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Innovations in Sensors and Controls for Building Energy Management

Research and Development Opportunities Report for Emerging Technologies

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Disclaimer

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List of Acronyms and Abbreviations

AEO	Annual Energy Outlook
AFDD	automated fault detection and diagnostics
ANL	Argonne National Laboratory
ARPA-E	Advanced Research Projects Agency–Energy
BACnet	Building Automation and Control Networks
BAS	building automation system
BEM	building energy modeling
BTO	Building Technologies Office
Btu	British thermal unit(s)
DER	distributed energy resources
DOE	U.S. Department of Energy
DR	demand response
ECM	energy conservation measure
EIA	U.S. Energy Information Administration
HVAC	heating, ventilating, and air conditioning
IEEE	Institute of Electrical and Electronics Engineers
ISO/IEC	International Organization for Standardization/International Electrotechnical Commission
IT	information technology
LBNL	Lawrence Berkeley National Laboratory
MEL	miscellaneous electric load
MPC	model predictive control
NREL	National Renewable Energy Laboratory
ORNL	Oak Ridge National Laboratory
PNNL	Pacific Northwest National Laboratory
quad	10^{15} Btu
R&D	research and development
VAV	variable air volume

Executive Summary

Sensors, actuators, and controllers, which collectively serve as the backbone of cyberphysical systems for building energy management, are one of the core technical areas of investment for achieving the U.S. Department of Energy (DOE) Building Technologies Office's (BTO's) goals for energy affordability in the national building stock—both commercial and residential. In fact, an aggregated annual energy savings of 29% is estimated in the commercial sector alone through the implementation of efficiency measures using current state-of-the-art sensors and controls to retune buildings by optimizing programmable settings based on occupant schedules and comfort requirements, as well as detecting and diagnosing equipment operation and installation problems (Fernandez et al. 2017).

Monitoring and control of building conditions and operations has advanced significantly, from the invention of the modern thermostat just before the start of the 20th century to the midcentury incorporation of direct digital control into devices, the introduction of open protocols and network communications at the end of the century, and finally the invention of cloud-based computing and additional advancements that have enabled remote operation and a proliferation of connected and intelligent devices in building automation. Despite this potential, however, two main challenges hinder widespread adoption of sensors and controls in building operations that can ensure savings for high-efficiency components and equipment (e.g., heat pumps, windows, and lighting devices), as well as additional savings from more sophisticated control architectures and algorithms.

First, centralized monitoring and control of operations through building automation systems (BAS) are prevalent in only 8% of floor space for small commercial buildings (<50,000 square feet) and 46% of floor space for large commercial buildings (>50,000 square feet) in the United States. This translates to 43% of the total floor space for the commercial building stock (U.S. Energy Information Administration [EIA] 2016). Similar to small commercial buildings, residential buildings typically do not have a centralized management system, although smart home assistants are beginning to take on this role. In the residential sector as of 2015, 41% of buildings had some type of programmable thermostat installed, but only 12% used the programmable functionality, and only 3% had a smart or learning thermostat that learns occupant behavior over time, eliminating the need for continual user activity (U.S. EIA 2017c). This number is steadily growing, with 40% of the 40 million thermostats sold in 2015 classified as smart (Parks Associates 2015).

Second, most centralized systems currently installed exclusively manage heating, ventilating, and air conditioning (HVAC). These systems are typically separated from control of other building end uses such as common area lighting and plug loads. For example, home energy management systems usually consist of programmable thermostats for central and single-zone space conditioning, rather than more holistic management across multiple loads and appliances. Even modern systems incorporate a limited range of inputs and prescriptively map these inputs to control strategies to meet occupant needs and sometimes save energy. Much of installed equipment in buildings today is also not capable of digital communication and control. These conditions result in approaches that are customized in nature with new devices managing their own operation through built-in capabilities and intelligence.

While efforts to embed intelligence in buildings that enable "smart" operations for energy management have proliferated in the past decade, they have generally lagged behind other sectors and applications (e.g., large-scale industrial process plants, automotive, aerospace) due to several factors. These include utilization in less operationally critical applications (e.g., occupant comfort instead of safety and security); the fragmented nature of the buildings market (e.g., owner-owned and tenant-occupied); the customized nature of incorporating intelligence into building equipment rather than integrating into the design process; and the diversity of systems configurations and limited modeling and integration capabilities of stochastic variables (e.g., occupants, weather forecasts). As such, building controls are still predominately designed to meet short-term thermal and ventilation loads and are rule-based and reactive, rather than adaptive and autonomous, in nature.

This document will inform the strategic direction of BTO in soliciting and selecting early-stage and innovative technology solutions to address these challenges. Researchers and decision makers within the broader community can also use this document as a blueprint to accelerate technology solutions for managing and optimizing operations of multiple building systems (e.g., HVAC, refrigeration, and lighting) at the whole-building level through connected and controllable loads with sufficient spatial and temporal resolution to minimize the provision of energy services while balancing external and sometimes misaligned stimuli (e.g., occupant comfort preferences, weather conditions).

As such, this document is organized around four interrelated focus areas that build from each other and are aimed at: (1) reducing the cost and improving the accuracy of sensing and submetering along with developing new sensing modalities (e.g., occupancy and building equipment health); and (2) optimizing replacements to rule-based controls over longer temporal periods (e.g., hours and days rather than minutes) and multiple spatial scales (e.g., occupant, zone, whole-building), as well as incorporating predictions (e.g., occupancy patterns, weather forecasts, equipment health) and current state information from which to learn and adapt.

The R&D focus areas examined are structured to address systems-level challenges prevalent across individual building end uses with a focus on integrated and coordinated approaches for monitoring and control at the whole-building level. The technical barriers that need to be addressed through 2030 for each of the priority areas (i.e., multifunction plug-and-play wireless sensor networks, advanced monitoring and data analytics, adaptive and autonomous controls, and occupant-centric controls) are summarized in Table ES-1 along with energy savings performance goals and the overall technical potential based on quantitative estimates using BTO's impact analysis tool, Scout. These estimates are calculated using energy conservation measures (ECMs) developed from energy savings results in the literature.

Evaluations of enabling technologies such as sensors and controls, whose impacts are at the systems level, are more challenging to properly attribute compared to component-based technologies. Scout translates simulation-based measure end-use savings estimates to a national scale using a consistent national building energy use baseline, establishing a level playing field for considering improvements to individual component-based technologies (e.g., a more efficient heat pump or higher-insulating window) alongside systems-level efficiency improvements (e.g., a controls measure for more energy-efficient building operation). Quantitative estimates are coupled with qualitative insights that account for technology characteristics not currently represented in the Scout analysis framework (e.g., ease of installation and maintenance through automation of the mapping, configuration, and commissioning of supported technologies).

While energy savings goals are only presented for end uses where sufficient measured performance and baseline energy data are available for estimation and analysis, addressing the identified technical barriers will enable savings across multiple building loads (e.g., HVAC, lighting, plug loads). At a portfolio level, sensor and control technologies are anticipated to save 1.7 quads in 2030 and 3.6 quads in 2050 with further technological advancements and sophistication of the approaches identified in the priority research areas. This 2050 estimate is equivalent to roughly 10% of total energy consumption from the buildings sector in 2018. Peak reduction is also anticipated with studies to date showing that 10%–20% of commercial building peak load can be temporarily managed or curtailed to provide grid services (Kiliccote 2016; Piette 2007). As such, innovations in sensor and control technologies will enable the conversion of demand flexibility into the provision of grid services that will strengthen the integration between buildings, other distributed energy resources, and the electric grid. Furthermore, adaptive control architectures are important to resilience by offering a flexible framework with which to mitigate impact from cybersecurity threats and maintain operations. In total, adoption of next-generation sensor and control technologies could generate $18 billion in annual energy savings by 2030.[1]

[1] Based on Energy Information Administration's (EIA's) *2017 Annual Energy Outlook* (AEO) numbers.

Table ES-1. Technical Barriers for Priority Research Areas and Associated Goals for 2030[2]

Focus Area	Technical Barriers	Relevant ECM	Sector	Installed Cost Target[3]	Energy Savings Goal	Technical Potential[4]
Multifunctional Wireless Sensor Networks	• Enhanced wireless communications • Operational power lifetime • Accuracy and reliability • Modular design and materials cost reduction • IT system expansion • Automated calibration • Automated recognition and configuration • Flexible placement methods.	Plug-and-play sensors	Residential[5]	$29/node	17% (HVAC); 35% (Lighting)	1.14 quads
			Commercial	$57/node[6]		0.99 quads
Advanced Monitoring and Data Analytics	• High-accuracy hardware • Enhanced wireless communications • Modular design and materials cost reduction • Load disaggregation and nonintrusive monitoring • Automated fault detection and diagnostics (AFDD) • Long-term accuracy and calibration • Automated configuration with existing or new building automation infrastructure • Occupant/operator engagement and feedback.	AFDD and submetering	Commercial[7]	$0.14/ft² floor	30% (HVAC)	1.18 quads

[2] Calculated based on EIA AEO 2017 data using Scout tool.
[3] Cost premium based on 1-year payback period.
[4] Full technical potential assuming no competition with measures from other technologies.
[5] Based on all residential buildings; single/mobile homes use 0.0021 nodes/ft² floor and make up ~87% of all residential square footage (from residential EIA AEO 2017 microtables); multifamily homes use 0.0041 nodes/ft² floor and make up ~13% of all residential square footage (EIA AEO 2017 microtables).
[6] Based on 0.002 nodes/ft² for large office commercial building.
[7] Based on all commercial building types.

Focus Area	Technical Barriers	Relevant ECM	Sector	Installed Cost Target[3]	Energy Savings Goal	Technical Potential[4]
Adaptive and Autonomous Controls	• Whole-building, coordinated controls • Predictive and adaptive capabilities • Automated fault correction, tolerance, and resilience • Automated configuration and implementation • Continuous commissioning.	AFDD				
Occupant-Centric Controls	• Occupancy detection and comfort • Adaptive models and control algorithms • Long-term accuracy and calibration • Occupant engagement and feedback • Automated recognition and configuration with existing building automation infrastructure.	Occupancy detection and comfort	Residential[8]	$92/occupant	40% (HVAC); 60% (Lighting)	3.14 quads
			Commercial[9]	$49/occupant		1.49 quads

[8] Based on a single-family home.
[9] Based on a large office commercial building.

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1 Introduction

1.1 Importance of Building Energy Consumption

The U.S. buildings sector accounted for 39% (38 quadrillion British thermal units [Btu], or 38 quads) of the primary energy consumption in 2016, more than either of the other two end uses: industry (32%) or transportation (29%). Within the buildings sector, residential and commercial buildings were responsible for 21% (20 quads) and 18% (18 quads) of primary energy consumption, respectively (Figure 1).

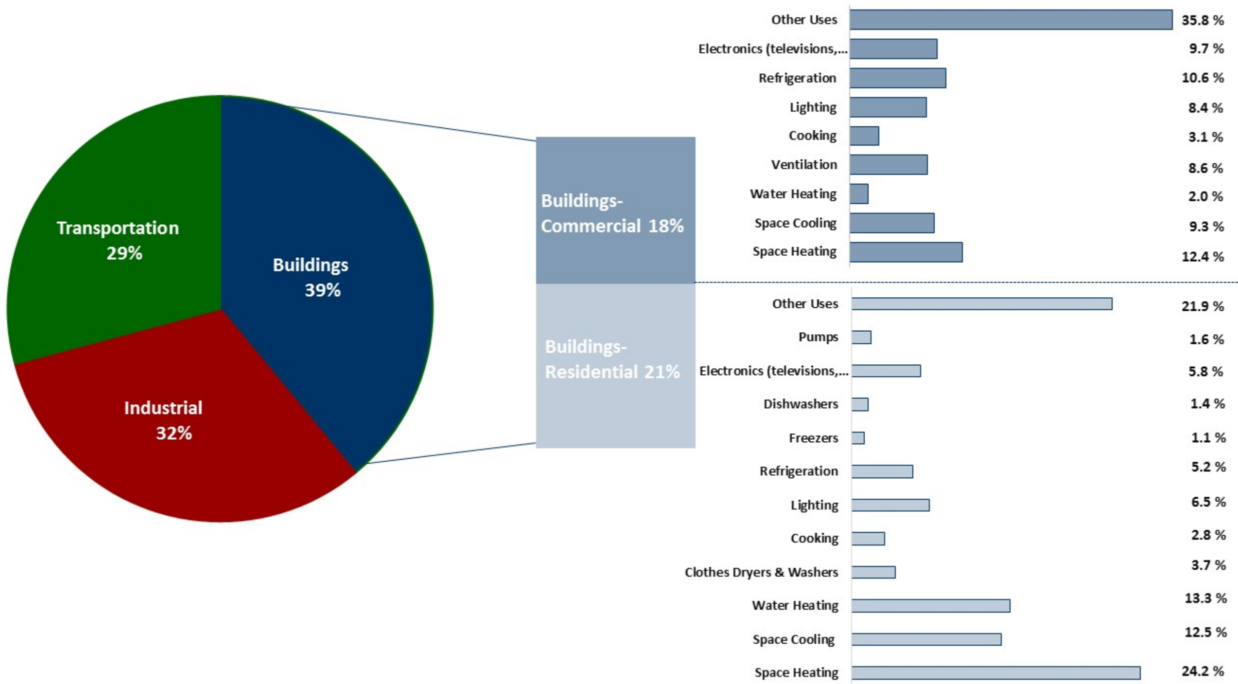

Figure 1. 2016 U.S. primary energy consumption

Source: U.S. EIA (2017a)

In both residential and commercial buildings, space heating was the largest category of energy end use in 2016 other than end uses labeled as "other."[10] Space conditioning (heating and cooling) along with lighting consumed 43% (equal to 8.7 quads) of total energy in residential buildings. In the commercial sector, space conditioning (heating, cooling, and ventilation) and lighting consumed 39% (equal to 6.8 quads) of the commercial building energy total. Overall, space conditioning consumed over one-third or 34% of total energy use in residential and commercial buildings combined (Figure 2). Lighting and electronics—which comprise plug loads such as televisions, computers, and related devices—as well as office equipment, consumed 7.4% (equal to 2.81 quads) and 7.6% (equal to 2.88 quads) respectively in residential and commercial buildings combined. The second largest consumer after space conditioning was the category of "other" end uses (28.4% or 10.8 quads), which includes plug loads not included in the electronics category and other hard-wired loads such as spas and automated teller machines. In the commercial sector, this "other" category consumed more than any other category (35.8% or 6.4 quads), including space conditioning. Refrigeration and water heating consumed 7.7% (equal to 2.92 quads) and 8.0% (equal to 3.02 quads) respectively in residential and commercial buildings combined. Refrigeration is the third largest consumer in the commercial sector after

[10] End uses labeled "other" include: for residential (small electric devices, heating elements, motors, swimming pool and hot tub heaters, outdoor grills, and any energy attributable to the residential buildings sector, but not directly to specific end uses) and for commercial (service station equipment, automated teller machines, telecommunications equipment, medical equipment, pumps, emergency electric generators, combined heat and power in commercial buildings, manufacturing performed in commercial buildings, and any energy attributable to the commercial buildings sector, but not directly to specific end uses).

"other" end uses and space conditioning (10.6% or 1.91 quads). Water heating is the third largest consumer in the residential sector after "other" end uses and space conditioning (13.3% or 2.66 quads).

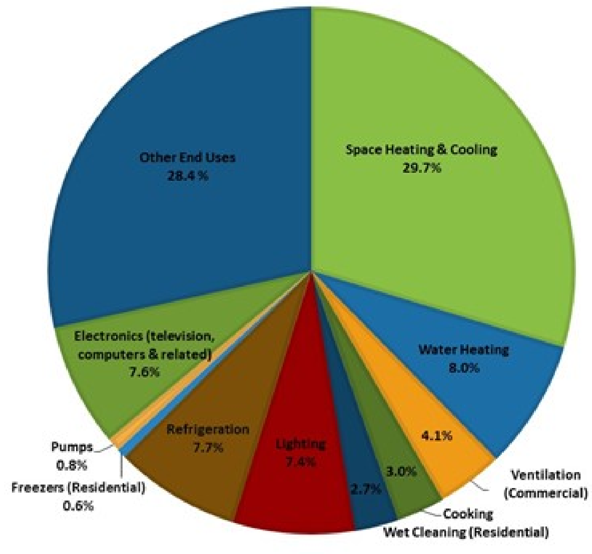

Figure 2. Breakdown of buildings energy consumption in the United States

Source: U.S. EIA (2017a)

Furthermore, electricity consumption from buildings—which includes the energy lost to generate and deliver it—has grown significantly, from 25% in the 1950s to 75% of U.S. electricity use in 2016 (see Figure 3), and even more of peak power demand. Another 4% is attributed to heating, ventilating, and air conditioning (HVAC) and lighting in the industrial sector.[11] Technologies that can reduce these losses are a key contributor to reducing total energy usage. Overall, building energy consumption represents an annual national energy bill of more than $380 billion, highlighting the economic importance for identifying and enabling technological advancements that can reduce usage and unlock opportunities for leveraging and investing the resulting financial savings for other purposes.

[11] 2010 Manufacturing Energy Consumption Survey, U.S. Energy Information Administration.

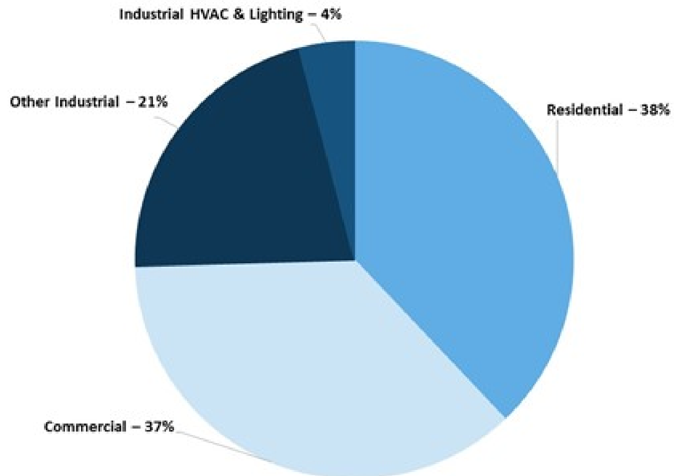

Figure 3. Total electricity sales for buildings—2016

Source: U.S. EIA (2017a)

1.2 Building Technologies Office

Research supported by the Building Technologies Office (BTO) is focused on reducing energy intensity and cost for technologies across the buildings sector, while maintaining or enhancing occupant comfort, productivity, and product performance. In essence, a building must use energy more productively and efficiently, not only use less energy. Progress toward achieving this goal will make building energy costs more affordable—especially beneficial to U.S. families and businesses.

BTO's approach to improving energy productivity includes its grid-interactive efficient building (GEB)[12] strategy, which advances the role buildings can play in energy system operations and planning. This strategy includes both new and existing residential and commercial buildings, including their energy-consuming and labor-saving equipment. BTO's strategy will support greater affordability, resilience, environmental performance, reliability, and other goals, recognizing that:

- Building end uses can be dynamically managed to help meet grid needs and minimize electricity system costs, while meeting occupants' comfort and productivity requirements;
- Technologies like rooftop photovoltaics, electrochemical and thermal energy storage, combined heat and power, and other distributed energy resources (DERs) can be co-optimized with buildings to provide greater value and resiliency to both utility customers and the electricity system; and
- The value of energy efficiency, demand response, and other services provided by behind-the-meter DERs can vary by location, hour, season, and year.

Developing next-generation building technologies, including building materials, components, equipment, energy models, and systems, is critical to increasing energy productivity cost-effectively.

[12] A grid-interactive efficient building is an energy-efficient building that uses smart technologies and on-site distributed energy resources to provide flexibility while co-optimizing for energy cost, grid services, and occupant needs and preferences, in a continuous and integrated way. For more information, see the recent *Grid-interactive Efficient Buildings Technical Report Series.* The *Overview of Research Challenges and Gaps* report can be found at https://www1.eere.energy.gov/buildings/pdfs/75470.pdf and contains introductory information as well as links to the other four technical reports in the series.

As shown in Figure 4, the complexity of the buildings industry extends beyond sector type (i.e., commercial versus residential), with variability across the building stock due to age and envelope type, building use, geographic climate, and occupancy. The commercial sector consists of 16 different building types based on their principal activity according to the Energy Information Administration (EIA). Space conditioning, ventilation, and equipment installation requirements and strategies are driven by the distinctions within each of these categories. These differences also need to be considered when researching and developing technological innovations to drive energy and cost savings and fulfill the BTO mission. Distinctions in research and development (R&D) approaches or areas of focus are also affected by these complexities. Examples include techniques for insulation upgrades or leakage detection in retrofit construction, occupancy detection and estimation for buildings with highly variable rather than fixed occupancy schedules, heat pumps for cold climates or dehumidification strategies, and high upfront capital cost investments in energy management systems for buildings with split incentives (i.e., landlord versus tenant). Given the slow turnover rate of the domestic building stock, BTO programs focus on developing new, energy-efficient technologies not only for incorporating into new construction, but also in retrofit applications.

As such, BTO has designed a multipronged approach across interdependent programmatic thrusts that focuses on high-impact areas with critical targets identified through rigorous techno-economic analysis and stakeholder input. Because the buildings sector consistently and significantly underinvests in R&D compared to the U.S. industry average, due in part to its highly fragmented structure highlighted in Figure 4, government investment in early-stage R&D of next-generation, high-impact technologies enables industry to develop and deploy affordable and energy-efficient advancements. Through technology validation and verification, BTO conducts building systems research to gain knowledge and understand physical phenomena that occur not only at the component or equipment level, but also at the whole-building level in real, operational buildings. Such insights can drive further innovation within the wide array of building systems and technologies, including heating and cooling, lighting, controls, windows, and the building envelope, all of which have their own technological and market complexities that need to be considered and explored. Each of these systems must be effectively integrated with each other for efficient operation, as well as optimal performance and occupant comfort. Design and decision tools help apply efficient operational practices and technologies through an improved understanding of their cost and benefits. Finally, BTO works with industry stakeholders to test and implement statutorily mandated efficiency standards. In addition, BTO evaluates changes in how to model building energy codes, which inform state and local building code processes.

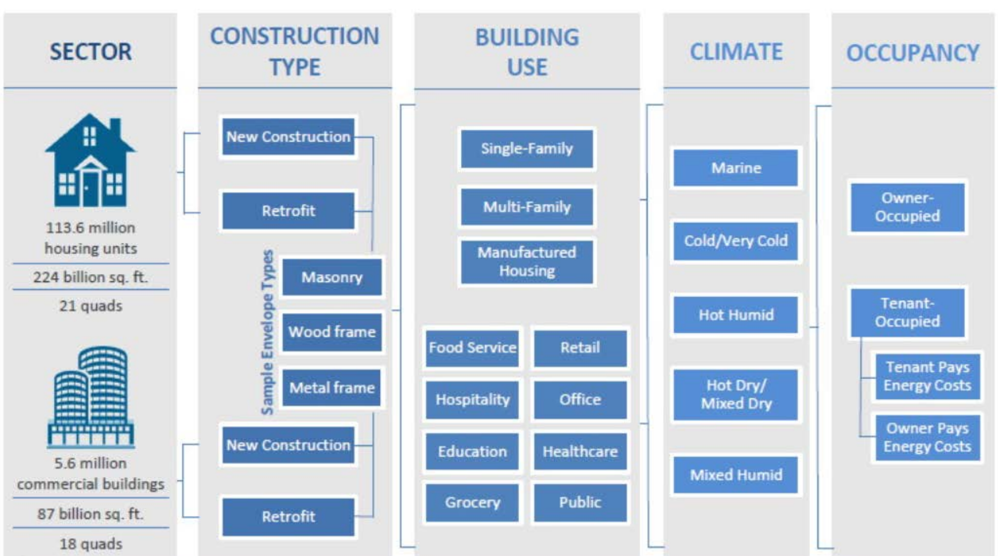

Figure 4. Complexity of energy use in the buildings sector

The focus of this report is on the opportunities for R&D in next-generation sensor and control technologies for intelligent building energy management that can be integrated with system-level validation and verification, as well as statutorily mandated efficiency standards and modeled building energy codes, all of which will ultimately contribute to BTO goals.

1.3 Building Energy Research & Development Program

The Emerging Technologies (ET) Program at BTO supports precompetitive, early-stage R&D in energy-efficient building technologies. The innovations supported through these efforts provide foundational insights to industry when defining new opportunities, in addition to enabling a range of industries in fields like building construction and renovation, as well as appliance and materials manufacturing to develop and deploy novel building technologies. Continual improvements in the performance and cost-effectiveness of building technologies will be key to the achievement of BTO's sectoral goals for 2030 and beyond. As such, the ET Program invests in the R&D of cost-effective, energy-efficient technologies for residential and/or commercial buildings through public–private partnerships with the DOE national laboratories, universities, industry, and small businesses.

In focusing on the opportunities to transform technologies that impact the largest energy-consuming building loads, the ET Program is organized around the core areas of solid-state lighting, HVAC and refrigeration (including water heating), and windows and envelope, along with the crosscutting enabling areas of sensors and controls, as well as building energy modeling. With the exception of sensors and controls along with building energy modeling, these areas represent more than half of building energy consumption (see Figure 2). Technology-specific targets are developed for these areas based on programmatic goals, as well as associated analysis and vetting with stakeholders (see Figure 5). Sensors, actuators, and controllers collectively serve as the backbone of cyberphysical systems for building energy management, enabling BTO's overall goals by optimizing programmable settings of energy-efficient equipment based on occupant comfort requirements, as well as detecting, diagnosing, and correcting equipment operation and installation problems. These systems also serve as the foundation for and are critical to advancing grid-interactive efficient buildings, an area in which the ET program and BTO as a whole maintain a growing interest. These efforts leverage BTO investments in transactive control methods for flexible building loads. Transactive control, which has been an active area of research over the past two decades, includes distributed control methods that use market mechanisms to allocate demand flexibility among autonomous building loads, model predictive controls (MPCs) to centrally manage building load flexibility, and other (e.g., hybrid) control methods to manage load flexibility for building and grid services.

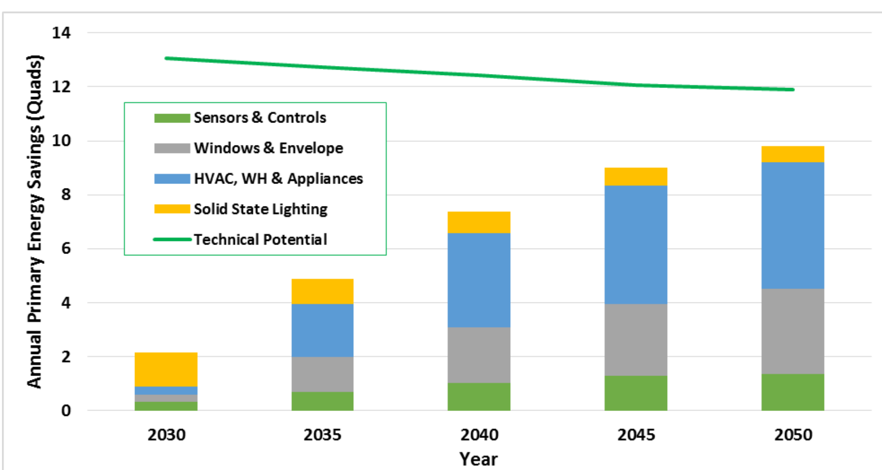

Figure 5. Annual energy savings from achievement of ET goals by technology

Source: DOE (2019c)

Going beyond BTO's historical investments in HVAC, refrigeration, and lighting loads, miscellaneous electric loads (MELs), both defined and undefined (e.g., consumer electronics), comprise a significant and growing portion of total building energy consumption. While this category consists of a large number of heterogeneous devices that each represent a small fraction of energy use, collectively their overall consumption also requires development and continuation of energy efficiency approaches, including advanced monitoring and control strategies. In fact, both total consumption and the share of building consumption from MELs is expected to increase between now and 2045, according to EIA (see Figure 6). MELs often include undefined loads classified within the "other" category in the EIA Annual Energy Outlook (AEO) because their consumption is too small to characterize individually and because stock, energy consumption, cost, performance, and lifetime data may not be available. As such, these loads are aggregated and modeled with less granularity in energy demand models such as the EIA National Energy Modeling System, which is used to produce the AEO. In fact, a portion of undefined loads consists of residual energy use based on a reconciliation of top-down supply-side modeling results from State Energy Data System, with bottom-up historical consumption estimates from the EIA building energy consumption surveys (Commercial Buildings Energy Consumption Survey and Residential Energy Consumption Survey), as well as commercial nonbuilding energy use (e.g., traffic lighting, street lighting, water/wastewater treatment, and cellular towers) not fully characterized in the National Energy Modeling System and residential energy use from select housing types (e.g., vacant homes, vacation homes, and common areas in multifamily buildings) not captured in the Residential Energy Consumption Survey. Improvements to both the National Energy Modeling System characterization of these end uses and consolidation of cost, performance, and lifetime data available in the technical support documents for covered products through the DOE Appliance Standards Program and other sources not currently included in the EIA AEO are underway to both develop energy savings goals similar to core end uses and better understand the technological approaches and strategies necessary to achieve those goals (Fares et al. 2018). While the emphasis of this document from the perspective of energy savings goals is on sensors and controls for space conditioning, ventilation, and lighting, due to current limitations on the data available for other end uses, the strategies outlined in this document are intended to serve as the basis for improved energy management of all building loads regardless of end use.

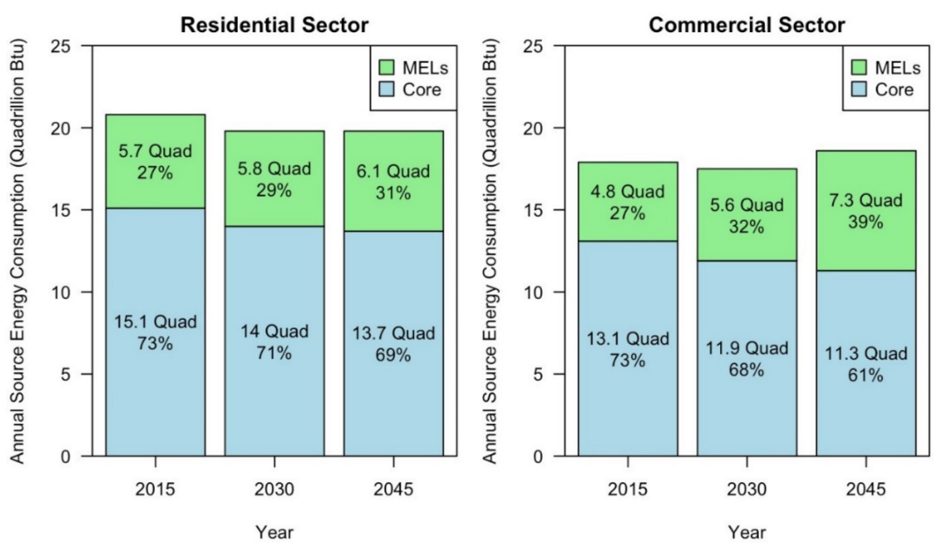

Figure 6. Total consumption and share of building consumption of miscellaneous energy loads

Source: Fares et al. (2018)

1.4 Building Technologies Portfolio Impact Analysis Tool

The complexity of the buildings sector, coupled with the unique opportunities and challenges of stand-alone building technologies and systems, also presents a challenge in the evaluation of the impacts of candidate energy efficiency technologies at an aggregated national scale. Technology-specific impact studies do not use comparable assumptions about the underlying building stock, which complicates the normalization of results for comparison. To address this need, BTO has developed Scout, a comprehensive analytical tool that assesses and compares a variety of available buildings-related energy efficiency technologies and activities and projects their potential value in future years using a common analysis approach (Harris et al. 2016).

The Scout tool is used by BTO to inform its programmatic strategy, investments, and goal setting by identifying impactful technology areas and setting performance and lifetime targets for technologies in those areas to create a portfolio that can meet overall BTO energy savings goals (see prior section).[13] Scout, which is under active development using an open-source license and the Python programming language, can be downloaded for use by interested stakeholders, including decision makers, researchers, and technology developers, among others.

Scout's full analysis methodology is described in detail elsewhere.[14] In short, Scout calculates the potential national-scale impacts of building energy conservation measure (ECM) adoption on baseline building energy use projections, drawing baseline projections out to 2050 from the EIA AEO. Impacts examined include primary energy use, carbon dioxide emissions, and operating costs. An ECM (or "measure") improves the energy efficiency of a comparable baseline technology or approach by achieving a higher equipment performance level (e.g., improvement in the coefficient of performance of an air-source heat pump) or through more effective systems-level operation (e.g., more energy-efficient HVAC operation through the application of advanced building control schemes). ECMs are primarily defined by their expected market entry and exit years, unit performance level, installed cost, and lifetime. The Scout analysis engine compares these cost, performance, and lifetime characteristics of the ECM against those of a comparable baseline building technology serving the same baseline energy use segment (or "market"); note that comparable baseline characteristics change across the projection horizon while the characteristics of each ECM definition remain constant. The current and projected energy consumption of each applicable baseline segment are updated to reflect the magnitude of the ECM's unit-level energy performance gain relative to the baseline technology, ultimately yielding the national energy savings potential from the proposed ECM.

ECM impacts are modified by their adoption potential using two scenarios: (1) a technical potential scenario, which assumes that as soon as an ECM is introduced, the entire baseline market instantaneously and completely switches to the new ECM, and the ECM retains a complete sales monopoly in subsequent years; and (2) a maximum adoption potential scenario, which assumes an ECM is only able to capture the portion of its baseline market associated with new construction and retrofit or replacement of existing equipment in a given year.

Adoption scenarios are further distinguished by whether they account for competition across ECMs that apply to the same baseline stock segments (a "competed" case) or consider each ECM in isolation (an "uncompeted" case). Here, ECM competition ensures that impacts are not counted twice across an ECM portfolio. Specifically, a market share is calculated for ECM using a logistic regression approach in the residential sector and a cost model in the commercial sector, adapting the approach EIA uses in the AEO. In general, both approaches assign market shares based on tradeoff between incremental capital and operating costs—ECMs with lower incremental capital costs and higher operational cost savings across their lifetime capture larger portions of competed market segments.

[13] www.scout.energy.gov
[14] See https://scout-bto.readthedocs.io/en/latest for full documentation.

Figure 7 provides an overview of Scout's workflow for defining and simulating ECMs, which involves the following steps:

1. Establish the initial ECM definition using a standard set of inputs (e.g., applicable market segments, market entry and exit years, initial energy performance, installed cost, and useful lifetime) and transparent data sources. Here, the applicable baseline market is defined by climate zone (e.g., hot and humid, cold), building type (e.g., hospital, single-family home), building vintage (e.g., new, existing), end use (e.g., heating, lighting), fuel type (e.g., electricity, natural gas), and technology type (e.g., heat pumps, sensors).

2. Finalize the ECM definition by integrating additional available performance data (where applicable) and retrieving total baseline and efficient energy, carbon dioxide, and operating cost market sizes from EIA AEO Reference Case simulation output files; baseline technology characteristics (cost, performance, and lifetime) from AEO input files; and baseline technology characteristics (cost, performance, and lifetime) from AEO input files.

3. Simulate the impacts of each ECM as either a stand-alone measure ("uncompeted") or as part of a full portfolio of potentially overlapping ECMs ("competed"). These impacts are assessed under the multiple adoption scenarios described above, and the cost-effectiveness of each ECM's impact is assessed in parallel under multiple metrics (e.g., internal rate of return, simple payback, cost of conserved energy/carbon). Scout simulations ultimately yield both the annual and cumulative impacts of an ECM portfolio across several decades, allowing results to be broken down by climate zone, building type, and end use, and screened for cost-effectiveness.

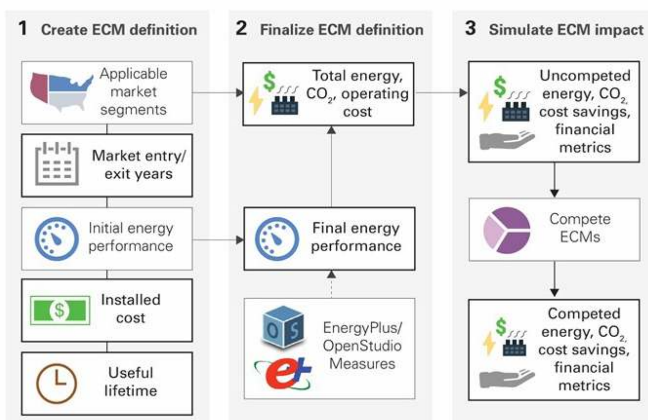

Figure 7. Analytical framework for Scout tool

Source: DOE (2019c)

Scout is utilized in this document to set unit-level cost and energy performance targets for next-generation building monitoring and control technologies given certain cost-effectiveness thresholds, as well as to estimate the national energy savings potential of these technologies for future years of interest. Additional details on the Scout analysis assumptions and applicable ECM definitions are provided in Section 3 and the Appendix. In general, impact evaluations for sensor and control technologies are more challenging than component-based technologies, as sensor and control technologies tend to enhance the performance of component technologies, and their impacts must be assessed at a system-wide level. Scout improves upon the capabilities of BTO's original technology impact assessment tool, known as the Strategic Prioritization Tool or "P-Tool" (Farese 2012), which was primarily designed for assessing traditional component equipment improvements at the technology level (see Appendix).

