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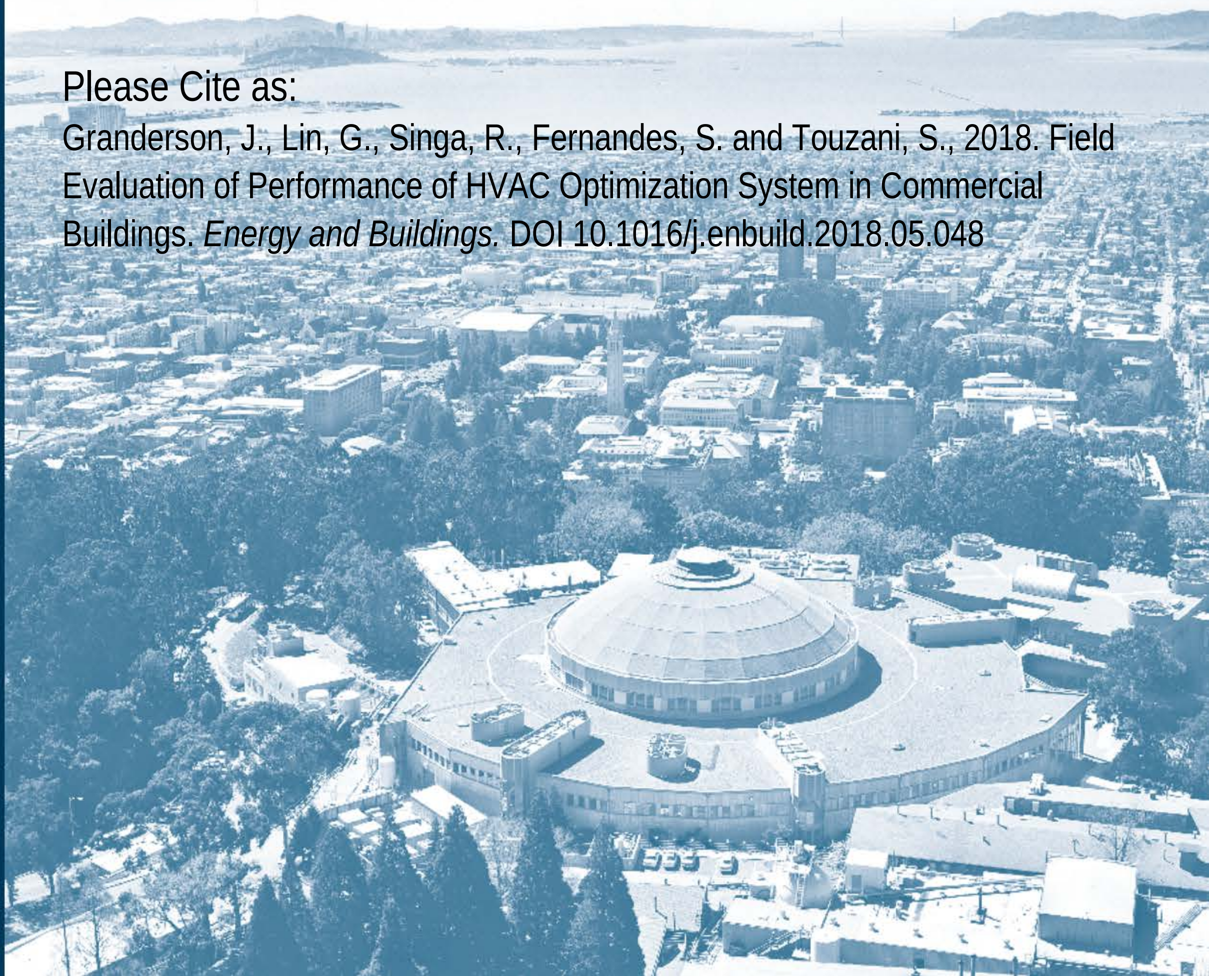

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Field Evaluation of Performance of HVAC Optimization System in Commercial Buildings

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Abstract
New smart building technologies that offer continuous dynamic optimization of Heating, Ventilation, and Air Conditioning (HVAC) control hold promise to advance building operations for efficiency and grid response. These technologies use data from the control system to determine the analytically optimal setpoints, and then write back the optimal setpoints into the control system to minimize system energy consumption or costs. There are limited studies documenting field validations of these technologies. This paper presents the results from a long-term field evaluation of a model-predictive HVAC optimization system that installed in four commercial buildings.

Energy savings analysis was conducted based on pre/post submetered energy use. Across the cohort of evaluation sites, HVAC savings following the implementation of the optimization system were mixed, ranging from 0-9%. Analysis of site operational data showed that occupant comfort was neither positively nor negatively impacted. Key technology adoption considerations and recommendations are summarized in the paper. The technology performs best when HVAC systems are in good working condition, and can be exercised to achieve the full range of its optimized setpoints - however it may not provide extensive additional savings over cases where best practice sequences of operation and reset strategies are already comprehensively implemented.

1. Introduction

In 2012, U.S. commercial buildings used 7.346 quadrillion Joule of total site energy: 4,474 quadrillion Joule of electricity, 2,372 quadrillion Joule of natural gas, 141 quadrillion Joule of fuel oil. Overall, total energy usage in commercial buildings increased 7% since 2003 (EIA 2016). Within commercial buildings almost 54% of end use energy use is due to heating, ventilation and cooling (EIA 2016). To achieve energy efficiency in commercial buildings therefore it is important to improve the energy efficiency of the heating, ventilation and air-conditioning (HVAC) system.

Model-predictive control (MPC) optimization approaches present a promising solution for increasing the operational efficiency of building HVAC systems. These techniques use a dynamic system model and disturbance forecast to predict system performance with a given control law, thereby allowing the control law to be optimized for a given objective and taking into consideration future events. They combine the model with the real-time data read from building automation system (BAS) to determine the optimal control setpoints (e.g. supply air temperature setpoint, chilled water leaving temperature setpoint, and zone air temperature set point), and write analytically based optimal setpoints back to the BAS. Two-way communication with BAS during HVAC operation process is the distinguishing feature of MPC solutions in this paper. This process of reading and writing happens repeatedly at regular time interval in the optimal operation process. The literature reflects a broad family of work to develop and test the performance of these solutions across a diversity of HVAC system types, modeling, and optimization approaches. The more commonly demonstrated HVAC optimization solutions are observed to rely upon data-driven models, given the practical implementation challenges associated with physics-based modeling approaches - particularly in terms of computational complexity as noted in Sun 2005, but also in terms of configuration and customization. Several publications provide a thorough examination of these modeling approaches which primarily include black box models that relate a signal to a response, and grey-box models that include some a priori knowledge of the physical representation of the HVAC system - see for example Li 2015 and Ma 2011.

