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A Survey on Home Energy Management

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ABSTRACT Energy is a vital resource for human activities and lifestyle, powering important everyday infrastructures and services. Currently, pollutant and non-renewable sources, such as fossil fuels, remain the main source of worldwide consumed energy. The environmental impact of their exploitation has boosted research and investments in alternative, clean and renewable sources, including photovoltaic and wind-based systems. As a whole, buildings are one of the major energy consumption sectors. Hence, improving energy efficiency in buildings will result in economical and environmental gains. In the case of households, home energy management systems are mainly used for monitoring real-time consumption and to schedule appliance operations so that the energy bill could be minimised, or according to another specific criterion. This work aims to survey the most recent literature on home energy management systems, providing an aggregated and unified perspective in the context of residential buildings. In addition, an updated literature list regarding commonly managed household appliances and scheduling objectives are included. Physical and operational constraints, and how they are addressed by home energy management systems along with security issues are also discussed.

INDEX TERMS Energy efficiency, home energy management systems, household appliance models, load management, optimal scheduling, smart homes, security.

I. INTRODUCTION

Energy is an essential resource to life and all living organisms. In current days, electrical energy plays a vital role in human lifestyle, powering key infrastructures and services. Fossil fuels still account for the production of the majority of worldwide consumed electricity. According to the United States Energy Information Administration [1], in 2018, fossil fuels ensured 62% of primary electricity production in the United States. Unlike clean and renewable alternative sources such as wind or solar, fossil-fuel exploitation has a strong environmental impact as a result of green house gas (GHG) emissions, global warming and health hazards. In addition, its current consumption surpasses natural regeneration, resulting in an inevitable depletion of resources, if other sources or options are not exploited.

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These concerns have fostered not only the search for alternative, renewable and clean energy sources, but also the awareness regarding energy efficiency and sustainability. In the last few years, the traditional power grid has been reshaped into an intelligent, highly reliable and fully automated infrastructure, paving the way to the so-called "smart" grid paradigm. This new power grid model supports the deployment and integration of distributed generation and storage resources, namely of renewable nature. It relies heavily on smart appliances and two-way communication channels linking the utility and consumers. This makes possible real-time coordination and dynamic optimisation of grid operation and resources [2].

At demand-side, smart homes incorporate digital sensing and communication devices, which allow for continuous consumption monitoring, intelligent appliance control and communication with the utility and grid. Smart homes are a key element to the operation and effectiveness of smart grids, not only by supporting optimised management to grid resources and infrastructures, but also by contributing to energy efficiency. Buildings are responsible for around 40% of worldwide energy consumption [3], which is expected to significantly increase over the next few years [4]. As such, efficiency improvements, implemented at global scale, can mitigate this trend, reducing energy consumption, wastage, costs and environmental hazards associated with generation.

In the last few years, there has been a growing interest in home energy management systems (HEMSs). They provide the means for automated and intelligent control of smart home appliances. HEMSs target efficient energy management, contributing to preserving finite fossil fuel resources, while lowering energy consumption, wastage and costs. The conceptualisation of HEMSs involves several aspects, including their definition, characterisation and overall architecture, as well as their underlying purpose in household environments. Optimisation-based techniques are extensively employed within HEMSs. They enable appliance allocation under dynamic objectives and constraints. In [5] this trend is highlighted, calling for further research to address HEMSs specific needs, in particular concerning scalability, model complexity and uncertainties. Intrinsically linked to the characterisation of HEMSs are: (i) their in-operation goals, including minimising the overall energy bill, reducing carbon emissions, or achieving a given target load profile, just to name a few; (ii) the strategies employed to achieve such goals, in particular how to schedule individual appliances or deciding upon which unnecessary loads should be turned off; (iii) managing household appliances; (iv) how they are individually modelled.

This paper provides a comprehensive review with respect to HEMSs, including an outlook on these systems and closely-related topics. Approaches aiming at household appliance modelling, scheduling strategies, operational and residential objectives and constraints are discussed. In addition, the incorporation of residential load uncertainties into HEMSs is also covered. Two main contributions are provided in this work. Firstly, a thorough review on recent HEMS developments is presented, including operational goals and strategies to meet them, household appliance management policies, incorporation of uncertainty in HEMSs' decision making, performance metrics, and common attack targets and corresponding counter-measures. Secondly, an updated literature list on HEMSs is included, which to some extent can be regarded as gateway to the most relevant and updated bibliography on the field.

The remainder of this paper is organised as follows. In Section II HEMSs are defined, characterised and contextualised within the smart grid digital paradigm. Centralised and distributed energy management schemes are discussed, as well as the most recent advances regarding the integration of plugged-in electric vehicles on the digital grid. Section III introduces the main approaches to energy saving in buildings. Section IV presents a literature categorisation regarding household appliances included in HEMSs infrastructures. Common managed appliances are presented, along with adopted strategies to model their behaviour and dynamics, including in-operation dynamics and uncertainties. Section V is devoted to appliance scheduling, being discussed common techniques, scheduling criteria and constraints. Section VI focuses on cyber attack vectors and counter-measures for HEMSs, while Section VII describes some of the challenges this field is facing, along with prospective research directions. Finally, Section IX concludes the survey.

II. HOME MANAGEMENT SYSTEMS

Smart buildings represent a branch of ubiquitous computing that comprises the incorporation of Internet of Things (IoT) technologies into buildings for comfort, healthcare, safety, security and energy efficiency [6], [7]. They are an integrating part of ongoing technological advancements in power grids, boosting the deployment of smart sensors and other advanced metering devices, which make remote communication, monitoring and actuation on household appliances possible.

Among different types of buildings, smart homes have been the subject of great research interest, particularly from the energy efficiency point of view. Smart homes offer better quality of life and efficiency by taking advantage of remote monitoring and self-adaptive context-aware mechanisms, in order to identify needs and preferences of residents, and also to coordinate appliance operation. Wired and wireless sensor and actuator networks are deployed on smart homes, being collected sensor data and contextual information stored in a central platform. This entity is also responsible for processing acquired information, enabling an optimised management and actuation of household appliances, for the sake of residents' comfort and energy efficiency.

Distributed power generation has also been boosted, particularly from renewable sources such as hydro, solar and wind [1]. Furthermore, individual households are also becoming players in the production of their own electricity, via local (micro) solar and wind systems. When power generation exceeds local demand, the resulting surplus can be used to charge local batteries, for subsequent domestic use, or inject into the grid with a given profit. Grid power injection requires a bi-directional interaction between the grid and local micro-generation systems, propped up on a two-way communication network, so as to ensure grid safety and stability. Taking advantage of advanced metering infrastructures (AMI) and remote control and automation systems, grid information can also be considered in managing power resources at household level. This is particularly valuable for utility and grid companies, as it allows them to predict future demands with superior accuracy, reducing electricity waste and decreasing generation costs.

From a demand-side perspective, HEMSs are in-line with the smart grid paradigm shift. A HEMS has the ability to interact with household devices and the utility, allowing appliance schedules to be adjusted, in order to cope with constraints and taking into account external information, such as updated grid prices or meteorological forecasts [8].

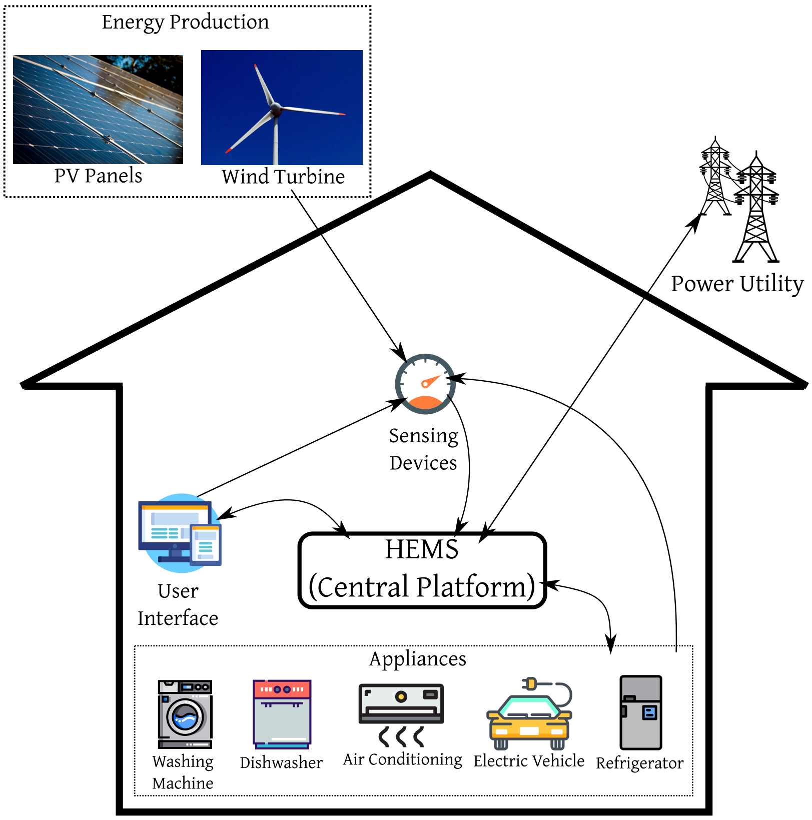

FIGURE 1. HEMS architecture[1].

