Chapter 6
Demand-Side Management and Demand Response for Smart Grid

Nur Mohammad and Yateendra Mishra

Abstract Demand-side management (DSM) and a market mechanism involving demand response (DR) receive significant attention. The DSM is an emerging initiative which is one of the key elements of restructured power systems. An objective of any DSM program could be peak load clipping instead of adding generation supply, by simply shifting timing from the peak load period to off-peak period. The DR seeks to adjust load demand instead of adjusting generation supply. Different types of load shaping objectives, such as peak clipping, valley filling, load shifting, produce the DR. A compensation for the DR is triggered by diverse policies, market mechanism and implementation models. The integration of DR resources in electric power system becomes worldwide due to advent of communication technologies and metering infrastructure. With the evolving restructured electricity market, aggregator as a mediator between market operator and end-user customers. This chapter discusses six major DSM aspects: (1) the DR resources, (2) possible DR program models, (3) enabler technology framework and policy, (4) role of DR exchange (DRX) market, (5) optimization algorithms used and (6) a few implementation issues like end-users engagement, privacy preservation, and DR rebounding. An optimization algorithm for specific DRX market structures and how the market participants interact is described in detail.

Keywords Demand-side management (DSM) · Demand response (DR) Electricity pricing · Electricity market · Operating cost · Demand response exchange (DRX) · Aggregator · Locational marginal price (LMP) · Bi-level optimization

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6.1 Introduction

The continuous depletion of fossil fuel-based energy accelerates renewable supply growth in the power industry throughout the world [1]. The renewable supply of primarily solar and wind with its inherent variability poses some substantial challenges for a reliable operation of the smart electricity grids. The different measures to deal with the variability lead to higher volatility in wholesale electricity price [2]. Further, the price trend spikes at the evening peak demand period, or hot summer days. When supply deficits enormous, the price even jumps several thousand times than usual cases. In this regard, flexibility and controllability from demand-side known as demand-side management (DSM) can play a significant role to reduce the price spike. The DSM is capable of balancing between supply and demand in almost all planning and operational timescale. It refers to varieties of load control activities and programs by engaging end-user customers. The customers change electricity usage behaviour in response to economic signals.

In contrast to investment in supply-side resources, coordination of demand-side resources like demand response (DR) , distributed energy resources (DER) and virtual power plant (VPP) makes the smart electricity grid smarter [3]. The emerging aggregator of the distribution side may be engaged for coordination purpose. In one hand, aggregator induces the end-user customer to modify their consumption and, on the other hand, reports to the market operator if the required DR is achieved. The operator updates the modified load demand at each network node and seeks supply offers from the conventional generation companies (GenCos) and large-scale renewable firms. The renewable suppliers are assumed to bid ex-ante based on the expected profile and adjust over- or underestimated power output in real-time operation. The operator determines the supply share of the generation companies and market price using merit order dispatch. When renewable picks up, DR would be adjusted to minimize overall operation cost. Locational marginal prices (LMPs)-based approach is usually used to evaluate electricity generation and consumption price, where LMP at each network node is found as a by-product in transmission constraint optimum power flow (OPF) model [4, 5].

The energy management scheduler (EMS) interfaced with the advanced metering infrastructure (AMI) is a key enabler to implement the DR [6]. Common ways of engaging customers in the DR programs include offering such a retail electricity rate which reflects the dynamic nature of wholesale electricity price or provides incentives to reduce load at critical peak load demand periods. The DR alleviates the necessity of generation from expensive peaking plants and defers network infrastructure expansion [7]. It reduces emissions of generating plants, improves the environmental impacts, and ensures efficient utilization of existing electricity grid capacity. Emerging applications of DR programs can improve power system's reliability by providing ancillary services. Overall, the generation, transmission and distribution companies get benefitted from a better ability to manage supply and demand. The end-users get benefitted from monetary incentives they receive as load adjustment.

With reference to the above introductory Sect. 6.1, the remaining sections are organized as follows. Sections 6.2 and 6.3 provide necessary background information about DR and DSM status in the major electricity markets. A variety of resources used are discussed in Sect. 6.4. The DR programs are reviewed in Sect. 6.5. A transactive approach for DR is introduced in Sect. 6.7. The enabler framework and pricing policy are discussed in Sects. 6.8 and 6.9, respectively. An abstract DR exchange market mechanism is provided in Sect. 6.10. Different types of DR model reported in the literature are explained in Sect. 6.11, followed by a chapter summary in Sect. 6.13.

6.2 Demand Response (DR)

DR refers to incentivized programs to reduce consumption during periods of peak demand or in response to dynamic price indications in return for monetary compensation [8]. According to [9], the DR can be defined as “changes in electric usage by the end-user from their usual consumption patterns in response to change 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” [9]. It seems to adjust load demand instead of adjusting generation supply. Market operator signals load demand reduction requests through the AMI installed in end-user’s premises. The signals are a variation of the price level. Figure 6.1 illustrates that DR consists of the area between optimized consumption and usual consumption. The DR may comprise of peak clipping (load is reduced at peak demand periods) and/or valley filling (load is activated to consume more at off-peak demand periods).

The load–duration curve (LDC) shown in Fig. 6.2 illustrates changes in yearly load demand. In LDC, the hourly load demand throughout the year is sorted largest to the smallest. The base, intermediate and peak load demands are separated by the horizontal dashed lines. With a higher share of RES, supply from the conventional generation reduces in the same hour, while peak load demand significantly increases. As seen, a higher share of variable RES though pushes overall LDC downwards, however, with a significant increase in peak consumption hours with a higher step.

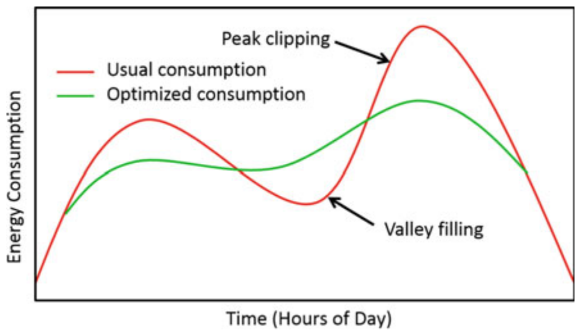

Fig. 6.1 Visualization of the DR which is the area between optimized consumption and usual consumption. Optimization clip peaks and fills valley in relation to electricity consumption, Reprinted by permission from Nature, Nat. Clim. Chang, “People power to the rescue”, S. van Renssen © 2014

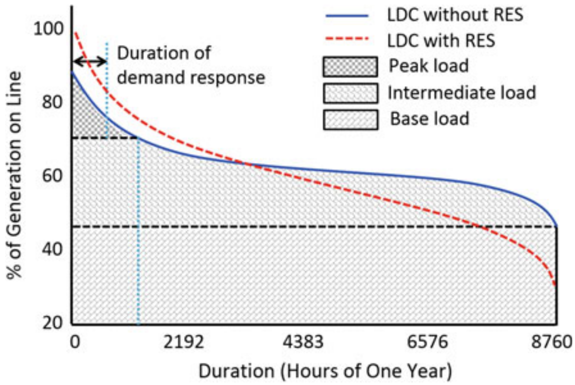

Fig. 6.2 Typical load duration curve. The peak demand data points in a year move over to the left and all the rest of the demand are on the right

Usually, peaking generations are the most expensive units in the system. A recent study shows that at least 10% of supply costs require to provide just 1% of hours of year [6]. This is a challenge for power system engineer and academic. The challenge can be dealt in a cost-effective way by engaging demand-side management.

6.3 Demand-Side Management

The DSM is considered to be one of the key elements of restructured power systems [10]. For electricity market operator (EMO), the coordination of DSM programs is a critical concern. The coordination is further intensified by the addition of distributed renewable energy firms from the supply side. Demand-side participation benefit from pricing point of view is illustrated in Fig. 6.3. The supply curve (SC) depends on marginal operation costs of the generation which usually increases with the generation levels. The position of the demand curve (DC) varies in accordance with the consumption level [11]. The projection of demand and supply curve (the point where both the curves intersect) on the price axis determines the market clearing price.

Let us consider two scenarios of demand by using the demand curve DC_1 and DC_2 for higher and lower demand, respectively. For the demand curve DC_2, the price is determined to be λ_1^P. If the end-users have flexibility in their electricity usage and reduce their consumption from D_1 to D_2, the price reduces to λ_2^P from the previous price λ_1^P. The total welfare gains from the DR are indicated by the shaded area BC_1C_2. It is interesting to see that a small amount of DR (ΔD) results in a large reduction in the generation cost. The generation cost shifted from the point C_1 to C_2. Thereby spike of the market clearing price reduces.