1.5 Role of Sensors and Controls in Building Energy Management and Demand Flexibility

Performance improvements to building system components and equipment (e.g., heat pumps, lighting devices) along with technological advancements in design and processing offer a significant opportunity to reduce building energy usage. The implementation of approaches to monitor and control these loads as integrated systems can ensure that these savings are achieved in both retrofits and new construction. Additional savings can also be achieved through R&D to enhance the sophistication of sensor and control technologies to respond to stochastic operating conditions (e.g., occupant preferences, weather conditions, peak electric demand) with sufficient temporal and spatial resolution. These strategies can also support the provision of grid services.

The use of sensors and controls to improve operations and minimize preventable energy losses in buildings is well documented. These studies, however, typically analyze only a specific building under a specific set of parameters (e.g., geographic region, season, type of controller). Discrepancies can also exist between simulated and actual operating conditions for specific case studies, limiting actual from estimated energy savings. Furthermore, studies that aggregate across multiple buildings only consider whole-building energy savings as opposed to delineating across individual or packages of ECMs (Mills and Matthew 2009). A comprehensive analysis of the commercial buildings sector was recently conducted by the Pacific Northwest National Laboratory (PNNL) and evaluated 14 building types representing 51% of the total floor space and 57% of the total energy consumption of the commercial stock (Fernandez et al. 2017). Overall, this study quantifies the potential for eliminating excess usage by optimizing programmable settings along with detecting and diagnosing operational faults. An aggregated annual energy savings of 29% of commercial building energy consumption or 4%–5% of overall U.S. energy consumption (i.e., 4 quads) is estimated by using current state-of-the-art sensors and controls to systematically and continually detect, diagnose, and correct operational problems (see Figure 8). Examples include adjusting set points and limiting space conditioning to when a building is occupied. More details can be found on the methodology and approach within the report itself (Fernandez et al. 2017). In summary, EnergyPlus®[15] models for prototypical buildings were used to simulate 34 ECMs both individually and as packages across the simulated building types for the 16 U.S. climate regions. Savings were estimated for each scenario based on three different penetration scenarios, depending on the prevalence and existing level of sensors and controls installed (see Figure 9). Limitations in available data and installation of monitoring and control strategies has precluded a similar study in the residential sector. Estimates for energy savings for individual strategies (i.e., connected thermostats, HVAC zoning, window covering control, occupancy-based lighting control, and circuit-level control) are calculated between 0.3–1.1 quads, or 1%–5% of residential energy consumption (Urban et al. 2016 and references therein). These savings are not aggregated because of the overlap between strategies (e.g., connected thermostats and HVAC zoning).

[15] https://energyplus.net

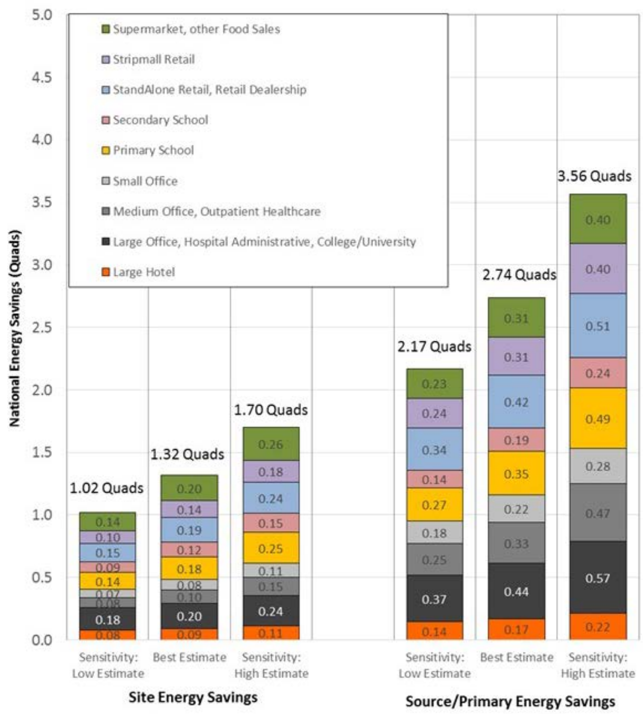

Figure 8. National energy savings potential for sensors and controls by commercial building use type

Source: Fernandez et al. (2017)

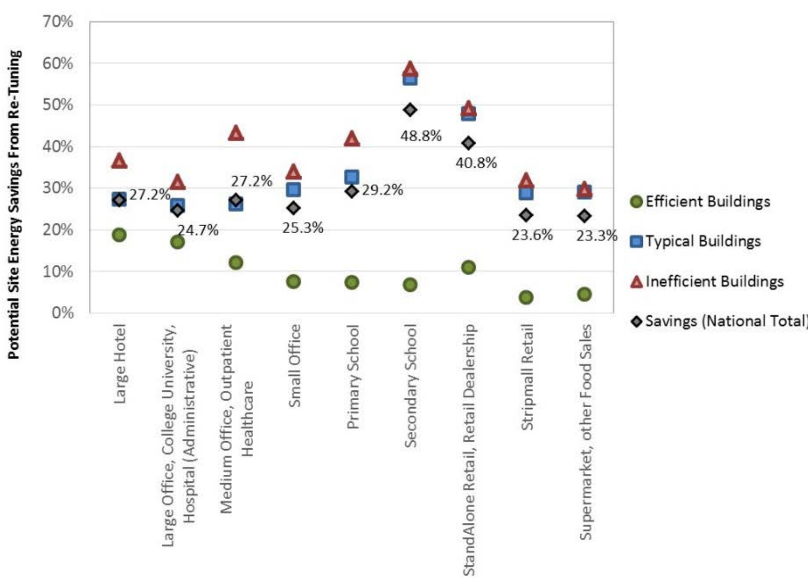

Figure 9. Savings from packages of monitoring and control ECMs for commercial buildings

Source: Fernandez et al. (2017)

Some form of control (e.g., on-off switching) is necessary for energy management in buildings. The variability and prevalence of control systems is largely dependent on the building type. More details on the different configurations for monitoring and control in both the residential and commercial sectors are provided in Section 2. The invention of the modern thermostat in the second half of the nineteenth century first introduced sensors and the actuation of controllers to building energy management by regulating and maintaining room temperature based on fixed set points (see Figure 10). Pneumatic-based controls were initially used for centralized multizone heating and cooling to balance energy consumption with scheduling and control. While the equipment being controlled remained pneumatic, the transition to direct digital control in the 1950s and 1960s enabled integration of multiple systems through the exchange of information and feedback between points. Subsequent development of wireless and network communication, open communication protocols, digital equipment operation, and cloud-based systems have been enabled through advancements in computing and allowed for embedding additional intelligence into control systems, including integration across loads and remote operation. A wide array of sensors (e.g., temperature, airflow, daylight levels) can now be used to monitor operating conditions. These measurements are then processed by device controllers to initiate the appropriate action (e.g., adjust temperature, airflow, light) through the corresponding actuators (e.g., dampers).

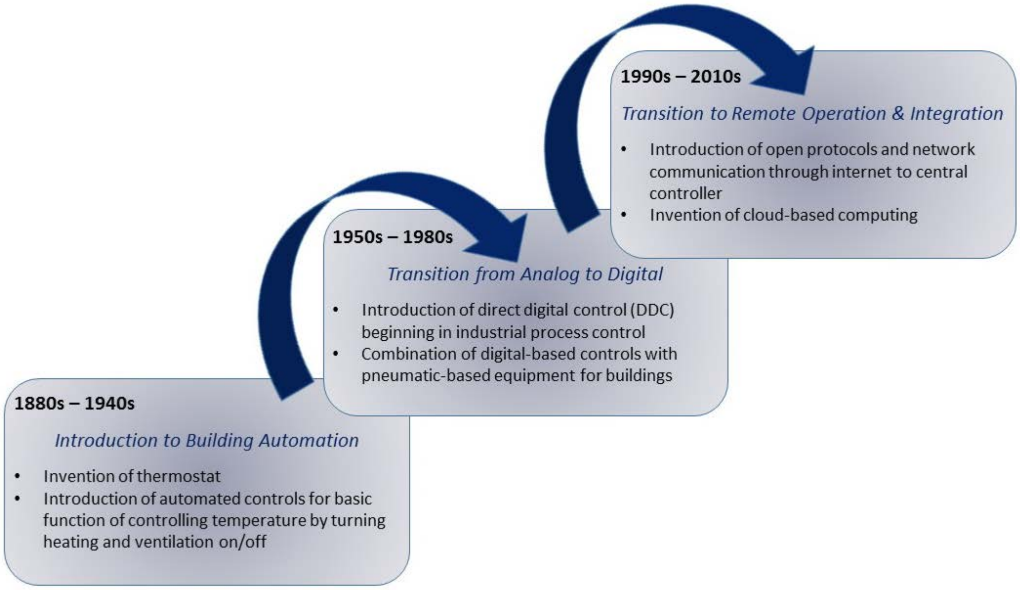

Figure 10. Historical evolution of building energy management

Building automation systems (BAS) consist of sensors and actuators that are centrally programmed using control logic to monitor and regulate operation of building equipment and systems in a coordinated fashion based on established set points. Regardless of their level of sophistication and loads controlled, these systems are broadly classified as BAS by EIA and include remote sensing and control elements along with software to monitor and interpret changes in building operating and/or environmental conditions. Other common terms, used interchangeably with BAS in this document and by others, are building control systems, building management systems, building energy management systems, and energy management and control systems.[16] Centralized management systems, however, are mostly found in large commercial buildings today and typically manage only HVAC with separate control of other building end uses such as common area lighting and plug loads. These current state-of-the-art systems are distinguished from previous systems by the use of computers to transmit information through communication links, or buses, and across layers from monitoring points to an operating terminal and control instructions from the operating terminal to actuators. Even these modern systems, however, still incorporate a limited range of inputs and prescriptively map these inputs to control strategies to meet occupant needs and sometimes save energy. As such, feature advancements targeted in this document include embedded intelligence, data collection, analytics, and both visualization and control of relevant loads and their energy use.

While efforts to embed intelligence in buildings that enable "smart" operations for energy management have proliferated in the past decade, they have lagged behind other sectors and applications (e.g., large-scale industrial process plants, automotive, aerospace). This is due to several factors that include utilization in less

[16] Energy management and control systems were used by EIA instead of BAS for the 2009 Commercial Buildings Energy Consumption Survey.

operationally critical applications (e.g., occupant comfort instead of safety and security), the fragmented nature of the buildings market (e.g., landlord versus tenant), the customized nature of incorporating automation and intelligence into building equipment rather than integrating into the design process, and the diversity of system configurations and limited modeling and integration capabilities of stochastic variables (e.g., occupants, weather forecasts). As such, building controls are still predominately designed to meet short-term thermal and ventilation loads and are rule-based and reactive, rather than adaptive and autonomous, in nature. Addressing these limitations through technological advancements will reduce the cost threshold and enable the anticipated energy savings from sensors and controls through wider adoption.

As cyberphysical systems, the hardware and software components are tightly interconnected and must be considered holistically when evaluating the optimization of operations. BTO maintains an R&D subprogram in this sector, and this document is intended to serve as a blueprint for ongoing and future activities for that subprogram. While the focus is on cyberphysical research and design for building energy management, the term “sensors and controls” is used to reflect the operations targeted. A full list of current and past projects funded by the subprogram is available online.[17]

Achieving the necessary intelligence to make buildings “smart” in their operations is dependent on advancements in both the design and standardized implementation of control logic. This includes integrating analytics (e.g., fault detection and diagnostics) at the whole-building level rather than simply monitoring individual equipment or loads. The replacement of rule-based algorithms (i.e., simple fixed reactions to certain conditions) with adaptive control strategies using data-driven and/or physics-based MPC approaches, along with modeling of dynamic conditions characteristic of buildings, will permit more optimized control. A feedback loop is necessary through enhanced analytics to interpret information collected from low-cost sensing and submetering, reach conclusions, and take action autonomously with sufficient temporal and spatial responses. Improving the accuracy of model inputs must be balanced with minimizing computational time as a function of maximizing energy savings. Ease of integration is dependent on automating the mapping, configuration, and commissioning processes for devices and controllers, as well as considering controls systems during the initial stages of the building design process. Finally, the building type and existing infrastructure will dictate the controls strategy and determine the optimal level of intelligence and sensing parameters required to avoid redundancy or unnecessary computational resources.

In addition to supporting energy efficiency measures, sensor and control technologies are also necessary for implementing flexible, grid-interactive strategies to further reduce and shift electricity consumption of buildings in order to minimize costs for customers and utilities, relieve system stress, and integrate renewables. This is beneficial because buildings are the primary driver of electric demand by not only consuming 75% of electricity, but also driving 80% of peak demand. Demand response (DR) is a well-established method for matching customer demand from the building with supply from the grid by altering when buildings consume energy to provide services to the grid (e.g., frequency regulation) or to respond to dynamic prices (e.g., load shedding during peak demand) (Parmenter et al. 2008). In comparison to efficiency strategies that are insensitive to timing and primarily aim to reduce cumulative building energy consumption on an annual basis, DR focuses on using energy when it is less valuable instead of using less energy to provide cost savings. The use of DR, which is implemented through a building’s smart thermostat or BAS, requires effective tuning of load control and selection of measures to maintain acceptable occupant comfort and limit peak shifting from excessive anticipatory DR responses (e.g., precooling) that can result in a peak higher than the original. Balancing load shaping over longer timescales with occupant comfort levels requires optimizing building control set points. Access and response to more accurate load forecasts are enabled by data obtained from sensors and meters along with supporting analytics used to optimize more advanced control strategies. At least 3% peak demand savings is reported in at least one commercial building type for 9 out of the 37 ECMs evaluated in the PNNL study of the energy savings impacts of current state-of-the-art sensor and control technologies (Fernandez et al. 2017). Over 10% savings is estimated for four of the nine measures.

[17] https://energy.gov/eere/buildings/listings/sensors-and-controls-projects

Furthermore, during the commonly implemented DR measure of critical peak pricing where the change in electricity consumption can be significant (i.e., up to 5%–6% increase for precooling), an aggregated 19% savings is estimated for both reactive and predictive packages of measures (see Figure 11). Measures that support ancillary services were not analyzed because their required rapid response is difficult to model with EnergyPlus. Previous studies have shown that 10%–20% of commercial building peak load can be temporarily managed or curtailed to provide grid services (Kiliccote 2016; Piette 2007). Demand response is a sizable resource with nearly 10 million customers providing 35.9 GW of demand response capacity in 2016 and 11.8 GW successfully deployed to reduce the annual system peak in 2016 (U.S. EIA 2017b).

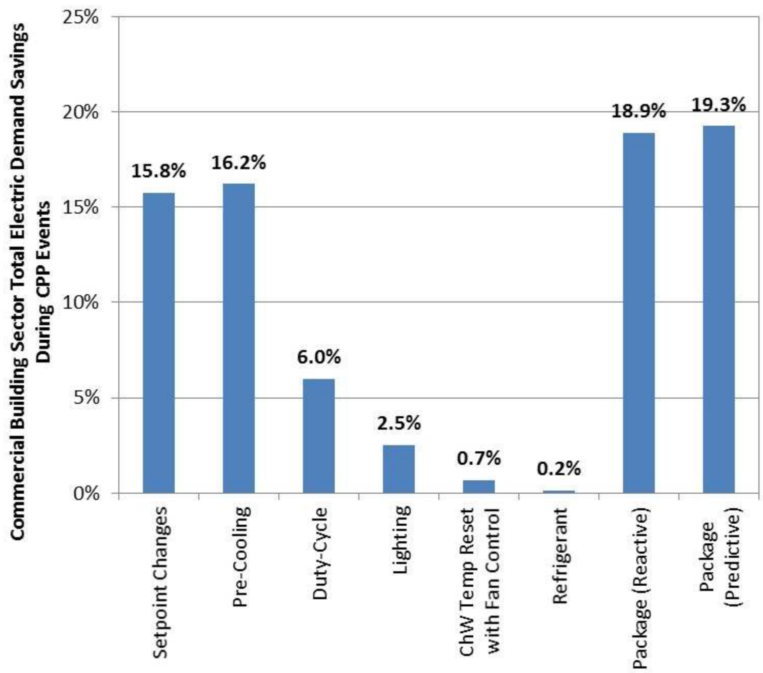

Figure 11. Aggregate national savings from demand response

The goal of the BTO sensors and controls subprogram and this document is twofold. The first is to improve the performance features of sensor and control technologies to accelerate the transition from open-loop systems designed for managing short-term building operation requirements to closed-loop systems that balance energy use alongside operations and environmental conditions to increase efficiency at a whole-building level while improving occupant comfort. The second is to support affordability of these systems by addressing scalability challenges to achieve cost reduction and energy savings on a national scale. Through R&D of cost-effective, high-performance sensor and control technologies that improve data collection and optimize building operating conditions, as well as effectively integrating building loads with the electric grid, building energy management and demand flexibility should be optimized.

1.6 Document Organization and Purpose

This document is intended to serve as an R&D blueprint for the optimization of systems at the whole-building level through connected and controllable loads for increased energy affordability, improved occupant comfort, and enhanced provision of grid services. Addressing the opportunities and barriers inhibiting progress will ultimately reduce electricity and utility costs for building owners and tenants. A comprehensive snapshot of relevant areas is presented that will inform the strategic direction of BTO in soliciting and selecting early-stage and innovative technology solutions in support of achieving its mission and goals. This document can also help guide researchers and decision makers to accelerate development and adoption of these next-generation technologies. As a result, this R&D plan is intended to be a living document that will require a concerted effort by all stakeholders to meet the goals laid out.

Section 2 of this document provides an overview of the current state-of-the-art for monitoring and control technologies in the building energy management sector, including a characterization of the buildings sector along with applications currently utilizing monitoring and control strategies.

Technology action plans are presented in Section 3 for the emerging strategies examined. Energy savings performance goals are calculated for each of these priority areas with timelines for technology development based on achieving these savings. The building sector type (i.e., commercial versus residential), along with the level of existing automation already installed, impact these goals and their subsequent cost targets. For this reason, certain performance features described will not be as impactful or necessary in all building types. A common theme throughout this document is the crosscutting nature of sensor and control solutions for buildings. The focus areas examined are structured to address systems-level challenges prevalent across individual building loads with a focus on integrated and coordinated approaches for monitoring and control at the whole-building level. With few exceptions, the focus is not on specific end-use strategies (e.g., low-cost, high-performance automated shading for space conditioning). Some emphasis is placed on HVAC applications as a case study due to several factors. These include the overall fraction of building energy usage attributed to space conditioning and ventilation compared to other loads, the higher levels of penetration of existing control technologies in HVAC, and the greater complexity of the HVAC systems themselves. While component-level innovation is important to advancing building energy management, it is outside the scope of this document because performance targets and overall prioritization will be dictated by the building use type (e.g., office or hospital) and configuration (e.g., installed equipment, applicable loads), as well as existing infrastructure and strategies for monitoring and control of operations. For this reason, control architectures are also not specified (e.g., centralized, distributed, agent-based). Instead, foundational development that can facilitate more efficient operation and widespread adoption is explored.

Many solutions (e.g., data analytics) are quick to market and require identifying market barriers to ensure early-stage R&D remains relevant and timely. Furthermore, a technology's ability to deliver grid services is defined by how quickly it can respond to utility signals and the resultant shape it is able to create in response. Integration of sensors and controls will enable a full array of flexible building technologies to be better harnessed for grid services. Section 4 provides an overview of these types of opportunities and challenges that need to be addressed to effectively implement sensor and control strategies across the buildings sector.

Formulation of this report builds on programmatic thrusts of the BTO R&D subprogram in sensors and controls. This document, which includes an update to the subprogram strategy, an action plan for implementation, and anticipated energy savings goals and associated cost targets in accomplishing this strategy, is the culmination of a collaborative effort with input and feedback from stakeholders and prominent leaders throughout the building automation and energy management ecosystem.

2 Overview of Energy Management Technologies in Buildings

2.1 State-of-the-Art in Monitoring and Control of Building Operations

Monitoring and control technologies are broadly utilized in applications spanning the consumer, medical, industrial, and automotive industries. The supply chain itself is also equally expansive and includes discrete component manufacturers, chipmakers, algorithm and software developers and vendors, service providers, control engineers, and building operators. Within the buildings sector, sensors and meters monitor and detect changes in variables affecting occupant comfort, as well as building performance and equipment operations such as energy and power consumption; temperature; light; occupancy and vacancy; indoor air quality and gas concentration levels (e.g., humidity, carbon dioxide, carbon monoxide, and volatile organic compounds); air, water, and other liquid flow and leakages (e.g., refrigerants). According to Navigant Research (2016), the market for advanced sensors in intelligent buildings was $1.2 billion in 2016 and is expected to double to $3.2 billion in 2025. Building controls, consisting of algorithms and computer logic, respond to input(s) from monitoring technologies to change environmental or operating conditions of building equipment loads or systems (e.g., lighting, windows and shading, ventilation) through a combination of controller devices and actuators. Overall, a control system consists of sensor packages with transducers to measure changes to the variable of interest, controllers to receive communication about these changes from the transducers and calculate the appropriate response, and actuators to transmit the output signal from the controllers to initiate changes in the controlled devices. Control systems with multiple devices and loads that need to be coordinated can consist of different configurations or architectures. Specifically, they can either operate with a single centralized controller or with smaller distributed nodes that coordinate across neighboring devices and that react autonomously to detected changes in their local environment. Advancements in other sectors have been and continue to be leveraged to focus on solutions to challenges specific to the buildings sector. Overall, the market for BAS products and services in the commercial buildings sector is expected to increase from $67.1 billion in 2016 to $102 billion in 2025 (Navigant Research 2016). Furthermore, the overall buildings market, including both residential and commercial, is expected to grow for building automation at a compound annual growth rate of 9.52% from 2017 to 2021, according to Technavio.[18]

2.1.1 Sensor Networks

Sensors in buildings can either be wired—where power is received from a building's electrical distribution network—or wireless, with an on-board electric power source to operate the necessary memory, processing, and communications hardware. Because they are typically concealed within the walls, floors, and ceilings of a building, wired sensor networks can be costly and difficult both to install in remote or inaccessible locations and to reconfigure after initial installation. However, wired sensors are also more reliable, less prone to disruptions and interference, and exhibit longer service lifetimes. Although the overall costs may be high due to additional labor and materials (i.e., wires and connectors) for installation, wired sensors themselves also tend to be less expensive than their wireless counterparts (Cree et al. 2013). Wireless sensor node prices can be an order of magnitude higher than wired sensors that serve the same monitoring purpose (i.e., current installed cost points up to $250/node). The installed cost includes the cost of the nodes, wireless gateway, associated software, and assembling the network and connecting to a BAS or centralized system. The total labor for installing a wireless sensor network in a building can be up to 7–8 hours (Kintner-Meyer and Brambley 2006). Compared to their wired counterparts, however, wireless sensors provide greater versatility in node installation.

Wireless sensor nodes consist of four units, as depicted in Figure 12: the sensor unit, which is composed of the sensor(s) or transducer(s) themselves that take measurements and convert measured signals into electrical signals; the power supply and management device, which monitors and regulates power from the source; the

[18] https://www.technavio.com/report/global-smart-buildings-market

microcontroller or processing unit, which converts electrical signals from the transducer into digital information; and the communication hardware, which consists of the wireless transceiver that transmits data for further processing by a central unit or gateway. For the purposes of this document, the term “sensor” will be used interchangeably with the terms “sensor node” or “package,” unless otherwise specified. In a wireless network, the four elements can be distributed between the sensor node and the centralized interrogator.

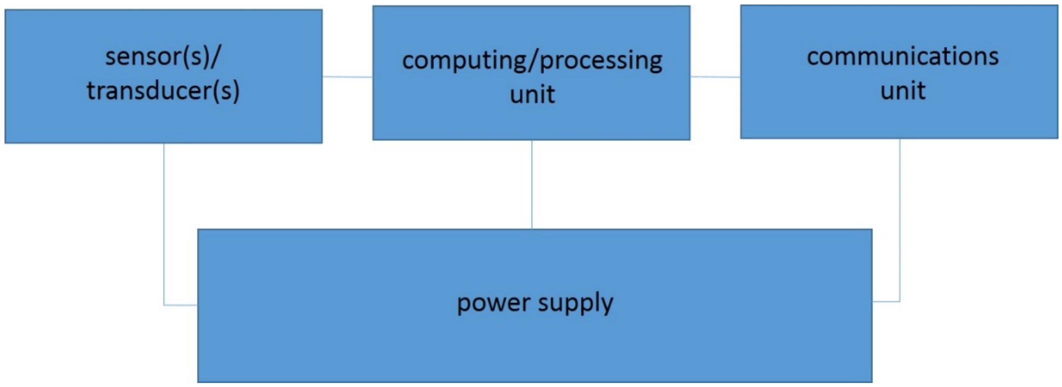

Figure 12. Wireless sensor node block diagram

Because wireless sensor nodes are self-powered, they have limited energy storage capacity and the lifetime of a node is typically dictated by its power supply. Limited-life batteries require replacement, which can be difficult depending on the placement of the sensor node and the added labor and maintenance costs. To address this challenge, a rechargeable storage element that includes capacitors or fuel cells can be utilized to supplement the battery, or the battery can be supplemented or replaced with an energy harvester such as photovoltaic, thermoelectric generator, or piezoelectric devices, together with an energy storage element. Depending on the source, either energy density (i.e., storage) or power density (i.e., harvesting) is the metric for characterization. Reducing the power consumption to extend the lifetime of the power source of wireless sensor nodes is necessary (Gholamzadeh and Nabovati 2008; Knight, Davidson, and Behrens 2008; Zahid Kausar et al. 2014).

The effective lifetime of the sensor node is limited if the power consumption of the node’s transducer, processor, and communications hardware is not optimized (Rault et al. 2014). The power consumption of the sensor node is dictated by the frequency of sensor measurements (i.e., number of samples per unit time) and the efficiency of data processing and transmission to the rest of the sensor network, which depend on the performance requirements for a specific sensing application. To reduce power consumption, for example, data filtering on the node can be employed so that only sensor readings of interest are communicated (Hempstead et al. 2008; Yick, Mukherjee, and Ghosal 2008). The communications unit is typically the primary source of consumption in the sensor node, in which activities such as idle listening or redundant communication—where multiple sensors within a similar distance generate and transmit the same data—need to be minimized due to the resulting energy loss. Therefore, an effective low-power design of the wireless sensor network and management of communications to overcome the constraints and meet the requirements of building applications are active areas of research, which includes on-duty cycling, data fusion, utilizing appropriate routing protocols, reducing network traffic, and optimally placing sensor nodes (Shu, Halgamuge, and Chen 2009; Rodrigues, Cardeira, and Calado 2010; Fafoutis et al. 2014). For example, medium access control protocols, which establish communication links between nodes and regulate access to shared wireless channels by multiple nodes, can be utilized in reducing power consumption.

Current ranges for commercially off-the-shelf low-power wireless networks are 100–300 m for bidirectional communication (i.e., transmission and reception). Actuators do not typically face the same power lifetime challenges as wireless sensors because they are connected to or embedded into the electrical equipment they control. Commercially available wireless sensors today exhibit a degree of plug-and-play capability for calibration and communication with a building control system. These sensors must follow guidelines established by the Institute of Electrical and Electronics Engineers (IEEE) 1451, Smart Transducer Interface Standard, to allow for access of transducer data through a common set of interfaces whether the transducers are connected to systems or networks via a wired or wireless means. Furthermore, current state-of-the-art wireless sensor nodes are typically designed to utilize communication protocols adopted by the IEEE 1451.5 standard within the IEEE 802 family, including Wi-Fi, Bluetooth, and ZigBee (IEEE 2007), to communicate over the network. Protocol selection depends on the amount of information that needs to be communicated and the wireless distance over which the data must be translated. For a BAS application, wireless sensor networks must operate efficiently with low energy consumption and reliably with a low error rate of data delivery and low delay (i.e., latency and throughput), as well as be scalable, mobile, and safe (Burrati et al. 2009). The data acquisition network consists of the sensor nodes and a base station with the data distribution network composed of the wireless or wired communication systems. Connectivity is achieved if the transmission range or base station can be reached from any node. Advanced versions of wireless sensors may deploy and communicate over a mesh network that extends coverage, or the quality of service, without significant range limitations and can reroute when a single point or node fails (Grindvoll et al. 2012; Rodenas-Harraiz 2013).

2.1.2 Network Communications

The network stack of communication protocols (see Figure 13) consists of five layers based on the Open Systems Interconnection model through which data are communicated within a network of devices (e.g., sensors, actuators, controllers) and power consumption managed. Each node uses the protocol stack to communicate to one another and to the sink. The protocol stack also includes power, mobility, and task management features. The power management features are responsible for communicating across a network when the power level for a given wireless node is low. The mobility management feature monitors the route of node movement so that each node can balance power usage and task processing based on their neighbors. Finally, the task management layer schedules tasks and balances workloads. Within the protocol stack, the physical or bottom layer of lower-level protocols manage physical interactions of and interfaces to hardware devices. Medium access control protocols, mentioned in the previous section, are part of the data link layer that is responsible for ensuring reliable node-to-node connections in the network and establishing communication links for data transfer between nodes. Power saving modes of operation can be implemented through the data link layers. The network layer routes data supplied by the transport layer and manages power consumption by setting appropriate delay thresholds for relaying data. The transport layer maintains data flow to and from applications in the network by ensuring reliability and quality of data.

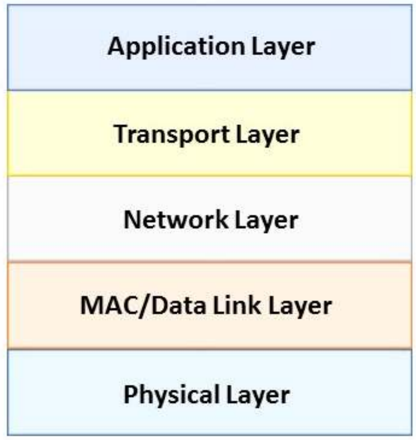

Figure 13. Protocol stack layers for wireless sensor networks

Source: Adapted from the Open Systems Interconnection model

Communication protocols for both wired and wireless networks buildings are summarized in Table 1, which follow versions of the Open Systems Interconnection model in Figure 13. The introduction of open protocols has allowed building management systems to communicate directly with disparate systems (i.e., HVAC, lighting, and security). Building Automation and Control Networks (BACnet), for example, is considered particularly flexible for future advancements due to its tiered network topology supporting multiple data link or physical layers (e.g., Ethernet, BACnet/Internet Protocol for communication between supervisory controllers, Master-Slave/Token Passing for communications between field and supervisory controllers, and LonTalk) and is independent of processor or programming language. LonWorks has less flexibility because it supports a single-link layer unique to LonTalk with a peer-to-peer architecture, but it facilitates interoperability because all supported devices use the same communications. In addition to specifying interoperability with other communication standards, some protocols can translate between different standards using vendor-specific gateways.

Recent advancements in network communications include incorporation of newly developed secured versions of protocols that previously did not include encryption (e.g., BACnet) by product vendors. The recently developed LoRa (Long Range) protocol is the first low-cost implementation of chip spread spectrum technology for commercial applications with long range connectivity (i.e., up to 10 km) through the management of data rates and latency. Additional improvements in communication performance will be enabled by the 5G network that will benefit building monitoring applications.

Table 1. Building Communication Protocols[19]

Protocol	Summary
Wired	
BACnet	• Widely used open protocol for BAS that is typically used in large commercial buildings with proprietary variants available across different bands • Established in 1995 and maintained by ASHRAE through ASHRAE/American National Standards Institute standard 136, International Organization for Standardization/International Electrotechnical Commission (ISO/IEC) 16484-5 • Uses a variety of networking technologies for communication and operates over various physical media (e.g., Ethernet, LonTalk, ZigBee) • Uses master/slave architecture and tree network topology • Specifies some security features, including encryption, but vendor implementation is not required
KNX/EIB	• Open standard based on ISO/IEC 14543 that is used for building control applications in both commercial and residential sectors • Uses tree network topology
LonWorks/ LonTalk	• Proprietary protocol for building control applications • Developed by the Echelon Corporation/Motorola and standardized as ISO/IEC 14908 • Uses peer-to-peer architecture • Messages sent without encryption but includes the ability to utilize a 48-bit authentication key when properly configured during installation
ModBus	• Widely used open protocol for industrial automation applications and some building control applications • Established in 1979 by Modicon • De facto standard for controller communications • Easy to implement and often used in communications for electrical devices such as meters and drives • Uses master/slave architecture • Does not support authentication and encryption.

[19] http://www.bacnet.org/Bibliography/AJ-6-2008.pdf
http://www.lonmark.org/
https://www.setra.com/blog/what-is-the-difference-between-bacnet-modbus-and-lonworks
http://www.simplymodbus.ca/FAQ.htm
http://www.tomsguide.com/us/smart-home-wireless-network-primer,news-21085.html
https://www.rs-online.com/designspark/eleven-internet-of-things-iot-protocols-you-need-to-know-about
https://www.bluetooth.com/
https://www.enocean-alliance.org/
http://threadgroup.org/
http://www.zigbee.org/
http://z-wavealliance.org/

Wireless	
Bluetooth	• Widely used for short-range (<10 m) communications • Consumes less power than Wi-Fi (<0.01 W) but has lower transfer speeds (~1–3 Mbps) • Master/slave architecture
Bluetooth Low Energy (BLE)	• Based on Bluetooth for devices that do not stream data continuously • Remains in sleep mode constantly unless a connection is initiated, reducing power consumption by 50%–99% and allowing for over one year of operation without charging
EnOcean	• Used in both homes and commercial building automation systems • Developed by the EnOcean alliance in 2008 and standardized as ISO/IEC 1453-3-1X and operates in sub-1 GHz frequency bands • Relies on energy harvesting technology • Supports mesh, point-to-point, and star networking technologies
Ethernet	• Low cost and widely used for communication between programmable logic controllers, supervisory control, and data acquisition in area networks (local area network (LAN), metropolitan area network (MAN), wide area network (WAN)) • Originally developed by Xerox PARC in 1973 and formalized by IEEE.802.3 standard • Available on three physical media (i.e., optical fiber, shielded twisted pairs, and coaxial cables)
Thread	• Developed by Google/Nest labs • Based on IEEE 802.15.4 with similar capabilities to ZigBee but uses 6LoWPAN standard that allows communication between IEEE 802.15.4 and IPv6 (internet protocol v6) networks
Wi-Fi	• Utilizes IEEE 802.11 family of standards • High transfer speed/data rates (~1 Gbps), but relatively high-power consumption (0.1–0.8 W) • Peer-to-peer architecture
ZigBee	• Open standard most often used in homes and some commercial building applications • Developed by the Zigbee alliance with upper layer communication protocols based on IEEE 802.15.4 and operates in the 2.4 GHz and 900 MHz bands • Relatively low power (~0.001–0.05 W), low speed (~40–250 kbps), and short range (~10–100 m) • Along with star and tree network topology, can use a mesh that allows for scalability and improvement in data rates • Peer-to-peer architecture • Includes both authentication and encryption
Z-Wave	• Proprietary standard licensed by 450 companies and used in 1,700 products as of 2017 • Low power (~0.01–0.09 W), low speed (~100 kbps), and longer range (33 m) • Uses a mesh network topology that allows for scalability.

2.1.3 Occupancy Sensing

Occupancy sensors span a wide spectrum of cost and performance. Approaches to monitoring occupancy patterns in buildings can be classified based on the method used for data collection and acquisition of occupant presence and movement. These include direct physical measurements and indirect virtual measurements, where occupancy is inferred based on monitoring of other parameters (e.g., specific appliance usage). A third category of fusion approaches combines more than one technology to leverage the advantages of each while offsetting their respective disadvantages. In addition to these passive approaches, active methods exist that require direct occupant input (e.g., smartphones, tablets, or desktop/laptop computers).

Current state-of-the-art occupancy monitoring faces two main challenges. First, the most commonly installed sensors are based on either passive infrared or ultrasonic technology. These sensing modalities are only capable of detecting binary values (i.e., presence versus no presence) for nonstationary occupants and are prone to false positives and false negatives. Second, emerging sensing modalities (e.g., passive and active vision) that can estimate load based on the number of occupants are generally cost prohibitive (>$100/node) due in part to site-specific installation and calibration system requirements. Furthermore, errors in tracking multiple occupants due to limited field of view and spatial resolution need to be addressed for sensors while not introducing privacy issues. Proxy approaches, which infer occupancy information based on measurements obtained from BAS data streams (e.g., air temperature, radiant temperature, air speed, relative humidity, and control states such as damper valve position in a variable air volume (VAV) system) or occupant activity levels (e.g., Wi-Fi connections), are also limited in their relative accuracy. Current state-of-the-art carbon dioxide sensors, which are primarily based on nondispersive infrared techniques, can also serve as a proxy occupancy measurement, but are high cost (>$100/unit) and need occasional recalibration due to sensor drift.