A snapshot of the more recent literature shows that optimized control solutions have been developed and tested for cooling plants (Ma 2011), pumping systems within complex cooling plants (Wang 2012), air handler units (AHUs) and variable air volume (VAV) terminals (Bengea 2015; Li 2015; Liang 2015; Platt 2011; West 2014), and packaged systems (Putta 2013). To test and evaluate these optimized control strategies, researchers commonly conduct simulation-based assessments, such as Ma (2011), Wang (2000, 2013), and Liang (2015). Simulation-based studies offer the obvious advantages of controllability, ease of permutation to quickly cover a variety of operational conditions, and ease of implementation, but may not reflect as-operated 'real world' conditions. Validations of these optimized control strategies in actual operational buildings are therefore very important. Such studies provide information on in-situ performance, including the natural non-idealized stochastic variability in building operations such as bandwidth-limited networks, diverse system design, faulty or missing sensor measurements, system degradations, complex control strategies, and occupant impacts. They can provide a valuable complement to simulation-based analyses, particularly in terms of technology's practical applicability, generalizability, and robustness.

Given the logistical complexities, time, and cost of conducting experiments in existing occupied buildings, field evaluations are often constrained in terms of scale of implementations (one subsystem, one floor, two buildings in rare case), or duration of the study (days to two months in selected seasons). For example, Platt (2011) demonstrates a 30% energy savings over a week-long testing period in one floor of an office building using a grey-box MPC system to determine optimal AHU on/off schedule and zone temperature setpoint. West (2014) continues Platt's research and provides evaluation results of the commercialized version of the technology in two buildings. The technology is shown to save 19% HVAC energy over a 51-day period in one office building, and 32% over a 10-day period in another office building. Bengea (2015) describes a fault-tolerant MPC system for AHUs and VAV terminals, and reports 30%-

60% HVAC energy savings for its implementation in a building for several days. Li (2015) implements a MPC in a rooftop unit and its associated VAV boxes in a medium-sized building. The MPC reduced the equipment's electricity use by more than 20% over 20 test days in swing season.

While these solutions have shown promising performance, model-based optimization is not yet the norm in commercially available building control and analytics technologies. In the realm of commercial solutions, "Energy Management and Information Systems (EMIS)" are understood to comprise a broad family of tools and services to manage commercial building energy use. These technologies offer a mix of capabilities to store, display, and analyze energy use and system data, and in some cases, provide control (CEE 2012; King 2017). They include: benchmarking and monthly utility bill analysis tools; energy information systems, that focus on interval meter data analysis; building automation systems (BAS); and fault detection and diagnostic (FDD) tools (Harry 2016; US DOE 2015). Within the EMIS technology space, the market has relatively recently begun to deliver automated system optimization technologies that provide model-predictive supervisory optimization through two-way communication with the BAS. Although relatively few examples exist in today's market, these offerings are becoming available for use in commercial buildings (Smart Energy Analytics Campaign 2017). In spite of their commercial availability, assessments of their performance most commonly take the form of vendor-provided case studies and customer testimonials.

Given the scope of prior research and current technology trends, more comprehensive field validations are critical to understand the state of MPC optimization technology, provide informative assessments to utilities and building owners, and to inform the research and development community of outstanding needs and implementation challenges. To this end, this paper provides five primary contributions to the literature. 1) It provides a field assessment of a commercialized model-predictive HVAC optimization product. 2) It comprises a comprehensive field evaluation across four building types, located in three different climate zones. 3) The field evaluation encompasses a long-term performance analysis based on pre/post submetered energy use over a period of 7 to 15 months. 4) The energy savings analysis is combined with an assessment of the impacts of the optimization on occupant thermal comfort based on measured data from the evaluation sites. 5) Practical recommendations are offered for future MPC development and to building owners for deployment decision-making.

In the material that follows, we describe the technology and the methodology that was used to evaluate its performance. We then present the evaluation findings followed by a discussion of the results. Finally, we present conclusions and review compelling directions for future work.

2. HVAC Optimization Technology Description

The technology evaluated in this study is a commercially available offering that dynamically optimizes commercial building HVAC control setpoints for system efficiency, occupant comfort, and cost. It integrates with the BAS to conduct supervisory control. The technology's algorithm defines optimal space air temperature setpoints that are automatically implemented at the VAV terminal units when possible, or through supply air temperature and duct static pressure setpoints at the AHU level. The algorithm aims to exercise temperature control between upper and lower control limits to maintain occupant comfort. The optimization is built upon a learned predictive grey-box model that provides a 24-hour ahead forecast of the building's load profile, using weather forecasts and historical operational data; this model is updated every 4 to 6 hours.

3. Evaluation Methodology

The HVAC optimization system was installed for evaluation in four sites. The evaluation was designed to assess:

- achieved energy and utility cost savings, and factors in building operations and technology use that influenced those savings
- impact of the optimized supervisory control on occupant comfort
- technology adoption potential, as indicated by installation and integration effort, and impacts on building management activities

3.1 Site Characteristics

The four sites at which technology was installed are summarized in Table 1, including their location, size, HVAC systems, and control baseline for the targeted optimization setpoints. This cohort reflects climatic diversity, spanning the Southern California (ASHRAE Zone 3B dry), Midwest (ASHRAE Zone 5A cool humid), Northeast and Mid-Atlantic (ASHRAE Zone 4A mixed humid) regions. It also represents diversity in commercial building types, including an office, a courthouse, a hospital, and a high school. These sites also offer a variety of baseline control strategies, including no reset, outdoor air temperature-based, return air temperature-based, and terminal damper position-based reset.

