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Evaluation of a cost-responsive supply air temperature reset strategy in an office building

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Abstract

This paper describes a new supply air temperature control strategy for multi-zone variable air volume systems. We developed the strategy with the intent that it is simple enough to implement within existing building management systems. At 5-minute intervals, the strategy estimates the cost of fan, heating and cooling energy at three different supply air temperatures (current, higher, lower), and chooses the one with the lowest cost as the setpoint. We then implemented this strategy in a seven floor, 13,000 m^2 office building and compared the energy costs to the industry best practice control strategy in a randomized (daily) controlled trial over a 6-month period. We showed that the new control strategy reduced total HVAC energy costs by approximately 29%, when normalized to the typical annual climate data for this location and operating only during typical office hours. These findings indicate that the current industry best practice control strategy does not find the optimal energy cost point under most conditions. This new control strategy is a valuable opportunity to reduce energy costs, at little initial expense, while avoiding more complex approaches, such as model predictive control, that the industry has been hesitant to adopt. We describe the new control strategy in language common to the industry (see sequence of operations included as supplemental material) so that readers may easily specify and implement this immediately, in new construction or controls retrofit projects.

Keywords: supply air temperature reset; controls; variable air volume; demand based reset; trim and respond; model predictive control.

Nomenclature

Notation	Description
k	time index with sampling interval 5 minutes
$\rho[\mathrm{kg/m^3}]$	density of air at standard temperature and pressure
$c_p[\mathrm{W/kg \cdot ^\circ C}]$	specific heat capacity of air at standard temperature and pressure
$c_{elec}[\$/\mathrm{Wh}]$	time-varying electricity cost
$c_{hw}[\$/\mathrm{Wh}]$	steam cost (including conversion factor)
COP	coefficient of performance
N	number of cooling requests to ignore
n	number of zones
α	exponential smoothing coefficient, $0.01 - 0.001$
$T^i[^\circ\mathrm{C}]$	zone i measured temperature
$\overline{T}^i[^\circ\mathrm{C}]$	zone i temperature cooling setpoint
$T_d^i[^\circ\mathrm{C}]$	zone i measured discharge air temperature
$V^i[\mathrm{m^3/s}]$	zone i measured discharge air flow
$\hat{V}^i\ [CFM]$	zone i estimated discharge air flow
$\underline{V}^i, \overline{V}^i[\mathrm{m^3/s}]$	zone i minimum and maximum air flow setpoint
$\Omega_h^i[\%]$	zone i measured or setpoint reheat coil valve position
R^i	zone i cooling request
$\Delta T_h^i[^\circ\mathrm{C}]$	temperature difference across the reheat coil when the valve is closed
$T_s[^\circ\mathrm{C}]$	measured supply air temperature
$T_m[^\circ\mathrm{C}]$	measured mixed air temperature
$\Omega_c[\%]$	measured cooling coil valve position
$\Delta T_c[^\circ\mathrm{C}]$	temperature difference across the cooling coil when the valve is closed
$V[\mathrm{m^3/s}]$	total air flow $V = \sum_{i=1}^n V^i$
R	total cooling request $R = \sum_{i=1}^n R^i$
$P_f[\mathrm{W}]$	measured fan power from variable frequency drive (VFD)
$P_c[\mathrm{W}]$	chilled water power
$P_h[\mathrm{W}]$	reheat power
$C[\$/\mathrm{hr}]$	total cost
$\tilde{T}_s[^\circ\mathrm{C}]$	supply air temperature setpoint (current or candidate)
$\Delta\tilde{T}_s[^\circ\mathrm{C}]$	change in supply air temperature setpoint from current value
$\mathcal{T}$	set of candidate supply air temperature $\mathcal{T} = \{T_{s_1}, \cdots, T_{s_p}\}$

Introduction

Variable air volume (VAV) systems are one of the most common type of heating ventilation and air conditioning (HVAC) systems for commercial buildings in North America. The air handling unit (AHU) in a VAV system is typically single duct with an airside economizer, a cooling coil, a supply fan driven by a variable frequency drive, optional heating coil, and either a return or a relief fan. Each individual thermal zone in the building has a VAV terminal unit that measures airflow and controls flow with a damper, and often also a reheat coil. There are many controllable setpoints to manage in a VAV system, from heating and cooling temperature setpoints, discharge temperature setpoints, and minimum airflow setpoints at the zone level, and to minimum outside airflow, supply air temperature and duct static pressure setpoints at the air handling unit (AHU) level. The zone level temperature setpoints are defined to maintain thermal comfort, according to standards such as ASHRAE 55 or ISO 7730 [1,2], and the most suitable setpoint values to use is a topic of ongoing research [3–5]. The airflow setpoints, both at the zone and the AHU level, are defined to maintain adequate ventilation and indoor air quality (IAQ) in the zone according to standards such as ASHRAE 62.1 or California Title 24, and again, the optimal values are a topic of ongoing research [6–8]. Similarly for the control of the airside economizer [9–11]. The temperature and pressure setpoints at the AHU level are equally complex problems, as at each point in time there is an optimal setpoint for both the duct static pressure and the supply air temperature (SAT) leaving the air handling unit, and these are the primary focus of this paper.

Current best practice

Initially, in the early implementations of VAV systems, building operators used constant values for duct static pressure and SAT setpoints. These constant setpoint strategies were improved to become linear resets that increase static pressure and decrease supply temperature with respect to increasing outside air temperature [12]. More recently, with the advent of Direct Digital Control with feedback from every zone in the building, demand based reset approaches are used where static pressure and SAT setpoints vary based on the requirements of the most demanding (‘‘critical’) zone [13], often using ‘trim and respond’ logic [14].

The duct static pressure should be just high enough so that the most demanding VAV terminal unit in the building (the ‘critical’ unit) has sufficient pressure to meet its current airflow setpoint. This control strategy is known as a duct static pressure reset, and it is required by both ASHRAE 90.1 [15] and California Title 24 [16]. It is typically achieved by ‘resetting’ the duct static pressure setpoint upwards when a zone requests increased pressure (typically when a VAV damper is nearly wide open and the airflow is still below the maximum airflow setpoint), and allowing the setpoint to slowly decrease when there are no requests [17]. This reduces static pressure (and fan power) to the minimum needed to meet the current airflow requirements for all of the zones in the building, and can generate fan energy savings from 30-50% compared to fixed duct static pressure setpoints [18]. Typically, there is also a user-defined number of requests that will be ignored, particularly in systems with many zones, as one faulty (‘rogue’) zone would otherwise drive the entire reset strategy.

Similarly, the SAT should be controlled using a SAT reset strategy, so that the most demanding VAV terminal unit receives supply air that is just cool enough to meet its zone cooling temperature setpoint, as defined by the thermal comfort requirements for that zone. This is typically achieved by ‘resetting’ the SAT setpoint downwards when a zone requests cooler air, and allowing the setpoint to slowly increase when there are no requests. As for the duct static pressure reset, there is also a user-defined number of requests that are ignored. SAT reset is currently prescriptively required in Title 24 and Standard 90.1 but the requirements allow the reset to be in response to representative building loads or simply to outdoor air temperature.

SAT reset based on outdoor air temperature is a common approach in systems without feedback from the individual zone, but it has a significant drawback in that it is an open loop feedback strategy that runs the risk of not maintaining comfort and not realizing maximum energy savings.

However, unlike a duct static pressure reset where lower values always provide energy savings, there is an additional consideration in the case of SAT reset: the potential to save energy by supplying lower temperature air while still meeting comfort conditions in the zones in the building. Reducing the SAT setpoint beyond the point at which comfort needs are met has three primary effects:
1) It reduces the airflow required by any zones that are currently in cooling mode, which reduces fan energy consumption in a cubic relationship with respect to airflow,
2) It increases the reheat energy used in any zones that are currently in heating mode, in a linear relationship to temperature,
3) It will increase cooling energy at the AHU depending on the status of the economizer, i.e., if the outside air temperature is higher than the SAT.

Thus, finding the SAT setpoint that generates the optimum energy cost is a dynamic optimization problem, subject to a constraint to meet comfort requirements. The optimum value depends on the status of the airside economizer, and the relative costs of fan energy, cooling energy, and zone reheat energy at that particular moment. The current best practice (see Figure 3 for a graphical representation), described in a proposed guideline under development by ASHRAE GPC 36 and in operation in many VAV buildings today, is a demand based reset that constrains the range of possible SAT setpoints based on the outside air temperature. Low outside air temperature allows full reset to the maximum SAT. As the outside air temperature increases the maximum possible SAT setpoint decreases. This limit on reset is meant to balance the tradeoff between fan energy and cooling energy at high load that is presumed to occur at high outside air temperature. See the Advanced Variable Air Volume Design Guide for more detail [13]. However, many factors other than outside air temperature affect the optimal values to use for this outside air temperature based constraint - from system sizing, design zone loads versus actual zone loads which vary temporally, type and operation hours of cooling energy source, etc. - and as yet, there is no proposed or demonstrated method for selecting the most appropriate values in practice, nor any simulation tools that are suitable to evaluate it.

Existing SAT reset strategies make inherent simplifications and assumptions about the relationship between SAT and total HVAC energy cost. As industry best practice has progressed – from a fixed setpoint; to a setpoint that varies based solely on outside air temperature; to the warmest possible setpoint that will still provide comfortable conditions based on feedback from every zone; to a combination of the last two approaches (current practice) – there has been an inherent assumption that each new strategy has improved overall energy efficiency. However, none of these approaches will find optimum SAT under all operating conditions, as that optimum value depends on a wider range of conditions in the building than simply the current outside air temperature and SAT. Furthermore, the first two strategies do not incorporate feedback from the zone, and thus had an additional issue - they do not guarantee that comfort conditions will be met in all zones in the building.

This paper presents a new, cost-responsive SAT reset strategy that is simple enough to implement within a typical building automation system. The new strategy dynamically estimates the total HVAC energy cost at a particular SAT setpoint, and then iteratively moves in the direction of least cost, while subject to the same constraint to maintain comfort conditions as the current industry best practice.

We strove to reduce complexity to a minimum to ensure that this approach is feasible to implement at scale within the building automation systems currently in use today. Similarly, to ensure that this could be implemented cost effectively, we also constrained the required measurements to a minimum set of data that are likely already present in a modern VAV system. We assume direct digital controls (DDC) to each zone, with an airflow measurement at each VAV terminal unit, and a zone discharge air temperature measurement after each reheat coil. At the AHU, we assume that there is a mixed air and supply air temperature measurement and a power output from the variable frequency drive. These are all very common measurements in a modern VAV system, many of which are requirements in codes and standards

Control strategy

Overview

Figure 1 shows a high-level overview of the proposed control strategy. At each (user-defined) time interval (typically 5 minutes), we compare the estimated HVAC energy cost at the current SAT setpoint with the estimated costs at alternative SAT setpoint values. We then adjust the setpoint to the lowest cost value and repeat the process at the next time interval. This strategy assumes that the energy and cost estimates are reasonably accurate, and the estimated value corresponds to the steady state power consumption of the system.

