Intelligent Management Systems for Energy Efficiency in Buildings: A Survey

ALESSANDRA DE PAOLA, MARCO ORTOLANI, and GIUSEPPE LO RE,
University of Palermo, Italy
GIUSEPPE ANASTASI, University of Pisa, Italy
SAJAL K. DAS, Missouri University of Science and Technology, USA

13

In recent years, reduction of energy consumption in buildings has increasingly gained interest among researchers mainly due to practical reasons, such as economic advantages and long-term environmental sustainability. Many solutions have been proposed in the literature to address this important issue from complementary perspectives, which are often hard to capture in a comprehensive manner. This survey article aims at providing a structured and unifying treatment of the existing literature on intelligent energy management systems in buildings, with a distinct focus on available architectures and methodology supporting a vision transcending the well-established *smart home* vision, in favor of the novel Ambient Intelligence paradigm. Our exposition will cover the main architectural components of such systems, beginning with the basic sensory infrastructure, moving on to the data processing engine where energy-saving strategies may be enacted, to the user interaction interface subsystem, and finally to the actuation infrastructure necessary to transfer the planned modifications to the environment. For each component, we will analyze different solutions, and we will provide qualitative comparisons, also highlighting the impact that a single design choice can have on the rest of the system.

Categories and Subject Descriptors: A.1 [**General Literature**]: Introductory and Survey; I.2 [**Artificial Intelligence**]: General; J.0 [**Computer Applications**]: Applications and Expert Systems

General Terms: Design, Algorithms, Measurement

Additional Key Words and Phrases: Building management systems, energy saving, ambient intelligence

ACM Reference Format:
Alessandra De Paola, Marco Ortolani, Giuseppe Lo Re, Giuseppe Anastasi, and Sajal K. Das. 2014. Intelligent management systems for energy efficiency in buildings: A survey. ACM Comput. Surv. 47, 1, Article 13 (May 2014), 38 pages.
DOI: http://dx.doi.org/10.1145/2611779

1. INTRODUCTION

Technological advancements stimulate novel products and services, which, however, inevitably result into intensive resource (e.g., energy) consumption. At the same time,

---

The work of S. K. Das is partially supported by the following NSF grants: 26-1004-54 titled the E2Home (Energy Efficient Home) project, IIS-1064460 and CNS-1150192.
The work of A. De Paola, M. Ortolani, G. Lo Re and G. Anastasi is partially supported by the PO FESR 2007/2013 grant G73F11000130004 funding the SmartBuildings project and by the PON R&C grant MI01_00091 funding the SeNSori Project.
Authors' addresses: A. De Paola, M. Ortolani, and G. Lo Re, Viale delle Scienze, ed. 6, Università degli Studi di Palermo, 90128 Palermo (PA), Italy; email: {alessandra.depaola, marco.ortolani, giuseppe.lore}@unipa.it; G. Anastasi, Largo Lazzarini n. 1, Università di Pisa, 56126 Pisa (PI), Italy; email: g.anastasi@iet.unipi.it; S. K. Das, 500 West 15th Street, Missouri University of Science and Technology, Rolla, MO 65409-0350, USA; email: sdas@mst.edu.

DOI: http://dx.doi.org/10.1145/2611779

global awareness about their costs in terms of energy footprint is arising for the sake of environment protection. In fact, current rates of worldwide energy utilization are no longer affordable, and therefore an increasing number of governments are promoting policies for sustainable development and clever use of global energy resources. Their ultimate aim is a significant reduction of the overall polluting emissions, and the adoption of suitable strategies for reducing unnecessary energy wastes. Merely limiting the use of novel services would, however, pose an unacceptable burden on the end user. Hence, rather than cutting services, the research in the field of energy efficiency must focus on the optimization of resource usage yet providing an adequate level of comfort for the users.

A proper characterization of energy consumption in an environment is necessary in order to identify the main causes of wastes. A relevant fraction of worldwide energy consumption is tightly related to indoor systems for residential, commercial, public, and industrial premises; it has been estimated that residential and commercial buildings account today for about 20% of the world's total energy consumption. In this domain, the energy bill due to environmental control—including heating, ventilation, and air conditioning (HVAC)—is dominating, especially in the developed countries [U.S. Energy Information Administration 2010]. Residential appliances consume about 30% of the total electricity consumption and produce 12% of all energy-related CO_2 emissions; for instance, about 54% of the energy consumption in US residential buildings is due to HVAC systems, and about 6% to artificial lighting, while in commercial buildings HVAC and artificial lighting systems account for 40% and 15% of energy consumption, respectively [Perez-Lombard et al. 2008].

A wide variety of systems and methodologies have thus been proposed in the literature to address the issue of reducing energy consumption in residential and commercial buildings. These proposals are based on different yet complementary perspectives, and often take an interdisciplinary approach, which makes it hard to obtain a comprehensive view of the state of the art in the energy management of buildings.

The lack of a structured and unifying view over the available approaches and methodologies to be adopted during the design of such energy-aware systems was the main trigger for undertaking the research underlying this survey. We specifically focused on the underlying architectures and methodologies, as well as on the necessary techniques that go beyond the well-established *smart home* paradigm, thus progressing toward intelligent Building Management Systems (BMSs), in accordance with the Ambient Intelligence (AmI) vision. The ideal application scenario for AmI considers the user as the focus of a pervasive environment augmented with sensors and actuators, where an intelligent system monitors environmental conditions and takes the proper actions to satisfy user requirements [Remagnino and Foresti 2005]. AmI systems are characterized by a low intrusiveness, by the capability to adapt themselves to the users' behavior and to anticipate their requirements. In the specific context of a BMS for energy saving, this visionary goal becomes even more complex due to the presence of contrasting goals, that is, satisfaction of user requirements and minimization of energy consumption.

Throughout this survey, we will identify the main components constituting a BMS; namely, a sensory infrastructure for monitoring energy consumption and environmental features, a data processing engine for processing sensory data and performing energy-saving strategies, a user interaction interface subsystem, and an actuation infrastructure for modifying the environmental state. For each component, we will analyze different solutions presented in the literature. Whenever possible, we will provide qualitative comparisons of various approaches with respect to their specific features. We will also highlight the impact that a single design choice can have on the rest of the system. To qualitatively evaluate different BMS, we will identify a set of relevant characteristics. In this assessment, the end users have a relevant role; besides being affected by too strict energy-saving policies, users might be hassled by other structural features, such as a set of invasive devices, or by algorithmic features, such as learning methods that force them to have a continuous interaction. In general, we will refer to these aspects as the "user comfort," and we will emphasize the characteristics of different solutions in terms of scalability and complexity of the proposed architecture, intrusiveness of the deployed sensory and actuating devices, and the resulting impact of technology on user comfort.

Although some effort has already been made in this domain [Cook and Das 2007; Froehlich et al. 2011; Lu et al. 2010b], there still exist significant research challenges. The focus on users imposes great commitment on reducing intrusiveness of the deployed equipment, and pushes toward the development of intelligent algorithms which do not require user-driven training. This entails reducing the amount of a priori information that needs to be provided by installers, as well as limiting preliminary off-line training and minimizing explicit interactions with users. Advances in this direction will allow for systems requiring minimal deployment effort, thanks to the lack of need for manual configuration, except for basic structural information. With such capability of self-configuration in place, it will be possible to devise BMSs able to self-adapt to previously unseen scenarios; the unpredictability of the environment may be due to variations in the performance of the actuators, modifications in the habits or preferences of users, or to changes in climate. In a visionary perspective, it is conceivable to think of self-organizing architectures able to modify their own software, given a simple high-level description, with the aim of developing truly autonomic systems.

In order to carry out the research underlying this survey, we considered papers appeared on journals and conference proceedings published by the most relevant research associations and publishers, in the last decade, with a specific focus on the past 4 years, besides a few less recent works, which can be considered as milestones in their field. The works included in the survey were selected on the basis of their relevance, scientific soundness and of the presence of significant results for the field.

Before starting with the discussion of each of the mentioned issues, Section 2 introduces the main approaches to energy saving in buildings, while Section 3 states the requirements of a BMS and describes a reference architecture. Then, Section 4 discusses a number of possible architectures proposed in the literature for practical BMSs. Section 5 provides an overview of the different approaches to energy monitoring, of the available sensory devices for measuring energy consumptions, and of energy models proposed in the literature. Section 6 focuses on technologies and methodologies for premise occupancy detection and learning the user preferences. Section 7 surveys intelligent techniques, such as user profiling, pattern detection, and pattern prediction, that are instrumental to energy saving.

2. GENERAL APPROACHES TO ENERGY EFFICIENCY

Four general approaches have been identified in the literature for reducing electrical energy consumptions in buildings [Corucci et al. 2011], namely user awareness about energy consumptions, reduction of standby consumptions, scheduling of flexible tasks, and adaptive control of electrical equipments. We will briefly discuss each of them in the following.

Energy Consumption Awareness. The simplest approach to energy efficiency is to provide appropriate feedback to the users about energy consumptions so as to increase their awareness and encourage eco-friendly behaviors. User awareness has been leveraged in many commercial and prototype systems such as *Google PowerMeter* [PowerMeter 2011], *Microsoft Hohm* [Microsoft Hohm 2011], *Berkeley Energy Dashboard* [Pulse Energy Inc. 2013], *AlertMe* [AlertMe 2013], *Cambridge Sensor Kit* (CSK) for Energy [Taherian et al. 2010] and *E2Home or Energy-Efficient Home* [Ghidini and Das 2012]. Providing simple feedback can valuably influence the user behavior [Darby 2006]. However, to reduce costs, these systems typically provide only aggregate measures of energy consumption. Hence, they do not allow to identify the specific device or behavior causing the highest energy waste. Although user awareness is the basic approach to energy efficiency, its effectiveness is quite limited. Experimental studies carried out in a real building [Jiang et al. 2009b] have shown that the sole provision of feedback is not sufficient to ensure significant energy savings in the long term.

Reducing Standby Consumption. Another simple approach consists in eliminating or drastically reducing energy wastes due to electrical appliances left in standby mode. Despite its apparent simplicity, such an approach can produce significant energy savings. It has been estimated that most consumer electronics (such as TVs, set-top boxes, hi-fi equipments) and office devices (e.g., printers, IP phones) consume more energy in standby mode than in active mode, as they remain in standby for very long times [International Energy Agency 2003]. The standby mode can be detected by monitoring the energy consumption of the specific device. This requires a metering infrastructure which, of course, should have a very low energy consumption [Jiang et al. 2009a]. Once the standby mode has been detected, the device can be switched off. To this end, different strategies can be used to trade off energy saving for user satisfaction. The easiest way is to let the user decide about when to switch off a device that entered the standby mode [Corucci et al. 2011]. A more sophisticated approach consists of taking into account information related to the user presence, or in learning their behavior.

Activity Scheduling. The widespread adoption of smart technology in many electrical appliances enables the scheduling of their activity plans for energy optimization. In case of constraints on the energy peak demand or in the presence of time-dependent fares, ad hoc strategies can be implemented for determining the optimal scheduling of energy-hungry tasks that do not require user interaction (e.g., washing machine, dishwasher). The BMSs proposed in Corucci et al. [2011] and The AIM Consortium [2008] allow the user to specify the exact time period when a certain task is to be executed by a specific appliance. Such a policy makes sense only when energy fares vary over time, but their variations are known a priori.

Adaptive control. A significant fraction of energy is wasted due to an expensive use of HVAC and artificial lighting systems, thus adaptive control on such systems is essential for effective energy management in buildings. The enacted policies should not negatively affect the comfort perceived by the user, otherwise the reaction would be an immediate rejection of any automatic control, thus discarding the possibility of energy saving. The use of intelligent techniques for user-presence detection and prediction is advised to adaptively tune the activation time of electrical equipments, especially for those whose latency in bringing the environment into the desired conditions is non negligible (see Section 7.1). Techniques for learning user preferences may also be extremely useful for adaptively managing electrical appliances, as they help to avoid overestimating user needs and just take into account their actual requirements.

3. THE REFERENCE BUILDING MANAGEMENT SYSTEM

To be effective, the previous general approaches need to be implemented in an automated BMS capable of enforcing an intelligent utilization of electrical appliances—with respect to user preferences—so as to reduce electrical energy consumptions in the buildings without negatively affecting user comfort.

The focus on energy-awareness imposes several *functional* requirements, related to:

—sensing the environmental conditions (e.g., temperature, light intensity);
—monitoring energy consumption;
—modifying the environmental conditions;
—interacting with users to send them notifications and to gather feedbacks and commands from them;

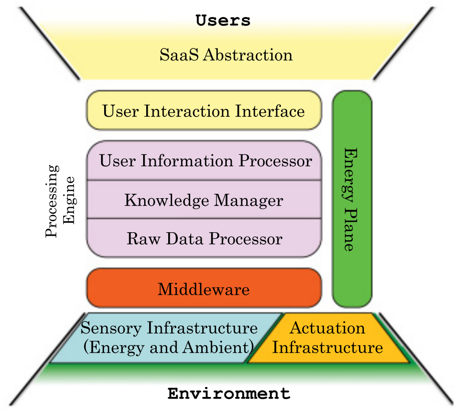

Fig. 1. Main components of the reference Building Management System for energy efficiency.

—detecting context (e.g., user presence, actions performed by the user);
—predicting the context;
—learning user habits and preferences;
—learning the energy consumption of appliances;
—learning the effects of the actuators on the environment state;
—planning the optimal sequence of actions leading to energy saving while satisfying the user requirements, according to system goals.

Moreover, it is highly desirable that the following *nonfunctional* requirements are also fulfilled:

—low intrusiveness of the interaction with the user;
—low intrusiveness of physical devices and infrastructure;
—scalability with respect to the number of devices, areas, and occupants;
—extensibility after addition of new devices, thanks to proper abstractions;
—ease of deployment;
—software modularity;
—interoperability, both with respect to physical devices and with respect to other software systems.

All these requirements should find correspondence in the choice for the architecture of the entire system. Even though the complexity of any significant BMS discourages the use of a single architectural paradigm to capture all of its essential aspects, some general considerations apply. For instance, most complex functionalities require the use of artificial intelligent techniques, whose implementation needs to preserve *unitarity* of reasoning, which is not easily obtainable in a fully distributed environment. On the other hand, such systems also rely on a close connection with the surrounding environment, which directly translates into the need for a pervasive physical infrastructure.

According to this general scheme a BMS should comprise the following components (see Figure 1), designed as suggested:

—**Sensory and Actuation Infrastructure:** constitutes the connection to the real world; the sensor devices will comprise energy/power meters for measuring energy consumptions, and sensors for acquiring environmental data (e.g., temperature, light intensity, etc.) and context information (e.g., user presence), whereas the actuation infrastructure will consist of all the physical devices in the building that can influence the state of the environment (e.g., HVAC or artificial lighting systems);

—**Middleware:** connects the lower distributed infrastructure with the centralized processing modules, dealing with the extreme heterogeneity of the devices nowadays available at the physical level. It should be easily extensible with respect to the adoption of new devices; an effective approach is to design these modules in a component-based fashion. The sensing and actuating devices in this case may be programmed as individual specialized software components, exporting a common interface allowing for their aggregation into more complex modules, to be used by the upper layers.

—**Processing Engine:** is constituted by specialized components implementing advanced functionalities, such as targeting the energy consumption of appliances, and the effects of the actuators on the environment, learning user preferences, and recognizing their current activities. A different architectural paradigm may be needed to tackle the inherent complexity of the intelligent core, and to ensure its modularity. The approach suggested here is to group the related software components into logical levels according to the provided functionalities, following a three-tier model mirroring the increasing level of abstraction during data processing from the environment up to the user. Those components will likely benefit from a centralized implementation.

