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A Case Study of Economic Optimization of HVAC Systems based on the Stanford University Campus Airside and Waterside Systems

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ABSTRACT

Commercial buildings account for $200 billion per year in energy expenditures, with heating, ventilation, and air conditioning (HVAC) systems accounting for most of these costs. In energy markets with time-varying prices and peak demand charges, a significant potential for cost savings is provided by using thermal energy storage to shift energy loads. Since most implementations of HVAC control systems do not optimize energy costs, they have become a primary focus for new strategies aimed at economic optimization. However, some industrial applications, such as large research centers or university campuses, are too large to be solved in a single MPC instance. Decompositions have been proposed in the literature, but it is difficult to evaluate and to compare decompositions against one another when using different systems. In this paper, we present a large-scale industrially relevant case study where solving a single MPC optimization problem is not feasible for real-time implementations. The study is loosely based on the Stanford University campus, consisting of both an airside and waterside system. The airside system includes 500 zones spread throughout 25 campus buildings along with the air handler units and regulatory building automation system used for temperature regulation. The waterside system includes the central plant equipment, such as chillers, that is used to meet the load from the buildings. Active thermal energy storage is also available to the campus. The models from this case study are made publicly available for other researchers interested in designing alternative control strategies for managing chilled water production to meet airside loads. The aim of the case study release is to provide a standardized problem for the research community and a benchmark for evaluating performance.

1. INTRODUCTION

The control of heating, ventilation, and air conditioning (HVAC) systems in buildings has drawn widespread attention in recent years. Due to the high energy usage and sheer number of applications, even moderate savings are impactful. Conventional control relies on tracking fixed setpoint for temperature regulation (Afram and Janabi-Sharifi, 2014). However, in markets with time-varying utility prices, there is substantial room for improvement, as economic optimization can produce significant energy cost savings.

1.1 Optimization of HVAC Systems

An example large-scale commercial HVAC application is depicted in Figure 1. There are two main components: an airside system and a waterside system. The airside system consists of the buildings, airspaces, and zone temperature regulation equipment. The waterside system consists of the large equipment, such as chillers and boilers, that is used to meet the load demand from the airside system. In these types of applications, the potential exists to achieve savings by running chiller and other electricity-intensive equipment at higher rates during night hours when the price of electricity is lower and less during the afternoon hours when prices are higher (Avci et al., 2013). This shifting