This is usually achieved by turning devices on or off, reducing the overall demand and considering periods of low electricity price and higher power generation.

A. HEMS COMPONENTS

Figure 1 presents the general architecture of a HEMS, which comprises the following components:

(a) *Sensing and measuring devices* – used to measure physical quantities, such as temperature, humidity or light, or to detect motion or room occupancy, just to name out a few. Smart meters are commonly used by HEMSs, collecting detailed energy consumption of individual appliances and other human activities-related information. Smart meters also facilitate two-way communication between HEMS and the utility.

(b) *Smart appliances* – consist of typical household devices (e.g., dishwasher, refrigerators or air conditioning units), enhanced with computing and communication capabilities. Energy generation devices such as photovoltaic (PV) panels and wind turbines are also considered. Smart appliances communicate with a central platform, which handles all measured data and coordinates appliance uses.

(c) *User interface* – a device via which residents can interact with the HEMS. Interfaces can be used to display information, such as current consumption or energy expenses, and for specifying residents preferences, including appliance priorities, comfort parameters or scheduling goals. Touch screen or mobile application interfaces are very common, although other less user-friendly options, e.g. a computer terminal, can also be considered.

(d) *Central platform* – aims at managing and optimising energy usage. It receives smart meter information and adopts a scheduling mechanism, usually computed via an optimisation approach, assuming a given performance index. Energy bill is a common choice, along with comfort, peak reduction and GHG emissions.

In a HEMS, sensors are continuously collecting information regarding household activities. Usually, individual appliance consumption signals are collected, although disaggregation techniques such as NonIntrusive Load Monitoring (NILM) [9] can be applied to extract individual appliance consumption. Collected data is then dispatched to the central platform, where it is stored and processed. It should be pointed out that billing data and weather forecast can also be retrieved and used in the optimisation stage. Furthermore, in a fully designed HEMS, the central platform complements residents' specifications and preferences with sensed and inferred information. A scheduling strategy is then

[1] Icons taken from https://www.flaticon.com.

employed to determine appliance operation times that meet user-defined preferences, under physical constraints. Proper communication protocols between the central platform and the underlying smart appliances ensure the implementation of computed optimal scheduling.

B. CENTRALISED VS DISTRIBUTED MANAGEMENT

Although HEMSs are often deployed to reduce electricity bill at demand-side, they can never operate in complete isolation from the grid and customers. The reason is related to the fact that the grid needs to ensure adequate supply to multiple customers under a dynamic load demand, namely by deploying additional generators. Furthermore, a HEMS needs to be aware of the demand required by other buildings, so that high demand stress on the grid is avoided, in particular during unexpected periods of time. If, for example, households start shifting many loads to night periods, the grid infrastructure may not be able to match demands within feasible time. This could result in power outages and blackouts, and therefore coordinated energy management is imperative.

Two approaches can be considered, namely centralised and distributed [10]. Centralised HEMSs implement methodologies for coordination of consumption and generation on a platform, which is located at the utility level. In this context, the central platform, mentioned in Section II-A, no longer handles appliance scheduling. It strictly assumes sensor data aggregation, processing and inference tasks. Under this topology, buildings should send to the grid consumption related information, including sensor data, appliance operation needs and constraints, just to name out a few. Next, taking this information into account, the grid centralised management platform schedules demand-side electricity and generator operations in order to optimise specific criteria, for instance operational costs, or peak-to-average ratio. This leads to a massive constrained optimisation problem, with the corresponding heavy computational burden.

Unlike centralised methodologies, distributed-based approaches rely on several independent decision-making entities to plan demand-side and grid operations. Commonly, they cooperate with one another and the grid to find a mutual agreement feasible solution that maximises individual goals, without compromising other decision-makers' goals or power supply stability. As grid resources are managed in a distributed way, the underlying computational burden is shared among all players, resulting in a significantly lower individual computational overhead. This makes distributed strategies very appealing, particularly in smart grid scenarios where many different assets need to be coordinated. In order to reach a global consensus, it demands frequent communication among participants. Despite the inherent increase in the volume of transmitted data over communication networks, sensitive information is typically not exchanged as much as for centralised-based scheduling. For example, instead of transmitting individual appliance operation needs and constraints, decision-makers should only provide the minimum required power level [11]. Decision-makers are mainly modelled by intelligent agents in game-theory and multi-agent-based techniques [10]–[12], or even mathematical optimisation-based approaches [13]–[15].

It should be mentioned that, although distributed energy management-based techniques are applied to groups of buildings [10], [11], [13], they can also be used for energy management at individual buildings level [14]. In such cases, agents are assigned a single appliance and are responsible for managing its operation.

C. ELECTRIC VEHICLE INTEGRATION

Throughout this review, an electric vehicle (EV) is any vehicle in which electricity accounts for some or all driving energy, which is ultimately supplied through a rechargeable battery [16]. In the last few years, EVs have attracted considerable interest from academia and practitioners alike [17]. They are set to play a major role in reducing global pollution, being a more efficient and less polluting alternative to conventional internal combustion engines [18].

A large-scale adoption of EVs raises important challenges for current and future power grids. As these vehicles require substantial electricity, customer demand is expected to significantly increase over the next few years. This results in higher demand stress and generation capacity needs from the grid infrastructure [17]. Furthermore, when the grid is not able to generate or provide the required demand of electricity, additional measures need to be adopted. In [19], [20] it is argued that there are two main approaches to address the challenges posed by EV charging: (i) to reinforce the grid infrastructure and build additional networks to accommodate substantial peaks; (ii) to develop and implement enhanced charging management strategies capable of controlling EV charging, while taking into account supply constraints of the grid. It should be mentioned that, based on the flow of electricity between the grid and a vehicle, charging can be classified as unidirectional or bidirectional [17].

1) UNIDIRECTIONAL EV CHARGING

In unidirectional charging, EVs are handled as any other electrical appliance, in the sense that an unidirectional flow of electricity moves from the grid to the vehicle while charging its battery. This category can be further split into uncontrolled or controlled charging. Uncontrolled or "dumb" charging follows traditional appliance use and charging behaviour, since a EV is plugged-in when it needs to be charged and unplugged by the owner, either when the battery is full or the vehicle is requested. The grid has no prior knowledge regarding EV's charging cycles, which implies that when a significant number of EVs is simultaneously plugged-in, unexpected demand peaks may occur. When the density of EVs served by a power grid is small, the network infrastructure can still be capable of supporting increased demands [17]. However, in the case of large-scale scenarios, peak-to-valley difference and the risk for network losses are significantly increased, overloading the infrastructure and causing undervoltage effects [21]. As for controlled or smart charging techniques, energy used in EV charging and demanded by other on-site appliances is safely balanced, thus allowing an efficient EV charging, while minimising demand peak and grid stress.

Two approaches for EV charging can be found in the literature, including centralised and decentralised topologies [17]. In decentralised methodologies, each vehicle is equipped with its own charging management system, which controls its charging cycles and communicates with other vehicles. As for centraliased charging schemes, a single entity is used to coordinate individual charging cycles, while taking into account global demand. Centralised solutions can be further split into [17] (i) aggregator-based, (ii) distributor system operator (DSO) based, and (iii) multi-agent-based. For both aggregator and DSO-based strategies, a single entity manages several vehicles from users with common interests. In aggregator-based schemes, an *aggregator* is adopted, whereas for the other approaches each distribution company ensures this service. As both aggregators and DSO managers deal with large electricity purchases, they have a stronger negotiating power than if EVs were considered individually, which results in lower bills.

Depending on the network topology, multi-agent systems can also be considered. As discussed in Section II-B, groups of independent decision-makers coordinate their demands, in this case EVs charging, looking for a mutual agreement that maximises individual goals without minimal impact on each decision-maker preferences or power supply stability.

2) BIDIRECTIONAL EV CHARGING

Bidirectional EV charging considers that electricity can flow not only from the grid to a vehicle, but also from a vehicle to the grid. This allows EVs to be used as both mobile energy storage systems and generators. As such, if EVs are capable of not only demanding power from the grid, but also injecting it in the grid through their own batteries as a source, then they can be exploited to accommodate the highly dynamic generation and demand in modern grids. When grid production exceeds current demands, not fully charged EVs parked at appropriate locations can accommodate overproduction, while when demand suddenly peaks and the grid needs to increase its generation, EVs can be used as local generators supplying the required demand. As such, proper billing mechanisms are thus needed in this dual interaction with the grid. Furthermore, EVs electricity supply needs to be carefully managed, avoiding EV battery drainage and weighing the impact on batteries lifetime.

Three bidirectional approaches are discussed in [17]: (i) vehicle-to-grid (V2G), (ii) vehicle-to-building (V2B) and (iii) vehicle-to-home (V2H). V2G is focused on temporary EV battery discharges to accommodate peak demands, and for general power regulation. Aggregator-based unidirectional approaches can also be considered, being several EVs managed by an aggregating unity, which coordinates charging and discharging cycles, taking into account the grid needs. Both V2B and V2H are variants of V2G, where local generation, usually from renewable sources, is balanced between building/home supply and EVs batteries charging. As renewable production is uncertain, power surplus can be partially stored in EV batteries. When demand exceeds current grid generation capacity, batteries can then be used to account, at least in part, for extra power demand. This contributes to power generation flattening and grid infrastructure optimisation.