In general, current state-of-the-art occupancy sensors are most common in the commercial sector, especially large commercial (>50,000 square feet) (see Figure 14) due to the presence of multiple zones and variable occupancy patterns. The most commonly deployed occupancy sensors are passive infrared sensors integrated into lighting systems for controlling on/off functionality (U.S. EIA 2016). Applications for space conditioning and plug load integration along with extending occupancy monitoring beyond presence detection have grown in recent years. Even with further advancements, however, these modalities (passive infrared and ultrasonic) will be mostly limited to the residential sector or lighting applications because monitoring of density and distribution of occupants is necessary for effective ventilation and space conditioning through precise temperature set point adjustment.

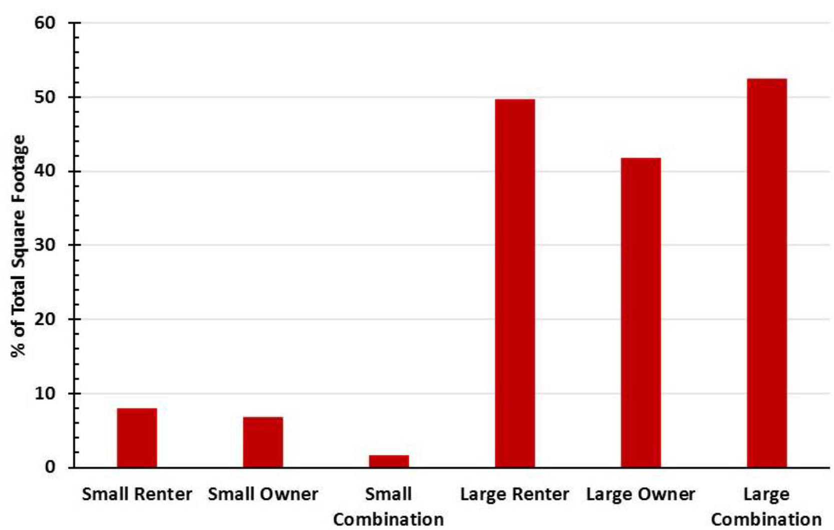

Figure 14. Occupancy sensors by commercial building type

Source: U.S. EIA (2016)

Occupant preferences along with actions or behavior are beginning to be incorporated into control strategies. Current research efforts are focused on a common ontology for representing occupant behavior to automatically integrate into building energy modeling (BEM) operations with limited manual intervention. The recently completed International Energy Agency Annex 66 developed a common framework for quantitative representations and classifications of occupant behavior; methods for occupant behavior measurements, survey, modeling, and evaluation; occupant behavior models in building performance simulation tools; and applications of occupant behavior models in design, evaluation, and operational optimization of buildings through a number of case studies (International Energy Agency 2017).

Comfort (both visual and thermal) is also a key occupancy metric for evaluating occupant behavior and incorporating into building control schemes (Nguyen and Aiello 2013). However, differences exist at an individual occupant level in terms of preferences and acceptable levels for both visual and thermal comfort.

Visual comfort, which is perception based, can be tuned by daylighting sensors that monitor natural illumination levels, lighting controls with on/off or dimming features, or automated shading controls. The building configuration and layout, along with the lighting (e.g., natural versus artificial) and window characteristics (e.g., position, size, number, glazing, and shading), will impact comfort levels.

Thermal comfort is also a complex measurement that depends on multiple variables. Currently, it is defined by four physical or extrinsic parameters (air humidity, air temperature, mean radiant temperature, and air velocity) and two subjective or personal parameters (clothing thermal insulation and metabolic rate). The latter are generally estimated by benchmarks for specific activities and building types. Comfort ranges are defined by ASHRAE Standard 55 for thermal environmental conditions for human occupancy and are assessed by the predicted mean thermal sensation vote (PMV) methodology on a scale of −0.5 to +0.5, where 0 is the target (i.e., neutral) (Fanger 1970). The defined comfort range is based on humidity and temperature levels over average time ranges of 3 to 15 minutes. Current state-of-the-art building controls typically rely on zone thermostats, which measure air temperature at a discrete spatial point, as their main feedback for providing zone-level space conditioning to maintain acceptable thermal comfort levels. Humidity and radiative temperature are not well accounted for. Similar to carbon dioxide sensors, humidity sensors experience drift over time due to absorption of particulates (Farahani, Wagiran, and Hamidon 2014). The spatial distribution of temperature and occupants across the zone, as well as skin surface temperature, are also not well incorporated. Recent results in the literature have demonstrated thermal comfort through surface skin temperature measurements (Lu et al. 2019). Localized comfort approaches have also recently been demonstrated that learn preferences from occupant inputs over time to adjust set points.

2.1.4 Metering

In addition to master meters that connect buildings to the electric grid to measure electricity consumption at the whole-building level, submeters at the circuit level and smart power strips or outlets at the plug level measure usage within a building by monitoring current and voltage with additional resolution in measurements (i.e., end load). Gas consumption is monitored by flow-based meters, and chilled and hot water and steam are monitored by flow- and temperature-based meters (sometimes called Btu meters). The transition from one-way communication through automatic meter reading to two-way communication through smart meters and advanced metering infrastructure offers additional energy management opportunities by not only communicating usage at up to 15-minute intervals, but also in receiving signals from the utility and/or remote operator to adjust usage. This information supports the provision of grid services and supplements BAS data to optimize energy management through nonintrusive load monitoring techniques (Zeifman and Roth 2011; Zoha et al. 2012). The number of smart meters installed in homes has almost quadrupled from approximately 18.4 million in 2010 to approximately 69.5 million in 2017. In the commercial sector, the number of installed meters has more than quadrupled from approximately 1.9 million in 2010 to approximately 9 million in 2017 (U.S. EIA 2018).

Submeters, which are classified into three main categories (see Table 2), are useful in energy management by influencing occupant usage patterns through more granular consumption data, facilitating measurement and verification of energy efficiency measures implemented, and identifying faulty equipment operations (see Section 2.1.5) through monitoring-based commissioning approaches explored in Section 3.5 (Ahmad et al. 2016). As such, submeters have already demonstrated reduced energy consumption in a number of case studies (NSTCCT 2011). Revenue-grade accuracy is set at a minimum of ±2% (American National Standards Institute c12.1-2008). Submetering can offer a more accurate alternative to nonintrusive load monitoring and disaggregating of whole-building level data to identify small loads with similar signatures or variable power draw while also being less intrusive than monitoring at the device level. Additional load disaggregation is necessary to identify loads that do not have their own dedicated circuit. Submetering can also be used to calibrate disaggregation algorithms for nonintrusive load monitoring.

Overall cost (>$400) is a hindrance to widespread adoption, mostly due to intrusive installation procedures and implementation of required safety measures and certifications (Ahmad et al. 2016; NSTCCT 2011).

Innovations in alternative form factors (e.g., split-current transformer or nonsocket clamp-on types) are reducing costs with less disruptive installation, but additional innovations are necessary to avoid sacrificing accuracy. The majority of materials cost associated with submetering is due to the connectivity hardware. Similar to sensors, enhancements in communication protocols and wireless capabilities (outlined in Sections 2.1.1 and 2.1.2) are contributing to cost reductions. Submeters, like sensors, can also benefit from innovations targeting the automation of the calibration and configuration processes to further reduce cost. Currently, recalibration of submeters is recommended every 3 to 4 years by the U.S. Environmental Protection Agency.

Table 2. Types of Current Submeters[20]

Technology	Description	Advantages	Disadvantages
Feed-Through Socket	Direct, physical connection between the supplying circuit, socket/outlet, and the selected end load	High accuracy and precision	Dedicated space in electric utility room required along with turning off power during installation
Current Transformer (CT)	Detects current along a wire or cable for loads whose current levels are too high (i.e., >400 A) for direct measurement	Traditional solid-core configuration is more accurate and less expensive than nonsocket alternatives. Split core configuration does not require shutting off power during installation.	Traditional solid-core configuration requires turning off power during installation and dedicated space in electric utility room. Split core configuration is more expensive and less accurate than solid core.
Stick-On	Nonsocket type, stick-on or clamp-on to front surface that senses emanated magnetic field	Ease of installation that does not require turning off power	Less accurate, not revenue grade, and does not include the necessary hardware connectivity to integrate into a BAS or software dashboard

2.1.5 Fault Detection and Diagnostics

The detection of faults in building operations and the identification of their root causes, otherwise known as fault detection and diagnostics, is necessary for eliminating approximately 0.3–1.8 quads of wasted energy in the United States each year in the commercial sector alone (Roth et al. 2005). Examples include conventional building equipment health monitoring where measurements from current state-of-the-art sensors (e.g., temperature, humidity, airflow rate, valve position, pressure) are used to detect faulty operation. Without automated fault detection and diagnostics (AFDD), faults can go undetected until routine maintenance is performed or the full effects are noticed by the building operator or occupants. AFDD, which is fairly mature in other sectors (e.g., industrial process control), was first introduced to the buildings sector in the 1990s (Braun 1999). With the growing reliance of network connectivity for building energy management, the AFDD methodology can be further extended to detect and diagnose faulty operations that limit potential savings stemming from malicious activity (e.g., cyberattacks) (see Section 4.2).

The AFDD process consists of three steps (see Figure 15). First, detection determines anomalous behavior. Second, isolation specifies the fault location, time of detection, and type of abnormality. Finally, identification determines the size and extent of the fault and evaluates its behavior as a function of time. As such, the same

[20] Adapted from NSTCCT 2011.

continuous monitoring and measurement for detecting, diagnosing, and correcting operational problems are also used for continuous or monitoring-based commissioning. Maintaining fault-free operations becomes increasingly important with added intelligence in buildings and sophisticated controls. While additional savings can be achieved through more intelligent controls that optimize a wider range of variables, the added complexity can also increase the risk for improper installation and operation, leading to additional faults.

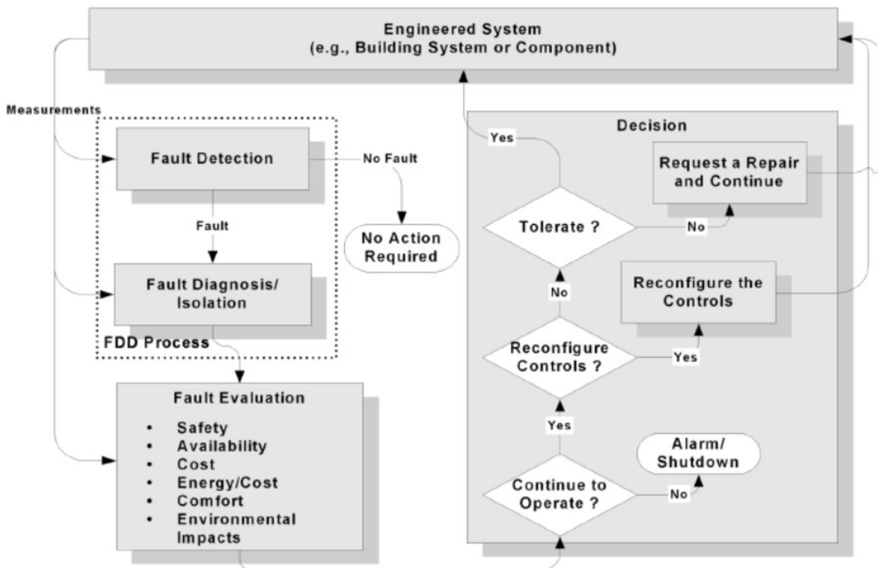

Figure 15. Framework for AFDD methodology

Source: Katipamula and Brambley (2005)

Faults can occur across a system, including sensors (e.g., drifting), dampers and valves (e.g., stuck open or closed), coils (e.g., blocked), and fans (e.g., belt slipping). In general, faults can be classified into two categories that are dependent on their root cause. The first includes hardware-related faults due to equipment degradation and/or failures (e.g., sensor drift or stuck damper). Software faults result from improper operation or configuration of the equipment itself or suboptimal implementation of control logic, including programming errors, incorrect settings, and schedules. The latter results from both errors and inconsistencies in the handwriting of sequences by mechanical engineers, as well as incorrect interpretation or translation by the programmer. These errors can occur during initial implementation, after renovation or repair, or when transferring customized sequences from one building to another. Common practice for identifying these types of faults is either through manual verification, which is costly and error prone due to the lack of standardized verification checklists and testing, or through AFDD. The challenge for AFDD with these types of faults is in the isolation process. The prevalence and severity of faults are dependent on the building and equipment type and configuration. In the residential sector, common faults include duct leakage, improper HVAC refrigerant levels (i.e., overcharging, undercharging, or leakage), and clogged air filters. In the commercial sector, AFDD processes are more common in large buildings (>50,000 square feet) than small buildings (<50,000 square feet) due to the overall expense associated with configuring, deploying, and maintaining AFDD software, along with the required BAS infrastructure. The prevalence of common faults in commercial air-conditioning units is estimated as 64% for economizer malfunction, 46% for improper charging, 42% for inadequate airflow, and 20% have failed sensors (Cowan 2004).

Methods for AFDD are classified into three types: qualitative model based, quantitative model based, and data driven (see Figure 16 for full classification within these categories) (Katipamula and Brambley 2005; Kim 2017). The most common method used in commercially available products installed in buildings is rule based. This method, which can be used both at the equipment level and the whole-building level, is based on a comparison of measured performance to a set of relational rules describing proper operation (i.e., thresholds). While the implementation of rule-based techniques is relatively simple and highly effective, this approach can be cost-prohibitive for many building owners due to the time-consuming nature and required engineering expertise for developing and tuning effective rules. False alarms or missed faults are generated if the threshold is not properly selected in relation to normal conditions. Furthermore, poor and limited instrumentation impacts feasibility of implementation of certain rules. As such, both quantitative model-based and data-driven techniques, as well as hybrid approaches, are emerging and active areas of research. Current literature for whole-building AFDD R&D consists of 38% black box, 25% gray box, 21% detailed physical models, and 17% rule based (Kim and Katipamula 2017). Measured energy consumption is compared against predictions obtained from a physics-based model for model-based approaches. The advantages to this approach are that fewer sensors are needed because the model can infer information from high-level data, and it is easier to tune the algorithm to minimize false positive because the primary detection criterion is deviation from expected energy consumption. Unfortunately, accuracy is dependent on the accuracy and quality of the model selected, which can be cost prohibitive due to the computationally intensive nature of model generation and tuning. Finally, data-driven approaches rely on training data to identify mathematical relationships between measured inputs and measured outputs for fault detection. While this approach is less cost prohibitive because it requires less information about the building physics and engineering, collection of a large amount of historical data is nontrivial, extrapolation beyond the range of the available data is limited, and any faults present in the training data itself cannot be detected because there is no comparison to a reference for proper operation (Frank et al. 2016).

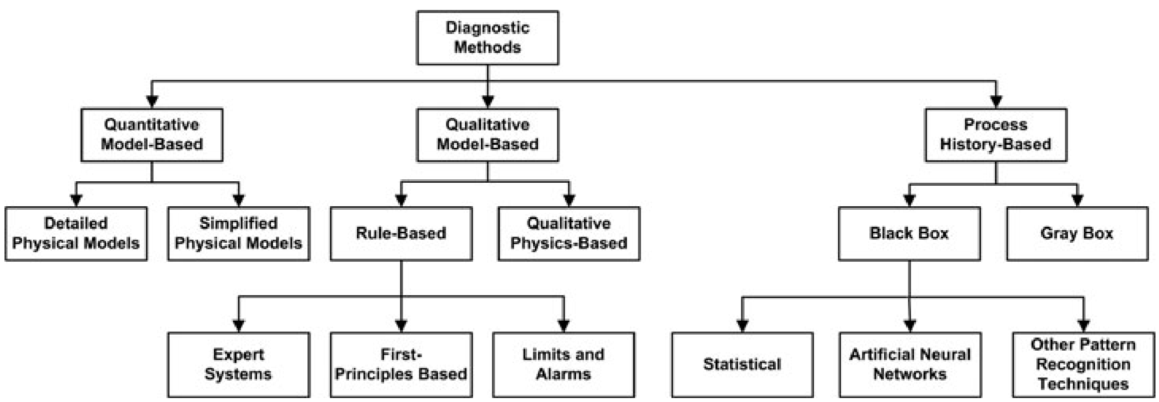

Figure 16. Classification of AFDD methods

Source: Katipamula and Brambley (2005)

Both the literature for AFDD development and products available on the market are heavily focused on HVAC systems. For example, out of 197 studies identified in the literature, 75% targeted VAV air handling units, chillers and cooling towers, air conditioners, and heat pumps while only 12% investigated buildings as a whole (Kim and Katipamula 2017). Limited literature is available for other end-use systems (e.g., lighting, refrigeration). Furthermore, whole-building AFDD that impacts multiple systems is mostly limited to fault detection. Isolating and diagnosing faults using data from the whole building is still challenging.

Despite the increasing number of products and services being introduced in recent years, the market for AFDD systems is highly fragmented with no common methodology or benchmark, making evaluation of the performance and accuracy of systems difficult (Granderson et al. 2017). Furthermore, in many cases, rather than continuous building equipment health monitoring capabilities, products conduct fragmented measurements using handheld instruments that require service technicians to detect faults, making it expensive and intrusive (e.g., accessing refrigerant lines to measure pressure). High-resolution instrumentation can assist in detecting physical faults by embedding software into the equipment itself. Additional barriers include a lack of common definitions of faults along with knowledge of overall prevalence and impact of faults with which to prioritize and assess AFDD strategies.

2.1.6 Building Energy Modeling

BEM is a physics-based simulation that calculates thermal loads, system responses to those loads, and resulting energy use. This is done by combining descriptions of the physical assets of a building (e.g., geometry, construction materials, equipment configuration, and component efficiencies) and its operations (e.g., schedules for occupancy, lighting plug loads, thermostat settings) along with forecasts or estimates about local weather conditions. Annual energy use is calculated based on these inputs at an hourly or finer time step interval. A number of public- and private-sector BEM engines exist, along with applications, user interfaces, and services. EnergyPlus,[21] which has been under continuous development since 1997, is DOE's flagship tool for BEM and is maintained by BTO. BEM has become an established method for supporting a variety of energy efficiency use cases. Examples include systems-level integrative design of new buildings and retrofits, energy efficiency code development and compliance (e.g., ASHRAE 90.1, California Title 24), and rating and certification program development and implementation. BEM has traditionally targeted "offline" applications, which are conducted ahead of occupancy or as a one-time audit.

BEM engines are increasingly also being used for "online" applications, including AFDD (see Section 2.1.5) and MPC (see Section 2.1.7). In these cases, real-time and operational instances rather than static ones are examined and optimized for energy efficiency. Current state-of-the-art BEM engines, however, are unable to represent and simulate the performance of actual control sequences because they model buildings under idealized conditions instead of actual operations, and with deterministic rather than stochastic outputs. While conventional BEM engines calculate the cumulative change in state over a specified time step, they have no visibility as to what path the system took to get to the new state, or events or state transitions within each time step, which matter for controls (e.g., equipment cycling). Instead, uniform or continuous behavior is assumed within a specified time interval. Historical sensor data, weather forecasts, and either engineering rules and/or approximate (i.e., reduced order) models are used to estimate future building needs and the effects of potential control actions from which to select. As such, the effects that control sequences have over the simulated time horizon are not modeled. Furthermore, the insufficient integration of BEM with control design, verification, and implementation tools and workflows leads to errors in the manual translation of control sequences of operation.

2.1.7 Control Architectures

As noted in Section 1.5, building controls consist of either centralized or distributed architectures. For the former, which are most common for HVAC loads and large commercial buildings, centralized observation and control of building conditions are enabled by a BAS through a hierarchical approach that is reflective of the hierarchy of the equipment within the building (see Figure 17). The field layer consists of sensors, actuators, and application-specific or field controllers at the subsystem level (e.g., chiller, ventilation box), which monitor conditions using sensors, make calculations based on these conditions using controllers, and perform actions to achieve set points sent from the supervisory or automation level based on these calculations with actuators. The supervisory controllers coordinate equipment operation across the system and execute control loops by calculating and sending set points to the field controllers based on instructions from the management layer. Data visualization and reporting, along with system configuration, are also handled by the management layer. For buildings without centralized automation and a supervisory layer, individual devices typically operate through "on-off" control to meet set points manually set by the building occupants or operators without direct communication or coordination between devices. Internet-connected thermostats and other smart devices have begun to take on the role of providing the type of visibility and controllability that a BAS does.

[21] https://energyplus.net

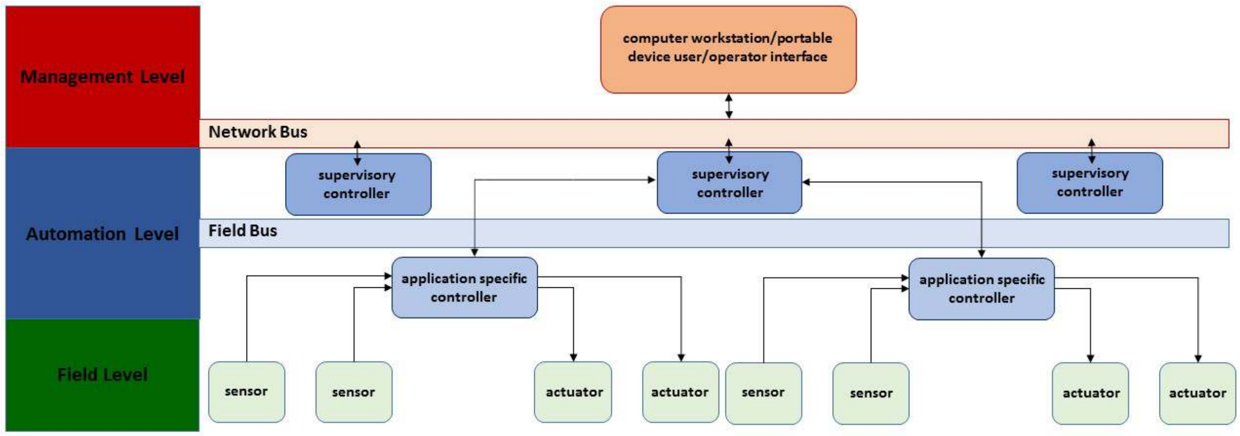

Figure 17. Simplified diagram of generic BAS

Control strategies in buildings with a BAS are traditionally rule based and implemented in the supervisory layer to establish appropriate set points for the field level based on input schedules. Similar to "on-off" control, simple "if-then" logic is used to calculate actions, but with a larger number of discrete building equipment states. Rule-based controls, however, react to set points and instantaneous sensor inputs without accounting for future predictions of changes in operating conditions (e.g., weather, occupancy) or impacts on other building systems. These set points can be informed by prior offline simulations, but usually match the objective constraints used in offline BEM design (e.g., thermostat set points identified in construction codes and standards). Proportional-integral-derivative control is another common control strategy for buildings with a BAS that is implemented at the field level. Proportional-integral-derivative control is more sophisticated than rule-based control because it uses continuous measurements of the variable being controlled to continuously tune the appropriate position of the actuator to achieve the desired set point, but it is also not predictive in nature.

Moving beyond reactive controls, MPC approaches, which are typically implemented at the supervisory level, evaluate future control actions by continuously predicting how the system will respond and then dynamically optimizing the selected control action based on the constraints (e.g., comfort) and objectives (e.g., reduce consumption) of the system using actual and forecasted inputs (e.g., weather, occupancy) (see Figure 18). As such, MPC relies on sufficiently precise models of the thermal dynamics of the building and is especially beneficial when evaluating long time horizons (i.e., hours to days) and/or multiple variables that need to be simultaneously tuned (Afram and Janabi-Sharaifi 2014; Mayne 2014). While MPC approaches were introduced in the 1970s and are common in other sectors (e.g., industrial processing plants, automotive cruise control), they have only been demonstrated in buildings for limited conditions (e.g., precooling or preheating based on weather forecasts) and in large commercial applications (examples include Henze et al. 2005; Ma et al. 2009; and Siroky et al. 2011). There are several challenges in implementing MPC in buildings today. First, model construction during design and calibration during operation is labor intensive, requiring significant engineering expertise and computational efforts that make MPC cost prohibitive and limit scalability for most building applications. Model generation and calibration can consume up to 70%–75% of implementation costs (Rockett and Hathway 2017). Models must also be simple enough that optimization calculations can be completed within the designated time horizon. Additional challenges for MPC include selecting a model that has sufficient accuracy and sufficiently captures the dynamics of the building (see Section 2.1.6). These factors impact energy savings, with a wide range of results possible depending on the case study in question. Improper parameter selection can result in performance that is worse instead of better than a traditional rule-based or proportional-integral-derivative strategy (Blum et al. 2019). Verification of savings is also difficult. While implementing centralized or hierarchical MPC architectures for buildings with multiple zones is challenging due to the computational requirements, decentralized or distributed architectures increase communication and optimization requirements.

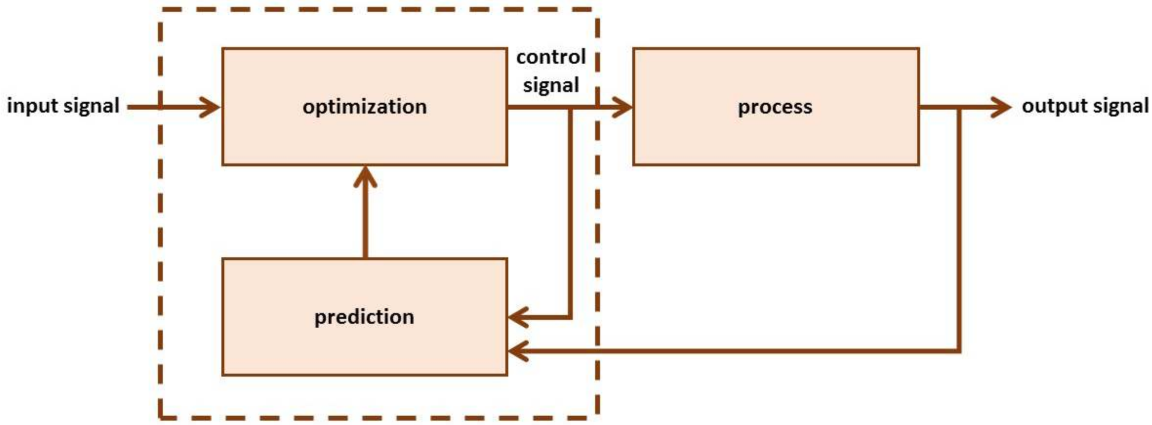

Figure 18. Model predictive control schematic

Physics-based representations of the building or systems in question are not necessarily required (Hou and Wang 2013). Reduced-order models (i.e., gray box) or purely data-driven models (i.e., black box) that are both computationally more efficient and simpler to construct can also be used (examples include Harb et al. [2016]; Moon et al. [2017]; and Macarulla et al. [2017]). Several challenges exist, however, including that, similar to the use of data-driven models and machine-learning approaches for building analytics applications (e.g., AFDD), the quality of the data used will impact results and events not included, or anomalies in the model's training data will not be accounted for. Researchers are exploring ways to automatically generate reduced-order MPC models from more detailed BEM models for hybrid MPC approaches.

2.1.8 Interoperability

Despite the advancements made in network communications in the past two decades that have supported the development and implementation of standard communication protocols referenced in Section 2.1.2, full interoperability in building control systems is still limited. Interoperability consists of a common shared meaning of information that is exchanged between multiple devices, applications, networks, or systems.[22] Full interoperability cuts across the hierarchy of layers within a BAS or other form of energy management within a building. Specifically, as shown along the horizontal axis of Figure 19, this starts from the device level (i.e., the field level in Figure 17) that consists of the sensors (i.e., inputs) and actuators (i.e., outputs); the application-specific or field controllers that calculate the actions of the actuators based on the inputs from the sensors and set points specified by the supervisory level; the supervisory layer that coordinates control across the system; and, finally, the management layer that is responsible for integrating across multiple building system applications at the enterprise level.

[22] ISO/IEC/IEEE Standard 24765, 2010.

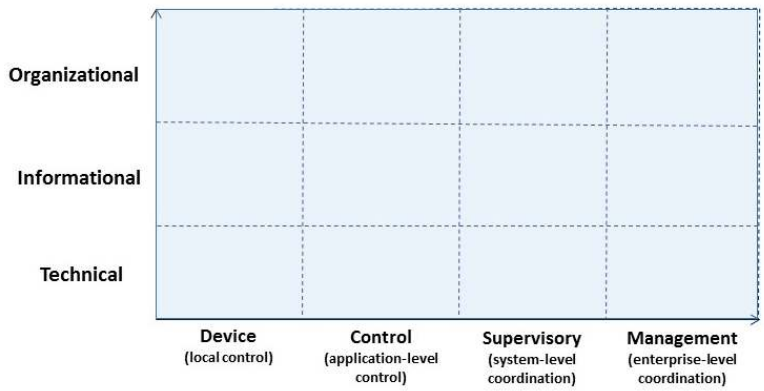

Figure 19. Interoperability layers

In addition to addressing the exchange of information across this hierarchy of building controls, full interoperability for energy management applications must also address the integration of the type of information exchanged. Overall, interoperability in buildings is defined by the 2008 GridWise Architecture Council Context-Setting Interoperability Framework, which consists of the three categories along the vertical axis of Figure 19. Technical interoperability, explored in Section 2.1.2, is defined by the ability of communication protocols to establish connections that exchange digital data in raw form across multiple devices and networks (i.e., connectivity) along with the ability to recognize different types of data structures or formats (i.e., syntax). This is the equivalent to using the same alphabet (i.e., communication protocol). Technical interoperability has been largely addressed through development efforts in the last three decades in network communications and connectivity. The next level, informational, consists of a common understanding of the semantics—or the definitions and meaning—of the data exchanged (e.g., location, timing, units, quantity being measured) and the relationships between them. This is the equivalent of using not only the same alphabet, but also the same language. Informational interoperability is achieved when the meaning and semantic understanding of the concepts contained in the message data structures and the relationships between the concepts represented in the message are understood. This contextual information can be captured and represented by a structured set of descriptive metadata. While existing standardized communication protocols (e.g., BACnet, LONWorks) from Table 1 address technical and syntactic interoperability, they do not include common semantic models for mapping data. Instead, manual translators are necessary, limiting the configuration process across connected equipment.

Common data or information models are necessary to provide a standardized approach to represent and translate the meaning of data. As such, standardized naming conventions, taxonomies, and schema (e.g., Project Haystack,[23] Industry Foundation Classes,[24] Ontologies) are currently under development. Limitations exist, however, in terms of completeness, including the ability to capture uncertainty and to develop relationships between points that are necessary when conducting searches in analytic applications (Bhattacharya, Ploennings, and Culler 2015; Schumann, Ploennigs, and Gorman 2014). This is being addressed through techniques to automate the conversion of data from existing buildings (Bhattacharya, Hong, Culler, et al. 2015; Balaji et al. 2015) and the development of a schema (i.e., Brick) that includes an open reference implementation standard for evaluation of its effectiveness (Balaji et al. 2016).[25] Brick will provide a uniform schema for representing metadata that captures all points and their relationships (i.e., completeness and expressiveness) and will be easy to convert to buildings applications (i.e., usability). The Brick consortium recently partnered with ASHRAE and Project Haystack to build off BACnet in integrating Project Haystack tagging with Brick information modeling to develop the newly proposed ASHRAE Standard 223P.

[23] https://project-haystack.org
[24] http://www.buildingsmart-tech.org/specifications/ifc-overview
[25] http://brickschema.org

Widespread adoption of common data models will rely on the ability to evolve and accommodate technological challenges, as well as integrate multiple applications and systems in order to achieve organizational-level interoperability. As interoperability maturity is achieved in buildings, it will need not only a means to measure, but also to assess and certify interoperability through common testing methods.

2.2 End-Use Characterization of Energy Management in Commercial Buildings

According to the EIA, 43% of the total commercial building floorspace (i.e., 37 of a total 87 billion square feet) had a system installed to enable some degree of centralized automation for at least one end use as of 2012, compared to 22% in 2003 (i.e., 16 of a total 72 billion square feet) (see Figure 20). The discrepancy in adoption of centralized automation systems between small (<50,000 square feet) and large (>50,000 square feet) commercial buildings, noted in Section 1 and shown in Figure 20, is due to several reasons. These include the small-commercial sector's smaller payback amounts resulting from fewer zones and less floorspace, limited on-site or dedicated energy manager resources due to smaller energy management budgets, and higher percentages of split incentives. Even commercial buildings without centralized automation will utilize at least basic on/off functionality (e.g., lighting fixtures controlled by light switches or circuit breakers, furnaces controlled by thermostats) as part of their control strategy.

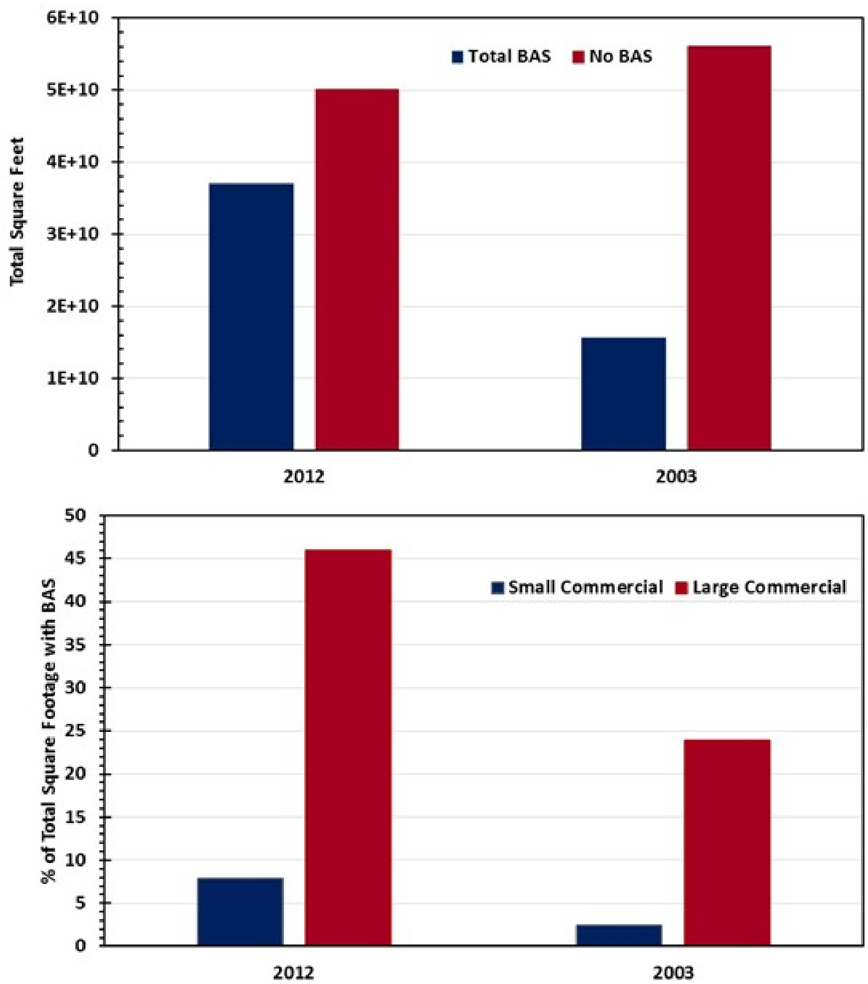

Figure 20. Building automation systems in the commercial buildings sector

Source: U.S. EIA (2016)

The average cost of a BAS is estimated to be around $2.50–$7 per square foot.[26] In general, installations for buildings with more floorspace or larger numbers of overall buildings (e.g., enterprise- or campus-scale) enable reduction in ongoing system costs (i.e., maintenance and software) due to the larger number of points monitored and controlled. This is also the case for energy information systems which provide data visualization software tools of energy consumption based on information collected by the BAS itself or other sensing and metering hardware. Both BAS and energy information systems are also characterized by wide and quickly evolving cost ranges that depend on the pricing models and levels of customization. The cost of an energy information system ranges from $0.001 to $0.40 per square foot with monthly maintenance and service costs of $0.01–$0.10 per square foot (Granderson and Lin 2016; Perry 2017). For the majority of commercial building floorspace, owners are the parties responsible for operation and maintenance, as well as the providers of direct input on energy-related equipment purchases (see Figure 21). Installed systems have historically not been integrated across multiple end uses. Instead, these systems, as well as nonenergy management monitoring and control systems (e.g., security, fire) are vertically integrated and vendor specific with separate sensors, actuators, controllers, and user interfaces. These systems are increasingly networked in large commercial buildings but still communicate using different protocols due to limited interoperability. According to a building operating management survey, 84% of respondents reported having a BAS that was connected to the internet in 2015.[27] Central monitoring and networking, as well as remote capabilities, are not as common in small commercial buildings (Katipamula et al. 2012), although recently developed control execution platforms are starting to be demonstrated, providing an environment to integrate and operate multiple applications and helping to drive down costs.[28]

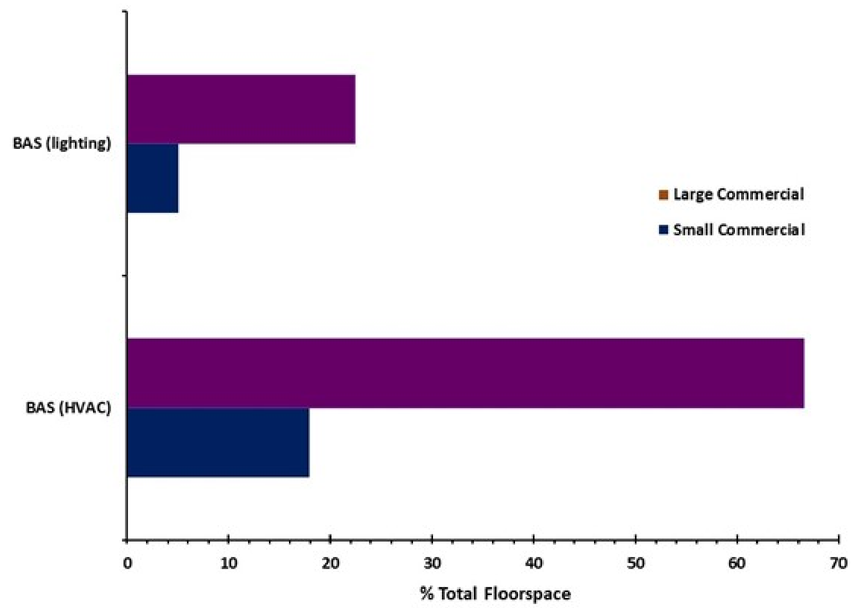

Figure 21. Breakdown of responsibility for commercial buildings in the United States (percent floorspace) (Left): Party responsible for operation and maintenance of energy systems; (Right): Provider of direct input on energy-related equipment purchases

Source: U.S. EIA (2016)

[26] https://blogs.intel.com/iot/2016/06/20/costs-savings-roi-smart-building-implementation/#gs.38434w
[27] https://www.facilitiesnet.com/buildingautomation/article/Why-Building-Management-Systems-Are-At-Risk-Of-Cyberattack--15558
[28] http://www.bemoss.org/overview/
http://sdb.cs.berkeley.edu/sdb/boss.php
https://buildingdepot.org/
https://www.tridium.com/en/products-services/niagara4
https://volttron.org/

HVAC followed by lighting are the dominant BAS-controlled end uses in both small and large commercial buildings (note that the Commercial Buildings Energy Consumption Survey does not delineate in situations where more than one end use is monitored and controlled by a BAS, whether this is conducted in an integrated way or stand-alone for each end use) (see Figure 22). HVAC equipment (space conditioning along with ventilation), is also the dominant end use, constituting almost half of the energy consumed. In small commercial, refrigeration and the "other" category, (i.e., all electronics not included in computing and office equipment along with other smaller loads referenced in Section 1), followed by lighting, cooking, computing and office equipment, and water heating are the next-largest consumers. Lighting and the "other" category, followed by refrigeration, computing and office equipment, water heating, and cooking are the next largest for large commercial buildings. Collectively, implementation of monitoring and control systems in the commercial sector is focused on HVAC, lighting, and MELs (e.g., plug loads), which constitute at least two-thirds of consumption (see Figure 23). Refrigeration is growing in overall consumption, and as a result, interest in pursuing sensor and control strategies is also increasing.