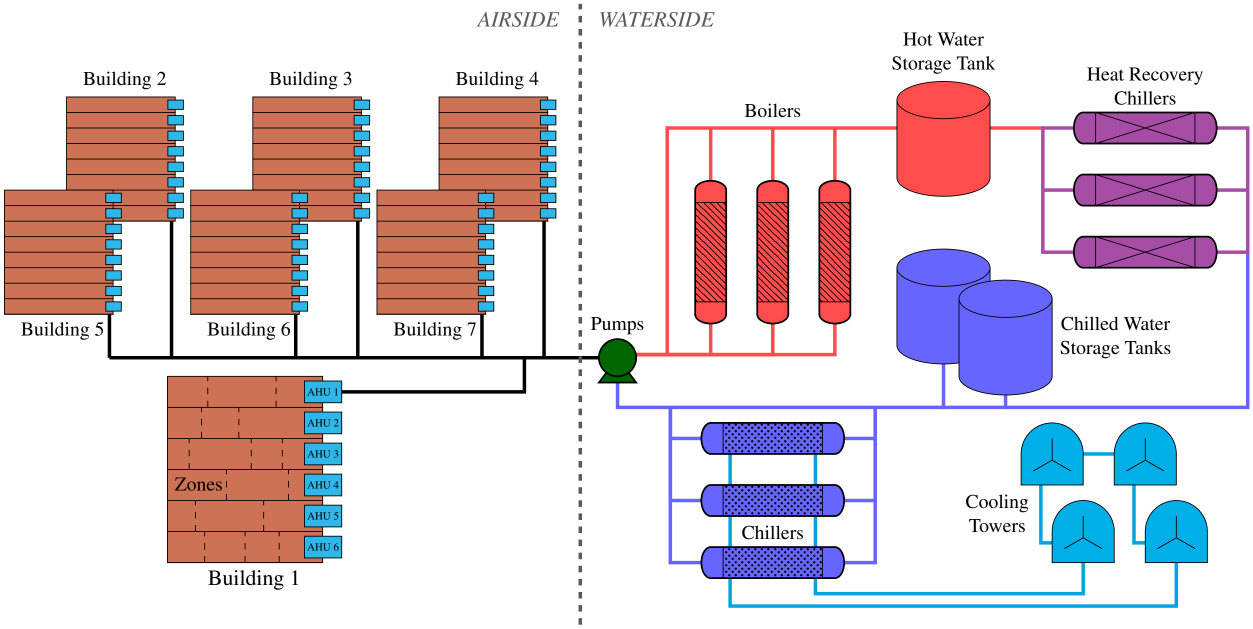

Figure 1: Diagram of a typical large-scale commercial application with the airside system (buildings) on the left and waterside system (central plant) on the right. Adapted from Raković and S. Levine (2018, Section 3.5).

of the load from peak to off-peak hours can be achieved by using thermal energy storage (TES). The two types of TES storage considered are *passive* and *active*. Passive TES exists in the mass of the airside system as building can be precooled. Active TES can exist in the form of a chiller water storage tank in the waterside system which can be charged by production from chillers and discharged to meet the cooling load (Henze, 2005). A control system is necessary to manage this decision making.

Model predictive control (MPC) has emerged as one popular method to achieve this load shifting, while respecting system constraints. MPC uses a model of the system to make predictions and to solve an optimization problem (Rawlings et al., 2017a). In economic MPC, the objective being optimized is economic as opposed to a conventional tracking error. Much research has shown the benefits of economic MPC over alternative strategies for HVAC control (Afram and Janabi-Sharifi, 2014). However, implementing MPC by solving a single large optimization problem online for such large-scale systems is not feasible due to the large number of zones and pieces of equipment that are present. It also may not be desirable due to the difficulty of maintaining such a system.

1.2 Motivation for Case Study

Several MPC-based schemes have been proposed in the literature. Some examples include Mayer et al. (2015), Moroşan et al. (2010), and Touretzky and Baldea (2016). However, it is difficult to evaluate the novel ideas and decompositions without having a common system against which to benchmark performance. In this paper, we present a case study problem definition based on an industrial application. This case study is made publicly available for other researchers in the HVAC community to design and test the performance and viability of various control systems.

The rest of the paper is organized as follows. In Section 2, the HVAC case study is presented. In Section 3, the models used for the system are outlined. In Section 4, sample simulations results are shown using one particular control architecture for this system. In Section 5, the major findings are listed.

Figure 2: The new heat-recovery system to provide heating and cooling to the campus constructed as part of the $485-million Stanford Energy System Innovations (SESI) project Blair (2016).

2. CASE STUDY

2.1 Background

The case study is modeled after the Stanford University campus (Rawlings et al., 2017b). Recently, Stanford University replaced an aging natural gas cogeneration plant with a new heat-recovery system to meet the cooling and heating loads of their campus as part of the $485-million Stanford Energy System Innovations (SESI) project (Blair, 2016). In addition to adding heat-recovery chillers to improve efficiency, thermal energy storage tanks were added for hot and chilled water. These large insulated tanks, along with the rest of the central HVAC plant, are depicted in Figure 2. Johnson Controls designed the control architecture for the new central plant. Results have shown that the MPC-based system achieves 10–15% more energy cost savings compared to the best team of trained human operators (Stagner, 2016). While this project was focused primarily on optimization of the waterside, the case study is being extended to include treatment of the airside system as well.

Certain aspects of this real-world problem have inspired research projects for creating economically optimal methods of controlling such a large-scale industrial system. For the case study presented in this paper, a simplified version of the Stanford project is used to highlight the complexity of controlling a large-scale combined airside and waterside system while removing some of the problem features and intricate details to increase clarity for a research perspective.

2.2 System

The HVAC system for the case study is a central plant that services the cooling needs of a 500-zone campus. The HVAC plant has eight conventional chillers along with their supporting pumps and cooling towers. For simplicity, we do not consider heating equipment, such as boilers or heat-recovery chillers. Each of the chillers has minimum and maximum cooling capacities of 2.5 MW and 12.5 MW, yielding a total plant capacity of 100 MW cooling. Chilled water supply temperature is held constant at 5.5 °C. In addition to the passive thermal energy storage present in the form of building mass, there is active thermal energy storage with a chilled water tank. The chilled water TES storage tank has a maximum capacity of 100 MWh cooling.

