

# **Demand Response in Future Power Networks: Panorama and State-of-the-art**

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### **Abstract**

One of the key features of future power networks, referred to as smart grids, is deploying demand side resources in order to reduce the stress at the supply side. This implies the active participation of electricity customers, as a societal network, in the power networks, as a physical network, which makes these two networks interdependent due to the effect of demand response programs on the power systems. Furthermore, in the future smart cities there is an exigent need to take advantage of demand side resources to supply the electricity in a sustainable manner. In this context, demand response programs play a pivotal role in the electricity market in order to achieve supply-demand balance by taking advantage of the load flexibility.

In this chapter, we provide a thorough review of the state-of-the-art approaches to implement demand response programs in the smart grid environment. To this end, we first introduce the available methods to model the load participation in the demand response programs, such as game theoretic frameworks, price elasticity, and direct load control. We then review the methods for integrating demand side resources into the power systems. Several aspects of demand response programs are reviewed in this chapter. Finally, an overview of the recent advances in demand response literature is presented.

**Keywords: Demand response, smart grid, power market, load management, bidding strategy, decision making frameworks, power systems, demand side management**

## **1. Introduction:**

### **1.1.Overview:**

One of the key features of future power networks, referred to as smart grids, is deploying demand side resources in order to reduce the stress at the supply side. This implies the active participation of electricity customers, as a societal network, in the power networks, as a physical network, which makes these two networks interdependent due to the effect of demand response programs on the power systems. Furthermore, in the future smart cities there is an exigent need to take advantage of demand side resources to supply the electricity in a sustainable manner. In this context, demand response programs play a pivotal role in the electricity market in order to achieve supply-demand balance by taking advantage of the load flexibility.

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### **1.2. Available Methods to Model the Demand Response Programs**

Demand response programs are defined as the end users' activities to change the electricity consumption pattern for mitigating the system problems [1]. Due to the increased consumption level, these programs are attractive for system operators, as well as customers [2, 3].

In order to assess the impact of Demand Response Programs (DRPs) on power system studies, multifarious models are developed in recent years. Economic models of responsive loads based on the concept of constant price elasticity have been addressed in references [4]-[8]. Schweppes and his co-workers developed the concept of spot pricing of electricity to evaluate variable costs of electric energy on an hourly basis and proposed three responsive load models, namely linear, potential and exponential demand functions [9]. A customers' response to the optimal real time prices has been modeled in [10] for the electricity applying multifarious mathematical load models. An optimization model to adjust the hourly load level of a given consumer in response to hourly electricity prices is

proposed in [11]. The further study utilizes up/down ramping rates to model variation in customer load. An approval function based on the acceptable energy costs for different clusters of customers has presented in [12]. Moreover, the customer's behavior versus the offered fixed prices for monthly bilateral contracts applying a type of market share function is proposed in [13]. Reference [14] has employed analytical and technical approach to validate the impact of DRPs. Customer baseline load (CBL) focusing on administrative and contractual approaches is applied for DRPs modeling in [15]. Moreover, the impact of demand response (DR) through optimization methods has presented in [11], however, intelligent approach such as multi-agent based and fuzzy logic method is used to model demand response [16, 17]. Authors in [18] have developed two markets for designing DRPs to match power supply and demand. DR models based on participation information of DRRs which are suggested in [18] can be useful for evaluating DR resources' values. Kirschen showed how this model could be taken into consideration when scheduling generation and setting the price of electricity in a pool based electricity market [19]. Market clearing programs are discussed in [20, 21], which takes their economic benefits in to account. An economic model of responsive loads has been derived and used for multifarious studies in [22]-[32]. In references [22]-[32], the elasticity of demand is considered as a fixed value for different values of incentive and penalty, which cannot precisely represent the customers' behavior. Therefore, in [33], extracting a dynamic economic model of responsive loads is suggested based upon the concept of "flexible elasticity of demand" and "customer benefit function". Indeed, under the smart grid environment, the short-term elasticity of demand can be suggested. Therefore, introducing the flexible elasticity as a consequence of smart electricity grids cause to more precise modeling of DRPs and hence, the rate of consumption decreasing coincides with the ISO perspectives from implementing demand response programs. References [4]-[33] have not assumed that demand response resources might fail or be perfidious to decrease their consumption. In other words, the previous studies have not concentrated that demand response resources are unstable, changeable and unpredictable. Additionally, Advanced Metering Infrastructure (AMI) system as a part of growing smart grid initiatives provides significant foundational platforms for demand response resources in response to the demand response events. It means that any destruction in AMIs can affect demand response

resource's participation while this serious matter has not been regarded in previous demand response models. In reference [34], a systematic method based upon frequency and duration approaches is utilized to present the multi-state modeling of multiple demand response resources considering repairable advanced metering infrastructures, the so-called demand response firm. In reference [34], a set of DRRs such as homes, industrials, large buildings, etc., which have the potential of participating in demand response programs and communicate with demand response aggregator through AMIs, are introduced as a negawatt Demand Response Firm (DRF). DRF is assumed as a virtual power plant that is similar to conventional units with derated output states. The failure and repair rates of AMIs are non-negligible in customers' participation in demand response programs. In this regard, the impact of several important factors like demand response firms' maximum achievable potential and forced outage rate of advanced metering infrastructures on the proposed model are assessed. Also, the effect of number of advanced metering infrastructures on the distribution probability of demand response firm states is investigated in [34].

Amini et al [35] proposed a multi-agent framework for load management in smart power distribution networks. In their framework, they modeled the distributed generation units as well as direct load control to achieve a peak reduction-based load management strategy. Moreover, a residential load management strategy was proposed by Amini et al [36] for the home appliances using mixed integer linear programming. Demand response programs may also affect the behavior of electric vehicle drivers, for instance, different pricing strategies (e.g., real time pricing, time of use pricing, and critical peak pricing) can considerably affect the behaviour of drivers [37]. Another aspect of implementing demand response programs is maintaining end-user privacy [38] and prevent adversaries to access the private information of customers.

## **2- Emerging methods to model Demand Response programs**

To make an easier interaction among customers and ISO for performing DR, DR

aggregators have been introduced. Likewise, DR aggregators play an important role to achieve all targets of DR implementation such as reducing peak demand, improvement the power systems security, decreasing the negative effects of renewable energy sources (RESs) uncertainties on power system operation and enhancement of economic aspects of the electricity market. In fact, DR aggregators are as an interface among customers and ISO to enter customers into the wholesale market.

In [39], the interaction among independent system operator (ISO) and DR aggregators has been presented through four options including load curtailment (LC), load shifting (LS), onsite generation and energy storage (ES) systems. In this method, DR aggregators submit the aggregated DR offers to ISO. Therefore, ISO makes the final decision about DR contribution in a day-ahead market through mixed-integer linear programming. This program has been solved by minimization of total operation cost. The framework of this model is demonstrated in Fig. 1.

