





Review

# An Overview of the Building Energy Management System Considering the Demand Response Programs, Smart Strategies and Smart Grid

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**Abstract:** Electricity demand is increasing, as a result of increasing consumers in the electricity market. By growing smart technologies such as smart grid and smart energy management systems, customers were given a chance to actively participate in demand response programs (DRPs), and reduce their electricity bills as a result. This study overviews the DRPs and their practices, along with home energy management systems (HEMS) and load management techniques. The paper provides brief literature on HEMS technologies and challenges. The paper is organized in a way to provide some technical information about DRPs and HEMS to help the reader understand different concepts about the smart grid, and be able to compare the essential concerns about the smart grid. The article includes a brief discussion about DRPs and their importance for the future of energy management systems. It is followed by brief literature about smart grids and HEMS, and a home energy management system strategy is also discussed in detail. The literature shows that storage devices have a huge impact on the efficiency and performance of energy management system strategies.

**Keywords:** demand response programs; electricity markets; home energy management system; smart grid

## 1. Introduction

The demand for electricity or load variation in the power grid is changing from time to time. Meeting the demand for electricity, especially during peak hours, poses a major challenge. During past decades, in many countries, power grid services were regulated and operated by governmental utility companies, and private energy companies hardly owned any power systems [1]. This power plant structure was not efficient enough to guarantee utility companies' profits [2]. The key solution for this issue was the privatization of power systems to offer the competitive market at diverse levels of generation, transmission and distribution [3]. Hence, the power industry was divided into two categories: the wholesaler and retailer sectors [4]. Governments were managing and controlling the wholesale sector, while the retailer sector was controlled by private companies. Previously,

the wholesale section was producing electricity in bulk volume, and transmitted it to the domestic and industry sections through transmission lines, while the retailer section purchased electricity on behalf of the demand, and sold it to customers. Therefore, customers dealt with electricity similarly to merchandise that is always available. Hence, only the generation side participated in this deregulated energy market to sell their power to consumers and raise their profits, whereas the demand side had not any competition to reduce their consumption. Thus, this issue exposed the inflexibility of the power system [5]. As a result, customers were also included in the electricity market. They must regulate electricity consumption and compensate for all electricity costs. Therefore, competition for electricity cost reduction was transferred from utility companies to consumers. Demand response programs (DRPs) were first introduced in the United States in 1970 to manage peak hours [6]. The main aim of DRPs was to encourage people to reduce their consumption during peak hours through incentives offered by utility companies [7]. Demand response systems helped the consumer to understand the advantages of DRPs to use energy, or to adjust it. However, DRPs were not as successful as expected in those days. DRPs could not control electricity consumption on their own without the participation of consumers. Most of the time, consumers did not want, didn't have enough awareness of, or could not spend their time to analyze their power consumption, nor to reschedule their appliances' operation time to reduce the peak hours or save their bill costs [8]. Hence, smart types of equipment besides smart grid infrastructure were introduced to be responsive to residential electricity consumption. Smart home technologies besides energy management systems (EMS) are the technologies that can respond to signals which come from utility companies independently and without human intervention. EMS technologies can shift or shed loads in response to electricity prices and according to human comforts, optimizing the electricity consumption at peak hours. DRPs are generally divided into incentive-based programs [9] such as direct load control, demand bidding programs and interruptible tariffs or price-based programs such as real-time pricing (RTP), critical peak pricing (CPP), day-ahead, etc. [10]. In the following sections, demand response programs and home energy management systems (HEMS) will be discussed briefly.

## 2. Demand Response Programs

According to statistics, the residential sector consumes 30–40% of the total produced electricity energy all around the world [11]. By increasing the end-users and consequently increasing the electricity demand, peak demand is increasing rapidly. Continuous growth on the peak demand can cause a failure of the power system, and also increase the price of electricity. Conventionally, utility companies tried to match between the supply and demand through traditional power plants, which are not preferred due to the increase in greenhouse gas emissions to the atmosphere. Therefore, utility companies dealt with this issue by increasing the generation capacity, enhancing the storage technologies, utilizing more renewable energies and deploying demand response programs (DRPs) during peak demand. DRPs provide a chance for customers to play an important role in the operation of power grids by curtailing or shifting their energy consumption in response to electricity price changes or other methods of financial incentives [12]. DRPs are being used by power companies as the new options for balancing demand and supply. Such programs can reduce the charge of energy production in wholesale markets, and in turn reduce electricity bills.

### *Types of Demand Response Programs*

DRPs are categorized as incentive- and price-based programs. An incentive-based program is an agreement between customers/industry and a utility company to give some degree of authority to the utility company to directly control, reduce or shed some loads to save electricity, and in exchange the user receives incentive payments or bill credits from the utility company. Some examples of this program are direct load control (DLC), emergency programs, demand bidding programs and interruptible tariffs [13]. The majority of DRPs are price-based programs executed by utility companies. Therefore, on one hand, customers are motivated to reduce their electricity bill in response to the

changes of the electricity cost over time, while on the other hand, utility companies can provide incentives to end-users to lower their electricity usage at peak hours, or when the grid is under stress and reliability is jeopardized. Some of the price-based DRPs for wholesale markets are real-time pricing (RTP) [14,15], critical peak pricing (CPP) [16] and time of use (TOU) tariffs. These tariffs provide the dynamic price of electricity at different time intervals with daily and seasonal variations. Incentive-based demand response programs were generally more popular with commercial and industrial customers, but increasingly, some of ISOs or regional utility companies are offering them to the demand customers as well. In these programs, participants are paid an incentive to reduce their load when requested by the utility company. These programs are triggered by either a grid reliability problem or the over-consumption of electricity, which enables utility companies to control thermal appliances such as air conditioners or water heaters during periods of peak demand, in exchange for a financial incentive and lower electric bills. DRPs are operating on a new infrastructure with bi-directional communication between demand and utility companies [17]. This infrastructure is called the smart grid. Smart meters are the essential parts of the distribution sector in the smart grid, which enable demand load management with the presence of home energy management systems (HEMS). HEMS are the middle layer between electrical appliances and smart grid, allowing us to schedule power consumption optimally by using the information on energy prices. Further details about the demand response paradigm are discussed in the following sections. Figure 1 presents some of the DRPs.

