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Residential Energy Management Systems Based on Multi-Agent Systems: A Survey

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ABSTRACT

Residential sectors all around the world use a significant amount of energy. The incorporation of automation technologies within the smart home (SH) is motivated by economic and comfort-based advantages to house owners. The transfer to demand response (DR) application and dynamic electricity pricing for residential clients indicates that the conventional home power strategies are neither flexible nor sufficient. An intelligent, efficient, and more flexible SH energy management system (EMS) is desired. A multi-agent system (MAS), due to its intelligence and its autonomous and distributed characteristics, is capable of solving such dynamic and complex problems. This paper reviews studies of home energy management systems (HEMSs) based on MASs, including HEMSs with the objective of minimizing residents' energy bills while maximizing their comfort, as well as those that only work to reduce the energy consumption in the user's house. Also, the pricing schemes, algorithms, and simulation platforms used are discussed as different characteristics of the surveyed HEMSs.

Keyword: *Home Energy Management System, Multi-Agent System, Demand Response, Smart Home, Energy, Comfort.*

1. INTRODUCTION

There is a rising interest in decreasing residential power consumption through the use of computational support and expanded sensor data for smart building management. This increase in interest is mainly driven by the notable portion of overall power consumption associated with smart homes (SHs) [1]. The power consumption of the global residential sector represents between 16% and 50% of the energy consumed by all sectors [2]. Additionally, with rapidly growing energy costs and increasingly energy-demanding products such as advanced HVAC systems and electrical vehicles in residential life, the demand for power has risen significantly and put enormous loads on the current energy grid [3].

One type of energy system, the smart grid (SG), is a promising option for facing these challenges. The SG enhances power efficiency in the energy systems through intelligent control technologies such as demand response (DR) programs [4], [5]. DR is defined by the US Department of Energy [6] as "a tariff or program established to motivate changes in electric use by end-use customers, in response to changes in the price of electricity over time, or to give incentive payments designed to induce lower electricity use at times of high market prices or when grid reliability is jeopardized". DR programs enable enhanced operation of residential appliances [7].

The SH, a significant unit of the SG, features a home energy management system (HEMS) that aims to reduce energy cost and conserve resident comfort by intelligently controlling and monitoring the energy consumption in the house. It does so by an integration between intelligent appliances, smart meters, and the house's power storage and generation system [8], [9]. Furthermore, it can also interact with other SHs and/or entities in the SG [10].

One of the challenging problems in power management for an SG is how to concurrently control the components for all SHs within a multi-user area in order to decrease the total energy price [11]. Therefore, the coordinated energy management in SGs for multiple SHs is examined by control method - centralized or decentralized. The centralized control method is utilized for SH coordination where one superior entity, which can be a utility company or an aggregator, collects detailed information from SHs and implements decisions. This method is effective in terms of managing the energy. However, it causes an overload on communication and computation resources. Also, clients usually are not comfortable with the idea of having a different entity managing their own devices and having their homes be fully controlled by machines. By contrast, in the decentralized control method, the households are independent decision-makers who can choose their strategies and manage their own electricity [10], [12].

The multi-agent system (MAS) is one of the most relevant technologies that has been discussed throughout the literature in regard to the difficulties of developing very decentralized intelligence systems. This is a computational system that consists of several autonomous smart agents. These communicate with each other to resolve particular problems that may exceed the ability of one system or one agent [13], [14]. In the SG field, the MAS-based systems have attracted critical interest as appropriate automation technology at both the single-home and multi-home levels [15]. Furthermore, the MAS easily allows the constituents of each SG - consumers, system operators, electrical generators, and aggregators - to act autonomously and communicate with each other [5].

Several surveys on energy management can be found in the literature [7], [16]. In [7], the authors present a study of coordination mechanisms for energy management in a community of SHs. In [16], the researchers provide a review of 121 papers that proposed systems for comfort and energy control in intelligent buildings. Conversely, many reviews focused on DR and SG [17]–[21]. In [17], the focus is on surveying the DR algorithms for households at individual and neighborhood levels. Furthermore, Siano [18] displays a review of DR's potential and benefits in an SG environment. In [19], a review of DR and its current use and potential application in an SG is given. Additionally, Vardakas et al. [20] provides an extensive survey of different DR programs and schemes, based on the incentives proposed to customers to cooperate in the programs. Finally, in [21] a review of the utilization of MASs in building for the coordinate of different buildings interaction and building processes within SGs is proposed.

The earlier literature survey [7], [16]–[21] reveals that although there have been many reviews of energy management systems (EMSs), the literature lacks an investigation of EMSs in SHs that are based on MAS technology at both the individual and community levels. Furthermore, most of the previous surveys cover EMSs based on MASs briefly. Taking into consideration the idea that the growing amount of publications in the field of agent-based SGs is proof of the importance of MASs [22].

Therefore, the purpose of this paper is to review recent research in intelligent control systems. The systems reviewed are based on MAS technology using DR in SGs for energy management in SHs at single-home and neighborhood levels. We also discuss the pricing schemes, algorithms, and simulation platforms used as different factors of the proposed HEMSs, together with the strengths and limitations of each system. Furthermore, we review the DR and MAS features.

