Intelligent Buildings of the Future

Cyberaware, Deep Learning Powered, and Human Interacting

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Intelligent buildings are quickly becoming cohesive and integral inhabitants of cyber-physical ecosystems. Modern buildings adapt to internal and external elements and thrive on ever-increasing data sources, such as ubiquitous smart devices and sensors, while mimicking various approaches previously known in software, hardware, and bioinspired systems. This article provides an overview of intelligent buildings of the future from a range of perspectives. It discusses everything from the prospects of U.S. and world energy consumption to insights into the future of intelligent buildings based on the latest technological advancements in U.S. industry and government.

U.S. and World Energy Consumption Predictions

The U.S. Department of Energy's (DOE's) Energy Information Administration (EIA) estimates the share of total U.S. electricity use by major consuming sectors in 2014 as follows: residential, 36%; commercial, 35%; and industrial, 28% (Figure 1) [1], [2]. In U.S. homes, the single largest use of electricity is for air-conditioning (cooling), followed by about 40% of electricity use by washers, dryers,

Digital Object Identifier 10.1109/MIE.2016.2615575
Date of publication: 21 December 2016

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Buildings consume 70% of the total electricity generated and 50% of total natural gas production in the United States.

and other appliances. In the commercial sector, lighting accounts for about 19% of energy usage and is the single largest user of electricity. This is because lighting includes office, institutional, public, and government buildings as well as public street lighting. Space and water heating (10%), space cooling (11%), and ventilation (6%) together make up 27% of all electricity used. While electricity use is projected to grow slowly, efficiency improvements and new appliance standards are expected to contribute to slower future growth. The EIA's "Annual Energy Outlook 2015" projected a total U.S. electricity use growth of less than 1% per year from 2014 to 2040 [1].

On the world level, the EIA, in its "International Energy Outlook 2013," projected that world energy consumption would increase 56% between 2010 and 2040, from 524 quadrillion to 820 quadrillion British thermal units [3]. Most of this growth will come from non–Organization for Economic Cooperation and Development countries, where demand is driven by strong economic growth. Renewable energy and nuclear power are the world's fastest-growing energy sources, each increasing 2.5% per year. However, fossil fuels are expected to continue to supply nearly 80% of the world's energy through 2040. Natural gas is the fastest-growing fossil fuel, as global supplies of tight gas, shale gas, and coal-bed methane increase.

The industrial sector continues to account for the largest share of delivered energy consumption and is projected to consume more than half of global delivered energy in 2040. Based on current policies and regulations governing fossil fuel use, global energy-related carbon dioxide emissions are projected to rise to 45 billion metric tons in 2040, a 46% increase from 2010. Economic growth in developing nations, fueled by a continued reliance on fossil fuels, accounts for most of the emissions increases.

Buildings consume 70% of the total electricity generated and 50% of total natural gas production in the United States [4]. Hence, the potential impact of increasing energy efficiency, while continuing to meet customer needs and comfort levels and simultaneously supporting grid operations, is substantial.

Smart Grids and Smart Homes

The concept of smart buildings, while typically referring to smart homes, can be easily extended to all types of buildings (residential, commercial, and industrial)—in other words, smart cities (Figure 2). The American Recovery and Reinvestment Act of 2009 (Recovery Act), cited by the DOE, Office of Electricity Delivery and Energy Reliability (OE), provided the DOE with US$4.5 billion to modernize the electric power grid and implement Title XIII of the Energy Independence and Security Act of 2007. The DOE OE was given the lead for modernizing the more-than-a-century-old U.S. electric grid that currently consists of more than 9,200 electricity-generating units, with over 1 million MW of generating capacity connected to more than 300,000 mi of transmission lines.

The concept of the original one-way communication and localized-generation-to-home

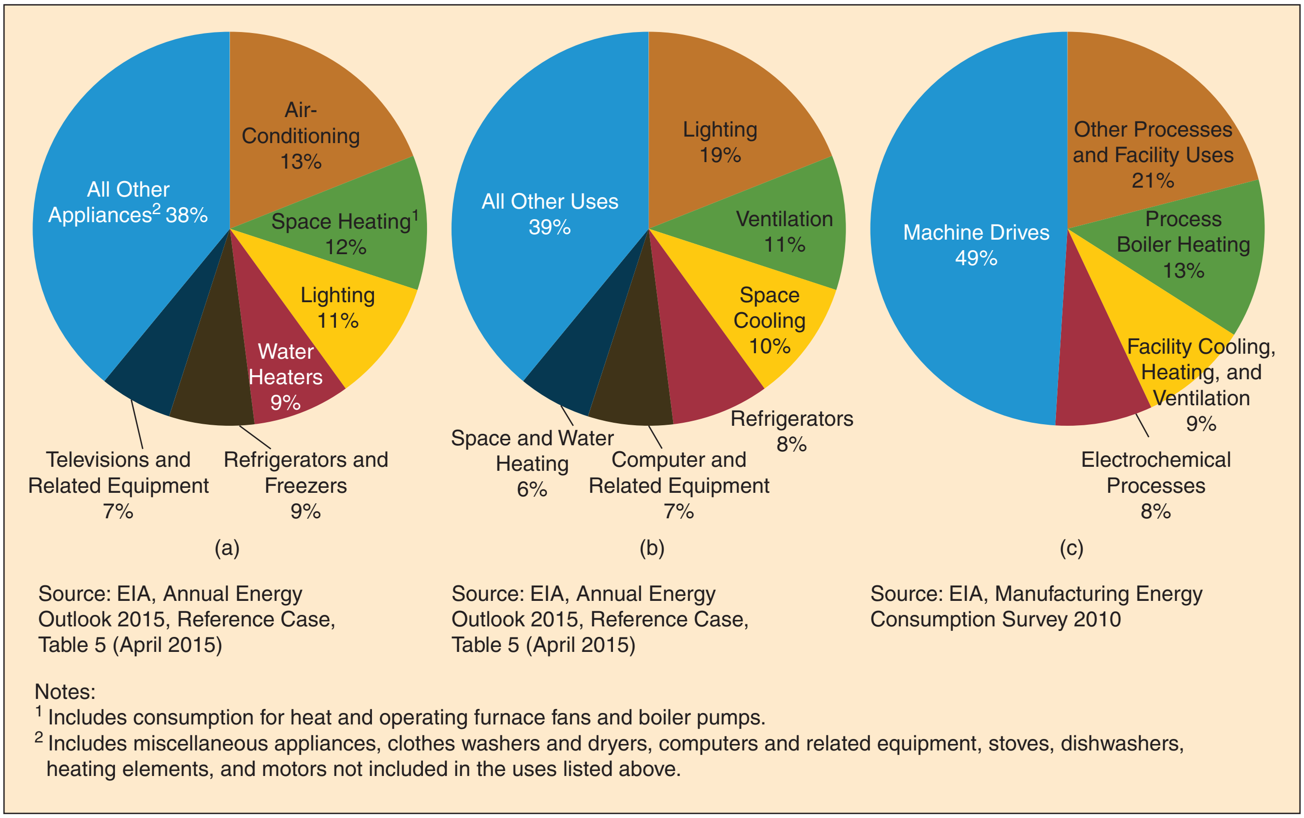

FIGURE 1 – U.S. electricity consumption in 2014 in the (a) residential, (b) commercial, and (c) manufacturing sectors [1]. (Courtesy of EIA.)

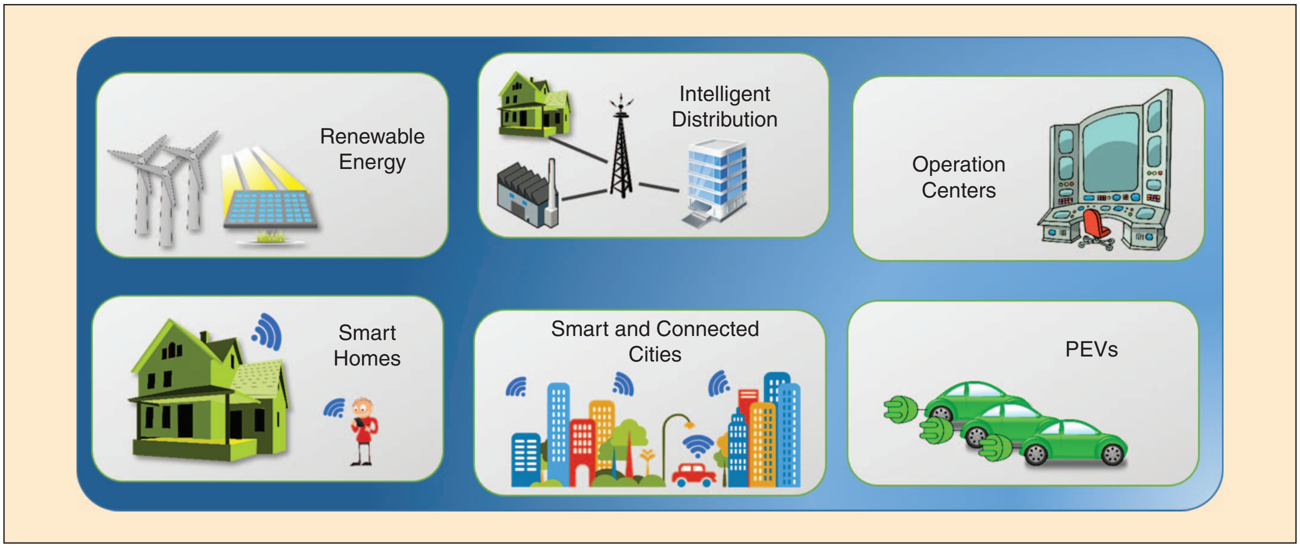

FIGURE 2 – A smart grid. (Images courtesy of and adapted from SmartGrid.gov.)

