A Survey on Demand Response in Smart Grids: Mathematical Models and Approaches

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***Abstract*—The smart grid is widely considered to be the informationization of the power grid. As an essential characteristic of the smart grid, demand response can reschedule the users' energy consumption to reduce the operating expense from expensive generators, and further to defer the capacity addition in the long run. This survey comprehensively explores four major aspects: 1) programs; 2) issues; 3) approaches; and 4) future extensions of demand response. Specifically, we first introduce the means/tariffs that the power utility takes to incentivize users to reschedule their energy usage patterns. Then we survey the existing mathematical models and problems in the previous and current literatures, followed by the state-of-the-art approaches and solutions to address these issues. Finally, based on the above overview, we also outline the potential challenges and future research directions in the context of demand response.**

***Index Terms*—Convex optimization, demand response, game theory, renewable energy, smart grid.**

I. Introduction

THE POWER grid is a large interconnected infrastructure for delivering electricity from power plants to end users. Over the past few decades, although great changes have taken place in information and control frontiers, the legacy power system has not kept pace with such technology innovation. Recent blackouts in North America and India have indicated the challenges of traditional electricity grids. As widely considered to be the next generation of the power grid, the vision of the smart grid (Fig. 1) has been proposed to fully upgrade the energy generation, transmission, distribution, and consumption. It can be defined as an informationized power grid that leverages information and communications technology (ICT) to automatically gather and act on meter data, in order to improve agility, reliability, efficiency, security, economy, sustainability, and environmental friendliness [1]–[4]. Smart features such as renewable generation, advanced metering infrastructure, and vehicle-to-grid (V2G) capability have been regarded as key components of the smart grid. In addition, with pervasive distributed energy resources (DERs), microgrids, a small power system that can operate independently from bulk generation, are becoming viable nowadays. Two operational modes, grid-connected and islanded, enable the microgrid being a "prosumer" (producer and consumer) in the smart grid.

By having smart meters installed at users' premises and two-way communications enabled between the power utility and users, demand response[1] (Fig. 2) becomes an essential characteristic of the smart grid (including the microgrid), with the ability to shape the users' electricity loads in an automated and convenient manner [5]–[7]. It can be defined as the rescheduling of the users' energy usage patterns in response to the variance of the power utility's incentive or electricity price, which is designed to reduce the demand at peak time periods or during system contingencies [8]–[10]. The demand response capability of the smart grid, in essence, enables the supply and demand sides to interact with each other by exchanging the price and demand information, in order to make wise decisions. When users are provided with sufficient incentives, they are willing to change their energy usage patterns to tradeoff between comfort and electricity bills. Up to now, a variety of smart grid pilots involving demand response research projects and industrial cases are developed or under development all over the world, including USA, Canada, China, Germany, Japan, and Australia. For example, Keio University Network oriented Intelligent and Versatile Energy saving System (KNIVES), an ICT-based distributed demand side management system for home energy management, has been developed at Keio University, Japan [11], [12]. Some case studies related to smart grid and demand response pilots and programs in USA and China are available in [13] and [14]. Some industrial applications and implementations of demand response and smart grid technologies are presented in [15].

The introduction of smart metering and availability of bidirectional communications are two main technical drivers for incorporating demand response into smart grids [16]. As depicted in Fig. 3, three types of communication networks that differ in size and location are employed for demand response. A variety of communication standards and technologies coexist in different communication networks of the smart grid. Home Area Networks/Business Area Networks/Industrial

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[1]Throughout the text, the terms demand response, demand management, demand response management, demand side management, load control, load scheduling, and energy consumption scheduling are interchangeably used.

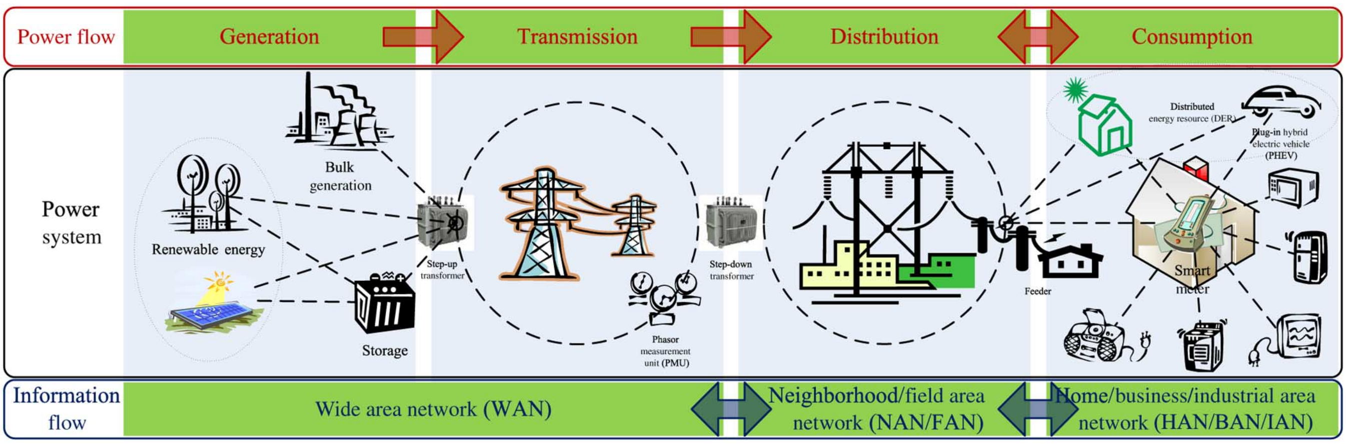

Fig. 1. Abstract picture of the smart grid. The physical part of the smart grid includes generation, transmission, distribution, and consumption. The cyber part of the smart grid includes WANs, neighborhood area networks/field area networks (NANs/FANs), and home area networks/business area networks/industrial area networks (HANs/BANs/IANs).

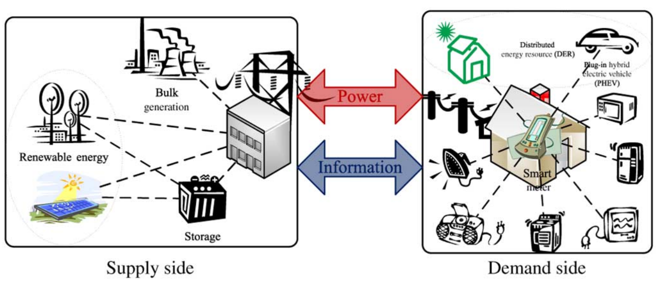

Fig. 2. Abstract picture of demand response. The mechanism of demand response involves the interplay/interaction between the supply and the demand sides by two-way flows of power and information.

