Intelligent Management Systems for Energy Efficiency in Buildings: A Survey

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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.

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1. INTRODUCTION

Technological advancements stimulate novel products and services, which however inevitably result into intensive resource (e.g., energy) consumption. At the same time, 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 inter-disciplinary 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, i.e., 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. 2010], 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 four 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, etc.);
- monitoring energy consumption;
- modifying the environmental conditions;
- interacting with users, in order to send them notifications, and to gather feedbacks and commands from them;
- 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 *non-functional* 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 the requirements listed above should find correspondence in the choice for the architecture of the entire system. Event though the complexity of any significant BMS discourages

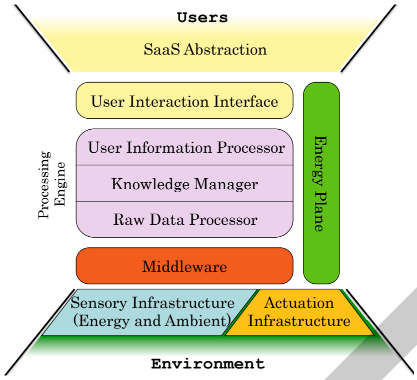

Fig. 1. Main components of the reference Building Management System for energy efficiency.

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 3-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 SaaS (Software as a Service) infrastruc-

ture. 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 described 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. multi-layer), *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, i.e., a power meter that measures the energy consumption of the appliance and sends the acquired 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 since 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

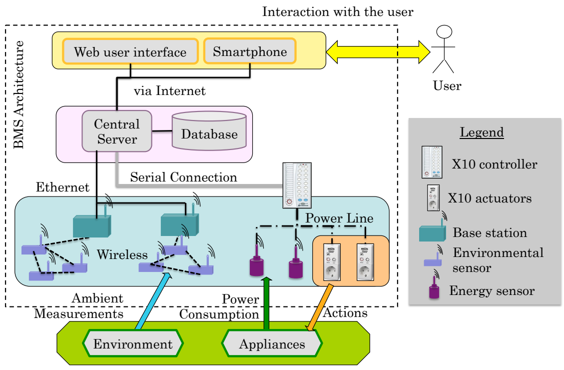

Fig. 2. *iPower* Architecture.

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 multi-layer 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, due to 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].

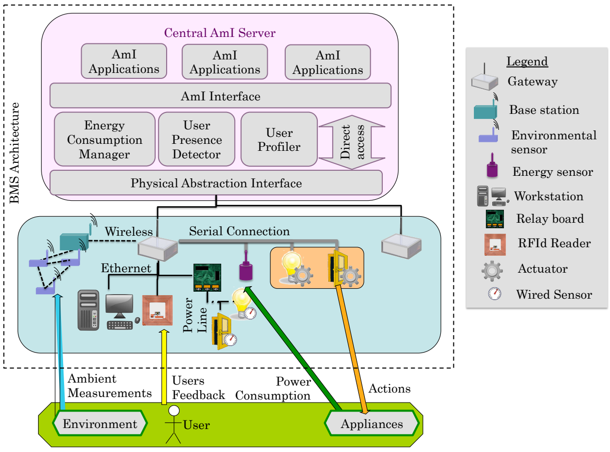

Fig. 3. *Sensor9k* Architecture.

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 *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; Tompros et al. 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, i.e., 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., towards 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

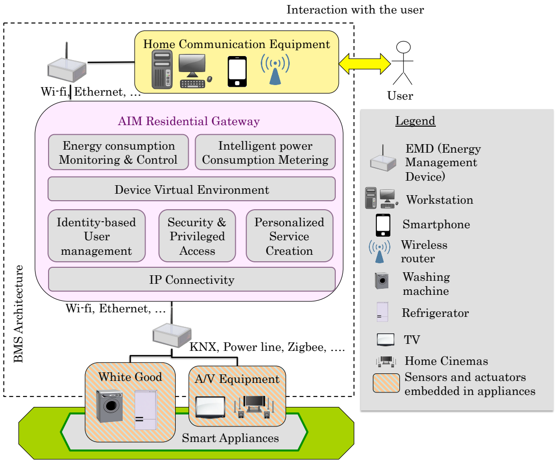

Fig. 4. AIM Reference Architecture.

or by turning 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

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	Multi-tier	Multi-tier	Multi-tier
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

