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Scalability through Decentralization: A Robust Control Approach for the Energy Management of a Building Community ⋆

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Abstract: Recent studies in the literature have shown that cooperative energy management of an aggregation of buildings may lead to substantial energy savings. These approaches typically assume the existence of a central operator that is capable of formulating and solving, within a reasonable amount of time, a centralized optimization problem. However, this requirement may be unrealizable in cases of large scale districts, and it also fails to address privacy concerns of the building occupants. In this paper, we deal with these issues by proposing a decentralized control scheme which only requires the individual buildings to communicate bounds on their energy demands. The proposed method partly alleviates concerns on privacy since this limited communication scheme does not reveal the exact characteristics of the energy usage within each building. In addition, it enables a distributed computation of the solution, making our method highly scalable. We demonstrate through a numerical study the efficacy of the proposed approach, which leads to solutions that closely approximate those obtained by the centralized formulation only at a fraction of the computational effort.

Keywords: distributed robust controller synthesis, decentralized control, predictive control, convex optimization, building energy management.

1. INTRODUCTION

Building energy management is an active field of research as the potential for energy savings can be significant. Around three quarters of the total electricity consumption in Europe and the US is attributed to buildings (Laustsen 2008). Therefore, substantial efforts have been devoted to develop sophisticated control schemes that are capable of reducing the energy consumption while maintaining the room temperatures within predefined ranges (Oldewurtel et al. 2012, Sturzenegger et al. 2016). Further savings can be obtained by cooperatively managing the aggregated energy demands of a collection of buildings via an energy hub (Parisio et al. 2012, Darivianakis et al. 2015, 2016). Most of the respective methods proposed in the literature assume the existence of a central operator that is capable of controlling both the buildings actuation systems and the energy hub devices. This assumption is rather restrictive in cases of large scale districts in which the formulation and solution of a centralized problem may be practically impossible, and also undesirable due to concerns of the building occupants about revealing their exact system characteristics (e.g., occupancy patterns, comfort bounds).

Distributed control approaches can potentially deal with these issues by dividing the overall system into a number of coupled subsystems that exchange information through an established communication network. In the model predictive control framework adopted here, distributed control schemes are usually categorized into cooperative or non-cooperative (Scattolini 2009). In the former paradigm, a system can achieve global optimal solutions at the expense of substantial communications (Venkat et al. 2005, Stewart et al. 2010), while in the latter, communications are reduced at the expense of optimality (Keviczky et al. 2006, Trodden and Richards 2010). Both cooperative and non-cooperative schemes typically require a centralized offline design phase. This requirement can be restrictive, making the distributed schemes suffer from similar complexity and privacy concerns as the centralized formulation. To alleviate these issues, it is desirable to develop decentralized schemes that exploit only local computational resources and information. In the literature, this is commonly achieved by each subsystem considering the worst-case effect of its neighbors as a bounded exogenous disturbance to its own system (Camponogara et al. 2002, Dunbar 2007, Farina and Scattolini 2012). Nevertheless, this can be conservative approach if the sets of bounded exogenous disturbances are calculated offline; therefore, disregarding the possibility of adapting their size based on the dynamical evolution of the system.

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This paper extends our previous works in (Darivianakis et al. 2015, 2016) by proposing a *decentralized* cooperative control scheme to operate the energy hub and the aggregation of buildings in a cost efficient manner. The method requires that the individual buildings communicate upper and lower bounds, uncorrelated over time, on their energy demands to the energy hub. The novelty of the proposed decentralized scheme is based on its ability to:

- decouple the optimization problems of the buildings and the energy hub. This is achieved with limited communication which is restricted to the exchange of simple bounds on the building energy demands;
- adapt online the size of the communicated bounds based on the dynamical evolution of the system;
- scale polynomially with respect to the number of buildings in the district. The resulting problem retains its decoupled structure allowing the use of distributed optimization algorithms to solve it.

The polynomial scalability is achieved by reformulating the original problem into a convex infinite dimensional optimization problem, and then approximating it using decision rules (Ben-Tal et al. 2004). The proposed method partly alleviates concerns on privacy by not revealing sensitive information regarding the operational characteristics of the buildings. It also promotes fairness in the community, imposing higher costs to buildings with large energy demands.

The paper is organized as follows. In Section 2, we briefly review the modelling approach and the centralized problem formulation presented in (Darivianakis et al. 2015). The main contributions are presented in Sections 3 and 4, where the proposed decentralized method and the techniques associated with the derivation of a tractable approximation to the original problem are discussed. Section 5 provides a numerical study to assess the efficacy of the proposed method. Proofs of the theorems are found in the Appendix.