The method used to select papers from the literature focused on journal and conference papers published between 2011 and 2017. Many search engines were used, including IEEE Xplore Digital Library, the ACM Digital Library, SpringerLink, ScienceDirect, and Google Scholar.

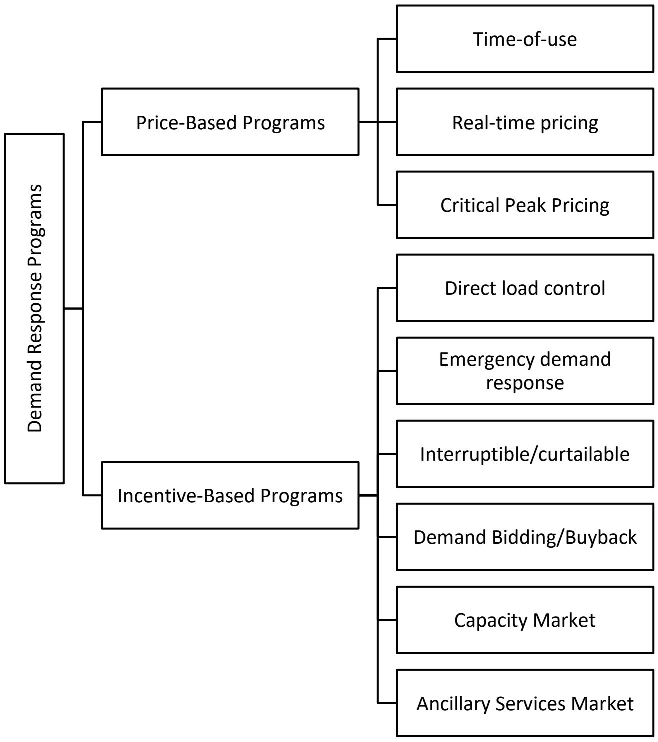

Figure 1. Demand response programs taxonomy [6].

The key search terms used include "smart home," "multiagent system," "saving energy," and "comfort". Primary consideration has been given to papers that discussed multi-agent technology and systems that targeted SHs.

Section 2 of the paper provides an overview of the SG, DR, SHs, HEMSs, and MASs. Section 3 reviews the proposed HEMSs at both individual and community levels. Section 4 discusses the results and provides a comparison of surveyed studies, and Section 5 concludes the paper.

2. BACKGROUND INFORMATION

The purpose of this section is to provide background information on critical concepts in the field of energy management: the SG, DR, the SH, the HEMS, and the MAS.

A. Smart Grid (SG) and Demand Response (DR)

The SG provides reliable, effective monitoring and control of two-way information and a transfer system for the use, distribution, transmission, and generation of electricity. The goal is to make the current energy system more efficient, reliable, and robust with the use of smart technologies [23].

DR is one of the key features of an SG. DR programs often apply mechanisms to encourage clients to decrease demand to limit the peak load. During periods of low demand and high production, these programs may also help increase demand [18]. Furthermore, DR, which enhances the efficiency and reliability of a power grid, can benefit both the user and the power grid itself [20]. Some benefits of DR for users include increased options when choosing a client due to a greater variety of electricity management pricing packages, savings on clients' bills, and savings on bills for other clients' which lowers total market costs, resulting in a usage shift toward lower-priced hours or using low-power settings when costs are high [18].

Generally speaking, there are two types of DR techniques: pricing-based programs and incentive-based programs. Figure 1 shows the main categories for each type of DR technique. The names vary in the literature, and here we have used the most popular.

There are three different types of pricing-based program: time-of-use pricing, real-time pricing, and critical peak pricing. The pricing-based programs that are also called time-sensitive pricing programs encourage the clients to voluntarily and individually adjust and manage their energy consumption, either by reducing energy use or shifting demand from peak times to off times to enhance electricity efficiency [9], [11], [18].

Conversely, incentive-based programs are based on an agreement between the clients and the utility company. The company can remotely manage the energy consumption and operations of specific devices, such as thermal equipment, lighting, and refrigerators. Currently, commercial and large industrial clients are the largest users of these programs [11]. The most common types of incentive-based programs are direct load control, interruptible/curtailable load, and emergency demand response. The popular DR programs in each category are explained in Table 1.

B. *Smart Home (SH)*

The SH is a home with a network that allows communication between all appliances, providing monitoring, control, and remote access of the HEMS [24]. An SH may also have local renewable power generation (such as a small wind turbine or rooftop solar panel), battery power storage, and an electric vehicle that are all connected with the SH [17]. The SH users are usually considered self-interested members with control and communication abilities who have the objective of enhancing their own benefits, such as lowered electricity bills [12]. Figure 2 represents the SH and its elements.

Table 1. Popular types of DR programs [6], [18].