—**User Interaction Interface:** provides interaction with the end users in order to send them notifications to stimulate appropriate behaviors, and to gather feedbacks and commands from them. A paradigm shift is necessary at this level; a fully distributed implementation is probably the wisest choice, and a smoother user experience can be provided by developing the applications in the context of a Software as a Service (SaaS) infrastructure. Besides favoring scalability, an immediate advantage for users would be that they would only need very thin clients to access the system so that the interaction may be very natural and the overall system would result minimally intrusive.

Besides these components, the BMS should include software modules for energy awareness. Unlike the other components, those modules should be spread across all layers for better efficiency, as indicated by the **Energy Plan** in Figure 1.

4. BMS ARCHITECTURES

After introducing the general architecture of a BMS for energy efficiency and briefly describing the main functionalities it should implement, we now survey a number of architectural solutions proposed in the literature, and we analyze and compare them from different viewpoints, such as *architectural model* (e.g., centralized vs. distributed), *internal organization* (e.g., single layer vs. multilayer), *networking protocols*, ability to support *heterogeneity* in sensing technologies, and so on. Moreover, we compare different solutions with respect to such software quality attributes, as *modularity*, *extensibility,* and *interoperability*.

4.1. Plain Support for Energy Awareness

The first considered solution is a monitoring system based on *Web-enabled Power Outlets* [Weiss and Guinard 2010]. Since the system is only intended to stimulate user awareness to energy consumption, there is no actuation infrastructure. A Web-based user interaction interface is responsible for sending appropriate notification messages to the user. Each appliance is connected through a power outlet, that is, a power meter that measures the energy consumption of the appliance and sends the acquired

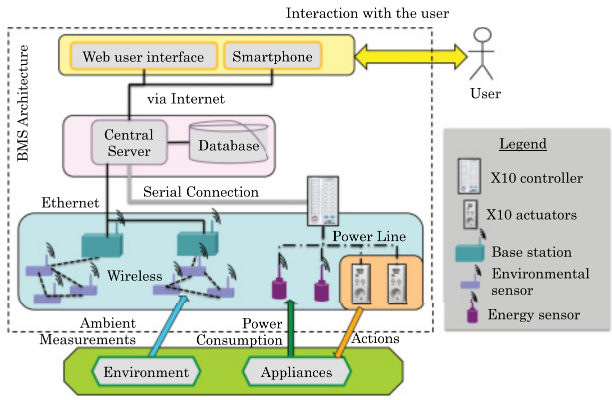

Fig. 2. *iPower* architecture.

information to a Gateway, using a standard communication protocol (e.g., Bluetooth or ZigBee). By providing a RESTful Application Programming Interface (API) [Richardson and Ruby 2007], the Gateway seamlessly integrates the smart power outlets into the Web. This allows users to easily access their energy consumption through a Web browser. At the same time, it opens the system to application developers. Such an approach would appear overly simplistic with respect to the ideal BMS; complete focus on energy monitoring does not allow to relate consumption to the current environmental state, nor does it allow to automatically control actuators. A very fine-grained energy monitoring by unintrusive devices would, on the other hand, be advisable for the realization of an ideal BMS, possibly based on a more complex architecture.

In the previous solution, the integration of power outlets with the World Wide Web is mediated through an intermediate gateway. A further evolution consists of a direct integration of power meters, and possibly any other smart device, by exploiting the *Web-of-Things* (WoT) paradigm. The latter is the extension of the well-known *Internet of Things* (IoT) paradigm to the Web [Guinard et al. 2011]. Following the WoT approach, any smart object (e.g., power meter, sensor, actuator) hosts a tiny web server. Hence, it can be fully integrated in the Web by reusing and adapting technologies and patterns commonly used for traditional Web content. An application framework for a smart home following the WoT paradigms has been proposed in *HomeWeb* [Kamilaris et al. 2011]; this solution is characterized by some degree of modularity because it is based on a Web-service approach.

The solutions discussed so far rely on a centralized architecture and are able to support heterogeneous embedded devices, thus providing a basic support for interoperability and extensibility, even if these potential characteristics are not fully exploited.

4.2. Integration of Actuators and Environmental Sensors

A centralized architecture is also implemented by the *iPower* system [Yeh et al. 2009] (see Figure 2). In *iPower*, a central server interacts with heterogeneous sensory and actuator devices. Specifically, a Wireless Sensor Network (WSN) [Benini et al. 2006] is used to monitor environmental conditions and to measure energy consumptions, while actuation is performed by X10 [X10 2013] devices connected to the server via Power Line Communication (PLC). Since wireless sensors have a limited transmission range, they may not be able to communicate directly with the server. Hence, to extend the system coverage, sensing devices send their data to a local base station. Base stations are then connected to the server through an Ethernet high-speed LAN. To manage heterogeneity with a sufficient degree of abstraction, *iPower* relies on a multilayer architecture.

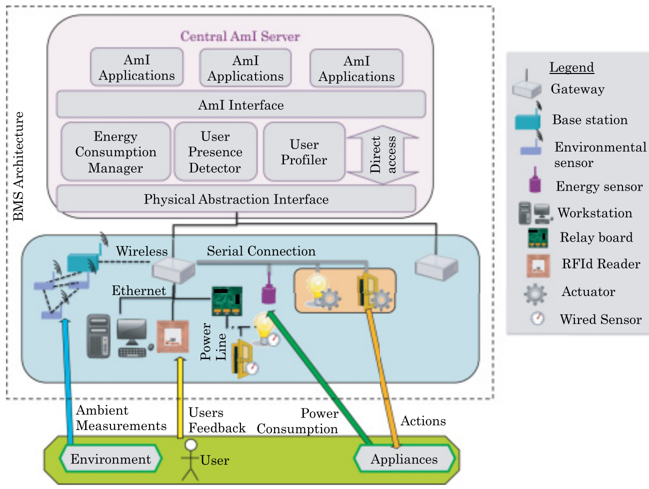

Fig. 3. *Sensor9k* architecture.

A Service Layer is defined, within the central server, to provide an abstraction over the physical layer (as defined by the interfaces of the *Open Service Gateway initiative* (OSGi) platform [Gu et al. 2004]) according to a service-based paradigm. On top of the Service Layer lies the intelligent system logic, based on a rule-based reasoning engine. Rules are defined by the system administrator by means of a high-level language and translated into service requests for the actuators. iPower paves the way for an interoperable, modular, and extensible solution. The iPower solution, despite the adoption of slightly more intrusive sensors and actuators, allows to monitor environmental quantities, besides energy consumption; moreover, a hierarchical organization vouches for medium scalability. However, it is our belief that a greater effort is necessary in terms of scalability, also with respect to the software components devoted to reasoning. The rule-based engine guarantees a coherent source of reasoning, albeit a reactive one, and does not support prediction. Finally, the actuating infrastructure appears too simple to enact automatic control of actuators, and merely allows for tuning their supply power.

A centralized approach, similar to that used in *iPower*, is also considered by *GreenBuilding* [Corucci et al. 2011]. Unlike *iPower*, *GreenBuilding* uses an unstructured (i.e., single-tier) architecture and combines the energy monitoring and control functionalities into a single infrastructure (i.e., power meters are also actuators). In addition, sensing devices for environmental monitoring can be fully integrated in the same unique wireless infrastructure. A similar solution is also proposed in Wen and Agogino [2008], where a prototype of a wireless actuation module is presented that can be fully integrated within the monitoring WSN. Using a single (wireless) infrastructure for monitoring and control lessens the burden of technology integration. On the other hand, it reduces the flexibility in deciding the granularity of the monitoring/control process. As for *iPower*, this architectural solution aims at the right direction, but does not appear fully adequate yet because of the simple actuating system and the lack of explicit support for intelligent reasoning.

4.3. Hierarchical Architectures for Improved Scalability

A more complex architecture capable of providing advanced support to heterogeneous sensory and actuator infrastructures is used in the *Sensor9k* system [De Paola et al. 2012]. As shown in Figure 3, the system architecture is organized according to a three-tier model. The *Physical* layer includes all the sensory and actuation devices, the

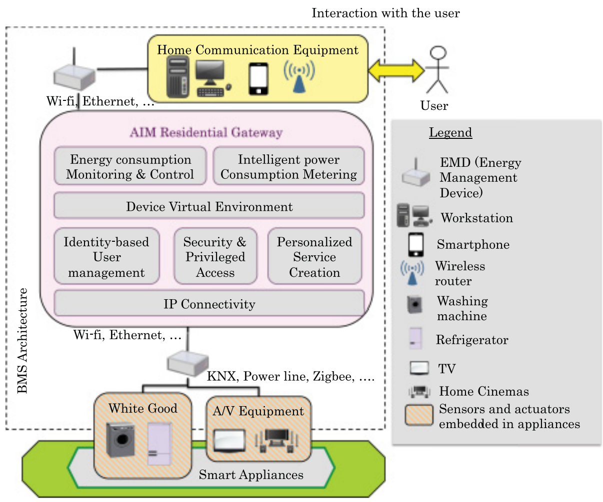

Fig. 4. AIM Reference architecture.

Middleware layer is composed of a set of building blocks for implementing basic services, and, finally, the *Application* layer hosts the control logic and consists of various AmI applications. The inclusion of a *Physical Abstraction Interface* ensures support against the heterogeneity of physical devices, as it takes care of exporting higher-level abstractions identifying the basic monitored units. Such system aims to address scalability with respect to the number of monitored areas, which is typically the major limitation of centralized solutions, through a hierarchy of gateways implementing different middleware functionalities. The sensory and actuating infrastructure of such architecture presents a degree of complexity suitable for implementing advanced energy saving strategies through adaptive control of actuators and user action monitoring. On the other hand, the high dependence on the available appliances requires ad-hoc design and development of sensors on actuators, thus limiting the generality with respect to the adoption across different scenarios.

The idea of a hierarchical architecture with gateways interconnecting different technologies is also proposed in Capone et al. [2009], in the context of the AIM project [The AIM Consortium 2008]. The main goal is the construction of a bridge between a smart home and the smart power grid in order to control the energy consumption of appliances. As shown in Figure 4, the proposed architecture is a two-level hierarchy. At the topmost level lies the AIM *Gateway*, whose task is the coordination of a set of *Energy Management Devices* (EMDs) [Tompros et al. 2008, 2009], each of which manages a number of appliances. EMDs implement the actual control logic that includes *power monitoring* and *power control*. These functionalities exploit the energy profiles of appliances, that is, the association between predicted energy consumption and operating mode of the appliance, as outlined in Section 5.3. EMDs represent the element, within the AIM Project architecture, allowing the abstraction from a specific physical layer; they may be implemented differently depending on the home network but still expose the same communication API to the AIM Gateway. The latter takes care of providing a unified interface for inter-EMD communication, both internally (i.e., for the system users) and externally (i.e., toward the energy provider). Most of the energy management functionalities, such as appliances control and user profiling, are hosted by the Gateway. By exploiting EMDs, the Gateway can learn the operating mode of appliances and take actions to modify it by deactivating the appliance or by turning

Table I. Comparison between Different Architectures

	Web-enabled Power Outlets	iPower	Sensor9k	AIM Architecture
Ambient Sensor Technologies	None	WSN	WSN, RFID, User action sensors	WSN, RFID
Energy-aware Technologies	Power meters	Wireless power meters and actuators	Root/Wireless power meters	Energy Management Devices (EMD)
Architecture Model	One-tier	Multitier	Multitier	Multitier
Support for Heterogeneity	None	OSGi	OpenGIS-based	OSGi
Control Logic Deployment	Centralized	Centralized	Centralized	Distributed
Interoperability	Low	Medium	High	High
Scalability	Low	Medium	High	High
Extensibility	Low	Medium	Medium	High

its operating mode to a less consuming one. AIM Gateways are implemented with ESTIA gateways [The ESTIA Consortium 2008]. This specific technology was chosen since these devices are based on the open services execution framework of OSGi [Lee et al. 2003; Gu et al. 2004]. Among the presented architectures, this is the one that allows for the greatest scalability, extensibility, modularity and interoperability due to its hierarchical architecture and also its partially distributed control logic with respect to high-level functionalities. These considerations would locate AIM close to the ideal reference BMS.

4.4. Comparison among Different Architectural Solutions

The main features of the architectures described so far are summarized in Table I. Those architectures may be regarded as representative of the three main types of approaches described in this section: *Web-enabled Power Outlet* represents the simplest possible solution, as it provides only a basic support for energy monitoring; *iPower* stands for solutions also integrating different actuators and sensors, thus moving toward an interoperable, modular and extensible BMS; *Sensor9k* and *AIM Architecture* represent hierarchical solutions that try to meet the requirements we identified for an ideal BMS; the respective peculiarities in their distributed approaches justify a deeper analysis of both proposals.

An interesting contribution to the definition of an appropriate level of abstraction for heterogeneous devices is presented in *BOSS* [Dawson-Haggerty et al. 2013]; although this work does not define a particular type of architecture, it proposes a distributed operating system to manage heterogeneous devices in a BMS. For this purpose, *BOSS* includes a Presentation Layer Hardware as an extension of sMAP [Dawson-Haggerty et al. 2010] and a Hardware Abstraction Layer that allows developers to interact with devices via semantic queries. In addition to the aforementioned architectures and other similar ones not considered here for the sake of space, a number of smart-home solutions have been proposed in the literature that fall into the broad field of Smart Spaces. They are typically general-purpose solutions, and do not specifically consider the goal of energy saving [Roy et al. 2007; Cook and Das 2004; Dawson-Haggerty et al. 2010; Helal et al. 2005]. Even if most of them could be extended to address energy efficiency, they are beyond the scope of this survey. A detailed review of solutions presented in the literature for smart environments and ambient intelligence systems is reported in Cook and Schmitter-Edgecombe [2009], Cook and Das [2007], and Sadri [2011]. Finally, an overview of wired and wireless communication technologies

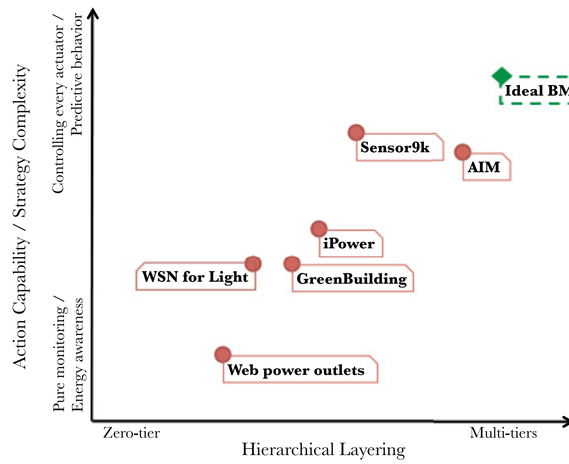

Fig. 5. Comparison among different architectures with respect to two qualitative dimensions. The assessed architectures are: Sensor9K [De Paola et al. 2012], AIM [Capone et al. 2009], iPower [Yeh et al. 2009], GreenBuilding [Corucci et al. 2011], WSN for Light [Wen and Agogino 2008], and Web power outlets [Weiss and Guinard 2010].

for building automation can be found in Qiu and Deconinck [2011] and Gomez and Paradells [2010], respectively.

As a final consideration, we can state that a requirement for an effective BMS for residential control is the presence of a rich sensory and actuating infrastructure, with good scalability. Figure 5 compares different approaches with respect to two qualitative dimensions, namely the hierarchical layering of their BMS architectures (and their complexity, which influences scalability) versus the support for advanced actuation capabilities and the resulting possibility of performing complex strategies of energy saving. According to this qualitative analysis, the ideal architectural choice would fall close to the solution proposed in Capone et al. [2009]. A solution providing no support for actuation, but just pure monitoring, only enables very simple energy saving strategies aiming at stimulating energy awareness in users, but entirely delegating to the users the choice about modifying their habits. On the other hand, a varied actuating system, allowing for individual control of actuators via specific signals, enables complex strategies. Intelligent systems may exploit such complexity, and plan the optimal sequence of actions that can satisfy users and minimize energy consumptions.

