Related Commercial Resources

CHAPTER 63. SMART BUILDING SYSTEMS

SMART building systems are building components that exhibit characteristics analogous to human intelligence. These characteristics include drawing conclusions from data or analyses of data rather than simply generating more data or plots of data, interpreting information or data to reach new conclusions, and making decisions and/or taking actions autonomously without being explicitly instructed or programmed to take specific actions. Enhanced situational awareness and the ability to balance trade-offs between multiple objectives are also traits of smart systems. These capabilities are usually associated with software, but they can also be possessed by hardware with embedded software code, or firmware. The line between systems that are “smart” and “not smart” is blurry, and, for purposes of this chapter, does not need to be absolutely defined. The purpose of this chapter is to introduce readers to emerging technologies that possess some of these smart characteristics.

Smart technologies offer opportunities to reduce energy use and cost while improving the performance of HVAC systems to provide better indoor environmental quality (IEQ). Smart building systems integrate and intersect with advancements in many domains, such as sensing and communication, computing and automation, fault detection and diagnosis, and the smart grid. This chapter begins with an introduction to existing resources that are relevant to smart building systems, and then provides more detailed treatment of smart systems and technologies in the fields of automated fault detection and diagnostics, sensors and actuators, and the emerging modernized electric power grid and its relationship to buildings and facilities.

1. USEFUL RESOURCES

Unless otherwise specified, chapters are in this volume.

Chapter 43*, *Supervisory Control Strategies and Optimization discusses how smart building systems may leverage mathematical optimization techniques to generate intelligent control decisions. This chapter provides extensive material on optimization of building systems. Supervisory and predictive control methods are discussed, along with near-optimal simplified heuristics.

Chapter 65*, *Occupant-Centric Sensing and Controls addresses various methods of observing and integrating occupant feedback into HVAC control systems. Smart building systems may have an increased ability to dynamically respond to dynamic occupant behaviors and preferences. Methods are contrasted in terms of application, system costs, and accuracy, among other attributes. The chapter also details occupant behavior modeling, as it pertains to building system simulation and control.

ASHRAE Smart Grid Application Guide: Integrating Facilities with the Electric Grid details how smart building systems can operate in consideration of the electric grid serving the resources to benefit both buildings and the grid. This publication contains guidance on the design and operation of building systems that may be responding to dynamic electric grid conditions and signals. The guide also highlights smart grid standards and regulations that are also relevant to facilities integrating with the electric grid.

ASHRAE* Standard *201, Facility Smart Grid Information Model defines an object-oriented information model that enables electric loads in homes, buildings, and industrial facilities to communicate with a smart electric grid and provide information to utilities and other electric service providers. The information model also enables appliances and control systems to manage electrical loads and generation sources in response to information from the smart grid.

***Chapter 7 in the 2021* ASHRAE Handbook—Fundamentals** covers foundational control system concepts such as terminology, component descriptions, control loops and algorithms, networks, and commissioning and operation. Smart building systems may build from or work in conjunction with traditional control approaches (e.g., proportional-integral controllers) and technologies.

Chapter 48*, *Design and Application of Controls builds upon the control fundamentals chapter by addressing control of typical HVAC systems, design of controls for system coordination, and control system commissioning.

Chapter 41*, *Computer Applications discusses software, big data, cloud computing, BIM and data integration, network architecture, and building automation system security, which may all interface in the context of smart systems.

ASHRAE* Guideline *13, Specifying Building Automation Systems provides background information, recommendations, and discussion of options available when designing a building automation system (BAS), with an emphasis on developing BAS specifications. Topics include BAS network design and architecture, network security, and system integration, among others.

ASHRAE* Guideline *36, High Performance Sequences of Operation for HVAC Systems outlines best in-class control sequences for common HVAC systems. In relation to smart systems, the guideline includes provisions for rule-based fault detection routines and recommendations for alarm configuration to support automated identification of performance degradations and fault conditions.

ASHRAE* Standard *135, A Data Communication Protocol for Building Automation and Control Networks provides communication protocols for conveying building automation data between devices commonly used in building applications. Smart systems often rely on communication among multiple devices across various mediums and networks. The 2020 release of the standard includes BACnet Secure Connect, bringing some of the latest network security and device authentication features to building automation systems.

IEEE* Standard *1547, IEEE Standard for Interconnection and Interoperability of Distributed Energy Resources with Associated Electric Power Systems Interfaces establishes the technical specifications for interoperability and interconnection of DERs with the electric grid. Smart building systems discussed may include, integrate, or interface with various distributed energy resources (DERs).

AHRI* Standard *1380, Demand Response Through Variable Capacity HVAC Systems in Residential and Small Commercial Applications establishes the definitions, test requirements, operating and physical requirements, minimum data requirements for published ratings, marking and nameplate data, and conformance conditions for variable speed HVAC to provide demand response (DR). DR may be provided by smart building systems that are capable of changing their operations based on signals from the electric grid.

Energy Information Handbook: Applications for Energy-Efficient Building Operations provides guidance on how to collect and analyze building energy data to improve performance. The handbook provides a primer on various tracking and reporting methods for building end-uses and equipment. Fault detection and diagnosis are also introduced.

In addition to the published resources above, there are a number of proposed publications that are highly relevant to smart building systems.

ASHRAE* Standard *223P, Semantic Data Model for Analytics and Automation Applications in Buildings defines machine-readable semantic models for representing building system information. The models provide a standard way of incorporating additional data descriptors, relationships, and classifications to facilitate data flow and utilization by other devices and applications. Ease of organization and use of data can be a key enabler for the development and scaling of smart building technologies and algorithms.

ASHRAE* Standard *224P, Standard for the Application of Building Information Modeling is a proposed standard that defines how to include BIM requirements in design, construction, and operations services contracts, and how smart building systems may leverage building information models throughout their lifecycle to improve performance.

ASHRAE* Standard *231P, CDL—A Control Description Language for Building Environmental Control Sequences defines a human- and machine-readable graphical programming language for building environmental control sequences. The language is designed to support specification of controls, implementation through machine-to-machine translation, documentation, and simulation. In the context of smart building systems, the language can streamline development, delivery, and testing of advanced control sequences through increased standardization and digitization of the controls delivery process.

ASHRAE* Standard *232P, Schema-Based Building Data Model Protocols defines building data structures and conventions for data exchange among building performance and HVAC&R software. The meta-schema can be uniformly referenced by other building data model and standards projects to reduce the fragmentation and duplicated efforts across projects. Such a meta-schema can facilitate further development and exchange among software tools and information technologies used in designing and operating smart building systems.

2. AUTOMATED FAULT DETECTION AND DIAGNOSTICS

Many buildings today use sophisticated building automation systems (BASs) to manage a wide and varied range of building systems. Although the capabilities of BASs have increased over time, many buildings are still not properly commissioned, operated, or maintained, which leads to inefficient operation, excess expenditures on energy, poor indoor conditions at times, and reduced lifetimes for equipment. These operation problems cause an estimated 15 to 30% of unnecessary energy use in commercial buildings (Katipamula and Brambley 2005a, 2005b). Much of this excess consumption could be prevented with widespread adoption of **automated fault detection and diagnostics (AFDD)**. In the long run, automation even offers the potential for automatically correcting problems by reconfiguring controls or dynamically changing control algorithms (Brambley and Katipamula 2005; Fernandez et al. 2009, 2010; Katipamula and Brambley 2007; Katipamula et al. 2003a; Lin et al. 2020).

AFDD is an automatic process by which faulty operation, degraded performance, and failed components are detected and understood. The primary objective is early detection of faults and diagnosis of their causes, enabling correction of the faults before additional damage to the system, loss of service, or excessive energy use and cost result. This is accomplished by continuously monitoring the operations of a system, using AFDD processes to detect and diagnose abnormal conditions and the faults associated with them, then evaluating the significance of the detected faults and deciding how to respond. For example, the temperature of the supply air provided by an air-handling unit (AHU) might be observed to be chronically higher than its set point during hot weather. This conclusion might be drawn by a trained analyst visually inspecting a time series plot of the supply air temperature. Alternatively, a computer algorithm could process these data continuously, reach this same conclusion, and report the condition to operators or interact directly with a computer-based maintenance management system (CMMS) to automatically schedule maintenance or repair services.

Automated diagnostics generally goes a step further than simply detecting out-of-bounds conditions. In this air-handler example, an AFDD system that constantly monitors the temperature and humidity of the outdoor, return, mixed, and supply air, as well as the status of the supply fan, hot-water valve, and chilled-water valve of the air handler, might conclude that the outdoor-air damper is stuck fully open. As a result, during hot weather, too much hot and humid outdoor air is brought into the unit, increasing the mechanical cooling required and often exceeding the capacity of the mechanical cooling system. As a result, the supply air temperature is chronically high. This is an example of how an AFDD system can detect and diagnose this fault.

Over the past several decades, fault detection and diagnostics (FDD) has been an active area of research among the buildings and HVAC&R research communities. Isermann (1984), Katipamula and Brambley (2005a, 2005b), and Rossi and Braun (1997) described an operations and maintenance (O&M) process using AFDD that can be viewed as having four distinct functional processes, as shown in Figure 1. In the last decade, several literature reviews were published about air-handling unit AFDD (Bruton et al. 2014; Yu et al. 2014), supermarket mechanical system AFDD (Behfar et al. 2017), residential air-conditioning system AFDD (Rogers et al. 2019), building system AFDD (Kim and Katipamula 2018; Shi and O'Brien 2019), artificial-intelligence-based AFDD (Zhao et al. 2019), data-driven AFDD (Mirnaghi and Haghighat 2020), sensor impact evaluation and verification for AFDD (Zhang et al. 2021), and fault modeling (Li and O'Neill 2018). Automated correction after detection and diagnostics also has been an active area of research in the past decade (Brambley and Katipamula 2005; Fernandez et al. 2009a, 2010; Katipamula and Brambley 2007; Katipamula et al. 2003a, 2003b; Lin et al. 2020).

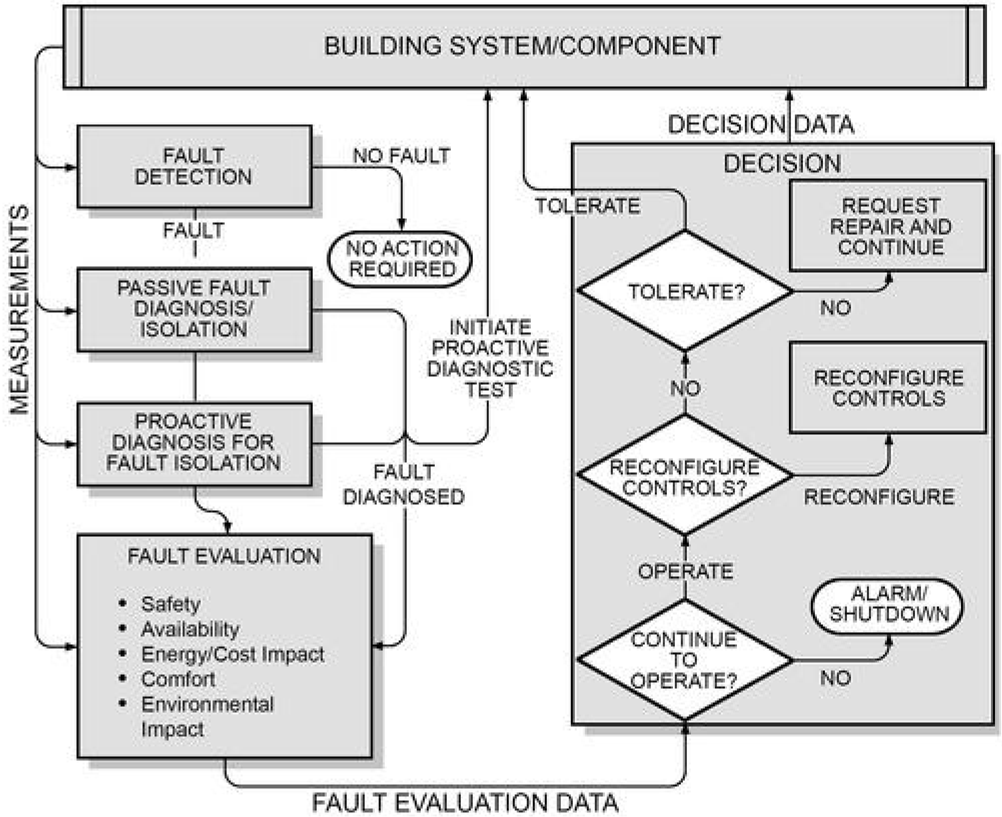


Figure 1. Generic Process for Using AFDD in Ongoing Operation and Maintenance of Building Systems Adapted from Katipamula and Brambley (2005a)

As shown in Figure 1, the first functional step of an AFDD process is to monitor the building systems and detect abnormal (faulty) conditions. This step is generally referred to as the **fault detection** phase. If an abnormal condition is detected, then the **fault diagnosis** process identifies the cause. If the fault cannot be diagnosed using passive diagnostic techniques, proactive diagnostics techniques may be required to isolate the fault (Katipamula et al. 2003a). Following diagnosis, **fault evaluation** assesses the impact (energy, cost, and availability) on system performance. Finally, a decision is made on how to react to the fault. In most cases, detection of faults is easier than diagnosing the cause or evaluating the effects of the fault. Detailed descriptions of the four processes are provided in Katipamula and Brambley (2005a, 2005b) and Katipamula et al. (2003a).

AFDD is different from BAS alarms. An alarm's analysis is limited to simple math on only the data available in the local controller, which usually covers a short duration and a few points. Alarms commonly detect sensor value deviation associated with a predefined threshold based on real-time conditions. The traditional BAS does not typically allow for sophisticated logic that interrelates multiple data streams and performs rule- or model-based diagnostics. FDD tools are most often applied as a separate software application that obtains data from the BAS and may provide a report of the duration and frequency of faults, cost and/or energy impacts, and relative priority levels. Figure 2 shows an example interface of the FDD tool, and Table 1 lists typical capabilities of BAS and AFDD software.

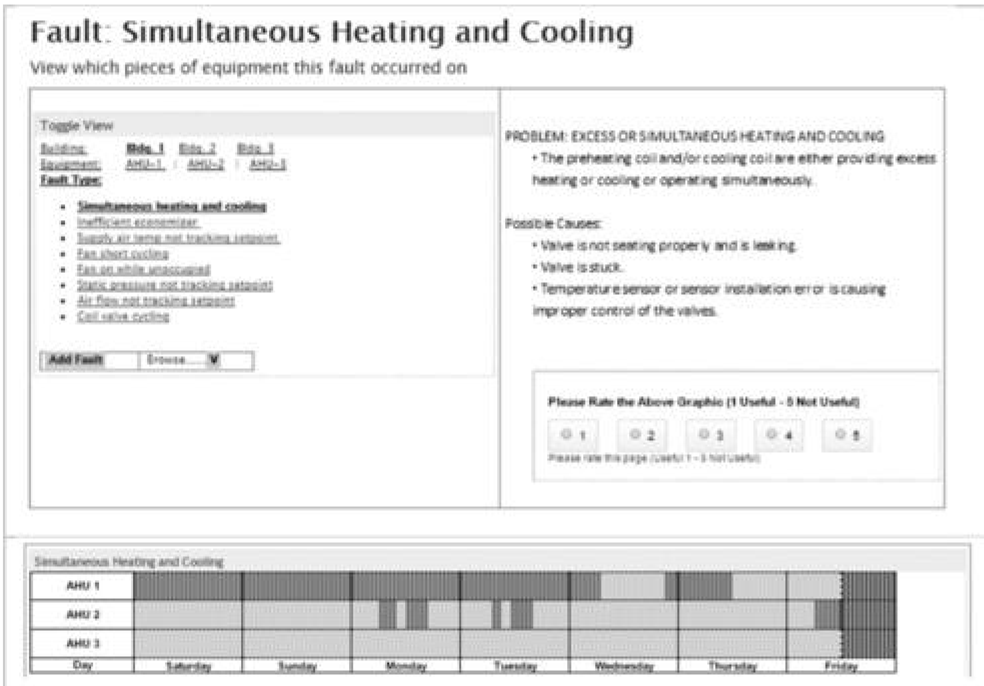


Figure 2. Example Graphics from Diagnostic Page (Gayenski et al. 2015)

Applications of AFDD in Buildings

AFDD has been successfully applied to critical systems such as aerospace applications, nuclear power plants, automobiles, and process controls, in which early identification of malfunctions could prevent loss of life, environmental damage, system failure, and/or damage to equipment. In these applications, AFDD **sensitivity**, the lowest fault severity level required to trigger the correct detection and diagnosis of a fault, is a vital feature; **false-alarm rate** is the rate at which faults are incorrectly indicated when no fault has actually occurred. A high false-alarm rate could result in significant economic loss associated with investigation of nonexistent faults or unnecessary stoppage of equipment operation.