Price-Based Programs	**Incentive-Based Programs**
Time-of-use: The cost of power is fixed for certain periods in the day. There are high-peak, medium-peak, and low-peak prices.	*Direct load control:* Clients get incentive payments for giving the program operator a level of control over specific devices.
Real-time pricing: Prices alter continuously, usually hourly, in response to the general cost of electricity. Clients are usually informed of real-time pricing costs on an hour-ahead or day-ahead basis.	*Emergency demand response:* Clients get incentive payments for capacity decreases when these are required to assure reliability.
Critical Peak Pricing: Its pricing is a combination of the time-of-use and real-time pricing schemes. The rate is prespecified and very high; it is triggered by the utility company and results in a limited number of hours.	*Interruptible/curtailable:* Clients get a rate discount for agreeing to decrease the load for system contingencies. Curtailable programs have usually only been allowed for the biggest commercial or industrial clients.

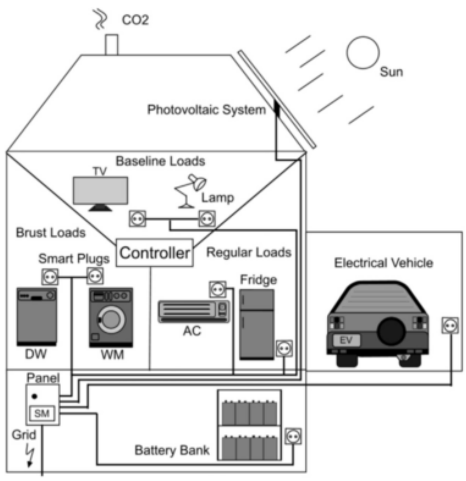

Figure 2. SH design model (air conditioner (AC), washing machine (WM), dishwasher (DW), smart meter (SM)) [7].

C. Home Energy Management System (HEMS)

A HEMS is a DR mechanism that reduces and shifts demand to increase SH power performance according to user comfort and electrical pricing [25]. The HEMS controls and manages smart devices within the SH and communicates with the utility companies. It also collects external data, such as solar power production, to produce a schedule for the household appliances and enhance the efficiency of power consumption [25], [26]. A HEMS is usually a software-based structure with intelligent control, monitoring, and optimization abilities [26]. It generally finds the optimal consumption schedule by taking into consideration goals such as environmental concerns, power prices, user satisfaction, and load profiles [25]. In addition, the HEMS has an important role in both preserving occupant 'comfort and managing energy in the SH [21]. HEMSs have multiple characteristics that can be used to compare different systems - goal, scale, and strategy [5]:

- The goal is an objective function in the problem of power management. The goal of a HEMS can be minimizing cost, maximizing reliability, maximizing user comfort, or a combination of these.
- The scale of a HEMS can be a community, a single home or office. Depending on the size of the HEMS, the complexity of the problem of power management can change.
- The strategy is an essential characteristic of the HEMS. A strategy can be described as "a decision-making path to obtain the optimum amount of objective function" [5]. The most frequently applied strategies in HEMS are decentralized, centralized, and hierarchical.

However, this survey focuses on systems with the goals of minimizing cost and/or maximizing user comfort. Two different scales are considered: community and single-home. Finally, the strategy for all systems is decentralized, since they use MASs. The subsection that follows will cover the MAS since MAS is the method used by all the papers reviewed.

D. Multi-Agent System (MAS)

A MAS is a combination of many agents operating in collaboration to accomplish the desired goal. These agents can coordinate and interact with each other as well as with the environment. The MAS has become an increasingly powerful tool to develop complex systems [1], [13]. An agent related to power management can be defined as "an autonomous agent that can be software or hardware that inhabits some dynamic environment, senses through sensors and acts upon environment through effectors" [27]. In fact, the essential feature that distinguishes a power-management agent from another software or hardware system agent is that it is flexible and intelligent [22], [28]. The primary goal in a MAS is replaced by the individual goals of each agent where information is asymmetrically distributed. Thus, not every agent has sufficient data to resolve the problem. That means that computation is asynchronous and there is no global control system [22].

In a MAS, the intelligent agent has three essential characteristics that help it to satisfy the system's objectives [22], [26], [28]:

- *Reactivity*: Allows the agent to respond to every change that occurs in the environment.
- *Proactivity:* Provides the agent with a goal-directed behavior that helps it to improve its actions towards its defined goals.
- *Social ability:* Communicates with different agents to exchange data between software applications and hardware; has the capacity to compete, cooperate, or negotiate with other agents.

In addition, the MAS can react to increasing computing difficulties due to its capabilities -- dealing with complex and massive problems, autonomy, intelligence, modularity, managing distributed information, flexibility, and extendibility [22], [28].

Furthermore, many optimization methods have been used by researchers, such as particle swarm optimization and genetic algorithms. These are applied as an optimizing algorithms in MAS. It is worth noting that MASs and particle swarm optimization are generally classified as two different fields: artificial intelligence systems and an optimization algorithm, respectively [29].