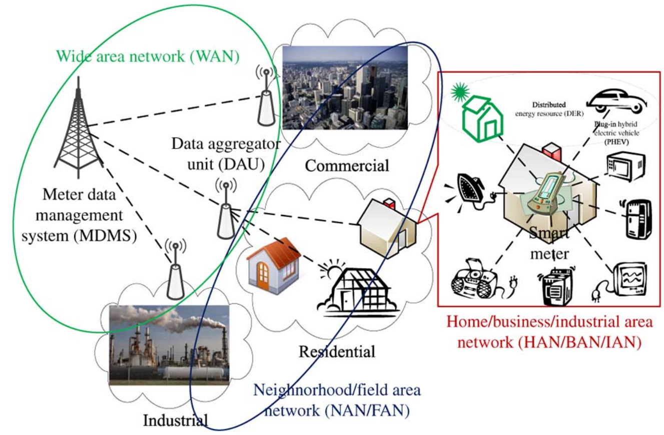

Fig. 3. Communication architecture for demand response. Three types of communication networks different in size and location coexist in the smart grid, with a variety of communication standards and technologies.

Area Networks (HANs/BANs/IANs) are deployed within residential units, commercial buildings, and industrial plants for connecting multiple electrical appliances to smart meter through IEEE 802.15.4 (ZigBee), IEEE 802.11 (WiFi), or power-line communication (PLC). Neighborhood Area Networks/Field Area Networks (NANs/FANs) support communications among distribution substations and field electrical devices for power distribution system and microgrid operation. They connect multiple smart meters to data aggregate unit (DAU) through IEEE 802.11 (WiFi), IEEE 802.16m [worldwide interoperability for microwave access (WiMax)], or cellular networks [e.g., general packet radio service (GPRS), 3G, and long-term evolution (LTE)]. WANs facilitate communications among bulk generation, power transmission system, and meter data management system (MDMS) through fiber-optic communication, microwave transmission, or cellular networks.

From the smart grid perspective, demand response is an effective means of rescheduling the users' energy consumption to reduce the operating expense from expensive generators and further to defer the capacity addition in the long run [17]. This technology will make the power system more reliable, enhance the transparency and efficiency of the electricity market, and lead to mutual financial benefits for both the power utility and all users; last but not least, this will reduce the generating emissions and alleviate the environmental impacts, by enabling a more efficient utilization of current grid capacity. In general, demand response could be categorized into the following three aspects (as illustrated in Fig. 4).

1) *Peak clipping* is to reduce the peak energy consumption, in order to prohibit the load from exceeding the supply capacity of distribution substations, or the thermal limit of transformers and feeders. Users would have their satisfaction/comfort reduced since peak clipping cuts down some of their demand.
2) *Valley filling* is to promote the off-peak energy consumption through energy storage devices, such as rechargeable batteries and plug-in hybrid electric vehicles (PHEVs).
3) *Load shifting* is to shift the energy consumption over the time horizon, e.g., to shift the demand from on-peak to off-peak time periods (the combination of peak clipping and valley filling), without reducing the users' total energy consumption within a day.

This paper is organized as follows. In Section II, we go over the demand response programs that power utilities take to incentivize users to reschedule their energy usage patterns. In Section III, we review the related works that propose mathematical models and formulate optimization problems in the

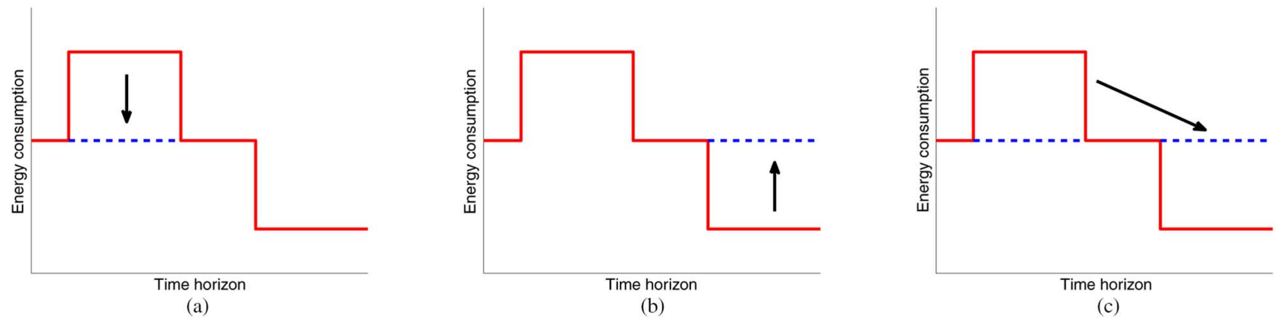

Fig. 4. Illustration of demand response. The function of demand response includes: (a) peak clipping; (b) valley filling; and (c) load shifting (the combination of peak clipping and valley filling).

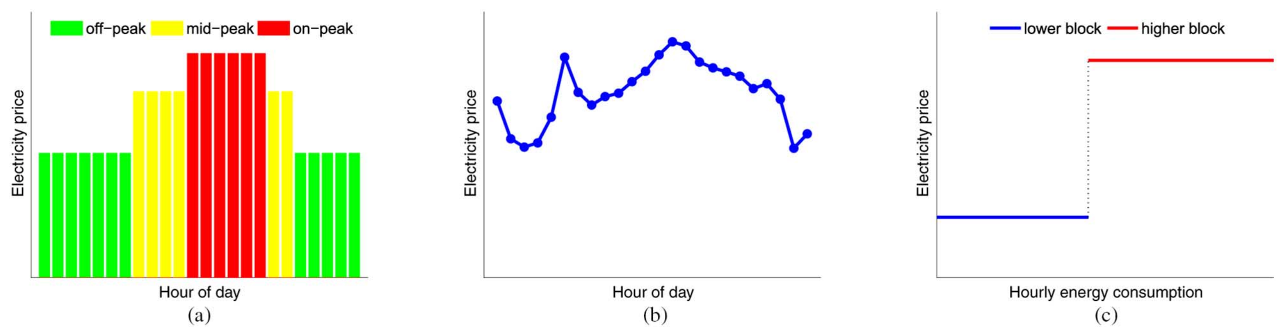

Fig. 5. Illustration of time-based pricing tariffs. The time-based tariffs include: (a) Time-of-use (ToU) pricing; (b) Real-time pricing (RTP); and (c) Inclining block rate (IBR).

context of demand response. We then present some recent results in Section IV, which provide various approaches and solutions to address these issues. Opening questions are outlined in Section V based on the above overview, and concluding remarks are drawn in Section VI. In addition, we refer to Appendix for important acronyms used in this survey.