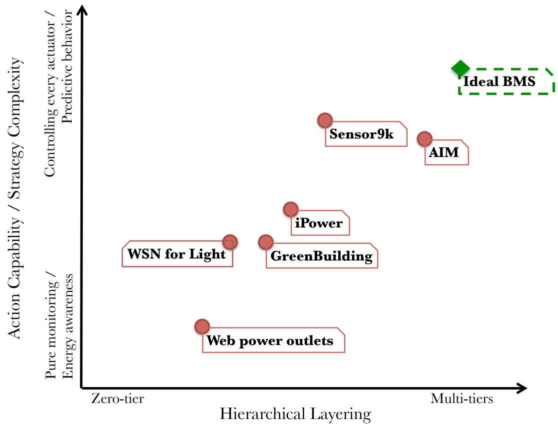

Fig. 5. Comparison among different architectures with respect to two qualitative dimensions. The assessed architectures are: Sensor9K [De Paola et al. 2012], AIM [Capone et al. 2009], iPower [Yeh et al. 2009], GreenBuilding [Corucci et al. 2011], WSN for Light [Wen and Agogino 2008], and Web power outlets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

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 above 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 too, 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; Sadri 2011]. Finally, an overview of wired and wireless communication technologies 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

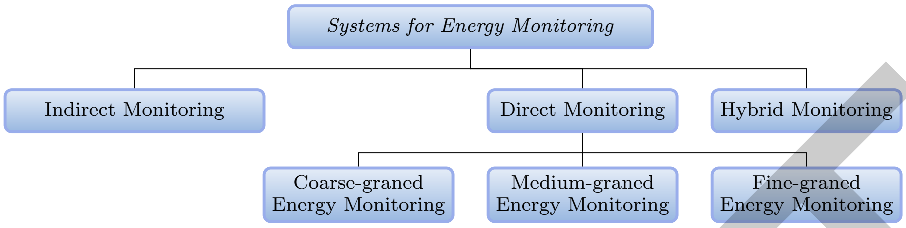

Fig. 6. Taxonomy of Energy Monitoring Systems.

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, e.g., the type of sensors they use, or the spatial granularity used for collecting 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 electro-magnetic 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 since 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 [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 pre-processing, are compared to consumption profiles for the various appliances in order to infer their activation or de-activation. 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. The authors of [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; 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 since 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

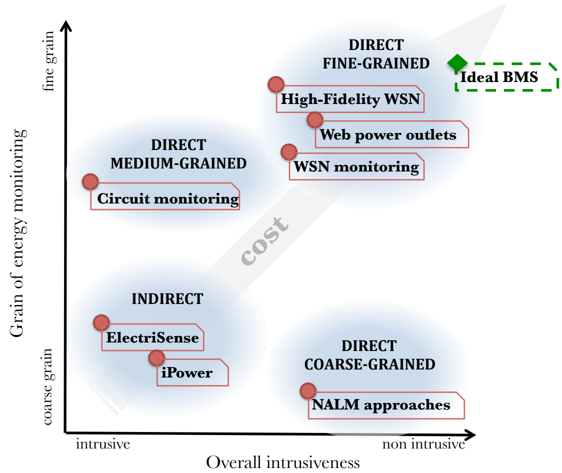

Fig. 7. Comparison of different systems for energy monitoring, with respect to two qualitative dimensions. The assessed energy monitoring systems are: High-Fidelity WSN [Jiang et al. 2009b], Web power outlets [Weiss and Guinard 2010], WSN monitoring [Schoofs et al. 2010], Circuit monitoring [Marchiori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

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 off-the-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 in [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. In [Lifton et al. 2007] the "Plug" network is described, 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 [WiSensys 2011], as suggested by the authors of [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 S. 2008]. However, this approach is viable only when it is not possible to adopt the above mentioned 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]:

– 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.
– 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.
– 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 run-time 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 run-time 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, e.g., 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 de-

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. 2010] [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. 2010] [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] [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 w.r.t. 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 w.r.t. installing/using the sensors.

tection 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 which 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 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], [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 on-going 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 cost of the individual detector is not negligible, it might make sense to monitor only those electric

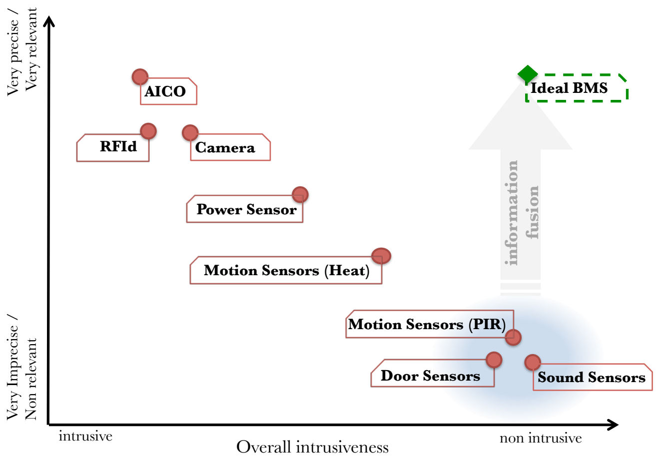

Fig. 8. Comparison of different technologies for context sensing, with respect to the precision and relevance of resulting information compared to the overall intrusiveness for the user. An information fusion process could improve the quality of the obtained information while maintaining a low intrusiveness.

