Chapter 2
Architectures and Algorithms for Building Automation—An Industry View

Petr Stluka, Girija Parthasarathy, Steve Gabel and Tariq Samad

2.1 Introduction

The importance of buildings in developed societies can hardly be overstated. Most of us live, work, and shop in buildings. When we travel, much of our time is spent in airports and hotels, restaurants, and museums. Our children are educated in schools and colleges. When we are ill, or for preventative purposes, we go to hospitals and other buildings housing healthcare services. Government offices, data centers, sports complexes, and law courts are other prominent examples.

If there is one parameter that highlights the prominence of buildings in society, it is energy. Altogether, buildings are responsible for over 40% of the energy, and almost 75% of the electricity consumed in the U.S. [1]. The consumption is marginally higher in residences versus commercial buildings. The energy footprint is correlated with the carbon footprint, with 39% of the nation's CO2 emissions coming directly (e.g., natural gas combustion for heating and cooking) and indirectly (emissions from fossil-fueled power plants that are generating electricity that is used in buildings) from buildings [2]. Both in terms of energy consumption and carbon dioxide emissions, buildings are the largest sector—more than industrial plants and transportation.

Much research in buildings is focused on energy efficiency and reducing energy use. Intelligent automation and control technologies in particular have garnered much attention. Specific topics of research include heating, ventilation, and cool-

P. Stluka (✉)
Honeywell Global Labs, Prague, Czech Republic
e-mail: petr.stluka@honeywell.com

G. Parthasarathy
Honeywell Global Labs, Golden Valley, MN, USA
e-mail: girija.parthasarathy@honeywell.com

S. Gabel
Honeywell Global Labs (retired), Golden Valley, MN, USA
e-mail: sgabel1974@gmail.com

T. Samad
Technological Leadership Institute, University of Minnesota,
Minneapolis, MN, USA
e-mail: tsamad@umn.edu

© The Author(s) 2018

J.T. Wen and S. Mishra (eds.), *Intelligent Building Control Systems*,
Advances in Industrial Control, https://doi.org/10.1007/978-3-319-68462-8_2

ing (HVAC) control; automated demand response for smart grids; optimization of equipment such as compressors and chillers; advanced lighting and comfort control; new vapor compression systems; and thermal energy storage through building envelopes and radiant slabs. All of these topics, among others, are represented in this volume, and some of our own work, which has also focused on several building energy management solutions, is discussed in more detail later.

Before we review this work, there is an important point that bears emphasis. Despite the high energy, electricity, and greenhouse gas footprint of buildings, substantial obstacles exist in incorporating promising, and even validated, research advances into commercial practice. These include the following:

- In many cases, buildings are occupied by tenants who do not pay utility bills themselves; these bills are paid by the building owner or manager. Thus, tenants have little economic incentive to adopt efficiency measures.
- Return-on-investment (ROI) periods on innovative energy-saving technologies, especially where new equipment needs to be installed, are often as long as a few years. The ROI is, of course, exacerbated by the current low price of energy.
- Energy expenditure is often not a significant part of the operating budget. Consider a home, overall, a 5% reduction in electricity use in most residences would have a huge impact on the nation's consumption and emissions, but a $5 reduction in a monthly utility bill may not be sufficient incentive for many homeowners to make the time or financial investment involved.
- Advanced technologies often require appropriately trained technicians and engineers to use them, and most buildings do not have such staff available; hiring such staff would be a significant additional expense.
- Retrofitting new technologies into existing buildings, which were designed and built without the prospect of such future enhancements, is especially expensive. Building lifetimes are typically on the order of a few or several decades, and building equipment typically has a lifetime of a few decades as well; it will be a long while before the building stock can accommodate research advances easily.
- While energy management systems are widely used for large commercial buildings, they are rare in small commercial buildings. Brambley et al. [3] reported that the percentage of buildings equipped with energy management and control systems (EMCS) increases from about 5% for buildings of 1,000—10,000 sq. ft. to about 70% for buildings larger than 500,000 sq. ft.
- Government investment in applied research and technology transfer in building technologies is low. A recent report [4] notes that *the federal government spends more than 30 times as much on research for electricity generation as it does on research on the buildings that consume three-quarters of this electricity*.

It is certainly not the case that energy efficiency plays no role when building developers or refurbishers are specifying a building automation system. But energy is not the sole concern and indeed it is usually not the principal concern. According to one market report, the substantial growth in Building Automation Systems (BASs) compounding at an annual rate of 10.65% to reach over $100 billion by 2022 is being led by security and access control [5].

The multifunctional nature of building automation systems [6] will be evident in the next section of this chapter, where we provide an overview of BASs using a major commercial product as an example and we discuss some related technology trends.

With this background, we then discuss three topics in building automation that leverage some of these technology trends in BASs:

- An adaptive control strategy for HVAC based on model predictive control principles, with models automatically updated as more data is collected. The algorithm is executed in the cloud, enabling applications where onsite computing resources may be limited. Results of pilot implementations are presented.
- Central plant optimization for campuses and large commercial buildings. Multiple models and forecasts are integrated into an optimization scheme. The solution was implemented at a large military base although issues with data quality did not permit reliable validation.
- Automated demand response, leveraging connectivity with the smart grid. In particular, we discuss the development of the OpenADR standard, which is facilitating applications worldwide.

These and other applications have been successfully implemented, but the path from research to practice can be tortuous. Therefore, in the final section, we present a path for technology transfer to commercial product and we describe some of the challenges involved.

2.2 Building Automation Systems

BAS control and monitor mechanical and electrical equipment, such as HVAC, lighting, power systems, fire systems, and security systems. Over the years, BASs have advanced through several major evolution stages [7]. They initially relied on pneumatic controls with compressed air (starting in the 1950s) but later these systems were replaced by microprocessors and Direct Digital Controls (DDC) in the 1980s, subsequently leading to the introduction of standardized building protocols, such as BACnet®, LONWORKS®, or Modbus®, in the 1990s. While the first decade of the new millennium brought significant progress with wide adoption of wireless technologies (ZigBee®, EnOcean®, Z-Wave®, Bluetooth®, etc.) that allowed individual devices and controls to communicate wirelessly, the follow-up trends evolved directly into the new era of the IoT that we experience today.

2.2.1 BAS Overview

BASs deliver multiple functions, including the following:

- Control of the building's environment is primarily delivered through the automated control of the HVAC system and its individual components (air handlers, fan coils,

fans, pumps, chillers, boilers, etc.). The other important aspects include the control of lighting and indoor air quality (IAQ).
- Energy management that aims to minimize overall energy costs in the building through the systematic monitoring and intelligent operation of HVAC systems with respect to occupancy, weather, and prices of electricity, gas or other energy sources.
- Monitoring of facility assets has the objective of detecting performance problems of HVAC equipment and addressing them early enough before they cause bigger issues.
- Security and access control help to minimize risks related to security breaches and improve situational awareness. Access control, video surveillance, and perimeter protection systems all together play important roles in mitigation of high-risk threats.
- Fire detection and life safety help to ensure that people and assets are protected from fires and other environmental risks. This is accomplished by the deployment of systems for fire and smoke detection, sprinkler supervision, and emergency communication.

All these functions enable building owners and facility managers to address a variety of operational goals, such as reducing energy consumption and maintenance and life-cycle costs, ensuring tenants' comfort and compliance with regulations (e.g., on the minimum required volume of fresh air in a given building), minimizing safety and security risks, and facilitating active participation in demand response or related energy trading schemes enabled by smart grid technologies [8].

The architectural complexity of today's building automation systems largely depends on the number of subsystems deployed. Figure 2.1 provides a complete view of one leading BAS, Honeywell Enterprise Building Integrator (EBI), with its modules for HVAC control (named Building Manager), energy management, life safety, security, and video surveillance. Each part can be installed independently of others but they together form a complete building management system.

2.2.2 HVAC Control Infrastructure

The infrastructure for monitoring and control of HVAC systems is the most commonly implemented part of any BAS, and it is also perhaps the largest and most complicated building system because of the variety of control devices involved and the multiple ways they can affect a building's operation. In Fig. 2.1, the HVAC control infrastructure is depicted in a simplified way inside the block labeled Building Manager. However, when physically deployed, it is usually structured into several logical layers of the traditional HVAC control architecture (see Fig. 2.2), complemented with the cloud environment that allows the implementation of additional functions:

- Field devices comprise the sensors, meters, variable speed drives, valves, and actuators that are used for monitoring or changing system variables, such as temper-

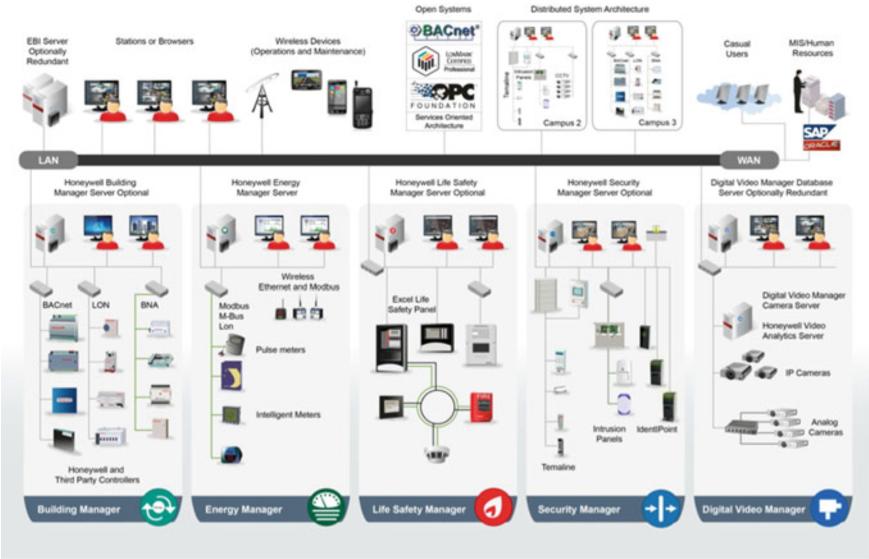


Fig. 2.1 Architectural view of the BAS system [9]

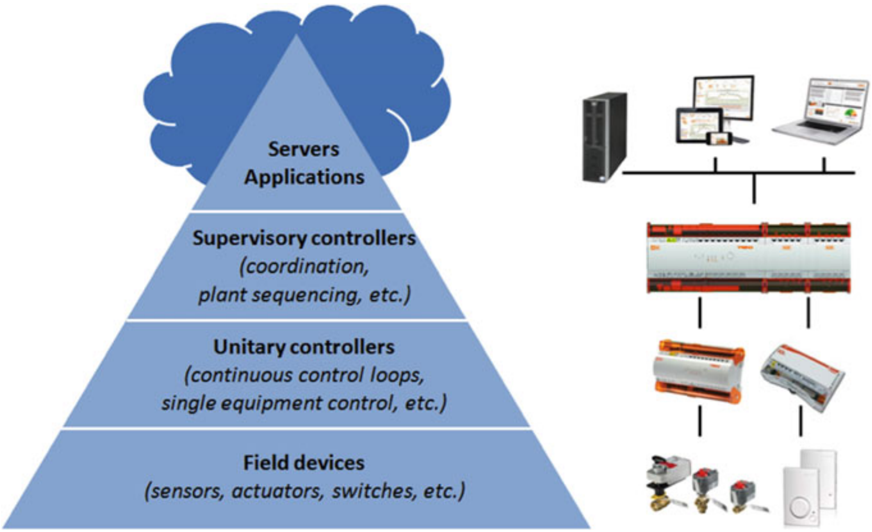


Fig. 2.2 Hierarchical layers of HVAC control architecture

ature, humidity, flow rate, and pressure. Efficient HVAC control depends heavily on the quality of the field devices and the information these provide.

