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A Cyber-Physical Approach for Residential Energy Management: Current State and Future Directions

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Abstract: In this work, we an envision Home Energy Management System (HEMS) as a Cyber-Physical System (CPS) architecture including three stages: Data Acquisition, Communication Network, and Data Analytics. In this CPS, monitoring, forecasting, comfort, occupation, and other strategies are conceived to feed a control plane representing the decision-making process. We survey the main technologies and techniques implemented in the recent years for each of the stages, reviewing and identifying the cutting-edge challenges that the research community are currently facing. For the Acquisition part, we define a metering device according to the IEC TS 63297:2021 Standard. We analyze the communication infrastructure as part of beyond 2030 communication era (5G and 6G), and discuss the Analytics stage as the cyber part of the CPS-based HEMS. To conclude, we present a case study in which, using real data collected in an experimental environment, we validate proposed architecture of HEMS in monitoring tasks. Results revealed an accuracy of 99.2% in appliance recognition compared with the state-of-the-art proposals.

Keywords: Cyber-Physical System; Home Energy Management System; Internet of Things; Machine Learning; Smart Grids

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1. Introduction

The continuous increase of the energy consumption in the residential sector has opened the door to the arrival of new technologies that promise to change the way in which electricity is produced, managed, and consumed [1]. To achieve sustainable development, it is of high importance to drastically decrease the usage of fossil fuels, not only because of their elevated costs, but for their polluting nature. In particular, the power sector has been a major contributor to global warming, being responsible for a considerable amount (about 38%) of carbon emissions in the past years [2]. As a consequence, the electricity industry is increasingly moving to a transformation, an evolution from a centralized network to a more distributed one, which requires significant interaction on the consumer part. The smart grid is a novel electric power system that supports a two-way energy and information flow between consumers and service providers. Smart Grids aim to manage new applications in the energy distribution system, such as smart meters, distributed energy resources (DER), electric vehicles (EVs), and energy storage systems (ESS) [3]. Electric vehicles provide several environmental and economic benefits; at the same time, they introduce new challenges due to their bidirectional mode of operation. With large-scale integration of EVs, the charging process can overload the power system mainly during peak hours. Other factors that may affect the power grid include voltage fluctuation, harmonics, frequency deviation, grid stability, and power outages [4].

In this context, in which smart homes and home automation arise, automatically controlling different home appliances or devices is essential. Smart home devices are able to acquire real-time information and improve customer safety and security [5]. Therefore, an efficient residential energy management methodology is required, in which Home

Energy Management Systems (HEMS) will allow households to effectively centralize the management of services, and will provide smart homes with functionalities for the internal and external information exchange. In this regard, HEMS must perform two main tasks: (1) real-time monitoring of the energy usage of householders, and (2) scheduling the optimal energy consumption of household appliances. In addition, through HEMS, electric utilities, or a third party, will provide consumers with an efficient control of home appliances [1].

Facing the fifth generation (5G) wireless networks era, several problems arise which affect the massive adoption of smart homes and HEMS. These are mainly related to interference, latency, and packet loss. At the same time, conventional Smart Grids are evolving towards Smart Grid 2.0 or Energy Internet (EI), which envisages autonomous grid operation replaces the current central authority governing the grid [6,7]. The 5G technology targets to support diverse vertical applications by connecting heterogeneous devices and machines with drastic improvements in terms of high quality of service, increased network capacity, and enhanced system throughput [8]. On the other hand, the continuous evolution of data acquisition systems, information technology (IT), and network technologies have led to new manufacturing strategies, such as the advanced Industrial Internet, and Industry 4.0. Smart technologies including cyber–physical systems (CPS), digital twins (DTs), and Internet of Things (IoT) technology are taking a central position [9–12]. The Cyber-Physical System is created as a consequence of the increasing number of households connected to the grid through multiple EI applications, which will result in countless access points and data sets threatening the grid security and obstructing its performance [6].

As a typical application of machine-type communications among 5G technologies, IoT was widely integrated into the grid, producing the so-called Power Internet of Things (PIoT) [13]. PIoT and data-driven approaches have become attractive solutions for enabling smart homes to achieve their goals in monitoring, protecting, and controlling through the incorporation of sensors, actuators, and metering devices while supporting various network functions and system automation [1,5,14–16]. In [13], the authors have discussed the role of PIoT as part of a Cyber-Physical System. In this scenario, PIoT will implement the interconnection of the wide-area devices and performs data collection, storage, and aggregation, while the CPS is more related to data analysis, making effective, reliable, accurate, and real-time control of the physical process in the smart grid. However, from the smart home perspective, the role of CPS has received less attention. Therefore, analyzing HEMS in this context—from home devices to data management and user interaction—becomes a task of significant importance.

1.1. Motivation

Several approaches have been discussed about how to monitor [16–28], control [14,15,29–31], and forecast [32–36] the main loads in a smart home, mainly focusing on Data Analytics and Communication Network. However, this analysis has been mostly performed independently. In order to fit the requirements of ”beyond 2030” communication (5G, 6G) and Industry 4.0 technologies, a more holistic approach is necessary.

In this paper, we propose a cyber-physical approach for Home Energy Management System (HEMS). The proposed architecture consists of three layers: Data Acquisition, Communication Network, and Data Analytics. We review state-of-the-art solutions for each layer highlighting and identifying the main challenges. In the Acquisition stage, we define a metering device based on the standard IEC TS 63297:2021. For Communication Network, we summarize different technologies deployed inside the house, and discuss the best candidates for communication in the smart city. In addition, we define the Analytics stage as the cyber part of a HEMS. We present a real case study in which a cyber-physical architecture is implemented and validated for monitoring purposes using real data collected in a house located in Valparaiso, Chile. To the best of our knowledge, no previous work has analyzed the requirements of HEMS to be deployed in the advent of beyond 2030 communication and CPS era.

1.2. Contribution

The main contributions of this work can be summarized as follows:

- We provide a comprehensive review on key enabling technologies and techniques for HEMS, defining these systems as CPS-based architectures of three main stages: Data Acquisition, Communication Technologies, and Data Analytics.
- In terms of Data Acquisition, we revised the main components and defined the main parameters of metering devices according to the IEC TS 63297:2021 standards, reviewed available solutions in the market, and summarized the main characteristics of available datasets.
- We reviewed available communication technologies for both HAN and WAN interconnection, opening the discussion for the introduction of "beyond 2030" communication (5G and 6G) in the context of HEMS.
- We identified Data Analytics as the cyber part of a CPS-based HEMS, in which several processes such as monitoring, scheduling, and forecasting, are carried out.
- The described architecture was validated during a testbed for monitoring purposes. This way, we established the guidelines for future work.

1.3. General Structure

The rest of this paper is organized as follows: in Section 2, recent relevant research work is analyzed, discussing the main benefits and limitations of current solutions. Following this, Section 3 defines the main stages of a HEMS. In Section 4, we discussed home appliances and metering devices, providing a standard definition based on IEC TS 63297:2021. Then Sections 5 and 6 discuss some of the most common technologies and techniques used for Communication Network and Data Analytics, respectively, based on recent literature. In Section 7, we present a case study of a cyber-physical approach for a HEMS. To validate this system, we implemented a real-case scenario for monitoring purposes. Finally, Section 8 identifies a series of challenges which demand the attention of the research community, arriving at conclusions presented in Section 9.

2. Related Work

Home Energy Management Systems (HEMS) have centered the attention of the research community over the last decade. Since the emergence of Smart Grids, HEMS have been defined to play a key role in centralizing the management of services. The main idea behind this concept is to provide customers with complete functionalities for internal information exchange. The authors of [3] pointed out, among other challenges, the need of having a robust and large-bandwidth communication infrastructure that can cope with the enormous volume of data, which indeed has been hardly discussed in recent years [8,37–42].

In that sense, the authors of [38] identified interference and wall penetration losses as the main challenges to be handled in smart homes. They built a simulator which allowed them to prove that cognitive radio communication technologies can help overcome the challenges by providing more flexibility in terms of unused spectrum. In addition, the authors highlighted the need for a 5G network which connects the smart homes and joins these into a smart city infrastructure. On the other hand, in [41], the authors discussed on how conventional wireless communication technologies, such as WiFi or Zigbee, are insufficient for communication range, energy consumption, and cost. As a solution, the authors advise low power wide area networks (LPWAN) which can operate at low data rates while covering kilometer ranges. Among these technologies, they remarked long range (LoRaWAN), which is an open standard, with built-in security, GPS-free geolocation, ability to have long range communication, low energy consumption, and options to have private deployments. However, its deployment in real-time application is limited due to its low data rate and duty cycle constraints.

The vast majority of previous works concerning HEMS is slightly related to Data Analytics. The usage of power data has provided HEMS with different functionalities such as load monitoring, load forecasting, comfort-level analysis, and scheduling the use of appliances in order to increase energy efficiency.

2.1. Load Monitoring Approaches

The process of load monitoring is conceived to facilitate the processes of identifying and monitoring main loads in the household [21,25,43]. Literature has identified two main categories to classify the methods to manage such processes: methods based on hardware, known as intrusive load monitoring (ILM), and those based on software, i.e., non-intrusive load monitoring (NILM) [44,45].

Most of the research work have been oriented to NILM, mainly motivated for its low-cost implementation and easy deployment requirements, using only one single point of sensing. This was the method selected in [19,21–28,46–59]. In contrast, in some countries, the access to smart meter is still limited. The main challenges lie in regulation and implementation issues. Moreover, high-resolution data cannot be achieved with most current commercial smart meters today having complexity in setup, data storage, and cost. On the other hand, IoT technology has been gaining increasing popularity becoming an affordable option to overcome the difficulty of implementing NILM solutions. However, different requirements must be considered regarding data resolution, accuracy, real-time operation, and the number of devices to be covered, which also have been openly discussed in literature [16,18,22,43].

2.2. Load Forecasting Approaches

The authors of [32] explained that the need for load forecasting is given by the advanced metering infrastructure (AMI), which is a main component of the smart grid. It encapsulates the main technological innovations in this domain: the smart meters. Then, cutting-edge applications such as DR models can be implemented. To be successful, DR campaigns need to profile and further forecast the energy usage reported by each smart meter within each AMI. In addition, the authors identified a need for characterizing and forecasting the usage patterns of individual appliances within a household, since it allows to manage the daily electricity usage of each appliance, to engage further in the DR using the smart meters over the AMI, and therefore select suitable price plans. The latter idea was stated in [35], in which the authors conclude that load forecasting can be useful to provide energy-efficient scheduling for smart homes.

Different from grid-level forecasting, which measures the total energy consumption in a household, i.e., at smart meter level, appliance load forecasting has received less attention in past years [32]. However, in recent publications, researchers have taken advantage of the many benefits it can bring for smart grid applications [32,33,35,36]. In these works, the authors agreed on the challenge of developing a single model that operates at the device level.

2.3. Comfort Level in Literature

The comfort level of households has been increasingly raising many concerns in the research community, being directly related to environmental indicators such as temperature, humidity, and water control [13,60]. In [14], the authors presented a reinforcement learning (RL) model to manage and control the heating system and domestic hot water (DHW), with photovoltaic (PV) self-consumption optimization. This approach allowed to balance energy savings and comfort according to the consumer's preferences.

