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Multi-rate dissipativity based control of process networks

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1. Introduction

ABSTRACT

An approach to multi-rate distributed control design for process networks is presented, where the local measurements, local control and controller communication are allowed to operate at different sampling rates. Dissipative systems theory is used to facilitate stability and performance analysis of the process network, based upon dynamic supply rates which have been lifted into a global sampling rate. Quadratic difference forms are used as supply rates and storage functions, leading to less conservative stability and performance conditions as compared to classical types of supply rates. These theoretical results are illustrated by a case study of a heat exchanger network.

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Control of chemical process networks is characterized by their scale, strong interactions, transport delays, and differing dynamics of each process unit (possibly on different time-scales) [1]. The scale of the problem means that centralized control approaches, whilst potentially offering high performance, may be impractical or even infeasible. A logical alternative may then be decentralized control, whereby local control lecisions based on local information only. A large number of approaches for analysis and design of such control systems have been reported in the process control literature, e.g. [2–5]. A difficulty of this approach, however, is that the interaction effects between process units are not explicitly captured, thus leading to potentially conservative results. This is particularly relevant in process control, where the process units may interact strongly. These strong interactions are often caused by material recycle and heat integration [1], which may be viewed as positive feedback loops within the process network. These deficiencies motivate investigation into distributed control offers the simplicity of decentralized control design, combined with high levels of performance as in centralized control. In particular, distributed model predictive control (MPC) has been an area of considerable interest recently in the literature, see for example, [6–10]. A particularly interesting aspect of distributed MPC approaches is their ability to achieve global performance and stability with respect to constraints.

Another key issue in plant-wide control design is the selection of the controlled variables, and subsequent pairing with the manipulated variables. The latter problem has been traditionally handled by approaches such as the relative gain array, which provides an easily calculated measure for loop pairing [11]. More recently, this concept has been extended to consider process dynamic information [12], and economic considerations through the relative exergy array [13]. An interesting approach to controlled variable selection is self-optimizing control, whereby a set of controlled variables is selected such that the process is kept close to its optimum in spite of disturbances or errors with constant setpoints [14]. Based on this, a thorough approach to control *structure* selection is presented in [1]. It is important to note that this issue is somewhat independent of, but complementary to, the *design* of the individual decentralized controllers. This paper is concerned with the design of the individual controllers once the controlled variables and pairing has been carried out. As such, any existing methods for control *structure* selection may be carried out in unison with the proposed approach (see for example [1,15,16], or the reviews [17,18] for more examples).

The focus of this work is to address the issue of distributed multi-rate control of process networks. This is motivated by the fact that many process units can have different time constants (due to, for example, different volumes, heat transfer areas or flow rates), thus requiring

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multiple sampling rates to avoid over or under sampling. It may also be preferable to sample critical variables at a higher rate than noncritical ones to decrease capital costs, or due to sensor limitations, requiring different processes and controllers or different controller input and output channels to have different sampling rates, for example, pressure and temperature are measured at different rates. In addition, the local measurement and control action ports, and remote communication ports of each controller may have different sampling rates. The proposed distributed multi-rate control approach will allow for the information exchange rate in the controller communication network to be slower than the sampling rates of local sensors and actuators, thus, reducing network traffic. This can be relevant for control systems for process networks, where certain network structures (i.e. recycle loops) are known to induce plant-wide dynamics on a slower time-scale than the individual units [19].

There are a number of distributed multi-rate control approaches reported in the literature. For example, a Kalman filter based distributed MPC approach is developed in [20]. In [21], a distributed multi-rate control approach is developed, where an interesting observation was made that the distributed approach had a larger stability region as compared to the centralized case. In [22], the passivity of the communication is used to ensure stability regardless of (fixed) communication delay. An approach with specific application to chemical process networks is presented in [23], where the decomposition of the network (into sub-units) is partially guided by the plant flow sheet, leading to an intuitively appealing approach, an advantage that is shared with this proposed approach. More multi-rate approaches in the context of chemical process control, although not distributed approaches, may be found in [24–28]. The advantage of the proposed approach is that it provides a scalable approach to distributed multi-rate control. However, it does assume that the sampling rates of the subsystems are constant.