The size of DR benefit crucially depends on the flexibility of the end-user. It can be represented by the slope of the load demand curve [12]. A horizontal demand curve (zero slope) refers to inelastic demand which means no change in the demand due to a unit change in the pool price. The more the slope of the demand curve,

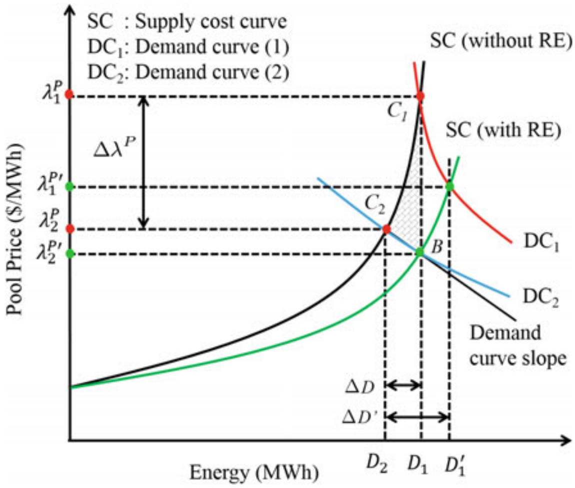

Fig. 6.3 Illustration of DR from supply–demand curve point of view

more the flexibility, means to change a larger amount of load in response to a smaller amount of price.

In case of renewable, the supply price curve moves to the right. In turn, the price reduces. The opposite could happen; when renewable power generation decreases, the price becomes higher. The DR mechanism by shifting the consumption to other periods deals the supply shortfall.

6.4 Demand Response Resources

A variety of load shaping objectives, such as peak clipping, valley filling and load shifting are presented in Fig. 6.4. The peak clipping and valley filling activities rearrange the load usages without overall demand reduction. In this case, loads differ from peak demand periods to off-peak periods [13]. Compared to the options shown in Fig. 6.4a, b, the load shifting option in Fig. 6.4c is relatively convenient to shape the load to follow generation as close as possible. Examples of user's load shifting include charging battery storage of electric vehicles (EV), space heating system and so forth. The first two DR options decrease the amount of generation supply needed to fulfil the demand, while the third one is not. However, all the options reduce power generation cost and increase the load factor. The load factor is defined as the average load divided by the peak load in a specified time.

A market operator sends a load demand reduction request through AMI installed in end-user's premises. The DR mechanism involving load/appliances needs to be automated and aided with communication technology. The end-users may have equipped with the EMS which enables ON/OFF for the DR-capable appliances. The EMS adjusts the temperature set-point of thermostatically controlled loads. The end-users

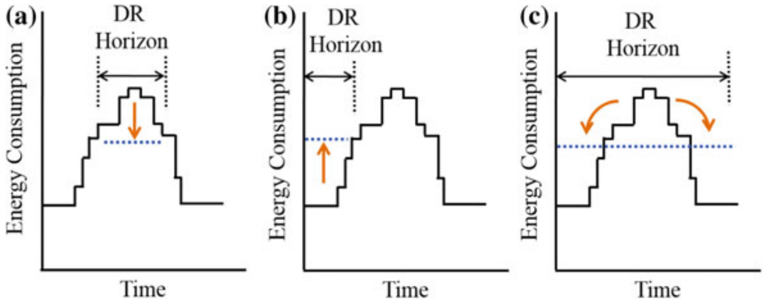

Fig. 6.4 Illustration of DR concept in relation to energy consumption flexibility. The DR activities include: **a** peak clipping; **b** valley filling; and **c** load shifting (both the peak clipping and valley filling)

have some sort of temporary inconvenience due to the load adjustment. In the EMS, users can calibrate their inconvenience based on the appliance type. The DR-capable load used by the residential customer can be categorized in the following forms:

6.4.1 Category-1: Deferrable and Interruptible Appliances

This type of appliances operates within a user's defined time window. Its operation is interruptible in the sense that it can be stopped during an operation. Also, the starting time within a preferred time window can vary. An example is the charging/discharging of the energy storage in the EV [14]. The charging tasks can be done within the user-defined time interval; further, it can be temporally interrupted with the intention of resuming at later to avoid peak period electricity price.

6.4.2 Category-2: Deferrable but Non-interruptible Appliances

This category includes washing machine, dishwasher which requires a pre-specified operation time. The interruption of the operation is not expected. However, the operation can be moved keeping its cycle throughout the day to receive a better compensation [15].

6.4.3 Category-3: Non-deferrable and Non-interruptible Appliances

These refer to thermostatically controlled loads (TCLs) such as heating ventilation air cooling (HVAC) systems, water heaters (WH), refrigerators. These devices have the most potential DR capability among the different types of residential loads used. A commercial HVAC heater/chiller may be well positioned to provide the DR by adjusting their temperature set-point. Adjusting variable speed drive of the air handling units of the fan in HVAC is another way to get the DR.

6.4.4 Onsite Generation (OG)

The rooftop solar photovoltaic (PV) systems, small-scale wind turbines, backup generators can be identified as onsite generation (OG) resources. Industry can reuse thermal energy that would usually be wasted and convert it into electrical power locally. This option can significantly backup its own electricity need during times of peak demand.

6.4.5 Energy Storage (ES)

Energy storage (ES)-capable loads can be plug-in to avoid the peak period electricity price. The battery storage in the EV, for instance, can be used to backup for the rooftop solar PV. The ES can be charged during off-peak night time when vehicles are usually parked in. It can be discharged out at the peak hours. Excess solar energy stored around the noon hours can be utilized at evening peak demand period when grid electricity price is usually higher. The enabler control system with a bidirectional communication system is used to coordinate the charging/discharging.

6.5 DR Programs

Providing some monetary incentives or adopting some dynamic tariff, the DR programs usually change the users' electricity load pattern. The DR programs can be categorized into the following three types: (1) indirect load control (ILC), (2) direct load control (DLC) and (3) transactive load control (TLC).

6.5.1 Indirect Load Control (ILC)

Indirect load control (ILC) also known as price-based DR. The end-users change their electricity consumption pattern in response to different types of time-varying pricing mechanism. The pricing mechanism is also called tariff [16]. In dynamic pricing, cost of electricity varies throughout the day.

Different dynamic pricing mechanism like time of use (ToU), critical peak (CP) and real-time pricing (RTP) indirectly induce users to change the consumption. Unlike a usual flat electricity price rate, the operator wants to change customer consumption behaviour indirectly by sending a wholesale level dynamic price caps integrated with the retail rate. The end-user reduces consumption at peak demand hours when prices are high; at the end, the users get benefited from reduced electricity consumption cost. The different time-based tariff options are as follows:

- *Time of use pricing (ToU)*
  In ToU, the usage charges vary at different time slots in a day, or different seasons of a year usually named as peak, shoulder and off-peak tariff. Generally, the ToU rate keeps unaltered for a long term.
- *Critical peak pricing (CPP)*
  The usual peak price rate replaced with much higher rate is called critical peak pricing (CPP).
- *Inclined block rate (IBR)*
  If hourly consumption rate changes after exceeding a certain threshold level, it is recognized as inclined block rate (IBR).
- *Real-time pricing (RTP)*
  RTP refers to the electricity charges when it varies at sub-hour interval [17].
  Among the pricing options discussed, RTP has been found most popular, though it requires intensive communication infrastructure.

6.5.2 Direct Load Control (DLC)

Direct load control (DLC) allows the operator to turn off until a defined ending time; it would be turned on again. Similarly, to operate a task for a few cycles with minimal consumption does not substantially affect performance. In the DLC program, large customers like industries curtail some of the electricity usages and emulate as a virtual spinning reserve. In contrast to ILC, the amount of load reduction in DLC is more specific, since the control action is done from the operator side. The users are committed to response.

Several threatening issues may raise in the DLC programs, for instance, customer right, user's preference and privacy. Also, there is a penalty which may be applied due to non-compliance. However, some recent study shows, the customer should have the right to override the ability of the operator to remotely control the loads. In that case, users agree to sacrifice some of the compensation users receive. The users having HVAC loads can easily involve in the DLC [18].

Generally, the DLC as ancillary service can be used to keep system voltage and frequency at reliable level so that electricity moves from generating sources to loads. Such a frequency and voltage regulation maintain a balance between the supply and the demand. Authors in [19] proposed a stochastic scheduling method for the controllable TCLs to provide frequency regulation services. In general, during the occurrence of any disturbances, when it is necessary to response within minutes or even shorter interval, the DLC can be a useful resource to bring back the system in the reliable state.

6.6 DR for Industrial Customers

This section aims to discuss the existing practice and idea on the industrial DR. Non-residential especially industrial customers require intense energy consumption with normal loads of hundreds of MWs. They have substantial potential to provide flexibility for power system grids. Compared to the residential users, who can reschedule their loads even near real time, in many industrial cases; however, to implement DR would be complex due to the reliability of the interdependent industrial process being difficult to isolate [20]. A disruption of the process may stop production or disregard the key operational constraints. In [21], a DR from the industrial facilities is investigated. The study found, when the dynamic price is above what is usual, the industry decreases its electricity consumption and uses the local OG and ES to recover the deficit.

