A Survey on Demand Response Programs in Smart Grids: Pricing Methods and Optimization Algorithms

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Abstract—The smart grid concept continues to evolve and various methods have been developed in order to enhance the energy efficiency of the electricity infrastructure. Demand Response (DR) is considered as the most cost-effective and reliable solution for the smoothing of the demand curve, when the system is under stress. DR refers to a procedure that is applied to motivate changes in the customers' power consumption habits, in response to incentives regarding the electricity prices. In this paper, we provide a comprehensive review of various DR schemes and programs, based on the motivations offered to the consumers in order to participate in the program. We classify the proposed DR schemes according to their control mechanism, to the motivations offered to reduce the power consumption and to the DR decision variable. We also present various optimization models for the optimal control of the DR strategies that have been proposed so far. These models are also categorized, based on the target of the optimization procedure. The key aspects that should be considered in the optimization problem are the system's constraints and the computational complexity of the applied optimization algorithm.

Index Terms—Smart grid, demand response, pricing methods, optimization algorithms.

I. INTRODUCTION

SMART grid uses new technologies, such as intelligent and autonomous controllers, advanced software for data management, and two-way communications between power utilities and consumers, in order to create an automated and distributed advanced energy delivery network [1]. In the next generation power systems, these intelligent technologies are incorporated across the entire system, from power generation, transmission and distribution, to consumption at the electricity customers' premises, with the aim of improving the efficiency, reliability, and safety of the system [2].

One of the key objectives in smart grid is the transition to an energy-efficient power grid [3]. Energy efficiency is obtained whenever volatile demands and renewable energy are managed, through the utilization of scalable information processing architectures. The concept of Demand Side Management (DSM) includes all activities which target to the alteration of the consumer's demand profile, in time and/or shape, to make it match the supply, while aiming at the efficient incorporation of renewable energy resources [4]. Furthermore, DSM can be also can be employed to facilitate the integration of distributed

generation that can yield significant savings both in the energy generation and transmission [5]. Other advantages of DSM include the blackouts elimination, the reduction of operational costs and decreased CO₂ emissions [6].

Currently, one of the main DSM activities is Demand Response (DR), since DR is considered as a subset of the broader category of DSM, together with energy-efficiency and conservation programs [5], [7], [8]. The US Department of Energy defined DR as "a tariff or program established to motivate changes in electric use by end-use customers, in response to changes in the price of electricity over time, or to give incentive payments designed to induce lower electricity use at times of high market prices or when grid reliability is jeopardized" [9]. Based on this definition, the idea is to make DR attractive to consumers, in order to manage their power usage preferences in a way that will benefit not only themselves, but also the power grid [10]. This customer-enabled power consumption management is the key smart-grid feature that enables the adaptation of power demands to time pricing or incentives, while improves the efficiency and the reliability of the power grid [11], [12]. It should be noted that some researchers and practitioners consider that DSM and DR are interchangeable [4], [6].

The design of efficient DR programs is a crucial component for the smart grid deployment [13]. To this end, the study of DR is an important issue and the various types of DR schemes and actual programs should be identified, in order to extract the advantages and limitations of these schemes. In this paper, we present various DR schemes that have been proposed in the literature. Specifically, we organize the DR schemes into three basic categories, as shown in Fig. 1. In the first category, DR schemes are classified according to the control mechanism into centralized and distributed [14]. In the centralized mode, consumers communicate directly to the power utility, without interacting with each other; while in the distributed mode interactions between users provide information to the utility about the total consumption [14].

In the second category, DR schemes are classified according to the motivations offered to consumers in order to reduce their power consumption [15]. In general, these motivations break down into time-based DR and incentive-based DR. In the time-based DR (also known as price-based DR [9], [16]), consumers are granted time-varying prices that are defined based on the electricity cost in different time periods. On the other hand, customers in incentive-based DR schemes are offered fixed or time-varying payments, in order to motivate the reduction of

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Fig. 1. Classification of DR programs.

their electricity usage during periods of system stress [17], but they are also under specific constraints or they are penalized for not participating in the program.

Finally in the third category, DR schemes use the decision variable to identify task-scheduling and energy-management-based DR schemes (also known as energy or power scheduling DR schemes) [18]. In task scheduling DR, the key function is the control on the activation time of the requested load, which can be shifted in peak-demand periods [19]. Different power consumption in peak-demand hours is achieved by the energy-management-based DR schemes through reducing the power consumption of specific loads [18].

In recent years, there has been an extensive research effort on the optimization and control of the smart grid. Fig. 2 presents the increased trend on the development of optimization models based on DR programs (indexed by Google Scholar) within the last 15 years. These efforts are comprehensively reviewed in this paper, and their key characteristics are presented, such as the objective function, the applied optimization technique and the constraints that are used to formulate the optimization problem. Furthermore, we organize these optimization models into 5 groups according to the target of the proposed optimization model. These categories are: a) minimization of electricity cost, b) maximization of social welfare, c) minimization of aggregated power consumption, d) minimization of both electricity cost and aggregated power consumption, and e) both the maximization of social welfare and minimization of aggregated power consumption. We also present game-theoretic methods that have been proposed for the solution of the demand-response optimization problem. Moreover, we highlight the optimization methods for two new smart grid paradigms: Vehicle-to-Grid (V2G) systems [20] and microgrids [21]. A V2G system is able to provide energy and ancillary services from an electric vehicle to the grid. This function is achieved through the utilization of bidirectional power flows that transfer the discharging energy back to the grid, or through unidirectional power flows by changing rate modulation [20], [22], [23]. On the other hand, microgrids are entities that coordinate distributed energy resources, energy

storage devices and electric loads in a decentralized way [21]. In a microgrid environment, the controller facilitates supply side management, demand side management, as well as voltage and frequency control [24]. In a grid-connected operational mode, these parameters follow the same policy that is used in the main grid. However, in an islanded mode, microgrids are independently controlled and therefore they efficiently deal with events like faults and voltage sags [25].

Other surveys on DR can be found in the literature [26]–[29]. In [26], the authors study the state of DR technology in electricity markets, and the magnitude of energy savings under DR and other efficiency standards that have been used in electricity markets. A description of existing DR architectures is presented in [27] with a report on their requirements, benefits and costs, and also a brief review of DR implementations in USA, Europe and China. Furthermore, authors in [28] perform a bibliographic survey on pricing signals in electricity distribution systems, while briefly reviewing some demand-side programs. Recently, a survey on DR programs is presented in [29], where authors present the enabling technologies and systems, such as smart meters, energy controllers, and communication systems that are required for the application of DR in smart grids. Our contribution complements these existing surveys by presenting a) an overall look and classification of DR schemes and actual DR programs, and recent research approaches that apply these schemes, b) optimization methods for the minimization of electricity cost/power consumption as well as the profits maximization, and c) the application of optimization methods in V2G systems and microgrids.

