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Building Energy Management Systems

The Age of Intelligent and Adaptive Buildings

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Building automation systems (BAS), or building control systems (BCS), typically consist of building energy management systems (BEMSs), physical security and access control, fire/life safety, and other systems (elevators, public announcements, and closed-circuit television). BEMSs control heating, ventilation, and air conditioning (HVAC) and lighting systems in buildings; more specifically, they control HVAC's primary components such as air handling units (AHUs), chillers, and heating elements. BEMSs are essential components of modern buildings, tasked with seemingly contradicting requirements—minimizing energy consumption while maintaining occupants' comfort [1]. In the United States, about 40% of total energy consumption and 70% of electricity consumption are spent on buildings

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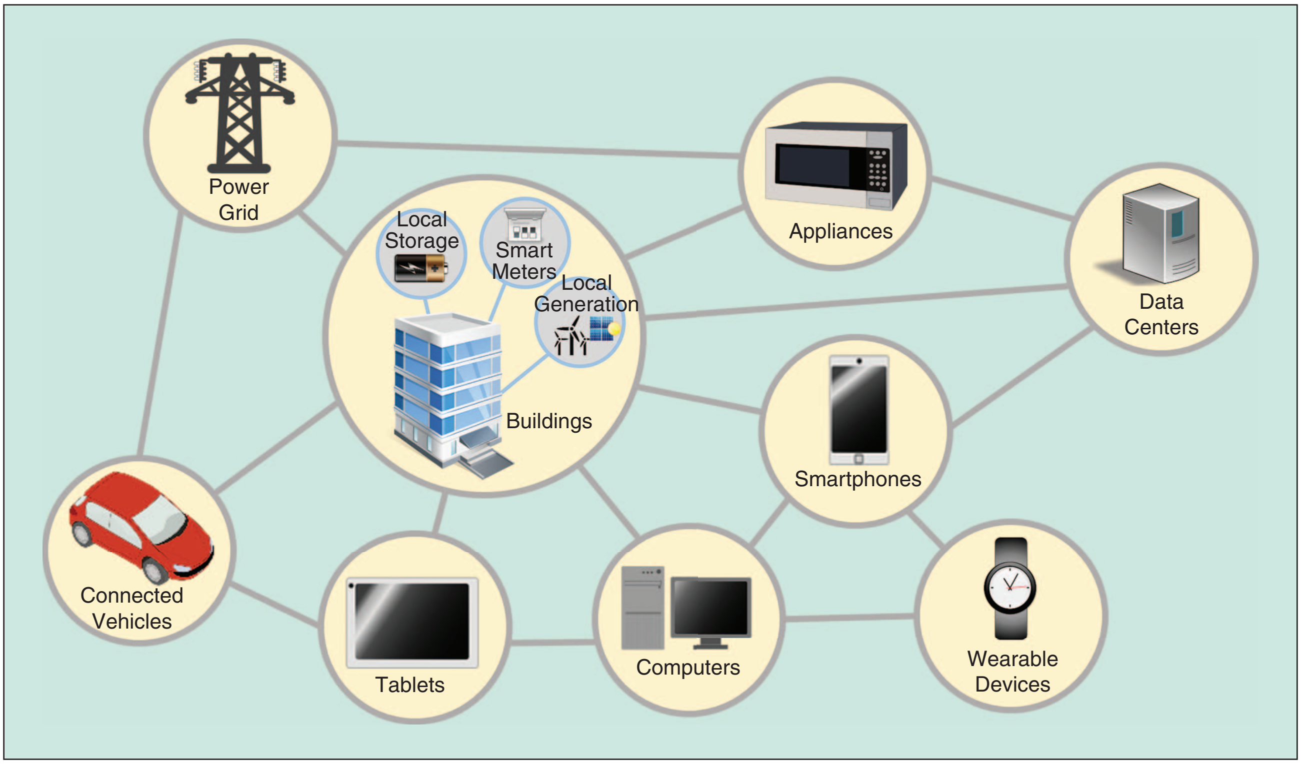

FIGURE 1 – An example of buildings as part of the global cyberphysical ecosystem [2].

every year. These numbers are comparable to global statistics that about 30% of total energy consumption and 60% of electricity consumption are spent on buildings. Buildings are an integral part of global cyberphysical systems (smart cities) and evolve and interact with their surroundings (Figure 1) [2]. As buildings undergo years of exploitation, their thermal characteristics deteriorate, indoor spaces (especially in commercial buildings) get rearranged, and usage patterns change. In time, their inner (and outer) microclimates adjust to changes in surrounding buildings, overshadowing patterns, and city climates, not to mention building retrofitting [3], [4]. Thus, even in cases of "ideally" designed BEMS/HVAC systems, because of ever-changing and uncertain indoor and outdoor environments, their performance frequently falls short of expectations. Unfortunately, the complexity of BEMSs, large amounts of constantly changing data, and evolving interrelations among sensor feeds make identifying these suboptimal behaviors difficult [1], [5]. Therefore, traditional data-mining algorithms and data-analysis tools are often inadequate.

This article provides an overview of issues related to modern BEMSs with a multitude of (often conflicting) requirements. Because of massive and often incomplete data sets, control, sensing, and the evolving nature of these complex systems, computational intelligence (CI) techniques present a natural solution to optimal energy efficiency, energy security, and occupant comfort in buildings. The article further presents an overall architecture where CI can be used in BEMSs and concludes with a case study of the practical applications of using CI techniques in the BEMS domain [6].

The primary areas of interest in BEMSs can be categorized into three areas: 1) energy efficiency, 2) integration of BEMSs with utilities and smart grid technologies, and 3) resilience and security. These are problematic and difficult to effectively address with typical BEMSs that do not have the necessary data processing, evaluating, and control methodologies. Some of the aspects that are lacking in typical BEMSs include (but are not limited to) adaptability, predictive modeling, multisensor fusion, dynamic optimization, state-awareness, providing actionable information, etc. These aspects are required in BEMSs to address the three primary issues highlighted above because of the highly complex and changing nature of buildings, such as a large number of heterogeneous sensors and controls, constant changes inside and outside the building (occupancy patterns, aging of materials and equipment, floor plan changes, etc.), and the need to address occupant comfort while maximizing energy efficiency.

Building Energy Consumption Relative to Other Industry Sectors

According to the U.S. Energy Information Administration (Figure 2), 41% of total U.S. energy consumption is consumed in residential and commercial buildings [7], with commercial and residential buildings consuming 72% of all electricity [8]. The International Energy Agency (IEA) estimates that, throughout the world, buildings represent 32% of total final energy consumption (energy that is supplied to the consumer for all final energy uses, such as heating, cooling, and lighting), and around 40% of primary (crude) energy consumption in most IEA countries [9]. The United Nations Environment Program estimates that residential and commercial buildings consume

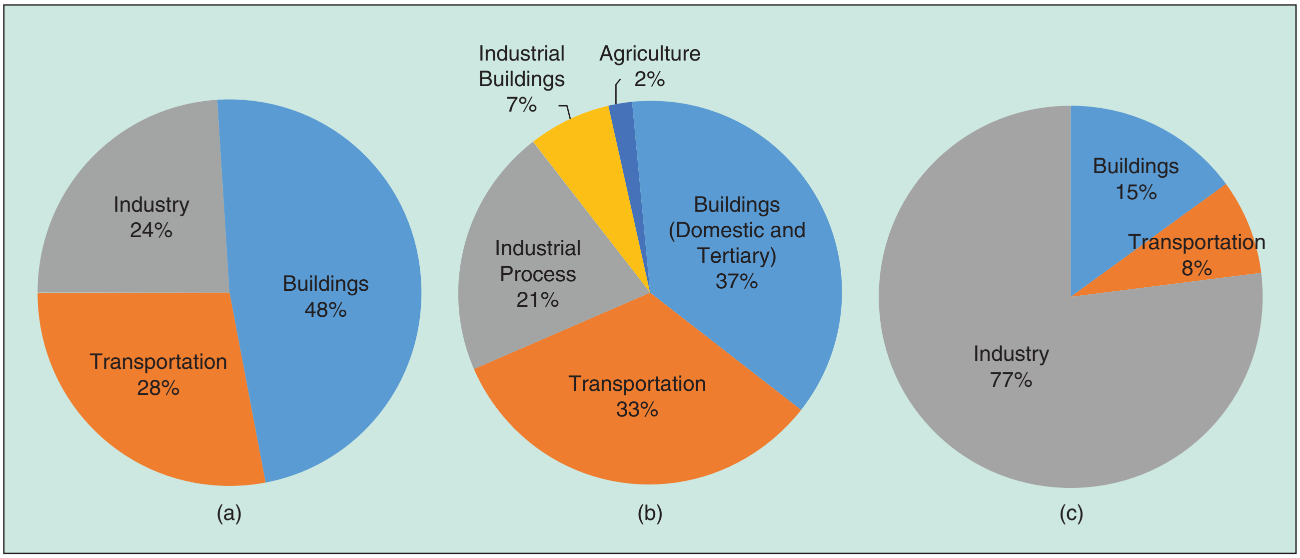

FIGURE 2 – The energy consumption by sector for (a) the United States, (b) the European Union, and (c) China [14]–[16].