Notation: Random vectors are represented in boldface, while their realizations are denoted by the corresponding symbols in normal font. For given vectors $v_i \in \mathbb{R}^{k_i}$ with $k_i \in \mathbb{N}$, $i \in \mathcal{M} = \{1, \ldots, m\}$, we define $[v_i]_{i\in\mathcal{M}} = [v_1^\top \ldots v_m^\top]^\top \in \mathbb{R}^k$ with $k = \sum_{i=1}^m k_i$ as their vector concatenation. Given time dependent vectors $\nu_t \in \mathbb{R}^\ell$ with $\ell \in \mathbb{N}$, we define $\nu^t = [\nu_1^\top \ldots \nu_t^\top]^\top \in \mathbb{R}^{\ell t}$ as their history up to time t. Dimensions of the vectors will be clear from the context.

2. PROBLEM FORMULATION

In this section, we describe the energy hub and buildings dynamics using discrete time, linear models affected by exogenous disturbances. We denote by $\mathcal{T} = \{1, \ldots, T\}$ the set of time indexes over the prediction horizon T, and $\mathcal{B}$ the set of buildings forming the district.

2.1 Building dynamics

We model the building dynamics using state space models, motivated by the resistance-capacitance models of (Sturzenegger et al. 2014). For each building $i \in \mathcal{B}$, we model its dynamical evolution,

$$\boldsymbol{x}_{i,t+1} = f_i(\boldsymbol{x}_{i,t}, \boldsymbol{u}_{i,t}, \boldsymbol{\xi}_{i,t}), \tag{1}$$

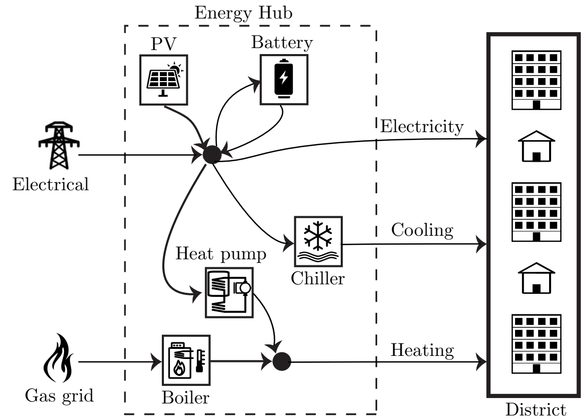

Fig. 1. Heating, cooling and electricity network of a building district.

where the states $\boldsymbol{x}_{i,t}$ capture the temperatures in the building components (e.g., rooms and wall layers). The vector $\boldsymbol{u}_{i,t}$ models the inputs to the building actuation systems (e.g., air handling unit (AHU), thermally activated building systems (TABS), radiators). The uncertain vector $\boldsymbol{\xi}_{i,t}$ encompasses all the disturbances affecting the dynamics of the i-th building (e.g., ambient temperature, solar radiation and internal gains). These disturbances are typically correlated over time, therefore their support, Ξ_i, is defined over the horizon, i.e., $\boldsymbol{\xi}_i \in \Xi_i$ with $\boldsymbol{\xi}_i = [\boldsymbol{\xi}_{i,t}]_{t\in\mathcal{T}}$. We assume that the function $f_i(\cdot)$ is linear in the states, inputs and disturbances; it actually reflects construction characteristics (e.g., number of rooms, construction material and actuation units).

We define the constraint set for the i-th building,

$$\begin{aligned}\mathrm{BD}_{i,t}\Big(\boldsymbol{\xi}_{i,t}\Big) = \Big\{(\boldsymbol{x}_{i,t}, \boldsymbol{u}_{i,t}, \boldsymbol{d}_{i,t}) :& \\ E_i \boldsymbol{x}_{i,t} + F_i \boldsymbol{u}_{i,t} + G_i \boldsymbol{\xi}_{i,t} \le h_i,& \quad (2)\\ \underline{x}_{i,t} \le \boldsymbol{x}_{i,t} \le \overline{x}_{i,t},& \quad (3)\\ \boldsymbol{d}_{i,t} = M_i \boldsymbol{u}_{i,t}\Big\}.& \quad (4)\end{aligned}$$

Equation (2) models the operational constraints (e.g., radiator and AHU limitations) with the matrices E_i, F_i, G_i, and h_i derived using the BRCM Toolbox (Sturzenegger et al. 2014). Comfort constraints are encoded in (3), with $\underline{x}_{i,t}$ and $\overline{x}_{i,t}$, denoting the lower and upper temperature bounds, which generally vary during the day due to building occupancy patterns. Equation (4) captures the demand of the i-th building for electricity, heating and cooling with M_i being a (0, 1)-matrix providing the mapping between the building actuation systems, $\boldsymbol{u}_{i,t}$, and their respective energy source, $\boldsymbol{d}_{i,t}$, (e.g., radiators and heating TABS are forming the heating demand).

2.2 Energy hub dynamics

The energy hub is defined as the *conceptual* entity housing the energy generation, conversion and storage devices (e.g., photovoltaics (PV), battery, heat pump, chiller) that are shared by the building community. As shown in the illustrative example in Fig. 1, the energy hub provides the interface between the building community and the energy grids by purchasing electricity and gas to serve the building demands for electricity, cooling and heating.