Intelligent energy management systems: a review

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Abstract

Climate change has become a major problem for humanity in the last two decades. One of the reasons that caused it, is our daily energy waste. People consume electricity in order to use home/work appliances and devices and also reach certain levels of comfort while working or being at home. However, even though the environmental impact of this behavior is not immediately observed, it leads to increased CO2 emissions coming from energy generation from power plants. It has been shown that about 40% of these emissions come from the electricity consumption and also that about 20% of this percentage could have been saved if we started using energy more efficiently. Confronting such a problem efficiently will affect both the environment and our society. Monitoring energy consumption in real-time, changing energy wastage behavior of occupants and using automations with incorporated energy savings scenarios, are ways to decrease global energy footprint. In this review, we study intelligent systems for energy management in residential, commercial and educational buildings, classifying them in two major categories depending on whether they provide direct or indirect control. The article also discusses what the strengths and weaknesses are, which optimization techniques do they use and finally, provide insights about how these systems can be improved in the future.

1 Introduction

Nowadays, electrical energy plays a vital role in various aspects of our life. However, the lack of ecological awareness along with the absence of energy-friendly infrastructures has led into increased energy consumption and waste. According to estimates of the United States Energy Information Administration USA (2019), 40% of the annual CO2 emissions

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are directly related to the electricity consumption. Out of these emissions, 40% of them concern residential and commercial consumers, and as Armel et al. (2013) and Darby (2006) mentioned, it is possible to achieve 20% savings if we use power more efficiently. Therefore, electricity consumption and wastage reduction can offer environmental and financial benefits to our society.

Different approaches and systems have been proposed in the literature that aim to reverse climate change and global warming. Intelligent energy management systems with incorporated automations is a promising approach towards the solution of these environmental problems. These systems convert a conventional home or building into a "smart" version of it. Smart Homes and Buildings, according to Energy (2021), include automations systems which provide the ability to monitor and control various services such as, lighting and heating-ventilation-airconditioning (HVAC), or devices such as fridges, ovens and washing machines. The set of installed sensors, actuators and smart devices constitute an Internet-of-Things (IoT) subsystem. When users are surrounded by microcontrollers and smart devices, they follow the paradigm of *Ubiquitous or Pervasive Computing*. When Artificial Intelligence (AI) methodologies enable the interaction of people with these devices, the environment embodies *Ambient Intelligence (AmI)* (Weiser 1993).

These environments play an important role in the *Smart Grid*. Smart grids consist of two parts, the *supply-side* and the *demand-side*, which optimize the energy production, transmission, distribution and consumption (Mir et al. 2021). Smart homes are a necessity for the demand-side of these grids because even if the supply-side is successfully optimized, a faulty demand-side, e.g. a conventional home/building, will decrease the total effectiveness of the system.

An immediate conversion of all residential and commercial buildings from conventional to smart, is a costly and time-consuming procedure. Even if governments around the world wanted to carry out this plan, the high deployment costs remain an impediment (García et al. 2017; Shigeyoshi et al. 2013). Therefore, research was expanded towards lower or no-cost energy saving solutions based on information and communication technologies (ICT) (Luo et al. 2017).

Research and development of energy management systems focused on new technologies that embody energy savings, and materials that decrease wastage of energy. However, the same attention wasn't given at users' behavioral change. Darby (2006), suggested that in order to improve the awareness on energy waste habits, consumers must firstly monitor their power consumption and then manage it after receiving appropriate advice. Governments and Non-Governmental Organizations support and facilitate energy-efficiency changes. However the impact of simple saving tips and peer devices' comparison is low because of the wrong time and place these occur (Cattaneo 2019). End-users must alter their routine completely and adopt an environmental friendly behavior (Becchio et al. 2018).

Recommendation systems are information systems that assist users to discover personalized content, based on their preferences (Resnick and Varian 1997). They are used in many different real-world scenarios (Martin 2009) and recently some implementations were applied into energy profile reshaping (Alsalemi et al. 2020; Sardianos et al. 2019b) using deep learning algorithms (Wei et al. 2020), data mining techniques (Ashouri et al. 2018), behavioral analytics and human decision-making processes to develop context-aware systems (Şimşek et al. 2016, Sardianos et al. (2019a)). Despite the fact that these systems emerged in the mid 90's (Resnick et al. 1994; Shardanand and Maes 1995), Himeur et al. (2021) reached the conclusion that the field of energy saving recommendation systems is still unexplored.

Intelligent Energy Management Systems (IEMS) are a necessary tool to reduce energy overconsumption in households, commercial, educational and industrial buildings and subsequently the total CO_2 emissions that are produced. To be more precise, studies indicate that commercial buildings are consuming almost 40% of the total energy in most developed countries (Cao et al. 2016). Therefore, real-time energy usage monitoring, along with systems that can offer ways to manage energy consumption and, alternative sustainable energy sources (e.g. solar panels), are of the highest importance (Mir et al. 2021). This work provides a comprehensive review of IEMS of the literature over the last decade. Our goal in this article was first, to provide the readers an overview of the influential factors of energy overconsumption and also an overview of various approaches towards energy efficiency. Second, we present a high level architecture breakdown for these systems. Third, we provide a review of the state-of-the-art components of each module and we introduce a novel classification for the IEMS in Direct control systems, i.e. systems that provide automations to the environment in order to control functionalities and conditions, and in Indirect control systems, i.e. systems that aim in the behavioral modification of the occupants. Fourth, for these two novel classes, we discuss their respective advantages and disadvantages which class to conclude which class is more suitable for each environment. Finally, we provide a short discussion about their limitations and problematic aspects and also some future research orientations.

The remaining of our study is organized as follows. Section 2 presents our motivation towards studying and comparing these two types of energy management systems. Section 3 discusses related work on this topic and refers to surveys performed on smart environments and recommendation systems for energy efficiency. Section 4 provides background information of the energy efficiency topic from a researchers' perspective. In Sect. 5, we present necessary specifications for an intelligent energy management system and an overview of their architectures. Subsequently, Sect. 6 presents a discussion and an analysis of the advantages of each class, their problematic issues and some suggestions for future research. Finally, Sect. 8 concludes our findings.

2 Motivation

Energy management systems are a promising solution towards energy wastage reduction. The variety of studies on smart environments, and the plurality of algorithms and techniques developed over the last decade for automations and recommendations' optimizations, are proofs of how important these systems are in our effort to reverse climate change and global warming. During our research, we noticed that in current literature, every discussion about smart environments involved mostly systems with integrated automations. Nevertheless, new systems emerged recently which incorporate recommendations mechanisms, aiming at occupants behavioral change rather than in automations. Therefore, we believe that a review was necessary in order to study both types of Intelligent Energy Management Systems.

From our perspective, studying, reviewing and eventually researching IEMS is an extremely important topic especially during the climate and energy crisis we have been experiencing in recent years. These systems can offer environmental solutions regarding efficient energy consumption in various building types, just by adjusting the type of actuation they will incorporate. Each type of building has different needs and capabilities to control its energy footprint and it is crucial for the community research to develop systems

with the right approach for each case. For these reasons, a review of the state-of-the-art IEMS, an analysis and the extraction of useful insights is necessary in the literature. To the best of the authors knowledge, a review that include all these topics in the way this article does, does not exist and that is why we start this specific investigation and research. Almost every review until know was focusing either on systems that incorporated automations in the actuation module or systems that were focusing on behavioral management. Moreover, none of these articles was comparing these two types of systems in terms of their suitability on a specific building type. In order to successfully develop and choose an IEMS, a comparison of their advantages was necessary and will give the readers better perspective.

Before referring to IEMS, it would be useful to discuss about efficient energy consumption. There are multiple influential factors that cause energy overconsumption both in residential and in commercial environments. Moreover, a small discussion about various approaches towards energy efficiency. Our goal was to figure out which are the ways to achieve energy saving results and which implementations seem more promising for each installation environment.

Next, we wanted to proceed with the presentation of the IEMS architecture, and provide the reader with a categorization of their components and a classification of their sub-parts. During our research, a classification occurred for the IEMS in Direct Control IEMS and Indirect Control IEMS. Every IEMS can be classified in one of these classes based on the design of its actuation part. Besides various state-of-the-artcomponents we wanted also to show state-of-the-artcomplete prototypes that have been developed by research teams.

In the final parts of this article, we wanted to discuss about the advantages and disadvantages of each class of IEMS, compare their different aspects, investigate their major open problems and discuss about research gaps and future research orientations that will be helpful for researchers.

3 Related work

In this section, we present surveys and reviews that are related to IEMS (Table 1). Our intention is to provide the reader an extensive look in the field of Energy Management Systems in Residential, Educational and Commercial Buildings. One could read the work of De Paola et al. (2014) in order to understand which are the general approaches to energy efficiency and also the main architectural, technological and algorithmic aspects of an energy management system. Leitao et al. (2020) proposed a similar architecture that also incorporates smart appliances, while Lin et al. (2017) presented a more abstract architecture for IoT-based systems, consisting of three layers: a *Perception layer*, a *Network layer* and an *Application* layer. Boodi et al. (2018) dealt with a review of the state-of-the-art Building Energy Management Systems (BEMS) focusing on three model approaches: White box, Black box and Grey box models. They also performed a comparative analysis of the factors that have the highest impact in energy consumption. Himeur et al. (2020) surveyed a large number of databases with data that refer to building power consumption, with several features compared and examined, such as geographical location, number of monitored households, sampling rate, etc. Moreover, this research team presented a novel dataset for power consumption anomaly detection. Such a dataset will be very useful for training and testing models that aim to detect anomalies in order to reduce energy wastage. Finally, they performed review on current trends and new perspectives in the field of anomaly detection of energy consumption systems. According to them, detecting an anomaly in

Table 1 Previous works related to intelligent energy management systems

Reference	Year	Description
Mir et al. (2021)	2021	State-of-the-art solutions for energy management
Himeur et al. (2021)	2021	Analysis of recommendation systems for energy efficiency in buildings
Dunne et al. (2021)	2021	Overview of the field of Ambient Intelligence
Ali et al. (2021)	2021	Compilation of latest developments and research orientations on intelligent energy management
Leitao et al. (2020)	2020	State of the art review of energy management systems in residential buildings
McIlvennie et al. (2020)	2020	Discussion between techno-centric and user-centric approaches on energy management systems
Cattaneo (2019)	2019	Discussion on barriers to the adoption of technologies for energy efficiency
Sardianos et al. (2019b)	2019	Users' micro-moments as influential factors of energy consumption behaviors
Sayed et al. (2019)	2019	Investigation on how behavioral change can achieve reduction of greenhouse gas emissions in high-income European countries
Steg et al. (2018)	2018	Discussion on how to promote active engagement in a more sustainable energy usage
Zhang et al. (2018b)	2018	Discussion on how occupants' behavior affect energy performance of buildings
Becchio et al. (2018)	2018	Importance of altering users' behavior
Boodi et al. (2018)	2018	Review on building energy management systems focusing on three model types
Shareef et al. (2018)	2018	Review of demand response techniques, smart technologies and scheduling controllers
González-Briones et al. (2018)	2018	Multi-agent systems as modelling tools for energy optimization applications
Lin et al. (2017)	2017	Overview on various aspects of Internet of Things systems
Beaudin and Zareipour (2015)	2015	Analysis of methods for modeling home energy management systems
De Paola et al. (2014)	2014	Presentation of architectural, technological and algorithmic aspects of intelligent energy management systems
Asare-Bediako et al. (2013)	2013	Proposal of multi-agent architectures for energy management
Park et al. (2012)	2012	Review on trending topics of recommendation systems

the energy data can help us prevent a problem before it gets big and spreads (Himeur et al. 2021).