The rest of this work is organized as follows. Section II provides the DR background by discussing the objectives of DR schemes, management issues, types of consumers that participate in DR programs and adversative conditions in DR implementation. Section III presents different categories of DR schemes that have been presented in the literature. In Section IV we tackle an extensive survey of the major optimization models that have been proposed for smart grid environments. Finally, Section V provides concluding remarks for this work, together with the lessons learned and future

Fig. 2. Increased trend of number of optimization models on DR programs.

directions. Furthermore, a list of abbreviations used in this survey is provided in Appendix A.

II. BACKGROUND: DR CONCEPTS

A. Main objectives of DR

The main objectives of the application of a DR scheme are summarized as follows:

- Reduction of the total power consumption, so that mutual profit for the power utility and the consumers is achieved. This reduction should occur not only in the consumer's demand, but also in the losses of the transmission and distribution systems [7].
- Reduction of the total needed power generation, which is the main result of the aforementioned objective. Under the successful implementation of a DR scheme, the need of activating expensive-to-run power plants to meet peak demands is eliminated, while it enables the energy providers to meet their pollution obligations [9].
- Change of the demand in order to follow the available supply, especially in regions with high penetration of renewable energy sources, such as solar panels and wind turbines, in order to maximize the overall power-system's reliability [30].
- Reduction or even elimination of overloads in the distribution system. This objective is met by the operation of a Distribution Management System (DMS) that monitors the operation of the distribution system, and takes near real-time decisions that enhance the reliability of the system [31].

A DR scheme should also consider security mechanisms, for the protection of personally identifiable energy usage information that is collected by smart meters for the DR provision [32]. Furthermore, DR schemes should target on the reduction of loads in the distribution system to unload transmission lines, in order to prevent emergency conditions [33]. Moreover, a DR scheme should be designed in such a way that attracts the interest of consumers to participate in the program, through the provision of incentives to change their power consumption habits, while at the same time minimizing the consumers' discomfort [34].

B. DR Management

The implementation of a DR method targets on the control of the customer's power consuming behavior, in order to meet the aforementioned objectives that are presented in Section II.A [35]. The adjustment of the customers' electric usage is realized as a response to changes in electricity price over time or when system reliability is threatened. This function is executed through the cooperation of four main participants [36], as illustrated in Fig. 3: a) energy consumers that take part in the DR program, b) a DR aggregator that is connected to the customers and executes the DR program, c) a Distribution System Operator (DSO) that controls the distribution grid and d) an Independent System Operator (ISO) or Regional Transmission Operator (RTO). In general, the process of a DR program starts by the ISO/RTO that determines the preferred demand volume and the time duration that it is offered. This information is submitted to the DR aggregators, who then select the participating customers based on their availability. By considering the number of customers that agree with the proposed DR, the aggregator calculates the total demand and reports back to the ISO/RTO. In order to evade uncertainty problems in the distribution system, the aggregators may initially report the total DR to the DSO, who then informs the most available substations about the total power demand [35]. In this case, the DR calculations are performed at the DR aggregators, and they are then used by the DSO for executing optimization procedures or for discovering problems in the distribution grid.

The aforementioned model of the four participants is general, and it may also involve a number of agents that interact in competition or in cooperation. In these multi-agent systems, distributed decision making is implemented either in a local domain or inside the entire system [37]. The decision making process is a result of negotiations and trading on an electronic market and involves procedures like DR and distributed generation [38]. There are several examples of multi-agent energy management systems that are proposed and described in the literature. PowerMatcher [39] is a hierarchical market based algorithm, in which multiple agents that control electronic devices can bid for energy, by considering their own bidding strategy. A similar multi-agent system, known as the Dezent project, is proposed in [40], where scalability is improved by incorporating balancing group managers instead of a central market place. A more scalable system is presented in [41], where agents not only use price information but also information about the environment and current status for their bidding strategies. Due to the nature of the multi-agent systems, they are well-fit in microgrid environments [42], [43].

C. DR Applicability

A DR program could increase its effectiveness by taking into consideration the types of consumers that are applied to. Typically, consumers are divided into the following three main categories, as illustrated in Fig. 4: residential, commercial and industrial consumers [44].

1) *Residential consumers*: The design of an efficient DR program for residential users is far more complicated, com-

Fig. 3. Main participants in a DR program.

pared to industrial customers, mainly due to their near-random consumption patterns that require vigilant modeling. This task can be achieved by designing residential load management programs that either reduce or shift power consumption [45]. The reduction of power consumption is realized through the encouragement of energy-aware consumption patterns and the construction of buildings with high energy efficiency [8]. However, by shifting consumption from peak demand to off-peak hours, a significant reduction of the peak-to-average ratio can be achieved. Consequently, there are possibly abundant opportunities for the DR application in domestic areas. Nevertheless, the applied DR program should not consider that all customers have the same power consuming behavior. As reported in [35], residential consumers can be grouped into different categories: a) short range consumers, who are only concerned about the power price at the current time instant, b) real-world advancing customers, with consumer perception in current and past periods only, c) real world-postponing consumers, whose perception depends on current and future prices only, d) real-world mixed consumers, who are a mixture of postponing and advancing customers, and e) long range consumers, who are able to shift their consumption over a wide range of time.

In addition to the consumer's response to the DR program, other factors should be taken into account during the design of DR programs for residential areas. The advent of Plug-in Hybrid Electric Vehicles (PHEVs) is expected to place a significant load on the power grid [46]. A smart scheduling of PHEVs charging hours (e. g. during the night) can reduce their impact on the grid. Another issue that should be addressed in a DR program is the proliferation of locally generated power at the residential level. This local generation provides the customers with the opportunity to supply their excess electrical power back to the grid.

2) *Commercial consumers*: Typically, commercial buildings are identical in terms of energy consumption patterns, which are determined by weather conditions, design styles, and operational behaviors. Furthermore, these types of consumers can be considered autonomous, regarding the way they response to electricity prices [47]. In such environments, the main power consuming processes are Heating, Ventilation and Air-Conditioning (HVAC), lighting systems and electronic equipment. The reduction of the power consumption on these

heavy loads can be achieved by either the adoption of energy-efficient building technologies, and/or by the control of the buildings' energy consumption behavior through price elasticity of power demand. By applying a DR program in a commercial environment, building operators or their automated control systems make modifications to building operations, with the aim of reducing the building's total electric load during peak electric usage times. These modifications vary, depending on the consuming process. HVAC systems usually use automated operational DR functions that are based on temperature and/or air distribution adjustments, in order to achieve power consumption reductions [47]. Lighting DR strategies depend on the season of the year and the time of day. For instance, on a summer day the demand reduction in over-lit buildings can provide savings, which can be further increased by cooling savings, since lighting produces heat [47]. For the results of the applicability of DR methods on various case studies regarding commercial buildings, the interested reader can refer to [47]-[53].