The ability to detect faults in HVAC&R systems has existed for some time, and has been used primarily to protect expensive equipment from catastrophic failure, ensure safety, and provide alarms when a measured variable goes outside its acceptable operating range. In recent years, the motivation for development and use of AFDD has expanded to include expectations of improved energy efficiency and indoor air quality (IAQ), as well as reduced unscheduled equipment downtime (Braun 1999; Kramer et al. 2020; Shi and Brien 2019). Developers expect that AFDD will someday be applied ubiquitously, leading to prolonged equipment life for everything from large equipment (e.g., chillers) to small components (e.g., individual actuators).

The need for AFDD capabilities has been established by surveys, site measurements, and commissioning assessments that have documented a wide variety of operational faults in common HVAC&R equipment and systems.

AFDD shows promise in three areas of building engineering: (1) commissioning, (2) operation, and (3) maintenance.

Commissioning of existing buildings involves, in part, ensuring that systems are installed correctly and that they operate properly. Faults found during commissioning include installation errors (e.g., fans installed backward), incorrectly sized equipment, and improperly implemented controls (e.g., schedules, set points, algorithms). Most commissioning actions that discover these faults, which include visual inspections and functional testing, are performed manually. Data are collected during some tests using automated data loggers, and analysis might be done with computers, but the process of interpreting the data and evaluating results is performed manually. AFDD methods could automate much of the functional testing and interpretation of test results, ensuring completeness of testing, consistency in methods, records of all data and processing, increased cost effectiveness, and the ability to continuously or periodically repeat the tests throughout the life of the facility (Katipamula et al. 2003a; PECI and Battelle 2003). AFDD methods applied during initial building start-up differ from those applied later in a building lifetime. At start-up, no historical data are available, whereas later in the life cycle, data from earlier operation can be used. Selection of methods must consider these differences; however, automated functional testing is likely to involve short-term data collection, whether performed during initial building commissioning or during routine operation later in the building's lifetime, and therefore, the same methods can be used regardless of when the functional tests are performed. Such a short time period is generally required for functional testing to eliminate the possibility that the system being tested changes (e.g., performance degrades) during the test itself. Besides use in functional testing, AFDD methods could be used to verify the proper installation of equipment without requiring visual inspection. Labor intensity could be minimized by only performing visual inspections to confirm installation problems after they have been detected automatically.

During **building operation**, AFDD tools can detect and diagnose performance degradation and faults, many of which go undetected for weeks or months in most commercial buildings. Many building performance problems are automatically compensated by controllers so occupants experience no discomfort, but energy consumption and operating costs often increase. For example, when the capacity of a packaged rooftop air conditioner decreases because of refrigerant loss, the unit runs longer to meet the load, increasing energy use and costs, and occupants experience no discomfort (until design conditions are approached). AFDD tools can detect these, as well as more obvious, faults.

Table 1 Typical Capabilities and Fault Types of BAS and AFDD Software

	BAS	AFDD software
Typical Capabilities		
27/7 building operations command and control	X	
Scheduling	X	
Real-time troubleshooting	X	X
Monitoring	X	X
Trending	X	X
Data tagging semantics standardization		X
Historical data analysis		X
Weather normalization		X
Virtual metering		X
System-level KPIs (e.g. cooling plant efficiency, fan system efficiency) tracking		X
Typical BAS Alarms/AFDD Fault Types		
Critical equipment failure	X	X
Manual overrides in place	X	X
Sensor outside of threshold	X	X
Scheduling, i.e., equipment use outside of intended hours of operation		X
Stuck/leaky valves and dampers in water- and air-side systems		X
Hunting or cycling, i.e., poorly tuned control loops, cooling tower fan cycling		X
Sensor errors/faults including drift, flatline, or complete failure		X
Unnecessary simultaneous heating and cooling due to sensor, valve, and control sequence issues		X
Suboptimal temperature/pressure/minimum airflow set point or reset or deadband		X
Suboptimal lockout temperature		X
Excessive outdoor air intake		X
Under or over economizing due to sensor, damper, or control sequence issues		X
Dirty filters		X
Rogue zones driving the AHU system to inefficient operation		X

AFDD tools not only detect faults and alert building operation staff to them, but also identify causes of faults so that **maintenance** efforts can be targeted, ultimately lowering maintenance costs and improving operation. By detecting performance degradation rather than just complete failure of physical components, AFDD tools can also help prevent catastrophic failures by alerting building operation and maintenance staff to impending failures before failure occurs. This condition-based maintenance allows convenient scheduling of maintenance, reduced downtime from unexpected faults and failures, and more efficient use of maintenance staff time.

AFDD Methods

AFDD tools use many different methods for detecting faults and subsequently isolating or diagnosing their causes. Figure 3 shows a categorization of these methods (Katipamula and Brambley 2005a), in which fault detection and diagnostic methods are organized into three primary categories: (1) quantitative models, (2) qualitative models, and (3) process history. Over 190 AFDD studies associated with building systems have been published (Kim and Katipamula 2018), with 62% classified as process history based, 26% as qualitative model based, and 12% as quantitative model based. Descriptions of these categories and representative studies from each are provided in the following sections. For convenience, Table 2 lists acronyms that may be encountered in AFDD technical publications. Note that they are not unique to AFDD.

Table 2 AFDD Acronyms

AFDD	Automated fault detection and diagnostics
ANN	Artificial neural network

AR	Autoregressive
ARMA	Autoregressive moving average
BPNN	Back-propagation neural network
CUSUM	Cumulative sum
GRNN	General regression neural network
JAA	Joint angle analysis
PCA	Principal component analysis
PID	Proportional integral and derivative
RNN	Recurrent neural network
SPC	Statistical process control
SAX	Symbolic aggregate approximation
SVM	Support vector machine

Quantitative model methods use quantitative models of the underlying equipment, relationships between types of equipment, and processes occurring in the equipment and its components. Sets of quantitative mathematical relationships capture the underlying physics of the processes. The quantitative results from applying the models to actual driving conditions represent baseline performance without faults. Differences between measured performance and the baseline performance from the models under identical driving conditions, known as **residuals**, are used to detect the occurrence of faults. Quantitative models can be based on detailed fundamental physical principles and engineering relationships or on simplified models representing the physical processes. Analyses of residuals can also be used to distinguish among possible causes of a fault to provide a fault diagnosis. Quantitative model-based methods are applicable to information-rich systems, where satisfactory models can be built in an affordable way and sufficient sensors are available to provide the data that are required. Methods described by Castro (2002), Dexter and Ngo (2001), Haves and Norford (1997), Li and Braun (2007a, 2007b, 2007c, 2007d, 2009a), Norford et al. (2002), Reddy (2007a), Seem and House (2009), Shaw et al. (2002), and Siegel and Wray (2002) fall into this category.

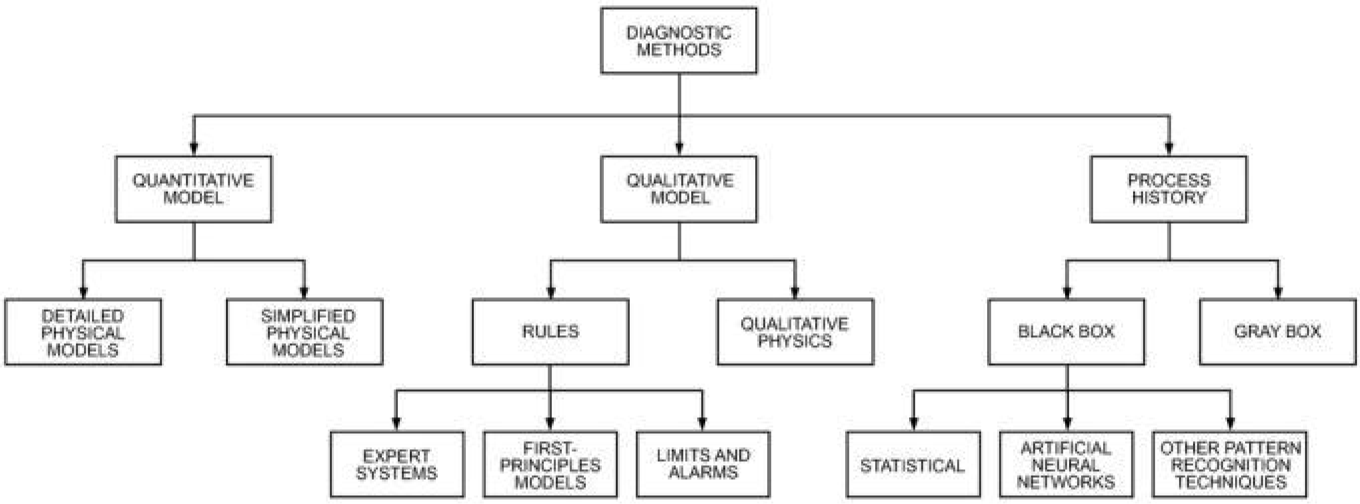


Figure 3. Classification Scheme for AFDD Adapted from Katipamula and Brambley (2005a)

Qualitative model methods include qualitative physics-based methods and rule-based methods. Qualitative-physics-based methods express the underlying physical relationships (equations) as qualitative expressions (De Kleer and Brown 1984) but have seen limited use in AFDD for HVAC&R. Rule-based methods have been applied widely as the basis for AFDD for HVAC&R, using rules based on the rules of thumb used by expert practitioners in a field (**expert systems**); rules derived from knowledge of the fundamental physical processes occurring in HVAC&R components, equipment, and systems (i.e., the equations governing the physical processes); and alarms based simply on conditions exceeding prescribed upper and/or lower bounds for acceptable values of variables during operation (e.g., an alarm triggered by duct static pressure exceeding its upper limit). The techniques presented by Dexter and Ngo (2001), Gerasenko (2002), House et al. (2001, 2003), and Lo et al. (2007) are some examples.

Process-history-based methods depend on the availability of a large amount of historical data. These methods include **black-box** (input-output) models derived from the data and **gray-box** models that use first principles or engineering knowledge to specify the mathematical form of terms in the model but with parameters (e.g., coefficients in the model) determined from process data. Of the 123 process-history-based studies, 72% are black-box models and the remainder are gray-box (Kim and Katipamula 2018). Black-box methods include statistically derived models (e.g., regression), artificial neural networks (ANNs), and pattern-recognition techniques. Of the 110 black-box studies, 63% are statistical models using polynomial regression, logical regression, principal component analysis (PCA), autoregression

(AR), and partial least squares methods (Kim and Katipamula 2018). Approaches based on process history primarily apply to large systems such as whole buildings, where it is difficult to construct an analytical model that captures all important physical behaviors adequately in a cost-effective way, but existing instrumentation yields sufficient data for analysis. Methods used by Bailey (1998), Choi et al. (2004), Li and Braun (2003), Reddy et al. (2003), Riemer et al. (2002), Rossi (2004), and Rossi and Braun (1997) can be classified in this category.

Kim and Katipamula (2018) provide an updated review of AFDD studies published since 2004. Table 3 lists new studies by category, as mentioned in the article.

Table 3 AFDD Studies Published After 2004 Referenced by Kim and Katipamula (2018)

AFDD Category	Subcategory	Method	Published Studies
Process history	Black box	Statistical: polynomial regression	Cui and Wang (2005), Fisera and Stluka (2012), Jacob et al. (2010), Namburu et al. (2007), Prakash (2006), Radhakrishnan et al. (2006), Wang et al. (2010), Zhou et al. (2009)
		Statistical: auto regression (Ar)	Armstrong et al. (2006), Hou et al. (2006), Jin et al. (2005), Ploennigs et al. (2013), Wu and Liao (2010), Yiu and Wang (2007), Yoon et al. (2011), Yuwono et al. (2015)
		Statistical: principal component analysis (PCA)	Du et al. (2007), Hao et al. (2005), Li and Wen (2014a), Wang and Qin (2005), Wang and Xiao (2004), Wu and Sun (2011a), Xiao et al. (2006)
		Artificial neural networks (ANN)	Du et al. (2014), Fan et al. (2010), He et al. (2011, 2012), Hou et al. (2006), Jones (2015), Kim et al. (2008), Mavromatidis et al. (2013), Rueda et al. (2005), Yuwono et al. (2015), Zhu et al. (2012)
		Pattern recognition	Ren et al. (2008), Sharifi and Dagnachew (2012), Han et al. (2011a), Najafi et al. (2012a, 2012b), Guo et al. (2013), Srivastav et al. (2013)
	Gray box		Nassif et al. (2008), Sun et al. (2014), Yu et al. (2011a, 2011b), Zogg et al. (2006)
Qualitative model	Rule based	Expert systems	Bruton et al. (2014), Cho et al. (2005), Choinière (2008), Schein and Bushby (2006), Schein et al. (2006), Song et al. (2008), Yang et al. (2008)
		First principles	Brambley et al. (2011), Fernandez et al. (2009b), Wang et al. (2012a)
		Limits and alarms	Alsaleem et al. (2014), Freddi et al. (2013), Li et al. (2012), Wang et al. (2011), Wang et al. (2012b)
		Fuzzy logic	Cimini et al. (2015), Lauro et al. (2014), Lianzhong and Zaheeruddin (2014), Marino et al. (2014)
	Qualitative physics based		Müller et al. (2013), Bonvini et al. (2014a), Sterling (2015)
Quantitative model	Detailed physical		Keir and Alleyne (2006), O'Neill et al. (2014), Thumati et al. (2011), Weimer et al. (2012)
	Simplified physical		Haves et al. (2007), Mele (2012), Papale (2012), Provan (2011)
Combined models		Black box with gray box or qualitative models	Fontugne et al. (2013), Bynum et al. (2012), Li and Braun (2007a), Lin and Claridge (2015), Wang and Cui (2006), Wang et al. (2013), Yang et al. (2013), Zhao et al. (2014)
		Quantitative model with black box model	Arseniev et al. (2009), Kocyigit (2015), Liang and Du (2007), Qin and Wang (2005), Wu and Sun (2011b)

For further details of each of the basic modeling techniques and AFDD methods, any constraints that would limit the application of each technique, and to assess strengths and weaknesses of each technique for application to fault detection and diagnostics, see Katipamula and Brambley (2005a, 2005b) and Kim and Katipamula (2018). The latter source also includes an analysis of AFDD methods by building system in addition to the review by AFDD method discussed above. Table 4 classifies the studies after 2004 by building component type.