communication concept has evolved toward two-way electricity and information exchange between utilities and their customers, offering unprecedented levels of consumer participation and thus creating the essence of the modern smart grid. The developing symbiosis of communications, controls, and automation makes the grid more efficient, secure, reliable, and green, according to SmartGrid.gov, a DOE information gateway. One of the pivotal ideas of the smart grid paradigm is distributed generation, with microgrids relying on typically renewable energy sources such as hydro, biomass, solar, wind, and geothermal, the concept enabling autonomous power generation and usage. The *distribution intelligence* (a term coined by the DOE OE) enables intelligent and automatic controls leading to self-healing and resilience to both malicious and benign failures. Buildings, estimated to be responsible for about 40% of all energy used in the United States, play a pivotal role in smart grids.

Interactiveness of Buildings and Smart Grids

One of the key elements of smart grid technologies is the interactive relationship between grid operators, utilities, and consumers. Smart grids can be viewed as interconnected resources and consumers of energy, with buildings as major entities of the equation [mainly because of central heating ventilation and air-conditioning (HVAC) and lighting]. Hence, buildings play roles in both energy usage and as energy generation entities (with storage capabilities). Through interaction with smart grids, smart buildings (as building blocks of smart cities [5], [6]) can perform load reduction and peak shaving (reducing demand for electricity during peak usage times) and load shifting, and can reduce blackouts (total loss of power) and brownouts (voltage drops). The concept of islanding in microgrids can be reduced to the level of buildings, where one or several of them can share distributed resources frequently integrated with distributed energy storage systems. Examples of distributed resources can entail renewables (such as rooftop solar, small turbine/wind, and hydro projects) and lately natural gas-based home fuel-cell systems, whereas distributed energy storage systems for buildings entail water tanks. VionX Energy, a US$12 million DOE National Energy Technology Laboratory project scheduled to be completed in 2018, aims at demonstrating competitively priced, multimegawatt, 6–10-h operation, 20-year operation lifetime vanadium redox battery energy storage systems [7]. Johnson Controls L1000 In-Building Distributed Energy Storage System features 40–65-kWh storage capacity increments of lithium-ion (Li-ion) cylindrical batteries with 20-year life expectancy [8]. Another aspect of distributed load and generation are plug-in electric vehicles (PEVs). In the future, PEVs will serve as distributed sources of stored energy that can put power back into the grid, a concept called *vehicle to grid* [9]. As mobile energy storage devices, PEVs have the potential to inject additional power into the grid at critical peak times and also to help integrate variable renewable power sources into the grid, which with adequate financial incentives can accelerate their market penetration.

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Connectivity (Smart = Connected + Analytics)

Another key concept of smart buildings is connectivity. In fact, in a context of smart buildings and smart devices, the words *smart* and *connected* are being frequently and interchangeably used to denote Internet of Things (IoT) devices. However, certain distinctions need to be made. The meaning of connected is typically reflected by the ability of buildings to communicate with other buildings, with the grid (for reasons of scheduling, islanding, and peak shaving), with utilities, with energy storage units (water tanks for hot or cold energy storage and batteries), with occupants (through comfort input by means of light, air, heat, and cooling controls), with other smart devices (thermostats and sensors), and so on. In other words, for the unit to be smart, it needs to be connected (e.g., a thermostat needs to know about its environment through an outside weather station or in-home usage patterns from sensors). On the other hand, connected does not necessarily imply smart. For example, the motion sensor may not be smart even though it is connected to the thermostat, but the thermostat has to be connected for it to deploy learning and prediction algorithms. Remote access alone does not imply smart aspects of devices.

IoT devices feature intelligent algorithms and are constantly increasing in local processing power. They operate interactively and autonomously while being wirelessly networked with other such devices or connected to the Internet directly. Sometimes simply referred to as *things* (Samsung's home monitoring kits are aptly named *SmartThings*), they are quickly entering the consumer world. Gartner Analytics predicts a 30% increase of such connected things from 2015 to 2016 or about 6.4 billion connected things and 21 billion things by 2020 (Figure 3).

HVAC and lighting systems, the largest energy consumers in buildings, are being highly modernized through the penetration of IoT devices. The key issue here is extracting knowledge from monitoring building energy and automation systems—in terms of what a particular machine or appliance is doing at what time. IoT devices provide quantitative measurements of the processes they are involved in, which in turn generate data streams that have not existed before. The need for big data hence arises to process and analyze large amounts of unstructured data and make predictions of future behavior.

The concept of smart appliances is based on several attractive features: convenience (e.g., remote control and monitoring via smartphones and tablets), intelligent automation and control (autonomous, intelligent learning and prediction of user behavior patterns, and smart scheduling), and the ability to control and improve energy efficiency. Connectivity is the underlying characteristic of IoT devices, such as connected coffee machines, beds, ranges, refrigerators, and frying pans. For example, Wi-Fi touchscreen smart refrigerators can sync across family calendars, perform smart inventory via integrated cameras that detect food expiration dates, notify users of food that needs restocking, and even automatically place orders for such food. While such products by General Electric, Whirlpool, Lucky Goldstar,

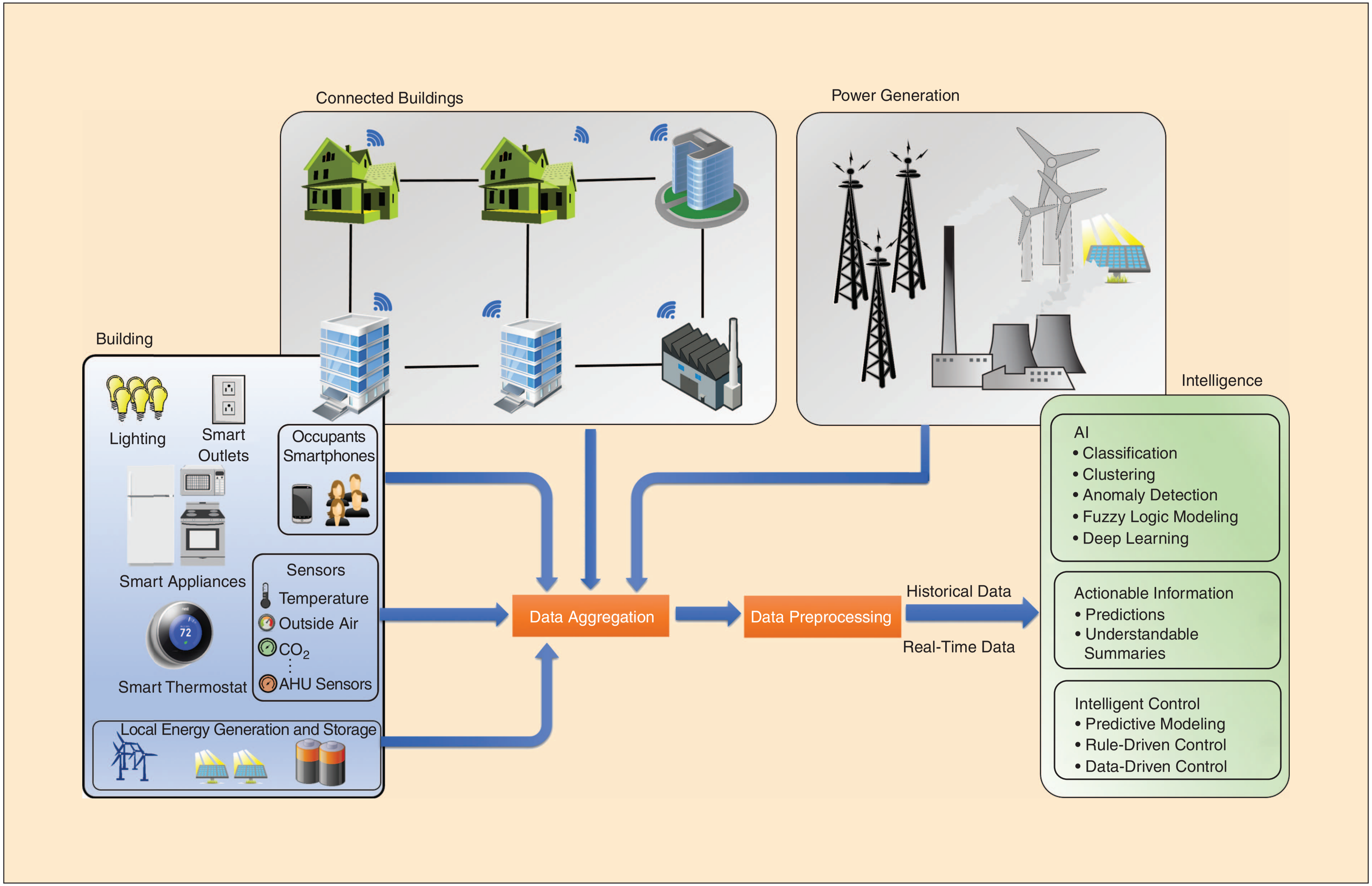

FIGURE 3 – Smart = Connected + Analytics. FL: fuzzy logic.