In our implementation, we first determine a vector of fixed temperature differences, $\Delta\tilde{T}_s$, e.g. $[-0.6\ °C, -0.3\ °C, 0\ °C, 0.3\ °C, 0.6\ °C]$ ($[-1.0\ °F, -0.5\ °F, 0\ °F, 0.5\ °F, -1.0\ °F]$). We use these to calculate a vector of candidate SAT setpoints within the feasible range of setpoint values. For example, if the current SAT setpoint is 11.8 °C (53.2 °F) and the feasible range of SAT setpoints is 11.7 °C (53 °F) to 18.3 °C (65 °F), then we calculate the candidate setpoints using the temperature difference vector, ensuring that the lowest and highest values remain within the feasible range: $[11.7\ °C, 11.7\ °C, 11.8\ °C, 12.1\ °C, 12.6\ °C]$ ($[53\ °F, 53\ °F, 53.2°F, 53.7\ °F, 54.2\ °F]$). At each iteration, we select the best candidate based on a cost estimation method that we describe in the next section.

In addition, cooling requests from zones take priority over the energy cost signals to ensure comfort requirements are met. If the number of zone cooling requests exceeds a user-defined number to ignore (e.g. 9 rooms in the building request more cooling while the threshold to ignore is 8), we default to the standard trim and respond logic to ensure that the VAV system meets comfort needs in the building in the same manner as current industry best practice meets those needs. However, the range of feasible setpoints in which the trim and respond logic can operate is not constrained by the outside air temperature limits used in the current best practice logic.

In case an exception or error occurs during the computation, the program falls back to the current industry best practice "trim & respond" strategy, and if an exception occurs there, the program writes a reasonable fixed default setpoint value.

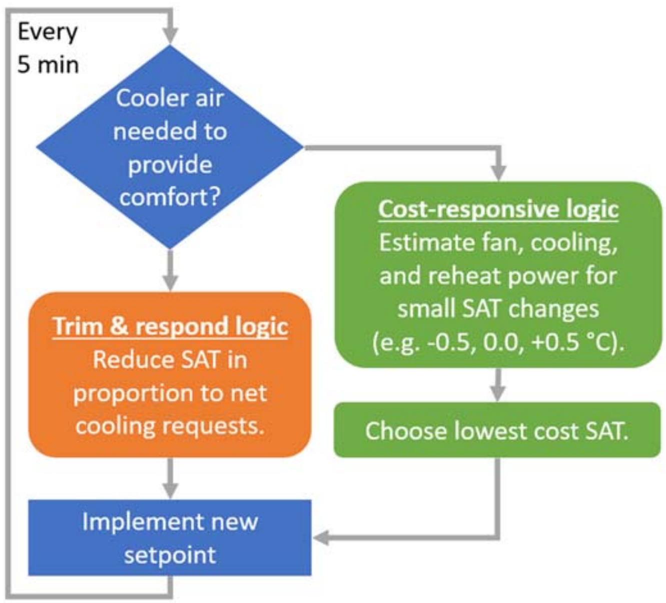

Figure 1: Overview schematic

Power estimation

Airflow and fan power model

We estimate the change in fan power change according to the candidate SAT setpoint values by first estimating each zone air flow rate at the new SAT, determining the new system airflow rate based on the sum of zones, and then calculating the fan power at that new airflow rate.

When a zone is not in cooling mode, or when it is making a cooling request, the zone airflow estimate is the same for all candidate SAT setpoints - the zone minimum airflow setpoint[1] or zone maximum airflow setpoint respectively. Where a zone is in cooling mode, the airflow estimate is[2]:

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[1] If using the time-averaged ventilation approach described in [7], we recommend using the ventilation setpoint instead of the current zone minimum airflow setpoint.

[2] Note that in the case study presented later, we implemented this equation slightly differently. We used the temperature differential between room and supply air temperature (typically 5 - 10 °C (10 - 22°F)), instead of between the room and discharge air temperature (typically 4 - 11 °C (8 - 20 °F)) that we present in the equation above. Using the discharge air temperature more accurately estimates the

$$\hat{V}^i(k+1) = V^i(k)\frac{\bar{T}^i(k)-T_d^i(k)}{\bar{T}^i(k)-(T_d^i(k)+\Delta\tilde{T}_s)} \in \left[\underline{V}^i, \overline{V}^i\right] \qquad (1)$$

There are accuracy concerns with these simplifications, as there are for the other estimation methods. When the zone temperature is just below the zone cooling setpoint, the zone will not be in cooling mode and the zone airflow estimate will remain at the zone minimum airflow setpoint. Clearly, moving to a candidate SAT that is higher than the current SAT will cause the zone to enter cooling mode, and the airflow will increase. This state change effect is not captured by this estimation method. However, it will be captured after a subsequent iteration of the controller - once the SAT moves to the new candidate setpoint, and the zone enters cooling mode. Also, this approach applies to zones that use either single-max or dual-max logic at the VAV box (see [8] for a detailed explanation of single- and dual-max logic). Even with dual-max sequences, when the airflow increases in the second stage of heating, that airflow increase is independent of the supply air temperature – it occurs at a fixed discharge air temperature setpoint.

Finally, we use the airflow estimate and the current airflow to estimate the change in fan power based on the fan affinity law:

$$P_f(k+1) = P_f(k) \times \left(\frac{\sum_{i=1}^{n}\hat{V}^i(k+1)}{\sum_{i=1}^{n}V^i(k)}\right)^3 \qquad (2)$$

Coil power model

The heating and cooling coils are air-water heat exchangers. In a simple coil model, we compute the instantaneous power used in a coil as the product of the air flow measured across the coil and the temperature difference between the inlet and outlet air. Note that there will be a temperature change across the coil when the valve is closed whether it is a coil in the air handling unit or a coil in a terminal unit. This temperature change can be caused by a combination of duct heat gain (or loss), a passing valve, fan heat gain, thermal capacitance of the coil and fluid in the coil, and/or measurement error. We estimate this temperature difference, i.e. ΔT, using the inlet and outlet temperature when the valve has been closed for an extended period (the default is 5 minutes).[3] This time period is long enough for the fluid in the coil to approach steady state temperature with the air. In this way, we dynamically 'calibrate' the temperature sensor pair so that we only estimate the heat transfer that is intentionally caused by valve operation. We smooth this temperature estimate using an exponential averaging function, where α is small (0.001-0.0001) to ensure that the smoothing occurs over a period of days.

The following equations describe the reheat power calculation:

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change in airflow due to a change in supply air temperature. This implementation difference does not significantly affect the results of the study as both approaches capture the direction of airflow change, as well as the majority of the magnitude of that change.

[3] If the air in the AHU is stratified downstream of the coil where the temperature is sensed using a single point sensor, this approach may be less accurate. This could be resolved by using an averaging temperature sensor in this location.

$$\Delta T_h^i(k+1) = \begin{cases} \alpha\left(T_d^i(k) - T_s(k)\right) + (1-\alpha)\Delta T_h^i(k), \ \Omega_h^i = 0 \\ \Delta T_h^i(k), \ \Omega_h^i > 0 \end{cases} \quad (3)$$

$$P_h(k+1) = \begin{cases} 0, \ \Omega_h^i = 0 \\ \sum_{i=1}^{n} \rho c_p \, max\left(0, \hat{V}^i(k+1) \times \left(T_d^i(k) - \tilde{T}_s(k+1) - \Delta T_h^i(k+1)\right)\right), \ \Omega_h^i > 0 \end{cases} \quad (4)$$

Aside from flow and temperature measurement accuracy concerns at the VAV box, there are several limitations to the above approach for estimating reheat power. The conditions in the building (e.g., temperature in the return plenum, supply air flow and temperature, etc.) are dynamic, so the temperature differential measured when the coil was last closed for an extended period may not be representative of the temperature difference when the coil is open, especially if the coil has been open for an extended period. Additionally, this approach ignores distribution losses (the heat lost from piping when a valve opens and closes), and the heat lost from the coil once the valve closes. Lastly, when the zone temperature is just above the zone heating setpoint, the reheat valve will be closed and thus, the reheat power estimate will be zero for that zone. Clearly, moving to a candidate SAT that is lower than the current SAT will cause this valve to open, and the coil will consume reheat energy. This estimation method above does not capture this secondary effect directly. However, it will capture this effect in the subsequent iteration of the SAT reset control - once the SAT moves to the new candidate setpoint, and the reheat valve opens.

Similarly, the following equations describe the cooling power calculation:

$$\Delta T_c(k+1) = \begin{cases} \alpha\left(T_s(k+1) - T_m(k+1)\right) + (1-\alpha)\Delta T_c(k), \ \Omega_c = 0 \\ \Delta T_c(k), \ \Omega_c > 0 \end{cases} \quad (5)$$

$$P_c(k+1) = \begin{cases} 0, \ \Omega_c = 0 \\ \rho c_p \, max\left(0, \hat{V}(k+1) \times \left(T_m(k) - \tilde{T}_s(k+1) + \Delta T_c(k+1)\right)\right), \ \Omega_c > 0 \end{cases} \quad (6)$$

In addition to the limitations mentioned for the reheat power calculation, the cooling power estimate also ignores dehumidification energy use. While this is not a major issue in some locations (e.g. many in California), it would be for many other climates, and we discuss potential solutions later, in the Discussion section.

Cost estimation & new setpoint calculation

Using time-of-use prices for electricity, cooling and heating, we can map the estimated reheat, chilled water, and fan power values to cost estimates. We sum these individual cost estimates to yield a total cost estimate at each candidate SAT setpoint, and then select the lowest total cost candidate as the new SAT setpoint.

$$\min_{\tilde{T}_s(k+1) \in \mathcal{T} = \{T_{s_1}, \cdots, T_{s_p}\}} \hat{C}(k+1) = c_{elec} \times \left(P_f(k+1) + \frac{P_c(k+1)}{COP}\right) + c_{hw} \times P_h(k+1) \quad (7)$$

Software implementation

We implemented this independently from the proprietary Building Automation System (BAS), directly over BACnet on a small fanless computer using the open source packages described below: sMAP and pybacnet. Implementing it independently from the BAS is a more scale-able approach, as the same control logic can be applied to other buildings with VAV systems and DDC controls to the zone level without modification. However, it would still be necessary to tag or otherwise identify which BACnet points correspond to which sensors and actuators, as there is no widely used naming convention for BACnet metadata. Peffer et. al. [19] discusses these packages and associated issues in more detail.

sMAP

The simple measurement and actuation profile [20] (sMAP) is a protocol for exposing and publishing timeseries data from various sources that provides: a specification of how physical data are described and transmitted; a large set of drivers for communicating with devices using native protocols which provides uniform access to the users to the devices; and tools for building, organizing, and querying large repositories of physical data.

pybacnet

Building Automation and Control NETworks (BACnet) is a communication protocol that defines services for communication between devices in a building. pybacnet [21] provides Python bindings for the BACnet stack [22], which is used in sMAP applications to poll data from BACnet sensors and write control actions to BACnet points.