approximately 60% of the world's electricity, in addition to using 40% of global energy, 25% of global water, and 40% of global resources. Because of the high energy consumption, buildings are also one of the major contributors to greenhouse gas production [10], [11]–[12], but also offer the greatest cost potential for achieving significant greenhouse gas emission reductions, with numbers projected to increase [11], [13].

Thus, energy efficiency in buildings is an important issue on a global scale [1]. However, by implementing very low-cost building management strategies alone, it has been shown that the energy efficiency of modern HVAC systems can be improved by more than 5% [17], [18]. Furthermore, it has been shown that the energy efficiency of HVAC systems can be improved by up to 40% by close monitoring and advanced control [19].

Integration of Buildings with Smart Grids

The cyberphysical ecosystems of the future will inevitably entail building-to-building (B2B) and building-to-grid (B2G) integration (Figure 3) [20]. B2B integration will enable "learning" the behaviors of other buildings, their energy usage patterns, and relationships between energy consumption and occupants' comfort. Furthermore, B2G integration has been underway for several years. The U.S. Department of Energy's (DOE's) Building Technologies Office has been coordinating integration and optimization of homes and commercial buildings with the nation's grid [21]. Pacific Northwest National Laboratory, with support from the U.S. DOE, developed VOLTTRON—an open-source common platform offering in-depth understanding of complex systems that integrate new challenges, such as renewable energy generation, energy storage, and electric vehicles [22]. However, integration of highly variable factors, such as renewable energy, demands control methodologies that are adaptable and dynamic [20]. The Engineering Laboratory of the National Institute of Standards and Technology (NIST) has been investing in building integration with the smart grid since 2011 [23]. NIST recognized the need for new standards enabling homes and buildings to interact with the grid, with buildings becoming both energy renewable generators and consumers. Electric vehicles will charge through plug-in connections managed by home and BAS. Buildings' utility-scale renewable generation systems will require responsive loads to match the fluctuations caused by varying wind and solar conditions [20]. And finally, consumers will access their own energy consumption data to make informed decisions about energy habits.

Thus, the integration of building systems with the grid is a critical part of the stability and success of the smart grid [20]. NIST efforts resulted in tools such as simulation and testing in the Virtual Cybernetic Building Testbed and Net Zero Energy Residential Test Facility [23].

New Aspects—Resilient and Secure BEMS

Buildings are inherent components of global cyberphysical systems and are

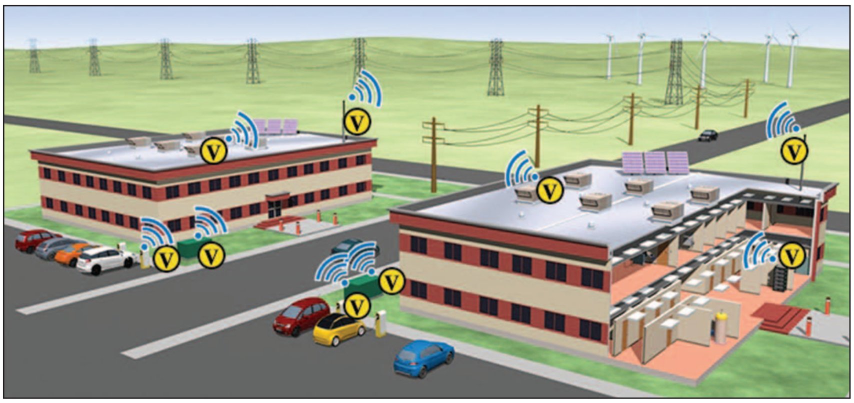

FIGURE 3 – The B2B and B2G integration [21].

considered mission-critical infrastructure from the aspect of their human inhabitants. Therefore, the impact of resilience and security of building energy management systems spreads both locally (electrical and mechanical equipment for continuous maintenance of occupants' comfort) and globally (the impact on grid and distributed energy systems). While resilience and cybersecurity standards are recognized in other critical infrastructure [24], such aspects in the building sector have only recently become of interest to researchers [25]. While some go back to Madni and Jackson's [26] systems resilience definition addressing "…systems able to circumvent accidents through anticipation, survive disruptions through recovery, and grow through adaptation," others view resilience through the energy efficiency and sustainability prism.

At the time of writing this article, both Donelly [27] and Zimmerman [28] cover the three ways sustainability complements building resilience: 1) energy efficiency; 2) exteriors, envelope, and ventilation; and 3) water and storm water. Just several months ago, Chipley [25] brought up the importance of these issues, while in early 2015 Levite and Rakow [29] highlighted energy resilience supported by nine steps to improve continuous performance. The U.S. Department of Defense (DOD), specifically, focuses on energy resilience in terms of recovering from utility disruptions: "the ability to prepare for and recover from energy disruptions that impact mission assurance on military installations" [30]. By implementing photovoltaic (PV) solar and other renewable energy sources, as well as various energy storage methodologies, microgrids [31] and buildings themselves can operate in islanded mode and maintain critical operations (DOD's Net Zero Energy initiative [32]) can operate in islanded mode and maintain critical operations (DOD's Net Zero Energy initiative [32]). Thus, resiliency in scenarios where primary power is lost can be achieved to a certain degree.

One example is the public safety building in Salt Lake City, Utah, as a "model of resilience." Wilson [33] states how emergency services must be maintained in situations such as an earthquake, storm, or terrorist attack that takes down the grid. This building's key resilience and sustainability features are net zero energy design (based on a 1-mW solar installation and 195-kW solar thermal system), islandable operation (1.56-mW diesel generators, 380-kW PV), efficiency measures that minimize loads during power outages, seismic design, stormwater management, etc. Evans and Fox-Penner [34] discuss resilient and sustainable infrastructure solutions which will require intelligence (predictive tools, advanced metering, and social media), redundancy (fault tolerance), and coupling and decoupling (islanding) during major storms or flooding, citing Mexico City as an example.

Cybersecurity, unlike resilience, has been recognized as a vital component of modern BAS (with BEMS being considered part of it). Though building controls naturally inherit industrial communication protocols, there are some specifics when it comes to BEMSs—a review of security of BAS by Peacock and Johnstone [35] and Ganzer and Kastner [36] focuses on the Building Automation and Controls Networks (BACnet), KNX, Unauthorized access to a BEMSs could potentially result in financial, physical, and structural issues (loss in employee productivity, service delivery, health of occupants (i.e., "sick building syndrome") and damage equipment or the building itself [37]. Examples vary from HVAC-controlled corporate centers [38] to lighting and HVACs of mission-critical systems, such as health care [39]. Sinopoli [39] further states how legacy building management systems are more vulnerable, such as in the Stuxnet cyberattack on programmable logic controllers, but also mentioning a wide range of advanced security protocols, such as BACnet and the agnostic Modbus protocol. Although BACnet is an American Society of Heating, Refrigerating and Air-Conditioning Engineers, American National Standards Institute, and International Organization for Standardization 164840 standard, it is a non-Transmission Control Protocol that cannot be secured by typical firewalls [40].