For the healthcare sector, comfort level analysis is one of the main concern in assistive living applications. In [61], the authors gave an insight into different types of ambient-sensor-based elderly monitoring technologies for the home. The authors emphasized on the types of sensors, their characteristics, and costs which can be used in this regard. They also presented a summary of previous research works that studied ambient sensors in mobile robotics. They concluded that using wearable sensors can result in uncomfortable for patients, especially if they are wearing the devices during extended hours on the body.

This, in turn, may result in a high risk of rejection by the patient. In contrast, ambient sensors do not suffer this drawback, and therefore they have greater acceptance.

2.4. Scheduling and Control Methods

Scheduling and control is one of the primary goals of HEMS. In [29], the authors conceived HEMS as a way to build consumption schedules based on several factors such as energy costs, environmental concerns, load profiles, and consumer comfort. In addition, the authors claim that these systems allow to save energy and efficiently manage the distributed energy resources and storage. They reviewed the evolution of HEMS from its emergence in 1979.

There are various methods for scheduling and control in the context of HEMS which have been discussed in literature throughout the years. Most of these methods have been presented as an optimization problem, in which the main objective is to minimize the peak load and electricity cost of a the smart home. The authors of [62] proposed a self-scheduling model based on behavioral modeling and prospect theory. On the other hand, the authors of [60] based their scheduling solution in optimizing thermal and visual comfort. In Table 1, we present a summary of some of the most recent publications in this regard. From Table 1, it is possible to notice that there are two main strategies to solve the problem: rule-based algorithms (Heuristics Methods, Markov Chains) or deep reinforcement learning (Deep RL) based approaches.

Table 1. Different methods to solve Scheduling and Control in HEMS.

Reference	Year	Method	Type
[15]	2020	Policy gradients (DDPGs)-based energy management algorithm.	RL-based
[1]	2020	Two-level distributed Deep RL (DRL) model.	RL-based
[63]	2020	Optimization based on user preference.	Rule-based
[14]	2020	Single/Multiple objective optimization.	RL-based
[64]	2020	Indoor and domestic hot water tank temperature control.	Rule-based
[65]	2020	Multi-objective optimization using discomfort index.	Rule-based
[60]	2020	Human comfort-based model.	Rule-based
[66]	2021	Fuzzy logic systems coupled with genetic algorithms.	RL-based
[67]	2021	Optimization model for cost reduction.	Rule-based
[35]	2021	Q-learning for offline optimization.	RL-based
[68]	2021	Appliance Scheduling-based Residential Energy Management System (AS-REMS).	RL-based
[69]	2021	Nonlinear models and adjustable parameters.	Rule-based
[62]	2022	Mixed integer linear programming (MILP) model.	Rule-based

As a consequence of appliance scheduling, comfort level of users may be affected. The authors of [65,70] argue that the user inconvenience may be caused due to forcing consumers to change the use of their home appliances, even when the economic factor does not compensate for the discomfort. Therefore, this is a significant fact to consider when deploying a HEMS. In [65], the authors proposed a multi-object optimization method for both the electricity bill and Discomfort Index.

2.5. Other Applications

Occupancy, death, or anomaly detection applications have been related to HEMS and also explored in literature. In [71], the authors proposed a method to tackle the problem of detection indoor office occupancy based on statistical approaches and Machine Learning techniques. The metering system was installed at the circuit breaker level in an office, thus contributing to building context awareness energy-efficient buildings. The authors of [72] proposed deep learning (DL) based approach to recognize daily activities performed in a smart home. The model separates the normal from the anomalous activities. In addition, they identify the anomalous days based on the number of activities performed in a day. On the other hand, in [73], the authors proposed a model to detect abnormal inactivities that included immobilizing medical conditions or sudden deaths of elderly or disabled occupants who live alone, which aroused the interest of the healthcare community.

2.6. Summary and Insights

The above analysis proves that HEMS is still undergoing research, in which, facing the 5G/6G communication era, it is undoubtedly in constant need of transformation. In [13], the authors conceived future HEMS as a cyber-physical architecture in which the sensing is oriented from appliances to the cloud, and the actuation is done in a reverse way.

3. Architecture for Home Energy Management Systems

A significant number of researchers has discussed IoT-based architectures for HEMS and other smart grid applications, such as activity recognition [16]. Commonly, three to five layers are needed including appliances, metering devices, communication technologies, middleware technologies, and user interaction. The authors of [74] described traditional three-layered architectures with a perception layer (including all meters and actuators), a communication network, and an application layer. Four-layered architectures usually define the communication system in two parts, one in the field (inside the house), and the remote network (referring to the external network that allows data exchange with the server in which data are processed) [74,75]. On the other hand, the authors of [16,76] proposed a five-layered structure that separates home appliances in a physical things layer from metering devices in the perception layer. These implementations are also known as cloud-based architectures since they benefit from middleware technologies for processing the data [74]. Table 2 summarizes the main characteristics of proposed architectures in the revised literature. The ”Validation” column refers to the practical implementation of the architecture, either a testbed or at a major scale.

Table 2. Main characteristics of previous IoT architectures for HEMS. Layers are represented as follows: Data Acquisition [Appliances and Meters] Layer (DA), Data Acquisition [Appliances] Layer (DAA), Data Acquisition [Meters] Layer (DAM), Communication Network Layer (CN), Middleware Layer [Storage and Analytics] (M), Middleware Layer [Storage] (MS), Middleware Layer [Analytics] (MA), Data Analytics (DAn), and Application Layer (A).

Reference	Type	Year	Layers	Validation
[77]	Survey	2017	DA, M, A	X
[78]	Technical	2017	DA, CN, M, A	X
[79]	Survey	2019	DA, CN, MS, MA, A	X
[80]	Technical	2019	DAM, CN, M, A	✓
[75]	Survey	2019	DAM, CN, M, A	X
[81]	Technical	2019	DA, CN, M	✓
[82]	Technical	2020	DA, CN, A	✓
[83]	Survey	2020	DA, CN, M, A, B	X
[84]	Survey	2021	DAA, DAM, CN, M, A	X
[66]	Technical	2021	DA, CN, M, A	X
[85]	Technical	2021	DA, CN, M	X
[47]	Technical	2021	DA, CN, M, A	X
[16]	Survey	2021	DAA, DAM, CN, M, A	X
[86]	Survey	2021	DA, M, A	X
[13]	Survey	2021	DA, CN, DAn, A	X
This work	Survey	2022	DA, CN, DAn	✓

Figure 1 highlights the main composition of the previous IoT architectures for HEMS. The major goal of existing studies is layered architectures to control and manage home appliances remotely. Four-layered architectures are an extension of three-layered architectures by dividing the communication network layer in home area network and remote communication network, which are also defined inside the middleware technologies. Therefore, both representations are very generic. The authors of [74] argued on the benefits of implementing three or four layers to the detriment of having five or more layers.

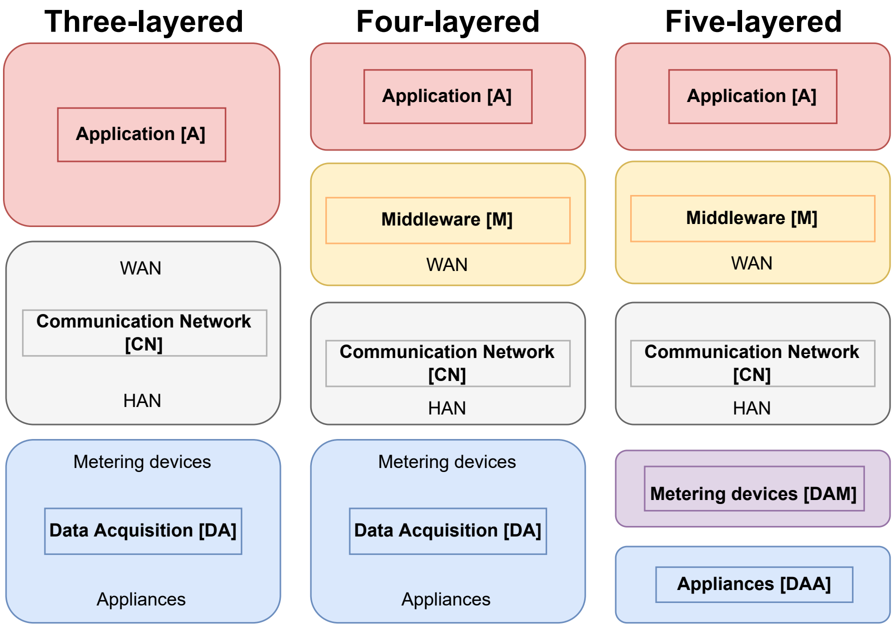

Figure 1. Composition of previous IoT architectures for HEMS.

Based on the analysis given above, we can identify a HEMS by three main stages: Data Acquisition, Communication Network, and Data Analytics, as shown in Figure 2. This is also highlighted in the last row of Table 2. The first stage includes both appliances and metering devices. A level up, the Communication Network Layer allows data exchange between the sensing devices and a server. Data is transmitted inside the home area network using WiFi, ZigBee, or other short-distance communication technologies. Then, the information is forwarded to the upper Data Analytics Layer through long-distance communication technologies such as 5G, allowing data transmission between physical devices and middleware technologies in which Data Analytics processing is hosted (i.e., provide connectivity through the WAN). Middleware solutions are used to integrate and coordinate the nodes, thus achieving a real-time status and management of the household. The Data Analytics Layer provides data storage, management and analysis (monitoring, forecasting, comfort-level analysis, etc.) to the data. Furthermore, at this stage, control tasks and scheduling algorithms are executed. Machine Learning techniques and different data processing strategies will translate the data to an easy and understandable form which can be visualized by the user. In addition, data visualization and user interactions are guaranteed in this layer through a user interface. The user interface provides consumers with advanced energy management applications and services. First, data are sensed and aggregated in the HAN, and once processed, actuation and control commands are sent back to physical devices according to energy consumption cost and user satisfaction. The proposed architecture shares the same basic structure of most traditional IoT-based HEMS. However, a higher combination and coordination between physical and computational elements is included, understanding data processing as a layer (Data Analytics), and thus, becoming a cyber-physical architecture for HEMS. Figure 3 shows a relationship between traditional IoT architectures and the cyber-physical based (CPS-based) ones. CPS includes complex analytics strategies, such as data mining, inference, and decision making. These systems benefit from massive wireless networks and physical devices ("things"), to provide intelligent services based on the knowledge of the surrounding physical world. Traditional IoT architectures focus on data acquisition and transmission, being less oriented to security and data processing [87]. In the proposed platform, security is conceived in every layer;

however, to deepen in this particular topic is out of the scope of this paper since it requires significant research efforts, being considered an independent research field.