D. SUMMARY

HEMSs provide automated and intelligent control of smart home appliances, propped up on IoT and smart grid paradigms. These management systems aim to improve efficiency, promoting renewable energy use and bill cut. They rely on smart sensors, appliances and AMI for continuous monitoring.

Commonly, HEMSs operate by scheduling domestic consumption loads, requiring two-way communication between the grid and other customers to coordinate load demands in order to avoid grid infrastructure overloading. This coordination can be achieved via centralised or distributed approaches. Centralised management-based approaches carry out all required operations on a single entity, which implies having access to sensor data, appliance operation needs, constraints and additional relevant information. This raises several issues, such as sending private information over the grid or dealing with the heavy computational burden associated to solving large-scale non-linear constrained optimisation problems. On the other hand, because all environment information is available, the optimality of solutions is generally guaranteed. As for distributed approaches, they rely on several independent decision-makers that cooperate with one another to plan demand-side and grid operations. Even though communication is more frequent than in centralised methodologies, decision-makers commonly do not exchange confidential data. Also, since information is generally incomplete, only suboptimal solutions are commonly obtained.

EVs are efficient and less polluting alternatives to conventional transportation. The wide-spread of these vehicles raises important challenges in terms of charging management, for current and future power grids alike. In unidirectional charging, EVs are handled as any common appliance, considering only grid consumption, while in bidirectional EV charging vehicles' batteries are used as additional storage units or generators. Bidirectional strategies rely on EVs to mitigate the effects of dynamic grid behaviour, in particular the unpredictability of renewable generation. In this context, V2G has attracted considerable attention, motivating variants for buildings (V2B) and households (V2H).

III. MANAGEMENT IN BUILDINGS

In a nutshell, household energy efficiency and bill reduction can be achieved mainly in two ways: by reducing total energy consumption, or deferring the operation of certain devices, taking advantage of local production and off-peak tariffs. This can be categorised as *consumption reduction* or *consumption* *shifting* [22]. Consumption reduction refers to reducing the overall energy consumption, usually by increasing consumer awareness, shutting down appliances not in use, purchasing energy-efficient devices, or improving building construction and design. Consumption shifting is, on the other hand, focused on deferring certain loads over time, usually to off-peak periods. Naturally, these two alternatives are not mutually exclusive and can be employed together. Nonetheless, consumption reduction is less popular within residential buildings, since it requires deeper, time-consuming and costly interventions. Furthermore, determining optimal load shifting times is also not a trivial exercise. In addition to physical and preference constraints, load shifting is also conditioned by the adopted billing scheme, local energy production, if available, and baseline demands.

In short, demand-side load regulation can be addressed through demand-side management (DSM) and demand response (DR) programs. Despite being often used interchangeably, these are not synonyms, as they comprise distinct techniques and strategies in order to achieve energy efficiency and bill reduction at consumption-side.

A. DEMAND-SIDE MANAGEMENT

Demand-Side Management comprises a collection of techniques to improve energy efficiency and reduce the overall energy bill at consumption-side [23]. DSM is a broad-spectrum field, encompassing and extending concepts such as energy efficiency and load management. Owing to the fact that DSM related literature is somewhat disperse, there is no general consensus regarding the classification and categorisation of the underlying techniques.

DSM techniques can be categorised based on their timing and customer impact [23]: (i) Energy Efficiency (EE), (ii) Time of Use (TOU), (iii) Demand Response, and (iv) Spinning Reserve. EE accomplishes permanent energy optimisation by promoting the adoption of energy-efficient appliances and improving building design and construction. Also considered within this category are end-user awareness and behavioural changes towards a more efficient usage of energy appliances. TOU and DR techniques share similarities, as both promote energy efficiency and grid stability by coordinating and shifting appliances operation, thus balancing demands throughout the day. While TOU bills demanded energy at different prices, conditioned by the time of the day, DR promotes changes in electricity use as a response to smart grid events, which can be, for instance, grid price updates. As for spinning reserve techniques, they aim to support traditional energy providers by adjusting loads on demand-side according to the grid frequency, either by increasing or decreasing demand. They also support communication among demand-side devices in order to promote fairness in grid incentives, and contribute towards grid stability.

A different categorisation has been subsequently proposed in [24]. The underlying techniques are split into (i) Energy Efficiency, (ii) Demand Response, and (iii) Strategic Load Growth (SLG). Comparing to the one proposed in [23], its main novelty concerns the inclusion of SLG techniques. Load growth programmes are implemented aiming at changing the load shape, by imposing increases or decreases in consumption in certain periods of the day. This approach can be used to foster consumption from renewable sources.

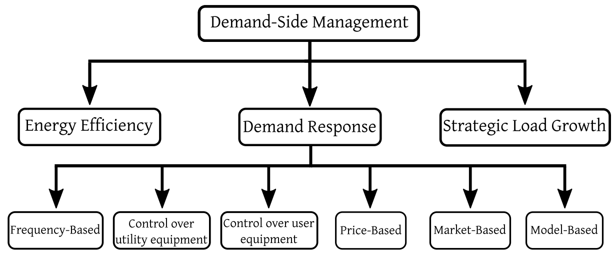

FIGURE 2. Demand-side management and demand response categorisation.

B. DEMAND RESPONSE

Demand response refers to changes in electricity use from normal consumption patterns exhibited by demand-side resources, as a result of changes in the price of electricity or induced by incentive payments, aiming at lowering electricity use when wholesale market prices are high, just to name out a few [3]. Moreover, the ability to change appliance schedules in real-time allows the accommodation of unexpected grid demand peaks, while contributing to demand flexibility. This is particularly important in addressing the variability of energy production from renewable sources, both at demand and supply sides. From a practical point of view, DR has been shown to cut peak demands, helping with the integration of renewable sources and supporting short-term balancing of the grid [25].

As for DR-based techniques, there is also no consensual categorisation. One of the proposals [23] considers splitting DR into *market* and *physical* techniques. Market DR techniques are directly focused on energy billing by means of load shifting, taking into account static or dynamic billing methods or financial incentives. On the other hand, physical DR is centred around the smart grid and underlying infrastructure, consisting of signals sent out by the utility to reduce or remove demands due to maintenance or failure events.

Another more exhaustive categorisation is proposed in [24]. Here, the authors split DR techniques into the following six categories (Figure 2): (i) frequency-based, (ii) direct control over utility equipment, (iii) direct control over end-use equipment, (iv) price-based, (v) market-based, and (vi) model-based. *Frequency-based* techniques use frequency-based mechanisms to control devices on the demand-side, switching them on or off, performing load shedding and restoration. *Direct control* over either utility or end-use equipment aims to control grid assets, such as transformers and feeders, or demand-side appliances. For utility equipment, the adoption of voltage reduction and protection relays is reported, while protection fuses and clock-based controllers can be considered at demand-side. In *price-based* techniques, indirect load control is carried out via tariffs such as TOU, real-time pricing (RTP) or critical-peak pricing (CPP), while in *market-based* demand-side resources are explicitly incorporated into electricity markets. Finally, *model-based* techniques focus on coordinating devices and resources at both demand and supply sides, in order to optimise energy use and billing. The authors focus their discussion on model-based predictive control (MPC), but alternative methodologies, such as machine learning-based techniques, can also be considered.

Recently, two additional categories were considered in [3] and [26], namely *price-based* and *incentive-based* techniques. Both categories, in essence, are focused on scheduling devices to minimise energy bill. Price-based techniques adjust loads to dynamic grid prices, while incentive-based techniques rely on deterministic and time-invariant policies, such as direct load control and interruptible loads, to promote load reduction. Customers of incentive-based programs should agree to reduce operative loads during specific periods. If they comply with this requirement a financial incentive is awarded, otherwise a penalty is applied.

In recent years, renewable energy and storage systems, both at demand and supply-side, have been increasingly integrated on power grids. On the other hand, AMI, dynamic billing policies, as well as automated DSM and DR also need to be properly incorporated. In addition, demand-side load adjustment should not be considered just to improve just a single criterion. The utility, smart grid and customers often have distinct and conflicting objectives. This has motivated extensive research on multi-objective optimal resource management, notably MPC [27], [28], linear programming (LP) and non-linear programming (NLP) [4], [29], [30] as well as evolutionary algorithms (EAs) [31]–[34].

C. ENERGY BILLING SCHEMES

In the past, utility companies commonly used to consider flat rate-based pricing, being customers charged according to a given static rate per energy consumed unit. Recently, owing to technological advances on smart metering, dynamic billing schemes have become increasingly preponderant. Five main billing approaches can be found in the literature (see e.g. [35], [36]), namely:

(a) *All-in-rate* – billing is carried out at a given static rate, which remains unchanged throughout the day.
(b) *TOU* – splits a given day into several periods. For each period, energy is billed at a fixed rate. Periods usually change over time, as well as the underlying billing rates. Periods and energy prices can depend on the season of the year, day of the week, or any other criterion.
(c) *CPP* – defines a peak rate at which customers are billed during critically overloaded periods. These periods are defined by the utility, based on a threshold regarding the total consumption for a customer. In the remainder of the time, this approach is exactly as TOU.
(d) *RTP* – energy tariffs are updated at a given rate, usually on hourly or daily basis.
(e) *Inclining Block Rate* (IBR) – IBR considers a unit electricity rate, which increases with consumption in blocks of several hundred kWh. By considering higher demands more expensive, this billing scheme promotes load distribution over time.