When IEMS are installed, they provide AmI at the environment. According to Cook et al. (2009), there are various definitions about AmI depending on the features that are included. These environments offer environmental, comfort, safety and financial benefits. AmI is also an umbrella term which applies into technologies embedded into a physical space to create an invisible user interface augmented with AI (Dunne et al. 2021). They presented an comprehensive survey on Ambient Intelligence (AmI) and Ambient Assistive Living (AAL) while referring to the state-of-the-art AI techniques and methodologies to implement these systems.

An interesting study was performed by Shareef et al. (2018) reviewing load scheduling controllers which integrate AI techniques such as, artificial neural networks (ANNs), fuzzy logic, adaptive neural fuzzy inference and heuristic optimization. Al-Ani and Das (2022) surveyed the use of Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL) techniques in home energy management systems (HEMS). They analyzed multiple RL algorithms, their objectives, and also their testing environments. RL and DRL seem like a very promising approach in simulation platforms but until now they are too slow during training and that is why only 12% of these approaches have been tested in the real world. Mason and Grijalva (2019) have also performed a review article about RL applications for autonomous building energy management. They showed that RL algorithms improve significantly the energy efficiency in domestic environments and also that DRL algorithms are usually preferred more than RL algorithms. Nevertheless, they found out that most of the RL approaches are tested mostly at simulation platforms and that an accurate simulation design is needed before these systems are installed in real world scenarios. An example of such a DRL algorithm was developed by Lissa et al. (2021). They proposed an algorithm for indoor and domestic hot water temperature control, aiming to reduce the total energy consumption by optimizing the way that solar produced energy is being used.

Leitao et al. (2020) conducted a survey about home energy management systems, where they discussed about the demand-side management, i.e. the collection of techniques applied to reduce energy costs on the consumption-side and improve energy efficiency. Furthermore, they discussed about dominant scheduling methodologies which are grouped into five categories. Additional energy saving techniques are presented by Mir et al. (2021), including statistical models, cloud computing-based solutions, fog computing, smart-metering-based architectures and also some IoT inspired solutions. Beaudin and Zareipour (2015) reviewed methods employed to model various aspects of residential energy management systems. Moreover, they discussed about complexity in such systems and presented also an overview of techniques for scheduling approaches, as well as a classification in mathematical programming, meta-heuristic search and heuristic scheduling techniques. Finally, a recent study by Ali et al. (2021) summarized research opportunities created by open issues in the field such as, blockchain-enabled IoT platforms for distributed energy management, deep learning models to handle, use and evaluate big energy data, peer-to-peer energy trading and demand-side energy management, context-aware pervasive future computing, resilience-oriented energy management, forecasting models, user comfort and real-time feedback systems as well as, Internet of Energy (IoE)-based energy management.

Multi-agent systems (MAS) is an approach used to model components of IEMS. An interesting article was published by González-Briones et al. (2018) reviewing state-of-the-art developments in MAS and how they are used to solve energy optimization problems. They discussed about the types of MAS architectures and also the reasons why they must be used as modeling tools. Asare-Bediako et al. (2013) proposed a multi-agent architecture

of distributed intelligence to solve the complex and dynamic decision process of optimal energy management. Their architecture was based on four groups of agents: control and monitoring, information, application and management and optimization agents. According to the definition of MAS (Poole and Mackworth 2010) an agent is comprised by a coupling of perception, reasoning and acting components. Mekuria et al. (2018) conducted a comprehensive literature review aiming to identify and characterize the reasoning systems in MAS-based smart environments and also presented the strengths and limitations of them.

During the last decades, researchers studied means in order to transit into more sustainable energy usage. Because of their daily consumption, households are responsible for 72% of global greenhouse gas emissions (Hertwich and Peters 2009). Saving energy and being more efficient in our daily power consumption is important to reduce our greenhouse gas emissions. As previously mentioned, occupants' behavior influences energy wastage, therefore behavioral changes of occupants remains a key objective for energy scientists. Steg et al. (2018) discussed of ways to promote the active engagement of people in a sustainable energy transition. According to them, some relevant behaviors must be managed and manipulated. Household consumption and behavioral decisions manipulation can offer a substantial reduction of greenhouse gas emissions if regulatory framework is set that supports behavioral changes (Dubois et al. 2019).

Recommendation systems are an important research field since the mid 90's. Their goal is to help users find online content based on personalized preferences using collaborative or content-based filtering along with AI techniques such as, association rules, clustering, decision trees, k-nearest neighbor, neural networks, regression, etc.(Park et al. 2012). Over the last decade, the research community began to integrate recommendation modules into the components of smart environment systems to persuade users to adopt a more Eco-friendly behavior. Steg et al. (2018) discussed on ways to make people more engaged into actions and habits that are more energy sustainable. Furthermore, they analyzed how these actions will affect their daily lifestyle and comfort. Based on recent studies, Zhang et al. (2018a) estimated that occupants behavior affect 10–25% of the consumption in residential buildings and around 5–30% in commercial buildings. Moreover, there are four topics where researchers must focus in order to identify the effects of occupants behavior in daily power consumption: understand occupants' actions that affect space heating or cooling, develop methods and techniques to collect data on behavior and building performance, model quantitatively occupants' behavior and building energy performance and finally, create an evaluation technique for the occupants to identify their energy saving potential.

For there recommendations systems and their applications, an extensive literature survey was conducted by Himeur et al. (2021) on energy saving recommendation systems in buildings, discussing how they evolved and also providing a taxonomy based on the nature of the recommender engine, their objectives, computing platforms and evaluation metrics. Furthermore, a critical analysis was also conducted to understand what the limitations of these systems are when they aim in energy efficiency. Additionally, Law et al. (2018) studied a set of recommendations published by companies and agencies, and designed micro-models to estimate how popular recommendations affect energy savings and conducted also a followup study to understand which types of recommendations were chosen and adopted more often.

From a theoretical point of view, Cattaneo (2019) analyzed the barriers towards the adoption of technologies for efficient energy usage and introduced ways to overcome them. Moreover, McIlvennie et al. (2020) indicated in their meta-review, that automation and control technologies are only "one piece of the puzzle". The other one is systems that embed humans in the procedure of excessive consumption reduction using

behavioral change techniques through recommendations and feedback. They suggested that the integration between techno-centric and user-centric approaches in more holistic implementations will be more effective.

In this section we mentioned various surveys that have been performed and are related to IEMS. In Table 2 we present a comparison between these surveys and our work. In the next sections, we will show that each IEMS, regardless of its type, follows a similar architecture. Our work breaks down their components and studies state-of-the-art designs, devices and algorithmic approaches. These IEMS implementations are based on requirements extracted from our need to tackle the factors that cause energy overconsumption. To the best of our knowledge, until now, no survey has been performed that both discusses approaches towards energy efficiency, factors that affect it and at the same time present a overview of the architecture, the components and their categories. Moreover, our work presents a novel classification on IEMS based on the type of actuation they incorporate and discusses major open problems of these classes and suggests research directions that will help community to develop better and more efficient IEMS, specialized for each specific installation environment.

Table 2 Comparison table between surveys that are related to IEMS

Reference	Energy efficiency	Direct control	Indirect control	Hardware	Data process	User interfaces	Future research
Mir et al. (2021)	–	✓	–	–	✓	–	✓
Himeur et al. (2021)	✓	–	✓	—	✓	–	✓
Shareef et al. (2018)	–	✓	–	✓	✓	–	–
De Paola et al. (2014)	✓	✓	–	✓	✓	–	✓
Leitao et al. (2020)	–	✓	–	–	✓	–	–
Himeur et al. (2022a)	–	–	–	–	✓	–	✓
McIlvennie et al. (2020)	✓	✓	–	–		–	–
Beaudin and Zareipour (2015)	✓	✓	–	✓	✓	–	–
Park et al. (2012)	–	–	✓	–		–	–
Himeur et al. (2020)	–	✓	✓	✓	✓	✓	✓
Ahmad et al. (2022)	✓	–	–	–	✓	–	✓
Elnour et al. (2022)	–	✓	–	–	✓	–	✓
Himeur et al. (2021)	–	–	–	–	✓	–	✓
Liu et al. (2022)	✓	–	–	–	✓	–	–
Himeur et al. (2022b)	–	–	–	–	✓	–	✓
Our paper	✓	✓	✓	✓	✓	✓	✓

4 Efficient energy consumption

4.1 Influential factors

The first step to achieve energy waste reduction is to understand where it originates from. According to Ashouri et al. (2018), there are four major influential factors of this phenomenon:

- *Building characteristics* Construction materials and insulation levels are obvious factors that increase energy waste in all types of buildings. van den Brom et al. (2018) conducted a research on performance gaps in energy consumption, revealing that recent buildings, constructed with modern materials, consume less energy than recently renovated older buildings. Furthermore, a difference between actual and theoretical (simulated) consumption was also noticed.
- *Occupants behavior* Occupants affect the overall energy consumption, especially in residential buildings (Bourgeois 2005). Even in buildings with the same energy labeling, discrepancies can occur in consumption, depending on heater/cooler set temperature, hot water wastage, requirements of indoor environmental quality, lighting usage, etc.
- *System efficiency and operation* Many buildings or households are equipped either with low efficiency or outdated appliances and devices. Systems' efficiency affects dramatically the total power consumption, as well as, neglected appliances such as oven, microwave, washing and drying machines.
- *Climatic conditions* Outdoor temperature, solar radiation, humidity and wind velocity can affect energy consumption, especially combined with the aforementioned factors. Even though, these conditions cannot be managed, it is important to realize how they increase energy wastage in order to search for effective solutions.

4.2 Approaches towards energy efficiency

4.2.1 General approaches

In order to confront climate change, society has to adopt a more energy efficient mindset. Corucci et al. (2011) identified four approaches towards energy efficiency: *user awareness about energy consumption*, *reduction of standby consumptions*, *plan and scheduling of flexible activities* and *adaptive control*.

Firstly, user awareness is a straightforward way to achieve energy wastage reduction (De Paola et al. 2014). Providing appropriate feedback, advice and recommendations along with detailed information about daily power consumption and total cost can encourage users to follow a more eco-friendly behavior (Darby 2006). However, aggregated measurements of energy consumptions make it difficult to understand which device or behavior causes the biggest waste (De Paola et al. 2014). Moreover, various studies (Himeur et al. 2021; Law et al. 2018; Jiang et al. 2009) show that behavioral change is still an ineffective strategy in the long term, therefore more research is required.

