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IoT-Enabled Proposal for Adaptive Self-Powered Renewable Energy Management in Home Systems

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ABSTRACT The new generation of communication networks can provide massive connectivity of devices, extremely low latency, higher capacity, and increased bandwidth. These features enable the deployment of management systems in different sectors such as energy and in a wide variety of environments such as agriculture, surveillance or home systems. In this regard, this paper proposes a self-powered adaptive and automated home energy control system enabled by the Internet of Things (IoT) technologies. The system aims to adapt the consumption patterns to the availability of self-generated renewable energy (produced from solar panels, wind-mills, etc.). Therefore, the renewable and non-renewable supply from the power grid is considered a secondary power source. As part of the proposal, this paper presents the consumption negotiation scheme for IoT devices, the management mechanisms to optimize the use of the available energy, and the related model. Given the complexity of the adaptive management process, the proposal also presents a heuristic strategy based on a prepartitioning method to obtain feasible solutions in a reasonable running time. The simulation results for offline and online scenarios validate the advantages of the proposed strategy, and the numerical improvements are presented.

INDEX TERMS Critical service, degradation, energy management, HEMS, heuristic, IoT, renewable energy, self-powered, shifting, workload scheduling.

I. INTRODUCTION

As Information and Communications Technologies (ICT) become more reliable, cheap, accessible, and are able to provide lower latency and higher bandwidth, a wide range of Internet of Things (IoT) devices are being extensively deployed worldwide. According to some studies [1], it is estimated that by 2022 the number of IoT devices will exceed 28.5 billion. This large number of devices, together with modern communications networks such as 5G and beyond, represents an essential component in our current digital society, which can be used in various vertical applications for different sectors, such as agriculture, transportation and energy. Specifically, in energy systems, the incorporation of ICT and IoT technologies has enabled the improvement of control, monitoring, and management operations and the deployment of Demand-Response (DR) schemes [2].

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DR schemes play a crucial role in current energy systems (smart grids), as they enable adaptive control by adjusting consumption to generation capacity through the coordination and negotiation between the Energy Supplier (ES) and Energy Consumers (EC). Adaptive energy management maintains the stability of energy systems, and reduces the risks of peak demand, outages, and energy waste [3]; also, its application is not restricted to power grids. For instance, another prominent scope of application is in domestic environments (including homes and buildings), which are active players in the energy sector and responsible for around 40% of the consumption of the total energy generated [4]. Considering the penetration of connectivity through access networks (such as Wi-Fi) in households and the automation and communication infrastructure available on modern appliances (e.g., a smart tv), implementing an IoT-enabled energy consumption solution in domestic environments is a feasible alternative with current technologies. This kind of approach in the literature is referred to as Home Energy Management

Systems (HEMS) and mainly aims to reduce consumption and improve energy efficiency [4].

Given that a reduction or efficient use of the available supply (mainly provided and distributed by the energy utility company) is not sufficient to address the ever-increasing demand, solutions such as integrating renewable energy sources (also referred to as green energy) into energy systems are envisioned as a sustainable alternative, in the road to replace completely the non-renewable sources. The energy obtained from sources such as sun or wind is practically an inexhaustible resource that generates a lower environmental impact than fuel or carbon-based energy and can be used to meet partial or total consumer requirements. In this regard, some research has analyzed the primary and exclusive use of green energy. For instance, major IT providers such as Google [5] and Microsoft [6] are already promoting networking infrastructures fully powered by renewable energy. For domestic environments, the use of self-generated renewable energy from solar panels or wind stations has also been recently promoted [7]. This trend has changed the traditional role of the end-user from consumer to energy producer; the term "prosumer" has even been coined to indicate the dual behavior of generation and consumption.

Energy production on the consumer side avoids extra generation by the ES (which can produce pollution) while contributing to a better distribution of the generated energy resource. However, considering that green sources have stochastic behavior and their production is affected by environmental conditions or geographical location, the available supply is frequently underused or wasted because it cannot be consumed or stored in mass amounts. Therefore, an adaptive HEMS focused on optimized utilization of self-generated green energy is essential because it has implications for the consumer side (lower tariffs and supplier independence), on the supplier side (lower level of production and reduction of power peaks), and on the environment (lower utilization of fossil fuel-based energy).

In response to this need, this paper proposes an IoT-enabled adaptive HEMS that aims to optimize the utilization of available supply. The proposed system considers self-generated green production as a primary source. However, the energy from ES (whether renewable or not) can also be used to meet the full demand. Optimized energy utilization is achieved by adapting consumption patterns to existing supply through efficient scheduling of energy demands using control mechanisms such as time-shifting, quality degradation, and rejection. The proposal includes a description of the HEMS, the negotiation scheme for IoT consumption, and the adaptive model through the characterization of supply and energy demands. To solve the problem of the proposal, a heuristic algorithmic strategy called PHRASE is proposed, which is based on a divide-and-conquer method. Simulation results validate the proposed system and strategy, showing improvements in energy consumption mainly related to green energy availability. The main contributions of this paper are summarized as follows:

TABLE 1. List of acronyms.

Acronym	Definition
CS	Critical Service
DR	Demand Response
EC	Energy Consumer
ES	Energy Supplier
GEM	Green Energy Manager
HAN	Home Area Network
HEMS	Home Energy Management System
ICT	Information and Communications Technologies
ILP	Integer linear programming
IoT	Internet of Things
MMKP	Multi-dimensional Multi-choice knapsack Problem
NCS	Non-critical Service
PHRASE	Prepartitioning strategy

TABLE 2. List of notations.

Notation	Definition
AR	Acceptance Ratio
E_{A_U}	Available energy utilization
P_A	Total available power
P_D	Total power demanded
P_{LACK}	Missing power
P_{ES}	Power from energy supplier
P_R	Self-generated renewable power
P_{RES}	Residual power

- An IoT-enabled architecture proposal for adaptive energy management in HEMS.
- A negotiation scheme in which the consumption of IoT devices is constrained to available energy.
- Management mechanisms, including prioritization, time-shifting, quality degradation and rejection, to adapt the consumption pattern to the available supply.
- The mathematical formulation of the proposed adaptive consumption model.
- A heuristic algorithmic strategy denoted as PHRASE to solve the adaptive energy model in a feasible running time.

Table 1 and Table 2 show the list of the most relevant acronyms and notations in this paper, respectively. The remainder of this paper is structured as follows. Section II briefly overviews the related literature. Section III formally introduces the energy management proposal. The heuristic strategy to solve the adaptive model is described in Section IV; meanwhile, its assessment is presented in Section V. Finally, conclusions and future work are discussed in Section VI.

II. RELATED WORK

This section discusses research work related to ICT- and IoT-enabled customer-side energy management, including the HEMS.

A. ICT- AND IOT-ENABLED CUSTOMER-SIDE ENERGY MANAGEMENT

The integration of advanced communications networks such as 5G and IoT infrastructures into modern energy systems (e.g., smart grids) improves energy efficiency and distribution, service quality, and cost in power generation and consumption [8]. ICT and IoT technologies also enable robust automation, control, monitoring, management processes, the enhanced inclusion of new power plants (mainly based on green sources), and bidirectional communication between ES and EC [2]. This latter feature is of paramount importance in current energy systems because it allows EC to participate in DR programs actively and make decisions to adapt consumption to availability. The adaptive customer-side management helps energy providers flatten the demand curve by allowing EC to schedule power usage from peak to off-peak periods [9], for instance adapting the charge of the electric car at home. These actions result in increased stability and sustainability of the energy system, reduced carbon emissions levels due to lower production and energy usage, and reduced overall operational cost through the optimization of available resources. In addition, EC can be motivated to participate in DR adaptive schemes by the variation of energy prices over time, incentives related to energy use, or when the energy system requires reliable and efficient operation.

To carry out adaptive energy management enabled by advanced communications systems, two components are required: (i) an appropriate communications network (low latency, enough capacity) that interconnects ES, EC, and other elements related to the energy system, and (ii) an ICT infrastructure with robust computational capacity (in terms of processing and memory) that deploys the strategies (DR algorithms) needed to adapt consumption to generation [10]. Regarding the first point, a variety of network technologies (wired or wireless), with different specifications, protocols, and interfaces can be adopted depending on the application scope (e.g., power grids, smart cities, industrial facilities, or households) and operational requirements (e.g., bandwidth, latency, or throughput) [8]. A technology leading the innovation in communication systems is the Software Defined Networking (SDN) paradigm, which, apart from being a key enabler in 5G networks, has been promoted into smart grids in recent years [11]. Regarding computational capacity, this has been growing according to the evolution of power grids. Thus, the first DR strategies have been deployed in small operation centers (or servers). Data centers have been used to implement energy management schemes [12]. Currently, cloud computing infrastructures and technologies such as Network Functions Virtualization (NFV) are considered a suitable environment to execute strategies for adaptive consumption control [13].

To implement DR schemas, various mathematical models and strategies (algorithms) have been proposed in the literature focused on different requirements and objectives to be achieved. In this regard, adaptive consumption has been modeled through the operational features of ES and EC, including in some cases price information, energy storage units participation [9], and green energy provisioning [14]. To mathematically formulate appropriated models, optimization methods such as integer linear programming (ILP) [15] and mixed-integer linear programming [16] have been used. In addition, different objective functions have been established for these models, such as minimization of power consumption (reshaping the peak demand) [17], maximization of user utility [18], and minimization of costs for the ES, EC, or both [9]. To solve the adaptive energy management problem (energy model), offline [19] and online [20] approaches have been analyzed in research works. For offline approaches the algorithmic strategy has complete knowledge of supply and demand during the time horizon of analysis to manage energy. For online approaches the algorithmic strategy has no future information about ES and EC, and decisions on loads are restricted as energy resources and demands evolve.

The offline and online approaches can be addressed by optimal or suboptimal methods. The optimal or exact strategies allow the best allocation of energy recourse through the optimal scheduling of loads [20]. However, these methods present an exponential complexity that grows as customers and management techniques (e.g., time-shifting and prioritization) increase; also, they are computationally expensive and time-consuming [21]. To overcome complexity limitation and for practical applications, some research work has focused on deploying sub-optimal and faster methods based on heuristics strategies [22]. For instance, for customer-side DR energy management Logenthiran *et al.* in [22] propose a heuristic strategy based on evolutionary algorithms for minimizing peak load demands; this strategy is tested for different types of loads in residential, commercial, and industrial service areas.

B. IOT-ENABLED HEMS

Communications systems such as Wi-Fi access networks and IoT infrastructures (including smart sensors, devices, appliances, and virtual assistants) allow home automation, as well as the control of loads. Regarding energy management, the ICT and IoT technologies facilitate the deployment of different schemes [23]. The proposed approaches can be limited to manual or partially automated control of consumption (through the activation or deactivation of appliances) or can comprise entire HEMS, in which a smart entity (i.e., software or hardware platforms) efficiently schedules the consumption of loads. The energy demands can be scheduled according to multiple criteria, including the consumption optimization, costs minimization, or ensuring certain comfort levels for customers. The HEMS can also operate in different application scopes (e.g., residential or professional) considering weather conditions, load and supply profiles, energy storage capability, green energy mixing, and interaction with other energy systems such as smart grids [24].

