a mixed integer nonlinear program (MINLP). Aiming at reducing the computationally demanding quadratic dynamic matrix control (QDMC), a decentralized QDMC algorithm was proposed by Charos and Arkun [5]. In this algorithm, it was assumed that the effect of other subsystems on a particular local controller is kept unchanged from the previous sampling time so iterations were not required leading to a significant reduction in computations but with loss in performance. Katebi and Johnson [11] proposed a decomposition–coordination scheme for generalized predictive control. Jia and Krogh [10] explored a distributed MPC strategy in which the controllers exchange their predictions and incorporate this information in their local policies. Camponogara et al. [4] discussed the distributed MPC problem and reported an algorithm for cooperative iteration. In addition, these authors proposed heuristics for handling asynchronous communication problems and studied the stability characteristics of distributed MPC. Mercangöz and Doyle [16] proposed a distributed model predictive estimation and control framework. Liu et al. [15] proposed a distributed MPC scheme for nonlinear systems by designing two

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