Secondly, standby devices and appliances are hidden sources of energy wastage. It was first identified as a new challenge in the early '90 s (Sandberg 1993) when analysts began to study the number of appliances that were "leaking" electricity. According to

Gram-Hanssen (2010), any plugged-in device in standby mode can consume some amount of energy, but the increased number of such devices in households and buildings lead to substantial increments in the total consumption. TVs, PCs, Coffee Machines and Printers, are some of the devices in every home, consuming energy without being used for long periods of time (De Paola et al. 2014). An interesting study was conducted by Hess et al. (2022), showing that education was positively correlated with the reduction of standby energy consumption. Moreover, households with children were using less multi-sockets and were less likely to waste standby energy, whereas high-income households were correlated with higher energy consumption.

Thirdly, activity planning and scheduling using modern smart automations systems can offer reduction of energy consumption during energy demand peak (De Paola et al. 2014). Scheduling activities, offers financial benefits when energy fares vary between day and night. Furthermore, as Bouakkaz et al. (2021) proposed, users can also save energy when a house is connected, through a hybrid energy system, into battery storage units.

Finally, another approach to reduce wasted energy is the installation of adaptive control mechanisms. HVAC and lightning systems waste energy in order to preserve user's comfort. However, the incorporation of AI techniques such as user-presence detection, behavior prediction or reinforcement learning control can tune activation times of these services to avoid unnecessary consumption (De Paola et al. 2014; Eller et al. 2018).

4.2.2 Energy hubs and microgrids

Besides the four aforementioned approaches, another way to move towards energy efficiency, on a higher level, is the deployment of ***micro-grids*** infrastructures in community areas, commercial areas, etc. A micro-grid is a local electrical grid with defined electrical boundaries, acting as a single and controllable entity (Hu and Lanzon 2018). Microgrids are important to successfully transform existing grids into smart grids. These grids lead to decrease of the operational costs, reduced emissions and increase of energy efficiency system reliability (Bandeiras et al. 2020). These interoperable energy systems consist of local energy production units to increase self-sufficiency using solar cells, heat pumps and recycling of wasted water to achieve sustainability. Another approach towards sustainable energy consumption are the energy hubs which are multi-generation systems that supply different types of energy demands simultaneously by both converting energy carries and using energy storage systems (Nasir et al. 2022).

Various research works have been done in recent years on these systems In order to improve energy efficiency of energy hubs, decrease pollution and improve their reliability, Zhang et al. (2015) devised in a novel framework for the optimal planning of energy hub systems, whereas Mansouri et al. (2022) developed a two-stage stochastic model for the design and operation of an energy hub in the presence of electrical and thermal energy storage systems. As mentioned earlier, energy storage systems are crucial parts towards energy efficiency. Energy hubs incorporate these subsystems along with different energy carriers and demand response programs. Javadi et al. (2022) described in their study the joint operation and planning problem as a two-stage optimization problem to successfully design a model that will achieve optimal sizing and siting of an electrical energy storage device, along with electricity tariffs due to demand response program. In order to optimize the efficiency of these multi-systems and their emissions, Mansouri et al. (2022) developed a multi-objective model to design a hub considering the variable efficiency of its converters, the degradation of its equipment and the annual growth both in load and in

energy prices. Nasir et al. (2022b) studied the day-ahead scheduling of these infrastructures considering also the uncertainties on each energy carrier. Finally, Mansouri et al. (2021) designed also a scenario-based framework for an energy hub that includes a power-to-gas system, proving that the implementation of an integrated demand response program, along with renewable energy sources, reduced energy costs and CO2 emissions.

Similar frameworks have been developed also for microgrids aiming to reduce operating costs for users. An optimization framework for planning active distribution networks have been developed by Matin et al. (2022). Mansouri et al. (2022) presented a framework for the scheduling of microgrids considering also the load demand, the market prices and the renewable power generation level. Last but not least, another two-stage stochastic optimization problem was solved by the researchers to design successfully microgrids with dispatchable generators and wind turbines for energy production (Jordehi et al. 2022).

4.2.3 Energy saving based on behavioral change

Many research works are focusing into the modification of human habits and are looking for ways to manipulate them towards energy efficiency. A recent example is a system aiming to detect repeated usage patterns from consumption logs, developed by Sardianos et al. (2021). Another energy-saving recommendation system is presented in Varlamis et al. (2022a), which fuses data from sensors, with users' habits and their feedback, to provide personalized advises to occupants at the right moment. This system is implemented in the $(EM)^3$ platform, which will be introduced in the next chapter. Two different edge-approaches were implemented by Sayed et al. (2021) and Alsalemi et al. (2021) that incorporate recommendation systems for energy efficiency into a home assistant and an edge-based custom device.

One major problem that energy related recommendations systems face is the user engagement. When actions are not automated and users must act, it is really difficult for them to retain engagement in the recommendations platform. Sardianos et al. (2020a) implemented real-time personalized recommendations system that also provided energy saving facts that aim to increase the persuasiveness of the recommendations. Besides the aforementioned apporaches, another way to produce optimized recommendations is Reinforcement Learning. Shuvo and Yilmaz (2022) proposed a DRL method which integrated human feedback and activity in the decision process to optimize electricity cost and users' comfort. This system was developed to be used in domestic environments. RecEnergy is recommender system aiming at energy consumption reduction in commercial buildings by human behavior modification (Wei et al. 2020). The overall testing over a four-week period showed energy reduction between 19% and 26%.

5 Intelligent energy management systems (IEMS)

A number of computer-aided tools and technologies were proposed in the last decade in order to effectively optimize energy consumption in our daily life. According to De Paola et al. (2014), each system or model that was developed must fulfill some basic functional and nonfunctional requirements. Each system has to perceive the environmental conditions of the place it will be installed, use the input data to learn users' habits, behaviors, preferences, consumptions per device or appliance and also detect or predict existing context. Moreover, it must provide a way for the users to monitor the consumption and at the same

time interact with them using notifications to gather feedback and commands. Finally, it should have the ability to modify its environment through actuation after planning optimized sequences of actions that will both reduce energy wastage and satisfy comfort preferences. In respect to the non-functional requirements, these systems have to maintain intrusiveness at low level in the matter of interaction with the user and the physical infrastructure. Furthermore, scalability and extensibility is desirable in such cases, meaning that the level of abstraction during the design should be high. Also, an intelligent system have to be easily deployed by the users and not not require installation from an expert. In the software engineering part of the implementation, the principle of modularity is really important to avoid problematic behaviors of the system. Finally, it is required to be interoperable, with respect to physical devices and other software components.

Energy management systems are developed in a unique way fulfilling the aforementioned requirements following the approaches of the previous section and also following a specific framework architecture (Leitao et al. 2020; De Paola et al. 2014). The main components of an IEMS are depicted in Fig. 1:

1. Sensing and Measuring Infrastructure
2. Actuation mechanisms
3. Processing Engine
4. User Interfaces

Another classification is shown in Fig. 2. Each IEMS requires at least one type of each component to work effectively.

Information that emerges from the sensing components is saved and processed by the Processing Engine. The engine is the specialized subsystem with components responsible for the process of all acquired data and also performs the optimization tasks based on the
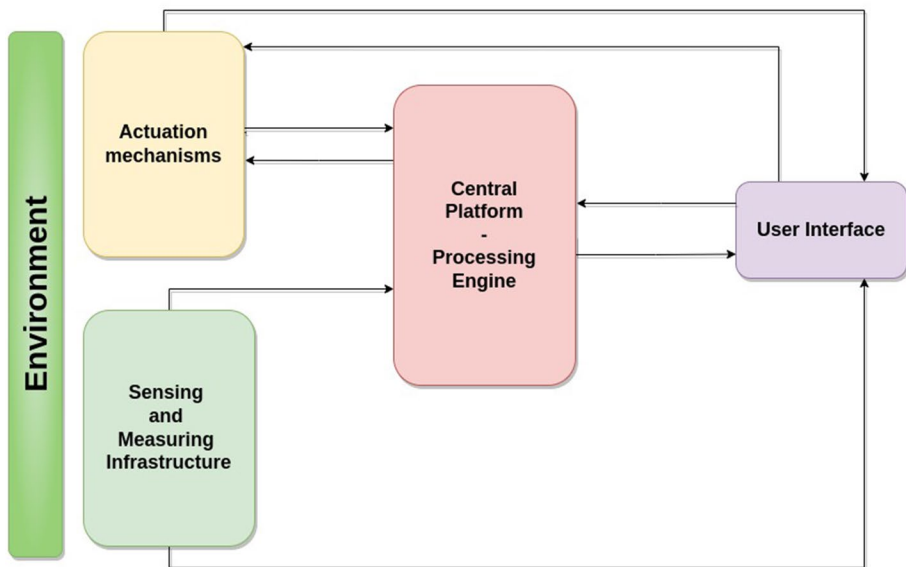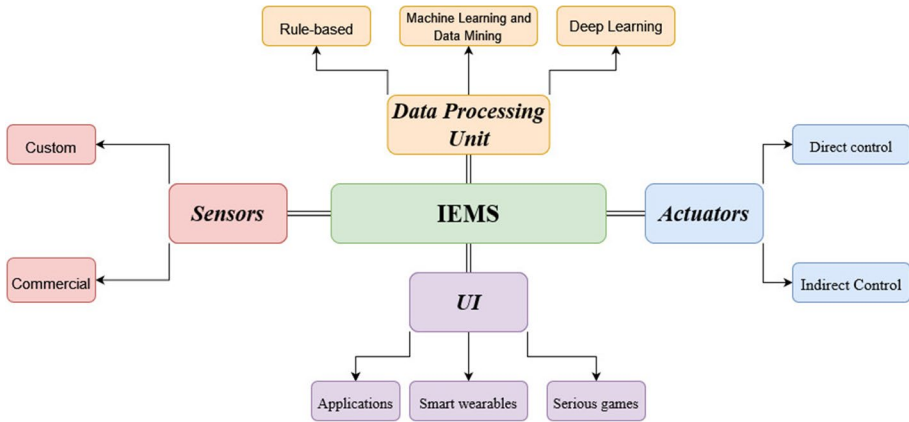

Fig. 1 Intelligent energy management system

Fig. 2 Classification figure of the components of an IEMS

end-users preferences. It should also learn and recognize occupants' activity patterns, communicate with the actuators and manage anomalies or outlier events. When decisions are made, they are transferred into the actuators to modify each appliance or device contextually. Along with the action commands, sometimes, the process engine provides recommendations to the end-users through the user interface to change behaviors that affect the total energy consumption. All these modifications are focused on the persuasion of a smaller energy footprint of our society, however economic impacts remain also a motive (Sardianos et al. 2020a). Furthermore, through the user interface, users have access to graphs showing daily consumptions. The most common form of a user interface is a computer or smartphone application.

A widespread approach to model state-of-the-art energy management systems is Multi-Agent Systems (MAS). MAS architecture is often used as a tool to model subsystems of an IEMS and is composed of multiple interacting intelligent agents (Hu et al. 2021). Each agent can be considered as "Intelligent" because it incorporated AI techniques such as decision-making or machine learning algorithms.