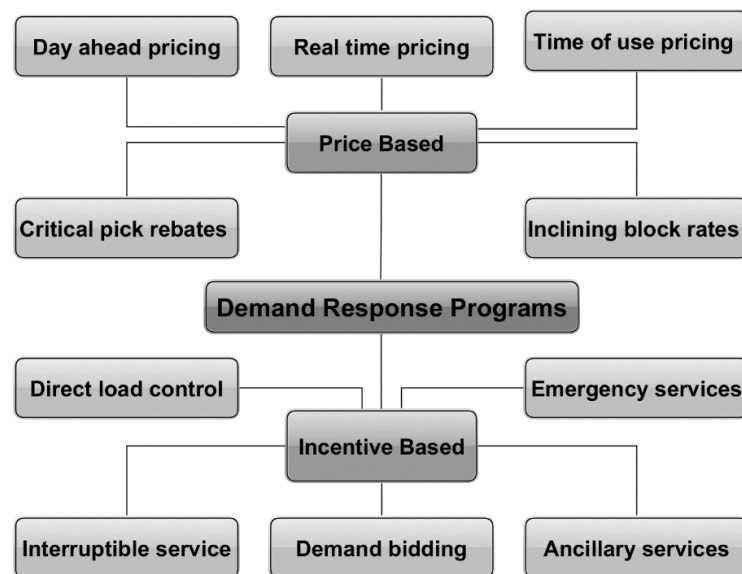
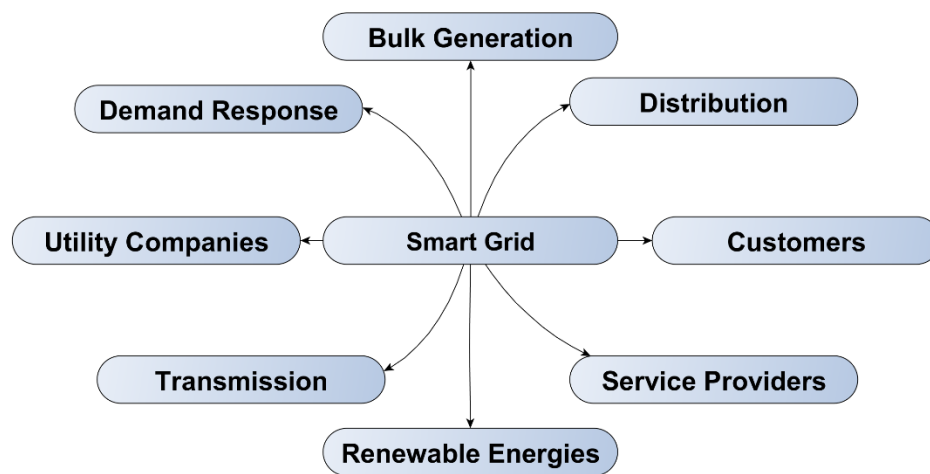


Figure 1. Some of the DRPs.

### 3. Smart Grid

In recent years, the conventional grids that have been built based on centralized and fuel-based generators are facing challenges such as greenhouse gas emissions and increasing the grid's productivity [18]. Furthermore, there are some vital factors to consider, such as the consumer's participation rate in the energy market, integrating the new technologies such as renewable energies, and improving the reliability of the grid. Therefore, smart grids are used in many countries. Figure 2 shows the basic structure of the smart grid. The definition of the smart grid can vary by local condition, and each country can have its own definition and progress on the smart grid. The improvement of the smart grid can be accrued by adding different layers of technology, capacity and operations to the existing grid system [19]. In general, the smart grid is an electric power plant that uses the data network to integrate all branches of producers and customers efficiently with low cost and high security. In the smart grid concept, the flow of the data, as well as the energy, is bidirectional between

utility companies and consumers. A smart grid increases the flexibility of the power grid by better monitoring and controlling the supply and demand. This can decrease electricity consumption and increase the reliability of the energy supply.



**Figure 2.** Basic structure of the smart grid.

### 3.1. Electricity Consumption Profiling in Smart Grid

Since the late 70s, when the bi-directional communication was established between demand and utility companies, one of the interesting features of the smart grid was electricity load profiling. According to [20], load profiling can use both top-down and bottom-up techniques. In the former approach, electricity suppliers gathered data from regional consumption. Such information in this method helps utility companies to optimize the energy dispatch, although the forecasting of single consumer consumption is impossible. Meanwhile, the latter approach uses the data that come from a single or group of houses, which are aggregated by smart meters and sent to utility companies. Such information in this method helps consumers to schedule their activity based on electricity prices. This approach provides a reliable prediction and loads profiling for long-term electricity consumption in wide areas. Indoor/outdoor temperature and appliances consumption are the common data that are needed for the bottom-up approach. This method is highly dependent on resident behavior and habits. So, by separating the consumption data, classifying the electrical appliances and day of usage such as weekdays and weekends, the weak point of this technique can be solved easily [21]. Such detail of the data is one of the advantages of the bottom-up level that enables us to develop technological advances in society. In the bottom-up technique, both statistics and engineering approaches can be used. Statistical analysis such as a neural network, regression and conditional demand analysis tries to predict the current and future consumption of the specific house based on the historical data and using different types of regression. Meanwhile, the engineering method tries to model the current consumption of the specific house based on the thermal model of the building, consumption characteristics of the electrical appliances and residents' activities. This method classifies the building by size, house type and characteristics of the appliances, and then the data of the appliance can be aggregated [22].

### 3.2. Types of Load Control

The general goal of demand response programs (DRPs) is to balance or adjust the loads during peak hours. Based on this scope, utility companies defined different strategies to control the loads. These strategies are listed as human-based load controls, direct load controls and smart load controls. One of the simplest ways to control the peak hour was the human-based load control. This strategy is human-based, which means consumers reduce their consumption during peak hours. This strategy is not effective, however, despite its easiness and cheapness for utility companies, as costumers are not following the utility companies' rules due to a lack of interest or knowledge about the appliances and

their energy consumption. The other approach is direct load control. Consumers, receiving financial motivations, allow utility companies to directly control some of their electrical appliances such as air conditioners, pool pumps or water heaters. This strategy has the highest impact on utility companies, as they can directly control the appliances of the customers, although it can lead to sacrificing consumers' comfort. Smart load control is a combination of human-based, direct load control and automation systems. In this method, smart controllers are located at home and adjust the consumption of the house according to the utility companies' signals and comforts. These automation systems are called home energy management systems (HEMS). In the following section, the HEMS will be discussed briefly.

#### 4. Definition of Home Energy Management System

The home energy management system (HEMS) is an automated device that provides communication between electrical appliances of the building and utility company to shift or shed the demand to reduce power consumption. Smart dispatching among the demand and utility companies is the main application of HEMS, which can help utility companies in clarifying the energy price, deploying demand response programs, and integrating more renewable and storage devices efficiently. Therefore, utility companies can measure the electricity consumption of a wide area of demand and find out the peak hours in detail. They also can send a signal to building controller systems to shift or curtail the electrical appliances to avoid blackouts during peak hours.

##### 4.1. Smart Meter

As mentioned before, the bottom-up approach for load profiling needs some series of equipment to measure energy consumption, and so on. Smart meters are the tools that can collect, analyze and control the electricity consumption of each house through bi-directional controlling signals. Smart meters provide services such as electricity voltage or electricity frequency monitoring, demand management, flexible tariffs, etc. Integrating such equipment in buildings may have economic and environmental benefits for both utility company and consumer sides. As an illustration on the customer side, users are informed about the energy charges and related electricity consumption. These data can be logged and presented online for customers. Furthermore, on the production side, dynamic tariff rules can be used by utility companies to perform demand response programs and control electrical appliances during peak hours. At the grid level, advanced measurement methods help utility companies to track the lines' voltage and frequency, monitoring the oil temperature of the transformers, the load capabilities and demand through smart meters. The smart meter can be connected to the home gateways, which are integrated with the home automation network and communicate with appliances through the internet to exchange data with utilities.