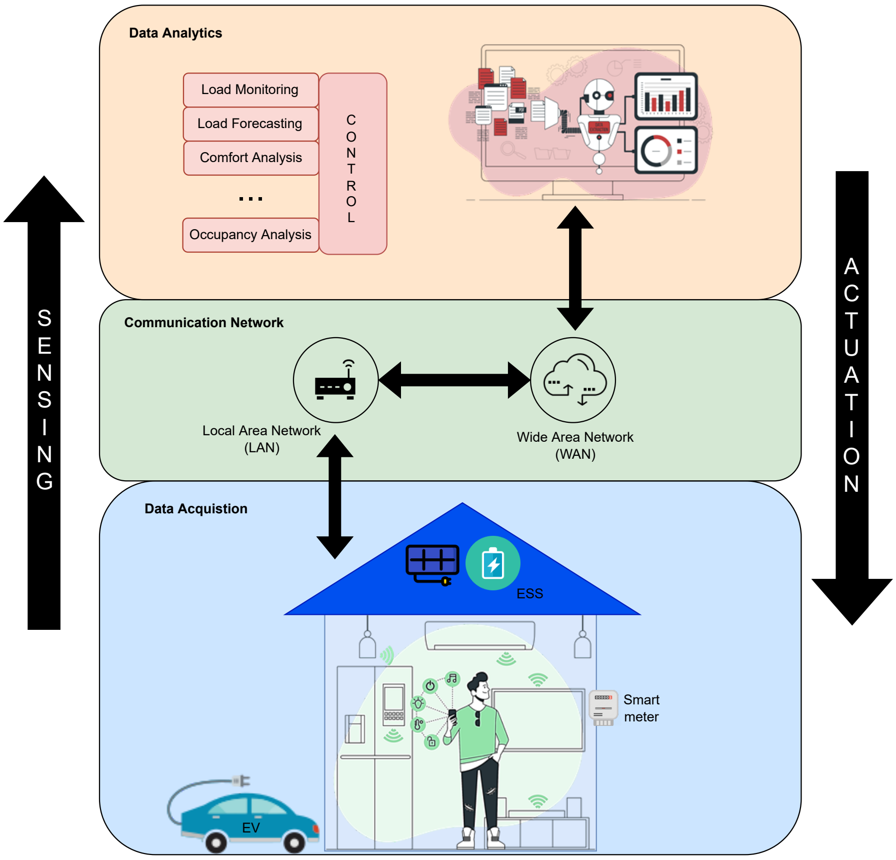

Figure 2. Schematic diagram of a Home Energy Management System (HEMS). Stages involved: Data acquisition, Communication, and Data Analytics.

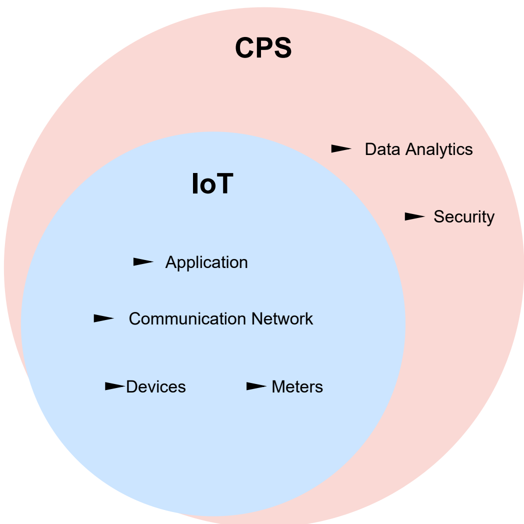

Figure 3. Relationship between traditional IoT architectures elements and the CPS-based.

The development of such systems benefits a wide variety of sectors ranging from remote healthcare to commercial services. Among these services, demand response (DR) and load planning programs focus on analyzing individual load levels in homes or buildings, which is promising in terms of energy efficiency. This analysis allows the possibility of identifying the less efficient or malfunctioning devices and implementing the appropriate actions intended for reducing consumption. In this scenario, consumers can have direct feedback on real-time power consumption effectively participating in the sustainable smart grid system. Additional useful information such as consumers' behavior patterns including occupation, sleep patterns, and other activities could also be inferred from appliance data. These activities are commonly known as activities of daily living (ADL), with applications in customer profiling, targeted marketing, monitoring of curfews, detection of illegal activities, and remote healthcare monitoring for elder people living alone, among other fields [16,18,20,21,43].

In an economic perspective, HEMS have a direct impact on reducing electricity consumption for households [30,88]. This can be mainly achieved through demand response and demand side management programs. These programs will allow to obtain efficiency and bill reduction in smart cities reducing the total energy consumption, or deferring the operation of certain appliances, especially during off-peak hours. The authors of [88] highlighted that HEMS is also eco-friendly technology that significantly impact environmental conservation.

Summary and Insights

In this section, the existing IoT architectures for HEMS have been surveyed and compared in Table 2 and Figure 1. Based on the given analysis, it was defined a CPS-based architecture for HEMS of three layers: Data Acquisition, Communication Network, and Data Analytics. The benefits of having such a system and the economic impact that it represents are also commented. The next sections provide a comprehensive description of each stage of the proposed architecture.

4. Data Acquisition

The Data Acquisition stage obtains the load measurement at an adequate rate, aiming to identify distinctive load patterns in the next stages [44]. This phase is carried out to have a generalized perception of the energy supply and the demand by sensors from different energy manufacturers, being also responsible for a precise control by the actuators [76]. Therefore, in the Data Acquisition phase, two main entities collaborate. One is household appliances, and the other is metering devices. Once data are collected, the measurements are sent to the following stages to be processed, as shown in Figure 4.

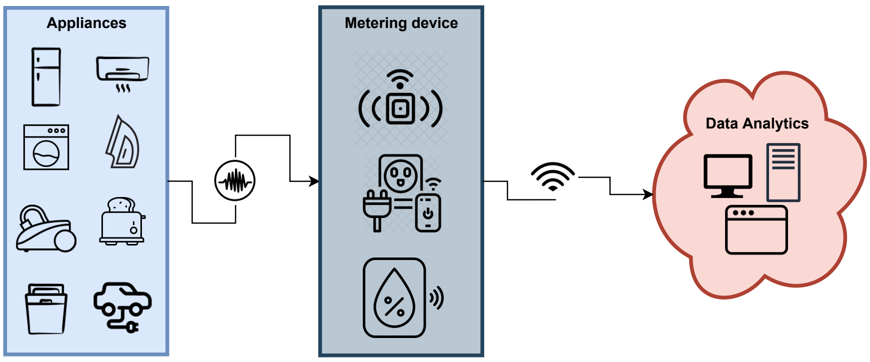

Figure 4. Schematic diagram of the data acquisition stage in Home Energy Management System (HEMS).

Household appliances have been classified in the literature depending on the target application. Figure 5 shows the main categories for appliances. For load monitoring systems, appliances are grouped in four categories, as proposed in [89]. These are as follows:

- ON/OFF: Devices with only two operational states, e.g., toaster, EVs, kettle, etc.
- Multi-state: Devices which are represented by finite state machines (FSMs), e.g., washing machines, refrigerators, heat pumps, etc.

- Continuously variable: Appliances with variable power absorption characteristics, e.g., electric drills, laptops, etc.
- Permanent consumer devices: Appliances which remain active for a long period of time (weeks or days) consuming energy at a constant rate, e.g., TV receivers, telephones set, smoke detectors, etc.

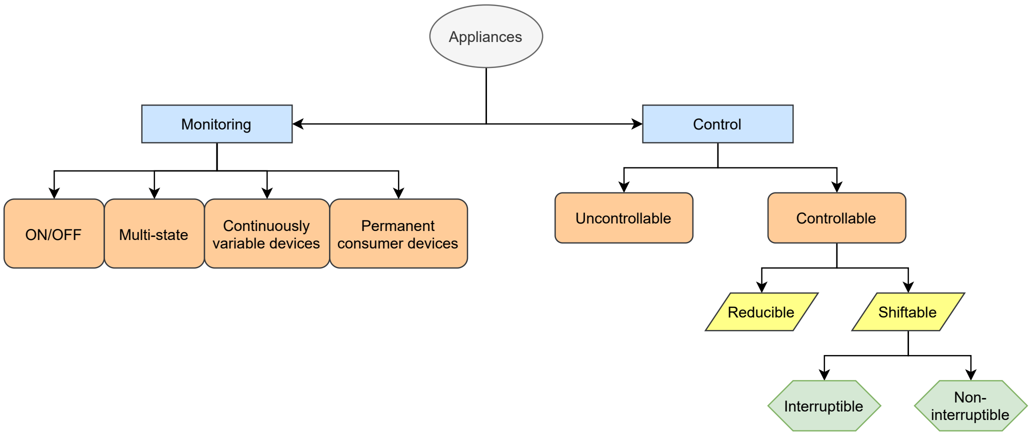

Figure 5. Schematic diagram for appliance categorization according to the target application.

In terms of control, the authors of [1] defined it in two categories:

- Uncontrollable: Refers to appliances which cannot be managed by HEMS, e.g., TVs, personal computers, and lighting.
- Controllable: Encompasses two subcategories: reducible appliances whose energy consumption can be reduced, e.g., air conditioner; and shiftable appliances which has two types of loads: interruptible (those whose functioning can be interrupted, such as ESS) and non-interruptible (such as the washing machine).

The above categories have been widely discussed in literature [1,14,19,30,89,90]. The authors of [90] modeled controllable appliances by a set of constraints. They claimed that controllable appliances should achieve their duty cycles within allowable time windows. In addition, they defined interruptible appliances as those whose operating cycle an be interrupted for convenience. The authors also explored thermostatically controlled appliances. On the other hand, metering devices have been less explored regarding standardization and categorization.

4.1. Metering Devices

The basis of residential energy management lies in metering. In the IEC TS 63297:2021 standard (see https://webstore.iec.ch/publication/66131 (accessed on 15 March 2021), https://webstore.iec.ch/publication/66131 (accessed on 15 March 2021)), sensing devices have been defined as gateways between the physical electrical installation and the system's data analytical. This standard was originally conceived for NILM. Considering that in every HEMS application, a certain number of points for sensing are needed, all with the same functionality (sampling at an adequate rate), it is possible to generalize the definition given in the IEC TS 63297:2021 standard to a more holistic approach related to HEMS. Therefore, the characteristics of residential energy management sensing devices are defined by three main parameters, shown in the schematic of metering device of HEMS in Figure 6:

- Input sampling frequency: The frequency at which the electrical signals are sampled by the metering device. This parameter is essential to the electrical waveforms production characterization.
- Output rate: The rate at which the metering device produces data that can be used by the Data Analytics stage. Typically varies from 1 set of data-per-second to 1 set of data-per-30 min.

- Data bit rate: The average bit-per-second (bps) over an hour at which the electrical signals are quantified by the metering device. Typically varies from a few bps to the Mbps range.

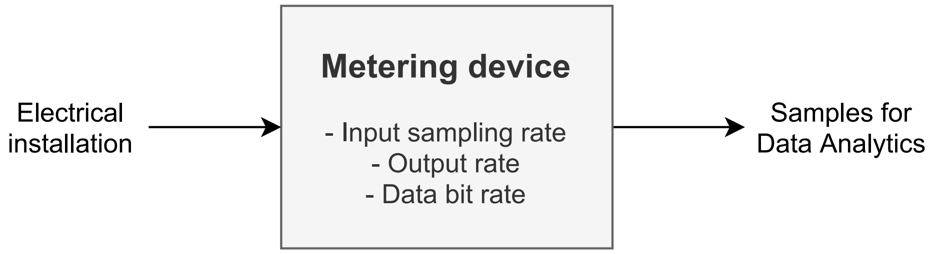

Figure 6. Schematic diagram of a metering device for HEMS according to IEC TS 63297:2021 standard.

In a household, there are current and voltage metering devices on the main power supply to measure the electricity consumption in an entire household. Additionally, there may be metering devices for specific appliances, as well as ambient sensors distributed throughout the household. The measurements are either sent directly to a central data server from the sensors or data are processed by the local data processing unit and then sent to the central data server. A central data server can be in the household's domains, i.e., installed in the Home Area Network (HAN), or at the utility level, which receives load data from multiple homes, i.e., the neighborhood area network (NAN) [43].

In a household, the metering devices can be installed at different levels. Therefore, HEMS can be categorized into four different groups according to equipment deployment granularity in the Data Acquisition stage. A general model of the three groups is shown in Figure 7.

