

Review

# Futuristic Sustainable Energy Management in Smart Environments: A Review of Peak Load Shaving and Demand Response Strategies, Challenges, and Opportunities

Bhagya Nathali Silva, Murad Khan and Kijun Han \*

School of Computer Science and Engineering, Kyungpook National University, Daegu 41566, Korea; nathalis@netopia.knu.ac.kr (B.N.S.); mkhan@knu.ac.kr (M.K.)

\* Correspondence: kjhan@knu.ac.kr

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**Abstract:** The emergence of the Internet of Things (IoT) notion pioneered the implementation of various smart environments. Smart environments intelligibly accommodate inhabitants' requirements. With rapid resource shrinkage, energy management has recently become an essential concern for all smart environments. Energy management aims to assure ecosystem sustainability, while benefiting both consumers and utility providers. Although energy management emerged as a solution that addresses challenges that arise with increasing energy demand and resource deterioration, further evolution and expansion are hindered due to technological, economical, and social barriers. This review aggregates energy management approaches in smart environments and extensively reviews a variety of recent literature reports on peak load shaving and demand response. Significant benefits and challenges of these energy management strategies were identified through the literature survey. Finally, a critical discussion summarizing trends and opportunities is given as a thread for future research.

**Keywords:** sustainable energy; demand side management; decision management; energy management; smart environments

## 1. Introduction

Rapid growth and technological advancements of smart things and devices significantly increased the trend of connecting everyday objects through existing networks [1]. Extensive attention towards connecting objects via the internet pioneered the concept of the Internet of Things (IoT). Transformation of traditional networks and the evolution of Wireless Sensor Networks (WSN), Machine to Machine (M2M) Communication, and Ubiquitous Computing (UC) domains further strengthened the IoT concept [2,3]. The fundamental definition identifies IoT as a network consisting of a collection of uniquely addressable smart things that operate without or with minimal human interaction [4]. These interconnected devices share information among recognized devices within the network, in order to facilitate intelligent decision making [1,5]. As a result of remarkable benefits and extensive attention from expert groups, the IoT concept has evolved rapidly to pioneer various applications i.e., smart home, smart city, smart transportation, smart healthcare, smart grid, etc. [6–11]. All aforementioned applications can be commonly named as smart environments. A collection of sensor-enabled devices deployed in a defined geographical area creates a smart environment [12]. Smart environments gather knowledge from their surroundings and intelligibly utilize them to accommodate the requirements of inhabitants, while improving their Quality of Life (QoL). Figure 1 illustrates some of the widely popular IoT-based smart environments.

Services offered by smart environments vary with the requirements of inhabitants/users. Smart home environments particularly focus on improving QoL of residents, while facilitating other demands, such as surveillance and energy management [13,14]. Improving Quality of Services (QoS) offered to urban citizens is one of the key concerns of smart cities. However, rapid urbanization has drawn communities' attention towards the depletion of natural resources. Hence, modern smart cities aim to build cities that promote sustainable resource utilization [15]. Smart grids were discovered to enforce sustainable energy management. Accordingly, smart grids benefit both users and utility providers by reducing energy wastage, monetary cost, and peak load demand. Moreover, modern smart grids enforce renewable energy and green energy concepts to assure sustainability and minimal adverse effects to environment [16]. In fact, the over-utilization of natural resources due to rapid urbanization and population growth have induced irreversible challenges on the environment, alerting us to the need for mindful resource consumption. Therefore, sustainable smart environments aim to retain the balance of the eco-system, while providing desired services and preserving non-renewable natural resources [1]. Figure 1 illustrates a few prominent smart environments based on IoT.



**Figure 1.** Internet of Things-based smart environments.

In the recent past, smart energy management has become a key concern in a majority of the smart environment design projects due to its importance and contribution towards sustainability. The smart energy notion was initially coined in 2012 by Lund et al. [17,18] to raise public awareness and to publicize the best practices of energy consumption. Green energy and sustainable energy concepts go hand in hand with smart energy to promote optimal energy utilization practices. However, smart energy is highly favored by experts in both industry and academia, as a holistic approach that unifies the benefits of green energy, sustainable energy, and renewable energy concepts. Increasing demand for renewable energy sources (RES) has drawn global attention towards embedding RESs to smart environments. Consequently, contemporary smart energy management systems incorporate RESs to ensure the sustainability of non-renewable energy sources, while reducing the carbon footprint

on environment. Additionally, smart energy introduces various energy management strategies to smart environments, in order to improve energy utilization and to reduce energy wastage and cost.

Peak load management is an energy management strategy that aims to mitigate the imbalance between energy demand and supply to reassure power system stability and to minimize tariff volatility over fluctuating demand. Demand Side Management (DSM) is another widely accepted efficient energy management strategy that adjusts energy usage in smart environments to significantly reduce energy wastage, peak load demand, and monetary cost of energy [19–22]. DSM strategies are categorized into energy-efficient strategies and demand response (DR) strategies [23]. Energy-efficient strategies facilitate minimal energy usage during the operation of a certain system or the production of certain goods and services. Utility energy-efficient programs offer significant monetary benefits to both utility providers and end users. Electricity load variation throughout the day encourages implementation of DR programs. In contrast to energy-efficient programs, DR programs change energy consumption routines. On the one hand, DR strategies change the usage patterns of end users to achieve monetary benefits. On the other hand, they assist utilities by shaving peak load demand [23–25]. In general, DR programs are categorized into incentive-based and price-based approaches and these approaches are elaborately discussed in later sections.

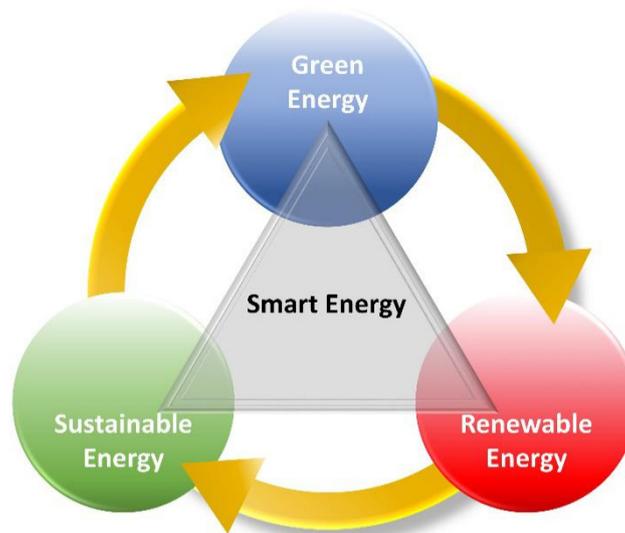
The rest of the paper is organized as follows: Section 2 elaborates on smart energy management. Following on from the analysis in recent works, Section 3 presents peak load management in smart environments, followed by demand side management in smart environments in Section 4. Section 5 identifies challenges and opportunities related to energy management. Finally, the conclusions are presented in Section 6.

## 2. Smart Energy Management

### 2.1. Overview

Unceasing population growth and rapid urbanization increased global demand for energy. As mentioned before, various energy management concepts i.e., green energy, sustainable energy, renewable energy, etc. were proposed during the last few decades to address the challenges that arise with increasing energy demand. The utmost goal of the green energy concept was to minimize adverse environmental and societal effects that arise from non-renewable energy utilization [26,27]. Hence, it reduces carbon emissions, greenhouse gas emissions, human health problems, etc., while meeting clean energy demands [28]. The sustainable energy concept was introduced with the goal of preserving and sustaining non-renewable energy sources for the benefit of present and future generations. In general, sustainable energy consolidates both renewable energy generation and energy conservation [29]. Renewable energy is another favored concept that incorporate RESs to fulfill global energy demand. Solar energy, wind energy, and tidal energy are some of the widely used RESs [30]. Over time, the cost of RES has been reduced and continues to decrease further. As shown in Figure 2, smart energy is the holistic approach that combines green, sustainable, and renewable energy concepts.

Presently, a major portion of energy demand is fulfilled by non-renewable energy sources, i.e., petroleum, coal, natural gas, and nuclear. Nevertheless, extensive efforts from domain experts have considerably increased the contribution of RESs to global energy demand. As a result, the conventional energy management paradigm is transforming towards a hybrid aspect, which combines both renewable and non-renewable energy sources. Although advancements in technologies have revolutionized conventional distribution grids into smart grids that intelligently coordinate the actions of all connected users and utility providers [31], some more features are required to manage hybrid energy generation. Thus, the smart grid paradigm is further evolving to accommodate renewable energy generation, renewable energy storage, distributed energy storage, etc. [30].



**Figure 2.** Consolidation of smart energy concept.

## 2.2. Energy Management in Smart Environments

From an energy saving perspective, energy management is a defined process of monitoring, controlling, and conserving energy in a particular environment including homes, organizations, grids, etc. Nevertheless, energy management was evolved to ensure adequate renewable energy generation and to manage and control personal load demands. Energy management practices benefit both consumers and utility providers. Cost reduction is the most appealing benefit of energy management in smart environments. Controlled energy consumption routines can reduce the cost of energy, while improving energy efficiency. Further, energy management makes a remarkable contribution in the environmental context as it reduces the carbon footprint. In addition to the environmental benefit, reducing the carbon footprint also assists organizations to build a green image, which comes along with lucrative business opportunities. Moreover, insulating energy management systems into smart environments ensures minimal risk of catastrophic blackouts and price fluctuations.

Considering the aforementioned undeniable benefits of energy management, a variety of works have been proposed for smart environments by embedding RESs, controlling appliances, energy trading, etc. Some works embedded RESs at the consumption end, whereas some other works embedded them at the grid end. A generic overview of an energy management model embedded with RESs is presented in Figure 3. A hybrid energy management system that incorporates solar and wind energy was proposed by Han et al. for a smart home scenario [32]. The home energy management (HEM) system proposed by Boynuegri et al. managed domestic energy consumption patterns, while considering user comfort [33]. Son et al. proposed a Power Line Communication (PLC)-based energy-efficient system to optimize energy consumption with the aid of appliance controlling [34]. To further extend energy management practices, researchers expanded the domain towards grids. Kanchev et al. proposed a micro grid energy management system that utilizes photovoltaic (PV) energy generators and storage [35]. Similarly, a plethora of other energy management solutions at the grid end were proposed during the past few years [36,37]. Table 1 presents the strategies, benefits, and drawbacks of some highly recognized energy management approaches proposed for smart environments.