Many architectures, software and hardware tools, platforms, and tesbeds have been proposed for implementing HEMS [25]. These approaches are based on existing communications networks, either wired (e.g., SDN [10] or power line communications [26]) or wireless (e.g., Wi-Fi [27]), and the vast range of IoT technologies and protocols (e.g., machine-to-machine communications protocols [28]) that are included or that can be easily incorporated into domestic appliances. Some approaches also exploit cloud computing solutions such as Thingspeak [29] and data analytics [30]. In addition, using renewable energy in HEMS is an important feature addressed in the literature to deliver an environmental friendly and cost-effective solution. For more than 15 years, studies have analyzed the possibility of using exclusively renewable energy in households [7]. In this regard, different renewable sources have been evaluated; however, due to the ease of installation (e.g., rooftop photovoltaic units [31]), accessibility in the market (easy installation kits [32]), and production capacity (e.g., 7000 [W] [32]), the use of solar energy (photovoltaic energy) has been analyzed in many research works.

Some studies describe entire HEMS while others focus mainly on the development of strategies (including DR schemes). For instance, AlFaris *et al.* in [23] present a HEMS that, using IoT-enabled appliances, sensors, actuators, smart meters, and a central hub (in which DR schemas are executed) wirelessly interconnected, performs consumption management of supply generated by photovoltaic panels. Regarding strategies, a variety of mathematical models and algorithms are proposed for HEMS by researchers (in a similar way to the customer-side management approaches in Section II-A). The proposed models are based on optimization techniques such as linear programming [14] and stochastic programming [31] and solved by optimal [18] or heuristic algorithms (e.g., based on evolutionary algorithms [33]). These latter are used for dealing with the complexity issues.

In summary, existing works show that ICT and IoT are key enablers for deploying customer-side management and HEMS. Most of the proposals analyze the HEMS as an extension of smart grids and as a component that can be managed to reduce the load of ES. In many proposals, HEMS are targeting the minimization of total energy consumption. In contrast, the proposal of this paper is focused mainly on the domestic environment. The proposed HEMS aims to optimize the utilization of available supply, primarily produced from green sources, through efficient scheduling of IoT-enabled consumers. In addition, the proposed solution, which maximizes the utilization of available supply at all times, allows the implementation of a battery-free HEMS system, which is in line with the recent concept of battery-free IoT networks [34]. The battery-free paradigm seeks to address the problems related to energy storage, such as limited storage capacity and lifetime of battery units, mandatory replacement, and pollution produced [35].

III. PROPOSAL FOR ADAPTIVE ENERGY MANAGEMENT IN HEMS

A. PROBLEM DESCRIPTION

In traditional energy systems (e.g., conventional power grids), the desynchronization between consumption and supply may provide insufficient available energy resource to meet the demand or wasted as it cannot be consumed. Adaptive energy management (through DR schemes) by adjusting consumption patterns to generation solves this problem [3]. This concept, applied to the domestic environment and deployed in a HEMS, allows optimizing the use of self-generated energy (mainly from green sources), avoiding wasted supply and reverse power flow if generation is sent to the power grid (substation) in an uncontrolled manner [36]. In this regard, it impacts in ES and distributors to change the exclusive centralized control and generation ecosystem to a paradigm in which the customer can autonomously manage the energy demands according to the self-generation. Furthermore, enabled by IoT, a HEMS can not only perform real-time monitoring and smart energy management of domestic appliances but also optimize energy utilization, by controlling the individual consumption of devices, specially on peak times [25].

B. IOT-ENABLED ARCHITECTURE PROPOSAL

This section presents the proposal for adaptive energy management in HEMS. Section III-B1 describes the components of an IoT-enabled HEMS. Section III-B2 presents the management mechanisms to achieve adaptive energy consumption. Section III-B3 summarizes the consumption management scheme for IoT devices.

1) DESCRIPTION OF THE IoT-ENABLED HEMS ARCHITECTURE

Fig. 1 shows the HEMS architecture; the components are described below.

- *Communications Technologies:* Communication systems are a fundamental component in modern energy systems because they allow bidirectional communications between generation and consumption. In HEMS, two communications systems can be identified: (i) the backbone network or Wide Area Network (WAN), which exchanges energy-related data (instructions and notifications) with the ES needed for DR programs (consumer-side participation) and (ii) the ICT in the premises of the end-user that allows the creation of a Home Area Network (HAN) in a domestic environment, a Building Area Network (BAN) in a building, and an Industrial Area Network (IAN) in industrial facilities to control, monitor, and manage loads. A variety of wired and wireless standards and communications technologies can be used according to the requirements and needs of control applications and customers. Different factors such as data rate, latency, power consumption, topology, network size (number of devices being controlled), reliability level, operating frequency, range of coverage, security level, and implementation costs can determine the choice communication systems [24]. For instance, for the WAN between HEMS and ES, a possible alternative is Power Line Communications (PLC) or Synchronous Digital Hierarchy (SDH), which can use an optical power ground wire (OPGW). For HAN (BAN or IAN), Wi-Fi is widely used, although

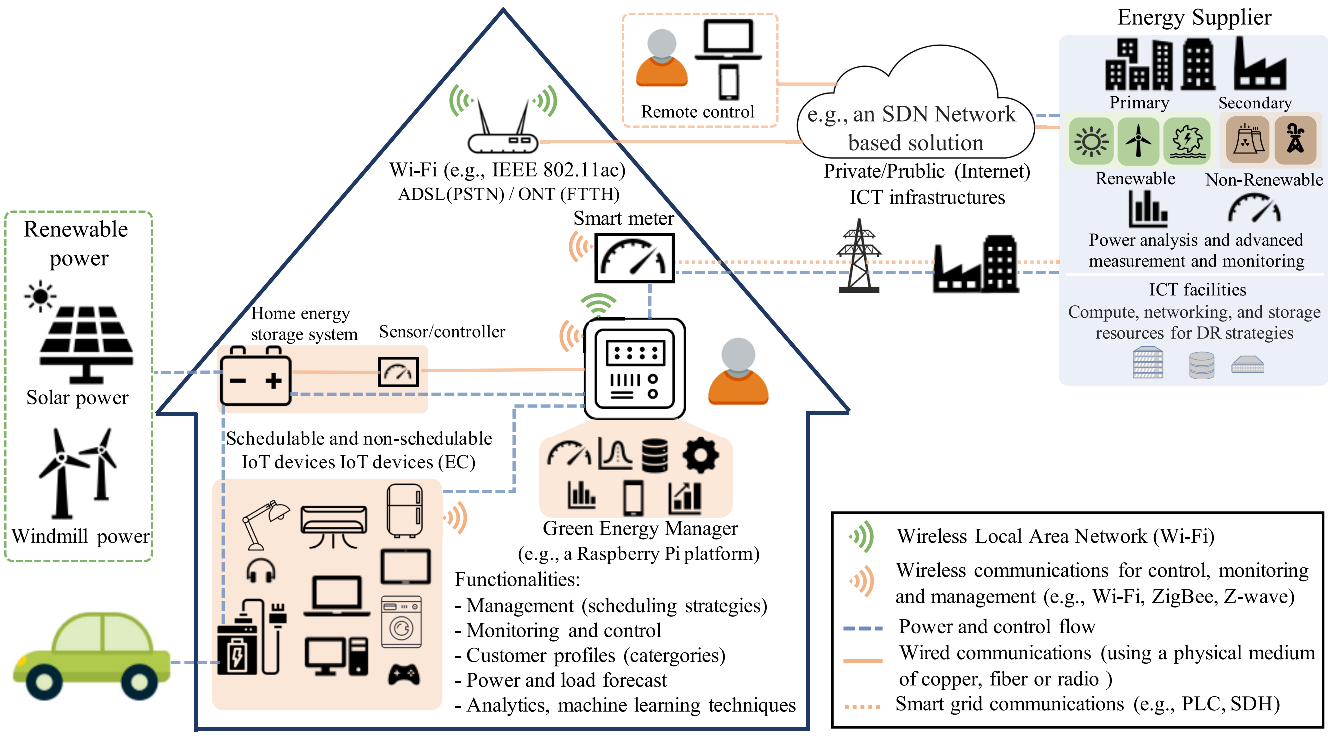


FIGURE 1. **IoT-enabled HEMS architecture proposal.**

other technologies can provide connectivity in HEMS. Table 3 shows a summary of possible ICT for deploying a HAN.

Depending on the application scope of the HEMS and customer requirements, more specific analysis such as channel modeling can be carried out to estimate operation limits of a particular technology for deploying a HAN (e.g., analysis on a PLC-based communications system). Other factors that can influence the selection of the technology for implementing a HAN are pace of technology innovation, upgradability, device ownership (e.g., smart meters from the utility company), interoperability (i.e., availability of compatible appliances or interfaces), self-managiability, maintainability, and resiliency. Because secure management in a HEMS is a relevant aspect that avoids compromising EC and ES operation, requirements such as client (device) authentication, integrity, and confidentiality of energy-related data must also be met by the selected HAN technology.

In addition, communication protocols compatible with wired and wireless technologies can be used to implement energy management applications. The proposed HEMS has no special constraints regarding the protocols architecture, it can use the Internet TCP/IP suite, a generic protocol stack in which physical, network, and application layers are defined, as discussed in [37], or even other radically different approaches, such as RINA [38].

The physical and data-link layer in HEMS are mostly defined by Ethernet, Wi-Fi or PLC protocols. For the network layer, IPv6 is preferred to IPv4, regarding the capacity to handle overcrowded scenarios with millions of IoT devices. About the transport layer, TCP is in favor of reliability and UDP for real-time operation. In upper layers, customized solutions can be implemented (e.g., a web server running the management application), or existing protocols such as COAP and MQTT [39] can be adapted to the application scope or need of EC.

- *Smart Meters:* The smart meters in HEMS are used to establish two-way communication with the utility company. They are responsible for sending consumption data, receiving signals (e.g., about energy pricing information) for participation in DR programs, and requesting energy resources if the self-generated renewable energy fails or becomes insufficient for the demand. Smart meters can display energy usage patterns to end-users and are coordinated by Green Energy Manager (GEM), which is the main controller in HEMS.
- *IoT Devices:* IoT devices are home appliances (e.g., a Smart TV) and other devices (e.g., access points) that participate in energy management process. They are connected, coordinated, and controlled by GEM. Each IoT device requires a unique identification (e.g., an IPv6 address) to send consumption information (periodically, when activation is needed, by polling, or others) and receive operating instructions (e.g., to change to an activation or deactivation state). IoT devices can incorporate sensors and actuators to perform measurement, monitoring, and control tasks. In the proposed

TABLE 3. Comparison of different communications and networking technologies for HEMS, based on [25] and [8].

Connectivity	Technology	Standard	Data rate	Range
Wired	Ethernet	IEEE 802.3	10-1000 Mbps	100 m
	X10	X10 standard	50-60 Kbps	300 m
	HomePlug	IEEE P1901	14-200 Mbps	300 m
	Insteon	X10 standard	1.2 Kbps	3 Km
	ITU G.hn	ITU G.hn	Up to 2 Gbps	500 m
Wireless	Wi-Fi	IEEE 802.11	54 Mbps at 2.4 GHz, 5 Gbps at 5 GHz	100 m
	Zigbee	IEEE 802.15.4	40 Kbps at 915 MHz, 250 Kbps at 2.4 GHz	100 m
	Thread	IEEE 802.15.4	250 Kbps at 2.4 GHz	30 m
	Bluetooth	IEEE 802.15.1	1 Mbps at 2.4 GHz	10 m
	Z-wave	Zensys, IEEE 802.15.4	40 Kbps	30 m
	6LowPAN	IEEE 802.15.4	20 Kbps at 868 MHz, 40 Kbps at 915 MHz, 250 Kbps at 868 MHz	75 m
	ONE-NET	Open source	38.4 - 230 Kbps	70 m
	EnOcean	EnOcean standard	120 Kbps	30 m
	LoRa	LoRa	10 Kbps at 863 MHz, 100 Kbps at 915 MHz	10 Km
	Sigfox	Sigfox	10 Kbps at 863 MHz, 100 Kbps at 915 MHz	10 Km

model, their operation is uninterruptible. In addition, these devices can be fully automated (e.g., washing machines, dishwashers, and air conditioners) or can require manual operation by the end-users (e.g., computer, television, and vacuum cleaner).