- Grid level: The metering device is set to measure the aggregated power consumption of the household, i.e., the utility's energy meter.
- Area level: The metering devices are used to monitor household areas, measuring the consumption after the utility's energy meter.
- Plug level: The metering devices are located next to the plugs to monitor directly appliances connected to the outlet or multi-outlet.
- Appliance level: The metering devices are embedded directly in the appliances or placed in a dedicated outlet (i.e., outlet for a specific appliance).

The smart meters are one of the key systems of future smart cities, forming an AMI. These devices collect information on energy use and send it safely to the service center or operations and control center of the smart grid [91]. Taking advantage of smart meter readings, the consumer can know how much energy is consumed in real-time, and decide whether to disconnect from the grid or not (depending on the price of electricity at that time). For utilities, it reduced the need for many labor-intensive business processes, such as manual meter reading, field trips for service connection and disconnection, on-demand reads, power outage and restoration management, and other metering support functions [3]. Smart meters have built-in current and voltage sensors to sense current and voltage quantities, providing the single point of sensing needed for NILM. However, the access to smart meter data is still limited in many countries due to regulations and privacy concerns, hindering its use for load monitoring [43].

Current and voltage sensors are one of the most popular electrical sensors for load control. Current transformers (CTs) are generally used for power measurement, thus both sensors may not be enough for monitoring and forecasting requirements. The main cause is that direct current (DC) and high frequency current signatures cannot be captured. To achieve device-level measurement, a considerable amount of current sensors are required, making it impossible to reach each individual device [43]. To overcome this constraint, the electromagnetic field sensor was proposed by the authors of [52] to indirectly obtain gross apparatus level operating states.

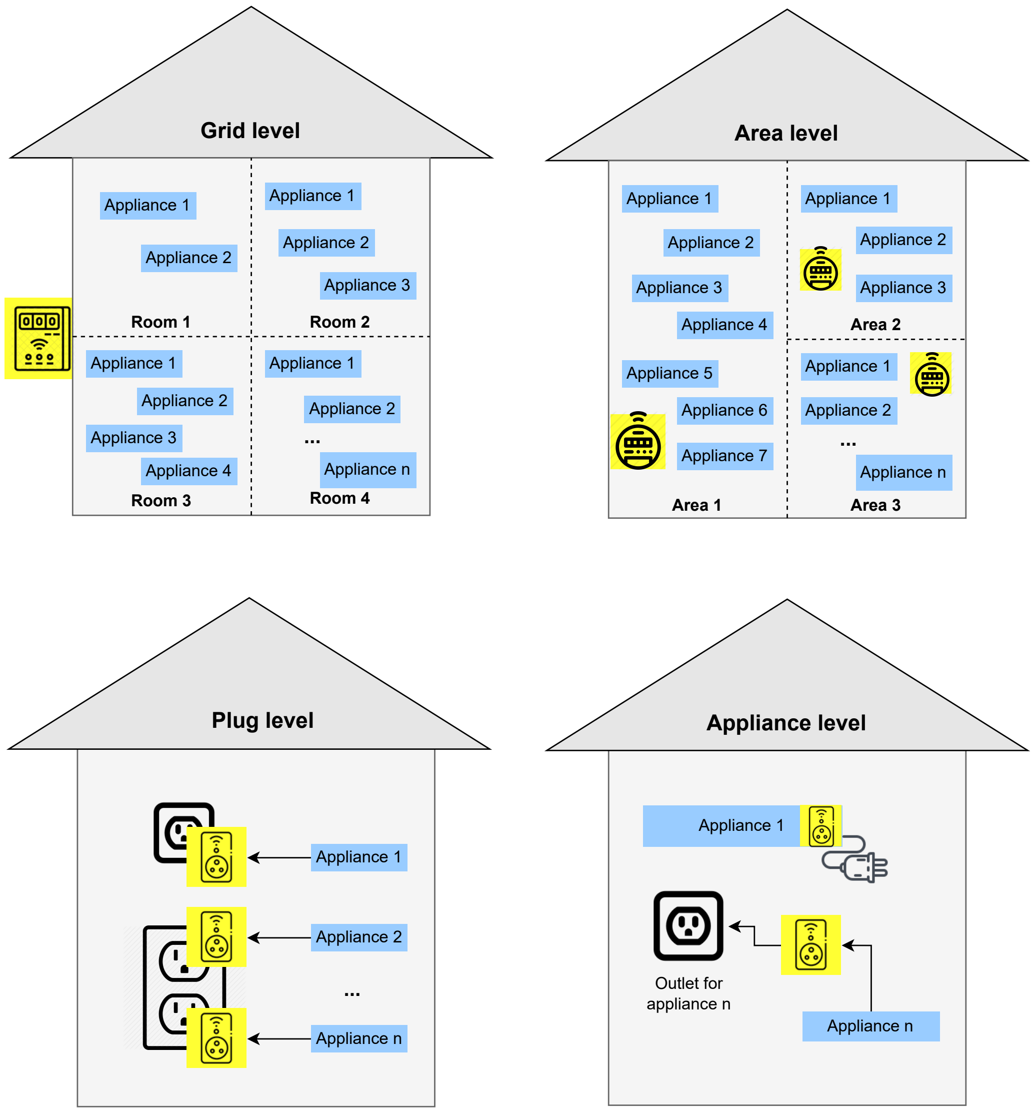

Figure 7. Schematic diagram of the four groups in terms of deployment granularity in HEMS.

In [92], the authors developed their own metering system using an off-the-shelf power strip using a voltage-sensing circuit, current sensors, and a single-board PC as a data aggregator. The six-port monitoring unit can achieve up to 50 kHz for all signals simultaneously. Two types of sensors (current and voltage sensors) were integrated to fully capture the energy consumption data of appliances. In the case of [93], the authors designed a smart socket composed of a common socket, a sampling module, and a processor. Among them, the sampling module adopts the alternating current (AC) power transmitter SUI-101A, which can measure parameters such as voltage, current, active power, power factor, frequency, and cumulative power consumption in real-time. In [94], the authors introduced a measurement system to capture the unique characteristics of the devices. Current and voltage signals were captured with current sensors and voltage probes for all three phases. These signals were input into a Siemens SENTRON PAC4200 network analyzer and an NI USB-6259 acquisition module.

The energy used by household appliances can be highly dependent on environmental conditions, such as temperature, humidity, light, and others. Therefore, ambient sensors have also been introduced in HEMS. As an example, in the BLUED residential charging dataset [95], light level, sound intensity, vibration, humidity, barometric pressure, and PIR motion were measured. In the case of the PECAN Street Dataport (see https://dataport.pecanstreet.org/ (accessed on 10 May 2021)), the water data was also taken into account.

For some authors [43], the information on the occupation of a house is also important to save residential energy because it involves the control of the heating, ventilation and air conditioning (HVAC) system, water heater, lighting, as well as residential energy storage such as batteries and electric vehicles (EV), in case there is any. A variety of sensors can be used to detect the presence, including acoustics, lighting, camera, motion, CO_2, temperature, laser beam, Radio Frequency Identification (RFID), and humidity [34,51]. As an economical solution, information from existing WiFi connections or HVAC sensors has also been used for presence detection.

Recent studies, such as [43], argue that efforts to develop high-frequency smart plugs to capture load signatures are not available for widespread deployment. However, in [96], the authors perceive smart plug's technology success addresses all aspects for effective load monitoring, such as prosumers (original fusion of the words producer and consumer) being able to make energy consumption and/or production changes, ensuring the security and privacy of metering data, and enabling to manage and store vast quantities of the collected data. Smart plugs were also highlighted in [97] as one of the leading technologies for data acquisition.

The appearance of a smart plug is an important aspect regarding the acceptability by users. It must be small, compact, and compatible with traditional plugs. Besides this, it should not add more complexity when it comes to installation and use. The design of commercially available smart plugs is possible when it largely satisfies the question of aesthetic appeal and form factor. Therefore, an ideal smart plug will be a smart combination of various technologies that have been routinely used independently until now [96].

With respect to healthcare applications, a recent approach in [17] aimed to design and develop an IoT end-to-end solution based on CT sensors to recognize electric appliances that could operate in real-time, considering low-cost hardware. Other approaches such as [98,99] presented a solution based on wearable sensors, such as accelerometers and smart devices, and in the case of [100], the authors used a camera to record the video and a processor that performed the task of recognition. A different solution is illustrated in [101], in which the authors designed a distributed platform to monitor patient's movements and the status during rehabilitation exercises. This information could be processed and analyzed remotely by the doctor appointed to the patient.

To summarize the above discussion, Table 3 lists devices commonly used for Data Acquisition in HEMS. The "Type" and "Category" columns refer to the nature of the device. If the device is classified as a sensor, then it changes a physical parameter to an electrical output. Otherwise, the actuator is a device that converts an electrical signal to a physical output [102]. The category describes the kind of measurement that can be expected using such devices. It could be either ambient (temperature, humidity, occupation, etc.) or electrical (to obtain power measurements). In addition, the last column of Table 3 shows some of the main manufacturers and sellers in the market up to date. This list is independent from the "References", meaning that the authors of previous papers could have used one device from these sellers or not.

Table 3. Commonly used consumer-side metering devices for data acquisition in HEMS.

Device	Type	Category	References	Manufactures
Temperature sensor	Sensor	Ambient	[76,78,81,103–105]	NCD, Ecobee, Sensibo, Google Nest
Humidity sensor	Sensor	Ambient	[76,95,103,106]	NCD, Aeotec, Aqara, Govee
Air quality sensor	Sensor	Ambient	[76,107]	Airthings, Eve, Awair, Bosch
Water sensor	Sensor	Ambient	[76,108], Dataport	Govee, Zircon, Fibaron, Moen
Occupancy sensor	Sensor	Ambient	[76,104]	Ecolink, Zooz, Fibaro, Apple,
Door sensor	Sensor	Ambient	[76,80,109]	Eve, Wyze, Geeni, Samsung
Current transformer (CT)	Sensor	Electrical	[17,19,43,52,110,111]	IoTaWatt, EmonLib, Schneider Electric, CrocSee
Smart Socket	Actuator	Electrical	[43,46,76,112–115]	YinQin, WeMo, TP-Link, Gosund

Table 3. *Cont.*

Device	Type	Category	References	Manufactures
Smart relay	Actuator	Electrical	[76,105,106]	Sonoff, Fibaro, INSTEON, Espressif
Smart plug	Actuator	Electrical	[20,76,96,97,106,116,117]	WeMo, TP-Link, Sonoff, Samsung
Smart switch	Actuator	Electrical	[76,118]	Sonoff, Duluck, WeMo, Ecobee
Smart meter	Sensor	Electrical	[19,21–28,46–59]	Schneider Electric, Itron, Siemens, Badger Meter
Prosumer meter	Sensor	Electrical	[76]	Develco
eGauge data logger	Sensor	Electrical	Dataport, [2]	eGauge Systems LLC

4.1.1. Sampling Frequency

The data sampling can be classified into high-speed sampling and low-speed sampling. Depending on the target application, the sampling rate for electricity consumption may vary. Some authors [21,43,45] define a fairly high sample rate as from 1 kHz to almost 100 kHz. For higher sampling rates, the authors in [45] state that the identification results are more precise, typically allowing to capture state transitions and eventually separating brands in the same category. To monitor the electro-magnetic interference generated by the switch-mode power supplies, the sampling frequency is required to be at least hundreds of kilohertz [43].