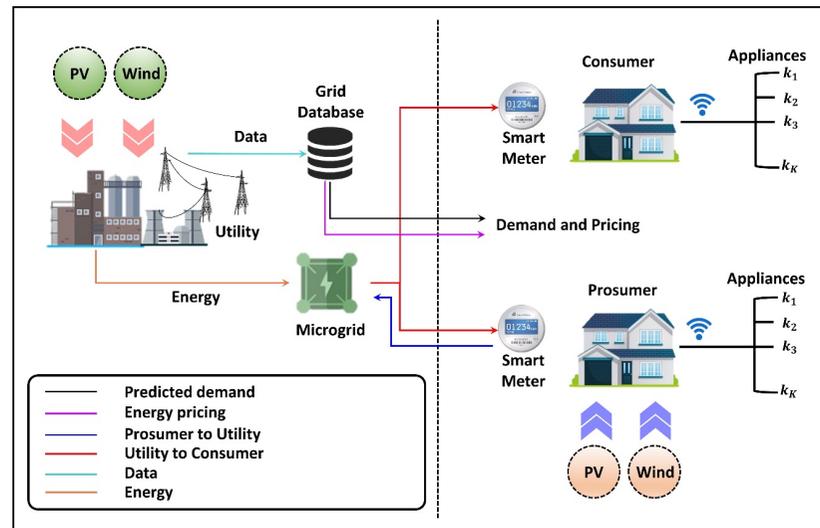


Figure 3. Generic overview of an energy management model.

Table 1. Comparison of strategies, benefits, and drawbacks of general energy management approaches for smart environments.

Scheme	Environment	Strategy	Purpose	Benefits	Drawbacks
Han et al. [32]	Smart home	Home energy management with renewable energy generation	Optimize home energy consumption	Reduce energy cost, Monitor solar panels using PLC for maximum generation capacity, Renewable energy forecasting	Cost analysis was not quantitative, Energy optimization is not tested in a real world scenario
Boynuegri et al. [33]	Smart home	Battery State of Charge (SOC) incorporated energy management with renewable energy sources	Reduce cost of energy considering SOC level, grid availability, and multi-rate tariff	Renewable energy generation, Energy cost reduction, Ability to operate with and without RES, User comfort	Cost reduction with RES is not significant
Son et al. [34]	Smart home	Intelligent controlling of appliances using smart metering and PLC	Provide easy to access real-time energy consumption information to coordinate appliances' operation	Intelligent controlling of domestic appliances, Renewable energy generation, Cost reduction, Peak load shifting	Customer comfort is compromised, Appliance controlling solely based on historic information
Kanchev et al. [35]	Smart grid	Determinist energy management system embedded with PV, Energy Storage System (ESS), and gas micro turbine	Perform central energy management at the grid and local energy management at the consumer end	Power planning, Renewable energy generation and prediction, Central and local energy management, Load balancing and dispatching	Day ahead power planning
Mohsenian-Rad et al. [36]	Smart grid	DSM based on game theoretic energy consumption scheduling	Achieve global optimal performance for minimizing energy cost at the Nash equilibrium of formulated scheduling games	Minimize cost of energy, Balance total domestic power load, Facilitate interaction among users and interaction between utility and each user	Considered only single energy source, No consideration on reducing energy consumption, Aimed to manage only residential loads
Erol-Kantarci et al. [37]	Smart grid	Residential energy optimization with flexible communication between consumer and controller	Achieve cost-effective energy management in presence of local energy generation, Real-Time Pricing (RTP), and prioritized appliances	Cost reduction, Priority-based scheduling, Peak load management	Consumer comfort is not considered, Appliances' pervasiveness is not considered

### 3. Peak Load Management in Smart Environments

Demand for electricity varies with the time of the day, creating off peak, average peak, and peak hours [38]. The load demand is continuously escalating with the increasing number of energy consumers, emphasizing the need for efficient strategies to meet the desired energy demand during peak time. In fact, increasing peak load demand originates major concerns such as the imbalance between energy generation and supply, and swift fluctuations in the monetary value of energy [39]. Previously, small power plants and isolated power plants were used to accommodate rising peak load. This approach is known as capacity addition. Nevertheless, managing these small scale power plants only to dispatch peak load demand was ineffective due to high maintenance cost [40,41]. Hence, peak load shaving came into the spotlight as a solution that addresses the challenges that arise with peak energy demand. Peak load shaving aims to reduce the load demand during peak times by shifting them to times that are with lower demands [40]. Owing to extensive attention from researchers, recently there have been numerous studies that focus on peak load shaving. The beauty of this approach is that it can be applied on a range of consumers despite of the context, i.e., residential, industrial, and commercial. Figure 4 illustrates the influencers on peak load, challenges that arise with increasing peak load, and appropriate solution strategies.

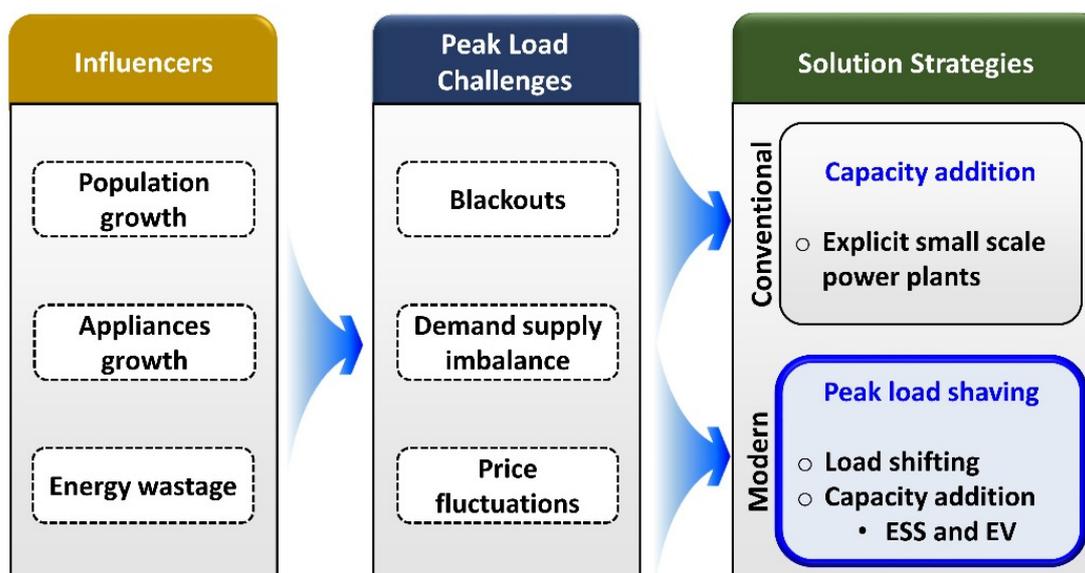


Figure 4. Peak load management overview.

#### 3.1. Peak Load Shaving Strategies

In the recent past, researchers earnestly worked on identifying peak load shaving mechanisms to alleviate the negative impacts of continuous growth of energy demand. Consequently, two major strategies were identified as potential candidates for effective peak load shaving. The first strategy incorporates an external storage that acts as a backup supplier during peak hours. The second strategy incorporates intelligent load management techniques that shift peak load to off-peak hours, considering numerous logical parameters.

Peak load shaving through external storage can be achieved by integrating an ESS or an Electric Vehicle (EV). This approach can be generalized and applied on a variety of smart environments including houses, grids, commercial buildings, industries, etc. ESS integrated systems should charge the ESS during off-peak hours and discharge the stored energy to be consumed during peak hours. However, peak load shaving with ESS should carefully determine the size of the storage to attain optimal performance with maximum monetary benefit. Although EVs are seen as potential candidates for storage-based peak load shaving, currently EVs are not widely used throughout the globe. However,

they are predicted to become more popular in the near future owing to their remarkable contribution towards sustainability. The storage of EV can be used for both travelling and peak load shaving. Previous related works suggest that peak load shaving through EVs can be achieved by using them for energy storage or by optimizing EV charging schedules [42]. DSM-based peak load shaving encourages consumers to alter typical energy consumption routines to reduce cumulative peak load demand. Although DSM can be either from energy efficiency, on-site backup, or DR, peak load shaving is efficiently achieved through DR, which is elaborately discussed in Section 4. Table 2 presents a comparative summary of existing peak load shaving strategies implemented for smart environments incorporating ESS and EV.

### *3.2. Benefits of Peak Load Shaving*

Peak load shaving comes with a handy pack of benefits. These benefits are not limited only for the utility provider, but also for consumers and the environment. Maintaining the balance between energy generation and energy supply is crucial, although increasing energy demand adversely affects this balance. If the demand surpasses generation, that might lead to voltage fluctuations, power instability, and devastating blackouts [59]. However, appropriate peak load shaving techniques can maintain the demand–supply balance, while improving the power quality. Moreover, peak load shaving assists utilities to improve system efficiency by reducing supply current during peak time [60]. In general, supply current has a non-linear relationship with power loss [61]. Hence, by reducing the supply current during peak hours, peak load shaving reduces power loss, simultaneously improving efficiency. As previously stated, peak load shaving emerged as a solution that maintains the balance between demand and supply. Typically, a grid should have the capacity to cater maximum peak loads without any disturbances or outages. However, generating and maintaining an energy capacity fit for maximum peak load tends to increase energy loss and production cost, due over generation in all other times except in peak hours. Therefore, applying an efficient peak load shaving strategy will enhance the capacity of utility providers to supply required energy demand throughout the day with minimal loss and production cost. Presently, experts in all major domains focus on sustainable utilization of non-renewable energy sources. Although renewable energy sources play a key role in global energy generation, the intermittent nature of these resources causes reliability issues for power grids. Nevertheless, despite these challenges, it is clearly evident from previous works that integrating renewable energy sources with peak load shaving strategies enhances non-renewable energy utilization, assuring sustainability. Furthermore, peak management is important for consumers as it reduces the electricity cost during peak hours. In general, conventional capacity addition methods for peak load management are expensive and inefficient. Ultimately, the extra cost of production will be added to consumers' bills [61,62]. Contrastingly, peak load shaving allows shifting peak load to other times of the day, which will reduce the cumulative peak load, while immensely benefiting the users in monetary terms [63]. In addition to all stated benefits, peak load shaving tremendously reduces the carbon footprint, promoting environmental sustainability. In summary, peak load shaving strategically handles unceasingly growing peak demand to reduce extensive fluctuations, production cost, and carbon emissions, while improving the operational efficiency of grids.