The 500-zone campus contains 25 buildings, each with 20 zones that have independent local temperature controllers. All zone temperatures need to be kept between 20.5 and 22.5 °C to ensure occupant comfort. The models for the

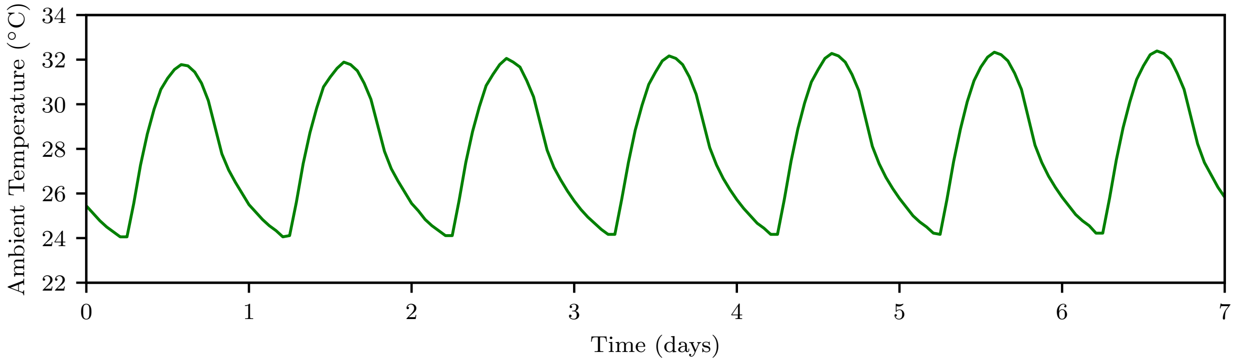

Figure 3: Representative ambient temperature data over a 7-day period in the summer Rawlings et al. (2017b). In this plot, zero corresponds to midnight.

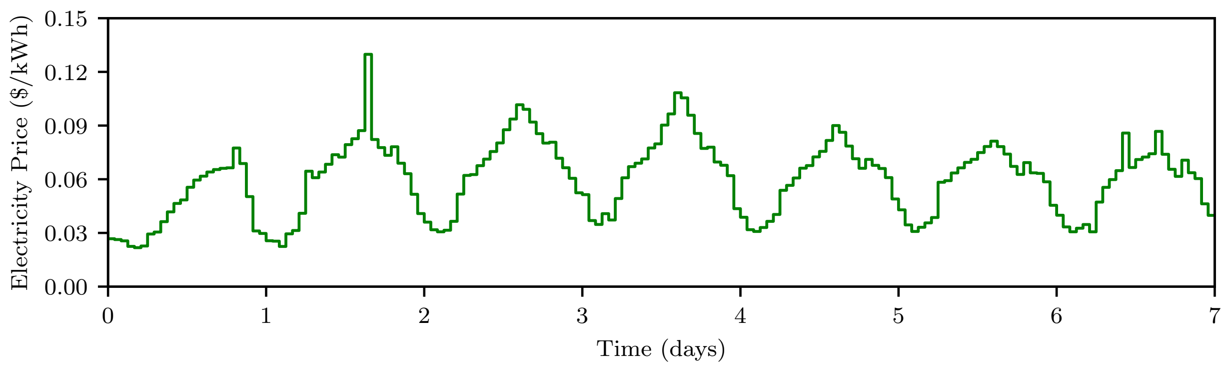

Figure 4: Representative electricity pricing data over a 7-day period in the summer. In this plot, zero corresponds to midnight. Data provided by Johnson Controls Rawlings et al. (2017b).

equipment and zones are presented in Section 3. The airside models describe the temperature dynamics in each of the 500 zones, and the waterside models describe the power consumption of the central plant equipment.

The aim of the control system is to minimize costs in the presence of time-varying electricity prices and a peak demand charge as well as environmental disturbances such as weather while meeting constraints on comfort and equipment. The control system must determine the zone temperature setpoints and waterside equipment operation schedule.

2.3 Parameters

Several loads are placed on the HVAC system. The primary disturbance considered in this study is the ambient temperature. Typical ambient temperature data during the summer for a city in the Southern U.S. is presented in Figure 3. To reject the loads placed on the campus, the HVAC system purchases power from the electricity market. Two components of the pricing structure are considered in this study: time-of-use charges, which assess time-varying prices on electricity use throughout the day, and peak demand charges, which are proportional to maximum rate of power consumption over period of time (typically a month). Electricity pricing data obtained from Johnson Controls over a week-long period is given in Figure 4. The monthly peak demand charge is $4.56/kW.