##### 4.2. Smart Appliances

Smart appliances must be capable of communicating via control signals. In order to operate effectively, HEMS have to be able to receive some essential information from appliances [23]. Appliances must be able to measure vital information such as current, voltage, power and temperature, send this data to the HEMS controller through signals, and receive instructions from HEMS. Therefore, appliances must be smart by themselves, or smart plugs need to be used to convert conventional appliances into smart appliances. As an example, a smart refrigerator can shift its frost cycle to off-peak hours, or a smart washing machine might defer its operation cycle until off-peak hours [24]. However, the majority of smart appliances are capable of being controlled manually by consumers to override the automated controls when needed. As an example, if the user needs to turn on the air conditioner regardless of the electricity price, they can do so. The communication system among smart appliances could be based on standard WiFi communication, which already exists in the house. The technologies that are commonly utilized in the buildings range from wired power line communication (PLC) to various technologies such as Zigbee with IEEE 802.15.4 standard, WiFi with IEEE 802.11, IEEE 802.15.4 standards, X10 with X10 standard and Ethernet with IEEE 802.3 standard [25]. As electrical appliances

have different characteristics in energy consumption, it is very difficult to develop a common model for all of them. Therefore, various research in the literature attempted to simplify the modeling complexity of HEMS by creating a limited category for all devices. By using these categories, devices are classified by their general behavior to the demand response programs (DRPs). Categorizing the electrical appliances based on their characteristics reduces the required information for modeling them in HEMS. Table 1 represents devices with their characteristics and response to DRPs.

**Table 1.** The electrical device's response to DRPs.

Category of Devices	Description	Other Names	References
Curtail-able devices	Devices that can be curtailed at any time without any temporal concerns	Price responsive devices	[26–31]
Uncontrollable devices	Electrical appliances that should be activated immediately when the users need them. Examples often include TV, video games, network devices, essential lighting, etc.	Non shiftable loads, must-run loads, baseline loads	[32–37]
Interruptible devices	Electrical appliances that can hold their operation and shift it to another time slot, such as air conditioners, refrigerators, etc.	Regulating devices, deferrable loads	[38–49]
Uninterruptible devices	Electrical appliances that must operate through a complete set of given tasks or need to run for a fixed time. Examples of these appliances include a washing machine, dishwasher, microwaves, etc.	Burst loads, shiftable loads	[50–54]
Storage devices	Devices that can be used to store and dispense energy when required. Commonly, storage devices are modeled along with regulating loads. Examples include battery and micro-CHP systems	Energy storage devices	[55–60]

## 5. Hems Strategies and Methods

Home energy management systems (HEMS) can reduce electricity consumption by scheduling electrical appliances with the aim of minimum human comfort violations. There are various strategies for HEMS to control electrical appliances during peak hours, ranging from artificial intelligence (AI) algorithms to optimization techniques and utilizing energy storage.

### 5.1. AI-Based Control

Nowadays, many AI strategies are used to control home appliances for users in smart houses. Genetic algorithms, fuzzy logic and artificial neural networks are some of the famous examples of AI algorithms, which can mimic human thoughts. AI algorithms are mostly used for forecasting or optimizing energy during peak hours.



### 5.1.1. Predictive Control

Forecasting models use historical data to predict either electricity consumption, the output power of renewable energies or electricity prices to find the optimum strategy to control electrical devices during peak hours. As an illustration, the HEMS optimizes the energy consumption of the electrical appliances in a building that has rooftop solar panels. Furthermore, load forecasting is playing a vital role in HEMS. In recent years, several researchers [61–66] used predictive models for precise short-term load forecasting to reduce the electricity bill or electricity consumption in peak hours. Ahmed et al. [67] used an artificial neural network (ANN), where HEMS forecasts the optimum status (ON/OFF) of electrical appliances to reduce the electricity bill. Authors in [68] used a genetic algorithm to predict the optimum heating temperature of heating appliances to reduce the building electricity bill. Authors in [69] used a forecasting model where the home energy management system controls the temperature, as well as some electrical appliances such as an electric vehicle and heat pump in a house. Authors in [70] used model predictive control (MPC) optimization strategy where HEMS controls a house's air conditioning. Authors in [71] used the MPC strategy, where HEMS optimizes the energy cost according to energy prices and weather conditions. Authors in [72] used an MPC predictive model to predict and control the temperature of the building. Pezzutto et al. [73] used a predictive model to forecast a long-term electricity market price in the European Union.

### 5.1.2. Optimization Control

The term optimization is usually used for finding the most suitable solution for the problem, after recognizing the objective function that is subject to restrictions. Literature shows that various techniques for optimization are used to find out the optimal energy consumption or load schedule. As an example, Mohsenian-Rad et al. [74] used a game theory control algorithm to optimize the energy consumption among neighbors who shared energy sources. Authors in [75] developed an optimization approach to reduce energy consumption and minimize electricity costs through the optimization of the operation of electrical appliances based on the price signals. Authors in [76] used a mixed-integer nonlinear algorithm to optimize the operation of electrical appliances for electricity cost-saving and a minimum sacrifice of human comfort. Authors in [77] used game theory to optimize the load scheduling, including the hybrid electric vehicle and the battery system. Authors in [78] used a gray wolf optimization technique (GWO), along with the photovoltaic system, to optimize the peak to average ratio (PAR) and energy cost. Authors in [79] used the multi-agent optimization algorithm to optimize the energy consumption. Authors in [80] used a heuristic backward/forward algorithm to minimize the electricity cost of thermal appliances and satisfy residence comfort. Authors in [81] used the binary-backtracking-search algorithm to limit the overall energy demand.

### 5.2. Linear Online Control

This category uses real-time algorithms or online scheduling to control the thermal devices, shift the controllable devices or curtail energy consumption and reduce electricity charges. Commonly, online control algorithms process inputs without any historical knowledge of upcoming inputs. In other words, inputs are usually called a task or a job, appear at each time interval, and the online controller should find the way to include it into the plan. Typically, the uncertainty is not modeled in this method, and the controller must find a way to include new items appearing in the queue. In this method, HEMS is responsible for establishing the status of the electrical appliances by monitoring and analyzing their data. At each time interval, if any device has to be turned on and there is no violation in demand limit, the HEMS decides to turn on the appliance. If in any situation demand limit is imposed, then HEMS curtails the operation of the electrical appliance with the lesser priority to keep the overall energy consumption of the building under the demand limit. Authors in [82] used a price-based demand response program (DRP) where HEMS controls the operation of the electrical appliances according to their preset priority. In this case, when the value of priority of electrical appliance is less

than that of the electrical price, the electrical appliance operation is stopped, and when the value of priority of the appliance is more than the value of electricity price, the electrical appliance operates.