At present, most commercial devices cannot achieve high-speed sampling. Furthermore, the complexity of data storage, transmission and processing for high-speed sampling is significantly increased compared to low-speed sampling. Therefore, high-speed sampling is not currently considered a practical approach for large-scale solutions. The low-speed sampling rate is usually set to 1 Hz or even less. As a result, the resolution of the data drops significantly. With low-speed sampling, the transient state of the electrical information can no longer be captured and features may overlap [43]. The type of information that can be inferred from metering devices data has proven to be slightly related to the sampling frequency [21]. Figure 8 illustrates the common sampling frequencies used in Data Acquisition, including the features which can be extracted from the data at each sampling frequency. This figure was built based on the information given in [21].

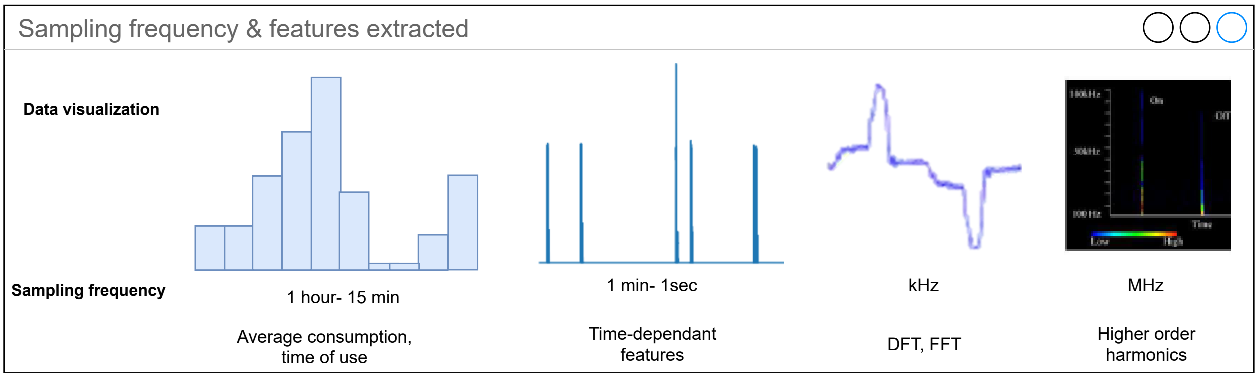

Figure 8. Visualization of the collected data and features which can be extracted at different sampling frequency ranges.

4.1.2. Publicly Available Energy Datasets

Energy datasets are vital for validation in energy-related problems. These datasets are the result of measurement campaigns in homes, buildings, or industrial facilities. Data are collected in such a way that it is transparent for the users, i.e., without interrupting the daily routines within the monitored space. In this way, the measurement will be as close as possible to reality. Commonly, ML models are tested on multiple datasets to demonstrate versatility and generalization skills [119]. The main reason why publicly available datasets are indispensables is that the implementation of high-resolution monitoring and control systems are still a challenge. Some factors such as complexity of setup, data storage, and cost make the practical implementation of these systems rather unreliable. The lack of real-world data is one of the main challenges in related studies [43]. Table 4 shows a comprehensive comparative study of the available energy datasets in terms of different attributes, including data acquisition granularity. With the information given, it is possible to analyze the devices used by the authors during the measuring campaigns.

Table 4. Details of most commonly used Energy Datasets.

Dataset	Resolution	Number of Houses	Duration	Features	Location	Metering Devices
REDD [120]	1 Hz, 15 kHz	6	2 weeks	p, i, v	USA	Enmetric wireless plug system
AMPds [121]	1 min	1	2 years	p, q, s, i, v	Canada	18 units DENT PowerScout
UK-DALE [122]	1 s, 16 kHz	5	3–51 months	p, i, v	UK	CT sensors
DRED [123]	1 Hz	1	2 months	p	Netherlands	*Without specification*
Dataport	1 min	1000	2012 present	p	USA	eGauge data logger
GREEND [124]	1 Hz	9	1 year	p	Italy & Austria	Plugwise kit
ECO [125]	1 Hz	6	8 months	p, q	Switzerland	*Without specification*
PLAID [126]	30 kHz	56	Summer 2013	i, v	USA	*Without specification*
REFIT [127]	8 s	20	2013–2015	p	UK	EnviR aggregator
GREEN Grid [128]	1 min	45	2014–2018	p	New Zealand	*Without specification*
BLUED [95]	12 kHz	1	7 days	i, v	New Zealand	Plug-level FireFly sensors
SustDataED [129]	12.8 kHz	1	10 days	i, v	Portugal	Plugwise system
iAWE [130]	1 Hz	1	73 days	p, f, Φ, i, v	India	LabJack U6 EM6400 smart meter CT sensors
COMBED [131]	30 s	-	1 month	p, i, e	India	jPlug water meter Schneider Electric EM6400 Schneider Electric EM6436
SmartCity	30 min	-	2010–2014	-	Australia	smart meters Plug level equipment
Smart [132]	1 Hz	3	3 months	p, s	USA	eGauge data loggers Smart Energy Switch thermostats
IDEAL [133]	1 s, 12 s	255	23 months	p	UK	CT sensors motion sensors door sensors Temperature sensors humidity sensors light sensors current/gas pulse plug-in probes

Note: i, v, p, q, s, f, e, and Φ represent current, voltage, real power, reactive power, apparent power, frequency, energy, and phase, respectively. SmartCity: Refers to Smart-Grid SmartCity Customer Trial Data. See https://data.gov.au/dataset/ds-dga-4e21dea3-9b87-4610-94c7-15a8a77907ef/details (accessed on 18 April 2021) Smart: Refers to UMass Smart Home Data Set.

4.2. Summary and Insights

In this section, a comprehensive description of the Data Acquisition stage, which involves both appliances and metering devices, has been performed. Appliances has been categorized in literature according to the target application of the HEMS, either monitoring or control. The schematic for appliance categorization can be in found in Figure 5. Metering devices, on the other hand, have been less explored in literature regarding standardization and categorization. In Figure 6, it is shown a schematic diagram of a metering device for HEMS according to IEC TS 63297:2021 standard. Publicly available datasets have been also analyzed, reviewing current solutions in the market and revising its main characteristics. The impact of the sampling frequency and its relationship with the feature extraction is also shown in Figure 8.

5. Communication Network

Communication is indispensable for Smart Grids and residential energy management. In order to connect metering devices to an application host or service provider, a communication network must be deployed. Inside a household, the home area network is used to provide monitoring and control over energy usage. The communication network carries control data generated by the metering devices and home appliances to the middleware technology in which the post-processing (monitoring, control, comfort analysis, occupancy, and other HEMS applications) is performed. Examples of communication technologies include wire field network IEEE 802.3 family, power line communications (PLC), serial communication RS-232/485, wireless field network (IEEE 802.11 family, IEEE 802.15 family, mobile field network) (GSM-based 2G, CDMA-based 3G, LTE-based 4G, NR-based 5G), and low power network (NarrowBand IoT, LoRa, Sigfox) [76,134]. Table 5 compares different technologies deployed in the context of smart homes. Wireless technologies have shown to be preferred over wire field technologies, mainly due to their ease of installation and their cost-efficiency and speed capabilities [135].

Table 5. Communication technologies deployed for residential energy management.

Technology	Type	Standard	Distance Covered	Data Rate
2G [13]	Wireless	GSM	35 km	Low
3G [13]	Wireless	UMTS	35 km	High
4G [13]	Wireless	LTE	35 km	High
5G [13]	Wireless	5G NR	200–500 m	Very high
Bluetooth [43]	Wireless	IEEE 802.15.1	100 m	Low
EnOcean [43]	Wireless	EnOcean	30 m	Low
Ethernet [43]	Wired	IEEE.802.3	100 m	High
HomePNA [43]	Wired	HomePNA	300 m	High
IEEE 802.15.3a [43]	Wireless	IEEE 802.15.3	10 m	Very high
ITU-T G.hn [43]	Wired	ITU-T G.hn	N/A	High
MoCA [43]	Wired	MoCA	-	High
ONE-NET [43]	Wireless	ONE-NET	100 m	Low
PLC [43]	Wired	Insteon, IEEE P1901	1–5 km	High
RFID [43]	Wireless	RFID	200 m	Medium
Serial [43]	Wired	RS-232/422/485	15–1.2 km	Low-Medium
6LoWPAN [43]	Wireless	IEEE 802.15.4	100 m	Low
Wave2M [43]	Wireless	Wave2M	1 km	Low
WiFi [43]	Wireless	IEEE 802.11n/11g/11ac/11ax	50–100 m	Medium-High-Very high
ZigBee [43]	Wireless	IEEE 802.15.4, ZigBee (Pro)	100 m–1000 m	Low
Z-Wave [43]	Wireless	Z-Wave	30 m	Low

Note: Data rate: Low (<1 Mbps), Medium (1–100 Mbps), High (100 Mbps–1 Gbps), and Very high (<1 Gbps).

Figure 9 shows a schematic diagram for HAN. The HAN network carries the control commands from the middleware to the appliances, energy generation, and storage devices, and from the utility to the appliances registered in the gateway. The home gateway serves mainly as an interface between consumers and the outside world. It also ensures a secure communication between the utility and consumers.

Middleware technologies can be located in the household domains (as part of the HAN) or in a cloud platform. In this last case, the communication between the home gateway and the cloud server can be carried out over the internet, connecting the neighborhood area and wide area networks. A smart city communication infrastructure must interconnect smart homes and cloud based service technologies handling the smart city big data load. The requirements of this communication infrastructure were detailed in [38]. As it is expected that smart homes produce a considerable amount of data, and the vast majority of smart grid applications are conceived to operate in real-time, e.g., real-time pricing, demand response, demand side management [3], achieving low latency communication is vital for the communication infrastructure. The 5G technologies rise as a potential candidate since they benefit from virtualization-based and software-defined architectures to provide end-to-end, and a multi-service ecosystem in which users share the physical infrastructure resources and use virtualization method to efficiently meet the requirements of a variety of applications. The main limitation relies on how to efficiently use the physical network, providing a reliable and secure data exchange at the same time [13]. A general overview of the smart city network infrastructure using 5G technologies in shown in Figure 10.

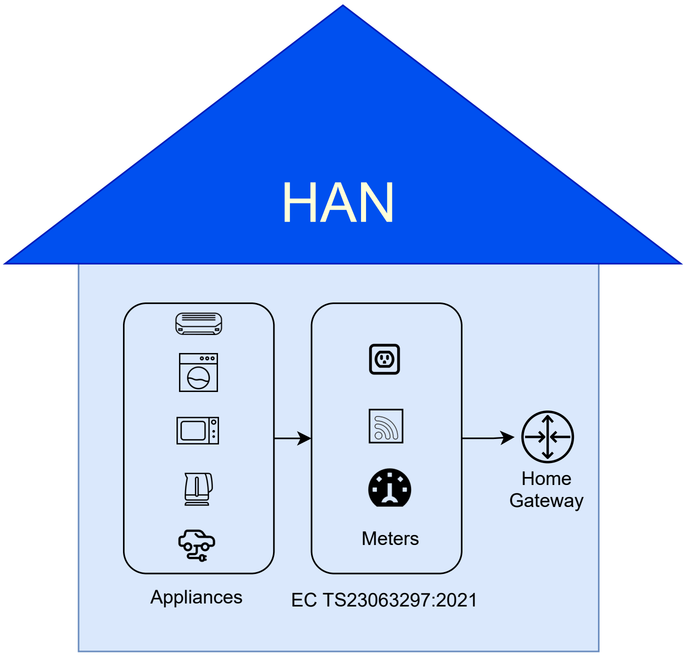

Figure 9. Schematic diagram of a Home Area Network (HAN).