**Table 2.** Comprehensive analysis of existing works on peak load shaving in smart environments.

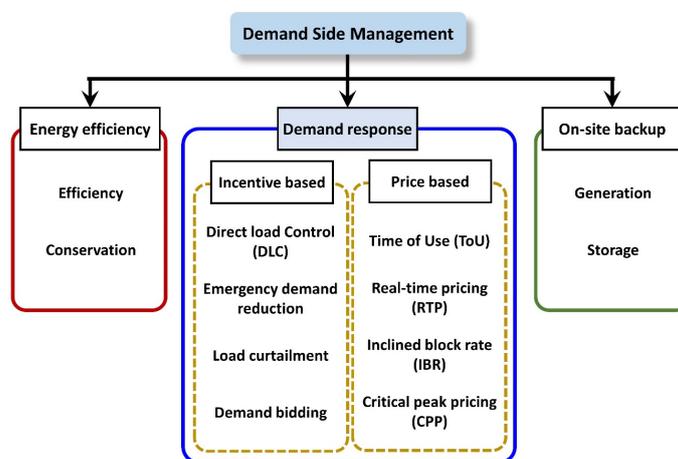
Work	Context	Strategy	Method	Remarks	Pros	Cons
Reihani et al. [43]	Grid	Battery operated ESS (BESS)	Forecast load curve to obtain SOC trajectory for peak load shaving, Shave peak load through power charging aligned with SOC trajectory, Real-time controlling of SOC level of BESS	Simultaneously perform load shaving and smoothing, Incorporated parallel and series-parallel methods for load forecasting	High accuracy in series-parallel processing predicted load for 20 min interval, Increased accuracy in real-time controlling of BESS SOC	Parallel processing forecasting for 24 h significantly deviates from actual load
Lavrova et al. [44]	Grid	BESS and DR	Demonstrated peak shifting with BESS, Smoothed PV output using BESS, Aggregate shaving and smoothing to maximize performance	Simultaneously perform peak load shaving and smoothing, Smoothed signal determined charging and discharging rates of BESS	Considered both residential and commercial loads, Obtained a minimum of 15% peak load reduction, Evaluated peak shifting, smoothing, DR, and financial benefit aspects	Rapid power variation of smoothing battery
Telaretti and Dusonchet [45,46]	Office	BESS	Peak load shaving through power diagram modification, Evaluated for multiple electrochemical storage systems	Peak load shaving to obtain flattest usage pattern, while maximizing consumer benefits, Calculated costs and estimated savings	Perfectly flattened consumer profiles during days with low peak load, Evaluate economic feasibility of installing BESS, Maximize load-flattening benefits	BESS sizing is defined as a user-chosen decision, According to results, at present, none of the BESS are cost-efficient compared to the cost
Lucas et al. [47]	Grid	BESS	Incorporated Vanadium Redox Flow Batteries (VRFB), Approving of charging and discharging requests are controlled by SOC thresholds	Simultaneously perform peak load shaving and frequency regulation, Charge BESS during off-peak hours and discharge during peak hours	Environmentally friendly. Faster frequency regulation	Supply power variation is not considered. Hence, unable to detect lower and upper bounds for power supply when demand change is significant
Zheng et al. [48]	House	ESS	Incorporated a variety of storage under realistic tariffs. Determined optimal shaving pattern based on dispatch strategy, cost levelling, battery lifetime, and load demand	Generated appliance level load profiles using an agent-based stochastic model. Storage dispatches energy upon noticing an aggregated demand that surpasses grid's demand limit (DL). Iterative simulation has optimized the complete system to increase profit margin	Obtained annual profit of 10–31% without seasonal DL dispatching. Obtained annual profit of 6–39% with seasonal dispatching (profit margin depends on the type of ESS). Allows to determine profitable storage system for a residential context	Weather conditions are considered although seasonal DL is proven to have a correlation with annual profit
Chua et al. [49]	University	ESS	Proposed a sizing method for ESS sizing. Optimal operation strategy for ESS Maximum peak shaving through adaptive threshold algorithm	Derived optimal size for ESS considering consumers' historic load profiles. Control algorithm determined peak shaving according to load profile	Optimize Return-on-Investment (ROI). Reduce electricity bill. Ensure maximum peak load shaving. Can extend to control Microgrid ESS with necessary modifications	
Leadbetter and Swan [50]	House	BESS	BESS sizing method. House load demand was used to determine DL of the grid	Input electricity profile for a household in 5 min interval. Determined optimal peak shaving based on grid DL, power capacity of ESS, and storage factors of BESS	Reduce peak load seen by the grid. Determined typical sizes of ESS for houses with low electricity consumption. Evaluate a variety of BESS	Capital investment for BESS installation is not considered. Maximum financial benefit is questionable. Applicability on high consuming households is not evaluated
Lu et al. [51]	Grid	BESS	Rolling method-based BESS sizing for peak load shaving	Simultaneously shave peak load and plan BESS capacity in real-time. Considered historical load profiles of same time of the day to forecast load using rolling method. BESS capacity was determined using forecasted load and real-time load requirements	Minimize peak load. Reduce gap between peak load and valley load. Reduce variance in daily load. Load forecasting. Determine minimum capacity of BESS	Fluctuation penalty cost
Wang and Wang [52]	Grid	EV	Proposed a Vehicle-to-Grid (V2G) architecture with constraints and an objective function for peak load shaving	Perform peak load shaving and valley filling. Derive maximum peak shaving by applying maximum livelihood strategy. Decrease the power of target curve to increase the shaving ability	Tested with real world city data. Quantitatively analyzed the influence of a connected number of EVs.	Assumed a known load. Does not consider power flow among EVs in a V2G architecture

Table 2. Cont.

Work	Context	Strategy	Method	Remarks	Pros	Cons
Mahmud et al. [53]	House	BESS and EV	Artificial Neural Network (ANN)-based peak load shaving by coordinated responses of distributed energy resources	Charging and discharging performed during off-peak and peak hours, respectively	Peak load shaving up to 77% with a 6 kWh BESS	Load prediction methods are not incorporated. Power capacity of the EV is not defined
Mägi. M [54]	Grid	EV	Evaluate bi-directional energy exchange between grid and EVs to shave peak load of the grid network	Enable EV to take over peak load from substation by acting as a storage source	Short term peak load shaving. Allow substation to act as a service provider to Microgrid. Can utilize to develop control algorithms for automated substations	Long term peak shaving is not supported
Lee and Choi [55]	House	BESS and Plug-in Hybrid Electric Vehicle (PHEV)	Peak shaving with optimized load scheduling	Peak load reduction using Linear Programming (LP)-based optimization. ESS charging and discharging take place during off-peak and peak hours, respectively	Reduced peak load up to 38%	Real-time load demand is not considered. Individual contribution from BESS and PHEV is not evaluated. PHEV charging period is not considered
Erden et al. [56]	Grid	Plug-in Electric Vehicle (PEV)	Adaptive controlling of EV charging and discharging for peak load shaving and load levelling	Adaptive controlling based on PEV, user choices, load forecast, and predefined reference operating points. Determine dynamic reference points based on historic mobility data of PEV and non-PEV load data	Simultaneous peak load shaving and levelling. Monetary benefit to the utility. Anxiety-free user comfort. Easy charging nodes implementation	Voltage fluctuations are not considered. Battery degradation cost is not considered for cost evaluation
Erdogan et al. [57]	Grid	EV	Two stage V2G discharging control system to minimize peak demand in distribution grids	Incorporated offline load forecasting and mobility model to determine required peak shaving and duration. Considered real-time grid load and EV characteristics to dynamically adjust EV discharging rates	Reduce peak load at substation. Dynamically adjust discharging rates. Efficient performance even at low penetration rates of EV	Considered only assumption-based mobility routines of EV
Gazafroudi et al. [58]	Residential	Multi agent system (MAS)	Incorporated EV and PV panels to transact with local electricity market	Adaptive controlling of agents with MAS implement	Consider PV uncertainty, Cost reduction at demand side	Less adaptive energy management

#### 4. Demand Side Management in Smart Environments

Demand side management concerns actions or activities that take place at the consumer end including load management, strategic conservation, electrification, etc. [64]. Although various definitions in various aspects have been proposed, in generic terms DSM aims to balance the energy demand and supply with minimum cost. DSM in a smart environment can be either from energy efficiency, DR, or/and on-site backup approaches. The utmost goal of energy efficiency is to conserve energy and to reduce energy consumption by efficient usage strategies or appliances. Reduced total energy consumption positively influences the environment with reduced carbon emissions. On-site backup has been used in load curve smoothing supported by load generation and storage. However, energy efficiency and on-site backup will not be further discussed in this article. The highly favored demand response aims to achieve monetary benefits by adjusting the consumption routines of consumers. In other words, DR shifts peak load to any other time slots that are with less demand. Figure 5 depicts a summary of DSM strategies used in smart environments and DR in smart environments is further discussed in this section.