Nest, Samsung, Sleep Number, and others improve quality of life and personal health, one of the major benefits is energy efficiency, energy savings, and peak shaving, starting with such simple tasks as deferring refrigerator defrost cycles or dishwasher and laundry deferral until off-peak hours [10], [11].

The sky is the limit when it comes to energy efficiency and smart devices today. Windows, doors, and skylights can gain and lose heat through conduction (U-factor) or radiation (solar heat gain coefficient). In 1990 alone, the energy used to offset unwanted heat losses and gains through windows in residential and commercial buildings cost the United States US$20 billion (one-fourth of all the energy used for space heating and cooling) [12]. Smart windows, smart glass, or switchable glass use the technology called *suspended particle devices* (SPDs) [13], adjusting ac voltage to the SPD film to quickly control the amount of light, glare, and heat passing through windows. Rayno windows use the polymer-dispersed liquid crystal technology, which combines polymers and liquid crystal materials to control transparency [14], [15]. Besides their use for energy efficiency, these technologies can be used in smart buildings for instant privacy, to eliminate the need for curtains, to filter ultraviolet rays, or as a rear-projection surface for theaters or high-profile corporate and retail displays.

Various manufacturers provide automation and energy-efficiency controls. Companies like Lutron, Honeywell, and Johnson Controls provide solutions ranging from commercial smart grid, whole building, and residential solutions for energy efficiency. Lutron's Quantum lighting control and energy management system offers "a smart decision for any building owner" in terms of scheduling of lights and lowering shades for energy savings and also for the comfort, safety, and security of occupants. Quantum and EcoSystem solutions enable shedding of a percentage of a building's lighting output during peak demand, instantly saving energy. The solutions also provide control, configuration, monitoring, and reporting on the lighting for any space in a building for maximum energy efficiency, comfort, and productivity [16].

The developing symbiosis of communications, controls, and automation makes the grid more efficient, secure, reliable, and green.

An example of such concepts is so-called *daylight autonomy*, a sustainable concept driven by Lutron that adapts to its environment and claims reducing daytime lighting energy use by 65% or more through the use of automated shades [16]. Designing for daylight autonomy involves understanding how the entire building is affected by the dynamic nature of daylight and creating a lighting control strategy to automatically adjust to these changes.

Security and Resilience of Intelligent Buildings

If intelligent buildings are the future, then so too are cyberthreats to building services [17]. According to Grand View Research, a San Francisco–based consulting firm, the intelligent building automation technologies market is expected to reach US$98.95 billion by 2024 [18]. The technology is expected to grow rapidly due to benefits such as increased energy efficiency, occupant comfort, and productivity as well as seamless operation of HVAC, electricity, lighting, and other systems. Furthermore, the increasing demand for security and life safety systems (e.g., systems that indicate the presence of fire) in education, hospitality, and large commercial complexes is expected to give a boost to the adoption of intelligent buildings automation.

Modern buildings heavily rely on several advantageous concepts: interoperability, connectivity, cloud services, remote monitoring and control, or programmable logic controllers. At the heart of all these are the communications among sensors, hubs, and numerous smart devices, whether small (e.g., coffee machines, power outlets, and smart locks) or large (e.g., large energy storage batteries and electric cars). As highly integrated as they are, such systems run high exposure risks. The same information flow that enables users and managers of large building complexes and residential home users to monitor and control smart buildings can, if compromised, give attackers unprecedented power to interact with devices and gain insight into behavioral patterns. For example, monitoring occupancy sensors can tell when a person leaves home, controlling cameras can provide ways for unlawful surveillance and invasion of privacy, and worse, usurping control power can remotely enable structural and material damage or even loss of life (in the case of critical infrastructure).

In the world of home automation, the security research firm Veracode in April 2015 published its security study on four different manufacturers of IoT devices, evaluating simple features such as the encryption of transmission between devices and back-end cloud services (Figure 4). The study revealed potential vulnerabilities, such as the nonexistence of two-factor authentication on any of the investigated platforms. In addition to potential software exploitation, such devices suffer from hardware security issues. Through physical access (a universal-serial-bus boot), an attacker can gain root access, as shown in 2014 [19]. Similarly, Fernandes et al. published in May 2016 two intrinsic design flaws in Samsung's SmartThings: 55% of apps were overprivileged (given excessive access to a system), and there were insufficient sensitive information protections [56].

On the enterprise level, the risks grow higher. One simple problem is the introduction of new IoT devices into a network. Data exfiltration through any device with built-in

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network connectivity creates a risk and requires constant monitoring of approved communications (e.g., if a smart refrigerator connects to the payment card zone) [20]. Another issue involves exposed undocumented application programming interfaces, device software that gives itself too many permissions, insuring that the network can properly handle influxes in the volume of data. An additional issue is the legality of storing IoT data [21].

In 2012, the U.S. Federal Bureau of Investigation reported a memo on the illegal hack into the heating and air-conditioning system of a New Jersey–based company. Widely reported security vulnerabilities in the Niagara Framework, a prevalent building automation software platform developed by Tridium Inc., a business entity of Honeywell International Inc., allowed the hack to occur, and it was serious enough to warrant a Department of Homeland Security alert [22].

Solutions in this area need to take into account various approaches. One is increasing resilience by segmentation of the network of connected devices (limiting the exposure), coupled with the use of strong user/password combinations. Cloud-hosted systems relieve customers of the burden of securing sensitive data and web services. Geographically separated redundancy increases resilience in case of catastrophic events at data centers in one location. Cloud services must include multifactor authentication via various proofs of identity—something that users know, through a password; something they possess, as with a phone; and something inherent to them, as with fingerprints [23]. In addition to the best cybersecurity practices being made an integral part of the deployment of equipment and training for building managers, contingency plans should be drawn up for periods during which intelligence is not available (known as *plan for the worst*). To maintain minimum acceptable levels of service, hardwired hardware may be a necessary cost for the resilience of mission-critical building automation systems, even at a cost of sacrificing the intelligent part of the automation [17].

Resilience—a system's ability to bounce back after malicious or benign failures or, from a business perspective, the ability to maintain continuity of business operations—assumes an intelligent response that goes beyond fault tolerance and is inextricably linked with cybersecurity [24]. The data-driven techniques overviewed in the following, sometimes referred to as *bio-inspired*, *self-healing*, and *reconfiguring*, represent an integral component of resilience. The interactiveness and interoperability of modern buildings, along with the ubiquitous IoT devices that generate large data streams, also bring bioinspired data mining and data analytics into the purview of resilience in the domain of intelligent buildings.

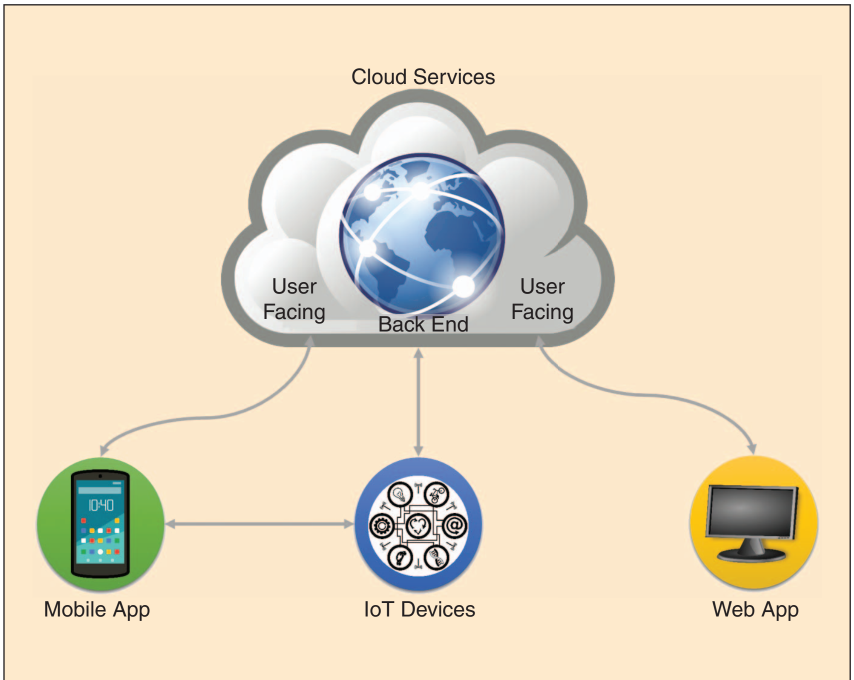

FIGURE 4 – The security of the IoT involves web and mobile applications and devices themselves [55]. (Courtesy of and adapted from the Veracode white paper 2015.)