- *Renewable Power:* Renewable power coming from green sources is the primary supply in the proposed HEMS. The distribution of this available supply is controlled and managed by GEM. DC/AC, AC/DC, or DC/DC converters can be used optionally into green energy generation to match different load requirements. Moreover, renewable energy production systems can incorporate battery units to ensure stable transitions between energy sources (either green or not). Battery units in a HEMS can also act as energy buffers, storing energy during surplus periods or releasing the stored capacity according the requirements of consumers (always under the coordination of GEM). In the context of a HEMS, the battery units already included in the structure of green sources (e.g., photovoltaic panels) can be used for these purposes. However, a more interesting approach (also part of smart cities) is the use of electric vehicles. Specifically, the battery units in modern electric vehicles can store the surplus energy generated, which can then be used when necessary by a single household, several households, or an entire building in a neighborhood, and can even be distributed to other locations in smart cities through coordinated actions between the HEMS and the ES. Since energy storage can improve HEMS performance, an analysis of battery sizing and characterization can be considered for future research.

  In the proposed HEMS model, the exceeding renewable energy self-generated can be incorporated to the general power grid. The management and control actions are performed by GEM and smart meter. On the contrary, if the available green energy is insufficient to meet all the demands, GEM and smart meter can execute actions to request extra energy from the ES.

- *Green Energy Manager:* GEM is a software and hardware platform with two main responsibilities: (i) creation and management of the HAN (or BAN or IAN) and (ii) control, monitoring, and energy consumption control. Once the network is created by the GEM, each IoT device must be associated. In this process, the device is authenticated, identified, registered, and assigned an IP address.

  To allow interaction with the end-user, GEM has an interface able to display information about the consumption (e.g., through a dashboard) and allows input of data related to the appliances and requirements. In general, the end-user provides parameters (such as the type of device, average consumption level, priority level, and possible operation intervals). If the user does not have information about the power demanded by the home appliance, GEM can use data stored in its database. Once integrated into the HAN, the IoT device can report real consumption data to GEM. To facilitate, GEM can provide the user with pre-defined profiles, (including parameters of the strategies such as time-shifting or quality degradation) or can be customized on basis of consumer preference. GEM can use different technologies to manage and control the consumers. However, one alternative that has been proven to be an effective solution in an IoT-enabled environment in recent years is SDN because this technology can offer scalable operation, efficient network usage, programmable behavior, and high-speed data/instructions related to energy consumption.

  The adaptive management of GEM, is summarized in the following three steps: (i) reception of information about the consumption of appliances, level of available supply (self-generated and coming from the ES), and data provided by end-user; (ii) execution of appropriate scheduling strategies; and (iii) transmission of orders to the appliances in order to handle the degree of energy consumption. GEM can include features such as logging for users, alarm reporting, and fault detection. In addition, through the smart meter or home gateway (e.g., access point), GEM can interact with external networks and allow remote monitoring and management (e.g., through web applications). In the latter case, the application of security mechanisms (e.g., encryption and hashing) is essential to guarantee user privacy and non-corruption of the energy management data. GEM could also incorporate other types of management strategies based on data analytic (e.g., generation and consumption forecasting) or machine learning techniques. These mechanisms are left for a future work.

2) MANAGEMENT MECHANISMS TO ADAPT CONSUMPTION TO THE AVAILABLE SUPPLY

The proposed HEMS considers a prioritization scheme defined by the end-user that differentiates the applicability of the management mechanisms upon the energy loads. Several priority levels can be created according to the preferences and needs of end-users; however, for practicality, these levels can be grouped into Critical Services (CS) and Non-Critical Services (NCS). CS includes appliances that are considered essential for the end-user. Since they are critical, they have labeled with the highest priority level. GEM must ensure the energy allocation (even if it comes from the ES) for their execution. In contrast, NCS covers appliances whose operation is secondary and subject to modification according to the strategies used. They belong to a range of priority levels. Their execution is conditioned to the available supply and the decisions coming from the management system. The mechanisms applied to NCS are the following:

- *Time-Shifting Capability:* This mechanism allows the GEM to schedule the execution of an appliance forward or backward. In this way, consumption can be adapted (flattened, smoothed) to the shape of the available supply, so improving energy efficiency.
- *Quality Degradation Level:* This mechanism allows to reduce the power consumption of an appliance, to the cost of degradation in quality. The degradation can be unappreciated in many devices with a minimum and maximum operating thresholds. Selecting the minimum threshold would cause less power to be assigned to a device, allowing adaptation of the demand to the current supply and potentially reserving power to execute another device.
- *Rejection:* The rejection is the maximum degradation degree. The management mechanism has not been able to allocate energy for the appliance in any of the possible combinations considered according to the algorithm (e.g., insufficient values of time-shifting or quality degradation). Figure 2 illustrates both the normal operation and the application of management mechanisms on appliances in HEMS.

As mentioned above, in a HEMS, there may be several levels of priority according to user requirements and the complexity of the desired management system. For instance, for a HEMS with three priorities, the first priority level would correspond to CS, and no management mechanism would affect appliances in this category. An example of service (appliance) in this category could be the operation of a refrigerator. For the second priority level, only time-shifting would be used with values established according to the interests of the end-user. An example of a service in this category would be the operation of a washing machine. For the third priority level, both time-shifting and quality degradation could be used; charging a laptop battery can be included in this category. In any case, the users could configure as many levels as they consider appropriate and establish the management mechanisms and their respective ranges for each priority according to their preferences. It is the task of GEM and specifically of load scheduling strategies to determine the best actions for each appliance.

3) CONSUMPTION MANAGEMENT SCHEME IN HEMS

Figure 3 summarizes the communication dialog or signaling between the appliances and the GEM in the HEMS. Unlike a traditional or baseline scheme in which no management mechanism is applied and consumption is carried out as soon as the device is turned on, the proposed energy management system establishes a dialogue/negotiation (handshake supported by the HAN) previous the consumption. In this negotiation, the existing supply, the parameters of the appliances (i.e., consumption, starting time, and duration), and the information provided by the end-user (priority levels and values of the management mechanisms) are considered. The GEM computes and notifies the appliances through the HAN, about the consumption conditions. This is basically the start time and the consumption levels (including degradation, if applicable). Subsequently, the appliance activates its operation using actuators or control circuits. Different communication schemes can be used to establish communication between the GEM and the appliances. A simple implementation can be based on a client-server architecture using a Wi-Fi access network and the classical Internet protocols to exchange operation conditions and consumption instructions, as exemplified in Fig. 3.

C. ADAPTIVE ENERGY MANAGEMENT MODEL

The characterization of the proposed energy model is given through the available supply, the appliances, and the adaptive energy management process. The total available power in the HEMS is identified as P_A and is composed, primarily, by the self-generated green energy that is denoted as P_R and, secondly, by the supply offered by the ES defined as P_{ES}, as shown in Eq. 1.

$$P_A = P_R + P_{ES} \tag{1}$$

The self-generated energy available in the HEMS can be composed of different green sources, such as sun or wind, as shown in Eq. 2; while, the energy supplied by ES can come from renewable (P_{ES}^{R}) and non-renewable (P_{ES}^{NR}) sources, as indicated in Eq. 3. If necessary, the HEMS (GEM) can

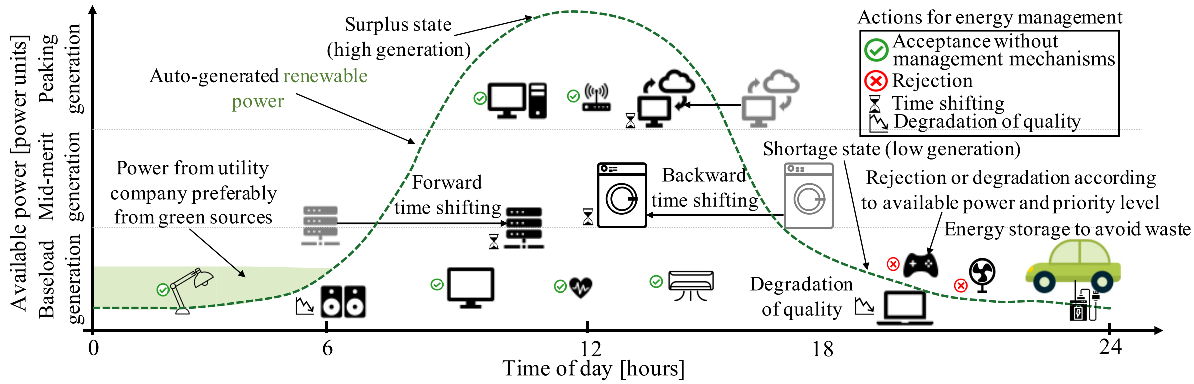


FIGURE 2. Example of the application of management mechanisms to achieve adaptive energy consumption.

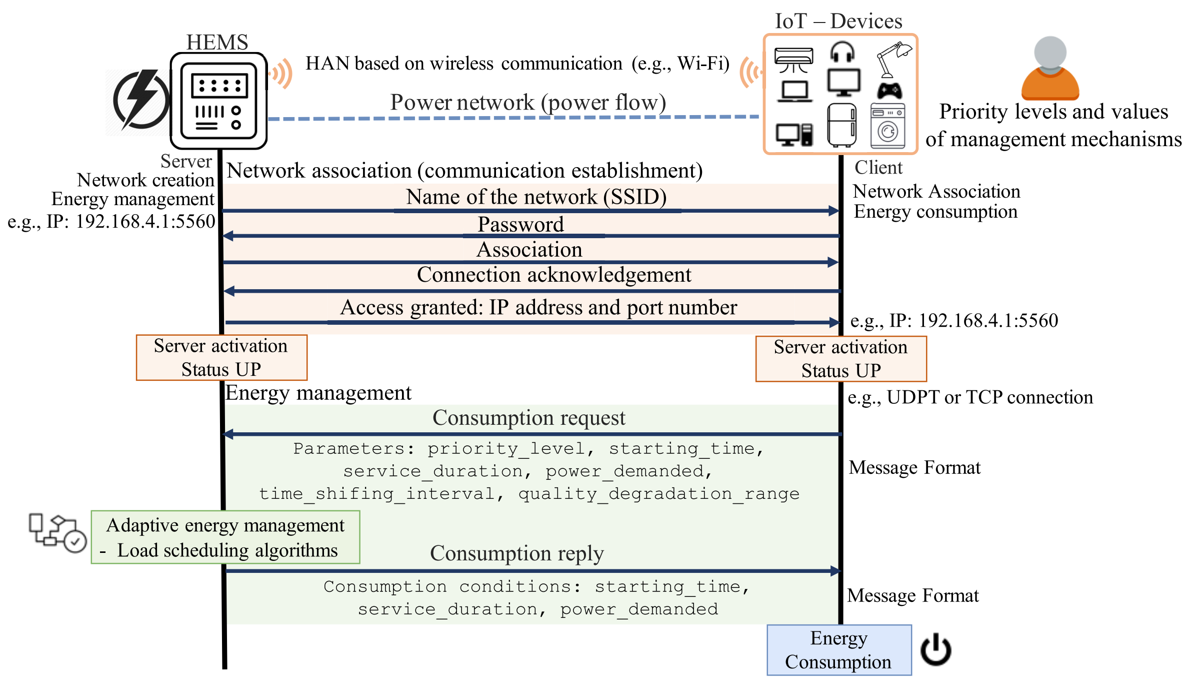


FIGURE 3. Summarized energy consumption negotiation process between the GEM and the IoT-enabled devices.