5. MEASURING ENERGY CONSUMPTION

A precise and timely knowledge of energy consumption is an essential requirement for enforcing any energy saving strategy. Hence, measuring energy consumption is the basic functionality of BMSs targeted to energy efficiency. The monitoring of energy consumption in buildings indirectly provides information about the user habits and context [Beckel et al. 2013], in terms of the occupancy levels and of the kind of activities carried on by the inhabitants [Kim et al. 2009b]. Thus, a relevant issue to be addressed during the design phase of a monitoring system is how to monitor energy consumption with the required precision and granularity while preserving the user privacy.

5.1. Systems for Energy Monitoring

Systems for energy monitoring can be classified according to different criteria, for example, the type of sensors they use, or the spatial granularity used for collecting

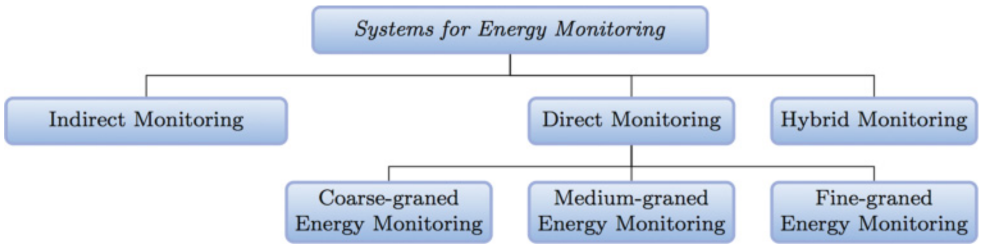

Fig. 6. Taxonomy of energy monitoring systems.

data. With respect to sensors, it is possible to distinguish between *direct*, *indirect*, and *hybrid* monitoring systems. Direct monitoring systems use electricity sensors for directly measuring energy consumption, while indirect systems infer energy consumption by measuring other quantities such as temperature and/or noise. Finally, hybrid systems rely on both approaches. Direct monitoring systems can be further classified into *fine-grained*, *medium-grained,* and *coarse-grained* systems, depending on the level of spatial granularity they use in collecting data about electrical energy consumption. The taxonomy is graphically summarized in Figure 6.

5.1.1. Indirect Monitoring. As expected, indirect monitoring systems are so called because they do not use electricity sensors for measuring the energy consumption of appliances. Instead, they indirectly infer information about energy consumption by measuring other physical quantities that are somewhat related to energy consumption. This approach leverages the fact that appliances typically affect other observable environmental variables, such as temperature, ambient noise, vibrations or electromagnetic field. Specifically, data provided by sensors are combined with a consumption model of the appliance in order to obtain an estimate of its energy consumption. An indirect monitoring system is proposed in Schoofs et al. [2010], where a wireless sensor network is used to measure physical quantities such as noise, temperature and vibrations. Each appliance is identified by a specific pattern of its sensory measurements. For instance, switching on a kettle is associated with temperature rising, a variation in vibration, and ambient noise. However, the paper does not specify how the system is provided with the association between sensory patterns and specific operating appliance; additionally, the simplicity of this approach limits its applicability to feedback-based systems. Given the use of signature-based models for environmental measurements, this solution could be viable in centralized intelligence architectures, using a distributed sensor infrastructure.

Whenever a model for appliance energy consumption is available, any system able of automatically detecting appliances could be used for performing indirect energy monitoring. Those systems include the approach proposed in Gupta et al. [2010], which exploits information coming from the energy distribution network, other than explicit energy consumption. The proposed approach analyzes high frequency electromagnetic interferences generated by the electronic devices powered through a switch mode power supply (SMPS) (used in fluorescent lighting and in many electronic devices). Due to the limited applicability to a specific class of actuators, such technology should be just regarded as complementary to the energy monitoring system. For instance, this approach could be suitable for fully centralized architectures where the pervasiveness of sensory devices is minimal.

With reference to the ideal BMS, indirect energy monitoring systems are not suitable because their use would require building models for actuators which, especially when environmental measurements are involved, would have to be done *in situ*, thus being invasive for users, not well generalizable, and consequently slowing down the deployment of the entire BMS.

5.1.2. Direct Monitoring. Unlike indirect systems, a direct monitoring system measures energy consumption through ad hoc electricity sensors, typically referred to as power meters. The granularity used for direct energy monitoring spans from a single point of metering to the monitoring of individual appliances. The rationale for using only a single power meter is keeping intrusiveness at a very low level. These coarse-grained systems are referred to as *NILM* (*Non-Intrusive Load Monitoring*) systems, or *NALM* (*Non-intrusive Application Load Monitoring*) systems if the focus is on individual appliances. On the opposite end, fine-grained systems allow to monitor individual appliances with a high precision but require the deployment of a large number of power meters. Obviously, the granularity of monitoring affects the approach to the artificial reasoning carried on the collected sensory data and, indirectly, also the possible energy-saving policies than can be used. NALM systems are well suited for centralized architectures, with limited pervasiveness of sensory devices.

The NALM approach has been initially introduced by Hart [1992], who proposed a system for measuring current and voltage at the root of the energy distribution network, which is typically organized as a distribution tree. Variations in collected measurements, after preprocessing, are compared to consumption profiles for the various appliances in order to infer their activation or deactivation. Hart's work has been seminal for a number of subsequent works in the field of energy monitoring.

Several approaches proposed in the literature are based on the processing of measurements collected by a single point of measurement [Laughman et al. 2003], and on the use of complex algorithms, such as Genetic Algorithms [Baranski and Voss 2004] or Support Vector Machines [Patel et al. 2007] in order to decompose the measurement into its components. However, some authors question the effectiveness of such disaggregation techniques in environments like office rooms, where many loads are based on switched power supplies [Jiang et al. 2009b]. A survey of disaggregation techniques for sensing energy consumption is presented in Froehlich et al. [2011]. The alternative approach to a single point of sensing consists of monitoring energy consumption at a finer grain. Brought to its ideal extreme, this approach would require a detailed knowledge of every branch of the power distribution network, which, of course, is not feasible in practice. Works presented in the literature only attempt to come close to this ideal goal. Jiang et al. [2009b] explore several practical techniques for approximately disaggregating the load tree using a relatively sparse set of power meters. The possibility of relying on a fine-grain monitoring system is extremely advantageous for an ideal BMS, as it allows to get information about consumption of specific appliances. Such detailed monitoring, not available in the approaches mentioned so far, is useful to avoid using consumption models for those appliances, thus eliminating the initial training phase with its costs in terms of user discomfort. This solution is along the same line of heavily decentralized architectures, such as those described in Yeh et al. [2009], Weiss and Guinard [2010], and Corucci et al. [2011]. Within the broad spectrum of granularity, there exists an intermediate position between NILM systems and systems targeting each device individually. Marchiori et al. [2011] contains a proposal about measuring energy consumption only for those branches of the energy distribution tree where some particular devices are connected. With respect to a fine-grained approach, this method requires installation of fewer monitoring devices, while compared to a NILM system, it allows to monitor the behavior of low-consumption devices, whose fingerprints would otherwise be overshadowed by high-powered devices. In particular, this can be obtained by powering the latter class of devices on a dedicated circuit. Within one specific branch, it is however necessary to use data analysis algorithms allowing for a disaggregation of partial data. A similar approach is adopted in Agarwal et al. [2009] for monitoring energy consumption of buildings in a university campus. In such medium-grained monitoring solutions, disaggregation techniques allow to obtain comparable results to fine-grained, direct monitoring systems with fewer monitoring devices, and hence possibly lower costs, but higher discomfort for users, due to the initial training phase for probabilistic models.

5.1.3. Hybrid Monitoring. Finally, a hybrid approach to monitoring, including both direct and indirect parts, involves using both specific sensors for energy measurement (typically in a single power meter at the root of the distribution tree), and indirect sensors for recognizing the operating status of appliances. An example of such a complex approach may be found in Kim et al. [2009a], where the authors propose a monitoring system based on WSNs with magnetic, light and noise sensors, and including a power meter for monitoring the overall energy consumption. The authors propose an automated calibration method for learning the combination of appliances that best fits the collected sensory data and the global consumption. The calibration method integrates two types of models. Specifically, a model of the influence of magnetic field, depending on two *a priori* unknown calibration parameters, is used for more complex appliances with many operating modes. On the contrary, appliances with fewer operating modes only require models associating the relative consumption to each specific mode, which is estimated via the noise and light sensors. The main disadvantage of this work is that the calibration is to be performed *in situ* and cannot be carried out before the deployment because many unpredictable external factors may influence the measured environmental variables. It is worth pointing out that hybrid systems are typically characterized by a coarse-grained direct monitoring of energy, with a single sensor at the root of the energy distribution tree. This is usually coupled with a fine-grained indirect monitoring.

5.1.4. Comparison of Different Energy Monitoring Systems. We believe that an ideal BMS that is able to provide accurate description for actuator consumption without demanding excessively intrusive deployment, naturally calls for fine-grained direct monitoring. However, when deployment costs are prohibitive, it is possible to reduce the number of used devices and to rely on a disaggregation technique, starting from the branches of the energy distribution tree.

Figure 7 reports a comparison of different energy monitoring systems together with some of the previously discussed architectural solutions according to two qualitative dimensions, namely the overall intrusiveness experienced by users, and the details on attainable monitoring. Values along the first dimension were attributed to assess both the intrusiveness of deployed devices and the discomfort perceived by the users during the training phase, while the second dimension is tightly related to the position of the assessed solutions within the taxonomy depicted in Figure 6. Note that, as regards the sensory infrastructure, costs get higher as the systems get closer to the ideal one. When it is important to keep installation costs below a given threshold, it will be necessary to trade part of the functionalities of the final BMS for cost.

5.2. Devices for Energy Sensing

Besides the different approaches to energy monitoring, it is also necessary to consider the technology to be used for creating the sensory infrastructure. In this section, we will mainly focus on the available technologies for energy sensing. However, we will not consider sensors for environment monitoring, as they are beyond the scope of this survey, although they are exploited into indirect and hybrid monitoring systems. A wide selection of sensory technologies for energy sensing is currently available of the

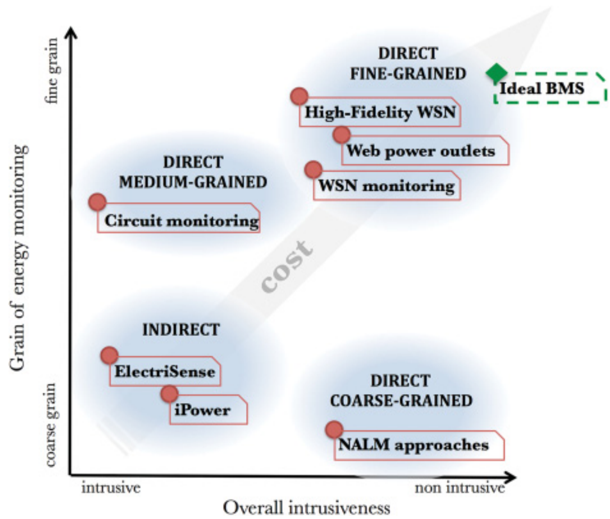

Fig. 7. Comparison of different systems for energy monitoring, with respect to two qualitative dimensions. The assessed energy monitoring systems are: High-Fidelity WSN [Jiang et al. 2009b], Web power outlets [Weiss and Guinard 2010], WSN monitoring [Schoofs et al. 2010], Circuit monitoring [Marchiori et al. 2011], ElectriSense [Gupta et al. 2010], iPower [Yeh et al. 2009].

shelf. The choice of a given technology directly affects the complexity of the architecture supporting the monitoring system and providing the integration with the rest of the BMS.

Coarse-grained direct energy monitoring systems exploit devices installed at the root of the power distribution network; this represents an extremely simple and inexpensive solution. Even though many devices have been designed to implement the "single point of sensing" approach, it is still advisable to carefully assess the impact of the technology on pre-existing premises, as well as its ease of deployment. In Ruzzelli et al. [2010] the RECAP (*RECognition of electrical Appliances and Profiling in real-time*) system is proposed for the identification of energy fingerprints of appliances, which relies on a single wireless energy-monitoring sensor clipped to the main electrical unit. The use of wireless communication links avoids the need for the deployment of a communication infrastructure from scratch. As regards the integration in the BMS architecture, NALM systems are more suited to approaches with few pervasive devices and oriented to centralization.

Devices for monitoring energy consumption in medium-grained and fine-grained systems are similar to the previously described ones, the only difference being the density of deployed devices. The monitoring system proposed by Jiang et al. [2009b] exploits a sensory system consisting of a network of heterogeneous wireless sensors, made of AC meters and light sensors. The energy sensing nodes allow to collect active, reactive, and apparent power measurements [Jiang et al. 2009a]; each node implements the IPv6/6LoWPAN stack, and the wireless sensor networks is connected to other TCP/IP networks via a router. Other solutions for AC power metering through a sensor network have also been presented in the literature. Lifton et al. [2007] describe the "Plug" network, which is composed of nodes fulfilling all the functional requirements of a normal power strip and equipped with an antenna and a CPU.

An alternative solution is to use integrated sensor/actuator platforms for energy consumption monitoring, through commercially available devices such as WiSensys [2011], as suggested by Corucci et al. [2011]. Currently such devices are still expensive, so it might be convenient to allow for coarser granularity of monitoring, by coupling a single energy sensor to a group of devices.

Monitoring and efficiently managing energy consumption of the sensing infrastructure itself would deserve a separate discussion. This issue is extremely important in case of sensor nodes powered by batteries with a limited energy budget, as in typical WSNs for environmental and context monitoring. However, this topic is beyond the scope of this survey (the reader can refer to Anastasi et al. [2009] for a detailed overview on power management in WSNs).

5.3. Models of Energy Consumption in Buildings

Energy consumption models of individual appliances represent an alternative tool for energy monitoring, as they allow to estimate the overall energy consumption of buildings simply relying on the knowledge about the status of each appliance (i.e., without requiring any specific sensing infrastructure). For some devices, the corresponding energy consumption in different operating modes can be retrieved from their technical specifications, such as the Code of Conduct (CoC) edited by the European Commission, which, however, do not cover the entire set of available appliances. A few years ago, in the context of the AIM project [The AIM Consortium 2008], an experimental estimation of energy consumption through some universal measurement methodologies was proposed [Foglar and Plosz 2008]. However, this approach is viable only when it is not possible to adopt the aforementioned energy monitoring approaches whose use could only be deferred to a later time. Recall that the mere employment of energy consumption models carries with it the burden of a preliminary training phase, which is likely to be done *in situ*, with consequent discomfort for users; furthermore, they often require the support of a sensory infrastructure for recognizing the activation state of actuators, just as in the indirect energy monitoring systems.

The specific methods to use depend on the particular class of appliances under consideration. To this end, the following three classes are distinguished [Tompros et al. 2009]: (1) Appliances whose instantaneous energy consumption is *steady*. This class includes appliances, such as lighting systems, whose energy consumption is approximately constant during the entire operating cycle. (2) Appliances whose instantaneous energy consumption is *predictable*. Such appliances are characterized by a time-varying energy consumption, for which a predictive model can be built. For instance, washing machines, dishwasher, and refrigerators fall in this class. (3) Appliances whose instantaneous consumption is *unpredictable*. This class includes appliances, such as HVAC systems, whose behavior is highly affected by external factors (e.g., ambient temperature).

Appliances belonging to the first two classes can be easily modeled through a synthetic profile, whereas those in the third class require an ad hoc infrastructure for measuring energy consumptions.