D. SUMMARY

Under the smart grid paradigm, DSM and DR have emerged as the two most dominant programs for automated load management at demand-side. While DSM-based approaches focus on reducing energy consumption and improving the overall efficiency, DR-based techniques adjust electricity use in response to grid price changes. The adoption of these programs can be beneficial for both end-users and utility companies.

DSM is categorised into energy efficiency, strategic load growth and demand response techniques. Energy efficiency techniques encourage energy-efficient appliance usage, building construction and design methods improvement, along with end-user awareness and behavioural changes. Load growth programmes are implemented for changing the load profile shape, in order to increase or decrease consumption at certain periods of time. DR techniques include the following standard categories, namely frequency-based, direct control over utility equipment, direct control over end-use equipment, price-based, market-based and model-based techniques. These categories were recently extended by including incentive-based and price-based techniques.

Further research on scheduling strategies, namely in terms of optimisation techniques, is required to balance exploitation of local production for self-consumption and grid injection. Uncertainties associated with appliance operation needs, energy consumption, local production and grid prices must also be addressed for the sake of robustness.

IV. HOUSEHOLD APPLIANCE MODELS

Buildings, both residential and non-residential, include a multitude of electrical devices, each with its own specific characteristics in terms of energy consumption and usage profile. In order to address the increasing heterogeneity of devices, HEMSs need to be adaptive and flexible enough to cope with changing requirements and to accommodate new challenges.

A. APPLIANCES CATEGORISATION

From a load scheduling point of view, household appliances can be categorised based on how they are managed by HEMSs. In [37] appliances are distinguished between *controllable*, according to which appliance operations can be scheduled over a given time horizon, and *non-controllable* appliances, for which scheduling is not available. Only the ability to define appliances' start time is possbile, while interrupting their operation or reducing their energy consumption are not available. A broader categorisation is proposed in [8], comprising the following six classes aiming to model different groups of devices:

(a) *Uncontrollable* loads – they cannot be changed or re-scheduled by a HEMS. This class considers loads that provide an added value to residents, sometimes completely controlled by users. Examples include, but are not restricted to, entertainment equipments such as tv sets, computers or sound systems.

(b) *Curtailable* loads – energy consumption can be adjusted mid-operation, usually with no significant impact to residents' comfort. Such adjustments restrict energy consumption by changing the underlying settings, with no subsequent compensation. One example concerns dimming indoor artificial illuminance during day-time as a function of daylighting.

(c) *Uninterruptible* loads – once started, they should run a complete cycle. Hence, the underlying HEMS, or residents, are only able to schedule the corresponding starting time. Dishwasher, clothes washing or dryer machines are typically included in this category.

(d) *Interruptible* loads – can be interrupted at any time, and subsequently resumed, with little impact on their operation. Appliances included in this category are usually modelled as equipments with constant consumption, easing the formalisation of underlying scheduling problems. Examples include plug-in hybrid electric vehicles and other rechargeable devices.

(e) *Regulating* loads – appliance operation states remain as close as possible to a given reference, which is defined by residents or a HEMS. Heating, ventilation and air conditioning (HVAC) systems are exmaples of this class.

(f) *Energy Storage* – comprise appliances such as external batteries that store energy for subsequent use.

It should be stressed that no household appliance categorisation scheme is currently globally accepted. Different terms are used to characterise identical concepts. As an example, in [26] household appliances are classified as *schedulable* or *non-schedulable* based on deferment flexibility, while in [37], [38], the classes *controllable* and *non-controllable* are analogous, even as *elastic* and *inelastic* loads in [35]. The latter work also suggests a new class for *smart loads*, further categorised in elastic and inelastic loads, resulting from their ability to adjust power consumption mid-operation.

It should be pointed out that even among authors following the categorisation proposed in [8], a consensus has not been reached yet on which appliances are assigned to each category. Refrigerators, for instance, are such an example due to their relatively short cycling characteristics. At hourly resolution, consumption cannot be adjusted, and thus they are regarded as uncontrollable devices [39], [40]. For lower time resolutions, consumption can in principle be adjustable, allowing them to be classified either as interruptible [41], [42] or uninterruptible loads [38], [43]. Finally, loads can also be categorised as thermostatically controlled, in the case they are related to maintaining indoor temperature close to a given reference value.

TABLE 1. Common controllable household appliances referenced in the literature.

Household Appliances	Number of Papers Citing this Appliance	References
Washing Machine	27	[30], [33], [34], [39], [41], [42], [43], [52], [53], [54], [55], [56], [57], [13], [58], [59], [60], [61], [62], [63], [64], [65], [66], [67], [68], [46], [69]
Dishwasher	25	[30], [34], [38], [41], [42], [43], [52], [53], [54], [55], [57], [47], [70], [13], [59], [60], [61], [63], [64], [65], [66], [67], [68], [46], [69]
Electric Vehicle	23	[30], [33], [34], [38], [40], [52], [56], [13], [61], [62], [63], [47], [70], [71], [72], [73], [74], [75], [76], [77], [78], [45], [46]
Dryer Machine	21	[30], [38], [40], [41], [42], [43], [52], [57], [13], [58], [59], [60], [61], [63], [64], [65], [66], [67], [70], [47], [71]
Air Conditioning	21	[30], [32], [33], [38], [40], [41], [42], [58], [60], [61], [62], [64], [47], [71], [73], [79], [80], [45], [68], [46], [81]
Water Heater	17	[30], [33], [34], [38], [40], [41], [42], [52], [53], [54], [55], [60], [64], [47], [72], [78], [69]
Light Spots	15	[33], [40], [41], [42], [43], [55], [62], [63], [79], [80], [82], [68], [45], [46], [69]
Heating System	14	[27], [28], [31], [39], [41], [42], [57], [58], [72], [78], [83], [84], [85], [69]
Refrigerator	11	[30], [38], [39], [41], [42], [60], [61], [79], [68], [46], [69]
Oven	9	[41], [42], [43], [55], [60], [63], [47], [70], [46]
Television	7	[30], [41], [42], [55], [79], [68], [46]
Water Pump (Well, Pool)	6	[38], [41], [42], [59], [72], [78]
Vacuum Cleaner	6	[30], [38], [55], [58], [63], [68]
Computer	5	[30], [41], [42], [55], [63]
Microwave	5	[30], [43], [55], [63], [68]
Iron	5	[30], [39], [55], [68], [46]
Battery/Energy Storage	4	[62], [64], [83], [46]
Cooker Hob	3	[43], [60], [63]
Fan	3	[30], [41], [42]
Toaster	3	[30], [33], [68]
Freezer	2	[41], [42]
Stove	2	[30], [38]
Kettle	2	[30], [68]
Cooker Hood	1	[30]
Blender	1	[30]
Hair dryer	1	[30]
Phone Charger	1	[30]
Water Purifier	1	[55]

B. TYPICAL CONTROLLABLE APPLIANCES

Table 1 presents the most common controlled appliances in the context of HEMSs found in the literature. As can be observed, there is a clear predominance for some types of appliances. Washing, dryer machines, dishwasher and charging of electric vehicles appear on the top of this list, with over 20 references each. Indoor temperature management is also common, and associated to heating or cooling systems. This finding is, to some extent, expected, as these appliances are responsible for a high share of overall household energy consumption. In comparison to other appliances equally important for comfort and lifestyle, such as phone chargers, personal computers, tv sets or entertainment systems, those devices are more prone to external management, making them top candidates for HEMS-based supervision.

C. RESIDENTIAL LOAD UNCERTAINTIES

In household environments, accurate predictions of electricity demand and local micro generation are difficult. If tariffs are fixed, utility grid prices can be determined, otherwise they can only be estimated, with a certain degree of confidence. These uncertainties have an impact on computed load schedules, which ultimately compromise energy bill and may lead to breaches of contracted power limits or even impacting residents' comfort level.

The main sources of uncertainty in HEMSs are: (i) appliance operation needs, (ii) appliance consumption, (iii) local micro energy production, and (iv) utility grid prices. A way to address uncertainties on forecasts is to remove predicted data from the decision-making process, and solely relying on past and present data. In such cases, it is suggested to consider heuristics and game-theory-based approaches, or when uncertainty is explicitly included, stochastic, robust, chance-constrained, (stochastic) dynamic programming and (stochastic) fuzzy optimisation approaches are recommended [8].

(a) *Stochastic optimisation* – uncertainties are modelled as random variables and explicitly included in both the objective function and constraints [44]–[46], being the optimisation carried out for the expected value of the objective function. If statistic distributions and corresponding parameters are known, a simple approach consists in replacing each random variable with the underlying expected value. In the case of finite uncertainty realisations, the expected value can be determined by computing the objective function value for all possible realisations and taking its expectation. For other cases, an approximation of the set of possible realisations can be computed via Monte Carlo sampling, assuming a stochastic model, or based on field observations [44], [47]–[49]. Finally, in some particular problems, decisions need to be obtained based on a sequential methodology, commonly via two-stage or multi-stage-based stochastic optimisation approaches [8], [50].