According to Wooldridge (2009), each agent in a multi-agent system has some important characteristics:

- *Autonomy* The ability to be at least partially independent, self-aware and autonomous.
- *Local view* The perception of the agent has boundaries and no agent has a global view. Otherwise, the agent will not be able to process that large amount of information.
- *Decentralization* No control authority exists inside the MAS.

Wooldridge (2009) called the ability of an agent to act at a local level, "Sphere of Influence". Each agent in a MAS has the ability to interact within a specific range. However, there are "spheres" which coincide, rising dependent relationships and creating a unified model. Because of that, MAS architectures are considered appropriate to model IEMS. González-Briones et al. (2018) argued that MAS are commonly used as models because of the communication, coordination and cooperation capabilities of the agents, and also because this design provides robustness to the system, when different tasks are assigned to each agent.

5.1 Sensors and measuring infrastructure

Sensors and measurement devices are installed on every smart environment, providing data about temperature, humidity and luminance levels, whereas different sensors are monitoring the presence of occupants. There are two types of IoT devices used for these tasks: *Custom-made* and *Commercial*. Arduino or Raspberry Pi microcontrollers are used by researchers to create custom modules that fit specific requirements, but in large-scale applications, commercial ones are a preferable option because of the default unified communication protocols.

5.1.1 Custom-made sensors

The most common sensors on these applications are the power consumption meters. Alsalemi et al. (2019a) used SEN-11005 components on a microcontroller NodeMCU to build a custom energy monitoring device (Fig. 3). Eridani et al. (2021) built from scratch their own circuit for an electronic sensor consisting of several sub-circuits for, voltage and current metering, voltage regulation and operational amplification. This sensor was incorporated within an Arduino UNO that was processing the input data which were transferred through an ESP8266 chip to an application. Furthermore, Oberloier and Pearce (2018) created an open-source power monitoring system, designed around the Digital Universal Energy Logger (DUEL) Node. Ahmed et al. (2015) also designed their own smart plug using Zigbee protocol. Finally, Jamal et al. (2020) used ACS712 and ZMPT101B for current and voltage measurements, respectively.

Temperature and humidity sensors were also commonly used in energy management systems. Mataloto et al. (2019), Sardianos et al. (2020a) and Alsalemi et al. (2019a) used DHT-22 sensors to receive real-time contextual information from the environment. DHT-22 sensor can measure both temperature and humidity levels. On the contrary, Reddy et al. (2016) used an LM35 temperature-only sensor. LM35 has an analog communication protocol, while DHT-22 has one-wire. Therefore, LM35 is faster in data transmission but it is more sensitive to noise. Also, Kodali et al. (2015) used LM35 in an ambient intelligent system with an Intel Galileo board.
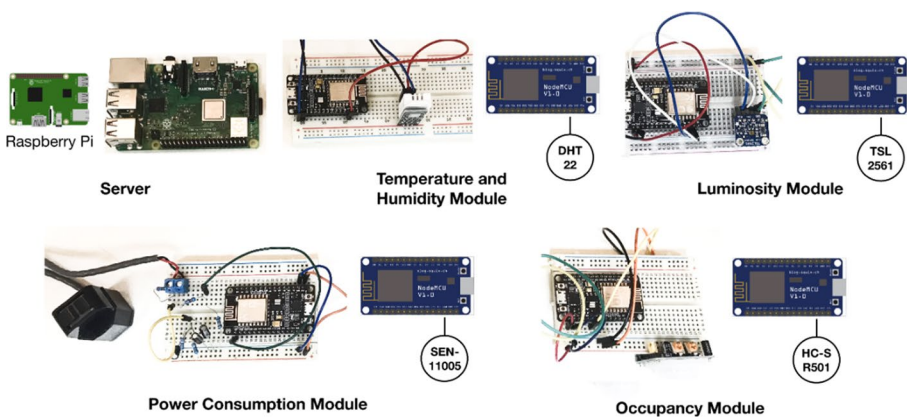

Fig. 3 Custom sensors by Alsalemi et al. (2019a)

Light and motion sensors are extremely important components for systems that aim to reduce energy wastage. Rooms and spaces that remain unoccupied tend to have increased consumptions due to switched on lights. Wei et al. (2020) and Alsalemi et al. (2019a) used a TSL2561 Adafruit sensor for light monitoring and HC-SR501 for motion sensing. Mataloto et al. (2019) also included photo-resistor sensors and motion sensors with passive infrared (PIR) in their custom sensor-board and Reddy et al. (2016), used a light dependent resistor (LDR) that reduces its resistance when light hits the surface of it.

Gomes et al. (2017) created EnAPlug (Fig. 4), a multi-sensor smart plug with the ability to switch on/off devices, and monitor power, reactive power, voltage and current. It also included four sensors for temperature, humidity, outside temperature and a door opener detector.

5.1.2 Commercial sensors

Many companies develop smart plugs that are used in energy management systems for environmental sensing, containing usually multiple sensors on a single device. These devices are utilized in smart homes and buildings and are easier to be used by the average user. Furthermore, researchers are selecting these devices when performing large scale experiments to save time from building custom sensor boards.

In their work, Gomes et al. (2018) used the following smart plugs with metering abilities and on/off control: the DSP-W125 by D-Link, the SP-2101W by Edimax and the TP-link HS110. The DSP plug has also the ability to monitor temperature. Papaioannou et al. (2018) employed Fibaro 4-in-1 sensor (Fig. 5) at the site of the experiment to receive data about temperature, humidity, luminosity, motion and presence simultaneously. Schweizer et al. (2015) used digitalSTROM systems which were acting as power meters communicating with other nodes inside a smart environment.

Popa et al. (2019) utilized three multi-sensors Aeon Gen5 to detect movement, read temperature, luminance and relative humidity values. Furthermore, they used a smart plug Aeon Smart Switch 6 to control devices and measure instant consumed power and energy and also provide with power consumption graphs for appliances. Last, another Aeon Gen6 multi-sensor was installed that could also provide ultraviolet light sensing data and also home energy meter was installed in the fuse box to measure instant consumption and energy for the entire home without noise.
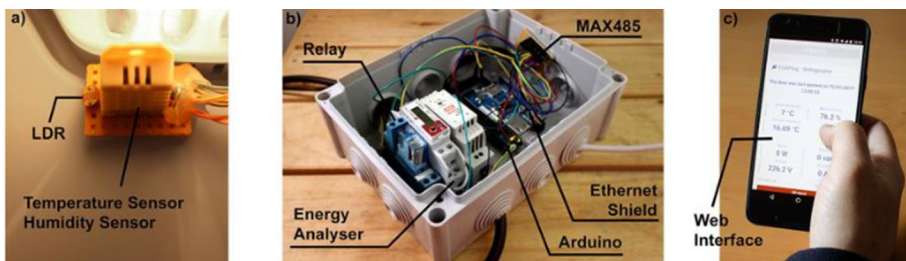

Fig. 4 EnAPlug implementation, a custom multi-sensor smart plug by Gomes et al. (2017)

Fig. 5 Fibaro 4-in-1 sensor

5.2 Actuators

5.2.1 Direct control

Actuators are the components of an IEMS that execute decisions and commands in order to perform actions so as to optimize power consumption. There are two possible ways to interact with the devices and appliances. The first one is a set of electronic actuators. Actuators are electrical components that interact with the appliances following the decisions of the process engine after the optimization is performed. All systems with the ability to modify their environment using actuators are called ***Direct Control IEMS***. This term encloses every system able to process data, take decisions and execute them on its own, without the intervention of an human being.

Elettra was an innovative system proposed by Cristani et al. (2014, 2015), allowing users to monitor their power consumption. It incorporated AmI techniques and algorithms to successfully measure and forecast consumptions of devices providing also direct control to sockets using smart plugs and sensors. Stavropoulos et al. (2014) proposed the framework Smart IHU, which was deployed at the International Hellenic University (IHU), an application with two components, a Manager and a Rule app. Their actuation infrastructure implementation had custom sensor boards and Z-Wave devices providing automations based on preferable statistics selected by the users.

Chojecki et al. (2020) implemented an energy management system in a smart meter device. They incorporated a fuzzy logic controller to perform automated actions on the appliances which were divided into two groups, a group of low power devices such as, consumer electronics and multimedia equipment, and a group of medium and high power devices such as, HVAC, water heaters and washing machines.

Another platform with direct controls was implemented by Luo et al. (2019). Their system was designed to minimize the costs per day of a home by optimally scheduling operations. To achieve this, it included controllable household appliances (smart devices) such as pool pump, dish washer, washing machine, clothes dryer, coffee

machine, dehumidifier and bread maker. The users were selecting preferred time range for operations and were providing information about their lifestyle.

5.2.2 Indirect control

Some recent approaches put humans in the position of the actuator forming human-in-the-loop architectures. Their purpose is to change the behavior of the end-users to stop energy wasting habits. In order to accomplish that, they use recommendations engines to send suggestions and advice through interfaces in order to motivate people to act optimally. These systems can also be extended to propose replacements of inefficient devices and appliances that waste energy (Leitao et al. 2020). They are called ***Indirect Control IEMS.***

There are different types of recommendations. The most typical of them are the *personal resources recommendations* which advise occupants to turn the lights or the HVAC appliances off in empty rooms or shut down idle devices such as, computers and printers. However, three more types of recommendations have been proposed by Wei et al. (2020). *Move recommendations* encourage occupants to change their working/living space to reduce services' requirements. *Schedule change recommendations* are extensions of move recommendations aiming to shift the period of time an occupant spends within a space and not the duration. Finally, *coerce recommendations* suggest to the building managers when to force people to evacuate rooms if the occupancy is small in relation to the size of the space.

Alsalemi et al. (2019); Sardianos et al. (2020a, b) designed (EM)[3], a framework aiming at occupants' behavioral change. Using recommendations from its engine, REHAB-C, the human actuator is getting trained by repetition to behave efficiently. ReViCEE by Kar et al. (2019) follows the same logic by predicting energy consumption ratings and offering personalized recommendations, stimulating user-engagement towards energy conservation and sustainability. ReViCEE's prototype implementation is show in Fig. 6.
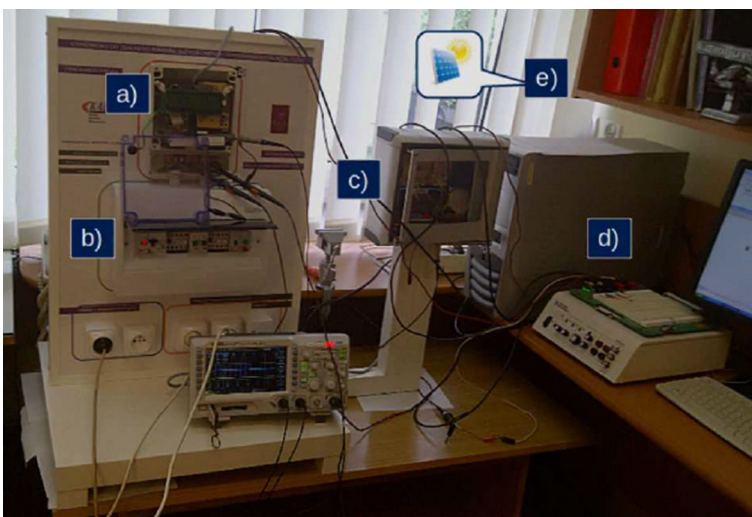

Fig. 6 ReViCEE prototype by Kar et al. (2019)

Popa et al. (2019) designed a modular platform named SHE (Smart Home Environment). The on-premises control was executed using some Z-Wave controllers, TKB Wall dimmer to control dimmable lights and the Aeon Z-Sticks, Gen-5 and S2, each designed to function on a specific location (US or Europe) depending on the allowed radio frequency for such devices. SHE was advising inhabitants about how they can improve their lifestyle and reduce the costs of energy consumption. Therefore, it provided notifications on a mobile device to motivate them to remotely turn on and off services.

