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END-USE EFFICIENCY (Y WANG, SECTION EDITOR)

Smart Meters and Smart Devices in Buildings: a Review of Recent Progress and Influence on Electricity Use and Peak Demand

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Abstract

Purpose of Review Electric grids face significant challenges with peak and variable demand and greenhouse gas emissions. As new technologies develop, they are used to modernize grids through improved monitoring and management of building electricity use. In this review, a range of technologies are discussed, including the state of their implementation and their current and future potential influence on building electricity contributions.

Recent Findings Recent literature has focused on the use of these devices individually for modeling building performance, influencing occupant behavioral energy efficiency, and model predictive control for more dynamically operated buildings.

Summary The results suggest that while smart meters are the most common device, other grid-connected technologies have the potential to further improve monitoring and management of the grid. However, there still remains significant gaps in the literature that require further study to take full advantage of the diversity of connected technologies to achieve a more energy-efficient built environment that can more dynamically consume electricity.

Keywords Smart grid · Smart meters · Residential buildings · Commercial buildings · Energy efficiency · Peak loads

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Introduction

The electric grids throughout the world currently face significant challenges. In recently years, the demand for electricity has steadily increased [1], requiring more power generation to meet these demands, also resulting in greenhouse gas emissions (GHGs). Buildings consume approximately 40% of total energy use [1, 2] and approximately 72% of electricity in the U.S as well as over half worldwide [1, 3]. Approximately, half of this consumption is from residential buildings and the other half from commercial buildings, thus buildings are a significant contributor to energy and electricity use. Electric grids also face challenges with increased variability in demand and peak loading, which cause transmission congestion, higher energy prices, and the need for the use of less-efficient and often higher greenhouse gas (GHG) emitting "peaker" power plants. Residential and commercial buildings have been found to be responsible for 50 and 25%, respectively, of the total peak demand [4].

In recent years, there have been significant investments in the electric grid and the technologies associated with this grid in effort to meet these challenges. Much of this investment has been in digital communication and data collection and management improvements to make the electric grid "smart". These innovations and technology goals are, in part, to enable more intelligent use of electricity, such that this electricity is created and used more efficiently. The focus of this paper is thus specifically on the review of recent advances in "smart" devices in buildings which play an essential role in the modernization of the electric grid and promotion and influence on energy efficiency implementation. These "smart devices" include (a) smart meters, (b) smart thermostats, (c) smart appliances, and (d) the Internet of Things (IoT). These devices are the focus of this work because they are the most prevalent (a), are associated with significant energy-intensive end-uses in buildings (b)(c), or generally have the potential to influence all other end uses (d).

This paper begins with a review of the smart grid, followed by a review of current progress of technology development of smart devices in buildings. The discussion of each device includes a review of the technology, rate of implementation, and recent research findings using these devices and their data. Finally, a discussion is included on current challenges and future research needs.

Background: the Smart Grid

A number of different governmental agencies have defined the term "smart grid" [5, 6]. As compared to a traditional electric grid that connects electricity producers with electricity consumers, the "smart grid" adds to this electric grid one- and two-way digital communication in the form of sensors to gather data, communication devices that transmit and receive this data, and automated controls to enable adjustments to the grid based on this data. Thus, the "smart grid" generally refers to an energy network that can, through the use of various technology and computer-based controls and automation, monitor the energy flow in an electric grid and adjust the energy supply and demand accordingly. Ideally, it is more efficient and modernized than its predecessor by allowing users to manage electricity supply and demand in a way that is more cost-effective and environmentally friendly. A number of different technologies enable the smart grid to be "smart". As this work focuses on the consumption side of the grid, only technologies associated with electricity demand are discussed herein.

Smart Meters

Of the various different technologies that contribute to the smart grid, perhaps the most ubiquitous is the smart meter. There are two main types of smart meters: AMR (automatic meter reading) and AMI (advanced metering infrastructure) [7, 8•]. AMR is an older one-way technology that collects building electrical energy use information and transfers this data to the electric utility company. AMI, however, is a more recent and advanced two-way technology that also collects energy use information from a building and transfers this to the utility but does so on a more frequent basis. This includes the recording of hourly or sub-hourly energy use data and its transmission to the utility and/or customer at least daily [9]. AMI can also collect other information such as time-of-use energy use, peak demand, voltage, and power factor, as well as transmit information such as energy pricing and demand response signals, enabling opportunities for more dynamic operation of the electric grid. In addition, today's smart meters can help to identify and fix power outages and optimize unit commitment.

