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Contents

Chapter 1

Demand and Response in Smart Grid

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Smart grid is envisioned as the modernization of the nation's electricity transmission and distribution system to maintain a reliable and secure electricity infrastructure that can meet future demand growth and integrate renewable energy sources. It involves significant new research challenges. Demand and Response (DR), which refers to the dynamic demand mechanisms to manage electricity demand in response to supply conditions, is one of the most important functions of smart grid. DR offers several benefits, including reduction of peak demand, participant financial benefits, integration of renewable resources, and provision of ancillary services. This chapter surveys the ongoing research through elaborating a representative number of DR methods and discusses future directions.

1.1 Demand and Response Overview

Actually, traditional DR mechanisms, such as Real-Time Pricing [1], Critical Peak Pricing [2], Demand Side Bidding [3] and Emergency Demand Response [4], are relatively mature in traditional electricity grids. This section will explain the significance of DR, the traditional DR methods in power grid, and the new requirements of DR in future smart grid are stated.

1.1.1 Significance of Demand Response

Demand Response, defined broadly, is that the users adapt their electricity usages in response to power grid supply conditions, economic signals from a competitive wholesale market or special retail rates [5]. In [6], it is defined more specifically as: *Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized.* Raising the temperature of the thermostat in response to short-term high prices, dimming/shutting off lights to match limited available electric energy and slowing down or stopping production at an industrial operation when the grid system reliability is jeopardized are common examples of DR.

Demand Response has received much attention, because it not only reflects consumers' abilities to reduce electricity consumption when wholesale prices are high or the reliability of the electric grid is threatened, but also improves resource-efficiency of electricity production and social welfare maximization due to closer alignment between customers' electricity charges and the value they place on electricity. Specifically, Demand Response can yield several benefits, which include, but are not limited to:

1. *Peak demand reduction.* The power grid usually needs to provide extra generation, transmission and distribution capacities to cope with the few peak demand hours. For example, in Spain about 4000 MW are required to attend 300 hours of peak consumption per year [7]. It not only increases the operation cost but also causes energy waste. By successful deployment of DR program, electrical load can be shifted from high demand periods to others, thereby flattening the load demand. It improves reliability and operational security of power grid and lowers maintenance cost.

2. *Participant financial benefits.* Participants save on the electricity bills by adjusting their

demand in response to time-varying electricity rates and even earn incentive payments because of certain incentive-based programs. In addition, Demand Response contributes to reduce peak demand. Over the longer term, sustained Demand Response lowers aggregate system capacity requirements, allowing electricity utilities and other retail suppliers to purchase or build less new capacity. Eventually these savings may be passed on to most retail customers as bill savings.

3. *Integration of renewable resources.* As various distributed renewable energy resources are increasingly integrated into power system, Demand Response plays an important role in better using these renewable resources. Both demand and renewable energy supplies are dynamic and fluctuating. As pointed out in [8], the objective of a smart grid is not to match the supply to the demand, but in contrast, to match the demand to the available supplies by using DR technology.

4. *Provision of ancillary services.* Using DR to supply ancillary services, i.e., regulation, load following, frequency responsive spinning reserve and supplement reserve, yields several advantages. These benefits include reduced transmission and distribution losses, increased transmission capacity and increased margin to voltage collapse [9].

1.1.2 Demand Response in Traditional Grid

In traditional grid, demand response is classified into two types [10], i.e., price-based demand response and incentive-based demand response. Each contains several typical methods, shown in Fig. 1.1. There are also various DR algorithms developed on these typical methods. Here, we only give a brief introduction of the typical ones. Interested readers can refer to [6, 11, 12] for details.

In price-based demand response programs, customers voluntarily adjust their electricity consumption based on time-varying pricing signals [13], mainly including Time of Use Pricing (TOU), Real Time Pricing (RTP) and Critical Peak Pricing (CPP). Customers can reduce their electricity bills if they adjust the timing of their electricity usage in order to take advantage of lower-priced periods or avoid consuming when prices are higher. The three typical price-based demand response methods are summarized as follows:

1. *Time of Use Pricing.* Electricity prices are fluctuant at different time blocks but fixed in specified periods. The prices are pre-established and known to consumers in advance, allowing them to vary their energy consumption in response to the prices and to manage their energy charges by shifting energy usage to a lower cost period or reducing their consumption. TOU rates reflect the average cost of generating and delivering power during those time periods, and lead customers to change their power consuming mode in order to flatten the load curve. However, the energy prices are mostly based on electricity supply cost of utilities and seldom take the consumer feedbacks to the prices into consideration[14].

2. *Real Time Pricing* [1]. It is an idealized instantaneous dynamic pricing policy. In practice, electricity prices may change as often as hourly (exceptionally more often), reflecting changes in the utility's generation cost and/or the wholesale price of electricity. RTP prices are provided to customers on a day-ahead or hour-ahead basis so that customers can plan energy consumption ahead in response to energy market. However, it increases the cost of installing communication and control equipment.

3. *Critical Peak Pricing* [2]. In power system, critical peak loads occur a few times due to weather or system conditions, but it is a threat to the whole grid system once critical peaks happen. To prevent critical peaks, a CPP method which is a combination of the TOU and RTP design was proposed. In fact, it is an advanced TOU pricing. The difference lies in the improvement that CPP event price under specified trigger conditions (e.g., when system reliability is compromised or supply cost is very high) is much higher than the normal peak price. Customers not only save money on their electric bills if they can reduce energy demands during these times, but also help to reduce greenhouse gas emissions and defer the construction of additional power plants.

Other incentive-based DR programs reward customers to reduce their electricity consumption relative to some administratively set baselines when the grid operator thinks reliability conditions are compromised. Some of these DR programs even penalize customers who have enrolled but failed to respond or fulfill their contractual commitments when events are declared. These types of DR approaches include [13]:

1. *Direct load control.* It is an approach in which the electricity utilities remotely shut down/start customers' electrical equipment during demand-peak periods [15]. The contracted customers win the incentive payment, usually in the form of credits on their electricity bill. DLC programs are primarily offered to residential or small commercial customers. The controlled electrical devices are those which would not affect customers' normal life by taking a short-term break, e.g., air conditioning, water heaters, pool pumps, clothes dryers.

2. *Demand Side Bidding* [3]. It is a mechanism that encourages customers to participate in the wholesale electricity market. Customers offer a bid which specifies the amount of demand reduction at a given time and the lowest reward that they can accept. Once the bid is accepted, customers are offered financial reward in the form of reduced electricity prices, or via a direct payment for electricity they have not consumed. DSB has become an important feature of energy markets, and has the potential to grow in importance as its operation becomes increasingly better understood. In contrast to DLC, DSB is mainly offered to large customers.

3. *Interruptible load.* An agreement about retail tariffs with curtailment options is signed between customers and electricity utilities [16]. Customers enjoy a rate discount or bill credit if they do reduce load during system contingencies. However, penalties may be applied due to failure of curtailment. IL programs have traditionally been offered only to the largest industrial (or commercial) customers.

4. *Emergency Demand Response Programs.* EDR provides incentive payments to customers for load reductions during periods when grid reliability issues arise, such as significant transmission constraints, shortages of generation or extremely high demand for electricity. It follows two models [4], i.e., voluntary programs and capacity programs. In voluntary programs, customers have the option to participate. Payments are issued for the amount that customers reduce during a system emergency. In capacity programs, customers are expected to participate and they are paid for their availability to participate, even if the utility does not call for a reduction in consumption.