Artificial Intelligence in Buildings

The Need for Intelligence

Due to the interactive, adaptive, and interconnected nature of buildings, their components, and outside environments, modern buildings must be capable of negotiating constantly changing scenarios. Continuous communications among smart hubs, sensors, and appliances within buildings as well as communications among smart meters, renewable energy generators, storage units, and utilities generate massive, heterogeneous data sets about every aspect of their operations. These big data sets require increasingly automated and adaptive approaches to information processing and real-time decision making.

Artificial intelligence (AI) and machine learning (ML) techniques exhibit proven capabilities for learning from heterogeneous data sets [25]. Such techniques can identify patterns or trends that exist in data and extract crucial performance knowledge, make accurate predictions of future system states, and identify anomalous scenarios that may lead to suboptimal behavior due to benign or malicious faults. These approaches can be effectively used for tasks ranging from building energy management and energy efficiency, self-healing, and adaptation to the security, information assurance, and resiliency of such systems.

Data exfiltration through any device with built-in network connectivity creates a risk and requires constant monitoring of approved communications.

Brief Overview of AI

AI and ML encompass a multitude of algorithms and techniques. Traditional techniques such as logistic regression, artificial neural networks (ANNs), fuzzy logic systems (FLSs) (Figure 5), support vector machines (SVMs), and different Bayesian probabilistic models are well-documented methods and have been extensively used in a wide array of domains for learning patterns and trends in data. Recently, the advent of deep learning revamped the field of AI by introducing algorithms that had an unprecedented capability to handle complex data. Deep learning has revolutionized a multitude of fields, such as speech recognition, natural language processing, and computer vision applications such as face recognition.

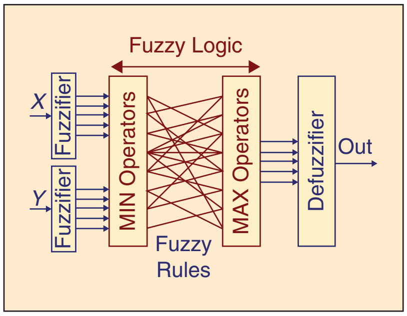

FIGURE 5 – FLS [35].

Deep learning extends the capabilities of standard ANNs by enabling architectures of many layers. Therefore, deep learning enables learning of complex patterns that exist in data through multiple layers of abstraction. The modern development of deep learning and its recent widespread use have naturally inclined researchers to investigate its effectiveness in the domain of intelligent buildings. The capability of learning complex patterns using the multilayered architecture enables deep learning algorithms to extract patterns and trends from growing and diverse data streams of intelligent buildings of the future. Therefore, through the effective use of deep learning, the capability of learning from data is augmented and hence intelligent decision making for optimizing energy efficiency is improved.

This section provides a very brief introduction to traditional ANNs and several deep learning architectures: convolutional neural networks (CNNs), long short-term memory (LSTM), and restricted Boltzmann machines (RBMs). These algorithms are selected since they are relevant to the concrete application and case study discussed in the next sections. However, it should be noted that there are more deep learning and traditional AI algorithms that can be used in building energy systems. Readers are referred to [26] for a comprehensive review of deep learning techniques and methodologies.

ANNs are AI architectures based on biological neural networks (see Figure 6). As in the latter, the basic unit of an ANN is a neuron. A biological neuron produces an output by comparing a weighted sum of inputs to a

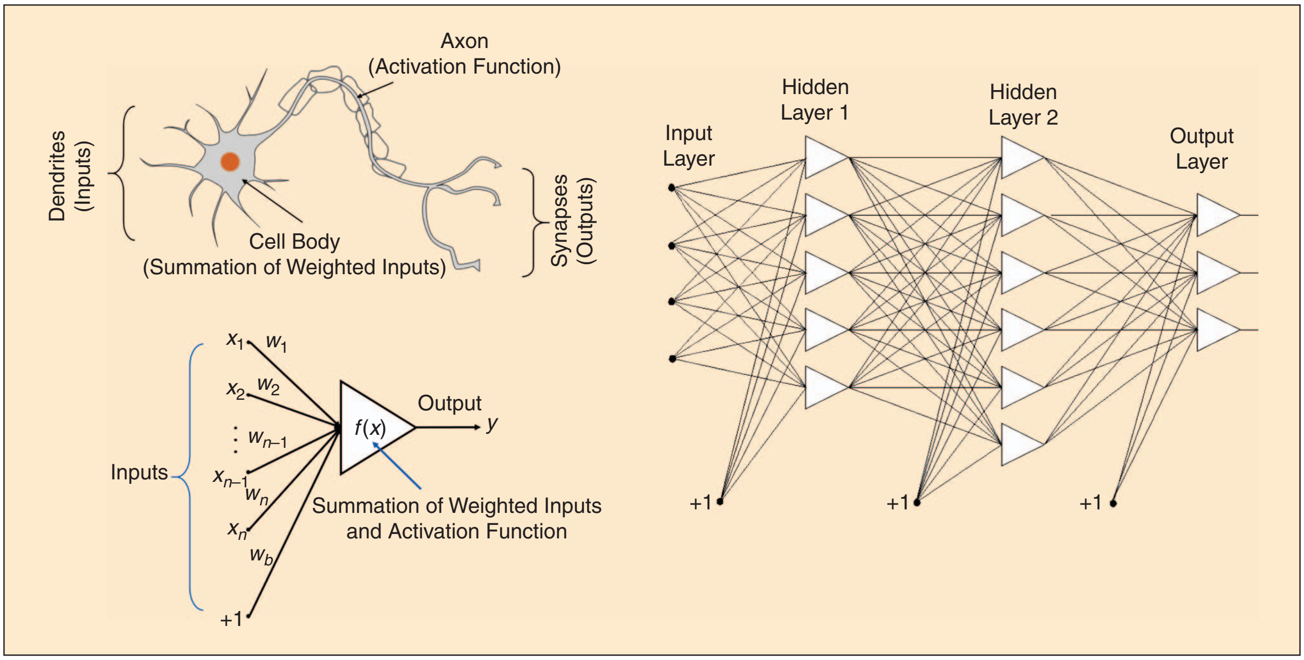

FIGURE 6 – An ANN architecture [35].

threshold. The artificial neuron mimics the biological neuron through a similar methodology of using weights and a threshold value to produce an output for a given input vector [27]. An interconnected layered network of such neurons is arranged to produce an output vector given an input vector. This interconnected network has the capability of learning the interdependencies between the inputs and outputs. Thus, a well-trained ANN has the capability of accurately estimating the outputs for inputs it has not seen in the past. ANNs are well documented and proven for being useful in many applications.

CNNs are a special type of neural network and are mainly used to process data with grid topology (Figure 7) [29]. The CNN learning process is a great example of how deep learning algorithms learn through layers of abstraction. As with ANNs, CNNs are biologically inspired; they attempt to mimic the biological visual cortex. CNNs possess a layered architecture where different layers can be trained to detect different features in data (e.g., edge detection in an image). Therefore, in a collection of layers, each of them will learn the existence of a different feature. Hence, when put together, CNN layers have the capability of learning very complex patterns and trends in data. Figure 7 shows the architecture of a standard CNN. CNNs have been shown to be extremely useful in fields such as computer vision, image classification, and time series data modeling.

LSTMs and RBMs are increasingly used in the literature as generative deep learning algorithms. LSTM algorithms, introduced by Hochreiter and Schmidhuber [30], are a type of recurrent neural network (RNN) composed of memory cells with self-connections. Figure 8 shows an LSTM architecture with multiple LSTM cells. These can be stacked in a multilayer architecture to create a deep network. LSTMs have been shown to be extremely useful in generative models, especially in the natural language processing domain. RBMs [31] are shallow two-layer neural networks. The first layer of an RBM is called the *visible layer*, and the second is the *hidden layer*. RBMs can learn features that exist in data in an unsupervised fashion. Therefore, they do not need preannotated data to learn the features. RBMs are the building blocks of deep belief networks (DBNs) [32] and have been used in a range of domains, including image processing and time series data modeling.