Case Study Building

Description

Sutardja Dai Hall (SDH) is a seven floor, 13,000 m^2 (141,000 ft^2) building that primarily contains open-plan and private offices. It is located on the University of California Berkeley campus in Berkeley, California, which has a cool summer Mediterranean climate: types Csb and 3C in the Köppen and ASHRAE climate classifications, respectively. There is also a laboratory, workshop areas, a 139-seat auditorium and a cyber café within the building. The building-wide HVAC system has two parallel 2.1 MW (600 ton) Trane chillers to provide chilled water to the AHUs and process loads, and uses a campus steam to hot water system to provide hot water reheat to the zones. Two large AHUs with air-side economizers, cooling coils, and variable-frequency drive supply and return fans supply air to a central duct that serves the majority of zones (138) in the building. Though there are other much smaller AHUs in the building that serve other zones (e.g., the laboratory), these two AHUs serve the vast majority of the building's floor area and are the focus of this study. Each of these 138 zones has a variable air volume (VAV) box with an airflow sensor and a controller that uses single-max control logic. Most of these zones (110) also have a hot water coil with a discharge air temperature sensor. The building uses a Siemens Apogee Building Management System (BMS).

In addition to the BMS, the building also has "Comfy" [23] , a web-based software that uses occupant feedback to dynamically adjust zone heating and cooling temperature setpoints. The resultant setpoints change over time, and may vary by zone, time of day, and day of week.

When Comfy is installed, the building manager often chooses a wider default range of temperature setpoints than is typical in office buildings. This allows for both energy savings and a wider range within which to learn more comfortable setpoints.

Though there is a lot of variation, most typical US office buildings have zone heating and cooling setpoints of 21.1 °C (70 °F) and 23.3 °C (74 °F) respectively. In contrast, in SDH, Comfy learns within the range of 20 °C (68 °F) and 23.9 °C (75 °F) for the heating and cooling setpoint respectively. Though Comfy has learned setpoints in many zones, at many times of the day and week, it is worth noting that the median values of the distribution of the observed, learned setpoints are equal to these default values.

Lastly, the AHUs run continuously in SDH, but the heating and cooling setpoints are set back to 18.3 °C (65 °F) and 26.7 °C (80 °F) in most zones from 8 pm to 6 am on weekdays, and throughout the entire weekend.

Airflow estimate accuracy

As noted in the introduction, we designed this control strategy based on a minimal dataset of measured data and so, even though we had an airflow measurement at each AHU, we did not use it in the control strategy as these sensors are not common. Also, even where these measurements are present they are often poorly calibrated. Instead, we calculate the AHU cooling power using the sum of the zone airflow measurements. Figure 2 shows that this assumption is quite reasonable for this building. It also shows a simple linear regression which could be applied to improve the accuracy of the AHU airflow (and coil power) estimates, and account for effects such as duct leakage – though there appears to be very little in this HVAC system. We did not apply this adjustment in this paper as we wanted to demonstrate the results at the lowest level of complexity and setup. Other implementations could do so if the improved accuracy was desired and a reliable AHU airflow measurement was available.

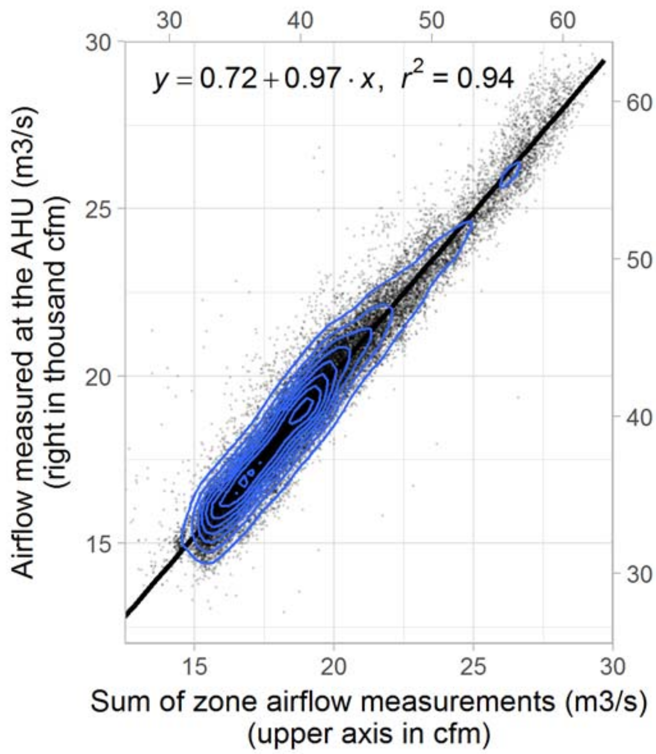

Figure 2: Scatter plot comparing the sum of airflows measured at the zone level to the sum of airflows measured at the two AHUs.

Power cost estimates

Aside from the hot water, chilled water, and fan power estimates, we also need a common basis for directly comparing them. We chose dollars per hour, as this seemed like the most relevant, however, it would also be valid to use site or source energy, or other similar metric.

We used the UC Berkeley campus estimate of $0.023/kWh for steam as the hot water cost estimate, as the campus district steam cogeneration system converts to a hot water system inside SDH. This underestimates the cost of hot water as the conversion process also includes losses which we were unable to easily quantify. This approach also ignores pumping power costs. It is also worth considering that a district steam cogeneration system is also relatively unusual. In comparison, a typical gas fired hot water boiler system would approximately double the cost per unit energy of hot water.

We used a fixed system coefficient of performance of 5.0 to convert the chilled water power to an electrical power value. This inherently assumes that chilled water consumption instantly corresponds to electrical power consumption, which is not the case in reality, and causes minor errors when the cost of electricity changes during the day. Also, the simple fixed COP estimate approach could be improved with a chiller model of varying degrees of complexity, but we deemed that to be outside the scope of this project.

For electricity consumption, we used the actual tariff data from the utility provider for this building which varies from $0.074/kWh in winter off-peak to $0.097/kWh in summer peak cost category periods. Note that we do not include the daily 'per meter' charges, or power factor correction charges, transformer losses, and transmission losses, each of which are a relatively minor part of the overall electricity cost. However, we also do not include the demand charges which are based on the monthly peak demand value within each cost category period, as that would require knowledge of the total campus electricity demand - information that was not readily available. It would also require a prediction of what exact time of the month the peak demand was expected to occur within each cost category period, and then applying an exceptionally high $/kWh cost during that window of time so that the optimal SAT would effectively prioritize minimizing electricity use over everything else (ignoring hot water use entirely). This would significantly complicate the proposed solution, and is a significant negative implication of these types of pricing structures on energy conservation measures in practice. These demand charges are significant - ranging from $8.31/kW in the winter off-peak to $24.06/kW during the summer peak period - and are approximately equivalent to 30-50% of the overall cost of electricity depending on when they occur, and how much electricity the AHU is consuming at that time. Incorporating these peak demand electricity costs would reduce the relative cost of hot water power and reduce its effect on the optimal SAT. In this particular building, that effect is already very minor.

Method

Randomized controlled trial

Thoroughly testing the effectiveness of an intervention in a building is a challenge due to the varying nature of weather, building occupancy, usage, HVAC setpoints, etc. For most Measurement & Verification activities, 12 months of pre (i.e., 'baseline') and post (i.e., 'intervention') data is the recommended amount of data, though recent research has shown that the results from 6 months of data yield similar results in most cases [24]. The concern always arises that something substantial may have changed in the building which is unrelated to the intervention that the analyst wishes to evaluate, and then confounds the results. For many interventions in buildings, it is only possible to test pre- and post- intervention and there is simply no choice in the matter. For example, physically replacing a chiller or boiler. However, for interventions that consist purely of changes to the control strategy in a building, it is feasible to perform a randomized controlled trial – i.e., randomly switch back and forth between the intervention and the baseline control sequences. This approach is far more robust as any changes in building operation will simply cancel each other out by the random selection process given a sufficient sample size.

We ran an experiment in SDH for 6 months, from September 1, 2016 to February 21, 2016. During this time, we randomly selected between two different supply air temperature reset strategies every day at midnight. This paper describes the industry best practice trim and respond logic with constraints based on outside air temperature as the 'Baseline' throughout, and describes the proposed new reset strategy as the 'Intervention' throughout. After discarding unrepresentative days in which this experiment was not running due to other experiments being performed in the building, or when scheduled maintenance or communication issues occurred, the random selection yielded 77 days of ‘Baseline’ data and 68 days of ‘Intervention’ data, collected at 5-minute intervals. We analyzed that data using the R software package (version 3.3.2).

Baseline

Mechanical engineering consultants at a HVAC engineering firm that has previously worked extensively to develop the current industry best practice approach evaluated our implementation of this strategy, described in detail in [13]. They also evaluated the user-defined setup parameters to ensure that they were appropriate and representative. The supply air temperature reset strategy – the ‘Baseline’ control strategy – operates at 5 minute intervals and uses the following settings: a trim value of 0.28 °C (0.5 °F), a response of 0.42 °C (-0.75 °F), a maximum response of 1.1 °C (-2.0 °F), and ignores up to 8 zone temperature requests. Figure 3 illustrates the outside air temperature based limits on the range of feasible supply air temperature setpoints for this building.

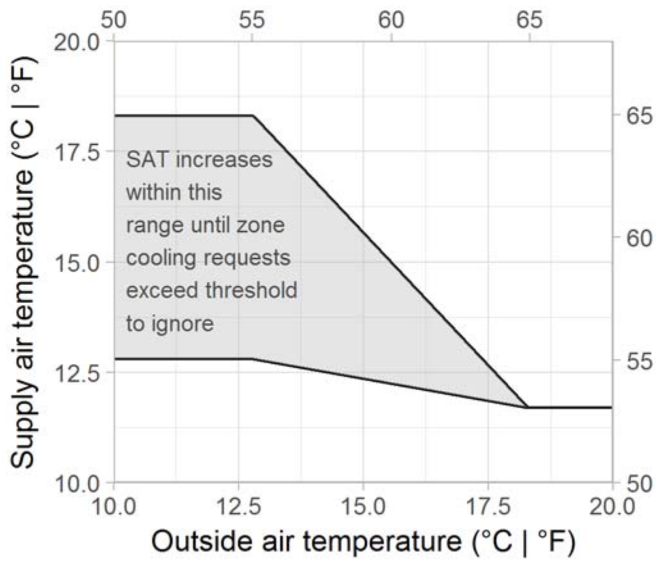

Figure 3: Outside air temperature based limits for supply air temperature setpoint under the existing industry best practice control strategy.

Outside air temperature distribution

Total HVAC energy cost is by far most closely correlated with outside air temperature for both reset strategies, and thus it is essential to ensure that there is a similar distribution of outside air temperature during the baseline and intervention periods. To a certain extent, using the randomized controlled trial approach mitigates this issue, but there will still be a difference between the outside air temperature distributions. Figure 4 compares the distributions and demonstrates that they are quite similar. The mean of the outside air temperature distribution during the intervention period is less than 0.05 °C (0.1 °F) higher than during the baseline period. A Fisher-Pitman permutation test shows that this difference in mean outside air temperature between the baseline and intervention periods is negligible. However, when compared to the climate data for this location, it is clear that the distributions are different. Thus, as well as presenting direct comparisons between intervention and baseline periods, we also fit machine learning algorithms to both datasets and use them to predict energy consumption using the climate data.