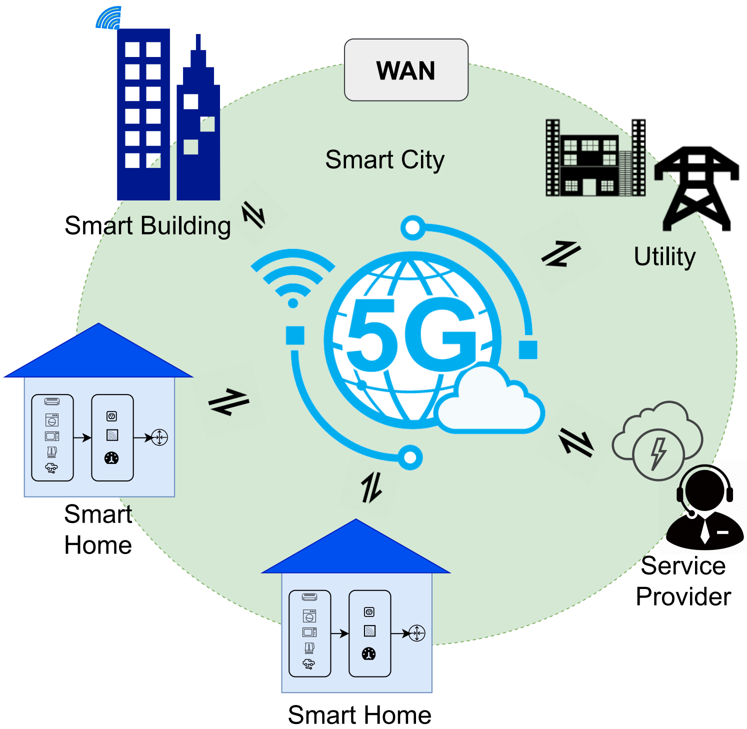

Figure 10. Deployment of Wide Area Network (WAN) using 5G technologies.

5G includes different slices, defined in [136] as a collection of logically customized network functions. These are:

- enhanced Mobile Broadband (eMBB) delivering peak data rates up to 10 Gbps and coverage requirements [136,137].
- ultra Reliable Low Latency Communication (uRLLC), also known as critical communications, which minimizes the delays up to 1 ms [136,137].
- massive Machine Type Communication (mMTC) which supports over 100 times more devices per unit area compared to the previous generation (4G) [136,137].

The support of machine-type communication (MTC) via wireless technology is a very demanding challenge in cellular communications. MTC collects a series of distinctive requirements compared to most internet traffic. Among them low or no mobility, time-controlled operation, tolerance to delay, and requirements for a secure connection to maintain data privacy, are a set of the main concerns in this regard [138].

The need for very low latency communication networks such as 5G imposes new requirements over HANs. According to [38], key challenges lie in wall penetration losses, path losses, and the handling of interference. Therefore, the infrastructure deployed inside the household will necessarily need to adapt and evolve. In [13], the authors proposed a case study in which data generated by household appliances are transmitted to the home gateway using a short-distance communication technology, such as WiFi or Zigbee. Then, the data is sent using long-distance 5G communication technologies to a cloud service provider (middleware). Once there, data storage, management, and analysis take place. The authors of [8] remarked that artificial intelligence (AI) will become indispensable in the near future to make residences more adaptive instead of "just automated". In [139], the authors highlighted the usage of cognitive radios in Smart Grids. They implemented different Zigbee configurations with energy-efficient spectrum-aware algorithms.

In the near future, IoT is expected to grow to become the Internet of Everything (IoE), which aims to trigger the massive deployment of metering devices, appliances, and CPS beyond the capabilities of 5G. Faced with this difficulty, the scientific community has started researching and envisioning sixth generation (6G) mobile communication networks. In the 6G era, applications such as holographic telepresence (HT), unmanned aerial vehicles (UAV), extended reality (XR), smart grid 2.0, industry 5.0, space and deep-sea tourism, and hyper-intelligent IoT are expected to become a reality. These applications require a Tbps data rate and around 0.1 ms of latency [137]. In [137], the authors gave a comprehensive review of the development towards 6G highlighting socio-technological trends, emerging applications, and the requirements to achieve the aforementioned applications. The authors explained that the launch of 6G communication networks by 2030 with a network reliability of over 99.999%.

Summary and Insights

This section has described the Communication Network Stage, comparing available solutions for HAN and WAN. The analysis for HAN is available in Table 5 and Figure 9, and in the case of WAN in Figure 10. The introduction of "beyond 2030" communication technologies has opened the discussion for facing new challenges in the context of HEMS.

6. Data Analytics

The hardcore of the Data Analytics stage is decision making (i.e., control plane). This stage consists of a cloud computing–based central processing mechanism and distributed computing intelligence to optimize both computing and control strategies. In the decision-making process, AI models are implemented, enabling personalize local energy management plans, and adapting the system to the routine and life habits of multiples householders. By this way, the data can be reused, accumulated, and visualized at any time [13]. To successfully develop a control plane for a HEMS, three main tasks need to be accomplished [91]:

1. Collect data from different metering devices, including at the grid level through the HAN.
2. Provide monitoring and analysis of the main loads inside a household.

3. Schedule the consumption of different appliances and resources aiming to use energy efficiently and satisfy user comfort and satisfaction expectancy.

Therefore, load monitoring and forecasting strategies need to be deployed in order to first identify major appliances in the household which are responsible for a higher electrical consumption, and then to build a consumer profile which provide useful information such as behavior patterns and other activities. These activities or patterns are commonly known as activities of daily living (ADL) [16,18]. Major appliances are mostly used by consumers for routine housekeeping tasks such as cooking, doing laundry, or food preservation. Using the information collected from ambient sensors is complementary specifically for load monitoring and forecasting, but it could be very useful for other HEMS applications such as comfort analysis. As an example, in [140], the authors conducted a study to evaluate the impact of ambient sensors in the appliance recognition process. They evaluated a set of features calculated from ambient sensor readings considering their relevance in different decision scenarios. All selected and evaluated features were shown to be relevant for at least one of the considered evaluations. Considering the usage of electrical and ambient features, results showed that systems integrating ambient measurements should consider electrical and ambient features at the same time and not within different decision mechanisms.

6.1. Understanding HEMS as a CPS

According to the above discussion, in the Data Analytics stage, a cyber-infrastructure analyzes the data following a model and/or operating mechanism, and sends instructions back to the physical devices. In [9], the authors defined CPSs as systems which embed the sensing, communication, computing, and control abilities into physical devices, allowing to achieve distributed sensing, reliable data transmission, and comprehensive information processing of the external environment. This way, real-time control is offered through an external loop. Based on this definition of CPS, a HEMS can be understood as a CPS which relates physical devices such as appliances and meters, with energy data. Measurements are collected, processed, and send to the cyber-system through a communication network, and then, control commands will be sent back once analyzed in the cyber-entity, as shown in Figure 11.

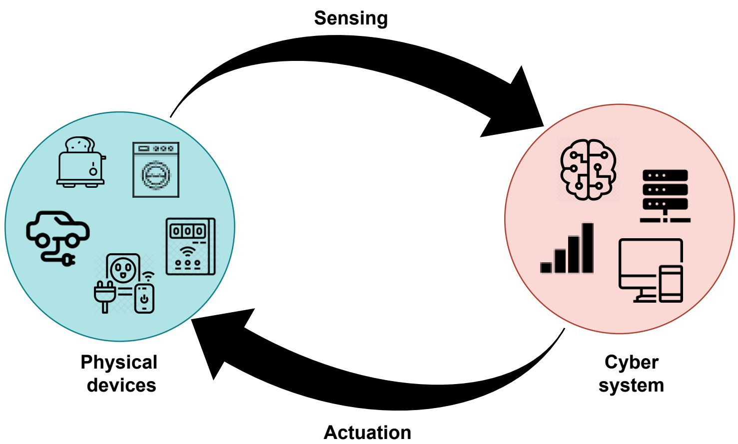

Figure 11. CPS framework for HEMS.

In more details, a control mechanism which can be either rule-based or RL-based will benefit from the data coming from different campaigns (energy monitoring, forecasting, comfort analysis), and signals originated in the grid (utility) to successfully carry out the decision-making process. Figure 12 depicts this idea of the Data Analytics scheme in a HEMS.

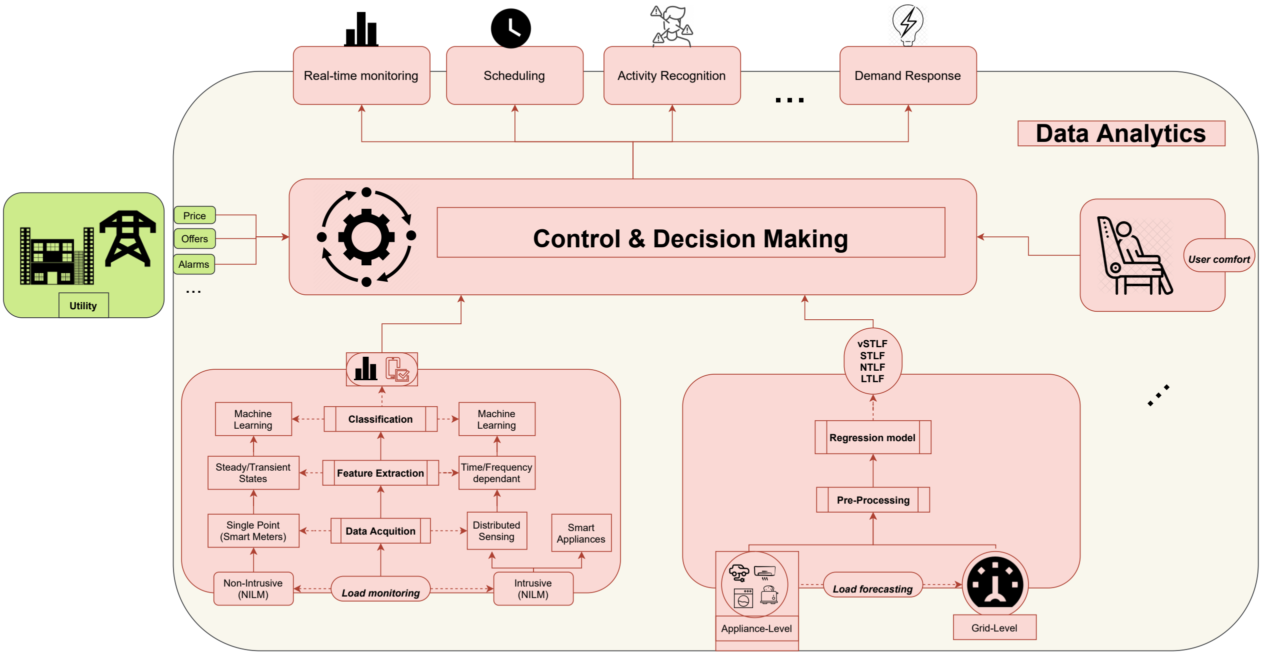

Figure 12. Data Analytics scheme in a HEMS.