(b) *Robust optimisation* – no assumptions regarding the underlying uncertain variables are made, being them modelled them based on intervals of values [47], [51]. These methods address uncertainties by considering realisations with stronger (worse) impact on problem solutions. For instance, minimisation of household electricity bill under uncertain non-schedulable demands considers non-controllable demands to be as high as possible. A generic formulation for a robust optimisation problem is as follows [50]:

$$\min_{x \in \chi} \max_{\omega \in \Omega} F(x, \omega) \tag{1}$$

where Ω is the uncertainty set and χ is the space of decision variables.

(c) *Chance-constrained* optimisation – not as strict as robust alternatives, since optimisation is conducted for the worst-case scenario with a predetermined confidence interval, which is represented by a parameter α:

$$\begin{aligned} &\min_{x \in \chi\ , \omega \in \Omega} F(x, \omega) \\ &\text{subject to} \\ &\qquad P\left(h_i(x, \omega) \geq 0\right) \geq p \\ &\qquad i = 1, \cdots, m \end{aligned} \tag{2}$$

In short, this method ensures that the probability of matching one or more constraints is above a given threshold. Therefore, it restricts the feasible region in order to guarantee a high confidence level on computed solutions. Unlike robust optimisation methods, chance-constraints can use unbounded distributions of uncertainty [8].

(d) *Stochastic dynamic programming* – relies on the estimation of a state-space model, such that for each state a finite set of actions can be taken with a given probability, thus resulting in transitions to other states. This method is applied recursively from the end nodes to the initial node. As a finite set of states must be defined, a rather simplistic and often incorrect model may be obtained. Since a significant number of states may emerge when modelling complex systems, stochastic dynamic programming-based problems can become NP-hard. Nevertheless, some approximations can allow solutions to be achieved in polynomial time [8].

(e) *Stochastic fuzzy optimisation* – consider fuzzy logic theory, such that truth values are in the interval [0, 1]. When dealing with forecasts, uncertainties can be replaced with non-crisp values, which enable HEMSs to make quick decisions that lead to approximate optimal schedules, within a certain level of confidence [8].

D. SUMMARY

HEMSs allow continuous monitoring and management of household appliances based on user defined criteria, such as the overall electricity bill or residents' comfort, just to name out a few. A clear lack of consensus concerning a unified categorisation of household appliances, from a HEMS management perspective, is noticed. Nevertheless, household appliances can broadly be categorised into appliances supporting remote HEMS control and management, and those not available for management. Controllable appliances can be further categorised based on how HEMSs regulate their operation: curtailable and regulating loads, where energy consumption is adjusted during in-operation stages; uninterruptible loads, which cannot be managed in any way after being started; interruptible loads, which can be interrupted and subsequently resumed at any point during execution; energy storage systems, allowing extra storage for later use. Some appliances are more appealing than others with respect to smart management and scheduling. This is the case of washing machines, electric vehicles and HVAC systems, in part due to their significant consumption and support for external management, with smaller impact on residents' comfort and lifestyle. HEMSs define appliances in-operation schedules over a future time horizon, based on appliance requirements, in terms of consumption and local generation, which are typically not known. As such, scheduling techniques need to deal with uncertainties. In this context, stochastic and robust methods, chance-constrained optimisation and stochastic variants of dynamic programming and fuzzy optimisation methods were discussed.

V. SCHEDULING

In order to improve energy efficiency and residents' comfort, HEMSs monitor household consumption and coordinate appliance operations. This can be achieved via consumption reduction or consumption shifting, with the latter far more popular in residential buildings. Consumption shifting relies on scheduling techniques to find optimal operation timing for household appliances. Prior to their adoption and deployment in real-world scenarios, critical choices need to be made concerning the devices to be managed, scheduling criteria, operational constraints, and the scheduling techniques to be considered. This section is devoted to discussing dominant scheduling techniques, criteria and constraints.

A. TECHNIQUES

In the context of consumption shifting, the choice of a particular scheduling technique involves a number of issues. Scheduling is conducted over a future time horizon, for which household demands and electricity generation cannot be perfectly predicted. As such, adequate and representative consumption profiles are required. In addition, the incorporation of uncertainties for future demands and generation should also be considered.

More strongly linked to the optimisation strategy is the process of modelling appliances by a HEMS and the underlying time domain representation. Its discretisation into equal-length slots is widely employed, namely hourly-based slots [57], [59], [86]. In some cases, time domain discretisation helps the specification of constraints related for instance to appliance models or comfort parameters, just to name out a few. Such representations, however, lead to a larger number of variables, increasing the corresponding computational burden. In such cases, the underlying problems should be reformulated to reduce the number of variables and constraints [87]. Continuous time domain representations can also be considered (see e.g. [88]–[90]), improving scheduling flexibility, as appliances in this case are not constrained to fixed slots.

A wide variety of methods and techniques have been suggested to improve energy usage through load scheduling [8], [35], [91]–[93]. These methodologies can generically be grouped into five categories: i) mathematical optimisation; ii) heuristic and metaheuristic methods; iii) model-based predictive control; iv) machine learning; v) game theory approaches.

1) MATHEMATICAL OPTIMISATION

HEMSs define appliance operation schedules over a given predefined time horizon, so that some particular criteria are optimised, while taking into account underlying constraints. A common approach to find feasible solutions relies on deterministic optimisation-based methodologies. The corresponding problem formulation can be grouped into the following categories:

(a) *Linear Programming* (LP) problems – the objective function and constraints are strictly expressed by linear relationships, being binary programming [4], [94] and mixed-integer linear programming (MILP) [30], [39], [43], [46], [55] the most predominant methods. LP problems are appealing due to their relatively low computation burden and the availability of specific software packages. Algorithms such as branch and bound, simplex or interior point can be employed. Commercial and non-commercial solvers with support for linear programming problems are also available, namely GLPK [95], CPLEX [96] or GAMS [97].

(b) *Non-Linear Programming* problems – either the underlying criteria or constraints, or even both, are expressed by non-linear functions. These techniques are more powerful than LPs, but on the other hand the computation burden is larger. Common solvers with support for non-linear problems include SCIP [98], [99], GAMS or LINGO [100]. Mixed-integer non-linear programming (MINLP) problems are commonly formulated in the context of HEMSs [29], [56], [101].

(c) *Convex Programming* problems – consider convex objective functions, linear equality constraints and concave inequality constraints. Convex programming problems can be solved by least squares, conic programming, geometric optimisation and Lagrange multiple methods [35].

(d) *Dynamic Programming* – the optimisation problem is structured into multiple stages, being scheduling decisions made sequentially, one at a time, and not independently at each time interval [102], [103].

A drawback of deterministic formulations, in the context of HEMS scheduling, is the lack of precise knowledge concerning demand, local micro generation or grid prices over the scheduling horizon. Although scheduling could be found by solving LP or MILP problems, by considering demand and production forecasts, optimal solutions can only be found if future uncertain realizations match forecasts. For uncertainty sources modelled by probability distributions, a stochastic optimisation approach can be used [70], [71], [104].

This methodology was followed in [44], leading to household energy bill cuts of around 41%, when compared to traditional deterministic optimisation approaches, with uncertainties were considered for household appliance consumption, operation times, and with respect to renewable electricity generation.

2) HEURISTICS AND METAHEURISTICS

For large problems, mathematical optimisation methods are computationally expensive, being heuristics and metaheuristics approaches a valuable alternative. They rely on high-level procedures to search for admissible solutions, resulting in a lower computational burden than mathematical optimisation methodologies. They are particularly attractive for problems where it is typically easier to find one suboptimal solution, but extremely difficult and time-consuming to find a global solution.

In this class of methods, genetic algorithms (GA) [31]–[34], [52], [92] and differential evolution (DE) [68] have stood out in the context of HEMSs, along with swarm intelligence-based algorithms, namely particle swarm optimisation (PSO) [33], [72], [79], [83] and tabu search [53], [54], [84].

3) MODEL PREDICTIVE CONTROL

HEMSs scheduling can be regarded as a receding-horizon optimal control problem, such as MPC. At current discrete time k, a horizon-dependent optimal control sequence is computed based on current states sampled from the system, being only the first control action implemented on the system. At next time step $k + 1$ this procedure is once again repeated. MPC supports dynamic modelling and disturbance prediction [57], [71], [92], [105], useful to address problem uncertainties. One of the drawbacks of MPC-based techniques is related to the stability of the underlying closed loop system and the sub-optimality of the corresponding control system. Nevertheless, MPC has been reported to achieve a satisfactory performance regarding the energy management of buildings, outperforming other control schemes, such as in the case of heating [106], [107], cooling [108], [109] and ventilation [110]. However, MPC-based methodologies involve very often significant modelling costs, as they require a detailed plant model, rely on data acquisition from the plant, along with the implementation of required observers, expert monitoring and deployment. This has been pointed out as a limitation regarding the application of MPC-based technologies in medium to large buildings [92].