From these two figures, it is evident that the heat load on the campus is typically greatest (corresponding to the peak in ambient temperature in the afternoon hours) when power costs are high. By purchasing more power when it is cheaper during the overnight and early morning hours, operational costs of the HVAC system can be decreased using the thermal energy storage for load shifting.

3. MODELS

3.1 Airside System

In the airside system, models are needed to describe temperature dynamics. The dynamics of cooling a single zone or building can be represented by an energy balance. One approach is to lump all of the zone mass and air properties into a single zone temperature. Other models can also be used to describe the airside system dynamics. Differential equations can be written to model the zone air and mass temperatures separately, and the mass temperature can be further separated into a shallow mass temperature and deep mass temperature.

For simplicity, we considered the lumped model for the temperature of zone i as given by

$$C_i \frac{dT_i}{dt} = -H_i(T_i - T_a) - \sum_{j \neq i} \beta_{ij}(T_i - T_j) - \dot{Q}_{c,i} + \dot{Q}_{\text{other},i} \tag{1}$$

in which C_i is the thermal capacitance of the zone, H_i is a scaled heat transfer coefficient with the ambient, T_a is the ambient temperature, $\dot{Q}_{c,i}$ is the cooling rate from the HVAC system, $\dot{Q}_{\text{other},i}$ is an external load place on the zone, and β_{ij} characterizes the degree of coupling between zones i and j. If zones i and j are not adjacent, then $\beta_{ij} = 0$.

Since the supervisory control system determines the zone temperature setpoints, a model is also need to relate the zone temperature setpoint $T_{\text{sp},i}$ to the cooling rate $\dot{Q}_{c,i}$ delivered to the zone. Using an ideal proportional-integral (PI) controller, the linear cooling duty controller model is given by

$$\begin{aligned} \dot{Q}_{c,i} &= \dot{Q}_{\text{ss},i} + K_{\text{c},i} \left[\varepsilon_i + \frac{1}{\tau_{\text{I},i}} \int_0^t \varepsilon_i(t')dt' \right] \\ \varepsilon_i &= T_{\text{sp},i} - T_i \end{aligned} \tag{2}$$

in which $K_{\text{c},i}$ and $\tau_{\text{I},i}$ are the PI controller parameters and ε_i is the tracking error. Saturation is included as feature for airside PI due to constraints on the maximum $\dot{Q}_{c,i}$ that is achievable. Since it may take zones up to an hour to respond to a setpoint change, the dynamics of zone PI controllers cannot be neglected by the supervisory control layer. For convenience, both models can be converted to state-space form.

3.2 Waterside System

In the waterside system, models are needed for equipment electricity consumption and storage tank dynamics. Equipment models are static, determining resource consumption as a function of relevant inputs for a given steady-state operating point. While these units do experience transient dynamics during startup and shutdown, these effects are moderated by local regulatory controllers, and rapid startups and shutdowns are prevented by enforcing explicit dwell time constraints in the waterside optimization problem. By contrast, storage tank models are necessarily dynamic, as storage tanks are used for time-shifting of demand.

For the chilling plant used in the case study, the three types of equipment are chillers, cooling towers, and pumps. Figure 5 shows the mass and energy flows for this system. Note that the real system consists of multiple pieces of each type of equipment arranged in parallel. Each chiller is modeled using the semi-empirical Gordon-Ng model, Lee et al. (2012) defined below:

$$W_{\text{CH}} := \left(Q_{\text{CH}} + a_1 T_{\text{CHWS}} + a_2 \left(1 - \frac{T_{\text{CHWS}}}{T_{\text{CWS}}} \right) \right) \frac{T_{\text{CWS}}}{T_{\text{CHWS}} - a_3 Q_{\text{CH}}} - Q_{\text{CH}} \tag{3}$$

The parameters a_1, a_2, and a_3 are obtained via regression with measured data. For the purposes of optimization, the temperatures are assumed to be fixed parameters. Each cooling tower uses a a simplified effectiveness model Jin et al. (2007) for calculating cooling duty, with a simple cubic fit for fan electricity Braun and Diderrich (1990).