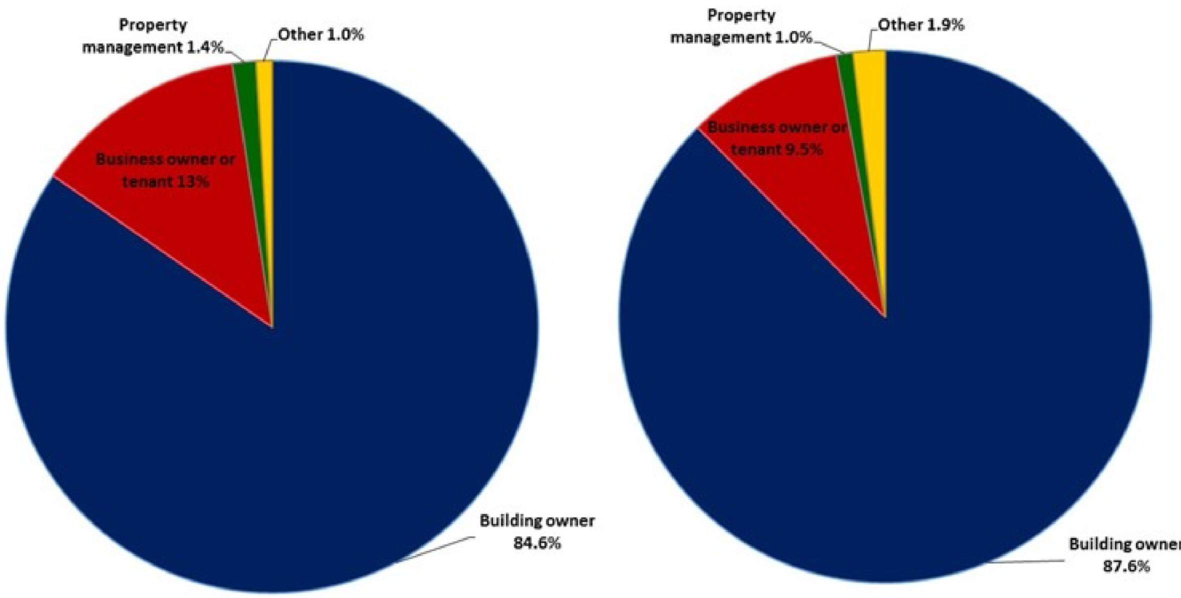

Figure 22. Breakdown of commercial building automation system by end use

Source: U.S. EIA (2016)

Commercial buildings types are diverse, with 11 major categories characterized by their principal building activity by the Commercial Buildings Energy Consumption Survey. These can be further divided into approximately 20 total subcategories (e.g., strip malls, enclosed malls, and retail other than malls in the mercantile category). For example, energy consumption is mostly from HVAC, lighting, and MELs in the case of healthcare (outpatient), education, mercantile, religious worship, and office buildings. Most of the energy consumption for food service and sales—the category with the highest overall energy consumption—is attributed to refrigeration. More than half of the floorspace for healthcare, education, mercantile, and office buildings have systems installed for monitoring and controlling HVAC (see Figure 24). The prevalence for lighting is smaller. Even when systems are installed, buildings might not fully exploit programmable functions (e.g., thermostat schedules are adjusted during nonworking hours). Secondary schools within the education category are estimated to have the largest national energy savings (49%) from the implementation of ECMs from state-of-the-art sensor and control technologies (e.g., managing occupancy schedules and optimizing set points) followed by stand-alone retail and dealerships in the mercantile category (see Figure 9). The breakdown in energy consumption, climate region, and prevalence of existing BAS, along with energy management budgets and requirements, largely shape both the ECM implementation and future technology development strategies based on the anticipated savings. Lodging, for example, can benefit from occupancy scheduling strategies based on conference and room bookings. The greatest opportunity for energy savings from current state-of-the-art sensor and control technologies across the commercial building stock is by increasing thermostat deadbands by ±1°–3°F and nightly temperature setbacks from 65°F–60°F (i.e., up to 7.7%) (Fernandez et al. 2017). Although lighting, plug load, and refrigeration strategies were also included in the 37 ECMs that Fernandez et al. evaluated, the four most promising measures were all HVAC-based when evaluating their cost-effectiveness or energy savings as a function of effort required to implement across building types and climate regions. This can be attributed to the penetration of HVAC-based controls (see Figure 22) and consumption of space conditioning and ventilation (see Figure 23) compared to other end uses. In addition to increasing deadbands and nightly setbacks, these ECMs included shortening schedules, minimizing damper flow reductions for systems with VAV, and optimizing morning start times (e.g., fans operating in advance of occupancy) (Fernandez et al. 2017).

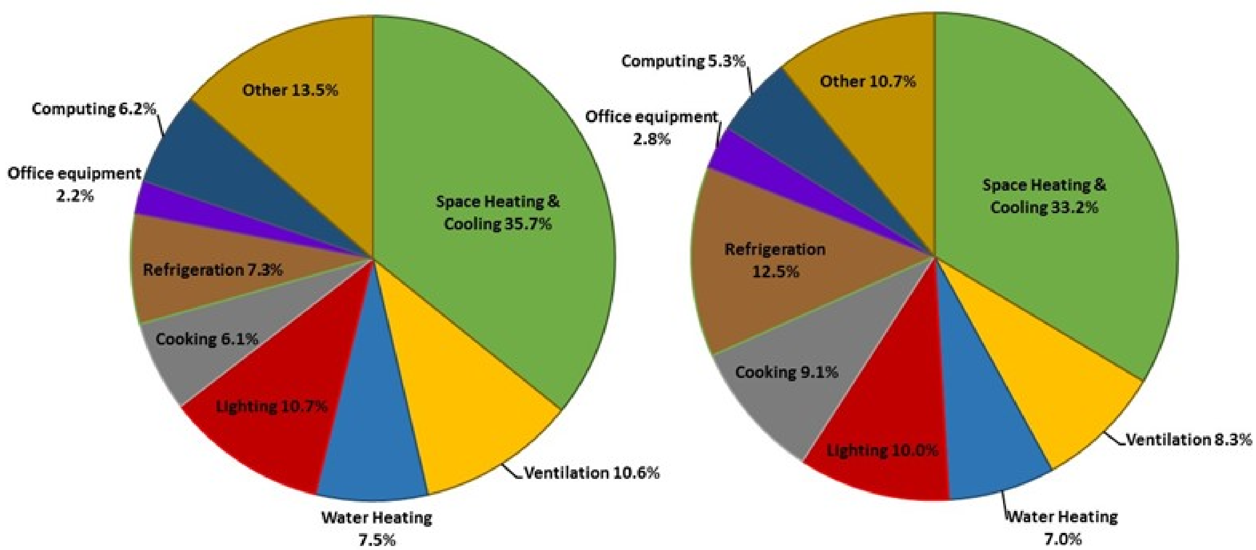

Figure 23. Breakdown of energy consumption (quads) for large commercial (left) and small commercial (right)

Source: U.S. EIA (2016)

Most HVAC systems are controlled by a thermostat with the overall system configuration dependent on the number of zones, occupant requirements, heating and cooling equipment (e.g., hot water or steam boiler; gas, oil, or electric furnace; heat pump; air conditioner), and budget. Data in the Commercial Buildings Energy Consumption Survey includes 14 different HVAC system types along with 15 control configurations (e.g., single duct VAV, dedicated outdoor air system). Design and layout of an HVAC system and control strategy are determined by the floorplan and expected usage patterns. For example, office buildings may have a central conditioning system with local air handling units to control zones where boundaries are clearly defined by a physical boundary (e.g., a wall). A large warehouse, however, may have several packaged rooftop units across the entire space where the area served by each rooftop unit is defined without physical boundaries and the zones are more thermally coupled. As such, a different control strategy is also necessary.

Small commercial buildings, especially <25,000 square feet, are similar to the residential sector. These buildings typically consist of individual zones with simple thermostat-based control (on/off or set point) of the HVAC system where the thermostat operates as both a sensor for monitoring space temperature and as an actuator for the installed heating or cooling system in maintaining occupant- or operator-specified temperatures. For the small commercial sector, 47% of buildings utilize localized control for heating and 28% for cooling through a packaged rooftop unit independently controlled by a thermostat, due to their low installation costs. Poor coordination among units can lead to high electric peak demand and short on/off cycling, which can result in poor part-load performance and degraded equipment life. Aside from packaged rooftop units, the breakdown of heating in small commercial buildings is 22% individual space heaters, 14% furnaces, 11% heat pumps, and 6% boilers (U.S. EIA 2016). The breakdown for cooling is 30% residential-type centralized air conditioning, 12% individual air conditioning, and 12% heat pumps (U.S. EIA 2016). Airside economizers can be utilized to reduce air-conditioning costs by using outside air for free cooling and to minimize compressor operation. Because the cooling system will maintain the targeted set point regardless of the economizer performance, failure is often not noticed, even if the true outside air temperature is not correctly measured.

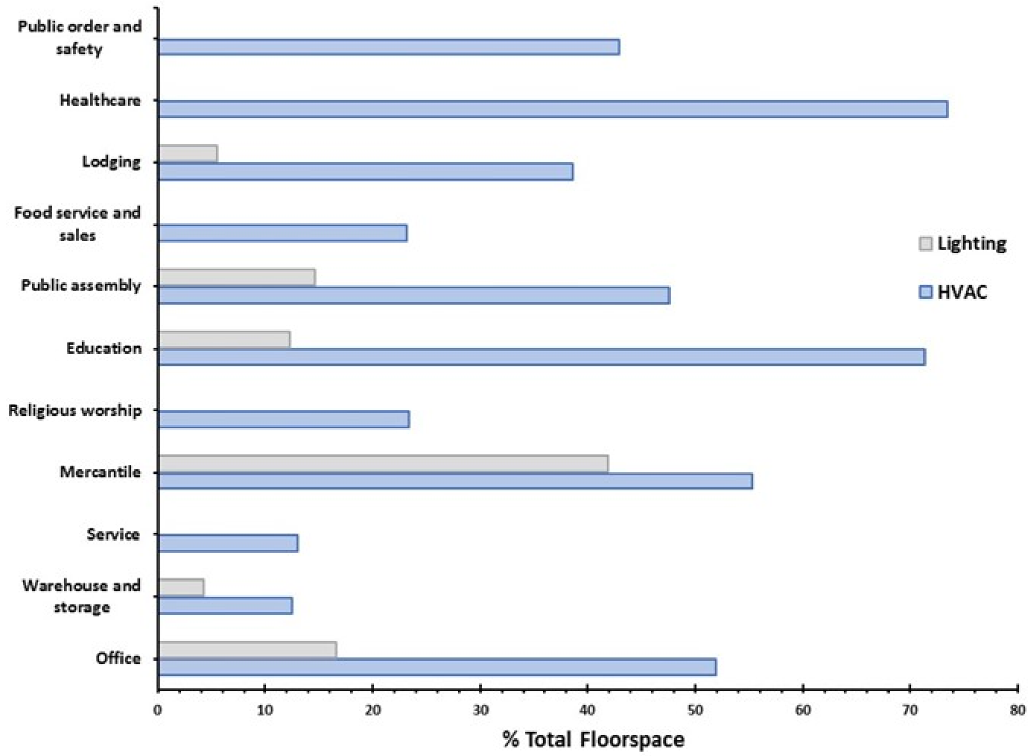

Figure 24. Commercial building automation system coverage for principal building activity types

Source: U.S. EIA (2016)

Central chillers and boilers, along with air handling units, are commonly used in large commercial buildings. Due to the overall building size, temperature control for multiple zones can be provided through VAV boxes that can tune the amount of air released in the conditioned space. The BAS typically uses relatively static set points where water and air temperatures levels are fixed and low, while volume, velocity, and pressure levels are fixed and high. Constant circulation of chilled water and air is necessary, and as a space gets warmer, more chilled water is released and the VAV dampers widen to introduce more cold air. This gradual warming and rapid cooling wastes energy and can lead to occupant discomfort. As previously noted, HVAC operations do not explicitly calculate heating and cooling load in order to choose a steady operating state to meet the load. Instead, the HVAC equipment cycles at maximum capacity to react to the temperature set points, which requires oversizing and increases overall costs. New control sequences are emerging that specify more stable operation through adaptive adjustment of equipment set points (Hydeman, Taylor, and Eubanks 2015). The first edition of ASHRAE Guideline 36 ("High Performance Sequences of Operation for HVAC Systems"), which was published in 2018, includes optimized control sequences for VAV and terminal units. Plans are underway to expand to other systems as well, with the goal of ultimately being incorporated into default control software packages (Taylor 2018).

Despite the potential for improving energy performance and occupant comfort with advanced control sequences (e.g., ASHRAE Guideline 36), many buildings are programmed with default sequences of operation that are neither fully optimized for the specific building configuration nor regularly updated. This can be attributed to the fragmentation of the BAS market (e.g., HVAC designers and engineers, general and mechanical contractors, BAS contractors and vendors, controls manufacturers, commissioning agents) throughout the design, implementation, and commissioning phases of building construction. The current state-of-the-art approach is for control engineers to use either fully programmable controllers, which allow for more flexibility but can lead to implementation errors that impact operations, or preprogrammed controllers, which have been fully debugged but require configuration adjustments and proper tuning at installation along with periodic retuning. The control system, however, is generally designed and specified by the HVAC designer or engineer who will include specifications for the controls engineer based on the mechanical system configuration. These specifications are generally written in English and might also be incomplete or include errors. The controls engineer must implement by interpreting and then translating these specifications into their chosen software language to program the controllers. Furthermore, as noted in Sections 2.1.5 and 2.1.6, the disconnect between simulation and implementation of controls contributes to additional inconsistencies and errors because simulated controls must be manually translated into actual control sequences. This in turn limits the ability to tune and optimize sequences and to test and verify their performance during actual implementation. The risk of translation errors discourages control engineers from incorporating more advanced control logic that may not only fail to deliver the promised energy performance, but might also lead to more occupant discomfort and operational issues than a traditional sequence.

While centralized control for lighting systems is not as common as HVAC systems in the commercial sector (see Figure 22), basic lighting controls are common in an increasing number of buildings with additional performance features regularly included in updates to ASHRAE Standard 90.1. Strategies for basic lighting control include infrared motion sensing, manual dimming, and simple clock-based scheduling. Both basic lighting controls, as well as emerging and more sophisticated strategies to reduce artificial lighting (e.g., daylighting, task-tuning, window shading) for optimizing visual comfort and energy performance are more prevalent in large commercial buildings (U.S. EIA 2016). The overall breakdown in all commercial buildings is approximately 15% occupancy presence sensing, 6% dimming, and 2% daylighting (U.S. EIA 2016). While advanced strategies can result in up to 40% energy savings, costs are still prohibitive for widespread adoption with payback periods of greater than three years (Perry 2017). Emerging lighting control systems that are networked using either wireless (e.g., IEEE 802.15.4) or wired communications provide built-in intelligence that can also be used as a power source (i.e., Power over Ethernet). These systems either use open communication protocols (e.g., BACnet, DALI) or proprietary ones. Improved interoperability and simplification of the system configuration processes are necessary to reduce costs. More accurate energy reporting measurements in Power over Ethernet systems are also necessary (Tuenge and Poplawski 2017).

2.3 End-Use Characterization of Energy Management in Residential Buildings

Residential buildings, similar to small commercial buildings, typically consist of "on-off" control for individual equipment (e.g., furnace, water heater, refrigerator) to meet set points manually set by the building occupants or contractor without direct communication or coordination between devices and without any changes to the underlying control methods. Residential buildings consist of two main types of units that collectively consume 95.5% of the energy consumed by the sector. Single-family homes (both detached and attached) consume 82.1% of residential energy use, and multifamily buildings consume 13.4% (see Figure 25). Of the 118 million residential units in the United States, 63% are owner occupied and 37% are renter occupied (U.S. EIA 2017c). As noted in Section 1.1, space conditioning (heating and cooling) is the largest consumer of total energy in residential buildings (i.e., 36.7%, or 7.3 quads), followed by "other" end uses (i.e., 21.9%, or 4.4 quads). Water heating is the third largest (i.e., 13.3%, or 2.7 quads), followed by lighting (i.e., 6.5%, or 1.3 quads).

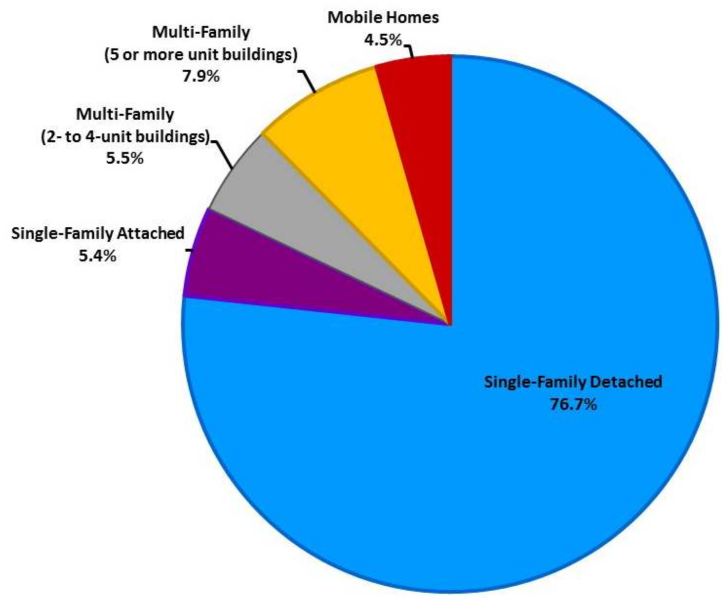

Figure 25. Breakdown of residential building types

Source: U.S. EIA (2017c)

As of 2015, approximately 87% of households used some type of air conditioning, with the majority (i.e., 65%) relying on centralized coordination either with or without a heat pump (U.S. EIA 2017c). The current design of HVAC control in most homes, however, is limited due to single zone coverage. Some larger homes are subdivided into separate thermal zones, but for most homes, temperature variations throughout the space are not incorporated. Instead, a single temperature sensor embedded in a centrally located thermostat is used for monitoring and detecting deviations from the desired set point. Also, mechanical ventilation systems, which are sized for a single zone, do not adjust for changes in occupancy patterns. Ventilation requirements in ASHRAE Standard 61 are based on binary occupancy presence in the residential sector, whereas the commercial sector (i.e., ASHRAE Standard 62) utilizes demand control ventilation to adjust airflow based on the number of occupants.

Programmable thermostats, which permit the setting and modification of set point schedules in advance without the need for manual adjustment, tend to operate using rule-based control strategies. Overall, 41% of residential buildings had some type of a programmable thermostat installed for air conditioning, but only 12% used the programmable functionality as of 2015. Similarly, for space heating, almost 50% included a programmable thermostat, but only 16% used the programmable functionality (U.S. EIA 2017c). Reasons for their limited use include occupant override, along with complicated user interfaces that are difficult to use (Meier et al. 2010; Metzger, Goyal, and Baechler 2017). The U.S. Environmental Protection Agency's ENERGY STAR® maintains guidelines on the proper usage of programmable thermostats, which were first introduced as a certified ENERGY STAR product in 1995 but removed in 2009 due to lack of occupant usage or resulting energy savings.

More recently, internet-connected and learning-based, or "smart," thermostats have emerged that incorporate communications and can program themselves over time based on occupant schedules and preference inputs. These thermostats have begun to take on the role of providing the type of visibility and controllability that a BAS does for HVAC loads and that can also enable applications like AFDD (e.g., short-cycling compressor) that exist in systems controlled by a BAS (DOE 2016c). Features can include remote control operation through electronic devices (e.g., tablets), built-in presence detection (or geofencing, which relies on a personal device detection to determine occupant location), and access and incorporation of weather forecasts. In 2015 only 3% of households had a smart or learning thermostat that learned occupant behavior over time, eliminating the need for continual user activity (U.S. EIA 2017c). This number is steadily growing, however, with 40% of the 40 million thermostats sold in 2015 classified as smart (Parks Associates 2015). Overall costs can be up to $250 for a smart thermostat (King 2018). Current state-of-the-art smart thermostats are estimated to achieve an average of 12% energy savings (York et al. 2015). However, the level of sophistication of the current state-of-the-art for these types of thermostats is limited by the use of built-in passive infrared sensors that cannot detect or account for occupancy movement, especially across zones. Furthermore, characteristics of the physics of the building are generally not incorporated. As the technology matures, however, common metrics and testing methodologies will be necessary to establish expected performance. As such, ENERGY STAR has recently developed specifications for connected thermostats.[29] Connected functionality is also included as a feature for achieving ENERGY STAR certification for a number of smart appliances (e.g., refrigerators, freezers, clothes dryers). Without full data standardization and common data models (see Section 2.1.8), products in the market are developing and releasing their own, which will eventually need to be harmonized across vendors for semantic interoperability. Wireless communication protocols (e.g., ZigBee, Z-Wave, Bluetooth, Wi-Fi) are generally used in these applications due to the ease of installation and connectivity, which is typically done by either a contractor or the homeowner. Integrated systems that monitor and control through a centralized hub across multiple end uses (e.g., HVAC, lighting, plug loads), known as home energy management systems, or home automation systems, have also recently emerged. These systems are still mostly proprietary and connected through the home's wireless network. The functionality that these devices provide, however, can facilitate embedded AFDD for appliances where persisting faults can go unnoticed by homeowners and require a contractor to fix.

Lighting control strategies tend to be driven more by aesthetics and convenience than energy, and, by extension, cost savings in the residential sector (Consortium for Energy Efficiency 2014). The most prevalent strategies are timers or dimmers (e.g., for ambience or low-level lighting), which are installed in 30% of homes for indoor lighting (U.S. EIA 2017c). Motion detectors or light sensors are incorporated into 38% of residential buildings for outdoor lighting applications (U.S. EIA 2017c). Emerging strategies include integrated sensors (e.g., occupancy) and controls (e.g., dimmers) that are networked and incorporated into home energy management systems. Window shading and daylighting strategies are less common in residential buildings (i.e., <1%) compared to commercial (i.e., 0%) because occupants have more direct control over their lighting and because natural light levels tend to be lower when occupants are most likely to be present (i.e., early mornings and evenings) (Urban, Roth, and Harbor 2016; U.S. EIA 2017c).

While comprehensive control strategies for plug loads are less widespread than lighting and HVAC, they are especially important in the residential sector because the "other" category, which includes a number of MELs, is the second largest end use after HVAC. A number of devices (e.g., computers, printers) already include basic control capabilities to transition to low power states or intelligently power down when not actively in use through advanced power strips. Emerging control solutions at the circuit level and plug level can similarly reduce power draw and wasted energy (Urban, Roth, and Harbor 2016 and references therein).

[29] https://www.energystar.gov/products/spec/connected_thermostats_specification_v1_0_pd

3 Opportunities for Emerging Sensor and Control Technologies in Buildings

3.1 R&D Topics Summary

Optimizing operating conditions to ensure maximum energy savings requires the design and implementation of high-performance and low-cost sensor and control systems with plug-and-play, adaptive, and automated performance features. By improving data collection, monitoring, and optimization of energy use, advancements in sensor and control strategies will increase energy affordability, improve occupant comfort, and support the provision of grid services through connected and controllable loads (e.g., HVAC, water heating, refrigeration, and lighting).

The priority research areas targeted within this document consist of four interdependent topics with individual action plans for each. Beginning at the sensor node level, each focus area builds on each other through their respective performance improvements and cost reductions aimed at facilitating systems-level integration across loads for optimized energy management. As such, the emphasis is on approaches that can be broadly applied as opposed to specific end-use strategies. For example, the steps for developing a more sensitive refrigerant leakage detection sensor or more efficient photosensor for daylighting controls are not evaluated in depth. Instead, performance improvements on specific monitoring variables (e.g., long-standing carbon dioxide sensors or more accurate current sensors) are considered within the context of achieving the applicable topic area targets. HVAC applications are elaborated on in more depth as a case study for several reasons. These include the overall percentage of building energy consumption attributed to space conditioning and ventilation, the level of penetration of existing control technologies in HVAC, and the complexity of the HVAC systems themselves. Ultimately, the specific sensing elements and features, as well as control schemes implemented, will depend on the existing load management strategies and building automation infrastructure along with the building configuration, usage, and requirements (International Energy Agency 1991).

Multifunctional wireless sensor networks – Advancing wireless sensor networks that are automated, plug-and-play, and capable of monitoring multiple parameters through effective power management will enable a low-cost approach to accurately detect and diagnose failures and resulting inefficiencies in building equipment and systems, while also allowing for optimal and localized whole-building control opportunities to improve building operations along with reducing energy use. Extending the operational power lifetime, reducing network infrastructure, and automating the configuration and calibration processes are all targeted in this action plan in order to reduce the cost by minimizing the complexity of the sensor node architecture. These solutions will also have applicability to cases where a singular variable is being monitored.

Advanced monitoring and analytics – Advancing pervasive monitoring (e.g., submetering) and supporting analytics, such that all relevant equipment and operations are being monitored at low cost and with sufficient accuracy and identification, will provide essential data to help maximize and verify energy savings, as well as provide critical information on the state and usage patterns of specific equipment to enable monitoring-based commissioning and aid in model calibration and training data collection for more sophisticated control strategies. Enhancing the hardware accuracy, improving load disaggregation algorithms and other analytic techniques (e.g., AFDD), and reducing the overall systems cost of monitoring at the individual load level through materials development are all required to address the remaining challenges and facilitate the correction of anomalous behavior to reduce whole-building energy use.

Adaptive and autonomous controls – Developing and optimizing integrated building control schemes at the whole-building level with predictive and adaptive capabilities to correct for faults and respond to external conditions (e.g., weather forecasts, grid events) and building equipment conditions over longer temporal and spatial periods will reduce energy consumption from building equipment and their associated controls not operating as designed. Dynamic models that simulate stochastic variables, along with machine learning approaches to train building controls to recognize complex patterns and adapt accordingly, are necessary.

Occupant-centric controls – Occupant-centric control schemes are essential in moving to a more localized paradigm of building conditioning where base-level conditioning is provided by central systems, personal preferences are made up via local devices, and the control system manages the integration and optimization of both central and local conditioning states. Cost-effective and accurate estimation and forecasting of individual and group-level occupant presence and comfort in building control schemes, along with timely response and adjustments of equipment controllers, will enable these strategies to match building operating conditions to occupancy patterns and preferences.

The technical barriers for each priority area that need to be addressed are divided into R&D and installation/maintenance barriers. The latter are akin to manufacturing barriers for component-based technologies, in that complex labor requirements and scale-up challenges are a burden on and can limit the performance and optimal adoption of these systems. While not included in the action plans themselves, market barriers beyond installation and maintenance are also presented because these challenges need to be considered when conducting R&D in a quickly evolving sector to ensure work remains relevant to building owners, occupants, and operators. Furthermore, technological advancements need to be targeted in a fashion that consider these challenges to ensure early-stage R&D ultimately impacts energy savings. The level of penetration of performance features targeted within each topic area will be influenced by the building sector type. For this reason, the overall benefit and impact of adoption are qualitatively evaluated for new, retrofit, residential, and small and large commercial buildings. For example, automating the point mapping process will be most critical to large commercial buildings that consist of thousands of monitoring and control point nodes. The overall timeline provided for technology development within each action plan is notional and based on the performance improvements that need to be achieved within the designated time frame in order to meet the energy savings targets calculated in Scout. Due to the interdisciplinary nature of this field, actual timelines are also dependent on advancements outside of building energy management in microelectronics, data analytics, and machine learning.

3.2 Impacts of Sensor and Control Technologies on Building Energy Management

The cost targets and energy performance goals calculated using the Scout tool as described in Section 1, based on innovations targeted in the action plans for each of the four focus areas of interest, are summarized in Table 3 (Sofos and Langevin 2018). A full description of the ECMs analyzed for each priority research area and their definitions are provided in the Appendix. All targets are based on the year of market entry for the performance improvements being researched and developed within each priority area and the applicable building sector (i.e., commercial versus residential). The nearer-term threshold for the market entry years 2020 and 2025, based on ongoing R&D pursued by BTO and other organizations, is intended to serve as a baseline when evaluating the longer-term energy performance goals for 2030 for the applicable end uses (i.e., HVAC and/or lighting). Figure 26 shows the expected range of achievable end-use reductions for each area, based on relevant literature studies. In general, market entry energy reduction targets are based on each technology's "medium" achievable reduction level, and targeted reductions for all technologies except for multifunctional sensors progress to the "high" achievable level by 2030. Although the topic areas have ample applicability across end uses, energy savings goals are only presented for end uses where sufficient baseline energy use data are available for estimation and analysis.

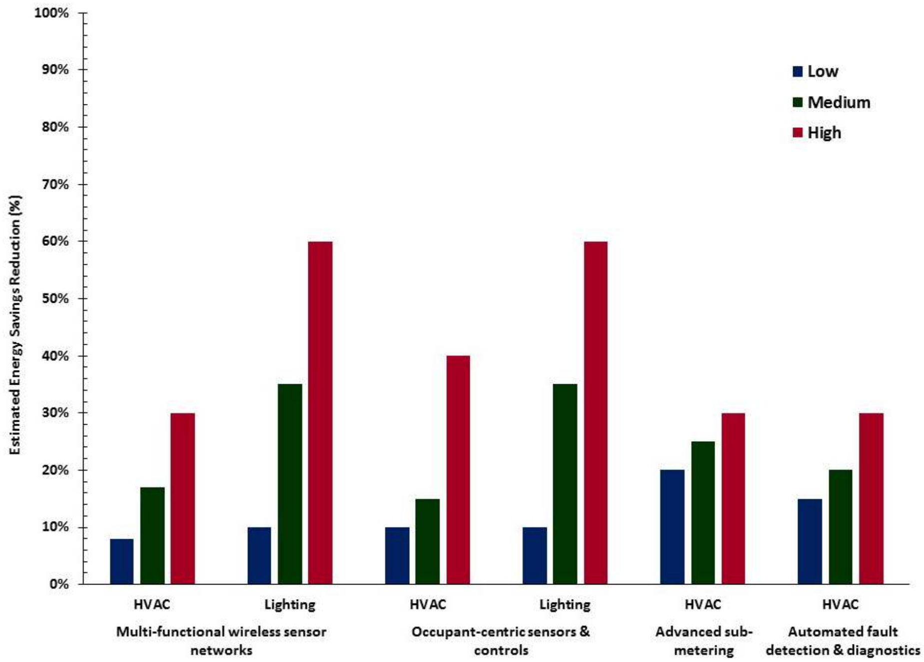

Figure 26. Sensitivity analyses for energy savings estimates in the market entry year for each priority area and applicable end use

In general, the installed cost targets are calculated based on the anticipated energy performance assuming a one-year payback period. Given the cost sensitivities for this sector, which are described in more detail in Section 4, a relatively aggressive payback period of one year is necessary and is the motivation for further performance improvements. This is in contrast to the conventional target of a two- to three-year return on investment for initial deployment or market entry and a less than one-year payback period achieved once scale has been achieved in the market. While performance improvements such as longer lifetime can be quantified and captured in Scout calculations, others, such as reduced drift or improved calibration, are not, but are still geared toward fundamental developments required to further automate the chosen technologies in a way that will facilitate adoption through improved installation and maintenance. Further cost reductions can be assumed with increased adoption over time.

Table 3. Energy Savings and Cost Goals for Priority Research Areas[30]

<table>
<tr><th rowspan="2">Focus Area</th><th rowspan="2">Energy Conservation Measure</th><th rowspan="2">Sector</th><th colspan="2">Installed Cost Target[31]</th><th colspan="2">Energy Performance</th><th>Technical Potential</th></tr>
<tr><th>Market Entry</th><th>2030 Target</th><th>Market Entry</th><th>2030 Goal</th><th>2030 Goal</th></tr>
<tr><td rowspan="2">Multi-functional Wireless Sensor Networks</td><td rowspan="2">Plug-and-play sensors self-powered with wireless communication</td><td>Residential[32]</td><td>$35/ node</td><td>$29/ node</td><td colspan="2" rowspan="2">17% (HVAC),
35% (Lighting)</td><td>1.14 quads</td></tr>
<tr><td>Commercial</td><td>$115/ node[33]</td><td>$57/ node</td><td>0.99 quads</td></tr>
<tr><td>Advanced Monitoring and Analytics</td><td>AFDD incorporating submetered energy data</td><td rowspan="2">Commercial[34]</td><td colspan="2">$0.14/ ft^2 floor</td><td>25% (HVAC)</td><td rowspan="2">30% (HVAC)</td><td rowspan="2">1.18 quads</td></tr>
<tr><td>Advanced and Auto-nomous Controls</td><td>AFDD</td><td>$0.12/ ft^2 floor</td><td>$0.14/ ft^2 floor</td><td>20% (HVAC)</td></tr>
<tr><td rowspan="4">Occupant-Centric Sensors and Controls</td><td rowspan="2">Occupancy counting inputs</td><td>Residential[35]</td><td colspan="2">$70/occupant</td><td rowspan="2">15% (HVAC),
15% (Lighting)</td><td rowspan="2">30% (HVAC),
40% (Lighting)</td><td>2.31 quads</td></tr>
<tr><td>Commercial[36]</td><td colspan="2">$36/occupant</td><td>1.10 quads</td></tr>
<tr><td rowspan="2">Occupancy comfort inputs</td><td>Residential</td><td colspan="2">$92/occupant</td><td rowspan="2">20% (HVAC),
30% (Lighting)</td><td rowspan="2">40% (HVAC),
60% (Lighting)</td><td>3.14 quads</td></tr>
<tr><td>Commercial</td><td colspan="2">$49/occupant</td><td>1.49 quads</td></tr>
</table>

Similar to the technology development strategies, the goals for each research area are also interconnected and build on each other. In particular, the multifunctional wireless sensor topic area initially focuses on just single-family homes and large commercial offices for the technology's 2020 market entry year. While the energy savings remain static, increasing their pervasiveness to the entire residential and commercial sectors through more aggressive cost targets will enable the development of subsequent research areas through the necessary sensing and wireless network infrastructure. More specifically, lower-cost monitoring should accelerate adoption, which will in turn support the goals of the occupant-centric and adaptive controls focus areas. Advanced metering will also benefit from improved communications. The 2030 targets for the rest of the research areas assume the same one-year payback cost numbers as for the market entry years, but push toward

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[30] Calculated based on AEO 2017 data using Scout tool.
[31] Cost premium based on one-year payback period.
[32] Based on all residential buildings; single/mobile homes use 0.0021 nodes/ft^2 floor and make up ~87% of all residential square footage (from residential AEO 2017 microtables); multifamily homes use 0.0041 nodes/ft^2 floor and make up ~13% of all residential square footage (AEO 2017 microtables).
[33] Based on 0.002 nodes/ft^2 for large office commercial building.
[34] Based on all commercial building types.
[35] Based on a single-family home.
[36] Based on a large office commercial building.

the higher end of the performance and energy savings ranges enabled by ubiquitous sensing to also make the payback for their associated ECMs less than one year by 2030.