Authors in [65] coordinated the appliances according to their favored time of use. In this technique, appliances assigned a timetable according to the constraint of energy usage at each time interval. The electricity price is brought up-to-date hourly and according to energy prices, and controllable devices such as thermal appliances are scheduled at each time interval. Uncontrollable devices can operate at each time, and they can change the prescheduled devices' operation. In the same way, Koutitas [83] used a real-time control algorithm where HEMS cuts the peak consumption hours when a building's overall consumption exceeds the prearranged threshold line. The authors in [84] use a primacy in thermal and shiftable appliances to bound the electricity usage of the building under the threshold line. Authors in [85] used an automated control system to adjust the operation of thermal appliances and switch off the curtailable appliances based on the price signal coming from the utility company. Authors in [86] used three layers of real-time monitoring, stochastic scheduling and controlling to find the appropriate appliance to be shifted or curtailed to keep the cost of electricity consumption under the predetermined value. Nevertheless, appliance scheduling approaches on their own have not realized much success. Storage devices are another viable demand response strategy that have been proposed as a key component of the future of the smart grid.

### 5.3. Storage System

Although storage devices were not previously widely utilized in energy management systems (EMS) due to high costs, as well as the short lifetime of batteries and economic reasons, interest in storage devices has been sparked due to some factors such as improvement in renewable energy technologies. Various research has been done in recent years to utilize the photovoltaic systems, accompanied with storage systems in the domestic section, along with energy management [87,88]. As an illustration, a hybrid domestic energy system which utilizes solar panel, fuel-cell and batteries is discussed in [89]. The goal of this approach is to reduce the yearly cost of energy and CO<sub>2</sub> emissions. In [55], researchers used a battery in a group of houses and investigated their charging and discharging based on electricity prices, in order to keep the electricity consumption of the group of the houses under a certain level. Authors in [90] used the state of charge of the battery (SOC) and time of use (TOU) tariff to manage the operation of the electrical appliances during peak hours to reduce electricity bills. In the same way, integration of the photovoltaic (PV) system, along with the hybrid storage system for the smart grid, is presented in [91] to reduce the cost of energy during a given day.

Researchers in [92] used an organized policy to share the energy storage among domestic buildings to decrease the wholesale energy bill, and accordingly decrease the grid investiture. Authors in [93] used a battery system as well as the grid to power up the electrical appliances. Batteries are charging through the grid when electricity prices are cheap, and supply energy when the electricity price is high. Authors in [94] used novel control signals which utility companies send to consumers to shift the operation of their appliances on renewable energies and storage devices. The author in [95] used the thermostatically controlled loads, as well as the energy storage, to reduce energy consumption during peak hours. Table 2 shows some of the strategies that researchers have tried previously to optimize electricity consumption during the last decade. The effect of the storage devices and renewable energies as a supplemental home energy management system has been discussed in [96]. Their findings show that energy storage can have a noteworthy impact on energy consumption to control the peak hours. As shown in Table 2, storage devices have a huge impact on the efficiency of the system, while the control algorithm is linear. These strategies can meet the resident comfort, and 10% cost savings are achievable as compared to the existing TOU-based control system without storage devices.



**Table 2.** Strategies on HEMS.

Author	Price Reduction (%)	Strategy	Algorithm	Reference
Arun et al. (2019)	18.32	Smart storage	Linear	[97]
Shakeri et al. (2018)	15	Smart storage + Priority	Linear	[58]
Rastegar et al. (2016)	4	Priority on appliances based on the electricity price	Linear	[82]
Paterakis et al. (2015)	10	Control the thermostatically and non-thermostatically loads	None-Linear	[98]
Tascikaraoglu et al. (2014)	4.28	Forecasting the output of renewable energy	None-Linear	[99]
Missaoui et al. (2014)	15	Optimizing the temperature of thermal appliances	None-Linear	[100]
Adika et al. (2014)	22	Smart electricity storage Multi-stage stochastic optimization for heater, ventilators,	Linear	[65]
Yu et al. (2013)	12	air-conditioned control (HVAC)	None-Linear	[101]
Roe et al. (2011)	8	Control thermostatically + Shifting (Online control)	Linear	[102]

According to our literature and based on statistics from Lens.org [103], the number of researchers focusing upon storage devices for demand-response is increasing rapidly over the last few years. It shows that energy storage is the future of the smart grid and HEMS.

## 6. Future Work and Recommendation

According to our literature, future research directions on demand response programs (DRPs) and home energy management systems (HEMS) can be divided into two categories. First of all, improvement of the infrastructure of the smart grid such as smart metering, smart appliances, communication technologies and control algorithms can optimize the peak hours efficiently. The improvement of smart grid infrastructure can reduce the dependency of DRPs to the user's willingness for participation in DRPs. Secondly, utilizing storage devices has a huge impact on the efficiency of DRPs. Storage devices allow users to efficiently shave the peak hours with minimum sacrifice of the users' comfort. Furthermore, based on our findings, the complexity of the control algorithm can lead to the complexity of the DRPs' implementation. Most of the uncertainties of the output of renewable energies or load scheduling can be solved by using storage devices. Due to this, our recommendation is that future research must emphasize the utilization of the storage devices in control algorithms in DRPs' application.

## 7. Conclusions

In this paper, demand response programs (DRPs), along with home energy management system (HEMS) strategies, have been reviewed. Literature showed that due to raised concerns about global warming, the environmental effects of using fossil fuels and the growing consumption of natural fuel sources, the traditional way of balancing between demand and supply is not suitable. Therefore, DRPs were born to optimize the energy consumption during peak hours. The main aim of DRPs is to reduce energy consumption during peak hours. DRPs are either price-based, such as time of use (TOU), real-time pricing (RTP), critical peak pricing (CPP), incremental block rate (IBR), day-ahead pricing, etc., or incentive-based such as direct load control (DLC). However, there are some challenges to perform DRPs completely through utility companies, such as the unwillingness of customers to participate in

DRPs and sacrificing customers' comfort levels. The other challenge would be the infrastructure for performing the DRPs. Smart meters, proper and stable communication, smart appliances and control algorithms for energy management are some of the examples of the required infrastructure for DRPs. Recently, by developing HEMS, utility companies such as demand response providers have been able to manage the energy demand. This helped utility companies to reduce loads at peak hours by shifting or shedding the loads, and increasing the demand at off-peak hours or when there is an excess of power. These programs are also more compatible with renewable energy resources, since they can immediately respond to the condition of demand or generation. Literature also showed that there are various strategies for HEMS to reduce the peak hours during high demand from AI-based algorithms to linear online algorithms and storage systems. The utilization of storage systems has recently gained the attention of researchers, due to the significant impact of storage devices on energy management. A rapid reduction in the price of storage devices due to developing technology is the other reason for the recent interest in storage devices. It also has to be mentioned that there are other possible methods, such as utilizing the renewable energy sources as a supplemental source besides the grid, which can be interesting for research to consider in future.