Table 1: Demonstration site characteristics

Site	Location	Size	HVAC System*	Control Baseline in Occupied Hours**
Office	Long Beach, CA	15,608 m^2	A central chiller/boiler plant as well as 1 AHU equipped with variable frequency drive (VFD) supply fans	AHU supply air temperature setpoint is reset based on outdoor air temperature. AHU duct static pressure setpoint is a fixed value.
Courthouse	Dayton, OH	15,621 m^2	A central chiller/boiler plant as well as 7 AHUs equipped with VFD supply fans	Both AHU supply air temperature and duct static pressure setpoints are reset based on VAV terminal damper positions.
Hospital	New York, NY	27,871 m^2	15 rooftop units (RTUs) equipped with VFD supply fans	RTU supply air temperature setpoint is reset based on return air temperature. RTU duct static pressure setpoint is a fixed value.
High School	Washington, DC	21,832 m^2	A central chiller/boiler plant, as well as 7 AHUs and 10 RTUs equipped with VFD supply fans	Some of the AHU and RTU supply air temperature setpoints are reset based on return air temperature and the rest are fixed values. The duct static pressure setpoints are fixed values.

* Except for the high school, all sites featured reheat at the VAV terminal boxes
** The HVAC system in all sites operates in occupied and unoccupied modes. During unoccupied hours, the system is off.

3.2 Energy and Utility Cost Savings

Rather than relying upon the technology's built-in savings measurement and verification capability, an independent assessment of energy savings was conducted according to Option B of the International Performance Measurement and Verification Protocol (IPMVP) (EVO 2012). Option B quantifies HVAC system energy savings through isolated measures of system load. Results from an Option C whole building analysis were used as a comparative cross check. Table 2 summarizes the data that was collected at each site to determine energy (and utility cost) savings.

Table 2: Data collected at each site to determine energy and utility cost savings

Quantity	Measurement	Level of Measurement	Source
Whole-building electricity	15-minute interval kilowatt (kW) data	Whole building	On-site meter
HVAC electricity	15-minute interval kW data	Submeters to isolate HVAC loads	On-site meter
Whole-building gas	15-minute interval energy or demand data	Whole building	On-site meter
Local outdoor air temperature	Hourly data	Area-local	Weather Underground data feed
Site-specific utility tariff proxies	n/a	n/a	Site-provided information
Other factors (i.e., occupancy levels, space changes, etc.)	n/a	n/a	Regular discussion with site operations staff

Under IPMVP Options B and C, energy savings are estimated as defined in Equation 1. A mathematical baseline model is created from data when the technology is not operating. The baseline model is then forward projected into the measure post-installation verification period to determine what the energy use would have been in the absence of the technology. The difference between this baseline projected energy use, and the metered post installation energy use is taken as the energy savings. The *Adjustments* term is used to capture the effects of variables not included in the baseline model, and not associated with the technology, such as increased internal loads, or changes to equipment or building occupancy.

$$\text{Savings} = \text{Baseline Projected Energy} - \text{Post Installation Energy} \pm \text{Adjustments} \qquad (1)$$

The baseline model that was used to characterize building energy use of the courthouse, hospital, and high school sites is a piecewise linear regression that relates load to time-of-week and outdoor air temperature (see equations 2-3). This model is defined in detail in the literature and has been tested and shown to predict energy use with a high degree of accuracy

(Granderson 2015, 2016; Mathieu 2011). A brief overview is provided: We divide a week into 15-minute-intervals (indexed by i), e.g., the first interval is from midnight to 12:15 on Monday morning, the second interval is from 12:15 to 12:30, and so on. A different regression confident for each time-of-week, α_i, allows each time-of-week to have a different predicted load. We also divide the outdoor air temperatures experienced by that building into six equally-sized temperature intervals. A temperature parameter, β_j with j = 1...6, is assigned to each outdoor air temperature interval. To achieve piecewise linearity and continuity, the outdoor air temperature T at time t (which occurs in time-of-week interval i), $T(t_i)$, is broken into six component temperatures, $T_{c,j}(t_i)$ with j = 1...6. Each $T_{c,j}(t_i)$ is multiplied by β_j and then summed to determine the temperature-dependent load. Let B_k (k = 1...5) be the bounds of the temperature intervals. Component temperatures are computed using the following algorithm:

1. If $T(t_i) > B_1$, then $T_{c,1}(t_i) = B_1$. Otherwise, $T_{c,1}(t_i) = T(t_i)$ and $T_{c,m}(t_i) = 0$ for m = 2...6, and algorithm is ended.
2. For n = 2...4, if $T(t_i) > B_n$, then $T_{c,n}(t_i) = B_n - B_{n-1}$. Otherwise, $T_{c,n}(t_i) = T(t_i) - B_{n-1}$ and $T_{c,m}(t_i) = 0$ for m = (n + 1)...6, and algorithm is ended.
3. If $T(t_i) > B_5$, then $T_{c,5}(t_i) = B_5 - B_4$ and $T_{c,6}(t_i) = T(t_i) - B_5$.

The temperature parameters β_j are only used when a building is operating in occupied mode since one would expect a building's response to temperature would change at unoccupied time period. For all buildings, occupied energy use, E_o, is estimated as follows:

$$\widehat{E_o}\left(t_i, T(t_i)\right) = \alpha_i + \sum_{j=1}^{6} \beta_j T_{c,j}(t_i) \qquad (2)$$

To predict energy use when the building is in unoccupied mode, we use a single temperature parameter, β_u since we expect a building doesn't response to temperature at unoccupied time period. Unoccupied energy use, E_u, is estimated as follows:

$$\widehat{E_u}\left(t_i, T(t_i)\right) = \alpha_i + \beta_u T(t_i) \qquad (3)$$

The parameters α_i and β_j and β_u are estimated using actual metered energy use and temperature data during the baseline time period with ordinary least squares. Each of the parameters is physically meaningful: power use varies in each 15-minute-interval in a week and varies as a function of outdoor air temperature.

For the office site, a different baseline model (linear daily) was used to obtain an improved fit over hourly the time-of-week and temperature model that was suitable for the other sites. The mathematical form of the model is defined as:

$$E_i = \gamma_0 + \gamma_1 \overline{T}_i + \gamma_2 sd(T_i) + \gamma_3 H + \sum_d \gamma_d D_d \qquad (4)$$

where $\overline{T}_i$ is the daily average outdoor air temperature, $sd(T_i)$ is the standard deviation of the daily outdoor air temperature, D_d are binary variable (dummy variable) corresponding to the day of the week, H is a dummy variable that is equal to 1 if the considered day is a holiday and 0 if not, and $\gamma_0, \gamma_1, \gamma_{2,} \gamma_{3,}$ and γ_d are model parameters that are determined from baseline data.