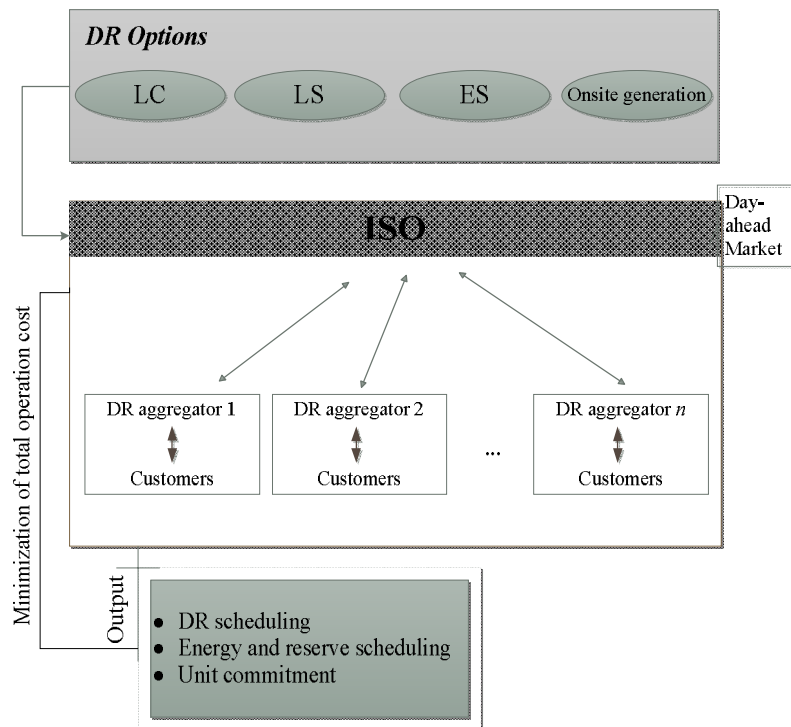


Fig. 1. Framework model of reference [39]

On the other hands, the interaction between DR aggregators and customers has been

taken into account in [40]. In this research work, the small or medium scale of customers offered their potential to participate in the market. In fact, the DR aggregators proposed four options including LC, LS, ES and onsite generation to customers for hourly demand response. Through maximization of DR aggregators' profit, optimum DR schedule for participation in the day-ahead energy market is obtained. This model is outlined in Fig. 2.

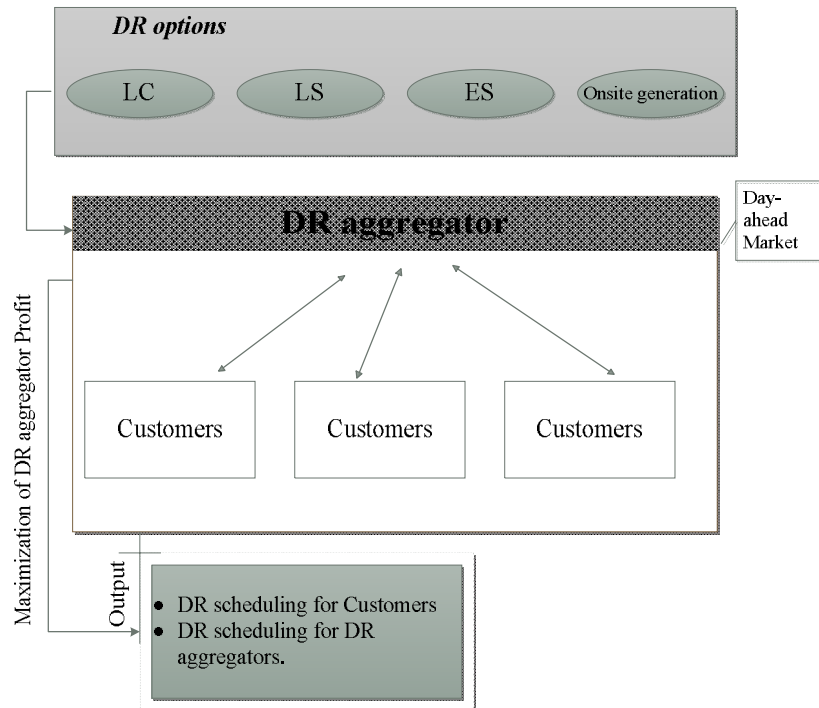


Fig. 2. Model of the reference [40]

In [41], on one hand, the interaction between ISO and DR aggregators and on the other hand the interaction between DR aggregators and customers has been taken into account, separately. The behavior of customers in DR programs including LC, LS and load recovery (LR) has been considered through a scenario-based participation factor. Moreover, uncertain prices were presented in day-ahead and balancing markets as well as predefined prices in forward contracts for trading share of DR between ISO and DR aggregators. This model is shown in Fig. 3.

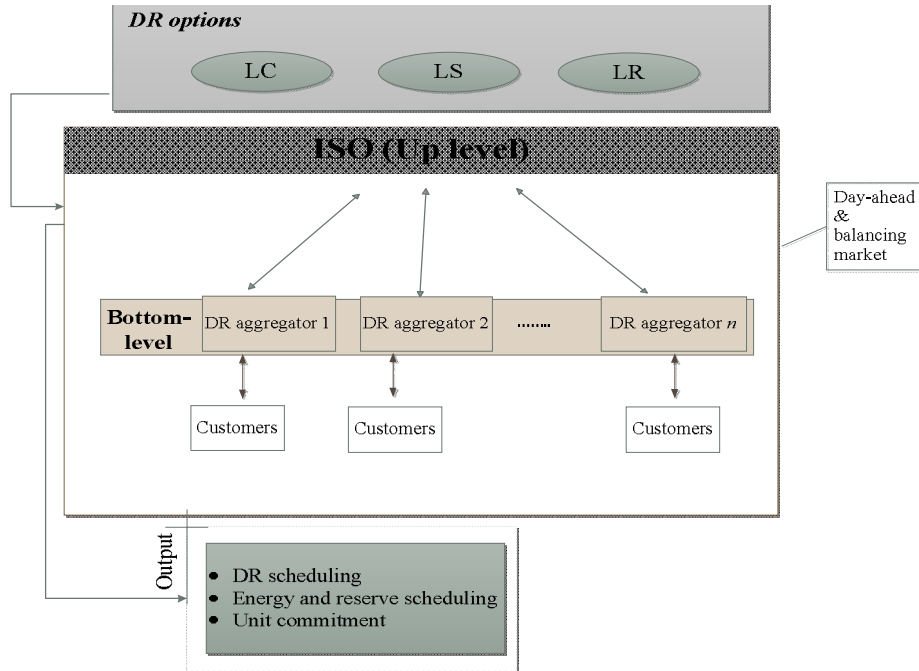


Fig. 3. Flowchart of model [41]

The interaction between load serving entity (LSE) and customers are formulated in a bilevel programming in [42]. In this model, LSE is the leader, and DR aggregators are the followers. LSE serve flexible loads with dynamic pricing tariff and inflexible loads with the fixed tariff. Flexible loads are integrated by some DR aggregators. Therefore, interaction among LSE and DR aggregators is in upper-level and the interaction among DR aggregators and customers is in the lower-level. Finding the optimal pricing tariff is the solution of this problem. The model is described as a flowchart in Fig. 4.