5. *Capacity Market Programs.* Customers commit to providing pre-specified load reductions when system contingencies arise. In exchange for being obligated to curtail load when directed, participants receive guaranteed rewards. Customers also face penalties for failure to curtail when called upon to do so. Capacity market programs can be viewed as a form of insurance, i.e., in some years load curtailments will not be called, but participants are still paid in order to be on call at any hour [17].

6. *Ancillary Services Market Programs* [10]. Customers bid a load curtailment in their transmission network operator (TSO) or regional transmission operator (RTO) markets as operating reserves. If their bids are accepted, they get payments for committing to be on stand-by, and if the curtailment is needed, they are called by the TSO/RTO and are paid according to their bid or the market price.

1.1.3 New Requirements in Smart Grid

The traditional DR methods introduced above are relatively mature, but they are difficult to apply to the future smart grid. As pointed out in [18], in ideal DR paradigm, electricity consumption should be treated symmetrically with production and the demand-side customers should be full participants. However, in most of these traditional DR methods, either customers are rewarded for reducing their consumption based on a baseline level, or the customers cut down their energy usage when informed by rise in energy price. In other words, customers just select the energy consumption pattern according to their willingness and receive information. Human selfishness and the lack of interaction among consumers and generators lead to the difficulty of improving energy efficiency and dealing with an emergency of power grid. The characteristic and advantages of smart grid technologies require more participation of customers in the Demand Response. It can be explained from the following two aspects.

Various renewable energy supplies such as solar or wind are being increasingly used in smart grid. In 2008, 11.8% of electricity was generated from renewable energy sources in California U.S. [19]. According to California's Renewable Energy Programs, by 2020, 33% of electricity will be generated from renewable energy resources. In Europe, 8.5% electricity was generated from renewable sources in 2005, and their goal is to achieve 20% by 2020 [20]. Renewable energy resources will spread to different regions and even each household so that energy users become both electricity consumers and producers. This could fundamentally change the power grid from a one-way energy broadcasting network to a two-way energy transmission network to support users to upload their extra energy to the grid and share energy with others. It is desirable that DR solution is achieved cooperatively by energy producers together with customers.

On the other hand, the advent of smart grid technologies such as digital communication devices and advanced metering infrastructures facilitates a better environment for sharing information and data more readily among energy consumers and producers. Besides, home area networks connected with smart grid [21] allows end-consumers to participate in demand side management. These make DR more intelligent. It has attracted attention and several results have been published. We will elaborate representative DR algorithms proposed in the literature under each following category.

1.2 Representative DR Algorithms in Smart Grid

1.2.1 Classifications

Although there are already various DR results in smart grid, they fall into several categories. Based on the demand management approach, DR algorithms fall into two categories known as centralized and distributed management:

- *Centralized demand management.* In this approach, the electric utilities control the domestic appliances according to a complex centralized algorithm. The large information flow as well as social and legal barriers of centralized solutions hinders their applications in smart grid [7].

- *Distributed demand management.* Under this strategy, the demand decisions are made locally and directly by the end-users. Several theories, such as game theory, consensus methods, and subgradient optimization provide potential solutions for distributed DR [7, 22].

The DR solutions can also be roughly classified in two categories according to the scheduling variables:

- *When to start requested electrical appliances.* In this group, such as [23, 24], it aims at controlling when the devices shall run with the consideration of several factors, e.g., available energy, and pre-defined deadlines. For example, a refrigerator could delay or advance the start time of its cooling cycle within a certain time period. In most literatures of this group, the energy price is dynamic but deterministic, e.g., it is provided by the energy market.
- *How much energy to allocate to users in a time slot.* The goal of this category is estimating the energy demand of consumers in a given time slot, subject to several constraints, e.g., minimum consumption requirements of the consumers, and maximum generation capacity during this time slot. For example, in summer, people will feel much cooler when the air-conditioner is set at $22°C$. However, people can tolerate a temperature under $28°C$. Thus, the demand is adjusted to match available generation in this time slot. Usually, in this case, it computes scheduling variable along with energy price which is related to the energy consumption in the time slot. Particularly, it has been demonstrated in [22, 25, 26, 27] that a set of Locational Marginal Prices, which achieve a market equilibrium point, emerge as the Lagrangian multipliers corresponding to power flow balance constraints.

However, regardless of how to deal with the DR problem, the purpose is to increase profit or reduce cost for electric utility or end users. Here, we summarize the representative DR methods into three categories according to optimization objective. The classification is shown in Fig. 1.2.

- *Customer profit optimization category.* The DR methods in this class aim to improve consumer welfare within generation capacity. The welfare can be usage benefit minus electric charge paid to the electric utility [28], or other similar expressions.

- *Operating cost of electric utility reduction category.* The goal of these DR methods is to reduce the operating cost of electric utility while guaranteeing users' minimum demand as much as possible. In some situations, electric utility will pay a rebate to users who are willing to reduce their energy consumption [29].

- *Social welfare maximization category.* Such DR methods aim at optimally matching demand and supply with the objective of maximizing the social welfare [27], which refers to the difference between consumers' efficiencies and producers' operation cost. Currently, in this class, the energy price is determined dynamically to optimize the profits for both consumers and producers.

1.2.2 Customer Profit Optimization Algorithms

Christian et al. in [7] utilize network congestion game [30] to achieve distributed load management. Each user is assumed to know his total electric demand on a daily basis and decides the exact demand distribution over 24 timeslots through game method, with the aim of minimizing the cost paid to energy provider while taking into account its own preference.

The power grid is composed of one energy provider and M users. Denote $\mathrm{d}_i = [d_1^i, \cdots, d_N^i]$, $N = 24$, as the demand distribution vector of user i. Firstly, model such system to a directed graph (V, E), as shown in Fig. 1.3. The edge e^j represents time slot j, i.e., the energy demanded by user on time slot j flows through edge e^j, so the total load in this edge, denoted by x_j, equals $\sum_{i=1}^{M} d_j^i$. Then the energy price in time slot j is $c(x_j)$. Next, map the demand management to a congestion game $\left\{P, E, \{s_i\}_{i \in M}, \{c_e\}_{e \in E}\right\}$, where P is the set of players, E is the set of resources, s_i is the strategy space of player i and c_e is a cost function associated with resource $e \in E$. More specifically, the correspondence between demand management and congestion game is listed: 1) Players: M users; 2) Resources: N edges, i.e., N time slots; 3) Strategy space of player i: $\mathrm{d}_i = [d_1^i, \cdots, d_N^i]$; 4) Cost of each resource j: energy price in each time slot j, i.e., $c(x_j)$.

In the game process, each user updates its strategy in order to minimize its weighted cost, under given strategies of other users. The cost function of user i is $c_i(s_i, s_{-i}) = \sum_{e^j \in s_i} w_j^i c(x_j)$, where s_{-i} indicates the current strategy of other users, and w_j^i denotes the cost weight in time slot j of user i according to its preference. The Nash equilibrium can be reached after several such repeated update processes. Once convergence is achieved, prices per hour and users' demand distribution are fixed, which are executed accordingly during the day.

In congestion game theory, it has been demonstrated that the Nash equilibrium point is not only a local optimum for the selfish user, but also is a global solution. In this demand management problem, simulation results have shown that it is possible to obtain a smoother demand curve. In addition, the problem is solved in a distributed manner, i.e., each user obtains its demand distribution vector locally. However, each user requires strategies of all other players, so a complex communication protocol is needed to support the information exchange among users.