- Unitary controllers are stand-alone devices executing basic control algorithms and routines, designed for specific control applications, such as controlling a fan coil unit or sequencing a pump. The scope of the controlled system is usually limited to a specific constrained environment, such as a single zone. The unitary controller receives signals from sensors and determines appropriate output signals for the actuators, based on the closed-loop control logic. Its operation can also be influenced by commands received from the respective supervisory controller.

- Supervisory controllers implement higher level control logic on the level of a plant, subsystem, floor, or entire building. This may include starting or stopping plants (boilers or chillers) according to correct or optimal timing, as well as adjusting the set points of unitary controllers based on conditions defined by weather or occupancy levels. These adjustments are typically implemented by a set of rules.
- Server applications integrate all useful data received from devices and controllers in a local data historian. It is possible to visualize trends, logs, alarms, and other events generated by the BAS. Server applications also typically include tools for system management and configuration. In addition, the computing power at this level can be leveraged for execution of building-wide optimization applications.

2.2.3 New and Emerging Trends

BASs are continuously evolving to efficiently address new challenges and enable flawless and cost-effective operation of high-performance buildings. The whole ecosystem of technologies that are being deployed in buildings has a direct influence on BAS, their architectures and functions. The most important technology trends over the last few years relate to the increasing use of cloud technologies and data analytics [10], prevalence of the IoT paradigm [11], and the growing emphasis on user experience and comfort [12, 13].

The cloud and data analytics have made significant progress over the last years in many domains and they continue to create impact in building applications. The capability to collect data from multiple and potentially heterogeneous data sources and move them to a cloud repository allows the implementation of powerful applications that may provide insights into building operations [14]. Cloud connectivity and real-time processing will enable the data to become fluid versus static with vast new opportunities. The sophistication of new and more powerful building analytics will likely be increasing from visualization and reporting dashboards to fault detection and diagnostics too, ultimately, applications in predictive maintenance and holistic dynamic optimization of buildings [10]. Currently deployed building analytics can better inform facility managers about deviations from the expected energy consumption, likely HVAC equipment faults [15] and underperforming controllers [16].

IoT paradigms enable connecting building automation components to the IT network and generally improves the interoperability and connectivity of control devices. The IoT can help overcome the issue of isolated building systems and support creation of more cohesive environments. In this new context, building automation systems will potentially require fundamental changes in how they are designed and installed. New types of intelligent devices and systems will be required that collect and move data directly to cloud databases, where it can be used by specific analytics applications and exposed to end users. Also, new IoT technologies and applications will have a major impact on building occupants whose interactions with *smart things* could be monitored and leveraged for improved control and delivery of personalized comfort in interior spaces [17].

User experience aspects play an important role in the design of new applications for facility managers and building owners that take advantage of connected HVAC equipment, devices, and automation systems whose data can be shared in real time. New types of applications and user interfaces are delivered via smartphones and tablets that can provide multiple real-time functions such as secure monitoring of equipment operation, changing set points, viewing and acknowledging alarms, and adjusting schedules. The other categories of users are tenants and occupants where the main emphasis is on delivering healthy and comfortable indoor environments [18]. This goes beyond traditional thermal comfort [19]; for example, modern LED bulbs can make lighting conditions far more personalized than before.

Collapse of control layers—With the proliferation of the cloud, open architectures, and IoT technologies, we already observe tendencies to separate typical functions into only two levels: highly intelligent field devices and the cloud. Although this direction might be more typical for low-end installation of BAS, e.g., light commercial buildings [20]—it can imply that powerful building controllers may not be needed in some cases [21, 22]. The base level closed-loop control functionality will be implemented through a flat architecture of cooperating field devices, while supervisory functions will be pushed to the cloud environment. This concept can potentially be cheaper to deploy but the overall impact on the performance of such a control architecture still needs to be explored, primarily with respect to the potential issues with latency, jitter, or bandwidth in nondeterministic communication networks.

Distributed optimization and analytics on the edge—Economic optimization of building systems can be formulated at the whole-building level, integrating all important subsystems such as HVAC, lighting, onsite generation, and storage. However, the fundamental issue with this approach lies with building-wide optimization models, which will always be too complex and hampered by significant inaccuracy, uncertainty, and lack of data measurements. On the other hand, distributed optimization approaches could be more viable; these would focus on meaningful subsystems and their optimization according to their local objectives but not independently of others. The topic of distributed cooperative control has already been studied in the areas of renewable generation [23], power storage [24], and control of HVAC systems [25–27].

Human-in-the-loop control—Given the increased emphasis on user experience and occupants' health and productivity, the thermal comfort and other environmental aspects of buildings, such as lighting quality, should be maintained in a way that satisfies the maximum number of occupants. This can be achieved by allowing individuals to define their personal comfort preferences and providing immediate feedback on the current comfort conditions [28, 29]. Then new algorithms will be needed to aggregate and properly process all such inputs from occupants to determine new global set points in the most cost-effective way, or alternatively make localized adjustments that would respond directly to occupants' feedback. Beyond optimized comfort control, similar crowd-sourcing mechanisms have already proven to be useful for learning of occupancy patterns [30], one of the difficult-to-measure disturbance variables in HVAC control applications. Occupancy and behavior patterns can also be learned by processing of the data generated by indoor location tracking systems [17] under the assumption that the new family of smartphone-based context-aware applications would be properly integrated with BAS where they will be leveraged for improved control.

All these technological trends are expected to have an enormous impact on the architecture of BAS and the mechanisms they use for delivering control functions.

2.3 Adaptive HVAC Control: A Cloud-Based Solution

2.3.1 Rule-Based Methods

Rule-based methods enable the translation of best practices, experience, and knowledge of HVAC control engineers into a set of rules, which are applied to manipulate key set points and schedules (optimal start/stop, pre-cooling, etc.) and ensure coordination between controllers. For instance, a rule-based control strategy for air handlers can involve the supply air temperature reset, night purge, CO2-based demand-controlled ventilation, and other concepts; see summaries in [31, 32].

Rule-based methods are popular because their implementation is intuitive and offers good opportunities to run HVAC more efficiently, under the assumption that rules are implemented properly. In practice, this approach has several limitations. With respect to the large variety of building types—and variety of HVAC systems used—application engineers have to configure customized solutions on a project-to-project basis, and the quality of rules may vary significantly with the knowledge and experience of the application engineer. Further, if the set of rules becomes too extensive, it is hard to ensure consistency within the rule set and the overall performance will deteriorate sooner or later. In other cases, the application engineers may have fairly limited time to tune the rules properly and keep the configuration regularly updated. Then, the natural tendency is to choose robust parameter settings for individual rule resets that will ensure occupant comfort for a wide range of conditions. However, this approach will control the HVAC system in a suboptimal way and with higher operating expenses.

2.3.2 Model Predictive Control

An attractive possibility for addressing the above limitations is represented by the model predictive control (MPC) strategy, which can dynamically adjust all main

HVAC set points based on current/future conditions. Unlike a safely defined set of set point resets, which requires adjustments relatively rarely and thus operates the HVAC system in more or less constant regimes for long periods of time, MPC has the capability to adjust set points several times per hour, operate the HVAC system more efficiently and closer to its boundaries, and ensure it is responding dynamically to changes in outdoor or indoor conditions.

An MPC-based solution is usually formulated to address the primary goal of HVAC control: to maintain predefined comfort levels in zones while minimizing the overall operating costs, which are usually reduced to the costs of primary energy sources. The MPC controller then determines the optimal actions based on relationships among optimized variables, zone comfort, and energy cost. Mathematically, the optimal control problem is formulated over a finite future horizon:

$$\min_{u_i} \sum_{k=0}^{N-1} c_k(x_k, u_k, y_k) \tag{2.1}$$

subject to

$$\begin{aligned}
&x_0 = x\\
&x_{k+1} = f(x_k, u_k, d_k) \qquad y_k = g(x_k, u_k, d_k)\\
&y_{\min} \le y_k \le y_{\max}\\
&u_{\min} \le u_k \le u_{\max},
\end{aligned}$$

where k is the discrete time step, N is the prediction horizon, and c_k is the cost function. x, y, u, and d are vectors defined as follows:

- x is a vector of system state variables that characterize conditions in zones (predicted thermal comfort, heating/cooling demand) or in the HVAC system (mode of operation).
- y is a vector of system output variables, which are maintained as close as possible to their reference values. Output variables are the temperatures in zones and potentially other parameters such as humidity. Their reference values are given by the desired comfort conditions. The other part of output variables includes energy consumption of the HVAC system.
- u is a vector of action variables or set points for supply air temperature, chilled water temperature, hot water temperature, pump speed, fan speed, and others.
- d is a vector of disturbance variables, including usually weather conditions but potentially also occupancy, if available.

The cost function c_k can be formulated as a tradeoff between the precision of tracking reference values (maintaining comfort) and energy costs, as discussed in detail in [33]. A numerical solver is typically used to minimize the function c_k over the defined optimization horizon N while keeping future comfort variables y as close as possible to their reference values and all set points satisfying the box constraints $u_{\min}$ and $u_{\max}$ (e.g., pump speed between 60 and 100%).