Three statistical goodness of fit metrics were used to verify the accuracy of the baseline models that were created: the coefficient of determination (R^2); the normalized mean bias error (NMBE), and; the coefficient of variation of the root mean squared error (CV(RMSE)). These metrics are used to characterize different aspects of model error. Formulas to compute these metrics can be found in ASHRAE Guideline 14 (ASHRAE 2014). They are defined as

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(E_i - \widehat{E_i})^2}{\sum_{i=1}^{n}(E_i - \frac{\sum_{i=1}^{n} E_i}{n})^2} \tag{5}$$

$$\mathrm{NMBE} = \frac{\frac{\sum_{i=1}^{n}|E_i - \widehat{E_i}|}{n}}{\frac{\sum_{i=1}^{n} E_i}{n}} \tag{6}$$

$$\mathrm{CV(RMSE)} = \frac{\sqrt{\frac{\sum_{i=1}^{n}(E_i - \widehat{E_i})^2}{n}}}{\frac{\sum_{i=1}^{n} E_i}{n}} \tag{7}$$

Where $\widehat{E_i}$ and E_i are the predicted values and actual metered energy use respectively, and n is the total number of predictions in the prediction horizon.

Over an evaluation period that ranged from 7 to 15 months, the technology's optimized controls were toggled on and off for one week at a time. The *off* periods were taken as the 'pre-installation' baseline for savings estimates, while the *on* periods were taken as the 'post-installation' performance period. This approach is consistent with that outlined in IPMVP 2012, Section 4.5.2 on Measurement Period Selection (EVO 2012).

Cost savings were estimated using a blended estimated cost of electricity from site-specific utility bills, in combination with energy savings. To determine how energy savings were achieved by the model-predictive optimized controls, trend log data from the BAS was inspected to compare operational parameters in the *on* and *off* periods.

3.3 Occupant Comfort

To verify that the HVAC energy savings gained from optimization were not achieved at the expense of occupant comfort, two types of analysis were conducted to compare conditions during *on*, and *off,* i.e. conventional, control: 1) changes in space conditions (temperature and relative humidity) relative to the ASHRAE thermal comfort zone; 2) changes in stability of space air temperature.

Changes in space conditions relative to the ASHRAE thermal comfort zone: This analysis used a simplified model of the ASHRAE thermal comfort zone (ASHRAE 2013), shown in Figure 1. In this model, regions of comfort for winter and summer are defined by boundaries on a plot of relative humidity versus air temperature, as measured in the interior space. To analyze the impact of the technology on comfort conditions, the fraction of points outside of the comfort zone when the optimization is on is compared to that when the optimization is off.

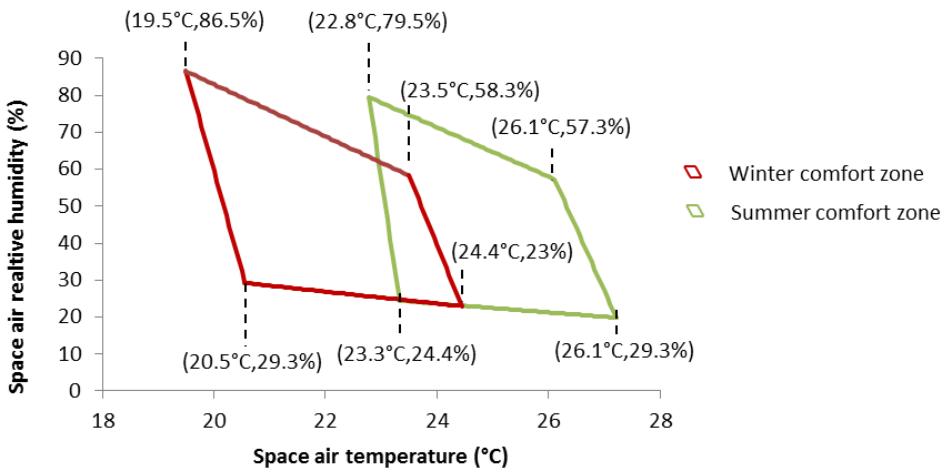

Figure 1: A simplified representation of the ASHRAE thermal comfort model, with comfort as a function of relative humidity and air temperature

Changes in stability of space air temperature: ASHRAE Standard 55 (ASHRAE 2013) specifies the maximum change in operative temperature allowed during specified time periods. The standard states that the operative temperature may not change more than 1.1°C during a 15-minute period, 1.7°C during a 30-minute period, 2.2°C during a one-hour period, 2.8°C during a two-hour period, or 3.3°C during a four-hour period. To determine the impact of the optimization on space air temperature stability, the number of departures from the maximum specified changes was compared during the time periods when the optimization was *on* versus when it was *off*.

3.4 Technology Adoption Potential

Conclusions regarding adoption potential and broad-scale applicability were important desired outcomes of the field validation, so factors such as setup and integration effort, tuning and troubleshooting, and impact on building management activities, were also included in the evaluation. Bi-weekly calls were held with site operations staff over the duration of the field assessment to document staff experiences installing and using the technology. In addition, the evaluation team conducted short, directed interviews with site points of contact after installation and configuration, and at the end of the evaluation. Finally, scale-up was evaluated in terms of HVAC system and control requirements, building size and type requirements, and other operational factors that were found to influence savings at each site in the validation cohort.

4. Results

4.1 Energy and Cost Savings

4.1.1 Baseline modeling and savings results

Table 3 summarizes the duration of the data collection period, number of days in the baseline and post periods, and goodness of fit for the baseline models. (In three sites, gas data could not be acquired due to absence of a meter or poor data quality.) Although recommendations vary, 'strong' fit is taken as R^2 greater than approximately 0.7, CV(RMSE) < 25%, and NMBE < 0.5%. While the values of some of the CV(RMSE) metrics were modestly higher than preferred, overall, the baseline model were deemed sufficient for the savings analysis.

Table 3: Baseline model goodness-of-fit metrics for each site at HVAC isolation level, for baseline data collected

Site	Extent of data period	# of days in the baseline	# of days in the post-installation	Baseline Goodness-of-fit Metrics at HVAC isolation level		
				R^2	CV(RMSE)	NMBE
Courthouse	6/30/2016-9/26/2017	166	170	0.88	37%	-0.1%
Office	8/23/2016-8/23/2017	116	108	0.81	39%	0.0%
Hospital	8/16/2016-3/14/2017	127	113	0.95	14%	-0.03%
High School	3/22/2016-2/28/2017	156	148	0.90	27%	0.34%

Table 4 shows the HVAC savings results for each of the four sites. In the table, the electricity savings observed at the HVAC submeter levels are presented, followed by the total HVAC savings for the site at which gas data was available. The final column contains the total absolute savings in kWh.