Benefits of Detecting and Diagnosing Equipment Faults

The benefits of AFDD have been validated in part by studies that documented common HVAC&R equipment operating faults and their effects (Behfar et al. 2019; Breuker and Braun 1998a; Breuker et al. 2000; Comstock et al. 2002; House et al. 2001, 2003; Jacobs 2003; Katipamula et al. 1999; Kim 2013; Lee and Lu 2010; O'Neill et al. 2014; Prakash 2006; Proctor 2004; Rossi 2004; Seem et al. 1999; Sutharssan et al. 2012; Wichman and Braun 2009). Faults examined included economizers not operating properly, incorrect refrigerant charges, condenser and filter fouling, faulty sensors, electrical problems, chillers with a variety of faults, air-handling units with too little or too much outdoor-air ventilation, stuck outdoor-air dampers, and other problems.

Table 4 Representative AFDD Studies by Building System

Building System	Detailed Physical Models	Simplified Physical Models	Rule-Based	Qualitative Physics	Black Box	Gray Box
AHUs and VAV boxes	—	Sterling et al. (2014), Provan (2011), He et al. (2015)	Bruton et al. (2014), Yang et al. (2008)	Müller et al. (2013)	Bashi et at. (2011), Jones (2015), Dehestani et al. (2011), Du et al. (2009), Guo et al. (2013), Jin and Du (2006), Lee et al. (2004), Li and Wen et al. (2014b), Wang and Xiao (2006), West et al. (2011), Xiao et al. (2014), Yang et al. (2011)	Xu et al. (2005)
Chillers and cooling towers	Bonvini et al. (2014b), Zhao et al. (2014)	Reddy (2007b)	Cui and Wang (2005)	—	Choi et al. (2004), Han et al. (2011a, 2011b), Magoules et al. (2013), Navarro-Esbri et al. (2006), Rueda et al. (2005), Xu et al. (2008), Lee and Lu (2010)	Sun et al. (2014)
Air-conditioner heat pumps	Li and Braun (2007b), Keir and Alleyne (2006)	—	Armstrong et al. (2006), Li (2012), Alsaleem et al. (2014), Kim et al. (2008)	—	Najafi et al. (2012b)	Kim (2013), Kim and Braun (2016)
Whole building	O'Neill et al. (2014)	Bynum et al. (2012)	Costa et al. (2013), Lin and Claridge (2015), Seem (2007)	—	Capozzoli et al. (2015), Liu et al. (2010), Miller et al. (2015), Narayanaswamy et al. (2014), Jacob et al. (2010)	—
Water heaters	—	—	Dibowski et al. (2016)	—	He et al. (2011)	—
Commercial refrigeration system	O'Neill and Narayana (2014)	Dong et al. (2013)	Keres et al. (2013)	—	Fisera and Stluka (2012), Kocyigit (2015), Mavromatidis et al. (2013), Behfar et al. (2019)	Behfar and Yuill (2020)
Lighting	—	Freddi et al. (2013)	Cimini et al (2015)	—	Sutharssan et al. (2012), Marino et al. (2014)	—
Fan-coil units	—	—	—	—	Lauro et al. (2014)	Ranade et al. (2020)

Studies of the benefits of HVAC fault detection and correction have found positive savings. Rossi's (2004) fault survey of unitary equipment used measurements by service technicians to compute four performance indices from which unit efficiency was estimated and savings potential calculated. Half of the equipment was estimated to have a savings potential of at least \$170/year, and 33% had a potential of at least \$225/year. (Note that costs were current as of 2004.) Li and Braun (2007e) investigated the following factors that affect the economics of air conditioning: (1) energy efficiency ratio (EER) or coefficient of performance (COP), which quantifies the energy performance of the refrigeration cycle (lower scores equal greater operating costs); (2) cooling capacity Q_{cap}, the degradation of which can affect comfort in the conditioned space, increase compressor run times, and reduce equipment lifetimes; and (3) sensible heat ratio (SHR), which can decrease with many faults, leading to higher total equipment load and greater energy consumption for the same sensible building load. All three factors can be combined in an overall **economic performance degradation index (EPDI)**, which is defined as the net increase in the total operating costs (Li and Braun 2007e) and is given by

$$\mathrm{EPDI} = \frac{1}{1-r_{\Delta\mathrm{SHR}}}\left(\frac{1}{1-r_{\Delta\mathrm{COP}}} \times \frac{\bar{C}_{utility}}{\bar{C}_{utility}+\bar{C}_{equip}} + \frac{1}{1-r_{\Delta cap}} \times \frac{r_{equip}\bar{C}_{equip}}{\bar{C}_{utility}+\bar{C}_{equip}}\right) - 1 \quad (1)$$

where

$r_{\Delta SHR}$	=	$\frac{(\text{SHR}_{normal} - \text{SHR})}{\text{SHR}_{normal}}$ = 1 − r_{SHR} = degradation ratio of SHR
$r_{\Delta COP}$	=	$\frac{(\text{COP}_{normal} - \text{COP})}{\text{COP}_{normal}}$ = 1 − r_{COP} = degradation ratio of COP
$r_{\Delta cap}$	=	$\frac{(Q_{cap,normal} - Q_{cap})}{Q_{cap,normal}}$ = 1 − r_{cap} = degradation ratio of capacity r_{SHR} = SHR/SHR$_{normal}$ = SHR ratio
r_{COP}	=	COP/COP$_{normal}$ = COP ratio
r_{cap}	=	$Q_{cap}/Q_{cap,normal}$ = capacity ratio
SHR	=	actual sensible heat ratio
COP	=	average actual coefficient of performance
Q_{cap}	=	average actual equipment cooling capacity
$\bar{C}_{equip}$	=	average equipment price, $/kWh
$\bar{C}_{utility}$	=	$\bar{C}_{elec}\bar{W}_{normal}$ = average normal cost of operation, $/h
$\bar{C}_{elec}$	=	average electricity price, $/kWh
$\bar{W}_{normal}$	=	power consumption of unit (including both compressors and fans)

The subscript "normal" on a variable indicates that the variable corresponds to the fault-free operating condition.

The total cost penalty ΔOC of not correcting faults, which equals the cost savings from servicing the faults, can be determined from the EPDI from the relation

$$\Delta\text{OC} = \text{EPDI} \times \text{OC}_{normal} = \text{EPDI}/(1 + \text{EPDI}) \times \text{OC} \quad \textbf{(2)}$$

where OC is the total cost of operation before servicing to correct faults, and OC$_{normal}$ is the total cost of operation expected after correction of the faults (i.e., the cost of fault-free operation).

Using this overall economic performance degradation index, Li and Braun (2007c) estimated the operating cost savings associated with the application of AFDD for rooftop air conditioners in California. Monitoring of 20 field sites, which included small retail, play areas for fast-food restaurants, and modular classrooms in coastal and inland California, for three years found operating cost savings from $17.6 to $180/ton · yr, the precise savings depending on the specific location and application.

AFDD has the potential to reduce service costs as well as operating costs. Li and Braun (2007b) also developed an economic evaluation procedure to estimate service cost savings, which includes savings from reduced preventive maintenance inspections, fault prevention, lower-cost FDD, better scheduling of multiple service activities, and shifting service to the low season. Based on the 20 monitored field sites, $105/ton · yr (around 70% of the original service costs) can be saved if the AFDD technology in Li and Braun (2007a) could be fully applied. To fully apply the AFDD technology, hardware and software costs were estimated at $250 to $600 for individual units, and $700 to $1500 for a site with four units. Payback periods were less than one year, with savings in operating costs of $20 to $180/ton · yr and an estimated 70% reduction in service costs. (Note that costs were current as of 2007.)

Criteria for Evaluating AFDD Methods

A general AFDD accuracy evaluation procedure is presented in Figure 4, consisting of six steps (Lin et al. 2020; Frank et al. 2019; Yu et al. 2017):

1. Determine a set of input scenarios, which define the driving conditions, fault types, and fault intensities.
2. Create a set of input samples drawn from the input scenarios, each of which is a test data set for which the performance evaluation will produce a single outcome.
3. Assign ground truth information associated with each input sample (e.g., faulted or unfaulted, and if faulted, which fault cause is present).
4. Execute the FDD algorithm that is being evaluated for each input sample. The FDD algorithm receives input samples and produces fault detection and fault diagnosis outputs.
5. Retrieve FDD algorithm outputs (fault detection and fault diagnosis results).
6. Evaluate FDD performance metrics: first, raw outcomes are generated by comparing the FDD algorithm output and the ground truth information for each sample; then, the raw outcomes are aggregated to produce performance metrics.

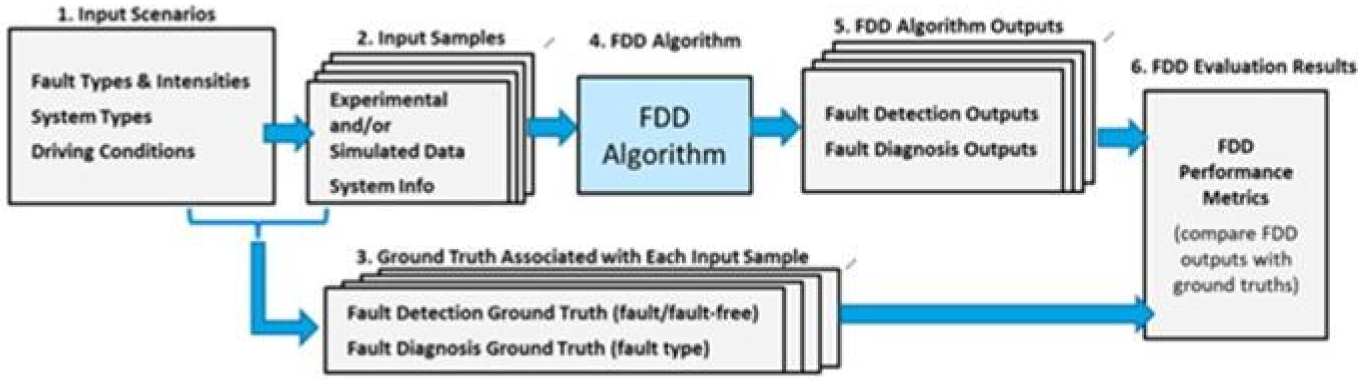


Figure 4. AFDD Accuracy Evaluation Procedure (Lin et al. 2020)

For input sample selection, an input sample of multiple measurements of the selected system variables recorded at a regular interval (e.g., 15 min) within a day is well suited for evaluating AFDD software. This is because many such tools provide results that building operators review daily or weekly. For portable service FDD tools, which are often used to perform spot checks, a best input sample is a single set of simultaneous measurements of the selected system variables when the system is at a steady state.

AFDD sensitivity and false-alarm rate are important accuracy metrics for evaluating AFDD methods not only for critical systems but also for HVAC&R systems. However, the trade-offs between the savings that could be achieved with early detection of a fault and the cost associated with a false alarm are not easily quantified. The sensitivity of AFDD for HVAC&R applications has been evaluated in terms of loss of efficiency and loss of capacity of the monitored system (Breuker and Braun 1998a, 1998b; Comstock et al. 2001; Reddy 2007b). Many early building automation systems provided an unmanageably large number of alarms, often leading to the alarms either being ignored or turned off. This experience suggests that overly sensitive AFDD methods that provide many false alarms could lead to frustration by users and be disabled by O&M staff. AFDD tools should, therefore, minimize the occurrence of false alarms. Another commonly used metric is correct diagnosis rate (Frank et al. 2019). Correct diagnosis refers to a true-alarm case, in which the illustrated fault type (diagnosed cause) reported by the algorithm matches the true fault type.

Sensitivity, false-alarm, and correct diagnosis rate are useful for quantifying performance of an AFDD tool; however, AFDD tools and the methods underlying them have numerous other characteristics that affect their performance and the cost of implementation. Dexter and Pakanen (2001) identified the following characteristics that should be considered when selecting an AFDD method or tool: (1) sensors and control signals used, (2) design data used, (3) training data required, and (4) user-selected parameters. Generally, it is desirable to limit each of these. Reddy et al. (2006), Venkatasubramanian et al. (2003), and Yu et al. (2017) provide more detailed lists of assessment criteria for a general FDD evaluation process.

Types of AFDD Tools

The prevalence of faults in HVAC&R systems, as evidenced by the findings of studies cited previously, and the expectation of performance gains achievable by detecting and diagnosing faults (e.g., improved energy efficiency, occupant comfort, indoor air quality, reduced unscheduled equipment downtime), have spurred the development of a wide range of AFDD algorithms. AFDD tools are created by implementing these algorithms in software. The level of complexity of an AFDD tool rises with the number of components and systems analyzed; however, addressing a broader range of components and systems also generally improves the richness of the types of faults that can be discovered. Some of the types of AFDD tools that have been developed for HVAC&R applications are described here.

Portable Service Tools. Portable service tools are generally applied while a technician is servicing equipment and, therefore, collect data over only short periods of time (e.g., minutes or hours rather than days, weeks, or months), which usually correspond to steady-state system operating conditions. These products are used by service technicians, commissioning agents, and others to evaluate system performance to guide selection and implementation of corrective measures to address faults. The sensors themselves may be temporarily or permanently installed. If permanently installed, a portable service tool is connected to them during equipment or system servicing. Common measurements include dry-bulb air temperature, air relative humidity, refrigerant temperatures measured on the surfaces of tubes, and refrigerant pressures. These portable tools can perform data acquisition and analysis, providing results on site during servicing.

An example portable AFDD service tool is one for rooftop packaged air-conditioners. For systems that use direct-expansion vapor compression, diagnostic tools use several performance indicators (e.g., superheat, subcooling, airflow rate) that have corresponding performance expectations based on system characteristics and operating conditions. Patterns of changes in these parameters compared to expected values during proper operation are used to identify occurrence of specific faults. Data and diagnostic messages are then provided to the user to guide the servicing or repair of the system. The diagnostic tool can then be used to validate that the repair has been performed properly and corrected the fault.

Controller-Embedded AFDD. Control-embedded AFDD software code resides in local device- (or application-) specific controllers, where it can be integrated tightly with control logic and have access to data at the sampling interval of the controller. Access to these higher-frequency data may enable the detection of faults, such as unstable control loops, that might be difficult to detect using data collected at longer data-trending intervals. Embedded AFDD tools can reduce network traffic by executing the AFDD code in local controllers and propagating only key parameters or results to higher levels of a BAS architecture for additional analysis, data visualization, and reporting. Embedding AFDD software in controllers can also facilitate integration of the outputs with the alarming capabilities of the building automation system. Computational and memory limits may place practical constraints on the complexity and size of the code embedded in local controllers.

AFDD Software Deployed on Networked Workstations

AFDD software deployed on a BAS-connected workstation uses data collected by the BAS and, in some cases, data from other sensors (e.g., a separate, non-BAS wireless sensor system). The software usually resides on a computer that is part of a BAS or has access to stored data from a BAS. The BAS may serve one or several buildings (e.g., a campus). Generally, workstation-based software uses data collected or recorded at sampling intervals between one and five minutes. Data acquisition and analysis may be near real time or periodic over longer time intervals (e.g., daily) and depend on the specific application. Because the AFDD is implemented on a computer having significant computational resources, analytical methods and historical data can be processed with more complex algorithms than possible with handheld devices and local controllers. A key strength of workstation AFDD software is its ability to detect system-level faults arising from interactions among components. For example, a rogue variable-air-volume (VAV) box controller may cause air-handling unit (AHU) fan power to exceed an expected level during an unoccupied period. In turn, if the VAV box controller has embedded AFDD, the workstation application will be able to report not only the fault at the AHU level, but also the underlying fault at the VAV box. Workstation AFDD software can require extensive effort for configuration before use. In particular, mapping points from the BAS to the AFDD tool can be cumbersome and depends on the number of measurement and control points used by the AFDD tool.