Consumption models of single appliances can be used for runtime energy monitoring in order to obtain an estimate of the current energy consumption of the building or to decide possible actions to be undertaken. They can also be used to steer the profiling process for appliances currently in use, based only on the aggregated data about consumptions, as in Prudenzi [2002], where consumption models and operating modes of appliances are used to train a neural network in order to recognize the appliances currently in use. Exclusive support for a posteriori analysis of appliance usage patterns makes such approach unfit for use in a BMS, which requires real-time knowledge about the state of actuators.

It is worth pointing out that the recognition of currently active appliances only based on the overall energy consumption is often a difficult task, due to the existence of appliances with nearly identical power consumptions. The importance of simultaneously considering both active and reactive power is highlighted in Ruzzelli et al. [2010], which distinguishes the different nature of various appliances. Specifically, an appliance can be classified as resistive, inductive, or capacitive. Generally, appliances consume active power to carry on their tasks; however, reactive power is also consumed due to the presence of inductors and/or capacitors in their circuit. Therefore, a *unique appliance signature* is proposed for combining several pieces of information that can be collected from the electricity distribution network, such as the active power and the power factor. The use of use active power, phase shift, current crest factor, and current signal harmonics is suggested in Englert et al. [2013] so as to classify appliances.

The problem of recognizing appliances in use starting from aggregate measurements is also addressed in Ducange et al. [2012], which exploits finite state machines based on fuzzy transitions (FSMFT) and a novel disaggregation algorithm. FSMFTs are used to coarsely model how each type of appliance works. The disaggregation algorithm exploits a database of FSMFTs for hypothesizing possible configurations of active appliances at each meaningful variation of active and reactive aggregate powers. This approach is different from previous NALM approaches because it exploits explicit construction of a model for energy consumption of actuators; however, both in terms of discomfort for users and monitoring detail, it suffers from the same limitations as NALM systems.

The energy consumption models discussed so far may also be used to tune the runtime behavior of the system. Furthermore, energy consumption models can provide valuable information during design phase of a BMS. For this purpose, it is also possible to build simulation tools for modeling the energy consumption of an entire building [Crawley et al. 2001; Ellis and Torcellini 2005].

6. ENVIRONMENT AND CONTEXT SENSING

BMSs are typically characterized by a wide set of functionalities, in addition to simple energy monitoring, that allow to enable sophisticated energy-saving policies and automated control of appliances. They include the ability to detect or predict the presence of occupants within the monitored areas, as well as the ability to observe user actions in order to learn their behavior. The practical integration of such functionalities into a BMS depends on the availability of the corresponding enabling technologies. Moreover, integrating heterogeneous sensors for environmental and context monitoring within the BMS sensor infrastructure requires the availability of a software architecture that can abstract from low-level devices, such as in Yeh et al. [2009] and Capone et al. [2009]. This section provides an overview of the additional technologies needed for the development of advanced, intelligent BMSs.

6.1. Technologies for Occupancy Detection

The presence of users or their activity may be detected by different technologies, from simpler ones (e.g., for motion detection or access monitoring) to more complex ones, for example, Radio-Frequency Identification (RFID), laser scan or Global Positioning System (GPS).

In Lu and Fu [2009], highly complex devices are developed for detecting user location in an indoor environment. The employed devices fall into the category called *Ambient Intelligence Compliant Object* (AICO), which includes apparently ordinary household objects pervading the environment, enriched with advanced functionalities such as transparent human-environment interaction monitoring. The device specifically designed for user location detection is called *floor-AICO* and consists of a floor tile with an embedded piezoelectric pad for sensing the pressure caused by a user stepping onto the tile; the floor-AICO is connected to a wireless sensor node that collects the sensory information and forwards it to a central server. The complexity of this kind of device may limit its deployment only to specific areas. Hence, even though the sensor

Table II. Technologies for Presence and Activity Detection

Sensor	Description and References	P	R	C	I
Camera	Indoor or outdoor deployment; requires ad-hoc software for user detection from their silhouettes [Koile et al. 2003; Kientz et al. 2008; Erickson et al. 2011; Khalili et al. 2010].	Variable	High	Med.	High
Motion Sensor	Based on passive infrared (PIR) technology for detecting people/things by analysing the flow between source and sensor [Lu et al. 2010b; Gao and Whitehouse 2009; Cook 2010; Lu and Fu 2009; Tapia et al. 2004; Wilson and Atkeson 2005; Mozer 1998; Agarwal et al. 2010; Milenkovic and Amft 2013].	Low	Low	Low	Low
Motion Sensor	Based on pyroelectric sensors, which detect human presence exploiting body heat [Kobayashi et al. 2011].	Low	Med.	Med.	Low
Door Sensor	Magnetic reed switches installed on doors/windows [Lu et al. 2010b; Gao and Whitehouse 2009; Cook 2010; Tapia et al. 2004; Wilson and Atkeson 2005; De Paola et al. 2012; Kobayashi et al. 2011].	High	Low	Low	Low
Floor Sensor	Piezoelectric sensors placed under floor tiles for detecting the pressure of a user stepping by Lu and Fu [2009] and Kidd et al. [1999].	High	High	High	High
Power Sensor	Current and voltage sensors installed between an electric appliance and a power source for measuring current flow and voltage [Lu and Fu 2009; Tapia et al. 2004; Milenkovic and Amft 2013].	High	Med.	Med.	Low
Object Id	RFID sensors installed on each relevant object to interact with users wearing an RFID-detecting glove in their proximity [Philipose et al. 2004].	High	High	Med.	High
Sound Sensor	Indoor low-quality microphones may detect ambient noise, with no recording of intelligible audio traces [De Paola et al. 2012].	Low	Low	Low	Low

Precision (P): accuracy of sensory measurements with respect to the monitored environmental quantity
Relevance (R): correlation between the monitored feature and the user presence or activity
Cost (C): cost for designing/buying/deploying the sensors
Intrusiveness (I): experienced intrusiveness for the user with respect to installing/using the sensors.

precision is fully satisfactory, the overall system precision, and its cost, may greatly vary depending on the chosen deployment density.

Table II, partially drawn from Lu and Fu [2009], lists some of the available technologies for user presence and activity detection. The choice of the most suitable one is not immediate, as it is necessary to weigh up many factors, such as costs, expected performance, intrusiveness, and privacy. The last two aspects, in particular, may prove critical for the acceptance of the proposed BMS by end users. The issue of privacy safeguard when using video and audio sensors has been discussed in Lu and Fu [2009], Campbell et al. [2002], and Tapia et al. [2004]. Privacy issues are also inherent when dealing with activity detection, regardless of the employed sensory technology. As mentioned in Section 5, similar questions are raised in Kim et al. [2009b] in the context of energy monitoring.

Several solutions also deal with tradeoff between cost and performance: Infrared (IR) motion sensors, for instance, are quite inexpensive and often deployed in households for surveillance purposes; however, they usually convey inaccurate information. On the other hand, door sensors are more accurate as regards the open/close status, but such information is only partially correlated to the user presence.

As Table II shows, energy monitoring can be used to detect ongoing activities, but the obtained information is particularly useful for those activities that involve usage of appliances with definite energy profile, as described in many existing works. As the

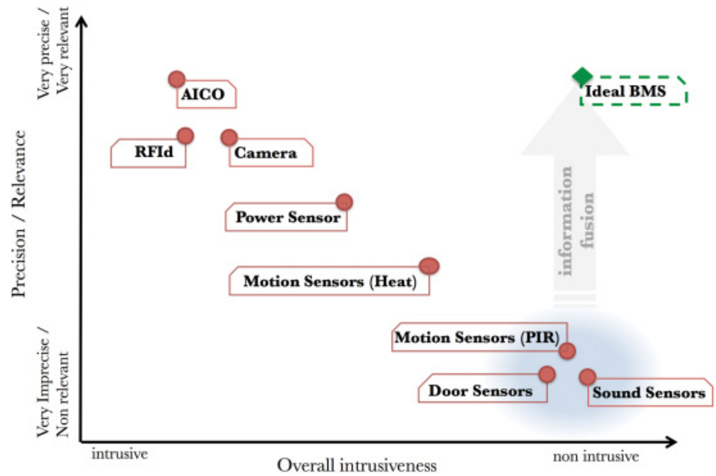

Fig. 8. Comparison of different technologies for context sensing with respect to the precision and relevance of resulting information compared to the overall intrusiveness for the user. An information fusion process could improve the quality of the obtained information while maintaining a low intrusiveness.

cost of the individual detector is not negligible, it might make sense to monitor only those electric appliances whose usage appears to be correlated with specific activities or, alternatively, to adopt activity analysis methods based on aggregated data about energy consumption.

The selection of the underlying technology needs a preliminary and accurate estimation of the obtainable performance in terms of costs. The advantage of using more expensive devices is that they generally provide more relevant information, whereas cheaper devices typically produce noisy data, which additionally may be just marginally correlated with the observed phenomenon (e.g., user presence or activity). On the other hand, the availability of cheaper devices allows for the development of a truly pervasive sensory system, with a broader coverage of the area of interest. We believe that performing multisensor fusion with plenty of data, even if partially noisy, is the best choice because it allows for keeping costs low without interfering excessively with user daily lives. While aiming at a low level of intrusiveness, an optimal choice for the BMS could be the adoption of a wide set of motion and door sensors such that the data coming from inexpensive devices are integrated with those coming from other preinstalled devices, such as noise or power sensors. A graphical comparison among different technologies for context monitoring is shown in Figure 8, which intuitively highlights how information fusion may provide valuable support with low intrusiveness. A detailed review of various information fusion methods for sensor networks is presented in Nakamura et al. [2007].

6.2. Technologies for Learning User Preferences

When user preferences are learned through explicit feedback, the system needs to include human-computer interfaces in order to collect the end user opinion about the various environmental conditions. A trivial solution is to use touchscreens through which users may communicate their preferences, possibly via a Web-based interface; analogous solutions may also be devised for personal mobile devices.

When considering implicit feedback, it may be necessary to add further sensing devices to the BMS, thus performing discrete monitoring of their interactions with the actuators. A very effective solution may allow such interactions only through digital interfaces, as part of the BMS itself. This is the choice adopted by *iDorm* [Hagras et al. 2007; Holmes et al. 2002], where the user can interact with the HVAC and lighting system exclusively via a PC-based interface, a portable personal digital assistant (PDA) interface, a mobile phone interface and a touchscreen interface. Such setting makes action monitoring extremely easy, as the necessary information is readily available at the BMS. An analogous approach is used in Kolokotsa et al. [2005], where users can control actuators only through an ad-hoc panel that later sends all settings to the BMS. User-given settings are also stored into a smart card to explicitly code the user preferences.

Albeit efficient, the option of forcing all user–actuator interactions to happen through the BMS, thus forbidding any direct interaction, gets rid of the traditional control tools (switches, remotes) which may make the whole system scarcely attractive to less experienced users, such as elderly people. On the other hand, maintaining traditional ways of interaction reduces the impact on the consolidated user habits, at the cost of a higher burden in terms of the technology to be developed and installed, as well as of the overall BMS architectural complexity. This approach has been adopted, for instance, in De Paola et al. [2012], which not only allows users to interact with actuators in the traditional way but also includes specifically devised sensors for capturing the signals originated by electrical switches, remote controls, and so on. In the scenario considered in Vainio et al. [2008], a feedback is obtained whenever the actuator state change was not caused by a command from the BMS; a similar approach is also adopted in Khalili et al. [2010]. In the *Neural Network House* [Mozer 1998], users triggering the actuators generate implicit feedback, even though it is unclear whether this is realized by imposing the use of a BMS interface or via the addition of ad-hoc sensors on the actuators.

Besides being a source of implicit feedback, user actions also produce changes in the environment state; it is thus necessary to handle the possible clashes between controls generated by the users and by the BMS itself. Vainio et al. [2008], for instance, forcibly leave the actuator control to the end user in the 15 minutes following any user interaction, thus avoiding an immediate overriding by the system in case the user preferences had not yet been perfectly assimilated.

7. INTELLIGENT SUPPORT TECHNIQUES

The energy-savings policies enacted by BMSs may vary greatly and, depending on the complexity of the adopted strategies, might require the use of artificial intelligence (AI) techniques. Many works presented in the literature focus on the design of various intelligent functionalities, such as user profiling, predicting the occupancy status of the monitored premises, or detecting the activity patterns of users.

This section describes possible intelligent functionalities to be added to a BMS for energy efficiency, while focusing on the main AI approaches used for their actual implementation. The same technique can be used for different purposes; likewise, different techniques may prove useful for reaching one goal. This section first discusses the desired goals for designing a BMS starting from its functional requirements. The correspondence between the underlying techniques and their purpose is summarized in Table III.

7.1. Occupancy/Activity Detection and Prediction

Contextual information is fundamental in systems designed for energy saving in buildings. The most relevant information is related to the presence of users in the areas of interest and the activities carried on. Details about user presence may be used to switch the system governing household into a low consumption regime whenever users are absent. Such systems must be extremely reliable and reactive and need to timely

Table III. Matching between Advanced Functionalities for BMS Support and the Corresponding AI Techniques

AI Techniques	Functionalities	References
Rules	Occupancy/Activity Detection	Mozer [1998], Agarwal et al. [2010]
Data Mining	Occupancy/Activity Prediction	Vazquez and Kastner [2011], Das et al. [2002]
Neural Networks	Occupancy/Activity Prediction Learning User Preference	Mozer [1998], Choi et al. [2005]
Bayesian Networks	Occupancy/Activity Detection Learning User Preference	Thanayankizil et al. [2012], Lu and Fu [2009] Kushwaha et al. [2004], Chen et al. [2006], Chen et al. [2009], Hasan et al. [2009], Lin and Fu [2007]
Hidden Markov Models	Occupancy/Activity Detection	Lu et al. [2010b], Cook [2010], De Paola et al. [2012], Duong et al. [2005], Milenkovic and Amft [2013]
Data Mining	Occupancy/Activity Detection and Prediction	Rashidi et al. [2011]
Fuzzy Logic	Learning User Preference	Hagras et al. [2007], Vainio et al. [2008], Kolokotsa et al. [2005]
Reinforcement Learning	Learning User Preference	Mozer [1998], De Paola et al. [2012], Khalili et al. [2010]

detect user arrival into the monitored site in order to avoid the perception of an unacceptable comfort reduction, or useless energy waste, thanks to the correct detection of when areas remain unoccupied.

The detection of ongoing activities represents an evolution from user detection systems; presence detection may indeed by regarded as a specific case of activity detection where the "state" associated with a user may only assume two values: "absent" or "present." Activity detection requires finer detail both at the sensory level and at the inference level. If the BMS includes a module for detecting/predicting activities carried on by users, it is possible to adjust the actuators with respect to each activity in order to closely match the user needs or to reduce, albeit partially, the overall energy consumption.

Most of the solutions reported in the literature are suited for integration into architectures with centralized control logic and present a varying degree of intrusiveness, depending on the employed sensor devices, and on the discomfort perceived by users during the learning process. A qualitative assessment of some of those works is presented in Figure 9, where different systems are evaluated with respect to two qualitative dimensions. The first criterion is the overall intrusiveness due to physical devices and to the user discomfort during the learning phase; the second criterion is the complexity of the adopted energy-saving strategy enabled by an adequate set of actuators. There exist several approaches that adopt a slightly intrusive sensory infrastructure composed of motion sensors, door sensors, or audio sensors. The complexity of the software infrastructure then makes up for it in terms of a wider set of energy-saving strategies.

7.1.1. Implementation Approaches. Although the desired goal may be merely occupancy detection of the monitored areas, the data provided by simple sensors, such as motion or door sensors, carry extremely relevant information with a sufficient degree of reliability. For example, this approach has been proposed in Agarwal et al. [2010], which suggests the use of a simple rule-based approach for detecting user presence from motion sensors and door sensors. As illustrated in Figure 9, such A solution is still too naive to support predictive energy saving and only allows reactive behavior.