Instead of applying weighted cost, Michael et al. in [28] consider monetary profit which is equal to monetary benefit that derives from energy services minus charged cost of energy consumption. They aim at maximizing this profit through scheduling hourly energy consumption of various appliances. Fig. 1.4 describes a case study in that paper [28]. The Photo Voltage (PV) system generates energy for local use. In case of shortage, energy is purchased from the wholesale market. Energy services include charging Plug-in hybrid vehicle (PHEV), running space heater, heating storage water heater, operating pool pump, as well as must-run service that contains all other energy services except the four kinds mentioned above. The must-run service requirements are assumed to be fixed over the day. The scheduler determines the hourly charging rate of the PHEV battery, the hourly heating power of the space heater, when the water heater is switched on, and when the pool pump shall run. Denote operation schedules by $x = \{x_i | i = car, heat, water, pool\}$, the scheduling is described as the following mathematical optimization problem:

$$Max \sum_{t=1}^{T} \left(\begin{array}{l} \lambda_{ES,must-run}(t) \times U_{ES,must-run}(t) + \\ \sum_i \left(\lambda_{ES,i}(t) \times U_{ES,i}(t, x_i)\right) - \lambda(t) \times P(t, x) \end{array} \right) \tag{1.1}$$

where $U_{ES,i}(t, x_i)$ represents the "energy equivalent", i.e. the service provided by appliance i of consuming x_i units energy. The relationship between them can refer to appendix in

[28]. $\lambda_{ES,i}(t)$ is the monetary value assigned to each unit of "energy equivalent" at time slot t. $\lambda(t)$ is energy price given by wholesale market. $P(t,x)$ is the amount of hourly energy purchased from wholesale market when local PV generation is short. This mathematical optimization problem is solved and compared by Particle Swarm Optimization (PSO) [31] and its variations.

These results can be readily extended to situations with more appliances. However, the maximum available energy capacity allocated to a household should be taken into account, as discussed in the following DR method.

Shalinee and Lawrence [23] focus on control mechanisms for residential electricity demand in smart grid. They first analyze in-home scheduling, and then a distributed approach to support neighborhood-level scheduling is considered.

First, in the in-home scheduling problem, they present a simple optimization model to determine the optimal operation timing of various appliances. The planning horizon is discretized into T time periods. When the user requests appliance n in period t, the decision of when to turn it on is to find s that solves:

$$\min_{t \leq s \leq t+d_n} (s-t)\psi_n^1 + \sum\nolimits_{r=s}^{T} \left(\prod_{i=s}^{r-1} (1-\mu_{ni}) \right) \pi_r c_n \tag{1.2}$$

where d_n and ψ_n^1 represent maximum allowable delay and the inconvenience to the user incurred by each period of delay, respectively; c_n is the amount of power consumed by appliance n when it is on. The electricity price in period t is denoted by π_t, and it is determined by the wholesale market. In addition, if appliance n is on in period t, then the probability that it completes operation in period $t+1$ is given by μ_{nt}; hence the product term in the second term calculates the probability that the appliance is still on in period r. The first term represents the delay cost, while the second one represents the expected energy cost while the appliance is on. Because users are selfish, they do not consider power constraints. Each appliance can be optimized individually through formulation (1.2). It is good for each user, but it fails to reduce the load peak, and may create a worse peak.

Next, they propose a distributed scheduling mechanism to reduce peak demand across a collection of local homes. Suppose the available maximum power for the neighborhood is denoted by $P_{\max,t}$ for period t. It also assumes that all Energy Management Controllers (EMCs) installed in households transmit/receive information with each other over a common control channel. Firstly, they design a channel competition mechanism to competes with other EMCs for the available power when a new demand request is generated, without considering minimum demand of others. It may result in some consumers receiving little or no power at certain periods. To overcome this problem, each home is allocated a base power level P_b. If the requested demand for a household is less than P_b, then its EMC is on standby. Otherwise its EMC uses its base power as much as possible and then compete with other EMCs to gain additional power. Finally, they introduce a dynamic programming (DP) [32] algorithm to optimize the timing of appliance operation, subject to the available power constraints for a household.

Under this mechanism, it is possible to optimize electricity consumption within a home and also to reduce peak demand within a neighborhood of homes. But DP suffers computational challenges; it is only suitable for small-sized problems.

Safar and Massoud in [24] study a scheduling algorithm for appliance operation to minimize the electricity bill while meeting the scheduling constraints and available power capacity. This algorithm relies on a quasi-dynamic pricing model, in which the energy price consists of TOU dependent base price and a penalty term that penalizes the users when their peak consumption over some recent time windows goes beyond a predetermined threshold. Both non-interruptible and interruptible situations are considered.

Suppose there are K appliances with two sequential power modes. Let $I_{k,m}$ and $P_{k,m}$ represent required operation time and power consumption of appliance k when it is in power mode m, respectively. Total power consumption at time t is denoted by $p(t)$. In the non-interruptible satiation, $p(t)$ is written as:

$$p(t) = \sum_{k=1}^{K} \begin{pmatrix} P_{k,0} f(t, a_k, a_k + I_{k,0}) + \\ P_{k,1} f(t, a_k + I_{k,0}, a_k + I_{k,0} + I_{K,1}) \end{pmatrix} \tag{1.3}$$

where a_k is the start time of appliance k, and $f(t, a, b)$ is a pulse function, i.e., $f(t, a, b) = 1$

if appliance is on during time interval $a \leq t \leq b$, otherwise $f(t, a, b) = 0$. The quasi-dynamic energy price is defined as $C(t)R(p(t))$, where $C(t)$ is TOU-based price, and $R(p(t))$ is the penalty function, with α and p_0 being predetermined constants:

$$R(p(t)) = \begin{cases} 1+\alpha, & p(t) > p_0 \\ 1, & p(t) \leq p_0 \end{cases} \tag{1.4}$$

Therefore, the task is to schedule start time for various appliances to achieve:

$$Min \left\{ \sum_{k=1}^{K} \begin{pmatrix} \int_{a_k}^{a_k+I_{k,0}} P_{k,0} C(t) R(p(t)) dt + \\ \int_{a_k+I_{k,0}}^{a_k+I_{k,0}+I_{k,1}} P_{k,1} C(t) R(p(t)) dt \end{pmatrix} \right\} \tag{1.5}$$

subject to

$$s_k \leq a_k, \quad a_k + I_{k,0} + I_{k,1} \leq e_k, \quad p(t) < P_{\max} \tag{1.6}$$

where s_k and e_k denote allowed starting-time and deadline of appliance k, respectively, and $P_{\max}$ is the power capacity. This nonlinear optimization problem is solved by Sequential Quadratic Programming (SQP)[33].

In the interruptible case, appliance k can complete its task of power mode 1 in L_k distinct, non-overlapping task fragments. When appliance K resumes working on its task, it takes $I_{k,2} \leq I_{k,0}$ time to restart. From another angle, appliance k is divided into L_k appliances. It equates to increase the number of appliances from K to $\sum_{k=1}^{K} L_k$, with additional constraint on internal order of L_k sub-tasks for appliance k. It is also solved by SQP. Furthermore, the authors discretize this optimization problem considering only a single power mode for each appliance. Dynamic programming is used to solve it.

This solution possesses two advantages. Firstly, the penalty term in the energy price contributes to flattening the demand curve. Second, this scheduling algorithm is readily extended to the situation where appliances have multiple power modes of operation. Nevertheless, it requires to know in advance, the characteristics of all appliances that request to be scheduled. It is hard to learn which appliances would be used, because the user selects an appliance randomly. The algorithm elaborated below studies this issue.