Table 4: HVAC energy savings at each site

Site	**HVAC Electricity Savings [%]**	**Total HVAC Savings (Electricity + Gas) [%]**	**HVAC Electricity Savings [kWh]**
Courthouse	1.4%	N/A due to poor gas data quality	5,662
Office	8.9%	N/A due to poor gas data quality	7,167
Hospital	-0.4%	N/A, no gas meter installed	-2,672
High School	1.9%	1.0%	11,425

In addition to the tabulated and reported savings determined from the HVAC electricity submeters, the electricity savings indicated at the whole-building meter were used as a cross check. Overall the savings observed at the HVAC submeter level were consistent with those at the whole building level – that is, they were in the same range of percent savings observed at the whole building level, given an assumed fraction of the whole building load that is attributable to HVAC end uses.

At the office site 9% HVAC savings were quantified. These savings were annualized to a 12-month kWh and combined with site-specific blended average electricity rates ($0.14/kWh) to determine annual cost savings. The calculations showed 17,200 kWh annual savings, with an associated annual cost savings of $2,410.

At the other three sites, savings ranged from zero to two percent. In the following sections each site is further discussed, including an analysis of how savings were achieved, and factors that could have compromised the realization of savings. These analyses were conducted through BAS trend log analysis and review with site operational points of contact.

4.1.2 Office Building Savings Analysis

Figure 2 shows the average HVAC electricity load for each day of the week at the site. The post-installation condition is plotted in blue, and the baseline projection is shown in red. The difference between the red and blue lines therefore represents the normalized average daily savings throughout the post-installation period. Tuesdays are excluded in Figure 2, as there was insufficient Tuesday data to provide statistically accurate results. This is because the technology was often switched from on to off, or off to on, on Tuesdays, precluding categorization of the entire 24 hour period as entirely representing either on or off operations.

Further analysis showed that this load reduction was in part attributable to a decrease in the AHU static pressure, and increase of the AHU supply air temperature affected by the optimized supervisory control. As illustrated in Figure 3 the averaged static pressure in the post-installation (*on*) mode is 2.8 kPa lower than in the baseline (*off*) mode, resulting in a decrease in fan speed. Engineering calculations estimate that the reduction in fan speed caused a 50% reduction in fan energy use.

In addition to decreases in AHU static pressure an increase in AHU supply air temperature (SAT) was effected by the model-predictive optimization algorithm, also contributing to energy savings. Figure 4 shows that when the optimization technology is operating and the outdoor air temperature is above 13.6 °C the averaged SAT is 0-1.7°C higher than when the technology is not operating (plotted in green). Increasing the SAT has three savings benefits: it reduces cooling energy as it reduces cooling load; it increases the number of hours when the economizer is able to provide all necessary cooling; and it also leads to a decrease in the amount of simultaneous heating and cooling (Murphy 2011).

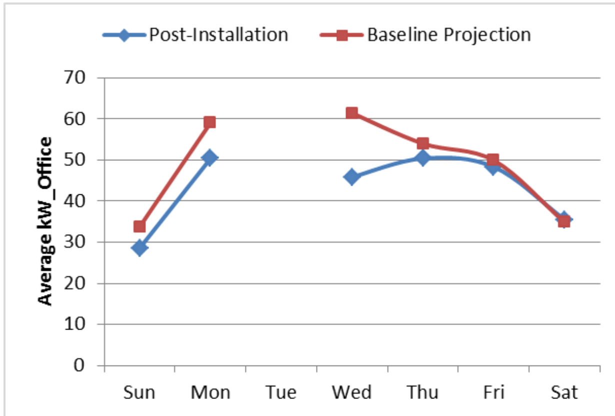

Figure 2: Daily power comparison for the HVAC system time averaged over the 12-month monitoring period at the office site

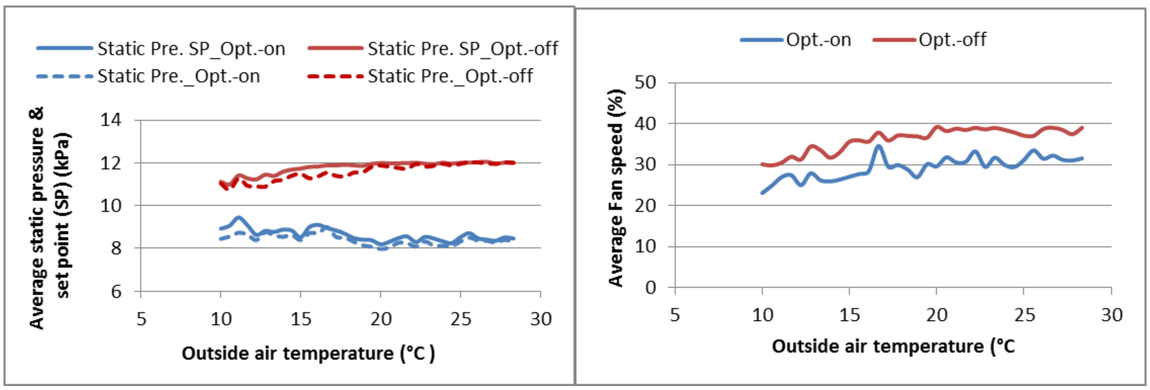

Figure 3: Decrease in AHU static pressure and fan speed at the office site

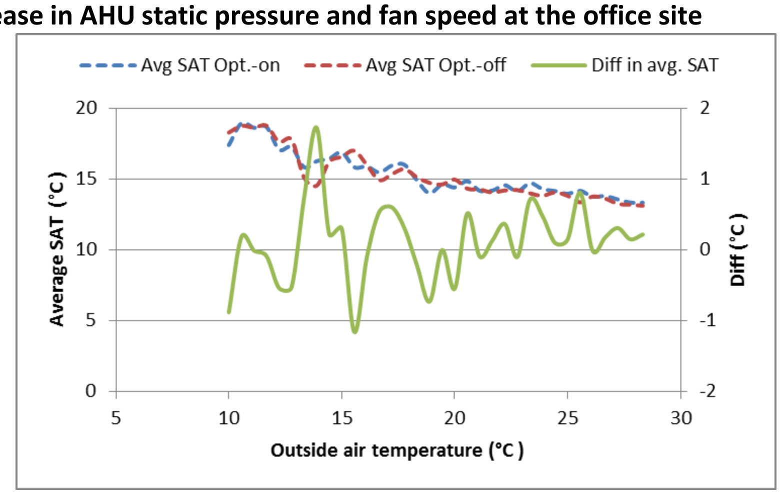

Figure 4: AHU supply air temperature comparison in *on* and *off* mode at the office site