The applicable building sector or subsector for baseline energy use is also based on available data, with evaluation of ECMs and projections in the future based on a qualitative assessment in subsequent sections of where technological performance features will be most applicable. For example, existing studies tend to focus on commercial building applications—particularly large offices. Nevertheless, residential applications are considered feasible for the multifunctional sensor and occupant-centric controls given the proliferation of smart thermostats and home energy management systems, which can serve as hubs for data collection and execution of control algorithms. Accordingly, these ECMs are evaluated in both the residential and commercial sectors. AFDD ECMs may also be incorporated into residential control systems, though in practice residential AFDD applications are currently rare. Accordingly, the current analysis limits AFDD application to commercial buildings. The applicable baseline energy use segments of both the plug-and-play sensors and occupant-centric controls ECMs are restricted at market entry, with a targeted expansion to a broader array of building types by 2030. Specifically, both ECMs are initially applied to single-family homes and large office buildings; by 2030, plug-and-play sensors expand to application in all residential and commercial buildings, while occupant-centric controls expand to application in all residential buildings and commercial buildings with long-term occupancy patterns (small office, lodging, assembly, education, and healthcare).

In the case of wireless sensor networks, a cost metric of $/node is chosen so as to focus on improvements to the performance without prescribing the particular sensing configuration pursued. Similarly, in order to be agnostic to the technical approach, a cost metric of $/occupant is selected for occupant-centric controls to emphasize the role of the occupant in driving energy consumption needs. The occupant-centric control focus area is also split across two ECMs for occupancy counting or recognition and occupancy comfort or preference. The comfort or preference portion, which is a more emerging technological field and will require a longer time horizon for initial innovation to enter the market, assumes an initial market entry year of 2025. The ECM for adaptive and autonomous controls only focuses on the potential energy savings potential from AFDD. While reports exist on savings from predictive and learning based control strategies, which are also part of the focus area, they are still fairly nascent for incorporation into an ECM and evaluation at this stage.

The energy savings from advanced monitoring and data analytics alone is fairly low (<5%) and not persistent over time. As such, the energy savings potential is evaluated by augmenting the ECM for AFDD. This reflects the savings enabled through improved energy consumption on data collection for comparison with appropriate baseline to more effectively diagnose operational or design-based faults and more effectively develop and optimize controls strategy. At this stage, the numbers for the focus areas of advanced monitoring and analytics, as well as adaptive and autonomous controls, are limited to the commercial sector and HVAC based on the data available, but the technological innovations identified will also be impactful to the residential sector for both stand-alone energy monitoring as well as incorporation into control strategies as applications in homes are more fully explored. More discussion on the projected cost targets and energy performance goals for each priority research area are discussed within the individual action plans. Additional data limitations preclude calculation of goals for end uses other than space conditioning and lighting (e.g., plug loads). Limitations on the accuracy of building prototype models (i.e., model inputs and simulation of building monitoring and control systems), which are discussed in Section 3.3.4, also impact the assessment of anticipated energy savings from the targeted advancements.

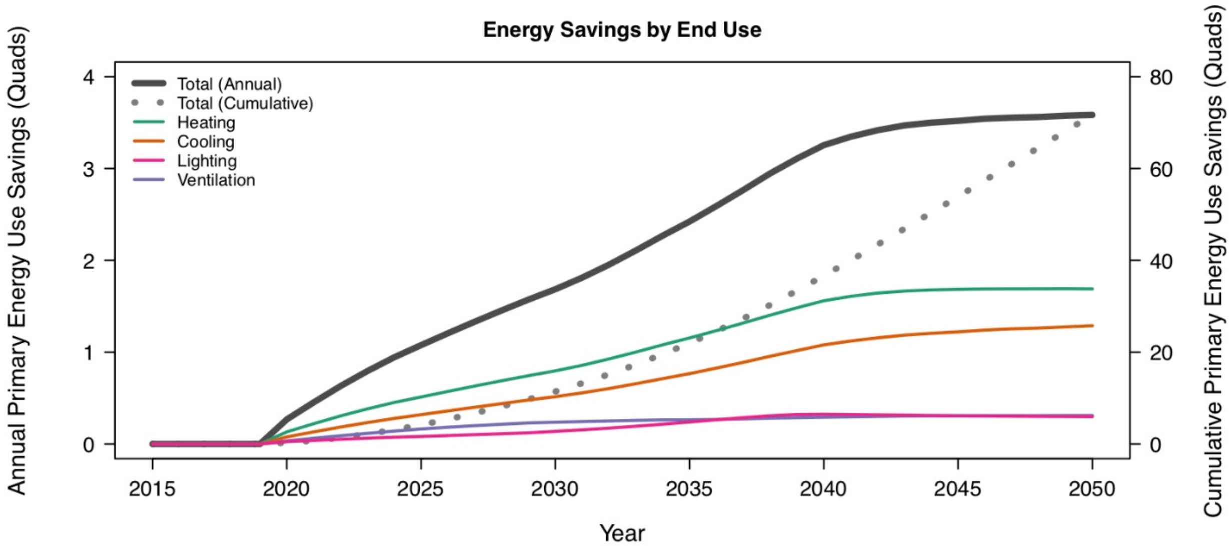

Figure 27. Total primary energy savings potential from sensor and control measures under a maximum adoption potential scenario that considers realistic rates of baseline stock turnover (e.g., rates of equipment replacement and retrofit and rates of new construction). Control measures are represented in Scout as "add-ons" that enhance the energy performance of baseline heating, cooling, ventilation, and lighting equipment.

The overall primary energy savings potential is also evaluated at a portfolio level across the designated priority research areas and applicable end uses. Figure 27 includes the results for each ECM under an adoption scenario that does not include interactions or competition between ECMs, but rather a winner-takes-all approach. In this scenario, each of the ECMs for each of the priority research areas exhibit at least one quad of primary energy savings by 2030 with the appropriate technological advancements. As noted, further savings should be possible for focus areas where not all performance features are incorporated into the ECMs. The savings potential for the residential sector ECMs are higher than the commercial sector ones due to the correlation with the higher energy consumption in residential. When aggregating at a portfolio level, Figure 27 shows the potential primary energy savings potential as a function of all applicable end uses, including those not fully evaluated for individual ECMs for a longer time horizon to 2050. As expected, space conditioning (heating and cooling) exhibits the largest savings potential, which correlates with the total energy consumption compared to other end uses. Overall, monitoring and control technologies are anticipated to save 1.7 quads in 2030 and 3.6 quads in 2050 with further technological advancements and sophistication of the approaches identified in the priority research areas. This 2050 target is equivalent to roughly 10% of total energy consumption from the buildings sector in 2018. Note that end uses such as refrigeration and electronics are not currently accounted for in this analysis but will be added in the future with expansion of the Scout tool and data inputs. As shown in Figure 28, the greatest opportunity for aggregated savings is in existing residential buildings with retrofit application opportunities, followed by new construction in both residential and commercial buildings. This can be attributed to several factors, including the slow turnover rate of the overall building stock, the larger overall energy consumption, and limited existing sensor and control capabilities in the residential sector. In total, adoption of next-generation sensor and control technologies are estimated to generate $18 billion in annual energy savings by 2030.[37]

[37] Based on Energy Information Administration (EIA) 2017 Annual Energy Outlook numbers.

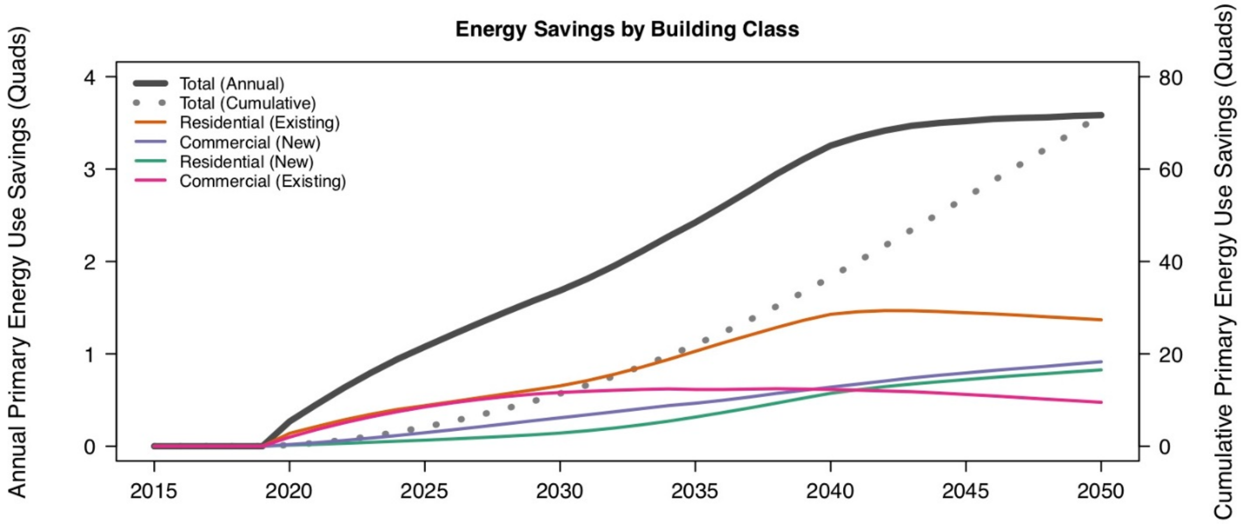

Figure 28. Total primary energy savings potential from sensor and control measures under a maximum adoption potential scenario broken down by building type

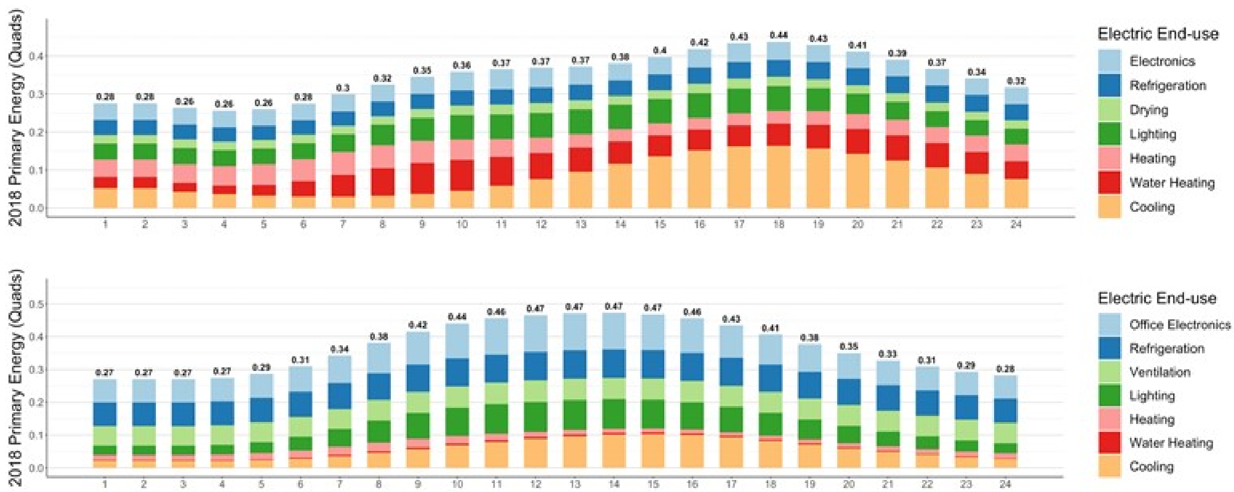

Figure 29. Total primary electricity use by end use and hour of day for U.S. residential buildings (top) and commercial buildings (bottom) in 2018

Source: DOE (2018b)

As noted in Section 1, the incorporation and enhancement of sensor and control schemes for energy efficiency, as laid out in this document, can provide the added benefit of serving as a framework for grid interactions, supporting reductions in peak-period energy demand along with the integration of variable renewable energy supply sources. In fact, studies have demonstrated that 10%–20% of commercial building peak load can be temporarily managed or curtailed to provide grid services (Kiliccote et al. 2016; Piette et al. 2007). Initial results from Scout analysis in Figure 29 show that the HVAC, lighting, and plug loads targeted by the efficiency measures in this document account for 982 terawatt-hours (TWh) of source electricity use annually between the peak hours of 2–8 p.m., which is well over half (57%) of annual peak period electricity use and worth $49 billion in electricity costs; these loads also account for 234 GW of average peak summer demand.[38]

[38] Estimated using time-sensitive analysis capabilities in Scout (https://scout-bto.readthedocs.io/en/latest/analysis_approach.html#time-sensitive-adjustment-of-total-co2-and-cost), which incorporate load shape data from the EPRI End Use Load Shape library (http://loadshape.epri.com/enduse) and

Accordingly, a controls measure that enables a 20% shed of peak period HVAC, lighting, and plug loads would avoid 196 TWh of annual electricity use, reduce average peak summer demand by 46 GW, and save $10 billion in consumer energy costs nationally, while a measure that shifted these loads earlier by 6 hours without reducing electricity use would still save $2.4 billion in electricity costs under time-varying electricity rates (see Figure 30).

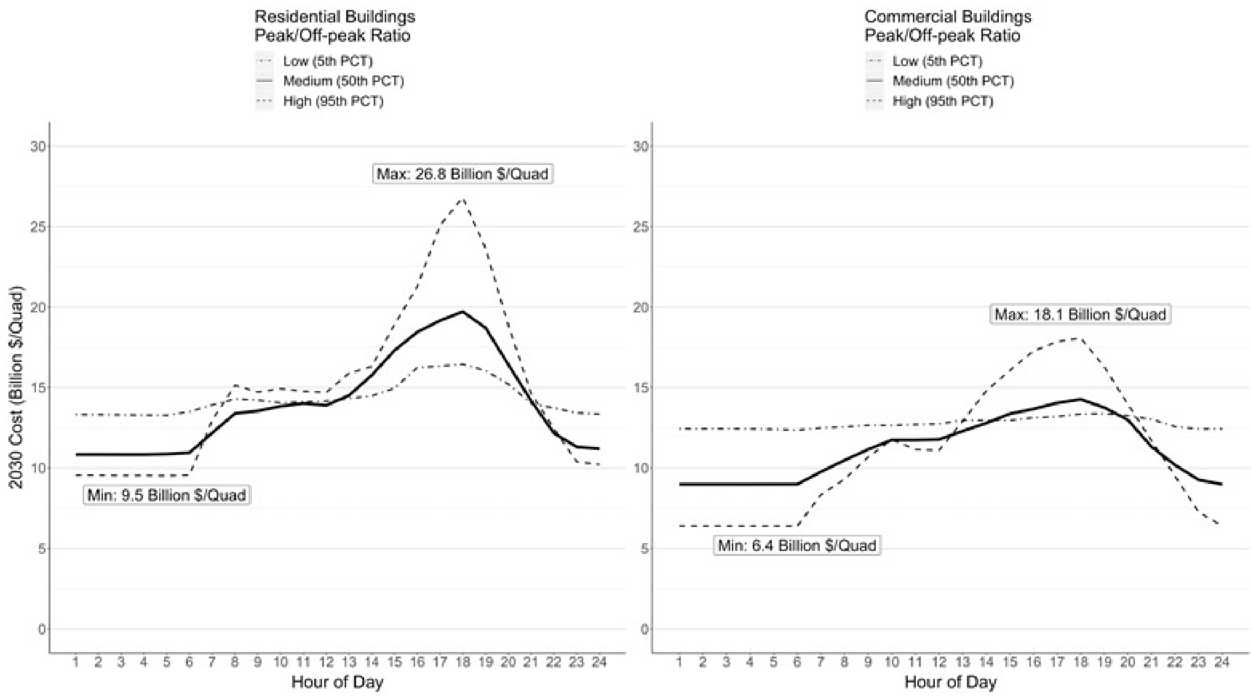

Figure 30. Current time-of-use electricity price curves for residential (left) and commercial (right) buildings reflecting 5th, 50th, and 95th percentile peak/off-peak price ratios

Source: OEI (2018)

3.3 Crosscutting R&D Strategies for Sensors and Controls in Buildings

This section briefly investigates emerging approaches that cut across the action plans in each of the R&D focus areas. Each of these strategies will contribute to enabling more cost-effective operation of sensor and control technologies within the buildings sector and accelerating the achievement of the identified performance and cost targets. Specifically, advanced manufacturing and materials, virtual sensing, data integration, and BEM are explored as enabling pathways to address the barriers identified within the R&D focus areas. These topics are not meant to be exhaustive, but rather represent approaches that are emerging or of increasing importance in their prevalence for building control systems. Some of these concepts are already established, and recent advancements in other sectors have made them more promising and viable solutions to explore in buildings. Others are still nascent and require tight coordination with other sectors to leverage emerging insights and findings from each other.

3.3.1 Advanced Materials and Manufacturing

Sensor performance improvements should benefit from advancements in the properties of the materials selected as the sensing media, energy storage or harvester devices, microcontrollers, and packaging enclosures and substrates. For the transducer, for example, new sensing modalities, improved sensitivity, longer-term accuracy, and faster response times have been enabled from the design and tuning of complex architectures of

Utility Rate Database (URDB, http://openei.org/wiki/Utility_Rate_Database). Peak demand estimates are based on average daily summer load shapes from the EPRI library. Costs are based on the 50th percentile time-of-use rate structure in the URDB, in terms of peak/off-peak price ratio.

nanoscale materials. Reduced dimensions and modifications to the surface area and chemistry of these materials (e.g., carbon nanotubes, perovskites) over the past two decades have demonstrated the ability to tune bulk mechanical and electronic properties (Shenderova, Zhirnov, and Brenner 2002; Correa-Baena et al. 2017). For example, the morphology and porosity of thin films used for humidity and carbon dioxide sensing will affect their adsorption of water and other chemicals (see Section 2). Advancements in nanomaterials for integrated circuits, including organic-based semiconductors, enhanced charge mobility and conversion efficiency of energy harvesting devices, and higher-density energy storage components can also be harnessed for improving microcontroller operation and power consumption management.

Organic or polymeric materials have also opened the avenue to flexible substrates, which can be patterned and printed using liquid phase materials (Rogers et al. 2010). In doing so, techniques such as inkjet printing offer a versatile and scalable alternative to conventional lithography for fabrication of the sensors themselves, as well as thin film transistors and integrated circuits, solar cells, and other devices. Ongoing research includes compatibility of solvents for different layers, feature registration and resolution, and uniform film deposition (Singh et al. 2010; Tekin, Smith, and Schubert 2008). Three-dimensional (3D) printing has emerged in the fabrication of complex and customized 3D geometries, which, similar to nanomaterials, can enable optimizing selected properties due to the high aspect ratios of the structures designed and the ability to precisely program and control the architecture. In contrast to two-dimensional (2D) techniques such as inkjet printing, 3D printing can also be used in the fabrication of electronic component interfaces in lieu of conductive glues and paints. To reduce the cost and enable mass production, however, the speed of the layer-by-layer nature of this fabrication technique needs to be increased (Mao et al. 2017; Leigh et al. 2012). Finally, molecular self-assembly is another bottom-up fabrication technique with active research in controlling nanoscale ordering as a means to optimize performance (Whitesides and Boncheva 2002).

3.3.2 Virtual Sensing

Virtual sensing is an alternative, low-cost method for estimating variables that are either difficult and expensive to monitor directly (e.g., measuring condensate discharge as an alternative to a humidity sensor), or for which installation of physical sensors is impractical or challenging (e.g., accessing refrigerant lines). This proxy approach can also be used to augment direct measurements and to calibrate installed physical sensors. Estimations are made through a combination of physical and/or virtual sensors of another variable(s), mathematical models, and property relationships. Modeling methods, which depend on the data available and application targeted, can be first principle or white box (i.e., physics based), black box (i.e., data driven), or gray box (i.e., a combination). Sensor outputs can be transient (e.g., feedback control) or steady state (i.e., where measured inputs change slowly or responses to input changes are fast). While virtual sensors have been used significantly in other sectors (e.g., automotive, industrial process control) over the past two decades, they have only recently emerged as a low-cost, noninvasive monitoring approach in buildings (Liu, Kuo, and Zhou 2009; Li, Yu, and Braun 2011).

Virtual sensors are particularly promising for real-time monitoring and diagnostics of equipment. Examples include vapor compression air conditioners (e.g., refrigerant charge, refrigerant pressure, refrigerant flow rate, compressor power consumption, energy efficiency ratio, compressor coefficient of performance), chillers (e.g., air humidity, condenser heat loss coefficient, reduced evaporator and condenser water flow), and air handling units (e.g., mixed air temperature, filter efficiency, supply and return fan airflow meters) (Li, Yu, and Braun 2011). Virtual sensing approaches are also emerging for other applications, including whole-building-level performance monitoring and fault detection and diagnostics (e.g., Frank et al. 2016) that can be applied in Section 3.5, as well as monitoring of occupancy variables (see Section 2.1.5) that can be applied in Section 3.7.

Similar to physical sensors, the performance of virtual sensors is based on their range, repeatability, sensitivity, and accuracy. For virtual sensors, these parameters are also dependent on the sensor inputs (both physical and virtual) and models used. There is a significant need for development of standard calibration and performance evaluation methods to assess the approach and inform further refinement of the physical inputs and models selected (Li, Yu, and Braun 2011). Furthermore, for situations where virtual sensors are utilized as cost-effective replacements to physical sensors, the accuracy and measurement error threshold relative to the systems-level performance (e.g., occupant comfort, operating efficiency) needs to be quantified for the given application to determine whether virtual sensing is the more effective energy savings approach.

3.3.3 Data Integration

Reducing the cost of building energy management technologies to achieve the goals laid out in this document (e.g., automating the discovery and configuration of connected devices and control systems) relies on methods that both harmonize descriptors and formats and automate the integration of data collected from points associated with sensors, actuators, and controllers within the system.

Data points include not just a single value, but rather a number of prescribed properties (e.g., sensor measurements, actuator outputs). Data inputs and outputs, including metadata (e.g., location of points, relationships between points), can be labeled in different formats—often assigned manually in inconsistent and customized formats depending on the vendor, manufacturer, or installer—that cannot be easily translated (Pritoni et al. 2018). Depending on the building size and level of monitoring and control, this lack of consistency in point names is especially challenging due to both the sheer volume of points and the manual nature of translation. The greatest limitation to cost-effectiveness of the approaches laid out in the individual action plans for advancing the intelligence in these systems is this manual and labor-intensive process for mapping and creating matches between the data streams for legacy building management systems and the emerging analytics engines or software applications that are responsible for adding more sophisticated control and embedded intelligence for energy management. Examples include the installation or upgrading of equipment, as well as the addition of or replacement of devices and reconfiguration of points. The point mapping process consists of classifying points (e.g., sensors, actuators) and determining relationships between points, and with equipment and physical systems within the building, to identify metadata that can be harmonized using a common taxonomy and then assigned to specific points. Standardized point names (e.g., Project Haystack) do not currently include all metadata or descriptive information about a point (e.g., sensor placement location) necessary for mapping. The manual assignment of semantics or meaning to distinguish points is also time consuming and subject to error. As such, common data or information models along with machine readable formats are under development.

As noted in Section 2.1.8, the recently announced ASHRAE Standard 223P will leverage Project Haystack and Brick to address the semantic dimension of interoperability for the BACnet protocol. Additional development is necessary for the tools and translators to reduce the time for generating and deploying Brick-based building applications (e.g., controls) and using them across a variety of communication protocols.

Automating the integration of these data sets through data point labeling and semantic inference is an active area of interest in the research community for buildings. Emerging approaches focus on the identification of patterns or correlations of points based on assigned relationships, including point values and names, to reduce the number of points that need to be mapped or assigned associations manually and semi-automate the process (Ortiz et al. 2013; Koc, Akinci, and Berges 2014; Bhattacharya, Hong, Culler, et al. 2015; Hong et al. 2015; Gao, Ploennings, and Berges 2015; Balaji et al. 2015). Along with accuracy and coverage, additional metrics that need to be considered when assessing enhancements to the integration and automation processes include the amount of time saved, as well as testing and automated translation techniques across diverse and heterogenous data sets and sets of buildings to address ongoing barriers to scale.

3.3.4 Building Energy Modeling

BEM development is critical to optimizing the performance of building control systems. Advances in control strategies (see Sections 3.6 and 3.7) explored in this document (e.g., algorithm design, implementation, and testing; continuous commissioning of control systems; and dynamic MPC development and application for energy efficiency optimization in real time) will rely on improvements made to address the barriers in conventional BEM engines (see Section 2.1.6). Current development efforts for EnergyPlus include the rearchitecture of the HVAC and control modules into a new implementation called Spawn-of-EnergyPlus

(Spawn) that incorporates the Functional Mock-up Interface standard for modular simulation along with the equation-based programming language, Modelica. These features provide several advantages, including addressing the gap in realistic modeling of controls (see Figure 31) (Wetter, Bonvini, and Nouidui 2016). Because Modelica allows for the creation of computationally efficient simulation engines with both dynamic and nonuniform varying time steps, high-frequency system dynamics can be modeled and, therefore, cycling behavior and other system changes that take place at arbitrary times can be accounted for (Wetter et al. 2015). In addition to varying time scales, the Functional Mock-up Interface and Modelica ease the integration with different engines to enable co-simulation of traditional applications (e.g., annual energy consumption) alongside building control system applications (e.g., AFDD and MPC) and incorporate information from both current building conditions and predictions for upcoming conditions (e.g., weather, occupancy, electric grid). The modular, plug-in simulation structure of Spawn also enables—depending on the market and application—evaluation of building-specific reduced-order or black-box models driven by measured data versus hybrid or gray-box approaches combining detailed models of the systems under control with a black-box model of the building and its loads (e.g., sensor, building state, and grid data streams). Spawn, which is currently under active development, is initially targeting control design and MPC use cases.

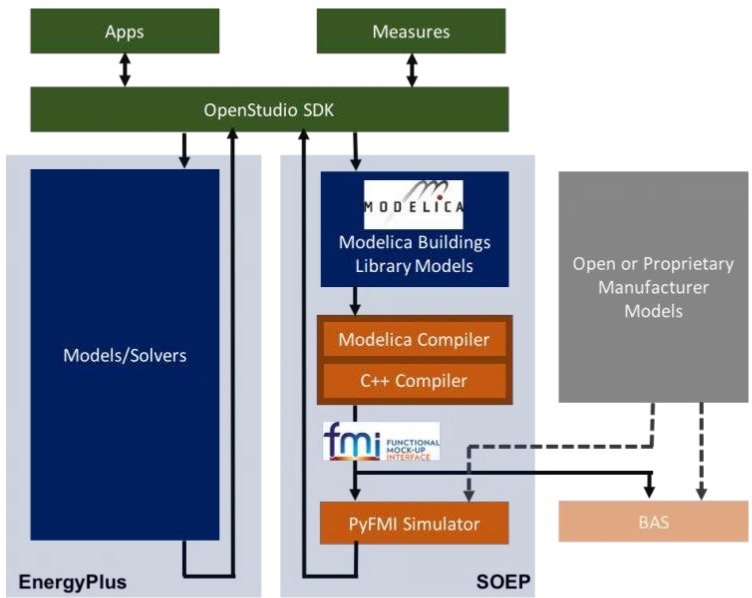

Figure 31. Next-generation simulation engine

Source: DOE (2019d)

In addition to realistically simulated controls, sequences written in Modelica can also be compiled and executed on actual control hardware, bridging the translation gap between control simulation and implementation. As such, integration of BEM tools with control design, verification, and implementation tools and workflows is also underway. OpenBuildingControl is developing translation and testing tools along with a Modelica library of high-performance control sequences (e.g., ASHRAE Guideline 36) to strengthen these bridges (Wetter, Grahovac, Hu, Eubanks, and Haves 2018). Unifying energy simulation and physical implementation using a single language and platform (see Figure 32) will eliminate translation inconsistences and errors between English descriptions of control strategies mentioned in Section 2.2 (Wetter, Grahovac, and Hu 2018). It will also align simulation with actual building controls to narrow the performance gap between design and operation through correct implementation and verification of control logic into physical controllers, and to reduce effort, cost, and error of designing, testing, and deploying control sequences.

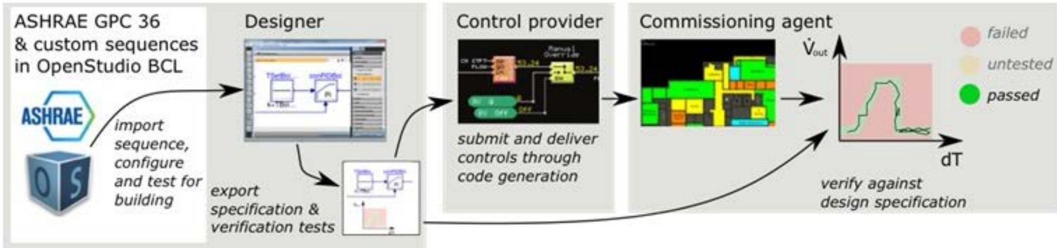

Figure 32. Framework for unifying energy simulation and physical implementation of building controls

Source: DOE (2019b)

These features will enable applications like continuous commissioning (see Section 3.5) that compare modeled operations to actual operations, and which can help building owners and operators detect and diagnose equipment and control logic faults. The ability to model faulty and degraded equipment can also help assess the trade-offs and impacts of correcting for suboptimal operations, as well as the development of adaptive control strategies. Finally, energy savings from sensor and control strategies can be more accurately estimated by simulating actual building operations and equipment performance.

3.4 R&D Focus Area #1: Multifunctional, Wireless Sensor Networks

3.4.1 Overview

The development of cost-effective, multisensing wireless networks with plug-and-play functionality should accelerate deployment of sensor networks in buildings and enable more efficient and effective building control strategies that save energy and enable more sophisticated and coordinated interactions with the electric grid. Wireless sensor networks represent a promising approach for data collection and monitoring building operations due to the elimination of power cables and wiring. These networks also enable flexibility in sensor placement and monitoring from remote locations, as well as the ability for relocation and reconfiguration of the system with changes in building layouts (Rodrigues, Cardeira, and Calado 2010). Many individual sensing elements required for such wireless networks are already commercially available and cost-effective. As noted in Section 2, current cost and performance (i.e., primarily long-term accuracy) limitations of existing sensors depend on the type of sensor. Even when the performance and cost of the sensors themselves are mature enough for building applications due to the advancements made in other sectors, the integration into a sensor node or package, coupled with installation and maintenance, can increase the cost substantially and present additional performance limitations. Exceptions that require advancements to the sensing medium itself include occupancy sensors, which are explored further in the Occupant-Centric Controls Focus Area (see Section 3.7). For the most part, however, sensor costs can be further reduced through integration into multifunctional sensing packages or networks that share processing and communication resources. Additional performance improvements—specifically long-term stability and accuracy of individual sensing elements, including indoor air quality, humidity, and daylighting—is also necessary.

Although multifunctional integrated sensors are commercially available, the cost of these packages is still high (typically >$100/node before installation, as identified in Section 2), and few options available offer the wireless transmission and systems-level integration capabilities needed for wider use as part of a building network. Moreover, the incorporation of multiple sensing elements on a single platform (see Figure 33 for an example) or network increases power consumption, reduces operational lifetime, and adds complexity to the calibration process for the system. The utilization of wireless communications will likely reduce the cost; however, such wireless solutions will require more efficient use of computing and power resources, improved positional accuracy and reliability, and extended data transmission ranges to achieve their full deployment potential.

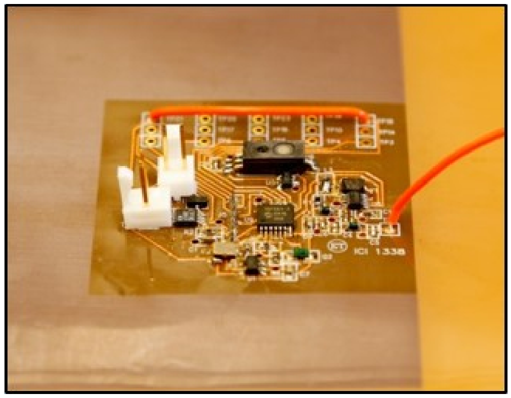

Figure 33. Wireless sensor circuit prototype on flexible polyimide substrate

Source: DOE (2016a)

Automated calibration at the system level through techniques such as data fusion and analytics can address the scalability challenges of the typical node-level approaches in identifying errors in sensor readings (e.g., noise, drift, bias) during both initial installation and ongoing operation. Automated configuration can significantly reduce BAS integration and commissioning efforts of newly connected sensors to meet application requirements of the network. For example, sensor data and the corresponding description of these data (e.g., position on a building schematic) are not currently represented in a format easily utilized by the energy management system, requiring manually mapping of points to a particular naming convention in order to be effectively digested (see Section 3.3).

Overcoming the barriers outlined in Table 4, along with the market deployment barriers listed in Table 5, will require achieving the following technical capabilities for multifunctional wireless sensor networks with plug-and-play functionality:

- **Long-lasting power sources** – Greater power efficiency will enable long-lasting power sources and reduce maintenance costs. Deployment of low-power approaches across the wireless protocol stack (see Section 2) will reduce the overall footprint of sensor packages, and more efficient energy harvesting and storage components will reduce manufacturing costs. Overall improvement in the mean time between sensor power source replacement or recharge will require: increasing the density and improving the performance of the power supply selected; optimizing the design of the sensor architecture and circuitry for signal conditioning to achieve lower power processors and systems; optimizing the network topology; increasing sensor communication range; and optimizing data processing for the designated end-use application and antenna design. The increased deployment of solid-state lighting also offers a potential source through the built-in circuitry to power not just lighting sensors, but other sensing elements as well.

- **Automated sensor node calibration** – Sensor node calibration includes correcting for errors of: (1) the sensing unit itself after manufacturing, (2) the sensor node after the sensors and other units are mounted, and (3) the change or drift in sensor characteristics over time due to age or damage. To enable plug-and-play functionality and further reduce installation and maintenance costs without the need for manual recalibration, automated calibration across the entire lifetime of accurate sensor operation (i.e., 5–10 years) is necessary, compared to the current 2- to 3-year calibration range. The lifetime reliability and accuracy of the sensing unit itself for indoor air quality and humidity must also be increased through material interface improvements, as addressed in Section 3.3.1. Automation at the system level is especially important in sensor networks consisting of multiple nodes and in multifunctional nodes consisting of multiple sensing elements, due to the scalability challenges of manual or node-level approaches. This will also be supported by improvements in AFDD techniques (see Section 3.5) through advances in data fusion and analytics.

- **Automated recognition and configuration** – Sensors placed within the range of a wireless network should automatically provide their identity, state, power use, and sensing capabilities to the network without requiring a physical connection. Automated sensor recognition should enable the location of sensors via unique identities and should be supported by secure communications between the sensing element and building control system; the positional accuracy and overall percentage of sensors correctly mapped are key areas of improvement for such approaches. Accurate sensor placement through automated point mapping will help ensure higher-quality measurements and optimal energy harvesting and wireless signal strength for uninterrupted operation. Automated point mapping (see Section 3.5) will also enable easier configuration of key sensor information in a building management system, streamlining sensor deployment in larger buildings with many sensor nodes.