A Consumer Automated Energy Management System (CAES) is proposed in [34], inspired by a fact that few users are willing to continuously make a sequence of decisions to defer or advance using a device, especially when it has limited financial impact on them. Users just select devices indicating their desires to run them, then CAES schedules when to run the devices and how much energy will be allocated, with the objective of minimizing the sum of: the time average financial cost of energy consumption, and the time average dis-utility to the user for delaying operations of the selected devices. Fig. 1.5 shows CAES, the time is discrete. The user has M devices. The demand request vector $z(t) \in R_+^M$ and energy price $p(t) \in R_+$ are taken as inputs. Both of them are modeled as Markov chains with unknown transition probability distributions. At time t, if device m is selected, then $z_m(t) = \gamma_m$, where γ_m is the required energy to operate it. Otherwise $z_m(t) = 0$. The output is $u(t) \in R_+^M$. The value of $u_m(t)$ is the energy allocated to device m at time t and it may be less than its pending energy requirement. So the pending energy backlog $x(t) \in R_+^M$ is created according to:

$$x(t+1) = x(t) + z(t) - u(t) \tag{1.7}$$

Next, define an auxiliary vector satisfying $y(t+1) = \theta y(t) + (I - \theta)x(t)$, where I is identity matrix and $0 \leq \theta \leq I$ is a diagonal matrix. Further, define a dis-utility function $\overline{U}_m(y_m(t)) \in R_+$, reflecting user's dissatisfaction with device m of waiting. The term θ parameterizes the dis-utility function. When $\theta \approx I$, user cares about the average delay of completing a device operation. But when $\theta = 0$, users care about the delay associated with the device currently selected. Let us denote the state vector by $\Omega(t) = [x(t); y(t); z(t); p(t)]$, the goal is to find optimal $u(t)$ that minimizes infinite time cost, with initial state Ω_0:

$$V_u(\Omega_0) = \lim_{T\to\infty} E\left[\sum_{t=1}^{T} \gamma^t \left\{\sum_{m=1}^{M} \left(p(t)u_m(t) + \lambda \overline{U}_m(y_m(t))\right)\right\}\right] \tag{1.8}$$

where $\lambda \geq 0$ gives the tradeoff between the financial cost and dis-utility cost, and $0 \leq \gamma \leq 1$ indicates that the user is more concerned about the immediate cost. Bellman's equation describing optimality condition for such Markov Decision Process [35] provides a solution. However, the Markov transition probabilities for $z(t)$ and $p(t)$ are unknown, the value function in the Bellman's equation is difficult to solve. CAES uses an online learning method termed Q-learning [36] to estimate it.

CAES factors in the statistical impact of future prices and the correlation between devices selected by the user. However, the assumption of requiring $z(t)$ and $p(t)$ to be Markov chains is still an over-strict hypothesis in some applications.

1.2.3 Operation Cost of Electric Utility Reduction

Stephane and George in [37] aim at reducing electric utility's operation cost during T periods by scheduling the start time of user demands. Suppose user n has a demand characterized by (d_n, τ_n, s_n), where d_n and τ_n denote instantaneous power consumption and the duration of completing this demand, and $0 \leq s_n \leq T - \tau_n$ is the flexible start time. It assumes that once the demand service is started, it cannot be interrupted until it is finished. Thus the total instantaneous load at time t is:

$$\lambda(t) = \sum_n d_n 1_{\{s_n \leq t \leq s_n + \tau_n\}} \tag{1.9}$$

Consider a ramp cost function for the electric utility:

$$C_L(\lambda(t)) = C_0 + C_1(\lambda(t) - L)^+ \tag{1.10}$$

where C_0 and C_1 represent the base cost and the overage rate. It implies that the energy generation cost equals the base cost if the total load is below a threshold L, otherwise it needs extra cost which is linear with the overages. Thus, the overall cost of the electric utility becomes:

$$\begin{aligned} GC_{ramp} &= \int_{t=0}^{T} \lambda(t) C_L(\lambda(t)) dt \\ &= C_0 \sum_n d_n \tau_n + C_1 \int_{t=0}^{T} \lambda(t)(\lambda(t) - L)^+ dt \end{aligned} \tag{1.11}$$

Since the problem of minimizing GC_{ramp} is NP-hard, the authors studied and compared different approximation methods based on how much information shared among users:

1) *Users know demand characteristics of each other and exchange observations in a timely manner.* According to game theory, if the electric utility charges user with b_i which is propor-

tional to both the energy he consumed and the global cost, e.g., $b_i = d_i\tau_i / \sum_n d_n\tau_n \times GC_{ramp}$, user will update its strategy to minimize GC_{ramp}, under given strategies of other players. Authors approve the best strategy for user i is to schedule his job at a time minimizing $\int_{s_i}^{s_i+\tau_i} \sum_{i\neq j} d_j\Phi_j(t)dt$, where $\Phi_j(t)$ is the probability of the job j being active at time t.

2) *Users do not share information with each other for privacy reasons, but they know the instantaneous total load.* Inspired by ALOHA protocol [38], at each period, un-scheduled user first judges whether it is his last possible scheduling slot. If so, it starts the demand immediately. If not, it starts the demand with probability p_i if the total instantaneous load currently adding his instantaneous power consumption is still below the threshold L, otherwise with probability q_i, $0 < q_i < p_i < 1$. Authors also discuss two variations of ALOHA strategy.

3) *There is no communication among users, but it assumes all customers have the same demand characteristics.* In this situation, the best strategy for each user is choosing the start time of its demand uniformly at random.

Simulation results confirm that the strategy with more knowledge setting performs better, exactly as our intuition. This literature offers instructive solutions for addressing such problems. However, it takes fixed threshold L in the cost function, which means integration of renewable energy sources is not considered. Because of uncertainties of renewable energy sources, it would thus be interesting to study the problem with time-varying threshold $L(t)$.

Soumyadip et al. in [29] also aim at reducing operation cost of the electric utility but from another perspective. They consider the electric utility has a basic generation capacity, and energy is purchased from the wholesale market in case of shortage. It encourages users to reduce their demand by paying them rebates. Therefore, the operation cost of the electric utility is comprised of rebates paid to all the users and the cost charged by the wholesale market. Rather than simply providing all users with the same rebate contracts, they design a customized, time-varying rebate plan for each user to achieve a minimal operation cost.

Firstly, a single-period situation is studied. Each user reduces its demand according to demand reduction function $f_i(a_i, r_i)$, where r_i is the per unit rebate of demand reduction for user i , and a_i reflects willingness of user i to reduce demand. Next, they consider a more complex multi-period problem. It is similar to single-period case, but it allows shifting some demand from one period to subsequent periods based on certain rule. Therefore the actual demand level before rebate at time t should take into account the demand shifted from time $1, \cdots, t-1$.

Indeed, demand reduction equates virtual generation. Besides, the fluctuation of demand corresponds to the uncertainty in renewable energy generator, although they may not be equivalent. This solution provides thought for transaction among users who have installed renewable energy resources.

Albert et al. published a series of results [39, 40, 41, 42] on demand side load management using a three-step methodology. The three steps are:

Step 1: Prediction. A system located at each house predicts the energy demand profiles for the upcoming day based on historical consumption pattern and external factors like weather.

Step 2: Global planning of a fleet. Aggregate all the predicted profiles, i.e., schedule the demand distribution of each household to spread the electricity consumption equally over the planning horizon, e.g., one day.

Step 3: Local control. Using steering signals from *Step 2*, a real time control algorithm decides when appliances are switched on/off, when and how much energy flows from or to the buffers, and when and which generators are switched on.