García et al. (2013) used the framework CAFCLA to develop a recommendation system for usage in homes to promote efficient energy usage. The system was identifying behavioral patterns and along with CAFCLA's real-time localization system and wireless sensor network it was used to provide personalized recommendations(García et al. 2017). KNOTES was a system developed by Shigeyoshi et al. (2011) that was proposing to the users how to change their life style using notifications, in order to save energy. The system was taking their personal data such as consumption, owned appliances, percentage of advice acceptance and evaluation history to find appropriate suggestions. Gamified approaches seemed also promising in terms of indirect control, especially in education facilities, due to the increased user engagement they provide, through an achievement system with rewards and leaderboards Papaioannou et al. (2018, 2017).

5.3 Processing engine

Processing engine of an IEMS is designed to optimize the energy usage on each compartment of a smart environment and manage the actions that have to be performed. After years of research on this field, different techniques have been developed. The majority of the state-of-the-art systems employ Rule Engines, Data and Pattern mining algorithms, Machine Learning and Deep Learning models

5.3.1 Rule engine

The most frequently encountered technique on IEMSs is *Rule Engines*. Cuffaro et al. (2017) introduced a general-purpose Rule Engine that pushes notifications or reports to the end-users based on a resource graph model. In (EM)[3] (Sardianos et al. 2020a) a goal-based context-aware rule-based system (REHAB-C) was implemented with a rule mining algorithm, a process responsible to gather data about frequency of users actions. Papaioannou et al. (2018), developed an event-driven rule process on a gamified system aiming to reduce energy-wasting behaviors where each challenge assigned to the end-users is represented by a specific rule. Stavropoulos et al. (2014, 2015), implemented a Rule App in their application in the form of a Hybrid Intelligent Agent. The agent had two interchangeable layers, the deliberative and the reactive. The reactive layer applies and maintains all energy-saving policies, while the deliberative layer incorporates a reasoner, based on defeasible logic to manage conflicting rules, responsible to optimize energy consumption while maintaining users' comfort. A similar rule-based architecture using defeasible logic was also implemented by Cristani et al. (2016). Chojecki et al. (2020) designed a system that combined a rule-based implementation along with a fuzzy logic algorithm, incorporated on a smart meter to perform direct control. Last, Papaioannou et al. (2018) proposed an event-based rule engine to change energy waste behaviors in public buildings.

5.3.2 Machine learning and data mining

Smart environments produce a lot of data by the IoT components. Even though this data is processed in order to control the environment remotely, until recently they were rarely used from the system to train the models and achieve autonomy. Meurer et al. (2018), designed a system that takes advantage of contextual meta-data that originate from smart devices, using extra-trees classifiers, a technique that combines machine learning and data mining. That way, the dimensionality of the produced data was reduced, without loss of important features. Subsequently, an artificial neural network was trained to complete a context-aware engine, with a continuous learning capability based on feedback from the end-users.

Data mining techniques are also used to monitor inhabitants' usage patterns. Schweizer et al. (2015), proposed a sequential pattern mining algorithm aiming on smart environments that predict future needs of their inhabitants. Thus, the system could avoid actions that lead to a comfort decrease.

Another system for energy management based on mining algorithms was developed by Dahihande et al. (2020). Their system provided personalized recommendations about turning on and off appliances at specific timestamps based on household profiles produced by association rule mining apporaches, such as Apriori and FP-Growth and also sequential pattern mining apporaches like RuleGrowth, TRuleGrowth, CMRules, ERMiner and CMDeo from a library created by Fournier-Viger et al. (2014).

5.3.3 Deep learning

On a smart environment where automated actions must be performed, human activities must be monitored. Recognizing patterns of a room occupant will provide necessary information to the back-end system, leading in more effective predictions. Deep learning techniques such as, convolutional and recurrent neural networks, showed great performance compared to others on human activity recognition Lentzas et al. (2019); Lentzas and Vrakas (2020). All this information combined with specific sensor measurements can also grant a context model. Using these models, anomalies and outliers can be detected which would affect energy consumption. Moreover, on more sophisticated systems, using all above can lead to residents' identification. That way the system can initialize optimizations and actions based on resident's profile. The aforementioned actions require complicated calculations, therefore Deep Neural Networks were employed (Popa et al. 2019).

The problem of the efficient energy consumption consists of two sub-problems, the non-intrusive load monitoring (NILM) and the energy load forecasting (ELF), which were resolved using deep learning models (Popa et al. 2019). NILM is a method used to monitor the energy profile of an environment and extract information about appliances consumption by disaggregating the total power consumption (Nalmpantis and Vrakas 2019). On the other hand, ELF is used to forecast patterns on energy consumption and detect anomalies that might increase energy consumption (Popa et al. 2019).

Another deep learning method used for energy saving is the deep reinforcement learning (DRL). Wei et al. (2020) used a DFL agent, trained along with the end-users' decisions. For each successful reduction of consumption, the agent received a reward aimed at maximizing the amount of energy saved. Lissa et al. (2021) developed such a model, based on Markov Decision Processes (MDP) to control the temperature of domestic hot water. Their goal was to reduce the consumption by optimizing the usage of energy produced

by photo-voltaic panels. Yu et al. (2019) suggested also a model using MDP to schedule optimally HVAC appliances and the energy storage system of a smart home. Finally, Shuvo and Yilmaz (2022), proposed a DFL model that incorporated human feedback in the objective function and human activity data in the reinforcement learning part of it to enhance optimization of energy.

5.4 User interface

IEM systems include necessarily a User Interface (UI) to allow interaction between them and the users. First of all, UI displays information about total power consumption or consumption per appliance. Secondly, it provides a mean for indirect or direct control of the devices in a smart space. Moreover, it is the only way for the users to change comfort parameters in direct control systems, schedule functions and set rules. Finally, the interface platform sends notifications stimulating recommended behaviors and receive feedback.

Nowadays, interfaces used by smart systems range from simple command-line environments, SMS texts to smartphone and smartwatch applications. There are also differences on the approaches of a user interface, meaning that, it could be a simple one just for system manipulation, or a complicated gamified environment, especially in systems aimed at behavioral changes.

5.4.1 Monitoring and management applications

A standard characteristic on every user interface application is the monitoring component. It usually consists of statistical graphs about consumptions or expenses. Zacharioudakis et al. (2017) designed a visualized performance graph of a building allowed the users to compare measurements from two different time periods. Moreover, the interface was used to provide alerts if outliers were detected. A simple monitoring agent was also introduced by González-Briones et al. (2018) providing statistical data about hourly consumptions and the ability to compare different days' consumptions while it displayed estimated costs for the total kWh consumed and calculated CO_2 emissions amount for a month. Another example of a monitoring application is shown in Fig. 7, implemented by Sayed et al. (2021) for an intelligent edge-based recommendation system.

A different approach in monitoring was given by Stavropoulos et al. (2014), where every room had its own section at the implemented Rule App, displaying statistics such as current power consumption, temperature, humidity, luminance and CO_2 levels, and an indication about motion detection. However, their implementation allowed direct manipulation of these variables so that the agent could adjust comfort levels. Stavropoulos et al. (2015), a new agent with a GUI was introduced allowing the management of the rule engine through a user-friendly interface. In Figs. 8, 9 and 10, we present the user interface that allowed users of Smart IHU (Stavropoulos et al. 2014) to select preferred statistics, desired rule sets and monitor the environmental conditions. A similar approach was implemented also by Cristani et al. (2014), Tomazzoli et al. (2020) with three main menu choices, allowing manual activation of physical devices, setting of rules, actions and scenarios and also measurement of energy consumption and displaying along with real-time and stored data.