4.1.3 Courthouse, Hospital, and High School Savings Analysis

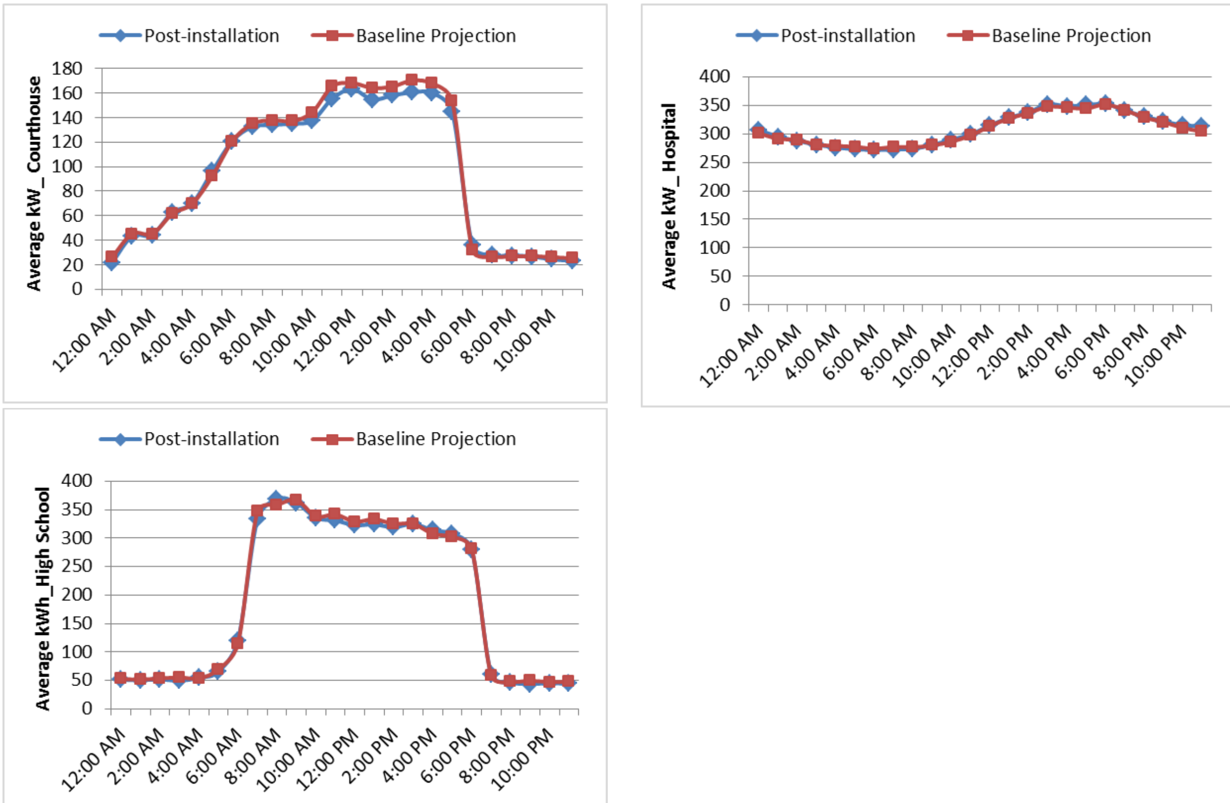

Figure 5: Time averaged HVAC power comparison at the courthouse (top left), hospital (top right), and high school (bottom left) sites; red indicates the baseline projected load for each hour of the day, and blue indicates the metered load under optimized control.

The HVAC savings identified in at the courthouse, hospital, and high school sites ranged from zero to two percent. Following the convention used in Figure 2, Figure 5 shows the average HVAC electricity load for each hour of the day at the three sites during the post-installation period. These plots show little difference between the post-installation (*on*) case and the baseline projection case.

Analysis of the issues that may have compromised savings at the three sites were conducted, and the findings were confirmed through discussion with the operations staff at each site. The issues are summarized below.

Fixed chilled water (CHW) valve position control requirement in AHU operation: AHU CHW valve usually modulates to maintain the SAT setpoint. This fixed valve position was necessary to maintain minimum flow to the chiller, but prevented the optimized SAT setpoint from being met in a unit that served approximately 35% its building's load.

Humidity control requirements: In one site, *the optimized SAT setpoint could not be met* due to required humidity control; this was observed across a set of units that served ~28% of the total building cooling load. Figure 6 shows a one-day example. During 7:00am and 8:30am, the SAT met the setpoint. After 8:30am, the AHU return air relative humidity (RARH) exceeded 50% which leaded to the 100% open of the CHW valve (CHWV). As a result, SAT was much lower than the proposed optimized setpoint.

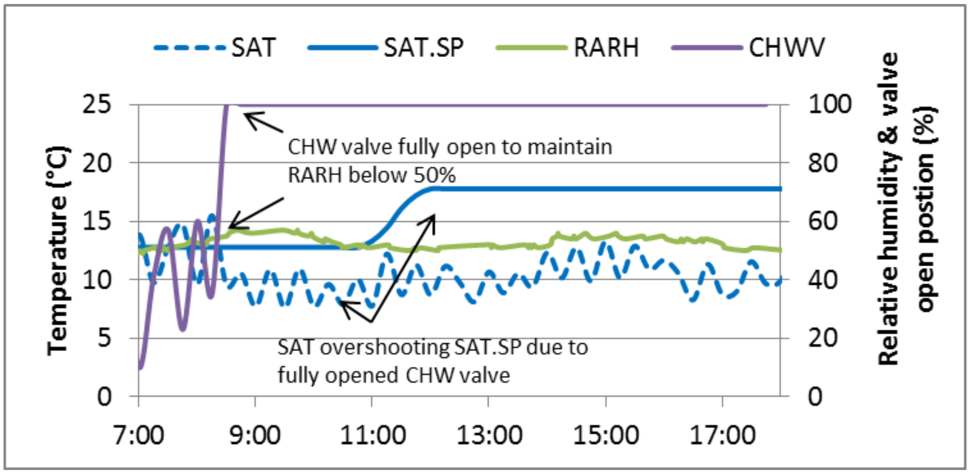

Figure 6: AHU supply air temperature and setpoint, return air relative humidity, and chilled water valve open position on September 19, 2016 at the high school site

Humidity and pressure control requirements: The hospital had strict space humidity and pressure control requirements. Optimized (reduced) duct static pressure setpoints will cause the decrease in space pressure, therefore, optimized setpoints were frequently overridden due to compensatory adjustments made by the operators to meet zone pressure setpoints.