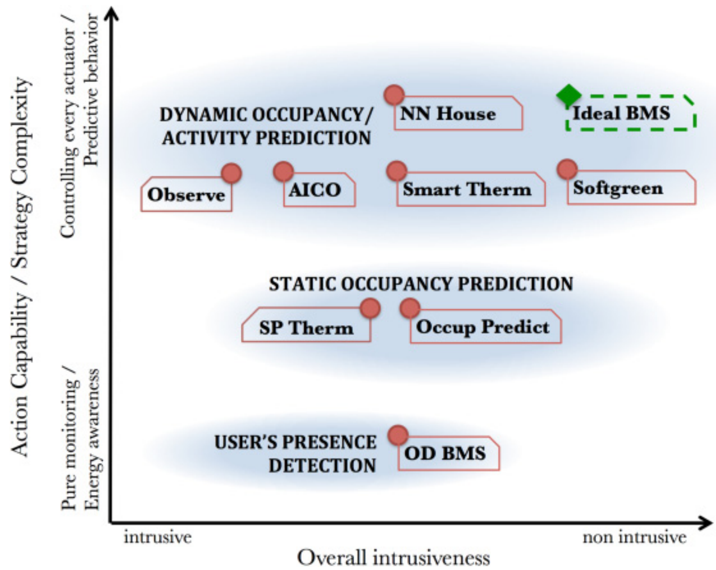

Fig. 9. Comparison of different BMS exploiting the "occupancy detection" intelligent functionality. The assessed BMS are NNHouse [Mozer 1998], Observe [Erickson et al. 2011], AICO [Lu and Fu 2009], Smart Therm [Lu et al. 2010b], Softgreen [Thanayankizil et al. 2012], SP Therm [Gao and Whitehouse 2009], Occup Predict [Vazquez and Kastner 2011], OD BMS [Agarwal et al. 2010].

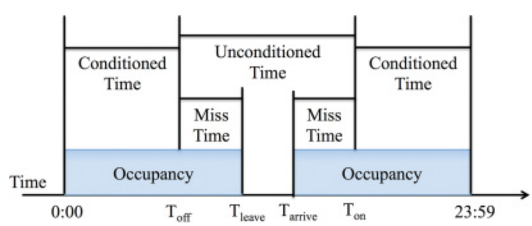

Fig. 10. A typical schedule used by the *self-programming thermostat* [Gao and Whitehouse 2009] on the basis of a static environment occupation model.

Besides detecting user presence, it is possible to implement a system for predicting it, typically based on user behavior patterns expressed in a statistical form or through a set of rules. The easiest way to do this consists of exploiting past sensory data to create an environment occupational profile to be used as a static prediction model. Such a model can be used to infer optimal configurations for the environmental control system (typically, for HVAC systems), but such configurations do not vary over time and do not adapt to changes, albeit minimal. A sample static environment occupation model can be found in Gao and Whitehouse [2009], as shown in Figure 10. In Vazquez and Kastner [2011], the construction of a statistical occupational profile is suggested by way of clustering techniques, used to extract patterns from large amounts of data. The authors proposed to gather sensory data from a simple set of door sensors and to perform clustering on all daily 24-dimension profiles. Representative occupation profiles are the centroids of identified clusters. The authors compare several clustering methods, such as fuzzy c-means, where the membership of inputs to cluster is not strict but smoothed by a degree of membership. Figure 11 shows the result of a fuzzy c-means performed on a set of one-dimensional data. Even though such solutions enable predictive energy saving, they are not sufficient to let the prediction mechanism adapt

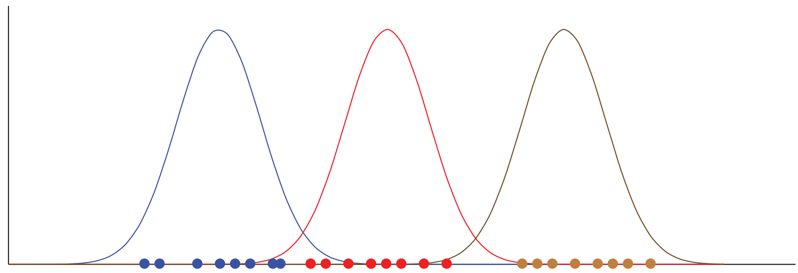

Fig. 11. Possible resuts of fuzzy c-means clustering on one-dimensional data.

to changes in user behavior, which is why this approach is positioned far from the ideal BMS.

Predictive models may also be realized by using neural networks, which allow inference of an unknown function starting from a training dataset. In *Neural Network House* [Mozer 1998], neural networks are used together with rules for occupancy detection to predict the binary occupational state of the monitored sites. Input data for the neural network is provided by sensory readings coming from (binary) motion sensors. Despite being one of the first works on this topic, this represents a good solution toward the ideal BMS logic. Specifically, it uses a relatively intrusive sensor infrastructure, made up of sound sensors, motion detectors, and door and window status sensors; nevertheless, it shows advanced actuating capabilities and adopts a complex energy-saving strategy. Such features result in a positive assessment which is represented by a position close to the ideal BMS as in Figure 9. As this work was proposed a long time ago, it does not include an infrastructure for direct energy monitoring or for a scalable modular architecture.

An approach capable of dealing with the intrinsic uncertainty present in sensory readings and their partial correlation with the environmental features to be inferred is provided by Bayesian (or Belief) networks. An overview of several approaches using Bayesian Networks (BN) for building occupancy detection is presented in Dodier et al. [2006]. A straightforward model for inferring the current occupancy of a site or the ongoing activities involves the use of statistical correlation of the instantaneous sensory information with the state of interest [Thanayankizil et al. 2012]. In Lu and Fu [2009], an augmented variant with a multiple enhanced BN is proposed that detects interleaved activities. The proposed model makes explicit use of localization information obtained through the smart floor for inferring the belief about a single activity. Moreover, the various sensory readings are ranked according to a usefulness index, depending on the correlation of the specific type of sensor with the activity to be inferred. In this way, the weight of a single sensory reading into the data fusion process is tightly related to its relevance. This kind of BN does not take into account past history of user behavior or previous sensory measurements. The above two solutions enable predictive energy-saving strategies; the first one [Thanayankizil et al. 2012] makes use of unintrusive information sources (such as ID badges, WiFi signals, online calendars, device activity status, which are likely already present in an office environment), which justifies its assessment in our figure. On the other hand, the solution proposed in Lu and Fu [2009] appears very intrusive, due to the massive use of *AICO*s, which might be perceived by the users as unnatural objects, requiring heavy modifications to pre-existing environments.

The most complete approach is certainly based on the use of a predictive model for site occupancy and on its refinement on the basis of current sensory readings, so as to obtain a dynamically evolving model according to actual environmental conditions. It

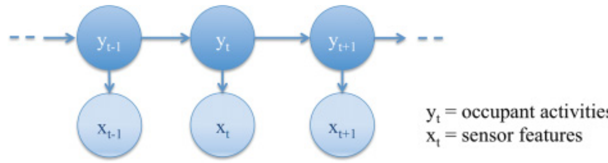

Fig. 12. A simple hidden Markov model; the current activity of a user (y_t) affects a set of sensory readings (x_t); the transition from an activity to another one is represented by a probabilistic state transition model.

is easily noticeable how detection and prediction of user presence is, at this level, just a special case of the more general problem of activity detection and prediction.

In order to include information about past states, one of the most common approaches is the probabilistic one, through the use of BNs or, more specifically, Hidden Markov Models (HMM). The easiest HMM is the traditional scheme, characterized by a state variable influencing the value of a set of variables for sensory evidence, where the probability to be in a given state only depends on the previous state. An example of this scheme, adopted by Lu et al. [2010b], is illustrated in Figure 12. The proposed model uses simple sensors to detect motion and doors status, deployed in the various environments of the house and in front of the main entrance. The obtained information may be merged into the typical user behavior pattern through an HMM estimating the probability distribution of the occupancy status of the house (*Away*, *Active* and *Sleep*). Together with Thanayankizil et al. [2012] and Mozer [1998], it represents the proposal more closely resembling the ideal BMS, even though its focus is exclusively on the HVAC system, disregarding artificial lighting. A similar model has also been proposed by Cook [2010] and De Paola et al. [2011]; in the latter case, the HMM takes into account both the room occupancy level, and the estimated number of the occupants.

Many modifications to HMMs with respect to the classical approach have been presented in the literature. In Duong et al. [2005], a hidden semi-Markov model is presented, which explicitly accounts for the possible duration of the activities. Another variant for human activity detection considers hierarchical HMMs, which capture the natural complexity of human behavior [Nguyen et al. 2005]. Erickson et al. [2011] proposed the use of models based on Markov chains accepting images gathered from a set of cameras as input. Even though the enabled strategies present sufficient complexity, their intrusiveness is considerably high due to the use of cameras, which pose serious threats regarding user privacy.

Some proposals use HMMs jointly with data mining algorithms for predicting the most likely sequence of actions. This is the approach followed in Rashidi et al. [2011], which proposed an activity discovering method based on data mining techniques for identifying the most frequent sensory event sequences, which are presumably associated with actions repeated over time. Such sequences provide the input for a set of multiple HMMs allowing to detect the most likely sequence of actions. The employed data mining techniques rely on a previous work [Das et al. 2002] that adopted a sequence matching approach for detecting potential correspondences between the current sensory event sequence and the system history in order to predict the most likely future actions.

As a final consideration, let us point out that the design of an ideal BMS must enable predictive energy saving, with sufficient complexity, but low intrusiveness. To this end, we suggest the adoption of sound sensors, motion detectors, and sensors for monitoring the status of doors and windows. Moreover, the target sensor infrastructure will allow energy monitoring and capturing the status of actuators in order to monitor user actions thus inferring its preferences. Such sensory infrastructure will also be exploited to gather information about user presence. Among the discussed methods, one of the most interesting proposals is an HMM-based algorithm that predicts user behavior and copes with intrinsic uncertainty in data.

7.1.2. Integration with Energy-Saving Policies. Information about user presence is generally exploited to actively modify the state of actuators. However, a few works are present in the literature where such information is used only to provide users with contextual feedback. For example, Kobayashi et al. [2011] use it to trigger notifications activated by simple rules, such as "if user presence is not detected, and lights are on, then send a notifications to the user." Control of the actuators is then delegated to the user, who may interact with the system via mobile devices.

The simplest systems using information about user presence for environmental condition controls are the *reactive* systems. Those immediately react to some specific sensory stimulus without relying on any model of the external world, or on any higher-level reasoning form. An example is provided by lighting systems activated by motion sensors, or, within HVAC systems, by the so-called "reactive thermostats" exploiting motion sensors, door sensors, or card key access systems. Such systems are often cause of a decay in user comfort because it is possible that the energy-saving mode is activated even when users are still present within the site. Furthermore, a low energy-saving rate is obtained in the long run because of the user habit of conservatively tuning the system in order to avoid an excessive reduction of their own comfort. The conservative mode may correspond to a wide temporal tolerance of inactivity before the energy-saving mode is triggered, or to setting large setback values to be used in the absence of users, so that no excessive discomfort is experienced when the user presence is undetected. A preliminary analysis of energy consumption associated with reactive thermostats can be found in Gao and Whitehouse [2009]. Agarwal et al. [2010] show that under some conditions, an approach relying on them is sufficient to obtain energy saving of about 10% to 15%. However, reactive systems may be used as a comparison baseline during experimental evaluation.

In case predictive models for site occupancy are adopted, slightly more complex policies for energy saving can be implemented. A static predictive model is adopted in Kastner et al. [2010], which opted for a very straightforward strategy. An artificial model is used to simulate the behavior of actuators to compute the necessary time to reach the predefined goal, given the present and the desired temperature conditions. Such information about latency is used to reach the desired conditions at the time when the user is expected to occupy the room.

Gao and Whitehouse [2009] propose the *self-programming thermostat*, a system exploiting a static model of environment occupation to automatically create a scheduling scheme for the high- and low-consumption modes of the HVAC system. The task of defining the trade-off between the expected comfort and the required energy saving is left to the user, who needs to indicate (i) the maximum tolerance over the time interval during which the user is present but the system (mistakenly) remains in the low-consumption mode, and (ii) the temperatures associated with the two operating modes. The employed sensors just detect motion and door status. More precisely, the goal is to determine the schedule minimizing the "miss time," on average, with respect to past statistics. As shown in Figure 10, the "miss time" is defined as the duration of the interval when rooms are occupied and the system is still in low-consumption mode. The scheduling efficiency is defined as the reduction in the conditioning time with respect to the baseline schedule.

As already mentioned, the use of an accurate predictive model, able to quickly respond to the changes in room occupancy state allows to use more "aggressive" settings for low-consumption mode (e.g., a very low temperature) thus obtaining greater energy saving as compared to reactive thermostats. Lu et al. [2010b] propose that a *smart thermostat* is exploits the information about user presence, obtained via a HMM. Occupancy patterns are used in the context of a hybrid approach aimed at minimizing the long-term expected energy usage. The system tries to infer the optimal schedule for using the actuators so that the area is heated whenever users are present, but not for unnecessarily longer periods, thus balancing the expected costs of preheating too early and preheating too late. The HMM is used to deactivate the HVAC system when the user presence is not deemed likely any longer and when it is necessary to timely react to the user unforeseen re-entry in order to recreate comfortable temperature conditions. The system also uses a statistical profile of average exit and re-entry times, computed based on the past data, to preheat the environment with the goal of minimizing the waste of energy in the long run without sacrificing the user's well-being. The predictive occupancy model for users and the timely detection of their arrival may be exploited by two kinds of actuators: a low-cost system with higher response time used to keep the environmental conditions consistent with the expected occupancy patterns and a more expensive one with respect to energy consumption but with lower latencies, which may be used to bring the environment back to the desired state after unforeseen changes in the occupancy status.

A predictive model is used in Erickson et al. [2011] for room occupancy to tune ventilation and temperature setting of the HVAC system. For temperature control, the authors propose a simple algorithm which activates the actuators to bring the room temperature at the desired value only if the probability for that room to be occupied overcomes a predefined threshold. For ventilation, the intensity is set proportionally to the expected number of occupants. An analogously simple model is proposed in Thanayankizil et al. [2012], where artificial lighting is tuned on the basis of a Bayesian model for room occupancy. The proposed system adopts a lazy strategy for switching off the lights if no occupant is detected within a given time interval; a fast trigger is performed if user presence is detected.

7.2. Learning User Preferences

Taken to its extreme, the optimal energy-saving strategy consists of minimizing consumption by switching off all environmental control systems. Such a radical strategy is clearly unacceptable as it does not take into account the secondary goal for any BMS, that is, maximization of the inhabitants' well-being. The latter criterion steers environmental control policies so that trying to reach both goals concurrently allows us to find solutions representing an acceptable compromise.

An ideal BMS would address the task of learning the mapping between user activities in all time slots and the preferred environmental conditions. Such information may be used for instance by the control system to infer the minimum acceptable comfort conditions that also result in energy saving.

7.2.1. Implementation Approaches for Managing User Preferences. Systems for managing user preferences can be classified according to the taxonomy presented in Figure 13.