request power from the ES, indicating the preference for green sources in the DR negotiation.

$$P_R = +P_{solar} + P_{wind} \tag{2}$$
$$P_{ES} = +P_{ES}^{NR} + P_{ES}^{R} \tag{3}$$

To guarantee the primary use of self-generated energy, the provisioning selection process by the GEM may be based on a cost function. The generalized form of this function is presented in Eq. 4. This expression is composed of the costs associated with P_R and P_{ES} and is affected by the weights w_1 and w_2 that can be set in the interval [0,1], if applicable. Considering the preference for P_R, its associated cost would be zero; in this case, the expression in Eq. 4 would be simplified as indicated in Eq. 5. The value of $Cost_{P_{ES}}$ would be proportional to the amount of resource demanded (used). Therefore, the prioritization of the self-generated supply would be given by minimizing $Cost_{P_{ES}}$ (i.e., minimization in the use of P_{ES}), as shown in Eq. 6.

$$Cost_{P_A} = w_1 \times Cost_{P_R} + w2 \times Cost_{P_{ES}} \tag{4}$$
$$Cost_{P_A} = Cost_{P_{ES}} \tag{5}$$
$$minimize\{Cost_{P_{ES}}\} \tag{6}$$

In the proposed energy management model, the appliances are characterized by their operation, considering the respective management mechanisms. Moreover, an appliance operation in the management model is denoted as an energy demand or a service. Thus, a service i is identified as S_i and is defined by the parameters in Table 4. In the energy management model, each service S_i has independent operation parameters t_i, p_i, and d_i, and belongs to a certain priority level l_i that defines the actions that affect the service. For instance, a service S_i can be subject to a forward time-shifting (i.e., when $t_i + Ts_i$) for delayed execution or a backward time-shifting (i.e., when $t_i - Ts_i$) for anticipated execution. If the

TABLE 4. Parameters of a service.

Parameter	Description	Unit/Comment
$\mathcal{N}$	Set of services	$\mathcal{N} = \{1, \ldots, N\}$, integer number
i	Service identifier	$i \in \mathcal{N}$
$\mathcal{L}$	Set of priority levels	$\mathcal{L} = \{1, \ldots, L\}$, integer number
j	Priority level identifier	$j \in \mathcal{L}$, $j = 1$ for CS, and $j = \{2, \ldots, L\}$ for NCS
$\mathcal{Q}$	Set of quality degradation levels	$\mathcal{Q} = \{1, \ldots, Q\}$ integers related to a multiplication factor
k	Quality level identifier	$k \in \mathcal{Q}$
t_i	Starting time of service S_i	Time units (e.g., units of minutes or hours)
d_i	Duration of service S_i	Time units (e.g., units of minutes or hours)
p_i	Power demanded of service S_i	Power units (e.g., units watts or kilowatts)
l_i	Priority level of service S_i	Integer number
q_i	Quality level of service S_i	Integer number related to a multiplication factor to decrease consumption (e.g., for q_i = 2, $p_i \times 0.75$)
Ts_i	Time-shifting value of service S_i	Time units, +Ts_i forward, -Ts_i backward

service S_i runs at its original time, then $Ts_i = 0$. In any case, the service S_i can be analyzed by the GEM (scheduling strategy) in the interval $\{t_i - Ts_i, \ldots, t_i, \ldots, t_i + Ts_i\}$. Analogously, the quality degradation q_i can affect the normal consumption p_i of the service S_i. It is the responsibility of the GEM to find the best action (i.e., values of the management mechanisms) for each service, so that the available energy supply is used optimally. In the worst case (the offline approach), the GEM must simultaneously perform the analysis for all N services. In this case, the total amount of power demanded denoted as P_D is equal to the sum of the contributions of each service, as indicated in Eq.7. This equation determines that each service can take only one priority value, time-shifting, and quality degradation simultaneously.

$$P_D = \sum_{i=1}^{N} p_i \tag{7}$$

Therefore, the objective of optimizing the available power consumption can be expressed as the difference between P_A and P_D, and, specifically, as the minimization of this difference, as indicated in Eq. 8. For practicality, hereinafter, the difference between the total generation and demand is defined as residual power and denoted as P_{RES}.

$$minimize\ \{P_A - P_D\} \tag{8}$$

The objective of the energy model or the objective function related to adaptive consumption is represented by the minimization of P_{RES}. However, to obtain a feasible implementation of the energy model, some assumptions must be considered, which are listed below:

- Use of a discretized time model that starts at time zero and in which each slot $w \in \mathcal{W}$, with $\mathcal{W} = \{1, \ldots, W\}$ has equal duration. In this model, the initial time of appliances or of P_A (denoted as $T_init^{P_A}$) can vary from zero to the maximum time horizon W, which usually is set to 24 hours. In addition, the size of the time slots can be configured based on the application scope and requirements of each end-user. For instance, a time slot w could represent 10 minutes or 1 hour.
- Processing of complete services. The proposed model does not accept partial processing of a service to avoid discontinuity. In case an appliance must be used in different intervals during the time horizon (e.g., throughout the day), these events are considered different services. Moreover, during the lifetime of a service, its power demand remains constant. Features such as partial processing or variation in consumption can be addressed in future work.

With the simplifications previously discussed, the objective function of the adaptive consumption model is expressed as.

$$\forall w \in \mathcal{W} : minimize \left\{ \sum_{w=1}^{W} (P_A[w] - P_D[w]) \right\} \tag{9}$$

In addition, the objective function in Eq. 9 is conditioned by the following constraints.

$$C1 : P_A[w] \geq 0 \tag{10}$$
$$C2 : (P_A[w] - P_D[w]) \geq 0 \tag{11}$$
$$C3.1 : \sum_{j=1}^{L} y_{ij} = 1, \quad i \in \{1, \ldots, N\} \tag{12}$$
$$C3.2 : y_{ij} \in \{0, 1\}, \quad i \in \{1, \ldots, N\}, \ \ j \in L \tag{13}$$
$$C4 : t_i \geq 0 \tag{14}$$
$$C5 : \{t_i - Ts_i\} \geq 0 \tag{15}$$
$$C6 : W \geq \max\{t_i + d_i + Ts_i\} \tag{16}$$
$$C7 : T_{init}^{P_A} \geq 0 \tag{17}$$
$$C8 : \sum_{k=1}^{Q} \sum_{i=1}^{N} \sum_{e \in G_i} (p_{kie} \times q_{kie})[w] \times x_{kie} \leq P_A[w] \tag{18}$$
$$C9.1 : \sum_{e \in G_i} x_{kie} = 1, \ k \in \{1, \ldots, Q\}, \ i \in \{1, \ldots, N\} \tag{19}$$
$$C9.2 : x_{kie} \in \{0, 1\}, \ k \in \{1, \ldots, Q\}, \ i \in \{1, \ldots, N\}, \ e \in G_i \tag{20}$$

$C1$ and $C2$, ensure a positive value for P_A and P_{RES}, respectively. $C3.1$ guarantees the assignment of a unique priority level for the service S_i. The variable y_{ij} is set to 1 if the priority $l_i = j$ of S_i exists, as shown in $C3.2$. The temporal constraints in the energy model are ensured by $C4$, $C5$, $C6$, and $C7$.

$C8$ constraints the maximum consumption capacity in the energy model. In $C8$, the decision variable shown in $C9.1$ and $C9.2$ guarantees the processing of the service S_i with unique values of time-shifting and quality degradation. The variable x_{kie} is set to 1 if the service S_i with priority $l_i = j$ and quality degradation level $q_i = k$ exists, as shown in $C9.2$. This limitation avoids the processing (energy allocation) of multiple copies of the same service S_i.

The application of time-shifting and/or quality degradation mechanisms on a service S_i produces different versions of the service S_i, which we define as *variations of the service* S_i. To know the dynamics of these variations in the proposed model, first, the impact of the time-shifting, and then the quality degradation on the N services, are analyzed. The use of the time-shifting mechanism on N services produces N mutually disjointed classes $G_1, \ldots, G_N$ of services. Each class G_i is composed of the shifted versions (variations) of the service S_i considering the complete time-shifting interval (i.e., including the original version of services, when $Ts_i = 0$). Once the shifted versions (variations) of the services have been obtained, including the original versions, we proceed to analyze the application of the quality degradation mechanism on them. As for the time-shifting mechanism, in the case of quality degradation, all possible values are considered. This procedure causes Q mutually disjointed classes $H_1, \ldots, H_Q$ of variations to be created. Each class H_k is composed of the degraded versions of the shifted variations of the service S_i (i.e., variations first affected by time-shifting and then affected by quality degradation).

Considering that the application of management mechanisms produces many variations, the adaptive energy management problem is summarized by choosing the best possible variations of services (i.e., for which x_{kie} takes on a value of 1), such that the utilization of P_A is maximized (and P_{RES} is minimized). In this context, the set of N or n (with $n \subset N$) variations simultaneously analyzed is defined as a *combination of variations* or *combination*, denoted as $Comb_f$ (e.g., $Comb_1$).Then, the objective of the load scheduling strategies (optimal or heuristics algorithms) is to find the best combination among all possible combinations (denoted as $AllComb$, with $Comb_f \in AllComb$) produced due to different variations of services.

1) ADAPTIVE ENERGY MANAGEMENT PROCESS: ALGORITHMIC APPROACH

Since adaptive management of consumption is summarized in finding the best combination of services (joint action of energy demands that minimize P_{RES}) through load scheduling strategies optimal (e.g., brute force methods) or approximate (e.g., heuristic methods), it is necessary to establish the criteria that allow: (i) assessment of the improvement in energy use, and (ii) selection of the most suitable combination among all possibilities. To meet the first criterion, this section presents the metrics in Table 5, which allows quantitative evaluation of the combinations (or individual variations) produced by the algorithmic strategies.

The proposed energy model establishes a cost function to evaluate the quality of the combination of variations ($Comb_f$) analyzed. Subsequently, the selection of the best combination of variations, the one that optimizes the use of energy (minimizing of P_{RES}) while maximizing the comfort level of the end-user, is performed using the value of this function. Specifically, the combination with the lowest cost represents the scheduling of services that optimizes use of P_A (i.e., adaptive energy management). The cost function denoted as $Cost_{comb_f}$ considers information from the metric AR ($Cost_{AR_f}$, with $\mathcal{M}$ a big value, e.g., $\mathcal{M} = 1000$) and the cumulative value of parameters l_i ($Cost_{L_f}$), q_i ($Cost_{Q_f}$), and Ts_i ($Cost_{Ts_f}$) of variations (services) in the combination f. Equation 21 defines $Cost_{comb_f}$, while the individual costs that are part of this expression are defined in Eq. 22, Eq. 23, Eq. 24, and Eq. 25. If necessary, the values of cost functions in Eq. 21 can be modified by GEM based on the preferences of the end-user, using the weights α, β, γ, and δ in the range [0,1]. For analytical simplicity, these weights are set to one in the proposed model.

$$\begin{aligned} Cost_{comb_f} &= \alpha \times Cost_{AR_f} + \beta \times Cost_{L_f} \\ &\quad + \gamma \times Cost_{Q_f} + \delta \times Cost_{Ts_f} \end{aligned} \tag{21}$$

$$Cost_{AR_f} = \begin{cases} 0 & \text{if } AR_f{=}100\%, \\ RejServ \times \mathcal{M} \times pri\,RejServ & \text{otherwise.} \end{cases} \tag{22}$$

$$Cost_{L_f} = \begin{cases} 0 & \text{if all services have } j = 1, \\ \sum_{i=1}^{N} l_i & \text{otherwise.} \end{cases} \tag{23}$$

$$Cost_{Q_f} = \begin{cases} 0 & \text{if all services have } j = 1, \\ \sum_{i=1}^{N} q_i & \text{otherwise.} \end{cases} \tag{24}$$

$$Cost_{Ts_f} = \begin{cases} 0 & \text{if all services have } j = 1, \\ \sum_{i=1}^{N} Ts_i & \text{otherwise.} \end{cases} \tag{25}$$

The cost function is computed for each $Comb_f \in AllComb$. As a result the energy model produces a list of costs denoted as $AllCost$. From this list, the best cost identified as $OptCost$ is the one with the lowest value, as shown in Eq. 26. As mentioned above, the combination ($OptComb$) that produces the lowest cost function represents the optimal scheduling of services that achieves adaptive energy consumption. In case there are several optimum costs, the selection can be made randomly.

$$OptCost = \underset{Cost_{comb_f} \in AllCost}{\arg\min} \; Cost_{comb_f} \tag{26}$$

2) HARDNESS OF ADAPTIVE ENERGY MANAGEMENT

The objective of adaptive energy management in our proposal consists of maximizing the use of the available energy supply (mainly from green sources) through the execution (selection) of the best possible variations of services (i.e., for which x_{kie} takes on a value of 1 in Eq. 18). This process is analogous to the objective of the 1/0 Knapsack problem of selecting

TABLE 5. Performance metrics to assess adaptive energy management.