Thus, achieving resilience and securing BEMS control architecture is quickly becoming a necessary component for modern buildings.

CI in Buildings

The Need for Intelligence in BEMSs

It is clear that the building energy systems of the future will need to deal with dynamic and diverse requirements. Modern BEMSs are creating massive, heterogeneous, often-imprecise data streams. CI algorithms are inherently capable of handling large amounts of data, as well as providing features such as anomaly detection, predictive modeling, optimization, and perhaps one of the most important premises of artificial intelligence—learning on their own.

Hence, CI-based approaches have the ability to identify and alleviate suboptimal behavior while controlling the building optimally and maintaining occupants' comfort. Further, predictive and dynamically optimizable control strategies that are derived from CI lead to energy efficient control of the BEMS. In addition, achieving microgrid goals of integrating renewables and various energy storage mechanisms can be realized and optimally controlled via CI-based algorithms [41]. Similarly, load shedding and peak shaving, which are critical for the current power grid and the microgrids of the future, can be achieved and optimized via CI techniques. Resiliency and security goals of buildings and the grid can also be achieved by CI-based optimal control and intrusion detection mechanisms. Next, we discuss how CI can be used to address the primary issues of BEMSs.

Bringing Intelligence into BEMSs

Figure 4 shows a typical legacy BEMS. As previously mentioned, with the increasing amounts of diverse and dynamically changing data, extracting relevant and actionable information through legacy BEMS is difficult. This leads to an inundation of data and decreased situational awareness, which may result in suboptimal building behavior. Furthermore, the control strategies employed are often static and nonpredictive; hence, they fail to adapt to changing environments and deteriorating building states. In addition to these shortcomings, it is difficult to incorporate new sensors into legacy control as a result of building retrofitting or additional control requirements.

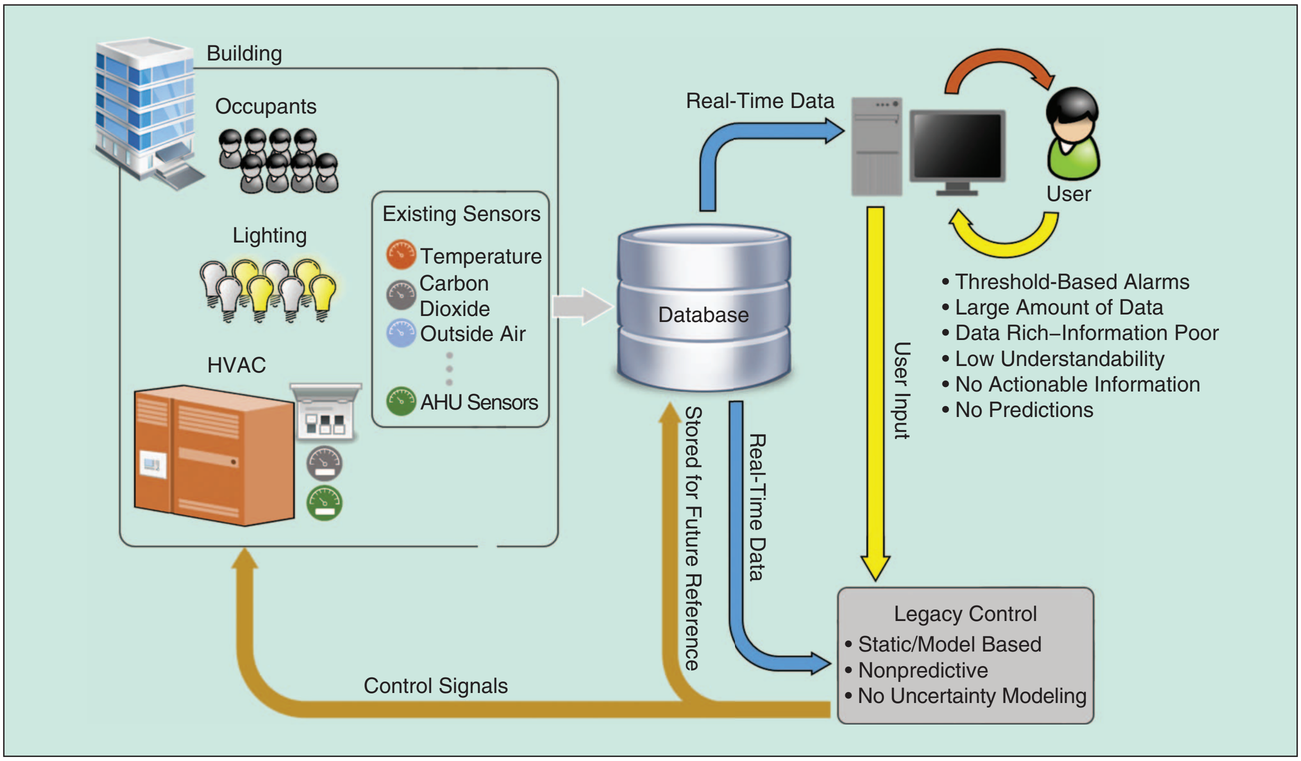

FIGURE 4 – An example of the typical legacy of BEMS architecture.

In contrast, various CI-based algorithms such as artificial neural networks (ANNs), fuzzy logic (FL) modeling, and evolutionary algorithms (EAs) [42], [43] enable the implementation of advanced control architectures, data-mining techniques, and optimization capabilities that can lead to better situational awareness and more efficient, dynamic, and adaptive control, as well as grid resilience and building data security.

Figure 5 shows a possible framework of CI algorithms used in a BEMS. CI-based techniques have the unique capability of handling large quantities of heterogeneous data from multiple sources and extracting the generalized behavior of the system. Furthermore, CI-based techniques are inherently adaptive and optimizable while being able to model uncertainties inherent in real-world measurements. Similarly, this data-driven approach can be complemented by expert-driven CI-based methodologies to enable the system to be more dynamic and accurate.

CI-based control (depicted in Figure 5) can benefit from various, proven CI-based techniques such as ANN, FL, evolutionary optimization, etc. Such methods have been shown to be capable of outperforming traditional control methods in a variety of industrial applications, including, but not limited to, building control [6], [42], [44]–[48]. ANNs enable dynamic, predictive, and holistic modeling of the system by learning the underlying interdependencies of the system and generalizing overall system behavior. These inherent generalization capabilities enable ANNs to accurately handle previously unseen and unexpected behavior. Furthermore, ANNs have the capability to adaptively change to new requirements via online learning techniques [44], [45], [48]. While ANNs are capable of extracting and modeling the general behavior of the system, FL modeling can be used to model and quantify uncertainties that inherently appear in data to ensure adaptable control even in the presence of noisy, unreliable data [1], [49]. FL also assists in easily incorporating expert domain knowledge into the control system by means of human interpretable linguistic rules. To achieve near optimal control, EAs may be used for dynamically optimizing both ANN and FL techniques as well as classical control methods [6], [47]. EAs provide the capability of converging on near-optimal results when the search space is too large to be searched exhaustively.

As depicted in Figure 5, CI-based algorithms can be used not only for control, but also for providing the user with understandable and actionable information [1]. ANN-based system modeling, advanced clustering-based system modeling, or FL-based expert rules can be used for anomaly detection of the entire system as well as the subsystems of the overall BEMS [1], [5], [50]. These anomaly detection techniques identify and make use of the underlying interdependencies of the system for determining potential suboptimal anomalous behavior and, therefore, are more expressive and useful than traditional threshold-based alarms [1], [5]. Furthermore, linguistic summarization can be used to provide clear, concise, and understandable information about suboptimal building behavior and its potential root-cause to the user [1], [50].