3) *Industrial consumers*: Industrial plants are high energy consumers, with typical peak loads of hundreds of MWs at high voltage levels. In such cases, power and voltage efficiency are extremely vital. Besides, many manufacturing processes have critical temporal dependencies, which must be scheduled with high timing precision. In contrast to the residential consumers, where it is sufficient to control loads based on near-real time data, in many industrial environments millisecond-scale monitor and control is essential [54]. Furthermore, security issues are particularly important in the industry. The access to information regarding the load profiles or load shapes is highly confidential and competition-sensitive, since it may indicate the type of equipment that is active and in what time periods. These requirements are vital for the innocuous operation of the industry equipment. Hence, for many years various industrial facilities participate in actions that are very familiar to the smart grid applications, frequently through the application of dynamic pricing models. A number of examples of such activities are listed in [54]. However, intelligent DR methods may increase the reliability of the industrial system and the economic efficiency of the electricity infrastructure [55], [56]. The application of these methods may also benefit the power utilities, through the collaboration with the industrial partners, to analyze DR and determine optimal solutions for the response at peak-demand hours, and to provide downstream benefits through end-use monitoring [57]. The results of the application of DR in different sections of industry can be found in [58] (industrial refrigerated warehouses), [59] (meat industry), [60] (cement industry) and [61] (food industry).

D. Adversative conditions in DR implementation

The execution of a DR program may have unpredicted results when specific conditions are encountered. An important drawback occurs when the end users consume more power than their original level of reported consumption. This increase in power consumption is usually caused by loads such as water heaters, air conditions or electric stoves, and is called

Fig. 4. Share of electricity consumed in 2011.

Cold Load PickUp (CLPU) [62]. On the other hand, voltage violations may occur when Voltage/Var control is applied in the distribution system. A possible solution to this deficiency is the integration of Voltage/Var control applications and DR, which may significantly increase the productiveness of the distribution management system [33]. Furthermore, violations associated to the DR activation may be the result of asymmetric DR balancing between phases. This may lead to the increase of neutral wire current and three-phase bus voltage imbalance [36].

The installation of smart meters in the consumers' premises allows the implementation of more dynamic pricing schemes, for the triggering of the peak-demand reduction. However, the application of such pricing schemes to a wide range of consumers may result in several important implications, regarding the consumers' reaction to these rates (especially low-income consumers) and the possible volatility in electricity prices. This is mainly due to low-income consumers, who have a significantly lower level of price-elasticity than higher-income consumers. An interesting article that considers these issues can be found in [63].

III. CLASSIFICATION OF DR MODELS

The design of DR programs in a smart grid environment has drawn much research attention in recent years. Fig. 1 illustrates the classification of these research efforts; this classification is based on the control mechanism of the DR procedure, on the motivations offered to customers to reduce or shift their demands, or on the DR decision variable. The following subsections present the main characteristics of each one of these DR schemes.

A. DR methods based on the control mechanism

This class of DR schemes can be further classified into centralized and distributed programs [64], according to where the response decision is made. In centralized programs, response decisions for load activation or load scheduling are only tackled by the power utility, through considering that a number of users form a group [65]. However, the operation and control of the grid in a centralized manner is highly difficult in complex and large grids. As an alternative, in large grids the communication between energy supplies and

consumers can be distributed [64]. In such distributed schemes, the power utility's main contribution is the transmission of price signals; users can coordinate directly with each other, in order to achieve an aggregated load reduction. In the following subsections we present more details on centralized and distributed DR schemes. Based on the aforementioned description, in centralized schemes communication connections are only necessary between the utility and the consumers (Fig. 5a), while distributed schemes require the additional consumer interconnection (Fig. 5b).

1) *Centralized schemes:* In a centralized scheme, the DR procedure is monitored and coordinated by a central controller, who collects demand information from consumers, and DR decisions are then made for the demand scheduling. For example, in [65] and [66] an aggregator is used in order to derive scheduling decisions. Centralized management of loads is an effective solution for controlling buildings ([67], [68]) and charging stations for PHEVs [69]-[72]. For instance, a centralized method for PHEV charging is proposed in [69] that schedules PHEV charging times based on weights, which define critical and non-critical demand periods.

Central controllers are used in islanded microgrids that have been introduced as a coordinated approach. They are used to simplify the penetration of distributed generation units into the utility network [73]. In microgrids, different power micro-sources operate as a single system that provides energy to a cluster of loads in a local area [74]. The main function of the microgrid is the conservation of power balance independently of the main grid. The application of DR in microgrids has been studied in several articles ([75]-[77]). For example, in [76], an active control load strategy is applied in a microgrid environment, which is triggered by the voltage level in the microgrid and it enables the full exploitation of the installed renewable energy sources.

2) *Distributed schemes:* Distributed DR control programs consider that demand information is not centrally collected and consumers can directly access indicators of the grid's state [78]. By using this information, consumers are able to react, if the system's state is critical. Many researchers have been inspired by the distributive nature of the Internet, in order to provide efficient control mechanisms in smart grid environments [79]-[81]. In [80], authors present a distributed scheme that is based on congestion pricing in Internet traffic control. Consumers receive only pricing information from the utility; this information is a function of the current aggregated load, while it is used by the consumers to adapt their loads. This is achieved by using a mechanism that is based on decentralized congestion control mechanism for IP networks. This scheme is also used in [79] and it is applied to a distributed charging system for PHEVs. In this scheme, the user's preference is modeled through a parameter for the willingness to pay, which can be seen as an indicator of differential quality of service. A similar study is presented in [81].

Distributed schemes are also used in cooperation with other mechanisms that target on the control of crucial system parameters. In [82], a distributed DR method is integrated with a volt/var control scheme that provides improved voltage

Fig. 5. Centralized and distributed control mechanisms.

control and reduction of power consumption. Additionally, in [83] the problem of frequency control is discussed and authors argue that frequency-sensitive demand-response could be achieved in such power systems. Furthermore, the presence of distributed energy resources is considered in [84]; authors provide distributed algorithms for the coordination and control of both DR resources and distributed energy resources.

The research articles from literature presented in this subsection are summarized in Table I, for both centralized and distributed schemes. Section IV presents several other research efforts that have been made on both these schemes that use optimization methods.

B. DR methods based on offered motivations

Another way to distinguish DR schemes is by considering the motivation method that is offered to customers for their efforts to reduce or shift their power demands. There exist two main classes within this group: time-based DR and incentive-based DR. The former group is usually more suited for residential customers, while incentive-based programs are more suited for industrial consumers [35]. For example, a study that is based on real data from several industrial and large-scale commercial customers proved that incentive-based DR programs are more suitable, through the provision of explicit bill credits or payments for pre-contracted or measured load reductions [7]. Furthermore, the application of a time-based DR program and an incentive-based DR-program to a 24-

bus IEEE Reliability Test System showed that the offered incentives have key impact on customer habit formation in response to DR programs [85]. The research articles from literature that are presented in the following two subsections are summarized in Table II and Table III, respectively.