Metric	Expression	Description
Energy Utilization	$E_{A_U} = \frac{\sum_{k=1}^{Q}\sum_{i=1}^{N}\sum_{e\in G_i} p_{kie}\times q_{kie}\times d_{kie}}{P_A\times W}\times 100\%$	This metric measures the amount of energy allocated to processed services (appliances) concerning available energy ($E_{A_U} = 100\%$, if $P_D = P_A$).
Acceptance Ratio	$AR = \frac{N - RejServ}{N}\times 100\%$	This metric measures the number of processed services. The no processed services if $P_A < P_D$ are defined as rejected ($RejServ$).
Missing Power	$P_{LACK}[w] = \mid P_A[w] - P_D[w] \mid$	This metric measures the amount of power needed to process all services if $P_A[w] < P_D[w]$, considering the current values of Ts_{kie} and q_{kie}.

the most valuable items without overloading the knapsack, which has been demonstrated to have a complexity level of $\mathcal{NP}$-hard [40]. Based on this analogy, we can then conclude that the proposed energy model falls in the 1/0 knapsack problem classification and presents a complexity that is $\mathcal{NP}$-hard.

IV. HEURISTIC ALGORITHMIC STRATEGIES

Adaptive energy management constrained to the available supply through management mechanisms, such as time-shifting and quality degradation, can be categorized as a 1/0 knapsack problem and specifically in the multidimensional multiple-choice knapsack problem (MMKP) category [40]. In the proposed energy model, the multidimensional property includes/refers to the magnitude and temporality of the supply and energy demands. Simultaneously, the multiple-choice characteristic refers to a time-shifting and/or quality degradation level applied while selecting an energy demand. In this context, we can conclude that the proposed adaptive consumption model has at least the computational complexity of an MMKP problem, proven to be NP-Hard. Since previous work [21] showed that the exact (optimal) method requires excessive execution (over 90 hours), large computational capacity, and has limited practical application (e.g., for $N > 9$, $Ts_i > 4$, or $q_i > 1$), we present a heuristic algorithm strategy to solve the adaptive management problem within a reasonable running time in this section.

A. PREPARTITIONING-BASED STRATEGY: PHRASE

The proposed strategy named Prepartitioning Home eneRgy mAnagement SystEm (PHRASE) is inspired by a divide-and-conquer approach. Instead of performing combinatorial analysis of energy allocation for the entire set of existing services as would be done in the optimal (exact) method, the suboptimal (approximate) PHRASE strategy iteratively analyzes subsets of services. Each subset z is denoted as a $partition_z$ ($partition_z \subset \mathcal{N}$) and has a length $lenPart_z$ that can be different for each partition, although previous work [13] demonstrated that equal size partitions produce better-quality results. The total number of partitions is identified as $NumPart$. For each $partition_z$ (i.e., services belonging to the partition), the strategy PHRASE analyses

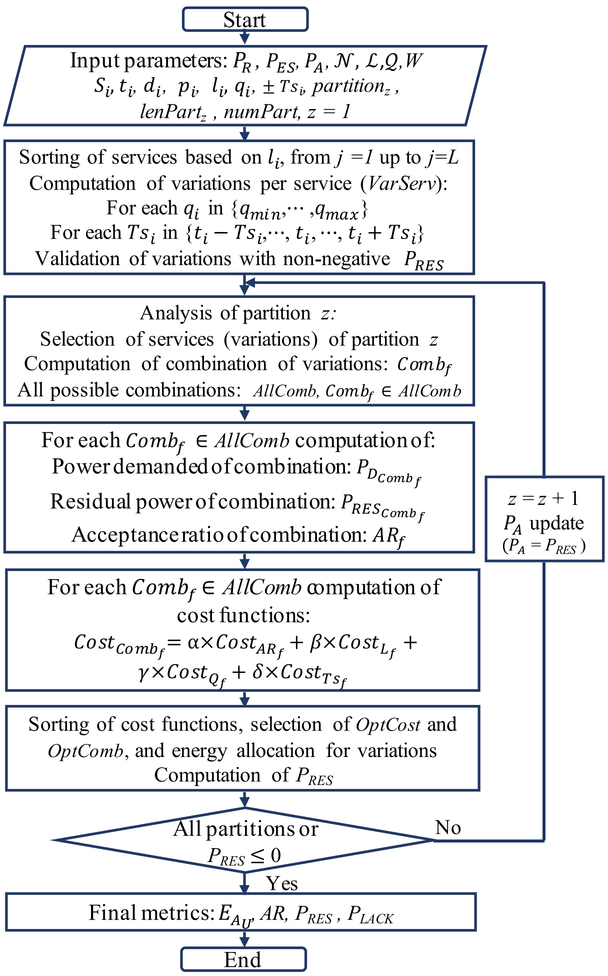


FIGURE 4. Flow chart PHRASE offline approach.

the application of management mechanisms (time-shifting and quality degradation) to produce variations, compute combinations and obtain partial solutions. Later, PHRASE merges these solutions to obtain the total allocation of energy resources and the corresponding scheduling of services that enables adaptive energy management. The PHRASE algorithmic strategy for both the offline and online approaches is explained in Fig. 4 and Fig. 5, respectively. The implementation of PHRASE for the offline approach is summarized as follows:

1) *Sorting of Services and Computation of Variations:* As a first step, the algorithm sorts the services according to their l_i (from $j = 1$ to $j = L$) to ensure the energy allocation for CS. Then the algorithm computes the variations of services considering all the values of time-shifting and quality degradation. Furthermore, to reduce possible invalid combinations (with $P_{RES} < 0$), the algorithm eliminates variations whose isolated execution produces $P_{RES} < 0$. This procedure improves algorithm performance in terms of running time by reducing the size of the search space for the best combination per partition.
2) *Analysis of Partitions and Combination of Variations:* The algorithm performs combinatorial analysis of variations belonging to each partition to obtain combinations. These combinations are made up of different variations of services. Regarding the complexity of PHRASE, we indicate that combinatorial analysis is dominant because as the values of Ts_i or q_i increases (and in the worst case both), the number of variations increases, and the generation of combinations increase exponentially [21].
3) *Selection of Best Combination and Final Performance Metrics:* Once the algorithm obtains all the cost functions, it sorts them in increasing order (e.g., through a quicksort method) and selects the first cost in the sorted list (i.e., cost function with the lowest value). This function represents the best combination of services, which allows for optimal service scheduling in the HEMS. The process continues iteratively until all partitions are analyzed. Finally, the algorithm computes the performance metrics.

The implementation of PHRASE for the online approach is summarized as follows:

1) *Initial Analysis of Services:* Given that for the online approach, the dynamics in terms of demand and energy resources evolve as a function of time slots, the application of the prepartitioning strategy in this environment needs some modifications and additional procedures regarding the offline approach implementation. The first difference is the limited application of forward time-shifting, due to reasons of causality. In this context, the performance for the online approach, in terms of energy utilization, is expected to be lower than the achieved for the offline approach, at most the same (never better). The second change is the differentiation of resources and processing for CS (P_{CS}) and NCS (P_{NCS}) services to ensure CS execution. In this regard, the algorithm assumes that once the service is accepted (in its first slot), there is sufficient energy for its completion (the model does not accept partial processing, as discussed in Section III-C). The last difference is the inclusion of a list named *waitingList*, which store information on the variations of services that were not processed in their natural starting time (t_i) due to lack of power or because the allocation was performed to higher-priority service.
2) *Analysis for CS:* If service S_i at time slot w is identified as a CS, the algorithm allocates the corresponding energy resource. Then the algorithm updates the P_{CS} for the remaining services with this priority level.
3) *Analysis for NCS:* If service S_i at time slot w is identified as a NCS, the algorithm performs a similar analysis to carried out for the offline approach, considering the simulated services with the analyzed service and the services (variations) in *waitingList*. Once the algorithm selects the best combination, the energy allocation is made, and the energy resources for subsequent NCS are updated.
4) *Final Metrics:* Once the analysis of all the services in the time horizon W has been carried out, the algorithm calculates the performance metrics.

B. COMPLEXITY ANALYSIS OF PHRASE

The complexity of PHRASE depends on the total number of analyzed combinations in the explored partitions. The most computationally demanding case arises when the approach is offline. Therefore, Eq. 27 expresses the complexity of PHRASE as a function of the number of services, the total number of quality degradation levels (Q), and the maximum forward and backward time-shifting value (Ts). In Eq. 27, the terms correspond to the original information of the services, the production of variations, and the generation of combinations of services in each partition, respectively. In Eq. 27, the last term is dominant and indicates that the growth rate of PHRASE is non-polynomial. However, as evidenced in previous studies [13], the number and size of partitions can be configured (e.g., $lenPart_z = 5$ services) such that complexity becomes tractable (i.e., feasible running time and usage of computational capacity) and hundreds or thousands of times smaller than the strategy without considering prepartitioning (i.e., when the exact method is applied).

$$f(N, Q, Ts) = N + Q \times (2 \times N \times Ts + N) + Q \times \left(\sum_{z=1}^{NumPart} (2 \times Ts + 1)^{lenPart_z} \right) \quad (27)$$

V. EVALUATION

In this section, the proposed strategy will be validated and evaluated using a data set from real scenarios in order to show the benefits in terms of the metrics defined, specially regarding the capacity to accept more appliances consuming in the period, while smoothing the peaks of power consumed. In addition, to demonstrate the performance of PHRASE, this section presents a comparison with the optimal solution (i.e., without considering the prepartitioning method) and other similar strategies from the literature.