$$Q_{\text{CT}} = Q_{\text{CH}} + Q_{\text{CH}} := \frac{c_1 (m_{\text{CW}})^{c_3}}{1 + c_2 \left(\frac{m_{\text{CW}}}{m_{\text{air}}} \right)^{c_3}} (T_{\text{CWR}} - T_{\text{WB}}) \tag{4}$$

$$W_{\text{CT}} := \kappa (m_{\text{air}})^3 \tag{5}$$

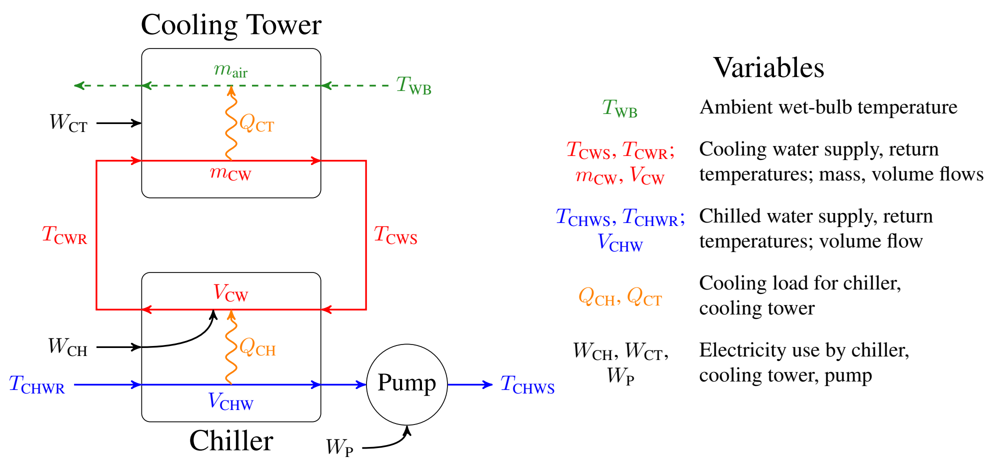

Figure 5: Diagram of a single chiller, cooling tower, and pump.

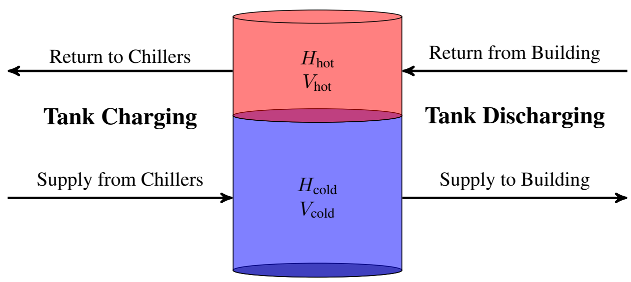

Figure 6: Diagram of stratified tank model.

With fixed T_{CWR} and known T_{WB}, (4) can be rearranged to solve for the required m_{air}, which is then used in (5) for electricity calculation. Coefficients c_1, c_2, c_3, and κ are obtained via regression. Finally, pumps are modeled with a black-box empirical model

$$W_{\text{P}} := b_1 \ln\left(1 + b_2 V_{\text{CHW}}\right) + b_3 V_{\text{CHW}} + b_4 \tag{6}$$

with regression coefficients b_1 through b_4. Note that the flows V_{CW} and m_{CW} are obtained from Q_{CH} and Q_{CT} via the appropriate constant-heat-capacity energy balances.

Active storage tanks are modeled using a two-layer stratified tank model similar to Ma et al. (2012). As diagrammed in Figure 6, the hot and cold sections are each assumed to be uniform in temperature, with heat exchange between the two layers (proportional to the temperature difference). Total volume $V_{\text{hot}} + V_{\text{cold}}$ is held constant. The dynamic model is a straightforward enthalpy balance (using known temperatures for streams entering the tank) and is omitted from the text for brevity.

In chilled water tanks, the main quantity of interest is the enthalpy of the cold section H_{cold}. For the purposes of optimization, the nonlinear tank model is replaced by a simple linear approximation of the form

$$\frac{ds}{dt} = -\sigma s + \eta \dot{Q}_{\text{storage}} \tag{7}$$

in which $s := H_{\text{cold}}$ is the enthalpy of the cold section and $\dot{Q}_{\text{storage}}$ is the rate of cold enthalpy inflow (positive) or outflow (negative). The coefficients σ and η are identified from data. Figure 7 shows simulations of the approximate linear model alongside the full nonlinear model. Even over the full 10-day horizon, the linear model fits very well, and thus is sufficient for optimization.