2.3.3 Implementation of Adaptive MPC

A specific implementation of MPC was pursued by the Honeywell team with the objective of delivering a concept that would be easy to commercialize [16]. Taking into account the specifics of the building controls industry, two important design decisions were made:

- The MPC controller was implemented as a cloud-based solution, following the high-level architecture depicted in Fig. 2.3 where the existing BAS is connected with the cloud controller via a dedicated communication interface.
- The standard MPC scheme was extended by a module for regular adaptation of the predictive model for state variables. This need came from the fact that in many application projects there are not enough observations available to identify good models, while running step tests to get a dynamic response of building systems is impossible due to the costs involved. Model adaptation is also useful in the long run because built environments are always subject to change.

The execution engine (see Fig. 2.3) is initialized every 15 min by a timer and it runs through the following sequence of steps.

1. The engine receives new data from the local BAS, which includes the latest sensor and meter readings as well as all relevant control signals and other parameters. Some of the data points need to be processed; for instance, cumulative meter consumption is converted to interval consumption. Then all new points are inserted into the data storage.
2. Regular update of model parameters is initiated with respect to the recent data and applied to all predictive models, which are typically specific instances of a general multi-input multi-output autoregressive exogenous (ARX) class model. This includes the state model, disturbance model, and energy consumption model that

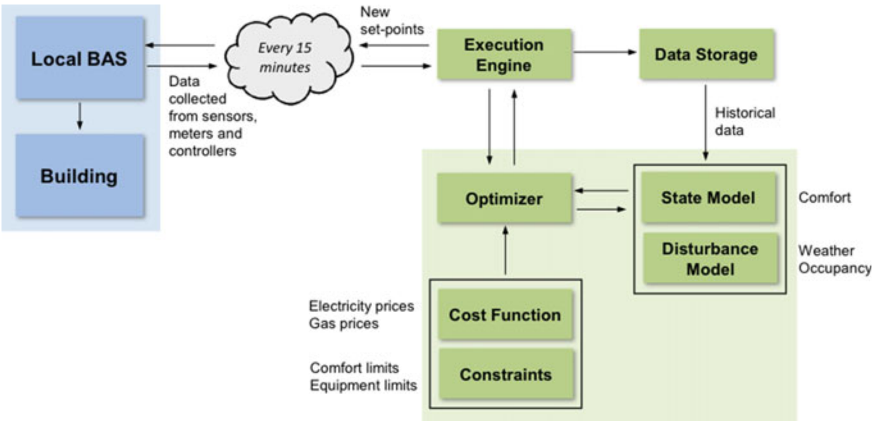


Fig. 2.3 High-level architecture of the cloud-based MPC controller

is used for evaluation of the cost function. New model parameters are estimated in a robust way ensuring iterative removal of outliers.

3. The optimizer runs a multistep optimization algorithm that is applied over a configurable time horizon, at least four steps or 1 h ahead. The previously updated models are used to predict future disturbances, states, and outputs. For practical reasons, two types of limits—soft and hard–were introduced for comfort variables. The optimizer then searches for a combination of actions that will ensure all comfort variables are within soft limits, or at least do not violate hard limits. If a hard limit is reached in any of the building zones, the optimizer just firmly defines set points that correspond to the maximum (or minimum) heating or cooling in a given zone.
4. New set points are transmitted back to the local BAS system. Although the optimizer generates a 1-hour-ahead schedule, only the first step is distributed to the plant controllers, which is in-line with the principle of receding horizon control.

The adaptation of model parameters and identification of alternative model structures helps to accommodate various HVAC system changes that can occur relatively frequently over the solution life cycle. It is then ensured that all model structures and model parameters represent key relationships between optimized set points and estimated energy and comfort variables. This approach also reduces the need for the engagement of a control or optimization expert during the solution setup and maintenance.

2.3.4 Validation

The adaptive MPC controller was validated at several sites for an extended period of time. Typically, it was able to reduce the HVAC operating costs related to purchases of gas and electricity by 15–40%, which is in-line with savings achieved by MPC in similar applications [34, 35]. The initial set of six pilot buildings was intentionally selected in a way to ensure diversity of HVAC systems ranging from the relatively simple (one boiler, chiller, and air handler, up to five zones) to the rather complex (several boilers and chillers, at least five air handlers, at least 15–20 zones). However, we realized that the levels of savings, and thus the commercial success, are influenced by many other aspects:

- The performance of the baseline solution, i.e., the control strategy that is currently in use, has a significant impact because in the case of poorly operated systems it is easy to achieve savings, while in other cases the bar is higher.
- The level of instrumentation in some building is insufficient for the implementation of the advanced control solution and the need to install new sensors or meters makes the ROI less attractive.
- Legacy control systems may prevent the manipulation of some set points, e.g., chilled water temperature, which means the new concept cannot be utilized to its full potential.

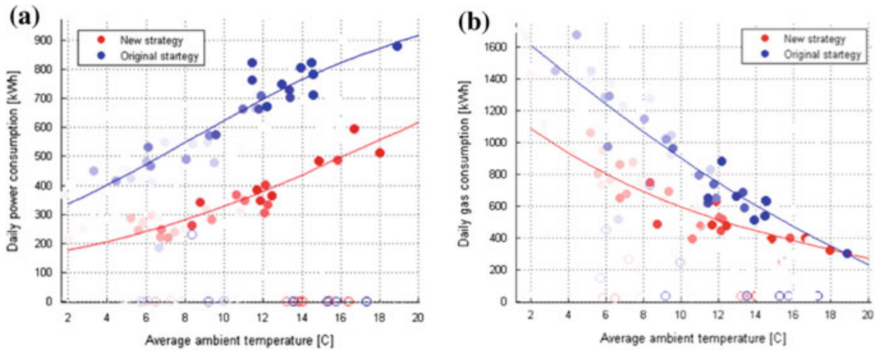


Fig. 2.4 Daily energy consumptions in power and gas conditioned by average ambient temperature

- In the case of a cloud-based solution, the quality of control can be influenced by such simple things as is the reliability of the Internet connection. Efficient local backup must be ready for the case when this connection drops.

As a part of the validation process, it was necessary to quantitatively assess performance improvements of the new solution in comparison with the original solutions. Despite differences in specifics, these legacy strategies primarily differed in how they manipulated important HVAC set points. Given that the operational patterns of any building follow regular daily cycles, the most suitable validation scenario was to switch between the two solutions on a day-by-day basis. Consequently, the results were assessed over the respective 24 h intervals. But when two different control solutions are running on different days, it is important to consider the different operating conditions, which are primarily characterized by the occupancy patterns and weather conditions. In some cases, it might be reasonable to omit the information about the occupancy. For instance, in the case of an administrative building with stable occupancy patterns during the working days when the individual control strategies are validated just on these days. But in general, the occupancy is an important parameter for the comfort control and should be used wherever it is possible to quantify it. Regarding the weather conditions, the most important influencing factor for the energy consumption is the ambient temperature. Figure 2.4 illustrates results of comparison of the original (baseline) and new control strategy, which were conditioned by the ambient temperature only. Despite some variation, it illustrates the systematic reduction in both power and gas consumptions achieved on our pilot sites.

2.4 Central Plant Optimization: Concepts and Prototype

In campuses such as universities and government facilities, large central plants deliver cooling or heating to individual buildings. In large buildings as well, a central plant is usually the primary source of cooling or heating, delivering thermal energy as chilled or hot water to the forced air HVAC system, or to radiators and other terminal units. Improving the efficiency of the generation and distribution of thermal energy reduces energy wastage at the source. A small percentage improvement can produce large overall savings because of the aggregation of energy production and distribution. There is potential for savings because central plants are currently operated to meet all demands reliably and not necessarily for fuel economy or energy efficiency. Plant operators run the equipment according to a preset, fixed strategy. However, plant equipment efficiencies vary with load and external conditions such as ambient temperature. In addition, central plants have multiple chillers, boilers, and power generators, which may differ from each other in capacities and performance. The ability to select equipment and operate it at optimized points to minimize the total energy cost of the plant is not intuitive to plant operators and has the potential to offer great benefits. Modeling the load dynamics offers the additional benefits of predictive optimization, for not just instantaneous energy savings but over future time horizons so that time-varying energy prices or weather-dependent equipment efficiencies can be considered in operating the entire system.

Optimization of HVAC systems and chiller plants has been a topic of research for many years. In [36], we find a comprehensive review of supervisory and optimal control of HVAC systems. An example of a more recent model predictive control of a chiller plant is in [37]. There are several other research implementations and some commercial products. However, many of these tackle either one-off implementations for research, rather than a general advanced optimization software product, or they tackle optimizing only part of the plant. We describe in brief a prototype central plant optimization system that has shown promise from the energy savings achieved in several pilots. The optimization system was recently implemented at a DoD central plant and this implementation is described next [38]. Our objective in this section is not to present another technique for optimization and its benefits, but rather to present the considerations involved in the practice of translating advanced control and optimization solutions developed in a research lab to a profitable commercial offering. In this context, see also [35], where the challenges in implementing model predictive control in buildings are described. Despite a mature prototype, field implementation remains difficult in advanced control applications and we explore the process, architecture, and standardization needed for easy diffusion in the marketplace.

2.4.1 Overview of Supervisory Optimization

The central plant optimization solution provides optimal schedules and operating points for all equipment in the plant. It relies on equipment performance models, forecasted load, a building load model, and energy price information. The equipment and building models are set up based on historical data and updated as new data becomes available. The optimization is based on minimizing energy costs and uses an evolutionary algorithm. The solution concept is illustrated in Fig. 2.5.