A. SIMULATION SETTING

The performance of the proposed heuristic strategies is evaluated through extensive simulations implemented on

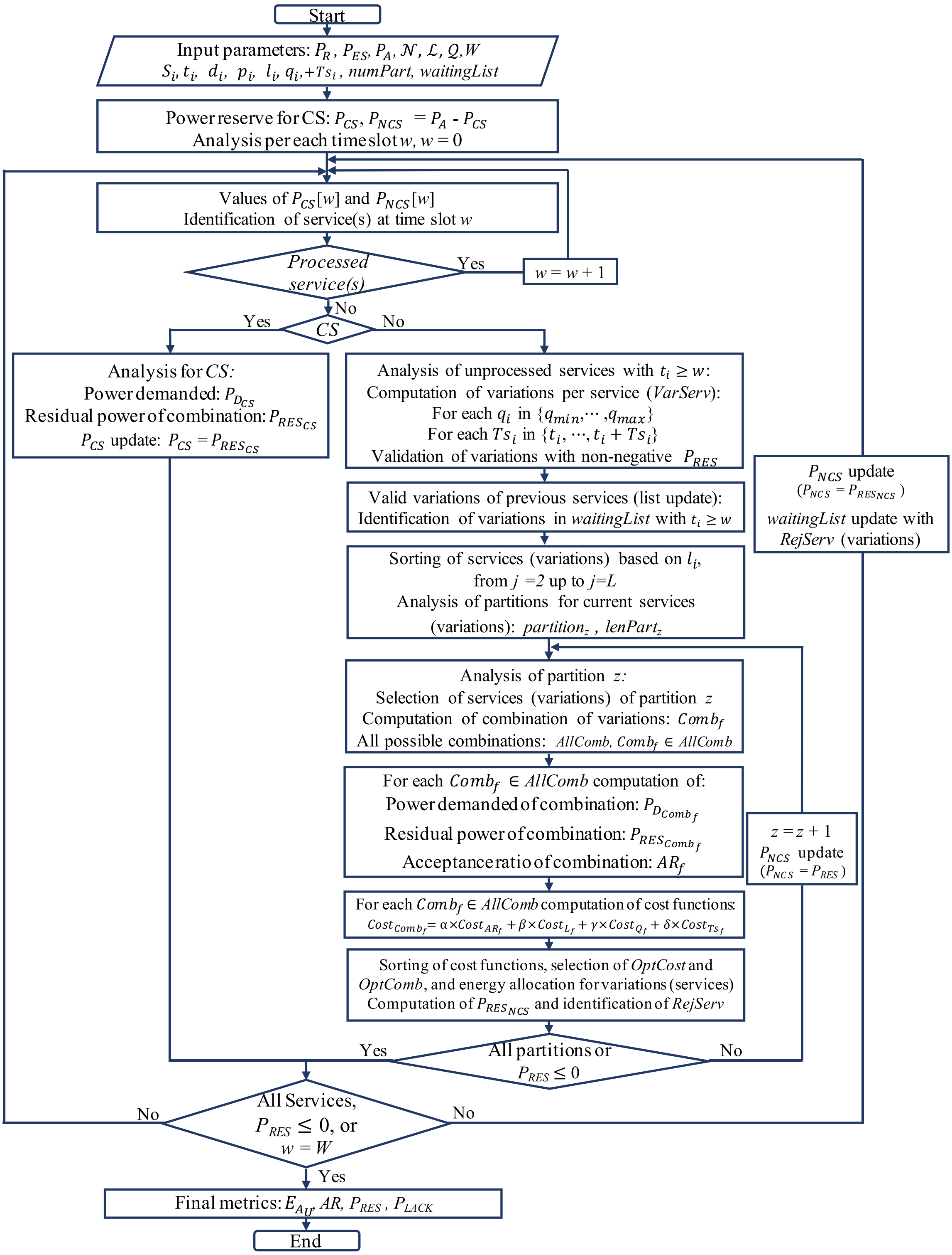


FIGURE 5. Flow chart PHRASE online approach.

Matlab (R2018b) and running on a machine equipped with a 3.33 GHz × 12 cores Intel Core i7 Extreme processor and 24 GB RAM. The simulations leverage parallel processing with the concurrent use of up to 6 cores. The results obtained of metrics E_{A_U}, AR, P_{RES}, and P_{LACK} are compared to the baseline scenario, which has no management mechanism (i.e., no time-shifting or quality degradation). Regarding the number of partitions, they are limited in PHRASE to five because, in previous work [13], this value has demonstrated to offer a trade-off in the running time to explore the

TABLE 6. **Description of the main HEMS scenario.**

Load description	Quantity	p_i [W]	t_i [Hour]	d_i [Hour]	l_i	Ts_i [Hour]	q_i
Fridge Freezer	1	190	00:00	24	1	0	1
Answer Machine	1	1	00:00	24	1	0	1
CD Player/Radio 1	1	17	06:00	3	1	0	1
CD Player/Radio 2	1	17	15:00	4	1	0	1
Clock	1	2	00:00	24	1	0	1
Phone	1	1	00:00	24	1	0	1
HiFi	1	109	18:00	5	3	0	2 ($\times$0.75)
TV 1	1	127	12:00	2	3	0	2 ($\times$0.75)
TV 2	1	127	18:00	5	3	0	2 ($\times$0.75)
VCR DVD	1	36	20:00	3	3	0	2 ($\times$0.75)
Laptop (charger)	1	146	09:00	8	2	$\pm$2	1
Hob 1	1	2401	08:00	1	2	$\pm$3	2 ($\times$0.75)
Hob 2	1	2401	18:00	2	2	$\pm$3	2 ($\times$0.75)
Oven 1	1	2128	08:00	2	2	$\pm$3	1
Oven 2	1	2128	16:00	3	2	$\pm$3	1
Microwave 1	1	1252	09:00	1	2	0	2 ($\times$0.75)
Microwave 2	1	1252	13:00	1	2	0	2 ($\times$0.75)
Microwave 3	1	1252	19:00	1	2	0	2 ($\times$0.75)
Kettle 1	1	2001	10:00	1	2	$\pm$1	1
Kettle 2	1	2001	15:00	1	2	$\pm$1	1
Small Cooking	1	1002	11:00	2	1	0	1
Tumble Dryer	1	2501	08:00	2	2	+8	1
Washing Machine	1	407	17:00	3	2	−8/+4	1
Dish Washer	1	1131	09:00	2	2	$\pm$8	1
Lighting 1	2	50	06:00	2	1	0	1
Lighting 2	2	50	17:00	7	1	0	1
Lighting 3 (not indispensable)	5	50	06:00	2	4	0	3 ($\times$0.5)
Lighting 4 (not indispensable)	5	50	17:00	7	4	0	3 ($\times$0.5)

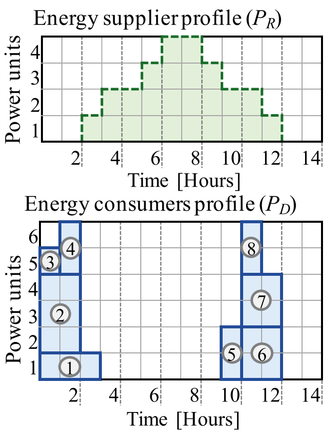


FIGURE 6. **Power supply and consumption profiles in a small-scale scenario.**

TABLE 7. **Description of the HEMS scenario for comparison of results (adapted from [33]).**

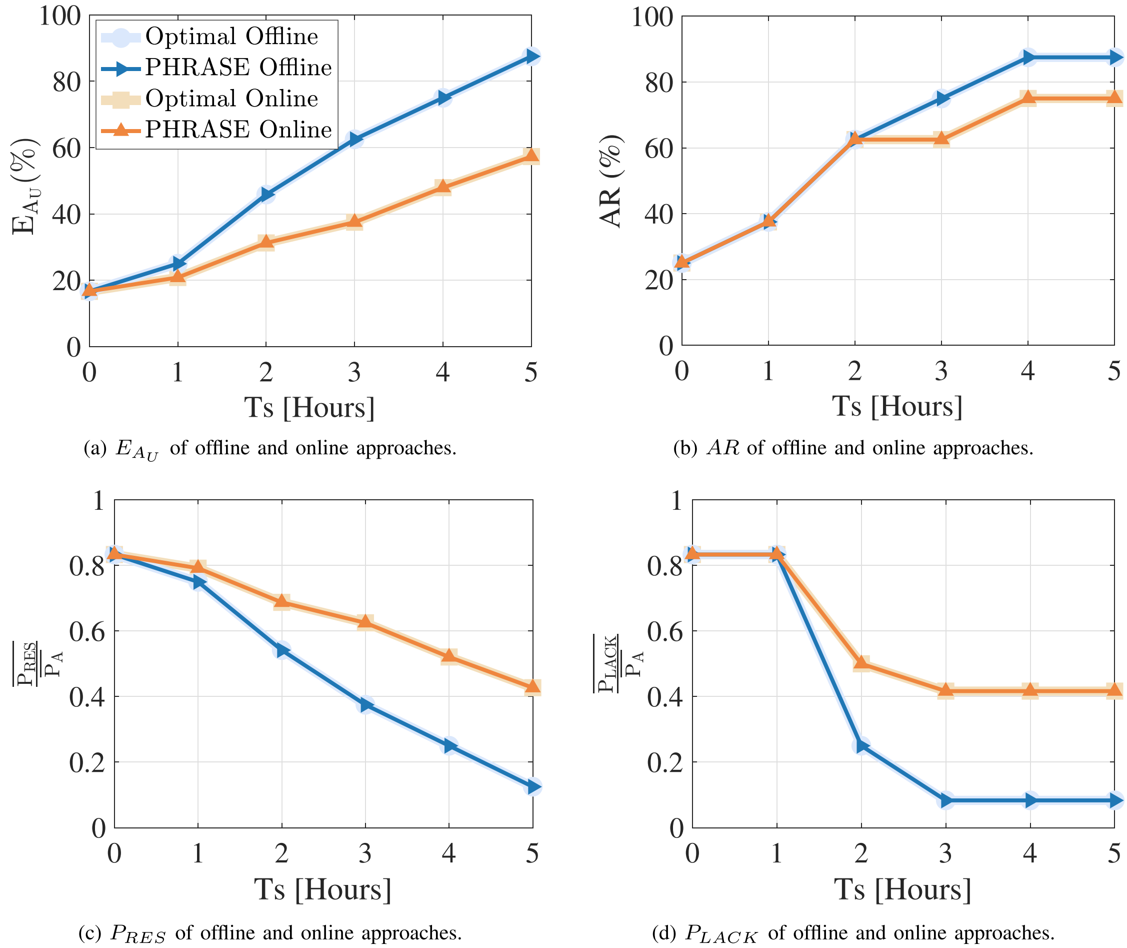
Load description	p_i [KW]	t_i [Hour]	d_i [Hour]	Ts_i [Hour]	q_i
Washing machine 1	1	01:00	1	$\pm$5	3 ($\times$0.5)
Washing machine 2	1	13:00	2	$\pm$5	3 ($\times$0.5)
Cloth dryer 1	4	01:00	4	$\pm$5	3 ($\times$0.5)
Cloth dryer 2	4	09:00	2	$\pm$5	3 ($\times$0.5)
Cloth dryer 3	4	19:00	2	$\pm$5	3 ($\times$0.5)
Electric vehicle 1	3	05:00	2	$\pm$5	3 ($\times$0.5)
Electric vehicle 2	3	09:00	1	$\pm$5	3 ($\times$0.5)
Electric vehicle 3	3	20:00	4	$\pm$5	3 ($\times$0.5)
Water heater 1	4.5	01:00	1	$\pm$5	3 ($\times$0.5)
Water heater 2	4.5	04:00	1	$\pm$5	3 ($\times$0.5)
Water heater 3	4.5	07:00	2	$\pm$5	3 ($\times$0.5)
Water heater 4	4.5	17:00	5	$\pm$5	3 ($\times$0.5)
Refrigerator	1	00:00	24	$\pm$5	3 ($\times$0.5)
Lights	1.5	00:00	24	$\pm$5	3 ($\times$0.5)

combinations of variations (approximately 483,153 combinations if $Ts_i = 5$ and $q_i = 3$) and the accuracy of the results.