Web-Based AFDD Software. Web-based AFDD software is an extension of controller-embedded and workstation-based capabilities. It may obtain data from the BAS, independent data acquisition systems, and controller-embedded AFDD software, but uses the Internet to remotely acquire and display results. This feature allows gathering data for many buildings and supports enterprise-wide reporting. The AFDD software can be cloud hosted or installed on a locally hosted onsite server. AFDD processing and analysis may be done locally at the building, with only results reported, or remotely. Updating software remotely is another advantage of web-based AFDD. A significant challenge for web-based AFDD is Internet security, which may require additional hardware and software administration, even if the access is periodic and not continuous.

Figure 5 represents an idealized architecture of a BAS, adapted from ASHRAE *Guideline* 13. Field devices (and controllers) connect to the sensors and actuators in the field. Network controllers typically provide supervisory control capabilities, scheduling, alarms, trending, local data storage, and user interfaces, in addition to some security features. Modern versions of these controllers have the ability to communicate via a BACnet® (a data communication protocol for building automation and control network) IP over an IP network. When such functionality is not available, a common integration strategy uses "integration gateways" (e.g., Niagara JACE) that translate from proprietary protocols to standard protocols, such as BACnet IP. For larger installations and campuses, the controllers or gateways are also connected to a BAS server that provides configuration and management, long-term data storage (i.e., databases), and visualization tools. FDD tools can be installed in the local IP network, run from the cloud, or have a combination of cloud and local components. Integration with the BAS is typically implemented through a one-way interface using one of these three FDD–BAS integration pathways:

- The FDD tool collects data from the central server database (common for large campus-wide installations) via a database application programming interface (API) (e.g., structured query language).
- The FDD tool collects data from a central server, controller, or gateway using vendor-specific API (e.g., Automated Logic web services).
- The FDD tool collects data directly via the BACnet IP network shared with other controllers and gateways.

Current State of AFDD in Buildings

There are more than 30 commercial FDD software products available in the U.S. market that are typically implemented as a layer on top of the existing BAS system (Kramer et al. 2020; Lin et al. 2020). They can be used by facility managers or engineers to improve building operational performance and are increasingly used by third-party service providers as a value-add to their customers. Areas of support that third-party service providers offer include (1) FDD software installation and commissioning, (2) FDD results reviewing and prioritizing, and (3) corrective actions implementation and savings verification. With data from over 90 million square feet of FDD installed space (18 organizations, 509 buildings), it was reported that FDD software enabled a median cost savings of $0.24/ft^2 and 9%

annually by the second year of installation (Kramer et al. 2020). Although commercial AFDD software are used by early adopters, they have not yet been widely implemented in the commercial building sector.

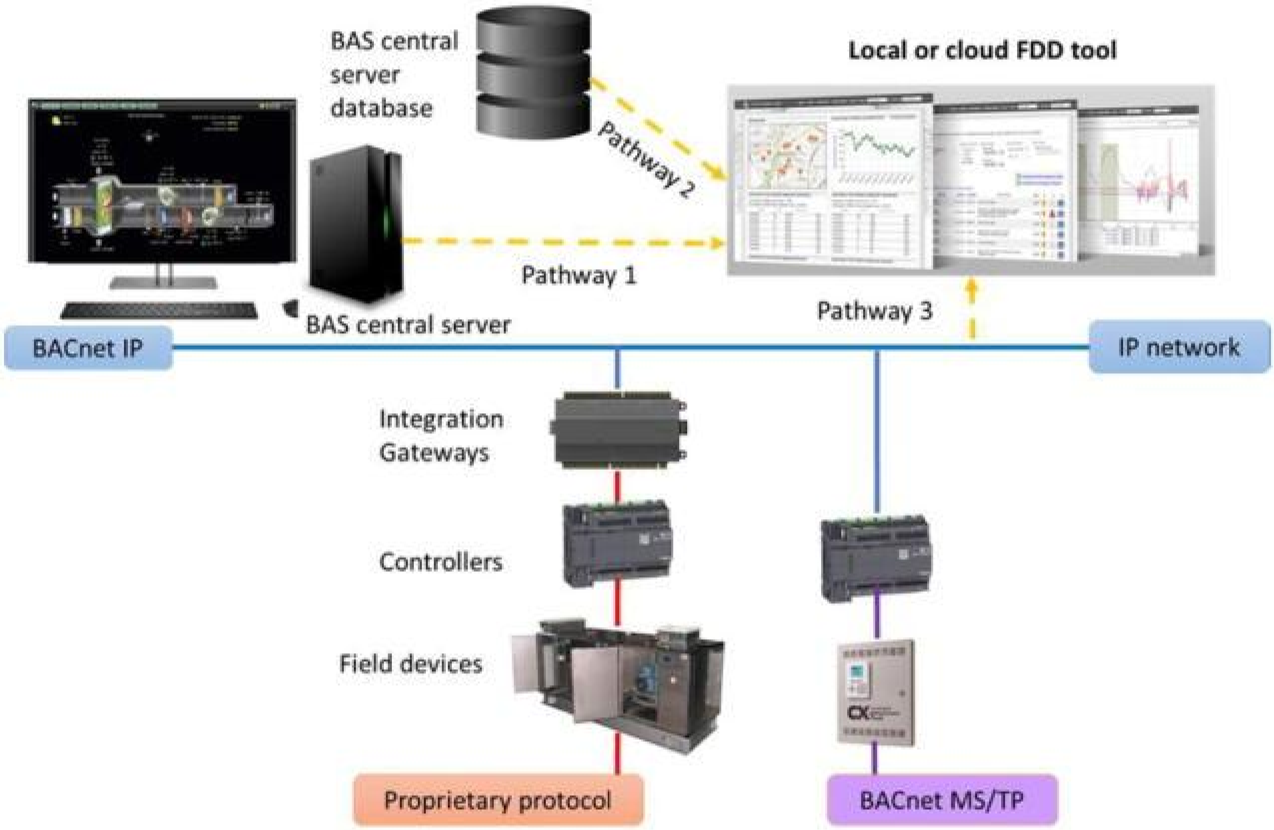


Figure 5. Schematic of Integration of Building Automation System Data into FDD Tools (BACnet MS/TP Protocol) (Lin et al. 2020)

Currently, the majority of the existing FDD is still based on simple rule-based methods that are implemented by the manufacturer of a component or system and do not take advantage of all of the existing sensor data (Behfar et al. 2017; Yu et al. 2017). In general, model-based FDD algorithms that were developed and proposed in laboratories and research articles have not been realized in practical applications. The main reason is that the models are specialized for a piece of equipment or building, and they often need high computational capabilities that require expensive infrastructure, programming, and custom engineering knowledge to develop and understand them.

Most AFDD methods developed to date work well when a single dominant fault is present in a system, but when multiple faults occur simultaneously or are already present when AFDD is initially applied, many of the methods fail to properly detect or diagnose the causes of the faults. Research in the last decade or so has begun to address detection and diagnosis of multiple simultaneous faults. For example, Braun et al. (2003) extended the previous work by Breuker and Braun (1998b) and Rossi and Braun (1997) to diagnose multiple simultaneous faults. This work has been extended by Li and Braun (2004a, 2004b, 2007a, 2007b, 2007c, 2007d, 2009a, 2009b, 2009c).

As with other software, AFDD tools require installation and, in some cases, input of configuration data before they are ready for use with building systems. Setup can include the installation of sensors dedicated to the AFDD tool or not present in existing monitoring and control systems. Configuration may require specifying the type and possibly even the model of equipment on which the AFDD will operate. It can also include specifying the kind of or basis for control (e.g., air-side economizers may be based on dry-bulb temperature or enthalpy; see the section on Air Handler Sequencing and Economizer Cooling in Chapter 42). Furthermore, fault detection and diagnosis must be followed by evaluation of the fault and decision making regarding whether, when, and how to correct the faults identified.

Future for Automated Fault Detection and Diagnostics

The commercial availability of AFDD tools is increasing, demonstrating some recognition of their value. As market penetration and experience in use increase, the need for improvements will accumulate. Key technical issues still to be completely addressed include the following (Katipamula and Brambley 2005b):

- Eliminating the need to handcraft and configure AFDD systems
- Automatic generation of AFDD systems

- Identifying the effective AFDD method for each HVAC&R application
- Developing decision-support tools for using AFDD in operation and maintenance
- Developing prognostic tools to transform HVAC&R maintenance from corrective and preventive to predictive, condition-based maintenance
- Lowering the cost of obtaining data for AFDD and O&M support

Some AFDD tools require users to implement data collection from building automation systems, which is often difficult, costly, and beyond the capabilities of many end users. Other tools require the input of values or selections for many configuration parameters (e.g., the specific method used to control an economizer). Solutions for these problems include (1) developing AFDD tools that include databases sufficient to cover many equipment models, (2) delivering AFDD as part of equipment control packages, and (3) developing methods for automatically generating AFDD tools. The first approach was introduced in a hand tool for air-conditioning service providers more than a decade ago. The second approach of embedding AFDD onboard equipment controls has started to be used by some manufacturers of equipment and equipment controls (e.g., chillers). The third approach, involving rapid automatic generation of AFDD, requires research before it emerges in products.

Fault auto-correction algorithms are becoming a focus in FDD research. Since mechanical faults typically cannot be corrected automatically, researchers focus on the faults that have such a potential, such as biased sensors (temperature, pressure, or flow rate), improper control parameter settings, and inefficient schedules (Brambley et al. 2011; Lin et al. 2020).

Progress in developing low-cost sensors is being made, although market penetration is still relatively low in the building industry. Joshi et al. (2015a, 2015b, 2015c) and Noh et al. (2015) describe integrated wireless sensors for temperature, humidity, and light level that are formed using inkjet-printed flexible substrates. Development of autonomous driving vehicles should aid in the development, availability, and cost reduction of sensors that have crossover potential to the building industry.

Use of open communication standards for BAS (e.g., BACnet®) is increasing, and the use of Internet and intranet technologies is pervasive. These developments make integration of third-party software with AFDD features that use BAS data easier, lowering the cost-to-benefit ratio of deploying AFDD systems. To benefit from these changes, facility managers, owners, operators, and energy service providers need the capabilities and resources to better manage this information and, as a result, their buildings and facilities.

3. SENSING AND ACTUATING SYSTEMS

Sensors

The typical sensors used in smart building systems are not far different from those used in all buildings. Smart building systems rely on sensors to measure quantities such as temperature, humidity, pressure, occupancy, electric power and energy use, fossil fuel energy use, light levels, air speeds, carbon dioxide, and electric harmonics. See Chapter 37 of the 2021 *ASHRAE Handbook—Fundamentals* for in-depth discussion of measurement techniques for such quantities.

Traditional sensors are connected to control systems via twisted pairs of wires, which conduct voltage or current signals. Sensor calibration (i.e., mapping from electronic signals back to measured physical quantities) can be complicated by nonlinear and/or time-varying functions, which are often implemented in software code by field engineers. The calibration process is time consuming and error prone. In practice, sensors are subject to various defects; therefore, sensor data should not be used without validation. Under certain conditions, multiple physical sensors of different kinds should be used for reliable measure of a physical quantity. Truly smart buildings require pervasive use of smart sensors that possess intelligence and memory to identify, recalibrate, and repair defective sensors.

The intelligence of smart sensors can be described in four categories, discussed in the following paragraphs.

Local Intelligence. In local intelligence, the signal and data-processing capability reside at the local sensor node. For example, some fire detectors are equipped with multiple physical sensors to reduce false alarms and increase reliability, using complicated algorithms. Other sensors may be equipped with flash memory to store historical data. Another type of local intelligence is the ability to compute information based on raw sensor measurements. For instance, a photoresistor can be used to measure luminance, but the mapping from voltage across the resistor in the meter to luminance is not linear. A smart sensor is equipped with circuitry that calculates the desired quantity onboard, either through analog or digital approaches.

Networking Intelligence. Sensors with networking intelligence allow bidirectional communications via scalable, secure, and robust computer networks. Traditional sensors are connected to ports on panels via twisted pairs of wires. While implementing control sequences, engineers must embed the port number and detailed sensor characteristics to calculate the physical quantity of measurement from electronic signals. In practice, there is usually only one quantity that is measured by each sensor, and the direction of information flow is always in one direction from the sensor to control panels. As shown in Figure 6, smart sensors support bidirectional communications, are individually addressable, and form scalable, reliable, and robust networks. Networked sensors can be integrated by either wired or wireless approaches:

- *Wired sensors.* Some sensors are equipped with network ports and can be plugged directly into building control networks. They may support protocols including BACnet (ASHRAE *Standard* 135), LonWorks® (ISO 2012), Modbus® (Modbus 2012), etc.
- *Wireless sensors.* Wireless protocols, such as ZigBee® (ZigBee Alliance 2008), Z-Wave® (Z-Wave® Alliance 2014), and WirelessHART® (IEC *Standard* 62591) are designed for low-energy, low-data-rate sensors. Wi-Fi (IEEE *Standard* 802.11), WiMax (IEEE *Standard* 802.16), Bluetooth® (Bluetooth SIG 2013), and GSM cellular protocols (Eberspächer et al. 2009) are also found in different types of sensors.

Data Object Intelligence. In this approach, structured data and commands are encapsulated within sensor data objects. Traditional sensors do not have computation capabilities to process high-level commands from control systems. For sensors with data object intelligence, sensor vendors ship sensors with detailed data sheets and sophisticated instructions on diagnostics. It is nontrivial work for field engineers to understand the detailed differences between hundreds of sensors and to implement proper sensor-handling logic in control systems; this type of intelligence automates those tasks. BACnet (ASHRAE *Standard* 135) and IEEE *Standard* 1451 are representative standards that support object models:

- *BACnet*. This protocol supports data objects in traditional system architectures. In addition to reading from sensors, a controller can send commands/messages to sensors. Note that commands are not sent to physical sensors, where information flow is always from sensor to panel. For example, the panel can receive a "who-is" query from other BACnet devices and respond accordingly to describe its attached sensors.
- *IEEE* Standard *1451.* This smart sensor standard has been adopted by the automobile industry for test data acquisition. It features **transducer electronic data sheets (TEDS)**, which make plug-and-play operation feasible. Because sensor data, including calibration parameters, are embedded in TEDS, calibration can be conducted automatically. Numerous IEEE *Standard* 1451 vendors provide smart sensors for HVAC systems. However, the technology has not yet been widely adopted by the building industry, partially because of its high device cost.