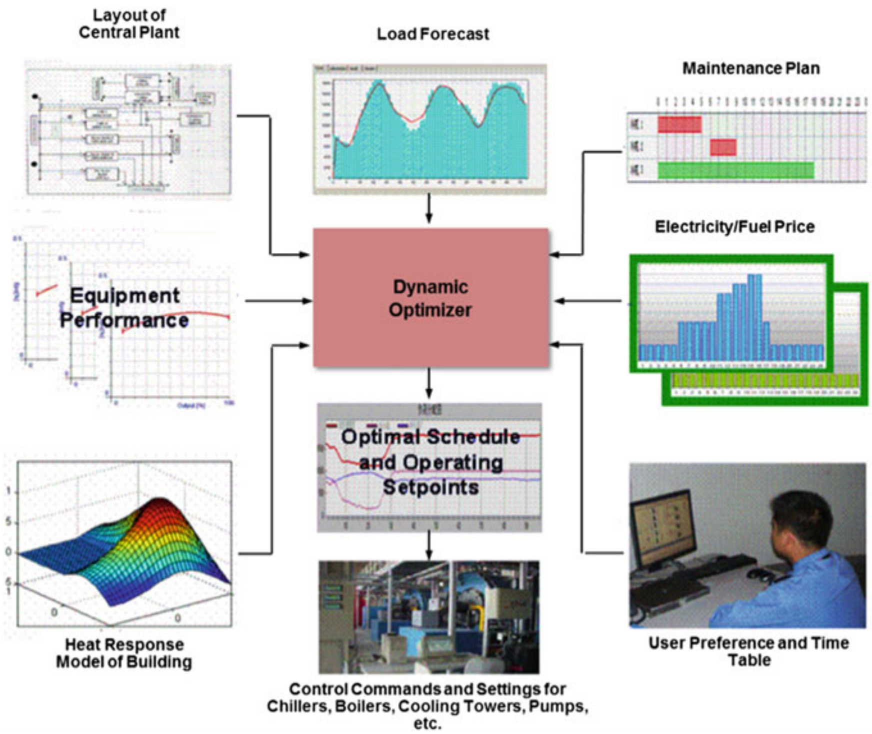


Fig. 2.5 Technology overview

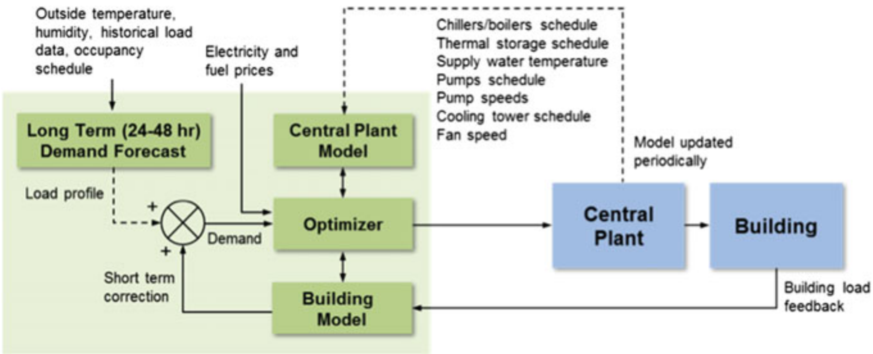


Fig. 2.6 Optimization solution

The online information flow is conceptualized in Fig. 2.6. A demand forecaster predicts loads for the next 24 h period of optimization based on the current weather, load history data, and occupancy criteria. The central plant model is configured from a library containing models of chillers, boilers, cooling towers, and pumps. A dynamic load model represents the building response to changes in energy supplied. Based on the inputs of upcoming demand loads, central plant performance, and building response, the optimizer solves the schedules and operating commands for the major equipment in the supply and distribution of chilled and hot water. Feedback from the buildings provides corrections to the long-term forecast load that is used to adjust the energy supplied.

The model library is an integral part of the optimization solution. Models are developed using historical data and are periodically updated with newly arrived data. The optimizer models are continuously updated and do not lose their efficacy when the equipment deteriorates.

The central plant optimizer had been piloted previously and has shown promising energy savings ranging from 9% to more than 40%. The energy savings depend on the extent of automation, existing controls, and processes in the baseline operation. The implementation described next is at a site where a cloud-based solution or remote monitoring and support was not possible.

2.4.2 *Prototype Implementation*

The control implementation architecture for a prototype version of the real-time supervisory optimizer implemented at a Department of Defense (DoD) facility (Fort Bragg, NC) [38] is shown in Fig. 2.7. The chiller plant serves about 80 buildings and consists of four chillers (total of 6300 tons), a free cooling heat exchanger, a 2

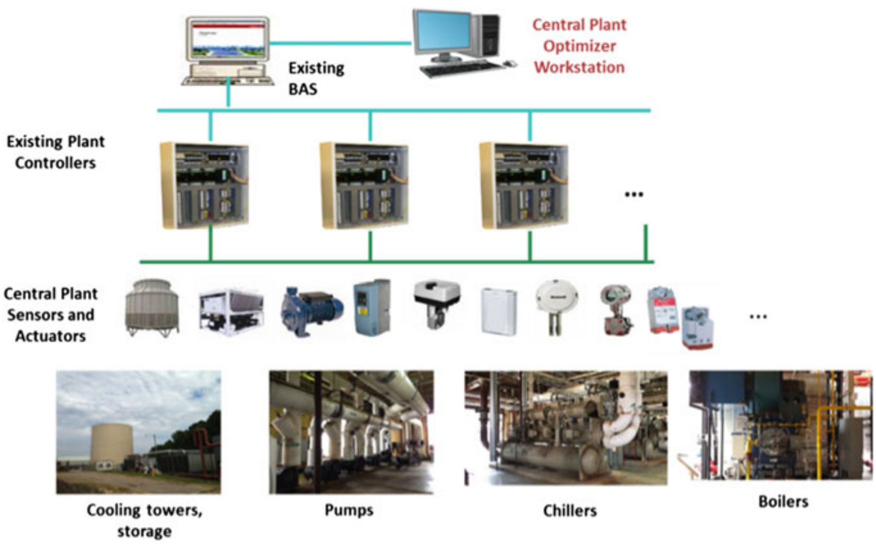


Fig. 2.7 Implementation architecture

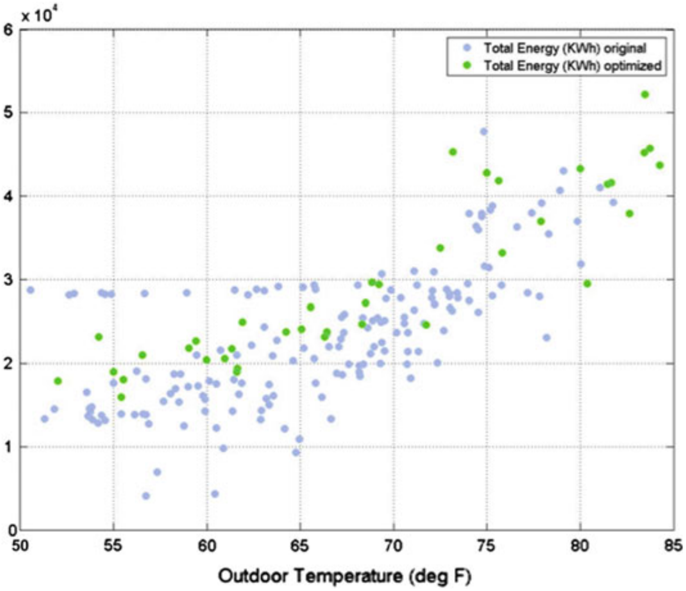


Fig. 2.8 Daily energy usage comparison

million gallon chilled water storage tank, and several primary and secondary pumps and cooling towers. For the prototype version of the optimizer, the control interface was through the Honeywell EBI building automation system.

The optimizer was brought online by following a systematic and thorough testing and commissioning process. It was handed over to the facility staff after training, but without remote access to the optimizer for observation or troubleshooting. The optimizer software was connected at the chiller plant for about a year, but controlled the plant only when enabled. The prototype included a mechanism for switching between the existing fixed control rules and optimized control to gather data for both systems. The data shows that the optimizer was enabled to operate the plant for 39 days in several continuous periods. During the same period, the data shows 164 periods of original control days.

The original control days data was normalized for weather—we considered several factors and used the best fit model after evaluating combinations of factors and regression model algorithms. The final analysis comparing daily overall energy usage between normalized baseline control and optimized control showed similar energy usage, within one standard deviation in most cases (see Fig. 2.8).

Comparing this overall result with an example of previous promising savings (Figs. 2.9 and 2.10) illustrates the inconsistency in the range of savings. Not only are baselines different for different implementations, but also conditions during operation can be tricky to monitor: Was the optimizer system operating ideally with the correct inputs? Were there other mitigating circumstances? We discuss the issue of

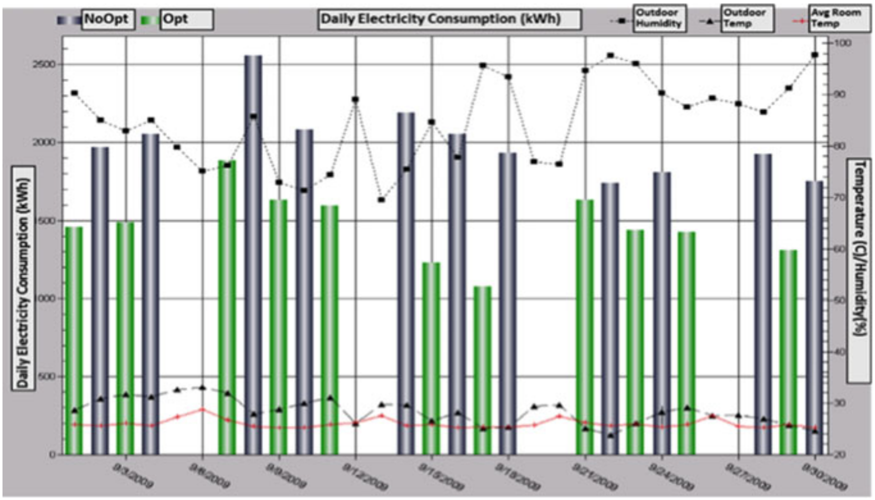


Fig. 2.9 Daily electricity consumption from the previous pilot with alternate day testing

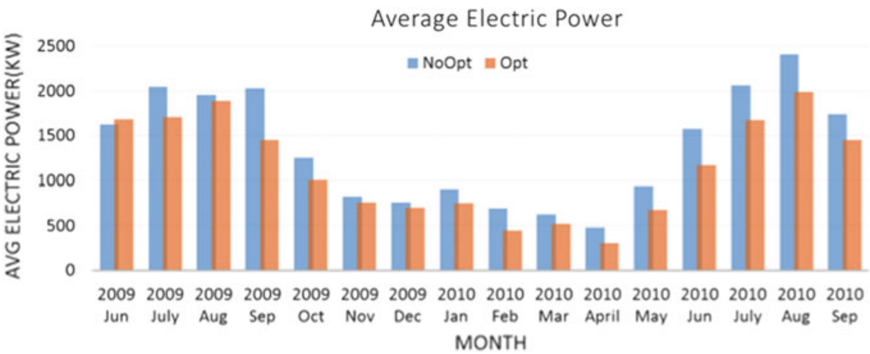


Fig. 2.10 Average electric power from the previous pilot

data quality in the next section, and further expand on the considerations involved in transferring advanced solutions from concept to commercialization later in this chapter.