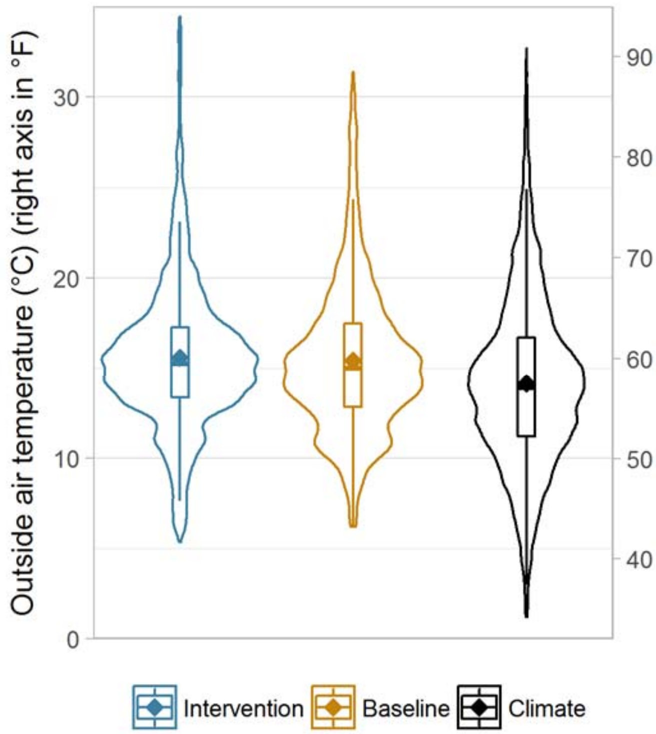

Figure 4: Violin plot with boxplot overlay of outside air temperature distribution during the baseline and intervention periods. The black line shows the typical meteorological year climate data for this location for context (California Climate Zone 3). The violin plot lines indicate a kernel density of the distribution (i.e., a smoothed histogram). The diamond shape indicates the mean of the distribution and the solid horizontal line indicates the median. Outliers are not shown in the boxplots as there are too many due to the number of data-points (25K) and the fact that the distributions are not Gaussian. Note that the same visualization method applies for all subsequent violin plots in this paper.

The other variables correlated with energy use, ranked in order of decreasing correlation, are: the presence of a temperature setback ("Setback"); the time of day ("Hour"); whether it was a weekend or not ("Weekend"); and whether the control strategy was running for consecutive days or not ("Consecutive"). The baseline and intervention periods contain a similar number of each of these variables due to the random sampling process.

Results

Overall results

The total HVAC energy cost was $0.43 /h (or 17%) lower during the intervention period than the baseline period. Figure 5 visually compares the total HVAC cost of the two control strategies for different overall building operating conditions and shows that the intervention generates significant cost savings. These savings occur under each of the three operating conditions, during which times the building loads and outside air temperature distributions are quite different.

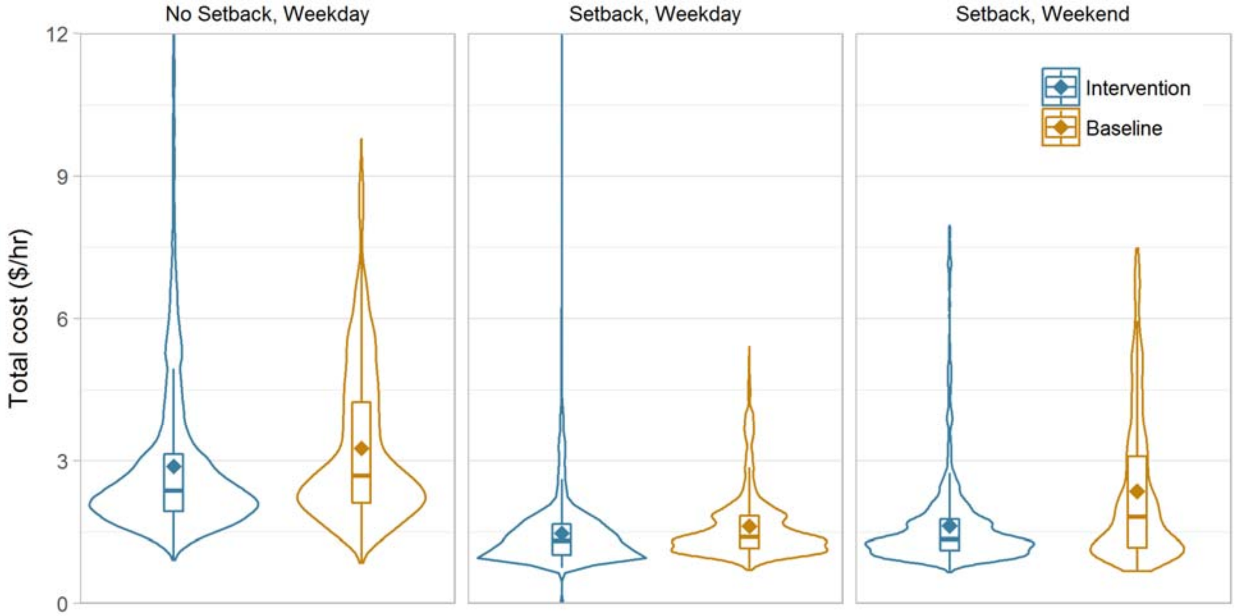

Figure 5: Violin plots showing the distribution of total HVAC cost for the two control strategies, subset by weekend and setback.

Supply air temperature and cost breakdown results

Figure 5 shows that the intervention strategy reduces total HVAC cost. The question is, how? Figure 6 shows that there are large differences between the supply air temperatures selected by the two control strategies at the same outside air temperatures. The intervention strategy uses notably higher supply air temperatures when it is warmer, and lower supply air temperatures when it is moderate (10 – 15 °C (50- 60 °F)) outside. The SATs converge to the same value – the upper limit of the SAT range - at lower outside air temperatures. However, at higher outside air temperatures they are almost exactly opposite. This is particularly the case during periods when there is little load, such as during weekend setbacks. The intervention strategy tends to maximize the use of outside air economizer, indicated by the proximity of the SAT to the black line (where SAT and OAT are the same). It is important to note that the cost-optimal control shown in Figure 6 is unique to this building, its HVAC system, and how it is currently occupied and operated. Though the outside air temperature is the dominant factor (at least in this case), a regression against outside air temperature alone cannot identify the optimal SAT. The optimal SAT for a given condition varies widely depending on a range of parameters.

There is also far more scatter in the supply air temperature data for the intervention strategy than for the baseline. This is particularly the case during the weekday, no setback period, when loads are more variable and there is likely to be more comfort driven cooling requests. This indicates that the new control strategy is responding dynamically to the conditions in the building at that time, and finding the point of lowest cost.

The second row of Figure 6 shows that total HVAC energy cost closely correlates with the outside air temperature, as one would expect. It clearly shows that the intervention strategy matches or outperforms the baseline strategy under all conditions. The savings generated by the intervention also depend highly on outside air temperature, and are largest in the range from approximately 15.6 °C (60 °F) to 23.9 °C (75 °F). For context, in this climate, the outside air temperature is within this range for just over half (53%) of typical office occupied hours (8am to 6pm) throughout the year.

The remaining lower three rows of Figure 5 show the breakdown of cooling, fan, and reheat costs. This illustrates that in general, the intervention strategy trades an increase in fan energy cost for a larger reduction in cooling and reheat energy costs combined. Quantifying this by directly comparing the intervention and baseline datasets over the entire study period shows that fan energy cost increased by \$0.24/hr (19%), while chilled water energy cost decreased by \$0.57/hr (63%) and reheat decreased by \$0.09/hr (24%), yielding the overall decrease in total HVAC energy cost of \$0.43/hr (17%) noted above.

Similarly, Figure 7 shows similar trends against the time of day, which is presumably a proxy for load within the building (as well as outside air temperature).

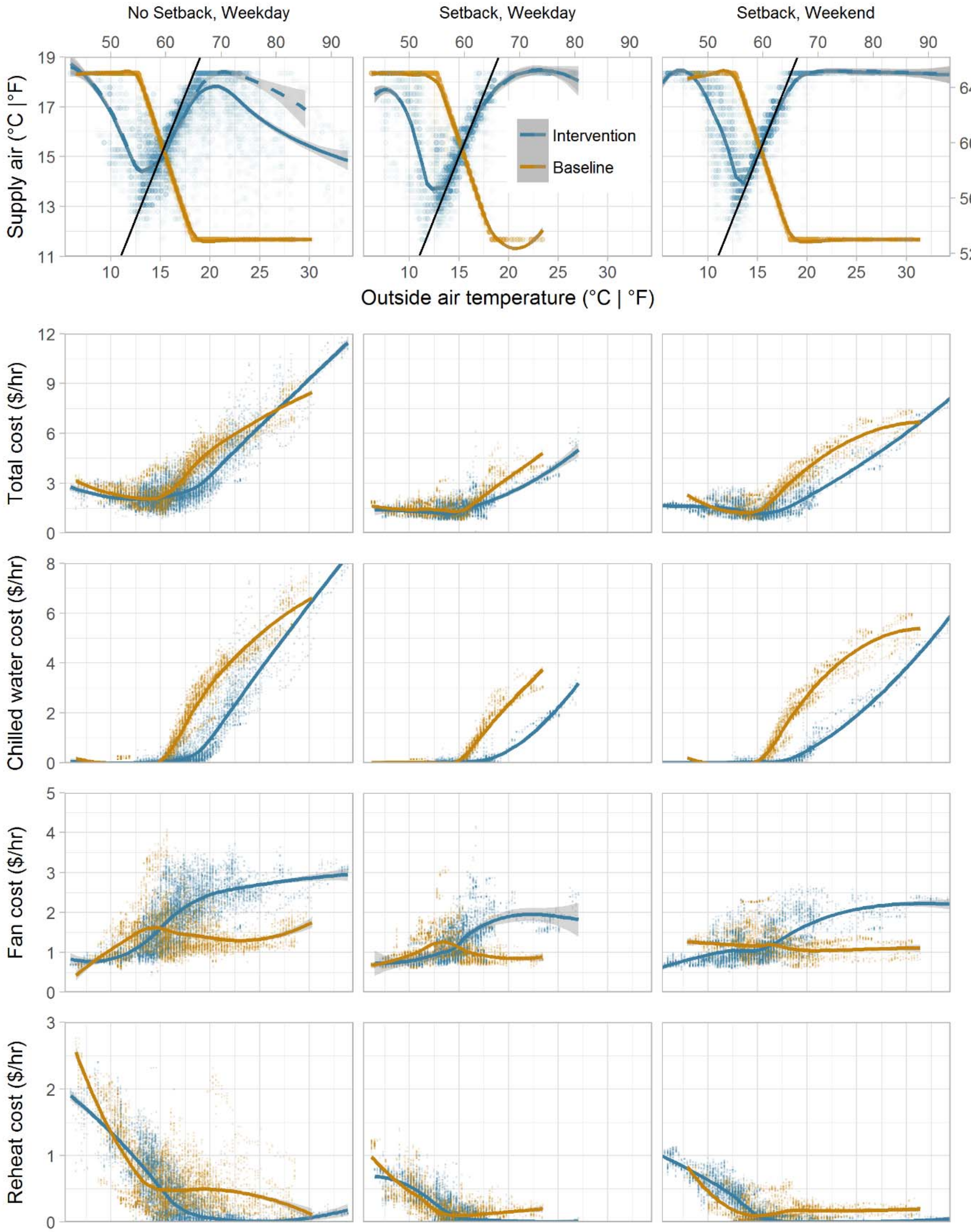

Figure 6: Scatter plots showing total HVAC supply air temperature and energy cost data by outside air temperature, subset by setback and weekend, for the two control strategies. Loess lines indicate the fit to the data, with a shaded grey area indicating the 99% confidence region. In the top row, the additional dashed lines indicate the loess fit excluding periods when the zone cooling requests were an active constraint on the supply air temperature setpoint at that time - i.e. zone cooling requests greater than 8 at any point within the previous hour. Similarly, in the top row, the black line shows where the supply air and outside air temperatures are the same (the 100% airside economizer line).