**Figure 5.** A pictorial summarization of Demand Side Management (DSM) strategies in smart environments.

##### 4.1. Demand Response Strategies

The key to promote the DR program is customer awareness and motivation [65,66]. Hence, utility providers should improve customer awareness by promoting the benefits of adjusting electricity consumption patterns i.e., cost reduction, reliability, and power quality [67]. In simple terms, DR is defined as the changes in energy consumption patterns or routines of consumers, which correlate with the changes of electricity price or incentives [38]. Accordingly, DR is categorized into price-based DR (PBDR) and incentive-based DR (IBDR). PBDR programs enforce time-dependent charging rates, whereas IBDR programs offer incentives to customers considering their usage pattern adjustments.

Further, Meyabadi et al. [68] categorized DR strategies as DR methods with and without dispatch capability. Although the classification criteria are different, classification outcomes are the same as PBDR and IBDR. Dynamic electricity pricing (price based) is incorporated in DR methods without dispatch capability to achieve DR goals. The retailers are obliged to satisfy the energy requirements of consumers either by purchasing from wholesale market or by employing distributed generations [68]. Techniques used for DR without dispatch capability are the same as PBDR methods shown in Figure 5. DR methods with dispatch capability focus on achieving DSM through financial incentives and special market strategies [68]. It allows incorporating demand side resources into the power system and offers incentives to the participants (incentive based). Incentive-based methods shown in Figure 5 are capable of handling DR with dispatch.

DR programs can be implemented in a range of smart environments including houses, commercial buildings, industrial complexes, etc. Advanced metering infrastructures (AMI), installed in the

demand side, measure energy usage and communicate usage patterns to the utility providers [23]. Converging related technological advancements, communication capabilities, and energy controllers drive smart environments toward effectual DR program implementation [69]. Prior to enrolling with a DR program, consumers can perform a cost–benefit analysis that ensures favorable outcomes considering uncertainties and risks.

#### 4.1.1. Incentive-Based Demand Response

As stated before, IBDR programs offer incentives to participating consumers. Consumers enrolled with IBDR voluntarily reduce energy consumption during peak hours or during certain events. IBDR programs are categorized into classical programs and market-based programs. Direct load control (DLC) and load curtailment are considered as classical IBDR programs. Emergency DR and demand bidding are examples of market-based programs. In classical IBDR, incentive payment can be received either as a bill credit or as a discount. Nevertheless, market-based programs reward money to their participants based on load reduction performance during critical periods [70]. IBDR programs have the benefit of achieving explicit operational goals. For example, IBDR performs localized load reduction to enforce grid reliability during a transmission congestion. It is worth noting that time intervals of IBDR are determined by triggering conditions and can vary from seconds to hours [71].

DLC programs operate with the key objective to reduce peak load demand. Herein, consumer appliances are registered in the program. Accordingly, utilities can remotely access and shutdown participating appliances as required. Typically heaters and air conditioners are registered with utilities and direct controlling take place during peak hours or during certain events [72]. In return, participants receive incentive payments. The DLC approach is widely implemented in residential and small commercial environments. Furthermore, DLC programs efficiently perform peak load shaving and load curve smoothing. However, progress and expansion of DLC programs are highly reliant on consumer acceptance.

Consumers agree upon a contract with utilities in load curtailment programs. Through these contracts, consumers are obliged to respond to utility requests on load curtailment when power system reliability is jeopardized [73]. Participants who respond during critical periods will receive incentives in the form of discounts on electricity bills. It is worth noting that load curtailment programs penalize participants who failed to respond appropriately. Hence, voluntary enrollment and self-load shedding are considered as key features of load-curtailing IBDR [68]. These programs ensure the security of the power system, while improving operation costs [74]. In general, industrial and large commercial environments implement and enroll in load curtailment programs to obtain incentives through shutting down industrial loads.

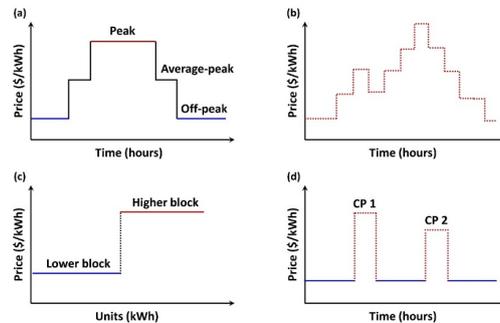
Demand bidding is a market-based IBDR strategy, which is available for large scale consumers who are typically larger than 1 MW. In this approach, consumers can bid to curtail a portion of their consumption during peak hours or system contingencies [75]. If the consumers respond to utility requests, they will receive incentives based on the market price, and otherwise they will be penalized [76]

Emergency demand reduction programs enhance the reliability of power systems during emergency events or accidents [77]. Large scale consumers can enroll in emergency programs and should act swiftly to utility requests. Owing to market-based price incentives, this approach encourages participants towards on-site generation.

#### 4.1.2. Price-Based Demand Response

Electricity price acts as the control signal of PBDR. The utmost goal of PBDR is to reduce overall energy consumption, while reducing energy cost by shifting a considerable portion of peak load demand into off-peak hours. Time of Use (ToU), Real Time Pricing (RTP), Inclining Block Rate (IBR), and Critical Peak Pricing (CPP) pricing techniques discussed below are used for PBDR. Electricity price fluctuations for these methods are shown in Figure 6. Initially, PBDR programs were used in

industrial contexts to reduce the energy cost, which correlates with production cost. Due to a lack of energy monitoring abilities, PBDR programs were not widely favored by other smart environments during the early stages. Nevertheless, expanded penetration of AMIs enabled real-time monitoring of energy utilization, encouraging various smart environments to implement PBDR programs.



**Figure 6.** Electricity price fluctuations of price-based demand response (DR) techniques. (a) Time of Use (ToU); (b) Real Time Pricing (RTP); (c) Inclining Block Rate (IBR); (d) Critical Peak Pricing (CPP).

The ToU pricing technique determines the electricity price that depends on the time of the day. In general, the ToU method divides a day into three phases namely, peak, average peak, and off peak. Energy consumption during peak hours increases the electricity bill extensively. Hence, ToU pricing encourages consumers to benefit from low charging rates during off peak hours by shifting shiftable peak loads into off peak hours. ToU-based DR programs are easy to follow and accommodate stable daily participating ratios [24]. Owing to these benefits, ToU is considered as the most favored PBDR technique [78]. However, time-based pricing of ToU has become disadvantageous, where load shifting creates new peaks. Hence, it is essential in ToU-based DR to mitigate new peak formation during load shifting.

From a theoretical perspective, RTP is considered as the most effective DR technique. In RTP, electricity price fluctuates in real-time as a response to wholesale market price. Dynamic price fluctuations are informed to users on hourly basis or daily basis. This allows retailers to participate in energy distribution tasks with less risks. Moreover, RTP-based DR encourages consumers to adjust their consumption routines to gain more monetary benefits. RTP-based DR implementation requires fully deployed smart metering infrastructures. Nevertheless, even with the required hardware implementations, residential consumers are still hesitant to embrace RTP due to the lack of ability in responding to real-time price fluctuations [79]. Level-based pricing is offered in IBR programs. Total electricity consumption of a consumer determines the electricity bill based on a two-level pricing strategy. If energy consumption surpasses the predefined threshold limit, the price for electricity increases drastically. The threshold limit can be defined on an hourly, daily, or monthly basis [80,81]. IBR programs help grids to reduce PAR value by enabling users to achieve monetary benefits through load distribution. IBR programs were popular with utility companies since the 1980s [82], as they curtail unnecessary investments in generation, transmission, and distribution systems [81].

The key objective of CPP programs is to maintain power system reliability. CPP incorporates high electricity prices to control electricity consumption during critical peak hours. CPP is introduced when the power system is at a vulnerable state due to extremely high peak load demands or when wholesale market price is high [83,84]. Hence, CPP is not considered as a daily DR program and can be used along with ToU. In CPP, participants who contribute to system reliability by shifting peak load or by reducing peak load are entitled for price discounts during non-critical peak hours. Although CPP programs are good at peak energy shifting, they are less beneficial in terms of cost reduction as they are not implemented as daily DR programs. Table 3 presents a set of the main research works conducted on DR in smart environments incorporating PBDR and IBDR methods.