The works in [22, 23] suggested a DR option for refrigerated warehouses. The study showed how a DR minimizes energy consumption cost for the industrial customers and thereby balances the electricity supply and demand. Those investigations, however, collectively left any specific DR algorithm for the interdependent industrial process.

The authors in [24] and [23] proposed a technique for production scheduling based on state task network (STN) to minimize electricity consumption cost. The STN consists of task nodes and state nodes, where the task refers operation processing while the state for input feeds, transitional and final products [25]. Also in [26] and in [20], a scheduling algorithm based on resource-task network (RTN) to minimize makespan of the operational units is suggested. The works in [26] suggested scheduling problem of the steel melting plant under energy constraints to minimize total electricity cost. The novel aspect of this model is to incorporate penalties in objective function so that deviations from a precontracted electricity load can be taken into consideration. The large manufacturing industry can use its operational shifting flexibility by altering electricity usage from on-peak to off-peak demand periods [27, 28].

In summary, these works [27, 20] consider practical scheduling constraints of the industry during DR. The DR programs for industrial facilities have helped to reduce the peak load demand for many years. The load management for the irrigation pumps in the agricultural sector is still largely untapped. Irrigation is well suited for DR because the involving pumps can be shut off even for the peak periods, which can last for several hours.

6.7 Transactive Approach for DR and DER

6.7.1 What Is Transactive Approach?

Transactive approach refers to the emerging market-based coordination for DR, DERs and storages at large scale to manage bulk-level intermittent renewable generation within an intelligent power system grid. The term "transactive" arises because operation decisions are made considering value-based economic information [29]. According to [30], transactive energy refers "A system of economic and control mechanisms that allow the dynamic balance of supply and load demand across the entire electrical infrastructure using value as a key operational parameter".

6.7.2 How Does Transactive Approach Work?

The transactive approach integrates flexible demand-side resources into smart grids. The enabler platform is strongly interdisciplinary, requires power systems, economics, and controls engineering knowledge. A large customer can directly take part in the market, while small end-users require a DR service provider aggregator. The transactive interaction between the end-users, aggregators and operator requires intelligent communication and automation deployment. The main principle is to combine economic and control techniques to improve smart grid reliability, efficiency and economic transparency.

6.8 DR Enabler Framework

The underlying enabler to implement DR is compatible communication infrastructure with the supported protocol. DR system requires energy management scheduler interfaced with the AMI, as detailed in the following sections.

6.8.1 Energy Management Scheduler

The EMS includes in-home displays, home area networks, programmable thermostat and smart plugs as part of the EMS system. The automation of those components provides significant functional platforms to enable the DR facilities. Consumption scheduling problem is operated by optimization model coded in the EMS [11]. Some of the optimization models are discussed in this chapter. In one hand, every EMS is remotely connected by world area network to the utility through the AMI; on the other hand, the DR-capable loads exchange its status with the EMS. A ZigBee network is used for this purpose which acts as a communicating gateway to connect appliances available in the home. The ZigBee is a technology based on IEEE 802.15.4 standard, consists of low-power wireless sensor and controls technology into the EMS.

The users have a choice of taking flat price or dynamic tariff. Being instructed by the operator; aggregators request to the affiliated users. The user responses to the request and reschedules the energy consumption. In general, the flexibility of DR considers the following three aspects, (1) overall disutility cost, (2) scheduling timing preference and (3) climatic comfort constraint such as temperature set-points [31]. The optimal scheduling decisions are either ON/OFF time of the DR-capable loads or charging/discharging of energy storage. The optimal scheduling decisions are taken while respecting the aforementioned aspect of the cost of energy consumption, timing and flexibility constraints.

6.8.2 Advance Smart Metering System

The AMI is another key technical driver for incorporating the DR into the smart grids. It is an integrated system of smart meters and bidirectional communications network with a customized protocol. The protocol enables interactive communication between utilities and end-user customers. It records time-based energy consumption data and communicates those data to the utility operator. Smart meters can receive execution commands from the aggregator [29] and send DR outcomes after communicating through the EMS.

6.9 DSM Pricing Policy

The DR valuation is activated by different sets of policies, market mechanism and implementation frameworks [32]. In the PJM electricity market of USA, the federal energy regulatory commission (FERC) advocates for the DR. A FERC order 745 empowers DR service provider such as large customers, independent third-party mediator on behalf of end-users to offer DR in aggregate. The DR provider must be compensated for reducing electricity load at the same rates as if they met that demand with generated electricity. The acceptance of the order 745 by US Supreme Court enhances a larger integration of DR. A significant economic impact is released in both the wholesale and retail levels [33]. The DR participates in organized wholesale markets and now gets remunerated for the service it provides at the LMP [34]. According to [35], the "LMP is the marginal cost of supplying, at least cost, the next increment of electric demand at a specific location (node) on the electric power network, taking into account both supply (generation/import) bids and demand (load/export) offers and the physical aspects of the transmission system including transmission and other operational constraints". This approach for compensating the DR removes barriers to the participation of DR resources. Competitive participation is realized from a variety of DSM providers, from a traditional DR to aggregated battery storage, the solar energy from the rooftop solar PV and electric vehicles.

The DR compensation rate is different in different electricity markets. For instance, leading California Independent System Operator (CAISO) and Pennsylvania New Jersey Maryland (PJM) both have a significant number of DR programs under the FERC pricing policy. The New England ISO's plan is on track for 2018 integration. In contrast to FERC order, a conceptual DR pricing policy is shown in Fig. 6.5.

The aggregator knows end-users expected baseline consumption. The end-user pays the retailer for their meter recorded consumption. The energy provided by the retailer is purchased from the wholesale market. The retailers purchase DR from demand response exchange (DRX) . The aggregators whereas sell the demand response in the DRX. The aggregator compensates end-user for the level of DR which is the difference between the customers' actual electricity consumption and predicted baseline consumption. The DR amount and cost settle in the DRX market which are reported to the EMO to consider it for the wholesale market.

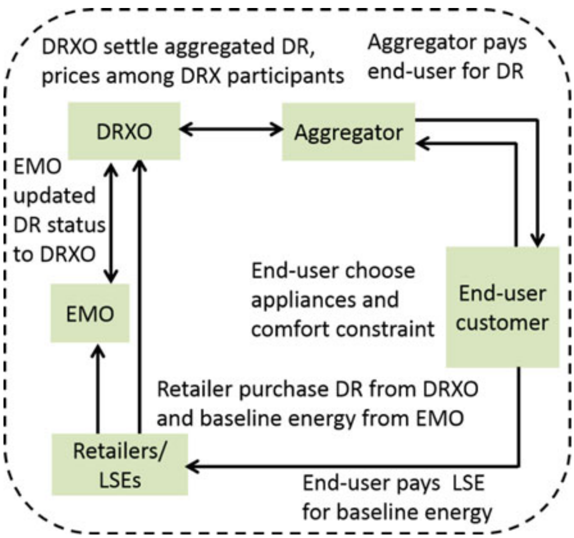

Fig. 6.5 Conceptual DR pricing and compensation for the market participants in different levels without FERC order 745 [36]

6.10 DR Exchange (DRX) Market

A DRX-integrated market model is presented in Fig. 6.6. Since introduced by authors in [14, 15], the DRX model is extended and modified to implement various market mechanisms. Authors in [37] discussed pool-based DR exchange in the day-ahead (DA) scheduling. The DR participants were expected to submit a selling or purchasing curtailment offers in separate DRX markets. The benefits of those models achieve in terms of reduced peak-hour LMP, lower power system operation and congestion cost. In the pool-based DRX model, the market participants are coordinated by a demand response exchange operator (DRXO). The participants require forming its bidding strategy to either sell or purchase the DR product directly from the DRX pool [14]. It is reported that such a pool-based DRX is cost-effective, reliable and improves economic transparency in DSM.