1) *Time-based DR*: These programs offer customers time-varying prices that are defined based on the cost of electricity in different time periods [27]. Customers receive this information and have a propensity for consuming less electrical power in time periods when prices are high. There are various pricing schemes that have been proposed for DSM, which are either retail price structures or DR-based programs [86]–[87]. In the former case, either fixed prices or consumption-based electricity rates are offered to consumers in order to reduce their electricity usage. However, customers do not participate in the determination of the prices, while no economic incentives are offered to the consumers to respond to hourly changes in electricity prices [86]. On the other hand, in DR-based programs the reduction of the electricity usage is achieved with the contribution of customers, who respond to motivation signals, being sent from the energy provider [95]. In the following paragraphs we present the different pricing schemes, by firstly introducing the retail pricing schemes and then the DR-based programs.

Flat pricing has been used in traditional energy systems and has been ingrained in the users' mind. Under this scheme, customers know that the only way to reduce their electricity bills is by simply using less electricity throughout the duration of the day. In some cases, seasonal flat pricing can be applied, where prices are fixed within a season but they can change from one season to another [86].

Time-Of-Use (TOU) pricing is the application of flat pricing in different time periods. Under a TOU pricing scheme, prices are retained fixed within different pricing periods, which can be different hours within a day or different days within a week [27]. For example, in California, USA, TOU is used for large commercial customers, who are charged different rates for the energy they consume in three different periods: off-peak, mid-peak and peak. During the off-peak period the customers are charged \$0.05/KWh, during the mid-peak \$0.078/KWh and during the peak \$0.099/KWh [87]. TOU tariffs are also used as incentives in a household simulation model that generates realistic load profiles in [88]. Based on this model, bill savings are estimated, when the household invest in the smart appliance technology. However, the effectiveness of such schemes to the reduction of the total power consumption is limited, since customers do not receive any practical incentives to reduce their demands. This customers' response to TOU schemes is also triggered by the fact that they receive attractive off-peak prices, but relatively high prices in peak-demand hours [89]. A study in [90] showed that TOU programs offer the smallest reduction in the peak demand among all tested programs.

Critical Peak Pricing (CPP) has similarities with TOU pricing, regarding the fixed prices in different time periods. However, the price for at least one period can change, either regularly or in most cases, due to occasions of system stress [91]. The participant consumers receive notification of the

TABLE I
CLASSIFICATION OF DR SCHEMES BASED ON CONTROL MECHANISM.

Control Mechanism	DR scheme
Centralized	[67], [68], [69], [70], [71], [72], [73], [74], [75], [76], [77]
Distributed	[78], [79], [80], [81], [82], [83], [84]

new energy price, usually a day ahead. As in the case of TOU, CPP is not economically efficient for the consumers, due to the preset prices. Furthermore, the ratio of on-peak to off-peak price is higher on CPP event days than in a TOU program [92]. On the other hand, from the energy provider point of view, significant load reductions during critical periods can be achieved under this pricing scheme [93], but with high probability of negative net benefits [94]. The implementation of a CPP program in California, USA, demonstrated respectable responses to the state's announced critical events [95]. A variation of CPP is the *Extreme Day CPP*, in which a critical peak price is applied to critical peak hours, but there is no variable tariff on other days [96].

In *Peak Load Pricing (PLP)* the day is divided into a number of periods and different prices are determined for each period. These prices are announced to the customers ahead of each day [97]. The price value for each time period is calculated based on the average power consumption of the consumers in each time period, in order to maximize the payoff of the energy provider [98]. Also, the price calculation targets on the demand shift away from peak-demand periods, by expecting a reaction from the customers' side according to the high price. A similar to the PLP pricing method is the adaptive pricing, where prices are not announced to customers at the beginning of day. Instead, based on the power consumptions on previous time periods, the energy provider calculates prices in real-time and announces them to customers at the beginning of each time period [99].

Under the *Peak Day Rebates (PDR)* pricing scheme customers decide whether they respond to a critical event. Specifically, customers are under their standard tariff, but they have the opportunity to receive a rebate payment for any load reduction they can achieve below an estimated baseline load threshold [86]. The results of a pilot study conducted in Connecticut, USA, showed that PDR is more advantageous compared to TOU, in terms of power reduction and consumer's satisfaction [100]. On the other hand, the same study showed that CPP is more beneficial than PDR. Furthermore, due to the fact that the baseline load threshold must be calculated for each customer and for every critical event, additional resources are needed. Besides, it is possible that some customers will receive rebate for the reduction of their power consumption that they would have made, regardless of the critical event [101]. An experiment involving 123 residential consumers of the city of Anaheim, CA, USA, showed that the rebate rewarded to consumers is pre-determined to be very high, which does not reveal the actual supply-demand balance at different operating conditions [102].

Another pricing scheme that is based on voluntary participation of customers is the *Vickrey-Clarke-Groves (VCG)* scheme. Customers are requested to provide their power demand information, which is then used by a centralized mechanism for the price calculation, for each time period [98]. Payments are provided to the customers in a way that they have motivations to provide their demand information truthfully. The VCG pricing scheme has been used in order to reduce the total power consumption [98], or to shift it to off-peak time periods [103].

Real-Time Pricing (RTP) requires the maximum customer participation. Under an RTP scheme, the energy provider announces electricity prices on a rolling basis; these prices are determined and announced before the start of each time period (e.g., 15 minutes beforehand) [104]. Therefore, the successful implementation of an RTP scheme relies on the two-way communication capabilities of the smart grid, which together with an Energy Management Controller (EMC) installed at the customer's premises, significantly increases the decision taking velocity [105]. EMCs support continuous flow of data and are based on the consumer's preferences. The consumers make smart decisions to modify the energy usage across the building, which will guarantee higher reductions in the electricity bill. The energy provider also makes decisions to define the prices for the upcoming time period. These decisions are influenced by random events, the total power consumption and the response of the consumers to the previous prices [106]. RTP mechanisms have already been applied to large industrial and commercial customers [107]. However, in the residential domain, RTP schemes have small implementation success, since most consumers are risk-averse and see the necessity of taking systematic electricity decisions as an important drawback [108], [109]. In addition, in some cases the cost savings resulting from the participation in an RTP program will exceed the costs imposed on customers to follow the program [63], [110].