Baseline reset strategy based on terminal boxes damper positions: In one site it was possible that the optimized setpoints were equally (but not more) effective as those in the baseline strategy.

Partial capacity of RTUs: In one site half of the RTUs were running at 50-60% of capacity due to refrigerant undercharge or issues with the compressor, constraining the extent to which the systems could be exercised for optimization.

Incomplete control of full HVAC load: In two sites units comprising 20-25% of the building cooling load were not placed under optimized control.

Poor controllability of chilled water valve position and supply fan speed: In one site a host of mechanical issues impacted the controllability of these parameters.

Overrides and reheat: At one site, for unknown reasons, a third party engineer intermittently overrode the optimized control setpoints. Additionally, during summer when the boilers were shut down, VAV reheat was not possible, reducing savings potential from reheat reduction.

4.2 Thermal Comfort

As outlined in Section 3.3 thermal comfort impacts were assessed by analyzing changes with respect to the ASHRAE comfort zone, and the stability of space temperature. Taken as a whole, these analyses indicate no significant changes in thermal comfort between baseline operations and post-installation operations.

4.2.1.Comfort Zone Analysis

The analysis of comfort using the simplified ASHRAE comfort model as described in Section 3.2 was performed at two sites where the zone temperature measurements in VAV boxes were available. Data were gathered from a set of AHUs and associated VAV boxes representative of standard occupied spaces. For each AHU, the linked VAV boxes that served typical spaces were studied. The analysis time period only included the hours when the building was heavily occupied.

The analysis was conducted for a total of 10 zones of space conditions. Across the 10 zones that were analyzed, 23 percent of the points were outside of the comfort zone in the baseline conditions when the optimization was not in operation, and 24 percent of the points were outside of the comfort zone it was in operation. Figure 7 shows the results when each of the 10 VAV zones was considered individually. In 6 zone spaces, the optimized operations showed a slight increase in the number of points outside of the comfort zone, and in 4 zone spaces, the optimized operations showed a modest decrease.

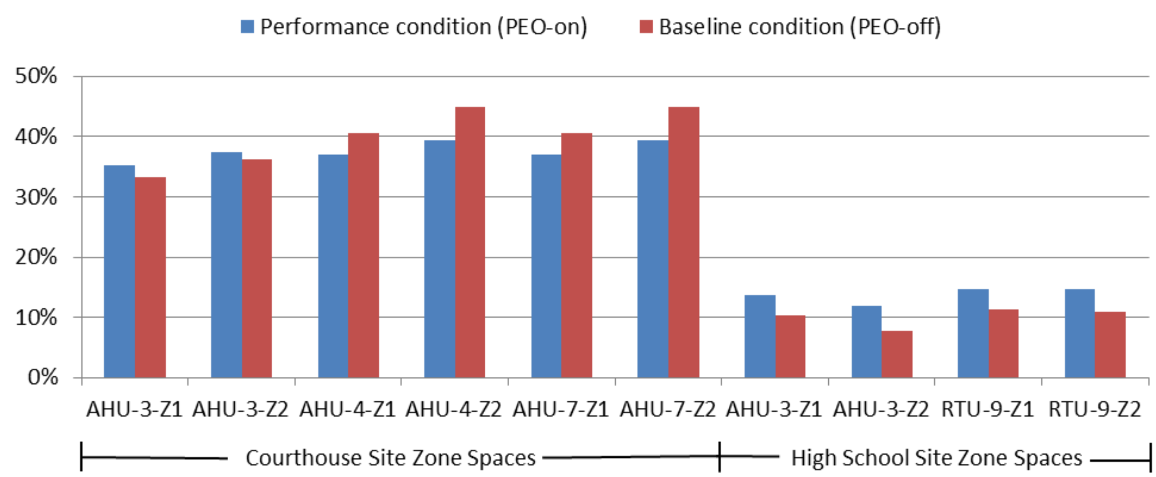

Figure 7: Percentage of operational points (space temperature paired with space humidity) outside of the comfort zone for each VAV, during the on (blue) and the off (red) time periods at the courthouse and high school

4.2.2 Space Air Temperature Stability

ASHRAE Standard 55 defines the maximum space air temperature changes allowed over several time periods: 15 minutes, half an hour, one hour, two hours, and four hours. Each of the VAV boxes that were analyzed according to the simplified thermal comfort model was also analyzed to evaluate departures from these temperature stability thresholds. Table 7 summarizes the number of times that the space air temperature at the courthouse and high school sites changed by an amount greater than that allowed under the standard. Across each of the 10 zones, and each of the time periods, there were 435 instances of departures from the standard when the technology was *off* and 295 instances when the technology was *on*. These data indicate that the optimized controls may have modestly improved space temperature stability.

Table 7: The number of times that the change in space air temperature exceeded the maximum allowable during the studied time period, for each time duration in ASHRAE Standard 55

PEO Status	Courthouse - Time duration (hours)					High school - Time duration (hours)				
	0.25	0.5	1	2	4	0.25	0.5	1	2	4
Baseline (Optimization off)	13	25	25	46	36	5	23	44	122	96
Post-installation(Optimization on)	7	6	14	21	14	4	17	29	87	96

4.3 Technology Adoption Potential

Consideration of adoption potential extends beyond energy and cost savings into issues related to ease of technology adoption, and general usability. The findings reported in the following subsections comprise information obtained from interviews with key points of contact at each demonstration site, as well as observations from the evaluation team.

Up to 3 days of the building operation staff's time was necessary to support system installation and configuration (this did not include time for IT staff or controls contractors), including interfacing with the IT department to acquire approvals for installation, provision of control specifications, device and system access, and scheduling site access and site walkthroughs. Additionally, up to 3 days staff time was required to help troubleshoot connectivity, and monitor stability as the system was brought into full control. While the overall staff time was modest, the calendar time for implementation can be protracted across many months, due to the lead-time to coordinate work amongst IT, controls contractors, and the technology team. The government courthouse and hospital facilities were most challenged in this respect. In the most difficult case, it took six months to obtain IT approvals.