The DRX customers are divided into two groups. The first group includes load-serving entities (LSEs), electricity service providers, retailers, even the EMO who purchases the DR to provide ancillary services [38]. The DR purchaser buys DR resources to enhance power system reliability, managing network congestion and avoiding price volatility spikes [34]. The second group includes DR sellers who offer DR resources in the DRX to get economic rewards. The DR sellers may be industrial, commercial and residential end-user. However, due to limited negotiation power, the residential users participate in DRX by aggregators. In the proposed market framework, aggregator serves as the agents who receive DR requests from

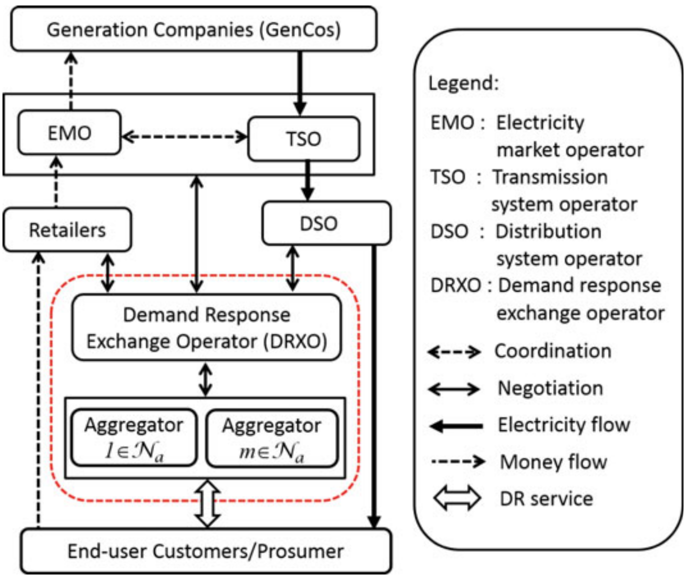

Fig. 6.6 Proposed DRX market and the role of aggregator for a smart electricity markets

DRXO, LSEs and electricity service providers [37]. The optimal DR pricing and the amount to be traded is determined in the DRX market. Such a pool-based DRX mechanism does not significantly modify the functionalities of participants in the organized wholesale markets. In the following section, role of different DRX market players is presented.

6.10.1 Role of EMO

The market operator places its DR requirement and seeks participation from the aggregators. The aggregator wants to value the flexibility of the end-users DR capability. Based on the wholesale forecasted price, the aggregator updates its bidding strategy and evaluates the end-user's responses.

6.10.2 Role of Aggregator

Due to limited negotiation power, end-user customers enjoin aggregator-provided DR service. The aggregator communicates with the end-users through local EMS unit which allows users to choose their consumption and compensation preference. The EMS is required to know the consumption pattern and relevant operating characteristics of the appliances. The aggregators offer compensation to the end-users and change it until the DR requirement achieves. The end-users must reveal their baseline consumption to get the compensation.

6.10.3 Baseline Demand Estimation

The end-users i participating in DR require their baseline electricity consumption to be measured. The baseline consumption indicates the quantity a user would normally use without DR as shown in Fig. 6.7. Aggregator measures the baseline consumption to entail the DR benefit for the load curtailment. Assuming D_{baseline} for baseline demand and D_{actual} for actual demand, the DR quantity (x) is defined by

$$x =: D_{\text{baseline}} - D_{\text{actual}}. \tag{6.1}$$

Further, consider an individual DR supply quantity vector x_i^k at each hour, $k \in \mathcal{T}$. There exist N_a appliances index by $a \in \mathcal{N}_a$. The DR supply is defined by

$$x_i^k =: \left[x_{i1}^k,\ x_{i2}^k,\ \ldots,\ x_{iN_a}^k\right]. \tag{6.2}$$

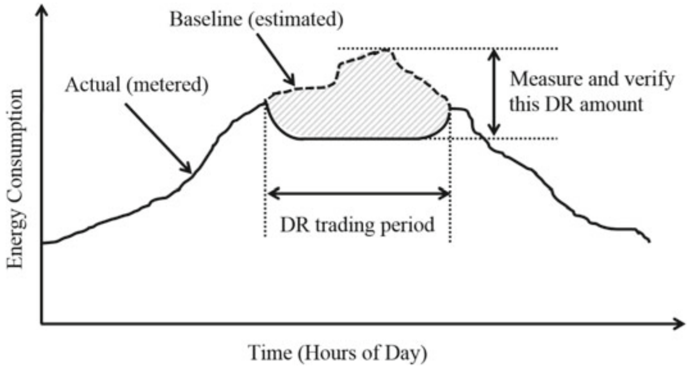

Fig. 6.7 Verifying DR dispatch by a customer [39], Figure, Courtesy of D. T. Nguyen, "Demand Response Exchange in a Deregulated Environment" © 2012

The aggregated DR over the trading period of interest from the N_i number of users can be expressed as

$$X = \sum_{i \in \mathcal{N}_i} \sum_{i \in \mathcal{T}} x_i^k. \tag{6.3}$$

To calculate the baseline demand, several methods like day matching and regression analysis are used as discussed in [40]. Historical consumption behaviour is also used for this purpose. The authors in [41] investigated a forecasting tool to determine baseline demand.

The load demand forecasting of the end-users having solar PV and other distributed resources is difficult to predict due to their inherent intermittency. The estimation relies heavily on the meteorological variables over in time and space. For a given site, if historical data are available, simple time series model provides an accurate estimation of the load even though meteorological conditions are unknown.

To obtain a realistic consumption while preserving end-user's privacy, it is required to estimate their consumption and refer it back to the aggregator. However, there is a challenge to get truthful data as the user may lie on purpose. The users may declare overestimated baseline consumption to claim increasing monetary compensation. This can be dealt with adopting a game theoretic optimization model. A game theoretic model guarantees that the users attain maximum DR benefit if they reveal true baseline consumption. No users could attain a higher benefit by reporting a baseline consumption different from its true value. Thereby, users avoid false reporting of their consumption. The AMI is being installed on the end-user's premises which records the consumption history. Those historical data are compared with the consumption in real time to calculate the compensation portfolio. Since the AMI technologies have been evolved, these are utilized for DR measurement and verification by the utilities. Figure 6.8 explains a scheduling horizon of DR-integrated market framework. The DSM can be arranged in almost all time scales of planning and operation.

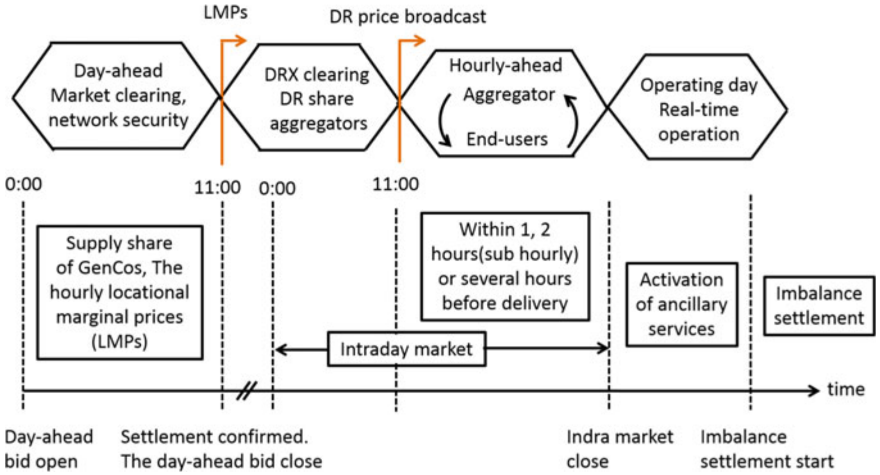

Fig. 6.8 Short-term planning to real-time operation window with activities for DR-integrated electricity markets [43]

Planning on the horizon of interest like long-term investment decision to operation level involving scheduling in DA can be performed. The required adjustment is made in near real time to deal over- and underestimation of the resources realized. The DA market usually settles on an hourly basis. The generation is scheduled over the operating horizon for actual dispatch on the following day, based on the hourly day-ahead forecasted demand [42]. The GenCos need to submit ex-ante operational scheduling for power generation. The EMO usually closes the DA market at 11.00 pm. The locational marginal price and generation share are set by running a security constraint economic dispatch program.

The GenCos communicate with balancing responsible party (BRP). The BRP settles imbalance (if any) in real-time net from the DA commitment. Such a market mechanism is better demonstrated in [14, 15, 37], by introducing a demand response exchange (DRX) market. To provide the committed DR quantity in the DRX market, the aggregator is required to communicate with the end-user. The aggregator acts as a mediator between DRXO and end-user customers. In the intraday market, the aggregator updates their compensation strategy until the DR requirement is achieved. The intraday market closes before few hours ahead of delivery.

The imbalance settlement is executed in real time. The estimated renewable energy amount committed in day-ahead and the probable imbalance is fixed up. A penalty is imposed due to over- or underestimated power generation. Following section discusses a few DR market mechanism models which are used to implement different types of DSM program.

6.11 Mathematical Models for DR in Smart Grids

The mathematical models for DR in DSM can be framed in a different perspective and from different point of views. The models differ in objective functions, solution methods, scalability, multiple appliance support, pricing scheme, communication requirement and so forth. Some of the important models that have to allow to model DSM programs are discussed below.