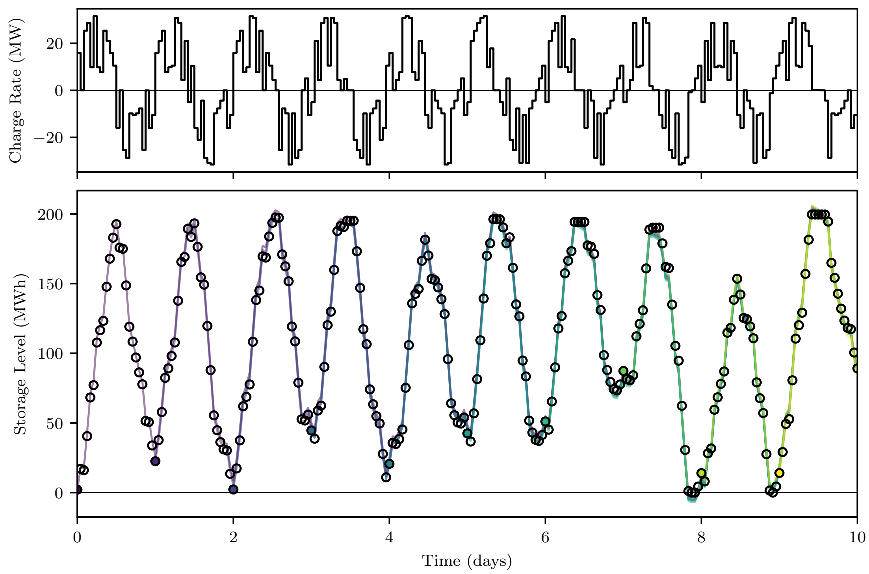

Figure 7: Linear fit of nonlinear stratified tank model. Open circles show data from the nonlinear model, while solid lines show forward simulations of the linear model starting from each day's initial condition.

3.3 Availability

The full set of data and model parameters for the case study are made publicly available for researchers in the HVAC community. They can be found on the following website: `https://hvacstudy.github.io/`. The aim of the release is to encourage other researchers to propose alternative control systems and to provide a common basis for performance evaluation of these strategies on a large-scale industrially relevant system. In the next section, we simulate the performance of one such control system that relies on a hierarchical two-layer structure.

4. SIMULATION STUDY

4.1 Control System

With the case study system defined, a supervisory control system can be used to make decisions. We consider the two-layer hierarchical control system presented in Patel et al. (2016). This structure relies on using a high-level problem with aggregate models of the airside and waterside systems to perform a plant-wide economic optimization. The solution is then sent to low-level airside and waterside controllers that use more detailed models to compute the dispatched trajectories which meet the constraints. The low-level controllers follow the load computed in the high-level problem as closely as possible. One low-level airside controller is used per building, to ensure the problem can be solved quickly online.

Within the optimization problem, the following simplifications are made in the low-level problems:

- Saturation of PI controllers is not explicitly modeled. This effect is moderated by including bounds on requested cooling, but it still may introduce mismatch when the saturation constraints are active in the physical system.
- The nonlinear equipment models in (3) through (6) are approximated as piecewise-linear. This approximation allows the waterside problem to be solved as an MILP, and arbitrary accuracy can be achieved by using more pieces, although at the cost of computational speed (Risbeck et al., 2017).
- The approximate linear model for the storage tank is used instead of the full nonlinear model.