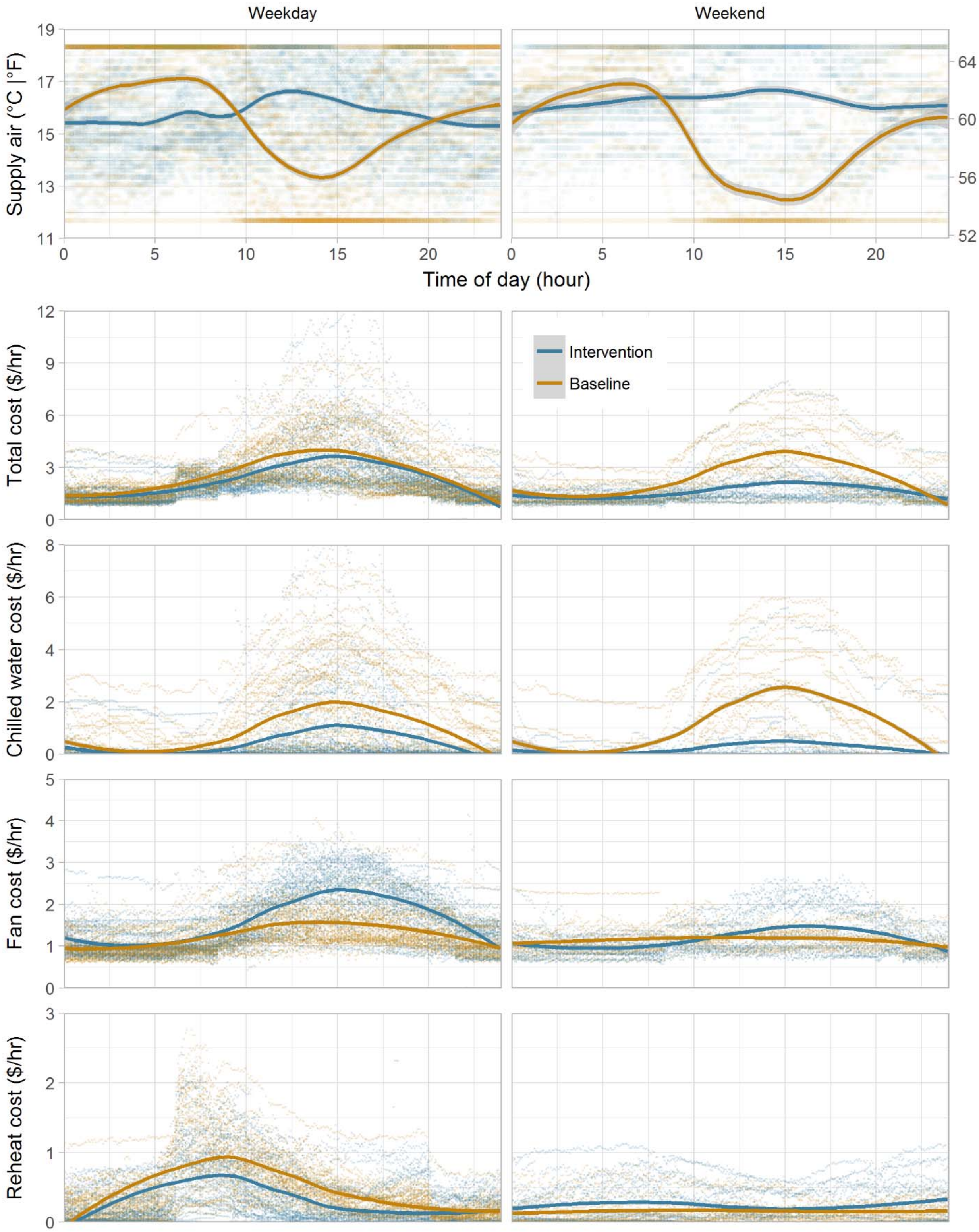

Figure 7: Scatter plots showing supply air temperature and energy cost by time of day, subset by weekend, for the two control strategies. Loess lines indicate the fit to the data, with a shaded grey area indicating the 99% confidence region.

Snapshots of cost breakdown at a point in time

Figure 8 illustrates cost estimates at a single point in time to better highlight the differences between the two strategies. The left pane illustrates a snapshot of the new control strategy in operation at an outside air temperature of 15 °C (59 °F) – approximately where the two strategies yield the same setpoint and cost (see Figure 6). In this case, near this SAT, the fan costs dominate the total HVAC cost. The control strategy selects the optimal setpoint from a total cost perspective. Reducing the SAT will decrease fan energy costs, but increase cooling and reheat energy costs. Conversely, increasing the SAT will increase fan cost while decreasing reheat costs, but will have no effect on cooling cost (as the AHU is in full airside economizer mode and does not require mechanical cooling). The industry best practice control strategy converges to the warmest setpoint within bounds that vary based on the outside air temperature. If the industry best practice control strategy was operating in this case, it would converge to 15.7 °C (60 °F) as the outside air temperature is 15 °C (59 °F), assuming it was not constrained by zone cooling requests. This yields a very similar, but slightly higher total cost than the setpoint used by the intervention control strategy.

The right pane of Figure 8 illustrates a snapshot of the industry best practice control strategy in operation at a higher outside air temperature of 17.2 °C (63 °F) – where the two strategies diverge in terms of setpoints and costs (see Figure 6). In this case, the industry best practice control strategy clearly does not select the optimal setpoint from a total cost perspective. At this outside air temperature, the upper bound of SATs that the control strategy can select is 13 °C (55.4 °F), which is the current setpoint. However, the cost estimates indicate that increasing the SAT beyond this constraint will decrease cooling and reheat costs, and that those savings will offset the increase in fan cost.

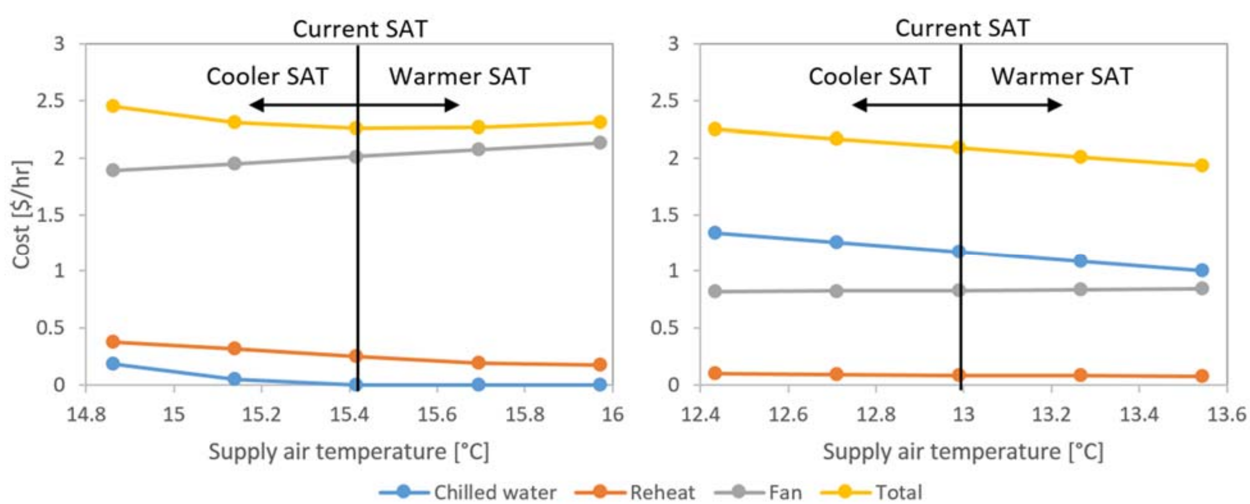

Figure 8: Snapshots in time showing the HVAC cost estimates by category for a small range of SAT setpoints around the current setpoint. (left) Cost based reset strategy operating at 15 °C outside air temperature and (right) the industry best practice operating at 17.2 °C outside air temperature.

The other conditions where the two strategies diverge in terms of setpoints and costs (see Figure 6) is when outside air temperature is less than 15 °C (59 °F). In this case, no mechanical cooling is required, and the new control strategy in general uses a lower SAT to achieve fan savings while dynamically adjusting for reheat costs.

For this particular building and HVAC system, the intervention control strategy typically finds the coldest supply air temperature at which mechanical cooling is not required. This is lower at night, and much higher during the day, than the SAT determined by the baseline strategy. The likely reason is that the cost based reset strategy is dynamically responding to the conditions in the actual building. As is common in many buildings, the fans in SDH are oversized and operate at low part load. Thus, fan cost is low relative to cooling cost. Also, loads in the actual building are far lower than the design condition, and thus airflow requirements are lower and the fan operates at low part load. In a building that was operating closer to its design airflow, the reset might follow a profile that was more similar to the existing reset strategy.

Interestingly, there is an example during study period that illustrates this. On 30th August, 2016, during the initial testing and debugging period, just before we started the randomized controlled trial, campus technicians shut down one of the two AHUs for several hours to replace a fan belt. The second AHU was able to meet the load in the building during this time, however, there was a significant fan power penalty as the AHU was operating much closer to its design condition (an increase from 18% to 73% design power for that one AHU). The total fan power increased from 27 kW to 55 kW while maintaining the same total airflow and keeping the other costs the same. Figure 9 shows that the intervention control strategy responded to the increased fan power cost by reducing the SAT from 17.2 °C (63 °F) to 11.7 °C (53 °F) – a slightly lower SAT than would have been used by the current industry best practice, and a more optimal setpoint under the new conditions.

There are other examples that clearly highlight the effect of the SAT control strategy on total cost. For example, when the software implementation encounters an error (typically either a BACnet communication error, or a HTTP error in communicating with the remote sMAP database), it defaults to the value predicted by the trim and respond strategy. When this occurred, the SAT setpoint often changed from 18.3 °C (65 °F) to 11.7 °C (53 °F) within a 5-minute period. Figure 10 shows that an example where this change incurred a significant total cost penalty because chilled water cost increased far more than fan costs decreased. This is likely due to the fact that many zones in the case study building spend the majority of their time operating at the minimum air flow setpoint [7], which is a relatively common pattern in office buildings [6,25]. The cost-responsive reset strategy recovered from the communication error and gradually converged back to the original setpoint of 18.3 °C (65 °F) over the course of the next 12 iterations (1 hour), with total cost decreasing with each increase in SAT.