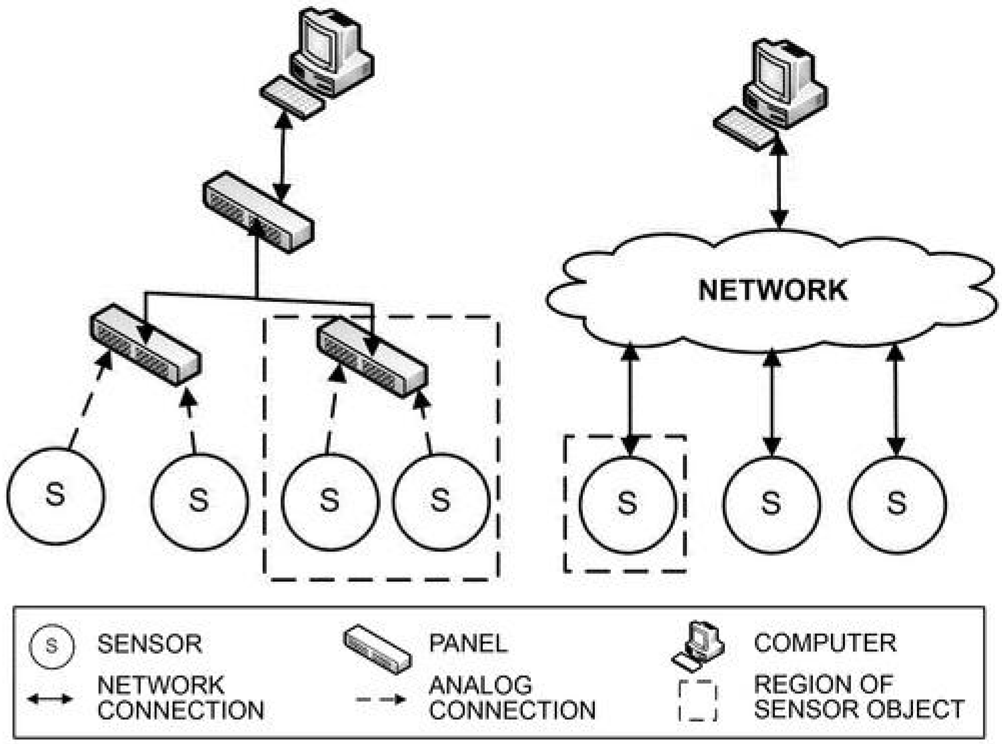


Figure 6. Traditional Twisted-Pair Wired Sensing Architecture Transmitting Analog Signals (Left) versus Computer Network Architecture Capable of Exchanging Digital Information (Right)

Web Automation Intelligence. With this approach, sensor data objects are exposed as web services and integrated with web applications. Today, many sensors are connected to the Internet and expose web services via standard or proprietary application programming interfaces (APIs). These devices are often referred to as the "Internet of things," or IoT. For example, a personal weather station can measure and submit air quality data to the cloud, where the data are shared with the world through the Internet. Various vendors collect building performance data from customer sites via the Internet, process the raw data in the cloud, and expose results of business analysis to the web for applications of weather monitoring, lighting control, remote FDD, and IEQ monitoring. Some web data object standards including XML standards, such as Sensor Model Language (SensorML) (OGC® *Standard* 12-000), Transducer Markup Language—TransducerML (retired) (OGC® *Standard* 06-010r6), and numerous OASIS standards for smart grid and security.

The four levels of intelligence for smart sensors are interdependent. Local intelligence is the foundation for the entire architecture. Networking intelligence enables bidirectional data exchange and shields users from the detailed data transport mechanism. Data object intelligence offers an abstracted and concise sensor data interface for effective software integration and serves as the enabling technology for plug-and-play sensors. As a result, engineers are liberated from tedious work such as manual sensor calibration. Web automation intelligence is the most advanced form of "smart" for sensors. Propelled by increasing applications in cloud computing, smart grid, and mobile devices, smart sensors with web automation intelligence could be widely used to enable smart building systems.

Actuators

The typical actuators used in smart buildings are similar to those used in all buildings. Smart buildings rely on actuators to, among other tasks, modify air flows through damper control and other means, modify chilled-water flow, adjust steam flows, shut off electrical devices, and adjust shading devices. See Chapter 7 of the 2021 *ASHRAE Handbook—Fundamentals* for in-depth discussion of control actuation approaches for building systems.

A smart actuator is one that can correct itself and is possibly self powered. It can also have some sort of display showing the status of the actuator, either on the actuator itself, or on monitoring software having data sent to it directly from the actuator.

Smart actuators are relatively new and are still in the research phase. Not many commercially available smart actuator technologies are currently on the market. Research is ongoing to develop self-correcting HVAC actuators that detect soft faults (e.g., problems in computer software, incorrect set points) and automatically correct to the proper operating condition, as well as to develop ways to automatically correct hard faults (e.g., bent damper linkages) by adjusting actuator response to compensate for the faults (Fernandez et al. 2009a; Siemens VAI 2008). Other efforts have pursued developing self-powered actuators that communicate using wireless mechanisms. These devices can control valves and dampers and are powered through harvested thermal or vibrational energy. Because actuators require more energy than sensors, power management is critical in such devices to ensure that they function as desired.

As smart actuators mature, the HVAC field could benefit from this new technology through potential energy savings (e.g., preventing energy waste from faulty actuators and by using self-powered actuators) and through potential maintenance cost savings (e.g., from automated calibration).

Sensor and Actuator Integration

To achieve truly smart buildings, smart sensors and actuators must take advantage of all data obtained throughout the building. Communication between devices is therefore critical. With a large number of sensing and actuating points, conventional sensor wiring may become impractical, especially when attempting to implement these systems on existing buildings. For these reasons, communication (via wireless means and power lines) is a vital technique to integrate smart devices to make a complete building network.

Chapter 41 provides an in-depth discussion of wireless technologies, suitable applications for wireless devices, and selection of wireless systems. For smart sensing and actuating, low-data-rate technologies are most appropriate, though radios based on IEEE *Standard* 802.11 could be used because of their large market. Although reliable communications are of paramount importance when considering wireless communications, low maintenance becomes critical when many devices are present in a building. One of the key maintenance concerns is the need to replace batteries, because many of these devices may not have convenient access to line power (or may use batteries in case of line power failure or interruptions). Protocols for low-data-rate applications attempt to minimize energy consumption of these devices by taking steps such as putting the devices to sleep when they are not actively taking measurements, performing actions, or transmitting or receiving commands. IEEE *Standard* 802.15.4 is one such protocol that specifies the physical layers and media access control of radios appropriate for low-data-rate applications. This standard forms the basis of specifications such as ZigBee (ZigBee Alliance 2008), ISA *Standard* 100.11a, WirelessHART (IEC *Standard* 62591), and proprietary protocols, such as MiWi™, which add upper layers to IEEE *Standard* 802.15.4 to increase usability.

Reliability of Wireless Communications in Buildings. Attenuation of signals by building materials and interference from other devices make long-distance signal travel difficult. To overcome these problems, different network topologies can be implemented to make the network more robust. For example, a mesh network can allow each device to transmit and receive, communicating with other devices to relay messages through the network to their intended destinations or to enable direct communication between devices without the need for central control equipment. The intelligence can, therefore, be moved down to specific portions of the building.

Wired Power Line Communications (PLC). Power line communication can also be used to reduce the cost and effort of deploying smart sensors and actuators throughout a building. In this type of communication, signals are sent over the same wires that carry alternating current (AC) electric power in a building. This approach reduces the need to run dedicated control system wiring and is especially useful in existing buildings. Some installation of wiring may still be needed to connect the sensor or actuator to the nearest electrical outlet. Modulated signals are typically sent at frequencies away from the common 50 to 60 Hz frequency of AC electricity. Bandwidth that is appropriate for streaming Internet traffic can be achieved, but noise on the lines and components of the electrical system (e.g., transformers) can make the signal unavailable in certain installations. IEEE *Standard* 1901 provides specifications for providing high-speed broadband networking over power lines using frequencies below 100 MHz. A variety of commercial protocols are available to provide a suite of products that can communicate with each other.

Physical integration of the sensors and actuators is not the final step in developing the components of a smart building; integrating the data streams seamlessly is a challenge, considering the potentially large number of devices. IEEE *Standard* 1451 provides guidance that aims to create plug-and-play devices that automatically report key operating parameters to other devices connected to them. Standards such as these will help to ease the burden of configuring sensing and actuating systems in buildings.

4. SMART GRID BASICS

This section provides the basis for understanding changes occurring in the electric grid infrastructure and how buildings now and in the future interact with the grid. Because this is a rapidly evolving topic area, readers are encouraged to seek additional information on the latest changes and future directions. For additional resources and information, refer to the *ASHRAE Smart Grid Application Guide for Building Professionals: Integrating Facilities with the Electric Grid*, and the U.S. Department of Energy's websites SmartGrid.gov, Energy.gov, and www.energy.gov/eere/buildings/grid-interactive-efficient-buildings.

Brief History of Electric Power Grid

In the early days of commercial electric power, direct current (DC) electricity was transmitted at the same voltage as end users (consumers) required, thus limiting the distance over which electricity could be transmitted. DC, however, could not easily be increased in voltage for long-distance transmission without incurring significant line losses. Different classes of loads (e.g., lighting, fixed motors, traction/railway systems) required different voltages, and so used different generators and transmission lines. This specialization of generation and transmission was inefficient for low-voltage, high-current circuits, because generators needed to be near their loads. Thus, the electric grid seemed to be developing into a distributed generation system, with large numbers of small generators located near their loads. However, as electricity use increased, it soon became apparent that using common generating plants and transmission networks for all loads yielded economies of scale that could lower costs and the overall capital investment required. This standardization of the grid also enabled more efficient use of all grid assets.

By allowing multiple generating plants to be interconnected over a wide area on a common network, the cost of electricity was reduced. The most cost-effective and efficient plants could supply electric power reliably to geographically distributed and temporally varying loads. Remote and low-cost sources of energy, such as hydroelectric power or mine-mouth coal, could be exploited to lower energy production cost.

Rapid industrialization in the early 20th century made electric power systems a critical part of the infrastructure in most industrialized nations. Interconnection of local generation plants and small distribution networks was driven by the needs of World War I, with large electric power plants built by governments to provide electricity to munitions factories. Later, these generating plants were used to supply civil loads through long-distance transmission lines. In the United States, an important part of developing the grid occurred with the passage of the Rural Electrification Act of 1936, which provided federal loans for installation of electrical distribution systems to serve rural areas of the United States. The funding was channeled through cooperative electric power companies, most of which still exist today. These member-owned cooperatives purchased power on a wholesale basis and distributed it using their own network of transmission and distribution lines. Because electricity must be produced at the exact rate at which it is consumed, the electric power grid is the largest and one of the most tightly controlled machines in the world today.

Electric Power Grid Operational Characteristics

The modern electric grid in the United States is modeled as three interconnected domains (Figure 7). The **generation system** produces electric energy. This domain contains a set of power stations and distributed energy generators (e.g., residential solar photovoltaic systems). The electricity generated is conditioned to reduce losses and is then transmitted over long distances across the **transmission system**. The transmission system typically consists of high-voltage wires that distribute electricity hundreds of miles. When needed to power loads within a region, the electricity is reconditioned (i.e., converted and/or stepped down in voltage) and distributed to customers over the **distribution system**. The distribution system is ordinarily a network of medium-voltage wires that distribute energy across a metropolitan area. The distribution system also includes electrical substations that transform the energy to the low voltages needed by customer loads and transmit it over the wires connected to the customer.

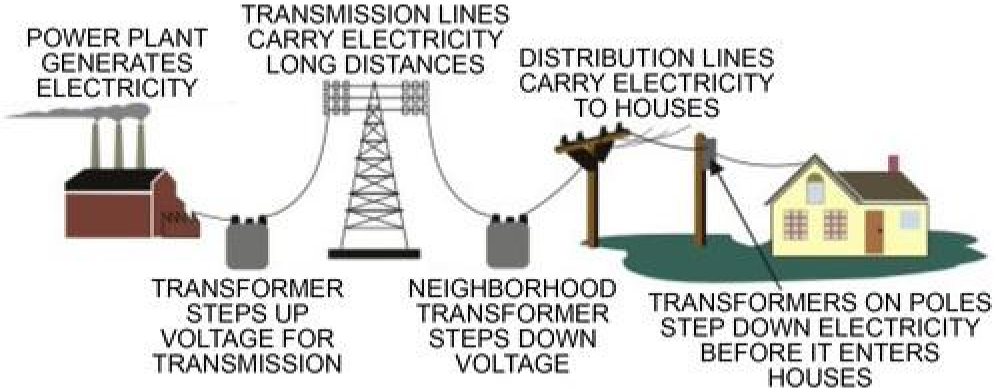


Figure 7. Electric Power Grid U.S. Department of Energy (undated)

A **transmission grid** is a network of power stations, transmission lines, and substations. Electricity is usually transmitted within a grid as three-phase alternating current (AC). Single-phase AC is used only for distribution to end users, because it is not suitable for large, polyphase induction motors. In the 19th century, two-phase transmission was used but required either four wires or three wires with unequal currents. Higher-order-phase systems require more than three wires, but deliver marginal benefits.

In the United States, the transmission grid is divided into several regional operating units that manage overall electric transmission within their own territories and between regions. More specifically, there are seven wholesale power markets (Figure 8) and three reliability regions (Figure 9).

The capital cost of electric power stations is so high, and electric demand so variable, that it is often less expensive to import some portion of the needed power than to generate it locally. Because nearby loads are often correlated (e.g., hot weather in the Southwestern United States might cause many people to use air conditioners simultaneously), electricity often comes from distant sources. Because of the economics of load balancing, wide-area transmission grids now span across countries and even large portions of continents. The web of interconnections between power producers and consumers ensures that power can flow, even when a few links are inoperative.

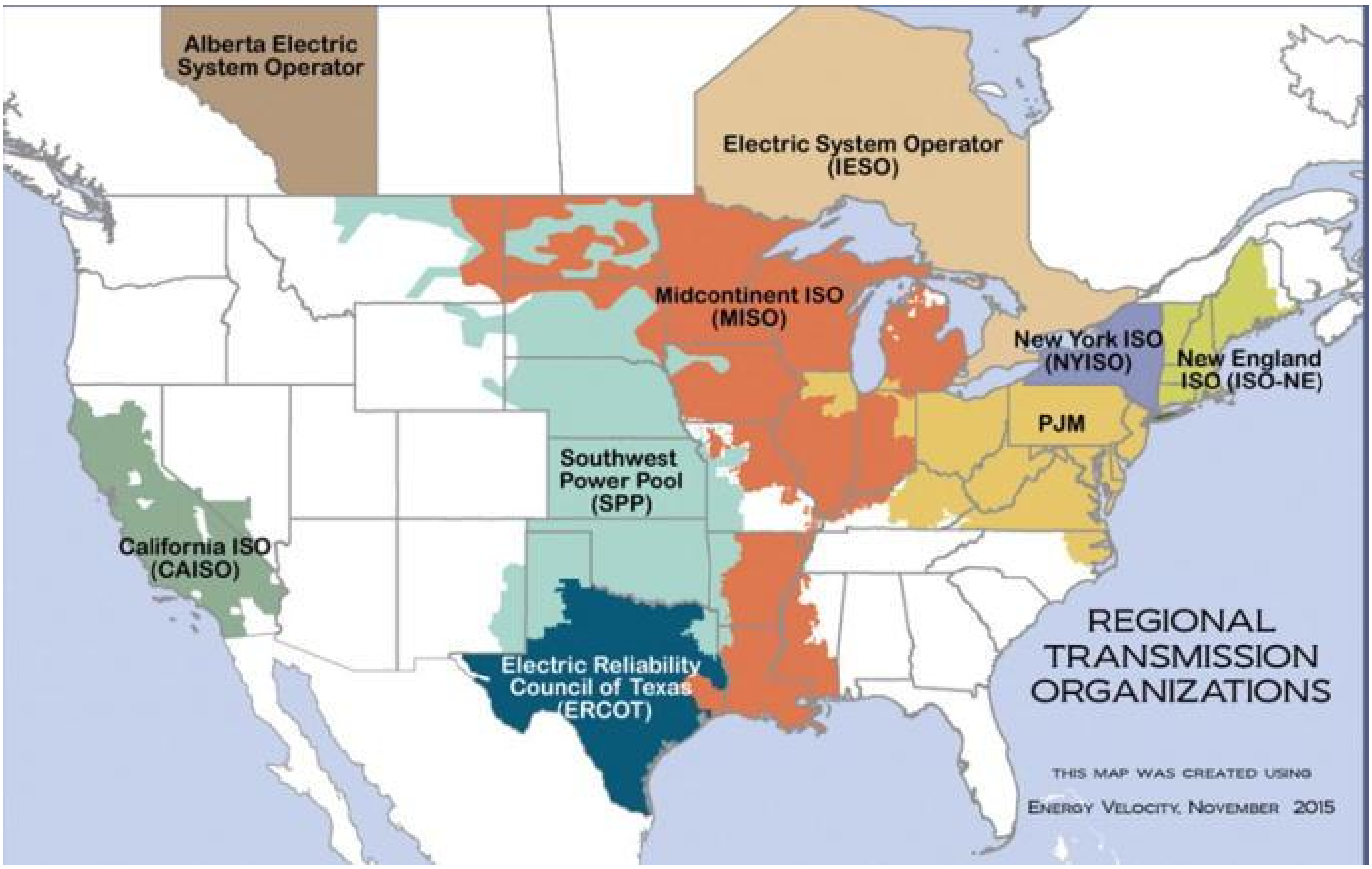


Figure 8. ISO/RTO Map: FERC 2019, Updated to Show MISO Presence in Canada (Federal Energy Regulatory Commission 2022)