Alsalemi et al. (2019) implemented $(EM)^3$, a system with an end-user web application contained on-line daily consumption monitoring, displaying also indoor and outdoor levels of temperature and humidity, providing at the same time recommendations about energy
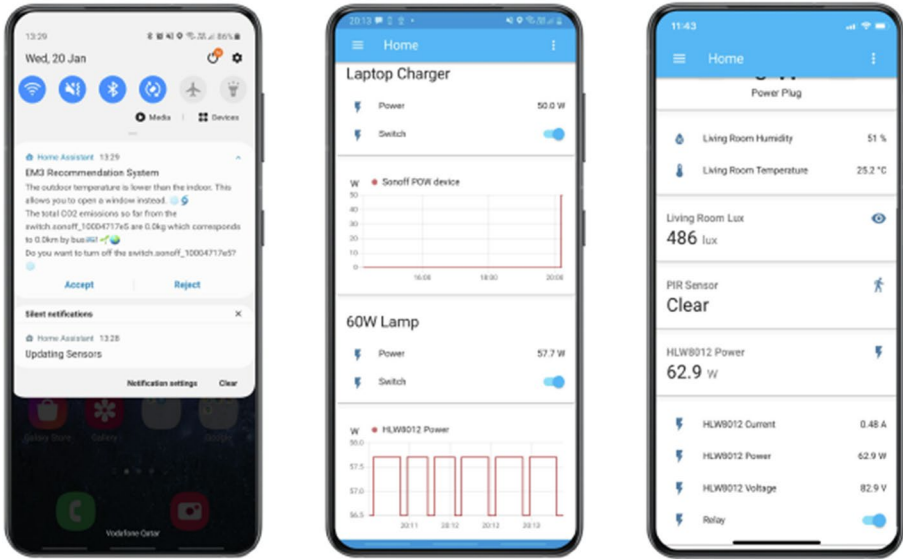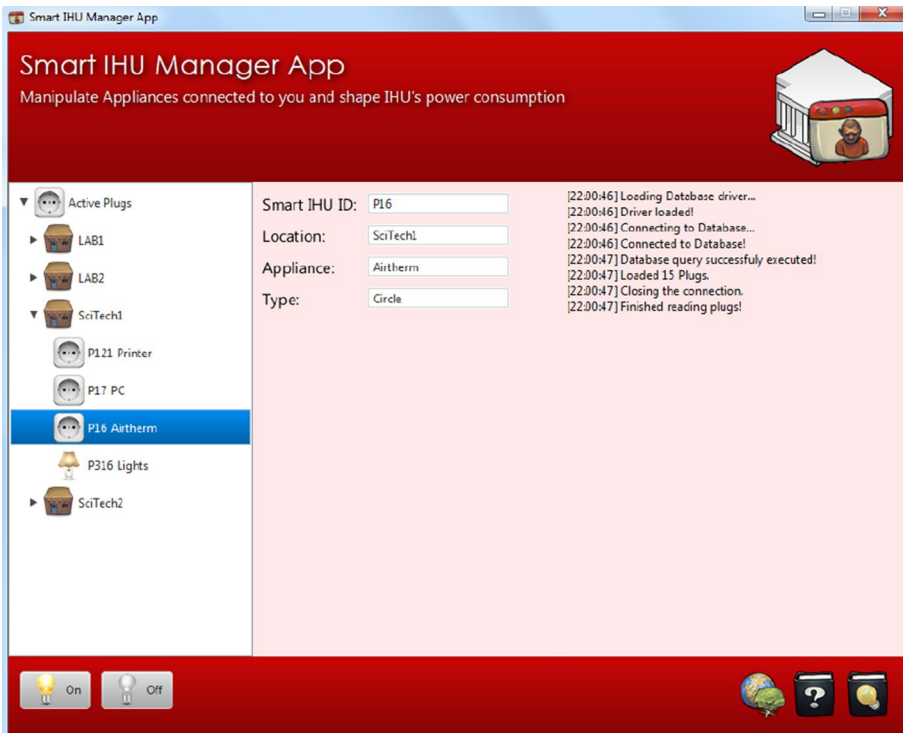
Fig. 7 Monitoring application
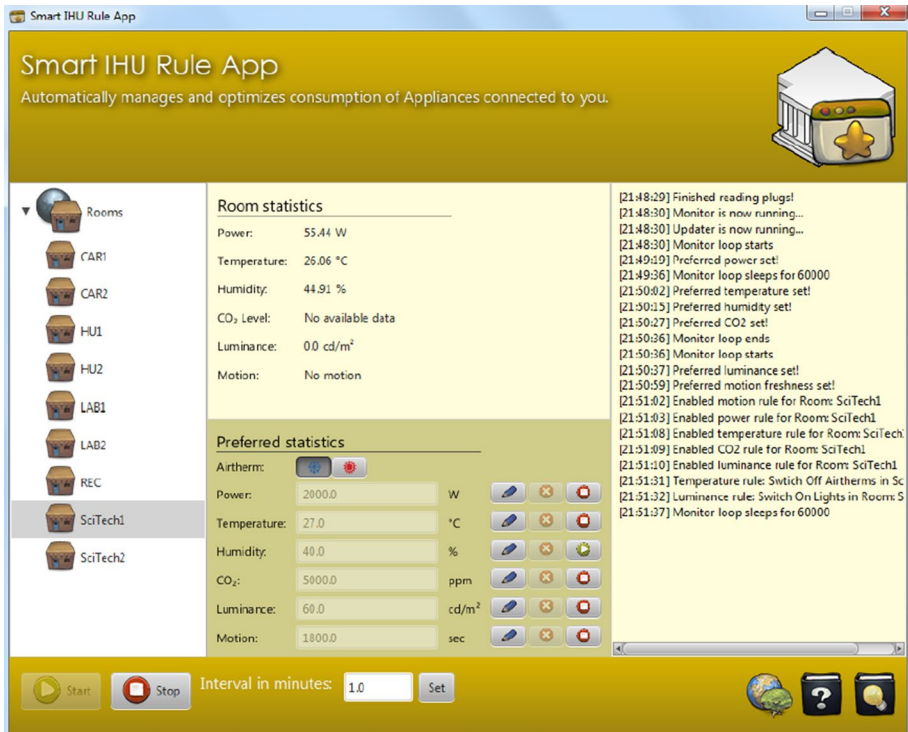

Fig. 8 Smart IHU Manager App

Fig. 9 Smart IHU Rule App

efficiency. Additionally it had also a control menu with switches to modify devices' activities. A similar user interface was prototyped also by Dahihande et al. (2020).

5.4.2 Smart devices notifications

Many IEMS are using smartphones and smartwatches as their user interface. Mobile devices offer the convenience of monitoring and managing consumption on the go. Sardianos et al. (2020b) and Schweizer et al. (2015), used the default text message services in order to push notifications with recommendations expecting feedback from the user to proceed in further actions.

Wei et al. (2017) proposed a real time energy usage tracking software, along with a web app, two mobile applications for iOS and Android devices and also one for Android wearables. The main dashboard of the system was in a more compressed form in the smartphone app, whereas the smartwatch app displayed only energy footprint breakdown and notifications when alarms were triggered. In Fig. 11 we show the user interface of the ePrints prototype.

5.4.3 Serious games: gamified approaches

For systems that aim at behavioral changes, gamified interfaces and applications seem to have impact. Papaioannou et al. (2018), Papaioannou et al. (2017) proposed a gamified approach
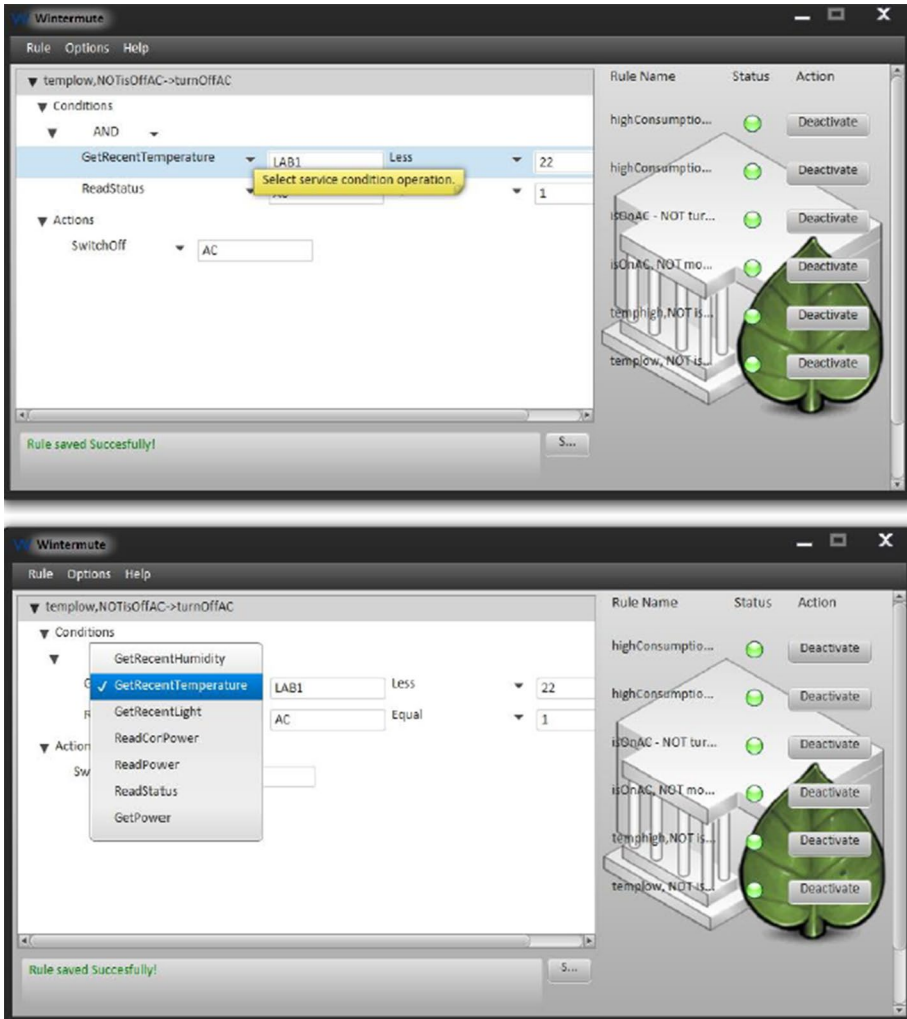
Fig. 10 Smart IHU UI to set desired rule sets

was introduced based on challenges for public buildings. End-users had a mobile application plus an NFC chip installed on their smartphones that showed available challenges, e.g. use staircases instead of the elevator or turn off your PC before leaving your office, and rewarded points in case of completion. The user interface contained also a leaderboard, where users were competing each other (Fig. 12).
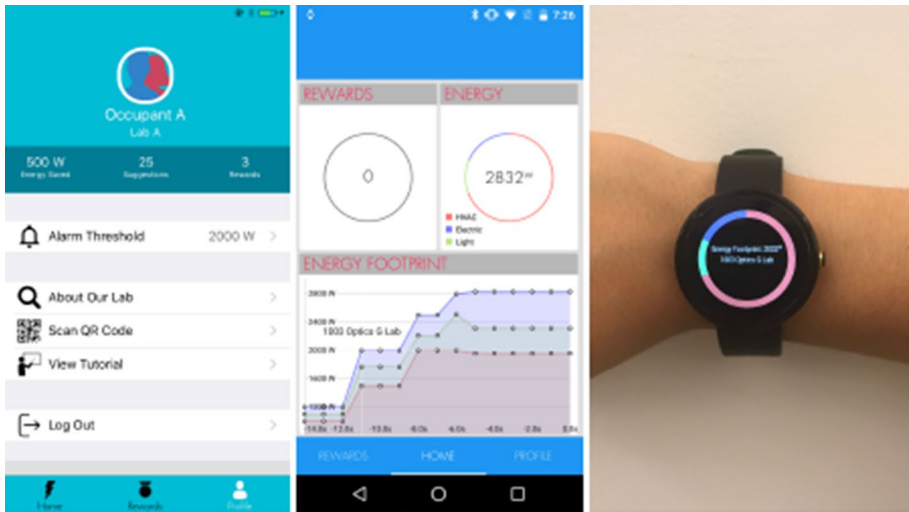
Fig. 11 ePrints apps by Wei et al. (2017)

6 Discussion

In our survey, we elaborated over the topic of Intelligent Energy Management Systems. Our goal in this work was to report state-of-the-art approaches of the area (Table 3). However, our work differs from previous surveys because it merges smart automation and recommendation systems under the umbrella term of IEM systems, considering them as two individual sub-classes, whereas in current literature, most articles about Home/Building Energy Management Systems (HEMS/BEMS) refer to systems with incorporated automations.

In this article, first, we referred to the major influential factors that increase energy consumption and wastage, and also presented some general approaches that should be followed in order to pursue energy efficiency. Second, we provided an IEMS architecture overview, based on some functional and non-functional requirements which arise from the aforementioned influential factors and discussed about the state of the art of these systems. Third, we showed that each IEMS can be classified as a Direct or Indirect Control IEMS based on the type of actuation it incorporates. When a system contains automation mechanics and the end-users choose only environmental preferences, the system is controlling the environment directly. On the contrary, when the end-users receive recommendations to perform actions, the performed control is indirect. More recent studies proved that recommendations systems provide improvements in terms of energy savings. For this reason, we classified automations and recommendation systems as Direct and Indirect Control IEMS, respectively, a novel classification that addresses the lack of a unified structure and helps new researchers to obtain a more accurate overview of the field. Following, we will discuss about the advantages of each IEMS control type (Table 4), as well as their major open issues, providing also some future research orientations.