2.4.3 Role of Data Quality

The prototype was the first to be implemented at a site with no possibility of remote observation of the system or ready access by the developers. The post-analysis showed several discrepancies in the data used as optimizer inputs. These included condenser, primary and secondary pump power, cooling tower power, and indoor and outdoor temperatures. Nonoptimal solutions were possibly provided to the plant based on wrong data, although the safety limits and layers in the optimizer prevented incorrect or unsafe operation of the plant. The safety layers also prevented knowledge of non-optimized operation when the optimizer was "enabled". On being apprised of a huge power spike in a condenser pump, the site staff immediately said that was probably why the chiller connected to it was never being switched on: "the optimizer hated chiller #4." The site operations staff are qualified to ensure that the plant operates correctly; however, it needed research labs staff to ensure the optimizer operates with the correct data inputs. In conclusion, as noted above, we were unable to validate the effectiveness of the optimization solution implemented, in large part, we believe, because of data quality issues. The root cause of bad data might have been communication issues or bad sensors. A supervisory optimizer requires data with a quality, resolution, and frequency that are not very common in current BASs. A reliable data infrastructure and data fault detection and adaptation system are essential for providing a supervisory advanced optimization solution. This experience highlights the importance of implementation-related issues that algorithm developers are often unaware of and that are often not resolved in time when research teams implement their prototype solutions. The challenges in transferring technology to the market are not restricted to data infrastructure only, but a combination of several factors that may suppress or augment technological weaknesses. We further discuss the considerations of transferring technology from R&D groups to commercial operation in a later section.

2.5 Automated Demand Response: Smart Buildings Meet Smart Grids

In many locations, building owners and operators have an opportunity to reduce their electric energy cost by participating in demand response programs offered by electric utilities or grid operators. These programs provide an economic reward for partially reducing or time-shifting electric demand during peak periods or other times when the electric grid is under stress. The rich sets of operating data available in intelligent buildings are a key enabler to make the best use of these demand response programs.

2.5.1 Background

Until relatively recently, electric utilities and grid operators in the United States generally had an abundance of generating capacity (aside from periods of equipment outages or extreme weather conditions) and had few constraints in using that capacity to satisfy electric demand. As the industry began to retire older less-efficient generating resources, they began to seek ways to make the grid more energy and cost efficient as well as more environmentally friendly. Studies found that in many cases, building owners and other electric customers' demand profiles could be adjusted slightly in order to assist with the balance between supply and demand on the electric grid. Experience has shown that some electric customers are willing to occasionally reduce their demand in return for some form of economic benefit, through demand response programs offered by their electric utility provider. These demand-side reductions can be either directly controllable by the electric utility (e.g., residential HVAC programs) or indirectly controllable at the option of the customer (e.g., for commercial building HVAC, lighting, etc.). Industrial customers have also been able to identify similar demand response (DR) opportunities in their operations. These reductions in electric demand (or "negawatts") are utilized by the utility or grid operator to fill imbalances between supply and demand, with the objective of ensuring grid reliability.

The U.S. Department of Energy (DOE) defines demand response as *a tariff or program established to motivate changes in electric use by end-use customers in response to changes in the price of electricity over time, or to give incentive payments designed to induce lower electricity use at times of high market prices or when grid reliability is jeopardized* [39]. The U.S. Federal Energy Regulatory Commission (FERC) defines a demand response event as *a period of time identified by the demand response program sponsor when it is seeking reduced energy consumption and/or load from customers participating in the program. Depending on the type of program and event (economic or emergency), customers are expected to respond or decide whether to respond to the call for reduced load and energy usage. The program sponsor generally will notify the customer of the demand response event before the event begins, and when the event ends* [40].

2.5.2 Participation in Retail and Wholesale DR Programs

Retail DR programs offered by electric utilities are often associated with the customer's electric utility rate tariff. In areas where organized wholesale energy markets exist, the procurement of electricity is typically orchestrated by the grid operator's wholesale market, which can include both supply-side and demand-side energy providers (which can include building owners).

A recent U.S. Department of Energy technical report outlines the utilization of various demand response resources in the planning and operation of the electric grid [39]. DR opportunities for building owners can include both price-based DR and incentive-based DR programs. Examples of price-based DR programs include the following:

- Time-of-use (TOU): an electricity rate having different unit prices for different blocks of time, typically defined across a 24 h day.
- Real-time pricing (RTP): an electricity rate in which the price fluctuates hourly reflecting changes in the wholesale price of electricity. Customers are notified of these prices on a day-ahead or hour-ahead basis.

- Critical Peak Pricing (CPP): a hybrid TOU structure having a provision for replacing the normal peak price with a much higher CPP event price under specified trigger conditions (e.g., when grid reliability is under stress or wholesale prices are very high).

Examples of incentive-based DR programs include the following:

- Demand Bidding/Buyback Program: a retail tariff with a DR option that enables the customer to offer bids to curtail electric demand (typically driven by high wholesale electricity prices).
- Emergency Demand Response Program: an option that provides utility bill credits for load reductions during specified periods (e.g., when there is a shortfall in electricity supply reserves).
- Interruptible/Curtailable Service: a retail electricity tariff with a DR option that provides a rate discount or bill credit for reducing electric load during utility or grid-level contingency periods.
- Ancillary Services Market Program: a program in which customers can bid load curtailments into the wholesale electricity market. If their bids are accepted, customers are paid the market price for committing to be on standby to reduce load. If their load curtailments are needed, they are notified by the utility or grid operator, and are typically paid the wholesale spot market energy price.
- Capacity Market Program: a program in which customers can offer load curtailments to serve as additional grid system capacity, to augment conventional generation resources.

Each of the above DR programs functions in a different way to contribute to grid reliability. These actions are applied at different points along the time continuum of utility and grid operations, from system planning (across months or weeks), down to timescales of minutes and less. This set of coordinated services is carefully managed by utility and grid operators to ensure reliable power delivery to electric customers. Intelligent buildings can play an important part in this complex and highly interactive system.

Recent rulings by utility regulators and policy changes at independent system operators and regional transmission organizations are creating new opportunities for building owners in wholesale electricity markets [41]. In the past, these grid balancing services were provided only by conventional electric power generation sources.

Demand response services in the wholesale market are delivered by qualified providers (or through qualified intermediaries) to the electric grid operator. Except for very large electric customers, building owners will typically participate in these markets through a qualified intermediary, either by contracting with their electric utility for the appropriate electric tariff or by contracting with a qualified demand response aggregator. In these arrangements, the electric utility or the DR aggregator participates in the electric grid market on the behalf of the building owner. Intelligent buildings are well positioned to participate in this process.

2.5.3 Automated Demand Response and OpenADR

Early experience with DR programs revealed that manual communication methods (i.e., telephone and fax notification of pending DR events) and manual control of equipment (i.e., manually shutting off power to equipment) were less reliable or predictable than desired. For this reason, work began on ways to automate the demand response. Over the past 20+ years, automated demand response (AutoDR) has progressed to an advanced state that now includes a broad range of HVAC DR control strategies.

AutoDR and intelligent buildings' participation in the smart grid vision requires an open, interoperable, and secure automation and communication method to facilitate reliable and cost-effective communication of electricity price and electric grid reliability signals. The Open Automated Demand Response (OpenADR) standard was developed beginning in 2003 to provide this capability and enable automated interactions between buildings and their electric utility and grid operator partners. OpenADR is being successfully applied by numerous utilities and grid operators.

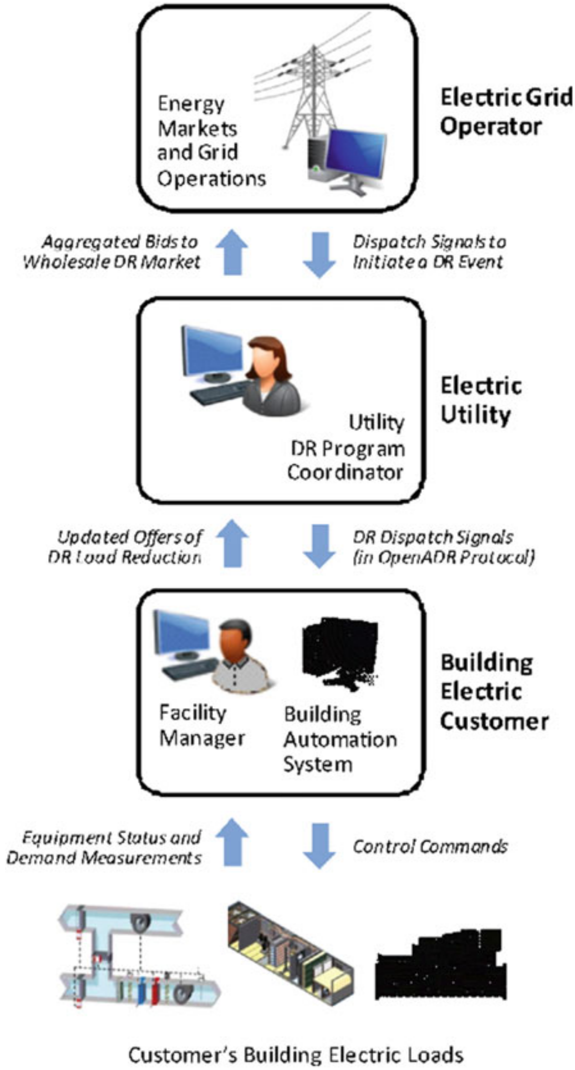
To extend and enhance the OpenADR standard, an international group of smart grid and buildings stakeholders have formed a working group in the Power Systems Management technical committee of the International Electrotechnical Commission (IEC) [42]. This activity will result in the development of an international standard for automated communications between intelligent buildings and the smart grid, which can be applied worldwide.