II. Demand Response Programs

Demand response programs can be considered as the means or tariffs that the power utility takes to incentivize users to reschedule their energy usage patterns [18]. In other words, the programs are able to shape the users' electricity load profiles to improve the reliability and efficiency of the grid. Demand response programs are mainly divided into the following two branches.

A. Incentive-Based Program

Incentive-based program pays participating users for demand reduction, triggered by peak load or system contingencies. This program provides these users with load modification incentives, which is in addition to or separate from electricity prices. Several main programs are listed as follows.

1) Direct load control (DLC): The power utility has remote access to/control of (shut down or cycle) certain electrical appliances/energy loads (e.g., air conditioner and water heater) of users whenever needed, on condition that the participating users are provided with incentive payments [19]. The key idea is to reduce the load at peak hours. DLC has been offered to residential and small commercial users for decades, such as the Baltimore Gas and Electric Company and the city of New Bern, NC, USA [9].

2) Interruptible/Curtailable Load: If users agree to cut down some portion of their interruptible/curtailable loads when the grid reliability is jeopardized, they will receive a certain incentive discount on electricity bills in return [20].

3) Demand Bidding and Buyback: In the case of peak demand or system contingencies, users can benefit from cost saving if they are willing to curtail some electricity usage at a specific bid price [21]. This program is mainly offered to larger users (1 MW or more); for small users, they need third parties or agents to unite and represent them to bid.

4) Emergency Demand Reduction: Users are provided incentive payments in reply to their load reductions (on very short notice) during emergency reliability accidents when the grid is out of reserve [22]. Under this program, larger users can provide auxiliary services to the power utility by reducing their demand, behaving as virtual spinning reserves.

B. Price-Based Program

An alternative to the legacy flat electricity prices is smart pricing. Price-based program provides users with different electricity prices at different times. Based on such information, users will naturally use less electricity when electricity prices are high, and thus reduce the demand at peak hours. In other words, this program indirectly induces users to dynamically change their energy usage patterns according to the variance of electricity prices, instead of directly controlling their loads. Various time-based pricing tariffs are involved (as illustrated in Fig. 5).

1) Time-of-Use (ToU) Pricing: When users consume energy at different time intervals of a day, or different seasons of a year, they are charged at different electricity prices. Typically, each time period is longer than 1 h [23]. For example, the three-level (on-peak, mid-peak, off-peak) time blocks-based ToU pricing is employed in Ontario, Canada (different in summer and winter). The electricity price at the on-peak time block is much higher than that at the mid-peak and off-peak time blocks, in order to induce users to shift their loads over the time horizon. ToU pricing is usually released far in advance, and keeps unchanged for a long time period.

2) Critical peak pricing (CPP): The basic rate structure of this tariff is ToU pricing except for certain days, when the grid reliability is jeopardized, and then the normal peak price is replaced by a prespecified higher rate to reduce the users' energy demand [24]. CPP is employed only for a limited number of hours or days per year, in order to guarantee reliability for system or balance demand with supply.

3) Real-Time Pricing (RTP): This tariff is also referred to as dynamic pricing, where the electricity price usually varies at different time intervals of a day (in each 15 min or each hours) [25]. RTP is usually released on an hour-ahead or day-ahead (DAP) basis. For example, the hourly based RTP, together with DAP, is employed in Illinois, USA. RTP has been widely considered to be one of the most efficient and economic price-based programs [26].

4) Inclining Block Rate (IBR): This tariff is designed with two-level rate structures (lower and higher blocks), such that the more electricity a user consumes, the more he/she pays per kWh [27]. In other words, the electricity price per energy consumption will climb up to a larger value if the user's hourly/daily/monthly energy consumption exceeds a certain threshold. IBR incentivizes users to distribute their loads among different times of a day to avoid higher rates, helping reduce the grid's peak-to-average ratio (PAR). This tariff has been widely adopted by many power utilities since the 1980s, such as Pacific Gas and Electric, Southern California Edison, San Diego Gas and Electric in USA, and British Columbia Hydro in Canada [27].

III. DEMAND RESPONSE ISSUES

Demand response is generally performed in the residential district instead of commercial and industrial sectors, since residential users are more sensitive to the electricity price, due to more shiftable/controllable/interruptible/deferrable/flexible/elastic/dispatchable appliances, e.g., PHEV, washer, and dryer. For these appliances, users only concern about whether their tasks will be finished within a time period, which means that their aggregate energy consumption should not be less than a threshold before a deadline [28], [29]. Based on two-way communications, smart metering could gather detailed information of users' electricity usage patterns and provide automatic control to household appliances, which forms the home energy management system (HEMS) [30], [31]. As illustrated in Fig. 6, there is an energy consumption scheduler (ECS) embedded in the smart meter at each household, whose role is to control the ON–OFF switch and operating mode of each appliance. The electricity price provided by the power utility and the user's energy demand are exchanging via HAN. The smart meter acts as a controller that coordinates all appliances to satisfy the user's need. After demand response, the smart meter will send ON/OFF control commands with specified operating modes to all appliances, according to the resulting energy consumption schedule.

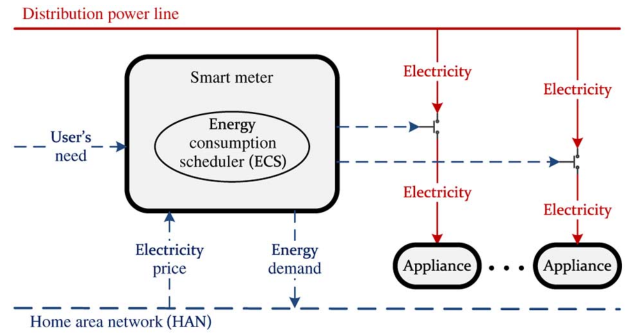

Fig. 6. Illustration of the HEMS. The electricity price and energy demand are exchanging via the HAN. The smart meter (with an ECS embedded) automatically coordinates all appliances to satisfy the user's need by demand response, via ON/OFF control commands with specified operating modes.