One of the main challenges for the implementation of an RTP scheme is that it requires continuous real-time communication between the energy provider and the customers, which is not attractive from the user perspective. [111]. Furthermore, the mass flow of data that is exchanged between the energy provider and the EMCs, the lack of efficient smart metering and the high complexity could limit the effectiveness of such a scheme. The Day-Ahead RTP (DA-RTP) is an alternative RTP-based solution, wherein the next day's predicted real time prices are announced to the customers beforehand and they are billed for their consumption based on the price of this day-ahead [86], [112]. A test system with 320 customers in Ontario, Canada showed that the DA-RTP scheme achieved flatter demand curve, lower losses, lower peak-to-peak distance and higher load factor [86]. Also, the integration of a DR program based on DA-RTP and Volt/Var control is proposed in [113], where the effects of demand reduction on system voltage are studied and results show significant improvement in system voltage under the proposed scheme.

The results of the application of the aforementioned time-based DR programs in various markets across the USA are presented in [100]. Several case studies are tackled, with a

wide range of consumer sizes, program durations and energy management services. In addition, the authors in [114] outline the benefits of the applied RTP programs by the American Electric Power (AEP) in Columbus, Ohio. Similar studies are presented in [87], [115] and [116], where time-based schemes in North America, in California and in the city of Chicago, IL, are respectively presented and analyzed.

2) *Incentive-based DR*: They consist of programs that offer fixed or time-varying incentives (payments) to customers that reduce their electricity usage during periods of system stress [31]. Customer enrollment and response are voluntary, although some of these programs penalize customers that fail the contractual response when events are declared. The incentive-based DR programs can be further sub-categorized into classical programs and market-based programs, while they can be offered in both retail and wholesale markets [117]. Consumers that participate in classical incentive-based programs receive participation payments, usually as bill credits or discount rates. In market-based programs, participants are rewarded with money for their performance, depending on the amount reduction of electricity usage during critical conditions.

The *Direct Load Control (DLC)* is a classical program, and it enables the power utility to remotely cycle or turn off consumers' electrical equipment [5]. These loads (typically appliances such as air-conditions and water heaters) may be directly dispatched by the power utility, based on the balance between consumption and generation. The load control is feasible through the installation of switches at the customer's premises that communicate with the power utility. In some cases, the power entity can also send control signals to the customer in order to influence the control action. DLC programs are mainly offered to residential or small commercial customers and they can be normally deployed within a relatively short notice [99]. Consumers that participate in a DLC program receive incentive payments in advance, in order to reduce their consumption below predefined thresholds. DLC has been considered in various DR programs [118]-[122]. For instance, a DLC program is considered in [118], which targets on the reduction of the power consumption in an in-home environment, where both real-time and scheduled appliances are considered.

Another classical program subclass is the *Interruptible/Curtailable (I/C)* load, where upfront incentives are also provided to participant consumers. An I/C program considers curtailment options, e.g. curtail a specific part of electric load or curtail the total consumption to a predefined level. Furthermore, they provide a rate discount or bill credit by agreeing to reduce load during system emergencies [28]. Customers that do not respond to these options receive a number of penalties that are defined in the program's terms and conditions [123]. These programs are traditionally offered to larger customers with power consumption that range from 200 KW, for the baseline interruptible program, to 3 MW [124].

Emergency DR Programs (EDRPs) are a kind of Market-based programs, but can be also considered as a combination of DLC and I/C programs, since they provide incentive payments to consumers for reducing their power consump-

TABLE II
CLASSIFICATION OF TIME-BASED DR SCHEMES.

Time-based motivations	DR scheme
TOU	[27], [87], [88], [89], [90]
CPP	[91], [92], [93], [94], [95], [96]
PLP	[97], [98], [99]
PDR	[100], [101], [102]
VCG	[98], [103]
RTP	[86], [104]-[117]

tion during reliability triggered events [125]. Consumers can choose not to curtail and therefore forgo the payments, which are usually specified beforehand. EDRP has been included in the programs offered by the New York ISO, which manages New York's electricity grid [126]: participants that are able to reduce consumption are subscribed to the EDRP and they are called during emergency conditions. The EDRP pays for energy during times of emergency, but does not pay for capacity [125]. In [127], the authors propose an event-driven EDRP scheme that prevents a power system from experiencing voltage collapse. The avoidance of a critical event is ensured by triggering DR, based on a table of DR actions that contains information regarding locations and the amount of electricity that are needed in these locations. However, several real cases of EDRP operation have pointed out that an excessive shedding of the EDRP could lead to unpredicted power oscillations, which complicate the sequential generation control [128].

Another Market-based program is the *Capacity Market Program (CMP)* that is offered to consumers who are able to provide predefined load reductions to replace conventional generation or delivery resources [129]. For the reduction of power consumption, customers that participate in a CMP usually receive a day-ahead notification and they are penalized if they do not contribute to the load reduction [28]. In [124] an economic model of both CMP and I/C programs has been developed and a simulation study has been conducted that reveal the strong relationship of the incentive-based program and the corresponding penalties, with the satisfaction level of both consumers and electricity suppliers.

Demand Bidding (DB) is another market-based program (also known as *negawatt program*) and it is usually applied to large consumers, who offer curtailment capacity bids in the electricity wholesale market [125]. A bid is accepted if it is less than the market price, where the consumer must curtail his load by the amount specified in the bid, otherwise he faces penalties [130]. The Federal Energy Regulatory Commission (FERC) considers that demand bidding "will be less costly than a program where an end user receives payments greater than the market-clearing price to reduce its demand", [4]. Authors in [4] argue that it is a debate whether this idea is acceptable, since the amount of the energy reduction is mainly based on the consumption history of the bidder; due to this fact, there are market designing problems that may arise. For example, the Electric Reliability Council of Texas (ERCOT) market has applied a balancing up load program, where demand bidding is permitted through the submission of formal bids from the consumers [131]. However, the capacity payment has not been sufficient enough to encourage consumers into

TABLE III
CLASSIFICATION OF INCENTIVE-BASED DR PROGRAMS.

Incentive-based DR		
	Classical programs	Market-based programs
DLC ¹	[119], [120], [121], [122], [123]	
I/C ²	[124], [125]	
EDRP ¹		[126], [127], [128], [129]
CMP ²		[28], [125], [130]
DB ³		[4], [131], [132], [133]
ASM ³		[127], [134]

1	Voluntary
2	Mandatory
3	Market-clearing

submitting formal offers. A possible solution to this problem could be the *DR-aided DB* [132], which is a combination of DR (by consumers) and demand bidding that allows energy retailers to request from consumers to curtail loads, in order to reduce peak demands.

As in the case of demand bidding programs, the consumers following the *Ancillary Service Market (ASM)* subfamily are allowed to bid on load curtailments, but the bids refer to the ancillary service market. If the bids are accepted, participating consumers are paid for committing to be on standby. In case the load curtailments are needed, the participants are notified by the power operator and they are paid for the energy provision [125]. For example, the Midwest ISO selected \$3500 per MWh as “the average cost to consumers of an interruption of firm demand” and the highest price on its ancillary services demand curve [133]. In addition, California ISO accepts bids for ancillary services through a demand responsiveness program and under specific terms and conditions [126]. Furthermore, New York ISO includes ancillary services through a demand side ancillary services program and it provides three different services: 10- Minute Spinning (Synchronous) Reserve, 10-Minute Total (includes 10-Minute Synchronous and 10-Minute Non- Synchronous Reserve), and 30-Minute Reserve Total (Synchronous and Non-Synchronous) [126].