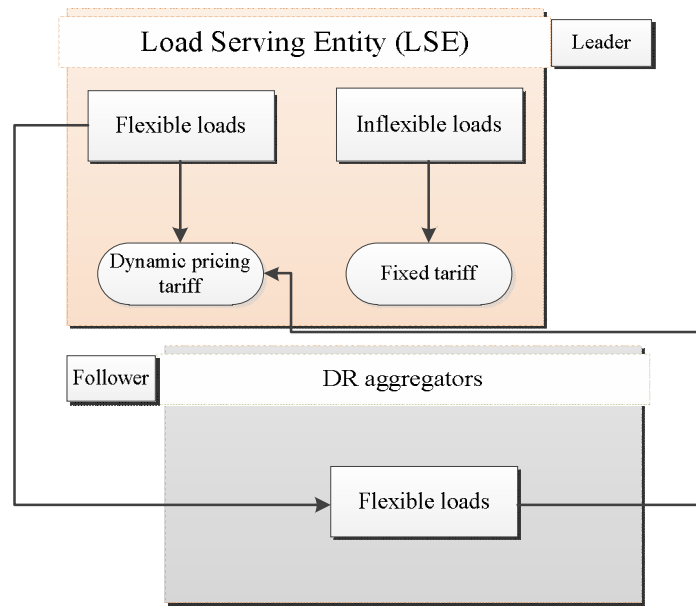


Fig. 4. Proposed model in reference [42]

To reduce the impact of thermal generation units ramping cost on operation cost, hourly demand response program is proposed in [43] in a day-ahead market. Balancing constraints, ramp constraints and DR constraints are formulated in a mixed integer quadratic constrained programming for a day-ahead scheduling. The Lagrange relaxation method to solve this problem is shown in Fig. 5.

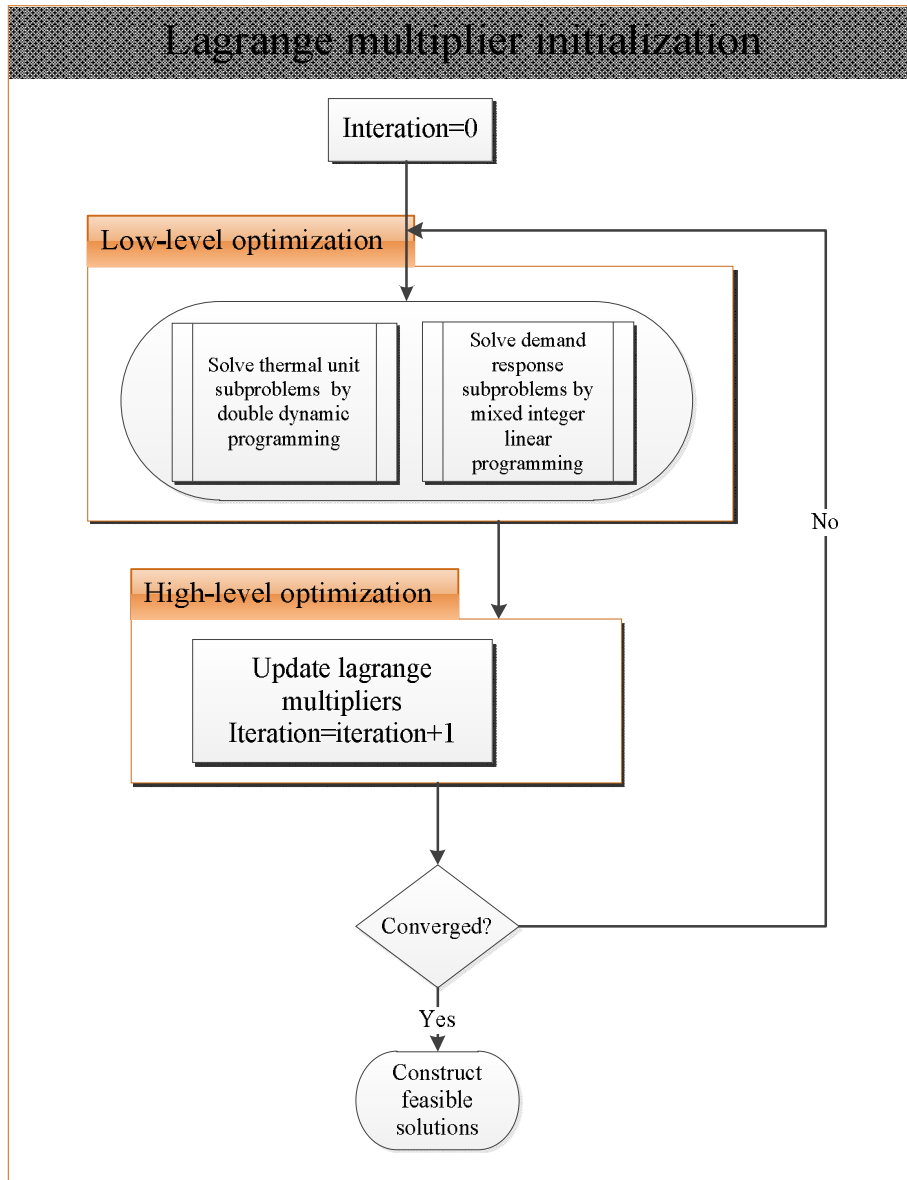


Fig. 5. Proposed LR method in reference [43]

### 3- The Integration of Demand Response Programs with other power system models

Three different kinds of demand response programs including centralized co-optimization of generation and demand, demand bidding and coupling of renewable energy resources (RES) with deferrable loads have been applied in [44] to evaluate the impact of large-scale RES penetration and demand response on reserve scheduling. In fact, a stochastic unit commitment is run in a network with large-scale RES to obtain the reserve requirements for three different kinds of demand response. Moreover, the coupling of these

demand response programs to cope with the weakness of each one has been evaluated. The model is described in the flowchart of Fig. 6.