B. SCENARIO DESCRIPTION

Three scenarios have been considered for the evaluation of PHRASE. The first scenario aims to compare the performance of PHASE with the optimal solution that is obtained when no partitions are used (i.e., when a brute-force search method is implemented). Previous studies [21] have demonstrated that the optimal solution is limited to a small number of services and time-shifting values (e.g., $N < 9$ and $Ts_i < 6$). Consequently, this scenario has been limited to $N = 8$ services (i.e., a small-scale scenario) and $Ts_i = 5 \; \forall \; S_i$. Fig. 6 summarizes the generation and consumption (load distribution) profiles used to evaluate the optimal solution and the proposed heuristic.

The second scenario corresponds to a real domestic environment in which the impact of PHRASE on adaptive energy consumption is exhaustively analyzed. For the evaluation of PHRASE in a domestic environment, a data set of real consumption over 24 hours obtained from the model provided in [41] is used as a reference. The consumption information has been adapted to the scope of the proposed adaptive model regarding the customized information of priority, time-shifting, and quality degradation, as summarized in Table 6. To simulate renewable energy generation (P_R) in a household, a generation profile following a Gaussian distribution has been used. In this profile, the total available energy is equal to the total energy demanded, and the peak value is



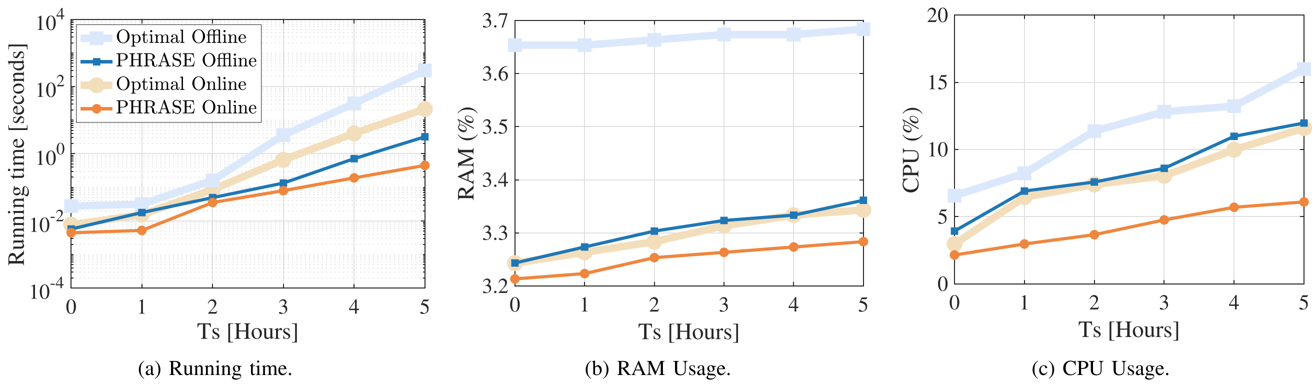
(a) E_{A_U} of offline and online approaches.

(b) AR of offline and online approaches.

(c) P_{RES} of offline and online approaches.

(d) P_{LACK} of offline and online approaches.

FIGURE 7. **Summary of performance metrics obtained by optimal solution and PHRASE strategy in the online and online approaches considering the maximum quality degradation level $q_i = 3$ (×0.5) and two partitions.**



(a) Running time.

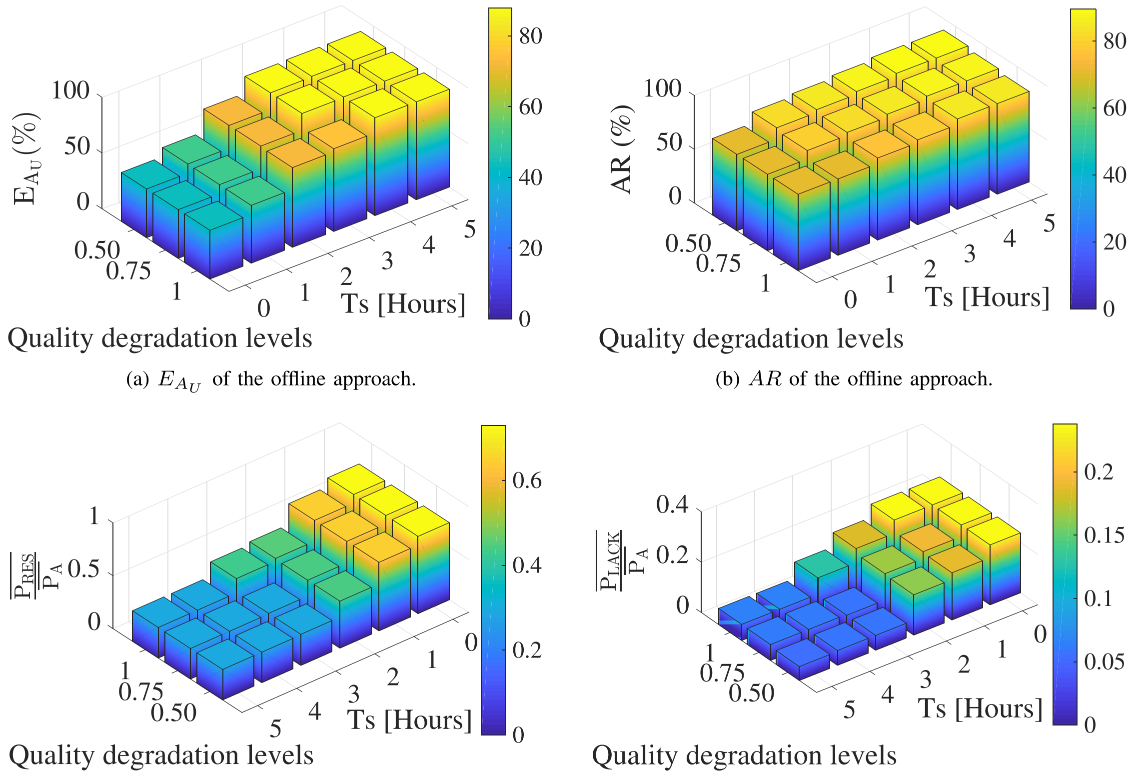
(b) RAM Usage.

(c) CPU Usage.

FIGURE 8. **Running time and computational capacity used by the optimal solution and PHRASE strategy in the offline and online approaches considering a maximum quality degradation level $q_i = 3$ and a single core.**

approximately 6300 watts. This value is within the range of production of real renewable energy systems for domestic environments, as exemplified in [32]. Besides, to simulate the eventual contribution of the energy utility company to the total available supply (P_A), in the proposed scenario, the use of a small fraction of renewable energy P_{ES}^{R} is considered (although it may also be P_{ES}^{NR}) to ensure the execution of services with the highest level of priority ($j = 1$).

In the last scenario, a brief comparison of the results delivered by PHRASE with other similar approaches in the literature is carried out. To this end, the consumption data provided in [33] and summarized in Table 7 have been used. In this case, all services are categorized as NCS with a $l_i = 2$. Moreover, the results of adaptive consumption (reduction of peak power) of PHASE for offline and online approaches are compared with the results obtained with other three



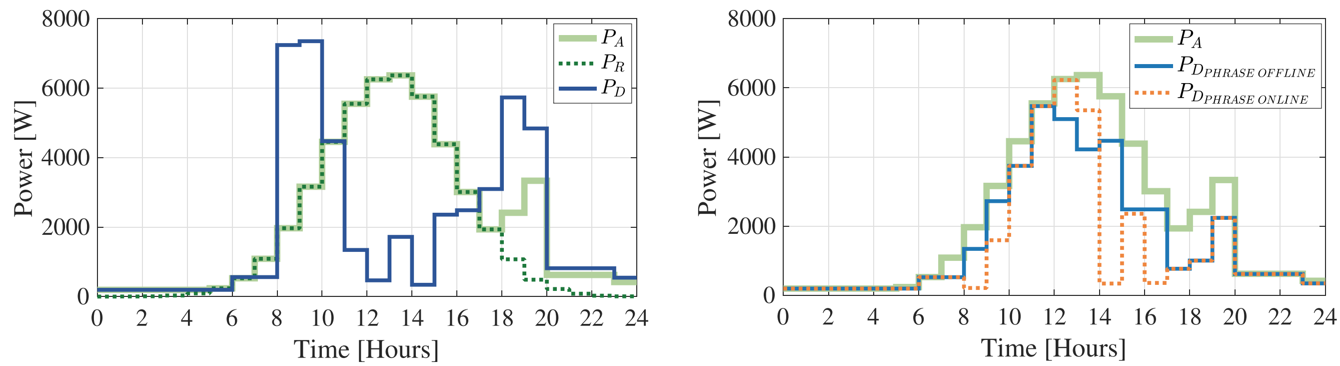
(a) E_{A_U} of the offline approach.

(b) AR of the offline approach.

(c) P_{RES} of the offline approach.

(d) P_{LACK} of the offline approach.

FIGURE 9. Performance evaluation of PHRASE for the domestic scenario described in Table 6 and metrics obtained of the offline approach. The simulation of PHRASE in the offline approach exploits parallel processing, and the total running time for all values of Ts_i and q_i is 352.57 seconds.



(a) Supply and consumption profiles before the application of the PHRASE strategy.

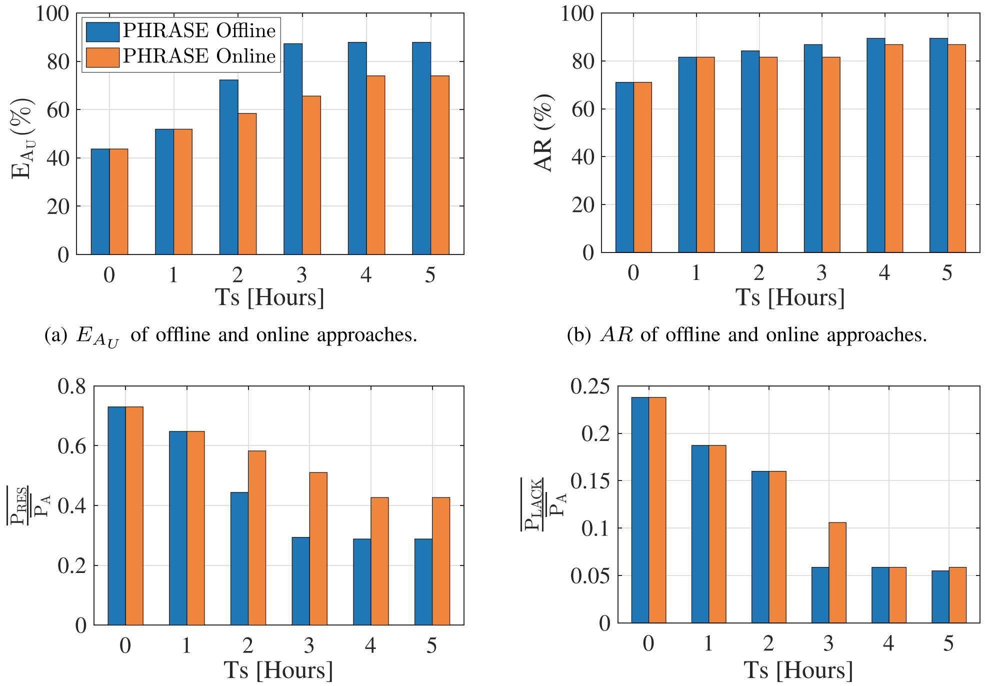
(b) Supply and consumption profiles after the application of the PHRASE strategy.

FIGURE 10. Comparison between the baseline scenario and PHRASE application in offline and online scenarios considering the maximum values of Ts_i and q_i.

evolutionary algorithms-based in [33], that are denoted as Cuckoo (cuckoo search), GA (genetic algorithm), and BPSO (binary particle swarm optimization).