3.4.2 Technical Barriers

Table 4. Technical Barriers to the Development of Cost-Effective Wireless Sensors

	Topic	Description
R&D Barriers	Enhanced wireless communications	• Reduction of current radio transmission power consumption levels to minimize network traffic • Elimination of interferences from other communication sources • Sufficient connectivity such that base station can be reached from any sensor node within a designated zone • Sufficient coverage for optimal quality of service throughout network
	Operational power lifetime	• Longer-lasting power supplies through more efficient energy harvesting and/or higher capacity energy storage • More efficient computing and lower resource algorithms and network topologies (i.e., for processing data and communications) to permit higher frequency sensing and automated operation (i.e., calibration, configuration) using limited power supplies • Optimization or elimination of conversion and processing of analog signals to digital format (i.e., on-board processing units consisting of microprocessors and analog-to-digital converters)
	Accuracy and reliability	• Elimination of measurement drift over time and longer-lasting accuracy of transducer and sensor node
	Modular design and materials cost reduction	• Additive manufacturing or printing of antenna, package, and other sensor node components • Pre-integrated sensors, components, and power connections for flexible placement during installation
Installation/Maintenance Barriers	IT system expansion	• Installation, maintenance, and operation of additional IT resources and support
	Fault tolerance	• Optimize intrusion detection and maintain communications and operation when a node in the network fails
	Automated calibration	• Self-calibration at the systems level based on relevant standards for the lifetime duration of accurate sensor operation without the need for manual or device-level recalibration
	Automated recognition and configuration	• Automatically provide identity, state, and power use • Eliminate manual configuration of sensor hardware and enable automated integration with a range of future and legacy systems and controls • Automated data validation, cleaning, and reporting methods to reduce intensive data scrubbing and provide real-time reporting of data collection faults
	Optimize placement methods	• Ability to easily mount and remount to any surface through flexible placement • Computerized optimization of placement location to maximize measurement and control performance.

3.4.3 Market and Deployment Barriers

Table 5. Market and Deployment Barriers to the Adoption of Wireless Sensors

Market/Deployment Barrier	Description
Cost	Installation and ongoing maintenance costs of these networks need to be reduced.
Interoperability	Common communication protocols and compatible sensing methods for multiple environmental characteristics and system variables, including future and legacy systems and controls, are necessary.
Cybersecurity	Latest developments from vendors and standards committees need to be incorporated to maintain secure communications across networks.
Building owner acceptance	Skepticism that the technology will not operate as reliably as wired solutions needs to be overcome where applicable.
Designer and technician acceptance and ability to understand and operate new systems	Designers and specifiers need to understand how wireless sensor networks function and how they should be configured for optimal performance. Technicians and facilities operations and maintenance staff need to understand how they function and how to maintain long-term functionality.
Lack of resources for installation and commissioning of sensors and related infrastructure	Proper installation, programming, and commissioning of sensors and controls are essential for proper operation, and most technicians do not have this training. Simplification and standardization of sensor and control systems along with training resources would improve successful deployments.

The technical capabilities listed above will enable the cost targets and energy performance goals for multifunctional, wireless sensors summarized in Figure 34. At market entry in both 2020 and 2030, the cost targets are higher for the commercial sector compared to residential. This is due to the smaller number of nodes per square foot assumed and the larger energy savings potential based on the larger amount of energy use per square foot for commercial buildings. The reduction in cost is more aggressive for the commercial sector as the technology evolves in 2030 compared to market entry. A 50% cost reduction is necessary by 2030 for an average one-year payback period across the entire commercial sector. The energy savings technical potential from these sensors is estimated to be at least one quad for both the commercial and residential sectors with 17% savings for HVAC and 35% savings for lighting. Table 6 lays out the action plan for addressing the identified barriers and achieving these goals.

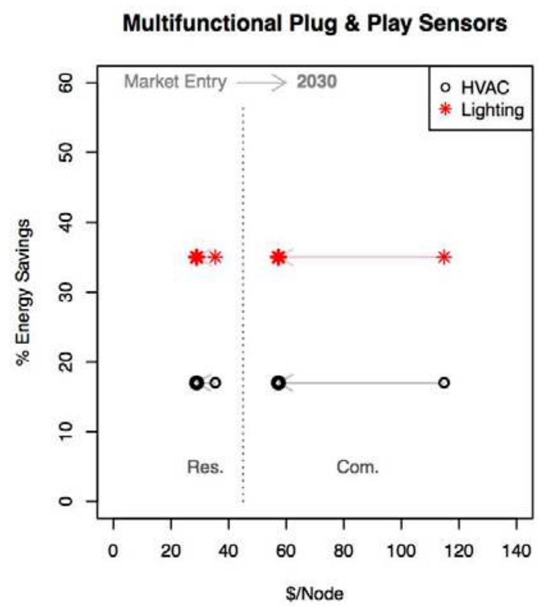

Figure 34. Cost targets and energy performance goals for wireless sensors networks

Ultimately, the objectives of the technology developers (e.g., selling as many sensors as possible, developing cheaper and higher-resolution sensors for all applications, and developing low power-consumption wireless sensors) need to be aligned with the needs of the end users (e.g., using as few sensors as possible, generating data from sensors that will reduce operational costs, and transferring large amounts of data). Cost reductions targeted in this action plan will permit higher sensor densities for more localized and personalized controls. Additional cost reductions can be achieved through increased deployment in the building stock. As outlined in subsequent R&D topic areas, the monitoring enabled by such sensors can serve as the basis for systems-level automated commissioning, and for the automated detection and mitigation of faults and disturbances in control systems. Depending on the end use and building size, achieving the specified performance targets will improve the observability and usability of sensor platforms with both a minimum number of nodes flexibly placed in the building and a minimum of equipment to be measured. An assessment of the minimum set of parameters critical to monitor for effective energy management system operation as a function of the building type, climate, occupancy patterns, and installed equipment and infrastructure can also reduce unnecessary costs while achieving optimal performance. Data collected can also be used to better learn the physical characteristics of the building to improve the accuracy of energy model inputs and model calibration.

3.4.4 Technology Action Plan

Table 6. Wireless Sensors Technology Action Plan

Topic Description: Wireless sensor platforms with plug-and-play functionality that consist of more than one sensing element with installed cost of $57/node for commercial and $29/node for residential by 2030.

<table>
<tr><th colspan="2">Activities</th><th>Milestones</th></tr>
<tr><td>Current (< 3 years)</td><td>• Test and demonstrate more efficient wireless communications
• Develop more efficient sensor nodes, more efficient energy-harvesting techniques, and longer-lasting energy storage (i.e., batteries)
• Develop self-calibrating sensors with microprocessor-assisted built-in self-tests
• Develop functional manufacturing prototypes of sensor nodes through printing approaches
• Further refine common protocols for connected (i.e., peer-to-peer) communication and optimize node- and network-level performance through standards-compliant communication interfaces
• Demonstrate abilities to leverage infrastructure and information from existing building and occupant systems to augment sensor and control systems.</td><td>• Order of magnitude reduction in radio transmission power consumption levels with elimination of interferences from other communication sources and demonstrated read distance of 10 meters
• Demonstrate >72 hours of continuous operation without recharging of multifunctional sensor node and >5 years of battery operation without replacement
• Drift and error in accuracy automatically identified and corrective/alert mechanisms in place
• Successfully test operation of printed sensor packages.</td></tr>
<tr><td>Mid Term (4–8 years)</td><td>• Demonstrate more efficient energy harvesting and longer-lasting batteries on installed sensor nodes during operation with optimized wireless communication (connectivity and coverage)
• Develop completely autonomous sensor calibration and correction mechanisms
• Scale up manufacturing of printed sensor nodes and components
• Optimize common protocols for distributed and integrated communication
• Develop and demonstrate commissioning and continuous calibration methods of wireless sensor networks.</td><td>• Order of magnitude reduction in ultra-low-power radio consumption levels for idle, sleep, and off-power states
• Sufficient connectivity and coverage achieved such that location of sensor node placement is not limited
• Demonstrate >96 hours of continuous operation without recharging of multifunctional sensor node and 10 years of battery operation without replacement
• Successful demonstration of auto-commissioning and continuous AFDD of wireless sensor networks in multiple building and system types.</td></tr>
<tr><td>Long Term (9–12 years)</td><td>• Optimize multifunctional sensor solutions that are fully automated in operation
• Optimize common protocols for enterprise communication.</td><td>• Optimize >96 hours of continuous operation without recharging of multifunctional sensor node and >10 years of battery operation without replacement, and with 99.9% reliability of data delivery for >10 years.</td></tr>
</table>

<table>
<tr><th colspan="3">Benefits and Impacts</th></tr>
<tr><th>Building Type</th><th>Impact</th><th>Description</th></tr>
<tr><td>New Construction</td><td>Medium</td><td>Cost reductions and automation of advanced, wireless sensor networks will provide greater versatility to install in remote or inaccessible locations.</td></tr>
<tr><td>Retrofit</td><td>High</td><td>Potential rewiring of existing, wired networks can be cost prohibitive. Transition to lower-cost wireless networks and improved connectivity will enable energy savings and advancements in control schemes through the easier installation of advanced, wireless sensors in locations that cannot be easily redesigned or reconfigured.</td></tr>
</table>

Activities		Milestones
Residential	Medium	Ease of installation and maintenance for wireless, plug-and-play sensor networks could assist in expanding beyond single-zone control configurations and provide additional data points for buildings lacking centralized infrastructure.
Small commercial	Medium	Ease of installation and maintenance for wireless, plug-and-play sensor networks will be useful where centralized building automation infrastructure is lacking by reducing the number of sensors needed and reducing installation costs through plug-and-play functionality in buildings >10,000 ft^2 with limited building energy management budgets.
Large commercial	High	Reduction of the number of sensors needed with addition of plug-and-play functionality (e.g., automated configuration and point mapping) will enable more cost-effective installation in buildings with large floor spaces and coverage requirements (i.e., >50,000 ft^2).

3.5 R&D Focus Area #2: Advanced Monitoring and Data Analytics

3.5.1 Overview

By capturing data downstream of the main utility meter, advancements in submetering, coupled with load disaggregation and analytic techniques (i.e., AFDD), will enable improvements to the monitoring of the actual energy consumption of individual building systems and components (e.g., air handlers, chillers), including providing information on the state and usage patterns of specific equipment along with essential data to verify energy savings. This level of granularity and ability to disaggregate loads can also serve as a means to monitor equipment health and usage. Comparing and verifying energy consumption can further enable monitoring-based commissioning by serving as a substitute to or supplementing data streams from the BAS (Parker et al. 2015). It is noted that this document focuses on electrical energy monitoring and not on other monetized energy flows such as gas, steam, and hot and chilled water. These other energy flows are very important but submetering is much more expensive and they can be estimated through other measurements.

Submeters provide crucial information for more granular or resolute measurement of energy consumption data. Unfortunately, submetering is still limited due to the meter costs as well as the technical complexity of installation, operation, and disaggregation. For example, plug loads are difficult to monitor because of their large number, low individual power consumption, and similar signatures, limiting the feasibility of complete coverage. Even with an order of magnitude in cost reduction of next-generation meters (see Section 2), cost is still a limiting factor, especially the labor required for installation. Recent hardware advancements in the field have included lower-cost clamp-on current transformers or "stick-on" meters, which also address installation concerns of traditional submeters. These devices, however, are neither revenue grade (<±2%) nor include the necessary hardware connectivity to integrate into a BAS or software dashboard. Innovations to the circuit board and outlets can help reduce overall cost and improve system performance (see Figure 35 for an example). The highest rated and most expensive submeter model currently available exhibits less than ±0.2% error of monitored energy use compared to actual energy use (Wall and Ward 2013). While developments in recent years have introduced next-generation smart meters to the market, the majority of existing installations are composed of traditional meters which require the exploration of retrofit pathways. Current transformers that are less bulky than in the past, for example, are being used to address safety issues with installation of new submeters, as well as "stick-on" approaches discussed. Other developments include automatic meter reading solutions that directly connect to the pulse output of traditional meters (Ahmad et al. 2016).

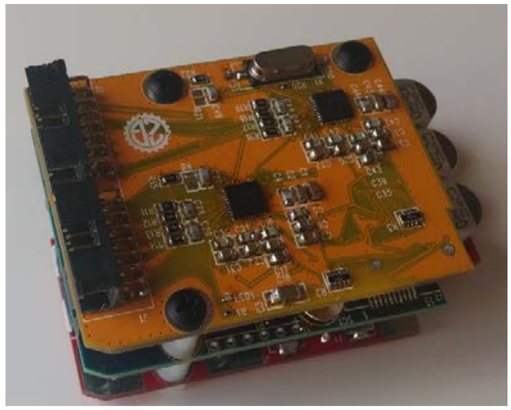

Figure 35. Representative submeter circuit board

Source: DOE (2018a)

Coupled with advancements to the submeters themselves and supporting connectivity elements, optimization of nonintrusive load monitoring can provide a low-cost pathway for collecting energy performance data by avoiding the installation challenges previously discussed. Load disaggregation techniques, through recent developments in software and data analytics, have demonstrated enhancements to the accuracy and resolution of measurements from existing hardware without additional metering installations. Evaluating and verifying data outputs from these techniques is required to better understand the extent to which they can overcome hardware deficiencies or installation barriers.

Finally, more cost-effective collection of more granular data on energy usage can be leveraged for improving AFDD methods (see Section 2 for more details). While a number of commercially available products exist, they tend to be rule based, requiring additional labor costs due to the tuning and customization required and result in high false positive rates when rules are violated (Frank et al. 2016). Both data-driven (i.e., black box) and empirical physics-based (i.e., white box) approaches, as well as hybrid options, are an active area of research due to the opportunity for improving detection and accuracy while minimizing the labor required (Kim and Katipamula 2017). Whole-building AFDD is still limited, however, due in part to the difficulty in isolating root causes of anomalous behavior. Systems-level abnormalities typically have a cumulative impact that arises from low-level impacts to various subsystems or equipment. For small commercial buildings and homes, approaches that minimize the reliance on a BAS for historical building performance data or on computational efforts to develop detailed models of the physical processes of the system will likely provide a pathway to incorporating AFDD. Ultimately, a combination of approaches will be necessary depending on the building size, configuration, and data available.

The desired technical capabilities summarized below require overcoming the barriers outlined in Table 7 along with the market deployment barriers listed in Table 8, such that revenue-grade submetering can be widely deployed as a cost-effective solution to building monitoring across all necessary loads along with whole-building AFDD approaches with sufficient accuracy to minimize false positives and negatives.

- **Advanced materials development** – Enhancements to the accuracy and resolution or granularity of energy performance measurements through next-generation submeters will require continued refinement to the magnetic properties of the materials selected and supporting connectivity hardware. This will include modular design options for reducing the overall systems cost and to overcome the installation challenges associated with connectivity to the electrical distribution system, as well as self-powered options to reduce overall installation and maintenance costs.

- **Enhanced analytics** – Advancements in machine learning approaches offer an opportunity to continue to explore and refine techniques for nonintrusive load monitoring and load disaggregation as an alternative to intrusive installation procedures and limited flexibility in retrofitting existing meter deployments. In particular, improvements to the quality of interval data and the impact on the accuracy of model calibration and fault detection, as well as the resulting energy savings, will need to be further evaluated and verified. The quality of data transfer in automatic meter reading and other communication solutions can also be further optimized through new and emerging analytical approaches. Machine learning approaches can also facilitate automated point mapping when installing AFDD or other analytic platforms on top of existing BAS infrastructure (see Section 3.3.3). In addition to scalable, whole-building AFDD approaches that isolate and diagnose faults, harmonizing fault definitions (i.e., condition based, behavior based, and outcome based), thresholds and evaluation metrics (i.e., if a fault can be correctly detected and isolated, the difference between the time when the fault occurs and the time when the fault is detected, the ratio of the fault detection number to the sample number under faulty conditions, the ratios of the false and missing fault detection numbers to the actual fault detection numbers, correct diagnoses rates), along with assessing the prevalence, severity, and impacts of common fault types will help prioritize opportunities for innovation and the development of proactive monitoring and corrective mechanisms, including fault tolerant features and adaptive controls that can temporarily adjust operations if repairs are required (see Section 3.6). Guidance for setting correct diagnoses rate targets will be particularly beneficial for whole-building AFDD algorithms that are designed to detect and diagnose many disparate faults. Smart devices, embedded with the appropriate computer logic, can allow for incorporation of diagnostic features as well.

- **Automated calibration, configuration, and connectivity** – Similar to Section 3.4, the ability to reduce measurement drift over time that is attributed to age and damage, along with automating the submeter calibration process, will enable plug-and-play functionality and further reduce installation and maintenance costs, which are especially sensitive to safety issues in metering applications. Automating the configuration process should enable integration with legacy building automation systems to enhance the monitoring-based commissioning process, as well as a variety of data acquisition and transfer systems depending on the building configuration and measurement needs.

3.5.2 Technical Barriers and Challenges

Table 7. Technical Barriers and Challenges to the Development of Advanced Monitoring and Analytics

	Topic	Description
R&D Barriers	High-accuracy hardware	• Removal of stray inductance and signal crosstalk • Elimination of measurement drift over time • Optimization of circuit board electronics and incorporation of higher accuracy transducers and devices
	Enhanced wireless communications	• Elimination of interference from other communication sources • Incorporation of connectivity features into submeters • Sufficient connectivity such that base station can be reached from any meter within a designated zone • Sufficient coverage for optimal quality of service throughout network
	Modular design and materials cost reduction	• Additive manufacturing or printing techniques for packages and relevant components • Pre-integrated components and power connections • Architecture designed for individual circuit breakers and for installation in space-constrained locations without sacrificing accuracy
	Automated fault detection and diagnostics	• Whole-building and system-level fault isolation with accurate root cause identification and diagnostic rates across multiple building systems • Severity of faults assessed, and diagnostics and correction prioritized, based on impact (cost and energy) and frequency • Improved detection of persistent, low-level faults with cumulative energy and cost impact • Minimized detection of inconsequential faults • Algorithm sensitivity and thresholds optimized to reduce false positive (i.e., false alarm) and negative (i.e., missed detection) rates
Installation/Maintenance Barriers	Long-term accuracy calibration	• Self-calibration through signal deconvolution without the need for manual recalibration, especially in hard-to-reach locations
	Automated configuration with existing or new building automation infrastructure	• Automatically provide identity, state, and power use • Configuration of meters to enable data acquisition and transfer to a variety of systems • Automated mapping of existing equipment points to facilitate integration of new analytics • Automated data validation, cleaning, and reporting methods to reduce intensive data scrubbing and provide real-time reporting of data collection faults
	Flexible placement methods	• Non-contact-based installation or approaches that do not disrupt electrical power connectivity to building operations • Options that are compatible with limited flexibility in connecting to the electric distribution system
	Occupant/operator engagement and feedback	• Occupant or operator platforms need to be user friendly to facilitate correct usage • Lack of guidance for installation, verification, and testing.

3.5.3 Market and Deployment Barriers

Table 8. Market and Deployment Barriers to the Adoption of Advanced Monitoring and Analytics

Market/Deployment Barrier	Description
Value proposition	Cost-benefit tradeoff for investment in advanced monitoring, data analytics, and AFDD is difficult to assess because information necessary to evaluate performance improvements with advanced analytics and fault impact (i.e., energy and cost) and repair is not easily available (i.e., installation and ongoing maintenance costs of products versus energy losses without).
Interoperability	Implement common communication protocols and compatible integration methods for multiple environmental characteristics, system variables, and hardware, including future and legacy metering systems and controls.
Cybersecurity and data protection	Incorporate latest developments from vendors and standards committees to maintain secure communications and ensure anonymization of individual energy consumption.
Safety and building codes	Specialized personnel and equipment need to be considered for submetering installation along with proper safety testing and certification for new approaches.
Building owner/tenant engagement	Split incentives, which may hinder installation, as well as limit impact to changes in consumption, must be considered; Usability and acceptance of AFDD and other analytic platforms challenged by suboptimal performance (e.g., false alarm rates), lack of trained personnel (e.g., on-site building energy manager or limited service contract), and lack of established performance baselines with which to evaluate purchases.

The R&D action plan shown in Table 9 will lead to the technical capabilities listed above, thereby enabling improved data analytics and AFDD through the incorporation of submetered energy data collected with higher accuracy and expanded coverage of relevant electric loads. While the energy savings attributed to submetering alone are minimal, a technical energy savings potential of 1.18 quads is estimated in the commercial sector alone for AFDD, enabled by advancements targeted in this action plan for achieving the cost targets and the outlined energy performance goals. Additional savings will be enabled with expansion into the residential sector as well. In fact, monitoring-based commissioning has demonstrated level or even slightly increasing savings over time when used on a consistent and ongoing basis (Mills 2011).

Advanced submetering will leverage enhancements to wireless communications and networking outlined in Priority Research Area #1. Similar to monitoring of environmental conditions through sensors, the final system configuration and hardware selected will be influenced by the application-specific requirements for monitoring of electricity consumption through submeters in a selected building. In addition to automated commissioning by comparing top-level or submeter information about building energy consumption to an appropriate baseline to automatically identify and diagnose operational faults, higher resolution energy use data enabled by low-cost, high-accuracy submetering will also facilitate more accurate model inputs and calibration of models to better align with actual operating conditions for predictive controls algorithms (e.g., MPC). Submetering usage can also contribute to occupancy energy usage and behavior along with schedule optimization (see Section 3.7). Additionally, detailed real-time information at a granular level can be aggregated to support the provision of grid services (see Section 4), as well as provide the necessary information to delineate the breakdown of usage with the “other” category and inform control strategies with which to enhance savings.

3.5.4 Technology Action Plan

Table 9. Advanced Monitoring and Analytics R&D Technology Action Plan

Topic Description: Advanced submetering with full coverage and revenue-grade accuracy of metered energy use for applicable loads in both residential and commercial buildings with an installed cost of $0.14/ft^2 floor for the commercial sector that will enable high-accuracy AFDD and monitoring-based commissioning.

	Activities	Milestones
Near Term (< 3 years)	• Evaluate degree of impact of enhanced accuracy and resolution (i.e., shorter time intervals for data collection) from emerging submetering solutions on improvements to AFDD, monitoring-based commissioning, and model calibration • Develop functional prototypes of hardware (meters, enclosure, and connectivity components) through new fabrication approaches and novel materials exploration • Investigate new machine learning approaches and data sets for load disaggregation and nonintrusive load monitoring • Develop and validate performance metrics and testing methodology for establishing baseline performance targets for AFDD design variants of HVAC systems.	• Revenue-grade submeters demonstrated in laboratory testing environment with a pathway to an installed cost of $0.14/ft^2 floor (for commercial buildings) • Performance metrics and baseline targets set for HVAC AFDD algorithms.
Mid Term (4–8 years)	• Develop completely autonomous data cleaning, calibration, and correction mechanisms • Scale up manufacturing of promising functional hardware prototypes • Optimize connectivity and data transfer algorithms based on power consumption and measurement requirements for inputs into monitoring-based commissioning and model calibration • Refine modeling and machine learning approaches for whole-building AFDD and optimize/scale across building types, systems, and subsystems • Refine testing methodology for AFDD design variants across building systems and establish acceptable performance targets for widespread adoption.	• Revenue-grade submeters tested and validated across building equipment and loads in building test beds at an installed cost target of $0.14/ft^2 floor (for commercial buildings) • Whole-building AFDD approaches tested and validated in building test beds at accessible performance targets.
Long Term (9–12 years)	• Optimize submeters across relevant equipment and load devices in real, operational buildings with built-in self-calibration capabilities and connectivity • Expand development and testing of whole-building AFDD algorithms across relevant building systems.	• Full coverage for installed building equipment and loads of interest with built-in "metering" of energy use at revenue-grade accuracy for both residential and commercial buildings and an installed cost of $0.14/ft^2 floor for the commercial sector • Whole-building AFDD algorithms embedded and validated in all relevant building systems.

Benefits and Impacts		
Building Type	**Impact**	**Description**
New construction	Medium	Enhanced capability for AFDD and monitoring-based commissioning through easier and lower-cost installation and commissioning during building design and construction.
Retrofit	High	The ability to incorporate metering into previously inaccessible spaces will be beneficial to ensuring energy savings from control schemes, participating in grid services, and conducting AFDD and monitoring-based commissioning on previously and newly installed loads.
Residential	Medium	Provides more information to residential utility customers on energy use (e.g., virtual auditing in multifamily) and identification of smaller loads, but AFDD less prevalent and overall savings limited without incorporation of control schemes and automation infrastructure to drive further savings. Cost targets still under development.
Small commercial	High	Provides more options for tenant-level measurements and controls to drive energy savings for buildings with a large number of small, heterogeneous loads and with limited automation infrastructure, existing AFDD, and energy management budgets.
Large commercial	High	Low-cost installation will be useful to larger buildings requiring additional monitoring and more granular data and enhanced analytics will be useful in implementing whole-building AFDD approaches where multiple, complicated systems are present.

3.6 R&D Focus Area #3: Adaptive and Autonomous Controls

3.6.1 Overview

The development of optimized, whole-building-level controls that are implemented correctly and respond proactively to timely information about building operations and predictions for the future (e.g., weather patterns, grid events, manifestation of faults and failures in equipment), with limited human intervention, should maximize the performance of building operations. Adaptive controls represent a promising approach to adjust operations based on dynamic and shifting conditions that impact energy usage. As noted in Section 2, advanced control schemes (e.g., MPC) have been demonstrated in limited cases for building applications (e.g., precooling and preheating in large commercial buildings). Advancements made in other sectors (e.g., industrial process control, automotive), where these control strategies are already more mature, can also be leveraged while addressing buildings-specific challenges. Performance improvements that minimize both manual and computational efforts in development, integration, coordination, and tuning are necessary for achieving affordable and reliable control schemes at scale and with sufficient spatial and temporal resolution.

Ubiquitous monitoring of building and equipment conditions through low-cost wireless sensor networks and submetering solutions, outlined in Sections 3.4 and 3.5, will greatly enhance evaluation of optimal parameters and resolution of data inputs for developing, training, and calibrating machine learning and forecasting approaches, along with model development for these control schemes. For example, site-specific weather forecasts for individual buildings can be useful in adjusting set points and calculating loads because weather-driven loads are the largest loads in buildings (Cooperman, Dieckmann, and Brodrick 2010). Given the importance of the role of the occupant in tuning operating conditions to account for comfort and movement, along with the challenges with current occupancy monitoring approaches and incorporation into control strategies, the topic of occupant-centric controls is evaluated in more depth in Section 3.6. Verification and validation of control performance and projected energy savings can also benefit from improved data collection.

Recent developments through Spawn-of-EnergyPlus and OpenBuildingControl, discussed in Section 3.3.4, are addressing the gaps in both realistic modeling of control sequences and equipment degradation or faults (e.g., sensor drift), as well as control implementation workflows through the re-architecture of the BEM engine, EnergyPlus, into the equation-based programming language Modelica. Improvements in modeling can be used to interpret and execute advanced control sequences directly for testing and optimization, integrate "real-time" data about building operating conditions instead of predefined input schedules, and save the simulation state and restart from the same state while changing selected variables. MPC approaches can benefit from these improvements through the ability to design, implement, and optimize control strategies in a sufficiently narrow time horizon (i.e., "real-time"). MPC, in turn, offers the benefits of coordinating across multiple systems, incorporating external parameter inputs, and considering future forecasts and disturbances (see Figure 36). Furthermore, enhanced occupant inputs evaluated in Section 3.7 can be integrated into the control loop. Machine learning techniques (e.g., deeply layered artificial neural networks) can be used to train building controls to recognize complex patterns that can be then used adapt to changes in operating conditions. Reduced order models (i.e., gray box) or purely data-driven (i.e., black box) approaches are promising alternatives because of their computational efficiency and simpler construction.

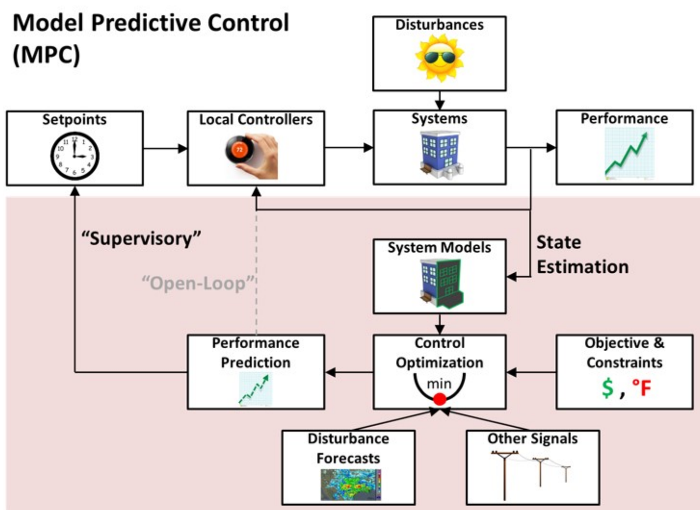

Figure 36. Representation of MPC approach

Source: DOE EERE (2019)

Overcoming the technical barriers outlined in Table 10, along with the market deployment barriers listed in Table 11, relies on the development of the following technical capabilities for adaptive and autonomous controls to be widely deployed and fully utilized as affordable solutions to optimize building operations:

- **Improved forecasting** – Improved forecasting with finer spatial resolution and over longer time horizons for stochastic variable inputs (e.g., weather) through physics-based and data-driven models or historical data will improve the accuracy and performance of autonomous control solutions. Proactive monitoring and improvements to predictive maintenance algorithms through the integration of real-time data about actual equipment performance, along with more realistic modeling of equipment degradation and faults, will enable more accurate predictions of future faults that will impact operations and will need to be accounted for in the control strategy selected. More realistic modeling of control sequences along with utilization of reduced order models when the details of the physics of the building or system are limited will inform predictive control design.

- **Optimized controls** – Control strategies that can capture the dynamics of the building with sufficient accuracy while permitting model development, calibration, and run times that are scalable and within the necessary time horizon for making adjustments to settings or taking corrective actions to maintain operations are required. Pattern recognition and machine-learning approaches, along with reduced order models, can contribute. Multi-objective optimization and prioritization is also necessary, along with optimization across local and top-level controllers in hierarchical architectures. The development of hybrid MPC approaches, where reduced-order MPC models are automatically generated from more detailed BEM models, along with reinforcement learning techniques, will be useful in balancing the tradeoff of approaches and developing flexible and reliable solutions that can tune to changing conditions with minimal customization.

- **Automated integration, coordination, and commissioning** – Equipment, devices, and other systems components must be capable of automatically sharing their identity, status, and availability with advanced building controls and operate successfully as an integrated system when necessary. Machine learning approaches to facilitate the automation of the point mapping process and standardization of control sequences and verification tests in an open, digital format will streamline the installation and implementation process for control systems in the building design or retrofit phase. More rigorous evaluation of control algorithms and establishment of expected performance will be possible through the use of recently developed building emulators.

3.6.2 Technical Barriers and Challenges

Table 10. Technical Barriers and Challenges to the Development of Adaptive and Autonomous Controls

	Topic	Description
R&D Barriers	Coordinated, system, and whole-building level controls	• Finer-grained optimization of multi-objective closed loop control across multiple systems and levels • Uniform, high-performance control sequences extended for all relevant end-use systems • Compatibility between local, individual controllers and whole-building-level operations, especially when BAS not present • Scalable calibration engine and approaches for integrating control algorithms across end uses • Improved integration of physics-based models with data-driven approaches across end uses and control system hierarchy • Improved communications for sending data and receiving commands across control systems.
	Forecasting/predictive capabilities	• Enhanced spatial and temporal resolution of forecasted data • Improved accuracy and precision of forecasted data, along with inputs and fidelity of energy forecasting models and algorithms • Improved calibration of simplified models and training data through improved sensor data inputs • Reduced computational intensity to expand prediction time horizon.
	Adaptive capabilities	• Enhanced data mining and cleaning techniques to automatically tune models based on shifting conditions • Real-time, automated optimization based on shifting conditions and competing constraints • Reduced computational intensity of adaptive control algorithms through optimal sensor placement and reusable sets of reduced-order models of building equipment and thermal conditions.
Installation/Maintenance Barriers	Automated fault correction, tolerance, and resilience	• AFDD integrated with risk management and critical controls • Prioritized correction based on prevalence and severity • System temporarily adapts when repairs are required or system is corrupted to ensure continuity of building operations.
	Automated configuration and implementation	• Reduced engineering labor and costs by automated tuning • Automated control logic implementation and verification with execution platform • Specification of high-performance control sequences in open digital format.
	Continuous commissioning	• Reduced customization and tuning by automating model generation to tailor to individual or groups of buildings • Incorporation of whole-building AFDD with minimally intrusive installation • Predictive maintenance algorithms to identify when and where scheduled maintenance needs to occur.

3.6.3 Market and Deployment Barriers

Table 11. Market and Deployment Barriers to the Adoption of Adaptive and Autonomous Controls

Market/Deployment Barrier	Description
Value proposition	Cost-benefit tradeoffs for advanced control strategies are difficult to assess due to existing technical challenges, uncertainty in guaranteed savings stemming from implementation and verification errors, as well as uncertainty in model or training data accuracy requirements and corresponding computational efforts compared to projected cost savings from performance improvements.
Interoperability	Common standards in data representation and semantics along with standard platforms for multiple communication protocols and control algorithms are necessary.
Building automation infrastructure	Retrofit installations on existing systems are hindered by legacy issues (e.g., manual point mapping, analog devices) and warranty concerns.
Capital expenditure	Alternatives or dramatic cost reductions are necessary for installing building automation infrastructure in buildings without existing equipment due to limited number of total zones and points that do not make the large up-front capital investment cost-effective.
Building owner and operator engagement	Comparison of performance features across products are difficult without established baseline, especially for risk-averse owners and operators. Lack of customer and operator education, interest, and awareness in new product development and implementation.
Privacy, cybersecurity, and resilience	Lack of network segmentation with other systems (e.g., financial, security, IT) and weak cybersecurity practices can compromise operation of control systems for energy management and accompanying data.

These technical capabilities listed above will be accomplished by the R&D action plan shown in Table 12 that will enable the cost targets and energy savings performance goals for the AFDD HVAC-based elements (see Figure 37) of the next generation of advanced and autonomous controls. As noted, the cost targets and energy performance goals are currently limited in this focus area to HVAC-based AFDD for the commercial sector. The earlier stage of development of this overall area precludes full evaluation of all technological performance features (e.g., MPC) in Scout and across applicable sectors. An initial increase in the installed cost target is expected (i.e., from $0.12/ft^2 floor in 2020 to $0.14/ft^2 floor in 2030) due to the incorporation of more sophisticated performance features (e.g., advanced submetering for AFDD). Similar to the results for incorporating comfort features into the occupant-centric sensors and controls focus area, this is observed along with a higher energy performance (i.e., from 20% savings in 2020 to 30% in 2030) due to more sophisticated control of building operations. More accurate estimations of energy savings attributed to control systems will result from more realistic prototypical building models and simulations developed through advancements in energy modeling (see Section 3.3.4) and inputs from monitoring data (see Sections 3.4 and 3.5). Incorporation of occupancy-based parameters through the advancements targeted in the next section (i.e., 3.7: R&D Focus Area #4) will also serve as a basis for optimizing control algorithms both spatially and temporally based on the impact of a broader set of stochastic variables on building operation conditions. Ultimately, the control architecture (i.e., centralized or hierarchical MPC versus decentralized or distributed) and approach selected (MPC versus machine learning) will depend on the building configuration and requirements. Implementing centralized or hierarchical MPC architectures for buildings with multiple zones required reduces the computational requirements, while decentralized or distributed architectures requires improving communication and optimization capabilities.

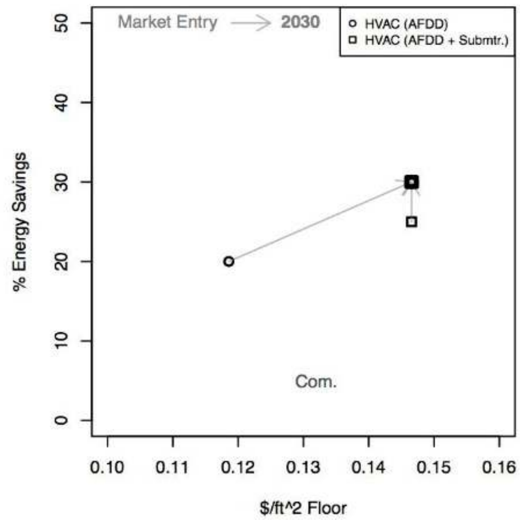

Figure 37. Energy performance goals for AFDD application in HVAC-based advanced controls

3.6.4 Technology Action Plan

Table 12. Advanced Controls R&D Technology Action Plan

Topic Description: Autonomous controls with an installed cost of <$0.14/ft^2 incorporating predictive and adaptive capabilities along with the ability to respond to anomalous behavior and stochastic environmental conditions in real time and over longer temporal periods at a whole-building level.

	Activities	Milestones
Near Term (<3 years)	• Develop new MPC algorithms with reduced development and run times, along with computational intensity • Develop framework to evaluate model accuracy and enhancements to energy savings based on development time and computational intensity • Develop hosting capability for testing innovative control algorithms with execution platforms and establish baseline key performance indicators for evaluating performance • Develop open digital format specification and verification for sophisticated HVAC-based control sequences	• Error-free implementation of advanced HVAC-based control sequences confirmed and >10% energy savings validated • Control algorithms that include enhanced AFDD for HVAC applications validated with an installed cost of $0.12/ft^2 in the commercial sector • Demonstrate virtual testing framework for evaluating algorithms using selected key performance indicators
Mid Term (4–8 years)	• Update assumptions of building performance and operating conditions (e.g., fault prevalence) in calibration of building energy models based on enhanced sensing, submetering, and forecasted data • Optimize advanced control algorithms (e.g., predictive, adaptive) using improved forecasting and data inputs over multiple spatial scales and longer time periods • Expand development of open digital format specification and verification for non-HVAC control sequences	• Formal process that connects design to operation and verification of design intent across all relevant building loads successfully implemented and available for developers, engineers, contractors, operators, and owners • Control algorithms that include enhanced AFDD for both commercial and residential sector applications validated • Controls algorithms that include hierarchical and multivariable optimization validated
Long Term (9–12 years)	• Fuller set of algorithms developed and optimized across building types at a whole-building and campus level • Validation of full system coverage.	• Formal process that connects design to operation and verification of design intent across all relevant building loads universally applied by control engineers in building installations • Control algorithms validated in both residential and commercial sectors with an installed cost of $0.14/ft^2 for HVAC-based AFDD applications in commercial.