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, while 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 multi-sensor fusion with plenty of data, even if partially noisy, is the best choice since 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 pre-installed 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 in order 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 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. The authors of [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 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 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 on-going 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

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. 2010] [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]

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 solution is still too naive to support predictive energy saving, and only allows reactive behavior.

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

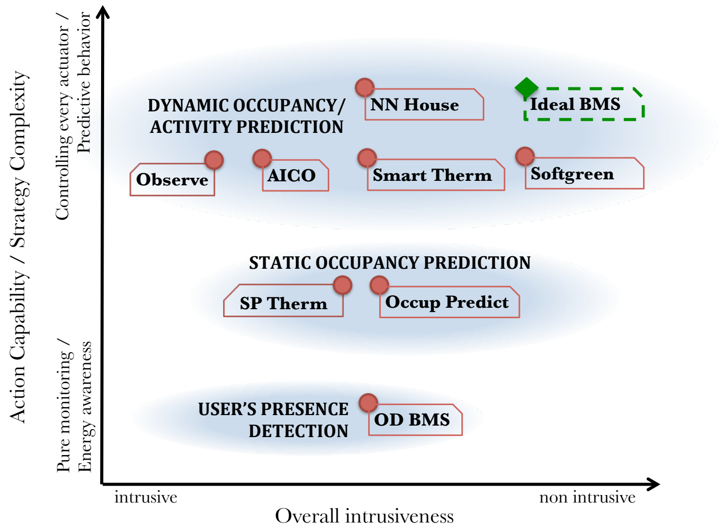

Fig. 9. Comparison of different BMS exploiting the "occupancy detection" intelligent functionality. The assessed BMS are: NNHouse [Mozer 1998], Observe [Erickson et al. 2011], AICO [Lu and Fu 2009], Smart Therm [Lu et al. 2010], Softgreen [Thanayankizil et al. 2012], SP Therm [Gao and Whitehouse 2009],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

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 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 towards the ideal BMS logic. Specifically, it uses a relatively intrusive sensor infrastructure, made up of sound sensors,

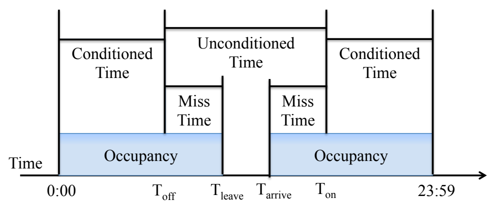

Fig. 10. A typical schedule used by the *Self-Programming Thermostat* [Gao and Whitehouse 2009], on the basis of a static environment occupation model.

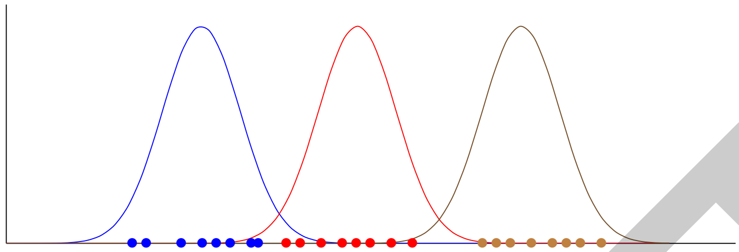

Fig. 11. Possible resuts of fuzzy c-means clustering on one-dimensional data.

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 while ago, it does not include an infrastructure for direct energy monitoring, nor 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 on-going 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 Bayesian Network (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 Bayesian network does not take into account past history of user behavior nor 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 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 Bayesian networks 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. 2010], 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

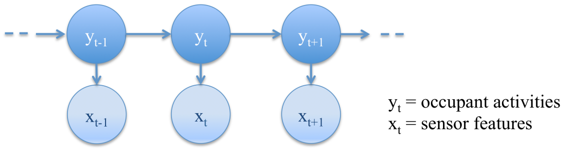

Fig. 12. A simple Hidden Markov Model; the current activity of a user (y_t) affects a set of sensory readings (x_t); the transition from an activity to another one is represented by a probabilistic state transition model.

typical user behavior pattern through a 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 in [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]. In [Erickson et al. 2011] is 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] which 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, the authors of [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 since 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 due to 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]. However, it is shown in [Agarwal et al. 2010] that under some conditions, an approach relying on them is sufficient to obtain energy saving of about 10% – 15%. Anyway, 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 in order 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.