6.11.1 End-User Aggregated Cost Minimization

Let us study a simple DR mechanism as reported in [44]. In this study, each end-user is assumed to submit a single bid reflecting a willingness to change consumption over the period k. Being aware of end-user's preference, the aggregator solves the following energy consumption cost problem given by (6.4).

$$\begin{aligned}
&\underset{(d_1,\ldots,d_{Nu})}{\text{minimize}} \sum_{i=1}^{N_u} C_r\left(\sum_{k=1}^{T_k} d_{r,k}\right), \quad \forall s, \forall k. \\
&\text{subject to} \sum_{i=1}^{N_u} d_{r,k} = G_k, \quad \forall k \\
&- L_{r,k} \leq d_{r,k} \leq D_{r,k}, \quad \forall r.
\end{aligned} \tag{6.4}$$

where d_{rk} is the DR provided by user r at time k, $d_r := \left[d_{r1}, \ \ldots, \ d_{rT_k}\right]$, and $D_{rk} \leq 0$ is maximum load quantity user could change at k. It is reported user's disutility due to changing load demand depends only on its total load demand adjustment, d_r. The term G_k is for the total amount of supply to meet the demand for all users. The rth user's load adjustment must lie in the interval $[-L_r, \ D_r]$. The cost function $C_r(d_r)$ in (6.4) is of the following form [44]

$$C_r(d_r) = \begin{cases} U_r d_r, & \text{if } d_r \leq D'_r. \\ U_r D'_r + H_r(d_r - D'_r), & \text{otherwise.} \end{cases} \tag{6.5}$$

where $D_r^{'}$ denotes for the maximum quantity of load change that the user can manage over the period T_k, with a specified deadline. Here, the $U_r > 0$ is for user's marginal disutility which appears due to deferring a task. The term $H_r(\cdot)$ replicates disutility if the task is not complete before its deadline.

6.11.2 Peak-to-Average Load Ratio Minimization

Another type of optimization problem is to minimize system peak-to-average ratio (PAR), a significant parameter to quantify DR [45]. The appliances having higher consumption rate can be activated during off-peak hours to decrease the PAR value. Let us consider $r \in \mathcal{R}_m$ end-user having flexible appliance set $s \in \mathcal{A}_a$. Energy consumption scheduling vector of appliance $s \in \mathcal{A}_a$ is defined as $\boldsymbol{d}_{rs} = \left[d_{rs}^1, \ \ldots, \ d_{rs}^{T_k}\right]$, where d_{rs}^k denotes hourly consumption by user r at hour k. The total load of user r can be expressed as $l_r^k = \sum\limits_{a \in A_a} d_{rs}^k, \quad k \in \mathbb{T}_k$. The daily peak and average load levels are calculated as

$$L_{\text{peak}} = \max_{\forall k} L_k \tag{6.6}$$

$$L_{\text{avg}} = \frac{1}{T_k} \sum_{\forall k} L_k \tag{6.7}$$

Therefore, the PAR in load demand is expressed as (6.8)

$$\text{PAR} = \frac{L_{\text{peak}}}{L_{\text{avg}}} = \frac{T_k \max_{\forall k} L_k}{\sum_{\forall k} L_k}. \tag{6.8}$$

The total energy consumed by all appliances in the system over 24 h is equal to the sum of the daily energy consumption of all loads/appliances.

$$\text{minimize} \ \frac{T_k \ \max\limits_{\forall k} \left(\sum_{r \in \mathcal{R}_{\text{m}}} \sum_{s \in \mathcal{A}_{\text{a}}} d_{r,s}^k\right)}{\sum_{r \in \mathcal{R}_{\text{m}}} \sum_{s \in \mathcal{A}_{\text{a}}} E_{rs}}, \quad \forall r, \forall s, \forall k. \tag{6.9}$$

However, the problem (6.9) is still difficult to solve in its current form due to the max term in the objective function. This can be resolved by introducing a new auxiliary variable Γ and rewriting the problem in the following form

$$\begin{aligned} &\text{minimize } \Gamma \\ &\text{subject to } \Gamma \geq \sum_{r \in \mathcal{R}_{\text{m}}} \sum_{s \in \mathcal{A}_{\text{a}}} d_{r,s}^k, \quad \forall r, \forall r, \forall k \\ &\qquad\qquad \gamma_{\text{r,s}}^{\text{min}} \leq x_{r,s}^k \gamma_{\text{r,s}}^{\text{max}}. \end{aligned} \tag{6.10}$$

We define the minimum standby power level $\gamma_{r,s}^{\text{min}}$ and the maximum power level $\gamma_{r,s}^{\text{max}}$ for each appliance $s \in \mathcal{A}_a$ for each user $r \in \mathcal{R}_m$. Standby power refers to the electric power consumed by each appliance while it is switched off or it is in a standby mode. It is considered the LSE has complete knowledge about this information. An energy consumption scheduling problem can also be devised in terms of minimizing the energy consumption costs to all users. The task of ECS is optimized in the function (6.11) to find the optimal choice of consumption vector d_{rs}

for each appliance at every hour. Given an hourly energy cost function, C_k, denoting the cost of distributing electricity, can be formulated to minimize energy consumption costs to the end-users

$$\underset{n\in\mathcal{X}_\mathrm{n}, n\in\mathcal{N}_\mathrm{n}}{\text{minimize}} \geq \sum_{\forall k} C_k \sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{A}_\mathrm{s}} d_{r,s}^{k}\,. \tag{6.11}$$

The cost function is assumed to be strictly convex, and the minimization problem in (6.10) has an optimal solution, given the coefficients of the cost functions [29]. The difference between the minimization of PAR and energy consumption cost is that the latter could have multiple optimal solutions. A game theoretic approach is used in [45] to solve both the problems (6.10) and (6.11).

6.11.3 Risk-Constrained Optimization Model

There exists a specific type optimization which can measure risk arising from the uncertainty of the involving decision variables. Bear upon this uncertainty, let us consider $f(x_D, w)$ be the profit function associated with a 'x_D' a choice variable. The D in suffix denotes for demand response. The 'w' represents a random variable arising from renewable (such as wind and PV firm) uncertainty. The profit–loss not beyond a threshold margin, α, is expressed by (6.12)

$$\Psi(x_D, \alpha) = \int_{f(x_D,w)\leq\alpha} \pi_w \,\mathrm{d}w. \tag{6.12}$$

As a function of α and for a decision x_D, Ψ is the collective spreading for the lower profit link to the x_D. The (6.12) is continuous increasing function of α. Given a probability β, a value-at-risk (β-VaR) and conditional value-at-risk (β–CVaR), pertaining to the x_D, is given by the following form, respectively [46]

$$\alpha^{\beta}(x_D) = \min\{\alpha{:}\Psi(x_D, \alpha) \geq \beta\}, \tag{6.13}$$

$$\rho^{\beta}(x_D) = \frac{1}{1-\beta} \sum_{f(x_D,w)\geq\alpha^{\beta}(x_D)} f(x_D, w)\pi_w \,\mathrm{d}w. \tag{6.14}$$

To reduce the profit–loss due to x_D decision, (6.15) is convex and piecewise linear [7].

$$\min_{(x_D,\alpha)} \left(\alpha + \frac{1}{N_w(1-\beta)} \sum_{w=1}^{N_w} \pi_w[f(x_D, w) - \alpha]\right). \tag{6.15}$$

The (6.15) denotes the existence of derivative and convexity for the critical values of α in the interval $(1-\beta)$. When a β–CVaR is found, the β–VaR can be calculated easily. Optimization of (6.15) provides the risk margin of profit–loss in uncertainty. The model (6.15) can be further modified by announcing a new supplementary variable $\vartheta_w \geq 0$ for all probable scenarios as expressed by

$$\min_{(x_D,\alpha)} \left(\alpha + \frac{1}{N_w(1-\beta)} \sum_{w=1}^{N_w} \pi_w \vartheta_w \right) \tag{6.16}$$

The aforementioned formulation is an operative risk control tool discussed in [47]. This risk metric is cast-off to optimize the probable profit and different types of uncertainties. Such a risk measurement tool is used for different market players, for instance, by the retailer [48], storage aggregator [38], GenCos [49] and virtual power plants [50]. Next section discusses a generation supply offer for economic market clearing problem.

6.11.4 DR-Integrated MCM from Network Perspective

The modelling of generation supply offer in economic market clearing problem (MCM) has been investigated by authors in [51–56]. In MCM, the generation offer bids are accepted and dispatched in merit order. A competition-driven supply-side bidding-based MCM is reported in [57–59]. In the majority of the cases, the objective was to minimize operation cost. A bulk-level demand bidding applied by large consumers was investigated [44, 60, 61]. However, the idea of demand bidding is debatable; rather a DR-integrated demand bidding is more practical. Since the later bidding allows the aggregator to observe the load status closely from a control perspective.