E. Agent Architectures

In a MAS, the agent architecture is the blueprint used when constructing an agent. It is the brain of the agent, as it defines how the agent will express information and knowledge [30]. Classic agent architectures include:

- *Reactive agent architecture:* This type of agent does retain any memory of past environmental states and makes its decisions at runtime. Therefore, this agent simply responds to changes in the environment [21], [27], [31].
- *Deliberative agent architecture:* This is a goal-driven agent. Because it is involved in the negotiation and planning process, it must be able to reason to accomplish coordination with other agents. This agent keeps an internal representation of their world [29], [32], [33].
- *Hybrid (layered) agent architecture:* This agent is a hybrid of the deliberative and reactive agent architectures. Therefore, it allows for both deliberate and reactive agent behavior [30].
- *Belief-Desire-Intention (BDI) agent architecture:* BDI architecture is one of the most famous architectures. It is a deliberative agent architecture containing explicit representations of mental state characteristics, namely: belief, desire, and intention. Belief corresponds to the set of data an agent has about its environment. Desire represents

the agent's possible choices or the motivation to carry out actions. Intention refers to the agent's commitment toward its beliefs and desires. Considering that, the intention aspect is essential to an agent's success [30], [33].

F. Control Method for MASs

MASs usually consist of large numbers of agents working together in quickly growing dynamic environments. Considering that the environment and data are decentralized, the responsibilities and roles of each smart agent must be determined with precision to resolve possible conflicts that may appear within the agents' communications. As detailed by the authors of [14], a MAS can have one of three control methods: centralized, distributed, or hierarchical:

- *A centralized MAS control method* is described as a set of purely homogeneous, non-communicative agents that are controlled by an individual control center in a master-slave relationship. This reflects the conventional control method with some extra functionality.
- *A distributed MAS control method* is described as a set of communicative agents that are controlled by an individual layer control structure. Every local agent is responsible for and knows its own part of the network, but no individual agent has a full understanding of the entire system. Rather, single agents are permitted to explore global data through coordination and communication with their neighbors.
- *A hierarchical MAS control method* is described as having some agents with authorization over the operations of other agents. This method can involve a two-level or three-level hierarchical system.

G. Implementation of MASs

A variety of platforms are used to develop and implement MASs in the literature, such as JANUS, Java Agent DEvelopment Framework (JADE), and ZEUS. However, JADE is the most broadly adopted software for the implementation of MASs in the HEMSs that have been surveyed and reviewed.

JADE [34] is a platform fully implemented in the Java programming language that enables the development of multi-agent systems and applications based on the agent paradigm. JADE provides standard agent technologies and offers the developer many features that simplify the development process. It also offers graphical tools that support both the debugging and deployment phases [35]. JADE is a distributed agent platform, which enables agent communication via message passing, and it uses standard interaction protocols to carry out communication with the software agents [35].

ZEUS [36] is a free agent-development platform implemented in the Java programming language. It provides developers with a runtime environment, a graphical user interface (GUI), and several helper tools for observing coordination strategies, debugging, process scheduling, and general-purpose planning. However, due to weak documentation for the ZEUS platform, new developers may face difficulties when using it to build new applications [14], [28].

VOLTTRON [37] is a distributed agent framework used explicitly for electrical energy systems. VOLTTRON is an open-source platform designed to support transactions among all networked entities that share an electrical grid. The control architecture is modelled as a three-level hierarchy of agent classes: the cloud agent that publishes data to and from a remote platform, the control agent that communicates with devices, and the passive agent that records data by communicating with sensors. An aggregate of agent classes can be applied to derive a variety of agents [14], [28]. Table 2 presents key points between the commonly used platforms for developing MASs.

Table 2. The critical key points between the commonly used platforms for developing MASs [14], [28].

Properties	JADE	ZEUS	VOLTTRON
Open source and free	Yes.	Yes.	Yes.
Programming Language	Java based.	Java based.	Programming language independent.
Editor	Command line.	GUI.	Command line.
Ideal application	Scalable microgrids.	Fast prototyping.	Power management application.
Operation system(s)	All that supports JVM.	All that supports JVM.	Linux.

3. ENERGY MANAGEMENT SYSTEMS (EMSs) BASED ON MULTI-AGENT SYSTEMS (MASs)

In recent years, there has been an increasing amount of literature published on HEMSs [3], [4], [9], [10], [12], [23], [24], [26], [27], [38]–[48]. This section reviews selected EMSs based on MASs, classified by two levels: the individual SH level and the multi-home/community level.

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First, we will describe the proposed studies that focus on single home energy management. Overall, these studies aim either to help the HEMS to minimize residents' energy bills while maximizing their comfort or else only reduce the energy consumption in the user's house. Second, we will review the solutions at the community level, which can be categorized as energy- and comfort-based or as energy-based. The classification of the selected papers is shown in Table 3.

Table 3. Classification of the selected reviewed EMSs based on MAS.

EMSs based on MASs.	Individual SH level.	Considering the trade-off between energy saving and user comfort.	[3], [4], [23], [26], [27], [48].
		Considering only control and management of energy consumption.	[24], [38]–[40], [49].
	Multi-home/community level.	Energy- and comfort-based.	[41]–[44].
		Energy-based.	[9], [10], [12], [45]–[47], [49].

A. EMSs Based on MASs at the Individual SH Level

Several studies have considered the trade-off between energy saving and resident comfort. To further investigate these studies, this review first looks to Gupta et al. [23], who introduced an agent-based SH HEMS. The system uses renewable energy and allows the user to plan appliance usage one day ahead, which means that the user need not monitor the electricity price on an hourly basis. Furthermore, the system enables the user to maximize the appliances' usage while it keeps the electricity bill under budget.