The authors of [13] claim that compared to traditional HEMS, CPS-based solutions improved essential parameters such as efficiency and planning, which are very low in conventional HEMS mainly motivated by the inadequate collection of information on energy consumption and analysis, which leads to high energy cost. By integrating CPS strategies in the system, the HEMS acquires powerful capacities for awareness and automatic control. This is achieved through an advanced network infrastructure and Machine Learning techniques, becoming smart HEMS.

6.2. Monitoring Appliances

The process of load monitoring facilitates identifying and monitoring main loads in the household [21,25,43]. There are two main categories to classify the methods to manage such processes: methods based on hardware and those based on software. In both, the goal is to recognize individual appliance loads through two stages, in addition to Data Acquisition: Feature extraction, and Classification [44,45]. In feature extraction, an additional process is performed on the collected samples to obtain a signature that corresponds to the appliance electrical consumption. Lastly, in the classification stage, the resultant features are frequently classified through ML models. The use of ML techniques for predicting the behavior of appliances and translating raw data (e.g., current waveforms, voltage, and power) into an easy and understandable form, are common processes which both methods share [44]. On the other hand, the main difference lies in the Data Acquisition stage. Software-based methods (NILM) collect measurements from a single point of sensing (generally the smart meter device), while hardware-based methods (ILM) usually have more than two points of collection. NILM offers an attractive solution essentially due to its low-cost implementation.

The feature extraction in NILM is mainly divided into two classes, namely, steady-state and transient features. Although these solutions have centered the attention of most studies in the field over the last five years, they have shown less precision and higher difficulty to its deployment in real-world scenarios compared to hardware-based methods. NILM's methodology is primarily based on event detection. It samples the aggregate signal to obtain individual signatures of electrical appliances. The aggregated power signal is usually very noisy, and therefore, only some electrical appliances can be detected, depending on the sampling frequency (e.g., oven, washing machine, air-conditioner, and EV) [23,25].

When facing these kinds of scenarios in terms of the type of appliance used, performance is still inconclusive on most common datasets. Techniques based on ILM consist of two sub-categories. One is the method in which energy appliances' power consumption is obtained using metering devices attached to appliances, also known as distributed sensing. The other is smart appliances (SA) which are devices with integrated capabilities to monitor and report their energy usage.

In ILM, the feature extraction consists of the resultant unique vectors (e.g., sliding window) which are set as input of Machine Learning classifier models. Although the main constraint of ILM is cost, it provides greater efficiency and reliability in place of NILMs. Direct sensors have the sensing and controlling operation of various devices and appliances since they can be collocated (i.e., be placed next to the target appliance). An additional benefit is related to the classification stage. In this regard, the ILM appliance recognition system assigns a label that corresponds to the appliance being used. However, in the future, load monitoring techniques are expected to be hybrid, which means that it will combine the benefits of both NILM and ILM to make a more efficient HEMS [43]. Nowadays, smart appliances usage has been limited due to the high market prices and interoperability issues of these devices. Therefore, distributed sensing becomes an attractive solution for a massive deployment, but it needs to take advantage of communication technologies to allow the integration of all electrical devices.

6.3. Forecasting Appliance Consumption

On the other hand, load forecasting can be performed at two different levels: grid level or appliance level. For the utility, the prediction of the load allows better management of the energy generation and distribution resources, and can inform dynamic pricing to reduce the peak demand. For the individual consumers, predicting the load allows the identification of energy loads that can be shifted to off-peak hours, therefore reducing the energy bill. In terms of control, load forecasting can be key to provide energy-efficient scheduling plans for smart homes [36]. In [33], the authors classified forecasting methods based on the prediction period:

- Very Short-Term Load Forecast (vSTLF): Referring to forecasting the load for the next several minutes.
- Short-Term Load Forecast (STLF): Refers to load prediction for the next several hours or a week ahead.
- Medium-Term Load Forecast (MTLF): Refers to predictions made for a week or a year ahead.
- Long-Term Load Forecast (LTLF): Referring to predictions made for the next several years.

Load forecasting is modeled as a time series problem in which ML techniques have shown promising results in recent years, especially those based on convolutional neural networks (CNNs) and long short-term memory (LSTM) networks. The input of the models are generally features which are based on the history of the householders. This means that these features can be based on historical power consumption or others more related to environmental parameters and economy. The output of the model can be either a single value or a sequence representing the future power consumption at a given time resolution (month, day, hours) [36]. In [141], the authors used continuous and categorical data of each consumer as input of three different models: feed-forward neural network (FFNN), a CNN, and an LSTM network. The model's objective is to predict monthly consumption at the grid level. The categorical data represents the months is to be predicted, the number of phases of the power and the class of the consumer (e.g., residential, industrial). The authors of [142] benchmarked a CNN and an LSTM model to estimate the peak demand at the grid level. They used historical demand records as input, along with temperature and economic index information. Moreover, in [142], the authors gave a literature review comparing the methods and resolutions used for forecasting.

Forecasting at the appliance level can be very useful for HEMS since it allows to identify usage patterns of individual appliances, which is a key fact for scheduling and control mechanisms. However, this is still a challenge, being a motivation for the ongoing research in recent years. In [36], the authors built an LSTM-based sequence-to sequence (seq2seq) learning model that could capture the load profiles of appliances. The LSTM network mapped a sequence of past-24-hours data to a fixed-size vector, then the appliance type was detected, and the input sequence was regenerated in a reverse form using another LSTM network. The output produced a sequence of energy consumption with resolution for the next hour. Different from this work, in [32], the authors performed a principal component analysis (PCA) feature selection, whose output is then passed to different ML models. The best results were shown by recurrent deep neural network (R-DNN). The selected features are based on historical consumption as well as environmental measurements such as temperature.

6.4. Utility Feedback and Other Applications

Finally, HEMS can benefit from certain instructions offered by the utility, which can be determinant for appliance scheduling. Examples include price signals, offers, or alarms. This information is also important for demand-side management or demand response campaigns. The commands or instructions given by the control plane of the HEMS have a wide spectrum of applicability. For example, the gathered information can be used for energy savings, such as in [14]. Other applications may depend on the context in which the system is being deployed. This is the case of remote monitoring, activity recognition and other healthcare services. In [2], the authors presented broad applications and used the view of Appliance-Level Energy Characterization (ALEC) including feedback, recommendations and customized marketing, energy-efficient appliances and labeling standards, utility and grid operations, flexibility for renewable energy integration, energy management and conservation, equipment manufacturing and technology development, smart security, surveillance and healthcare, in addition to social sciences and economics benefits.

6.5. Summary and Insights

This section has provided a detailed description of the Data Analytics stage. In this layer, the HEMS must accomplish three main tasks: data collection, monitoring, and decision making. By this way, real-time control is performed in a closed loop, in which two main entities interact: physical devices (appliances and meters) and a cyber system that process the data, thus defining a CPS-based HEMS. The framework of such a system is shown in Figure 11. The schematic for the Data Analytics stage of the CPS-based HEMS is shown in Figure 12. In addition, an insight to some of the most significant applications offered at this stage is provided. Among them, appliance monitoring and forecasting are emphasized due to their impact in the decision-making process.

7. Case Study: Appliance Monitoring

Based on the given definitions and discussion presented in the previous sections, we envisioned a cyber-physical approach for a HEMS. To validate our statement we proposed a platform tested in a real-case scenario. To validate the proposed architecture we implemented a testbed in a house in Valparaiso, Chile. The testbed is a proof of concept demonstration which allows to assess the performance of the system. It consists of the implementation of the short-scale in a laboratory environment presenting a considerable higher degree of complexity when compared to simple simulation. Dealing with real-time data causes some new challenging, especially in the pre-processing and early manipulation stages of data. In the current stage, we focus only on monitoring purposes.

Based on the discussion given in Section 4, smart plugs have become a reliable option for smart metering in the data collection phase. Their relatively low market prices make them a very attractive solution. In the Chile market, some devices are usually mislabeled as smart plugs, having only capabilities to turn on or off the power supplied to the appliance connected directly instead of collecting readings regarding their power consumption. In the case of Sonoff S31, although it fits the required features for the Data Acquisition stage, it is incompatible with the Chilean electric plug socket (C and L). With this consideration in mind, none of the available smart plugs in Chile were useful for Data Acquisition stage. To overcome this issue, we modified one device available on the market, the Sonoff Pow R2, shown in Figure 13A. This device is able to acquire power readings from an appliance, but its form factor does not provide a plug. As a solution, the modified version can be seen in Figure 13B,C. Sonoff devices have some limitations with the provided firmware, not having the capability for being plug and play. Therefore, we chose Tasmota (see https://tasmota.github.io/docs/ (accessed on 15 July 2021)), an open-source firmware, for configuring the Sonoff devices. This firmware allows controlling the Sonoff device through a web interface, called Web UI, where different parameters can be configured, such as the Message Queue Telemetry Transport (MQTT) communication protocol.

Figure 13. Equipment for Data Acquisition stage: Sonoff Pow R2 (**A**) and customized version used as smart plug (**B**,**C**).

Following a cloud service-oriented approach, we developed a five-domain architecture using Amazon Web Services (AWS). The IoT domain encompasses AWS IoT Core, which serves as a message broker allowing to connect multiple IoT devices through MQTT protocol. The Log and Metrics domain is a monitoring and observability domain which uses CloudWatch services to collect and process input data in the form of a record provided by the IoT domain. On the other hand, the Data Stream domain provides IoT Analytics and IoT Events. IoT Analytics allows to clean, transform, and enrich IoT data before storing it in a database. In the case of IoT Events, it enables early detection of events to activate alerts and automatic actions to respond to events. The serverless backend domain includes a DynamoDB, an AWS non-SQL database service to store data from the IoT devices, and an API Gateway, which guarantees access to applications (End User Frontend domain), and to logic or functionalities from the backend services, including Lambda functions that facilitate table updates in DynamoDB. The End User, Frontend domain, includes a S3 Bucket, which stores a CloudFront web app that uses Cognito to provide control of user authentication. Figure 14 shows a plot with the power consumption from the refrigerator and the washing machine over a 3 h interval.

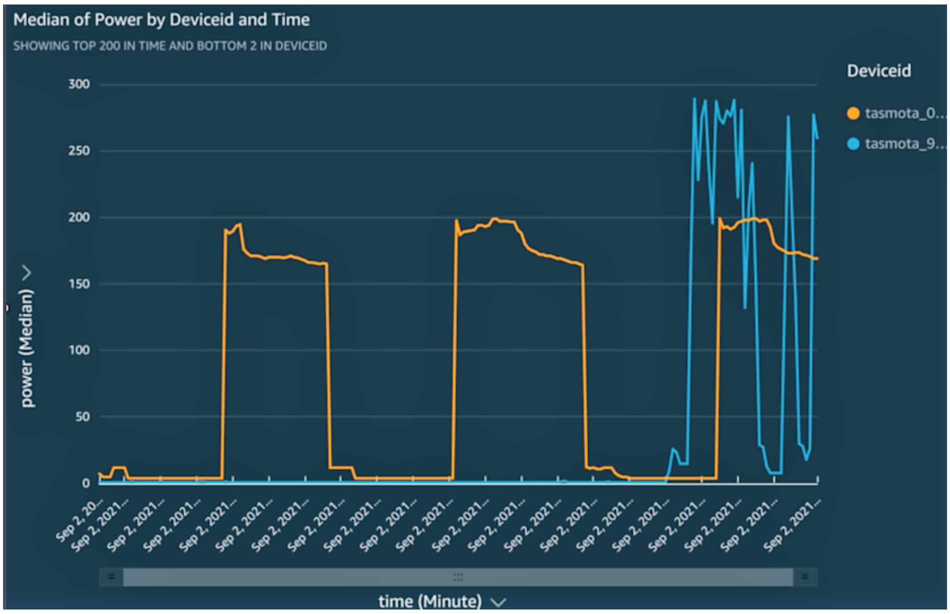

Figure 14. Power consumption of a refrigerator and a washing machine collected through Sonoff Pow R2 devices.