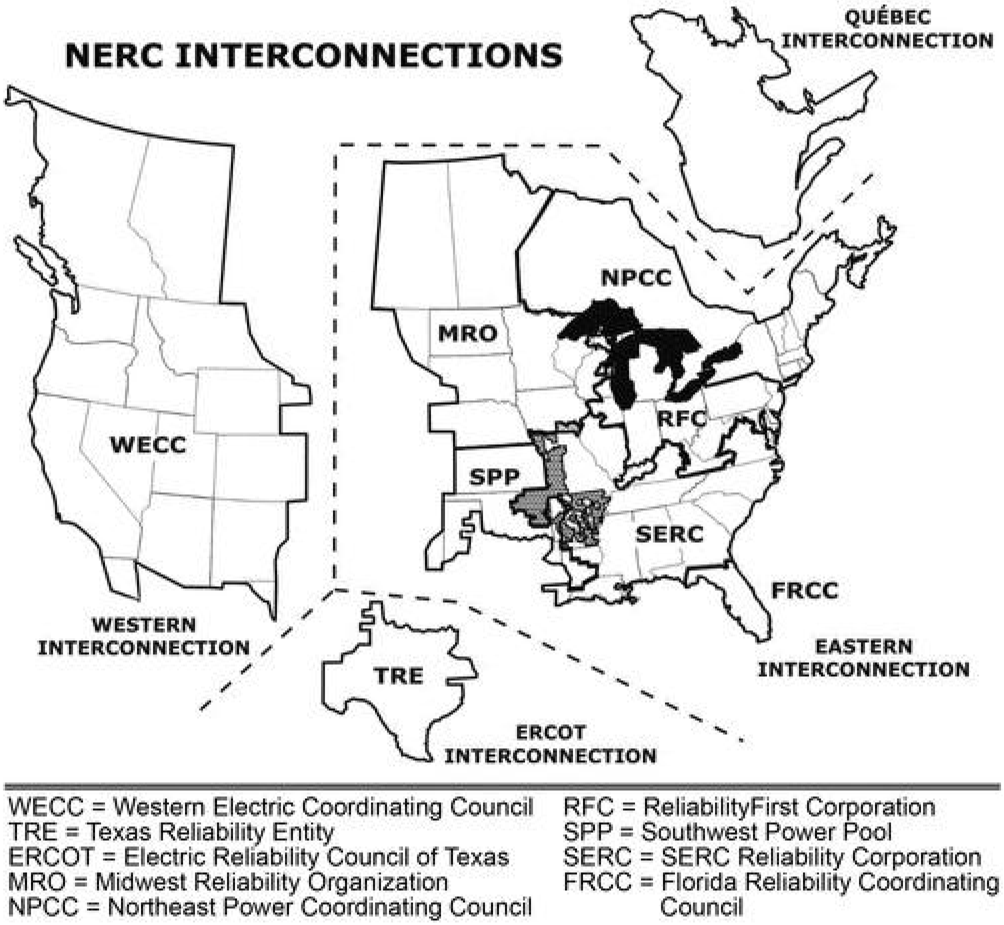


Figure 9. Interconnections in Area of Responsibility of North American Electric Reliability Corporation (NERC) NERC (2012)

The unvarying (or slowly varying over many hours) portion of the total electric system demand is known as the **base load** and is generally served by large generation facilities (which are efficient for this purpose because of economies of scale) with low variable costs for fuel and operations. Such facilities might be nuclear or coal-fired power stations or, in some locations, hydroelectric plants. Variable renewable energy sources, such as solar photovoltaics, wind, and wave power, because of their intermittency, are not considered base-load capable (unless firmed by storage) but can still add power to the grid. The remaining power demand is supplied by intermediate load-following plants and peaking-power plants, which are typically smaller, faster-responding, and higher-cost sources, such as combined-cycle or combustion turbine plants fueled by natural gas.

Subtransmission is part of an electric power transmission system that runs at relatively lower voltages. It is uneconomical to connect all distribution substations to the high main transmission voltage, because the equipment is larger and more expensive. Typically, only larger substations connect with this high voltage. The electric power is stepped down and sent to smaller substations in towns and neighborhoods. Subtransmission circuits are usually arranged in loops so that a single line failure does not cut off service to a large number of customers for more than a short time. Although subtransmission circuits are usually carried on overhead lines, buried cable is also used in urban areas.

The amount of power that can be sent over a transmission line is limited. These limits vary depending on the length of the line and can depend on the ambient temperature. For a short line, heating of conductors because of line losses sets a thermal limit. If too much current is drawn, conductors may sag too close to the ground or other obstructions (e.g., trees), or conductors and equipment may be damaged by overheating. For intermediate-length lines on the order of 62 mi, the limit is set by the voltage drop in the line. For longer AC lines, system stability limits the power that can be transferred. Approximately, the real power flowing over an AC line is proportional to the cosine of the phase angle difference of the voltage and transmitting ends. This angle depends on system loading and generation, and it is undesirable for the angle to approach 90°. Very approximately, the allowable product of line length and maximum load is proportional to the square of the system voltage. Series capacitors or phase-shifting transformers are used on long lines to improve stability. High-voltage DC lines are restricted only by thermal and voltage drop limits, because the phase angle is not material to their operation.

To ensure safe and predictable operation, the components of the transmission system are controlled with generators, switches, circuit breakers, and even loads. The voltage, power, frequency, load factor, and reliability capabilities of the transmission system are designed to provide reliable and cost-effective performance for customers.

The transmission system provides for base- and peak-load capability, with safety and fault tolerance margins. The peak-load times vary by region largely because of differences in the industry mix. In very hot and very cold climates, home air-conditioning and heating loads can have a significant effect on the overall load at times. These loads are typically highest in the late afternoon in the hottest part of the year, and in mid-mornings and mid-evenings in the coldest part of the year. This variability causes the power requirements to differ by season and the time of day. Distribution system designs take the base and peak loads into consideration.

Electricity produced by the generation system has to match the energy consumed by the loads; otherwise the system becomes unstable (blackout in the worst case). The transmission system usually does not have a large storage capability to match the varying energy consumed by loads. Thus, fast-acting balancing generation units (known as spinning reserves) are connected to the transmission system and kept matched to the load to prevent overloading failures of the generation equipment.

Typical Building Load Profile

Figure 10 depicts a typical commercial building electrical load profile in relation to the utility system load profile. The profile reflects the building's individual characteristics, including building use, occupancy and equipment schedules, equipment characteristics, and building control strategies used. In contrast, the utility system load is the aggregate of all the individual loads, including commercial, residential, industrial, and public facilities. Although individual commercial facility electric loads may have the same general shape as the utility system load, they may not have an identical shape and may peak at different times given the aggregation of the many loads that make up the system load. Understanding the relationship between the load profile of an individual facility and the overall system profile provides the basis for optimizing electricity use and costs to the mutual benefit of the grid and the customer.

Increasing Need of Demand Flexibility for Renewable Energy Integration and Grid Decarbonization

The increasing penetration of renewables that is changing classical load profile patterns and the growing pressure of diminishing greenhouse gas emissions increase the need for flexible demand resources. To understand this better, refer to the CAISO (California independent system operator) duck curve shown in Figure 11. The graph shows the change of net load profile for a spring day (March 31) as more renewables are being installed. The belly of a duck appears during the mid-afternoon, and the neck of a duck follows during the evening. The belly gets deeper and might touch the baseline power supply from, e.g., the nuclear power plants. It is essential to curtail renewable energy to maintain the base load generators. Figure 12 shows the monthly wind and solar curtailment for the CAISO from 2019 to 2021 (different colors represent different years). A significant portion of renewable energy generation is currently wasted, and the renewable energy is expected to be curtailed more as more renewable resources are being installed in CAISO territory. The other issue occurs on the neck of a duck: Because of the rapid drop of solar energy, the net load increases quickly. To meet the high ramping rate of the load, dispatchable generators with short response time (order of minutes) such as gas turbine generators have to run and emit significant CO_2 (an order of thousands of metric tonnes of CO_2 equivalent per hour) during the neck period.

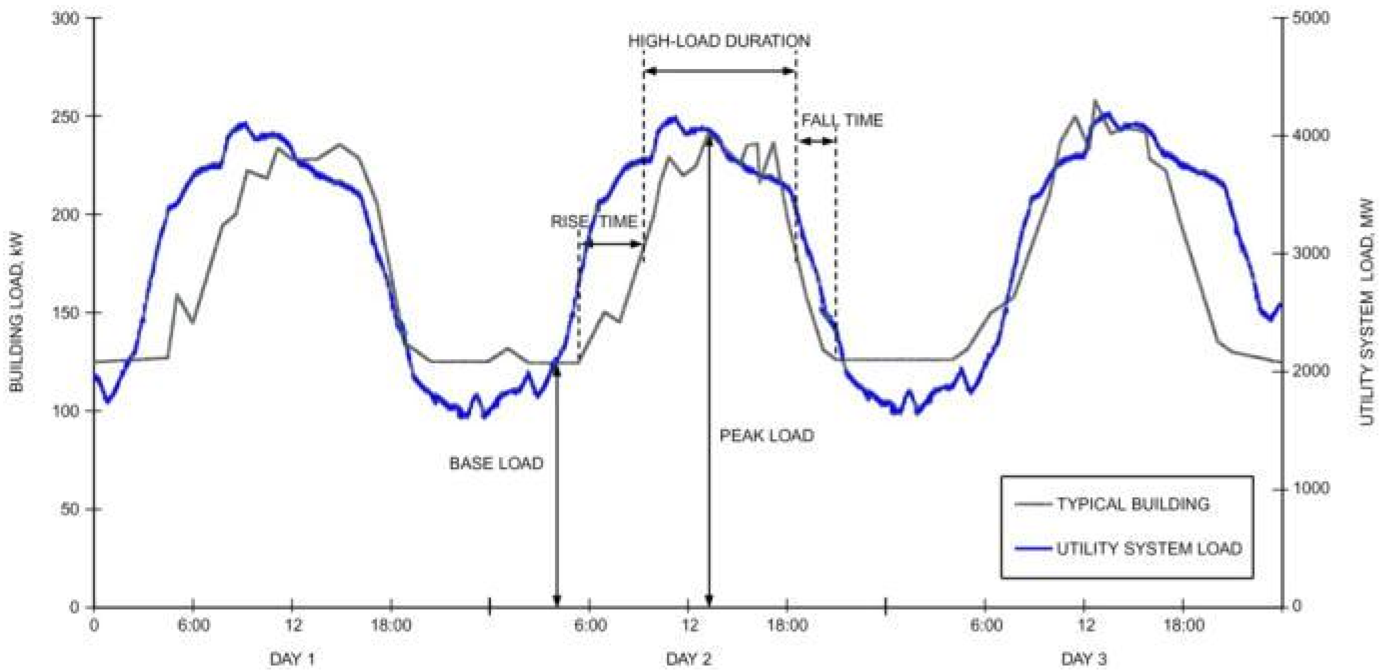


Figure 10. Example Commercial Building Load Profile in Relation to Utility System Load Adapted from Price (2010)

Grid-interactive Efficient Building (GEB) and Grid Services

Modern buildings have the capability to provide certain grid services by manually or automatically adjusting building load to help balance electricity supply and demand. Since buildings consume over seventy percent of electricity in the United States, buildings are significant and one of the most cost-effective demand response resources. According to the U.S. Department of Energy (DOE 2019), a grid-interactive efficient building (GEB) is "an energy-efficient building that uses smart technologies and on-site Distributed Energy Resources (DER) to provide demand flexibility while co-optimizing for energy cost, grid services, and occupant needs and preferences, in a continuous and integrated way." DER is broadly defined here as behind-the-meter electricity-producing resources, energy storage, or controllable loads.

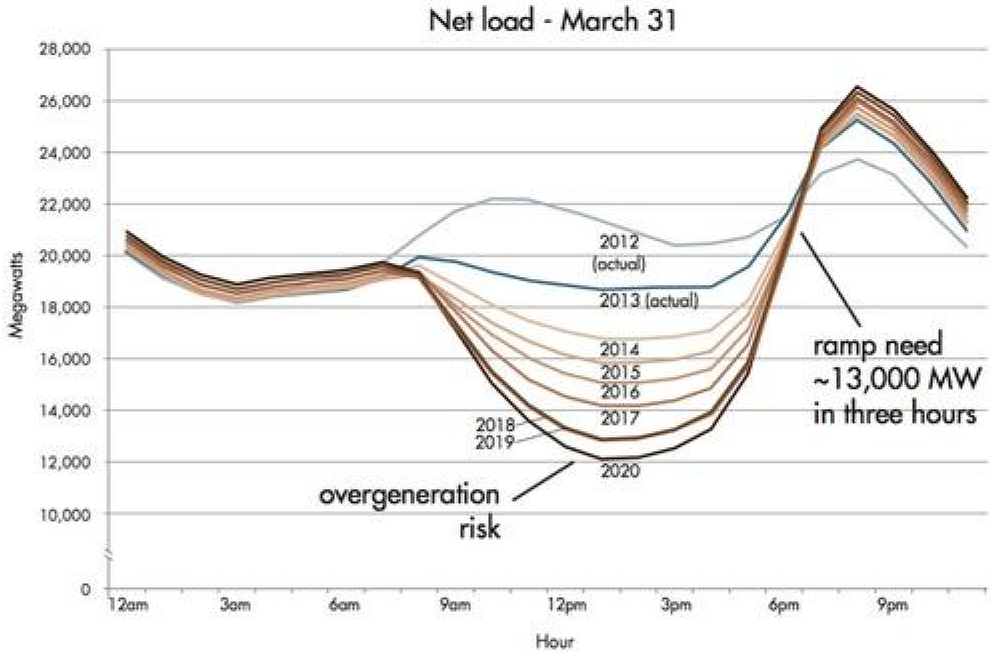
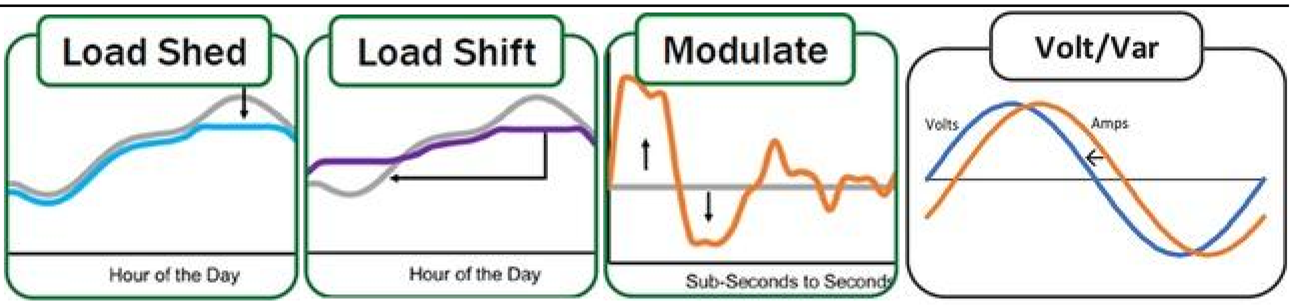