A multi-agent demand-side management approach is presented by Li et al. [26]. The proposed method is inserted into the HEMS. That allows the agents to react and communicate with the appliances and power sources of the SH to reduce the electricity cost and achieve optimal energy usage.

Rasheed et al. [27] designed a residential load management system that uses the multi-agent technology with the goal of comfort and cost management. The smart devices in the smart home are modelled as agents and controlled using optimization algorithm. Also, the agents communicate and cooperate with each other using agent communication language with the objective of reducing the power cost and high peaks without affecting customer comfort. The study results showed that scheduling with optimization algorithm preserves electricity payment and power consumption in comparison to the unscheduled case, where loads are controlled randomly.

A multi-agent control system is introduced in [4]. It aims to manage energy and comfort in the smart building with the use of a distributed control strategy to integrate distributed energy resources, including wind, solar, and batteries that provide energy to the entire building. A particle swarm optimizer is used in the development of a multi-agent control system that consists of multiple local controller-agents, a central coordinator-agent, and various load agents that are employed in emergency situations. The result of the case study implemented by the authors demonstrates that the framework can accomplish efficient power and comfort management in a green building.

Zupančič et al. [3] proposed a MAS for intelligent buildings to manage the space cooling and heating operations. The control system is composed of four kinds of agents: sensor, control, housekeeper, and machine-learning agents. Every agent has its tasks and is linked to the others in the system. The control agent uses a control algorithm to achieve temperature setpoint delegation for the cooling and heating systems. The proposed algorithm applies machine-learning methods to ascertain the occupants' behavior and the environment. Predictions of resident occupancy were applied to improve power savings and to reduce power consumption. The experiments performed by Zupančič et al. [3] indicate that the proposed MAS increased comfort significantly while slightly increasing power consumption.

Another scheme that can be used to manage the energy in the buildings is a division of the entire building into multiple zones. The authors in [48] applied this scheme and proposed a MAS for managing the indoor environment of a multi-zone building. Particle swarm optimization is used to decide the optimal solution to reach the highest possible level of user comfort when energy is limited. The simulation results proved the efficiency of the particle swarm optimization algorithm.

The other studies have considered only control and management of energy consumption in the residential house. In [38], a MAS for SH energy management that uses multiple optimization strategies for concerns such as cost, comfort, demand-side management, and energy efficiency is proposed and evaluated. The primary goals of these four strategies are to provide the customer with energy and cost savings while providing the household flexibility and control over its energy use. The results of the simulations show that the system optimizes user energy consumption within the customer-specified comfort conditions.

Another HEMS that uses the MAS for SHs is proposed by Shah et al. [39]. The system applies priority techniques in combination with the electrical supply system. To achieve optimal scheduling of appliances in a SH, the binary particle swarm optimization technique is used. The proposed system allows two kinds of priority techniques, one focusing on achieving the lowest consumption and one focusing on user comfort. The experimental evaluation indicated that the user-comfort priority technique provides better results regarding consumer demand and electricity cost as compared to the lowest-consumption priority technique.

An agent-based SH electricity system that consists of a prediction engine and an EMS is presented in [24]. The system links the SH to the power grid and enables it to buy or sell electrical energy while controlling and managing the energy consumption within the SH. An optimization method (Modified Stochastic Predicted Bands) is applied to model the uncertainty of decision-making variables in the SH energy management problem.

Another HEMS, based on both logic programming and object-oriented methods, is proposed by Hirankitti [40]. This agent framework can help occupants to use power more efficiently by using the renewable energy that the SH itself can produce.

A MAS project entitled Mas2tering [49] intends to develop a new information and communication technology platform to optimize the management and monitoring of local communities for end users. To evaluate the effectiveness of proposed solutions, the project relies on many usage cases. Each usage case deals with a distinct part of a low-voltage grid. The first case focuses on a home area network (HAN) and the services that comprise a domestic low-voltage end user. The range is defined as the interoperability between the HAN's control system, gateway, and smart meter, which provides the bi-directional connection between the end user and the remainder of the low-voltage grid. The objective is to illustrate that such communication can assist with consumption profile optimization and optimize the energy bill at the domestic house level [49]–[51].

B. EMSs Based on MASs at the Multi-Home/Community Level

In the previous section, the proposed systems neglected the power consumption of other SHs when managing their loads. In standard DR programs, all clients get the same signal from the grid, leading to the risk that all households may move their devices to operate during the same time periods [7]. As discussed above, the solutions in the studies on the community level are categorized as energy- and comfort-based or as energy-based.

A recent study by Jiang and Fei [42] introduces an agent-based power ecosystem to optimize DR application and distributed energy resource control in a community of residential sectors by applying hierarchical agents. Five elements combine in the power ecosystem: distributed generation, utility grid, energy storage, users, and appliances. The proposed system aims to minimize electricity payment and reduce peak demand for all households. Simulations indicate that the proposed system is efficient in decreasing the electricity bill while conserving customer preference.