A. Mathematical Models

Demand response involves the interaction between the power utility and the users, and thus the behaviors of them should be mathematically modeled at first.

1) Utility Function: The behaviors of different users are modeled by different choices of utility functions. More formally, the utility represents the level of comfort/satisfaction obtained by the user as a function of his/her energy consumption, which is nondecreasing and concave. The quadratic utility functions are usually considered, which correspond to linear decreasing marginal benefit. For example, $U(x) \triangleq \begin{cases} \omega x - (\alpha/2)x^2, & 0 \le x < \omega/\alpha \\ \omega^2/(2\alpha), & x \ge \omega/\alpha \end{cases}$ [32], [33], where $x \ge 0$ is the amount of energy consumption, $\omega > 0$ varies among users at different times of a day, and $\alpha > 0$ is predetermined. Another example is $U(x) \triangleq \begin{cases} -(\kappa/2)(x-y)^2, & 0 \le x < y \\ 0, & x \ge y \end{cases}$ [34], [35], where $\kappa > 0$ is the weight to capture the user's willingness to load shifting and $y \ge 0$ is the user's target energy consumption.[2] In fact, demand response accommodates any form of utility functions as long as they satisfy the following two properties [32], [33].

1) As the user consumes more power, he/she can accomplish more tasks and gain more, until reaching the desired energy consumption level. Mathematically

$$\frac{\partial U(x)}{\partial x} > 0, \quad 0 \le x < y.$$

[2]The target energy consumption is defined as the user's pure power demand regardless of electricity price. In other words, the user's comfort/satisfaction (utility) is maximum with the target energy consumption. When considering price, while users enjoy lower bills, they also incur discomfort due to deviation from the target demand.

The utility function is increasing before the user's energy consumption reaches the desired level.

2) The marginal benefit to the user is decreasing as

$$\frac{\partial^2 U(x)}{\partial x^2} < 0, \quad 0 \leq x < y.$$

The utility function is concave, which means that the comfort obtained by the user will gradually get saturated when his/her energy consumption reaches the target level.

More complicated and realistic load models for different home appliances are elaborated as follows.

1) Type 1: The must-run appliances such as lighting or cooking that must be kept ON for a certain period of time, denoted by $\mathcal{T}_a$ for appliance a. Such appliances have strictly defined constraints

$$\begin{cases} x_a^t \equiv b_a^t & \forall t \in \mathcal{T}_a \\ x_a^t = 0, & \text{otherwise} \end{cases}$$

where b_a^t denotes the baseline demand that appliance a must consume at time slot t.

2) Type 2: The shiftable appliances, e.g., PHEVs, for which the users only concern whether the task can be finished within a certain time period, denoted by $\mathcal{T}_a$ for appliance a. Such appliances are subject to the constraints

$$\begin{cases} 0 \leq x_a^t \leq \overline{x}_a^t & \forall t \in \mathcal{T}_a \\ x_a^t = 0, & \text{otherwise} \end{cases} \quad \text{and} \quad \sum_{t \in \mathcal{T}_a} x_a^t \geq e_a$$

where $\overline{x}_a^t$ denotes the maximum energy level that appliance a can consume at time slot t and e_a denotes the elastic demand that appliance a requires to finish task.

3) Type 3: The special subset of shiftable appliances such as washer or drier whose elastic demand needs to be satisfied without being interrupted. The task of such noninterruptible appliances should be finished within a consecutive time period. Let r_a^t denote the remaining demand that appliance a requires at the beginning of time slot t

$$r_a^t = \begin{cases} e_a, & t = 1 \\ e_a - \sum_{\tau=1}^{t-1} x_a^\tau, & t = 2, \ldots, T. \end{cases}$$

At the beginning of time slot t, if the task has not started yet, i.e., $r_a^t = e_a$, then the appliance can choose to wait or start. Conversely, if the task has started, i.e., $r_a^t < e_a$, then the appliance must continue working until completing the task, i.e., $r_a^t = 0$. Such noninterruptible appliances are subject to the additional constraints

$$\begin{cases} \underline{x}_a^t \geq 0, & r_a^t = e_a \\ \underline{x}_a^t > 0, & 0 < r_a^t < e_a \\ \underline{x}_a^t = 0, & r_a^t = 0. \end{cases}$$

2) Cost Function: The expense of generating and delivering electricity by the power utility is modeled by the cost function, which is increasing and strictly convex. The piecewise linear cost function (corresponding to IBR) and the quadratic cost function are two alternatives, e.g., $C(l) \triangleq al^2 + bl + c$, where $l \geq 0$ is the amount of provided energy; $a > 0$ and $b, c \geq 0$ are predetermined parameters. In fact, demand response accommodates any form of cost functions as long as they satisfy the following two properties [36], [37].

1) The energy cost will always increase when the total load increases. Mathematically

$$\frac{\partial C(l)}{\partial l} > 0.$$

2) The marginal expense to the power utility is increasing as

$$\frac{\partial^2 C(l)}{\partial l^2} > 0.$$

It should be noticed that the above-summarized mathematical models for demand response are most commonly used in academic research literatures, and there would be a gap between academic research and practical implementation. For example, for a real power system, more realistic factors such as short-term requirements (production ramps, hydro-availability limits) and long-term plans (startup costs) should be incorporated into the cost function modeling.

B. Mathematical Problems

Based on the models, demand response is usually formulated as the following mathematical problems.

1) Utility Maximization: From the social perspective, the grid desires to increase the sum of comfort obtained by each user and to decrease the expense imposed to the power utility. For example, the objective in [32] is to maximize the grid's social welfare, i.e., the sum of utility functions of all users minus the cost function of the power utility, while the energy demand is constrained by the limited supply capacity. The price and demand interact with each other in a distributed manner, and finally converge to a win–win agreement beneficial to both the power utility and all users. Specially, if there is excess demand, additional energy would be bought from the spot electricity market to balance supply with demand [34], [35]. Thus, the social welfare maximization is to maximize the user's utility minus the procurement capacity cost, the day-ahead reserving energy cost, and the real-time balancing energy cost. The authors in [29] additionally involve the cost of operating rechargeable batteries and PHEVs in the utility maximization problem since the introduction of energy storage could further improve the performance of demand response. Therefore, the social welfare is the total user comfort minus the power utility cost and the energy storage operational cost. From the user's view, it is desired to increase the level of satisfaction and to decrease his/her electricity bill. For example, the goal in [33] is to maximize the user's individual welfare, i.e., his/her comfort minus payment. Similarly, the work in [38] is to maximize the profit of operating PHEVs, i.e., the revenue obtained by selling electricity minus the cost of charging vehicles.