The relationship of the three steps is shown in Fig. 1.6. The main concern here relates to the second step in [41]. To spread the computation and communications, the planning methodology is organized in a tree structure. The root planner decomposes the desired energy profile in subparts to his child planners. Again the sub-desired profile is delegated to lower planners. The planners on the bottom of the tree are directly connected to the controllers located in the house. To achieve the delegated profile, the bottom planner uses a local dynamic programming subject to local constraints and a price vector. The price vector is affected by all the other planners' planning in the current iteration. Then the steering signals are sent to the domestic controllers. Further the domestic controllers generate a planning for the coming day and feed it back to the planner. On every level, the data is aggregated and sent further upward in the tree. Based on the mismatch between the planning and the desired profile, the root planner adjusts the decomposition of the profile, and the process starts again. This iterative process is organized so that after several iterations, the resulting profile falls between the lower and upper bound.

Utilizing tree structure, the complex demand planning problem is divided into smaller, and more easily managed problems that can be computed by dynamic programming in practice.

Michael et al. in [43] investigate the problem of allocating fluctuant renewable energy to delay tolerant demands, using the Lyapunov optimization technique [44] initially developed by themselves for dynamic control of queuing systems in wireless networks.

The time is discrete. During each timeslot t, the renewable resource provides $s(t)$ units of energy, the amount of energy requested is $a(t)$, and the price of purchasing energy from wholesale market is $\gamma(t)$. All the three are assumed time-varying and unpredictable, and bounded by constants $s_{\max}, a_{\max}, \gamma_{\max}$, respectively. It also assumes that no storage is considered, i.e., $s(t)$ must either be used or wasted during period t. Energy demands are buffered in a queue and served in a First-In-First-Out (FIFO) manner. Denoting $x(t)$ as the amount of energy purchased from wholesale market, the total amount of energy requests pending in the queue on timeslot t is updated according to:

$$Q(t+1) = \max[Q(t) - s(t) - x(t), 0] + a(t) \tag{1.12}$$

The goal is to choose $x(t)$ minimizing the expected time average cost experienced by the electric utility, i.e.:

$$\begin{array}{ll} \min & \lim\limits_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathrm{E}\{\gamma(t)x(t)\} \\ \text{s.t.} & \lim\limits_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathrm{E}\{Q(\tau)\} < \infty \\ & 0 \le x(t) \le x_{\max} \qquad \forall t \end{array} \tag{1.13}$$

The first inequality is a constraint on the expected time average queue backlog. Introduce a virtual queue $Z(t)$ with $Z(0) = 0$:

$$Z(t) = \max[Z(t) - s(t) - x(t) + \alpha 1_{\{Q(t)>0\}}]. \tag{1.14}$$

Following Lyapunov optimization technique [44], define Lyapunov function $L(\Theta(t)) = \frac{1}{2}[Z(t)^2 + Q(t)^2]$, where $\Theta(t) = (Z(t), Q(t))$. Then the conditional 1-slot Lyapunov drift is:

$$\Delta(\Theta(t)) = \mathrm{E}\{L(\Theta(t+1)) - L(\Theta(t))|\Theta(t)\} \tag{1.15}$$

The control algorithm is designed to observe $s(t)$, $a(t)$, $\gamma(t)$, $Q(t)$ and $Z(t)$, then to choose $x(t)$ to minimize a bound of the following equation on each timeslot t:

$$\Delta(\Theta(t)) + V\mathrm{E}\{\gamma(t)x(t)|\Theta(t)\} \tag{1.16}$$

where V is a positive parameter that affects tradeoff between time average cost and delay. It is intuitive to compute:

$$\begin{aligned} \Delta(\Theta(t)) + V\mathrm{E}\{\gamma(t)x(t)|\Theta(t)\} \leq B &+ V\mathrm{E}\{\gamma(t)x(t)|\Theta(t)\} \\ &+ Q(t)\mathrm{E}\{a(t) - s(t) - x(t)|\Theta(t)\} \\ &+ Z(t)\mathrm{E}\{\partial - s(t) - x(t)|\Theta(t)\} \end{aligned} \tag{1.17}$$

where $B = \frac{(s_{\max}+x_{\max})^2 + a_{\max}^2}{2} + \frac{\max[(s_{\max}+x_{\max})^2, \alpha^2]}{2}$. Obviously, minimizing this bound is equivalent to solving the following optimization problem in every timeslot t:

$$\begin{aligned} \min \quad & x(t)[V\gamma(t) - Q(t) - Z(t)] \\ \text{s. t.} \quad & 0 \leq x(t) \leq x_{\max} \end{aligned} \tag{1.18}$$

Thus the solution of $x(t)$ is given by:

$$x(t) = \begin{cases} x_{\max}, & Q(t) \geq \max[s(t) + x(t), V\gamma(t) - Z(t)] \\ \min[Q(t) - s(t), 0], & \text{otherwise} \end{cases} \tag{1.19}$$

It has been approved that all energy requests are fulfilled with a maximum delay $D_{\max} = (2V\gamma_{\max} + a_{\max} + \partial)/\partial$, while the expected time average cost of the electric utility satisfies

$\frac{1}{t}\sum_{\tau=0}^{t-1}\mathrm{E}\{\gamma(t)x(t)\} \leq c^* + B/V$, c^* is the infimum time average cost without consideration of delay constraint. The parameter V can be tuned to provide average cost arbitrarily close to optimal, with a tradeoff in delay.

The proposed Lyapunov optimization does not need a priori statistical knowledge of the supply, demand and market price. It is very useful in smart grid with unpredictable demand and renewable energy generation. It also provides broad space for the research, since some assumptions in this model could be improved, e.g., energy demand should be served first with highest priority, instead of in a FIFO manner.

1.2.4 Social Welfare Maximization

Pedram et al. in [22] not only consider the profits of users or electric utility, they also focus on social welfare. From a social fairness standpoint, it is desirable to utilize the available energy in such a way that the sum of all user-utilities is maximized and the cost imposed on the energy provider is minimized.

Suppose there are N energy users and one energy provider. The planning time is divided into K timeslots. Denote the energy consumed by user i in time slot k by x_i^k, and the energy offered by the provider is L^k. Both x_i^k and L^k have to fall into a pre-determined interval. Also, the minimum generation capacity should always cover the minimum requirements of all users, i.e., $L_k^{\min} = \sum_{i\in N} m_i^k$, $\forall k \in K$. The social welfare optimization is stated as:

$$\begin{aligned} &\underset{\substack{m_i^k \leq x_i^k \leq M_i^k,\\ L_k^{\min} \leq L^k \leq L_k^{\max}}}{\text{maximize}} && \sum_{k\in K}\left\{\sum_{i\in N} U(x_i^k,\omega_i^k) - C_k(L^k)\right\} \\ &\textit{subject to} && \textstyle\sum_{i\in N} x_i^k \leq L^k, \quad \forall k \in K \end{aligned} \tag{1.20}$$

where $C_k(L^k)$ is a cost function that indicates the cost experienced by the energy provider offering L^k units of energy, and $U(x_i^k,\omega_i^k)$ is a utility function representing user's satisfaction level of consuming x_i^k units of energy while meeting its preference ω_i^k. Quadratic utility function and quadratic cost function are used. Clearly, (1.20) could be solved independently for each time slot. Let λ^k denote Lagrange multiplier, and the dual optimization problem for timeslot k is written as:

$$\underset{\lambda^k>0}{\text{minimize}}\, D(\lambda^k) = \sum_{i\in N} B_i^k(\lambda^k) + S_k(\lambda^k) \tag{1.21}$$

$$B_i^k(\lambda^k) = \underset{m_i^k \le x_i^k \le M_i^k}{\text{maximize}}\, U(x_i^k, \omega_i^k) - \lambda^k x_i^k \tag{1.22}$$

$$S_k(\lambda^k) = \underset{L_k^{\min} \le L^k \le L_k^{\max}}{\text{maximize}}\, \lambda^k L^k - C_k(L^k) \tag{1.23}$$

It is observed that $D(\lambda^k)$ is decomposed into N separable subproblems in form of (1.22) that can be solved by each user and another subproblem in form of (1.23) which could be solved by the energy provider. Using sub-gradient method [45], during each timeslot k, each user i estimates his power consumption x_i^k through iterative computation, and the energy provider determines generation amount L^k and the Lagrange multiplier λ^k:

Step 1: The energy provider initializes L^k and λ^k randomly and broadcasts λ^k to users.