A double multi-agent control system for cost operation of both the SG and SHs is introduced in [43]. The particle swarm optimization technique is used to reduce the power consumption and maximize the comfort level. Simulations performed by Hurtado et al. [43] show that the work of the SH can be dynamically switched to maintain the voltage managed by the local power grid, without risking the house's central purposes, such as comfort.

Maryam et al.[44] presented a practical power- and comfort-management framework based on multi-agent technology for optimal handling and monitoring of a community of SHs that use controllable loads and multiple renewable power resources. Various agent types, such as complex learning agents and simple-reflex agents, work with each other to achieve the system's objectives.

Asare-Bediako et al.[41] introduced a HEMS based on multi-agent technology. The system combines smart metering technology with resident preferences and utilizes control price signals for household power optimization. Furthermore, dynamic price signals are used, combining the loading of the household distribution network, the fluctuating prices of the electricity, and the fixed tariffs. To examine the proposed system, Asare-Bediako et al.[41] carried out a series of experiments that illustrate that household devices can be programmed to react to external signals while preserving resident comfort.

In contrast to the previous systems, the following systems are energy-based. An agent-based system that models the SHs as autonomous agents and models the grid as an MAS is described in [46]. The SH agent can buy electricity from the grid and store or sell the generated electricity with its own energy generation and storage system. Furthermore, the house agent prioritizes its decisions based on the predicted production. The SH aims to minimize electricity cost, while the grid intends to flatten the total demand curve.

An agent-based model is proposed by Kahrobaeea et al. [45] where various types of users are modeled as autonomous and self-interested agents that can interact with their neighbors in a SG environment. The dynamic user agents have a power storage and generation system and can trade power with their neighbors to reduce their electricity costs. Furthermore, every user agent is encouraged to decrease its electricity cost by taking into account the generation of renewable power and the present and predicted future demands. The proposed agent-based model can be utilized in many communities: an aggregate of commercial, industrial, and residential users, or a uniformly residential userbase.

A day-ahead electricity management algorithm that coordinates SHs with generation and storage systems in neighborhood areas is described in [12]. The proposed decentralized algorithm is used to schedule appliances and share energy between SHs to reduce the electricity bills of the householder. A MAS is applied, and the utility company, aggregator, and SHs are modeled as smart agents. Furthermore, the problem of optimization is resolved in a distributed way with the genetic algorithm by house agents.

The same authors propose another multi-agent decentralized algorithm [10] for coordinated power-sharing between SHs in neighborhood areas, using a non-cooperative game-theoretic method. The proposed algorithm considers many SHs and one aggregator, all modeled as agents. House agents are selfish, independent decision-makers that only care about maximization of their own welfare and reducing their own electricity costs. The case study results indicate that the algorithm can minimize the peak load consumption and the total neighborhood cost.

A distributed multi-agent algorithm for energy management in a residential neighborhood is proposed by Mets et al.[47]. The system uses virtual power prices, historical price data, and levels of renewable power in the real-time generation mix to shift the loads to times when there is higher generation of renewable power, leading to a reduction in the cost of energy for the residential houses. A case study consisting of three scenarios used to evaluate the proposed algorithm illustrates that the self-consumption of renewable power is improved in the household neighborhood and that the peak and average loads for externally provided energy are reduced.

A recent study by Wang et al.[9] proposed a MAS for modeling optimal residential DR implementation in multiple heterogeneous homes. The agent system is capable of control and predicts power load demand. Moreover, a convex programming problem is used to formulate the optimal control of power consumption to decrease waiting time and electricity bills under a real-time pricing scheme. Simulations performed by Wang et al.[9] show that electricity bills are decreased by using the proposed system and the stability of the energy system improved with DR implementation.

Another usage case of the Mas2tering project, which was mentioned in the previous section, focuses on the community level. The range for this case illustrates that MAS optimization, when implemented at the local community level, is sufficient for power management and local balancing. The objective is to optimize and decrease the costs associated with power bills for each end user within the community [49].

4. DISCUSSION

In the preceding section, we have detailed each study that has been reviewed in this investigation. When we looked to the energy sources in the papers, we found that more than half of the studies utilized renewable energy from sources such as wind and solar energy along with the energy from conventional sources in their solutions. Furthermore, more than half of the proposed solutions considered user comfort and user preferences. We also found that the pricing schemes in the studies mostly utilized price-based DR programs. Conversely, the optimization method used varies in these studies. JADE is clearly the implementation platform most commonly used in the reviewed papers, followed by MATLAB. Table 4 compares the proposed solutions discussed above and shows their contributions. Table 5 presents a list of strengths and limitations of the reviewed residential EMSs.

Table 4: Summary of the studies that focused on multi-agent EMSs.