Apart from their classification to classical and market-based programs, the aforementioned incentive-based programs can be also classified as voluntary, mandatory and market clearing programs [134]. Voluntary programs are DLC and EDRP and therefore participants are not penalized for not contributing to the program. Mandatory programs are I/C and CMP, where participants that do not curtail loads receive penalties. Demand bidding and ASM are market clearing programs, where usually large customers inform the utility operator for the amount of load that they are willing to curtail at posted prices.

Incentive-based programs not belonging to the aforementioned categories have been also proposed as parts of DR programs in other research efforts. An incentive-based model implemented at end-user’s premises to curtailing/shifting electric loads to the right time of the day has been presented in [135]. This model targets on spreading out the demand profile and allowing the utilization of renewable energy sources. In [136], a coupon incentive-based DR program is presented that exploits the capabilities of mobile communication and smart grid technologies. This scheme preserves a simple flat retail rate structure, while it also provides a voluntary

incentive-based structure to trigger demand reduction, instead of paying the high wholesale price. In [137], authors propose an incentive-based DR scheme that covers the in-home load management with the objective to control appliances, such as air conditioning, water heaters, clothes-dryers and electric vehicles. This method considers that appliances have different priorities, depending on the degree of necessity of use. Finally, the interested reader may refer to [138] for an overview of DR programs (both price- and incentive-based) that have been implemented in competitive electricity markets.

C. DR methods based on the decision variable

DR methods can be also sub-classified according to the decision variable into two main groups: the first group refers to DR programs that decide when to activate the requested loads, while DR programs in the second group decide the amount of energy can be allocated to each consumer (or appliance) during each time period [28]. The research articles from literature that are presented in the following two subsections are summarized in Table IV.

1) *Task scheduling DR methods*: The key function of these DR programs is the control of the activation time of the requested loads. Two types of loads are considered: must-run (or non-schedulable) loads that cannot tolerate any activation (e.g. illumination or refrigerators) and schedulable loads that can be stopped, adjusted, or shifted to other time slots (e.g. water-heaters or PHEVs) [139]. Other parameters that are taken into account are related to the available energy, predefined deadlines and operating times of the loads [140]. The main target of these DR programs is to reduce the power consumption in peak-demand hours by shifting loads to off-peak hours. This is typically realized by using a target power level that should not be reached at peak-demand hours. Such a target power level is used in [118], as a method based on communication protocols in order to achieve uniform overall power consumption. Furthermore, the current power consumption is used in order to decide the scheduling of power requests in [19], where two power demand control policies are proposed and corresponding analytical models are presented. The first policy assumes that a power controller activates immediately or postpones power requests, based on the current power consumption. In the second policy, a new request is activated immediately if the total power consumption is lower than a threshold, else it is queued.

The shifting of the activation time should be followed by electricity bill reductions or incentive provisions. In [65] a direct load scheduling algorithm is proposed, that mediates between the central control model of DLC and RTP. In this scheme, costumers voluntarily release the control of their loads to a central controller, so that their energy use is manipulated to follow a desired demand profile closely. A DR formulation that takes into account both must-run and scheduled services is presented in [141], by considering the DA-RTP pricing scheme. The problem of optimally scheduling a set of appliances is mapped to the multiple knapsack method and uniformity in the home energy profile is achieved. In addition, a TOU pricing scheme is used in [142], which defines the energy price

in two different scenarios: the *Power-Constrained, Minimum-Cost Scheduling with Fixed Prices* scenario considers that boundaries for the total power consumption of the consumer, while the *Minimum-Cost Scheduling with Power-Dependent Variable Prices* scenario assumes that the electrical energy price is also a function of the total power usage of the consumer.

In the literature, there is a large number of research articles that target on the optimization of the task scheduling procedure in order to minimize the total power consumption and/or to maximize the social welfare. These methods are presented in Section IV.

2) *Energy-management-based DR methods*: The main objective of energy-management-based DR programs is to reduce the power consumption of specific loads, so that the total power consumption in peak-demand hours is reduced [18]. This is realized by controlling the appliance's operation to consume less power during system stress. For example, in a summer day an air condition could be adjusted to 25°C instead of 22°C, thus less power is consumed and people still feel comfortable. To motivate consumers to control the power consumption of their appliances, bill reductions or other incentives are provided by the power utility. The satisfaction level to the results of energy management is the subject of the study in [64], where a power-scheduling scheme is proposed. This scheme is driven by the Quality of Experience (QoE) factor that describes the consumer's satisfaction degree on the grid's performance and defines the social welfare of the system.

The consideration of schedulable and non-schedulable loads in an energy-management scheme is taken into account in [64], [143]-[145]. In these studies a task-scheduling scheme is considered for appliances that consume power in adjustable time-slots and an energy-management scheme for appliances that have flexible demands but are non-schedulable. Therefore, these DR programs decide when to activate a specific set of appliances, while they also decide how much energy to allocate to appliances during each time-slot. In [143], a water-filling based scheduling algorithm is proposed that allows consumers to shift part of their loads to off-peak hours in a probabilistic way. This algorithm has low complexity, since it utilizes statistical information on power consumption, which is available from the power utility. On the contrary, a cooperative scheduling approach in [144] requires detailed and continuously updated information between the utility company and the consumers. Apart from schedulable and non-schedulable loads, this scheme also considers loads that must consume a certain amount of power (e.g. rechargeable batteries and PHEVs). Finally in [145], a distributed incentive-based algorithm for scheduling power consumption is presented. The optimal energy consumption schedule for each consumer is derived based on an optimization algorithm, while game theory is used to derive a pricing model that offers a motivation for consumers to reduce their loads. Optimization methods and game theoretic analysis have been also used in a number of DR programs. These programs are presented below, in Section IV.

TABLE IV
CLASSIFICATION DR PROGRAMS BASED ON THE DECISION VARIABLE.

Decision variable	DR scheme
Task-scheduling	[19], [65], [119], [140], [141], [142]
Energy management	[64], [144], [145], [146]

IV. OPTIMIZATION: METHODS IN DR PROGRAMS

In this section we review the work on the optimization of various DR programs and schemes. Given that optimization is defined as the process of finding the conditions that give the maximum benefit or minimum cost of a process ([146]), published studies on optimization of DR programs target on minimization of the total power consumption and/or the maximization of the social welfare. The latter term refers to the utility's profit (total consumer willingness to pay) minus the total cost experienced by all the generators and wastage cost caused by transmission losses [18]. Therefore, the maximization of the social welfare is achieved by maximizing the difference of the utility's profit by total electricity cost.