Step 2: Each user updates his consumption value x_i^k by solving (1.22) based on received value of λ^k, then transmits the estimated value of x_i^k to the energy provider; The energy provider computes the generation amount L^k by solving (1.23) based on the value of λ^k.

Step 3: The energy provider updates the value of λ^k, according to $\lambda^k = [\lambda^k - \gamma \frac{\partial D(\lambda^k)}{\partial \lambda^k}]^+$ upon receiving x_i^k from all users, where γ is pre-determined step size. Again, broadcasts updated λ^k to users.

Step 4: Repeat *Step 2* to *Step 3* until predefined precision is achieved.

Interestingly, (1.22) is the welfare that the user searches for, while (1.23) is the profit that the energy provider attempts to achieve. In fact, if the energy provider charges the users at a price λ^{k*}, i.e., the solution of the dual problem, the computed optimal consumption amount x_i^{k*} maximize the welfare of user i, and L^{k*} maximizes the profit of energy provider.

Mardavij et al. in [25] investigate a similar problem. The difference is that they consider distributed energy suppliers with different retail prices, instead of a single provider. Besides, energy transmission is taken into account.

Suppose the power system is composed of n buses (nodes), r transmission lines and m energy providers. All loads connected to one node are treated as a homogeneous demand. The goal is to find optimum demand vector $d = [d_1, \cdots, d_n]^T$, supply vector $s = [s_1, \cdots, s_m]^T$ and line current flow vector $I = [I_1, \cdots, I_r]^T$ so that social welfare $W(s, d)$ is maximized:

$$\begin{aligned} \text{maximize} \quad & W(s,d) = \sum_{j=1}^{n} u_j(d_j) - \sum_{i=1}^{n} c_i(s_i) \\ \text{subject to} \quad & Ks + EI = d, \ RI = 0 \\ & -I_{\max} \le I \le I_{\max}, \ s_{\min} \le s \le s_{\max} \end{aligned} \tag{1.24}$$

where $K \in \{0,1\}^{n\times m}$, $E \in \{-1,0,1\}^{n\times r}$, and $R \in \Re^{p\times r}$ are matrix describing the transmission grid. They are matrix aggregating the output of several suppliers connected to one node, graph incidence matrix and loop-impedance matrix. Thus, $Ks + EI = d$ and $RI = 0$ account for Kirchhoff's current and voltage laws (KCL and KVL), respectively. Utilizing dual formulations which are similar to (1.21)-(1.23), we can easily draw the conclusion that a set of Locational Marginal Prices (LMPs) emerge as Lagrange multipliers corresponding to KCL constraints. The Independent System Operator (ISO) is in charge of computing the LMPs, and users and producers take actions after receiving LMPs messages in order to maximize their individual profit. However, ISO may not know user utility functions for privacy reasons. On the other hand, if d is fixed, social welfare function becomes $W(s,d) = \sum_{i=1}^{n} c_i(s_i)$. In this case, ISO can derive LMPs without knowledge of user utility functions. This motivates authors to present an alternative solution:

Step 1: Before each period t, ISO computes the LMPs $\lambda_t = [\lambda_{1,t}, \cdots, \lambda_{n,t}]^T$ based on forecast demand that is of the form $d_{l,t} = \widehat{D}_t(d_{l,t-1}, \cdots, d_{l,t-1-T})$, $l = 1, \cdots, n$. Then ISO announces retail prices $\pi_t = [\pi_{1,t}, \cdots, \pi_{n,t}]^T$, which correspond to following equations:

$$\begin{aligned} \pi_t &= \textstyle\prod_t (\tilde{\lambda}_t, \tilde{\pi}_{t-1}) \\ \tilde{\lambda}_t &= [\lambda_t, \cdots, \lambda_{t-T}] \\ \tilde{\pi}_{t-1} &= [\pi_{t-1}, \cdots, \pi_{t-1-T}] \end{aligned} \tag{1.25}$$

Step 2: Upon receiving $\pi_{l,t}$ from ISO, user l adjusts its energy consumption during $[t, t+1]$

according to:

$$d_{l,t} = \arg \max_{x \in \Re^+} u_j(x) - \pi_{l,t} x, \ \ l = 1, \cdots, n \tag{1.26}$$

Step 3: During $[t, t+1]$, producers match all the demand.

Step 4: Repeat *Step 1* to *Step 3* for next period.

The authors have proved that this method converges to a small neighborhood of solution of (1.24).

Both results in the two literatures above achieve a market equilibrium point which satisfies the following criteria: 1) maximizing welfare for each generating unit; 2) maximizing profit for every individual consumer; 3) maximizing social welfare.

Clearly, market equilibrium is significant. Another research group discusses two analogous market models in [26]. One considers demand shaping by subjecting customers to real-time spot prices and incentivizing them to shift or even reduce their load, which is similar to the technique in [22]. The other designs a DR method to match a deficit supply by shedding users' energy consumption. In this model, the user who sheds its energy consumption is equivalent to an energy generator, while the deficit of supply is viewed as demand. A similar analytical approach of market equilibrium is adopted.

In addition, Arman et al. in [27] focus on perturbation analysis of market equilibrium in the presence of fluctuations in renewable energy resources and demand. They firstly analyze the overall market equilibrium formulation under nominal conditions.

They model the overall electricity market similar to [22, 25] above, including three components:

1) *Generation modeling.* There are N_G generating units, and the production of unit i is divided into N_{G_i} power blocks. Denote the production and associated linear operation cost of power block b in unit i by $P_{G_{ib}}$ and $\lambda^C_{G_{ib}}$, respectively. For generating units, the goal is to

maximize the overall profit p_g which is stated as:

$$p_g = \sum_{i=1}^{N_G} \sum_{b=1}^{N_{G_i}} (\rho_{n(i)} - \lambda_{G_{ib}}^{C}) P_{G_{ib}} \tag{1.27}$$

where $\rho_{n(i)}$ is the LMP of unit i which is located at node n in the power network. The power production should be subject to the maximum available constraints.

2) *Consumption modeling.* There are N_D users owning several consumers for each. Let $P_{D_{jk}}$ and $\lambda_{D_{jk}}^{U}$ represent the power consumed by consumer k of user j and corresponding linear utility, respectively. The consumption modeling aims at maximizing user welfare u as follows:

$$u = \sum_{j=1}^{N_D} \sum_{k=1}^{N_{D_j}} (\lambda_{D_{jk}}^{U} - \rho_{n(j)}) P_{D_{jk}} \tag{1.28}$$

subject to both minimum and maximum energy consumption requirements of users.

3) *ISO modeling.* It is responsible for maximizing social welfare s i.e.:

$$s = \sum_{j=1}^{N_D} \sum_{k=1}^{N_{D_j}} \lambda_{D_{jk}}^{U} P_{D_{jk}} - \sum_{i=1}^{N_G} \sum_{b=1}^{N_{G_i}} \lambda_{G_{ib}}^{C} P_{G_{ib}} \tag{1.29}$$

subject to several constraints, including power flow balance in each node and power line capacity.