Organizational requirements for network and data security can vary greatly in stringency. Depending on the scope of these requirements, higher-level approvals from within IT business units may be necessary to implement the technology as it requires two-way communication (read and write) with the BAS. In highly protected networks such those in government facilities, custom solutions may need to be defined – although once defined they can be replicated across properties. Once the system is up an running, results from the field installations in this study suggest that the connectivity between the on-site gateway and the BAS or cloud can be somewhat brittle to power outages, power disconnects, and network addressing changes.

5. Discussion

In general the savings achieved by the demonstrated MPC technology in this field study, at 0-9%, are lower than the results reported in previous simulation and experimental studies of similar technologies for AHU/VAV systems (Platt 2011, West 2014, Bengea 2015, Li 2015, and Liang 2015). In addition to longer testing periods in this study, and the different optimization algorithms, there are three potential causes for the difference in savings.

1) Non-idealized system conditions: As described in Section 4.1.3, in one building the systems were not well tuned or operating properly upon adoption of the MPC, and in another building operational and mechanical issues led to poor controllability preventing realization of the optimized setpoints from the MPC algorithm.
2) Complexity of baseline control strategies: At all sites (Table 1), the AHU or RTU supply air temperature setpoints are reset between minimum and maximum limits based on variables representing the actual loads within the spaces. One site implemented a reset strategy for the duct static pressure setpoint as well. Reset is proven to be more efficient than strategies that use fixed value settings, thus the already some-what optimized baseline control limits the savings percentage. Similar constraints are noted in Ma (2011) which documents relatively small MPC savings due to an effective control baseline, whereas Liang (2015) documents 28% savings relative to a *fixed* AHU SAT baseline control strategy. Finally, three sites in this study had specialized control requirements (space pressure, space humidity, and minimum chiller flow) that impacted efficacy of the MPC.
3) Control variables optimized: The MPC product evaluated in this study provides optimized setpoints for AHU supply air temperature and duct static pressure. Other studies include the same and/or additional control variables such as AHU start on and shut off schedule (Platt 2011, West 2014), outdoor air damper position (Liang 2015, Bengea 2015), VAV terminal flow rate and reheat coil valve position (Bengea 2015, Li 2015).

The varying levels of MPC savings observed in this study suggest several opportunities to advance the state of knowledge and deployment practices in several areas. Expanding the scope of optimization to consider the most effective combination of optimized control parameters in more systems and their interactions could potentially drive deeper and more reliable savings. Robust optimization algorithms are needed to adapt to imperfect system conditions and special control needs. Furthermore, it will be valuable to document the conditions under which predictive control optimization can be expected to provide significant savings with respect to best practices sequences of operation. It is notable that demonstration site engineers, and contracted engineering service providers deemed each site in this study a suitable fit for the technology, with high savings potential in spite of the three factors described above.

Although results were mixed across the cohort of evaluation sites, the field study and site participants surfaced several recommendations to maximize success in implementing the type of technology in future:

- Solutions to accommodate cyber security requirements can be identified, but may take some time to define, and should be communicated to peers for replication.
- Ensure that the IT department, contractors, energy managers, and operations staff are all engaged, and clearly understand the scope and intent of technology installation and use - each has a critical role in ensuring smooth and timely installation and operation.
- Phase in the extent of administrative privileges that are granted to the supervisory controls over time, expanding as site operations staffs become increasingly comfortable with the system.
- Understand when system or equipment problems are not related to the optimization technology, to make sure these problems can be resolved by the appropriate contractors. There may be a (mis)perception that the optimization system is meant to resolve all aspects of HVAC system operation; however, there will still be need for standard maintenance and service support for areas outside the scope of the supervisory control system.
- Before beginning installation, document any known mechanical issues, collect mechanical system drawings, and document space usage details.
- Before initiating the optimal control policies, allocate resources to resolve all mechanical issues, as successful optimization and associated savings potential is severely challenged if systems are underperforming or not operating well.

6. Conclusions and Future Work

In this study, a commercially available MPC technology was implemented at four sites and evaluated over a period of 7 to 15 months. These sites represented a diversity of commercial building types, control strategies, and geographies, including a courthouse, school, hospital, and office. The evaluation was designed to assess energy and cost savings attributable to use of the technology, impacts on occupant comfort, and scale-up considerations to inform future adoption. Across the cohort of evaluation sites, HVAC savings following the implementation of the optimization system were mixed, ranging from 0-9%. Analysis of site operational data showed that occupant comfort was neither positively nor negatively impacted. At the site that was most successful in achieving savings were attributable to the implementation more aggressive and comprehensive AHU supply air temperature and static pressure reset strategies. In cases where savings were modest or not achieved, several factors were identified that could have compromised the technology’s effectiveness.

Complementing the energy and cost savings findings, key technology adoption considerations were identified in the course of the field evaluations. Modest time is required from building staff to support system installation, configuration, and tuning. However, the calendar time for implementation can be much longer, due to the lead-time to coordinate and schedule work amongst IT department, controls contractors, and the technology team. Data security and IT approvals are still challenges for technology implementation.

Taken as a whole, the detailed findings from the field evaluation coupled with guidance from the technology team indicate that the technology is best suited for application in large buildings such as offices and schools. Buildings such as hospitals that have specialized pressure and humidity requirements may be constrained in benefitting from the technology without changes to operational and control strategies in the affected areas. The technology performs best when HVAC systems are in good working condition, and can be exercised to achieve the full range of it's optimized setpoints - however It may not provide extensive additional savings over cases where best practice sequences of operation and reset strategies are already comprehensively implemented. The technology is not well suited for buildings without variable air volume controls. Organizations that are not able to integrate the activities of IT, facilities, and operations will be challenged to successfully install, maintain, and sustain ongoing value from the technology. Most sites reported that they would recommend the technology to their peers, but emphasized the importance of the success factors noted in the Section 5.

Future work is needed to continue publicly documenting field studies of commercialized optimization products to provide a deeper understanding of what today's technology is delivering and how it can be improved upon. From a practical standpoint of technology development, machine-to-machine integration presents further opportunity for advancement. For example, truly pervasive "plug-and-play" functionality is still being developed, as are solutions to automatically extract and semantically interpret data across diverse systems and data types. A convergence of the capabilities of fault detection and diagnosis systems and control optimization systems would provide beneficial streamlining for building operators and managers. It could also potentially offer and enhanced ability to ensure that operational design intent is correctly implemented and maintained over the duration of the operational stage in the building lifecycle.

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