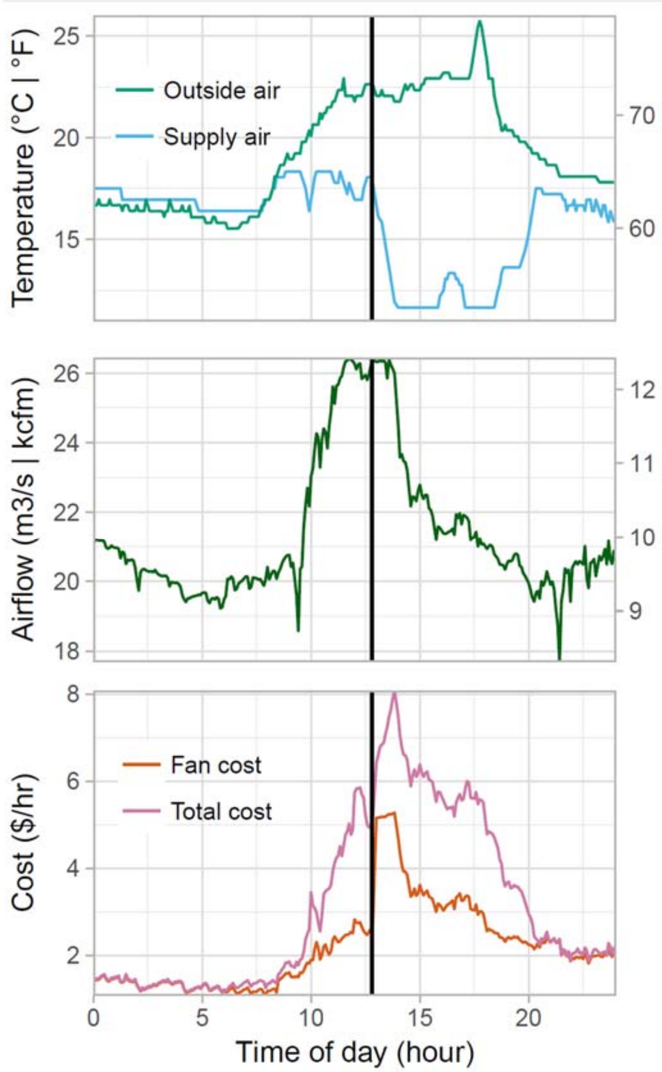

Figure 9: Timeseries plot of one day showing the response of the intervention strategy to a fan shut down. A vertical black line indicates the time at which the fan shut down.

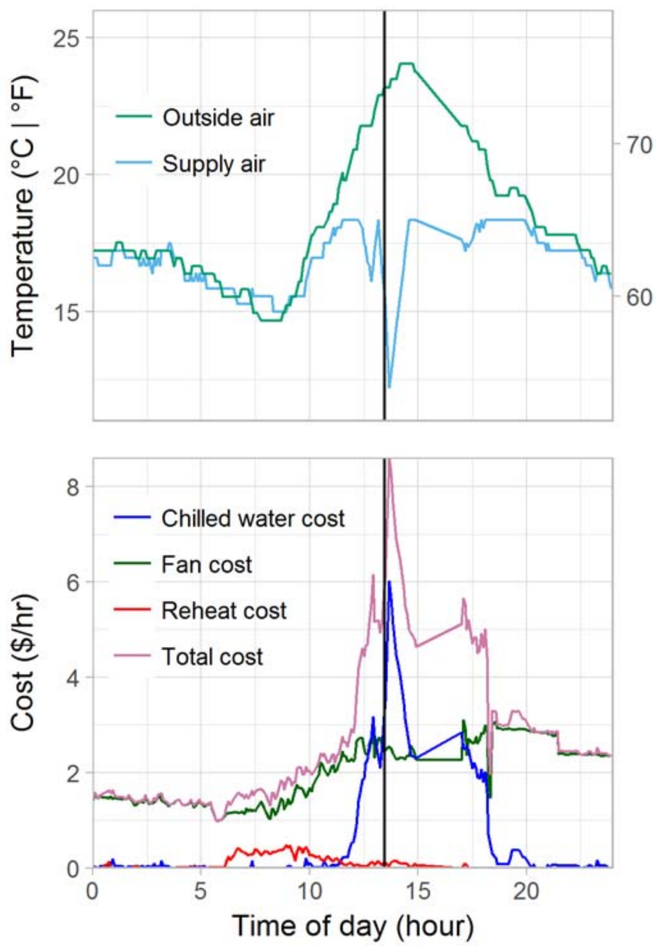

Figure 10: Timeseries plot of one day showing the response of the intervention strategy to a HTTP communication error. A vertical black line indicates the time at which the error occurred.

Additionally, there are other interesting cases in which the ability of the intervention strategy to dynamically respond to changing conditions is apparent. For example, though reheat cost is typically much lower in this building than fan or chilled water costs, the cost-responsive reset strategy dynamically responds to increased reheat power use in the early morning period, by increasing SAT when zones come out of nighttime setback.

Zone temperatures

The software implementation for both control strategies uses identical code to respond to comfort requests (i.e. zone cooling requests). Thus, both strategies successfully maintain zone cooling requests at or below 8 (a value selected by the building operator), and maintain zone temperatures within the range of zone heating and cooling setpoint temperatures in all zones that are not making a request. However, though both strategies have a similar low number of hours with zone cooling requests above the predefined number to ignore, because the SAT setpoints are typically higher during the day for the intervention strategy, the *median* zone air temperature in the building is slightly higher than for the baseline strategy. The difference in the median value of the temperature distributions across all zones in the building throughout the 6-month trial period is less than 0.3 °C (0.5 °F). This can have either a positive or negative effect on comfort in each zone, depending on whether a zone is overcooled or not, and in any case the effect is quite small as both control strategies maintain the zone air temperature to be between the heating and cooling setpoints for the vast majority of zones in the building. Those setpoints, by definition, define the range within which the occupant is assumed to be comfortable in a given zone. Furthermore, in this building the individual occupants have access to these setting through the Comfy application described above, and can change them based on their comfort preference if needed. Though we did not explicitly survey the occupants to assess their thermal comfort preferences, we did have access to the Comfy vote data. We analyzed this data and did not find a statistically significant difference between the baseline and intervention periods.

Consecutive days operating the same control strategy

As Figure 6 and Figure 7 show, there is a notable difference between the supply air temperatures selected by the two control strategies, and as discussed in the previous section, this affects the temperatures within the building within the zone temperature setpoint range. This may positively or negatively affect energy consumption on the subsequent day. As we randomly select which control strategy to use each day at midnight, we were concerned that this might affect the results. For example, if the operating control strategy supplies colder air, and we switch to the other strategy, it may benefit from a precooling effect later during the subsequent day. Thus, we separately analyzed the data for days in which the control strategy was the same for consecutive days and those in which it changed. The total HVAC cost savings were 4% higher for consecutive days than non-consecutive days, indicating that the cost saving results would likely be slightly higher if the intervention strategy operated continuously.

Estimating savings on an annual dataset

We fit models to the dataset using four different machine learning and statistical methods. These were random forest regression, binned linear models (with interactions), k-nearest neighbor regression, and stochastic gradient boosted regression. The input features were the type of control strategy in use, the outside air temperature, the time of day, whether the zone temperatures were setback or not, whether it was a weekend or not, and whether the same control strategy was operating for consecutive days or not. The output of the model was the total HVAC energy cost.

We created a training dataset by randomly selecting 80% of the total available data. We held out the remaining data (20%) as a blind test set. We fit the models to the training data using repeated k-fold cross validation (where k was 10 and the number of repeats was 2) to choose the optimal tuning parameters for each algorithm. Figure 11 shows the results of the fit to the blind test dataset. Though it was closely followed by k-nearest neighbor, the best performing algorithm was the random forest regression, with root mean squared error (RMSE) and R-squared values of \$0.22 /hr and 0.98, respectively, on the blind test dataset.

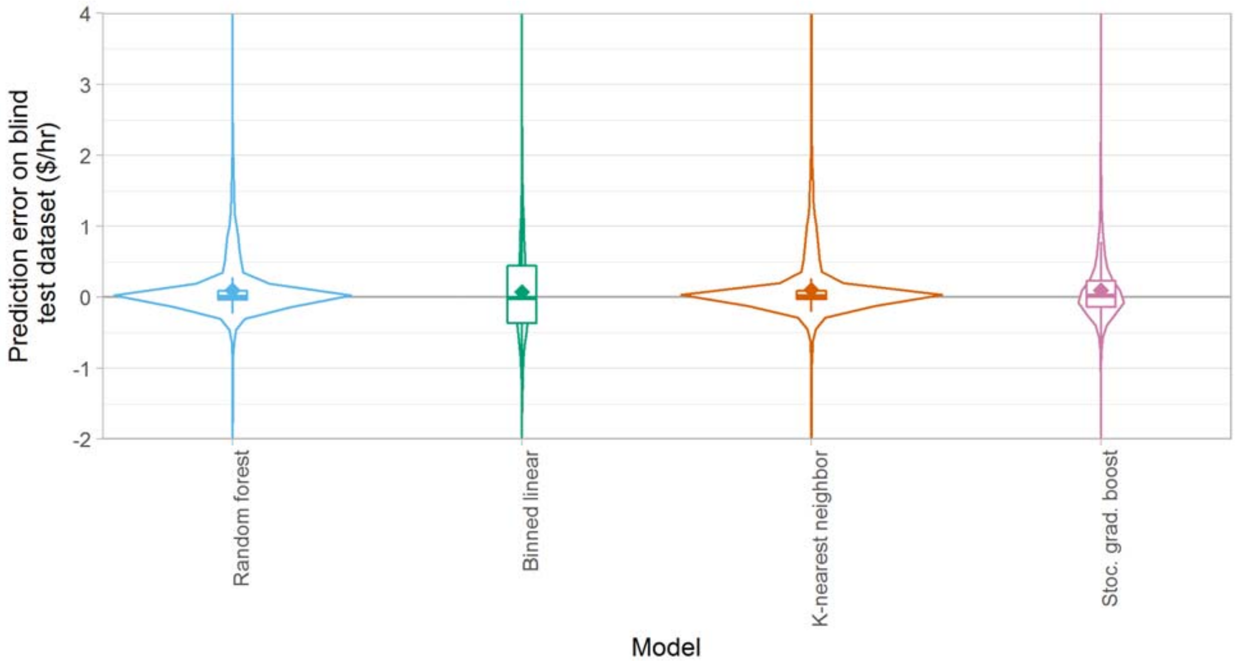

Figure 11: Violin plots showing the distribution of total cost prediction error for each of the four modelling methods on the blind test dataset.

We first used the models to predict what the total cost savings would have been if both control strategies ran for the entire study period. We assumed that the control strategies run consecutively within that annual period. The results showed a mean saving of $0.40 /hr to $0.48 /hr (or 17.3% to 20.9%) depending on the algorithm used. However, as Figure 4 shows, the study period does not entirely match the typical distribution of outside air temperatures for this climate. So, as an additional step, we used each of these models to predict the difference between the two control strategies on the climate data for this location. In our case, this was California Climate Zone 3. Figure 12 shows that the energy savings estimates were again reasonably consistent between the model algorithms. The mean saving in this case was $0.35 /hr to $0.41 /hr (or 15.3% to 17.9%) depending on the algorithm used. This is a few percentage points lower than the previous estimate, which is to be expected as the climate data differs from the study period in that it includes more data below 15.6 °C (60 °F), the point at which the two strategies begin to yield similar total costs.