C. NUMERICAL RESULTS

In the small-scale scenario, the evaluation of PHRASE demonstrates that the proposed adaptive model leads to optimized energy consumption, which is reflected in an increase in E_{A_U} and AR and a decrease in P_{RES} and P_{LACK} as time-shifting increases, as shown in Fig. 7a, Fig. 7b, Fig. 7c, and Fig. 7d, respectively. Particularly, in this scenario, the evaluation of PHRASE confirms that this strategy produces adaptive consumption and high-quality results compared to those obtained with optimal strategy. In the analyzed scenario, the suboptimal results (from heuristic) are identical to those obtained with the optimal solution with a reduced running time and less computational capacity, as shown in Fig. 8. Although in diverse scenarios, the performance of PHRASE may be lower than that of the optimal solution, its lower complexity (adjustable by varying the number of cabinets) makes



(a) E_{A_U} of offline and online approaches.

(b) AR of offline and online approaches.

(c) P_{RES} of offline and online approaches.

(d) P_{LACK} of offline and online approaches.

FIGURE 11. Summary of performance metrics obtained by the PHRASE strategy in the online and online approaches considering the maximum quality degradation level $q_i = 3$ (×0.5).

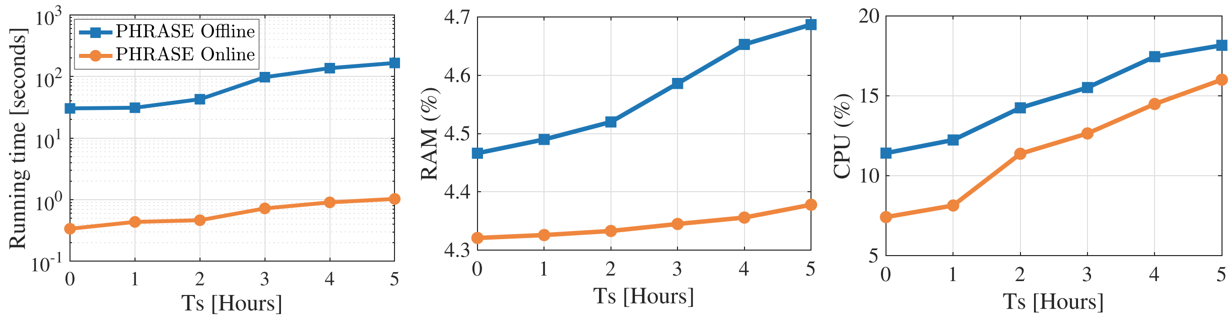
it a feasible solution in a variety of application environments such as the HEMS. As an example of comparison, Fig. 8a reports that PHRASE (for the offline approach) runs over 90 times faster than the optimal solution. Moreover, partitions make it possible to exceed the limits imposed on the optimal solution in terms of the number of services and the value of time-shifting.

~~For~~ the HEMS scenario in Table 6, the simulation results show that the proposed adaptive model and the PHASE strategy lead to optimized energy consumption and the efficient use of renewable resources. As time-shifting and quality degradation levels increase, the algorithmic strategy improves the ability to allocate the consumption demands to the existing energy resource, preventing unnecessary energy wastage. For practicality, Fig. 9 only shows the simultaneous action of time-shifting and quality degradation mechanisms for the offline approach. Fig. 9a, Fig. 9b, Fig. 9c and Fig. 9d show an increase in E_{A_U} and AR values and a decrease in P_{RES} and P_{LACK}, respectively, indicating that the available supply utilization improves with an increase in time-shifting and/or quality degradation value. The comparison of consumption profiles before (baseline scenario) and after the application of PHRASE is shown in Fig. 10a and Fig. 10b, respectively.

To compare the operation in offline and online approaches, the analysis of PHRASE is carried out for the maximum level of quality degradation (i.e., $q_i = 3 \, \forall i \in \mathcal{N}$) and considering a variation in time-shifting (from 0 to 5 hours), as shown in Fig. 11. Simulation results for these conditions report that PHRASE achieves better metric values in the offline approach, as shown in Fig. 11a Fig. 11b, Fig. 11c, and Fig. 11d. This difference in the online approach obeys the limited use of forward-time shifting because of the causal principle and the lower amount of simultaneous variations analyzed. The metric results, specifically the AR, show the limitation of the PHRASE strategy, as the scenario conditions are designed to reach an optimal solution ($AR = 100\%$). A more sophisticated method might achieve an optimal solution. Therefore, future research could address the development and evaluation of adaptive solutions based on genetic algorithms or dynamic programming.

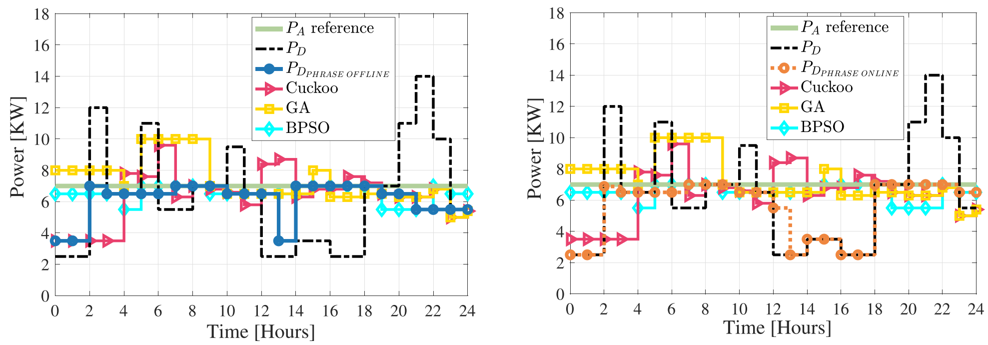
The metrics E_{A_U} and AR summarize the effectiveness of PHRASE in energy consumption. Fig. 11a indicates that the E_{A_U} metric shows a 44.17% improvement (from 43.71% to 87.88%) and 30.3% improvement (from 43.71% to 74.01%) for offline and online approaches, respectively. The AR metric improves by 18.42% (from 71.05% to 89.47%) and 15.79% (from 71.05% to 86.84%) for offline and online approaches, respectively, as seen in Fig. 11b. Although the improvement in AR does not appear to be significant because it is produced by the rejection of several small energy demands (with the lowest priority), the real operation of PHRASE is supported by the value of the E_{A_U} metric. Regarding the reduction of power peaks, Fig. 10b shows that PHRASE produces a reduction of 25.58% and 15.3% for offline and online approaches, respectively.

On the other hand, Fig. 12 reports that PHRASE solves the most demanding case ($Ts_i = 5$ and $q_i = 3$) with a running time of 165.31 seconds in the offline approach with the maximum usage of 4.69% RAM and 18.16% CPU. For the online scenario, the maximum running time is approximately



(a) Running time. (b) RAM Usage. (c) CPU Usage.

FIGURE 12. **Running time and computational capacity used by the PHRASE strategy in the offline and online approaches considering a maximum quality degradation level $q_i = 3$ and a single core.**



(a) E_{A_U} of the offline approach. (b) AR of the offline approach.

FIGURE 13. **Performance evaluation of PHRASE for the scenario described in Table 7 considering two partitions and comparison with similar approaches in [33].**

1 second using a maximum of 4.38% of RAM and 16.01% of CPU. The results in Fig. 12a, Fig. 12b, and Fig. 12c show that PHRASE can be executed with a reasonable running time using a small amount of computational capacity. Thus, this strategy can be applied to plan renewable and non-renewable energy consumption or energy management in real-time scenarios. Furthermore, the strategy could be deployed into an embedded device with limited computational resources such as a Raspberry Pi 3 Model B platform [42].

Regarding the comparison with existing strategies in the literature, the results of the third scenario in Fig. 13 report that PHRASE produces solutions similar to more sophisticated approaches such as those based on evolutionary algorithms [33]. The results in this scenario show that even though the structure of PHRASE is simple (based on prepartitioning), its internal management mechanisms (mainly time-shifting and quality degradation) allow obtaining an efficient adaptive consumption for offline (Fig. 13a) and online (Fig. 13b) approaches. Specifically, the results in Fig. 13 indicate that PHRASE, like the existing strategies (Cuckoo, GA, and BPSO), enables peaks power reduction. Even as shown in Fig. 13a and Fig. 13b, the proposed heuristic compared to the others strategies analyzed offers a lower level of power peaks (lower than 7[KW]) and a consumption conditioned to availability (P_A) throughout the time horizon. Moreover, PHRASE produces an improvement in service processing (use of P_A) of 42.86% (from $AR = 57,14\%$ up to $AR = 100\%$) for the offline approach and 35.72% (from $AR = 57,14\%$ up to $AR = 92.86\%$) for the online approach, verifying the validity of the model in terms of adaptive consumption conditional on availability.

VI. CONCLUSION

This paper proposes an IoT-enabled automated and adaptive HEMS that optimizes self-generated renewable energy utilization, which can use as a secondary source the provisioning from the energy utility company if necessary. The proposal includes a description of the architecture, the negotiation scheme for the consumption of IoT devices, and management mechanisms, such as time-shifting and quality degradation, to adapt the demand to the available power while maximizing its utilization. This paper also provides the mathematical formulation associated with the adaptive consumption model. To solve the energy model, a heuristic called PHRASE is provided, which bases its operation on a divide and conquer approach.

To verify the validity of the proposed system and the operation of PHRASE, a simulation is carried out in a domestic environment based on real consumption data generated from [41]. The results of the metrics E_{A_U}, AR, P_{RES}, and P_{LACK} in the simulation performed reveal that the proposed energy model and algorithmic strategy deliver improvements in a way that available energy is used compared to the baseline scenario in which no management strategies are applied.

Particularly, if PHRASE uses the maximum values of Ts_i and $q_i = 3$ (i.e., $Ts_i = 5$ and $q_i = 3$), E_{A_U} improves by 44.17% and AR by 18.42%, and the peak power is reduced by 25.58% for the offline scenario. In the online scenario, the improvement in E_{A_U} is 30.30% and AR is 15.79%, while the power peak is reduced by 15.30%.

Regarding the running time of the algorithmic strategy and computational resources used, the results of the simulations indicate that for the offline scenario, the maximum running time reached is 165.31 seconds (for $Ts_i = 5$ and $q_i = 3$) using a maximum of 4.69% of RAM and 18.16% of CPU. For the online scenario, the maximum execution time (for $Ts_i = 5$ and $q_i = 3$) is approximately 1 second using a maximum of 4.38% of RAM and 16.01% of CPU. The online scenario results demonstrate the feasibility of PHRASE in real-time applications and the possible deployment in current embedded devices of limited computational capacity. Therefore, it can be implemented in low cost devices, and attached to the smart meter.

Although the PHRASE algorithm produces improvements in renewable energy consumption in a reasonable running time, other strategies, such as genetic algorithms or dynamic programming, could be evaluated in future work. Furthermore, since the online operation of PHRASE is limited to the use of forward time-shifting, a prediction mechanism of the generated supply could be included in the adaptive model to potentially expect better energy allocation and demand processing. To this end, different techniques could be used, among which we can mention supervised learning techniques such as random forest or artificial neural networks, which are pretty popular today. Also, despite the proposed system encouraging battery-free adaptive management, a battery unit's possible inclusion could serve to store energy in periods of abundance and provide energy if the P_R is not sufficient to meet all demands. This would not only improve system performance but also reduce dependence on energy utility provisioning.

Finally, the proposed system, model, and strategy presented in this paper can be extended to other application environments, such as the energy management of electric vehicles, for nano-networks (where the energy is very limited and usually from very critical harvesting strategies), or for spatial bases in the Moon or outer space.

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