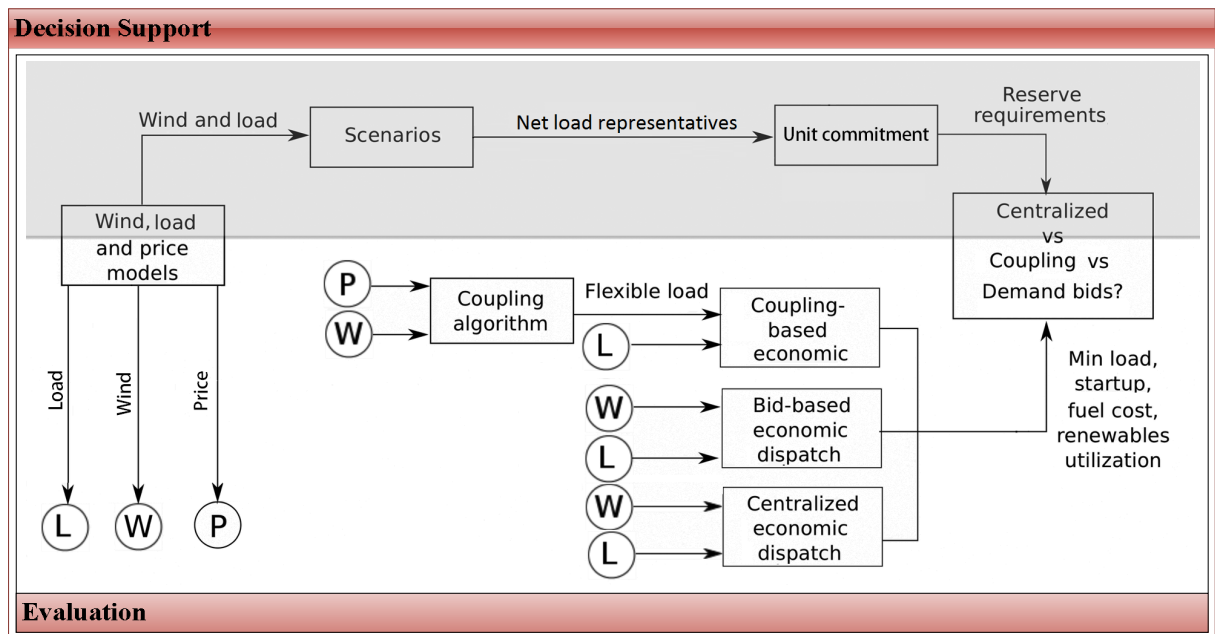


Fig. 6. Flowchart of model [44]

In [45], a dynamic market mechanism has been proposed to get the market equilibrium by dynamic negotiations among key market players. Meanwhile, DR is presented to overcome the variability of renewables. This market mechanism considers DR devices based on the magnitude, runtime and constraints of demands. The level of desired social welfare has been analyzed eventually by a combination of DR devices in the presence of renewables.

The optimal behavior of plug-in electric vehicle (PEV) parking lots is presented in [46] for energy and reserve market. To this end, parking lots are considered as responsive loads either in price-based or incentive-based demand response programs. Therefore, the effects of different demand response programs on parking lots are elaborated, and the participation level of parking lots in demand response programs can be obtained. A stochastic programming has been applied to solve this problem by considering electricity market and PEVs uncertainties.

Amini et al. [47] modeled the effect of electricity price on the electric vehicle owner's behavior. According to [48], allocation of electric vehicle parking lots plays a crucial role in smart distribution networks. Further, Amini et al. [49] presented a two-stage optimization framework to optimize the distribution network's loss. In their method, they considered the benefits of electric vehicle parking lot's investor as well as the distribution network operator. The uncertainty of renewable resources is modelled by capacity credit concept. Mozafar et al. [50] proposed a comprehensive framework for large-scale integration of vehicle-to-grid and grid-to-vehicle systems in future power networks.

Paper [51] evaluates the unsupervised charging of plug-in electric vehicles (PEVs) at the dwellings. It presents a statistical modelling and a closed-form statistical expression for PEVs' uncoordinated expected charging power demand.

A distributed demand response (DR) technique is proposed and evaluated for residential vehicle-to-grid (V2G) enabled PEVs during their random connection times to the power grid in [52]. The authors show that their proposed fast converging and distributed DR algorithm is successful in managing the charging tasks of 1,000 PEV users in order to minimize the peak of the aggregated daily power demand profile and make the peak demand even the same as when there is no PEVs in the system, without any changes in the users' commuting behaviours and by preserving their privacy.

In [53] and [54], a decentralized algorithm for managing V2G enabled PEVs' electricity assignments (charging and discharging) to lower the overall electricity procurement costs for electricity retailers bidding to operational day-ahead (DA) and real-time (RT) markets. The proposed algorithm jointly uses DA demand shaping and RT demand altering for the DA and the RT markets, respectively.

The importance of reducing the emissions of greenhouse gases (GHGs) has been captured in the proposed DR technique by the authors of [55]. They illustrate that with some incentives and/or regulations from the power system regulator, the retailers or aggregators could help lessen GHGs emissions by using their proposed decarbonized demand response (DDR) technique.

The impacts of demand response on the reliability of power systems through different electricity market mechanism have been analyzed in [56] from technical, economic and

environmental aspects. The main goal of this work is providing the balancing active power, enhancing system reliability and maintaining grid stability through demand response in different electricity market schemes. Different demand response programs based on the market is presented in Fig. 7.

Therefore, power system reliability, which can be dropped due to unexpected generation or transmission line outages, can increase by applying demand response programs in electricity market instead of some conventional approach from generation side.