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## References

1. Brinker, L.; Satchwell, A.J. A comparative review of municipal energy business models in Germany, California, and Great Britain: Institutional context and forms of energy decentralization. *Renew. Sustain. Energy Rev.* **2020**, *119*, 109521. [\[CrossRef\]](#)
2. Datta, S. Decoupling and demand-side management: Evidence from the US electric industry. *Energy Policy* **2019**, *132*, 175–184. [\[CrossRef\]](#)
3. Triebs, T.P.; Pollitt, M.G. Objectives and incentives: Evidence from the privatization of Great Britain's power plants. *Int. J. Ind. Organ.* **2019**, *65*, 1–29. [\[CrossRef\]](#)
4. Koltsaklis, N.E.; Dagoumas, A.S. An optimization model for integrated portfolio management in wholesale and retail power markets. *J. Clean. Prod.* **2020**, *248*, 119198. [\[CrossRef\]](#)
5. Guo, H.; Chen, Q.; Zhang, Y.; Liu, K.; Xia, Q.; Kang, C. Constraining the oligopoly manipulation in electricity market: A vertical integration perspective. *Energy* **2020**, *194*, 116877. [\[CrossRef\]](#)
6. Dorahaki, S.; Rashidinejad, M.; Abdollahi, A.; Mollahassani-pour, M. A novel two-stage structure for coordination of energy efficiency and demand response in the smart grid environment. *Int. J. Electr. Power Energy Syst.* **2018**, *97*, 353–362. [\[CrossRef\]](#)
7. Hurley, D.; Peterson, P.; Whited, M. *Demand Response as a Power System Resource*; The Regulatory Assistance Project: Montpelier, VT, USA, 2013.
8. Faruqui, A.; Sergici, S. Household response to dynamic pricing of electricity: A survey of 15 experiments. *J. Regul. Econ.* **2010**, *38*, 193–225. [\[CrossRef\]](#)
9. Albadi, M.H.; El-Saadany, E.F. A summary of demand response in electricity markets. *Electr. Power Syst. Res.* **2008**, *78*, 1989–1996. [\[CrossRef\]](#)

10. Haider, H.T.; See, O.H.; Elmenreich, W. A review of residential demand response of smart grid. *Renew. Sustain. Energy Rev.* **2016**, *59*, 166–178. [\[CrossRef\]](#)
11. Wu, Z.; Zhou, S.; Li, J.; Zhang, X.-P. Real-time scheduling of residential appliances via conditional risk-at-value. *IEEE Trans. Smart Grid* **2014**, *5*, 1282–1291. [\[CrossRef\]](#)
12. Da Silva, I.R.; de AL Rabêlo, R.; Rodrigues, J.J.; Solic, P.; Carvalho, A. A preference-based demand response mechanism for energy management in a microgrid. *J. Clean. Prod.* **2020**, *255*, 120034. [\[CrossRef\]](#)
13. Mortaji, H.; Ow, S.H.; Moghavvemi, M.; Almurib, H.A.F. Load shedding and smart-direct load control using internet of things in smart grid demand response management. *IEEE Trans. Ind. Appl.* **2017**, *53*, 5155–5163. [\[CrossRef\]](#)
14. Javaid, N.; Khan, I.; Ullah, M.; Mahmood, A.; Farooq, M.U. A survey of home energy management systems in future smart grid communications. In Proceedings of the 2013 Eighth International Conference on Broadband and Wireless Computing, Communication and Applications, Compiegne, France, 28–30 October 2013; pp. 459–464.
15. Chen, Z.; Wu, L.; Fu, Y. Real-time price-based demand response management for residential appliances via stochastic optimization and robust optimization. *IEEE Trans. Smart Grid* **2012**, *3*, 1822–1831. [\[CrossRef\]](#)
16. Khan, I.; Mahmood, A.; Javaid, N.; Razzaq, S.; Khan, R.; Ilahi, M. Home energy management systems in future smart grids. *arXiv* **2013**, arXiv:1306.1137.
17. Khomami, H.P.; Javidi, M.H. An efficient home energy management system for automated residential demand response. In Proceedings of the 2013 13th International Conference on Environment and Electrical Engineering (EEEIC), Wroclaw, Poland, 1–3 November 2013; pp. 307–312.
18. Costanzo, G.T. *Demand Side Management in the Smart Grid*; École Polytechnique de Montréal: Montréal, QC, Canada, 2011.
19. Muthamizh Selvam, M.; Gnanadass, R.; Padhy, N.P. Initiatives and technical challenges in smart distribution grid. *Renew. Sustain. Energy Rev.* **2016**, *58*, 911–917. [\[CrossRef\]](#)
20. Howard, B.; Parshall, L.; Thompson, J.; Hammer, S.; Dickinson, J.; Modi, V. Spatial distribution of urban building energy consumption by end use. *Energy Build.* **2012**, *45*, 141–151. [\[CrossRef\]](#)
21. Zotteri, G.; Kalchschmidt, M.; Caniato, F. The impact of aggregation level on forecasting performance. *Int. J. Prod. Econ.* **2005**, *93*, 479–491. [\[CrossRef\]](#)
22. Swan, L.G. Residential Sector Energy and GHG Emissions Model for the Assessment of New Technologies. Ph.D. Thesis, Dalhousie University, Halifax, NS, Canada, 2010.
23. Zhou, B.; Li, W.; Chan, K.W.; Cao, Y.; Kuang, Y.; Liu, X.; Wang, X. Smart home energy management systems: Concept, configurations, and scheduling strategies. *Renew. Sustain. Energy Rev.* **2016**, *61*, 30–40. [\[CrossRef\]](#)
24. Grogan, A. Smart appliances. *Eng. Technol.* **2012**, *7*, 44–45. [\[CrossRef\]](#)
25. Han, J.; Choi, C.; Park, W.; Lee, I.; Kim, S. Smart home energy management system including renewable energy based on ZigBee and PLC. *IEEE Trans. Consum. Electron.* **2014**, *60*, 198–202. [\[CrossRef\]](#)
26. Beaudin, M.; Zareipour, H.; Schellenberg, A. A Framework for Modelling Residential Prosumption Devices and Electricity Tariffs for Residential Demand Response. Submitted to IEEE Transactions on Smart Grids. 2014. Available online: <http://www.Ucalgary.ca/Hzareipo/Files/Hzareipo/Part1.Pdf> (accessed on 3 January 2017).
27. Parizy, E.S.; Bahrami, H.R.; Choi, S. A low complexity and secure demand response technique for peak load reduction. *IEEE Trans. Smart Grid* **2018**, *10*, 3259–3268. [\[CrossRef\]](#)
28. Hayn, M.; Zander, A.; Fichtner, W.; Nickel, S.; Bertsch, V. The impact of electricity tariffs on residential demand side flexibility: Results of bottom-up load profile modeling. *Energy Syst.* **2018**, *9*, 759–792. [\[CrossRef\]](#)
29. Imani, M.H.; Yousefpour, K.; Andani, M.T.; Ghadi, M.J. Effect of changes in incentives and penalties on interruptible/curtailable demand response program in microgrid operation. In Proceedings of the 2019 IEEE Texas Power and Energy Conference (TPEC), College Station, TX, USA, 7–8 February 2019; pp. 1–6.
30. Afrasiabi, M.; Mohammadi, M.; Rastegar, M.; Kargarian, A. Multi-agent microgrid energy management based on deep learning forecaster. *Energy* **2019**, *186*, 115873. [\[CrossRef\]](#)
31. Aalami, H.; Moghaddam, M.P.; Yousefi, G. Demand response modeling considering interruptible/curtailable loads and capacity market programs. *Appl. Energy* **2010**, *87*, 243–250. [\[CrossRef\]](#)
32. Gatsis, N.; Giannakis, G.B. Residential load control: Distributed scheduling and convergence with lost AMI messages. *IEEE Trans. Smart Grid* **2012**, *3*, 770–786. [\[CrossRef\]](#)
33. Rastegar, M. Impacts of residential energy management on reliability of distribution systems considering a customer satisfaction model. *IEEE Trans. Power Syst.* **2018**, *33*, 6062–6073. [\[CrossRef\]](#)