In addition to the refrigerator and the washing machine, data from two more appliances were stored, including a kettle and a microwave. Using the data from these last three devices (washing machine, kettle, and microwave) we extracted a set of seven features every for 10-samples window. These features are: the mean, the maximum, and the minimum values, in addition to the kurtosis, the skewness, the coefficient of variation, and the number of samples above the mean inside the windows. The features, which are given in [16,18], were used to train a FFNN classifier aiming to recognize the appliances attached to the Sonoff devices. Figure 15 shows the confusion matrix obtained after identifying appliances with data coming from the test set.

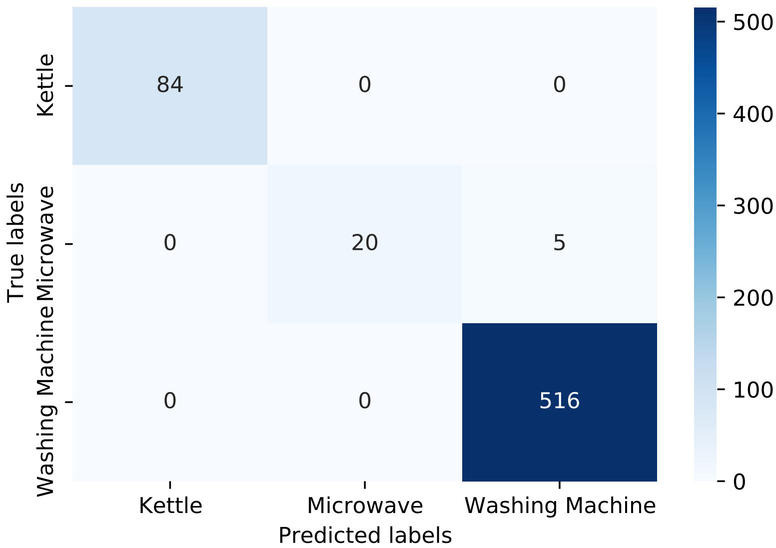

Figure 15. Confusion matrix obtained after training a FFNN classifier using the data coming from three different appliances: a washing machine, a kettle, and a microwave. The data was collected using Sonoff Pow R2 devices.

As shown in Figure 15, only five samples were incorrectly classified, which is reasonable since they correspond to the minority class (i.e., the class with the lower amount of samples). An accuracy of 0.992 was achieved, which represents a very good result compared to [16,18] regarding appliance recognition and load monitoring. The samples have been collected for several months using these data for training. With this smart HEMS implementation, comprehensive visibility, flexibility, and monitoring of home appliances is given can guarantee user satisfaction and comfort.

Summary and Insights

Based on the analysis performed in the previous sections, a case study was carried out in one house in Valparaiso, Chile. This way, it was developed a testbed implementation to validate the proposed architecture, shown in Figure 2, for monitoring purposes. The equipment used can be seen in Figure 13. The results are shown in Figures 14 and 15. Future work will be focused on implementing the control part, thus closing the loop of the CPS-based HEMS.

8. Challenges and Main Research Directions

In a general perspective, the main challenges to be handled in HEMS are related to achieving energy efficiency and dealing with implementation costs. To this end, a standard approach which allows to attend every HEMS application based on the collected data, is still a source of discussion in the research community. According to the aforementioned stages, a series of challenges were identified.

Considering Data Acquisition, the following challenges exist:

- Access to smart meter measurements is still limited in some countries due to regulation and implementation issues.
- High-resolution data cannot be achieved with most commercial smart meters today with complexity in setup, data storage, and cost.
- Smart appliances usage has been limited due to the high market prices and interoperability issues of these devices.
- Sensors capable of measuring at high sampling rates are needed to satisfy large-scale implementation requirements of HEMS.

In terms of Communication Network, the following challenges were identified:

- Interference and wall penetration losses are the main challenges to be handled in smart homes.
- More flexibility is needed, which translates into taking advantage of the unused spectrum.
- There is a need for technology which connects the smart homes toward developing a smart city infrastructure, and allowing real-time operation of multiple applications. The 5G and 6G technologies are strong candidates. However, identifying the requirements for embracing these technologies at different levels (home or city) is still a subject of debate.
- Conventional wireless communication technologies, such as WiFi or Zigbee, are insufficient for communication range, energy consumption, and cost of most HEMS applications today.

Regarding Data Analytics, the following issues were found:

- Different requirements must be considered regarding data resolution, accuracy, real-time, and the number of devices to be covered.
- NILM methods have less precision and higher difficulty to their deployment in real-world scenarios compared to ILM. The latter, in contrast, offer more reliability at expenses of cost. Therefore, developing a hybrid solution is an attractive solution for load monitoring. However, it introduces several challenges that need to be attended.
- Appliance level can be very useful for HEMS since it allows to identify usage patterns of individual appliances. However, this task has received less attention from the research community. Building a unique model which forecasts the consumption of different appliances is still more complicated to achieve.

- Although reinforcement learning and rule-based approaches have been proposed for scheduling and control mechanisms, a detailed comparison (through a sensitivity analysis and/or evaluation) of both cases is needed.
- Consumer privacy can hinder the deployment of Smart Grids and HEMS since energy data expose the common habits and routines of users. Therefore, secure access to authenticated parties must be provided through cybersecurity and encryption mechanisms.

9. Conclusions

The continuous increase in energy demand in recent years has led to the appearance of Smart Grids, which promise to change the way in which electricity is produced, managed, and consumed. At the user end, the smart grid aims to manage several entities such as smart meters, electric vehicles (EVs), and energy storage systems (ESS). Thus, an efficient residential energy management methodology is required in which Home Energy Management Systems (HEMS) allow households to effectively centralize the service management and provide users with functionalities for the internal and external exchange of information. In that sense, HEMS must perform two main tasks: real-time energy monitoring of consumers using meters and smart devices, and scheduling the optimal energy consumption of household appliances. Recently, data-driven approaches, based on various Machine Learning (ML) methods and Internet of Things (IoT) technologies represent an attractive solution to achieve the goals in monitoring, protection, and control by incorporating sensors, actuators, and measuring devices. The development of such systems brings benefits in a wide variety of sectors from remote healthcare to business services.

In this paper, a survey on state-of-the-art concepts and techniques regarding residential energy management are given. We proposed a cyber-physical approach consisting of three stages: Data Acquisition, Communication Network, and Data Analytics. In terms of Data Acquisition, a thorough review of the relevant literature yielded different available solutions and products which represent safe options for smart metering devices in the data collection phase. IEC TS 63297:2021 Standard has opened the door for standardization providing the main parameters for a device that should be considered as a meter, which represents a huge advantage to be adapted in future solutions. For the Communication stage, different technologies were reviewed in terms of HAN and WAN. The wireless data exchange using WiFi, Zigbee, and LoRa are well-known technologies offering reliable connection between appliances and metering devices. However, to meet the requirements of beyond 2030 communication technologies, such as 5G and 6G, these solutions will need to evolve to allow the implementation of new smart grid applications. Regarding Data Analytics, we analyzed relevant literature highlighting this stage as the cyber part of the HEMS.

Based on the performed analysis, we proposed a three-layered architecture for HEMS. The proposed cyber-physical platform was capable of providing monitoring of the main appliances inside a household. To validate the system operation, we deployed the testbed in a house in Valparaiso, Chile. The results showed an accuracy above 99% for appliance recognition. Future work will focus on expanding this proof of concept, adding more capabilities such as energy consumption forecasting and real-time control of appliances.

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Abbreviations

The following abbreviations are used in this paper:

EVs	Electric Vehicles
ESS	Energy Storage Systems
HEMS	Home Energy Management Systems
ML	Machine Learning
IoT	Internet of Things
CPS	Cyber-Physical Systems
5G	Fifth Generation
6G	Sixth Generation
DER	Distributed Energy Resources
EI	Energy Internet
IT	Information Technology
DT	Digital Twins
PIoT	Power Internet of Things
HAN	Home Area Network
WAN	Wide Area Network
DR	Demand Response
ADL	Activities of Daily Living
LPWAN	Low Power Wide Area Networks
LoRaWAN/LoRa	Long Range
ILM	Intrusive Load Monitoring
NILM	Non-Intrusive Load Monitoring
AMI	Advanced Metering Infrastructure
RL	Reinforcement Learning
DHW	Domestic Hot Water
PV	Photovoltaic
DDPGs	Policy Gradient
DRL	Deep Reinforcement Learning
AS-REMS	Appliance Scheduling-based Residential Energy Management System
MILP	Mixed Integer Linear Programming
DL	Deep Learning
FSM	Finite State Machines
TV	Television
NAN	Neighborhood Area Network
CT	Current Transformer
DC	Direct Current
PC	Personal Computer
AC	Alternating Current
BLUED	Building-Level fUlly-labeled dataset for Electricity Disaggregation
HVAC	Heating, Ventilation and Air Conditioning
CO_2	Carbone Dioxide
RFID	Radio Frequency Identification
REDD	Reference Energy Disaggregation Dataset
AMPds	Almanac of Minutely Power Dataset
UK-DALE	United Kingdom Domestic Appliance-Level Electricity
DRED	Dutch Residential Energy Dataset

GREEND	GREEND ENergy Dataset
ECO	Electricity Consumption and Occupancy
PLAID	Plug Load Appliance Identification Dataset
REFIT	Electrical Load Measurements dataset
GREEN Grid	Renewable Energy and the Smart Grid
SustDataED	SustData for Energy Disaggregation
iAWE	Indian Dataset for Ambient Water and Energy
COMBED	Commercial Building Energy Dataset
SmartCity	Smart-Grid SmartCity Customer Trial Data
Smart	UMass Smart Home Dataset
IDEAL	IDEAL Household Energy Dataset
USA	United States of America
UK	United Kingdom
IEEE	Institute of Electrical and Electronics Engineers
PLC	Power Line Communications
RS-232/485	Recommended Standard 232/485
GSM	Global Communication System
CDMA	Code Division Multiple Access
3G	Third Generation
LTE	Long Term Evolution
4G	Fourth Generation
NR	New Radio
NarrowBand IoT	Narrowband Internet of Things
2G	Second Generation
ITU	International Telecommunication Union
MoCA	Multimedia over Coax Alliance
eMBB	enhanced Mobile Broadband
uRLLC	ultra Reliable Low Latency Communication
mMTC	massive Machine Type Communication
AI	Artifitial Intelligence
IoE	Internet of Everything
HT	Holographic Telepresence
UAV	Unmanned Aerial Vehicles
XR	Extended Reality
vSTLF	Very Short-Term Load Forecast
STLF	Short-Term Load Forecast
MTLF	Medium-Term Load Forecast
LTLF	Long-Term Load Forecast
CNNs	Convolutional Neural Networks
LSTM	Long Short-Term Memory
FFNN	Feed Forward Neural Network
R-DNN	Recurrent Deep Neural Network
ALEC	Appliance-Level Energy Characterization
Web UI	Web User Interface
MQTT	Message Queue Telemetry Transport
AWS	Amazon Web Services
SQL	Structured Query Language
API	Application Programming Interface

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