Legislation has been a significant driver in the implementation of smart meters. A total of about 138 million advanced meters (AMI) are in place, nearly 38% of all meters in the USA [9]. This is due in part to the American Recovery and Reinvestment Act of 2009 which helped fund many smart meter projects. Smart meter penetration is also predicted to increase in the USA moving forward. In Europe, initiatives such as the European Energy Performance of Building Directive (EPBD) [10] encourage smart metering. The Third Energy Package [10] ensures implementation of smart metering in member countries where the cost-benefit analysis indicates a positive benefit, with the goal of an 80% market penetration. Many other countries have similar goals [11–13]. Globally, as a result of recent legislation, it is estimated that there will be 454 million smart meters by 2020. Asia will have the most smart meters, followed by Europe, North America, South America, and Africa. The cost of implementation will be over $100 billion; however, it is estimated that the benefits will outweigh the costs. [14].

Smart meters can be implemented in any building consuming electricity; however, they are most common in residential buildings. Globally, residential applications account for 83% of shipments [15]. In the USA, approximately 88% of smart meters are installed in residential buildings, covering slightly under 50% of residential buildings [16•]. As of March 2015, there were 271,000 residential smart meters installed in the US Smart Grid Demonstration Program (SGDP), but only 21,000 and 2000 for commercial and industrial buildings, respectively [17]. However, the demand for commercial applications is expected to grow in future years [15].

Recent research on smart meters has focused on the use of their data, through data analytics techniques, to (a) better understand the energy use of existing buildings and building systems, (b) develop data-driven models for future energy prediction, and (c) determine the peak load reduction potential of building systems and appliances. Nearly all recent studies discussing smart meter data have focused on residential buildings; however, there have been some limited studies in commercial buildings or a combination of both residential and commercial buildings [18, 19].

One of the most commonly studied uses for smart meters is in the use of frequent interval energy use data for a better understanding of energy use patterns of communities of buildings (e.g., Sevlian and Rajagopal 2014 [20]), whole buildings (e.g., Gouveia and Seixas 2016 [21]), and individual building systems (e.g., Cetin et al. 2014 [22]). This can be consumer-oriented, which focuses on helping end-users to reduce electricity consumption [19, 23], or producer-oriented, which aims to assist utilities with consumers' daily habits for the purpose of load forecasting and clustering [19, 24–26]. Most recent studies use a combination of meter data and survey or energy audit results to provide additional information about the buildings studied.

A variety of techniques have been used for analysis of energy use data to explain use pattern recognition, classification/segmentation of load profiles, and evaluation of an explanation of variability of energy use. These techniques include supervised and unsupervised learning, cluster analysis [27–31], regression and change point models [23, 32, 33], energy efficiency frontiers [34, 35], probabilistic methods [28], Markov models [36, 37], and frequency analysis [27]. These studies have used energy use data to determine housing characteristics such as socio-economic status and dwelling type [38] and energy efficiency classification [34, 35], disaggregation of energy use into end-use categories [21, 23, 33, 37, 39–41], and clustering of buildings into groups by use pattern [30]. Energy use data is also being used to develop data-driven models for future electricity use and electricity demand predictions. These include short-term forecast methods [42] and more generalized methods (e.g., [43, 44]).

The studies which have focused on algorithm development for electricity use and demand prediction and for disaggregation can provide an improved understanding of energy use for the end-users, who can utilize these insights to guide their energy behaviors. As of 2012, over 156 studies have been conducted on energy use feedback methodologies and effectiveness [45], finding up to 10–20% savings in energy use. However, there are some debates as to the robustness of some of these studies [46]. The type of feedback provided to the consumers correlates with achieved energy savings. "Indirect" feedback, which provides energy consumption information to the consumer after the energy is consumed, such as in a monthly or daily statement with feedback on what can be done to reduce energy loads, has achieved energy savings of 3.8–8.4% [41]. "Direct" feedback, which provides real-time information, has found an average 9.2% energy saving if using whole-home energy data and the greatest savings if providing submetered or disaggregated data [47]. This disaggregation isolates individual appliances and high energy users, allowing for the enhanced ability to provide personalized recommendations for energy reduction strategies [41].

Smart Devices and Enabling Technologies: Smart Thermostats, Smart Appliances, and IoT

Two-way communication smart meters can also directly influence energy efficiency and peak demand when combined with an enabling technology, such as a smart thermostat, IoT device, or smart appliance. Either through a smart meter or via the internet, a building can receive and transmit a signal from the utility, which can then be transmitted to one or more enabling devices that can adjust their settings to reduce load and energy use. Several of these enabling technologies are discussed in the following sections.