4) MACHINE LEARNING

Traditionally, utility companies have heavily relied on control systems, physical modelling and numerical calculations to monitor and manage grid infrastructures [111]. With the recent technological advances in IoT and smart grid technologies, a new generation of digital sensors equipped with computing and communication capabilities is being deployed. This results in the collection of massive data volumes, which need to be subsequently processed. On the other hand, renewable energy generation increases both the complexity and uncertainty of grid management. As this new set of challenges is not fully addressed by traditional strategies, the application of machine learning and data science-based techniques have been suggested in the context of building and grid management [93], [111], in particular for: (i) appliance scheduling, and (ii) forecasting building energy consumption.

5) APPLIANCE SCHEDULING

Artificial neural networks (ANNs), as a class of universal approximators, can learn to solve scheduling problems by means of supervised training. Among ANN topologies, feedforward architectures are commonly chosen, while considering as inputs, for instance, future demands and generation forecasts, time of day and occupancy information. When multiple devices need to be simultaneously managed, two strategies can be followed. One considers training an individual ANN for each appliance [112], while the other approach considers training a single ANN to control multiple devices [113].

Reinforcement learning (RL) has evolved around the concept of an intelligent agent in a dynamic environment. This agent iteratively learns how to best act while performing a given task. At each iteration, the agent observes and evaluates the current environment state, takes an action from a previously defined set and receives a reward as a result of the conducted action. The goal of an agent is to either maximise rewards or their expected values [114].

6) BUILDING ENERGY CONSUMPTION

Predictive models can be used to estimate electricity consumption, either for the entire building or for some specific uses, including eating, cooling, washing and dryer machines [115]. They can also be used to predict micro generation for sources such as solar or wind [116]–[118]. In essence, this problem can be regarded as time-series forecasting, for which machine learning-based approaches can be considered [93], [111], [116], [119]:

(a) Statistical and conventional regression methods, such as time-series decomposition, ARMA, AIRMA, multiple linear regression [120] or ordinary least squares regression [121] offer a balance between simplicity and performance. However, for non-linear time-series the underlying prediction error tends to be unacceptable [119] unless an online parameter adjusting mechanism is implemented.

(b) Artificial neural networks, including multilayer perceptron and feedforward neural networks [122], convolutional neural networks (CNNs) [111], [123], recurrent neural networks (RNNs) [111], [124] and restricted boltzmann machines (RBMs) [111], [125]. Concerning RNNs, long short-term memory (LSTM) architectures are effective in dealing with a variety of high complex problems [124], [126]. The incorporation of additional layers within deep ANN architectures significantly improved generalisation performance, both for short and long terms. The main drawback of these high complex topologies is the training computational burden.

(c) Capsule networks rely on the concept of a capsule, which is capable of learning implicit features over a limited domain of input deformations [127], [128]. They have also been considered to forecast time-series data, namely to building energy forecast [129], [130].

(d) Support vector machines (SVMs) [131] are intrinsically adapted to solve regression problems, under the so-called support vector regression (SVR) modelling. Furthermore, they provide satisfactory results even when few data samples are available [119]. The application of SVR-based techniques to building energy forecast has been suggested in a number of works (see e.g. [132]–[134]), being the underlying prediction performance superior to traditional techniques and even to some ANN-based data-driven models.

(e) The joint application of segmentation and regression techniques rely on the concept of shape-similar data clustering. Instead of using all available data to train a machine learning-based model, it adjusts models to capture data patterns assigned to a given cluster. In [135] a K-means clustering algorithm was used to segment electricity readings on a hourly basis, along with a CNN model used to approximate each cluster, while in [136] household electricity loads are predicted by using classification and regression trees, together with self-organising map data clustering.

(f) Gaussian process regression (GPR) is a non-parametric method based on gaussian processes (GPs) [137]. GPs represent time-series as a collection of jointly multivariate gaussian random variables, and they are completely specified by a mean and covariance function. Given a training data set, they can be regarded as defining a set of functions that pass through the observations and are otherwise normally distributed, in log marginal likelihood sense [138].

(g) Ensembles of several models combine different techniques, while taking advantage of their individual strengths. They have, in the last few years, gained considerable interest in building energy consumption modelling and forecast. In some cases, they have shown to outperform regular single models, although their adoption has been hampered, in part due to implementation complexity and computational burden. Examples include random forests and boosting decision trees [119].

7) GAME THEORY

Game theory-based approaches are usually employed within a multi-agent framework, where each agent chooses a strategy to maximise an individual utility function. Agents' utility functions are defined according to the underlying operation objectives, and conditioned by other agents' strategies [35]. Two main categories can be found, namely *cooperative* and *non-cooperative* games. The former considers communication among agents, acting as a group to reach a common goal, while in the latter category agents are self-interested and do not communicate with one another, unless for self-enforcing purposes.

For a single household, cooperative games are not the most appropriate techniques, as they target scenarios with multiple customers, which coordinate behaviours in order to minimise the overall consumption, optimise grid resource usage or maximise social welfare [139]–[142], just to name out a few. In the case of multiple households, cooperation principles should be incorporated within DSM programmes [143]. From the utility company point of view, balancing demands from individual households in a given supplied region enables flattening energy consumption throughout the day, which leads to a sustainable and more efficient use of grid resources.

Although customer coordination could be centralised and implemented based on heuristics and mathematical optimisation techniques, it implies a significant computational burden, in particular when the number of agents is large. In these cases, distributed DSM-based approaches are superior to traditional DSM strategies, which solely focus on utility-consumer interactions, enabling peak-to-average ratio, energy costs and customers' daily charges to be reduced.

B. CRITERIA

In the following, some of the criteria commonly considered for scheduling appliances are listed [35]:

1) *Electricity bill* – is the most common objective, as the main motivation of residential consumers is to minimise the underlying bill, while taking into account available tariffs and renewable micro-generation [13], [46], [49], [58], [59], [69], [73], [74], [144], [145].
2) *Distribution system losses* – due to Joule effect in power lines and other equipment deployed along the grid network, namely transformers, a fraction of generated power is lost. A common approach to deal with this problem includes deploying generation sources along the power line, regulated by an optimal dispatch strategy [60], [75], [76].
3) *Peak load* – utility companies encourage customers to minimise peak load demand or even to achieve a particular load profile, which benefits grid management [46], [80], [82], [146], [147]. By defining individual target loads, utility companies promote a balanced use of power grid resources, expressed as peak-to-average load ratio (PALR). The closer this ratio is to one, the flatter consumption load is throughout the day [38], [61].
4) *Carbon emission* – taking into account the environmental impact of energy consumption, HEMSs can incorporate carbon and other GHG emissions as additional criteria [77], [148]. Penalty fees can also be charged to consumers based on GHG emission levels, as considered in [147], where pollutant emissions are indirectly reduced through electricity cost minimisation.

5) *Customer comfort* – the solution to the underlying scheduling problem provided by HEMSs can take into account customers' comfort and preferences, commonly under the form of constraints. If considered as an objective function, they are complemented by additional criteria, such as energy bill. In [85] appliance usage and customer comfort were taken into account in managing air-to-water heat pumps connected to a residential floor heating system, while in [58] a multi-objective mixed integer non-linear programming model was developed for optimal energy use in a smart home, ensuring a meaningful balance between energy saving and comfortable lifestyle.
6) *Social welfare* – can be regarded as the balance between consumer grid benefits and their associated costs [35]. As such, HEMS considering this goal aim to improve social welfare of a community of consumers, at a global scale [13], [62], [149].

C. SCHEDULING CONSTRAINTS

The household energy management problem includes the following two main groups of constraints: *appliance constraints* and *comfort constraints*. Appliance constraints are related to how household appliances are modelled. In this context, average non-varying consumption [59], [63]–[65], [69], [78] is often adopted instead of individual consumption profiles assigned to each operation cycle phase [43], [63], [66], [67], [94]. This is mainly due to model simplicity and lack of detailed consumption profile data for controllable appliances. Other constraints include household contracted power, energy generation and availability of external batteries.

Evaluation of customer comfort is a very complex task, in part due to the perception and subjectiveness of individual's comfort. Customer comfort can be assessed in terms of [8], [35]:

(a) *Inconvenience due to timing* – is related to discomfort perception resulting from scheduling appliances outside their preferred time window.
(b) *Inconvenience due to appliance use* – considers any discomfort stemming from a load that was prematurely stopped, whose intensity was reduced or not even performed at all. Examples include premature stop of a clothes dryer load and lowering indoor reference temperature for HVACs, resulting in a deterioration of indoor thermal comfort.
(c) *Inconvenience due to appliance priorities* – refers to any precedence and priority of certain appliances over others. A common example is related to clothes washing and dryer machines operation, as laundry needs to be previously washed before being dried out. User-defined priorities concerning household appliances are also addressed here. For instance, a customer can specify which clothes washing loads should be given preference over dishwashing. Failure to comply with such priorities can be modelled by a HEMS through discomfort penalties.