34. Pooranian, Z.; Abawajy, J.; Vinod, P.; Conti, M. Scheduling Distributed Energy Resource Operation and Daily Power Consumption for a Smart Building to Optimize Economic and Environmental Parameters. *Energies* **2018**, *11*, 1348. [[CrossRef](#)]
35. Li, C.; Cai, W.; Luo, H. Power Consumption Strategy in Smart Residential District with PV Power Based on Non-cooperative Game. In Proceedings of the Advances in Green Energy Systems and Smart Grid, Chongqing, China, 21–23 September 2018; pp. 264–273.
36. Joo, I.; Choi, D. Distributed Optimization Framework for Energy Management of Multiple Smart Homes With Distributed Energy Resources. *IEEE Access* **2017**, *5*, 15551–15560. [[CrossRef](#)]
37. Mets, K.; D’hulst, R.; Develder, C. Comparison of intelligent charging algorithms for electric vehicles to reduce peak load and demand variability in a distribution grid. *J. Commun. Netw.* **2012**, *14*, 672–681. [[CrossRef](#)]
38. Bastani, M.; Thanos, A.E.; Damgacioglu, H.; Celik, N.; Chen, C.-H. An evolutionary simulation optimization framework for interruptible load management in the smart grid. *Sustain. Cities Soc.* **2018**, *41*, 802–809. [[CrossRef](#)]
39. Xie, Z.; Li, X.; Xu, T.; Li, M.; Deng, W.; Gu, B. Interruptible Load Management Strategy Based on Chamberlain Model. In Proceedings of the International Conference of Pioneering Computer Scientists, Engineers and Educators, Zhengzhou, China, 21–23 September 2018; pp. 512–524.
40. Luo, J. *Research on Interruptible Load Management of Electric Vehicle Charging Considering Price Risk*; IOP Conference Series: Materials Science and Engineering; IOP Publishing Ltd.: Bristol, UK, 2019; p. 042030.
41. Wang, C.-l.; Yang, Y.-B. Research on Interruptible Scheduling Algorithm of Central Air Conditioning Load Under Big Data Analysis. In Proceedings of the International Conference on Advanced Hybrid Information Processing, Nanjing, China, 21–22 September 2019; pp. 346–354.
42. Hu, J.; Wen, F.; Wang, K.; Huang, Y.; Salam, M. Simultaneous provision of flexible ramping product and demand relief by interruptible loads considering economic incentives. *Energies* **2018**, *11*, 46. [[CrossRef](#)]
43. Lan, Z.; Xueying, Z.; Zhang, X.-P.; Zheng, Y.; Shuxin, G.; Longjun, T. Integrated resources planning in microgrids considering interruptible loads and shiftable loads. *J. Mod. Power Syst. Clean Energy* **2018**, *6*, 802–815.
44. Althaher, S.; Mancarella, P.; Mutale, J. Automated Demand Response from Home Energy Management System Under Dynamic Pricing and Power and Comfort Constraints. *IEEE Trans. Smart Grid* **2015**, *6*, 1874–1883. [[CrossRef](#)]
45. Shirazi, E.; Jadid, S. Cost Reduction and Peak Shaving Through Domestic Load Shifting and DERs. *Energy* **2017**, *124*, 146–159. [[CrossRef](#)]
46. Wang, D.; Meng, K.; Gao, X.; Qiu, J.; Lai, L.L.; Dong, Z.Y. Coordinated Dispatch of Virtual Energy Storage Systems in LV Grids for Voltage Regulation. *IEEE Trans. Ind. Inform.* **2018**, *14*, 2452–2462. [[CrossRef](#)]
47. Claessens, B.J.; Vanhoudt, D.; Desmedt, J.; Ruelens, F. Model-free control of thermostatically controlled loads connected to a district heating network. *Energy Build.* **2018**, *159*, 1–10. [[CrossRef](#)]
48. Bao, Y.-Q.; Chen, P.-P.; Zhu, X.-M.; Hu, M.-Q. The extended 2-dimensional state-queueing model for the thermostatically controlled loads. *Int. J. Electr. Power Energy Syst.* **2019**, *105*, 323–329. [[CrossRef](#)]
49. Zabello, E.; Evseev, A.; Gimadiev, R. Usage of Electric Drives of Units at Group Pump Stations as Regulating Loads of Active and Reactive Energy and Power. *ENERGETIKA. Proc. CIS High. Educ. Inst. Power Eng. Assoc.* **2018**, *3*, 5–13.
50. Iftikhar, H.; Asif, S.; Maroof, R.; Ambreen, K.; Khan, H.N.; Javaid, N. Biogeography Based Optimization for Home Energy Management in Smart Grid. In Proceedings of the Advances in Network-Based Information Systems, Toronto, ON, Canada, 24–26 August 2017; pp. 177–190.
51. Elyas, S.H.; Sadeghian, H.; Alwan, H.O.; Wang, Z. Optimized household demand management with local solar PV generation. In Proceedings of the 2017 North American Power Symposium (NAPS), Morgantown, WV, USA, 17–19 September 2017; pp. 1–6.
52. Ihsane, I.; Miègeville, L.; Aït-Ahmed, N.; Guérin, P. Real-time management model for residential multi-class appliances. In Proceedings of the 2017 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC), Bangalore, India, 8–10 November 2017; pp. 1–6.
53. Alowaifeer, M.; Alamri, A.; Meliopoulos, A.P.S. Reliability and Cost Impacts of Home Energy Management Systems. In Proceedings of the 2018 IEEE International Conference on Probabilistic Methods Applied to Power Systems (PMAPS), Boise, ID, USA, 24–28 June 2018; pp. 1–6.