**Table 3.** Research works on DR in smart environments.

Works	Context	Strategy	Method	Remarks	Pros	Cons
Chen et al. [85]	Residential	PBDR (RTP)	RTP-based DR through stochastic and robust optimization	Determine optimal operation schedule for 5 min slots, Minimizes cost per day, Minimizes worst cost incurred	Automatic execution, Considered RTP uncertainties, Achieve significant cost reduction	Increased computation load with stochastic optimization
Qian et al. [78]	Grid	PBDR (RTP)	RTP-based DR scheme for smart grids using simulated annealing-based price control	User and retailer together determine optimal price, User responds to RTP, Retailer defines RTP to maximize profits	Reduce PAR, Reduce electricity cost, Increase profits of retailers, Considered quality of service	Considered larger time intervals to predict RTP
Yoon et al. [86]	Residential	PBDR (RTP)	Dynamic DR controller that schedules heating, ventilation, and air conditioning (HVAC) loads according to RTP	Control HVAC loads by comparing RTP and user defined threshold price values	Preserve user comfort, Reduce peak load, Reduce electricity cost	Correlation between of retail price and wholesale price is not considered
Yousefi et al. [87]	Energy retailers	PBDR (RTP)	Comprehensive DR model to represent customer responses to RTP and to assist retailers to derive day ahead RTP	Retailers derive most favorable RTP based on Q-learning method's principles.	Intelligent retail agents, Fine tune day ahead pricing to use it as RTP	Considered hourly behaviors of consumers
Ozturk et al. [88]	Residential	PBDR (ToU)	ToU-based decision support system to schedule and control residential loads	Derives optimal schedule considering user constraints, ToU, and user behaviors	Reduce electricity bill, Consider user comfort, Accurate behavior predictions	Evaluated predictions only for 2 appliances, Semi-flexible appliance scheduling is not considered
Wang et al. [89]	Manufacturing systems	PBDR (ToU)	ToU-based DR program for manufacturing systems considering production target constraints	Derived optimal schedule using binary particle swarm optimization (BPSO), Considered ToU, machine reliability, and buffer capacity for schedule optimization	Reduce total electricity consumption, electricity cost, production cost	Performance evaluation is limited
Muratori et al. [90]	Residential	PBDR (ToU)	Automated DR strategy based on multi-level ToU	Introduced multi-ToU pricing to avoid new peak formation, Derive optimal schedule through dynamic programming (DP) and stochastic optimization	Independent schedule optimization for each household, Reduce cost, mitigate new peak formation	User comfort is compromised by relying only on estimations based on deadlines and waiting times
Silva et al. [91]	Residential	PBDR (ToU)	DR strategy using ToU for residential communities using ant colony optimization (ACO)	Optimized flexible and semi-flexible appliances scheduling, Control PAR using power consumption constraints, Introduced mutation operator to ACO to avoid premature convergence during scheduling	Minimize electricity bill, waiting time, PAR	Renewable energy sources were not incorporated, user experience is not evaluated
Aslam et al. [92]	Residential	PBDR (CPP & RTP)	Heuristic optimization-based appliance scheduling incorporating RTP and CPP	Evaluated scheduling using three heuristic algorithms with integrated ESS for single house and multiple houses scenarios	Reduce electricity bill, waiting time, PAR	ESS considered without any on-site energy generation
Javaid et al. [93]	Residential	PBDR (CPP & RTP)	Hybrid scheduling algorithm using enhanced differential evolution and teacher learning-based optimization	Derived priority-based schedules for single house and multiple houses scenario	Reduce cost and PAR with maximum user comfort	RTP was defined for hourly intervals and have less control
Rastegar et al. [94]	Residential	PBDR (IBR)	Determine operational priority based on value on lost load (VOLL)	Schedule domestic appliances considering appliances' VOLL, tariff, and operational constraints	Reduce electricity	Forceful appliance termination compromise user comfort

Table 3. Cont.

Works	Context	Strategy	Method	Remarks	Pros	Cons
Rastegar et al. [79]	Residential	PBDR (IBR & ToU)	Manage residential loads using a hybrid pricing strategy	Incorporated a hybrid version of ToU and IBR to mitigate new peak formation incorporating ESS and EV	Reduce electricity cost, mitigate new peak formation	Simulation performed only considering flexible appliances
Zhu et al. [95]	Microgrid	IBDR (DLC)	Integrated resource planning (IRP) based on DLC	Classical DLC-based IRP model optimization for diesel generators, PV, wind turbines, and ESS	Optimal peak shaving and load shifting with minimal total social costs	Does not consider actual runtime behavior and duty cycling control (DCC)
Evora et al. [96]	Grid	IBDR (DLC)	DLC-based DR program using multi-objective particle swarm optimization (MO-PSO)	Divide power restrictions among neighbors and calculate multiple local optimizations to derive optimal global solution	Preserve grid stability, while maintaining user comfort. Scalable according to grid size	Evaluated for fewer appliances, with same operational time for all appliances and same comfort profile for all users
Aalami et al. [73]	Community	IBDR (Load curtail)	Economic model that allows independent system operators (ISO) to determine DR parameters	ISO determine DR parameters to improve load curve, ISO identifies user behavior based on incentives, penalties, satisfaction, and load profiles' elasticities	Improve load curve and benefit users with incentives	Not evaluated for real-time data
Yan et al. [74]	Grid	IBDR (Load curtail)	Interruptible load management to improve static security of grids	Applied traditional N-1 analysis [73] with interruptible load management at demand side and considered interruptible load and power flow constraints	Improve transmission limit of the grid section, security of the grid, operational economy	User comfort is not addressed
Wang et al. [97]	Industrial	PBDR (ToU)	Mixed integer linear programming problem was solved to optimize operation of thermostatic loads and renewable generation	Control HVAC loads and renewable energy generation considering ToU pricing	Derives optimal operational schedule, Reduce electricity cost and peak load demand, Generalizable to many industrial contexts	Optimal energy storage sizing is not considered
Huang et al. [98]	Industrial	PBDR (ToU)	Actor-critic-based deep reinforcement learning derives optimal operational schedule	Considered all operations of steel powder manufacturing industry	Reduce energy costs, Maintain demand and supply balance, Meet production targets	Plausibility of generalizing is not addressed
Gomes et al. [99]	Grid	MAS	Distributed agent-based intelligent system that address demand response at grid end	The system connects various physical resources to allow simulation on real devices	Considered many DR programs, intelligent operation	Limited generalizability, less participants in simulation

#### 4.2. Benefits of Demand Response

Technological advancements and awareness among users have significantly promoted DR as a reliable option that improves user experience as well as power system reliability. This synchronizes well with the modern trend of sustainable and renewable energy generation in grids. Hence, flexibility of DR can be used to mitigate adverse effects that arise from uncertain behaviors of renewable energy generation [100]. For example, conventional wind power generation requires a considerably larger reserve generation to assure power system stability over generation fluctuations. However, Kirby [101] and Callaway et al. [102] state that the load shifting and load curtailment aspects of DR can be used to provide power system security services at a lower cost and with a lower generation capacity. In general, power generation and capacity maintenance directly correlates with total costs [103]. Nevertheless, utilizing DR programs to reduce the cost of maintaining capacities significantly reduces cumulative cost. In fact, DR programs come with a variety of cost benefits to consumers, suppliers, and generators [104]. DR enforces responding to localized demands and price variations, which reduces the chances of manipulating wholesale electricity price by larger producers [105]. Further, DR programs reduce average wholesale electricity price and the unpredictability of peak prices [106]. Conventional flat rate energy consumption does not notify users regarding potential benefits and incentives they can achieve through load shifting. Contrastingly, time varying prices offered by DR programs expose attractive benefits and motivate a larger portion of energy consumers to participate in and experience a range of benefits including cost reduction and satisfaction [107,108].

Moreover DR programs benefit utility providers by reducing electricity generation margins. Generally, utility providers should be able to generate more than the maximum load requirement during peak hours. As stated above, DR programs in general encourage consumers to shift loads to reduce peak demand. Subsequent to reduced peak load demand, the required energy generation margins for utility providers get lowered. Increasing electricity demand results in congestion in distribution and transmission networks, which require costly network upgrades. It is worth noting that many studies have claimed that diversity of demand can be used to alleviate these congestion issues and maximize network utility without any pricey network upgrades [109–111].

### 5. Challenges and Opportunities of Energy Management in Smart Environments

Although energy management in smart environments is well implemented and widely accepted, addressing existing challenges is crucial for the global expansion. Determining existing challenges leads the way towards future energy management opportunities. Hence, this section identifies existing challenges for energy management in smart environments through an extensive literature review. Moreover, this section presents opportunities and future directions related to smart environment energy management, which were identified through research experience and a literature review.

#### 5.1. Challenges for Smart Environment Energy Management

This article critically reviewed peak load shaving and demand response strategies in various smart environments. This section gives insights to number of existing challenges that hinder further improvement of peak shaving and demand response in terms of deployment, acceptance, and benefits. Figure 7 gives a concise overview of challenges faced by peak load shaving and demand response in smart environment energy management.

Although peak load shaving using ESS is extensively studied, some significant challenges in ESS are required to be solved in order to maximize the desired benefits. Deriving optimal schedule for ESS charging and discharging still remains as a concern to be addressed in a real world context. Though few works have been proposed to optimize ESS' operational schedule, a generalizable approach is not yet implemented. Addressing this issue will tremendously benefit users to achieve lucrative monetary benefits, while contributing to power system reliability. Determining the perfect size of ESS is another challenge for effective peak shaving in smart environments. In fact, ESSs do not match with the required

capacity demands, leading to higher installation costs, maintenance costs, and lower monetary benefits. If the capacity is lower than desired, it will lead to power outages as well. Even though installing ESS for energy management is effective, cost is a significant barrier for practical implementation and maintenance, especially in large scale ESSs.



**Figure 7.** Challenges for energy management in smart environments.

Incorporating EV for peak shaving is another energy management approach that has been studied extensively during the last decade. Although EV-based energy management is efficient in all theoretical means, practical implementation faces various challenges. Readily accessible deployment has become one of the major concerns, since EVs contribute to power systems only when parked and practical implementation of integrating EV energy to power line is still evolving at the infant stage. Moreover, security and privacy concerns of vehicle owners is another challenge that limits the popularity of EV-based energy management in smart environments. When considering peak shaving, a single EV is not capable of managing peak load demand. Synchronized controlling of multiple EVs offers excellent performance. However, due to privacy and security measures, vehicle owners are hesitant to grant authority of controlling EVs to a mediator. Grid integration availability is another challenge that arises when performing EV-based energy management. Even though EV integration to the grid is conceptually available, infrastructure demands for real world deployment are still lagging and remain as a key area to be addressed, in order to realize EV-based energy management in future smart environments.

Energy management with DR is a well-established concept, although real world implementation is still evolving at a slow pace. Many reasons affect DR implementation and a lack of Information and Communication Technology (ICT) infrastructure is one of the key challenges. Sophisticated metering systems, control strategies, communication systems, and other information technologies are not appropriately available in current power distribution and transmission systems. Although infrastructure development is essential for the broadening of real world implementations, the demand

for massive investments hinders this progress. Implementing DR in a power system increases the overall complexity as it requires additional controlling mechanisms. However, cost reduction and uncertainty management benefits of DR will promote implementing DR programs in the near future, overseeing the complexity demands. Consumer hesitance in embracing DR mechanisms is another concern that requires extensive attention. This is mainly due to lack of awareness and compromised user comfort. Users are not well informed about benefits and incentives, although discomfort occurring from DR is apparent. Hence, consumers become hesitant to participate in DR-based energy management programs and their hesitance declines the rapid expansion of DR implementation in smart environments.