Reference	Year	Renewable Energy	User Comfort and Preference	Pricing Schemes	Optimization Method	Sector		Simulation Platform		
						Individual	*Community*	*JADE*	*MATLAB*	*Other*
[23]	2016	√	√	Time-of-use	-	√	-	-	-	-
[26]	2016	-	√	-	-	√	-	√	-	-

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[39]	2017	-	-	Time-of-use	Binary Particle Swarm Optimization	√	-	√	-	-
[27]	2017	-	√	Real-time pricing	-	√	-	√	-	-
[40]	2015	√	-	-	- Object-oriented approach. - Logic programming approaches.	√	-	-	-	Python
[4]	2011	√	√	-	Particle Swarm Optimization	√	-	-	-	-
[3]	2014	-	√	-	-	√	-	√	-	- Controls Virtual Test Bed - EnergyPlus
[41]	2013	√	√	Dynamic price signals	-	-	√	√	√	-
[48]	2013	√	√	-	Particle Swarm Optimization	√	-	-	-	-
[38]	2013	-	√	Time-of-use	-	√	-	√	√	-
[24]	2017	-	-	Time-of-use	Modified Stochastic Predicted Bands	√	-	√	-	-
[9]	2017	-	-	Real-time pricing	Convex Programming Problem	-	√	-	-	TRlabs Execution Environment for Mobile Agents
[45]	2014	√	-	-	-	√	√	-	-	-
[46]	2013	√	-	Real-time pricing	-	-	√	-	-	-
[42]	2015	√	√	Critical Peak Pricing	Particle Swarm Optimization	-	√	-	-	Java
[43]	2015	-	√	-	Particle Swarm Optimization	-	√	-	√	-

[12]	2017	√	-	Time-of-use	Genetic algorithm	-	√	√	√	-
[10]	2017	√	-	Time-of-use	Nash equilibrium	-	√	√	√	-
[47]	2012	√	-	-	-	-	√	-	-	OMNeT++
[44]	2017	√	√	-Real-time ricin g -Time-of-use	-	-	√	√	√	GAMS
[49]	2014 2017	√	-	-	-	√	√	-	-	-

Table 5: Strengths and limitations of the reviewed residential EMSs.

Reference	Strengths	Limitations
[23]	1) Households can maximize the devices used within the same budget. 2) The proposed system gives the households the ability to plan device usage one day ahead.	The resilience and reliability of the system when operating it for a relatively long period (e.g., six months or one year) are not tested.
[26]	The system provides efficient power usage and reduces the cost of electricity bills.	It does not use clustering techniques for appliances.
[39]	1) The system maintains a balance between demand and supply. 2) It uses two priority techniques: priority of lowest consumption and priority of user comfort.	N/A
[27]	1) The agents communicate and interact with each other using agent communication language. 2) 29.37 % cost saving is achieved using the proposed system.	The optimization algorithm used is not clear.
[40]	The proposed HEMS employs an object-oriented approach which supports the concepts of software components.	The method to manage and integrate the alternative source of energy (solar or wind energy) is not explained.
[4]	1) The system allows different users to set various comfort ranges based on their preferences. 2) It considers thermal comfort, visual comfort, and air quality.	The peak to average ratio reduction is neglected.
[3]	The system presents a prediction of the need for cooling and heating that can be transferred to the utility company,	1) The proposed system does not consider multiple occupants.

	enabling the company to predict the power demands of the premises.	2) Energy consumption increases slightly when user comfort is significantly improved.
[41]	The system applies a dynamic pricing mechanism that considers the changes in the power market and network loadings.	The objective function for all households is assumed to be cost minimization. Therefore, the system neglects the different goals of houses during different times of the day.
[48]	It categorizes the building as a multi-zone space; therefore, when controlling energy and user comfort, it takes into consideration the different environmental conditions for each zone.	The system does not consider energy saving as part of its optimization objective.
[38]	The system applies several optimization strategies for energy management (cost-preferred, demand-side management, energy efficiency-preferred, comfort-preferred).	N/A
[24]	The system uses a novel optimization method that models the uncertainty in residential energy management problems.	It does not control electrical power in real-time operation.
[9]	The proposed system uses an algorithm for scheduling heterogeneous SH power usage that may also operate to reduce the electricity bill in a single HEMS.	The system does not apply real-time actual electricity consumption for the heterogeneous home agents.
[45]	1) The system incorporates industrial, residential, and commercial client divisions and their special demand characteristics. 2) The households using the system could expect to save up to 40% on their power payment.	The reliability of communication in neighborhood power transactions is not considered in the system.
[46]	The system uses two price rates to influence the home agents to participate: one for selling power to the grid and the other one for buying power from the grid.	The trading of energy among the neighbors is not considered.
[42]	1) The system uses a hierarchical optimization method based on distributed and centralized agents. 2) The energy storage systems and wind turbines are shared by the whole community.	The reliability and security of communication in community is not considered in the system.
[43]	1) The system is utilized in multi-zone buildings. 2) It uses bottom-up architecture that reduces the flow of useless information, which is important in larger systems.	N/A
[12]	The system proposed two kinds of coordination models: turn-based models and group-based models.	The constraints on the distribution grid, line capacity, and transformers are not considered.
[10]	The system allows the households to make decisions and optimize the runtime of electrical devices and the control inputs of their batteries.	1) The study did not consider forecasting errors in either generation or consumption profiles. 2) The system did not apply the coordination of several aggregators.
[47]	The proposed algorithm considers the current cost data and historical costs, together with the percentage of green power in the real-time production mix.	The system was not evaluated under different weather conditions.