Fig. 12 Charged gamified application by Papaioannou et al. (2017)
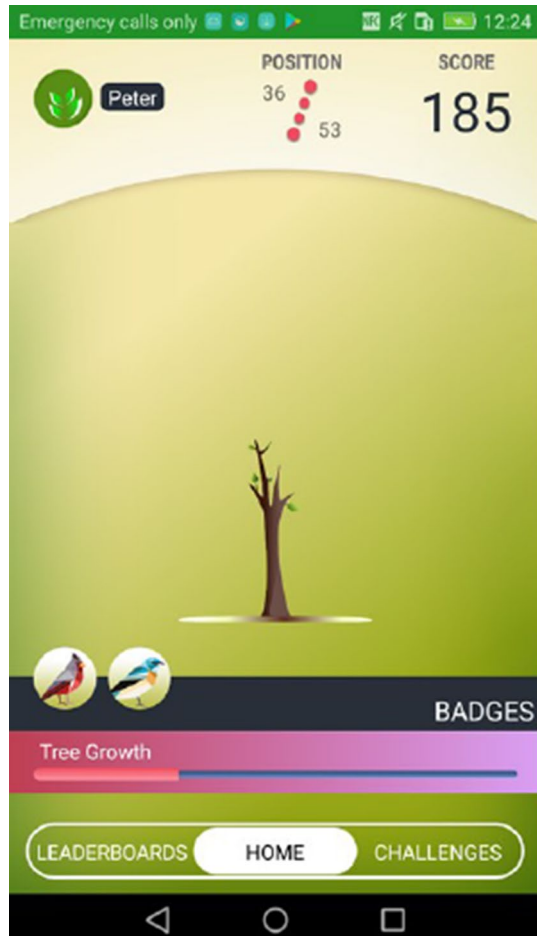
6.1 Advantages of direct control IEMS

Direct control IEM systems have the ability to automate procedures and actions. Their major advantage is that the occupants of a smart environment are not obliged to alter their routine. Once preferences are set, the system receives input data, optimizes and sends action commands to all required appliances, without the need for further interaction. For example, when an occupant leaves a room and no human presence is detected, the lights can be turned off. Similarly, the TV can automatically be turned off if the room is empty.

Another argument in favour of direct control is the plan and scheduling ability, allowing users to set long-term ecological or economical goals on the system. Moreover, scheduling techniques can offer consumption shifting on various operations to find optimal time frames in order to reduce energy demand and cost.

Furthermore, smart environments with automations can protect occupants from emergency situations that can occur, e.g. an excessive power consumption caused by electricity "leakage" from a faulty appliance. A leaky device is wasting energy and is also hazardous for the occupants because it can cause accidents, such as fire or

Table 3 Complete state-of-the-art Intelligent Energy Management Systems Implementations

References	System's name	Control type	Sensors	Processing engine
Alsalemi et al. (2019a)	(EM)[3]	Indirect	Custom	Rule-based + recommendations techniques (REHAB-C)
Chojecki et al. (2020)	–	Direct	Custom	Rule-based using fuzzy logic
Cristani et al. (2014)	Elettra	Direct	Commercial	Rule-based using defeasible logic
García et al. (2017)	–	Indirect	Commercial	Neural networks + recommendations techniques(CAFCLA framework)
Kar et al. (2019)	ReViCEE	Indirect	Custom	Recommendations techniques
Papaioannou et al. (2017)	ChArGED	Indirect	Commercial	Rule engine
Popa et al. (2019)	SHE	Indirect	Commercial	Various deep learning models
Stavropoulos et al. (2014)	Smart IHU	Direct	Commercial	Rule-based using defeasible logic
Wei et al. (2017)	ePrints	Indirect	Custom	Deep reinforcement learning (recEnergy)

Table 4 Advantages of each IEMS class

Direct control IEMS	Indirect control IEMS
Automated procedures leave occupants' routine intact	Behavioral changes leading to more eco-friendly mindsets have wider and long-term impact on the environment
Provide plan and scheduling abilities to set long-term goals	Human-in-the-loop applications offer cheaper implementations
Incorporate techniques to protect occupants in case of an emergency situation	Non-controllable appliances can take part in energy consumption management
Accessibility features allow installation in households with elderly or handicapped occupants	Extended designs can provide suggestions to replace appliances and devices based on users' profiles

electrocution. Automated actuators have the ability to turn off appliances when necessary, reducing the energy wastage and offering also a safer environment.

Finally, fully automated IEMS can be applied in households where handicapped or elderly people live. A properly designed user interface along with ambient assisted living devices, such as Amazon's Alexa, which support voice commands, will allow these people to modify easily the comfort parameters of their environment and the energy consumption will remain optimized.

6.2 Advantages of indirect control IEMS

The application of recommendation modules in IEMS is a very promising field of research. As it was mentioned in chapter 4, occupants' behavior is one major influential factor of inefficient energy consumption. Therefore, recommendation systems are useful tools to confront this issue. There is one significant advantage towards these systems. When the occupants follow recommendations for a long time, they acquire an eco-friendlier mindset. Thus, people trained from a home recommendation system will also apply the same aware behavior on every other aspect of their life, e.g. their workplace. Therefore, indirect control will eventually have wider impact.

A major difference from direct control systems is the lack of actuation infrastructure, which provides three important advantages. Firstly, these systems are cheaper and easier to buy. Deducting the cost of smart devices and appliances from the total cost of an IEMS, these systems become more affordable. Secondly, a system with less electrical parts connected to the internet, is less vulnerable to cyberattacks. Even if a false data injection attack is performed on them, the worst case scenario is a system that produces irrational recommendations. Moreover, these systems can also run using a local area network or a Bluetooth area network, which are more secure. Thirdly, the architecture of indirect control systems allows non-controllable appliances to take part into the optimization procedures without any modification on their hardware.

Last, an additional feature of these systems is that it is possible to extend their design so that they can help consumers acquire appliances, based on input data from existing appliances in a household, power consumption of available models on the market, their price, manufacturer and other specifications (Himeur et al. 2021).

6.3 Open issues

There has been great progress in the development of energy management systems, both towards direct and indirect control. However, various issues and limitations hinder the wide installation of such systems in commercial, residential and educational buildings. We will discuss the most important problematic aspects of each class.

6.3.1 Security

Direct control IEMS convert conventional buildings into smart ones. Therefore, they can be part of the demand-side of a smart grid, one of the most complex cyber-physical systems. According to He and Yan (2016), every infrastructure based on cyber-physical systems is vulnerable to various types of attacks.

False Data Injection (FDI) is the most frequent type of attack. Sethi et al. (2020) proved that these attacks affect electricity bills and load consumption drastically, proposing afterwards a resilient scheduling algorithm to overcome these effects. Furthermore, Dayaratne et al. (2019) showed that small fluctuations in energy demand from FDI attacks significantly increased the unit price and provided financial benefits to the attacker. Because of the nature of the demand response scheme, these situations lead to inefficient energy consumptions by the system, increasing the energy footprint.

Additionally, another type of attack is the Denial of Service (DoS) attack. Yi et al. (2016a) revealed a vulnerability of metering infrastructure using "Puppet Attack", a DoS attack that exhausts the communication bandwidth, proposing also detection and prevention mechanisms. Moreover, Yi et al. (2016b) demonstrated that some DoS attacks can cause disruption in the whole smart grid. However, they proposed an algorithmic solution to isolate the attacked nodes to continue data transmission.

Other types of attacks are, Control Signal Adulteration (Esfahani et al. 2010), which affects the automatic generation controller that regulates the frequency and power exchange between controlled areas and Information Leakage (Sankar et al. 2012). Data leakage of smart metering data can lead malicious user to detect the absence of occupants, a sensitive information that can offer chances for attacks on households.

He and Yan (2016) provided a classification of the attacks based on the part of the grid they occur.

- *Generation systems attacks* Attacks against power generation and power lines of the smart grid damaging the balance between generation and supply.
- *Transmission systems attacks* Attacks aiming to damage and interrupt the delivery of the generated energy through power stations and lines. These attacks can be classified as (a) Interdiction attacks and (b) Complex network attacks. (He and Yan 2016)
- *End-user attacks* Attacks on IoT devices and appliances at the end-user side, i.e. smart devices, appliances and electrical actuators. These attacks are serious, according to Pearson (2011), because in smart metering and monitoring devices there are stored private information about users, such as user's activities, consumption and idle time and when user's location is empty or not.
- *Electricity market attacks* Attacks that exploit vulnerabilities in the transmission management that affect the price of the electricity. That way, they make illegal profits and cause congestion to the power lines.

6.3.2 Cold start problem and data sparsity

Cold Start Problem (CSP) refers to the lack of initial data on a recommendation system. This issue occurs for various reasons, mostly in collaborative filtering models. Content-based and knowledge-based systems tend to be more robust (Aggarwal 2016).

According to Bobadilla et al. (2012), there are three cases that cause CSP. First, the *new community* problem refers to the lack of ratings from the recommendation database. This usually occurs when there are not enough users to rate or vote for the proposed advice, therefore the precision of the recommendation can't be calculated. Second, the *new item* problem. The new item problem occurs when new actions or recommendations are imported in the database of the system. These recommendations contain no rating, therefore it is rare for them to be chosen. However, if a recommendation remains unnoticed for a long time, it acts like it doesn't exist at all, even though it could be useful. Finally, the greatest CS problem is the *new user* problem. Someone who uses the system for the first time has zero votes on contained recommendation. The filtering methods of the system have no prior information about the new user and no history of ratings to calculate a "neighborhood" of appropriate recommendations (Son 2016). Therefore, the performance of the system is negatively affected because it cannot produce meaningful recommendations (Safoury and Salah 2013).

Some recommendation systems are based in collaborative filtering (CF), which can be viewed as a classification and regression generalization (Aggarwal 2016) and it is the most mature and commonly implemented technique (Jain et al. 2020). This technique is making predictions about users' preferences based on data collected from users with similar profiles. Ratings between users and items are stored in a matrix which is sparse, sometimes up to 99% (Guo 2012). This problem is known as *Data Sparsity* in CF recommendation systems.

Sparsity exists when there is lack of knowledge about new users who start using the system and also, because they ignore the evaluation process after a recommendation. Moreover, new users rarely report their feedback on received suggestions. In CF systems, data sparsity is what causes the cold start problem (Guo 2012).

To tackle these problems, some approaches have been proposed in the literature. Himeur et al. (2021) proposed that some explicitly stated preferences by the newcomers can be used as metrics to include them in some preexisting cluster of older users. Lika et al. (2014) proposed a model consisting of classification algorithms and similarity techniques that retrieved optimized recommendations. Furthermore, Liu et al. (2014) mentioned that promoting new items into new users is not very effective, but promoting new items into less active users showed some performance improvement. Jain et al. (2020) suggested an algorithm based on Sequence and Set Similarity Measure that utilized Singular Value Decomposition removes sparsity from the user-item-ratings matrix and Natarajan et al. (2020) proposed two methods to overcome sparsity using linked open data from the "DBpedia" knowledge base to create a recommendation system using Matrix Factorization.