In this paper, dissipative systems theory is used to facilitate stability and performance analysis of the process network. Dissipativity is fundamentally an input-output property of systems, which together with the topology of process network, can be used to analyze plant-wide interaction effects (e.g., [29–32]). These approaches are scalable, as the dissipativity properties of the process network may be determined as a linear combination of that of the individual processes and controllers when the network structure is taken into account. The proposed approach shares these advantages with aforementioned methods. It differs, however, in that a more general type of dissipativity is used. Quadratic difference forms (QdFs) are used as dynamic supply rates and storage functions, leading to much less conservative stability and performance conditions as compared to classical types of supply rates [33]. To deal with multiple sampling rates, the dynamic supply rates of individual process units are lifted into a global sampling rate. In addition, in the proposed work the dissipativity of the process network is formulated at an open-loop level, rather than as a network of closed-loop systems as in [32], providing a flexible approach that deals with arbitrary control network structures.

The results presented here may be viewed as an extension to those in [34] to multi-rate control. In the current paper it is assumed that there is no time-delay in the controller communication, or that it is time invariant. In some cases this is a valid assumption as compared to the time scale on which process systems operate, modern communication systems are very fast. Distributed control with asynchronous state measurements is considered in [35] using the Lyapunov model predictive control technique recently developed by Christofides et al. [36]. This approach assumes that there is no delay in the controller communication or process interconnection, however. Conversely, a decentralized control approach designed specifically to handle uncertain time-delays in the process interconnections was presented in [37]. Decentralized adaptive control has also been proposed as a solution to time-varying delays in process networks, [38], which has the advantage of also being able to handle process nonlinearities. Time varying delays in the process and/or communication network (but not varying time-delays in the process measurements) has been studied by the authors previously in the context of dissipativity based distributed control [39], and controller communication failure in [40]. A related approach for uncertain time-delays is the integral quadratic constraint based approach proposed in the current paper can be applied concurrently with the previous developments of the authors allowing for these issues to be tackled alongside of multi-rate control. Whilst the focus of this work is on distributed control, fully decentralized and centralized control may also be considered in this framework, leading to a holistic approach to control of networks.

Some notation used in the remainder of this paper is briefly introduced. $A > (\geq)0$ for a symmetric matrix A, implies that A is positive definite (semidefinite), similarly $A > B \Leftrightarrow (A - B) > 0$. diag (A_1, \ldots, A_n) denotes the formation of a block diagonal matrix with A_i as its *i*th block diagonal entry and zeros elsewhere. $\| \cdot \|_2$ denotes the 2-norm of a vector. $\phi(\zeta, \eta) \in \mathbb{R}^{n \times m}(\zeta, \eta)$ denotes an $n \times m$ dimensional two variable polynomial matrix in the indeterminates ζ and η with real coefficients. The degree of such a matrix, denoted by deg (ϕ) is defined as the maximum power of ζ and η appearing in any element of $\phi(\zeta, \eta)$. Analogously, $\phi(\xi) \in \mathbb{R}^{n \times m}(\xi)$ denotes a one-variable polynomial matrix with real coefficients. The operator ∂ takes a two-variable polynomial matrix and produces a one-variable polynomial matrix, that is, $\partial \phi(\xi) = \phi(-\xi, \xi)$. The inertia of a matrix is a triple (q_-, q_0, q_+) referring to the number of negative, zero and positive eigenvalues. ρ denotes that forward shift operator, thus $\rho^n v(t) = v(t + n)$.

The remainder of this paper is structured as follows, in Section 2 some required background material is presented. Following this, in Section 3 the multi-rate dissipativity based analysis and control design framework is presented. A case study is presented in Section 4, followed by some concluding remarks.

2. Background and preliminaries

As an input-output property of systems, dissipativity is useful in studying interconnected systems as it allows for much of the complexity of the problem to be shifted to the interconnection relations, rather than studying centralized models. Once the dissipativity of the subsystems is ascertained, the dissipativity based analysis for complex networks can be performed easily, yielding a scalable approach. First introduced in [43], a discrete time dynamical system with input, output and state $u \in \mathbb{R}^p$, $y \in \mathbb{R}^q$ and $x \in \mathbb{R}^n$ respectively is said to be dissipative if there exists a function defined on the input and output variables, called the supply rate s(u, y) and positive semi-definite function defined on the state, called the storage function V(x(t)) such that:

$$V(x(t+1)) - V(x(t)) \le s(u(t), y(t))$$

for all time steps t. The following (Q, S, R)-type of supply rate is commonly used:

$$s(u(t), y(t)) = y^{T}(t)Qy(t) + 2y^{T}(t)Su(t) + u^{T}(t)Ru(t).$$
(2)

(1)

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