Constraints are not all equally processed by HEMSs. Some need always to be met at the risk of major household impact, while others may only be partially met. The degree to which a constraint is not satisfied distinguishes hard from soft constraints, being for instance the capacity of external batteries and contracted power common examples of hard constraints. It should be mentioned that the majority of comfort constraints can be incorporated as soft constraints, since a lower comfort lever can be perfectly acceptable if it leads to a meaningful energy bill reduction. Constraints can be addressed in two different ways, either by including them as part of the objective function within an unconstrained multi-objective framework or by explicitly formulating the scheduling problem as a constrained optimisation problem [150].

1) MULTI-OBJECTIVE TRANSFORMATION

Multi-objective transformation addresses constrained optimisation problems by regarding constraints as additional objectives, leading to an unconstrained multi-objective problem (MOP). MOPs can be solved by computing a representative approximation of the set of pareto optimal solutions, using commonly heuristic and metaheuristic-based techniques, mostly in the form of EAs [151]–[158]. However, a more common approach transforms the MOP into a single-objective problem (SOP), usually by means of a weighted sum of the underlying objectives [4], [159]–[162].

Bounded objective and physical programming methods are common alternatives to single-objective problem transformation via weighted sum [8]. As for bounded objective methods, they consider all but one objective as constraints, within an acceptable range. This implies that the chosen objective is more relevant to the problem, otherwise it would had been taken as a constraint. Concerning physical programming methods, a deeper knowledge of the underlying problem is required, as they rely on explicitly functions to model trade-offs between objectives.

A HEMS can, thus, come up with an optimal scheduling programme by combining its operational objectives and constraints into a single objective function, associating a scalar weight to each objective and constraint. An alternative approach explicitly considers all constraints, as described in Section V-C.2.

2) EXPLICIT CONSTRAINT HANDLING

The way constraints are handled by HEMSs strongly depends on their scheduling strategies. Current frameworks for MPC, LP or NLP typically provide native support for hard constraints, ensuring the feasibility of computed solutions. On the other hand, soft constraints can also be considered, usually by relaxing the constraint specification by means of a user-defined infeasibility degree or by removing the original constraint and penalising deviations from it.

Heuristic optimisation methods intrinsically allow to solve unconstrained problems [163]–[165], which implies the selection of constraint-handling techniques (CHTs). These techniques are categorised into early CHT (up to year 2000) and current techniques (2000s-2010s) [165]. Although they have been designed for heuristic-based methods, some of them can also be employed in other scheduling techniques.

3) EARLY CONSTRAINT-HANDLING TECHNIQUES

All CHTs present similar shortcomings, namely in terms of generalisation capacity, parameter fine-tuning and premature convergence. They can be grouped into the following subcategories [163], [164]:

(a) *Penalty functions* – constraints are replaced with an additional term on the adopted criteria function $f(x)$, which penalises the evaluation of a given solution, according to its degree of constraint violation. This term is usually represented by means of a penalty function, $\phi(x)$, being a solution evaluated as $\text{eval(x)} = f(x) + \phi(x)$.
Penalty functions of different types have been considered, namely: (i) static penalties [164], [166] which define fixed-value penalisations, (ii) dynamic penalties [167]–[171] computed based on information from the evolutionary process, namely infeasibility degree, generation number or best fitness in the population [164], and (iii) less popular alternatives derived based on co-evolution [172] and segregated GA [173] principles.
Penalty functions are extensively adopted, mostly due to their simplicity, ease of implementation and integration with existing optimisation-based scheduling strategies, but they require proper tuning, in particular in terms of optimal penalty values. As such, it has been suggested adopting the *minimum penalty rule* [164], according to which penalisation should be kept just above the limit below which infeasible solutions become optimal. The most tricky aspect of the penalty function approach is how to find appropriate penalty parameters in order to guide the search towards a constrained optimum.
(b) *Special operators* – in evolutionary and genetic algorithms, crossover and mutation operators are used to maintain population genetic diversity. As infeasible individuals may be generated, tweaks have been proposed to preserve the feasibility of candidate solutions [174]–[178]. Some examples include GENOCOP [163], GENOCOP III [179], decoders [180], [181] and repair algorithms [182]–[184], just to name out a few.
(c) *Separation of objectives and constraints* – treating objectives and constraints separately, unlike penalty functions. Examples include co-evolutionary techniques [185], [186], optimising objectives and constraints in two distinct populations, and multi-objective optimisation [187]–[189].
Feasibility rules [190] consist of a set of rules that govern comparisons between individuals, assuming an explicit preference for feasible solutions over infeasible alternatives [191]–[193]. A drawback of this methodology is a poor exploration of infeasible regions, which can lead to a premature convergence to a solution, resulting in a suboptimal solution.

4) CURRENT CONSTRAINT-HANDLING TECHNIQUES

The so-called current CHTs consist mostly in modifications to existing techniques, split into the following main approaches [165]:

(a) *Feasibility rules* – widely employed in heuristic and metaheuristic methodologies considered in the context of GA [194], [195], DE [196]–[199], PSO [200]–[202] and artificial bee colony (ABC) [203], [204].
(b) *Stochastic ranking* (SR) – this technique was originally proposed to address the shortcomings of penalty functions, resulting from poor tuning [205]. SR has been widely applied together with evolutionary strategies [205], DE [206], [207] and ant colony optimisation [208], [209]. It is based on the definition of a penalty function, which quantifies the degree of constraint violation of a candidate solution, implementing an adaptive ranking of candidate solutions, taking into account the underlying objective and penalty function values. Pairs of feasible solutions are compared based on the objective function, whereas for pairs with one or both infeasible solutions a user-defined probability P_f determines whether comparisons are carried out using the objective or penalty functions. Other ranking-based techniques can be found in the literature, namely adaptive ranking mutation operator [210] and multiple ranking [211], [212]. The popularity of these techniques is mainly due to simplicity and ease of integration with population-based heuristic and metaheuristic algorithms.
(c) *ϵ-Constrained method* [213] – the objective function is employed in comparing pairs of feasible solutions, being candidate solutions considered infeasible if and only if they exceed a user-defined degree of infeasibility $\epsilon \in \mathbb{R}$. This parameter has a strong influence on the selective pressure of feasible solutions [165]. Larger values allow deeper infeasible regions to be explored, while smaller values increase selective pressure, which results in fewer feasible solutions. Hence, a careful tuning of this parameter is required, being a constant value is commonly adopted, although a dynamic conditioning version of ϵ can also be found in the literature (see e.g. [214]).
(d) *Penalty functions* – despite their shortcomings, they still remain a popular CHT, in particular those embedding adaptive features [165]. New penalty functions have explored co-evolution and multi-population concepts, such as in [172], [215], [216]. Heuristic and metaheuristic algorithms, such as DE [172], [216], GA [217], PSO [218] and artificial immune systems [219] take advantage of this approach.
(e) *Special operators* – despite the active research interest, the inherent problem-dependency of specialised operators hinders a proper categorisation of published works. Furthermore, as specialised operators are developed for nature-inspired heuristic algorithms, their adoption and incorporation with other techniques can be quite challenging [165].

(f) *Multi-Objective Optimisation* – in recent years, highly competitive constraint-handling techniques based on MOPs were developed [165], implemented within frameworks such as evolutionary [220], [221] and pareto dominance [152], [222], just to name out a few.
(g) *CHT Ensembles* – motivated by the *no-free-lunch theorem* [223], multiple CHTs can simultaneously be applied to the same problem, exploring individual strengths and mitigating shortcomings. CHT ensembles result in a high computational burden, which have hampered their extensive use. Some examples include ensembles of feasibility rules, penalty functions, ϵ-constrained and SR [224]–[226].

Constraint metamodelling [227] is another group of techniques focusing on the development of metamodels for constrained optimisation problems. They can be particularly useful in black-box scenarios, where constraint boundaries are not explicitly provided. Metamodels can be used in feasibility checking and prediction, constraint estimation and repair of infeasible mutations [228].

D. SUMMARY

Mathematical optimisation-based scheduling techniques are the most popular choice for small and medium-sized scheduling problems addressed by HEMSs. For large enough problem instances, less computational demanding methodologies such as heuristic-based techniques have been favoured. Machine learning-based approaches have also been successfully applied to building energy management problems, both for scheduling appliances and forecasting household demand, along with micro generation. Among residential consumers, electricity bill remains one of the most selected criteria, followed by customer comfort and carbon emissions. On the other hand, distribution losses, peak load and peak-to-average load reduction are more aligned with utility's goals. Scheduling constraints can be addressed differently by HEMSs, namely by including them in the objective function or by considering explicitly constraint devoted methodologies. As for explicit constraint-handling, penalty functions have remained popular over the years, in particular adaptive penalty methodologies. Feasibility rules are also another popular choice, in particular for heuristic optimisation-based scheduling. In the last few years, the trend on CHTs has been more oriented to problem specialisation based on existing techniques than to the synthesis of novel formulations.

VI. SECURITY

Grid infrastructures are inevitably exposed to threats, such as related to information privacy or equipment and transmission failures, just to name out a few, which may threaten the stability of power generation and supply, with possible severe socio-economic impact. As such, improving the resilience of grid infrastructures has attracted considerable interest from academia, governments and industries [229]. Security challenges emerge at both physical and cyber spaces of HEMSs and smart grids [230]. At the physical level, power system security measures focus on the coordination of distributed power generation and energy storage, in order to ensure a stable power supply, particularly in addressing time-variance and uncertainties associated with renewable energy resources [231]. At the cyber level, the main challenges concerns the lack of embedded security features in most field devices, which can be exploited by attackers to gain unauthorised access to the overall system, or launching remote coordinated attacks [230].