The authors of [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. In [Lu et al. 2010] a *Smart Thermostat* is proposed to exploit 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, in order to pre-heat 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

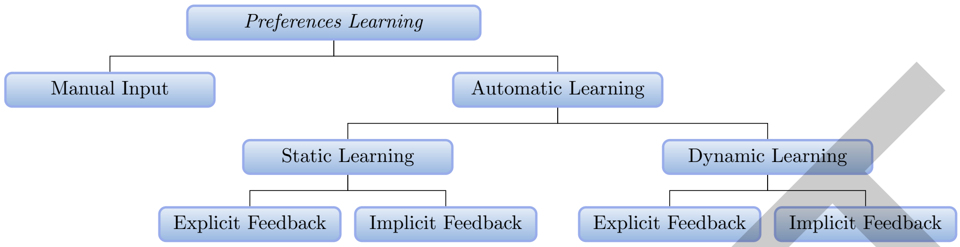

Fig. 13. Taxonomy of systems for managing user preferences.

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 in order 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, i.e., 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 off-line, even on real data, before the system is actually functioning and the user preference profile does not change over time. An example which belongs to such class is a system that records the interactions between the user and the HVAC 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 on-line functioning, and by a periodic computing of the preferred temperature through a mobile average. In order 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 non-intrusive user monitoring, by observing their interactions with the actuator or face expressions, and 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, while 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, since 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, since 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 Bayesian Network 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; Chen et al. 2009]. As an example, the authors of [Boton-Fernandez and Lozano-Tello 2011] propose a system capable of recognizing activities performed by the user and which dynamically learns frequent patterns in order 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 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 in order to minimize user discomfort; dynamic learning lets the system avoid the off-line learning phase, while on the other hand it is possible to obtain autonomous adaptability to new scenarios. In order 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 in [Choi

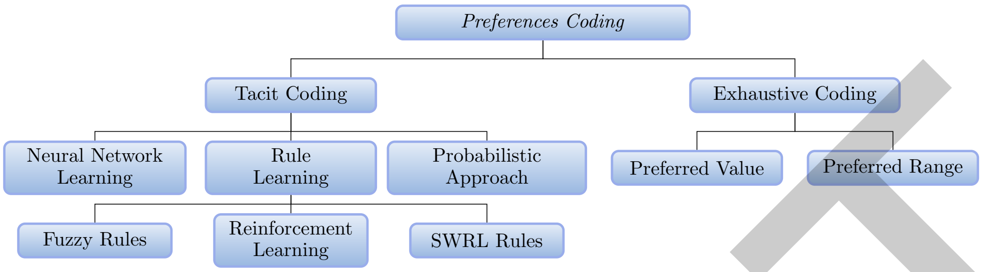

Fig. 14. Taxonomy of systems for representing user preferences.

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 on-line, 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, in order 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, since 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; 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 off-line training are successively tuned during the on-line 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 which 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 SWRL (Semantic Web Rule Languages). 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 on-line, and the user can trigger a change in the rules in any instant, by providing feedback about the system performance.

In order 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, Bayesian networks (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, since no on-line adjustment is performed over the user profile. In [Chen et al. 2006] BNs are used for coding user preferences by a semi-supervised 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; 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 *Self-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 [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], 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 Bayesian networks). 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; Lin and Fu 2007], SWRL rules or Bayesian networks 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];
– *Multi-objective optimization*: this approach consists of considering two separate functions, adopting a multi-objective 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 on page 21). 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 pre-fixed range.

In [Pan et al. 2008; 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 multi-user 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, i.e., in terms of currency. Action selection is performed in order 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 non negligible.

Finally, another approach exists that considers user preferences and energy consumption as two incommensurable quantities; thereby a multi-objective 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 multi-objective 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 in order 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 non negligible 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, semi-automated 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, in order 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, in order to make the systems aware of their physical structure, in terms of constituting components.

An analogous challenge must be addressed at a higher level, i.e., 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 Bayesian network-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 re-used 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 non negligible 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 semi-automated 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.