Smart Thermostats

Thermostats control the heating, ventilation, and air-conditioning (HVAC) system in a building, which is often the largest single electricity consumer. Approximately 83% of residential buildings and nearly all of commercial buildings have an A/C system and nearly all buildings have a heating system in the USA (US EIA 2009). These are responsible for nearly 50% of use in some climates; thus, it is logical to target this high energy and load-demanding system using smart technology. And, while the relative contribution of HVAC energy and electricity use and demand is lower in many countries, the rate of adoption and use of HVAC systems are predicted to increase significantly in future years [48].

Smart thermostats can (a) achieve electricity demand reduction through connections and communications to the grid and (b) energy savings by more optimally adjusting to occupants' preferences and schedules. For (a), a utility company or third party can remotely control the thermostat, via WiFi or radio signal, by cycling it or changing the setpoint temperature when grid demand or energy price is high. For (b), some thermostats are also "learning" thermostats which include embedded learning algorithm software with the goal of improved energy savings based on the occupants' schedules, occupant sensors, and/or preference settings over time. The most significant challenge in reducing electricity use and demand using the HVAC is to ensure that if the building is occupied, the occupants remain comfortable [49, 50].

The rate of adoption of smart and connected thermostats is significantly less than that of smart meters. Unlike many regulations mandating smart meters, smart thermostats have generally either been purchased by the building owner, or provided by the utility free of cost or for a reduced price in exchange for agreeing to be a part of a demand response program. However, the number of smart thermostats in use predicted to grow moving forward [51].

Recent literature has demonstrated the impacts of smart thermostats on energy savings and peak load reduction in both residential and commercial buildings, with peak load reductions of between 10 and 35% and energy savings of up to 17% found. Davis et al. [52] reviewed the results of 32 pilot studies, finding that smart thermostats (or other smart devices) in conjunction with dynamic pricing reduced peak demand by up to 14% in residential buildings. Newsham and Bowker [53] reviewed time-of-use pricing strategies trials, including those combined with smart thermostats, finding that a peak load reduction of 30% with this enabling technology is a reasonable expectation, as compared to 5% reduction relying only on occupant energy efficiency behavioral change. Newsham et al. [54] found 10–35% peak load reduction of residential buildings in Canada using an increase of 2 °C for 4 h. Yoon et al. [55•] found that controlling the HVAC using smart thermostats based on real-time energy price signals could reduce peak loads by 25% and reduce energy use by 4.3% annually. To achieve energy savings, much of recent literature has focused on improved occupancy detection and prediction methodologies combined with smart thermostats, as discussed in Klemiminger et al. [56].

The energy benefits of smart thermostats in commercial buildings are not clear. A pilot study conducted by DTE Energy [57] revealed "marginal results" using 500 learning thermostats for small commercial buildings. Small and medium-sized commercial buildings will certainly see the benefits brought by the smart thermostats. These buildings often do not have the building management systems (BMSs) that facilitate the HVAC system control. The smart thermostats thus enable the HVAC equipment and system in these buildings to be more energy efficient, like a BMS. It is estimated that smart thermostats in non-residential setting are fewer than 50,000 units per year; however, the market is expected to grow approximately to 20–50% [58].

Smart Appliances

Similar to HVAC systems, large household appliances contribute significantly (approximately 30%) to electricity use [59]; thus, efficiency of these appliances is important. These appliances are found in most (dishwashers, washers, dryers, microwave) and nearly all (refrigerator, water heater, stove/oven) residential buildings (US EIA 2009). Significant improvements in energy efficiency have been made to these large appliances in recent years due to programs such as EnergyStar and mandatory government efficiency requirements. Replacement of old, inefficient appliance has also been encouraged through utility-sponsored rebate programs. Smart appliances, like smart thermostats, are able to connect to the electric grid via internet or radio-smart meter. These appliances can turn off, delay start, or pause, based on signals from utility companies or third party providers. Commercially available smart appliances are have just recently become available; thus, adoption is limited currently. As appliances are high cost items for a building owner, likely adoption rate will be driven by replacement cycles in which future appliances are, by default, smart and grid-connected.

Recent smart appliance research has focused on both (a) developing methodologies for the scheduling of smart appliances for demand response events and based on electricity pricing schemes [60–62] and (b) evaluation of the peak load reduction and potential energy and cost savings that can be achieved through the use of smart, grid-connected appliances [63–69]. Those studies have shown approximately 20% energy savings and 9–31% peak demand reduction.