54. HassanzadehFard, H.; Moghaddas-Tafreshi, S.; Hakimi, S. Effect of energy storage systems on optimal sizing of islanded micro-grid considering interruptible loads. In Proceedings of the Proceedings of the 2011 3rd International Youth Conference on Energetics (IYCE), Leiria, Portugal, 7–9 July 2011; pp. 1–7.
55. Adika, C.O.; Wang, L. Smart charging and appliance scheduling approaches to demand side management. *Int. J. Electr. Power Energy Syst.* **2014**, *57*, 232–240. [[CrossRef](#)]
56. Shakeri, M.; Shayestegan, M.; Abunima, H.; Reza, S.S.; Akhtaruzzaman, M.; Alamoud, A.; Sopian, K.; Amin, N. An intelligent system architecture in home energy management systems (HEMS) for efficient demand response in smart grid. *Energy Build.* **2017**, *138*, 154–164. [[CrossRef](#)]
57. Zhang, D.; Liu, S.; Papageorgiou, L.G. Energy Management of Smart Homes with Microgrid. In *Advances in Energy Systems Engineering*; Springer: Cham, Switzerland, 2017; pp. 507–533.
58. Shakeri, M.; Shayestegan, M.; Reza, S.M.S.; Yahya, I.; Bais, B.; Akhtaruzzaman, M.; Sopian, K.; Amin, N. Implementation of a novel home energy management system (HEMS) architecture with solar photovoltaic system as supplementary source. *Renew. Energy* **2018**, *125*, 108–120. [[CrossRef](#)]
59. Marzband, M.; Ghazimirsaeid, S.S.; Uppal, H.; Fernando, T. A real-time evaluation of energy management systems for smart hybrid home Microgrids. *Electr. Power Syst. Res.* **2017**, *143*, 624–633. [[CrossRef](#)]
60. Comodi, G.; Giantomassi, A.; Severini, M.; Squartini, S.; Ferracuti, F.; Fonti, A.; Cesarini, D.N.; Morodo, M.; Polonara, F. Multi-apartment residential microgrid with electrical and thermal storage devices: Experimental analysis and simulation of energy management strategies. *Appl. Energy* **2015**, *137*, 854–866. [[CrossRef](#)]
61. Agnetis, A.; de Pascale, G.; Detti, P.; Vicino, A. Load Scheduling for Household Energy Consumption Optimization. *Smart GridIEEE Trans.* **2013**, *4*, 2364–2373. [[CrossRef](#)]
62. Samadi, P.; Mohsenian-Rad, H.; Wong, V.W.S.; Schober, R. Tackling the Load Uncertainty Challenges for Energy Consumption Scheduling in Smart Grid. *Smart GridIEEE Trans.* **2013**, *4*, 1007–1016. [[CrossRef](#)]
63. Sianaki, O.A.; Masoum, M.A. A multi-agent intelligent decision making support system for home energy management in smart grid: A fuzzy TOPSIS approach. *Multiagent Grid Syst.* **2013**, *9*, 181–195. [[CrossRef](#)]
64. Salinas, S.; Ming, L.; Pan, L. Multi-Objective Optimal Energy Consumption Scheduling in Smart Grids. *Smart GridIEEE Trans.* **2013**, *4*, 341–348. [[CrossRef](#)]
65. Adika, C.O.; Lingfeng, W. Autonomous Appliance Scheduling for Household Energy Management. *Smart GridIEEE Trans.* **2014**, *5*, 673–682. [[CrossRef](#)]
66. Basu, K.; Hawarah, L.; Arghira, N.; Joumaa, H.; Ploix, S. A prediction system for home appliance usage. *Energy Build.* **2013**, *67*, 668–679. [[CrossRef](#)]
67. Ahmed, M.; Mohamed, A.; Homod, R.; Shareef, H. Hybrid LSA-ANN based home energy management scheduling controller for residential demand response strategy. *Energies* **2016**, *9*, 716. [[CrossRef](#)]
68. Reynolds, J.; Ahmad, M.W.; Rezgui, Y.; Hippolyte, J.-L. Operational supply and demand optimisation of a multi-vector district energy system using artificial neural networks and a genetic algorithm. *Appl. Energy* **2019**, *235*, 699–713. [[CrossRef](#)]
69. Liberati, F.; Giorgio, A.D.; Giuseppi, A.; Pietrabissa, A.; Habib, E.; Martirano, L. Joint Model Predictive Control of Electric and Heating Resources in a Smart Building. *IEEE Trans. Ind. Appl.* **2019**. [[CrossRef](#)]
70. Godina, R.; Rodrigues, E.M.; Pouresmaeil, E.; Matias, J.C.; Catalão, J.P. Model predictive control home energy management and optimization strategy with demand response. *Appl. Sci.* **2018**, *8*, 408. [[CrossRef](#)]
71. Alrumayh, O.; Bhattacharya, K. Model predictive control based home energy management system in smart grid. In Proceedings of the 2015 IEEE Electrical Power and Energy Conference (EPEC), London, ON, Canada, 26–28 October 2015; pp. 152–157.
72. Balan, R.; Stan, S.; Lapusan, C. A model based predictive control algorithm for building temperature control. In Proceedings of the 2009 3rd IEEE International Conference on Digital Ecosystems and Technologies, Istanbul, Turkey, 1–3 June 2009; pp. 540–545.
73. Pezzutto, S.; Grilli, G.; Zambotti, S.; Dunjic, S. Forecasting electricity market price for end users in EU28 until 2020—Main factors of influence. *Energies* **2018**, *11*, 1460. [[CrossRef](#)]
74. Mohsenian-Rad, A.-H.; Wong, V.W.; Jatskevich, J.; Schober, R. Optimal and autonomous incentive-based energy consumption scheduling algorithm for smart grid. In Proceedings of the 2010 Innovative Smart Grid Technologies (ISGT), Gaithersburg, Maryland, 19–21 January 2010; pp. 1–6.
75. Tsui, K.M.; Chan, S.-C. Demand response optimization for smart home scheduling under real-time pricing. *IEEE Trans. Smart Grid* **2012**, *3*, 1812–1821. [[CrossRef](#)]