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A

Intelligent Management Systems for Energy Efficiency in Buildings: A Survey – Appendix

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1. EVALUATION APPROACHES

In order to complete our survey on methodologies for BMS design and evaluation, we will examine potential ways for researchers to conduct the experimental assessment of their proposals. Namely, many other factors besides the main goal of energy saving must be considered, e.g., user comfort and system accuracy. During experimental evaluation, it may be useful to compare one's own approach with an ideal theoretical system, which would show the desired behavior depending on the ground truth for the considered environmental quantities (temperature, lighting, room occupancy). For instance the performance of a system for lighting control (including both a reactive and a predictive component) with a purely reactive baseline algorithm is compared in [Lu et al. 2010a], using the same sensors and actuators, and with an optimal algorithm capable of estimating the exact lighting level at any time of the day. The optimal algorithm does not introduce delays, always satisfies the user, and provides the theoretical upper bound on energy saving and user comfort.

Additional meaningful comparisons can be made about the performance of currently available commercial systems, or the state of the art from research. The main difficulty in comparing different approaches is the strong dependence from the BMS physical infrastructure and from the real trend of environmental quantities, whereas it would be highly desirable to devise a comparative evaluation preliminarily to the physical deployment. A solution to this problem could be provided by the adoption of simulation tools. As regards to the HVAC system control, a comparison can be performed with the clues provided by the *EnergyPlus* simulator [Crawley et al. 2001], which allows to reproduce indoor heat flows starting from the structural model of the building, and from the actuator model and settings. The advantages arising from the adoption of Energy Plus derive mostly from its supply of predefined packages with models of actuators and buildings which may be easily composed in the simulation so as to allow researchers to focus on the policies and algorithms for energy saving.

The remainder of this section describes the criteria to adopt for assessing BMS performance, and specifically user comfort and energy saving. In particular, the subsection dealing with energy saving assessment will present many of the simulation techniques reported in the literature.

1.1. User Comfort

One of the most relevant features a BMS must possess is the ability to guarantee user comfort. Such characteristic allows critical assessment of the achieved energy saving by discriminating between the contribution due to the user action and the one due to the effectiveness of the energy policies; the metric to be used, however, largely depends on the examined approach.

Even though the literature contains several explicit models to measure user comfort [Pfafferott et al. 2007; Schumann et al. 2010], such models are generally too complex and depend on too many variables to be of practical interest. An example is the *thermal comfort* index presented in [Olesen and Parsons 2002], which is computed as a function of air temperature, radiance, humidity, air speed, occupants' clothing and activity. Due to their intrinsic complexity, such indices are seldom adopted, as explained in [Erickson et al. 2011]. Analogous indices exist for evaluating the adequacy of the ventilation system, such as the standard proposed by ASHRAE [Ashrae Standards 2013], which assesses ventilation speed with respect to the number of people present in the room and to the affected area.

At the opposite end of the spectrum of approaches for user comfort evaluation are all methods relying on subjective assessment by the users themselves. The easiest way, but also the least effective and most intrusive one, consists of asking them to fill in forms to express their opinion about the system performance. Such an approach may become extremely dull for users as well as for evaluators, since they need to devise such forms, propose them to users and process the answers. Nevertheless, it has been adopted in [Kolokotsa et al. 2005; Fernández-Montes et al. 2009] since it does not require developing any specific hardware or software for automated collection and processing of user feedback.

If the proposed system requires user preferences (e.g., desired temperature) to be static and known a priori, a good indicator may be the time interval when the system is not meeting the requirement, as in the case when the system keeps the low consumption mode while the area is occupied by users. Such a metric has been proposed for instance in [Lu et al. 2010b], where the "miss time" is measured as the time during which the home is occupied but the temperature has not reached the desired level. The authors compare the obtained performance with the theoretical optimum, whose miss time would always be zero, indicating an instantaneous response time. This comparison is useful for verifying the impact on user comfort, as well as to provide an upper bound for energy consumption. In this case, the goal is to obtain a tradeoff comfort and consumption, by minimizing the latter while regarding the former as a constraint.

The lighting control system in [Lu et al. 2010a] uses, as a discomfort metric, the root mean square error of the actual light intensity at the desk over the (known a priori) user desirable setpoint, and an analogous choice was also made in [Khalili et al. 2010]. Similarly, the schemes in [Pan et al. 2008; Yeh et al. 2010] measure the user comfort via an explicit preference model, either in terms of preference interval, as proposed in [Wen and Agogino 2008], or in terms of a Gaussian centered on the preference value and considering two indices. In the first case, a "GAP" index is used, representing the difference between the provided lighting and the requested one; if lighting falls within the desired interval, the gap is 0, otherwise it is computed as the interval range. In the second case, the comfort index is directly provided by the value of the Gaussian function. Clearly, an explicit model for the user preferences does not require direct interaction with them to check whether their preferences have been satisfied or not. However, it is dubious if this assessment method can account for the variability and unpredictability of real-life scenarios.