The identified critical vulnerabilities of HEMSs and smart grids fostered the development of counter-measures to these attack vectors. In the following, prominent HEMSs and smart grid attack vectors and counter-measures are discussed. The reader is referred to [229], [230], [232], [233] and references therein for a thorough discussion on this subject.

A. ATTACKS ON SMART GRID

Smart grid attack schemes can be grouped into the following subcategories [230]:

(a) *Generation systems* – power generators are managed by automatic generation control (AGC) systems, which employ load-frequency control (LFC) and distribution mechanisms to maintain a desirable generation-supply balance with minimum operational costs. False data injection [234], [235] and control signal adulteration [236] attacks are commonly aimed to damage generators and power lines, being responsible for interrupting power supply and for power swinging.
(b) *Transmission systems* – interdiction of transmission lines and tripping of transformers, generators, buses or substations are common attack vectors carried out by manipulating commands or due to false data injection [230]. Alternatively, attackers can gain unauthorised access to system topology information, identifying strategically vulnerable components as future attack targets [237].
(c) *Customer-side* – customer-side equipments generally lack built-in security features, which attackers may take advantage for energy theft [238], information leakage [239] and denial-of-service [240] attacks. It should be noted that, even though isolated single-building attacks have a very insignificant impact on grid stability, synchronised attacks over large clusters of consumers can severely damage transmission lines and cause large-scale power outages [230].
(d) *Electricity market* – this kind of attack exploits higher prices in dynamic pricing schemes, such as RTP, during periods of higher demand stress, for illegal profit based on the price margin between on-peak and off-peak tariffs. The scheme is propped up on buying additional electricity at lower prices to be sold at higher rates during a subsequent attack [230].

B. COUNTER-MEASURES

Counter-measures to the aforementioned attack vectors can be categorised into three distinct classes, namely protection, detection and mitigation [230]. Mechanisms implemented for protecting the overall system aim to avoid external attacks before they could occur. They compromise several strategies, such as secure communication channels and protocols, re-configuration of topological information and preservation of critical information, being the latter strictly shared on a "need-to-known" basis. When protection mechanisms fail to prevent an attack from occurring, the second defence level is used to detect malicious activities through intrusion detection systems (IDSs) and intrusion prevention systems (IPSs) [241], physical watermarking of control inputs [242], model-based [243], game-theoretic [244], kalman filters [245] or machine learning-based techniques, namely ANNs [246]. Using information provided by detection mechanisms, mitigation counter-measures are subsequently employed to accommodate ongoing attacks, relying on optimisation-based approaches [247], [248] and game-theory techniques [249]–[252].

C. SUMMARY

False data injection and information manipulation, along with interception, are the most prevalent vectors of attack in HEMSs and smart grids. These attacks aim to steal confidential information and feed monitoring entities with false/erroneous information, thus inducing, as a response, a wrong reactive behaviour, which ultimately can lead to power supply infrastructure damage and compromise the underlying stability. Counter-measures to these attacks are focused on three distinct levels: protection mechanisms act as primary filters that prevent malicious attackers from gaining access to the system and subsequently deploying attacks; detection mechanisms identify malicious activities related to attacks; mitigation systems aim to accommodate ongoing attack events.

VII. CHALLENGES AND RESEARCH OPPORTUNITIES

In the following, some relevant challenges in the context of HEMSs and smart grids are discussed:

(a) *Grid infrastructure reliability* – in the last few decades, energy demand has been increasing at a global scale, a trend expected to further accelerate with exponential growth of plugged-in electric vehicles in the next few decades, as a result of their impact in terms of consumption patterns. As such, actions should be taken on the grid infrastructure side, in order to accommodate this increasing demand. On the other hand, load management algorithms for balancing customers' demand and reduce peak-to-average ratios are required to be more efficient, which is expected to foster new computational paradigms.

(b) *Consumption coordination* – Load scheduling algorithms addressing heterogeneous and uncertain information are required, being decentralised solutions favoured, as they bring more flexibility to the coordination of clusters of customers or sections of the grid. Besides, data mining-based algorithms can be exploited in scheduling consumption, modelling and forecasting demand-side loads, thus providing tools for integrating automatic context discovery, artificial context awareness and human-in-the-loop interaction, leading to improved self-adaptive and self-reconfigurable management algorithms.

(c) *Distributed energy resources* – Coordination among all grid generators is crucial for a stable supply, in particular regarding renewable generation units, due to uncertainty and intermittent power output. This implies further investigation on optimal placement of energy resources. Finally, improved management of plugged-in electric vehicles resources is also required, taking into account their dual profile, namely as consumers and generators.

(d) *Security and privacy* – Securing sensitive information and protection against cyber attacks are paramount in the context of HEMSs and smart grid systems. The main potential sources of attack these systems face, following the trend in the industrial sector, are related to industrial espionage for obtaining competitive advantages in a liberalised market, cybercriminals launching mass attacks, or cyberwarfare from a hostile State. Improving the overall resilience in such a dynamic environment requires continuous monitoring and follow-up of potential threats and vulnerabilities, using the best practices and developing sophisticated frameworks to deal with these challenges.

VIII. SIMILAR WORKS

Several surveys focusing on energy management and HEMSs have been published in the last few years. In Table 2 the major similarities and differences with the present work are listed, considering the last 5 years.

The present survey aims to provide a comprehensive update on HEMSs literature, focusing on: (i) appliance scheduling approaches [8], [26], [35], [91], [92]; (ii) constrained scheduling problem in terms of goals and constraints [8], [26], [35] and SOP and MOP formulations [8]; (iii) categorisation models of appliances, which are typically considered on HEMSs [5], [8], [26], [35]; (iv) cyber-security in terms of vulnerabilities, attack vectors and counter-measures [230], [233]. A recent survey worth to be mentioned for its thorough and clear review on energy management solutions, performance metrics and optimisation objectives to improve consumption-side energy usage is that of [253], but it lacks in addressing issues concerning to distributed energy resources in new generation smart power grids. These issues, in terms of smart grid techniques and their contributions to rational energy usage are covered in the present survey, being their shortcomings and research directions discussed.

TABLE 2. Comparison between previous surveys and the present work.

Reference	Year	Description
[91]	2014	This work reviews the goals and challenges of smart home energy management systems.
[92]	2014	Intelligent control systems applied to improve energy and comfort management in smart buildings are reviewed. Building energy and comfort-related trends and future research directions are also provided.
[8]	2015	It provides a comparative analysis of the literature on HEMS, with focus on modelling approaches and the underlying impact on HEMS operations and outcomes.
[26]	2016	It presents an overview on smart HEMS infrastructures, architectures and supported appliances, being some home appliance scheduling strategies reviewed.
[230]	2016	This work presents a comprehensive and systematic coverage regarding critical threats and attack vectors within the smart grid, and present common and effective defence strategies.
[35]	2017	The state-of-the-art of behind-the-meter energy management systems is discussed, being literature on BTM energy management systems classified into three main categories: technology layer, economic layer, and social layer, including an overview on enabling technologies and standards for communication, sensing, and monitoring.
[93]	2017	The application of data science techniques to building energy management is reviewed, with special focus on load forecasting, economic analysis, operation monitoring and fault detection.
[3]	2018	It reviews measures to improve load flexibility in commercial and residential buildings, and presents a framework for systematic evaluation of buildings' demand flexibility.
[253]	2018	It discusses key concepts of DSM schemes regarding consumers' demand management. DSM schemes under various categories and home energy management based DSM are also discussed, along with DSM performance metrics, optimisation objectives, and solution methodologies.
[233]	2019	This work presents a thorough overview on cyber attack vectors in traditional and smart metering networks, as well as common defence and mitigation strategies in order to accommodate this type of events.
This survey	2019	This work presents a thorough review on HEMSs, including operation goals and strategies to meet them, household appliance management, incorporation of uncertainties on HEMSs-based decision-making and performance metrics. Cyber-attacks targeted to HEMSs and smart grids are also addressed. Finally, an updated literature list on HEMSs is provided and some prominent challenges in the field discussed.

IX. CONCLUSION

Home energy management systems make possible real-time monitoring of household electricity consumption, remote control and planning of appliance operation. These systems enhance traditional homes with "smart" capabilities, playing an active role in the new power grid paradigm. In this context, the present survey presents a thorough review on HEMSs, including in-operation goals and strategies to meet them, along with household appliance management, uncertainties in HEMSs' decision-making and performance metrics. Security issues and resilience to cyber attacks are also discussed. In addition, this work presented the readers with insights on the current challenges these systems are facing, namely regarding dynamic infrastructure management, dynamic scheduling in the context of dual distributed energy sources and consumer clustering, and cyber-physical resilience. Addressing these issues will imply further research on automatic and dynamic context discovery and identification of behavioural changes, self-adaptation, self-reconfiguration, artificial awareness, uncertainty modelling and outlying pattern detection.

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