ANN, FL systems, and other CI-based predictive algorithms have been successfully applied in various control systems, including BEMSs, for sensor data prediction [3], [4], [51], [52]. Sensor value prediction enables the system to be proactive rather than

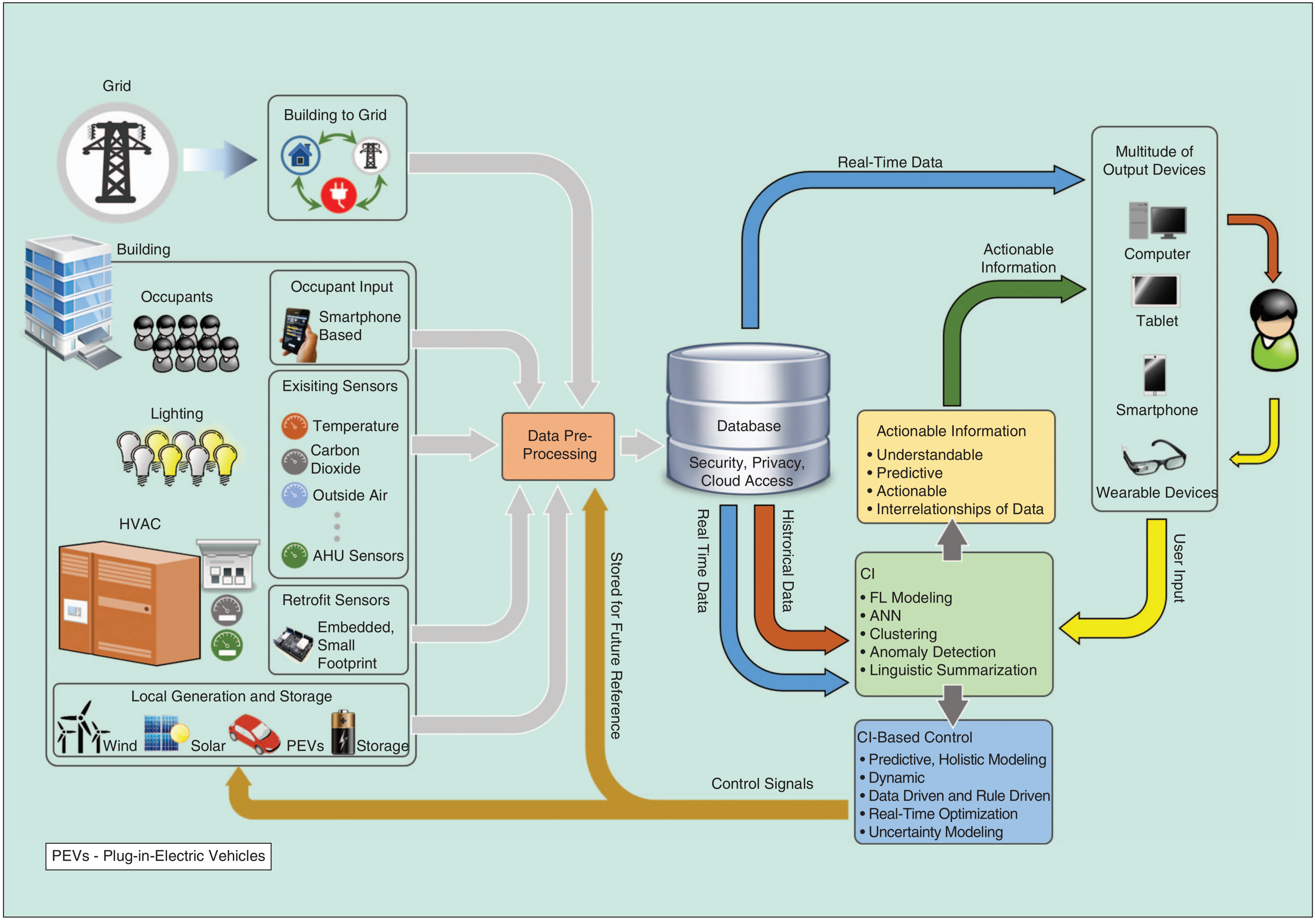

FIGURE 5 – The CI-based BEMS architecture.

reactive by using the predicted values for predictive control and generate predictive alarms. Furthermore, these predictions can be used in cases of sensor failure or when higher granularity is required for higher situational awareness [3], [4], [52].

These advantages, along with the versatility of CI-based algorithms for incorporating additional sensor information, enable advanced resilient control that would otherwise be difficult and suboptimal [6], [45], [53], [54]. For example, ANN- and FL-based control along with EA-based optimization can be used to incorporate local generation and energy storage systems into buildings (see Figure 5). Because of the highly fluctuating nature and the difficulty of modeling dynamics of renewables and stored energy [20], predictive and adaptive control (that can be offered by CI) is a necessary part of achieving realistic goals for optimal control and utilization. Thus, incorporating CI enables the possibility to achieve grid resiliency and energy security goals required for stable microgrid systems via local power generation and storage [31], [41], [55].

Another requirement of resiliency in the grid is security. Thus, data communication and storage systems need to be monitored and secured accordingly. CI methodologies may be used for security as well. For example, similar to identifying physical anomalies, CI can also be used to detect and mitigate cyberanomalies [52]. CI-based data fusion that utilizes techniques such as ANNs and FL may be used for identifying malicious sensor data manipulation [52]. Furthermore, intelligent and dynamic intrusion detection using CI techniques have been shown to be effective in critical infrastructure security applications [56].

One of the primary advantages of most of these techniques is that the CI-based control and state awareness methodologies can be implemented without replacing the existing mechanisms and can act as complements to existing BEMSs [1], [52], [42]. Thus, integral parts of connected smart buildings such as optimal control, state awareness, and security can be implemented through CI-based techniques. Furthermore, the inherent qualities of CI-based techniques make them ideal for application in modern BEMSs. Hence, the three primary issues of energy efficiency, connecting BEMSs to the grid, and resiliency can be solved through CI-based techniques.

However, only a small corpora of potential advantages of implementing several types of CI-based algorithms were discussed above, and it is by no means exhaustive. Various other CI strategies may be used in different points of the overall BEMS architecture to enable the adaptive, secure, and resilient buildings of the future. Furthermore, while the method presented in this article focuses on illustrating advantages of using CI for control of a nonlinear dynamic system, the presented methodology can be extrapolated to state-awareness and resilience, as well as security.

Further examples of CI techniques that have been successfully used in BEMSs are given in the "Concrete Applications" section.

Underlying CI Techniques

The area of CI encompasses different types of algorithms [43]. ANNs, FL modeling, and EAs are three prevalent techniques [42], [43] and are relevant to the work presented in this article. It should be noted that there are other CI-based methods that can be useful for intelligent BEMS.

ANNs are CI architectures based on biological neural networks that have the capability of "learning" interdependencies and trends in data. The basic unit of an ANN is a neuron, which is functionally similar to a biological neuron. It has a set of inputs and produces an output based on the inputs [57]. An artificial neuron mimics the biological neuron by using weights and a threshold value and producing an output vector for a given input vector. Each dimension in the input vector is assigned a weight, and a weighted sum is calculated. The weighted sum is then applied to a mathematical function called the "activation function," which determines the final output. Artificial neurons are arranged in multiple interconnected layers, namely, input layers, hidden layers, and output layers. The inputs are connected to the input layer, and the outputs of the network are obtained from the output layer. The hidden layers are placed between the input and the output layers, and there may be more than one hidden layer [58]. Thus, this creates an interconnected network of neurons, which combines to produce an output based on a number of weights, aggregations, and comparisons (Figure 6) [57].

FL was first introduced by Lotfi Zadeh in 1965 to explain system complexity in simpler terms [53], [54], and to model complex phenomena that is difficult or suboptimal to be modeled by classical mathematics [59], [60]. FL can be viewed as a system that provides a methodology for modeling and calculating humanlike imprecision and reasoning [49], [60], [61]. FL relies on fuzzy set theory for representation of imprecise models and reasoning. Fuzzy set theory is similar to classical set theory but uses fuzzy sets instead of classical sets. Furthermore, FL systems (FLSs) use rule-based knowledge repositories in linguistic terms and is easy for human operators to understand [62]. FLSs have been useful in control, classification, prediction, data mining, and other applications (Figure 6) [49], [63]–[65].