2.5.4 AutoDR Control Methods for HVAC Applications

Building owners and facility managers can benefit by investigating utility and grid operator DR programs to identify ways to take advantage of operating cost benefits resulting from AutoDR. Assistance from utility customer service representatives is helpful in determining the best courses of action. AutoDR control strategies are typically implemented in the electric customer's building automation system, including the necessary digital communications link to the electric utility or grid operator. These strategies can be selected and configured as a collaborative effort of the building facility manager, operating staff, BAS provider, and outside consultants as appropriate. The implementation of AutoDR control strategies using OpenADR communications and the role of the BAS are shown in Fig. 2.11.

The energy R&D community has devoted significant effort to identify and implement DR applications and control strategies for HVAC systems. Examples of proven DR applications can be found in the published literature [8]. These applications include DR control strategies which apply to most or all of the various types of HVAC equipment. The timing of DR events often coincides with peak demand periods, which are typically driven by cooling-related energy use. DR events can also be driven by peaks in heating-related energy use, depending on the locale.

Fig. 2.11 AutoDR control and OpenADR communications



Example DR applications for HVAC include control adjustments to [43]

- Space temperature set points (e.g., variable air volume systems),
- HVAC supply air temperature,
- Chilled water temperature,
- Duct static pressure,
- Motor speed control (e.g., fans, pumps, etc.),
- Demand limiting for major equipment (e.g., for chillers).

These HVAC DR strategies can be scheduled to begin at the start of a DR event. The strategies can be employed with price-based DR as well as incentive-based DR programs. Appropriate configuration of the DR strategies can limit associated indoor comfort impacts that could occur during and after the DR event. Other non-HVAC-related DR opportunities also exist in most buildings. Examples include indoor lighting, miscellaneous equipment and appliances, etc.

Some of these DR strategies can also be set to occur prior to a DR event to time-shift the building's demand profile, thereby providing a demand reduction during the period of the DR event. Example time-shifting strategies include pre-cooling of the occupied space. With careful design and configuration, these time-shifting strategies have shown good results.

2.5.5 Role of Intelligent Buildings

Initial efforts in developing DR control strategies generally relied on the rather limited amount and quality of measured data that was available from typical BAS. As BAS technology has advanced in recent years, more sophisticated DR control strategies are now practical due to the greater amount of data that is made available in today's BAS.

The rich building HVAC operating data which is present in intelligent buildings can be utilized to develop improved AutoDR control strategies. These strategies can provide greater economic benefits to building owners and improved DR performance desired by utility and grid operators. These improved AutoDR control strategies can be tailored to make best use of the various DR programs which are available to each specific building and locale. An intelligent building is also an important enabler for emerging advancements in AutoDR. Examples include data-driven control strategy development and improved building models for demand response [44–46].

Taking a holistic view, intelligent buildings can integrate their demand response strategies with related energy systems in complementary ways to drive greater cost and energy benefits. Examples include renewable energy, energy storage, microgrids, transactive energy, energy efficiency initiatives, and onsite power generation.

In [7], four international implementations of automated demand response, all relying on the OpenADR standard noted above, are discussed:

- China's first automated demand response pilot project, implemented in the Tianjin Economic Technological Development Area (TEDA). Additional projects are underway as a result of this project.
- A microgrid for the U.S. Food and Drug Administration's White Oak campus. The microgrid can operate in both grid-connected and islanded modes. With its onsite generation capacity the microgrid supplies more electricity to the grid than it purchases from it.
- An ancillary services project at the Los Angeles Air Force Base, which relies on electric vehicle batteries to provide frequency regulation to the grid. Fleet vehicles

at the base have been replaced with electric vehicles and charging stations. 700 kW of power will be available for the grid when the project is complete.
- The Thames Valley Vision Project in the U.K. As of June 2014, 20 buildings were participating in the project and over 100 load-shed events had been conducted with an average participation rate of 98%.

2.6 From Research to Practice—Considerations and Challenges

2.6.1 Understanding the Context for Applied Research

Technology transfer from R&D to commercial products has several challenges. There are gaps in translating the technology to practice, developing tools for smooth deployment, and mobilizing a trained team for installing, commissioning, and troubleshooting. Adding to that, advanced automated optimization and control principles create black-box-like paradigms for the operation of a plant or building. These do not always translate to operator familiarity and comfort with the system. Hence, user experience principles must be baked into the commercial offering.

In academia and industrial research teams, the focus for advanced control researchers is on proving a concept and in developing a working prototype. The engineering problem to be solved is abstracted up to a mathematical or statistical problem. Research involves developing and testing computation-aided solutions which are tested in simulations, which tests the technological feasibility and performance, but not the other aspects of field implementation such as configuration or end-user experience. Assumptions are made during research to contain the scope and solve the core complex mathematical problem, without getting bogged down by varied field control systems and equipment. This leads to several valuable theoretical advances and evolves the state of the art. However, the commercialization plan is about making a profitable offering that solves a real-world problem. There are many considerations in addition to the advanced solution which may determine the technology's viability and success in the marketplace.

The following questions are important when fielding an advanced optimization and control product:

- What is the current state of a typical building or plant? For example, is it operated manually, and if automated, how often does the operator revert to manual operation?
- How well is the building or plant instrumented? Is enough data being obtained at the resolution and sampling time the advanced algorithm requires?
- Is the typical building automation and communication system robust? Will there be periods of no communication or delayed communication?

- What is the typical architecture of the control and automation system? Do we need to bring information from different systems together, or pipe in several different sensor or control inputs?
- What is the typical information about a plant or building needed to customize or configure the advanced solution? How will this information be readily available in a typical facility?
- Are the right people in place to be first adopters (wanting to solve a problem, save energy, etc.) and dedicated to transitioning to a new system?

The answers to these may be more important than the advanced control solution itself and have the potential to derail a promising solution from moving forward as a commercial offering.

Unlike other domains such as aircraft systems and refineries, buildings, and their control systems are very diverse. There are numerous ways an HVAC system may be configured, and there are always exceptions to established practices in the field. Buildings change over time where additions are built or modified and occupancy changes, and in addition the end user has some control over the environment. These often result in ad hoc control changes to facilitate the addition of new equipment or changes in zone functions. Since these could be undocumented, it usually requires the knowledge of a facility operator to unravel the HVAC infrastructure and control system changes and to understand the full picture. This full picture is needed if a supervisory level optimized control is to be implemented.

The end user experience cannot be over-emphasized and it is important for applied researchers to understand the work environment. The workflow in large facilities is very cost efficient. One or two operators may manage several plants (roving operators) and are trained to know only what is needed to operate the plants and buildings correctly; special displays are created so that the operators may focus on only the most important information at that time. Control technicians program controllers and have knowledge of the logic implemented in the controllers for different systems and equipments. The building automation programmers connect all pieces together including controllers, sensors, and meters. The operations staff are not motivated to try new controls and optimization software, because operational reliability is their number one goal. In many cases, control expertise or knowledge of the specific system does not reside with facilities management of a building, but with control and building automation services provided by automation companies with their own technical staff.

2.6.2 Role of Architecture

Typically, feasibility is established when the advanced algorithm produces correct or optimal results for test cases. The research engineers usually work with building experts to develop a prototype that works in the field. However, this is also the phase when the control and software architecture and user interfaces need to be designed because the advanced solution must create the least disruption for the facility operators, even at the prototype stage, to be accepted, and this can be critical in the introduction of new operational software. This does not mean that the prototype must be the final product. However, the main structure and functional delineations of the control decisions should have been defined, because of their critical role in proliferating technological solutions smoothly. A typical architecture for supervisory optimizers is shown in Figs. 2.2 and 2.7. The advanced optimization at the supervisory level provides top-level set points and on-off commands to major equipment. Lower level feedback control loops such as those for pump flow and cooling water temperature run on local controllers. The local controllers also encompass individual equipment control from the manufacturer, such as chiller control.

Let us illustrate these remarks using the prototype chiller plant optimization system described previously. A chiller plant with varying chiller sizes and types, and not undersized, is generally a good candidate for optimization, because the loading and operating set points for maximum efficiency of the plant as a whole are not intuitive to the operator. However, the chiller plant is also complex and optimizing the entire chiller plant including the pumps and fans makes delineation of the control hierarchy difficult. The schematic of one of the example chiller plants is shown in Fig. 2.12.

Commands such as chiller on/off switching or supply temperature set points may be provided by a supervisory level optimizer. Pumps are part of the lower level functionality in the chiller plant: they deliver the required flow to the chillers, the cooling towers, and the building loads. Optimizing pump speeds and switching on/off schedules intertwines the supervisory control with the lower level control. Although

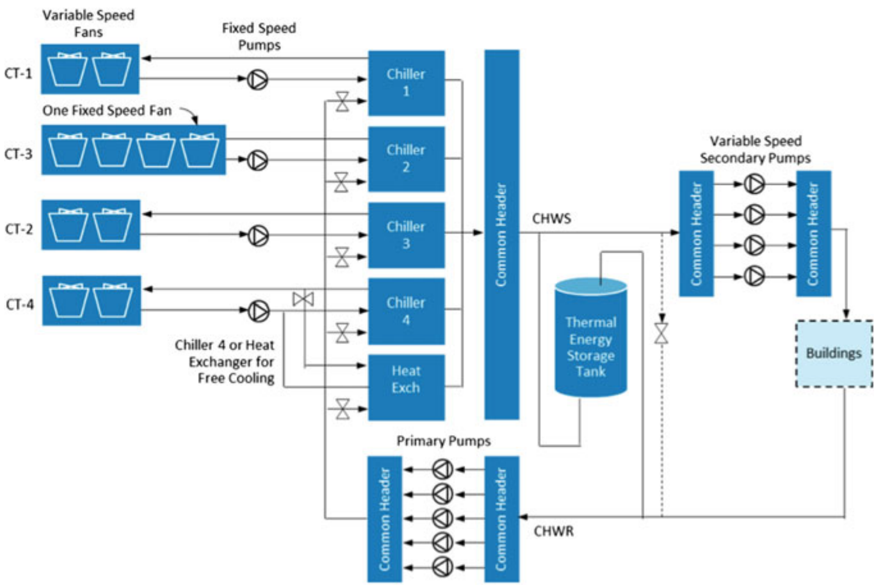


Fig. 2.12 Chiller plant layout

chillers are the main energy consuming equipment in the plant, the pumps and fan motors in a large plant can add up to a high energy cost. If our objective is to optimize the operation of all equipment, including the primary and secondary pumps and cooling tower fans, which are operated by lower level closed-loop control, then the clean delineation requires thought and careful design. For example, a chiller on/off command involves a combination of primary pumps (shared among several chillers that may be on or off) to be switched on or commanded to increase flow within several constraints. The controller is programmed with preset rules for pump combinations and speeds to satisfy the chiller flow requirements. In the case of secondary pumps, the lower level controllers use a differential pressure set point across the pumps to control their speeds.

