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Analyzing the effects of comfort relaxation on energy demand flexibility of buildings: A multiobjective optimization approach

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ABSTRACT

We present a multiobjective optimization framework to evaluate the effects of comfort relaxation on the energy demands of buildings. This work is motivated by recent interest in understanding demand elasticity available for real-time electricity market operations and demand response events. We analyze the flexibility provided by an economics-based control architecture that directly minimizes total energy and by a traditional tracking control system that minimizes deviations from reference temperature and relative humidity set-points. Our study provides the following insights: (i) using percentage mean vote (PMV) and predicted percentage dissatisfied (PPD) constraints within an economics-based system consistently gives the most flexibility as comfort is relaxed, (ii) using PMV and PPD penalization objectives results in high comfort volatility, (iii) using temperature and relative humidity bounds severely overestimates flexibility, and (iv) tracking control offers limited flexibility even if used with optimal set-back conditions. We present a strategy to approximate nonlinear comfort regions using linear polyhedral regions, and we demonstrate that this reduces the computational complexity of optimal control formulations.

1. Introduction

Commercial buildings are valuable assets to power grid operators because they can enable demand elasticity [1]. Such flexibility is necessary to accommodate intermittent renewable power at a large scale and to avoid the construction of new generation plants. Demand flexibility can be achieved in buildings by shifting the demand profile in time and by relaxing comfort conditions to shed demand. Assessing the economic benefits that comfort relaxation can bring is nontrivial because system flexibility is a function of many factors such as the building design, real-time weather conditions, control architecture, and occupant acceptance [2,3].

The heating, ventilation, and air conditioning (HVAC) system of a building comprises a large number of equipment units and material and energy resources that are monitored and coordinated in real time by a building management or control system (BMS). Thermal comfort and air quality conditions need to be enforced as occupancy levels, ambient conditions, and energy prices change. Two main control architectures are used in BMS systems. The traditional architecture (still dominating industry) determines set-points for equipment units such as delivery temperatures and economizer positions (recycle rates) as well as set-points for internal conditions such as zone temperatures, relative humidity, and pressure. Such set-points usually are tuned by experienced operators or by operational rules embedded in the BMS system. The set-points are then tracked by low-level, single-loop controllers such as thermostats. A key question that arises under this architecture is how to properly predict the amount of demand that the system will use for a given combination of set-points. This is particularly difficult because of the complex feedbacks and physical interactions that exist between equipment units and controllers. Limited knowledge of these interactions introduces a disconnect between global economic performance (e.g., total energy demand) and low-level control performance (e.g., set-point tracking) and can result in severe inefficiencies. This disconnect has been widely studied in the chemical industry [4–6].

Because of the inefficiencies of traditional control architectures, the building automation industry has recently shifted its interest to model-based management systems (also known as predictive control systems) [7–11]. These supervisory control

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architectures use dynamic models to predict the interactions between global HVAC variables and local zone conditions. In addition, they can directly optimize economic objective functions of different forms [12]. Consequently, these systems are also referred to as economics-based control systems [35]. All these features allow these advanced systems to predict and trade off energy (or cost) and comfort by manipulating multiple building variables simultaneously.

The vast majority of the building industry uses neither comfort models nor occupant feedback routinely in operations. Consequently and, contrary to what is normally believed, most buildings operate under poor comfort conditions [13]. In addition, and to the best of our knowledge, only limited insights are available in the literature on the energy flexibility provided by different control systems as comfort conditions are relaxed. One can find many control formulations reported for which economic and energy savings potentials are evaluated. We refer the reader to the studies reported in [7–12,14–17] and the comprehensive review [18]. None of these studies evaluates energy flexibility and control system behavior under relaxed comfort conditions.

The poor comfort performance of legacy control architectures results in resistance by occupants and building owners to consider emerging automation technologies. In addition, the limited understanding of the trade-offs between economic performance and comfort makes it difficult to fully appreciate the economic value of new technologies over prevailing ones and thus can makes it difficult to commercialize them. We believe that performing more studies to evaluate these trade-offs is necessary to accelerate the deployment of new technologies. This, in turn, is essential to enabling demand response and elasticity at a large scale [3,19].

Several multiobjective optimization studies for buildings are available in the literature. In [20,21] control studies are presented on the competing effects of air quality and energy consumption to demonstrate that significant energy reductions on energy use are possible with small relaxations of air quality conditions. In [22] the authors analyze the benefits of using multiobjective optimization in energy retrofit tasks. None of these works analyze trade-offs between energy use and thermal comfort.