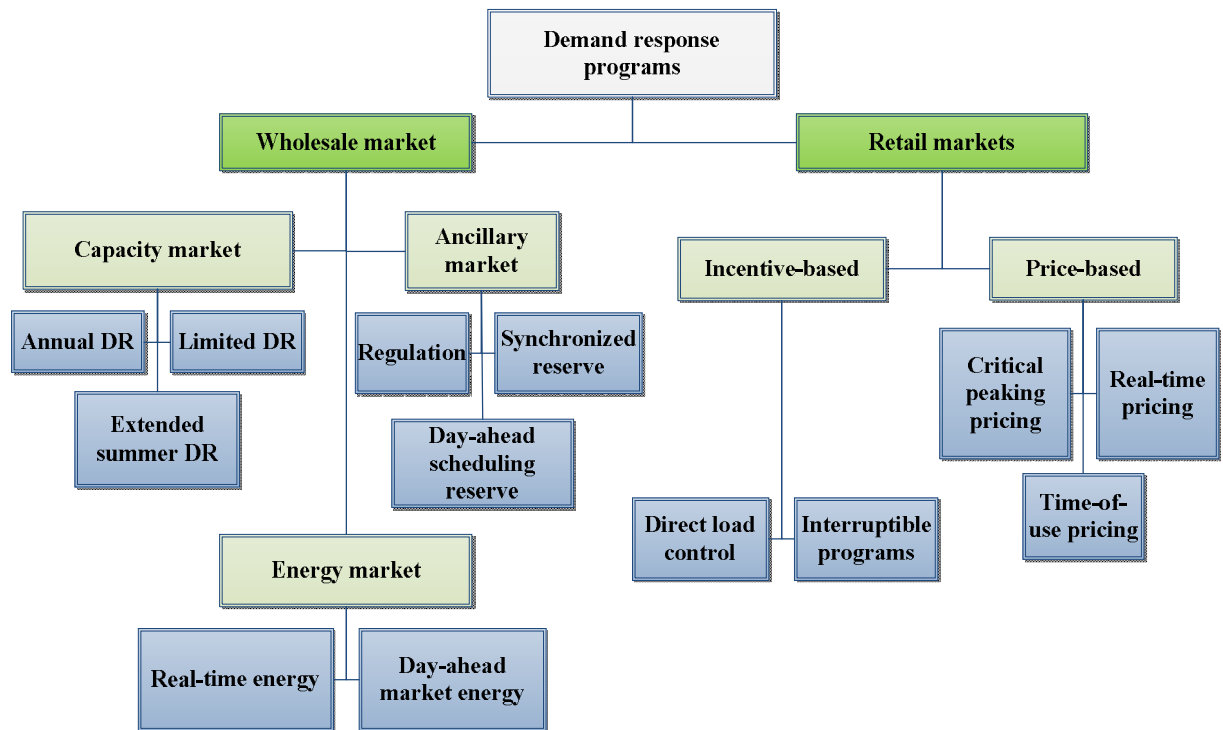


Fig. 7. Demand response programs based on markets [56]

In [57], a stochastic day-ahead scheduling for a microgrid has been conducted, and the impact of ancillary service demand response program on total operation cost has been studied. Stochastic nature of RESs including wind farms and photovoltaic systems as well as loads have been considered through Monte-Carlo simulation method and generation of lots of scenarios. Likewise, the outage probability of distribution generators (DGs) inside the microgrid and probability of disconnection of upstream network and microgrid have

been included through this approach.

The problem has been solved by a stochastic two-stage programming in a mixed-integer linear programming. To this end, in the first stage, the day-ahead market is cleared through a have a look at different scenarios for balancing market in the second stage. The framework of proposed model is presented in Fig. 8.

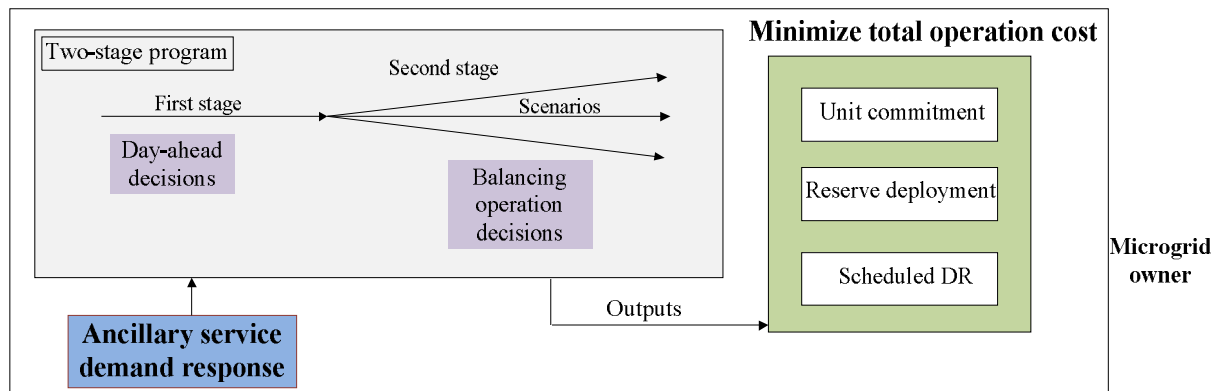


Fig. 8. The framework of proposed model in [57]

#### 4- The Effect of Demand Response Programs on the Short-Term Participation Strategy

In a short-term perspective, electricity market participants deal with bidding and offering strategy problem every day. They should trade energy in the day-ahead market in a high level of uncertainty. In such conditions, they can increase their profit by devising a proper method for their participation strategy. These methods have been widely reported and analyzed in the literature [58]-[62]. These methods help the decision maker to analyze the market and its uncertainties economically.

In addition to the economic tools, electricity companies can get benefit from physical sources and contracts. For example, bilateral contracts can effectively reduce the risk of participation in the day-ahead market [63]. Self-generation is a perfect option for retailers to hedge the risk of buying energy from the uncertain day-ahead market [64]. Hybrid companies that manage generation companies in one side and retailers and load aggregators on the other sides, can strongly control the associated risk of day-ahead market [58]-[60].

Demand response programs (DRPs) can also be used as an effective tool for reducing the risk of participation strategy of electric companies in the short-term day-ahead market. Hybrid companies can use the advantages of DRPs in their offering strategy methods. The diagram of hybrid companies is provided in Fig. 9. As can be seen from this figure, the Hybrid companies are managing both of generation and retail sides, together. There is an internal energy transaction between these two parts. The external energy in the generation company (GenCo) is sold in the day-ahead market. The retail part submits its bids to the day-ahead market to buy the external consumption. The retail side has two types of contract with its clients. The first one is regular contract based on the fixed pricing; and the second one is DRP-based contract.

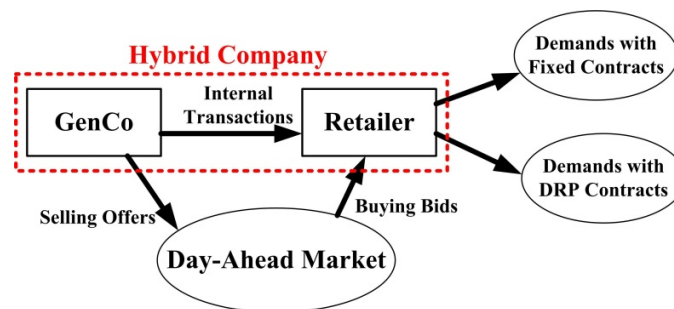


Fig. 9. Diagram of hybrid companies considering DRP contracts

It is worth to mention that only short-term DRPs can affect the short-term bidding and offering strategy of electricity companies. The longer-term DRPs such as Time of use programs are known during the scheduling horizon of one day. As an example of short-term DRPs, the day-ahead real time pricing (DA-RTP) can be mentioned in which, the predicted prices of day-ahead market are sent to the contracted loads, one day before operation, to schedule their consumption. In DA-RTP contracts, the customers' base load (CBL), which is defined base on the consumption history of clients, is used to calculate real-time payments [58]-[60]. This process is better illustrated by Fig. 10. In this figure, the CBL and actual consumption are plotted for a three-hour horizon. As can be seen, during the first interval the real consumption is higher than contracted level of CBL. Thus, the customer should pay the extra consumption to the company base on the real-time prices sent to him/her, one day before. This procedure is reversed during the third interval. In this

period, the company will charge the client's account base on day-ahead prices. During the second interval in which, the consumption is exactly equal to the contracted CBL, no real-time payment is considered.