The target of an optimization problem is to find a set of variables that minimizes (or maximizes) a function (or a set of functions) of this set of variables, while these variables are subject to a set of constraints. The set of variables is known as the *design vector*, while the function is termed as the *objective function* [147]. The design vector is defined by the variables of the specific DR problem. For example, in a task-scheduling scheme the design vector can be determined by the demand request start time, the operational time of the load, the type of load (e.g. the type of an appliance in the consumer's residence) and the priority of the request. Also, in an energy-management based scheme, the design vector can be defined by the load type, the amount of power that is reduced and the load operational duration under the reduced load. The objective function is defined based on the desired characteristic that is optimized, e.g. the total power consumption or the social welfare. Finally, the constraints are determined based on the conditions of the DR scheme under study. Typical parameters that are constraints in an optimization problem refer to the operation of the system, such as capacity constraints, energy storage constraints and appliance constraints (e.g. the total energy required for the operation of an appliance).

Optimization problems can be classified based on the nature of the design vector, the objective function and the constraint functions. For example, if at least one of the objective and constraint functions is non-linear and if some or all the variables of the design vector are integers, then the problem is an integer, non-linear programming problem [146]. Furthermore, based on the deterministic or the stochastic nature of the variables involved, optimization problems can be classified into deterministic and stochastic programming problems; the latter case defines optimization problems that deal with renewable energy sources, due to the stochastic nature of these sources, or other uncertainties and correlations. Based on the type of the optimization problem, a technique is defined for the derivation of the solution; therefore for

an integer linear programming problem, an integer linear technique is applied for the optimal solution derivation. It should be noted that optimization does not necessarily mean that an optimum solution is reachable. There are optimization problems (e.g. NP-hard problems), where a solution is not feasible to find [148], or the computational times are too high. In such cases, classical optimization procedures, such as linear programming (which have been widely deployed when large problems are modeled), or quadratic programming cannot be applied; therefore, if the complexity of a solution technique is high, heuristic approaches can be used, since they provide fast and near optimal solutions.

In this section we firstly categorize the optimization approaches in DR problems based on the target of the optimization procedure. These categories are: a) minimization of electricity cost, b) maximization of social welfare, c) minimization of aggregated power consumption, d) joint minimization of electricity cost and aggregated power consumption, and e) joint maximization of social welfare and minimization of aggregated power consumption. Therefore, the first three categories deal with a single objective function, while the target of the last two categories is the optimization of two objective functions. Furthermore, we present game-theoretic methods for the determination of the optimal solution, which either refer to the minimization of electricity cost or the maximization of the social welfare. Finally, we highlight the optimization models for two important smart grid paradigms; V2G systems and microgrids. We also categorize the optimization problems based on the solution method that is used in order to derive the optimal solution. Table V presents the DR optimization models for each one of the aforementioned categories, together with the solution methods that have been considered for each case. Furthermore, in Table VI we classify these optimization models according to the control mechanism, the decision variable and the pricing scheme. Finally, in Table VII the presented optimization models are classified according to the ability to include uncertainties, scalability, responsiveness, communications requirements, and support of multiple load types.

A. Minimization of electricity cost

The main objective of an optimization algorithm aims to bring the final load curve close to the objective load curve, such that the desired objective of the DR strategy is achieved. The objectives of a DR strategy could be to maximize the use of renewable energy resources, to maximize the economic benefit for the power utility, to minimize the electricity or generation cost, and/or to reduce the peak load demand. The formulation of the cost minimization problem is based on the derivation of an optimal load scheduling procedure and the application of an appropriate pricing scheme. There are several research articles that aim to the cost minimization objective [149]-[152], [157]-[170]. These articles can be further sub-categorized based on the applied optimization procedure and the technique that is used for the derivation of the solution.

A number of cost minimization problems are solved by using complex, well-known optimization procedures. An *Integer*

Linear Programming (ILP) method is used in [149] to derive the minimum electricity cost for local (single house) or global (multiple houses) applications. Furthermore, a *Mixed Integer Programming (MIP)* method is used in [150] to minimize the total cost (operation, reserve and expected load-not-supplied cost). The calculation of operation and reserve costs is based on two utilization patterns of DR methods. The Peak Clipping DR activates a task-scheduling procedure when the system is at stress, while the Reserve Supplying DR is an I/C-based DR method that is applied as a reserve and it is activated in emergency conditions. A *Mixed Integer Linear Programming (MILP)* method is used in [151] for the minimization of the household's electricity payment by optimally scheduling the operation and energy consumption for each appliance, while considering the waiting time as a comfort setting for the operation of each appliance, and an RTP scheme. In addition, an appliance commitment algorithm is presented in [152] and solved with a *multiple-looping algorithm* and enhanced by a *linear sequential optimization process*. This algorithm schedules Thermostatically Controlled Appliances (TCAs) based on price and consumption forecasts. Customer comfort constraints are incorporated in the proposed approach, by specifying time-varying temperature ranges for each TCA.

The optimization model of [153] considers two types of appliances: the first type consists of task-scheduling appliances (their consumption can be adjusted across time), while the second type consists of energy-management appliances (their consumption can be reduced but cannot be shifted to next time-slots). Together with the electricity cost minimization, the formulated problem deals with the minimization of the consumers' discomfort, due to the adjustments in the appliances' operation. The resulting optimization problem is non-convex. In general, non-convex optimization models are difficult to solve, since they are computationally intractable and convex relaxation techniques should be applied, in order to convert the problem to a convex optimization problem [154]. However, in [153] under the consideration of a continuous time horizon, the non-convex problem has a zero duality gap (difference between the primal and the dual problem, which is usually observed in convex optimization problems), and it can be solved by using Lagrangian algorithms. Similarly, the model in [155] considers multiple appliance's types; the dual optimization problem of minimizing the electricity cost and maximizing the consumer's satisfaction is balanced into the optimization problem of maximizing its payoff. This problem is also non-convex and a simulated-annealing-based price control algorithm is developed to provide the optimal solution.

The aforementioned optimization approaches that are based on linear or convex programming provide efficient solutions, with polynomial time complexity, while the optimality of the solution is definite [156]. However, the main problem of these approaches is their high complexity, especially when a large number of consumers is considered. For such cases, heuristic approaches can provide fast and near optimal solutions. For example, a heuristic-based evolutionary algorithm is proposed in [157], with primary objective to reduce the utility bills of consumers in residential, commercial and industrial areas. This is realized through a load shifting technique, for the support

TABLE V
CLASSIFICATION OF DR OPTIMIZATION PROBLEMS AND THE SOLUTION METHODS FOR EACH CASE.