2) Cost Minimization: From the power utility's viewpoint, it is desired to decrease the expense of generating and delivering electricity. The objective in [36] and [37] is to minimize the cost function imposed to the power utility. Another objective is to minimize the system PAR, which is a critical indicator to the efficiency and stability of smart grids. These two problems can be related to each other depending on the choice of cost functions. From the user's viewpoint, it is desired to decrease his/her individual electricity bill for the operation of household appliances [39]. For example, the goal in [40] is to minimize the energy bill of an air conditioner under the constraint that the indoor temperature is kept inside a user-defined range. Similarly, the work in [41] is to minimize the electricity payment of a water heater on the condition that the water temperature reaches the predetermined comfort constraint. The work in [28] and [42] additionally introduces the cost of waiting time (inconvenience cost) into the cost minimization problem to tradeoff between the user's comfort and payment. Thus, the objective is to minimize not only the user's electricity bill, but also the waiting time for the operation of household appliances.

3) Price Prediction: RTP has been widely considered to be one of the most efficient and economic price-based programs, but if the power utility releases electricity rate only 1 h ahead of time, the price prediction capability will be required by demand response. The authors in [28] find that the electricity price has high statistical correlations with the prices on yesterday, the day before yesterday, and the same day last week. They suggest an efficient price prediction model as $\hat{\omega}^h[t] = k_1\omega^h[t-1] + k_2\omega^h[t-2] + k_7\omega^h[t-7]$, in order to reduce the prediction error to as low as average 13%. This price prediction model has also been introduced into a HEMS [30]. The parameter ω^h is inferred from its pervious values 1 day ago $\omega^h[t-1]$, 2 days ago $\omega^h[t-2]$, and 7 days ago $\omega^h[t-7]$. Taking advantage of the price prediction capability, demand response could not only cut down all users' daily energy expenditures, but also reduce the grid's PAR.

4) Renewable Energy: Integrating the uncertain and intermittent renewable generation (such as wind turbines and solar photovoltaic panels) into the bulk generation will be challenging, due to the reliability requirement that the generation and load should always remain balanced [43]–[45], as well as the grid synchronization issue for DERs [46]. Traditionally, the power utility maintains an additional generation capacity (such as fast-start diesel generators), at a significant cost, to address the supply uncertainty [47]. To reduce such a cost so as to support high penetrations of renewable generation, demand response has been more and more leveraged and implemented to smooth the stochastic and fluctuate renewable energy [48]. In face of random supply, the demand response operation is performed over two timescales.

1) With the statistical information on renewable energy, day-ahead procurement is decided.
2) When renewable generation is realized, additional energy is purchased to balance the real-time supply and demand [34], [35].

The impact of the mean and variance of renewable energy on the demand response performance is also investigated, providing guidance on efficient scale-up utilization of such clean but volatile generation. The authors in [49] introduce and employ opportunistic electricity users (demand uncertainty) to reduce the cost incurred by renewable generation (supply uncertainty). The supply and demand uncertainties could potentially cancel each other out, which will consequently improve the penetration of renewable energy into smart grids. Moreover, intelligent and flexible operations of "gridable vehicles" (PHEVs with V2G capability), as loads, sources, or energy storages, can potentially accommodate renewable energy so as to reduce both generation cost and transportation emissions [50]–[52].

5) Energy Storage: In future smart grids, the proliferation of energy storage (such as rechargeable batteries and PHEVs) will be expected as one of the promising means of efficiently utilizing electricity and reducing the reliance on fossil fuels [53]–[58]. Taking advantage of energy storage, users can charge their batteries or PHEVs within off-peak periods, and discharge them to drive other appliances within peak periods, instead of using the expensive electricity from the grid [29]. However, if all users try to charge their energy storage at the same time, it will cause an additional peak load, and would make the grid vulnerable and unreliable. To alleviate such issues, the work in [59] strategically guides users when to charge and discharge their batteries or PHEVs. The proposed agent-based microstorage management framework converges the energy storage behavior toward Nash equilibrium. As a popular existence of energy storage, PHEVs are emerging as a transportation alternative to reduce greenhouse gas emissions; however, the large electricity demand of widespread adoption of PHEVs will also pose significant challenges to the existing stable grid [60]–[64]. To avoid such challenges, the charging and discharging of multiple PHEVs should be intelligently coordinated, which can not only shave the peak demand [65], [66], but also provide frequency regulation service to smart grids [67]. Taking advantage of the V2G capability and technology, the batteries on PHEVs can be used to boost DERs by feeding electricity back to the grid when they are parked. At the user side, PHEVs can decide to charge at off-peak hours to reduce cost, and to discharge at peak hours to obtain additional revenue (PHEVs can draw cheap electricity in from while feed expensive electricity back to the grid) [38]. At the grid side, PHEVs can efficiently manage load fluctuation, reduce the dependency on expensive energy resources, and hence decrease the generation and operational cost [68]. In addition, the renewable intermittency can also be effectively smoothed by PHEVs instead of expensive diesel generators, which will reduce greenhouse gas emissions as well as grid infrastructure cost, since the PHEV expenditure has been split over users [50]–[52]. Finally, compared with the traditional stationary batteries, PHEVs, with the electricity store-carry-and-deliver characteristics, involve mobility with the ability to achieve more efficient performance of demand response [69]. The proposed strategy utilizes the statistical information of PHEV mobility to achieve daily energy cost reduction through the nonstationary demand response.

IV. Demand Response Approaches

Demand response is usually formulated as optimization problems, which are solved by various approaches.

A. Convex Optimization

Convex optimization is the problem whose objective and constraint functions are convex. Mathematically, it is defined as $\min_x f_0(x)$ under constraints $f_i(x) \le b_i,\ i = 1, \ldots, m$, and $f_0, \ldots, f_m$: $\mathbb{R}^n \to \mathbb{R}$ are all convex functions. Demand response is usually formulated as utility maximization or cost minimization. Note that the utility function is concave, whereas the cost function is convex. Meanwhile, the problem of maximizing a concave function f can be reformulated equivalently as minimizing the function $-f$, which is convex. Moreover, the constraint functions of demand response are usually convex, or especially, linear. For example, the energy demand of one user is constrained by lower and upper bounds [28], [32]. The minimum energy consumption level represents the baseline demand from must-run household appliances, whereas the maximum energy consumption level indicates the total energy demand if all appliances are ON. In addition, users are concerned about whether their tasks will be finished within a time period, which means that the aggregate energy consumption should not be less than a threshold before a deadline [28], [29], e.g., a total of 16 kWh is needed to charge a PHEV for a daily 40-mile drive, or a dishwasher after lunch should finish washing dishes before dinner. Finally, the total energy demand of all users in the distribution grid suffers from a limited supply capacity, coming from the supply limit of distribution substations, or the thermal limit of transformers and feeders [28]. All the above constraint functions are linear, and therefore, demand response can be formulated as convex optimization.