User preferences may be manually defined by the system administrator, as in Gao and Whitehouse [2009] where the users specify the minimum and maximum temperature setpoints, or they may be automatically learned by the system. In the latter case, a more realistic model for user preferences can be constructed, which more closely matches the true user requirements and is free from potential evaluation errors by the system administrator. Learning may be static or dynamic; in the first static case, the system is trained offline, even on real data, before the system is actually functioning and the user preference profile does not change over time. An example that belongs to such class is a system that records the interactions between the user and the HVAC

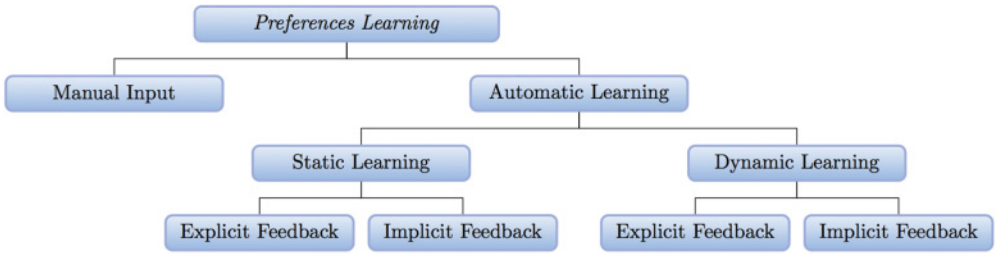

Fig. 13. Taxonomy of systems for managing user preferences.

system only for a training period and then computes the average temperature preferred by the user. A dynamic learning system allows to modify the user profile as the system acquires up-to-date information. It is thus able to adapt to preference modifications due to seasonal, mood, or health changes of the involved users. The previous example may be turned into a dynamic one by extending the recording of user-HVAC interactions also during the online functioning and by a periodic computing of the preferred temperature through a mobile average. To carry on the preference learning, two different kinds of feedback may be required from the users: explicit or implicit. Explicit feedback is obtained when a user voluntarily ties a judgement to a given environmental condition, for instance, by using an interface (e.g., a touchscreen) installed in the monitored area. In contrast, implicit feedback is obtained when the BMS is able to perform nonintrusive user monitoring by observing their interactions with the actuator or face expressions, and it interprets the gathered information by associating it with a hypothetical appreciation degree of current environmental conditions. For instance, a BMS enriched with sensors on actuators and with the capability of perceiving the user presence could reason as follows: if users interacts with the actuators, their preferences are expressed by the chosen settings, whereas if users are present but do not interact with the actuators, this fact implicitly signals that they accept the current environmental conditions. Explicit feedback is more challenging to obtain because it is unreasonable to force a user to express their opinion about environmental conditions with excessive frequency, especially in the case of actual deployments. Moreover, such systems are indeed more invasive and might not be well tolerated. Implicit feedback is perceived as more discreet because the user may even ignore to be monitored, but it generally requires installation of additional ad-hoc devices that have to be integrated with the rest of the BMS. Information coming from explicit and implicit feedback can be used both for static and dynamic learning. The works proposed in Fernández-Montes et al. [2009] and Kushwaha et al. [2004] exploit statical learning of user preferences. The former adopts explicit feedback obtained through a questionnaire compiled by users about preferred lighting conditions; the latter adopts implicit feedback obtained by recording the sequence of tasks performed by the user during a training phase and then builds a BN through a case-base reasoning for coding the user preferred sequence of tasks. A more common solution is to adopt explicit feedback within a dynamic learning engine [Boton-Fernandez and Lozano-Tello 2011; Chen et al. 2006, 2009]. As an example, Boton-Fernandez and Lozano-Tello [2011] propose a system capable of recognizing activities performed by the user and which dynamically learns frequent patterns to define a set of rules; the user is required to validate the proposed rules and their acceptance or rejection is intended as an explicit feedback for the learning engine. The prevalent approach for performing dynamic learning of user preferences is to exploit implicit feedback [Hagras et al. 2007; Kolokotsa et al. 2005; Vainio et al. 2008; Mozer 1998; De Paola et al. 2012; Khalili et al. 2010; Hasan et al. 2009; Lin and Fu 2007; Choi

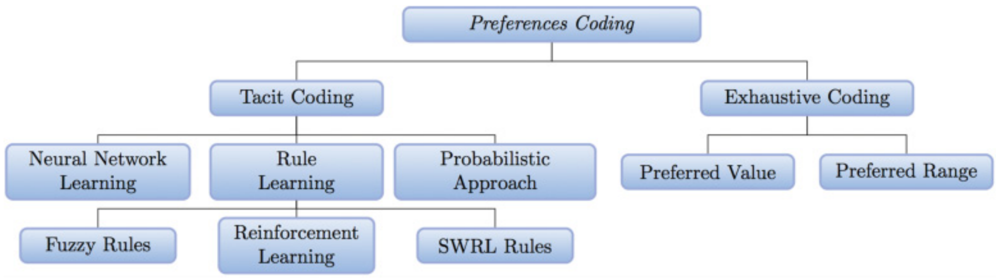

Fig. 14. Taxonomy of systems for representing user preferences.

et al. 2005]. An example is a BMS that evaluates the interaction of the users with the actuators, as previously described, for obtaining an instantaneous evaluation of the adopted policy and a learning mechanism based on a moving average for implementing a dynamic behavior.

In our opinion, this solution is the one more closely matching the ideal requirements. Using implicit feedbacks is very suitable to minimize user discomfort; dynamic learning lets the system avoid the offline learning phase, while, on the other hand, it is possible to obtain autonomous adaptability to new scenarios. To support this functionality, the sensory infrastructure needs to include appropriate sensors for detecting user interactions with the actuators.

7.2.2. Implementation Approaches for Coding User Preferences. Methods for learning user preferences may be divided into two great classes: *tacit* coding of preferences, by learning the rules to be used to control actuators, and *exhaustive* coding, by associating the preferred environmental conditions with every possible context (see Figure 14).

Tacit Preferences Coding. This category comprises all those approaches aiming at the realization of "controllers," with varying degrees of intelligence, whose rules reflect the behavior expected on part of the user. A very simple approach has been proposed by Choi et al. [2005], where a neural network is trained to reproduce the association between context information and the services selected by the users. Although the learning system is online, hence dynamic, this method does not allow to consider imprecisions in the gathered data.

A different approach consists in a tacit coding by learning the set of rules to be performed by the BMS to satisfy user preferences. This subclass includes approaches based on fuzzy controllers that adapt their rules based on the received feedback. Fuzzy controllers are largely employed in home automation because they realize quite robust systems even in the presence of uncertain or imprecise data. The use of a fuzzy system is suggested in Doctor et al. [2005] and Hagras et al. [2007], which exploits three-dimensional membership functions explicitly including a footprint of uncertainty. The use of a fuzzy controller exploiting contextual information has also been proposed in Vainio et al. [2008], which exploits additional information, such as user preference and the time of day, besides information related to environmental conditions (e.g., lighting). In both approaches, the set of rules learned during offline training are successively tuned during the online usage, on the basis of implicit feedback obtained from the users.

Reinforcement learning (RL) [Sutton and Barto 1998] is another technique suitable for dynamically learning the rules that better match user preferences, which are thus indirectly modeled. Each action, performed in a specific situation, is associated with a quality value that is dynamically determined as a function of the rewards produced by the reaction of the environment. When RL is used to learn the user preference, a negative reward is typically associated with the last performed action if the user, operating on the actuators, overwrote the setting proposed by the system; this approach is used in the *Neural Network House* [Mozer 1998]. In Khalili et al. [2010], the Hierarchical Reinforcement Learning (HRL) is adopted to understand user preferences. This technique aims to address the slow convergence shown by traditional RL systems. Some works in the literature propose the adoption of ontologies for representing the rules for controlling the actuators, thus providing a tacit coding of user preference. *IntelliDomo* [Boton-Fernandez and Lozano-Tello 2011], for instance, expresses control rules as Semantic Web Rule Languages (SWRL). The system exploits data mining techniques to discover frequent and periodic patterns in the user behavior. Once those are found, they are coded into rules. Learning is dynamic and online, and the user can trigger a change in the rules in any instant by providing feedback about the system performance.

To learn user preferences, it may be extremely useful to adopt a probabilistic approach when considering potential uncertainty in the collected data, as well as possible slight, sudden and irregular modifications in user behavior. In this case, BN represent an invaluable tool, as they allow to express probabilistic connections among different features of the world. A BN is used in Kushwaha et al. [2004] to identify the sequence of actions to perform on the actuators in order to carefully imitate the user past behavior. Learning is carried on by recording user actions, which represent implicit feedback for the system, and by performing a Case-Based Reasoning (CBR). Relationships between actions are represented via conditional probabilities tables. Learning is automatic, but static, because no online adjustment is performed over the user profile. In Chen et al. [2006], BNs are used for coding user preferences by a semisupervised learning approach exploiting both labeled and unlabeled data. Labeled data is obtained from explicit interaction with the users, who are explicitly interviewed whenever the system perform environmental control actions that are not validated by the users themselves; such data is used to learn and modify the structure of the BN. Unlabeled data is used during the system normal functioning and records the association between the environmental conditions and the actuators state; such data is used to update the conditional probability tables. A similar approach is adopted in Chen et al. [2009] and in Yeh et al. [2011]. The works in Hasan et al. [2009] and Lin and Fu [2007] also make use of BNs to code multiple user preferences. Such a task is particularly challenging because more than one user interacts with the same appliances, making it necessary to recognize which user performed which action and also because users interact with and influence each other. Both approaches exploit implicit feedback to build the preference model, using data gathered from sensors deployed in the environment; moreover, both approaches rely on a two-tier system, where the lower tier uses a BN to represent the preferences of an individual user, and the upper tier uses an additional BN to coordinate the underlying one.

Exhaustive Preferences Coding. A complementary category of approaches considers the exhaustive coding of the desired environmental conditions in a given context, as opposed to coding them implicitly by learning control rules. The exhaustive coding of user preferences may point out a single preferred value (e.g., temperature, lighting) [Gao and Whitehouse 2009], or a preferred range per given physical quantity [Kolokotsa et al. 2005; Fernández-Montes et al. 2009; Wen and Agogino 2008; Pan et al. 2008].

The s*elf-programming thermostat* [Gao and Whitehouse 2009] uses exhaustive coding for user preferences in terms of both the desired temperature and delay tolerance before reaching the optimal conditions. In this case, preferences about environmental conditions are coded via a single constraining value, while tolerance is expressed as a function of the transition delay.

A very simple coding for users preferences regarding artificial lighting is proposed in self-programming thermostat [Fernández-Montes et al. 2009]. Here the system restricts itself to learning the threshold for lighting below which the user would perceive insufficient illumination. Learning is based on explicit feedback obtained by periodically interviewing users with question forms about the perceived lighting level quality. This training phase is carried out from the beginning of the deployment and is not adjusted during normal functioning.

The same category also includes the work proposed in [Kolokotsa et al. 2005] self-programming thermostat, where the rules of a fuzzy system are modified according to the user preferences, exhaustively coded into a smart card used for authentication and for interacting with the BMS. In this case, preferences do not represent a tight constraint; rather they are coded as tolerance intervals regarding the considered phenomena. Learning aims to identify which actions over the many available actuators permits a reduction on the energy consumption, while allowing to reach the requested environmental conditions.

The adoption of an exhaustive coding for user preferences is not as common in the literature, especially because it introduces an additional layer for knowledge representation inside the BMS, thus adding complexity and increasing the possibility of errors. The tacit representation of preferences within the system forces knowledge representation to be functional to the adopted processing model (e.g., utility function for reinforcement learning, conditional probability tables for BNs). Such representation could not be suitable for interaction with the user, but it allows us to easily learn what the system needs and does so in the most useful form.

7.2.3. Integration with Energy-Saving Policies. An intelligent module for learning user preferences can be exploited in order to automate the control of the system actuators according to the designed energy-saving strategy. Many works for automatic learning of user preferences consider user satisfaction as their only goal, disregarding energy-saving issues altogether. This is the case, for instance, in Hagras et al. [2007] and Vainio et al. [2008] where the fuzzy controller is designed to learn the set of rules allowing the BMS to behave exactly as the users would, and to adapt to their needs. Also, in Boton-Fernandez and Lozano-Tello [2011], Kushwaha et al. [2004], Chen et al. [2006], Hasan et al. [2009], and Lin and Fu [2007], SWRL rules or BNs are used only to select the action presumably preferable for the user. Clearly, this direction is not much of interest in order to design a BMS for energy saving. When user preferences are considered for energy-saving purposes, three main classes of approaches may be followed:

—*Single objective function with a constraint*: this approach considers matching user preferences as a tight constraint and energy saving as an objective function to be maximized [Gao and Whitehouse 2009; Fernández-Montes et al. 2009; Wen and Agogino 2008; Pan et al. 2008];
—*Single objective function*: this approach considers both user well-being and energy saving as part of the same objective function [Mozer 1998; Khalili et al. 2010; Singhvi et al. 2005];
—*Multiobjective optimization*: this approach consists of considering two separate functions, adopting a multiobjective optimization method [De Paola et al. 2012].

The self-programming thermostat [Gao and Whitehouse 2009] falls into the first class. The user poses a tight constraint over the desired temperature and the system cannot modify that value; the system tunes the actuators so as to choose the optimal time to reach that set point with the goal of saving energy whenever the user is not present in the area (see Figure 10). An even simpler approach is proposed in Fernández-Montes et al. [2009], where, starting from the minimum acceptable value of lighting for the users, it is suggested to tune the actuators so as to keep the lighting level just above that threshold. Also, the scheme in Wen and Agogino [2008] proposes to combine energy saving and user preferences, by considering the former criterion as an objective function to maximize (actually, energy consumption is minimized) while the latter as a constraint to satisfy. In particular, the problem is formulated as a linear optimization on the lighting value for the actuators to be set on. The goal is to minimize lighting (assumed to be proportional to energy consumption) constraining the lighting value to fall within a prefixed range.

In Pan et al. [2008] and Yeh et al. [2010] a control system is presented for artificial lighting capable of respecting the constraints posed by user preferences (meant as desired lighting range) and which attempts to minimize energy consumption. The system is devised for a multiuser scenario; if the constraint combination does not allow any admissible solution, the preference ranges are iteratively relaxed. Also, in this case, the problem is formulated in terms of linear programming, if user satisfaction is considered as a binary variable, or in terms of sequential quadratic programming, if user satisfaction is considered as a continuous variable, expressed as a Gaussian centered on the preference value.

In the *Neural Network House* project [Mozer 1998], the user discomfort and energy consumption are regarded as two terms contributing to the same objective function to be minimized. To this end, both quantities are expressed in the same measurement unit, that is, in terms of currency. Action selection is performed to minimize the single objective function, which includes a dynamically modified term in order to learn user preferences. A similar approach is also adopted in Khalili et al. [2010], which attempts to minimize a convex function depending on the energy cost and user perceived utility. The adoption of one only objective function is proposed in Singhvi et al. [2005], which expresses it as a linear combination of the user satisfaction function and the cost utility function (which is inversely proportional to the energy saving). Moreover, a predictive model for user presence is embedded into their general model, by taking user preferences into account only if the probability that the user is in the controlled area is nonnegligible.

Finally, another approach exists that considers user preferences and energy consumption as two incommensurable quantities; thereby, a multiobjective approach may consequently be adopted. This choice is made for instance in De Paola et al. [2012], where the user preferences and the model of energy consumption are provided as input to a multiobjective optimization system comparing various solutions by assessing their Pareto dominance. This way, a potentially optimal set of solutions is selected, and the action to be performed is selected therein according to a prefixed heuristic. In the reported case study, the solution representing the median of the dominant front is chosen.

8. CONCLUSION AND CURRENT CHALLENGES

The significance of using energy-saving strategies in building management has now been fully recognized both from industry and the academic world. In this survey article, we have analyzed the technological, architectural, and algorithmic aspects that contribute to the design of an energy-aware building management system (BMS). Our work has pointed out that the guidelines for designing a BMS stem from the chosen policy for energy saving. Depending on its complexity and on the possibility for future expansions, the designer will have to select the sensory and communication technology to deploy in the building, as well as the whole system architecture and the software modules providing intelligent support.

Despite the research efforts, many open issues remain to be addressed, also with respect to potential industrial exploitation of BMSs. This aspect must not be disregarded, as it is likely to affect the diffusion and the actual impact of BMSs on global energy saving.