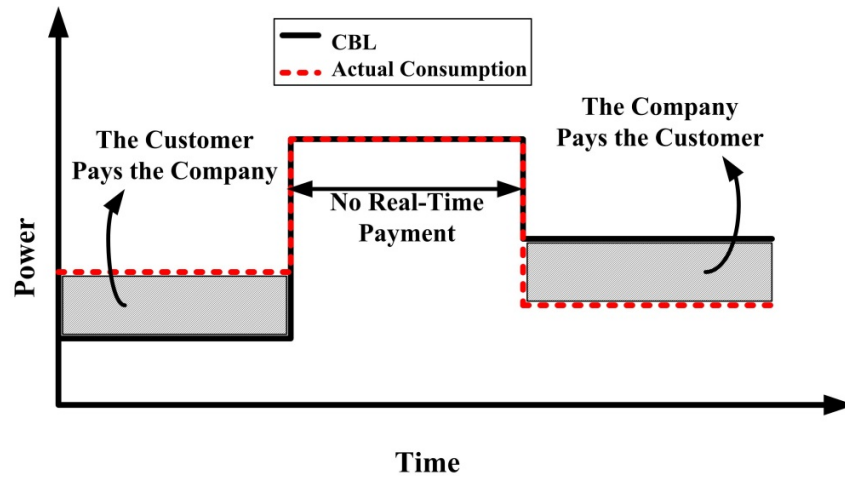


Fig. 10. Real-time payments of DA-RTP program

In order to analyze the effect of DA-RTP programs on the short-term participation strategy of hybrid companies, we have divided them into two categories, price-taker and price-maker companies. The following subsections investigate this effect separately.

#### A. The effect of DA-RTP programs on price-taker companies

Comparing to the whole network capacity, a price-taker company is small enough in the size, that its bidding or offering strategy would not affect the market price. Therefore, it is common in the literature of such companies to use the prediction of day-ahead prices to evaluate the optimum participation strategy [58]. The diagram of this method is simply provided by Fig. 11.

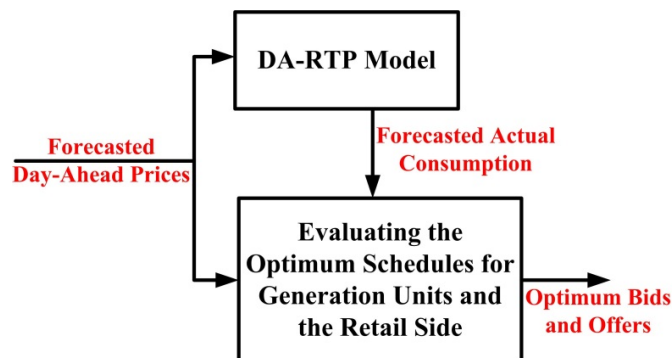




Fig. 11. The diagram of DA-RTP programs on the scheduling of price-taker hybrid companies

From this figure, the forecasted day-ahead prices are the input of two blocks. The upper one model the behavior of DA-RTP contracted clients. For this purpose elasticity coefficients can be used to calculate the actual level of consumption in the retail side [65]. The second block uses both of predicted prices and actual consumptions to evaluate the optimum schedule for the generation units and the retail side.

In this way, DA-RTP programs can be considered as a feedback in the short-term scheduling of electricity companies. For example, during the days that day-ahead price is forecasted to be high, it is more profitable for the company to sell more power in the market instead of feeding the contracted loads of retail side. In this situation, the DA-RTP program would reflect the high level of the next day's price to the customers and they will reduce their consumptions to get benefit. In this way, the company would have more capacity to participate in the day-ahead market. This situation is reversed during the low price days. It can be concluded, DA-RTP programs can reduce the risk of uncertain prices. DA-RTP programs will compensate the level of contracted loads in a way to be profitable for the company.

#### **B. The effect of DA-RTP programs on price-maker companies**

This problem for price-maker companies is more complicated, because their strategy would affect the market price significantly. Here, instead of forecasting the market price, rivals' bids and offers should be predicted and base on that, the optimum participation strategy can be evaluated [60]. This procedure leads to a bi-level optimization problem. In the first level the company's profit is maximized; and in the second level, the market clearing process is simulated.

In addition to the previously mentioned advantage of DA-RTP programs, i.e., reduction the associated risk of forecasted parameters, it can also be useful in removing line congestion. Transmission line congestion may result in different nodal prices. In its extreme, the system operates in islanding mode, electrically not physically. This extreme situation can lead to a very high price in the created island. Therefore, the congestion may increase the cost of feeding contracted demands in the retail side. DA-RTP programs are strong feedbacks that can remove congestions. If the price is increased due to the line

congestion, this would be reflected to the demand side by DA-RTP programs. By this feedback, the affected loads will reduce their consumption and the congestion can be removed.

### **5- Market Strategies of Demand Response Players (DR Aggregator, Electricity Retailer, Wind Power Producer)**

DR programs were firstly proposed with the aim of mitigating the deficiencies of the systems. However, nowadays, these programs are considered as virtual resources, due to their high potential in power system studies [66, 67].

Demand Response (DR) has been widely developed in electricity markets, where a great deal of attention has been paid on how to model various load management programs for electricity consumers. The recent challenges in electricity markets, however, urge the need for active involvements of DR in wholesale electricity markets, which indeed introduces DR aggregators as new entities in markets. DR aggregators mainly act as an intermediary between consumers and wholesale markets. These players are able to trade their DR either directly into the market or through other market players [68].

Among market players, electricity retailers would utilize DR to avoid facing with market price spikes, and thus to increase their profit. A real-time DR is proposed in [69], through which retailers procure their energy through real-time DR beside their traditional resources, i.e. pool markets and long-term contracts. A stochastic programming approach is formulated in which pool prices and consumers' behavior are associated with uncertainty. The given model, thus, gives retailers an option to determine their share from the given traditional and DR resources according to their ability to take risk, which is modeled through Conditional Value-at-Risk (CVaR).

Another DR model is presented in [70], where electricity retailers are given an opportunity to procure their DR through long-term bilateral contracts to short-term DR. Various DR contracts such as forward DR and DR options are developed. Retailers buy forward DR at a fixed price and volume for a specific period, which obliged them to execute the contract in real time. DR options, however, give some level of flexibility to retailers through which they can decide not to apply the agreed contract in real time if they see it unnecessary,

given that they pay a predefined penalty to DR providers. As for short-term DR, a reward-based DR program is formulated in which consumers' participation in this program is considered uncertain. The overall problem is formulated in a two-stage stochastic model whose feasibility is evaluated on a realistic case of the Australian National Electricity Market (NEM). Fig.12 illustrates the overall model for electricity retailers considering their options to employ demand response to meet their demand.