With recent improvements in computing and optimization theory, convex optimization is nearly as straightforward as linear programming. The authors in [32] intend to maximize the social welfare, while the energy demand of all users is constrained by the limited supply capacity. Although it can be solved by traditional convex optimization techniques in a centralized way, e.g., the interior point method, however, to avoid revealing the private information[3] of the power utility and each user, the problem is dually decomposed and solved in a distributed manner. Due to strong duality, the dual problem is equivalent to the primal one. The convex optimization problem in [29] is distributively solved based on the Karush-Kuhn-Tucker (KKT) condition in a similar way. The power utility and users interact with each other via price and demand information, and jointly compute a mutually beneficial solution. Furthermore, the cost minimization problem in [28] can be transformed into a linear one and efficiently solved within manageable computational time duration. However, if we consider the users' energy consumption as discrete other than continuous variables, the cost minimization problem would be as more complicated as mixed-integer linear programming, and thus, other computing softwares such as CPLEX or YALMIP are needed for efficient solution. In summary, convex optimization is generally taken as one of the basic approaches to demand response, although sometimes if we consider more complicated scenarios, the problem will become more challenging, which requires many other novel methodologies in addition to convex optimization.

B. Game Theory

Game theory is a study of selfish and rational individuals, and/or a model of interactive decision-making processes. A game $\mathcal{G}$ consists of three fundamental components: 1) players $\mathcal{N}$; 2) strategies $\{\mathcal{X}_i\}_{i\in\mathcal{N}}$; and 3) payoff functions $\{W_i\}_{i\in\mathcal{N}}$. Each player $i \in \mathcal{N}$ will select a strategy $x_i \in \mathcal{X}_i$ to maximize his/her payoff $W_i(x_i, \boldsymbol{x}_{-i})$, which is dependent on not only his/her strategy x_i but also all other players' strategies $\boldsymbol{x}_{-i}$. Nash equilibrium is one of the most important concepts in game theory. It is a static and stable strategy that no player has any benefit from unilaterally deviating from this strategy. Demand response involves the game relationship between the power utility and users. In the context of demand response, game theory is leveraged to devise incentive- or price-based programs, and to model the interaction between the power utility and users [70]. The game-theoretic approaches for demand response generally converge to Nash or other equilibriums, which may lead to an optimal solution for both supply and demand sides. Thus, game theory becomes an effective approach to facilitate intelligent decision-making in demand response frameworks.

The work in [71] investigates the demand response games in two market models for smart grids: 1) competitive; and 2) oligopolistic markets. In both scenarios, the proposed distributed demand response approaches gradually arrive at the optimal equilibriums. The authors in [59] and [67] propose distributed approach through game theory to manage energy consumption/storage and coordinate PHEVs' charging/discharging, respectively, at each user's premise. Both works have proved that the achieved Nash equilibriums have the globally optimal performance, in terms of minimizing grid generation costs and providing frequency regulation service. In [72], the authors devise distributed demand response mechanisms based on the congestion game to reduce each user's electricity bill and manage the total load of the system. Such an approach is naturally derived from a typical network congestion problem in the scope of computer networks. The benefit is that congestion games are equivalent to potential ones, whose Nash equilibrium always exists. Taking advantage of bidirectional communications, the energy consumption scheduling algorithms proposed in [36] and [37] aim to minimize the cost when multiple users share a common energy source coordinately. The game-theoretic approaches not only guarantee the achievement of the Nash equilibrium of the formulated problem, but also maintain the privacy of both the supply and the demand sides. In addition to game theory, more economic approaches are employed to deal with demand response problems, such as price theory [73], auction [74], [75], and hedging [76]. These approaches play an important part to facilitate the modeling of the economic behaviors and interactions of the power utility and users for demand response. In summary, game theory has the potential to address the interaction between the power utility and users in the context of demand response, and also faces some design challenges such as scalability issues, which need more investigation and research in future.

C. Dynamic Programming

Dynamic programming decomposes the complex problem into a sequence of subproblems, which are solved backward over each stage. Such a method will consume less time than heuristical approaches, especially for the subproblems with overlapping characteristics. For example, the authors in [35] focus on the demand response problem with time-correlated

[3]The cost function of the power utility and the utility function of each user are their private information. Since the cost function could infer the revenue-to-cost ratio of the utility company, and the utility function could infer the energy usage pattern of each user, so they do not want to reveal.

decision-making (i.e., decisions made at a given moment will impact decisions made at later ones), and formulate a multistage dynamic program over the time horizon. When considering the time-correlated energy demand, demand response cannot be optimized independently at each time period; the optimal policy should be dynamically solved. The time slot-based dynamic programming is also employed in [39] for electricity bill minimization, and the approach is much more efficient for achieving the optimal solution. The drawback is that dynamic programming usually consumes higher memory and computational overhead.

The approaches in [66], [77], and [78] are extended to account for the uncertainties using stochastic dynamic programming, where the uncertainty aspect comes from the random characteristics of (renewable) generation, consumption, etc. For example, the authors in [66] consider that it is not possible to exactly predict future residential loads. The stochastic inputs in [77] and [78] are derived from uncertain electricity price and the random nature of renewable production. The approaches in [79] and [80] are extended to address the multistage optimization using approximate dynamic programming, where the long-term problem is decomposed into a number of short-term subproblems, and solved effectively and efficiently by a computational learning system. The challenge lies in the development of an approximation of the value function as a function of the state for nondeterministic problems. In summary, the motivation for dynamic programming stems from the pervasive presence of time-varying parameters in demand response, such as renewable generation and RTP, among others. In this context, dynamic programming is generally taken as one of the basic approaches to address these parameters and improve the performance of demand response.