Concrete Application of AI: Deep Learning–Based Load/Demand Forecasting for Buildings

Load/demand forecasting is predicting the energy consumption of an individual building or an aggregate, such as a city or a county, for a future time step. Accurate load forecasts are extremely beneficial for decision making at the grid level as well as at the individual building level [33]. Modern building design is heading in a direction to incorporate energy storage devices, such as thermal energy storage tanks [34], and/or renewable energy generators, such as photovoltaics or windmills. Thus, smart buildings will have to make decisions on what proportions of utility energy, stored energy, and locally generated energy to use to attain optimal energy efficiency [35]. Therefore, at the building level, accurate energy load forecasting helps make building-level decisions, such as optimal local energy storage control [34] or renewable energy control. From a grid perspective, smart grids have to optimally utilize the various energy sources, including renewables [36]. Smart grids promise an unprecedented level of flexibility in energy management, making power generation and distribution more efficient and minimizing energy waste [33], [38], [39]. Therefore, at the grid level, accurate future predictions of individual demand help the grid adapt to the variable demand, and having individual building-level energy forecasting helps the grid carry out the demand response locally [33]. In other words, local demand can be met with local distribution, which leads to more efficient energy transmission and distribution. Therefore, it can be seen that demand prediction can be discussed from an aggregate standpoint and an

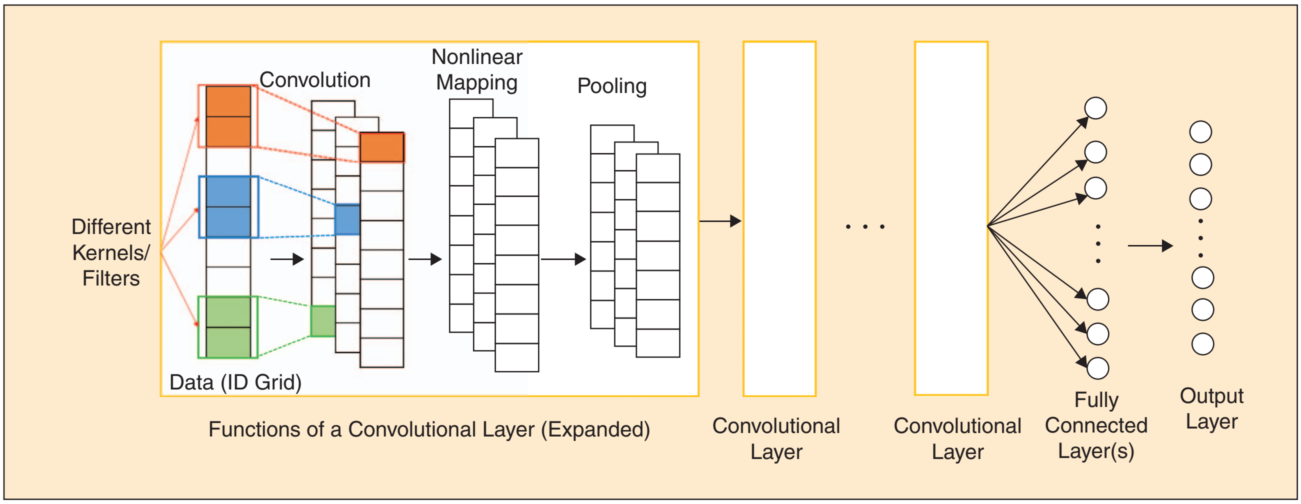

FIGURE 7 – A CNN architecture [28].

individual standpoint. However, in the interest of brevity and of remaining consistent with the theme of this article, the discussion in this section is focused on recent developments in building-level load forecasting.

Load forecasting can be classified into three classes: 1) short-term load forecasting, 2) medium-term load forecasting, and 3) long-term load forecasting [33], [39]. Regardless of the type of forecasting, to accurately predict energy consumption, the forecasting methodology should be able to accurately model the dependencies between building factors and energy consumption. Research has shown that load forecasting is an extremely difficult problem [33], [40]. Hence, a range of methods—physics principles-based and statistics and AI based—have been proposed in the literature. This article focuses on the recent advancements in AI-based building-level load forecasting.

One of the most recent advances in building-level load forecasting has been the introduction of deep learning into the domain. Several recent efforts exist in the literature that investigate and prove the effectiveness of using deep learning techniques over traditional techniques. Mocanu et al. tested two variations of the RBM: the factored conditional RBM (FCRBM) and the conditional RBM (CRBM) [33]. In the study, the CRBM and the FCRBM were compared to the ANN, SVM, and RNN. The authors concluded that the FCRBM outperforms all the other methods.

In another study, DBNs, which are architectures built with layered RBMs, were used for electricity load forecasting by Dedinec et al. [41]. The authors concluded that the DBN-based method outperforms traditional ANNs. Qiu et al. used an ensemble of DBNs coupled with a traditional SVM-based regression technique [42]. The authors showed that the presented ensemble DBN method outperforms methods such as ANN, SVM, and even single DBN for the data set it was tested on. Therefore, it can be seen that deep learning techniques have shown promise in improving the performance of load-forecasting methodologies and hence have

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the potential of having a significant impact on the smart grids, smart homes, and smart cities of tomorrow. Next, we look at a case study conducted by the authors to compare the performance of deep learning techniques.

Case Study: Comparison of Deep Learning Algorithms for Demand Forecasting in Buildings

As mentioned, deep learning methodologies have been shown to be beneficial in the domain of building-level demand forecasting. However, the published studies lack comparative analyses among deep learning techniques. The presented case study discusses the work conducted by the authors to bridge that gap. In this work, we discuss the effectiveness of deep learning-based demand forecasting using three deep learning architectures implemented on the same data set. The architectures were:

- the standard LSTM-based load forecasting architecture
- the LSTM-based Sequence-to-Sequence architecture (LSTM S2S)
- the CNN-based architecture.

All three architectures were tested on a benchmark data set for a single residential energy consumer. The same data set that was used in [33] was used in the study so that the three tested architectures could be compared to the FCRBM method. Furthermore, to keep the tests uniform, the same training and testing data were used as in [33].

Data Set

The data set contains electrical consumption data for a single residential customer [43]. The data set is composed of electrical consumption data for a residential building for four years (December 2006–November 2010). The study was conducted on 1-h-resolution data. For all three architectures, the first three years were used as the training data and the last year was used as testing data. For all the architectures, the electricity consumption for the next 60 h was predicted.

Figure 9(a)–(c) illustrates the variability present in the data set. Figure 9(a) shows the monthly energy consumption across the four years. Note that the energy consumption toward the middle of the year is less than the consumption at the start and the end. Figure 9(b) depicts the

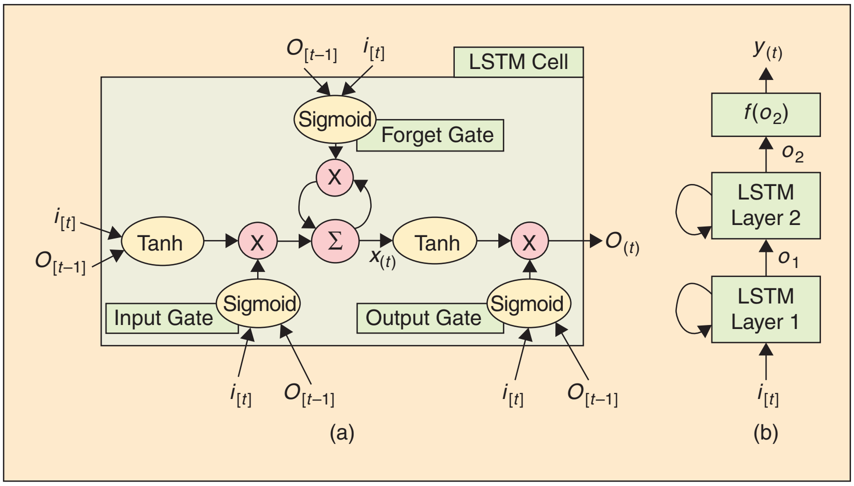

FIGURE 8 – (a) An LSTM cell and (b) a multilayer LSTM network [39].

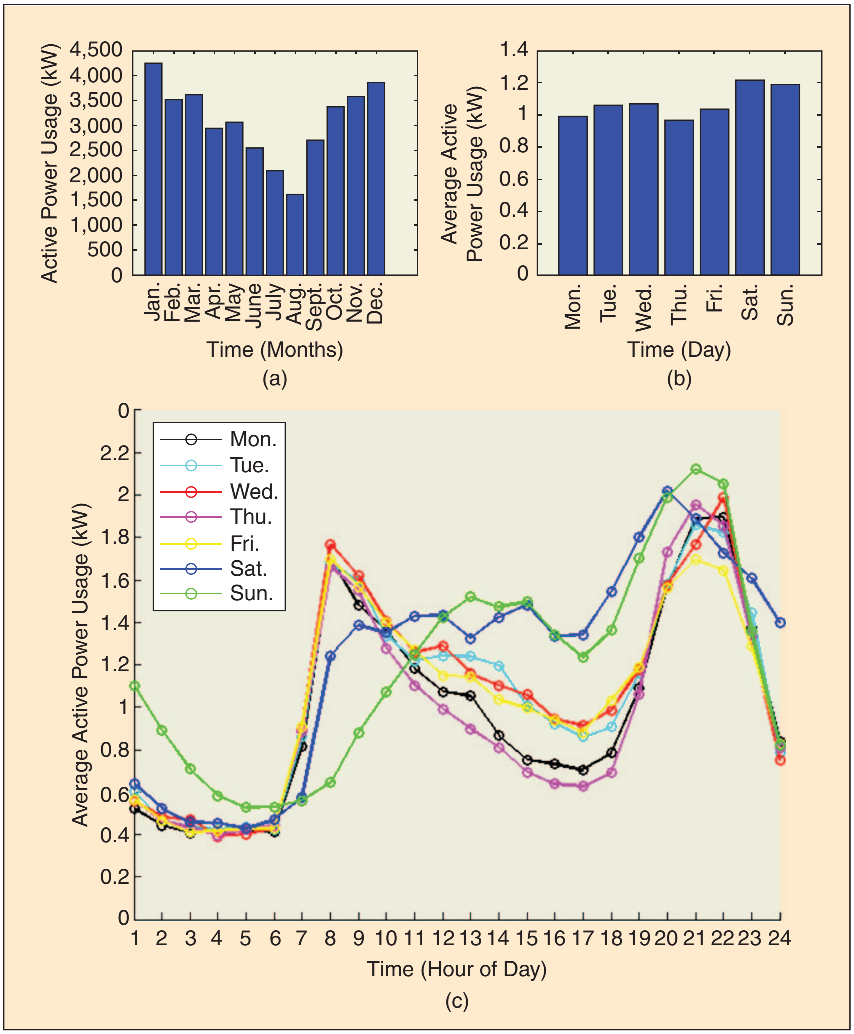

FIGURE 9 – (a) The monthly energy use [46]. (b) The energy use per day of the week [46]. (c) The change in energy use per hour per day of the week [46].