The initial control architecture of the prototype optimizer with black-box models generated a hybrid set of outputs: set points and on/off commands for the chillers and the control actions for low-level equipment such as pumps and cooling tower fans. This may work temporarily in the prototype test scenario, but may be accepted with reluctance by the facility operators and managers. The more effective process is to construct the architecture for the advanced optimizer to specify the set points (within operating limits) for all lower level controllers, but this is not trivial in some cases. Taking the case of the secondary pumps, specifying the differential pressure set points to lower controllers involves modeling the flow loop and the pump curves (see Fig. 2.13). This is not a trivial task and to be able to generalize to a software product software tools will need to be built for configuring such models; the tools would bridge the gaps between the supervisory and local control, and the optimization developer and the application engineer. Without such translation from advanced solutions to field practice, the operational costs of advanced modeling and optimization skills needed in implementation will be high, and productization cannot be sustained.

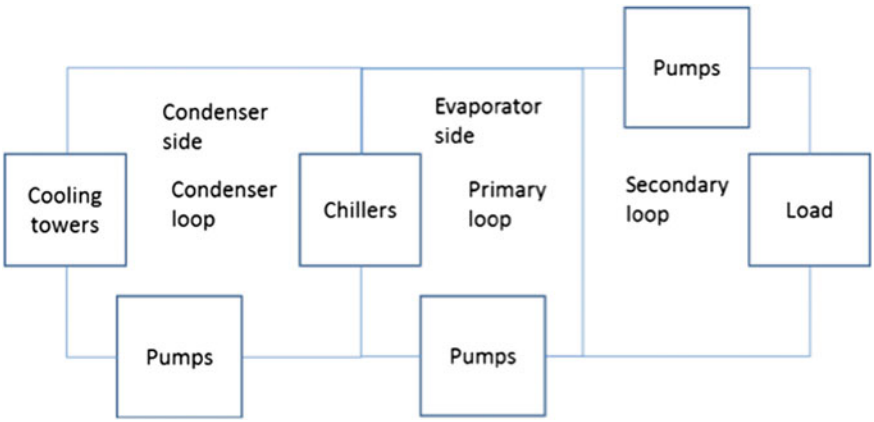


Fig. 2.13 Example layout for flow modeling

2.6.3 *"Supply Chain" for Technology Transfer*

First, let us look at what happens when an advanced control solution is sold and implemented at typical large facilities (Fig. 2.14). A typical implementation progresses from initial customer contact by a sales team to a site audit and putting together the solution to meet the customer needs by a solution assembly team. This team would typically assemble the full solution (that includes upgrades other than the advanced control) for the customer by selecting from a set of equipment, control, and automation solutions. Once approved by the customer, application engineers would configure the advanced control solution for the site (setting up the generic software for the site: number of chillers and their interconnections, specifications of equipment, and so on). The solution would also be set up with all I/O points for the specific plant to communicate with the building automation system or controllers during installation and commissioning, and handed over to facility operators after training.

Next, who should be in the "supply chain" of technical professionals who develop the solution? The advanced control solution is only one part of several functions that need to be designed for a cost-effective product that fulfills the objective, be it energy savings, comfort, or staff productivity. Figure 2.15 shows the different functions and skillsets that should be involved; this is not meant to convey that each team is separate, or that there need to be separate individuals for each role, but that the essential role of the skills and functions should be acknowledged and understood early, so that the advanced solution may be architected for ease of deployment and maintenance. The advanced control developer is the control theory and optimization expert who researches and develops the computational algorithms. The building domain expert has general knowledge of all aspects of a typical building: the equipment, the building

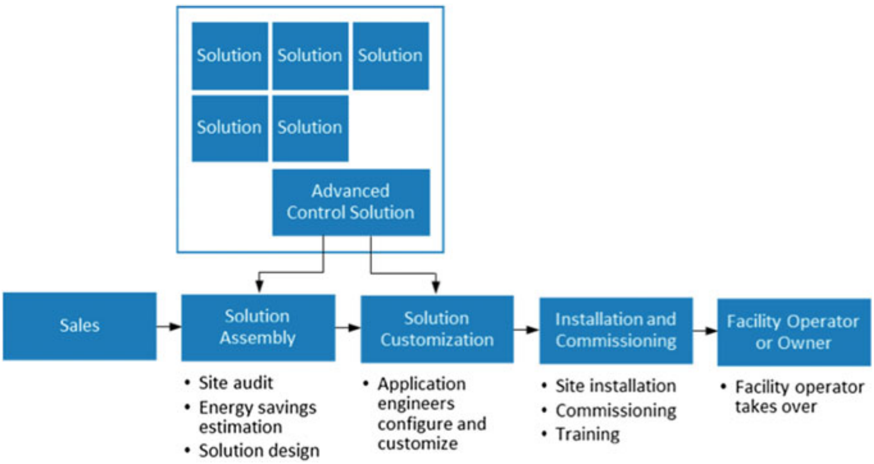


Fig. 2.14 Organizational chain in advanced control application

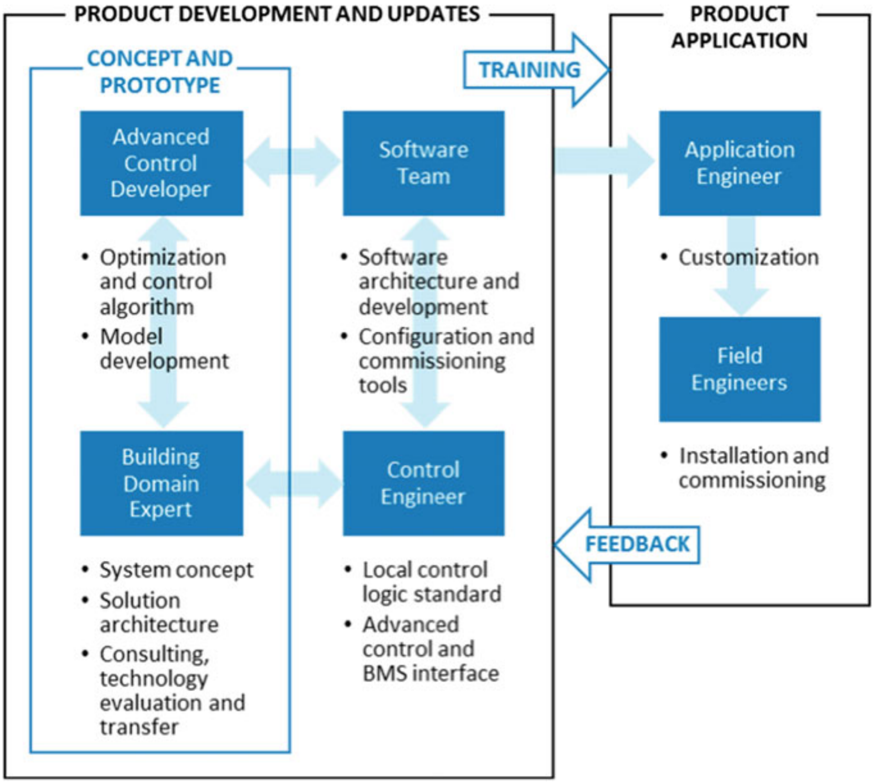


Fig. 2.15 Supply chain of professionals in tech development and transfer

and plant controls, HVAC distribution, local control, and BAS. The control engineer has practical knowledge and experience of control programming and implementation with several low-level controller brands. He/she works with the advanced control researcher and building domain expert to architect the control functional layers, and provides the local control knowledge to standardize on them for use by the advanced solution. The software team collaborates with the other teams to design the right software architecture for the computation, storage, data access, and cycle times required. These separate entities bring their expertise so that together the constraints and the best practices from each may be incorporated in the final product.

2.7 Conclusion

Our experience with implementation of mature prototypes, their deployment and validation in real pilots, and their transfer to commercial teams, as well as others' similar experiences, prompt a few thoughts and recommendations.

- Advanced control and optimization bring real benefits to building energy management and bring us much closer to reducing the building sector's energy use and emissions. It is vital that control and optimization experts also become the champions in translating advanced concepts to widespread commercial use.
- The challenge to bring to market innovative energy-saving technologies is exacerbated by the low ROI compared to other investment options, as noted before. Indeed, an unfavorable cost-to-benefit ratio continues to be one of the major limitations for a wider adoption of advanced control and optimization applications in buildings. The costs considered over the entire solution life cycle include primarily installation costs and maintenance costs, which creates pressures on short and easy configuration, discourages inclusion of additional hardware, and favors keeping the effort needed for supervision and re-tuning to minimal levels.
- Energy projects shift from purely energy-savings-driven to automation-upgrade-driven, depending on market conditions. It is important for practitioners to understand the market driver, and develop the tools and mobilize the trained workforce that makes a commercially viable product or service.
- The energy savings benefit provokes the chicken-and-egg game of demonstrating savings in order to find the investment to mature the technology. A prototype can only show the benefit if well deployed and accepted, which needs additional investment. Therefore, control architecture and operator considerations are of top importance, even at the prototype stage.
- Standard implementation tools must also be developed to quickly and reliably configure the advanced software and connect it to the local control on site. These includes general tools such as ontology-driven data modeling libraries [47] that facilitate all data-intensive applications, as well as specific tools for pre-configuring of software and plug-and-play type implementation. The new solution should not require a skilled advanced control expert as is the norm in the industrial domain. HVAC field engineers are heavily time constrained and that is why they prefer an intuitive plug-and-play configuration, which ideally does not require any additional sensors, actuators, or meters.
- In those situations where building operators use new tools as advisory systems, their experience and acceptance should be improved by providing explanations of major actions by the supervisory optimizer, such as "turning off chiller 4 and turning on chiller 2 at higher load operates the plant at 4% higher efficiency."

For complex solutions that require advanced knowledge and skillsets, considerations of control and software architecture force the question of marketplace viability early in the development process. Appropriate decisions at that stage can then guide the developers in formulating and solving the most commercially viable problem, and not just pushing through a mathematically complex or convenient problem. This also informs where additional development funding needs to be focused, for smooth technology adoption and diffusion in the market.