In the energy market model above, the decision variables are $P_{G_{ib}}$, $P_{D_{jk}}$ and $\rho_{n(i)}$. As mentioned previously, LMPs relate to Lagrange multipliers corresponding to power flow balance constraints in ISO model, $\rho_{n(i)}$ can be viewed as fixed values in both generation and consumption modeling. So the three models are linear programming problems. Therefore, the three sets of Karush-Kuhn-Tucker (KKT) optimality conditions are both necessary and sufficient for describing overall market equilibrium. In addition, the three KKT sets result in a Mixed Linear Complementarity Problem (MLCP).

Further, they introduce uncertainties ΔG_{ib} into generators, as $\bar{P}_{G_{ib}} = P_{G_{ib}}(1 - \Delta G_{ib})$. For demand fluctuation, let a control parameter $0 < \kappa_{D_{jk}} < 1$ denote the response of the consumers to change in the Real Time Price so that $\bar{P}_{D_{jk}} = P_{D_{jk}}(1 - \kappa_{D_{jk}})$. Replace $\bar{P}_{G_{ib}}$ and $\bar{P}_{D_{jk}}$ with $P_{G_{ib}}$ and $P_{D_{jk}}$ in the three sets of KKT optimality conditions, respectively. Using properties of MLCP, the authors have proved that these perturbations lead to a limited shift off the equilibrium in nominal conditions.

1.3 Summary of the DR Methods and Future Directions

This section summarizes recent DR results in Table 1.1. Each has strengths and weaknesses. We will analyze these strengths and weaknesses, and discuss future research directions.

The advantages in the customer profit optimization group are mainly embodied in two aspects. Firstly, the decision variables under this category are either scheduling the operation timing of requested appliances or computing demand distribution over time. Both imply that power consumption spreads throughout the time, which helps to avoid a demand peak. Secondly, although the goal is to optimize the profit of customer and users are always selfish, some reasonable steps are taken to limit this selfishness, e.g., authors in [24] restrict maximum available energy for user. However, most results only consider the individual user with several appliances. In fact, interactions among customers are very important to both customers and the whole system, especially when distributed renewable energy resources are increasingly integrated. For example, the user with redundant energy can upload its extra energy to the grid to share with others. Authors in [23] design a channel competition mechanism to compete with neighborhood for the power, providing a good example.

We observed that DR methods in operation cost of electric utility reduction group possess the first advantage in customer profit optimization group. Particularly, the result in [43] can deal with a situation where both demand and supply are stochastic, although the model is simple. Because they focus on the cost of electric utility, the profit of customer cannot be guaranteed. As mentioned previously, DR methods in social welfare maximization category can achieve market equilibrium. They also consider interaction among users and generators. Unfortunately, only social welfare in a single period is discussed. Indeed, social welfare in the long term makes more sense.

According to the analysis above, an ideal DR method should possess the following properties: 1) achieving electricity transaction among customers; 2) spreading energy consumption throughout time; 3) balancing the welfare for both users and electric utility. Thus, further research could focus on two aspects:

1. *Fast distributed DR solution.* Because of privacy reasons and large information flow of centralized solutions, the user with redundant energy should locally decide whether to upload its extra energy to the grid to share with others or satisfy its other demand in advance. Similarly, the users who are short of energy compute when and where to purchase the energy. It is also related to distributed energy routing problems in the transmission grid. Besides, the fluctuations of both demand and renewable supplies require that the distributed DR method possess the property of fast convergence. This also helps to stabilize the power system quickly to avoid cascaded failure when there is a failure in one of the transmission lines.

2. *Long-time average social welfare optimization.* The ultimate goal of DR method is to flatten the demand curve over a long time. So it should consider demand shifting on the time axis, i.e., delay or advance starting the appliances. On the other hand, the social welfare introduced in a previous section should be the key point of DR research. Only in this way do both energy producers and energy customers become participants in DR. Therefore, the DR method that focuses on long-time average social welfare optimization will be an interesting topic.

1.4 Conclusion

In this chapter, we have surveyed the state-of-the-art of DR in smart grid. According to the different taxonomic approaches, the DR algorithms can be classified into several groups. This chapter focuses on a classification that is based on the optimization objective. A representative number of DR methods have been stated, which belong to the customer profit optimization category, operation cost of electric utility reduction category and social welfare maximization category. Finally, according to the analysis on strengths and weaknesses of each DR category, we believe that fast distributed DR solutions and long-time average social welfare optimization problems are the two research directions for DR in smart grid.

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Table 1.1: Summarization of Demand Response Algorithms.

	Optimization Objective	**Scheduling Variables**	**Energy Price**	**Constraints**	**Solution**
[7]	weighted electric charge (user)	demand distribution over 24 timeslots	proportion to total load	no	congestion game
[28]	difference of electric charge and utility (user)	hourly energy consumption of appliances	provided by energy market	no	Particle Swarm Optimization
[23]	sum of electric charge and delaying cost (user)	operation timing of requested appliances	provided by energy market	compete for available energy, demand deadline	Dynamic Programming
[24]	electric charge (user)	operation timing of requested appliances	proportion to total load	available energy, demand deadline	Sequential Quadratic Programming
[34]	sum of infinite horizon electric charge and delaying cost (user)	the amount of energy allocated to pending devices over time	Markov chain with unknown transition probability	no	Dynamic Programming, Q-learning
[37]	energy generation cost (electric utility)	operation timing of requested appliances	not involved	demand deadline	Game method; ALOHA; random selection
[29]	sum of energy purchase cost and rebates to users (electric utility)	time-varying rebate of each user	provided by energy market	no	Steepest Descent method
[41]	flatten the demand curve (electric utility)	demand distribution over time	proportion to total load	local constraint	Tree structure
[43]	time average cost of purchasing energy (electric utility)	the amount of energy purchased over time	unpredictable	bounds of demand, renewable supply, and energy price	Lyapunov Optimization
[22]	social welfare	amount of energy consumption and generation	Lagrange multiplier	generating capacity; demand bound	Subgradient method
[25]	social welfare	amount of energy consumption and generation	Lagrange multipliers	power line capacity; generating capacity; KCL and KVL	alternative solution based on Subgradient method
[26]	social welfare	amount of demand reduction	Lagrange multipliers	fixed total demand reduction	Subgradient method
[27]	social welfare	perturbation analysis with fluctuations in suppliers and demands	Lagrange multipliers	generating capacity; demand bound; KCL and KVL; power line capacity	KKT optimal conditions