TABLE 1 – THE TIME STAMP INPUTS FOR THE DEEP LEARNING ALGORITHMS.

INPUT VARIABLE	DESCRIPTION	VALUES
Hour of the day	Hour of the day for the first prediction	[1, 24]
Month	Month of the first prediction	[1, 12]
Day of the week	Day of the week for the first prediction	[1, 7]
Day of the month	Day of the month for the first prediction	[1, 31]
Weekend flag	Flag that is set if the day of the first prediction is a weekend	[0, 1]

average energy consumption across the seven days of the week. It can be seen that the weekend has higher energy consumption compared to the weekdays. Figure 9(c) illustrates the variability of energy use across the hours of the day for the seven days of the week. A significant variance in use across the 24 h can be seen. Furthermore, it shows that the weekdays show a similar use pattern while weekends are different.

Standard LSTM-Based Load Forecasting

The standard LSTM algorithm was used as the first architecture to perform the building-level electricity load forecast. The electrical consumption of the previous step and time stamp data are fed into the model. Table 1 lists the time stamp data used as inputs to all three models. The output from the LSTM network is the predicted power consumption for the next time step. To predict further into the future, the prediction of the next time step can be used. The model is trained using the standard backpropagation through time (BPTT) method [44] with gradient descent. For the elaborated methodology, readers are referred to [39].

LSTM-Based S2S Architecture for Load Forecasting

S2S architectures for neural networks were proposed by Sutskever et al. [45] as a method of mapping sequences of arbitrary lengths. The LSTM S2S architecture for load forecasting contains two standard LSTM networks, namely, the encoder and decoder. The objective of the encoder is to convert input sequences of variable length into a predefined, fixed-length vector. This fixed-length vector is then used as the input for the decoder. The decoder produces the output vector, which is the energy load forecast for the next n steps. This architecture enables inputs of arbitrary length. In the energy load forecasting context, this means that an arbitrary number of historical energy consumption data can be fed into the architecture as inputs. The encoder network is trained alone as a preprocessing step, using the same methodology mentioned in the standard LSTM method. Then the encoder is plugged to the decoder, and both networks are trained together using BPTT. For the elaborated methodology, readers are referred to [39].

CNN-Based Load Forecasting

Time series energy consumption data are viewed as a one-dimensional grid. To perform the CNN-based energy prediction, the CNN is fed with a predefined number of historical energy consumption data. Only the historical consumption data are fed into the convolutional layers. The time stamp data are not used in this phase. Once the historical energy consumption data are subjected to the convolution and pooling phases, the output is fed into a fully connected network. Time stamp data are introduced into the system at this phase. The training of the architecture is carried out using BPTT with a gradient descent model. For the elaborated methodology, readers are referred to [46].

Experimental Results

As mentioned, all three architectures were tested on the benchmark data set on the single residential customer, with an identical training/testing split. Figure 10 shows a sample prediction obtained from the standard LSTM. It can be observed that the LSTM is able to follow the general trend of the prediction. However, it can be seen that the LSTM fails to adapt to certain changes. Figure 11 shows a sample prediction produced by the S2S architecture. It can be observed that the S2S model manages to estimate the rapid changes that appear in the data. Figure 12 shows a sample CNN prediction. It can be seen that the CNN performs in a similar fashion. A standard ANN was implemented on the same data set, and the prediction was carried out for the purpose of comparison. Figure 13 shows a sample ANN prediction. Table 2 presents the average prediction errors in terms of root-mean-square-error values obtained for the three deep learning architectures and the ANN. It can be seen that all three deep learning architectures outperformed standard ANNs for the tested data set. Furthermore, it can be seen that all three deep learning architectures produced results comparable to each other and also comparable to [46].

Buildings and Humans

As discussed before, elements such as connectivity and AI are essential for achieving energy-efficient and smart buildings and the cities of the future. However, while those elements play a huge role in energy efficiency, another important aspect of buildings is ensuring occupant comfort [34], [47]–[49]. Even with the recent advances in intelligent control schemes, it has been shown that a significant portion of occupants are still left dissatisfied with the comfort provided by building thermal conditions [47]. Hence, it is evident that mechanisms should exist for humans to interact with and provide feedback to the building management system. Humans in the building can be divided into two main categories: 1) occupants or users of the building and 2) building managers. The behavior of the occupants plays a significant role in energy consumption and greenhouse gas emissions [47]. Occupant behavior is a combination of human activity and preferences [50]. Occupants thus have a huge impact on a building's energy demand. Therefore, the human element from the perspective of the occupants should be taken into consideration on the following two fronts to optimize a building's

Mechanisms should exist for humans to interact with and provide feedback to the building management system.

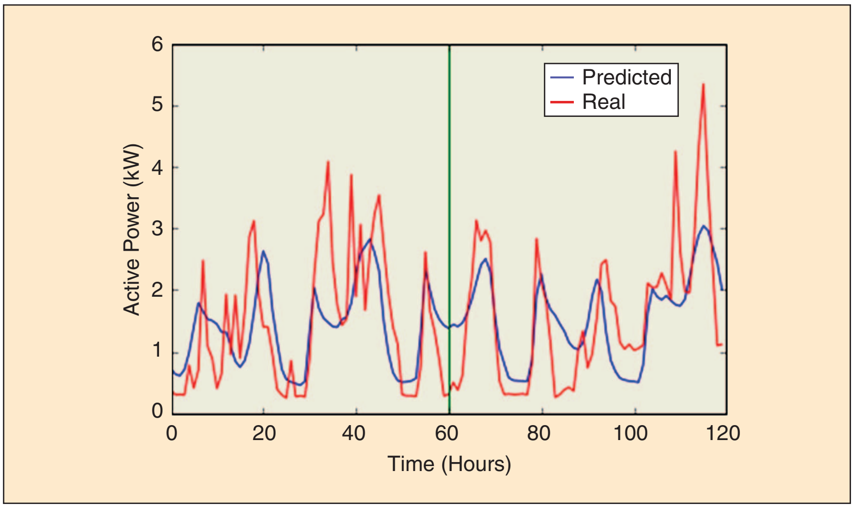

FIGURE 10 – The prediction results for the standard LSTM [39].

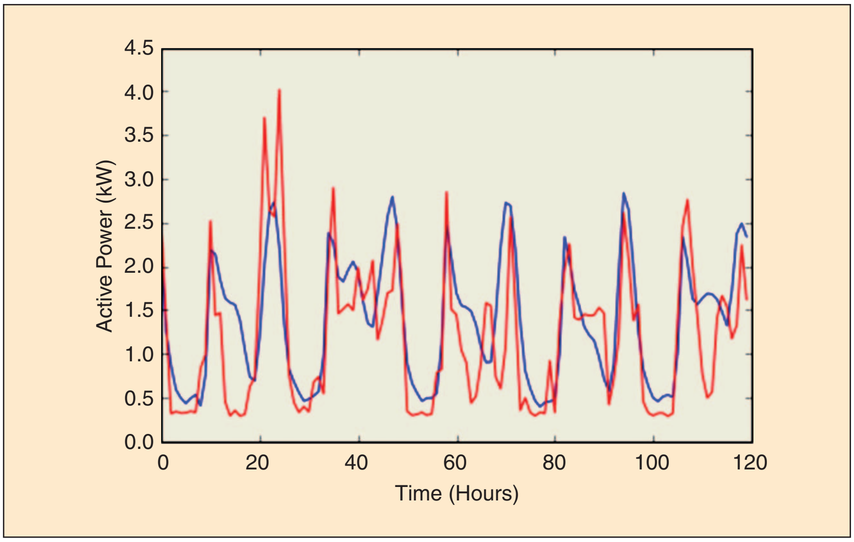

FIGURE 11 – The prediction results for the LSTM-based S2S [39].