If the system was designed to include the necessary devices to monitor user actions, it may use such information to obtain a measure of the comfort perceived by users in a given environmental condition. Whenever the users interact with the actuators to modify the settings imposed by the BMS, they are in fact implicitly conveying a negative assessment about the chosen management policy. Additionally, the farther the user setting is from the system one, the more negative the opinion of the user. Such kind of assessment is reported in the literature mainly for systems which attempt to dynamically learn user preferences. The authors of [Doctor et al. 2005], for instance, indirectly use this metric; since they propose a fuzzy system whose rules are dynamically adapted based on user feedback, the authors consider the cumulative number of rule adaptations as a metric and observe its trend to assess the user satisfaction over time. Finally, in [Hasan et al. 2009] is considered as discomfort indicator the fact that users overwrite the system setting for more than three times for a specific service.

1.2. Energy Saving

Besides user comfort, the other important metric to take into account is energy saving, typically expressed with respect to a baseline system. The comparison can be carried out in many ways, e.g., by measuring the actual energy consumption through an energy monitoring system, by performing a theoretical assessment, or by simulating the consumption through specific software tools.

An actual comparison via monitoring does not require the baseline system to be managed by a BMS. It is sufficient that the considered scenario includes a tool for energy measurement (e.g., the sensor for aggregated measures at the root of the distribution tree). Such a comparison can provide a ground truth during assessment of a new proposal. However, exact monitoring in certain comparison scenarios is impractical, so a straightforward, yet relatively simple approach is to hypothesize an energy consumption model to be used to assess the hypothetical performance of the proposed system. To this aim, some of the models proposed in the literature could be adopted, although sometimes they may become excessively complex and simplified models are used instead. This mainly occurs with artificial lighting systems; for instance, in [Wen and Agogino 2008] and [Pan et al. 2008] the lighting measure is assumed to be directly proportional to the energy consumption. This assumption greatly simplifies experimental assessment, but it must be noted that it may prove to be unrealistic in the presence of artificial lighting sources realized with heterogeneous technologies, or in spaces where artificial lighting is combined with natural one. Furthermore, the presence of HVAC systems makes the computation of the theoretical consumption more difficult.

For all the above considerations, software simulation is the most widely used solution for the assessment of different approaches in diverse environmental conditions. The most well-known and widespread tool for simulation of energy consumption in buildings is *EnergyPlus* [Crawley et al. 2001], which is based on thermal modeling of the entire building. It has been developed by the U.S. Department of Energy and allows for assessing the effect and the energy consumption of different HVAC and lighting systems, under different operating modes and external environmental conditions. The used energy model is highly detailed and requires a precise description of the physical characteristics of the building (such as building materials, facing direction of walls, floors, roofs, windows, and doors) as well as of all the installed actuators, from HVAC to lighting systems. It is also possible to provide information about the occupational pattern of users in their rooms in order to assess their wellness. *EnergyPlus* allows either to make use of "templates" for modeling the energy consumption of different devices, or to explicitly provide the specifications to be coded into the simulator. The simulator computes the outdoor climate trends based on known models and on past sensing obtained from the most common weather stations. Such information is then used to employ some well-known thermal-transfer equations in order to compute the instantaneous indoor environmental conditions, as well as the global energy consumption. The main advantage of using such a "global" simulator, as opposed to considering the energy consumption models of different devices individually, is that it also takes into account the tight coupling of loads, system and plant, as well as the possibility to model the availability of renewable energy sources. Moreover, it is possible to obtain simulation models for the energy consumption in buildings where the impact of the environmental factors on the consumption itself is non negligible and not trivial to capture, as in the case of skyscrapers, for which environmental conditions (e.g., temperature, wind speed and direction) may significantly vary between different floors [Ellis and Torcellini 2005]. Furthermore, some of the modules added in recent releases allow to model also the environmental emissions due to energy use. The work in [Lu et al. 2010b] is a meaningful example of *EnergyPlus* adoption; the *Smart Thermostat* is tested over several environmental conditions, which could only be realized in practice with a large-scale experimentation that would require relevant funding. The validation of the simulated model was compared against the sensory measurements obtained through a set of devices actually deployed in a residential building. The use of this simulator allowed to test the proposed system under different building conditions and climate zones. The idea of a preliminary simulation to drive the design of eco-friendly buildings, by an automated multivariate optimization tool was exploited in [Ellis et al. 2006] and [Lee and Braun 2006] which use *EnergyPlus* to assess different approaches to actuator control.