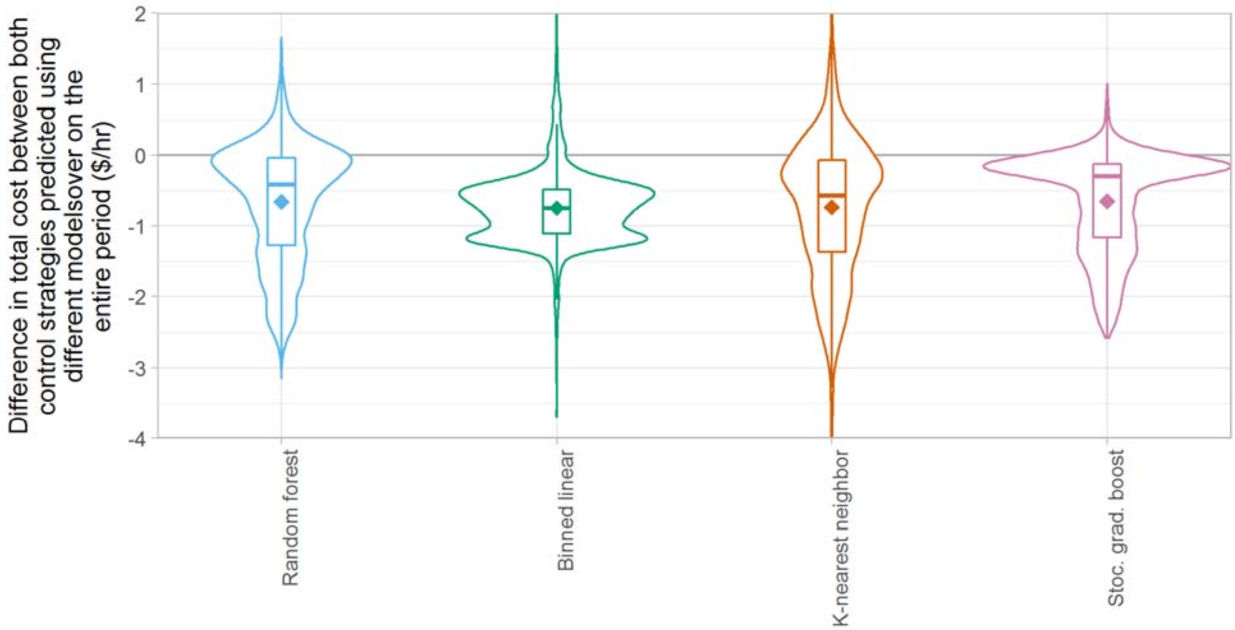

Figure 12: Violin plots showing the savings between the intervention and baseline control strategies, estimated by each of the four models on the annual climate data for this location (California climate zone 3).

It is worth noting that the energy savings discussed above include both nighttime and weekend operation, which is not typical for office buildings in the US. Analyzing a subset of the predicted savings for the climate that only includes typical occupied hours (8am to 6pm) yields significantly higher energy savings in both relative and absolute terms. This is because the outside air temperature distribution for this time of day maps more closely to the outside air temperatures where the two strategies differ from each other than the 24 hour dataset. The mean savings in this case was $0.65 /hr to $0.75 /hr (or 28.3% to 32.7%) depending on the algorithm used. Though this period is typically when most office buildings typically operate, and thus it is likely that the savings would be higher for a similar building operating only during occupied hours, it cannot be estimated with any degree of certainty as the case study building operates continuously, and thus we have no way of knowing if the nighttime and weekend operation has a significant effect on the results.

Note that in this section, we report the savings using the minimum and maximum estimates predicted by all four methods. Elsewhere in the paper, we simplify this by reporting the savings from the method that provided the best fit to the blind test data (the random forest regression method), which also always provided either the lowest or second lowest estimate of the four methods, yielding a conservative result.

Discussion

Practicality

We believe that the setup time for both approaches must also be considered for a new control strategy to truly be an improvement over current best practice. The number of parameters required to set up either strategy is quite similar, as the current best practice and the proposed strategy require much of the same information. The differences are that the four parameters that define the outside air temperature based limits for the baseline strategy are no longer required, but instead are replaced by four parameters related to cost data for the intervention strategy - for electricity, hot water, chilled water, and supply fan motor rating.

In terms of initial implementation costs, as noted above, we constrained our use of sensor data to those sensors that are already typically included in modern VAV systems, many of which are required by applicable codes and standards. Thus, the additional hardware cost to implement the proposed control strategy is zero. That said, the outcome could likely be further improved by specifying more accurate and reliable sensors, such as averaging temperature sensors instead of single point temperature sensors.

However, the intervention strategy is clearly more complex to implement than the baseline strategy. We estimate that it would take an additional 2 - 10 hours to implement and test this control strategy, depending on how familiar the controls contractor was with the concept and project, and whether reusable blocks of code were available for this control strategy from past projects – as is often the case once something becomes standard practice within a controls company. For the study building, in a location which has rates up to $200/hr, the implementation costs have a simple payback of between 6 and 28 weeks based on the observed energy cost savings.

True model predictive control (MPC) lies on the other side of the complexity argument. Though a valid approach for SAT reset (e.g. [26–28]), it requires expertise that is not common in the HVAC controls industry, and it requires additional hardware as it is too complex to implement inside the hardware and software environment of a building management system controller. Furthermore, many approaches require long training or parameter initialization periods. The industry has been hesitant to adopt MPC due to its complexity and cost, as well as a lack of expertise and robustness concerns. In contrast, the proposed approach can be expressed as a sequence of operations, in language common to the HVAC controls industry (see attached example in supplementary material). However, if MPC is successfully commercialized at scale for this application, then it would replace the approach presented in this paper.

Practical implementation notes

In the initial debugging, prior to the start of the study period, we tested the intervention strategy with a narrower range of candidate SATs ranging from -0.1 °C (-0.2 °F) up to -0.1 °C (-0.2 °F). We did this with the intent that it would minimize the number of state changes encountered within the range of candidate SATs as these are not captured by the estimation method. However, the noise in the airflow measurements at the damper level appeared to cause issues with robustness and stability within this narrow interval of candidate SATs.

Airflow fluctuation at the zone level (due to the operation of the airflow PI control loops at each zone) was also a concern throughout the implementation. We overcame this by using the setpoint values for the airflow estimates instead of the actual measured value.

As a side benefit of this project, we identified and resolved many faults through an in-depth review of the HVAC system. We found faults at the zone level, such as faulty thermostats, incorrect thermostat settings, manual valve position overrides, incorrect airflow setpoints, passing coils, and also at the AHU level, such as stuck dampers. Many of these adversely affected the results (of both the baseline and intervention control strategies) until the faults were identified and resolved prior to the start of the study period. For future projects, we recommend using automated fault detection methods for AHUs and VAV terminal units [29–33], to identify and resolve these issues prior to implementing either supply air temperature reset strategy.

We describe the new control strategy in language common to the industry (see an example sequence of operations included as supplemental material) so that readers may easily specify and implement this immediately, in new construction or retrofit projects.

It is also worth noting that high values of the long-term temperature correction from reheat coil discharge air temperature to SAT (ΔT_h^i) (e.g. values > 2.8 °C (5 °F)) likely indicate an issue such as a passing valve. The proposed sequences will also automatically notify the building operator when this occurs so that they can further investigate.

Other practical implementation notes to consider are: that if programmed into the existing zone and AHU controllers, memory to store the additional programming logic may be a constraint in some cases; and that this strategy requires additional network traffic (e.g. to transmit the zone airflow, discharge air temperature, and reheat valve position), which may be a constraint on some older networks, or very large newer networks that do not use controllers with Internet Protocol (IP) capability.

Limitations to the application of this control strategy

Aside from the limitations discussed earlier, we developed this control strategy for HVAC systems where the three individual cost functions are convex and monotonic within the evaluated range of feasible SATs within the 5-minute iteration time interval. This ensures that there is only one global minimum cost for the SAT to converge towards, and this assumption applies reasonably well to the heating and fan power estimates. It also applies to the cooling power estimates when a central chilled water plant supplies the cooling. However, for packaged DX AHUs, there is a significant energy cost penalty to using a small amount of cooling - the energy cost function is not continuous at this point. This will pose issues in implementation, or will yield less than optimal results if ignored. For example, for many of the operating hours in the SDH study, the cost-responsive reset converged to an SAT setpoint that was just above or below the point where cooling was needed. If this was a packaged DX unit, it would ensure that the compressors cycled frequently, which is far from ideal. Thus, this control strategy is widely applicable to buildings with VAV systems served by chilled water plans and reheat served by hot water plants. The control strategy can likely be extended to DX cooling and electric heat with additional research.

The other limitation to application is in climates with significant dehumidification loads, as mentioned previously. While this is not a major issue in dry climates (e.g. many climate zones in

California), it would be for other climates. Given the lack of robust and reliable sensors for measuring moisture content in air (e.g., humidity, enthalpy, or dew-point sensors), and the fact that these are not common within most AHUs, this is a significant limitation in climates where latent cooling makes up a significant portion of total cooling. However, the control strategy can likely be extended to account for dehumidification costs with additional research, and/or could be modified to function with an additional constraint for dehumidification control. For example, we could use the typical meteorological data for each location to calculate a coefficient that increases the cooling cost calculation (see Equation 6) to account for typical dehumidification at a particular combination of SAT and outside air temperature. This is an approximate approach, but it simply uses weather data (information that is readily available at no cost), and does not require additional instrumentation.

Note also that though all SAT reset strategies will affect indoor humidity levels, neither the proposed cost-responsive SAT reset, nor the existing best practice SAT reset, address humidity control as this is not common in air handling units outside of applications in clean rooms, hospitals, museums, and other demanding environments. Instead, in most applications humidity is controlled implicitly by the upper limit placed on feasible SAT setpoint values. In other conditions, or where those humidity levels are of concern, either the upper SAT setpoint limit should be lowered accordingly, or the AHU control logic should include sequences to explicitly address humidity control.

Limitation of this study and of extrapolating savings results to other buildings

We would prefer to have had waterside measurements to validate the chilled water and reheat power estimates, but this was not possible given the resources available for this study.
We expect the energy savings results to vary quite widely between buildings, and that this will depend on a wide variety of factors, such as:

1. the relative costs of fan, chilled water and reheat energy use.
2. the size of the HVAC system relative to the actual building loads, both at system and individual zone level
3. the zone minimum airflow fraction
4. the zone setpoint temperature range
5. the building operating hours
6. the climate

While SDH is a reasonable representation of many buildings in regard to the first three points, the same does not apply for the last three. SDH has a slightly wider zone setpoint temperature range than usual due to the use of Comfy, and the building operates continuously. Neither of these are representative of a typical office building and thus, extrapolating the magnitude of the energy savings results of this study to other buildings is not valid. SDH also uses the relatively unusual combination of single-max controls (i.e. relatively high zone minimum airflow setpoints), and demand based supply air temperature resets. Lastly, the mild climate has more operating hours within the range of outside temperatures that provide larger energy savings than many other climates. Further implementations in other buildings and simulation-based analysis are valid methods to estimate the energy savings potential in a broad population of buildings.