The first issue to be considered to encourage a commercial diffusion of BMSs is an accurate evaluation of the Return of Investment (ROI). Indeed, even disregarding the costs of software design and development, the mere deployment of the required hardware (sensors, actuators, communication infrastructure) has a nonnegligible cost. To the best of our knowledge, in the literature there is no proposal about a simple and effective tool for estimating the yearly energy saving due to the adoption of a specific BMS, and consequently the number of years required to recover the investment. Without such evaluation, it is difficult to envision a wide distribution among families and small institutions.

Other important issues concern the design of effective BMSs characterized by an easy management. One of the goals yet to be met is the definition of straightforward, semiautomated configuration procedures, thus allowing for easy porting to home configurations or small work environments without the need for the presence of specialized operators. The difficulty lies both in the physical deployment of the sensing technology, which might nevertheless require the intervention of technicians, but also in the association of meta-information to sensors. This is required, for instance, to figure out which sensors are deployed in which area, or which energy-sensing device is installed close to which appliance. It would be advisable to transfer the know-how of *Autonomic Computing* into BMSs, and more generally into Ambient Intelligence, to make the systems aware of their physical structure, in terms of constituting components.

An analogous challenge must be addressed at a higher level, that is, when considering the intelligent modules supporting the BMS. As shown, the majority of the intelligent approaches supporting advanced energy-saving policies requires a learning phase in order to let the system acquire the necessary preliminary knowledge to carry its own activities. For instance, a BN-based system needs to learn the conditional probability tables, and a fuzzy system needs to learn its own rules, so the designer is often at a crossroads. It might be assumed that such knowledge will be coded a priori into the BMS by some domain expert, or through test scenarios analysis, and later reused in different deployments, with no relevant impact on the precision of inference (although such hypothesis does not appear very reasonable). Otherwise, we need to accept that a nonnegligible technical as well as theoretical gap is still present between the creation of BMS prototypes and their practical applicability at a large scale. Such gap is indeed represented by the lack of a semiautomated mechanism for adapting the described intelligent systems to new scenarios. It is probably possible to get to a compromise consisting of coding a priori part of the necessary knowledge (regarding, for instance, the type of considered environment or the generic connection between the type of environment and the activities carried on therein), and subsequently proceed to finely and adaptively tuning for new scenarios, based on the collected data or due to limited contribution by the end user.

Finally, a very important topic, which we could not examine in depth within this survey, for the sake of brevity, is related to the use of techniques of intelligent planning for a completely automated energy-savings policy. The discussed examples of advanced policies for actuator control just consider specific issues and typically act almost reactively based on some pre-coded behavior. To the best of our knowledge, current literature does not report works addressing the issue of the design of a comprehensive system, making full use of intelligent techniques in order to become completely autonomous in controlling all aspects of building management. Such a system should be able to correctly infer the environmental state, to learn the needs and preferences of its inhabitants, and to predict the optimal sequence of actions to carry on to reach its energy-saving goals while respecting the user requirements. The main difficulty lies in the substantial computational cost of traditional intelligent techniques for planning, especially in the context of complex scenarios, such as BMSs, which require planning over time. In our opinion, the direction to follow in this case might be to identify a trade-off between long-term planning systems, and reactive ones, whose task would be to modify the long-term plans in order to address the unavoidable environmental fluctuations, and the variations in user behavior.

ELECTRONIC APPENDIX

The electronic appendix for this article can be accessed in the ACM Digital Library.

ACKNOWLEDGMENTS

The authors are grateful to the anonymous reviewers for insightful comments and constructive suggestions that helped us improve the quality of the manuscript significantly.

REFERENCES

Y. Agarwal, B. Balaji, R. Gupta, J. Lyles, M. Wei, and T. Weng. 2010. Occupancy-driven energy management for smart building automation. In *Proc. of the 2nd ACM Work. on Embedded Sensing Syst. for Energy-Efficiency in Building (BuildSys'10)*. 1–6.

Y. Agarwal, T. Weng, and R. K. Gupta. 2009. The energy dashboard: Improving the visibility of energy consumption at a campus-wide scale. In *Proc. of the 1st ACM Work. on Embedded Sensing Syst. for Energy-Efficiency in Buildings (BuildSys'09)*. 55–60.

AlertMe. 2013. (2013). Homepage. Available at http://www.alertme.com/.

G. Anastasi, M. Conti, M. Di Francesco, and A. Passarella. 2009. Energy conservation in wireless sensor networks: A survey. *Ad Hoc Networks* 7, 3 (2009), 537–568.

Ashrae Standards. 2013. Homepage. Available at http://www.ashrae.org/standards-research–technology/standards–guidelines.

S. Attia, L. Beltrán, A. De Herde, and J. Hensen. 2009. Architect Friendly: A comparison of ten different building performance simulation tools. In *Proc. of the 11th Int. IBPSA Conf.* 204–211.

M. Baranski and J. Voss. 2004. Genetic algorithm for pattern detection in NIALM systems. In *Proc. of the 2004 IEEE Int. Conf. on Syst., Man, Cybern.*, Vol. 4. 3462–3468.

C. Beckel, L. Sadamori, and S. Santini. 2013. Automatic socio-economic classification of households using electricity consumption data. In *Proc. of the 4th Int. Conf. on Future energy Systems*. 75–86.

L. Benini, E. Farella, and C. Guiducci. 2006. Wireless sensor networks: Enabling technology for ambient intelligence. *Microelectronics Journal* 37, 12 (2006), 1639–1649.

V. Boton-Fernandez and A. Lozano-Tello. 2011. Learning Algorithm for Human Activity Detection in Smart Environments. In *Proc. of the 2011 IEEE/WIC/ACM Int. Conf. on Web Intelligence and Intelligent Agent Technology (WI-IAT'11)*, Vol. 3. 45–48.

R. Campbell, J. Al-Muhtadi, P. Naldurg, G. Sampemane, and M. D. Mickunas. 2002. Towards security and privacy for pervasive computing. In *Proc. of the 2002 Mext-NSF-JSPS Int. Conf. on Software Security: Theories and Syst. (ISSS'02)*. 1–15.

A. Capone, M. Barros, H. Hrasnica, and S. Tompros. 2009. A New Architecture for Reduction of Energy Consumption of Home Appliances. In *Proc. of the Europ. Conf. of the Czech Presidency of the Council of the EU "Towards eEnvironment."* 1–8.

Y. H. Chen, C. H. Lu, K. C. Hsu, L. C. Fu, Y. J. Yeh, and L. C. Kuo. 2009. Preference model assisted activity recognition learning in a smart home environment. In *Proc. of the 2009 IEEE/RSJ Int. Conf. on Intelligent Robots and Syst. (IROS'09)*. 4657–4662.

Z. Y. Chen, C. L. Wu, and L. C. Fu. 2006. Using semi-supervised learning to build bayesian network for personal preference modeling in home environment. In *Proc. of the 2006 IEEE Int. Conf. on Syst., Man, Cybern. (SMC'06)*, vol. 5. 3816–3821.

J. Choi, D. Shin, and D. Shin. 2005. Research and implementation of the context-aware middleware for controlling home appliances. *IEEE Trans. on Consumer Electronics* 51, 1 (2005), 301–306.

D. J. Cook. 2010. Learning setting-generalized activity models for smart spaces. *IEEE Intell. Syst.* 27, 1 (2010), 32–38.

D. J. Cook and S. K. Das. 2004. *Smart Environments: Technology, Protocols and Applications*.

D. J. Cook and S. K. Das. 2007. How smart are our environments? An updated look at the state of the art. *Pervasive and Mobile Computing* 3, 2 (2007), 53–73.

D. J. Cook and M. Schmitter-Edgecombe. 2009. Assessing the quality of activities in a smart environment. *Methods of Informaion in Medicine* 48, 5 (2009), 480–485.

F. Corucci, G. Anastasi, and F. Marcelloni. 2011. A WSN-based testbed for energy efficiency in buildings. In *Proc. of the 16th IEEE Symp. on Computers and Commun. (ISCC'11)*. 990–993.

D. B. Crawley, L. K. Lawrie, F. C. Winkelmann, W. F. Buhl, Y. J. Huang, C. O. Pedersen, R. K. Strand, R. J. Liesen, D. E. Fisher, M. J. Witte, and others. 2001. EnergyPlus: Creating a new-generation building energy simulation program. *Energy and Buildings* 33, 4 (2001), 319–331.

S. Darby. 2006. The effectiveness of feedback on energy consumption. Technical Report, Environmental Change Institute, University of Oxford. Available at http://www.eci.ox.ac.uk/research/energy/downloads/smart-metering-report.pdf.

S. K. Das, D. J. Cook, A. Battacharya, E. O. III Heierman, and T. Y. Lin. 2002. The role of prediction algorithms in the MavHome smart home architecture. *IEEE Wireless Commun.* 9, 6 (2002), 77–84.

S. Dawson-Haggerty, X. Jiang, G. Tolle, J. Ortiz, and D. Culler. 2010. sMAP: A simple measurement and actuation profile for physical information. In *Proc. of the 8th ACM Conf. on Embedded Networked Sensor Syst.* 197–210.

S. Dawson-Haggerty, A. Krioukov, J. Taneja, S. Karandikar, G. Fierro, N. Kitaev, and D. Culler. 2013. BOSS: Building operating system services. In *Proc. of the 10th USENIX Symp. on Networked Syst. Design and Implementation (NSDI'13)*. 443–458.

S. Dawson-Haggerty, J. Ortiz, X. Jiang, J. Hsu, S. Shankar, and D. Culler. 2010. Enabling green building applications. In *Proc. of the 6th Workshop on Hot Topics in Embedded Networked Sensors*. 1–5.

A. De Paola, S. Gaglio, G. Lo Re, and M. Ortolani. 2011. Multi-sensor fusion through adaptive Bayesian networks. In *AI*IA 2011: Artificial Intelligence Around Man and Beyond*. Lecture Notes in Computer Science, Vol. 6934. 360–371.

A. De Paola, S. Gaglio, G. Lo Re, and M. Ortolani. 2012. Sensor9k: A testbed for designing and experimenting with WSN-based ambient intelligence applications. *Pervasive and Mobile Computing* 8, 3 (2012), 448–466.

F. Doctor, H. Hagras, and V. Callaghan. 2005. A type-2 fuzzy embedded agent to realise ambient intelligence in ubiquitous computing environments. *Information Sciences* 171, 4 (2005), 309–334.

R. H. Dodier, G. P. Henze, D. K. Tiller, and X. Guo. 2006. Building occupancy detection through sensor belief networks. *Energy and Buildings* 38, 9 (2006), 1033–1043.

P. Ducange, F. Marcelloni, and D. Marinari. 2012. An algorithm based on finite state machines with fuzzy transitions for non-intrusive load disaggregation. In *Proc. of the IFIP/IEEE Int. Conf. on Sustainable Internet and ICT for Sustainability*. 1–6.

T. V. Duong, H. H. Bui, D. Q. Phung, and S. Venkatesh. 2005. Activity recognition and abnormality detection with the switching hidden semi-markov model. In *Proc. of the 2005 IEEE Computer Society Conf. on Computer Vision and Pattern Recognition (CVPR'05)*, Vol. 1. 838–845.

P. G. Ellis, B. Griffith, N. Long, P. Torcellini, and D. Crawley. 2006. Automated multivariate optimization tool for energy analysis. In *Proc. of the 2006 IBPSA-USA Conf. (SimBuild'06)*. 42–48.

P. G. Ellis and P. A. Torcellini. 2005. Simulating tall buildings using EnergyPlus. In *Proc. of the 9th Int. IBPSA Conf.* 279–286.

F. Englert, T. Schmitt, S. Kößler, A. Reinhardt, and R. Steinmetz. 2013. How to auto-configure your smart home?: High-resolution power measurements to the rescue. In *Proc. of the 4th Int. Conf. on Future energy Syst. (e-Energy'13)*. 215–224.

V. L. Erickson, M. A. Carreira-Perpinan, and A. E. Cerpa. 2011. OBSERVE: Occupancy-based system for efficient reduction of HVAC energy. In *Proc. of the 10th ACM/IEEE Int. Conf. on Information Processing in Sensor Networks (IPSN'11)*. 258–269.

A. Fernández-Montes, L. Gonzalez-Abril, J. A. Ortega, and F. V. Morente. 2009. A study on saving energy in artificial lighting by making smart use of wireless sensor networks and actuators. *IEEE Network* 23, 6 (2009), 16–20.

R. T. Fielding and R. N. Taylor. 2002. Principled design of the modern Web architecture. *ACM Trans. Internet Technol.* 2, 2 (2002), 115–150.

A. Foglar and S. Plosz. 2008. Appliance Profiles Specification. AIM Consortium, Deliverable 2.3. Available at http://www.ict-aim.eu/fileadmin/user_files/deliverables/AIM-D2-3v1-0.pdf.

J. Froehlich, E. Larson, S. Gupta, G. Cohn, M. Reynolds, and S. Patel. 2011. Disaggregated end-use energy sensing for the smart grid. *IEEE Pervasive Computing* 10, 1 (2011), 28–39.

G. Gao and K. Whitehouse. 2009. The self-programming thermostat: Optimizing setback schedules based on home occupancy patterns. In *Proc. of the 1st ACM Work. on Embedded Sensing Syst. for Energy-Efficiency in Buildings*. 67–72.

G. Ghidini and S. K. Das. 2012. Improving home energy efficiency with E2Home: A Web-based application for integrated electricity consumption and contextual information visualization. In *Proc. of the IEEE 3rd Int. Conf. on Smart Grid Commun. (SmartGridComm)*. 471–475.

C. Gomez and J. Paradells. 2010. Wireless home automation networks: A survey of architectures and technologies. *IEEE Commun. Magazine* 48, 6 (2010), 92–101.

T. Gu, H. K. Pung, and D. Q. Zhang. 2004. Toward an OSGi-based infrastructure for context-aware applications. *IEEE Pervasive Computing* 3, 4 (2004), 66–74.

D. Guinard, V. Trifa, F. Mattern, and E. Wilde. 2011. From the internet of things to the web of things: Resource-oriented architecture and best practices. In *Architecting the Internet of Things*. 97–129.

S. Gupta, M. S. Reynolds, and S. N. Patel. 2010. ElectriSense: Single-point sensing using EMI for electrical event detection and classification in the home. In *Proc. of the 12th ACM Int. Conf. on Ubiquitous computing*. 139–148.

H. Hagras, F. Doctor, V. Callaghan, and A. Lopez. 2007. An incremental adaptive life long learning approach for type-2 fuzzy embedded agents in ambient intelligent environments. *IEEE Trans. on Fuzzy Syst.* 15, 1 (2007), 41–55.

F. Hammad and B. Abu-Hijleh. 2010. The energy savings potential of using dynamic external louvers in an office building. *Energy and Buildings* 42, 10 (2010), 1888–1895.

G. W. Hart. 1992. Nonintrusive appliance load monitoring. *Proc. of the IEEE* 80, 12 (1992), 1870–1891.

M. K. Hasan, K. A. P. Ngoc, Y. K. Lee, and S. Lee. 2009. Preference learning on an OSGi based home gateway. *IEEE Trans. on Consumer Electronics* 55, 3 (2009), 1322–1329.

S. Helal, W. Mann, H. El-Zabadani, J. King, Y. Kaddoura, and E. Jansen. 2005. The gator tech smart house: A programmable pervasive space. *Computer* 38, 3 (2005), 50–60.

A. Holmes, H. Duman, and A. Pounds-Cornish. 2002. The iDorm: Gateway to heterogeneous networking environments. In *Proc. of the Int. ITEA Work. on Virtual Home Environments*. 1–8.

Integrated environmental Solutions - Virtual Environments (IES-VE). 2013. Homepage. Available at http://www.iesve.com/.