### *5.2. Opportunities in Smart Environment Energy Management*

As per the challenges identified through extensive literature review, herein potential future directions and opportunities are presented for the betterment of energy management in futuristic smart environments. Determining the optimal operational schedule for ESSs remains as an issue to be addressed. Hence, identifying influential parameters and developing generalizable algorithms that are flexible with varying load demands could be a promising future direction to maximize the benefits of integrating ESSs to power systems. Moreover, automatically adjustable ESS sizing mechanisms can be proposed in future to minimize unnecessary implementation and maintenance costs as well as sudden catastrophic blackouts. Since large scale ESSs require large sum investments, promoting the deployment of multiple small scale distributed ESSs will be a better solution for the future. In this regard, distributed ESSs should cooperate with each other in a synchronized manner to realize smart environment energy management. Therefore, working on synchronization algorithms that control integration of distributed ESSs to power systems is a promising opportunity for domain experts. Further, extensive economic feasibility analysis and cost–benefit analysis performed on ESS deployment will uncover valuable implementation measures that determine the best ESS parameters to achieve the highest efficiency with the lowest cost.

As stated in the previous section, a single EV is not capable of managing smart environment energy demands. Similar with ESSs, when multiple EVs are connected to the power system, synchronized control is essential. Hence, developing scalable algorithms that control EVs in sync will be a potential future direction. Moreover, developing dedicated, secure, and privacy-preserving controlling algorithms is another leveraging opportunity for EV integrated energy management. Consequently, it will raise consumer awareness and convince users that the EVs are not vulnerable to security and privacy threats.

Load uncertainty management is essential for the effectiveness of any DR program. However, very few studies considered uncertainty in their proposed DR solutions. Therefore, considering load uncertainty to maximize the benefits of DR programs is a worthwhile future direction. Developing consumer-attractive DR strategies is another promising opportunity, since consumer attraction plays a major role in popularizing DR programs. Moreover, increasing awareness and promoting DR benefits is mandatory to attract more participants, especially residential consumers. User satisfaction is the key to the success of DR programs. Nevertheless, a few studies have evaluated this concern. Hence, proposing scalable and flexible DR optimization solutions that also assure user comfort is recommended as a thread for future research. Further, research on environmental aspects of DR will be a promising area of research, since sustainability and ecosystem balance are the key concerns of modern smart environments.

## **6. Conclusions**

Energy management emerged as a service in smart environments, which aims to utilize energy efficiently and sustainably. Energy management benefits are versatile and applicable to any smart environment. This article presented an overview of the relationship between smart environments and energy management. Existing works on generic energy management in smart environments were reviewed to deliver the gist of the smart energy management concept. Moving on

to specific energy management approaches, peak load management and demand side management are described. Peak load shaving under peak load management and demand response under demand side management are extensively reviewed through existing literature reports. The literature survey identified the advantages and disadvantages of the proposed works as well as the overall benefits of each energy management strategy. Further, loopholes and challenges faced by smart environment energy management strategies identified through a rigorous review process are presented towards the end of the article. Although energy management is a trending domain of this era, it still faces various challenges that hinder further evolution and progress. Hence, this article identified a list of potential opportunities and directions that provide guidance for future research and enrich the knowledge base on smart environment energy management.

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## References

1. Silva, B.N.; Khan, M.; Han, K. Towards sustainable smart cities: A review of trends, architectures, components, and open challenges in smart cities. *Sustain. Cities Soc.* **2018**, *38*, 697–713. [[CrossRef](#)]
2. Silva, B.N.; Khan, M.; Han, K. Internet of things: A comprehensive review of enabling technologies, architecture, and challenges. *IETE Tech. Rev.* **2018**, *35*, 205–220. [[CrossRef](#)]
3. Li, J.; Silva, B.N.; Diyan, M.; Cao, Z.; Han, K. A clustering based routing algorithm in iot aware wireless mesh networks. *Sustain. Cities Soc.* **2018**, *40*, 657–666. [[CrossRef](#)]
4. Gubbi, J.; Buyya, R.; Marusic, S.; Palaniswami, M. Internet of things (iot): A vision, architectural elements, and future directions. *Future Gener. Comput. Syst.* **2013**, *29*, 1645–1660. [[CrossRef](#)]
5. Vermesan, O.; Friess, P.; Guillemin, P.; Giaffreda, R.; Grindvoll, H.; Eisenhauer, M.; Serrano, M.; Moessner, K.; Spirito, M.; Blystad, L. Internet of things beyond the hype: Research innovation and deployment. In *IERC Cluster SRIA*; River Publisher: Gistrup, Denmark, 2015.
6. Khan, M.; Silva, B.N.; Han, K. Internet of things based energy aware smart home control system. *IEEE Access* **2016**, *4*, 7556–7566. [[CrossRef](#)]
7. Jabbar, S.; Khan, M.; Silva, B.N.; Han, K. A rest-based industrial web of things' framework for smart warehousing. *J. Supercomput.* **2018**, *74*, 4419–4433. [[CrossRef](#)]
8. Siano, P. Demand response and smart grids—A survey. *Renew. Sustain. Energy Rev.* **2014**, *30*, 461–478. [[CrossRef](#)]
9. Catarinucci, L.; De Donno, D.; Mainetti, L.; Palano, L.; Patrono, L.; Stefanizzi, M.L.; Tarricone, L. An iot-aware architecture for smart healthcare systems. *IEEE Internet Things J.* **2015**, *2*, 515–526. [[CrossRef](#)]
10. Silva, B.N.; Khan, M.; Han, K. Integration of big data analytics embedded smart city architecture with restful web of things for efficient service provision and energy management. *Future Gener. Comput. Syst.* **2017**, *107*, 975–987. [[CrossRef](#)]
11. Silva, B.N.; Khan, M.; Jung, C.; Seo, J.; Muhammad, D.; Han, J.; Yoon, Y.; Han, K. Urban planning and smart city decision management empowered by real-time data processing using big data analytics. *Sensors* **2018**, *18*, 2994. [[CrossRef](#)] [[PubMed](#)]
12. Ahmed, E.; Yaqoob, I.; Gani, A.; Imran, M.; Guizani, M. Internet-of-things-based smart environments: State of the art, taxonomy, and open research challenges. *IEEE Wirel. Commun.* **2016**, *23*, 10–16. [[CrossRef](#)]
13. Khan, M.; Silva, B.N.; Jung, C.; Han, K. A context-aware smart home control system based on zigbee sensor network. *KSII Trans. Internet Inf. Syst.* **2017**, *11*, 1057–1069.

14. Silva, B.N.; Khan, M.; Han, K. Load balancing integrated least slack time-based appliance scheduling for smart home energy management. *Sensors* **2018**, *18*, 685. [[CrossRef](#)] [[PubMed](#)]
15. De Jong, M.; Joss, S.; Schraven, D.; Zhan, C.; Weijnen, M. Sustainable-smart-resilient-low carbon-eco-knowledge cities; making sense of a multitude of concepts promoting sustainable urbanization. *J. Clean. Prod.* **2015**, *109*, 25–38. [[CrossRef](#)]
16. Tuballa, M.L.; Abundo, M.L. A review of the development of smart grid technologies. *Renew. Sustain. Energy Rev.* **2016**, *59*, 710–725. [[CrossRef](#)]
17. Lund, H.; Andersen, A.N.; Østergaard, P.A.; Mathiesen, B.V.; Connolly, D. From electricity smart grids to smart energy systems—a market operation based approach and understanding. *Energy* **2012**, *42*, 96–102. [[CrossRef](#)]
18. Lund, H. (Ed.) Definitions. In *Renewable Energy Systems: A Smart Energy Systems Approach to the Choice and Modeling of 100% Renewable Solutions*; Academic Press: Cambridge, MA, USA, 2014; pp. 6–10.
19. Li, C.; Yu, X.; Yu, W.; Chen, G.; Wang, J. Efficient computation for sparse load shifting in demand side management. *IEEE Trans. Smart Grid* **2016**, *8*, 250–261. [[CrossRef](#)]
20. Werminski, S.; Jarnut, M.; Benysek, G.; Bojarski, J. Demand side management using dadr automation in the peak load reduction. *Renew. Sustain. Energy Rev.* **2017**, *67*, 998–1007. [[CrossRef](#)]
21. Yaghmaee, M.H.; Leon-Garcia, A.; Moghaddassian, M. On the performance of distributed and cloud-based demand response in smart grid. *IEEE Trans. Smart Grid* **2017**, *9*, 5403–5417. [[CrossRef](#)]
22. Palensky, P.; Dietrich, D. Demand side management: Demand response, intelligent energy systems, and smart loads. *IEEE Trans. Ind. Inform.* **2011**, *7*, 381–388. [[CrossRef](#)]
23. Jordehi, A.R. Optimisation of demand response in electric power systems, a review. *Renew. Sustain. Energy Rev.* **2019**, *103*, 308–319. [[CrossRef](#)]
24. Yan, X.; Ozturk, Y.; Hu, Z.; Song, Y. A review on price-driven residential demand response. *Renew. Sustain. Energy Rev.* **2018**, *96*, 411–419. [[CrossRef](#)]
25. 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](#)]
26. Rathnayaka, A.D.; Potdar, V.M.; Dillon, T.; Hussain, O.; Kuruppu, S. Goal-oriented prosumer community groups for the smart grid. *IEEE Technol. Soc. Mag.* **2014**, *33*, 41–48. [[CrossRef](#)]
27. Steinheimer, M.; Trick, U.; Ruhrig, P. Energy communities in smart markets for optimisation of peer-to-peer interconnected smart homes. In Proceedings of the 8th International Symposium on Communication Systems, Networks & Digital Signal Processing (CSNDSP), Poznan, Poland, 18–20 July 2012; IEEE: Piscataway, NJ, USA, 2012; pp. 1–6.
28. Midilli, A.; Dincer, I.; Ay, M. Green energy strategies for sustainable development. *Energy Policy* **2006**, *34*, 3623–3633. [[CrossRef](#)]
29. Chu, S.; Majumdar, A. Opportunities and challenges for a sustainable energy future. *Nature* **2012**, *488*, 294–303. [[CrossRef](#)]
30. Olatomiwa, L.; Mekhilef, S.; Ismail, M.S.; Moghavvemi, M. Energy management strategies in hybrid renewable energy systems: A review. *Renew. Sustain. Energy Rev.* **2016**, *62*, 821–835. [[CrossRef](#)]
31. Gelazanskas, L.; Gamage, K.A. Demand side management in smart grid: A review and proposals for future direction. *Sustain. Cities Soc.* **2014**, *11*, 22–30. [[CrossRef](#)]
32. Han, J.; Choi, C.-S.; Park, W.-K.; Lee, I.; Kim, S.-H. Smart home energy management system including renewable energy based on zigbee and plc. *IEEE Trans. Consum. Electron.* **2014**, *60*, 198–202. [[CrossRef](#)]
33. Boynuegri, A.R.; Yagcitekin, B.; Baysal, M.; Karakas, A.; Uzunoglu, M. Energy management algorithm for smart home with renewable energy sources. In Proceedings of the Power Engineering, Energy and Electrical Drives (POWERENG), 2013 Fourth International Conference on, Istanbul, Turkey, 13–17 May 2013; IEEE: Piscataway, NJ, USA, 2013; pp. 1753–1758.
34. Son, Y.-S.; Pulkkinen, T.; Moon, K.-D.; Kim, C. Home energy management system based on power line communication. *IEEE Trans. Consum. Electron.* **2010**, *56*, 1380–1386. [[CrossRef](#)]
35. Kanchev, H.; Lu, D.; Colas, F.; Lazarov, V.; Francois, B. Energy management and operational planning of a microgrid with a pv-based active generator for smart grid applications. *IEEE Trans. Ind. Electron.* **2011**, *58*, 4583–4592. [[CrossRef](#)]