6.4 Comparison of direct and indirect control IEMS

Every developed IEMS design has advantages and disadvantages that occur from the actuation type it incorporates. Both direct and indirect control can offer benefits to the end users, however, the installation environment that is most suitable for each class,

Table 5 Comparison of complete IEMS in various aspects / criteria

IEMS Type	Cost	Daily life intrusiveness	Security	Comfort	Efficiency	Ease of installation
Direct control	–	✓	–	✓	✓	–
Indirect control	✓	–	✓	–	–	✓

Table 6 (Continue:) Comparison of complete IEMS in various aspects / criteria

IEMS Type	Accessibility	Safety	Planning / Scheduling	Awareness
Direct control	✓	✓	✓	–
Indirect control	–	–	–	✓

varies. In Tables 5 and 6 we compare these systems with respect to the following characteristics: cost, daily life intrusiveness, security, comfort, efficiency, ease of installation, accessibility, radius of influence, planning and scheduling features.

In terms of cost, IEMS with automations require a greater number of equipment to control all necessary devices, appliances and services of the installation environment. Each one of these needs an exclusive actuator, which most of the times increases the cost considerably. Because of that, systems which produce recommendations are more affordable options for daily user.

Regarding the intrusiveness of such a system in users daily life, indirect control tend to be more intrusive. People must take actions every time a new recommendation arrives in order to get the best out of their system's effectiveness. However, this means that the system is highly intrusive in their life, so in this case a system with automations is a better choice.

Security issues are a main concern for all users especially in recent years. Both direct and indirect control systems incorporate a sensing infrastructure, i.e. smart meters and the rest of the sensors that measure environmental variables. Data collected from these devices are extremely sensitive and multiple security measures should be taken into account. As mentioned earlier, absence detection from residential meter data is an extremely dangerous situation, if this information reaches in dangerous people. Nevertheless, the fact that indirect control systems do not incorporate digital actuators make them more resilient to cyber-attacks and no-one can interfere with the functionality of a device or a service.

In every aspect of their life, people are looking for conditions that increase their comfort, whether at home, at work or out for shopping. An energy management system tends to interfere with peoples comfort in all environments in order to achieve energy savings. A system with automations allows the end users to keep their daily routine intact, requiring only an initial setup and minor adjustments during its use. On the other hand, recommendation modules use humans as actuators, therefore their comfort is more affected.

The fact that indirect control systems have a human-in-the-loop design, decreases also their final efficiency. According to the aforementioned studies, user engagement is a major influential factor for the decrease of their efficiency, which makes systems with automations a better choice from this viewpoint.

In terms of ease of installation, direct control systems consist of many more different devices, such as metering, actuators and sensors rather than indirect control systems. On the contrary, an indirect control system can function even with one metering device in the power supply line and one application on a smartphone. Thus, these systems are easier to be installed and they usually are not requiring technical assistance.

The aspect of accessibility is rarely being considered during the design of an IEMS. Systems with automations are more suitable for environments where elderly or handicapped people live or work because usually it is more difficult for them to control the functionality of the services that need to be managed.

There are cases in our daily life where electricity can cause dangerous incidents. A typical example is the malfunction of an appliance. During the monitoring of the energy consumption an appliance can appear to consume energy, even though occupants know that it is not functioning. That might be a case of energy leakage from an old or faulty device. A direct control system can automatically turn of the power supply of this apparatus and protect users from getting electrocuted.

Another aspect IEMS is the planning and scheduling of energy saving actions. Direct control IEMS are capable of lowering HVAC temperature when temperature and humidity reach certain levels autonomously. Therefore, systems with automations have an advantage over recommendation IEMS.

Finally, energy awareness is another aspect of these systems. Usually, designers and developers of IEMS are focused only to achieve energy consumption reduction on the installation environment. However, by focusing on users behavioral management through recommendations systems, people can become more energy aware. When they learn to follow a specific pattern of actions at home, they can act similarly in any other place. This implies that IEMS with incorporated recommendation modules can have a long term effect in a broader set of environments.

7 Future research

7.1 Research gap

This subsection discusses some insights about the research gap in the field of Intelligent Energy Management Systems.

In order to better understand some topics that are related to IEMS, more reviews focused are necessary. First, we found out that *Machine and Deep learning techniques* are, in most cases, the state-of-the-artapproaches towards the solution of a problem. IEMS are IoT based systems which produce high volume of data, therefore fast and accurate processing is required. Furthermore, these data are, in some cases, collected and processed in real time and decisions must be taken. Therefore, an extensive survey on Machine and Deep learning techniques with applications in IEMS needs to be done so the research community has a better perspective about the limitations of these techniques and how they can be overcame.

Second, another important issue of the IEMS is *security*. As previously mentioned, security issues occur in IEMS and can be dangerous both for the users and for the energy providers and producers. Incidents such as false data injection attacks or DoS attacks are serious and must be taken into consideration during the development. Until now, due to different standards and communication stacks involved in the IoT technologies, traditional measures against cyberattacks are not always applicable (Sicari et al. 2015). Threats like

systems' failure, smart meters' data corruption, infection by malware, spoofing of user-names and addresses and unauthorized access, show the necessity for research towards threat and risk modelling, IoT forensics, intrusion detection and prevention techniques (Kitchin and Dodge 2019; Atlam and Wills 2020). Also, Energy Theft is another recent problem that is mostly important for the Distribution System Operators which are managing and distributing produced energy into customers. During our research, we concluded that there is a gap on the area of energy related cyber-security issues and we consider it of great importance for the evolution of IEMS.

Finally, another topic that requires to be studied are ways to increase ***user engagement*** in recommendation systems. Indirect control IEMS which involve recommendations through notifications systems seem to be very promising. However, no such system can guarantee that users will remain engaged into the suggested actions and that they will act respectively. Moreover, the fact that recommendations systems suffer from the cold-start problem decreases more the chances for engagement, thus the effectiveness of these systems drops compared to systems with automations. Because of that, we consider it necessary for a study to be carried out that will investigate all problematic aspects of behavioral modification systems, focusing on user engagement.

7.2 Research opportunities

The field of IEMS is still developing, therefore many aspects of these systems need to be improved. Regarding indirect control systems, explainability of recommendations remains an issue that needs further study. The lack of explainable recommendations lead users to ignore advice, reducing the effectiveness of a system and the trustworthiness of it (Zhang et al. 2020). Each recommendation should be accompanied by answers to the questions "why to perform an action" and "what the benefits are" (Himeur et al. 2021). In (EM)^3 system, (Sardianos et al. 2020a; Varlamis et al. 2022b), each recommendation had a reasoning and a persuasion feature, which resulted in 20% increase in the acceptance ratio. Moreover, Wilkinson et al. (2021) presented that it is more effective to provide justifications on why an action should be performed rather than why not.

Another research opportunity is towards gamified frameworks for systems with recommendation modules. They are more engaging than conventional ones when they aim to change certain behaviors (Papaioannou et al. 2017). These approaches are preferred for school buildings, in order to improve energy awareness in students. An example by Mylonas et al. (2018), was implemented through the GAIA project, where IoT lab kits where used along with a serious game resulting in acceptance of energy aware behaviors.

Reinforcement learning is a popular AI technique to develop smart frameworks that perform control actions. These frameworks can be incorporated in smart home energy management devices to offer higher levels of saved energy. According to Mason and Grijalva (2019), RL frameworks are capable of learning more complex policies than other neural networks implementations and because of the always increasing data volume, these frameworks will become eventually a necessity. Another opportunity is to develop multi-tasking RL frameworks that will be trained to follow different policies. Until now, many multi-objective optimization methods exists, but none of them utilizes Reinforcement learning. Furthermore, RL control frameworks are not tested yet in extreme condition changes. Minor changes at the environmental conditions have been handled until know (Mason and Grijalva 2019) but cases like extreme weather conditions, increase or decrease of occupants, solar panel failure, etc, have not been tested yet. Finally, RL apporaches in IEMS

are relatively new (Al-Ani and Das 2022). Another research direction would be to perform a comparison between these new approaches with the traditional ones such as rule-based frameworks and other neural network based implementations.

Regarding privacy issues, protecting sensitive users' information is essential, therefore some research directions could be towards the improvement of resilience of IEMS to cyberattacks by developing frameworks with less vulnerabilities. Until now, due to different standards and communication stacks involved in the IoT technologies, traditional measure against cyberattacks are not always applicable (Sicari et al. 2015). Threats like systems' failure, smart meters' data corruption, infection by malware, spoofing of usernames and addresses and unauthorized access, show the necessity for research towards threat and risk modelling, IoT forensics, intrusion detection and prevention techniques (Kitchin and Dodge 2019; Atlam and Wills 2020).

8 Conclusions

This paper has reviewed state-of-the-art approaches of Intelligent Energy Management Systems. Within the area of energy efficiency, IEMS are considered as a way to confront climate change. These systems follow a similar architecture consisting of four components: Sensors, Actuators, Processing Engine and a User Interface.

There are two types of sensing infrastructures in the literature, custom-made and commercial. Researchers choose their preferred type based on the goals and the scale of the application. In large-scale projects, commercial sensors provided convenience and sometimes a unified communication protocol, whereas custom made sensors were preferred for small-scale projects because they could embed more components.

Moreover, this review proposed a novel classification, based on the type of actuation. IEMS can be divided into direct and indirect control systems, depending on who is performing the actions to optimize energy consumption. IEMS with incorporated automation modules are controlling the consumption directly, whereas IEMS aimed at behavioral changes suggest actions and allow the users to decide about actions. Direct control provides convenience through automations and also safety in case of emergency situations. However, improving energy awareness through indirect control can bring about changes in larger scale.

Nevertheless, all of these systems have weak points and vulnerabilities. Systems with automations are mostly vulnerable against cyberattacks. False Data Injection attacks in such systems, can cause an increase of consumed energy. Systems with recommendations suffer from the Cold Start Problem which occurs when new users begin to use the system and when new actions are imported. These problems must be addressed to ensure the effectiveness of these applications.

Our intentions are to keep researching in the field of IEMS. We consider the area of Reinforcement Learning very promising for applications in energy management using direct control. Trying to overpass problems such as the slow training rate is one of our goals. Moreover, another research opportunity regarding the recommendations' modules is to implement an application or a serious game that will drastically improve users' engagement in order to create a more affordable and interesting way for people to become more energy aware.

To conclude, IEMS are going through a constant evolution. Direct control approaches seem like a better option for commercial buildings, where a large number of people is

present. In that scale, recommendation systems are not very promising. On the contrary, indirect control seems an appropriate choice for educational buildings because eventually, they will increase the awareness of students and will provide long term advantages. Finally, for residential environments, systems with automations are currently more advanced, however, the installation of a complete smart home is still very expensive and unaffordable for the majority of households. Therefore, we suggest that more indirect control applications must be developed for domestic environments in the future.

Data availibility Data sharing not applicable to this article as no datasets were generated or analysed during the current study

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