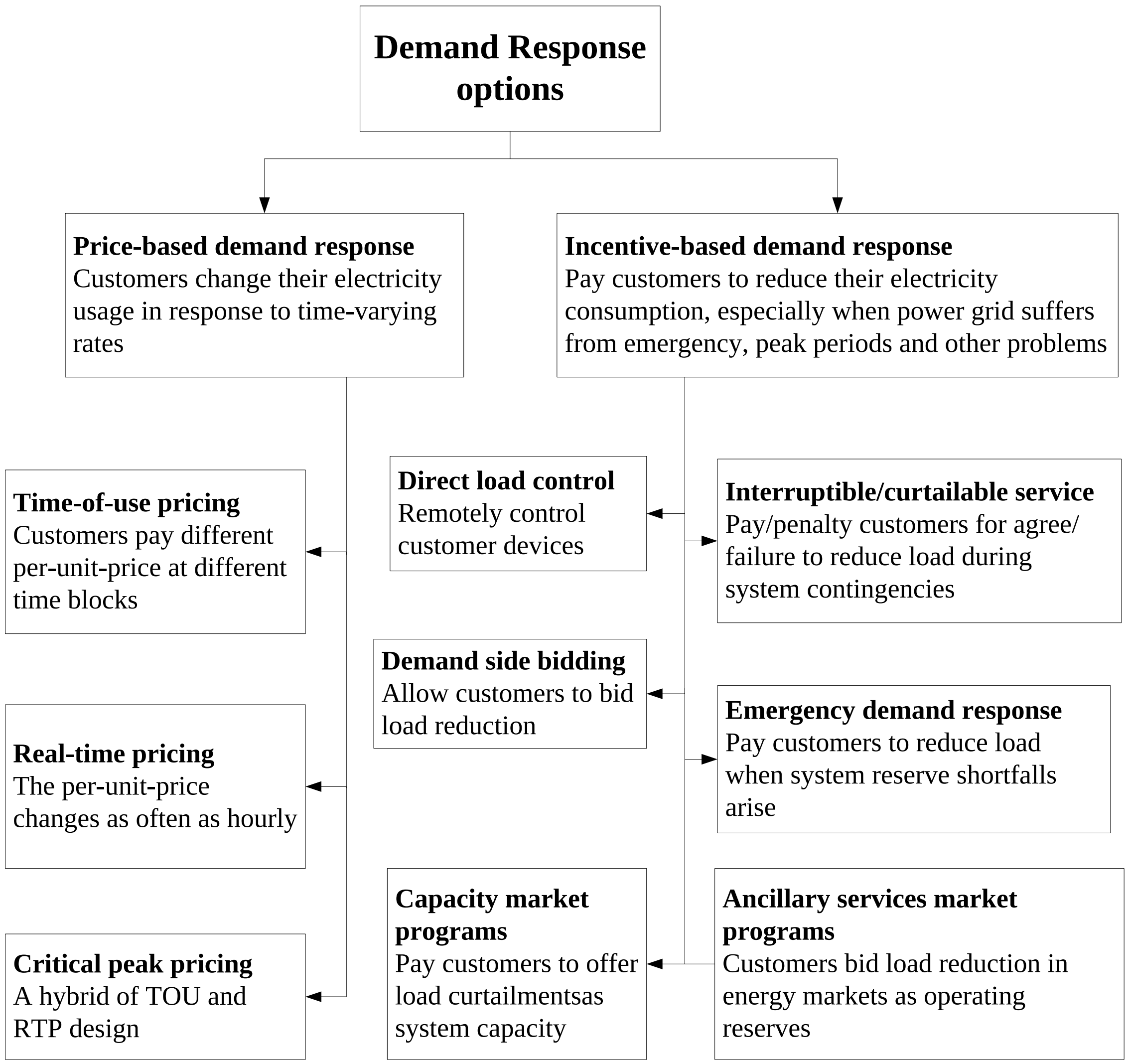

Figure 1.1: Taxonomy of traditional DR methods.

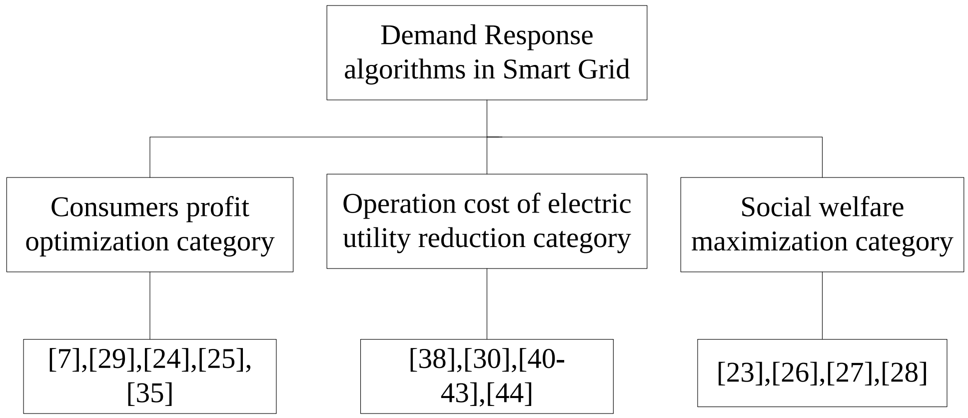

Figure 1.2: Taxonomy of DR algorithms in smart grid

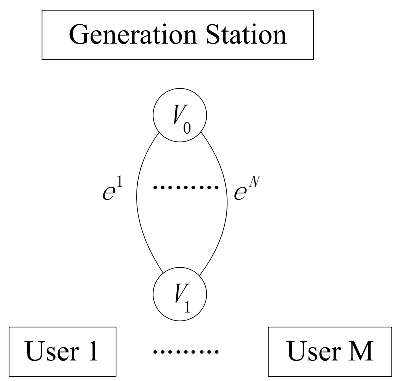

Figure 1.3: Model a power grid system to a directed graph.

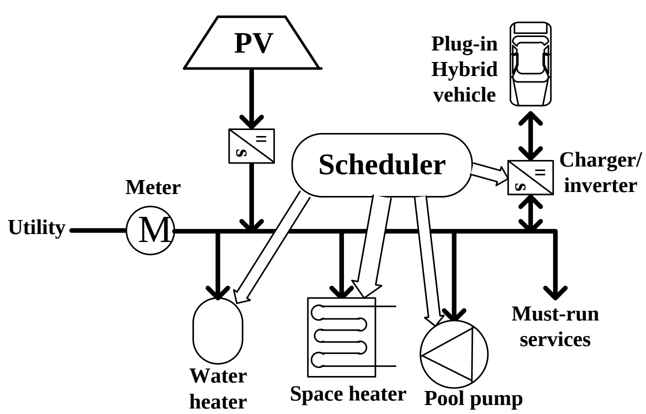

Figure 1.4: A case study in [28].

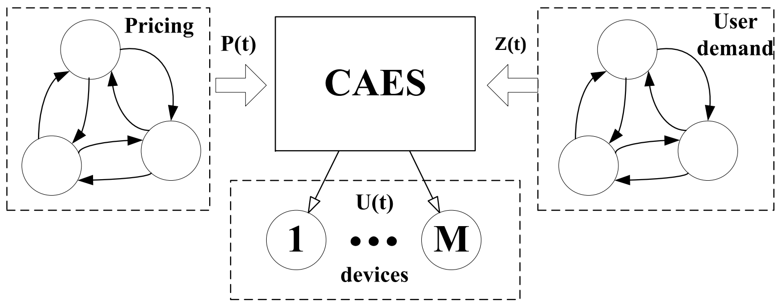

Figure 1.5: CAES energy management system.

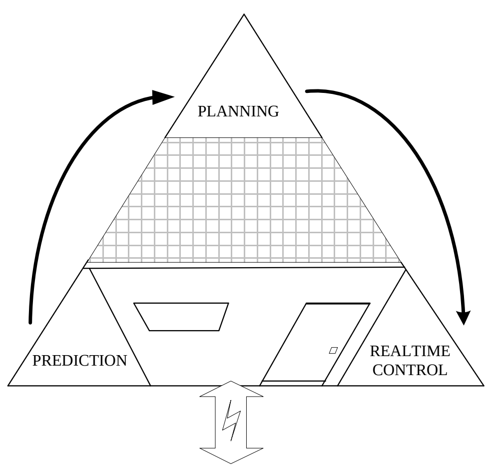

Figure 1.6: A three-step optimization methodology for demand side load management.