36. Mohsenian-Rad, A.-H.; Wong, V.W.; Jatskevich, J.; Schober, R.; Leon-Garcia, A. Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid. *IEEE Trans. Smart Grid* **2010**, *1*, 320–331. [[CrossRef](#)]
37. Erol-Kantarci, M.; Mouftah, H.T. Wireless sensor networks for cost-efficient residential energy management in the smart grid. *IEEE Trans. Smart Grid* **2011**, *2*, 314–325. [[CrossRef](#)]
38. Uddin, M.; Romlie, M.F.; Abdullah, M.F.; Halim, S.A.; Kwang, T.C. A review on peak load shaving strategies. *Renew. Sustain. Energy Rev.* **2018**, *82*, 3323–3332. [[CrossRef](#)]
39. Sinha, S.; Chandel, S. Review of software tools for hybrid renewable energy systems. *Renew. Sustain. Energy Rev.* **2014**, *32*, 192–205. [[CrossRef](#)]
40. Van den Bergh, K.; Delarue, E. Cycling of conventional power plants: Technical limits and actual costs. *Energy Convers. Manag.* **2015**, *97*, 70–77. [[CrossRef](#)]
41. Shirazi, E.; Jadid, S. Cost reduction and peak shaving through domestic load shifting and ders. *Energy* **2017**, *124*, 146–159. [[CrossRef](#)]
42. Charles, G.T.; Maples, B.A.; Kreith, F. The use of plug-in hybrid electric vehicles for peak shaving. *J. Energy Resour. Technol.* **2016**, *138*, 011201.
43. Reihani, E.; Motalleb, M.; Ghorbani, R.; Saoud, L.S. Load peak shaving and power smoothing of a distribution grid with high renewable energy penetration. *Renew. Energy* **2016**, *86*, 1372–1379. [[CrossRef](#)]
44. Lavrova, O.; Cheng, F.; Abdollahy, S.; Barsun, H.; Mammoli, A.; Dreisigmayer, D.; Willard, S.; Arellano, B.; Van Zeyl, C. Analysis of battery storage utilization for load shifting and peak smoothing on a distribution feeder in new mexico. In Proceedings of the IEEE PES Innovative Smart Grid Technologies (ISGT), Washington, DC, USA, 16–20 January 2012; IEEE: Piscataway, NJ, USA, 2012; pp. 1–6.
45. Telaretti, E.; Dusonchet, L. Battery storage systems for peak load shaving applications: Part 1: Operating strategy and modification of the power diagram. In Proceedings of the IEEE 16th International Conference on Environment and Electrical Engineering (EEEIC), Florence, Italy, 7–10 June 2016; IEEE: Piscataway, NJ, USA, 2016; pp. 1–6.
46. Telaretti, E.; Dusonchet, L. Battery storage systems for peak load shaving applications: Part 2: Economic feasibility and sensitivity analysis. In Proceedings of the IEEE 16th International Conference on Environment and Electrical Engineering (EEEIC), Florence, Italy, 7–10 June 2016; IEEE: Piscataway, NJ, USA, 2016; pp. 1–6.
47. Lucas, A.; Chondrogiannis, S. Smart grid energy storage controller for frequency regulation and peak shaving, using a vanadium redox flow battery. *Int. J. Electr. Power Energy Syst.* **2016**, *80*, 26–36. [[CrossRef](#)]
48. Zheng, M.; Meinrenken, C.J.; Lackner, K.S. Smart households: Dispatch strategies and economic analysis of distributed energy storage for residential peak shaving. *Appl. Energy* **2015**, *147*, 246–257. [[CrossRef](#)]
49. Chua, K.H.; Lim, Y.S.; Morris, S. Energy storage system for peak shaving. *Int. J. Energy Sect. Manag.* **2016**, *10*, 3–18. [[CrossRef](#)]
50. Leadbetter, J.; Swan, L. Battery storage system for residential electricity peak demand shaving. *Energy Build.* **2012**, *55*, 685–692. [[CrossRef](#)]
51. Lu, C.; Xu, H.; Pan, X.; Song, J. Optimal sizing and control of battery energy storage system for peak load shaving. *Energies* **2014**, *7*, 8396–8410. [[CrossRef](#)]
52. Wang, Z.; Wang, S. Grid power peak shaving and valley filling using vehicle-to-grid systems. *IEEE Trans. Power Deliv.* **2013**, *28*, 1822–1829. [[CrossRef](#)]
53. Mahmud, K.; Morsalin, S.; Hossain, M.; Town, G. Domestic peak-load management including vehicle-to-grid and battery storage unit using an artificial neural network. In Proceedings of the IEEE International Conference on Industrial Technology (ICIT), Toronto, ON, Canada, 22–25 March 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 586–591.
54. Mägi, M. Utilization of electric vehicles connected to distribution substations for peak shaving of utility network loads. *Electr. Control Commun. Eng.* **2013**, *2*, 47–54. [[CrossRef](#)]
55. Lee, J.Y.; Choi, S.G. Linear programming based hourly peak load shaving method at home area. In Proceedings of the 16th International Conference on Advanced Communication Technology, Pyeongchang, Korea, 16–19 February 2014; IEEE: Piscataway, NJ, USA, 2014; pp. 310–313.
56. Erden, F.; Kisacikoglu, M.C.; Erdogan, N. Adaptive v2g peak shaving and smart charging control for grid integration of pevcs. *Electr. Power Compon. Syst.* **2018**, *46*, 1494–1508. [[CrossRef](#)]

57. Erdogan, N.; Erden, F.; Kisacikoglu, M. A fast and efficient coordinated vehicle-to-grid discharging control scheme for peak shaving in power distribution system. *J. Mod. Power Syst. Clean Energy* **2018**, *6*, 555–566. [[CrossRef](#)]
58. Gazafroudi, A.S.; Pinto, T.; Prieto-Castrillo, F.; Corchado, J.M.; Abrishambaf, O.; Jozi, A.; Vale, Z. Energy flexibility assessment of a multi agent-based smart home energy system. In Proceedings of the IEEE 17th International Conference on Ubiquitous Wireless Broadband (ICUWB), Salamanca, Spain, 12–15 September 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 1–7.
59. Gajduk, A.; Todorovski, M.; Kocarev, L. Stability of power grids: An overview. *Eur. Phys. J. Spec. Top.* **2014**, *223*, 2387–2409. [[CrossRef](#)]
60. Kalkhambkar, V.; Kumar, R.; Bhakar, R. Energy loss minimization through peak shaving using energy storage. *Perspect. Sci.* **2016**, *8*, 162–165. [[CrossRef](#)]
61. Ha, M.P.; Kumar, L.; Ananthapadmanabha, T. A novel approach for optimal allocation of a distributed generator in a radial distribution feeder for loss minimization and tail end node voltage improvement during peak load. *Int. Trans. Electr. Comput. Eng. Syst.* **2014**, *2*, 67–72.
62. Bradley, P.; Leach, M.; Torriti, J. A review of the costs and benefits of demand response for electricity in the uk. *Energy Policy* **2013**, *52*, 312–327. [[CrossRef](#)]
63. Chua, K.H.; Lim, Y.S.; Morris, S. A novel fuzzy control algorithm for reducing the peak demands using energy storage system. *Energy* **2017**, *122*, 265–273. [[CrossRef](#)]
64. Gellings, C.W.; Chamberlin, J.H. *Demand-Side Management: Concepts and Methods*; 1987. Available online: <https://www.osti.gov/biblio/5275778-demand-side-management-concepts-methods> (accessed on 5 July 2020).
65. Shariatzadeh, F.; Mandal, P.; Srivastava, A.K. Demand response for sustainable energy systems: A review, application and implementation strategy. *Renew. Sustain. Energy Rev.* **2015**, *45*, 343–350. [[CrossRef](#)]
66. Soares, A.; Gomes, Á.; Antunes, C.H. Categorization of residential electricity consumption as a basis for the assessment of the impacts of demand response actions. *Renew. Sustain. Energy Rev.* **2014**, *30*, 490–503. [[CrossRef](#)]
67. López, M.; De La Torre, S.; Martín, S.; Aguado, J. Demand-side management in smart grid operation considering electric vehicles load shifting and vehicle-to-grid support. *Int. J. Electr. Power Energy Syst.* **2015**, *64*, 689–698. [[CrossRef](#)]
68. Meyabadi, A.F.; Deihimi, M.H. A review of demand-side management: Reconsidering theoretical framework. *Renew. Sustain. Energy Rev.* **2017**, *80*, 367–379. [[CrossRef](#)]
69. 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](#)]
70. Albadi, M.H.; El-Saadany, E.F. Demand response in electricity markets: An overview. In Proceedings of the IEEE Power Engineering Society General Meeting, Tampa, FL, USA, 24–28 June 2007; IEEE: Piscataway, NJ, USA, 2007; pp. 1–5.
71. Enernoc. *The Demand Response Baseline*. Available online: [https://www.naeseb.org/pdf4/dsmee\\_group3\\_100809w3.pdf](https://www.naeseb.org/pdf4/dsmee_group3_100809w3.pdf) (accessed on 5 July 2020).
72. Cui, Q.; Wang, X.; Wang, X.; Zhang, Y. Residential appliances direct load control in real-time using cooperative game. *IEEE Trans. Power Syst.* **2015**, *31*, 226–233. [[CrossRef](#)]
73. 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](#)]
74. Yan, L.; Fang, S.; Gang, S.; SONG, Y.-W.; WU, Z.-H.; PEI, Z.-X.; FAN, J.-Y.; MAO, A.-J. Transmission capability of the grid cross section considering the interruptible load management. *Destech Trans. Environ. Energy Earth Sci.* **2016**. [[CrossRef](#)]
75. Saebi, J.; Taheri, H.; Mohammadi, J.; Nayer, S.S. Demand bidding/buyback modeling and its impact on market clearing price. In Proceedings of the 2010 IEEE International Energy Conference, Manama, Bahrain, 18–22 December 2010; IEEE: Piscataway, NJ, USA, 2010; pp. 791–796.
76. Wu, C.-C.; Lee, W.-J.; Cheng, C.-L.; Lan, H.-W. Role and value of pumped storage units in an ancillary services market for isolated power systems-simulation in the taiwan power system. In Proceedings of the IEEE/IAS Industrial & Commercial Power Systems Technical Conference, Edmonton, AB, Canada, 6–11 May 2007; IEEE: Piscataway, NJ, USA, 2007; pp. 1–6.
77. Tyagi, R.; Black, J.W. Emergency demand response for distribution system contingencies. In Proceedings of the IEEE PES T&D, New Orleans, LA, USA, 19–22 April 2010; IEEE: Piscataway, NJ, USA, 2010; pp. 1–4.