Figure 11. CAISO's Official Duck Chart (CAISO 2013; *What the Duck Curve Tells Us about Managing a Green Grid*)

Table 5 Grid Services



	Load Shed	Load Shift	Modulate	Volt/Var
What the facility provides	• Reduction in peak demand to keep grid from being overloaded. • Reduction in peak demand to lower prices.	• Reduction in peak demand with increase in minimum demand.	• Frequency regulation • Ramping	• Voltage compensation for distribution circuits
Why is it needed by the grid?	• Replaces expensive peaker plants. • Defers need for transmission or distribution capacity upgrades. • Allows grid time to respond to temporary generator or transmission problems.	• Minimizes need to curtail renewable generation. • Lowers costs by shifting energy usage from high cost periods to low cost periods.	• Grid needs to buy time for slower responding generators to respond to unplanned generator outages. • Grid needs to buy time for slower responding generators to ramp.	• Inductive loads on long distribution circuits can cause line voltage problems and equipment overheating.
Example Market Programs	• Capacity programs • Non-wires solutions	• Time-of-use rates • Realtime rates	• Ancillary Services	• Ancillary Services

		• Non-wires solutions		
Example Applicable Systems	• Dispatchable distributed generation • Lighting systems • Elevator systems	• Energy storage systems	• Battery storage • VFDs • Advanced inverters	• Advanced inverters

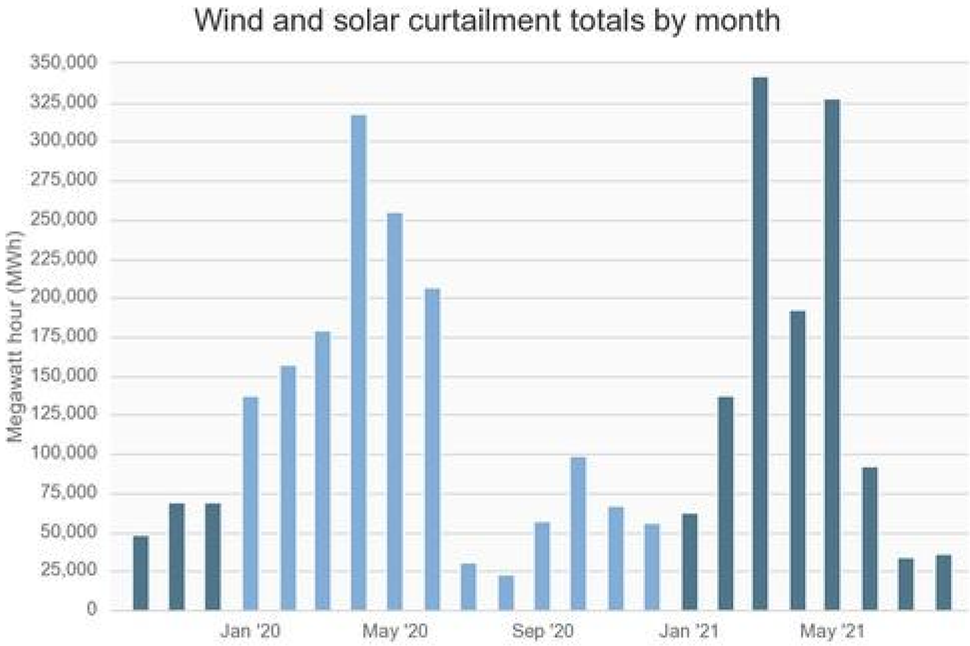


Figure 12. Wind and Solar Curtailments by Month in California ISO (CAISO; www.caiso.com)

Buildings can provide grid services that support the generation, transmission, and distribution of electricity and provide value through avoided electricity system costs (generation and/or delivery costs.) Building energy efficiency and behind-the-meter distributed power generation are traditional grid services buildings can provide. Table 5 (ASHRAE 2020) shows other grid services and they can be categorized into (1) load shedding, (2) load shifting, (3) load modulation, and (4) voltage/var support. Load shedding and load shifting are also called demand response.

Utility Demand Response Strategies

Demand response is the change in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized (DOE 2006).

Flexible load shape attempts to achieve a load shape composed of end-use services with varying degrees of reliability, allowing the utility to control/adjust end-use demand in accordance with supply capability. In exchange for accepting a lower level of reliability, a customer receives some financial incentive. A flexible load shape may be achieved using interruptible loads, energy management systems, or individual customer load control devices imposing service constraints.

Load shedding or **peak shaving** reduces the amount of energy purchased from a utility company during the peak. Many businesses pay for their electricity consumption on a time-of-use basis. Peak demand charges typically apply to electricity consumed within the peak hours, whereas lesser charges apply to the remainder of the day.

Direct load control involves the utility disabling and enabling consumer end uses (e.g., turning off an air conditioner during grid contingencies). A communication system between the utility and the customer transmits control instructions to a receiver and control actuator on the customer's premises that enables activation/deactivation of customer loads. Many utilities use direct load control to reduce peaking requirements, and consider control only during the most probable days of the system peak. Other utilities use direct load control to reduce operating cost and dependence on critical fuels.

Valley filling involves increasing energy consumption in a time period when the electric system is under used. Valley filling may be particularly desirable where the long-run marginal cost of electricity is less than the average price of electricity. Properly priced off-peak load can decrease the average price for the customer and provide cost or capacity benefits to the utility. Valley filling can be accomplished in several ways, including using thermal energy storage (water or space heating or cooling).

Load shifting moves energy consumption to another time period, typically when prices are lower. Common options include preheating or precooling the building, storage water heating, storage space heating, cool storage, combining with time-of-use or other special rates. The shifting usually occurs within a 24 h period. The total energy used by a customer need not be significantly affected by load shifting.

Strategic conservation is directed at reducing end-use consumption, often through increased efficiency. The change reflects a reduction in sales and a change in the use pattern. Examples include weatherization and appliance efficiency improvement.

Strategic load growth increases end-use consumption by increasing energy sales beyond the valley-filling strategy. The emphasis is often on increasing total sales without regard to the seasonal or daily timing of the load. Strategic load growth may involve area development, electrification, and increased market share of loads that are or can be served by competing fuels.

Ancillary Services

Electric power ancillary services are grid services and functions to support the continuous flow of electricity and maintain grid stability. These services generally include frequency control, active and reactive power control, and voltage control, on very short-term timescales.

Frequency regulation is the use of generation/advanced inverters, battery storage, or load that is equipped with automatic control to track and correct the load and generation fluctuations at seconds or minutes level. It helps to maintain power frequency and match generation to load (Kirby 2004). Besides battery storage, researchers have suggested that HVAC equipment such as chillers, rooftop units, and heat pumps can be used for frequency regulation by controlling variable-speed compressor or fan motors.

Ramping or **load following** is the use of generation/advanced inverters, storage, or load equipment to track the intra- and inter-hour changes in customer loads (Kirby 2004).

Reserves are designed to account for unpredicted system reliability events. When an emergency occurs, spinning reserves are to be deployed within 10 min, while non-spinning/supplemental reserves can be deployed in half an hour or so.

Volt/var support is the use of generation/advanced inverters or battery storage technologies to inject or absorb reactive power to maintain power voltages within required ranges. This service requires very fast response (within seconds.)

Figure 13 illustrates frequency regulation and load following/ramping.

Utility Bill Savings and Revenue Streams

Many electric utilities offer programs that encourage customers to make changes in end-use equipment or the ways and times they use electricity to achieve avoided costs (reduction in cost to generate and transmit electricity) for the utility. In turn, the utility typically provides a form of incentive to customers for participation. Whether mandated by a regulatory agency or developed by the utility, these programs can represent one way a smart building with enabling grid services can generate value for the customer. Some utilities also provide programs that are designed to ensure distributed resources, such as rooftop solar generation, are connected safely to the distribution grid and that customers are compensated for excess energy fed back onto the grid. To fully obtain the financial benefits of smart grid technologies, a building owner or operator should reach out to their electricity provider and determine which programs might generate sources of value, from free services, rebates for equipment upgrades, or even direct compensation for participating in the program. Usually, utility programs are described on utility websites, and utility staff are available to discuss specific program requirements and features with any customer. Interacting directly with the local utility is usually the most reliable and direct source of information about which programs could generate additional value for a building owner or operator when deploying smart grid systems.

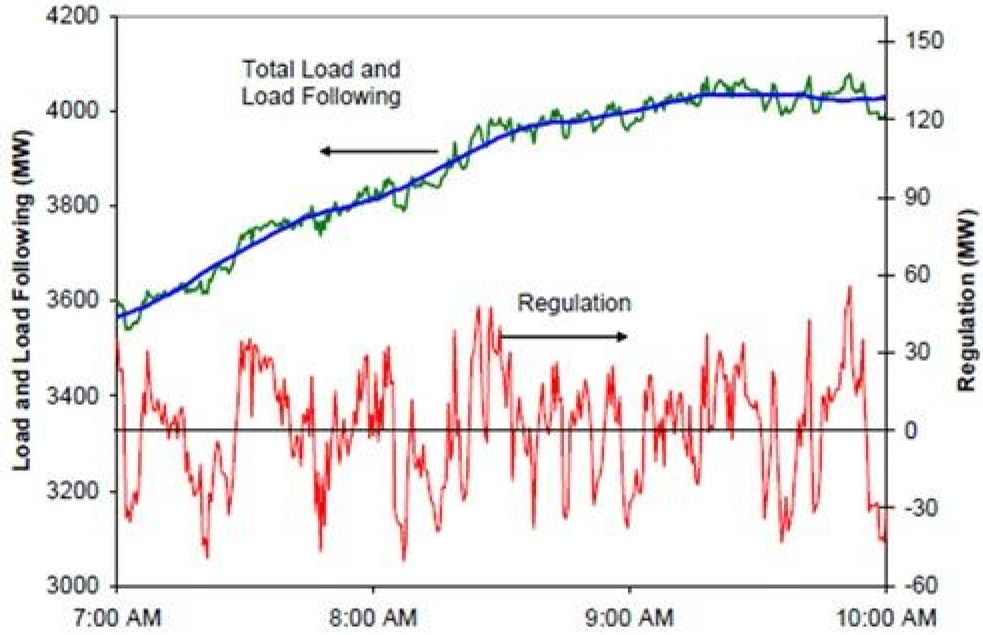


Figure 13. Example Frequency Regulation and Load Following/Ramping (Kirby 2004)

Rate Options for Demand Response

Public regulatory bodies provide incentives to drive customer behaviors using electric tariff design. To increase the reliability and use of existing generation assets or reduce the need for additional generation/transmission assets, there are two methods to reduce customer demand during peak consumption times. Utility customers can be induced to provide demand response either through **dynamic pricing tariffs**, retail electric rates that reflect short-term changes in wholesale electricity costs (e.g., hourly pricing or critical-peak pricing), or through **demand response programs** that offer customers payments in return for reducing consumption when called upon to mitigate high market prices or reserve shortfalls. Table 6 shows common types of demand response programs.

Rate Options for Distributed Generation

Electric utilities often have special rates and requirements for a customer that owns onsite generators. The rate options may include qualifying facility, net metering, net billing, feed-in tariff, and value of solar. Rate options for distributed generation are presented in Table 7 (ASHRAE 2020).

Table 6 Common Types of Demand Response (DR) Programs: Price Options and Incentive- or Event-Based Options

Price-Based DR Programs: Higher Prices Used to Induce Demand Reduction	
Time of use (TOU) rates	Rates with fixed price blocks that differ by time of day.
Critical peak pricing (CPP)	Rates include a pre-specified, extra-high rate that is triggered by the utility and is in effect for a limited number of hours.
Real-time pricing (RTP)	Rates vary continually (typically hourly) in response to wholesale market prices.
Incentive- or Event-Based Programs: Incentives Provided to Induce Demand Reduction	
Direct load control	Customers receive incentive payments for allowing utility a degree of control over certain equipment.
Demand bidding/buyback programs	Customers offer bids to curtail load when wholesale market prices are high or identify how much they would be willing to curtail at posted prices.
Emergency demand response programs	Customers receive incentive payments for load reductions when needed to ensure reliability, but curtailments are voluntary.
Capacity market programs	Customers receive incentive payments or rate discounts/bill credits for providing load reductions as substitutes for system capacity.
Interruptible/curtailable programs	Customers receive a discounted rate or bill credit for agreeing to reduce load upon request. If participants do not curtain when requested, they can be penalized.
Ancillary services market programs	Customers receive payments from a grid for ancillary services provided. Require that customers are able to adjust load quickly.

Sources: FERC (2006), Goldman et al. (2010).

Modern Smart Grid Strategies

The smart grid represents a modern grid concept that would replace dated infrastructure with currently available and future technologies that enable safe and secure two-way flows of electricity and information between customers and their electricity providers. In the typical grid configuration, energy predominately flows one way, from utilities to consumers, and information flows almost exclusively one-way, from consumers' power meters to grid operators. However, with the smart grid, energy and information would flow easily from the grid to customers, and vice versa, in real time.

The vision for the modern electric grid is one that

- Motivates and includes the consumer
- Accommodates all generation and storage options
- Enables markets
- Provides power quality for 21st-century needs
- Resists attacks
- Self heals
- Optimizes assets and operates efficiently
- Provides less expensive electric power more cleanly

Two-way flows of energy and information would provide customers with valuable information about their electricity prices and consumption patterns. This would enable customers to better manage their electricity use. On the utility side, the grid could be more accurately balanced, brownouts or blackouts could be avoided, and outages could be quickly mitigated. Advantages of the smart grid to the utility and to consumers are compared in Figure 14.

Investments in the smart grid are expected to yield the following four long-lasting effects (Lott et al. 2011):

- Next-generation electric power grid infrastructure that replaces the existing grid
- Substantial improvements in energy efficiency that bring financial and environmental benefits
- Greater use of renewable generation
- Widespread use of distributed generation

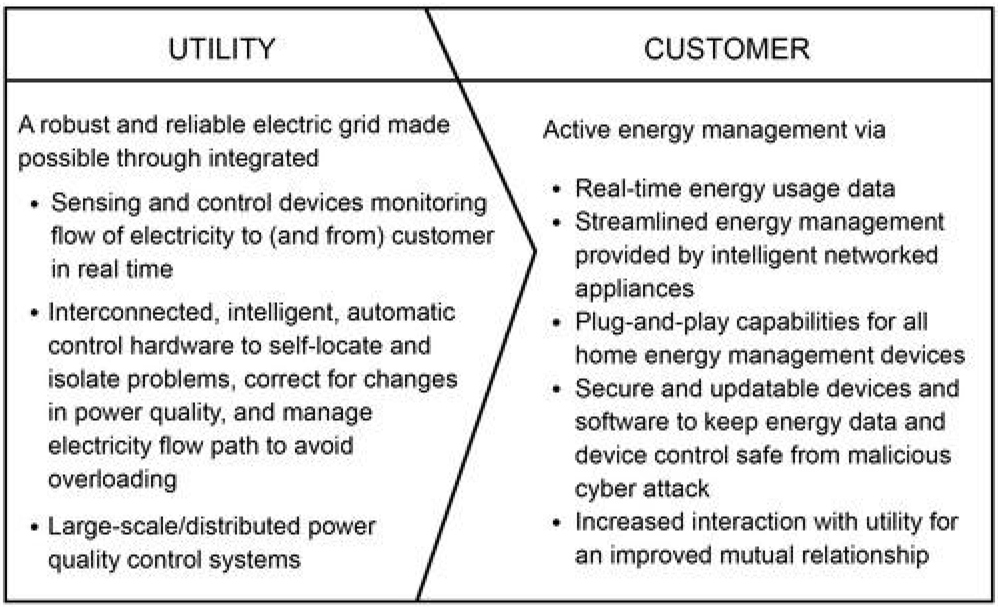


Figure 14. Benefits of Smart Grid as Viewed by Utilities and Customers Lott et al. (2011)

In addition to these four effects, future changes include the development and application of various energy storage (distributed and centralized) strategies (e.g., electrochemical batteries, thermal energy storage) that will benefit from increased research, as well as development and commercialization efforts by educational, government, and industry entities. Other DER types include photovoltaics, advanced inverters, electric vehicles, and energy efficiency.