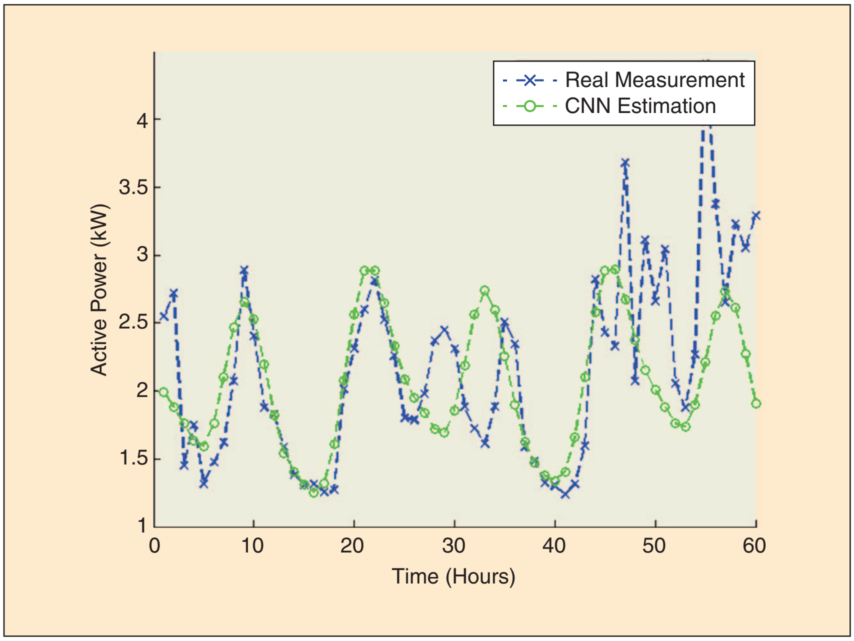

FIGURE 12 – The prediction results for the CNN [46].

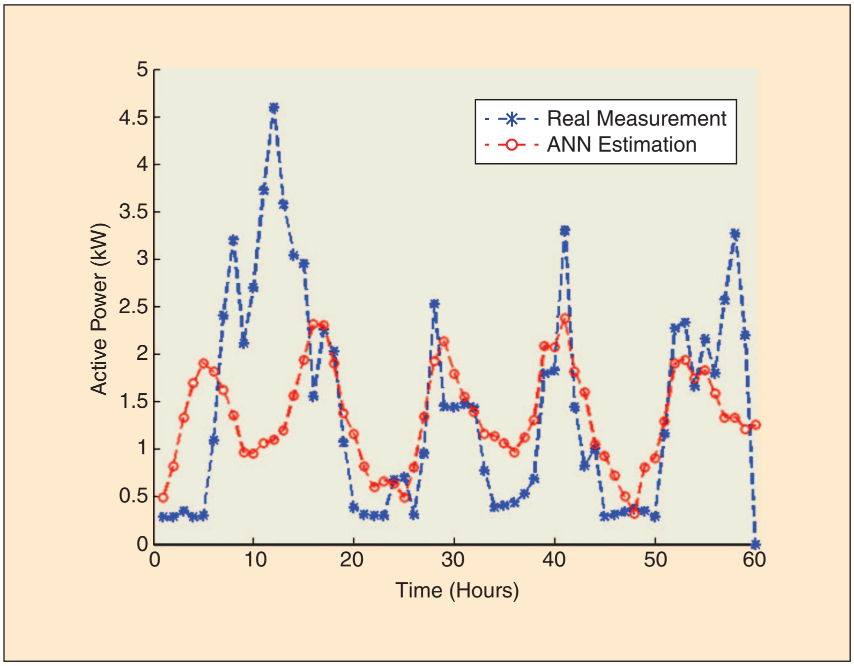

FIGURE 13 – The prediction results for the ANN [46].

TABLE 2 – THE PREDICTION ERRORS FOR THE TESTED METHODOLOGIES (RMSE).

ARCHITECTURE	TRAINING ERROR (RMSE)	TESTING ERROR (RMSE)
LSTM	0.752	0.684
LSTM S2S	0.701	0.625
CNN	0.714	0.677
ANN	0.788	0.697

energy usage while maintaining occupant comfort:

- modeling occupant activity
- enabling personalized comfort feedback and mechanisms to optimally incorporate subjective comfort feedback.

In addition to the occupants, from a building manager's perspective, automated building controls can be supplemented with human-in-the-loop, semiautomated control strategies. Such strategies have the capability of using the knowledge of an experienced building manager to supplement the intelligent control schemes in place.

Human–Building Interaction for Comfort and Energy Efficiency

While data-driven intelligent algorithms can provide control for increased energy efficiency, balancing performance with occupant comfort involves acquiring data at the individual workstation level. However, current building energy-system designs lack the implementation of sensors at individual work locations. Therefore, these systems are dependent upon aggregate or zone understanding of the parameters for achieving individual comfort. Individual occupant feedback is extremely important for maintaining comfort levels because human comfort is subjective. Accurately understanding the impact on individuals and variables such as radiation from windows or inadequate airflow is of the essence, especially since those factors are subjective. Therefore, the unavailability of highly granular information for the entire building may lead to areas of low comfort and low energy dissipation going unnoticed. To alleviate this, a method of acquiring individual comfort feedback is necessary. Therefore, methods need to exist that enable direct communication between occupants and the building energy management system (BEMS). Human–computer interaction methodologies should be incorporated to provide easy-to-access and intuitive interfaces for occupants to send their comfort-level feedback to the BEMS.

While automating building control is crucial for achieving building energy efficiency, it is difficult to ignore the impact that an experienced building manager can make in optimizing and supplementing the automated control. For this to be possible, it is imperative to have an appropriate interface between the human manager and the control system. The interface should be able to provide the building manager with data streams from different building sensors (information processing being an essential task in automation [51]) and information about the control system. In addition, the interface should be able to provide the manager with information about the control actions in real time.

Case Study: Human–Machine Interaction for Incorporating a Human Element

The main objective of the performed study was to devise strategies to incorporate the human in the building automation and control to increase energy efficiency and occupant comfort. Two types of human interaction with the building and the BEMS were identified: 1) by building managers and 2) by building occupants. Therefore, strategies were developed to incorporate human interaction with the BEMS using two different methods: 1) incorporating expert control through building managers to supplement the automated control for increased energy efficiency and 2) incorporating occupant feedback for increasing occupant comfort.

Building Manager Interaction

A user-friendly visualization tool was developed that presents a real-time data stream from sensors, anomalies in the data streams, and linguistic summaries of the data. Anomalies in the data are identified using an AI-based framework [52]. In the anomaly detection process, AI-based data-mining algorithms extract and model the normal behavior of the building and thus are capable of identifying behavior that is anomalous and potentially harmful. Similarly, linguistic summaries of data are generated using an AI-based framework [52]. In this framework, the data from the building are summarized using human-interpretable linguistic terms. Therefore, a summary of data trends pertaining to building performance is given to the building manger in an understandable manner. Both AI-based frameworks were developed by the authors. However, those frameworks are out of the scope of this article. The developed visualization tool focuses on increasing the building manager's situational awareness by providing a comprehensive overview of building performance.

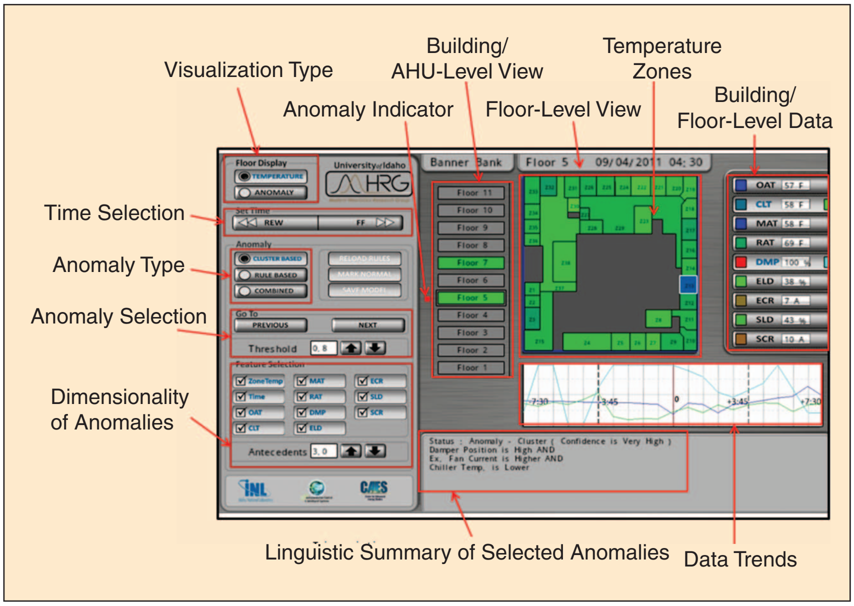

FIGURE 14 – The interface of the developed tool for incorporating the building manager (Windows and Android Versions).