Acknowledgements Part of this material is based upon work supported by the U.S. Army Corps of Engineers, Humphreys Engineer Center Support Activity under Contract No. W912HQ-13-C-0058. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s), and do not necessarily reflect the views of the U.S. Army Corps of Engineers, Humphreys Engineer Center Support Activity, and should not be construed as an official Department of Defense position or decision unless so designated by other official documentation.

Note: BACnet is a registered trademark of ASHRAE. LonWorks and LON are registered trademarks of Echelon Corporation. Modbus is a registered trademark of Schneider Automation Inc. ZigBee is a registered trademark of ZigBee Alliance, Inc. EnOcean is a registered trademark of EnOcean GmbH. Z-Wave is a registered trademark of Zensys Inc. Bluetooth is a registered trademark of Bluetooth SIG, Inc. Honeywell Enterprise Building Integrator (EBI) is a trademark of Honeywell International, Inc. OPC is a registered trademark of OPC Foundation.

References

1. U.S. Department of Energy, Buildings energy data book, building technologies program, U.S. Department of Energy, Technical report (2012). http://buildingsdatabook.eren.doe.gov/. Accessed 5 September 2016
2. Environmental and Energy Study Institute, Buildings and climate change, Environmental and Energy Study Institute, Technical report (2016). http://www.eesi.org/files/climate.pdf. Accessed 5 September 2016
3. Brambley MR et al (2016) Advanced sensors and controls for building applications: Market assessment and potential r&d pathways, Pacific Northwest National Laboratory, PNNL-15149 (2005). http://apps1.eere.energy.gov/buildings/publications/pdfs/corporate/pnnl-15149_market_assessment.pdf. Accessed 14 September 2016
4. Kelly H (2016) The potential of more efficient buildings. Issues Sci Technol 32(4):21
5. Markets and Markets (2016) Building automation system market worth 100.60 billion usd by 2022. http://www.marketsandmarkets.com/PressReleases/building-automation.asp. Accessed 5 September 2016
6. Honeywell Building Solutions (HBS), HBS retail complex diagram (2016). https://buildingsolutions.honeywell.com/en-US/newsevents/resources/Publications/honeywell-hbs-retail-complex-diagram.jpg. Accessed 6 September 2016
7. Sauter T, Soucek S, Kastner W, Dietrich D (2011) The evolution of factory and building automation. IEEE Ind Electron Mag 5(3):35–48
8. Samad T, Koch E, Stluka P (2016) Automated demand response for smart buildings and microgrids: the state of the practice and research challenges. Proc IEEE 104(4):726–744
9. Enterprise Building Integrator (EBI), Building integration, Honeywell, Technical report. https://www.ebi.honeywell.com/PublishingImages/Integration.jpg. Accessed 5 September 2016
10. Association CABA (2015) Report on intelligent buildings and big data. Technical report, CABA Association
11. Friess, P (2013) Internet of things: converging technologies for smart environments and integrated ecosystems. River Publishers
12. Clements-Croome, DJ (2014) Sustainable intelligent buildings for better health comfort and well-being, Report for DENZERO project

13. World Green Building Council (2015) Report on health, wellbeing and productivity in offices, the next chapter for green building, World Green Building Council, Technical report
14. Derguech W, Bruke E, Curry E (2014) An autonomic approach to real-time predictive analytics using open data and internet of things. In 2014 IEEE 11th international conference on ubiquitous intelligence and computing and 2014 IEEE 11th international conference on and autonomic and trusted computing and 2014 IEEE 14th international conference on scalable computing and communications and its associated workshops (UTC-ATC-ScalCom). IEEE, pp 204–211
15. Capehart BL, Brambley MR (2014) Automated diagnostics and analytics for buildings. Fairmont Press, Inc
16. Stluka P, Mařik K, Endel P (2014) Advanced control solutions for building systems. In IFAC, vol 47, no 3. Elsevier, pp 606–611
17. Akkaya K, Guvenc I, Aygun R, Pala N, Kadri A (2015) Iot-based occupancy monitoring techniques for energy-efficient smart buildings. In Wireless communications and networking conference workshops (WCNCW), 2015 IEEE. IEEE, pp 58–63
18. Bluyssen PM (2009) The indoor environment handbook: how to make buildings healthy and comfortable. Routledge
19. Zhao Y, Zhao Q, Xia L, Cheng Z, Wang F, Song F (2013) A unified control framework of HVAC system for thermal and acoustic comforts in office building. In 2013 IEEE international conference on automation science and engineering (CASE). IEEE, pp 416–421
20. Samad T (2016) Control systems and the Internet of Things. IEEE Control Syst 36(1):13–16
21. Li F, Vögler M, Claeßens M, Dustdar S (2013) Efficient and scalable IoT service delivery on cloud. In IEEE sixth international conference on cloud computing (CLOUD). IEEE, pp 740–747
22. Vögler M, Li F, Claeßens M, Schleicher JM, Sehic S, Nastic S, Dustdar S (2015) COLT collaborative delivery of lightweight iot applications. In Internet of things. User-centric IoT. Springer, pp 265–272
23. Spudić V, Conte C, Baotić M, Morari M (2015) Cooperative distributed model predictive control for wind farms. Optimal Control Appl Methods 36(3):333–352
24. Morstyn T, Hredzak B, Agelidis VG (2015) Distributed cooperative control of microgrid storage. IEEE Trans Power Syst 30(5):2780–2789
25. Putta V, Donghun K, Cai J, Hu J, Braun J (2014) Distributed model predictive control for building HVAC systems: a case study. In International high performance buildings conference, West Lafayette, IN
26. Joe J, Karava P, Hou X, Hu J (2016) Model predictive control of a radiant floor cooling system in an office space. In 4th international high performance buildings conference, West Lafayette, IN
27. Joe J, Karava P (2017) Agent-based system identification for control-oriented building models. J Building Perform Simul 10(2):183–204
28. Purdon S, Kusy B, Jurdak R, Challen G (2013) Model-free HVAC control using occupant feedback. In IEEE 38th conference on local computer networks workshops (LCN workshops). IEEE, pp 84–92
29. Gupta S, Kar K, Mishra S, Wen J (2014) Smart temperature control with active building occupant feedback. In 19th world congress of the international federation of automatic control
30. Maaijen R, Zeiler W, Boxem G, Maassen W (2012) Human centered energy control: taking the occupancy in the control loop of building systems. REHVA J
31. Mařik K, Rojiček J, Stluka P, Vass J (2011) Advanced HVAC control: theory versus reality. IFAC 44(1):3108–3113
32. Gwerder M, Gyalistras D, Oldewurtel F, Lehmann B, Wirth K, Stauch V, Tödtli J (2010) Potential assessment of rule-based control for integrated room automation. In 10th REHVA world congress clima, pp 9–12
33. Cigler J, Siroky J, Korda M, Jones C (2013) On the selection of the most appropriate mpc problem formulation for buildings. In 11th REHVA world congress CLIMA 2013, no. EPFL-CONF-183457

34. Širokỳ J, Oldewurtel F, Cigler J, Privara S (2011) Experimental analysis of model predictive control for an energy efficient building heating system. Appl Energy 88(9):3079–3087
35. Cigler J, Gyalistras D, Široky J, Tiet V, Ferkl L (2013) Beyond theory: the challenge of implementing model predictive control in buildings. In Proceedings of 11th Rehva world congress, Clima, vol 250
36. Wang S, Ma Z (2008) Supervisory and optimal control of building HVAC systems: a review. HVAC&R Res 14(1):3–32
37. Ma Y, Borrelli F, Hencey B, Coffey B, Bengea S, Haves P (2012) Model predictive control for the operation of building cooling systems. IEEE Trans Control Syst Technol 20(3):796–803
38. Parthasarathy G (2013) Central plant optimization for waste energy reduction (cpower): final report (draft), ESTCP Program, EW-201349
39. U. D. of Energy (2006) Benefits of demand response in electricity markets and recommendations for achieving them: a report to the united states congress pursuant to section 1252 of the energy policy act of 2005, February 2006. http://energy.gov/oe/downloads/benefits-demand-response-electricity-markets-and-recommendations-achieving-them-report
40. F. E. R. Commission (2007) Assessment of demand response and advanced metering - staff report, September 2007. http://www.ferc.gov/industries/electric/indus-act/demand-response/dem-res-adv-metering.asp
41. Rahimi F, Ipakchi A (2010) Demand response as a market resource under the smart grid paradigm. IEEE Trans Smart Grid 1(1):82–88
42. International Electrotechnical Commission, WG 21, Interfaces and protocol profiles relevant to systems connected to the electrical grid. http://www.iec.ch/dyn/www/f?p=103:14:0::::FSP_ORG_ID,FSP_LANG_ID:8572,25
43. Motegi N, Piette M, Watson D, Kiliccote S, Xu P (2007) Introduction to commercial building control strategies and techniques for demand response, Lawrence Berkeley National Laboratory, LBNL-59975, May 2007. http://drrc.lbl.gov/publications/introduction-commercial-building
44. Lee K, Braun J, A data-driven method for determining zone temperature trajectories that minimize peak electrical demand, California energy commission, public interest energy research program. http://drrc.lbl.gov/sites/all/files/lee-braun-data-driven.pdf
45. Piette M, Granderson J, Wetter M, Kiliccote S (2012) Intelligent building energy information and control systems for low-energy operations and optimal demand response, Lawrence Berkeley National Laboratory, LBNL-5894E, May 2012. http://drrc.lbl.gov/publications/intelligent-building-energy
46. Rongxin Y, Kiliccote S, Piette M (2014) Linking measurements and models in commercial buildings: a case study for model calibration and demand response strategy evaluation, Lawrence Berkeley National Laboratory, LBNL-7006e, December 2014. http://drrc.lbl.gov/publications/linking-measurements-and-models
47. Prairie D, Samy MKG, Petze J, Petock M (2016) Project haystack, a caba white paper. http://project-haystack.org/file/22/CABA-White-Paper-on-Project-Haystack.pdf

http://www.springer.com/978-3-319-68461-1

Intelligent Building Control Systems
A Survey of Modern Building Control and Sensing Strategies
Wen, J.T.; Mishra, S. (Eds.)
2018, XXII, 313 p. 118 illus., 84 illus. in color., Hardcover
ISBN: 978-3-319-68461-1