Benefits and Impacts		
Building Type	**Impact**	**Description**
New construction	High	Emerging and sophisticated control sequences and architectures, along with applications and platforms, can be considered and incorporated into the building design phase for near optimal implementation and verification, maximizing the opportunity of achieving anticipated energy savings.
Retrofit	High	Easing implementation and integration of emerging and sophisticated control sequences and architectures, along with applications and platforms with legacy infrastructure, will facilitate adoption and maximize potential energy savings.
Residential	Medium	Approaches that reduce the need for additional sensor installation and centralized automation infrastructure will enable energy savings, especially in multitenant, multizone, or connected residences that exhibit more overall opportunity for savings.
Small commercial	Medium	Approaches that reduce the need for additional sensor installation and centralized automation infrastructure, as well as dedicated on-site energy management personnel, will facilitate adoption, although overall anticipated energy savings will be dependent on number of zones and monitoring and control points.
Large commercial	High	Emerging and sophisticated control sequences and architectures, along with applications and platforms, as well as more automated installation and maintenance approaches, should lead to substantial savings due to the high square footage potential and complexity of operations.

3.7 R&D Focus Area #4: Occupant-Centric Controls

3.7.1 Overview

The development of affordable and accurate occupant-centric operations relies on improved monitoring of occupancy conditions (i.e., presence, comfort, and adaptive behavior), improved understanding and modeling of occupant interactions and behaviors, and incorporation of these parameters into control strategies in a timely fashion to improve occupant comfort and productivity while reducing unnecessary energy usage and driving additional savings. In particular, improved sensing methods along with estimation and forecasting algorithms to monitor occupancy conditions should allow control systems to optimize operations based on these measurements. For example, plug load energy savings controls for computers and monitors can be improved by up to 80% using occupant distraction-recognition schemes to initiate sleep mode or disable when not in use (Munir et al. 2014). Unnecessary lighting and space conditioning can also be turned off based on occupancy detection. In fact, savings of up to 40% is well documented for both lighting and HVAC when simulated across multiple residential and commercial building types (Nguyen and Aiello 2013, and references therein). In more advanced systems that include variable drive air handling units, occupancy levels can be used to more accurately control temperature and ventilation proportional to the load that results from the number of occupants present. As much as one quad of annual energy savings is reported for such systems (Zhang et al. 2013). Most commercial buildings, however, still overestimate occupancy in design and operation, which results in conditioning and ventilating by assuming maximum rather than actual occupancy with static schedules. Furthermore, comfort measurements remain oversimplified through the use of standard acceptable temperature ranges, which are typically estimated at the group level. Even when preference feedback is available, it is often not incorporated due to slow equipment response times. These conditions can lead to actions such as occupant override (e.g., opening a window while the building is operating in heating mode). In the residential sector, settings are typically based on single zone coverage and readings from limited numbers of sensors. Ultimately, the result is wasted energy and suboptimal occupant comfort in zones where actual preferences do not warrant the use of space conditioning. As such, occupant-centric control schemes are essential in moving to a more localized paradigm of building conditioning where a base level of conditioning is provided by central systems, personal preferences are made up via local devices, and the control system manages the integration and optimization of both central and local conditioning states.

Response rates for adjusting space conditioning is limited due to delays from the underlying mechanical (e.g., compressors) and thermal (i.e., heat transfer) systems, which will need to be improved to provide more rapid and isolated thermal control in response to enhanced occupancy sensing. This is especially true in certain building configurations (e.g., open floor plans) due to the dynamic nature of occupancy (e.g., stochastic patterns in movements, differences in behavior and feedback) and poorly defined zones. In contrast, basic lighting controls can more commonly rely on simple binary detection and have instantaneous response times (i.e., automated on/off). Improved estimates and predictions of spatial and temporal occupancy patterns, along with timely incorporation into and response of equipment controls, will assist in maintaining acceptable comfort. This will likely not only prevent energy waste from overestimated operational settings but will also allow for detection of unexposed equipment and control logic faults through improved occupant engagement and feedback.

While maintaining occupant comfort is not always aligned with minimizing energy usage, multiple studies have reported savings enabled by incorporating occupant feedback and behavior on preferences. For example, one lighting study shows up to a 79% reduction in energy consumption from a control strategy that adjusts occupant lighting (Bourgeois, Reinhart, and Macdonald 2006). In the case of HVAC, 10%–40% savings are reported from tuning thermostat set points to individual comfort preferences (Erickson and Cerpa 2012; Murakami et al. 2007; Feldmeier and Paradiso 2010; Zhao et al. 2015). Additional savings were reported by including energy use with learned occupant comfort ranges in a multi-objective optimization scheme (Ghahramani, Jazizadeh, and Becerik-Gerber 2014). The mechanism for occupant feedback has to be evaluated, however, such that occupants do not override automated settings intended to achieve savings in a manner that results in equipment damage or in discrepancies between expected and measured energy usage (Turner and Frankel 2008). For example, the comfort requirements across a group of occupants can differ due to their heterogeneity, challenging communal thermostat settings. Furthermore, active occupant feedback (e.g., smartphones, tablets) is not always feasible or desired and surveys can only be conducted in controlled environments. The typical metric (i.e., air temperature) used as an occupant comfort proxy in control routines needs to be updated to incorporate multiple variables that affect comfort (e.g., metabolic rate, clothing insulation level, humidity, radiant temperature) through long-term, cost-effective, and calibrated measurements.

The following technical capabilities are necessary to address the R&D barriers listed in Table 13 along with the market barriers listed in Table 14 to enable optimized occupant-in-the-loop systems as shown in Figure 38 and the energy savings targeted in Figure 39:

- **Accurate occupancy detection** – Advancing existing approaches identified in Section 2, along with developing new sensing modalities, combining multiple modalities with improved fusion algorithms (e.g., Bayesian filter, particle filter), and leveraging pattern recognition and machine learning approaches will improve occupancy detection and positional accuracy, as well as reduce the time to determine changes in occupancy patterns. In addition to longer-lasting power sources and automation of the calibration, recognition, and configuration processes outlined in Section 3.4, cost reductions of the sensing medium and node components are also important because moving to decentralized and subzonal control requires more sensors. Increasing the effective sensing range of detection can also reduce overall systems cost by enabling the deployment of fewer nodes.

- **Integration of improved comfort and behavior measurements** – Beyond effective interfaces for occupant feedback and incorporating preferences, noninvasive and cost-effective approaches to measure or extrapolate direct comfort indicators—such as instantaneous and time-lagged physiological responses (e.g., skin temperature and heart rate)—and incorporate into models of real-time thermal comfort under current environmental conditions, are necessary. Improvements to the long-term performance and drift reduction of indoor environmental parameters that can also serve as proxies to occupancy monitoring (i.e., carbon dioxide) will also be useful. Viable and cost-effective ways to collect large-scale behavior data and to improve model evaluation and validation will allow for better coupling with comfort assessments. By effectively incorporating such models and data into control schemes, improved comfort and indoor environmental parameters will reduce energy used in zones where conditioning is not required.
- **Human-in-the-loop controls** – Timely and accurate adjustment of equipment controllers is necessary to match occupant dynamics (e.g., number of occupants, behavior, comfort, indoor air quality) with sufficient temporal and spatial resolution to better tune set points to real-time occupant conditions and preferences. This requires aggregating real-time data from building planning information, occupancy, local thermal environment, and comfort status across multiple occupants and effectively feeding the data into building management systems. Integration and optimization of both central and local conditioning will allow for personal preferences to be met by local devices that complement base-level conditioning from central systems. Modeling, along with deep learning using historical data, should reduce the reporting burden by determining individual occupancy and comfort profiles that can be used in place of direct feedback to the system. Reduced order models can address the challenges around strictly data-driven or physics-based approaches. Adaptive controls are treated in depth in Focus Area #3 (see Section 3.6).

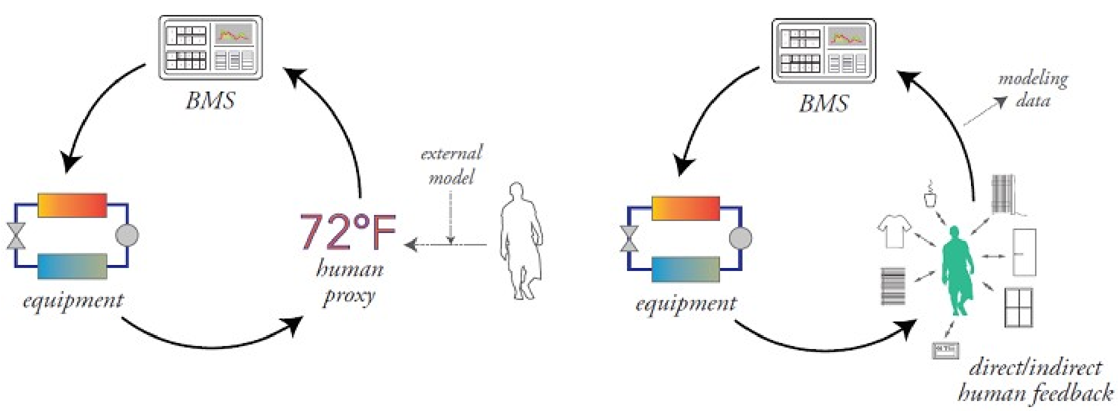

Figure 38. Comparison of current state-of-the art (left) incorporation of occupant comfort into building controls versus approaches under development (right)

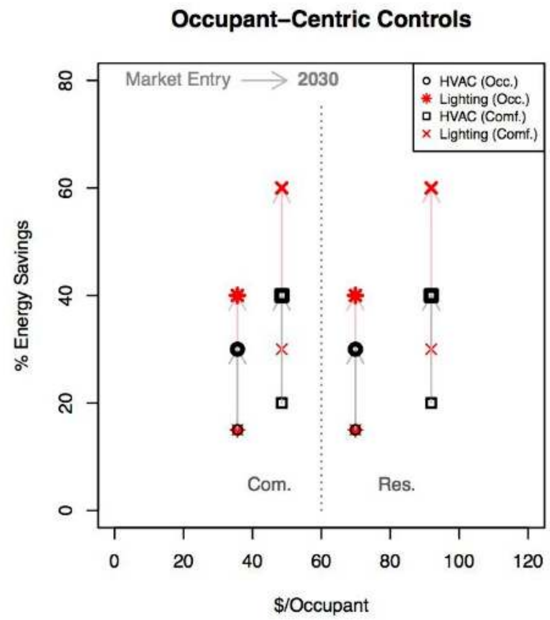

Figure 39. Cost and energy performance targets for occupant-centric sensors and controls

3.7.2 Technical Barriers and Challenges

Table 13. Technical Barriers and Challenges to the Development of Occupant-Centric Controls

Topic		Description
R&D Barriers	Occupancy detection	• Improve sensor accuracy and automated corrections for existing occupancy detection modalities limited by false positives and negatives • Lower cost of novel occupancy counting sensing mechanisms • Improve field of view and depth sensing (i.e., whole field) • Improve zonal coverage
R&D Barriers	Occupant comfort	• Account for occupant heterogeneity with different thermal comfort thresholds and adaptive behaviors • Clear correlation between novel physiological measurements (e.g., skin temperature measured via wearables) and comfort • Real-time comfort estimation based on direct occupant feedback to supplement secondary or model-based estimation • Improve indoor air quality and illuminance monitoring and understanding of the impact on occupant health and comfort thresholds
R&D Barriers	Adaptive models and controls algorithms	• Incorporation of heterogeneity of occupant comfort preferences; learning individual occupant comfort profiles given limited amounts of training data • Stochastic modeling of occupant actions and behavior • Adaptive control algorithms utilizing occupancy sensing data, rather than occupancy schedules, that balance multiple occupant comfort requests • Temperature, humidity, and occupancy (i.e., status, count, comfort, and interactions) with systems (e.g., windows, shades, lights, and thermostats) integrated into control schemes • Factors beyond single metric of air temperature (e.g., human metabolic rate, clothing level, and radiant temperature) incorporated into centralized control schemes • Integration and optimization of local conditioning devices with centralized control schemes where applicable • Limited availability of effective technologies for local occupant comfort including thermal, visual, and acoustic
Installation/Maintenance Barriers	Long-term accuracy and calibration	• Reduced drift for longer operation of CO_2 and humidity sensors • Automated calibration of new sensing modalities
Installation/Maintenance Barriers	Occupant engagement and feedback	• Reduced occupant override • Reliable and consistent occupant feedback that minimizes reporting burden (e.g., via a hybrid approaches) • User-friendly feedback mechanism to maximize utility
Installation/Maintenance Barriers	Automated recognition and configuration with existing building automation infrastructure	• Eliminate manual configuration and ensure interoperability with a range of future and legacy systems and controls • Commission to ensure proper operation prior to occupancy • Higher spatial resolution and temporal response times of equipment based on improved occupancy/comfort information • Subzone-level service provision for open/shared spaces effectively integrated with existing centralized control schemes and equipment designed for individual room/zone level.

3.7.3 Market and Deployment Barriers

Table 14. Market and Deployment Barriers to the Adoption of Occupant-Centric Controls

Market/Deployment Barrier	Description
Cost	High cost of existing occupant sensing modalities, as well as installation and ongoing maintenance; High cost of personalized heating and cooling devices that can integrate individual-level comfort and behavior data (e.g., heated and cooled chair); Relationship between improved occupant comfort and both energy savings and productivity must be incorporated into return on investment calculations.
Interoperability	Harmonization of communication in protocols necessary to support integration of occupant-centric feedback devices and central building management systems.
Privacy	Noninvasive approaches to detecting and counting occupancy and receiving individual-level comfort feedback are necessary; Relevant data collection must be securely stored without personally identifiable information and discarded after use.
Building codes	Oversimplified representation of occupants; Demand control ventilation is only required in ASHRAE 90.1-2013 for high-occupancy areas (i.e., spaces larger than 500 ft^2, >25 people/1,000 ft^2 of floor area, and served by systems with air-side economizers, automatic modulating control of outdoor and/or design outdoor airflow greater than 3,000 ft^3/m) and is based on 100% static occupancy; the standard 80% thermal acceptability target in ASHRAE Standard 55 is based on correlations between environmental and personal variables and thermal acceptability that were developed in the 1970s and are only appropriate for use at the group level given steady-state environmental conditions.
Distributed sensing platforms	Wearables and web-based applications are not available or desired by all occupants; Limited occupant intervention and interaction desired.
Building owner and operator engagement	Lack of customer and operator education, interest, and awareness of new product development and implementation; Understanding the benefits of sensors and controls as well as the trade-offs between different available technologies.

These technical capabilities listed above will enable the cost and performance targets in Figure 39 through two stages of development: (1) more accurate representation of occupant presence, followed by (2) improved estimation of real-time comfort and behavior. The incorporation of comfort into occupant-based controls schemes by 2025 increases the cost (i.e., from $70/occupant in residential and $36/occupant in commercial for occupant detection alone, compared to $92/occupant and $49/occupant with the incorporation of comfort) due to the added performance features and system complexity, while at the same time enabling further energy savings (30% savings for HVAC and 40% savings for lighting with occupancy detection alone, compared to 40% savings for HVAC and 60% savings for lighting with comfort). Occupant-centric sensors and controls exhibit a higher installed cost target at both market entry and 2030 for the residential sector compared to commercial—reflecting a substantially lower occupant density in the former sector and allowing a higher cost per occupant (Figure 40). These targets will be accomplished by the R&D action plan shown in Table 15.

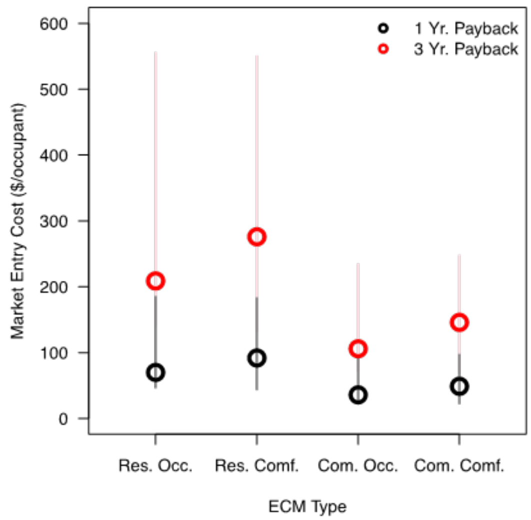

Figure 40. Cost target sensitivity analyses for occupant-centric sensors and controls

Ultimately, enhanced monitoring of occupant conditions coupled with effective incorporation into building equipment operations through dynamic modeling and adaptive controls will allow for an optimal balance between occupant satisfaction and energy savings. Different strategies (e.g., real-time versus pattern prediction of occupant movement and preferences) will be applicable for different sectors (e.g., transient patterns for public spaces like shopping centers and restaurants compared to fixed patterns for spaces like private offices). In the commercial sector, productivity will also benefit due to the correlation with comfort, increasing the attractiveness of such measures due to the substantially higher value of improving employee productivity when compared to saving energy (Lan, Wargocki, and Lian 2011). In addition, the implementation of DR and dynamic load shifting can be improved to better minimize unnecessary or unacceptable impacts to building occupants. Improved occupant engagement and feedback can also detect otherwise unexposed equipment and control logic faults highlighted in previous focus areas (see Sections 3.5 and 3.6). Finally, occupant information can be used as an input for both validating building simulation models and simulating new building or control designs based on realistic occupancy profiles.

3.7.4 Technology Action Plan

Table 15. Next-Generation Occupant-Centric Controls R&D Technology Action Plan

Topic Description: Local provision and control of space conditioning and lighting at the individual occupant level with installed cost of $49/occupant in the commercial buildings sector and $92/occupant in the residential buildings sector.

	Activities	Milestones
Current (<3 years)	• Develop techniques to reduce false positives and negatives of emerging, less privacy-invasive occupancy counting modalities (e.g., Doppler) • Correlate relationship between environmental factors (e.g., radiant temperature) and occupant comfort in the field, and incorporate it, along with metabolic rates and clothing insulation levels, and direct occupant feedback into updated thermal comfort models • Develop predictive and adaptive models with both traditional occupancy schedule data and more accurate primary occupancy data • Advance stochastic modeling of occupant movement and behavior • Improve schemes for machine learning of occupancy patterns and/or occupant preferences given minimal training data • Develop integrated occupant-centric indoor environmental quality control strategies with inputs from multiple occupants.	• Occupancy monitoring achieved at the room/subzone level and incorporated into enhanced building control scheme of $36/occupant for the commercial sector and $70/occupant for the residential sector with sufficient accuracy to achieve 15% savings in HVAC and 15% in lighting usage • Drift reduced to demonstrate a lifetime of >3 years for indoor air quality sensors (i.e., carbon dioxide, humidity) • Validate hierarchical models using a building emulator, as well as co-simulation of occupancy patterns and energy use.

	Activities	Milestones
Mid Term (4–8 years)	• Develop novel materials and interfaces, as well as device designs, for: (1) new and hybrid occupancy detecting modalities with wider field of view and depth; and (2) reduced drift of indoor air quality • Integrate occupancy recognition and indoor environmental quality sensing into modified subzone and microclimate control schemes for testing and validation of equipment response • Improve collection of more accurate occupancy recognition data along with stochastic models of occupant movement/behavior and incorporate into equipment control schemes • Update thermal comfort models to include more accurate real-time occupant data from newly developed sensors and assess comfort accurately at the individual level, accounting for the heterogeneity of and adjustments in individual comfort preferences over time • Automate configuration with a range of future and legacy systems and controls • Test, enhance, and update cybersecurity of emerging occupancy counting methodologies.	• Occupancy monitoring achieved at the room/subzone level and incorporated into enhanced building controls at $49/occupant for the commercial sector (including comfort estimation) and $92/occupant for residential (including comfort estimation) with sufficient accuracy to achieve 20% savings in HVAC and 30% in lighting usage • Drift reduced to demonstrate a lifetime of >5 years for indoor air quality sensors (i.e., carbon dioxide, humidity) • Models of personalized (individual level) thermal and visual comfort profiles that are trained using minimal occupant feedback data and easily updated given new data over time with median predictive accuracy >70% • Demonstrate improved controls with occupancy recognition sensors.
Long Term (9–12 years)	• Improve integration of occupant information into controls and equipment spatial and temporal response along with large-scale testing and commissioning to ensure proper operation prior to and during occupancy • Test, enhance, and update cybersecurity of improved occupancy-centric controls infrastructure • Inform updates to relevant codes and standards with more accurate and dynamic occupancy and thermal comfort information.	• Occupancy monitoring achieved at the room/subzone level and incorporated controls at $49/occupant for the commercial sector (including comfort) and $92/occupant for the residential sector (including comfort estimation) with sufficient accuracy to achieve 40% savings in HVAC and 60% savings in lighting usage • Integration of personalized comfort models and real-time subzone-level occupant feedback into centralized control sequences with model runtimes of >15 minutes and median predictive accuracy of >80% • Drift reduced to demonstrate a lifetime of 10 years for indoor environmental sensors (i.e., carbon dioxide, humidity).

Benefits and Impacts		
Building Type	**Impact**	**Description**
New construction	Medium	Reduced energy use and improved indoor environmental quality and occupant productivity will be enabled with ease of installation during building design and construction
Retrofit	High	Beneficial where system design and installation (e.g., easily configurable, plug-and-play) are essential due to legacy systems or lack of existing infrastructure in place
Residential	Medium	Occupancy counting is not as essential and additional impact will be dependent on incorporation of multizone strategies
Small commercial	High	Beneficial to areas with high occupancy and variability in occupancy patterns that need better zoning and can incorporate strategies without an existing centralized system in place
Large commercial	High	Especially impactful in areas with high occupancy and variability in occupancy patterns that are dependent on multizone strategies and automated tuning of demand control ventilation requirements

4 Crosscutting Challenges and Opportunities for Building Energy Management

4.1 Overview

Current performance limitations, along with buildings-specific scalability challenges for cyberphysical systems, are barriers to building energy management. As an enabling and crosscutting solution, the utilization of sensor and control technologies is just as dependent on external forces—both technology- and market-driven—as it is on performance improvements and cost reductions. Strategies for cybersecurity, the conversion of demand flexibility into grid services, and whole-building systems integration, supported by testing and validation in operational buildings, all need to be considered to ensure that innovations in these technologies achieve the desired energy savings and affordability objectives for buildings. A tight interconnection exists, and the success of these strategies also relies on achieving the targets identified in this document.

4.2 Cybersecurity

The integration of building energy management with information technology (IT) systems and growing use of network connectivity discussed in this document also introduce vulnerabilities to cyber-related attacks. While some protection is usually in place for access to user interfaces, the building energy management sector has historically invested less in cybersecurity than in critical infrastructure (e.g., electric grid), as compared to the security and financial sectors. Connectivity and cloud-based computing are relatively new, and the information collected through energy management systems has generally been less attractive to a potential hacker. For this reason, open communication standards for building automation (see Section 2) have provided little intrinsic security and data encryption in the past. If not properly addressed, the threat of potential cyber-related attacks, both real and perceived, can introduce additional risks that ultimately limit adoption of these connected systems and the benefits they provide.

The implementation of cybersecurity measures for control systems in buildings face several challenges. These include legacy systems originally designed for closed networks that may lack computational capabilities to incorporate state-of-the-art security features (e.g., software updates and patches) or to respond to attacks. A mixture of analog and digital controllers and devices can also make the identification of the point of compromise difficult. The added complexity and resulting cost to implement and maintain security practices also increases the overall payback period of these systems. Finally, human inputs—either intentional or accidental, including insufficient implementation of security measures or modification of device configurations or control parameters—remain a main point of entry into these systems. In the case of large commercial buildings this is exacerbated by limited training of building engineers and operators on IT practices, and limited training of IT personnel on building operations and design. In fact, manual reconfiguration or modification is the principal security threat for BACnet-based systems according to ASHRAE. The situation is similar in the residential and small commercial sectors, where without a building energy manager or operator, the owner must rely on their own expertise or support from a contractor or the vendor to install and protect a system and then ensure that regular updates are made and best practices are followed.

Cyber-related attacks can target either the network or the device layers of a cyberphysical energy management system to either gain access to the equipment being monitored and controlled or as an entry point into other IT systems (e.g., financial, security), also known as vector attacks. While vector attacks are of higher risk due to the information being targeted, they are also easier to protect against through separation and segmentation of network systems (Wendzel et al. 2018). In addition to network segmentation, system hardening, encrypting, authenticating accounts, documenting connection and access points, anonymizing data, and selecting upgradeable infrastructure that are regularly patched are all necessary to protect systems. These security measures are continually updated by vendors and standards organizations to address new and emerging threats and vulnerabilities. Furthermore, the National Institute of Standards and Technology Cybersecurity Framework provides standards, guidelines, and best practices that can be voluntarily followed to manage potential risks.[39] Underwriters Laboratory, which offers services for product testing primarily for electrical safety, is developing new testing and certification standards for cybersecurity in products including building controls through the Cyber Assurance Program.[40]

Evaluation of the level of robustness of security practices implemented is available through the DOE buildings Cybersecurity Capability and Maturity Model (B-C2M2), which has been adapted from the Cybersecurity Capability Maturity Model (C2M2) for building control systems (Glantz et al. 2016). The Department of Homeland Security maintains the Cyber Resilience Review to measure operational resilience and cybersecurity best practices.[41] Conducting impact assessments of vulnerabilities in network-connected equipment and building energy management systems is challenging due to the lack of data on prevalence and types of cyber-related attacks. Sensitivity analyses and testing frameworks are also necessary for developing responses for maintaining critical building operations once control algorithms are exposed to a malicious threat.

In addition to incorporating cybersecurity solutions and protection measures already established in the IT sector into connected equipment and control systems, as well as properly educating and training building owners and operators on IT and cybersecurity best practices, new control algorithms moving forward need to be developed from the onset of design with consideration for implementing cybersecurity schemes to ensure compatibility. While a balance between functionality and security is necessary, interoperability can also assist by identifying, addressing, and upgrading against attacks and evolving threats resulting from the reduction interfaces and translation layers on a frequent, consistent, and coordinated basis (Widergren et al. 2018). Predictive and adaptive controls explored in this document are also better suited in their design to respond to anomalous behavior compared to rule-based controls that are reactive in nature. In fact, adaptive control architectures are currently under development for mitigating attacks (e.g., Yucelen, Haddad, and Feron 2016). Cyber-related attacks on building controls can manifest themselves as suboptimal building operating conditions (e.g., occupant discomfort, equipment damage). As such, current methods for detecting faults originating from either adversarial (e.g., hacker) or benign (e.g., normal equipment wear and tear, engineer error, and incorrect control logic implementation) sources are similar. Differentiation between the two to identify the root cause of faulty operations is still challenging because unique patterns or symptoms may not be present. Additional development is necessary in techniques to properly isolate and diagnose a fault in order for the system to respond accordingly. Optimization methods are also useful in learning from faults and anticipating future attacks and responses of the system with minimal impact on operations and energy efficiency. Assessing and quantifying the prevalence of attacks on connected equipment and building controls, along with the energy losses resulting from cyber-related attacks that compromise operations, will be helpful.

4.3 Demand Flexibility

Demand-side resources, such as energy efficiency measures in buildings, not only save energy and reduce utility costs for the owner or occupant but can also lower electricity system costs for all customers by reducing energy and capacity needs. As previously noted, energy efficiency measures can be further combined with grid-interactive strategies (e.g., DR, distributed energy storage) to further reduce and change electricity consumption to minimize consumer and electricity systems costs, relieve system stress, deliver grid operational benefits through ancillary services, and integrate building-level distributed energy resources (DER). By converting demand flexibility into grid services, buildings can play an important role in modernizing the electric grid and supporting the transition to combined centralized and decentralized generation with intelligent load control (DOE 2015).

In general, the inherent flexibilities of buildings are not fully factored today and only whole-building meter readings are considered by connected DER and across the meter by the grid. Increasing the flexibility of demand side management from buildings relies on optimizing the interplay between energy efficiency, DR,

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[39] https://www.nist.gov/cyberframework
[40] https://industries.ul.com/cybersecurity
[41] https://www.us-cert.gov/ccubedvp/assessments

and energy storage. DR has evolved significantly since its introduction nearly three decades ago from one-way communication using phones and pagers for emergency events (e.g., limited generation capacity or constrained delivery capacity), or when wholesale prices were high, to two-way communication with increased locational capabilities allowing customers to opt out if needed through voluntary requests (Peak Load Management Alliance 2016; Smart Electric Power Alliance 2017). The control layer for DR between the requestor (i.e., utility or grid operator) and the offeror (i.e., building operator) consists largely of communication protocols and not actual engineering control methods. The actual control logic and actions are carried out either within buildings themselves or through a DR aggregator that sits between buildings and the electric grid. The vision for the next iteration of DR currently underway is for buildings to function as a main hub for autonomous communication by the BAS and other connected devices in response to dynamic electricity prices and/or other grid conditions. As such, advancements supporting the transition from reactive, rule-based controls in buildings to achieve energy efficiency goals are also critical both to the advancement and expansion of DR, and more broadly, optimizing the flexibility of buildings for effective interactions with the electric grid.

By both shifting loads to off-peak hours and shedding noncritical loads, building controls contribute to grid services that reduce generation capacity costs, as well as reduce delivery costs by deferring electric grid system upgrades. For the latter, distribution-level services are likely to be impacted most significantly by changes in building loads, whereas transmission services are less likely impacted. Extending building controls beyond energy-efficient operations to be grid interactive requires adding capabilities for interoperating with the grid and other DER equipment, as well as incorporating local DERs into control strategies and operational savings evaluations (DOE 2019a).

Overall, advancements laid out in this document can contribute to the conversion of demand flexibility into grid services in three ways. First, more affordable and accurate monitoring and analytics support characterization of a building's energy assets; modes and quantity of flexibility available to offer; and the impact of exercising this flexibility on the occupant. Second, executing control strategies on a continual basis that are optimized for changing conditions within the building can be leveraged for across-the-meter operations. MPC, for example, has already been demonstrated in use cases when implementing short-term control strategies to reduce energy demand during previously referenced peak periods (e.g., Pavlak, Henze, and Cushing 2014). Finally, both verification of building actions and reduction of electricity consumption and demand are enabled by more sophisticated monitoring and analytics, along with verification of correct control logic implementation. For example, AFDD methods can be useful in assessing the extent to which specific grid services are actually provided by a building.

Additional developments beyond this document are necessary to fully leverage sensor and control technologies at the building level to optimally support grid services. For example, key performance indicators for the co-optimization of energy efficiency and building load flexibility will need to be incorporated into sensor and control technology development. Furthermore, which grid services can be provided and coordinated by different control mechanisms (i.e., on-off versus continuous or modulated control), control architectures (i.e., equipment level versus end-use level versus whole-building level control) and system configurations (i.e., BAS versus non-BAS), needs to be determined. Characterization of the density and granularity of monitoring and analytics necessary to support control logic and actions, estimation and valuation, and measurement and verification of grid services, is also needed. In parallel, the extended visibility into grid operations resulting from advancements in sensing and measurement can provide critical information to building operations (e.g., preparation for impending blackout) (DOE 2015). As such, building and grid data streams will need to be aligned to address timescale and other integration issues.

4.4 Systems Integration and Field Testing

Innovations in sensor and control technologies will support optimized building operations that minimize occupant discomfort and energy waste. The incorporation of sensors and controls into equipment and systems will rely on additional R&D (beyond this document) when implemented and tested in operational buildings to verify and validate effective integration. The focus on automation and systems-level development in this document is intended to facilitate this. Harnessing technological advancements to achieve anticipated energy savings will rely on incorporating sensor and control strategies into the early stages of the design of building systems. The topics in this section should be considered at inception and the earliest stages of R&D because of the nature of the challenges in optimizing energy management in buildings.

4.4.1 Commissioning

A comprehensive analysis of commissioning projects indicates a median 16% whole-building energy savings for existing buildings (i.e., retro-commissioning) and 13% for new construction by testing the entire building under various conditions to verify intended performance, including the tuning of control parameters (Mills 2011). While commissioning is becoming more routine, the required cost, complexity, and customization are still issues. Sensors and controls play an important role in the commissioning process, including detecting errors that would otherwise go unnoticed (Roth et al. 2005; Fernandez et al. 2017). As noted within the individual focus areas and actions plans in this document, innovations in sensor and control technologies can be applied to enhance (e.g., AFDD), automate (e.g., automated point mapping), and extend (e.g., minimized sensor drift) both the initial or retro-commissioning processes, as well as continuous or monitoring-based commissioning. Incorporating the commissioning of controls themselves as part of installation during the building design phase will also maximize the actual energy performance so that these systems are not misused or abandoned. Definitions and best practices for commissioning will need to continue to be updated regularly based on new developments (Ferretti, Miyata, and Baumann 2018).

4.4.2 Data and Benchmarking

The generation of real, operational data through physical testing, as opposed to simulation, is essential to improving the fidelity of building energy modeling of controls, as well as benchmarking and assessing the performance of newly designed control algorithms (e.g., AFDD) and informing future R&D and product development. For example, MPC or techniques based on artificial intelligence (e.g., machine learning) rely on input or training data for development and optimization during execution. The utilization of real data can also help inform the minimal or optimal monitoring and sensing requirements of identifying building conditions and equipment status. Data, especially at the whole-building level, however, can be difficult to obtain and the quality of data is not always satisfactory enough for utilization. As such, correct and complete documentation and compilation of data sets along with identifying appropriate testbeds are all critical. Standard methods for understanding and describing the validity of building data measurements are also necessary. Finally, depending on the nature of the data collection, anonymity must continue to be considered and protected.

4.4.3 Decision Science

The decision-making process of building occupants helps elucidate intentions behind behavior and actions. Advancing the building control schemes outlined in this document require an understanding of not just occupant behavior, but also the intentions and decision making behind the behavior. As previously noted, one of the challenges of incorporating behavior into control schemes is that it is a key source of uncertainty in building energy models, with a range from –50% to +90% change reported in simulated energy consumption due to variations in behavior-related inputs (Hong and Lin 2013). Occupant intent and decision making will be influenced by the building type, occupant activity, and environmental stimuli. For example, task performance and productivity can be a driver for investment in technology upgrades in the commercial office setting. In better understanding the role of decision science on occupant behavior and actions, other factors that need to be considered include the way in which systems and user interfaces are designed. While this topic is outside the scope of this document, understanding and evaluating decision science will inform adoption and optimal use of intelligent sensor and control platforms.

4.4.4 Role of Building Engineer/Operator

In the commercial sector, building owners are the party responsible for operation and maintenance of energy systems for 84.8% of buildings and business owners or tenants are responsible in 13% of buildings (U.S. EIA 2016). For instances where the building owner is a landlord to a tenant, the split incentive structure can limit adoption. For example, there is little incentive to invest when the tenant is responsible for the energy bill, but the landlord is responsible for maintenance. In addition, energy management budgets are generally small relative to overall operating budgets with minimal support for training, even though installation and maintenance can be a large fraction of energy management expenses. The focus on automation and additional performance features in this document can assist with this issue. At the same time, opportunities to become familiar with new equipment and systems, along with training for installation, operation, and maintenance need to be considered. For example, many operational issues or faults can be attributed to improper use or programming of systems. Poor specification of control sequences and the high risk of improper implementation due to the level of customization required generates reluctance on the part of engineers, as well as controls vendors and installation contractors, to deviate from the status quo. Verification and validation data will be important to gain operator trust in new and more sophisticated systems.

4.4.5 Role of Energy Service Provider/Utilities

Building from existing programs, such as DR, energy service providers and utilities can benefit from increased incorporation and sophistication of building controls targeted within this document. Ultimately these systems can enable building flexibility and dispatch of DERs by integrating distributed demand-side management and DERs; reducing peak demand and managing load curves; enabling ancillary services such as ramping and frequency regulation; improving platforms for energy efficiency and demand-side management resources; and improving measurement and verification for utility- and/or government-sponsored energy efficiency and demand-side management programs, including pay-for-performance. Incentive structures by utilities and energy services providers can also facilitate the purchase and upgrade of building energy management systems by building owners.

4.4.6 Payback/Return on Investment

As previously noted, building controls and supporting technologies require aggressive payback periods (i.e., less than two years) due to limited energy management budgets for most buildings, especially those lacking automation infrastructure, along with the high upfront capital costs and necessary labor for installation and maintenance of these systems. Even when payback periods are sufficient, the return on investment is compromised if systems are not correctly installed and recommissioned during operation. As such, performance features are targeted throughout the individual action plans that will enable automated verification and validation. Solutions are also targeted for buildings lacking existing infrastructure (e.g., model-based AFDD). Furthermore, cost targets for each R&D focus area are based on a one-year payback period. Finally, while the integration of controls across building equipment and systems may not always produce additional energy savings, it can reduce the payback period and increase the return on investment by reducing capital expenditures through the sharing of automation infrastructure.