D. Markov Decision Process

Markov decision process refers to sequential decision-making based on periodic or continuous observation on Markov random dynamic systems, where the system actions are random but the state transition probabilities do exhibit Markov properties. For example, under the environment of hourly based RTP, the exact future electricity prices are unknown, but their statistical information could be obtained from a large number of historical data. Due to the future price uncertainty, the problem of energy consumption scheduling to minimize the electricity bill of a whole day is naturally cast as a Markov decision process [81]. The basis is to assume that future prices depend on certain probability density functions, but independent of past prices and user activities. Similarly, with the uncertainty of wind generation, the reliability of smart grids will be affected, which is treated as a multitimescale Markov decision process in [49]. This is because, in general, the nonstationary wind turbine output could be modeled and predicted by a stationary Markov chain. The authors in [69] show that the mobility nature of PHEVs makes the underlying Markov chain nonstationary, and thus, the state transition probabilities are time-varying. The authors further investigate such nonstationary Markov decision process and obtain the optimal Markov policy for PHEVs charging/discharging. The work in [82] models both residential energy consumption and electricity prices as Markov decision processes, but the state transition probabilities of the underlying Markov chains are generally unknown, so reinforcement learning is employed to continuously learn from and adapt to such unknown information over time. The advantage is that the approach still works if the structure of the underlying Markov chain changes. In summary, Markov decision process specially addresses the time-varying parameters in demand response that exhibit Markov properties, which complements the approach of dynamic programming to further improve the performance of demand response.

E. Stochastic Programming

Stochastic programming is leveraged to deal with uncertain optimization problems, taking advantage of the fact that probability distributions are known or can be estimated. The authors in [34] propose a stochastic gradient algorithm to deal with renewable generation uncertainty, and also investigate how the volatility of renewable energy will impact on the system performance. The stochastic gradient approach is based on some statistic knowledge about future renewable production, which could be acquired from a large number of historical data. Specifically, for stochastic wind power, the authors in [83] propose a wait-and-see approach in the discipline of stochastic programming. The wait-and-see approach is available because the authors could derive the closed-form solution to the stochastic programming problem under some conditions. Since it is not possible to exactly predict the future energy demand of users, the authors in [65] introduce stochastic programming to model such demand uncertainty as a certain probability density function. The stochastic aspects come from the prediction error of the household load profiles. Similarly, in the presence of load uncertainty as well as equipment failures, the authors in [84] and [85] formulate and solve the stochastic mixed-integer programming problem for demand response. The integer variables represent the allocation of generating units to energy and reservers with the minimum production cost in the unit commitment stage. In summary, stochastic programming specially addresses the time-varying parameters in demand response whose probability distributions are known or can be estimated. As a special type of dynamic programming, stochastic programming can make wise decisions for demand response by incorporating statistical knowledge about random parameters.

F. Particle Swarm Optimization (PSO)

PSO is one of the bio-inspired methods resulting from the modeling of the fish school or bird flock behavior, which iteratively drives a population of potential solutions to solve the optimization problem. Each particle (candidate solution) is driven to move around, with its trajectory influenced by the experience of itself and other particles, toward the best solution. Specifically, the motion of particles is dynamically adjusted by inertia, personal best, and group best.

In [68], the unit commitment problem with V2G capability is solved by PSO, so is the economic dispatch problem in [86]. The advantage of PSO approaches is through which the complex-constrained optimization problems could be easily and accurately solved without unnecessary memory and dimensional overhead. The economic dispatch problem is to allocate the output of each generation facility with the minimum production cost, and the PSO method performs better than other approaches in the economic dispatch stage. The authors in [87] apply the PSO approach to solve the problem of cooperative scheduling of pervasive DERs, due to its easy implementation and manageable computational time duration. The drawback is that the PSO approaches may converge to near-optimal solutions; thus, repetition is needed to explore better ones. In addition, co-evolution enables PSO to handle more complex and high-dimensional problems, such as the problem of developing the reliability-stipulated microgrid architectures [88]. For the co-evolutionary version of PSO, multiple particle swarms are in charge of different optimization objectives, e.g., some swarms optimize the charging/discharging of PHEVs, whereas others optimize the water heater schedule, etc. The solution is that the multiple objectives will co-evolve to the optimum.

Instead of continuous variables, the binary or integer PSO approach can deal with the problem with discrete variables, which will largely reduce the search space dimension. For example, in [38], when a PHEV is in a parking lot, it runs binary PSO to determine whether to charge, discharge, or do nothing at each time slot. The position of particles represents any of the three possible statuses of each vehicle, with two binary bits. Similarly, the authors in [89] use binary PSO to schedule the interruptible loads with the minimum total payment. The binary variables correspond to whether one of the interruptible loads will be curtailed or not during one certain time interval. In [68] and [52], the authors apply binary PSO to intelligently schedule the optimal ON/OFF state of electricity generator units, and integer PSO for the optimal number of gridable vehicles that are parked. In such a way, the dimension and complexity of the problem would be greatly reduced, with the capability of reaching to suboptimal solutions within manageable computational time duration. In summary, PSO is a heuristic approach to deal with more complicated optimization problems in demand response, so that convex optimization cannot apply. In this context, some other similar approaches, such as ant-colony optimization, simulated annealing, neural network, or genetic algorithms, are also of interest to help improve demand response by tackling challenging optimization problems.

V. Future Extensions

Although demand response in smart grids is encouraging and promising, it still faces certain unsolved issues worth exploring. The possible challenges as well as potential future extensions are summarized as follows.

A. *Coupled Constraint*

As mentioned in Section IV-A, demand response is usually formulated as convex optimization, with temporally- or spatially coupled constraints. For example, users are concerned about whether their tasks will be finished within a time period, which means that the aggregate energy consumption should be not less than a threshold before a deadline. That is, each user's energy demand is (temporally) coupled across the time horizon. In addition, the total energy demand of all users in the distribution grid suffers from a limited supply capacity, coming from the supply limit of distribution substations, or the thermal limit of transformers and feeders. That is, one user's energy demand is (spatially) coupled with other users to avoid exceeding the limited supply capacity. Furthermore, if energy storage devices (such as rechargeable batteries and PHEVs) are considered in the context of demand response, the dynamics of state of charge (SOC) of batteries are also coupled across the time horizon. With these coupled constraints, the convex optimization problem cannot be directly tackled, especially in a distributed manner. Surplus variables associated with such coupled constraints shall be needed to decompose the original problem into a series of independent subproblems, which can be solved separately [90]. For demand response games with coupled constraints, a novel state-based game framework shall be employed to provide insights into the coupled-constraint game, guaranteeing that Nash equilibrium of such games satisfies the coupled constraints [91].