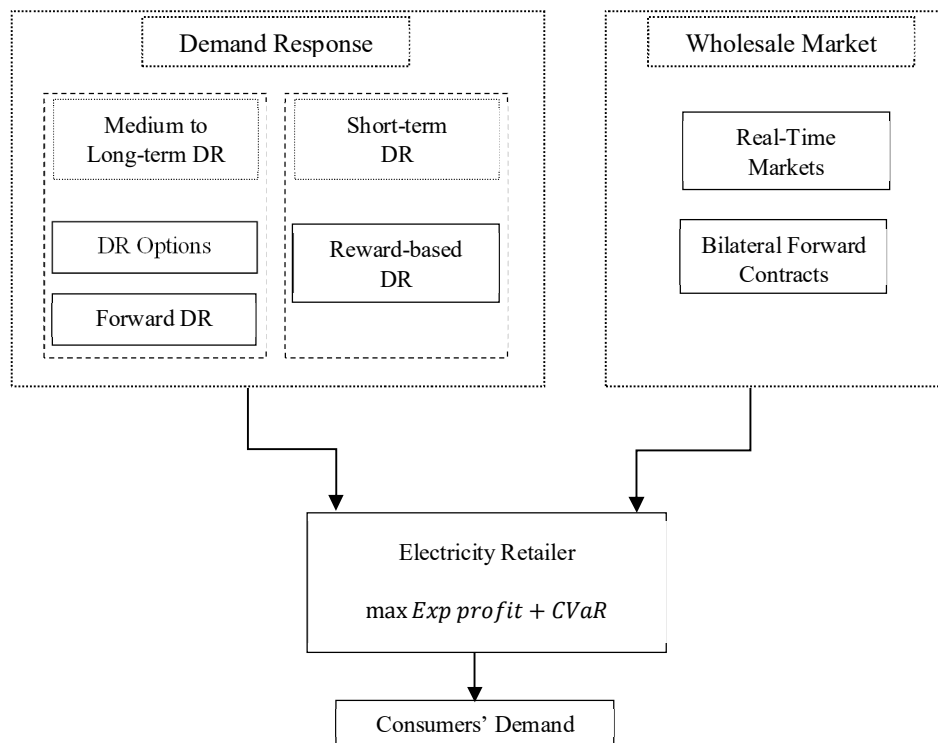


Fig.12. Demand Response for Electricity Retailers

Arasteh et al. [71] addressed the policy of a retailer to participate in electricity and Demand Response Exchange (DRX) markets with the aim of maximizing the expected profit. The presented decision making framework includes the elastic response of end users regarding the electricity prices. Fig. 13 shows the presented framework. It should be noted that, DRX is a market-based concept to trade DR that has been introduced in [72]. DRX requires an operator to collect DR offers/bids to clear the market and determine the equilibrium point [72, 73]. In [73], suitable methods have been proposed for DR buyers and sellers to participate in DRX market.

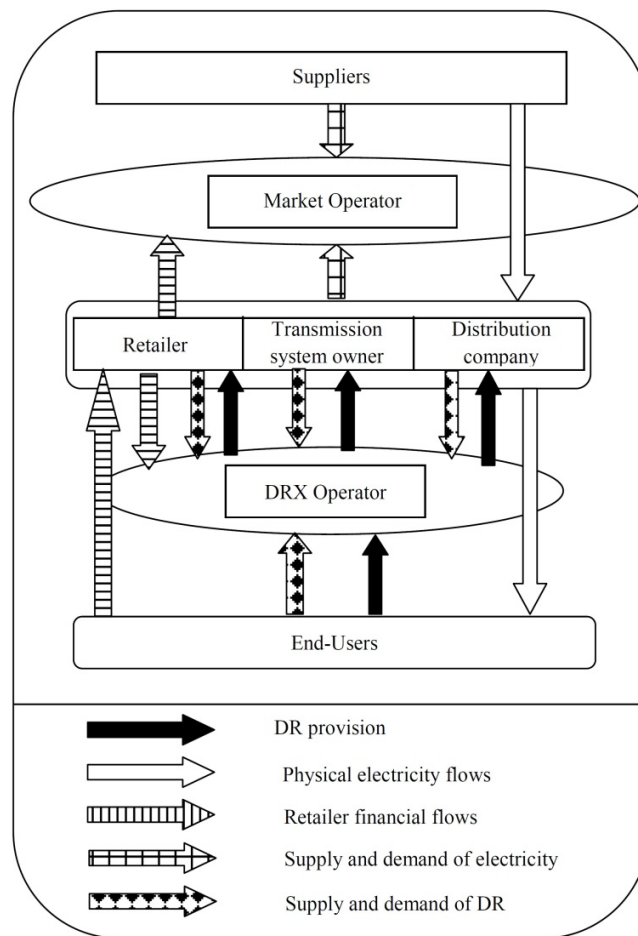


Fig. 13: The retailer framework to participate in electricity and DR markets [71]

A wind power producer is another market player that is interested to employ demand response. As wind power penetration in electricity markets increases, it is expected that these producers are treated as similar to existing generators in that they are responsible for any real-time mismatch between their offer and actual production. As a result, they can either compensate for their mismatch in real-time markets or utilize DR for this purpose. A bidding strategy by wind power producers is proposed in [74], where these producers can have a set of DR agreements with DR aggregators with which traded their energy. Besides forward DR agreements and DR options, a new DR contract is developed in which although the contract is set with a given price and DR volume, in real time, a wind power producer can distribute the contracted volume over the given period in order to better

manage its mismatch. That is, during the time a flexible DR contract is set, only total DR volume is agreed for a specific period. However, in the delivery time, the wind power producer is able to use this volume over the given period according to its requirement. The proposed problem is formulated in a two-step model in which the wind power producer seeks to maximize its profit through offering in the market, while utilizing the given DR agreements. The feasibility of the given model is then evaluated on the Australian National Electricity Market (NEM) [74] and the Nordic market [75] according to their specific features. While the Australian NEM is cleared as a single settlement market, the Nordic market comprises spot and balancing markets, which are cleared on the day-ahead basis and in real time, respectively.

DR aggregators are able to trade their DR with various DR purchasers as well as in the wholesale market. DR aggregator's behavior is modeled in wind power offering in [76]. A game theoretical model is proposed in which a wind power producer needs to buy DR from a DR aggregator while considering its rival competitors. A bilevel problem is mathematically formulated in which the wind power producer maximizes its profit in the upper level, while the lower-level problem addresses the DR aggregator's profit maximization model. That is, the wind power producer sells its energy in the market while trading with the DR aggregator. The DR volume depends on how competitive the wind power producer is compared to other options that the DR aggregator has to trade its DR. This is indeed determined in the lower level, where the DR aggregator has to maximize its profit through trading its DR with other purchases, the given wind power producer, and the wholesale market. The proposed bilevel problem is then transformed into a single-level linear problem to be solvable using commercially-available tools. The paper is then studied on a case study, where the proposed model is evaluated using several illustrative cases.