6.11.4.1 Operation Cost Minimization

Assuming a power system with $\mathcal{N}_b$ buses and $\mathcal{N}_l$ transmission lines; Suppose $\mathcal{N}_b$ and $\mathcal{N}_l$ denote sets of the system bus and line, respectively. Further define $\mathcal{N}_g := \{1, 2, \ldots, N_g\}$ for the GenCos [62]. The following optimization task is solved in day-ahead for each of the kth trading periods [63].

$$\underset{\Psi_{nk}(P_g,P_w)}{\text{Minimize}} \quad \sum_{\forall n \in \mathcal{N}_g} c_n\left(P_{g_{nk}}\right) P_{g_{nk}} + \sum_{\forall m \in \mathcal{N}_r} \lambda^d_{mk} d_{mk} \tag{6.17}$$

subject to:

$$\sum_{\forall n \in \mathrm{N_g}} P_{g_{nk}} + \sum_{\forall i \in \mathrm{N_b}} (1 - \chi_w) D_{ik} = \sum_{\forall (i,j) \in \mathrm{N_l}} B_b(\vartheta_{ik} - \vartheta_{jk}) \tag{6.18}$$

$$B_f(\vartheta_{ik} - \vartheta_{jk}) \le F_{ij}, \quad \forall (i, j) \in N_l, \forall k \tag{6.19}$$

$$F_{ij}^{\min} \le F_{ij} \le F_{ij}^{\max}, \quad \forall (i, j) \in N_b \tag{6.20}$$

$$P_{g_{nk}}^{\min} \le P_{g_{nk}} \le P_{g_{nk}}^{\max}, \quad \forall n \in N_g, \forall k \tag{6.21}$$

$$R_n^{dn} \le P_{g_{nk}} - P_{g_{nk-1}} \le R_n^{up}, \forall k, \quad \forall n \in N_g, \forall k \tag{6.22}$$

$$R_n^{dn} \le P_{w_{nk}} - P_{w_{nk-1}} \le R_n^{up}, \forall k, \quad \forall n \in N_w, \forall k \tag{6.23}$$

$$\vartheta_i^{\min} \le \vartheta \le \vartheta_i^{\max}, \vartheta_{i=1} = 0, \quad \forall i \tag{6.24}$$

$$0 < D_{ik}, \ \chi_w \in \mathrm{R}, \quad \forall k, \forall i \in N_b \tag{6.25}$$

The first part of the objective (6.17) includes generation offer cost. The second part refers demand reduction price of the flexible loads. The supply–demand balance equality constraint is given in (6.18). The second term in this expression is the wind variability adjustment parameter. In the nodal power injection term, the B_b is a matrix of dimension $N_b \times N_b$ for the power system bus admittance. The term (θ_{ik}–θ_{jk}) is for the voltage phase angles. The power flow through the transmission lines $\forall(i,j) \in N_1$ is provided in (6.19). The line and generation capacities limits are expressed by (6.20) and (6.21), respectively. The constraints (6.22) and (6.23) are for ramp rate. The constraint (6.24) enforces the lower and upper bounds the phase angles. The constraints in (6.25) are some decision variables obtained by solving the DRX problem.

6.11.4.2 Social Welfare Maximization

A social welfare maximization is another class of problem where the sum of utility functions of the end-user minus generation cost of the supplier is maximized [54, 58, 64, 65]. This type of problem involves a utility function $B_{jrs}(p_{jrs})$ of energy usage that allows load adjustment as follows [66].

$$\underset{(P_{g_{nk}}\, p_{jrs}^{k})}{\text{Maximize}} \sum_{j=1}^{N_a} \sum_{r \in \mathrm{R_j}} \sum_{s \in S_{jr}} B_{jrs}(\mathbf{p}_{jrs}) - \sum_{k=1}^{T_k} \sum_{n=1}^{N_g} c_n(P_{g_{nk}}) \tag{6.26}$$

$$\text{subject to : Constraints in (6.25)–(6.34)} \tag{6.27}$$

$$p_{jrs} \in \mathrm{P}_{jrs}, \quad r \in \mathrm{R_j}, \quad s \in \mathrm{S_j} \tag{6.28}$$

where p_{jrs} belongs to the polyhedron P_{jrs} describing a set of linear inequalities and equalities. The P_{jrs} simply takes the following form

$$\mathrm{P}_{jrs} = \left\{ \boldsymbol{p}_{jrs} | p_{jrs}^{\min} \le p_{jrs}^{k} \le p_{jrs}^{\max} \right\}, \quad \text{if } k_{jrs}^{\mathrm{st}}, \ldots, k_{jrs}^{\mathrm{end}}, p_{jrs}^{\mathrm{k}} = 0, \quad \text{otherwise.} \tag{6.29}$$

The constraint (6.29) denotes the appliances/loads operate within a user's defined time window. The starting time within a time window can vary. Also, the operation is interruptible in the sense that the appliance can be stopped during operation. The load category defined in Sect. 6.4.1 includes the constraint (6.29). An example is the charging of energy storage in EV.

6.11.5 Bi-Level Optimization

A bi-level optimization is a mathematical program, where an optimization problem contains another optimization problem as a constraint [67]. Let us start with a simple example involving payoff maximization GenCos in the electricity market. The payoff is the difference of revenue earned by selling electricity and generation cost. However, the selling price is determined by EMO who solve MCM aiming to minimize operation cost and obtained market clearing price. In bi-level setting GenCos, payoff maximization is referred to an upper level and EMO's market clearing is referred to a lower-level problem. The bi-level optimization deals with a hierarchic decision-making between two independent and conflicting decision-makers [68]. Defining the upper-level decision vector by x and the lower-level decision vector by y, the bi-level programming problem can be provided as follows

$$\text{Minimize } F(x, y(x)) \tag{6.30}$$

$$\text{subject to: } G_i(x, y(x)) \leq 0 \tag{6.31}$$

$$H_j(x, y(x)) = 0 \tag{6.32}$$

$$\text{and subject to: } \left\{ \; y(x) \in \arg \text{Minimize } f(x, y) \right. \tag{6.33}$$

$$g_i(x, y) \leq 0 \tag{6.34}$$

$$h_j(x, y) = 0 \tag{6.35}$$

$$\left. x \in X, y \in Y \right\} \tag{6.36}$$

The upper level deals minimization of the objective function $G(x, y(x))$, and the lower-level deals minimization of the objective function $f(x, y)$. Both subproblems are subject to a set of constraint. The two problems are inter-reliant because the upper-level objective (6.31) and constraints (6.32)–(6.33) depend on the decision of the lower-level variables y. Similarly, the objective (6.33) and the constraints of the lower-level problem (6.34)–(6.36) depend on the upper-level variable x. The, $G(x, y(x))$ and $H(x, y(x))$ denote for an inequality and equality constraint functions in the upper-level problem, respectively. The, $g(x, y)$ and $h(x, y)$, respectively, denote inequality and equality constraints functions in the lower-level problem. Eq. (6.36) refers to a variable bound. Clearly, the lower-level problem is resolved assuming a fixed decision in the upper level. The main difference between the aforementioned bi-level optimization model (6.30)–(6.36) and a general optimization model (6.49)–(6.51) is the enforcement of the associated conditions set (6.33)–(6.36) which appears as constraints.

Figure 6.9 presents a bi-level optimization model. The upper level considers security constraint optimal power flow model. The lower level involves two optimization problems. The lower-level problem consists of two problems. The problem#1 represents a social welfare optimization in the DRX. The problem#2 represents an appliance scheduling model in the EMS. Consider as problem#2 in the lower level of the bi-level programming setup. In most of the cases, mixed integer linear programming (MILP) is used to solve the problem#2 due to a binary nature involved decision variables.

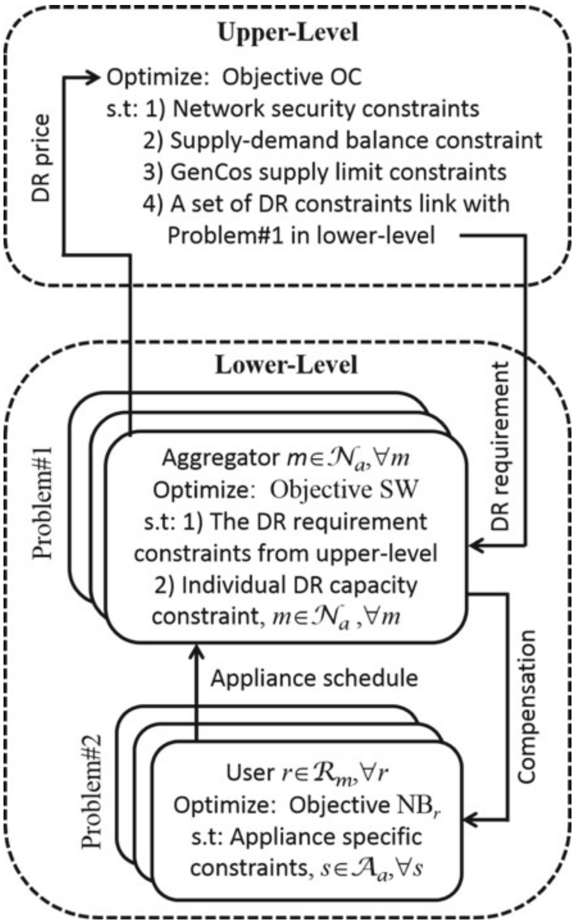

Fig. 6.9 Bi-level optimization model. There exist multi-objective versions of the bi-level optimization problems accommodating multiple objectives at one or both levels. The lower-level model consists of problem#1 and problem#2

A significant number of study consider the bi-level optimization model, for instance, offering strategy of bulk storage units [69]; supply-side capacity extension problems [70, 71]; demand bidding of big customers [72, 73]; wind energy firm integration without DR [74] and with DR [75, 76]; electricity trading model considering flexible demand-side resources [77–79] and so forth.