Energy Storage

Two common types of energy storage are electrochemical batteries and thermal energy storage. Batteries are generally the primary option for backup power and for grid services (where rates and incentives are favorable) such as frequency regulation, demand charge reductions, capacity bidding, and time-of-use bill management. **Thermal energy storage (TES)** stores and discharges thermal energy rather than electrical energy. It includes various technologies such as solar thermal collectors, heat pump water tanks, chilled-water tanks, phase-change materials (PCMs), and even building thermal mass (as a passive TES). Cool thermal storage makes use of the fact that air conditioning and refrigeration are often operating when the grid is most in need of relief. Cool storage can be discharged during these times, allowing compressors to remain off. There are a few forms of cool thermal storage:

- **Ice storage.** The oldest method, storing ice that can be melted to provide cooling.
- **Chilled-water storage.** Similar to ice storage, but in liquid form (a much larger tank is needed because there is no phase change occurring).
- **Phase-change material thermal storage.** Specially formulated chemicals placed in the space that melt and freeze near the thermostat set point can provide a more passive type of thermal storage.
- **Refrigeration thermal storage.** Refrigeration systems can make use of both ice storage and phase-change materials, but require special equipment for the colder temperatures of refrigerated spaces.

The first two types of cool thermal storage are well established, and an ASHRAE design guide with complete best practice guidance exists just for them (Glazer 2019). There is less guidance available for the other two forms, though the capacity of refrigeration thermal storage systems is substantial. Cool thermal storage typically lasts longer, has higher cycle efficiency, and is generally cheaper to own than batteries.

Table 7 Overview of Rate Options for Distributed Generation

Rate Option	Provisions	Value Provided to DER Customer
Qualifying facility (Q.F.)	Energy provided by co-generators and small power producers, using renewable energy sources, is compensated at utility's avoided cost.	Avoided cost of utility, varies widely across industry. Energy sold to utility may be net of Q.F.'s load.
Net metering	Customer's generation avoided retail purchase of electricity, and any excess kWh is credited/purchased by the utility.	Avoided retail electricity purchases, credit for excess energy, timing differences – excess energy from one period off-set purchases during another period.
Net billing	Customer's generation avoids retail purchase of electricity and any excess is settled at difference between retail sales price and excess energy purchase price.	Similar to net metering but lower since retail prices normally exceed credit/payment to customer.
Feed-in tariff	Customer is paid for generation at a price that achieves a target rate of return for the customer.	The targeted rate of return.
Value of solar ("value tariff")	All generated energy is purchased/credited by the utility. All customer load is purchased at retail price.	Purchased/credited energy.

Photovoltaics

Photovoltaics (PV) systems use the photovoltaic effect to convert sunlight into electricity. An inverter then converts and conditions the direct current created by the PV array into alternating current. Cloud cover and the sun's motion throughout the day and year cause PV system generation to vary significantly. The primary benefits of a PV system are reduced utility bills from the decrease in grid-provided electricity. Typical components of a PV system are shown in Figure 15 (ASHRAE 2020).

Advanced Inverters

Inverters convert electrical power from direct current (DC) to alternating current (AC) while synchronizing with the grid's frequency and phase. They also automatically disconnect DER when these grid properties are adversely affected. Inverters are therefore a critical piece in ensuring DERs operate effectively with the grid. As DER capacity increases, their destabilizing effect on grid quality will become increasingly pronounced. Advanced inverters are one solution (NREL 2014, 2015). Advanced inverters improve upon standard inverters by allowing DERs to continue to operate for longer periods while simultaneously actively stabilizing the grid's power quality. Additional communication capabilities allow utilities to see advanced inverter status and potentially control their behavior. Some of the primary functionality includes remote disconnect, power curtailment, power factor, real power, and reactive power control, and under/over voltage and frequency ride-through (NREL 2014; EPRI 2012, 2016).

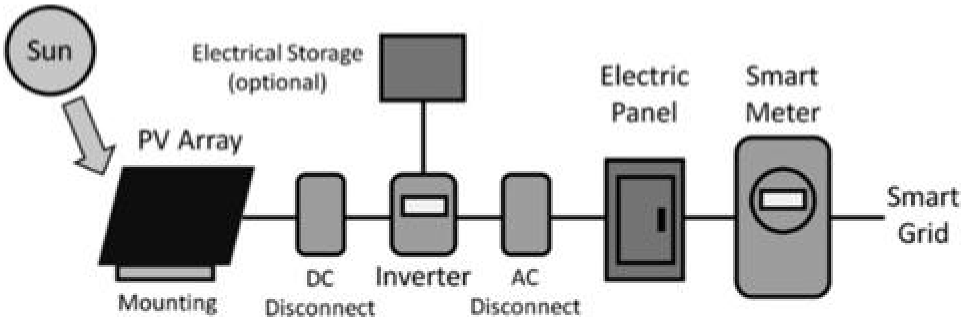


Figure 15. Typical PV System Components

Advanced inverters can operate independently or pair with communications systems. This enables DER visibility and remote control, which will be particularly useful to utilities as communication capabilities are further developed.

Electric Vehicles

Electric vehicles' market penetration is increasing rapidly due to improved performance and decreasing cost. Electric vehicles use electricity as their primary fuel, storing electrical energy in a battery and using an electric motor to convert it into motion. Since electric vehicles plug in to recharge, they may be considered an extension of a building's electrical system. **Electric vehicle supply equipment (EVSE)** is the equipment that electric vehicles use to recharge, and may include conductors, plugs, fittings, and outlets among other components. EVSE falls into three categories: Level 1, Level 2, and DC Fast Charging. Each level will charge at different rates. Level 1 uses 120 V and is most typical in residential settings. It is the slowest charging category. Level 2 is most applicable to commercial buildings and uses 240 V. DC Fast Charging is used in transportation corridors, using 208 to 600 V.

An increasing proportion of EVSE are capable of automatically managing the time and rate of charging. This managed charging provides extra capacity to the utility when needed and can absorb surplus generation from renewable energy sources.

Energy Efficiency

Building automation systems can implement different demand response strategies in response to utility/grid operators' demand response signals. Table 8 lists common demand response strategies for these systems.

These smart-grid strategies are intended to enable a new kind of load response, in which loads and generation are on an equal footing with equal visibility of the value of electricity in real time. It includes use of automation and other tools to enable even small customers to manage load in response to the real-time value of energy. It focuses on integrating renewables and higher reliability and resiliency, as well as DERs and advancing the regulatory framework to enable customers (and small generators) to manage the DERs and load in a variable-price environment. Building operators can deploy smart grid technologies to achieve demand cost savings through power bills using various strategies, including load interruptions, peak shedding, peak shifting, and operating in intentional island mode.

Table 8 Summary of Common Demand Response Methods

Energy System	Equipment	D.R. Strategy	Notes
HVAC	Terminal unit	Zone temperature set-point reset	Load shedding
	Terminal unit	Lower zone temperature set point during off-peak hours (precool the space)	Load shifting
	Air handling unit	Supply air pressure and temperature set-point change	Load shedding
	Fan or pump with VFD control	Limit or reduce the maximum speed of VFD output	Load shedding
	Cooling valve	Limit or reduce the maximum valve position	Load shedding
	Chiller	Increase chilled-water supply temperature or turn off chiller	Load shedding
	Thermal energy storage	Charge storage in off-peak hours and discharge in peak hours	Load shifting

	Rooftop unit	Reduce the compressors speeds or on and off cycling	Load shedding
Lighting	Luminaires	Switch non-critical zones off	Load shedding
	Luminaires	Luminaire/lamp switching or stepped dimming	Load shedding
	Dimmable luminaires	Continuous dimming	Load shedding
	Networked lighting system	Advanced networked lighting controls	Load shedding
Plug Loads	Non-critical equipment	Turn off non-critical plug loads	Load shedding

Another important consideration is understanding energy impacts, including energy efficiency and conservation interactions with DER, supplying energy to the electric grid, and how to strategically increase energy consumption when necessary by taking advantage of electric rate designs that encourage off-peak energy usage. Although most energy efficiency and conservation initiatives would not fall under the smart grid definition, pursuing efficiency and conservation in concert with deploying smart grid technologies can help drive benefits further than just smart grid deployment. Facilities that encourage efficient use of energy and behaviors aimed at conserving energy can not only lower total energy usage but also can affect additional demand charge savings too. If a building installs on-site generation, the potential to supply energy to the electric grid exists and thereby represents a potential source of benefit. Interconnecting with the grid requires meeting the utility's interconnection requirements and may require getting the generator certified as a qualifying facility (QF), which can represent an additional cost to the owner of the generator. Furthermore, utilities may require that insurance be carried on the generator. However, these costs should be weighed against the potential benefit of selling power to the electric utility when the generator produces more electricity than is needed to meet the demand for the building.

Relevance to Building System Designers

As the modern grid develops, buildings will need standardized, two-way grid communications to know the condition of the grid and to determine how to respond to it, and then send information back to the grid. Facilities can be operated in ways that support grid reliability while potentially lowering their costs of operation by managing loads and storage to contribute to balancing grid-wide demand and changes to the generation mix.

An example of a nonproprietary, open, and standardized communications specification to automate demand response (ADR) is Open Automated Demand Response (OpenADR™). The current version OpenADR 2.0 (a and b) are profiles of the OASIS Energy Interoperation (EI) standard and is designed to facilitate ADR actions at the customer location, whether it involves electric load shedding or shifting. OpenADR is also designed to provide continuous dynamic price signals such as hourly day-ahead or day-of real-time pricing.

Another example of a standard protocol for demand response and DER communication is IEEE *Standard* 2030.5. While BACnet is the predominant open protocol used within the building automation systems, the capability for BAS to directly communicate with utility ADR signal servers through OpenADR or other ADR protocols is still limited. VOLTTRON, an open source, distributed control and sensing software platform, can be used to bridge the communication and platform gap among facility BAS, utility, and DERs.

Design considerations for BAS need to include planning a demand response strategy model (centralized, distributed, or hybrid), control network architecture, controller selection, and software that are capable of implementing various ADR control strategies. Buildings and facilities should be designed for operation in an environment where electricity is valued in real time, varying throughout the day. Building owners, managers, and designers should consider incorporating automation to allow shifting and shedding loads, as well as planning to allow for thermal energy storage and renewable energy generation systems integration. Further, there should be some consideration of microgrid operations, with additional fossil-fuel-based distributed generation (fuel cells, diesel generators, etc.) and electrical storage capability on site.

ASHRAE *Standard* 189.1-2020 "provides minimum requirements for the siting, design, construction, and plans for the operation of high-performance green buildings to enhance resilience to natural, technological, and human-caused hazards." The standard contains mandatory provisions that apply to on-site renewable energy systems, energy consumption management, and automated demand response. It also includes prescriptive options for on-site renewable energy systems, building envelope, HVAC, service water heating, power, lighting, and other equipment. The latest Leadership in Energy and Environmental Design (LEED™) v4.1 for Building Design and Construction lists point requirements for advanced energy metering, demand response, renewable energy production, and green vehicles.

In the future, not only will electricity costs become more dynamic, energy prices will continue to rise. Controlling energy costs begins with energy efficiency as the cornerstone of an overall energy management plan, but will expand to include grid services such as peak demand reduction, continuous load management, and frequency regulation. A **grid-interactive efficient building (GEB)** will make it possible to maximize the electric utilities' incentives for both energy efficiency and demand response.

The success of the smart grid depends on interoperability and communication between energy service providers and facility energy management systems to effectively manage supply and demand. ASHRAE *Standard* 201, Facility Smart Grid Information Model, defines an abstract, object-oriented information model to enable appliances and control systems in homes, industrial facilities, and other buildings to manage electrical loads and generation sources in response to communication with a smart electrical grid and to communicate information about those electrical loads to the utility and other electrical service providers. This model defines a comprehensive set of data objects and actions that support a wide range of energy management applications and electrical service provider interactions, including on-site generation, demand response, electrical storage, peak-demand management, direct load control, and other related energy management functions. This standard will become part of the Smart Grid Interoperability Panel (SGIP; www.sgip.org) catalog of standards recommended for adoption by utilities and energy service providers. The BACnet Smart Grid Working Group is referencing this standard in defining a building energy services interface to serve as a bridge between BACnet and other ADR protocols such as OpenADR 2.0.

Microgrids

A microgrid is "a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid" (DOE 2011). It can "connect and disconnect from the grid to enable it to operate in both grid-connected or island-mode" (Ton and Smith 2012). A microgrid allows for the integration and co-optimization of multiple different types of smart grid components. Because a microgrid consists of an integrally controlled collection of DER assets, the benefits of each independent asset can be leveraged to provide greater benefit. For instance, the operation of assets can be optimized for profit, cost reduction, or emission reduction.

Individual DER assets are required to de-energize in the presence of certain grid faults. However, DERs aggregated as a microgrid can island under the same set of circumstances, providing backup power to the facility. This contributes to building resilience. A microgrid can transition to island mode for various reasons, including enhanced reliability, economic dispatch, or preemptive isolation in anticipation of severe weather or other events. Microgrids are also presented as solutions or options for building designers in a few different scenarios, including

- Buildings where a significant portion of the load will require backup power. By using a microgrid instead of traditional backup power, renewable resources can be integrated, which provide benefits even when backup power is not required. Additionally, by integrating a mix of sources, the duration over which backup power is available can be improved beyond the limit of on-site fuel storage.
- Buildings requiring process heat or steam. Although a CHP system would often be considered in such cases, integrating CHP through a microgrid gives a building additional cost control, including the ability to export power to the grid and operate during grid outages.
- Buildings planned for or with access to significant renewable power supplies. Much of the planning and infrastructure necessary for a solar PV system overlap with that needed for a microgrid. The added benefits of a microgrid in this case may outweigh the lower additional cost.

Relevance to Decarbonization

Smart grid strategies are essential to achieving building sector decarbonization goals set by policy makers to confront climate change by integrating building energy demands with the power grid as well as output of on-site and grid renewable energy assets. Smart grid technologies will need to be implemented in both new and existing building stocks to achieve decarbonization targets set by jurisdictions. Many jurisdictions, such as New York and California, are already using utility demand response and rate option strategies, as well as other modern smart-grid strategies in order to achieve decarbonization goals. These smart grid technologies are used for demand management and energy efficiency improvements, which help maintain a reliable grid by reducing both system generation and transmission. These reductions are necessary to support the equitable diversification in energy resources as the grid transitions from fossil fuel sources to renewables. The means have also been developed to evaluate the carbon intensity of the grid at an hourly or sub-hourly level. This creates another significant decarbonization benefit that grid interactive buildings can yield: the ability to shift load from times of higher carbon to lower carbon on the grid. This can be done in real time or using rules-based approaches based on typical carbon profiles over time.

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The preparation of this chapter is assigned to TC 7.5, Smart Building Systems.