In this work, we present a multiobjective optimization framework to evaluate the impact of comfort relaxation on energy demands. We compare the flexibility of different economics-based and traditional control architectures reported in the literature and used in practice. To perform our studies, we use a physical model of a single-zone building conditioned by an air-handling unit (AHU), and we incorporate a detailed PMV/PPD thermal comfort model. We emphasize that the intent of the multiobjective framework presented is not to obtain absolute numbers on the impact of comfort relaxation on demand flexibility. Such a study would require the consideration of many factors such as climate, building and HVAC design, and operational conditions. Instead, the intent of our study is to provide insights into the types of biased comfort perceptions and system volatility that can arise if inefficient control architectures and inappropriate comfort metrics are used in the control formulation. In addition, we seek to highlight the advantages that a multiobjective setting provides for analyzing and quantifying the benefits of economics-based control technologies.

The paper is structured as follows. In Section 2 we describe the dynamic model of the HVAC system and the thermal comfort model used in the optimal control formulations. In Section 3 we present the multiobjective framework used to analyze the behavior of different control formulations and comfort relaxation strategies. A numerical study is presented in Section 4, and computational issues are discussed in Section 5. Conclusions and future work are discussed in Section 6.

2. Dynamic model of HVAC system

The building model considered in this work was presented in [23]. We use the thermal comfort model described in the ASHRAE standard 55-2004 [24]. The building model seeks to capture the effect of different global control variables on energy demand and local zone conditions. In particular, the model captures the dynamics of the zone CO_2 concentration, humidity, pressure, and temperature as well as the behavior of the AHU and the recycle temperatures, flows, and concentrations. We only describe the main variables of interest in the narrative. The full model notation and parameters are presented in Appendix A.

2.1. Material balances

The total mass balance in the building zone is given by

$$\frac{dm(\tau)}{d\tau} = \rho \cdot (q^{in}(\tau) - q^{out}(\tau)) \tag{1}$$

where τ denotes time and $q^{in}(\cdot)$, $q^{out}(\cdot)$ are inlet and outlet zone flows, respectively. The individual component dynamic mass balances are described by

$$V \cdot \frac{dC_i(\tau)}{d\tau} = q^{in}(\tau) \cdot C_i^{in}(\tau) - q^{out}(\tau) \cdot C_i(\tau) + n(\tau) \cdot n_{tot} \cdot G_i, \quad i \in \{CO_2, H_2O\}. \tag{2}$$

The occupancy signal of the space is given by $n(\tau)$, which takes a value of 1 if the space is occupied and a value of zero if it is unoccupied at a given time τ. The total number of occupants during occupied times is n_{tot}.

If we assume air with constant density and heat capacity the mass balance in the recycle is

$$q^{out}(\tau) + q^{amb}(\tau) = q^{ex}(\tau) + q^{m}(\tau) \tag{3a}$$

$$C_i(\tau) \cdot q^{out}(\tau) + C_i^{amb}(\tau) \cdot q^{amb}(\tau) = C_i(\tau) \cdot q^{ex}(\tau) + C_i^{m}(\tau) \cdot q^{m}(\tau), \quad i \in \{CO_2, H_2O\}. \tag{3b}$$

The mass balances in the AHU are given by,

$$q^{in}(\tau) = q^{m}(\tau) \tag{4a}$$

$$m_i^{rm}(\tau) = q^{in}(\tau) \cdot C_i^{in} - q^{m}(\tau) \cdot C_i^{m}(\tau). \tag{4b}$$

The mass removal rates in the AHU are denoted as m_i^{rm}. We consider $m_{CO_2}^{rm} = 0$ because this component is not removed in the AHU (only moisture is removed or added). The relationship between the zone pressure, mass, and temperature is given by the ideal gas law,

$$P(\tau) = \frac{m(\tau) \cdot R \cdot T(\tau)}{M \cdot V}. \tag{5}$$

The zone relative humidity is given by

$$RH(\tau) = 100 \cdot \frac{C_{H_2O}(\tau)}{C_{H_2O}^{sat}(\tau)}, \tag{6}$$

where $C_{H_2O}^{sat}(\tau)$ is the saturation density (concentration) and is computed from Antoine's equation [25],

$$\log_{10}(C_{H_2O}^{sat}(\tau)) = 8.07131 - \frac{1730.63}{T(\tau) - 39.73}. \tag{7}$$

The concentration of CO_2 in parts per million (ppm) is computed from

$$ppmV_{CO_2}(\tau) = 1000 \cdot \frac{C_{CO_2}(\tau) \cdot R \cdot T(\tau)}{M_{CO_2} \cdot P(\tau)}. \tag{8}$$