Conclusions

This paper describes a new supply air temperature control strategy for multi-zone variable air volume systems and an evaluation of its performance against current best practice in a randomly controlled trial in a large office building. The results show that the new control strategy reduced total HVAC energy costs by approximately 29% when normalized to the typical annual climate data for this location, operating during typical office hours. These findings indicate that the current industry best practice control strategy does not find the optimal energy cost point under most conditions. The control strategy presented in this paper finds a lower cost SAT setpoint under a wide range of operating and design conditions that typically occur within these systems. The proposed control strategy requires no additional sensors or hardware beyond what is typically installed for a modern VAV system. Setup requires very limited information about the building's HVAC system, all of which is easily available (primarily energy rates). The underlying programming logic is portable between buildings and, unlike other solutions, this strategy does not require a training period or detailed climate & building specific analysis before implementation. Furthermore, though there are limitations to the application of this control strategy that require further research (e.g. for VAV systems using DX cooling systems, or in climates with high dehumidification loads), the new control strategy is immediately applicable in many HVAC systems without modification.

This new control strategy applies to multi-zone VAV systems that use chilled water systems for cooling and that have DDC controls to the zone level. This type of system represents an enormous number of buildings in the world. For context, commercial buildings in the USA consume the equivalent of approximately 2.2 PWh (7.5 quad BTUs) of energy to heat, cool, and ventilate buildings per year. VAV buildings consume the majority of this; approximately 1.8 PWh (6 quad BTUs) according to CBECS 2012 data [34]. Thus, the new control strategy provides a valuable opportunity to significantly reduce energy use, and combat climate change, at little initial expense.

Acknowledgements

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Supplementary Material

The following pages present an approximation of the control strategy described in this paper as a sequence of operations document, common to the HVAC industry. The intent is to promote immediate adoption by providing readers with a document in a format that a controls contractor would be familiar with. To accommodate the potentially less capable programming environments available within proprietary building automation system software, we also made minor changes to the implementation to provide similar functionality with less programming complexity. For example, we avoid vectorized calculations and implement three candidate SATs instead of the vector of 5 values used in this paper.

1.1 SEQUENCES OF OPERATION

A. Multiple Zone VAV Air Handlers

1. This sequence excerpt applies to multiple zone VAV air handlers and is written to integrate with ASHRAE Guideline 36 High Performance Sequences of Operation for HVAC Systems. See Guideline 36 for explanation of Trim & Respond logic and for related sequences.

2. Supply Air Temperature Control

   a. Control loop is enabled when the supply air fan is proven on, and disabled and output set to zero otherwise.

   b. Supply Air Temperature Setpoint

      1) During Occupied Mode and Setup Mode: Setpoint shall be reset from Min_SAT (the lowest cooling supply air temperature setpoint) up to Max_SAT using Trim & Respond logic with the following parameters:

Variable	**Value**
Device	Supply Fan
SP_0	SP_{max}
SP_{min}	Min_SAT
SP_{max}	Max_SAT
T_d	10 minutes
T	5 minutes
I	2
R	See below
SP_{trim}	+0.5ºF
SP_{res}	-0.5ºF
$SP_{res\text{-}max}$	-2.0ºF

      2) Requests:

         a) If $R_{cool} > I$, where R_{cool} = Zone Cooling SAT Requests, then $R = R_{cool}$

         b) Otherwise, $R = R_{cost}$ where

            (1) If $C_{lower} < C_{current}$ and $C_{lower} <= C_{higher}$, $R_{cost} = I + 2$ (decrease supply air temperature by SP_{res})

            (2) If $C_{higher} < C_{current}$ and $C_{higher} < C_{lower}$, $R_{cost} = 0$ (increase supply air temperature by SP_{trim})

            (3) Else, $R_{cost} = I + 1$ (no change in supply air temperature)

         c) See Cost-Based Optimization section below for cost calculations: $C_{lower,}$ $C_{higher,}$ and, $C_{current}$

      3) During Cool-Down Mode: Setpoint shall be Min_SAT.

      4) During Warm-Up and Setback Modes: Setpoint shall be 95°F.

   c. Cost-Based Optimization

1) This cost-based optimization approach is intended to apply to single-duct VAV reheat systems with chilled and hot water sources. It requires discharge air temperature sensors at reheat terminals as well as airflow measurement at every VAV terminal. This sequence is not intended to apply to systems with DX cooling, heating coils at the air handler, or electric reheat. Logic shall be provided to incorporate failsafe operation in the event of out-of-range measurements or non-numeric values due to device failure or calibration issues or communication loss and to protect against divide-by-zero calculation errors. Logic shall also be provided to limit excessive network traffic such as by limiting the update of values based on a change of value threshold or a set time interval (e.g. 30 seconds).

2) Energy use measurement and estimates for this system shall be evaluated at the current SATs and at each of two alternate SAT setpoints (current SAT + SP_{trim} and current SAT + SP_{res})

3) Airflows

    a) Measured airflows (in cfm) at current SAT shall be determined as follows:

        (1) Zone supply airflow Vz = airflow measured at each cooling-only and reheat VAV box

        (2) System supply airflow Vs = the sum of Vz values from all associated VAV boxes

    b) Estimated airflows (in cfm) at alternate SATs shall be determined as follows:

        (1) For each reheat VAV zone in cooling mode: Estimated zone supply airflow Vz_alt = (Tz – Td) / (Tz – Td_alt) * Vz, where

            (a) Tz = Zone air temperature

            (b) Td = Discharge air temperature at zone terminal

            (c) Td_alt = Discharge air temperature at zone terminal at alternate SAT and is calculated as Td + (Ts_alt – Ts)

            (d) Vz = Zone supply airflow

            (e) Ts = Supply air temperature setpoint at air handler

            (f) Ts_alt = Alternate supply air temperature setpoint at air handler

            (g) Vz_alt shall be constrained to be no less than zone minimum airflow setpoint Vmin and no greater than zone maximum cooling airflow setpoint Vcool-max. If Tz is more than 1 °F greater than the zone cooling setpoint, the normal calculation shall be bypassed and Vz_alt set equal to Vcool-max.

        (2) For each cooling-only VAV zone in cooling mode (if no discharge air temperature sensor available): Estimated zone supply airflow Vz_alt = (Tz – Ts) / (Tz – Ts_alt) * Vz, where

            (a) Vz_alt shall be constrained to be no less than zone minimum airflow setpoint Vmin and no greater than zone maximum cooling airflow setpoint Vcool-max

(3) For each zone in heating or deadband mode: Estimated zone supply airflow Vz_alt = Vz. Zone airflow does not directly change due to SAT adjustments when zone is in heating or deadband modes.

(4) Estimated system airflow Vs_alt = the sum of Vz_alt values from all associated VAV boxes

4) Cooling coil energy rate (or power, in Btu/h) shall be estimated at current and alternate SATs based on a sensible heat balance across the cooling coil when the valve is open, as follows. Note that this approach does not directly account for latent cooling:

a) At current SAT: P_{chw} = max[0, 1.08 * (Tm – Ts + ΔTc) * Vs]

b) At alternate SATs: P_{chw_alt} = max[0, 1.08 * (Tm – Ts_alt + ΔTc) * Vs_alt]

c) Where

(1) Tm = Mixed air temperature at air handler

(2) ΔTc is a temperature correction to account for fan heat, sensor drift, and/or passing control valves and is an exponential average equal to [k * (Ts – Tm) + (1 – k) * (ΔTc from last time step)] calculated during periods when the chilled water control valve has been closed for a minimum of 5 minutes and when airflow is proven. The value of ΔTc is fixed at its last value prior to the valve opening and for 5 minutes after closing. The exponential smoothing coefficient k is user-adjustable, with a default value between 0.01 and 0.001.

5) Reheat coil energy rate (or power, in Btu/h) shall be estimated at current and alternate SATs based on a sensible heat balance across each zone reheat coil when reheat control valve is open, as follows. Note that this approach does not directly account for waterside distribution losses:

a) At current SAT: P_{rh} = max[0, 1.08 * (Td – Ts – ΔTh) * Vz]

b) At alternate SATs: P_{rh_alt} = max[0, 1.08 * (Td – Ts_alt – ΔTh) * Vz]

c) Where ΔTh is a temperature correction to account for fan heat, duct gain, sensor drift, and/or passing control valves and is an exponential average equal to [k * (Td – Ts) + (1 – k) * (ΔTh from last time step)] calculated during periods when the reheat valve has been closed for a minimum of 5 minutes and when airflow is proven. The value of ΔTh is fixed at its last value prior to the valve re-opening and for 5 minutes after closing. The exponential smoothing coefficient k is user-adjustable, with a default value between 0.01 and 0.001.

d) Note that Td and Vz are unchanged regardless of SAT adjustment

e) Total reheat coil energy rate P_{hhw} for this system shall be equal to the sum of P_{rh} from each associated zone, and evaluated for each SAT.

6) Fan power (in kW) shall be determined for current and each alternate SAT as follows

a) At current SAT: fan power P_{fan} = power measured by variable speed drive or dedicated meter

b) At alternate SATs: estimated fan power $P_{fan\_alt} = P_{fan} * (Vs\_alt / Vs)^3$ based on affinity laws

7) Thermal energy conversions. Thermal energy use for each of the current and alternate SATs shall be converted to utility energy use as follows:

a) Cooling power P_c (kW) = $P_{chw} * E_c *$ (1 ton /12000 Btu/h), where E_c is the chiller plant efficiency in units of kW/ton. This value may be a constant based on expected plant performance (e.g. 0.7 kW/ton), calculated based on performance curves, or may be replaced with real-time kW/ton measurements if power from all plant components and total ton measurements are available.

b) Heating power P_h (Btu/h) = P_{hhw} / E_h, where E_h is the dimensionless boiler plant efficiency. This value may be a constant based on expected plant performance (e.g. 0.8), calculated based on performance curves, or may be replaced with real-time efficiency measurements if boiler gas use and total Btu/h measurements are available.

8) Energy cost calculations. HVAC energy cost calculations shall be evaluated for each of the current and alternate SATs ($C_{current}$, C_{lower}, C_{higher}). Though calculated in real time at each time step, energy costs are evaluated in units of cost per hour.

a) Fan energy cost per hour C_{fan} ($/hr) = $P_{fan} * R_e *$ 1 hr

b) Cooling energy cost per hour C_{cool} ($/hr) = $P_c * R_e *$ 1 hr

(1) Where R_e is the utility electricity rate in $/kWh. The R_e rate may vary according to time of day, time of year and/or volume block depending on local utility rates, but only energy charges are included. This approach cannot directly account for electricity demand charges.

c) Heating energy cost per hour C_{heat} ($/hr) = $P_h *$ (1 therm / 100,000 Btu) $* R_g$ * 1 hr

(1) Where R_g is the utility natural gas rate in $/therm. The R_g rate may vary according to time of day, time of year and/or volume block depending on local utility rates.

d) Total HVAC energy cost per hour C ($/hr) = $C_{fan} + C_{cool} + C_{heat}$.