ATPlus is another proposal for a simulation software devised to model heat flows in buildings considering the presence of multiple HVAC appliances and taking into account the specifics of the weather model to adopt. This simulator was used in [Kastner et al. 2010] to test a control strategy exploiting neural networks in order to establish the best moment to activate the actuators.

The use of simulators to assess energy saving performance is reported in the literature mainly with regard to HVAC systems, even though some works exist which exploit such tools for artificial lighting. For example, in [Hammad and Abu-Hijleh 2010] is adopted the *Integrated environmental Solutions - Virtual Environments* (IES-VE) [Integrated environmental Solutions - Virtual Environments (IES-VE) 2013] commercial package to assess the effectiveness of various configurations of the proposed system with dynamic external louvers. An overview focusing on the usability of some commercially or academically available simulators for the assessment of the energy performance of buildings is contained in [Attia et al. 2009].

Besides choosing the simulation platform in order to estimate the parameters of interest, it is also necessary to select some similar systems to be used as a comparison. Such comparison may help assessing the actual effectiveness of the employed techniques and may provide justification for the adoption of a more complex and more effective systems instead of a cheaper one. For instance, if the proposal regards a technological innovation for some of the actuators, it may be more meaningful to compare it against the most common commercial devices. The performance of *Smart Thermostat* [Lu et al. 2010b] is compared against the devices actually deployed in a residential building. In [Hammad and Abu-Hijleh 2010], a comparison is made between their dynamic external louvers (able to modify the amount of lighting filtering through the windows depending on the outdoor conditions, on the indoor perceived lighting, and on the user feedback) with other lighting systems generally present in office buildings. If, on the other hand, the focus is not on the individual device but on the overall comparison strategy, it may be convenient to compare the proposed management policy with a theoretical one, used on the same set of appliances. In [Kastner et al. 2010] the control strategy for an HVAC system is compared with another strategy, typically adopted in actual deployments, which forces the activation of the HVAC system to occur 45 minutes earlier to the occupants' arrival, regardless of the delay actually required by those appliances before reaching the desired temperature. The performance of the lighting control system is compared in [Lu et al. 2010a] exploiting natural sources as much as possible in order to reach the desired lighting level with a schema that purely relies on artificial lighting to maintain the setpoint defined by the user at the desk level. As regards to HVAC systems, it is possible to make a comparison with a policy using the setpoints for times and temperatures recommended by EnergyStar [U.S. Environmental Protection Agency (EPA) 2013], a joint program of the U.S. Environmental Protection Agency and the U.S. Department of Energy. This is the solution chosen by the works proposed in [Lu et al. 2010b; Gao and Whitehouse 2009]. Another good comparison term for environmental conditions is the standard proposed by ASHRAE both with respect to the temperature and ventilation system. This is the solution adopted in [Erickson et al. 2011], where the authors compare their control strategy for HVAC systems – based on the predicted patterns of user occupancy – to the baseline provided by the ASHRAE set points. The ASHRAE baseline operates as a purely reactive system which activates the HVAC system only after detecting user presence.

A mere comparison among the performance of the different strategies might however not be sufficient. The authors of [Taherian et al. 2010] state that the analysis of building energy consumptions requires a more in-depth inspection, by isolating the non-reducible fraction due to appliances that can never be deactivated. For instance, such "baseline energy use" includes the energy due to: home security systems, alarm systems, the refrigeration unit, and the IT infrastructure. Hence, the authors claim that the comparison should be made over the *ineffectiveness factor*, which is obtained by excluding the "baseline energy use" from the observed energy consumption. This factor represents the amount of energy due to the habits of the human occupants, i.e., the quantity presenting the largest room for improvement; this quantity is also defined as the *Human-driven Energy Use*.

1.3. Inference Accuracy

If the system includes "intelligent" modules for inferring some environmental conditions starting from the available sensory data, it is advisable to individually estimate the accuracy of those components, in order to assess their potential influence on the energy consumption of the BMS and the residual margin for improvement. The only way to assess the accuracy of the intelligent modules is to compare the results of the inference with the ground truth; in case the system infers discrete concepts, its correctness may be measured by the percentage of correct inferences, and in terms of false positives and false negatives. This approach is adopted for instance in [Lu et al. 2010b] to evaluate the accuracy of the HMM used to deduce the presence of users. If the inferred concept is measurable by a continuous indicator, it is advisable to provide at least the average error and the statistical variance. If the intelligent modules use a probabilistic approach to represent the belief over a specific characteristic of the world, then it is possible to use metrics which allow to express the distance between the belief probability distribution and the ground truth. To this aim, the *Kullback-Leibler divergence* or the *Jenesen-Shannon divergence* may be used, as proposed, for instance, in [Erickson et al. 2011] to estimate the accuracy of the system for user presence prediction by comparing the statistical model of their system with the distribution associated with the ground truth.