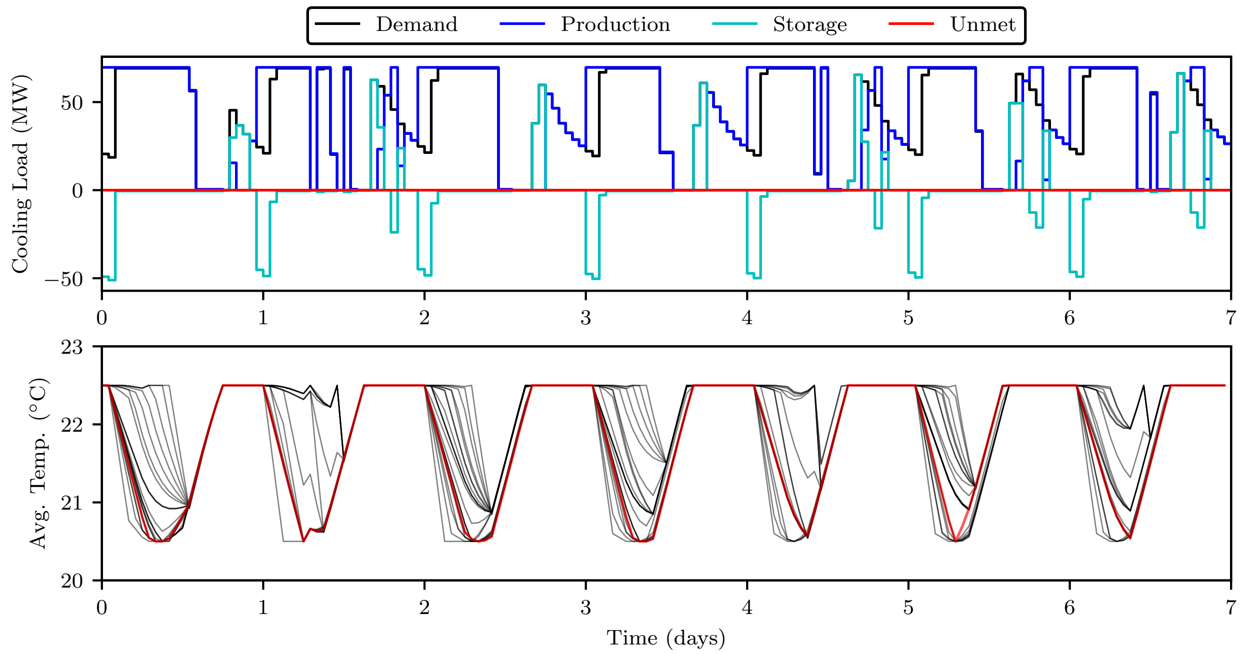

Figure 8: Results from the High-Level Problem. The top plot shows the overall optimal production schedule. Negative values of storage here denote charging of tank, while positive values indicate discharging of tank. The bottom plot shows the average building temperatures. The red line highlights one particular building, with the remaining ones shown in black.

4.2 Results.

This control architecture was applied to the case study system. The results from the high-level optimization are shown in Figure 8. The high-level problem decides to use a combination of active and passive thermal energy storage to shift the power load from peak hours to off-peak hours. These load profiles are sent to the low-level problems. Figure 9 shows the low-level airside results for all 500 zones, including the zone temperature setpoints dispatched to the system. Figure 10 shows the equipment operation schedule computed by the low-level waterside optimization to meet the load from the high-level problem. Load shifting is able to reduce costs by purchasing more power when prices are lower during the early morning hours and charging the active storage tank as well as precooling buildings and purchasing less power when prices are more expensive during the peak hours by discharging the storage tank and letting the zones heat up to the upper bound of the comfort zones. As a result, the total cost for this control policy is $78,689. For comparison, the cost without load shifting is $94,878, hence using optimization with TES results in 17% cost savings.

5. CONCLUSIONS

An industrially relevant case study for large-scale commercial HVAC systems is presented. The study is based on the Stanford University central plant. Both airside and waterside systems are considered as well as thermal energy storage. Models and data are made publicly available for the research community to investigate various control system designs. A sample simulation is performed for one particular decomposition which can be solved in real-time for an online implementation of MPC for large HVAC systems.

Future research includes extending the data set to from one week to one year and performing a year-long simulation. Additionally, a small-scale system for which the centralized MPC solution can be computed may be used as a benchmark to measure the performance of the decomposition.