78. Qian, L.P.; Zhang, Y.J.A.; Huang, J.; Wu, Y. Demand response management via real-time electricity price control in smart grids. *IEEE J. Sel. Areas Commun.* **2013**, *31*, 1268–1280. [CrossRef]
79. Rastegar, M.; Fotuhi-Firuzabad, M.; Choi, J. Investigating the impacts of different price-based demand response programs on home load management. *J. Electr. Eng. Technol.* **2014**, *9*, 1125–1131. [CrossRef]
80. Deng, R.; Yang, Z.; Chow, M.-Y.; Chen, J. A survey on demand response in smart grids: Mathematical models and approaches. *IEEE Trans. Ind. Inform.* **2015**, *11*, 570–582. [CrossRef]
81. Mohsenian-Rad, A.-H.; Leon-Garcia, A. Optimal residential load control with price prediction in real-time electricity pricing environments. *IEEE Trans. Smart Grid* **2010**, *1*, 120–133. [CrossRef]
82. Borenstein, S. Equity Effects of Increasing-Block Electricity Pricing. 2008. Available online: <https://escholarship.org/content/qt3sr1h8nc/qt3sr1h8nc.pdf> (accessed on 5 July 2020).
83. Kato, T.; Tokuhara, A.; Ushifusa, Y.; Sakurai, A.; Aramaki, K.; Maruyama, F. Consumer responses to critical peak pricing: Impacts of maximum electricity-saving behavior. *Electr. J.* **2016**, *29*, 12–19. [CrossRef]
84. Jang, D.; Eom, J.; Park, M.J.; Rho, J.J. Variability of electricity load patterns and its effect on demand response: A critical peak pricing experiment on Korean commercial and industrial customers. *Energy Policy* **2016**, *88*, 11–26. [CrossRef]
85. 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]
86. Yoon, J.H.; Baldick, R.; Novoselac, A. Dynamic demand response controller based on real-time retail price for residential buildings. *IEEE Trans. Smart Grid* **2014**, *5*, 121–129. [CrossRef]
87. Yousefi, S.; Moghaddam, M.P.; Majd, V.J. Optimal real time pricing in an agent-based retail market using a comprehensive demand response model. *Energy* **2011**, *36*, 5716–5727. [CrossRef]
88. Ozturk, Y.; Senthilkumar, D.; Kumar, S.; Lee, G. An intelligent home energy management system to improve demand response. *IEEE Trans. Smart Grid* **2013**, *4*, 694–701. [CrossRef]
89. Wang, Y.; Li, L. Time-of-use based electricity demand response for sustainable manufacturing systems. *Energy* **2013**, *63*, 233–244. [CrossRef]
90. Muratori, M.; Rizzoni, G. Residential demand response: Dynamic energy management and time-varying electricity pricing. *IEEE Trans. Power Syst.* **2015**, *31*, 1108–1117. [CrossRef]
91. Silva, B.N.; Han, K. Mutation operator integrated ant colony optimization based domestic appliance scheduling for lucrative demand side management. *Future Gener. Comput. Syst.* **2019**, *100*, 557–568. [CrossRef]
92. Aslam, S.; Iqbal, Z.; Javaid, N.; Khan, Z.; Aurangzeb, K.; Haider, S. Towards efficient energy management of smart buildings exploiting heuristic optimization with real time and critical peak pricing schemes. *Energies* **2017**, *10*, 2065. [CrossRef]
93. Javaid, N.; Ahmed, A.; Iqbal, S.; Ashraf, M. Day ahead real time pricing and critical peak pricing based power scheduling for smart homes with different duty cycles. *Energies* **2018**, *11*, 1464. [CrossRef]
94. 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]
95. Zhu, L.; Yan, Z.; Lee, W.-J.; Yang, X.; Fu, Y.; Cao, W. Direct load control in microgrids to enhance the performance of integrated resources planning. *IEEE Trans. Ind. Appl.* **2015**, *51*, 3553–3560. [CrossRef]
96. Evora, J.; Hernandez, J.J.; Hernandez, M. A mopso method for direct load control in smart grid. *Expert Syst. Appl.* **2015**, *42*, 7456–7465. [CrossRef]
97. Wang, J.; Shi, Y.; Zhou, Y. Intelligent demand response for industrial energy management considering thermostatically controlled loads and EVs. *IEEE Trans. Ind. Inform.* **2018**, *15*, 3432–3442. [CrossRef]
98. Huang, X.; Hong, S.H.; Yu, M.; Ding, Y.; Jiang, J. Demand response management for industrial facilities: A deep reinforcement learning approach. *IEEE Access* **2019**, *7*, 82194–82205. [CrossRef]
99. Gomes, L.; Faria, P.; Morais, H.; Vale, Z.; Ramos, C. Distributed, agent-based intelligent system for demand response program simulation in smart grids. *IEEE Intell. Syst.* **2013**, *29*, 56–65.
100. Mount, T.; Anderson, L.; Zimmerman, R.; Cardell, J. *Coupling Wind Generation with Controllable Load and Storage: A Time-Series Application of the SuperOPF*; PSERC Publication 12-29; PSERC: Madhya Marg, India, 2012.
101. Kirby, B.J. Load response fundamentally matches power system reliability requirements. In Proceedings of the IEEE Power Engineering Society General Meeting, Tampa, FL, USA, 24–28 June 2007; IEEE: Piscataway, NJ, USA, 2007; pp. 1–6.

102. Callaway, D.S.; Hiskens, I.A. Achieving controllability of electric loads. *Proc. IEEE* **2010**, *99*, 184–199. [[CrossRef](#)]
103. Allcott, H. Rethinking real-time electricity pricing. *Resour. Energy Econ.* **2011**, *33*, 820–842.
104. Silva, B.N.; Lee, K.; Yoon, Y.; Han, J.; Cao, Z.; Han, K. Cost-and comfort-aware aggregated modified least slack time-based domestic power scheduling for residential communities. *Trans. Emerg. Telecommun. Technol.* **2019**. [[CrossRef](#)]
105. Zarnikau, J.; Hallett, I. Aggregate industrial energy consumer response to wholesale prices in the restructured texas electricity market. *Energy Econ.* **2008**, *30*, 1798–1808. [[CrossRef](#)]
106. Qdr, Q. *Benefits of Demand Response in Electricity Markets and Recommendations for Achieving Them*; Technical Report; US Department: Washington, DC, USA, 2006.
107. De Jonghe, C.; Hobbs, B.F.; Belmans, R. Optimal generation mix with short-term demand response and wind penetration. *IEEE Trans. Power Syst.* **2012**, *27*, 830–839. [[CrossRef](#)]
108. Pinson, P.; Madsen, H. Benefits and challenges of electrical demand response: A critical review. *Renew. Sustain. Energy Rev.* **2014**, *39*, 686–699.
109. Strbac, G. Demand side management: Benefits and challenges. *Energy Policy* **2008**, *36*, 4419–4426. [[CrossRef](#)]
110. Dorini, G.; Pinson, P.; Madsen, H. Chance-constrained optimization of demand response to price signals. *IEEE Trans. Smart Grid* **2013**, *4*, 2072–2080. [[CrossRef](#)]
111. Sundstrom, O.; Binding, C. Planning electric-drive vehicle charging under constrained grid conditions. In Proceedings of the Power System Technology (POWERCON), International Conference on, Hangzhou, China, 24–28 October 2010; pp. 1–6.



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