When the inference system has to deal with user presence detection or with on-going activity detection, a preliminary evaluation of its accuracy may be obtained by relying on one of the several publicly available databases, provided by research groups active in the field. The use of such datasets allows to address the issue of ground truth extraction from sensory data, which is typically a very long and tiring task. One of such datasets is the Tulum dataset [Cook and Schmitter-Edgecombe 2009], created within the WSU CASAS project, by monitoring the occupants of a house for a period of approximately one month, recording the sensory readings obtained through a set of sensors pervasively installed in the monitored areas, and annotating the DB with the activities performed by the users. Similarly structured, and also quite popular, is the Kasteren dataset [van Kasteren et al. 2011]. Works exploiting those public datasets include [Lu et al. 2010b; Gao and Whitehouse 2009]. A survey on more elaborate criteria for the assessment of user activity recognition systems may be found in [Tapia et al. 2004].

2. RESEARCH CHALLENGES AND OPEN ISSUES

2.1. BMS Architectures

Some of the issues characterizing the design of BMS architectures have been identified by the authors of [Cook and Das 2004], although many of them still remain open or have not been conclusively resolved. Among these, the support for heterogeneity has a preminent role. As previously described, there are different approaches in the literature for the definition of middlewares allowing for an abstraction from the physical layer, but a standard solution is still missing. This limits the interoperability and the ability to compose truly modular systems. The definition of a standard would be a big plus for several stakeholders of BMS, notably for producers of sensors, actuators and appliances for BMSs. Such a connection architecture should allow the automatic discovery of resources available, allowing for device plug-and-play, and minimizing the burden well. Each device would be commercialized together with its software driver, and the final user would have the possibility of selecting the best solution for his requirements.

2.2. Measuring Energy Consumption

Many solutions have been presented in the literature, concerning the design of BMSs capable of monitoring energy consumption. Nevertheless, more research efforts need to be devoted to the definition of configuration procedures which minimize human intervention. The ideal goal is a system whose installation is performed by simply deploying energy sensors near to the significant appliances, and by indicating through a friendly interface in which room, and near which appliances each device is installed. The energy consumption models should be automatically learned simply by exploiting collected measurements. Moreover, a mechanism capable of supporting the final user in the design phase of the energy monitoring system is missing in the current literature.

2.3. Intelligent Support Techniques

The main challenge related to the adoption of intelligent support techniques is the reduction of the burden required for the learning phase. Many techniques require a labeled training set for tuning the system behavior, but gathering these data may cause a relevant discomfort to the user. We believe that much effort have to be devoted to the definition of semi-automated labeling procedure which would allow to reduce such discomfort. Obviously, in order to learn preferences or habits of the users, it is mandatory to interact with them, but it is also necessary to make this interaction as natural as possible in order to develop intelligent BMS truly able of "disappearing into the background" [Weiser 1991].

ACRONYMS

6LoWPAN	IPv6 over Low power Wireless Personal Area Networks
AI	Artificial Intelligence
AICO	Artificial Intelligence Compliant Object
AmI	Ambient Intelligence
API	Application Programming Interface
API	Aggregate Power Index
BMS	Building Management System
BN	Bayesian Network
CBC	Case-Based Reasoning
CoC	Code of Conduct
EMD	Energy Management Device
FSMFT	Finite State Machines based on Fuzzy Transitions
GPS	Global Positioning System
HMM	Hidden Markov Model
HRL	Hierarchical Reinforcement Learning
HTTP	HyperText Transfer Protocol
HVAC	Heating, ventilation and Conditioning
IoT	Internet of Things
IP	Internet Protocol
IR	Infrared
LAN	Local Area Network
NALM	Non-intrusive Application Load Monitoring
NILM	Non-Intrusive Load Monitoring
OSGi	Open Service Gateway initiative

PDA	Personal Digital Assistant
PIR	Passive Infrared
PLC	Power Line Communication
RECAP	RECognition of electrical Appliances and Profiling in real-time
REST	Representational state transfer
RFID	Radio-Frequency IDentification
RL	Reinforcement Learning
SaaS	Software as a service
sMAP	Simple Measurement and Actuation Profile
SMPS	Switch Mode Power Supply
SOAP	Simple Object Access Protocol
SWRL	Semantic Web Rule Languages
TCP	Transmission Control Protocol
WoT	Web of Things
WSN	Wireless Sensor Network

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