EAs are a broad set of methodologies primarily used for optimization. The major unifier of EAs is the application of simulated biological evolution. Simulated evolution is inspired by, and analogous to, Darwin's theory of evolution and has been translated into an effective tool for global optimization [47]. The algorithm maintains a set of unique candidate solutions to the problem; this is similar to a set of individuals in a population. The ability of each solution or individual to solve the problem can be evaluated based on an objective fitness function, and is known as the *fitness of an individual*. This fitness is subsequently used to drive the evolution of the population based on the theories of natural selection. Thus, at each iteration, the fitness of each individual is calculated. Based on the fitness evaluations, certain individuals are removed from the population, and new individuals are introduced. The removal and introduction of individuals are analogous to Darwin's

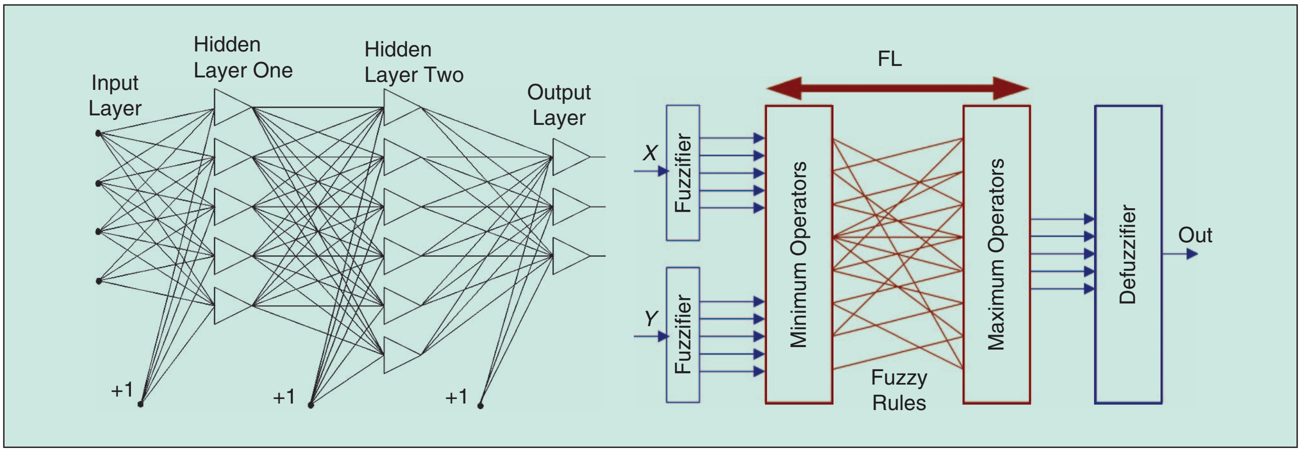

FIGURE 6 – An example of ANNs and FLSs.

"selection of the fittest" in terms of biological reproduction.

Other techniques that are related to and/or derived from these methods, such as various clustering and classification techniques, are also significant areas of CI [66]. These methods rely on the underlying dependencies of multidimensional data to generate generalized clusters and classification boundaries. A multitude of CI techniques that are capable of handling large sets of highly multidimensional data is available for these tasks.

Concrete Applications

CI techniques are predominantly data-driven techniques. While theory teaches us to combine physics-based and data-driven techniques, in practice, data-driven techniques prove to be easier, more accurate, and more capable of keeping up with the evolution of buildings as floor plan and usage pattern change, thermal features deteriorate, and HVAC systems age and get replaced. However, in cases where sufficient data are not available, the thermal energy storage (TES) model can be created as a physics-based model.

Smart buildings offer the possibility to buffer excess energy from fluctuating renewable sources in thermal and electrical storage units increasing autonomy from utilities and resilience to brownouts. From shifting energy-intensive processes, saving energy in another form, or producing regenerative energy themselves, buildings have become an integral part of an intelligent cyberphysical systems to produce, store, and consume energy. Researchers have examined the use of ANNs to control BEMSs [66], [67], showing advantages of self-learning with fast convergence time and fast learning in the presence of time delays and model uncertainties and predictive control for thermal comfort and energy savings in public buildings. Ferreira et al. [66] demonstrated ANN deployment for balancing desired thermal comfort level and energy savings at the University of Algarve with energy savings of more than 50%.

Energy consumption has been the focus of research interests as well. For example, Li et al. [51] have used classification techniques for daily electricity consumption in buildings in Birmingham, England, demonstrating 99% correct prediction. Yuce and Rezgui [68] have used an ANN-GA approach for semantic rule generation for better energy performance prediction, demonstrating a 25% energy reduction while satisfying occupants' comfort.

Zhang and Chen [46] demonstrated a particle swarm optimization (PSO)-radial basis function (RBF) ANN solution for building energy consumption, while Quintero and Mares [69] presented an ANN-FL approach demonstrating 25% energy savings while maintaining customers' comfort. RBF ANNs have been used for electric load forecasting for large office building load forecasting [70], capturing 97% of variability in hourly electric load of test buildings (based on weather and electric power consumption alone). Tran and Tan [48] used feedforward ANN for improving building illumination energy efficiency, demonstrating 95% accuracy with more than 28% energy savings.

Dealing with uncertain information has been evidenced in fuzzy and fuzzy-agent-based control. Yordanova et al. [71] used a simple two-variable fuzzy data acquisition control [71]. Hurtado et al. [72] present fuzzy multiagent control of a BEMS in a smart grid framework that shows reduced energy demand and points to even bigger savings in larger buildings due to thermal inertia.

Martirano et al. [73] demonstrated a fuzzy building automation control system with several fuzzy rules for energy and comfort balancing on three case studies of a smart office equipped with an automated/dynamic shading, lighting, and HVAC control. Keshtkar et al. [74] present an FL rule-based algorithm using outdoor temperature, load demand, electricity prices, and occupant presence as inputs for residential building load management.

Genetic and evolutionary approaches have been evidenced in energy efficiency predictions. Wang and Wang [75] have demonstrated 15% electricity savings using intelligent control (fuzzy-PSO approach) of ventilation for maintaining indoor carbon dioxide in comfort zones with reduced energy consumption. Such techniques have been used to develop thermal models [76], energy assessment [77], and planning of daily consumptions and occupant satisfaction [78].

Combined CI techniques attracted special attention of researchers in building energy systems. Techniques such as fuzzy *c*-means clustering, support vector machines, and GAs have been used for energy consumption behaviors profiling [79], [80]. Adaptive HVAC control was discussed by Bruckner et al.

[81], presenting intelligent control techniques in reviews of trends in building automation. The need for zero-average energy consuming buildings that actively stabilize grids is also explored [81]. Guest editorials have tackled similar applications of intelligent buildings, BEMSs, and smart grids [82].

Case Study: CI-Based Predictive Thermal Energy Storage Control

The main objective of the CI-based TES is to illustrate the effectiveness of intelligent control strategies, exemplified in TES but applicable to any other types of energy storage systems. In addition, the concept of energy storage can also be extended to incorporate renewables and small power-generating units into the grid. The ability to scale up to a large number of buildings and energy storage units is also evident. This specific task was selected for incorporating CI into a BEMS for a multitude of reasons. For example, the highly nonlinear and complex nature of building power utilization, utility load profiles, and energy storage units makes them difficult to be modeled by traditional methods. Also, the dynamic nature of the involved systems also renders static models inadequate. Finally, to optimally use the energy stored in storage units, the ability to predict energy usage/availability patterns is necessary. Thus, optimally controlled energy storage systems strongly benefit from the advantages of CI techniques.

The energy storage system discussed in this article is a TES system. To achieve the optimal control of TES, three CI components were introduced into the overall TES control system:

- building power requirement (BPR) prediction
- utility load prediction (ULP)
- ANN-based controller.

Figure 7 shows the overall architecture of the developed system. The ANN-based controls use the outputs from predictive units (BPR and ULP), as well as the TES energy availability.

BPR prediction provides information about the future power requirements of the building to the controller, so that the controller can make an informed decision whether to use TES based on current system values and trending of future power requirements. The ULP provides a controller with predictions on expected loads on the utility side. This module is included in the methodology since the overall utility load may govern the price in a varying price environment. Furthermore, it aims to provide the controller with information about the peak loads, which can be used to assist the utilities in performing peak shaving on their end. For example, the controller could be designed to use more energy from the TES when the overall load at the utility is high.