B. *Hierarchical Game*

As mentioned in Section IV-B, demand response, in general, involves the interaction between two players: 1) the power utility; and 2) all users. A large number of existing studies on demand response concentrate on the game relationship between the power utility and users, and/or the interaction among users. However, the case of multiple energy sources and the competition among them draw very little attention. Considering the scenario of multiple sellers and multiple buyers, each of them aims to maximize their individual payoffs. For example, each power utility will maximize his/her own revenue by setting appropriate electricity price; based on such prices, each user chooses from which power utility to buy electricity and how much to buy, so as to maximize his/her own welfare. In turn, the price set by one power utility will depend on the prices of other power utilities. With such complicated interactions, some sophisticated hierarchical games shall be leveraged to shed light on the multiseller–multibuyer demand response problem, such as Stackelberg games [92], [93], where power utilities play a noncooperative game and users play an evolutionary game, converging to Nash or other equilibriums.

C. *Communication Impact*

In demand response, the interaction between the power utility and users is enabled by bidirectional communications between them. Communications are critical to the accuracy and optimality of demand response, and hence at the core of realization and performance of the smart grid. Advanced metering infrastructures enable the power utility and smart meters at users' premises to exchange information such as power demand and electricity price. However, most existing studies assume perfect two-way communications, which is too strong for practical applications, whereas the impact of communication unreliability on the demand response performance has not been well

- Demand Response
  - Demand Response Programs
    - Incentive-based Program
      - Direct load control (DLC) [19]
      - Interruptible/curtailable load [20]
      - Demand bidding & buyback [21]
      - Emergency demand reduction [22]
    - Price-based Program
      - Time-of-use (ToU) pricing [23]
      - Critical peak pricing (CPP) [24]
      - Real-time pricing (RTP) [25], [26]
      - Inclining block rate (IBR) [27]
  - Demand Response Issues
    - Mathematical Models
      - Utility function [29], [32]–[37]
      - Cost function [32], [33], [36], [37]
    - Mathematical Problems
      - Utility maximization [29], [32]–[35], [38]
      - Cost minimization [28], [36], [37], [39]–[42]
      - Price prediction [28], [30]
      - Renewable energy [34], [35], [43]–[52]
      - Energy storage [29], [38], [50]–[69]
  - Demand Response Approaches
    - Convex Optimization [28], [29], [32]
    - Game Theory [36], [37], [59], [67], [70]–[76]
    - Dynamic Programming [35], [39], [66], [77]–[80]
    - Markov Decision Process [49], [69], [81], [82]
    - Stochastic Programming [34], [65], [83]–[85]
    - Particle Swarm Optimization (PSO) [38], [52], [68], [86]–[89]
  - Future Extensions
    - Coupled Constraint [90], [91]
    - Hierarchical Game [92], [93]
    - Communication Impact [94], [95]

Fig. 7. Summary of demand response in smart grids. The summary includes the four major aspects: 1) programs; 2) issues; 3) approaches; and 4) future extensions.

revealed or defined. Some cutting-edge communication technologies shall be employed to improve the communication quality, although they may bring in more expensive monetary cost. Thus, there exists a fundamental tradeoff between the communication cost and the demand response performance in smart grids [95]. Appropriate scheduling of different communication means to maintain satisfactory performance of demand response with the minimum communication cost shall also be encouraged in future smart grids [94]. In addition, smart meters, since they play an important part in the bidirectional communications between the power utility and users' premises, become one of the most interesting and vulnerable target for attackers. Therefore, it is important to assess possible consequences of attacks and develop mechanisms to maintain reliability and resilience of smart grids in the face of unanticipated events.

VI. Conclusion

Demand response emerges as a promising technology to promote the interaction and responsiveness of end users with the aim of not only reducing their bills or saving energy, but also benefiting system operation, expansion, and market efficiency, by means of actively adapting demand to supply or fast reacting to system contingencies. Taking advantages of smart meters and enabled two-way communications, smart pricing plays a major role in incentivizing users to reschedule their energy usage patterns and involve in demand response programs. The integration of renewable energy, DERs, PHEVs, and energy storage in demand response brings additional flexibility to further improve the system performance, as well as complexity that requires innovative methodologies to address. In this context, in addition to conventional optimization approaches, more novel and heuristic technologies are eagerly anticipated to manage increasingly challenging demand response problems.

This paper provides an overview of the area of demand response in smart grids. Due to the potential importance of demand response in smart grids, this survey comprehensively explores the four major aspects: 1) programs; 2) issues; 3) approaches; and 4) future extensions. The demand response programs are divided into two branches: 1) incentive-; and 2) price-based programs, respectively. For the incentive-based programs, we have reviewed DLC, interruptible/curtailable load, demand bidding and buyback, and emergency demand reduction. For the price-based programs, we have reviewed ToU pricing, CPP, RTP, and IBR. The demand response issues include mathematic models and problems. We have described commonly used utility and cost functions to model the demand response activities. Based on the models, most of the existing works aim at utility maximization, cost minimization, price prediction, renewable energy, and energy storage-oriented problems. For the demand response approaches to these problems, we have reviewed the works related to convex optimization, game theory, dynamic programming, Markov decision process, stochastic programming, and PSO. From the existing efforts on demand response, we have also outlined future extensions such as coupled constraint, hierarchical game, and communication impact. To conclude, this survey is summarized in Fig. 7.

However, due to so many research activities in these areas, we might have missed some literatures and would like to apologize for that.

Appendix

Some important acronyms in the context of demand response in smart grids are summarized in Table I.

TABLE I
ACRONYMS

CPP	Critical peak pricing
DAP	Day-ahead pricing
DAU	Data aggregate unit
DER	Distributed energy resource
DLC	Direct load control
ECS	Energy consumption scheduler
HAN/BAN/IAN	Home/business/indusrial area network
HEMS	Home energy management system
IBR	Inclining block rate
ICT	Information and communications technology
KKT	Karush-Kuhn-Tucker (condition)
MDMS	Meter data management system
NAN/FAN	Neighborhood/field area network
PAR	Peak-to-average ratio
PHEV	Plug-in hybrid electric vehicle
PLC	Power-line communication
PMU	Phasor measurement unit
PSO	Particle swarm optimization
RTP	Real-time pricing
SOC	State of charge
ToU	Time-of-use (pricing)
V2G	Vehicle-to-grid
WAN	Wide area network

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