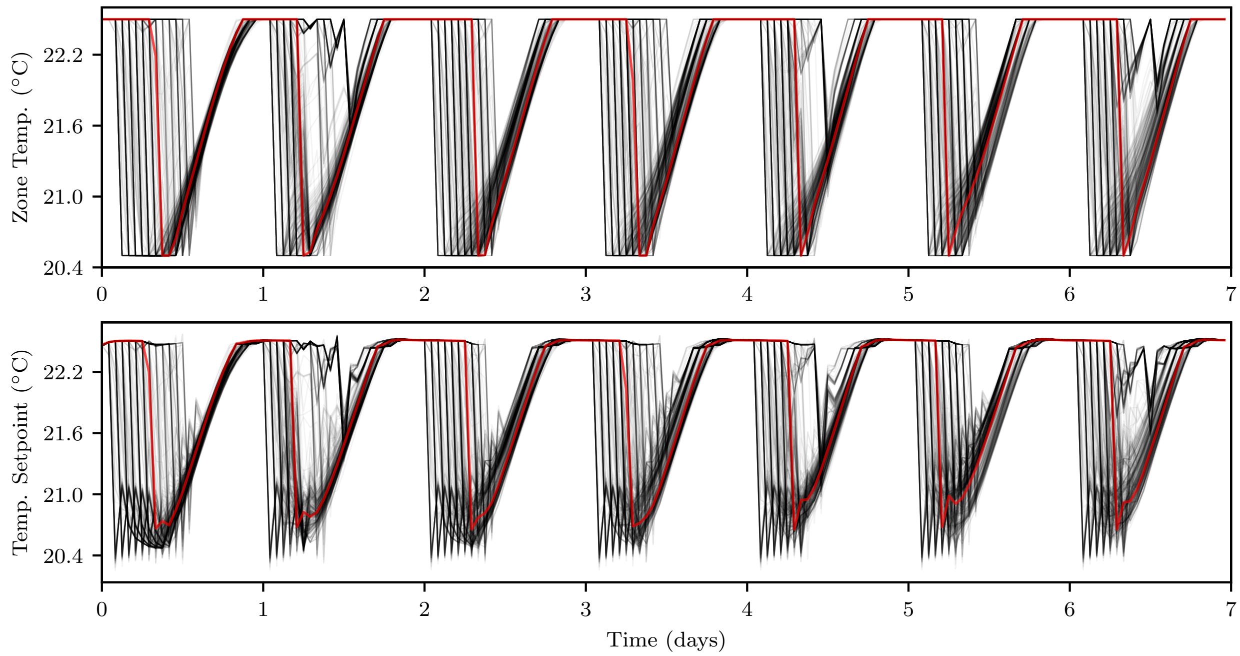

Figure 9: Results from the Low-Level Airside Problems. The optimal zone temperatures and setpoints computed from all 500 zones are shown with the red line denotes one particular zone as an example.

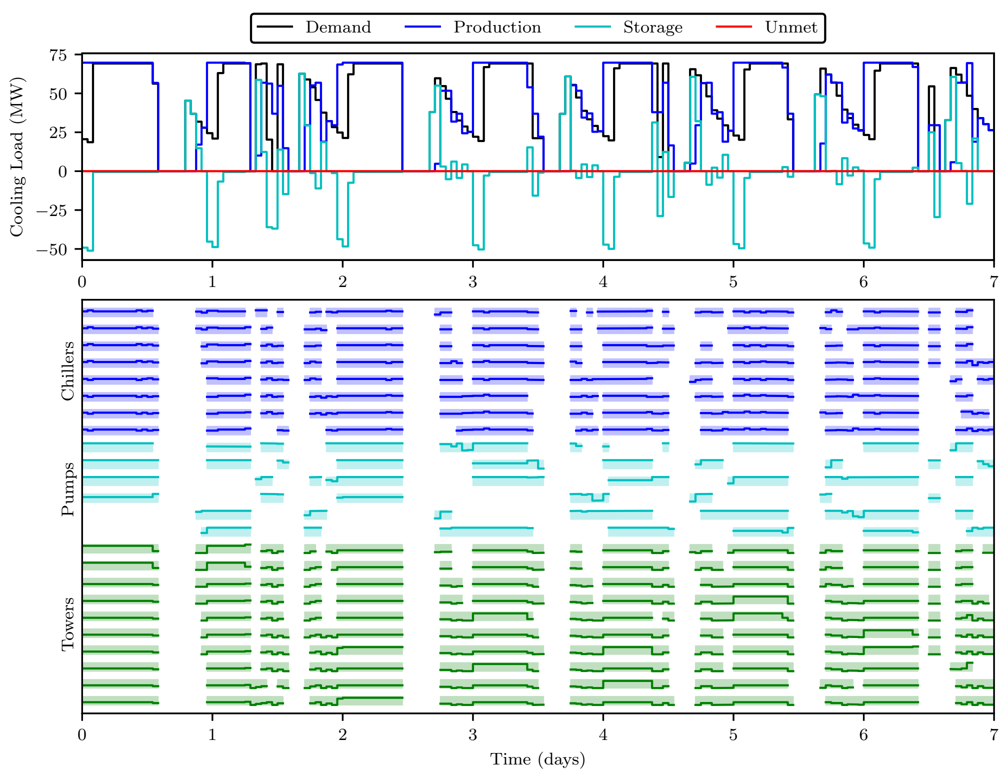

Figure 10: Results from the Low-Level Waterside Problem. The Gantt chart for central plant equipment shows the optimal equipment operation schedule, where boxes show on/off state of the equipment with dark lines inside showing individual unit loading.

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