Internet of Things

In addition to smart thermostats and appliances, the Internet of Things (IoT), while still in its infancy, is another set of devices that could have an impact on electricity use and demand. The IoT includes everyday objects that have network connectivity, allowing them to send and receive data through different communication protocols such as those discussed in Ahmad et al. (2016) [70]. In the building sector, the most significant application of these devices has been in their use for "smart" homes, i.e., residential buildings that have connected devices to monitor and control a building's performance and use. The number of companies and devices that have been commercialized in recent years has increased significantly. Recent market studies project 21% CAGR growth by 2020 [71], or a total of 38 billion devices [72]. For commercial buildings, a recent survey of 400 commercial and industrial building leaders found that IoT and building maintenance strategies are starting to converge [73]. Facility professionals are beginning to want to deploy advanced building technologies with IoT that can take advantage of the big datasets from buildings, with the goal of more self-aware, self-diagnosed, and self-calibrated buildings.

Some of these devices have applications in energy savings and improved thermal comfort, and others for use in applications such as building security, automation, and convenience. Cetin and Kallus [74] reviewed some of the IoT devices that can be used for data collection to inform building energy performance analysis and modeling, categorized based on the data and information they can collect. As discussed in Hong et al. [75•], gathering this information is the next frontier in sustainable design. Improvements to IoT sensors, their accuracy, and type of information collected had led to research progress in the monitoring of occupant movement and thermal comfort, as well as the monitoring, automation, and control of devices such as window shades, lighting, and electrical equipment. While various devices that accomplish similar goals have existed for some time, the advances in wireless communication, small electronics, and data storage have enabled this field to develop quickly.

Conclusions and Future Research Needs

While significantly more research has been conducted in recent years using smart devices in buildings, many more opportunities still remain to take advantage of the benefits of this relatively newly available data and connectivity.

(1) First is to compare energy use patterns and energy and peak load reduction of proposed methods, models and devices across countries and climate zones. Studies of smart meter and other smart device data have been conducted in recent years generally in a specific region. However, there are no

recent studies that compare the findings of these different researched areas together to determine if the models and conclusions developed in one location are applicable to others. Also, as pointed out by Davis et al. [52], it is challenging to compare the results of recent studies to each other. In some cases, there are biases that may affect the applicability and usability of the results. Thus, a standard methodology may be merited.

(2) Second, the frequency and quality of data from smart meters and other devices cited in recent research efforts vary significantly. The frequency ranges from subsecond level to monthly use. Most studies develop models based on one frequency of data; however, there is limited study of what frequency of data is really needed to develop meaningful insights, or a comparison of the level of information that can be obtained depending on the level of frequency of data available. While most smart meters deployed today collect data on a 15-min-to-hourly frequency, it is possible that in future years this data will be higher frequency. At higher frequencies, recent studies have raised security concerns over this data (e.g., Greveler et al. [76]), thus determining a balance of privacy and application is needed [76, 77].

(3) Third is the quality of data. In some cases, there are errors and gaps in data [22] that must be addressed, particularly with large datasets or when datasets are merged together. How to better utilize and manage the big data generated from smart meters and other devices is a significant challenge and could overwhelm the existing resources. Smart meter data analytics includes data ingestion, pre-processing, analyzing, and visualization [26]. Some initial research has been conducted to attempt to streamline smart meter data analytics [26]; however, more is needed to determine the frequency of data is ideal for the insights desired and how to streamline this process.

(4) Fourth is the application of insights of smart meter and other smart device equipped buildings to those without smart meters with more limited data. While there are many buildings that do have smart meters, but many also that do not, but could still benefit from insights from the limited data available. Some initial research has been done in this area [78]; however, more is merited.

(5) Fifth is the application of smart meter data analysis to other building types. Most of the research has focused on residential buildings. Commercial buildings are equally responsible for energy demands and could also benefit from parallel studies. Industrial facilities also play a part in energy consumption and also merit study [78, 79].

(6) Sixth is that with now a more substantial number of years of energy data available from smart meters and increasingly large datasets from other smart devices, the research community could also benefit from the study of longer periods of data to determine if use patterns of energy use change over time, and the causes for these changes such as change in energy behaviors, potential faults or other energy inefficiencies that could be identified with this data. As this data has only become available in recent years for study, there is now multiple years worth of data available for study and data analysis that makes this data more valuable.

(7) Seventh is the development of insights which take advantage of the data from multiple smart devices. Combined, multiple sets of data have the advantage of being able to check each others' assumptions and conclusions and build off of each other to develop deeper energy insights.

(8) Finally, there is opportunity in collaboration in parallel but currently separately operating fields of researchers. The study of smart meters, their data, and their use for various applications generally lies in electrical and computer engineering with experts in signal analysis; data processing and algorithm development; and the mechanical, civil, and architectural engineering, with experts in building science, building systems, and energy performance. With each domain of researchers focusing on similar areas, these two domains of researchers could benefit from collaboration and discussions to merge the knowledge bases together.

Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

Human and Animal Rights and Informed Consent This article does not contain any studies with human or animal subjects performed by any of the authors.

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