4.4.7 Codes and Ratings

To enable widespread adoption, advancements targeted in this document will need to consider how they will be implemented in the building design process to meet requirements for codes (e.g., ASHRAE Standard 90.1) and rating certifications (e.g., LEED, ENERGY STAR). Updates to ASHRAE Standard 90.1, which is the basis for energy codes adopted by U.S. states for buildings, with the exception of low-rise residential, include incorporation of additional sensor and control features (e.g., daylight sensors) along with requirement modifications. For example, the latest revision in 2016 included additional lighting controls and fault detection and diagnostics for economizers. Performance improvements outlined in this document can also inform updates to ASHRAE Standard 55 for the thermal environmental conditions for human occupancy, as well as ASHRAE Standards 62.1 and 62.2 for ventilation requirements. As this sector matures with additional intelligence embedded into monitoring and control systems, a rating for classifying smart buildings themselves might also be useful once technologies are widely commercialized for establishing expected performance.

References

Afram, Abdul and Farrokh Janabi-Sharaifi. 2014. "Theory and Applications of HVAC Control Systems – A Review of Model Predictive Control (MPC)." *Building Environment* 72: 343–355.

Ahmad, Muhammad Waseem, Monjur Mourshed, David Mundow, Mario Sisinni, and Yacine Rezgui. 2016. "Building Energy Metering and Environmental Monitoring – A State-of-the-Art Review and Directions for Future Research." *Energy and Buildings* 120: 85–102.

Balaji, Bharathan, Arka Bhattacharya, Gabriel Fierro, Jingkun Gao, Joshua Gluck, Dezhi Hong, Aslak Johansen, et al. 2016. "Brick: Towards a Unified Metadata Schema for Buildings." *BuildSys* '16.

Balaji, Bharathan, Chetan Verma, Balakrishnan Narayanaswamy, and Yuvraj Agarwal. 2015. "Zodiac: Organizing Large Deployment of Sensors to Create Reusable Applications for Buildings." *BuildSys* '15: 13–22.

Bhattacharya, Arka A., Dezhi Hong, David Culler, Jorge Ortiz, Kamin Whitehouse, and Eugene Wu. 2015. "Automated Metadata Construction to Support Portable Building Applications." *BuildSys* '15: 3–12.

Bhattacharya, Arka A., Joern Ploennigs, and David Culler. 2015. "Short Paper: Analyzing Metadata Schemas for Buildings – The Good, The Bad, and the Ugly." *BuildSys* '15.

Blum, D. H., K. Arendt, L. Rivalin, M. A. Piette, M. Wetter, and C. T. Veje. 2019. "Practical Factors of Envelope Model Setup and their Effects on the Performance of Model Predictive Control for Building Heating, Ventilating, and Air Conditioning Systems." *Applied Energy* 236: 410–425.

Bourgeois, Denis, Christoph Reinhart, and Iain Macdonald. 2006. "Adding Advanced Behavioural Models in Whole Building Energy Simulation: A Study on the Total Energy Impact of Manual and Automated Lighting Control." *Energy and Buildings* 38: 814–823.

Braun, James E. 1999. "Automated Fault Detection and Diagnostics for the HVAC&R Industry." *HVAC&R Research* 5(2): 85–86.

Burrati, Chiara, Andrea Conti, Davide Dardari, and Roberto Verdone. 2009. "An Overview on Wireless Sensor Networks Technology and Evolution." *Sensors* 9: 6869–6896.

Consortium for Energy Efficiency. 2014. "Residential Lighting Controls Market Characterization." https://library.cee1.org/system/files/library/11458/CEE_LightingMarketCharacterization.pdf.

Cooperman, Alissa, John Dieckmann, and James Brodrick. 2010. "Using Weather Data for Predictive Control." *ASHRAE Journal*: 130–132.

Correa-Baena, Juan-Pablo, Antonio Abate, Michael Saliba, Wolfgang Tress, T. Jesper Jacobsson, Michael Grätzel, and Anders Hagfeldt. 2017. "The Rapid Evolution of Highly Efficient Perovskite Solar Cells." *Energy and Environmental Science* 10 (3): 710–727.

Cowan, Alan. 2004. "Review of Recent Commercial Rooftop Unit Field Studies in the Pacific Northwest and California." New Buildings Institute, report to the Northwest and Conservation Council and Regional Technical Forum. White Salmon, WA.

Cree, J., A. Dansu, P. Fuhr, S. Lanzisera, T. McIntyre, R. Muehleisen, M. Starke, P. Banerjee, T. Kuruganti, and C. Castello. 2013. "Sensor Characteristics Reference Guide." Pacific Northwest National Laboratory, PNNL-22484.

Erickson, Varick L. and Alberto Eduardo Cerpa. 2012. "Thermovote: Participatory Sensing for Efficient Building HVAC Conditioning." *Proceedings of Buildsys* '12.

Fafoutis, Xenofon, Thomas Sørensen, and Jan Madsen. 2014. "Energy Harvesting – Wireless Sensor Networks for Indoor Applications using IEEE 802.11." *Procedia Computer Science* 32: 991–996.

Fanger, Povl Ole. 1970. *Thermal Comfort: Analysis and Applications in Environmental Engineering*. Copenhagen: Danish Technical Press.

Farahani, Hamid, Rahman Wagiran, and Mohd Nizar Hamidon. 2014. "Humidity Sensors Principle, Mechanism, and Fabrication Technologies: A Comprehensive Review." *Sensors* 14: 7881–7939.

Fares, Robert, Marina Sofos, Jared Langevin, Robert Hosbach, Alan Meier, Joshua Butzbaugh, and Paul Ehrlich. 2018. "Improving Characterization of Miscellaneous Energy Loads in Energy Demand Models." *2018 ACEEE Summer Study on Energy Efficiency in Buildings*.

Farese, Philip, Rachel Gelman, and Robert Hendron. 2012. "A Tool to Prioritize Energy Efficiency Investments." National Renewable Energy Laboratory, NREL/TP-6A20-54799.

Feldmeier, Mark and Joseph A. Paradiso. 2010. "Personalized HVAC Control System." *Proceedings of the Internet of Things* (*IOT*).

Fernandez, N., S. Katipamula, W. Wang, Y. Xie, M. Zhao, and C. Corbin. 2017. "Impacts of Commercial Building Controls on Energy Savings and Peak Load Reduction." Pacific Northwest National Laboratory, PNNL-25985.

Ferretti, Natascha Milesi, Masato Miyata, and Oliver Baumann. 2018. "A Retrospective on the Impact of Annex 40 and 47 Research on the International State of Building Commissioning." *Energy and Buildings* 158: 54–61.

Frank, Stephen, Michael Heaney, Xin Jin, Joseph Robertson, Howard Cheung, Ryan Elmore, and Gregor Henze. 2016. "Hybrid Model-Based and Data-Driven Fault Detection and Diagnostics for Commercial Buildings." *2016 ACEEE Summer Study on Energy Efficiency in Buildings* 12: 1–14.

Gao, Jingkun, Joern Ploennings, and Mario Berges. 2015. "A Data-Driven Meta-Data Inference Framework for Building Automation Systems." *BuildSys* '15: 23–32.

Ghahramani, Ali, Farrokh Jazizadeh, and Burcin Becerik-Gerber. 2014. "A Knowledge Based Approach for Selecting Energy-Aware and Comfort-Driven HVAC Temperature Set Points." *Energy and Buildings* 85: 536–548.

Gholamzadeh, Bahareh and Hooman Nabovati. 2008. "Concepts for Designing Low Power Wireless Sensor Network." *International Journal of Electrical, Computer, Energetic, Electronic and Communication Engineering* 2 (9): 1869–1875.

Glantz, Clifford, Sriram Somasundaram, Michael E. Mylrea, Ronald M. Underhill, and Andrew K. Nicholls. 2016. "Evaluating the Maturity of Cybersecurity Programs for Building Control Systems." *2016 ACEEE Summer Study on Energy Efficiency in Buildings*.

Granderson, Jessica and Guanjing Lin. 2016. "Building Energy Information Systems: Synthesis of Costs, Savings, and Best-Practice Uses." *Energy Efficiency* 9 (6): 1369-1384, DOI 101.1007/s12053-0169428-9.

Granderson, Jessica, Guanjing Lin, and Mary Ann Piette. 2013. "Energy Information Systems (EIS): Technology Costs, Benefit, and Best Practice Uses." Lawrence Berkeley National Laboratory, LBNL-6476.

Granderson, Jessica, Rupam Singla, Ebony Mayhorn, Paul Ehrlich, Draguna Vrabie, and Stephen Frank. 2017. "Characterization and Survey of Automated Fault Detection and Diagnostic Tools." Lawrence Berkeley National Laboratory, LBNL-2001075.

Grindvoll, Hanne, Ovidiu Vermesan, Tracey Crosbie, Roy Bahr, Nashwan Dawood, and Gian Marco Revel. 2012. "A Wireless Sensor Network for Intelligent Building Energy Management Based on Multi-Communication Standards – A Case Study." *Journal of Information Technology in Construction* 17: 43–61.

Harb, Hassan, Neven Boyanov, Luis Hernandez, Rita Streblow, and Dirk Müller. 2016. "Development and Validation of Grey-Box Models for Forecasting the Thermal Response of Occupied Buildings." *Energy and Buildings* 117: 199–207.

Harris, Chioke, Jared Langevin, Amir Roth, Patrick Phelan, Andrew Parker, Brian Ball, and Larry Brackney. 2016. "Scout: An Impact Analysis Tool for Building Energy-Efficiency Technologies." *2016 ACEEE Summer Study on Energy Efficiency in Buildings*.

Hempstead, Mark, Michael J. Lyons, David Brooks, and Gu-Yeon Wei. 2008. "Survey of Hardware Systems for Wireless Sensor Networks." *Journal of Low Power Electronics* 4: 1–10.

Henze, Gregor P., Doreen E. Kalz, Simeng Liu, and Clemens Felsmann. 2005. "Experimental Analysis of Model-Based Predictive Optimal Control for Active and Passive Building Thermal Storage Inventory." *HVAC&R Research* 11.2: 189–213.

Hong, Dezhi, Hongning Wang, Jorge Ortiz, and Kamin Whitehouse. 2015. "The Building Adapter: Towards Quickly Applying Building Analytics at Scale." *BuildSys* '15: 123–132.

Hong, Dezhi, Jorge Ortiz, Kamin Whitehouse, and David Culler. 2013. "Towards Automatic Spatial Verification of Sensor Placement in Buildings." *Proceedings of the 5th ACM Workshop on Embedded Systems for Energy-Efficient Buildings*.

Hong, Tianzhen and Hung-Wen Lin. 2013. "Occupant Behavior: Impact on Energy Use in Private Offices." Berkeley, CA: Lawrence Berkeley National Lab. https://www.osti.gov/servlets/purl/1172115.

Hou, Zhong-Sheng and Zhuo Wang. 2013. "From Model-Based Control to Data-Driven Control: Survey, Classification, and Perspective." *Information Sciences* 235: 3–35.

Hydeman, H., S. Taylor, and B. Eubanks. 2015. "Control Sequences and Controller Programming." *ASHRAE Journal* 57 (3): 58–63.

Institute of Electrical and Electronic Engineers (IEEE). 2007. "IEEE 1451.5: Standard for a Smart Transducer Interface for Sensors and Actuator – Wireless Communication Protocols and Transducer Electronic Data Sheet (TEDS) Formats." NY: IEEE.

International Energy Agency. 1991. "A Guide to Sensors for BEMS." *Energy Conservation in Buildings and Community Systems Programme* Annex XVI, Building and Energy Management Systems: User Guidance.

International Energy Agency. 2017. "Definition and Simulation of Occupant Behavior in Buildings." Annex 66.

Katipamula, S., R. M. Underhill, J. K. Goddard, D. Taasevigen, M. A. Piette, J. Granderson, R. Brown, S. Lanzisera, and T. Kuruganti. 2012. "Small- and Medium-Sized Commercial Building Monitoring and Controls Needs: A Scoping Study." Pacific Northwest National Laboratory, PNNL-22169.

Katipamula, Srinivas and Michael R. Brambley. 2005. "Methods for Fault Detection, Diagnostics, and Prognostics for Building Systems - A Review, Part 1." *HVAC&R Research* 11 (1): 3–25.

Kiliccote, Sila, Daniel Olsen, Michael D. Sohn, and Mary Ann Piette. 2016. "Characterization of Demand Response in the Commercial, Industrial, and Residential Sectors in the United States." *WIREs Energy Environ.* 5: 288-304. doi.org/10.1002/wene.176.

Kim, Woohyun and Srinivas Katipamula. 2017. "A Review of Fault Detection and Diagnostic Methods for Building Systems." *Science and Technology for the Built Environment*: 1–19.

King, Jen. 2018. "Energy Impacts of Smart Home Technologies." *American Council for an Energy-Efficient Economy, Report A17801*. https://aceee.org/sites/default/files/publications/researchreports/a1801.pdf.

Kintner-Meyer, Michael and Michael R. Brambley. 2006. "Are Wireless Sensors and Controls Ready for the Building Automation Industry? Selected Case Studies and Technology Development Activities." in World Energy Engineering Congress (WEEC) 2006 Proceedings, Association of Energy Engineers, Atlanta, GA.

Knight, Chris, Joshua Davidson, and Sam Behrens. 2008. "Energy Options for Wireless Sensor Nodes." *Sensors* 8: 8037–8066.

Koc, Merthan, Burcu Akinci, and Mario Berges. 2014. "Comparison of Linear Correlation and Statistical Dependency Measure for Inferring Spatial Relation of Temperature Sensors in Buildings." *BuildSys* '14.

Lan, Li, Pawel Wargocki, and Zhiwei Lian. 2011. "Quantitative Measurement of Productivity Loss Due to Thermal Discomfort." *Energy and Buildings* 43 (5): 1057–1062.

Leigh, Simon J., Robert J. Bradley, Christopher P. Purssell, Duncan R. Billson, and David A. Hutchins. 2012. "A Simple, Low-Cost Conductive Composite Material for 3D Printing of Electronic Sensors." *PLOS ONE* 7 (11): 1–6.

Li, Haorong, Daihong Yu, and James E. Braun. 2011. "A Review of Virtual Sensing Technology and Application in Building Systems." *HVAC&R Research* 17 (5): 619–645.

Liu, Lichuan, Sen M. Kuo, and MengChu Zhou. 2009. "Virtual Sensing Techniques and Their Applications." *IEEE International Conference on Networking, Sensing, and Control*.

Lu, Siliang, Weilong Wang, Shihan Wang, and Erica Cochran Hameen. 2019. "Thermal Comfort-Based Personalized Models with Non-Intrusive Sensing Technique in Office Buildings." *Applied Sciences* 2019, 9, 1768.

Ma, Yudong, Francesco Borrelli, Brandon Hencey, Andrew Packard, and Scott Bortoff. 2009. "Model Predictive Control of Thermal Energy Storage in Building Cooling Systems." *IEEE Conference on Decision and Control*: 392–397.

Macarulla, Marcel, Miquel Casals, Nuria Forcada, and Marta Gangolells. 2017. "Implementation of Predictive Control in Commercial Building Energy Management System Using Neural Networks." *Energy and Buildings* 151: 511–519.

Mao, Mao, Jiankang He, Xiao Li, Bing Zhang, Qi Lei, Yaxiong Liu, and Dichen Li. 2017. "The Emerging Frontiers and Applications of High-Resolution 3D Printing." *Micromachines* 8 (113): 1–20.

Mayne, David Q. 2014. "Model Predictive Control: Recent Developments and Future Promise." *Automatica* 50 (12): 2967–2986.

Meier, Alan, Cecelia Aragon, Becky Hurwitz, Therese Peffer, and Marco Pritoni. 2010. "How People Actually Use Thermostats." *2010 ACEEE Summer Study on Energy Efficiency in Buildings*.

Metzger C. E., S. Goyal, and M. C. Baechler. 2017. "Review of Residential Comfort Control Products and Opportunities." Pacific Northwest National Laboratory, PNNL-27141. https://www.pnnl.gov/main/publications/external/technical_reports/PNNL-27141.pdf.

Mills, Evan. 2011. "Building Commissioning: A Golden Opportunity for Reducing Energy Costs and Greenhouse Gas Emissions." *Energy Efficiency* 4: 145–173.

Mills, Evan and Paul Matthew. 2009. "Monitoring-Based Commissioning: Benchmarking Analysis of 24 UC/CSU/IOU Projects." Lawrence Berkeley National Laboratory, LBNL-1972E.

Moon, Jin Woo, Younju Yoon, Young-Hoon Jeon, and Sooyoung Kim. 2017. "Prediction Model and Control Algorithms for Predictive Applications of Setback Temperature in Cooling Systems." *Applied Thermal Engineering* 113: 1290–1302.

Munir, Sirajum, John A. Stankovic, Chieh-Jan Mike Liang, and Shan Lin. 2014. "Reducing Energy Waste for Computers by Human-in-the-Loop Control." *Emerging Topics in Computing, IEEE Transactions* 2 (4): 448–460.

Murakami, Yoshifumi, Masaaki Terano, Kana Mizutani, Masayuki Harada, and Satoru Kuno. 2007. "Field Experiments on Energy Consumption and Thermal Comfort in the Office Environment Controlled by Occupants' Requirements from PC Terminal." *Building and Environment* 42: 4022-4027.

National Institute of Standards and Technology (NIST). 2014. "Framework for Improving Critical Infrastructure Cybersecurity: Version 1.0."

National Science and Technology Council Committee on Technology (NSTCCT). 2011. "Submetering Of Building and Energy Usage."

Navigant. 2016. "Advanced Sensors in Intelligent Buildings Expected to Exceed $1 Billion in 2016." *The ACHR NEWS*. February 1, 2016. https://www.achrnews.com/articles/131638-advanced-sensors-in-intelligent-buildings-expected-to-exceed---billion-in--.

Nguyen, Tuan Anh and Marco Aiello. 2013. "Energy Intelligent Buildings Based on User Activity: A Survey." *Energy and Buildings* 56: 244–257.

Open Energy Information (OEI). 2018. "Utility Rate Database." Last modified August 17, 2018. https://openei.org/wiki/Utility_Rate_Database.

Parker, S. A., W. D. Hunt, K. M. Fowler, W. F. Sandusky, G. P. Sullivan, B. K. Boyd, K. L. McMordie Stoughton, T. M. Koehler, and R. Pugh. 2015. "Metering Best Practices: A Guide to Achieving Utility Resource Efficiency, Release 3.0." Pacific Northwest National Laboratory, PNNL-23892. https://www.energy.gov/sites/prod/files/2015/04/f21/mbpg2015.pdf.

Parks Associates. 2015. "Over 40% of thermostats sold in 2015 will be smart thermostats." July 15, 2015. http://www.parksassociates.com/blog/article/pr0715-smart-thermostats.

Parmenter, Kelly E., Patricia Hurtado, Greg Wikler, and Clark W. Gellings. 2008. "Dynamic Energy Management." *ACEEE Summer Study on Energy Efficiency in Buildings*: 10-118–10-132.

Pavlak, Gregory S., Gregor P. Henze, and Vincent J. Cushing. 2014. "Optimizing Commercial Building Participation in Energy and Ancillary Service Markets." *Energy and Buildings* 81: 115–126.

Peak Load Management Alliance. 2016. "Evolution of Demand Response in the United States Electricity Industry." https://www.peakload.org/assets/dr-dialogue/Evolution-of-DR-White-Paper.pdf.

Perry, Christopher. 2017. "Smart Buildings: A Deeper Dive into Market Segments." *American Council for an Energy-Efficient Economy* Report A1703.

Piette, Mary Ann, David S. Watson, Naoya Motegi, and Sila Kiliccote. 2007. "Automated Critical Peak Pricing Field Tests: 2006 Pilot Program Description and Results." Lawrence Berkeley National Laboratory, LBNL-59351.

Pritoni, Marco, Chris Weyandt, Deirdre Carter, and John Elliott. 2018. "Towards a Scalable Model for Smart Buildings." *ACEEE Summer Study on Energy Efficiency in Buildings*.

Rault, Tifenn, Abdelmadjid Bouabdallah, and Yacine Challal. 2014. "Energy Efficiency in Wireless Sensor Networks: A Top-Down Survey." *Computer Networks* 67: 104–122.

Rockett, Peter and Elizabeth Abigail Hathway. 2017. "Model-Predictive Control for Non-Domestic Buildings: A Critical Review and Prospects." *Building Research and Information* 45 (5).

Rodenas-Herraiz, David, Antonio-Javier Garcia-Sanchez, Felipe Garcia-Sanchez, and Joan Garcia-Haro. 2013. "Current Trends in Wireless Mesh Sensor Networks: A Review of Competing Approaches." *Sensors* 13: 5958–5995.

Rodrigues, F., C. Cardeira, and J. M. F. Calado. 2010. "The Impact of Wireless Sensors in Buildings Automation." *Ibersensor*, Lisbon, Portugal.

Rogers, John A., Takao Someya, and Yonggang Huang. 2010. "Materials and Mechanics for Stretchable Electronics." *Science* 327: 1603–1607.

Roth, Kurt W., Detlef Westphalen, Michael Y. Feng, Patricia Llana, and Louis Quartararo. 2005. "Energy Impact of Commercial Building Controls and Performance Diagnostics: Market Characterization, Energy Impact of Building Faults and Energy Savings Potential." TIAX LLC.

Schumann, Anika, Joern Ploennigs, and Bernard Gorman. 2014. "Toward Automating the Deployment of Energy Savings Approaches in Buildings." *BuildSys*.

Shenderova, O., V. Zhirnov, and D. Brenner. 2002. "Carbon Nanostructures." *Critical Reviews in Solid State and Materials Sciences* 27 (3-4): 227–356.

Shu, Feng, Malka N. Halgamuge, and Wei Chen. 2009. "Building Automation Systems Using Wireless Sensor Networks: Radio Characteristics and Energy Efficient Communication Protocols." *Electronic Journal of Structural Engineering*: 66–73.

Singh, Madhusudan, Hanna M. Haverinen, Parul Dhagat, and Ghassan E. Jabbour. 2010. "Inkjet Printing–Process and Its Applications." *Advanced Materials* 22: 673–685.

Siroky, Jan, Frauke Oldewurtel, Jiri Cigler, and Samuel Privara. 2011. "Experimental Analysis of Model Predictive Control for an Energy Efficient Building Heating System." *Applied Energy* 88: 3079–3087.

Smart Electric Power Alliance. 2017. "2017 Utility Demand Response Market Snapshot." https://sepapower.org/resource/2017-utility-demand-response-market-snapshot/.

Sofos, Marina and Jared T. Langevin. 2018. "Laying Down the Foundation: An R&D Roadmap for Energy Savings through Advancements in Smart Building Technologies." *2018 ACEEE Summer Study on Energy Efficiency in Buildings*.

Taylor, Steven T. 2018. "Making VAV Great Again." *ASHRAE Journal*: 64–71.

Tekin, Emine, Patrick J. Smith, and Ulrich S. Schubert. 2008. "Inkjet Printing as a Deposition and Patterning Tool for Polymers and Inorganic Particles." *Soft Matter* 4: 703–713.

Tuenge, Jason and Michael Poplawski. 2017. "PoE Lighting System Energy Reporting Study." U.S. Department of Energy. https://www.energy.gov/sites/prod/files/2017/04/f34/2017-02%20ssl-poe_part1_0r.pdf.

Turner, Cathy and Mark Frankel. 2008. "Energy Performance of LEED for New Construction Buildings." Washington, D.C.: New Buildings Institute. http://www.usgbc.org/Docs/Archive/General/Docs3930.pdf.

Urban, Bryan, Kurt Roth, and Chimere (David) Harbor. 2016. "Energy Savings from Five Automation Technologies: A Scoping Study of Technical Potential." *Final Report to the Consumer Technology Association*, Fraunhofer USA Center for Sustainable Energy Systems.

U.S. Department of Energy. 2015. "Grid Modernization Multi-Year Program Plan." https://energy.gov/sites/prod/files/2016/01/f28/Grid%20Modernization%20Multi-Year%20Program%20Plan.pdf.

U.S. Department of Energy, Building Technologies Office. 2016a. "Low-Cost Wireless Sensors for Building Applications." https://www.energy.gov/eere/buildings/downloads/low-cost-wireless-sensors-building-applications.

U.S. Department of Energy, Building Technologies Office. 2016b. "Multi-Year Program Plan Fiscal Years 2016–2020." https://www.energy.gov/sites/prod/files/2016/02/f29/BTO_MYPP_2016.pdf.

U.S. Department of Energy, Building Technologies Office. 2016c. "Overview of Existing and Future Residential Use Cases for Connected Thermostats." https://www.energy.gov/sites/prod/files/2016/12/f34/Overview%20of%20Existing%20Future%20Residential%20Use%20Cases%20for%20CT_2016-12-16.pdf.

U.S. Department of Energy, Building Technologies Office. 2018a. "Low-Cost Submetering." https://www.energy.gov/eere/buildings/downloads/low-cost-submetering.

U.S. Department of Energy, Building Technologies Office. 2018b. "Welcome to Scout." https://scout-bto.readthedocs.io/en/latest/index.html.

U.S. Department of Energy, Building Technologies Office. 2019a. "Request for Information (RFI) DE-FOA-0002070: Efficient and Flexible Building Loads." https://eere-exchange.energy.gov/#FoaIdd5fd318d-0a38-44fc-b1ab-aa54579c6177.

U.S. Department of Energy, Building Technologies Office. 2019b. "OpenBuildingControl." http://obc.lbl.gov/.

U.S. Department of Energy, Building Technologies Office. 2019c. "Scout." https://www.energy.gov/eere/buildings/scout.

U.S. Department of Energy, Building Technologies Office. 2019d. "Spawn-of-EnergyPlus (Spawn)." https://www.energy.gov/eere/buildings/downloads/spawn-energyplus-spawn.

U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy (EERE). 2019. "Hierarchical Occupancy-Responsive Model Predictive Control (MPC) at Room, Building and Campus Levels." Lawrence Berkeley National Laboratory. https://www.energy.gov/sites/prod/files/2018/06/f52/94150b_Piette_050218-1200.pdf.

U.S. Energy Information Administration (EIA). 2016. "Commercial Buildings Energy Consumption Survey 2012." Washington, D.C.: EIA. https://www.eia.gov/consumption/commercial/data/2012/bc/cfm/b6.php.

U.S. Energy Information Administration (EIA). 2017a. "Annual Energy Outlook 2017 with Projections to 2050." Washington, D.C.: EIA. https://www.eia.gov/outlooks/aeo/pdf/0383(2017).pdf.

U.S. Energy Information Administration (EIA). 2017b. "Annual Electric Power Industry Report." Washington, D.C.: EIA- 861 data file.

U.S. Energy Information Administration (EIA). 2017c. "Residential Building Energy Consumption Survey 2015." Washington, D.C.: EIA. https://www.eia.gov/todayinenergy/detail.php?id=32112.

U.S. Energy Information Administration (EIA). 2018. "Electric Power Annual 2017." Washington, D.C.: EIA. https://www.eia.gov/electricity/annual/pdf/epa.pdf.

Wall, J. and J. K. Ward. 2013. "A Comparative Analysis of Electrical Sub-Metering Accuracy and Cost for Commercial Building Applications." *International Journal of Application or Innovation in Engineering and Management* 2 (5): 524–534. http://www.ijaiem.org/Volume2Issue5/IJAIEM-2013-05-31-109.pdf.

Wendzel, Steffen, Jernej Tonejc, Jaspreet Kaur, and Alexandra Kobekova. 2018. "Cyber Security of Smart Buildings." In *Security and Privacy in Cyber-Physical Systems: Foundations, Principles, and Applications, First Edition*, 327–351.

Wetter, Michael, Jianjun Hu, Milica Grahovac, Brent Eubanks, and Philip Haves. 2018. "OpenBuildingControl: Modeling Feedback Control as a Step Toward Formal Design, Specification, Deployment and Verification of Building Control Sequences." *Proceedings of the Building Performance Modeling Conference and SimBuild*: 775–782.

Wetter, Michael, Marco Bonvini, and Thierry S. Nouidui. 2016. "Equation-Based Languages – A New Paradigm for Building Energy Modeling, Simulation and Optimization." *Energy and Buildings* 117, 290–300.

Wetter, Michael, Milica Grahovac, and Jianjun Hu. 2018. "Control Description Language." *1st American Modelica Conference*, Cambridge, MA.

Wetter, Michael, Thierry S. Nouidui, David Lorenzetti, Edward E. Lee, and Amir Roth. 2015. "Prototyping the Next Generation EnergyPlus Simulation Engine." *BS2015, 14th Conference of International Building Performance Simulation Association*: 403–410.

Whitesides, George M. and Mila Boncheva. 2002. "Beyond Molecules: Self-Assembly of Mesoscopic and Macroscopic Components." *Proceedings of the National Academy of Sciences* 99 (8): 4769–4774.

Widergren, Steven E., Mark R. Knight, Ronald B. Melton, David Narang, Maurice Martin, Bruce Nordman, Aditya Khandekar, and Keith S. Hardy. 2018. "Interoperability Strategic Vision." doi:10.2172/1430426. https://www.osti.gov/servlets/purl/1430426.

Yick, Jennifer, Biswanath Mukherjee, and Dipak Ghosal. 2008. "Wireless Sensor Network Survey." *Computer Networks* 52: 2292–2330.

York, Dan, Steven Nadel, Ethan Rogers, Rachel Cluett, Sameer Kwatra, Harvey Sachs, Jennifer Amann, and Meegan Kelly. 2015. "New Horizons for Energy Efficiency: Major Opportunities to Reach Higher Electricity Savings by 2030." *American Council for an Energy-Efficient Economy*, Report U1507. https://aceee.org/sites/default/files/publications/researchreports/u1507.pdf.

Yucelen, Tansel, Wassim Michael Haddad, and Eric M. Feron. 2016. "Adaptive Control Architectures for Mitigating Sensor Attacks in Cyber-Physical Systems." *Cyber-Physical Systems*: 1–24.

Zahid Kausar, A. S. M., Ahmed Wasif Reza, Mashad Uddin Saleh, and Harikrishnan Ramiah. 2014. "Energizing Wireless Sensor Networks by Energy Harvesting Systems: Scopes, Challenges, and Approaches." *Renewable and Sustainable Energy Reviews* 38: 973–989.

Zeifman, Michael and Kurt Roth. 2011. "Nonintrusive Appliance Load Monitoring: Review and Outlook." *IEEE Transactions on Consumer Electronics* 57 (1): 76–84.

Zhang, J., R. G. Lutes, G. Liu, and M. R. Brambley. 2013. "Energy Savings for Occupancy-Based Control (OBC) of Variable-Air-Volume (VAV) Systems." Pacific Northwestern National Laboratory, PNNL-22072. https://www.pnnl.gov/main/publications/external/technical_reports/pnnl-22072.pdf.

Zhao, Qianchuan, Zhijin Cheng, Fulin Wang, Zheliang Chen, Yi Jiang, and Zhipeng Zhong. 2015. "Experimental Assessment of a Satisfaction Based Thermal Comfort Control for a Group of Occupants." *IEEE International Conference on Automation Science and Engineering*: 15–20.

Zoha, Ahmed, Alexander Gluhak, Muhammad Ali Imran, and Sutharshan Rajasegarar. 2012. "Non-Intrusive Load Monitoring Approaches for Disaggregated Energy Sensing: A Survey." *Sensors* 12 (12): 16838–16866.

Appendix: Scout Tool Results

This section describes the Scout ECMs that were used to quantitatively assess each of the identified priority R&D focus areas. All inputs listed in Table A-1 are based on results from the published literature on emerging building strategies for monitoring and control. As such, an ECM description is limited to the end uses and technological improvements within a focus area for which data from the literature are available.

Table A-1. Sources and Notes for Scout Tool Energy Conservation Measures

Priority Focus Area	Energy Conservation Measure	Source(s) used for Measure	Relevant Notes
Multifunctional wireless sensor networks	Multifunctional, plug-and-play sensors self-powered with wireless communication	• Kazmi, A., M. O'Grady, D. Delaney, A. Ruzzelli, and G. O'Hare. 2014. "A Review of Wireless Sensor Network Enabled Building Energy Management Systems." *ACM Transactions on Sensor Networks,* 10 (4): 1–43. • Dietrich, I. and F. Dressler. 2009. "On the Lifetime of Wireless Sensor Networks." *ACM Transactions on Sensor* Networks, 5 (1): 1–38.	Energy savings potential of 17% (8%–30%) for HVAC and 35% (10%–60%) for lighting (Kazmi et al. 2014) with an average lifetime of 10 years (Dietrich and Dressler 2009). Assumes typical node density per square foot floor area.[42]
Advanced monitoring and data analytics	Automated fault detection and diagnostics incorporating submetered energy data	• Goetzler, W., J. Burgos, H. Hiraiwa, J. Young, and R. Zogg. 2011. *Energy Savings Potential and RD&D Opportunities for Commercial Building HVAC Systems.* Washington, D.C.: Navigant Consulting, Inc. https://www1.eere.energy.gov/buildings/publications/pdfs/corporate/savings_potential_comm_hvac.pdf. • Navigant Consulting. 2016. *Updated Buildings Sector Appliance and Equipment Costs and Efficiencies.*	Additional energy savings potential of 5% for HVAC (Goetzler et al. 2011) with an average lifetime of 15 years for HVAC equipment being monitored (Navigant 2016).
Adaptive and autonomous controls	Automated fault detection and diagnostics	• Roth, K., D. Westphalen, M. Feng, P. Llana, and L. Quartararo. 2005. *Energy Impacts of Commercial Building Controls and Performance Diagnostics.* Cambridge, MA: TIAX LLC. • Frey, D. and V. Smith. 2008. *Advanced Automated HVAC Fault Detection and Diagnostics Commercialization Program.* Boulder, CO: Architectural Energy Corporation, CEC-500-2013-054. http://www.energy.ca.gov/2013publications/CEC-500-2013-054/CEC-500-2013-054.pdf.	Energy savings potential of 20% (15%–30%) for HVAC (Roth et al. 2005; Frey and Smith 2008).

[42] https://scout-bto.readthedocs.io/en/latest/ecm_reference.html

Priority Focus Area	Energy Conservation Measure	Source(s) used for Measure	Relevant Notes
Occupant-centric controls	**Occupant counting/presence inputs**	• Nguyen, T. A. and M. Aiello. 2005. "Energy Intelligent Buildings Based on User Activity." *Energy and Buildings,* 56: 244–257. • Williams, A., B. Atkinson, K. Garbesi, F. Rubinstein, and E. Page. 2012. "Quantifying National Energy Savings Potential of Lighting Controls in Commercial Buildings." *2012 ACEEE Summer Study on Energy Efficiency in Buildings*, 3-393–404.	Energy savings potential of 15% (10%–40%) for HVAC and lighting (Nguyen and Aiello 2005; Williams et al. 2012). Assumes typical occupant density per square foot floor area.[43]
	Occupant comfort/preference inputs	• Ghahramani, A., F. Jazizadeh, and B. Becerik-Gerber. 2014. "A Knowledge-Based Approach for Selecting Energy-Aware and Comfort-Driven HVAC Temperature Set Points." *Energy and Buildings*, 85: 536-548. • Williams, A., B. Atkinson, K. Garbesi, F. Rubinstein, and E. Page. 2012. "Quantifying National Energy Savings Potential of Lighting Controls in Commercial Buildings." *2012 ACEEE Summer Study on Energy Efficiency in Buildings*, 3-393–404.	Energy savings potential of 20% (10%–40%) for HVAC and 30% (10%–60%) for lighting (Ghahramani et al. 2014; Williams et al. 2012). Assumes typical occupant density per square foot floor area.[44]

Several improvements in Scout, as compared to the PTool, provide expanded capabilities in assessing the impact of sensors and controls technologies analyzed in this document. These include:

- Ability to represent and assess the unit-level energy performance of measures with system-level effects (e.g., relative energy savings across multiple end uses)
- Explicit stock-and-flow and competition logic for controls measures (assessed as "add-ons" that assume the stock-and-flow dynamics of the component technologies they enhance)
- Built-in handling of cost units that are relevant for assessing controls measures ($/ft^2, $/node, and $/occupant)
- Ability to assess controls measures individually or as part of a larger program portfolio (removing any overlapping energy impacts across the portfolio in the latter case)
- Consistent baseline energy use data that are regularly updated with each new version of the EIA AEO, supporting regular tracking and reassessment of goals over time as the building energy landscape changes
- Platform (scout.energy.gov) for sharing and soliciting feedback on sensor and control target measure definitions from the research community.

43 https://scout-bto.readthedocs.io/en/latest/ecm_reference.html
44 https://scout-bto.readthedocs.io/en/latest/ecm_reference.html

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