Assuming a Karush–Kuhn–Tucker (KKT) conditions are necessary optimality in the lower-level follower problem. Considering the KKK conditions, the bi-level optimization model can be modified to make equivalent single-level mathematical problem with equilibrium constraint (MPEC) as follows

$$\text{Minimize} \qquad F(x, y(x)) \tag{6.37}$$

$$\text{subject to:} \qquad G_i(x, y(x)) \leq 0 \tag{6.38}$$

$$H_j(x, y(x)) = 0 \tag{6.39}$$

$$\nabla_y f(x, y) + \sum_{i=1}^{m} \mu_i \nabla_y g_i(x, y) + \sum_{j=1}^{p} \lambda_j \nabla_y h_j(x, y) = 0 \tag{6.40}$$

$$\mathrm{g}_i(x, y) \leq 0 \quad \forall i = 1, 2, \ldots, m \tag{6.41}$$

$$h_j(x, y) = 0 \quad \forall j = 1, 2, \ldots, p \tag{6.42}$$

$$\mu_i \geq 0 \quad \forall i = 1, 2, \ldots, m \tag{6.43}$$

$$\mu_i g_i(x, y) = 0 \quad \forall i = 1, 2, \ldots, m. \tag{6.44}$$

where λ and μ, respectively, denote the dual variables related to constraints $g(x, y) \leq 0$ and $h(x, y) = 0$, the lower-level problem (6.33)–(6.36).

The benefit of above single-level devising is the replacement of the lower-level problem with the set KKT constraints in (6.37)–(6.44), which results in a single-level optimization problem that fits the general formulation (6.49)–(6.51). However, note that solving a single-level program is far from trivial. This is because the complementarity KKT conditions in (6.44) are non-convex and nonlinear.

Different methods to solve MPEC have been suggested, and the one in [3] is widely acceptable because of its simplicity. A complementarity condition (6.44) of the form $0 \leq \lambda \perp g(x, y) \geq 0$ can be substituted by the following set of linear constraints:

$$\lambda_i \geq 0; \quad g_i(x, y) \geq 0 \quad \forall i = 1, 2, \ldots, m \tag{6.45}$$

$$\lambda_i \leq (1 - u_i) M_{2i} \quad \forall i = 1, 2, \ldots, m. \tag{6.46}$$

$$g_i(x, y) \leq u_i M_{1i} \quad \forall i = 1, 2, \ldots, m. \tag{6.47}$$

where $M_i \in \mathbb{R}_{++}$ is sufficiently large positive constant and $u_i\{0, 1\}$ is binary variables.

Despite linearization of those constraints, added computational efforts may be required because of the existence of nonlinear cost function. However, the nonlinear terms can be approximated by a piecewise linear function. The usual practice is to submit generation blocks, $q > 0$, $\forall q \in \{1, 2, \ldots, Q\}$; supplier wants to sell at the price and constitutes segmented linear price-quota curves given by

$$c_n\left(P_{g_{nq}}\right)=\begin{cases} a_{n1}\left(Pg_n-P_{g_{n1}}\right)+b_{n1}, & P_{g_n}\leq P_{g_{n1}} \\ a_{nq-1}\left(P_{g_n}-P_{g_{nq-1}}\right)+b_{nq-1}, & P_{g_{n1}}<P_{g_n}\leq P_{g_{nq-1}} \\ \vdots & \vdots \\ a_{nk}\left(P_{g_n}-P_{g_{nq}}\right)+b_{nq}, & P_{g_{nq}}<P_{g_{nQ}}. \end{cases} \tag{6.48}$$

Each of the segments is discreetly linear and characterized by a slope and b_{nq} intercept. The coefficients are taken from [71]. The number of blocks and its size depends on individual capacities of the GenCos. In this paper, the block quantity index q is replaced by k to quantify changing generation profile at kth time step.

6.12 Some Key Implementation Issues

DSM should be coordinated with the end-users temporal order of activities and schedules. Primarily, the residential end-users have some crucial factors should be duly considered. Deferring household activities and appliances rescheduling sometime affect dependent activities. Thereby, we should deal with practicality of adopting such a beneficial technology in smart grid carefully to improve its functionality [80]. To participate in DR programs, users must reveal their willingness, preference, in-home activity data and so forth which may breach privacy [81]. Some of the critical implementation issues are as follows:

6.12.1 Privacy Preservation

Privacy and contextual integrity are one of the vital human rights. The DLC-based DR activities and behaviour by mining time-based consumption data in a smart grid at sub-hourly intervals may jeopardize customer privacy. The DR programs provide detailed interval electricity consumption data in real-time nature. Such data having occupants' activities have interest in access and may be reused or misused by the third party; hence, require some privacy protection measures.

6.12.2 End-User's Engagement

Usually, end-users have very little practical knowledge about their flexibility and usually unaware of their usage patterns and behaviour. Hence, participants in DR programs usually show lower response than expected levels. Aggregators require analysing the flexibility, passing financial benefits of dynamic electricity pricing and advertise properly to engage more end-users actively. The aggregator categorizes the end-users into different groups based on interval energy consumption and usage characteristics, such as the type of appliances used and its DR flexibility. The level of involvement of DER and ES is also a concern which is needed to be taken into consideration.

6.12.3 DR Rebounding

DR rebounding in DSM is a secondary peak demand scenario after mitigating the primary one, which usually appears due to quick activation of those loads which were inactive or partially active in DR events. Figure 6.10 illustrates the phenomena. According to [82], the DR rebounding could be improved by coordinating the onsite DER, rational energy pricing model and last but not least by behavioural change of energy consumption.

6.13 Summary and Conclusions

This chapter presented different aspects of the DSM for the smart electricity grids. Techno-economic management of the DR in emerging power system is crucially important and has a lot of financial benefits. Varieties of DR resources have been categorized, DR programs practised are discussed, and how automated DR system work is explained. The DR implication model comprises smart meters, and energy management scheduler is outlined. The key DR enabler such as the AMI and the

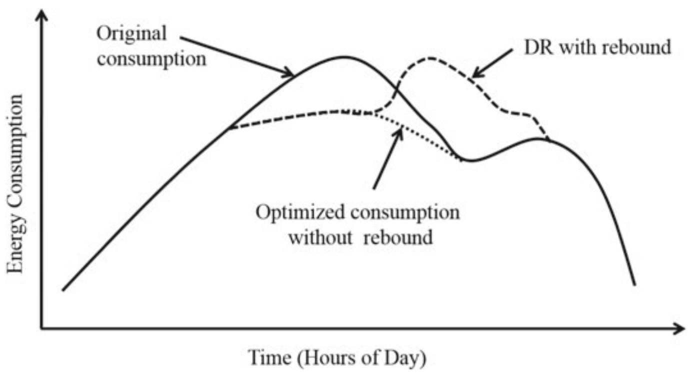

Fig. 6.10 Illustration of DR rebounding, appear due to quick activation of those loads which were inactive or partially active in DR events [83], Reprinted by permission from IEEE Transactions on Industrial Informatics, "Demand Side Management: Demand Response, Intelligent Energy Systems, and Smart Loads", Peter Palensky et al. © 2014

EMS rapidly rollout in different power systems over the world is discussed. The emerging transactive approach of electricity market models both for the wholesale and retail levels are briefly outlined. The importance of the DRX market mechanism and the role of EMO, aggregator and end-user are explained. A few reported DR mechanism models and applications are compared.

The DR programs are divided into three classes: (1) indirect load control (2) direct load control, and (3) transactive approach, respectively. For the indirect load control, different price-based tariffs have been reviewed. In a majority of the case, dynamic RTP-based programs in the direct load control are found popular. The transactive approach of electricity market models, both for the wholesale and retail levels, are discussed. With this approach, DR trading decisions are made based on a monetary value while respect power system and individual resources constraint. Details on bi-level optimization models and the solution methods are discussed. Also, some examples are provided to illustrate the realistic DR market mechanism. The DR optimization objectives with strength and weakness are reported. Some implication issue like DR rebounding, privacy breaching may raise in DR are outlined at the end.