The presented methodology illustrates the task of optimization of the extracted energy from TES to cool the building(s). While cooling the building is chosen as illustration of the overall CI BEMS overview, the same lessons apply to using TES for heating buildings.

The overall case study focuses on controlling TES so the optimal balance between energy used from utility and energy used from TES is achieved. This balance optimization task minimizes the cost and assists in the peak shaving task for utility. CI-based controllers are inherently suitable for these tasks due to the highly nonlinear and dynamic nature of the optimization problem.

The Predictor Modules—BPR and ULP

The BPR predictor module is designed to predict the BPR for a given time in the

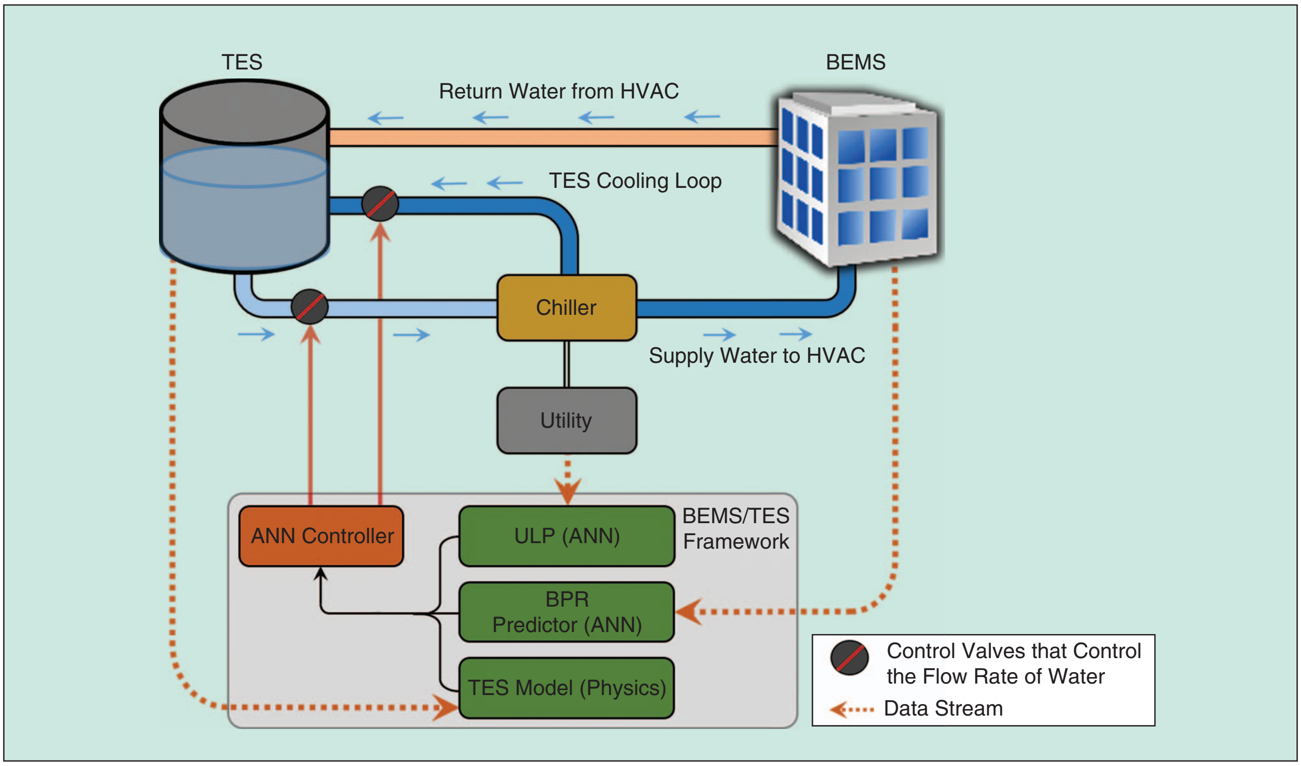

FIGURE 7 – The overall architecture for predictive TES control [6].

future. It performs the prediction based on historical data, i.e., it depends on how the building actually behaves in the real world.

BPR carries out the prediction process based on the power usage patterns of the building and weather patterns. To extract information on usage and weather patterns, BPR acquires data from the BEMS sensors to determine the current state of the building pertaining to power requirements. The output from the model is the estimated BPR for time step(s) in the future.

The ULP predicts the load of the utility for the following hour(s). This module is included in the system to provide the controller with information about the upcoming load curves so that the power used from the utility is minimized during high usage hours (peak-shaving) and purchase power when the price of utility power is lower. The output from the module is the estimated load of the utility for time steps in the future.

For both BPR and ULP, the extent of how far into the future predictions should go is driven by the requirements of the specific application. In this case study, both BPR and ULP are modeled using ANNs with error backpropagation as the training architecture using Levenberg–Marquardt enhancement [58], [83], [84].

TES Model

The effectiveness of the devised TES control strategy is predicated on the high fidelity of the model of energy storage at hand (TES in this case). This model should also incorporate the charge/discharge dynamics of the energy storage; in this case, it includes the effect of usage patterns and weather patterns.

Again, as CI techniques are data-driven techniques, they are inherently suitable for constantly changing and evolving building ecosystems. While physics-based, close-form solutions may be adequate in the design phase of the building, during operation, building and HVAC components age and floor plans and usage patterns change. Thus, only the instrumentation-based sensor data remain as indicators of realistic conditions inside the building. Therefore, data-driven techniques are more capable of handling building ecosystem evolution. Therefore, all of the building blocks of our CI-based BEMS are primarily based on data-driven techniques. In cases where sufficient data were not available, physics-based approaches might need to be used.

The flow of energy arriving and energy leaving TES is illustrated in Figure 8. Because the TES insulation is imperfect, some energy inevitably dissipates. The chiller cools the water from the TES before reaching the building and recools the TES as needed. After running through the building, water heated by absorbing heat from the building returns to the TES, thus reducing the "cold" energy stored in the TES.

ANN-Based Control of TES

The control module controls how much energy is being used by the TES at each time step. Controls are achieved by regulating the flow rate at which water is being extracted from the TES. The controller is CI-based.

As mentioned, the advantage of using TES is to replenish stored energy at times of lower electricity costs and use the stored energy when the power rates are higher. Furthermore, TES can be used for peak shaving of the utility load so that less energy will be used at peak hours. To achieve these goals, the controller should be able to take into account the predicted BPR, the predicted utility load profile, and TES behavior to determine the optimal use of the TES (listed in Table 1).

Looking as far ahead as possible enables the controller to make a well-informed decisions about when and how to use TES energy. Both BPR and the utility load can be used to achieve optimal cost savings as well as peak shaving. Furthermore, the available chillers have to be able to cool the TES back to a given temperature during cooling hours; thus, the TES controller should also take into account the recooling ability and times.

Therefore, the controller has to take into account the amount of energy needed to cool the building, the available energy in the TES, and the predicted utility load to a optimize both cost and peak shaving. The controller also has to use the TES in manner that allows it to be cooled down to a desired temperature within the available time frame. Thus, the outputs from each predictive block in Figure 7 will be used to generate the final control signal.

CI-based techniques are well suited for such control tasks because of their inherent capability of discovering underlying interrelationships between data and learning them to produce optimal control.

The ANN controller optimizes four factors to achieve the mentioned overall goals of the TES:

- total cost of cooling of both building and TES
- total money "wasted" as a result of overshooting the energy requirements by the building
- the amount of power to be purchased from utilities at peak hours
- the difference between the preset TES temperature lower limit and the actual TES temperature at the beginning of each week.

Each of these factors was minimized using the PSO technique [85].