At high level of wind power penetration, some wind power producers might act strategically to affect the market. They will use their market power to increase their profit by altering the market clearing price. On the other hand, these producers may employ demand response to manage their market power by coping with their power production variability and uncertainty. To this end, a bilevel model with a single upper level, i.e. a wind power producer, and two lower level problems, i.e. market clearing and DR aggregator profit function, is formulated [77]. The wind power producer aims at

maximizing its profit while affecting the market price, determined in lower-level problem 1, and procuring DR from the DR aggregator in lower-level problem 2. A risk-constrained stochastic model is proposed for the wind power producer through which the share of day-ahead and balancing markets as well as DR volume are determined, while the day-ahead offer and DR price are fed to lower level problems 1 and 2, respectively. As a result of these decisions, the market price as well as the acquired DR volume are determined in their corresponding lower-level models. The problem is transformed into a single-level problem by replacing the lower-level problems with their KKT conditions. Further, using proper techniques, the equivalent single-level problem is linearized and then solved using the CPLEX solver under GAMS. A case of the Nordic market is used to assess the proposed model, where the impact of DR on the strategic behavior of the wind power producer is addressed. There are several distributed algorithms that have capability of solving large-scale power system problems in an efficient manner, such as the proposed method in [78][79]

Fig.14 provides DR applications by wind power producers.

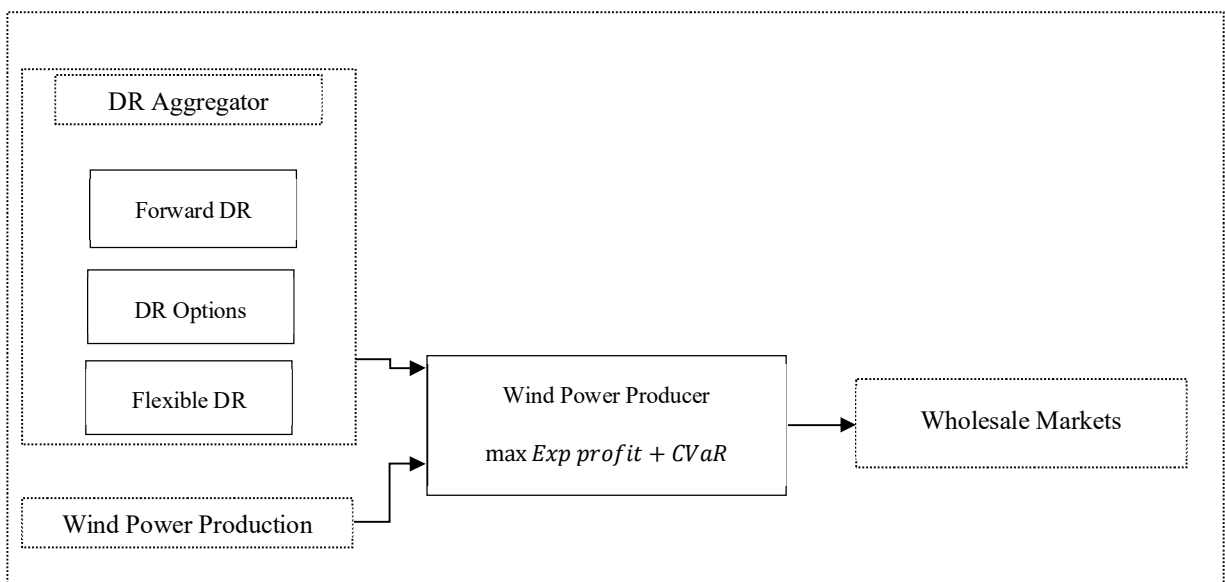


Fig.14. Demand Response for Wind Power Producers

## **6- Recent Studies on Demand Response**

Demand Response allows management of energy loads by addressing objectives such as cost savings and peak load reduction [80]. The DR management strategy requires algorithms for addressing such objectives like economic dispatch [81]. Researchers in [82] utilized a multi-objective strategy for solving the DR objective.[83] proposes a new methodology for control of power systems through voltage correction. The strategy minimizes control costs by maintaining a desired Load Margin (LM). However these algorithms require enforcement of practical constraints for utilities and market price. [84] set up the background issues behind the implementation of storage heating systems in DR frameworks. Ghavidel et al.[85] proposed a self-scheduled framework for demand response which considers consumer and electricity market price uncertainties. In [86] a solution to these issues was proposed by designing a short-term design strategy based on an electrical retailer point of view. In [87] a new short term DR strategy was devised which takes into account consumer behavior. Researchers in [88] used distributed techniques to assist demand response integration in serving the needs of the customer. In [89] an optimal probabilistic scheduling model is used to determine demand response. The strategy has been proved to be optimal which minimizes total cost of the hub. In [90] the demand response applications are integrated in renewable energy frameworks. The strategy has been proved to adapt to the dynamics of the renewable generation and energy storage in the network. In [91] a real time low complexity demand response module was designed for thermostatically controlled loads. The proposed scheme was considered to be adaptive to changes in renewable generation. In [92,93], a demand response enabled distribution system was designed. The system can tackle noisy inputs and is capable of accurate state estimation. Researchers in [94] devised an algorithm to mapping the demand response problem with energy flow in renewable energy based heating systems. Srivastava et. al [95] devised regression models for demand response predictions and determined that these models are highly functional in urbanized areas. Crosbie et al.[96] assessed demand response for applications in buildings. Viana et al.[97] analyzed demand response for a renewable distributed generation system. Their framework proved to be an important

resource for power utility planning. Thornton et al.[98] followed the internet of things approach to studying the demand response in a distributed manner. The hardware-in-loop system proved to be scalable for integration in real time systems. In [99] a Stackelberg game based approach was used demand response calculations for vehicle charging. The approach proved to be quite effective for multiple utility environments. Motaleb et al.[100] considered dynamic programming for calculating demand response while scheduling storage loads. The strategy minimized demand-side electricity cost throughout the period of simulation.

## **7- Conclusion**

This chapter reviewed the demand response programs (DRPs) as one of the key features and components of the smart grids. DRPs are essential to cope with the upcoming challenges of the future systems and lead the operation and development of the systems in a sustainable manner. Therefore, we provided a comprehensive survey on the state-of-the-art and the future trends of the DRPs. Although DRPs were firstly introduced with the aim of mitigating the system deficiencies (such as reliability problems and price spikes), currently they are considered as the virtual resources due to their beneficial potential. In this regard, the methods to model these programs are introduced in this chapter. In addition to the investigation of the available and novel models, the integration of DR programs with other models in power system studies is investigated. Furthermore, the participation strategies of market players in electricity and DR markets are addressed and the decision making frameworks are explained. All the investigation results express the benefit of the DR implementation in various domains of power system.

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