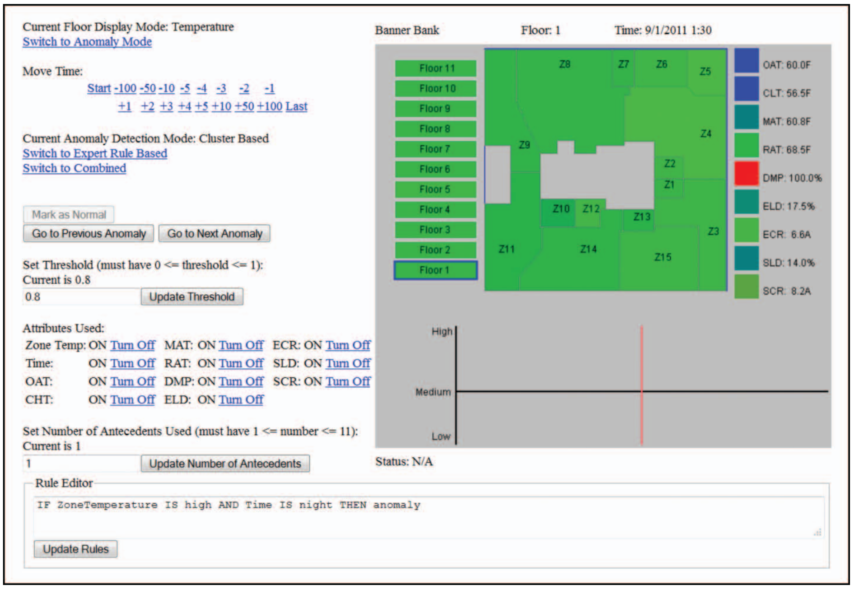

FIGURE 15 – The web interface of the building manager tool.

The visualization tool was developed for different platforms. First, the interface was developed for a Microsoft Windows–based platform. To provide mobile capability, the interface was developed as an Android application. The functionality was kept identical across the two versions. Figure 14 shows the interface for the Windows and the Android versions. Furthermore, the tool was extended to a web-based version to make it platform independent. Figure 15

Buildings will continue their evolution toward becoming living and breathing cyberphysical mechanisms.

shows the interface for the web-based application.

The tool was designed to be interactive so the user would be able to select different information to visualize. Furthermore, the user is able to use the tool to update the anomaly detection algorithm. That is, the building manager is able to provide feedback on the detected anomalies. For example, the building manager is given the capability of validating a detected anomaly. If the detected anomaly is a false positive, the anomaly detection algorithm will learn that and will refrain from tagging that behavior as an anomaly thereafter. Therefore, the knowledge of the experienced building manager is incorporated in the building automation through the developed interface.

Occupant Interaction

Implementing an extensive sensor network to achieve individual workstation thermal environments is time consuming and entails a significant financial commitment. Therefore, the cost-effective and feasible method of acquiring the required data is a user-centered approach. A user-centered approach will ease the task of building managers and the automated building controller to proactively monitor occupants' comfort levels and adjust building states for optimal comfort and efficiency through the interface elaborated in the section above.

Therefore, a user-centric data collection methodology was developed to acquire highly granular readings of the ambient environmental conditions in buildings and the subjective comfort levels of users. To acquire highly granular recordings of ambient environmental conditions in the building, a low-cost sensor was developed [53]. The sensor has a modular design so that new components can be added to it without much effort [53]. The designed sensor includes measurements such as temperature, humidity, CO_2, and visible light. Figure 16 shows the designed sensor.

Even though deploying sensors at individual workstations can help obtain highly granular data, it does not factor in the subjective human feedback. The current BEMS systems lack a methodology for the users to interact with the building managers. Therefore, to provide a method for the users to interact with the building control, a smartphone app was developed because of the ease of access and use. Figure 17 shows the developed smartphone application. Through the developed comfort app, the users are able to report back to the building managers about comfort levels in terms of such things as lighting, temperature, and ventilation at their specific location. Once the necessary information is acquired from the occupants, the imprecise human feedback is handled in linguistic terms [52]. Then the feedback is incorporated in the building control to improve the comfort level of the individuals.

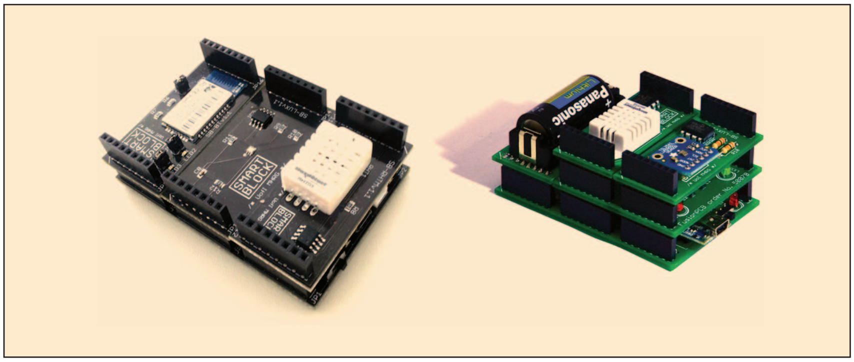

FIGURE 16 – The developed modular wireless sensor.

In addition to reporting comfort data, users are able to use the mobile application to report system failures to the managers. This method can be used to send specific information about which system failed, comments regarding the failure, and even images of the failure. This information can be used with the anomaly detection algorithms mentioned in the previous section to provide the building manager with more information on the suboptimal behavior of the building. Furthermore, the developed smartphone application connects to the developed modular sensor to acquire the data for localized details.

Looking into the Future

Buildings will continue their evolution toward becoming living and breathing cyberphysical mechanisms. The U.S. Green Building Council, under its Leadership in Energy and Efficient Design program, may be only the beginning of the transition toward the concept of living buildings. The Living Building Challenge certification program that started in 2006 continues the promotion and advocacy of sustainability in the building environment. While net-zero buildings (buildings with zero net energy consumption, i.e., not using more energy then they themselves generate) are still rare, they may become more common with advances in renewables and distributed storage technologies, such as Li-ion batteries and PEVs. In the future, buildings with a surplus of energy may be able to buy and sell that energy to the grid or to other buildings.

The concept of living buildings will likely further the analogy with human beings. Just as the human body sweats to release excess heat, buildings may use evaporative roof systems. Rain-absorbing matting could act in the same way as perspiration to

With the growth of ubiquitous IoT devices, modern buildings seamlessly integrate with the environment, lowering energy-related expenses and increasing productivity and the quality of life.

cool the buildings as the rain evaporates. Similarly, as blood vessels constrict or dilate to preserve or release heat, buildings will be using intelligent adaptive insulation systems and smart transparent windows and shading. Although natural breathing systems such as wind towers and wind catchers have been used in buildings for centuries, modern technologies will enable more effective, automated, and predictive controls, using modern polymers and biomaterials (such as self-healing concrete) and architectures of such structures. Modern renewables generators, turbine designs, and wind energy towers will increase buildings' autonomy and building grid islanding.

At the smart grid level, smart loads will interact with utilities to reduce peak demand or respond to demand dispatch (increasing loads at times of excess generation). Grid-interactive hot and cold thermal energy storage systems (tanks) will further advance load shifting and increase the sustainability and autonomy of smart buildings. Advanced power electronics will be able to provide subminute load management [54].

When it comes to human–building interactions, the increase of modalities and platforms of heterogeneous sensor systems will lead to the seamless integration of buildings into the everyday lives of humans. The novel interaction technologies emerging with smart devices via sound, voice, and three-dimensional touch will become a norm for communicating with smart building components. A homeowner's arrival at his or her house will trigger preset rules, and the owner will be able to ask for the curtains to be closed or the lighting and music adjusted. Interesting questions will arise, such as the personification of smart building components (as with therapeutic robots like Paro), or questions of human changes in response to continuous interactions with buildings.

Software will play an increasing role in the buildings of the future. Similar to software virtualization (hard disk drives or software-defined networks), the virtualization of power plants that combines geographically dispersed resources (e.g., smart homes, local renewables, and PEVs) can increase the correlation between resources and enable greater flexibility, while decreasing the uncertainty associated with individual resources used in isolation [54]. The aggregated resources could be bid into wholesale electricity markets and provide other grid services if allowed. One emerging concept is the Distributed Energy Resource Management System software platform.

AI techniques are expected to continue their way into the buildings of the future. From automation and occupant behavioral pattern learning and prediction to processing of the big data generated by buildings and smart grids, AI techniques have already been established as an approach to the autonomous execution of routines on behalf of users. With regard to energy efficiency as one of the most important aspects of future smart cities, approaches such

FIGURE 17 – The smartphone application and its features.

as deep learning (Google's DeepMind) were reported in July of this year to have cut cooling energy use by 40% and total energy use by 15% in Google's data centers.

Conclusion

This article presented an overview of the state of the art and the future of smart buildings. Starting with U.S. and world energy consumption predictions, we overviewed the most important aspects of smart grids and smart buildings, elaborating further on the interactiveness and interoperability between the two. We then discussed the emerging aspects of smart homes—connectivity and analytics—while recognizing the increasingly evident issues of the security and resilience of intelligent buildings and the corresponding need for research in these areas. The article additionally overviewed the cutting-edge AI techniques, reflecting on the recent hot topics in deep learning. Also presented were the results of case studies done by the authors on two highly relevant problems: load/demand forecasting for buildings and human–building interaction. The article concluded with insights into the future of intelligent buildings.

Modern intelligent buildings are becoming cohesive cyberphysical ecosystems that live and breathe with their surroundings. Intelligent buildings adapt to external (seasonal) and internal (occupancy and usage patterns) changes and are doing so with increasing autonomy and sustainability. Modern buildings thrive on data sources that were previously nonexistent (sensors) or ignored and feature highly reconfigurable infrastructure and control elements. With the growth of ubiquitous IoT devices, modern buildings seamlessly integrate with the environment, lowering energy-related expenses and increasing productivity and the quality of life.

Biographies

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