The recooling control of the TES is based on preset thresholds and

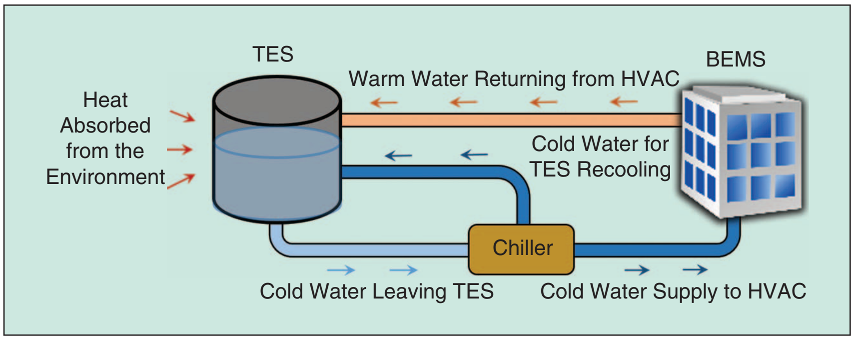

FIGURE 8 – The TES energy inputs and outputs.

parameters. For example, recooling time is the time interval in which the TES can be recooled (from 9:00 p.m. to 6:00 a.m.). During this time, lower utility pricing will be taken advantage of and the TES will not be used to cool the building. Therefore, TES will be recooled to the temperature threshold, 2 °C in the case of a small tank with a lower temperature limit (see Table 2). The chillers will operate at maximum capacity until the desired temperature is reached or the recooling time is over.

TABLE 1 – INPUTS TO THE CONTROL ANN.

INPUTS	DESCRIPTION
Predicted power requirement of the building for the next k time steps	Predicted power requirement of the building for cooling at time step t. The prediction is for k time steps starting from $t+1$ to $t+k$. Multiple time steps can be used for a more informed decision.
Predicted utility load for the next k time steps	Predicted utility load percentage at time step t. The prediction is for k time steps starting from $t+1$ to $t+k$. Multiple time steps can be used for a more informed decision.
Hour of day	Identifying the hour of the day as the time affects cooling patterns (for example, 9 a.m.–5 p.m. in an office building).
Day of week	Identifying the day of the week since cooling patterns will differ based on the day (for example, weekday versus weekend).
Current outside air temperature	The current outside air temperature is taken as an indication of the prevailing weather conditions.
Current averaged room temperature	This is the averaged room temperature of the whole building across all floors.

Experimental Results

The data set for the case study was generated using the U.S. DOE's free, open-source EnergyPlus simulation software [86]. The data set was a time period of five months, where one month was used for training and the remaining four months were used for testing the ANN architecture.

Figures 9 and 10 show the mean absolute percent errors (MAPE) obtained in the BPR and ULP, respectively. It can be observed that as the prediction time increases, the errors and standard deviations increase. However, the prediction errors are below 1% for the BPR and 5% for the ULP.

A simulated building was used to carry out the experimentation due to privacy issues, but the lessons learned from this study would remain the same regardless whether real building data were used. The simulated building consisted of ten floors, with five occupant zones on each floor. For the sake of simplicity, the assumption of identical floors with identical cooling demand was made.

To calculate the costs for the peak and off-peak hours, real-world pricing information was used. The prices were obtained from freely available data from a power company in Richmond, Virginia [87]. The pricing schedule used for calculations was US$0.09001 per kWh during peak hours (from 7:00 a.m. to 8:00 p.m.) and US$0.02405 per kWh during off-peak hours (from 8:00 p.m. to 7:00 a.m.) [87].

Three TES tanks of different sizes were used in this case study to evaluate the effects of capacity and other aspects of storage devices. The parameters of the test tanks were driven by best industry practices (Table 2). Each tank had a different size and maximum flow rate. Table 2 provides details of the different tanks used for testing. Furthermore, two sizes of chillers were considered for each tank, a high-power chiller (with the capacity to recool the tank to a desired temperature at night) and a low-power chiller (which does not have the capacity to cool down the TES). The last two rows in Table 2 list the specifications of the considered chillers.

TABLE 2 – VALUES OF THE TESTED TANKS.

TANK VARIABLE	UNIT	SMALL TANK	MEDIUM TANK	LARGE TANK
TES height	m	5	10	15
TES radius	m	1	7	15
Tank wall thickness	m	0.3	0.3	0.3
Thermal conductance	W/mK	0.1	0.1	0.1
Gallons in tank	gal	4,000	400,000	2,800,000
TES temprature. upper limit	°C	17	30	30
TES temprature. lower limit	°C	2	2	2
Maximum flow rate	kg/s	0.5	5	
Efficiency ratio of TES	None	0.85	0.85	0.85
Efficiency ratio of chiller	None	0.9	0.9	0.9
Chiller watts low	W	4,000	50,000	75,000
Chiller watts high	W	40,00	100,000	150,000

Therefore, with the experimental setup for TES and chillers, six test cases can be specified:

- test case one: small tank and low-powered chiller
- test case two: small tank and high-powered chiller
- test case three: medium tank and low-powered chiller
- test case four: medium tank and high-powered chiller
- test case five: large tank and low-powered chiller
- test case six: large tank and high-powered chiller.

For each test case, three different TES usage controllers were tested. These controllers will determine the amount of power that will be sent from the TES to the building in the next time step. The three controllers tested were a classical nonpredictive PD controller, an ANN 1 Hour (1H) control looking 1 h (time step) ahead, and an ANN 6 Hours (6H) control looking 6 h ahead.

The PD controller (Figure 11) represents a classical controller with no predictive capability. The PD controller determines the amount of power to be used by the TES for the next time step, based on current and previous power requirements of the building.

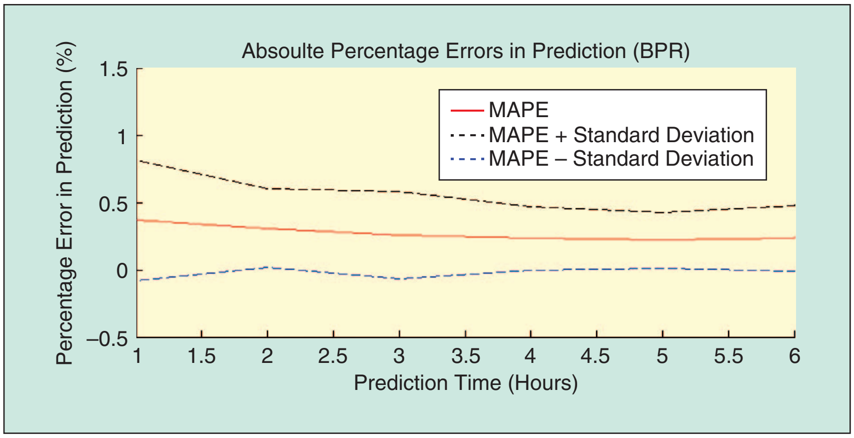

FIGURE 9 – The MAPE for the predictions of BPR.

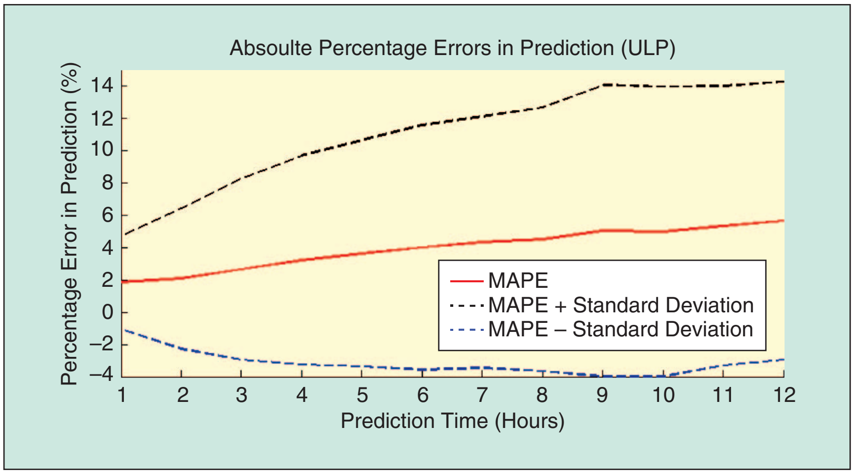

FIGURE 10 – The MAPE for the predictions of ULP.

Table 3 shows the experimental results for test cases one and two. For these test cases, both ANN controllers performed better for all test metrics (cost with and without TES, savings, "wasted" cost, and peak usage). Peak usage is the amount of power used from utilities during peak times (the lower, the better). For test case one, The ANN 6H showed better cost savings and peak shaving performance than the ANN 1H.