[44]	The system uses two different kinds of agents (simple reflex agents and complex learning agents).	The security of communication in the community was not taken into consideration in the proposed system.
[49]	The project ensures data privacy to the end users and delivers cost-effective energy optimization tools.	N/A

In the literature, the appliances studied within the HEMS vary widely. A histogram that shows the frequency of the appearance of particular appliances in the literature on the residential sector is displayed in Figure 3. Although this histogram does not represent the entire field, it gives us a sample of which devices are usually taken into consideration. Appliances limited to a single study include the following: toasters and hair dryers [12]. PC printers, Wi-Fi, answering machines, clocks, CD players, ovens, and hobs [9]. Speakers and laptops [26]. Incandescent bulbs and electric dispensing pots [39]. Fans and motors [27]. Electrical inverters [23].

Since every appliance has different features, it is difficult to create a model that represents each one. Hence, various studies in the literature have tried to facilitate modeling complications by developing specific classes for all appliances. In these classes, the appliances are categorized by their overall DR behavior and therefore require fewer data for modeling [25]. Table 6 provides the classes of appliances used in the literature.

	Washing Machine	Air conditioner/ HAVC	Dishwasher	Vacuum cleaner	Light	Electrical Vehicle	Clothes dryer	Iron	Desktop computer	Television	Kettle / water boiler	Water heaters/ Bathroom heater	Fridge/ Refrigerator	Tower fan/ Standing fan	Microwave	Coffee maker	Heat pump	Rice cooker
7	[47]																	
6	[10]	[43]																
5	[12]	[38]	[10]	[12]														
4	[38]	[3]	[47]	[9]	[12]	[47]	[10]	[12]	[10]	[10]								
3	[39]	[27]	[12]	[39]	[48]	[9]	[47]	[39]	[12]	[12]	[47]	[39]	[9]					
2	[26]	[39]	[38]	[26]	[27]	[38]	[12]	[26]	[39]	[39]	[12]	[26]	[39]	[39]	[12]	[10]	[43]	[26]
1	[23]	[23]	[23]	[23]	[39]	[26]	[9]	[23]	[26]	[26]	[9]	[23]	[26]	[26]	[9]	[12]	[38]	[39]

Figure 3: Histogram of appliances studied in the residential sector in the literature (references in square brackets)

Table 6: Classes of appliances used in the literature

Class Name	Used In	Common Names	Description	Appliances Example
Controllable appliances	[9], [10], [12], [23], [26], [38], [39], [47].	● Deferrable loads ● Shiftable appliances ● Non-interruptible appliances	These devices are not time-dependent, and their operation start time can be shifted. Also, the appliances have a fixed time duration for their operational cycles. However, their operation cannot be stopped until their cycle is over [10], [41].	Washing machines, dishwashers, and clothes dryers
Non-controllable appliances	[10], [12], [26], [27], [39], [48]	● Non-deferrable loads ● Non-shiftable appliances	The operation of this class of appliances cannot be moved to later hours of the day. Also, there are two subgroups in this class of devices: non-critical appliances that can be switched off without the need to turn them on later, and critical appliances, for which the operations are must be preserved without intervention [10], [41].	Essential lighting and television
Thermal loads	[3], [23], [27], [38], [39], [43]		Thermal loads are cooling and heating appliances; their operation depends on weather conditions and user behavior [41]. Also, thermal loads must keep an appliance's power state in a proximity to a desired state.	Air conditioning and space heating

The use of MASs in residential EMSs can benefit both households and utilities in many ways. However, as we review these papers, we still find some challenges. These include:

- *Security and privacy:* Since most methods generally need to access a large amount of household data and the household's electrical loads, they can expose user behavior and other relevant data. The security and privacy of the household can be a key concern. The trade-off between security and performance is therefore a problem [7], [52].
- *Communication*: The MAS's communication has a significant impact on the agents' choices. MAS communication systems still face some difficulties, such as noisy data, packet loss, incomplete data, and delay in real-time data transfer [22], [26].
- *Portability*: Since most of the current MAS implementations of EMSs are software simulations using platforms such as MATLAB or JADE, there is a need to widely test the performance of MAS approaches on actual hardware [14].

5. CONCLUSION

The purpose of the current paper is to review previous studies in the field of residential energy management that focus on HEMSs based on MAS techniques, both at the single SH level and the multi-home level. The reviewed solutions vary in objectives; some optimize the users energy consumption while maximizing their comfort, and some only consider optimizing the energy consumption in the user's house. The different DR programs are also reviewed and compared, as well as the devices and the classes of appliances that are considered and used in these systems.

The reviewed articles confirm that using the MAS technique in building operation provides an increase in the comfort and energy performance of residential buildings. Nevertheless, various difficulties must be addressed to facilitate the development of reliable and secure house power management systems. Moreover, there is a need to develop a HEMS that takes into consideration the user's monthly budget and is also capable of managing and controlling the SH's energy for a relatively long period. Future research should concentrate on solving some of these challenges, including the need to widely test the performance of MAS approaches on actual hardware.

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