76. Nagpal, H.; Staino, A.; Basu, B. Automated Scheduling of Household Appliances Using Predictive Mixed Integer Programming. *Preprints* **2019**. [\[CrossRef\]](#)
77. Mirabbasi, D.; Beydaghi, S. Optimal scheduling of smart home appliances considering PHEV and energy storage system. In Proceedings of the 2015 4th International Conference on Electric Power and Energy Conversion Systems (EPECS), Sharjah, UAE, 24–26 November 2015; pp. 1–6.
78. Molla, T.; Khan, B.; Moges, B.; Alhelou, H.H.; Zamani, R.; Siano, P. Integrated optimization of smart home appliances with cost-effective energy management system. *CSEE J. Power Energy Syst.* **2019**, *5*, 249–258. [\[CrossRef\]](#)
79. Asare-Bediako, B.; Kling, W.L.; Ribeiro, P.F. Multi-agent system architecture for smart home energy management and optimization. In Proceedings of the IEEE PES ISGT Europe 2013, Lyngby, Denmark, 6–9 October 2013; pp. 1–5.
80. Golmohamadi, H.; Keypour, R.; Bak-Jensen, B.; Radhakrishna Pillai, J. Optimization of household energy consumption towards day-ahead retail electricity price in home energy management systems. *Sustain. Cities Soc.* **2019**, *47*, 101468. [\[CrossRef\]](#)
81. Ahmed, M.S.; Mohamed, A.; Khatib, T.; Shareef, H.; Homod, R.Z.; Ali, J.A. Real time optimal schedule controller for home energy management system using new binary backtracking search algorithm. *Energy Build.* **2017**, *138*, 215–227. [\[CrossRef\]](#)
82. Rastegar, M.; Fotuhi-Firuzabad, M.; Zareipour, H. Home energy management incorporating operational priority of appliances. *Int. J. Electr. Power Energy Syst.* **2016**, *74*, 286–292. [\[CrossRef\]](#)
83. Koutitas, G. Control of Flexible Smart Devices in the Smart Grid. *IEEE Trans. Smart Grid* **2012**, *3*, 1333–1343. [\[CrossRef\]](#)
84. Pipattanasomporn, M.; Kuzlu, M.; Rahman, S. An Algorithm for Intelligent Home Energy Management and Demand Response Analysis. *IEEE Trans. Smart Grid* **2012**, *3*, 2166–2173. [\[CrossRef\]](#)
85. Chen, X.; Wei, T.; Hu, S. Uncertainty-Aware Household Appliance Scheduling Considering Dynamic Electricity Pricing in Smart Home. *IEEE Trans. Smart Grid* **2013**, *4*, 932–941. [\[CrossRef\]](#)
86. Vivekananthan, C.; Mishra, Y.; Li, F. Real-Time Price Based Home Energy Management Scheduler. *IEEE Trans. Power Syst.* **2015**, *30*, 2149–2159. [\[CrossRef\]](#)
87. Sharma, I.; Dong, J.; Malikopoulos, A.A.; Street, M.; Ostrowski, J.; Kuruganti, T.; Jackson, R. A modeling framework for optimal energy management of a residential building. *Energy Build.* **2016**, *130*, 55–63. [\[CrossRef\]](#)
88. Vieira, F.M.; Moura, P.S.; de Almeida, A.T. Energy storage system for self-consumption of photovoltaic energy in residential zero energy buildings. *Renew. Energy* **2017**, *103*, 308–320. [\[CrossRef\]](#)
89. Ren, H.; Wu, Q.; Gao, W.; Zhou, W. Optimal operation of a grid-connected hybrid PV/fuel cell/battery energy system for residential applications. *Energy* **2016**, *113*, 702–712. [\[CrossRef\]](#)
90. Boynuegri, A.R.; Yagcitek, B.; Baysal, M.; Karakas, A.; Uzunoglu, M. Energy management algorithm for smart home with renewable energy sources. In Proceedings of the 2013 Fourth International Conference on Power Engineering, Energy and Electrical Drives (POWERENG), Istanbul, Turkey, 13–17 May 2013; pp. 1753–1758.
91. Wang, Y.; Lin, X.; Pedram, M.; Park, S.; Chang, N. Optimal control of a grid-connected hybrid electrical energy storage system for homes. In Proceedings of the Design, Automation & Test in Europe Conference & Exhibition (DATE), Grenoble, France, 18–22 March 2013; pp. 881–886.
92. Wang, Z.; Gu, C.; Li, F.; Bale, P.; Sun, H. Active demand response using shared energy storage for household energy management. *IEEE Trans. Smart Grid* **2013**, *4*, 1888–1897. [\[CrossRef\]](#)
93. Zhu, T.; Mishra, A.; Irwin, D.; Sharma, N.; Shenoy, P.; Towsley, D. The case for efficient renewable energy management in smart homes. In Proceedings of the Third ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings, Washington, DC, USA, 1 November 2011; pp. 67–72.
94. Ramchurn, S.D.; Vytelingum, P.; Rogers, A.; Jennings, N.R. Agent-based homeostatic control for green energy in the smart grid. *ACM Trans. Intell. Syst. Technol. (TIST)* **2011**, *2*, 35. [\[CrossRef\]](#)
95. Al Essa, M.J.M. Home energy management of thermostatically controlled loads and photovoltaic-battery systems. *Energy* **2019**, *176*, 742–752. [\[CrossRef\]](#)
96. Khan, A.A.; Razzaq, S.; Khan, A.; Khursheed, F.; Owais. HEMSs and enabled demand response in electricity market: An overview. *Renew. Sustain. Energy Rev.* **2015**, *42*, 773–785. [\[CrossRef\]](#)

97. Arun, S.L.; Selvan, M.P. Smart residential energy management system for demand response in buildings with energy storage devices. *Front. Energy* **2019**, *13*, 715–730. [[CrossRef](#)]
98. Paterakis, N.G.; Erdin, O.; Bakirtzis, A.G.; Catal, J.P.S. Optimal Household Appliances Scheduling Under Day-Ahead Pricing and Load-Shaping Demand Response Strategies. *IEEE Trans. Ind. Inform.* **2015**, *11*, 1509–1519. [[CrossRef](#)]
99. Tascikaraoglu, A.; Boynuegri, A.R.; Uzunoglu, M. A demand side management strategy based on forecasting of residential renewable sources: A smart home system in Turkey. *Energy Build.* **2014**, *80*, 309–320. [[CrossRef](#)]
100. Missaoui, R.; Joumaa, H.; Ploix, S.; Bacha, S. Managing energy smart homes according to energy prices: Analysis of a building energy management system. *Energy Build.* **2014**, *71*, 155–167. [[CrossRef](#)]
101. Yu, Z.; Jia, L.; Murphy-Hoye, M.C.; Pratt, A.; Tong, L. Modeling and Stochastic Control for Home Energy Management. *IEEE Trans. Smart Grid* **2013**, *4*, 2244–2255. [[CrossRef](#)]
102. Roe, C.; Meliopoulos, S.; Entriken, R.; Chhaya, S. Simulated demand response of a residential energy management system. In Proceedings of the 2011 IEEE Energytech, Cleveland, OH, USA, 25–26 May 2011; pp. 1–6.
103. Lens.org. Available online: <https://www.lens.org/> (accessed on 29 April 2020).



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