Table 4 shows the overall experimental results for test cases three and four. The ANN controllers performed better than the PD counterpart. The only metrics that the PD controller performed better in was the lower wasted cost in test case three. For test case four, the ANN 6H performed better across the board.

Table 5 shows the overall experimental results for test cases five and six. As in previous test cases, both ANN-based controllers outperformed the classical PD controller for all test metrics except the wasted cost for test case five and peak shaving for test case six. The PD controller performed better than the ANN 1H controller in terms of wasted cost in test case five. Similarly, the PD controller performed better than the ANN 1H controller for the peak shaving in test case six.

In both test cases five and six, the ANN 6H controller performed better that the two other controllers for all test metrics.

Conclusion

This article analyzes the main issues associated with the development of efficient BEMSs. It was shown that CI techniques are particularly well suited to address the challenges of managing huge amounts of dynamically changing data, the BEMS being subject to conflicting requirements, and to extract valuable information that can be used for increased situational awareness as well as optimal control. It was elaborated how highly nonlinear modeling capabilities and human-centric system abstractions of CI techniques can enable BEMS technologies of future.

A CI-based BEMS architecture has been shown to provide excellent results in terms of energy savings under different scenarios. Although this has been proved through a case study of CI-based control of a TES unit, the architecture can be extended and achieved conclusions extrapolated. For example, other energy storage types can be used, and a multitude of buildings and energy storage units at different scales can be included.

The presented CI-based BEMS was composed of three parts, a BPR predictor, a utility load predictor, and a TES control module. The experimental

TABLE 3 – EXPERIMENTAL RESULTS FOR THE SMALL TANK (TEST CASES ONE AND TWO).

TANK SIZE	CHILLER WATTAGE	CONTROL	COST WITHOUT TES (US$)	COST WITH TES (US$)	SAVINGS (US$)	SAVINGS (%)	WASTED COST (US$)	PEAK USAGE (%)
Small	Low (test case one)	PD	8,370.508	8,290.878	79.630	0.951	134.737	78.144
		ANN 1H	8,370.508	8,188.689	181.818	2.172	**0**	78.301
		ANN 6H	8,370.508	**8,187.480**	**183.027**	**2.187**	**0**	**78.079**
	High (test case two)	PD	8,370.508	7,455.746	914.761	10.928	3.703	68.415
		ANN 1H	8,370.508	7,432.460	938.048	11.207	**3.100**	**67.687**
		ANN 6H	8,370.508	**7,428.485**	**942.023**	**11.254**	3.326	68.219

results confirmed that it consistently outperformed a classical, nonpredictive PD controller. The BEMS can be trained on real-world data (building, TES, and utility) to obtain performance benchmarks for real-world control systems.

Despite its excellent performance, this BEMS can be further improved by extensive experimentation on different CI-based control strategies and predictive algorithms. For instance, the possibility of incorporating expert knowledge into the controller could be explored through use of FL. Furthermore, different ANN architectures could be experimented with to provide higher prediction accuracies and increased prediction times.

The concept behind the presented work is not confined to controlling thermal storage units. It can easily incorporate renewables into a BEMS. Renewable energy sources such as windmills and PV batteries could be incorporated to achieve financial savings, peak shaving, and grid stability. A similar CI-based approach could be followed to control the usage of such renewables to obtain the optimal benefits from them.

Smart buildings, such as intrinsic parts of cyberphysical ecosystems, will naturally play a crucial role in the overall resiliency of ecosystems of which they are part. Intelligent (CI-based) aspects of smart buildings will significantly contribute to the capabilities of balancing local generation, energy efficiency optimization, and energy storage (electrical vehicles). In this way, buildings will become resilient units, acting as flexible energy storage/responsive load systems, interacting with smart grids, and accommodating fluctuations in local energy generation and energy consuming habits. Along with

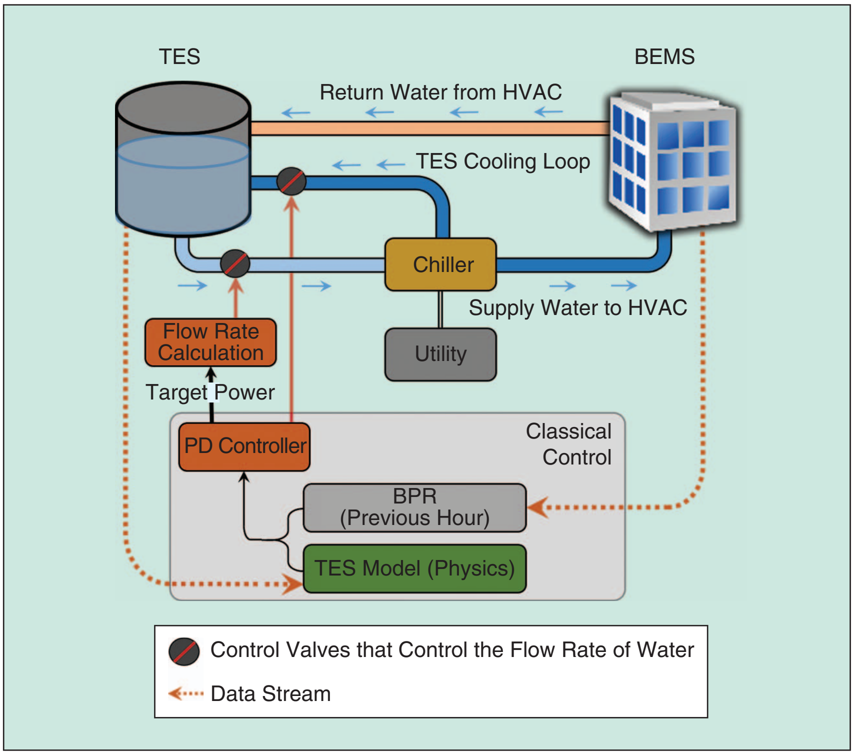

FIGURE 11 – The control structure of the classical PD controller.

TABLE 4. EXPERIMENTAL RESULTS FOR THE MEDIUM TANK (TEST CASES THREE AND FOUR).

TANK SIZE	CHILLER WATTAGE	CONTROL	COST WITHOUT TES (US$)	COST WITH TES (US$)	SAVINGS (US$)	SAVINGS (%)	WASTED COST (US$)	PEAK USAGE (%)
Medium	Low (test case three)	PD	8,370.508	6,532.240	1,838.267	21.961	**0**	39.316
		ANN 1H	8,370.508	**6,422.214**	**1,948.293**	**23.276**	**0**	38.180
		ANN 6H	8,370.508	6,431.000	1,939.508	23.171	8.627	**35.980**
	High (test case four)	PD	8,370.508	4,761.879	3,608.628	43.111	546.578	14.304
		ANN 1H	8,370.508	4,421.861	3,948.647	47.173	144.123	13.897
		ANN 6H	8,370.508	**4,217.703**	**4,152.804**	**49.612**	**57.504**	**12.282**

TABLE 5 – EXPERIMENTAL RESULTS FOR THE LARGE TANK (TEST CASES FIVE AND SIX).

TANK SIZE	CHILLER WATTAGE	CONTROL	COST WITHOUT TES (US$)	COST WITH TES (US$)	SAVINGS (US$)	SAVINGS (%)	WASTED COST (US$)	PEAK USAGE (%)
Large	Low (test case five)	PD	8,370.508	7,591.848	778.660	9.302	0	33.547
		ANN 1H	8,370.508	7,682.410	688.098	8.221	28.370	31.323
		ANN 6H	8,370.508	**7,570.861**	**799.647**	**9.553**	**0**	**30.910**
	High (test case six)	PD	8,370.508	5,459.915	2,910.592	34.772	494.534	9.795
		ANN 1H	8,370.508	5,459.547	2,910.960	34.776	253.989	10.733
		ANN 6H	8,370.508	**5,257.788**	**3,112.719**	**37.187**	**136.023**	**9.635**

the resilience, buildings are expected to become great real-world test beds for issues in cybersecurity and data privacy for instrumentation and controls as well as human-originated cyberdata flows.

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