6.14 Further Reading

Readers interested in a wide-ranging synopsis of the strategic DR initiatives undertaken in North America and European electricity markets are referred to [9, 84, 85]. Further on the DSM mechanism and pricing policy can be communicated with [36]. An equivalent thermal model of HVAC for a commercial facility is presented in [86]. Supplementary reading on DR model for industrial customers is referred to [20, 23, 26, 27]. A practical transactive DR model can be referred to [87]. The optimization models presented in Sect. 6.11.5 are based on techniques of bi-level programming and complementarity modelling [56, 67, 88, 89]. The reader interested in applications of the complimentary modelling to electricity markets is advised to read [90]. The Appendix is referred to revisit basic of optimization formulation and solution approach, while several textbooks [91, 92] discussing the topic at a tertiary stage. For a comprehensive overview on CVaR-based stochastic optimization, the interested readers are referred to [47].

Appendix: Optimization Methods Revisit

Optimization is a method to obtain the optimal variables that suggest minimum cost or maximum welfare of an objective function. The variables in the optimization problem are subject to a set of constraints [40]. The variables may be scheduling consequences of the physical process. Constraints can be categorized as a hard or soft constraint. The first constraint is the condition that must be satisfied. The latter has some degree of flexibility to select the variable. It can penalize objective if the conditions set of variables are not satisfied [93]. Further, the optimization can be characterized based on polynomial nature of the objective function. If at least one of the objective function is nonlinear, the optimization is said to be a nonlinear optimization, otherwise linear one. If some of the variables are integers, the optimization is said to be a mixed integer optimization. The integer variables take care of yes/no decision on the concerned variable. Additionally, the variables in a problem may be deterministic or the stochastic. Accordingly, the optimization can be categorized into deterministic and stochastic optimization problems. A constraint optimization model involving the equality and inequality constraints is provided in the next section followed by a step by step solution process.

Formulation of an Optimization Problem

An optimization problem in general form is given by [88].

$$\text{Minimize} \quad f(x) \tag{6.49}$$

$$\text{Subject to :} \quad g_i(x) \leq 0, \quad i = 1, 2, \ldots, m \tag{6.50}$$

$$h_j(x) = 0, \quad i = 1, 2, \ldots, p \tag{6.51}$$

where $x \in \mathbb{R}^n$ is a vector including n optimization variable. The objective function $f(x) : \mathbb{R}^n \to \mathbb{R}$ is differentiable convex functions. The $f(x)$ maps the variable x close to a real value depicting the desirability of a solution to the decision-maker. Usually, the $f(x)$ represents a cost function in minimization problem and a payoff in maximization problem. The $g_i(x) : \mathbb{R}^n \to \mathbb{R}$ and $h_j(x) : \mathbb{R}^n \to \mathbb{R}$, respectively, represent inequality and equality constraint of the problem. There are such m number of equality and p number of inequality constraints exist in the optimization. The simplest form of an optimization model is a linear programming problem. This is obtained when the objective functions (9.49) and the constraints (6.50) and (6.51) are linear. A linear programming problem can be reformulated as

$$\text{Minimize} \quad c^{\mathrm{T}}x \tag{6.52}$$

$$\text{Subject to :} \quad A_I x \leq b_I \tag{6.53}$$

$$A_E x = b_E \tag{6.54}$$

$$x_l \leq x \leq x_u \tag{6.55}$$

It is worthy to note that functions $f(\cdot)$, $g(\cdot)$ and $h(\cdot)$ are affine expressions involving b vectors and matrices A. In (6.52), the term $c \in \mathbb{R}^n$ is the cost coefficient of the optimization variable, x. The inequality matrix, $A_I \in \mathbb{R}^{p \times n}$, and $b_I \in \mathbb{R}^m$ define the m linear inequality constraints (6.53). The equality matrix, $A_E \in \mathbb{R}^{p \times n}$, and $b_E \in \mathbb{R}^p$ define the p equality constraints (6.54). The constraint (6.55) denotes the variable bonds within lower x_l and upper x_l limits. The linear programming deals with a wide variety of practical problems including economic dispatch, unit commitments, supply and demand-side bidding and so forth.

Duality in Linear Programming

Defining a new set of m variables $\mu \in \mathbb{R}^m$ for inequality (6.53) and set of p variables $\lambda \in \mathbb{R}^p$ for equality (6.54), one for each constraint, there is a corresponding dual problem associated with the primal problem (6.56)–(6.58) discussed earlier given by:

$$\text{Maximize} \quad b_I^{\mathrm{T}}\mu + b_E^{\mathrm{T}}\lambda \tag{6.56}$$

$$\text{subject to :} \quad A_I^{\mathrm{T}}\mu + A_I^{\mathrm{T}}\mu = c \tag{6.57}$$

$$\lambda \geq 0. \tag{6.58}$$

The dual problem in (6.56)–(6.58) is a transposed form of the primal problem. Note that, the primal and dual are through deals objective function minimization. However, it holds for objective function maximization, by minimizing its negative.

Lagrangian Function

Assuming $m = p = 0$, the problem is said to be unconstrained and the optimal solution of $f(x)$ simply occurs at a point x^* if $\nabla f(x^*) = 0$, i.e. at those x^*, where the first derivative of the objective vanishes. This is called first-order necessary conditions [93]. In a constrained optimization, the decision variable $x \in \mathbb{R}^n$ is said to be feasible, if it satisfies the bound constraints (6.53), (6.54) and (6.55). Additionally, amid the set of possible variables, the one produces the minimum value of the function (6.52) is said to be optimal. In this case, first-order necessary conditions for optimality written by adding weighted sum of the constraints to the objective give the Lagrangian in the following form [93, 88].

$$\mathrm{L}(x, \alpha, \beta) = f(x) + \sum_{i=1}^{m} \mu_i g_i(x) + \sum_{j=1}^{p} \lambda_j h_j(x) \tag{6.59}$$

The weighting elements of $\mu \in \mathbb{R}^m$ and $\lambda \in \mathbb{R}^p$ are collectively named as dual variables of Lagrangian function.

Karush–Kuhn–Tucker (KKT) Conditions

Assuming some regularity conditions for problem (6.52)–(6.55), if the optimal $x^* = (x_1^*, x_2^*, \ldots, x_n^*)$ minimize objective $f(x)$ in (6.52), subject to the constraints (6.53) and (6.54) then there exist some dual optimal $\mu^* = (\mu_1, \mu_2, \ldots, \mu_m) \geq 0$ and $\lambda^* = \left(\lambda_1^*, \lambda_2^*, \ldots, \lambda_p^*\right) \geq 0$ such that

$$\nabla f(x^*) + \sum_{i=1}^{m} \mu_i \nabla g_i(x) + \sum_{j=1}^{p} \lambda_j \nabla h_j(x) = 0 \tag{6.60}$$

$$g_i(x^*) \leq 0 \quad \forall i = 1, 2, \ldots, m \tag{6.61}$$

$$h_j(x^*) = 0 \quad \forall j = 1, 2, \ldots, p \tag{6.62}$$

$$\mu_i \geq 0 \quad \forall i = 1, 2, \ldots, m \tag{6.63}$$

$$\mu_i g_i(x^*) = 0 \quad \forall i = 1, 2, \ldots, m \tag{6.64}$$

The first set of KKT in (6.60) is known as stationarity condition found by differentiating the Lagrangian (6.59) concerning the relevant variables and then equating to zero. Constraints (6.61) and (6.62) enforce feasibility of the primal variables, while the constraint in (6.63) is feasibility of the Lagrangian multipliers. The constraint in (6.64) enforces complementary slackness which is also known as KKT complementarity. Complementary slackness can be rewritten in many equivalent ways. One way is the pair of conditions given by

$$\mu_i^* > 0 \Rightarrow g_i(x^*) = 0, \quad \forall i = 1, 2, \ldots, m \tag{6.65}$$

$$g_i(x^*) < 0 \Rightarrow \mu_i^* = 0, \quad \forall i = 1, 2, \ldots, m \tag{6.66}$$

Another way, the notion in (6.65), (6.66) can be compacted in the following form given by (6.67)

$$0 \leq \mu_i^* \perp g_i(x^*) \geq 0, \quad \forall i = 1, 2, \ldots, m \tag{6.67}$$

The orthogonality sign $\perp$ in (6.67) of the form $0 \leq \mu_i^* \perp g_i(x^*) \geq 0$ indicates, at most one between the dual, $\mu \in \mathbb{R}^m$ or the constraint, g associated with the dual $\mu \in \mathbb{R}^m$ can take a strictly nonzero value [93].

Economic Interpretation of the Dual Variables

It is worthy to mention that the dual variables $\mu \in \mathbb{R}^m$ and $\lambda \in \mathbb{R}^p$ have key to an economic explanation. In economics, it refers to a marginal worth of any resources [88]. These are also known as shadow price. Indeed, shadow price penalizes objective function marginally for unit variation in the variable value. In minimization problem, dual variable non-negative $\mu \geq 0$; while for a maximization problem, it is negative, $\mu \geq 0$. In fact, a marginal change of any component of the inequality vector $b_I \in \mathbb{R}^m$ would yield a narrower solution space, thereby achieve an inferior value of the objective function.

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