International Energy Agency. 2003. *Cool Appliance - Policy Strategies for Energy Efficient Homes*. IEA Publications, Paris, France. Available at 62.168.68.98/StandardsLabels/downloads/01.pdf

X. Jiang, S. Dawson-Haggerty, P. Dutta, and D. Culler. 2009a. Design and implementation of a high-fidelity ac metering network. In *Proc. of the 2009 Int. Conf. on information Processing in Sensor Networks*. 253–264.

X. Jiang, M. Van Ly, J. Taneja, P. Dutta, and D. Culler. 2009b. Experiences with a high-fidelity wireless building energy auditing network. In *Proc. of the 7th ACM Conf. on Embedded Networked Sensor Syst.* 113–126.

A. Kamilaris, V. Trifa, and A. Pitsillides. 2011. HomeWeb: An application framework for Web-based smart homes. In *Proc. of the 18th Int. Conf. on Telecommunications (ICT'11)*. 134–139.

W. Kastner, M. J. Kofler, and C. Reinisch. 2010. Using AI to realize energy efficient yet comfortable smart homes. In *Proc. of the 2010 8th IEEE International Work. on Factory Communication Syst. (WFCS'10)*. 169–172.

A. H. Khalili, C. Wu, and H. Aghajan. 2010. Hierarchical preference learning for light control from user feedback. In *Proc. of the 2010 IEEE Computer Society Conf. on Computer Vision and Pattern Recognition Work. (CVPRW'10)*. 56–62.

C. Kidd, R. Orr, G. Abowd, C. Atkeson, I. Essa, B. MacIntyre, E. Mynatt, T. Starner, and W. Newstetter. 1999. The aware home: A living laboratory for ubiquitous computing research. In *Cooperative Buildings. Integrating Information, Organizations, and Architecture*. Lecture Notes in Computer Science, Vol. 1670. 191–198.

J. A. Kientz, S. N. Patel, B. Jones, E. Price, E. D. Mynatt, and G. D. Abowd. 2008. The georgia tech aware home. In *Proc. of the SIGCHI Conf. on Human Factors in Computing Syst.* 3675–3680.

Y. Kim, T. Schmid, Z. M. Charbiwala, and M. B. Srivastava. 2009a. ViridiScope: Design and implementation of a fine grained power monitoring system for homes. In *Proc. of the 11th Int. Conf. on Ubiquitous Computing*. 245–254.

Y. Kim, T. Schmid, M. B. Srivastava, and Y. Wang. 2009b. Challenges in resource monitoring for residential spaces. In *Proc. of the 1st ACM Work. on Embedded Sensing Syst. for Energy-Efficiency in Buildings*. 1–6.

K. Kobayashi, M. Tsukahara, A. Tokumasu, K. Okuyama, K. Saitou, and Y. Nakauchi. 2011. Ambient intelligence for energy conservation. In *Proc. of the 2011 IEEE/SICE Int. Symp. on System Integration (SII'11)*. 375–380.

K. Koile, K. Tollmar, D. Demirdjian, H. Shrobe, and T. Darrell. 2003. Activity zones for context-aware computing. In *Proc. of the 5th Int. Conf. on Ubiquitous Computing (UbiComp'03)*. 90–106.

D. Kolokotsa, K. Niachou, V. Geros, K. Kalaitzakis, G. S. Stavrakakis, and M. Santamouris. 2005. Implementation of an integrated indoor environment and energy management system. *Energy and Buildings* 37, 1 (2005), 93–99.

N. Kushwaha, M. Kim, D. Y. Kim, and W. D. Cho. 2004. An intelligent agent for ubiquitous computing environments: smart home UT-AGENT. In *Proc. of the 2nd IEEE Work. on Software Technologies for Future Embedded and Ubiquitous Syst.* 157–159.

C. Laughman, K. Lee, R. Cox, S. Shaw, S. Leeb, L. Norford, and P. Armstrong. 2003. Power signature analysis. *IEEE Power and Energy Magazine* 1, 2 (2003), 56–63.

C. Lee, D. Nordstedt, and S. Helal. 2003. Enabling smart spaces with OSGi. *IEEE Pervasive Computing* 2, 3 (2003), 89–94.

K. Lee and J. E. Braun. 2006. Evaluation of methods for determining demand-limiting setpoint trajectories in commercial buildings using short-term data analysis. In *Proc. of the 2006 IBPSA-USA Conf. (SimBuild'06)*. 107–114.

J. Lifton, M. Feldmeier, Y. Ono, C. Lewis, and J. A. Paradiso. 2007. A platform for ubiquitous sensor deployment in occupational and domestic environments. In *Proc. of the 6th Int. Conf. on Information Processing in Sensor Networks*. 119–127.

Z. H. Lin and L. C. Fu. 2007. Multi-user preference model and service provision in a smart home environment. In *Proc. of the 2007 IEEE Int. Conf. on Automation Science and Engineering (CASE'07)*. 759–764.

C. H. Lu and L. C. Fu. 2009. Robust location-aware activity recognition using wireless sensor network in an attentive home. *IEEE Trans. on Automation Science and Engineering* 6, 4 (2009), 598–609.

J. Lu, D. Birru, and K. Whitehouse. 2010a. Using simple light sensors to achieve smart daylight harvesting. In *Proc. of the 2nd ACM Work. on Embedded Sensing Syst. for Energy-Efficiency in Building*. 73–78.

J. Lu, T. Sookoor, V. Srinivasan, G. Gao, B. Holben, J. Stankovic, E. Field, and K. Whitehouse. 2010b. The smart thermostat: Using occupancy sensors to save energy in homes. In *Proc. of the 8th ACM Conf. on Embedded Networked Sensor Syst. (SenSys'10)*. 211–224.

M. L. Marceau and R. Zmeureanu. 2000. Nonintrusive load disaggregation computer program to estimate the energy consumption of major end uses in residential buildings. *Energy Conversion and Management* 41, 13 (2000), 1389–1403.

A. Marchiori, D. Hakkarinen, Q. Han, and L. Earle. 2011. Circuit-level load monitoring for household energy management. *IEEE Pervasive Computing* 10, 1 (2011), 40–48.

Microsoft Hohm. 2011. Homepage. Available at http://www.microsoft.com/environment/.

M. Milenkovic and O. Amft. 2013. An opportunistic activity-sensing approach to save energy in office buildings. In *Proc. of the 4th Int. Conf. on Future Energy Syst.* 247–258.

L. Mottola and G. P. Picco. 2011. Programming wireless sensor networks: Fundamental concepts and state of the art. *ACM Comput. Surv.* 43, 3 (2011), 19:1–19:51.

M. C. Mozer. 1998. The neural network house: An environment hat adapts to its inhabitants. In *Proc. of the Intelligent Environments AAAI Spring Symp.* 110–114.

E. F. Nakamura, A. A. F. Loureiro, and A. C. Frery. 2007. Information fusion for wireless sensor networks: Methods, models, and classifications. *ACM Comput. Surveys* 39, 3 (2007), 9:1–9:55.

N. T. Nguyen, D. Q. Phung, S. Venkatesh, and H. Bui. 2005. Learning and detecting activities from movement trajectories using the hierarchical hidden Markov model. In *Proc. of the 2005 IEEE Computer Society Conf. on Computer Vision and Pattern Recognition (CVPR'05)*, Vol. 2. 955–960.

B. W. Olesen and K. C. Parsons. 2002. Introduction to thermal comfort standards and to the proposed new version of EN ISO 7730. *Energy and Buildings* 34, 6 (2002), 537–548.

M. S. Pan, L. W. Yeh, Y. A. Chen, Y. H. Lin, and Y. C. Tseng. 2008. A WSN-based intelligent light control system considering user activities and profiles. *IEEE Sensors Journal* 8, 10 (2008), 1710–1721.

S. N. Patel, T. Robertson, J. A. Kientz, M. S. Reynolds, and G. D. Abowd. 2007. At the flick of a switch: Detecting and classifying unique electrical events on the residential power line. In *Proc. of the 9th Int. Conf. on Ubiquitous Computing*. 271–288.

L. Perez-Lombard, J. Ortiz, and C. Pout. 2008. A review on buildings energy consumption information. *Energy and Buildings* 40, 3 (2008), 394–398.

J. Ü. Pfafferott, S. Herkel, D. E. Kalz, and A. Zeuschner. 2007. Comparison of low-energy office buildings in summer using different thermal comfort criteria. *Energy and Buildings* 39, 7 (2007), 750–757.

M. Philipose, K. P. Fishkin, M. Perkowitz, D. J. Patterson, D. Fox, H. Kautz, and D. Hahnel. 2004. Inferring activities from interactions with objects. *IEEE Pervasive Computing* 3, 4 (2004), 50–57.

Google PowerMeter. 2011. Homepage. Available at http://www.google.com/powermeter.

A. Prudenzi. 2002. A neuron nets based procedure for identifying domestic appliances pattern-of-use from energy recordings at meter panel. In *Proc. of the 2002 IEEE Power Engineering Society Winter Meeting*, Vol. 2. 941–946.

Pulse Energy Inc. 2013. Berkeley Energy Dashboard. Available at https://us.pulseenergy.com/UniCalBerkeley/dashboard.

Z. Qiu and G. Deconinck. 2011. Smart Meter's feedback and the potential for energy savings in household sector: A survey. In *Proc. of the 2011 IEEE Int. Conf. on Networking, Sensing and Control*. 281–286.

P. Rashidi, D. J. Cook, L. Holder, and M. Schmitter-Edgecombe. 2011. Discovering activities to recognize and track in a smart environment. *IEEE Trans. on Knowledge and Data Engineering* 23, 4 (2011), 527–539.

P. Remagnino and G. L. Foresti. 2005. Ambient intelligence: A new multidisciplinary paradigm. *IEEE Trans. on Syst. Man Cybern. A Syst. Humans* 35, 1 (2005), 1–6.

L. Richardson and S. Ruby. 2007. *RESTful Web Services*.

A. Roy, S. K. Das, and K. Basu. 2007. A predictive framework for location-aware resource management in smart homes. *IEEE Trans. on Mobile Computing* 6, 11 (2007), 1270–1283.

A. G. Ruzzelli, C. Nicolas, A. Schoofs, and G. M. P. O'Hare. 2010. Real-time recognition and profiling of appliances through a single electricity sensor. In *Proc. of 2010 7th Annual IEEE Commun. Society Conf. on Sensor Mesh and Ad Hoc Commun. and Networks (SECON'10)*. 1–9.

F. Sadri. 2011. Ambient intelligence: A survey. *ACM Comput. Surveys* 43, 4 (2011), 36:1–36:66.

A. Schoofs, A. G. Ruzzelli, and G. M. P. O'Hare. 2010. Appliance activity monitoring using wireless sensors. In *Proc. of the 9th ACM/IEEE Int. Conf. on Information Processing in Sensor Networks*. 434–435.

A. Schumann, M. Burillo, and N. Wilson. 2010. Predicting the desired thermal comfort conditions for shared offices. In *Proc. of the Int. Conf. on Computing in Civil and Building Engineering (ICCCBE'10)*. 95–96.

V. Singhvi, A. Krause, C. Guestrin, J. H. Garrett Jr, and H. S. Matthews. 2005. Intelligent light control using sensor networks. In *Proc. of the 3rd Int. Conf. on Embedded Networked Sensor Syst.* 218–229.

R. S. Sutton and A. G. Barto. 1998. *Reinforcement Learning: An Introduction*.

S. Taherian, M. Pias, G. Coulouris, and J. Crowcroft. 2010. Profiling energy use in households and office spaces. In *Proc. of the 1st Int. Conf. on Energy-Efficient Computing and Networking*. 21–30.

E. Tapia, S. Intille, and K. Larson. 2004. Activity recognition in the home using simple and ubiquitous sensors. In *Pervasive Computing*. Lecture Notes in Computer Science, Vol. 3001. 158–175.

L. V. Thanayankizil, S. K. Ghai, D. Chakraborty, and D. P. Seetharam. 2012. Softgreen: Towards energy management of green office buildings with soft sensors. In *Proc. of the 2012 4th Int. Conf. on Communication Systems and Networks (COMSNETS'12)*. 1–6.

The AIM Consortium. 2008. AIM—A Novel Architecture for Modelling, Virtualising and Managing the Energy Consumption of Household Appliances. Available at http://www.ict-aim.eu/.

The ESTIA Consortium. 2008. Enhanced Networked Architecture for Personalised Provision of AV Content within the Home Environment. Available at http://www.gorenjegroup.com/en/filelib/gorenje_group/eu_projects/eu_project_estia.pdf.

S. Tompros, N. Mouratidis, M. Caragiozidis, H. Hrasnica, and A. Gavras. 2008. A pervasive network architecture featuring intelligent energy management of households. In *Proc. of the 1st Int. Conf. on PErvasive Technologies Related to Assistive Environments*. 1–6.

S. Tompros, N. Mouratidis, M. Draaijer, A. Foglar, and H. Hrasnica. 2009. Enabling applicability of energy saving applications on the appliances of the home environment. *IEEE Network* 23, 6 (2009), 8–15.

U.S. Energy Information Administration. 2010. International Energy Outlook 2010—Highlights. Report DOE/EIA-0484(2010). Available at http://www.eia.doe.gov/oiaf/ieo/highlights.html.

U.S. Environmental Protection Agency (EPA). 2013. EnergyStar Program. Available at http://www.energystar.gov.

A. M. Vainio, M. Valtonen, and J. Vanhala. 2008. Proactive fuzzy control and adaptation methods for smart homes. *IEEE Intell. Syst.* 23, 2 (2008), 42–49.

T. van Kasteren, G. Englebienne, and B. Kröse. 2011. Hierarchical activity recognition using automatically clustered actions. In *Ambient Intelligence*. Lecture Notes in Computer Science, Vol. 7040. 82–91.

F. I. Vazquez and W. Kastner. 2011. Clustering methods for occupancy prediction in smart home control. In *Proc. of the 2011 IEEE Int. Symp. on Industrial Electronics (ISIE'11)*. 1321–1328.

M. Weiser. 1991. The computer for the 21st century. *Scientific American* 265, 3 (1991), 66–75.

M. Weiss and D. Guinard. 2010. Increasing energy awareness through web-enabled power outlets. In *Proc. of the 9th Int. Conf. on Mobile and Ubiquitous Multimedia*. 20:1–20:10.

Y. J. Wen and A. M. Agogino. 2008. Wireless networked lighting systems for optimizing energy savings and user satisfaction. In *Proc. of the 2008. IEEE Wireless Hive Networks Conf. (WHNC'08)*. 1–7.

D. Wilson and C. Atkeson. 2005. Simultaneous tracking and activity recognition (STAR) using many anonymous, binary sensors. In *Pervasive Computing*. Lecture Notes in Computer Science, Vol. 3468. 329–334.

WiSensys. 2011. Homepage. Available at http://www.wisensys.com.

X10. 2013. Homepage. Available at http://www.x10.com.

H. W. Yeh, C. H. Lu, Y. C. Huang, T. H. Yang, and L. C. Fu. 2011. Cloud-enabled adaptive activity-aware energy-saving system in a dynamic environment. In *Proc. of the 2011 IEEE 9th Int. Conf. on Dependable, Autonomic and Secure Computing (DASC'11)*. 690–696.

L. W. Yeh, C. Y. Lu, C. W. Kou, Y. C. Tseng, and C. W. Yi. 2010. Autonomous light control by wireless sensor and actuator networks. *IEEE Sensors J.* 10, 6 (2010), 1029–1041.

L. W. Yeh, Y. C. Wang, and Y. C. Tseng. 2009. iPower: An energy conservation system for intelligent buildings by wireless sensor networks. *Int. J. of Sensor Networks* 5, 1 (2009), 1–10.

Received September 2013; revised December 2013; accepted April 2014