Optimization method Target of optimization	Integer Linear Programming	Mixed Integer Programming	Mixed Integer Linear Programming	Mixed Integer Non-Linear Programming	Mixed discrete/continuous Non-Linear Programming	Convex optimization problem	Non-convex optimization problem	Non-Linear Programming	Heuristics	Particle Swarm Optimization	Binary Particle Swarm Optimization	Stochastic optimization problem	Markov Decision Problem	Robust optimization method	Other methods	Game theory
Min. Cost	[149] ¹⁹	[150] ¹⁹	[151] ² [169] ⁸	[167] ²		[111] ¹⁹ [162] ⁷	[153] ²² [155] ⁸	[152] ³	[157] ⁴ [160] ⁵	[158] ¹⁹ [23] ¹⁹ [167] ¹⁹ [168] ²	[158] ¹⁹	[161] ⁶				[8] ¹
Max. Welfare			[205] ²		[174] ¹⁰	[18] ⁹ [98] ¹ [171] ¹⁹ [172] ¹⁹ [173] ¹⁹		[86] ¹¹		[179] ¹⁴			[70] ¹²		[177] ⁵ [177] ¹³	[201] ¹⁹ [202] ¹³ [203] ¹⁹ [204] ²
Min. Consumption	[181] ¹⁵	[186] ¹⁹	[187] ¹⁸ [189] ²	[180] ²		[183] ¹⁶	[185] ¹⁹			[184] ¹⁷ [190] ²						
Min. Cost AND Min. Consumption			[195] ²			[197] ¹⁹								[194] ¹⁹	[196] ¹⁹	[104] ¹⁹ [205] ¹⁹
Max. Welfare AND Min. Consumption						[144] ²⁰ [99] ¹ [197] ²¹ [198] ²¹										

1	Interior point method	12	Q-learning algorithm
2	Commercial software	13	Filling method
3	Multiple-looping algorithm	14	Co-evolutionary PSO algorithm
4	Evolutionary algorithm	15	Branch and Bound method
5	Greedy search algorithm	16	Parallel distribution computation
6	Lyapunov optimization technique	17	Signaled Particle Swarm Optimization
7	Relaxed convex programming technique	18	Model predictive control
8	Simulated annealing technique	19	Authors' software
9	Lagrange-Newton method	20	Distributed subgradient algorithm
10	Sequential Quadratic Programming	21	Iterative decentralized algorithm
11	Benders decomposition algorithm	22	Lagrangian dual algorithm

of a large number of loads of various types. The *Binary Particle Swarm Optimization (BPSO)* heuristic algorithm is used in [158] for the optimization of the demand management and a *Particle Swarm Optimization (PSO)* [159], for the optimal resource management. A near optimal solution is also provided in [160], which is based on a *greedy search* heuristic. Furthermore, the proposed cost minimization problem in [161] is transformed to a relaxed problem with lower complexity, which is solved by a modified *Lyapunov optimization technique*. In this approach, various types of appliances are considered by taking into account both inelastic (must-run) and elastic (shift-able) power demands from various residential appliances, renewable energy sources and energy storage devices, for the formulation of the optimization problem. In the same way, the convex programming problem of cost minimization is relaxed in [162], so that it can be applied to a large number of consumers. This is realized by relaxing the binary

decision variables, associated with the consumer-appliances' status, from integer to continues values, in order the use of a complicated ILP scheme.

Several research efforts appear in the literature that deal with the optimization problem in V2G systems. The formulation of these problems should consider a number of challenges in both unidirectional and bidirectional V2G solutions. In the bidirectional power flow option, additional hardware is required in the vehicles to pump the energy back to the grid, while the power utility must convince consumers to allow discharging their batteries. On the other hand, the limitations in unidirectional systems refer to the reduced participation times, due to battery charging and the lower power levels. This is mainly due to the inability to pump the energy stored in the batteries back to the grid, and the lower overall performance of the unidirectional option, compared to the bidirectional solution [163], [164]. Nevertheless, it is acknowledged that

both V2G systems have the potential to provide financial benefits to utilities [165], CO₂ emission reductions [166] and power consumption increase during off-peak hours [167].

It should be noted that the optimal resource scheduling problem that leads to the minimization of the cost may have significant computational complexity, especially if the V2G system supports a large number of vehicles. To overcome this problem, artificial-intelligence-based techniques can be used in order to reduce the execution time. PSO is a technique that exploits simple analogues of social interaction, instead of purely individual cognitive abilities. This technique is used in [23] and [167] for the cost minimization, while considering renewable energy sources. The effectiveness of the PSO approach is verified through its comparison with a reference methodology based on *Mixed-Integer Non-Linear Programming (MINLP)* in [168]. This comparison reveals that the PSO approach achieves significantly shorter execution times, but slightly higher total cost (production cost plus V2G discharge cost), compared to the MINLP solution. A similar conclusion is presented in [169] for the performance of another technique that reduces the algorithm execution time. This technique is called *simulated annealing technique* [170], and its application to a V2G system is based on several constraints regarding the electric vehicles, such as battery capacity, charging/discharging rates, starting travel times and minimum travel distances. The evaluation of this technique under a scenario that considers 1000 vehicles led to a faster solution, compared to both mixed-integer nonlinear and linear programming approaches, but its solution is slightly more expensive, compared to the optimal solution of the linear approach.

B. Maximization of social welfare

Various solutions have been proposed for the maximization of the social welfare. These solutions vary depending on the implemented optimization technique, the applied pricing scheme and the constraints that are taken into consideration in the problem formulation.

The maximization of the social welfare has been formulated as a convex optimization problem in a number of research approaches. The model in [171] assumes that specific payment rules should be applied to consumers that are unwilling to reveal their real power demands. The proposed convex optimization model is solved based on the knowledge of the consumers' demands. This solution determines the optimal power allocation to each user and provides the maximum social welfare. Convex optimization problems are also formulated in [172], [173], that affect the energy procurement decisions of the consumers for the amount of the purchased balancing power needed to meet the aggregated demand. In this case, the social welfare maximization is the result of a joint optimization procedure. The first part of the overall problem refers to the power utility decisions for the day-ahead procurement of electricity on the wholesale electricity markets, and the second part refers to the real-time decisions of consumers for the load schedule. In addition, the model captures the uncertainty of the electricity supply from renewable energy

sources. Furthermore, the convex optimization problem that is presented in [18] is solved by a decentralized *Lagrange-Newton* method. For the determination of the maximum social welfare, the model considers the energy demand and the generation decisions that reduce transmission losses. The *interior point method* is used for solving the convex problem of maximization of the social welfare in [98]. This approach considers that users are independent decision makers and schedule their loads so that predefined power consumption levels are met. The energy-based scheduling is motivated by a VCG pricing method, which is proved to be a more efficient solution than a PLP method, by providing a numerical evaluation.

A *mixed discrete-continuous optimization nonlinear problem* with a single integer variable is presented in [174], which tackles the optimal integration of renewable energy systems. A number of constraints, such as voltage level, active and reactive power constraints for generators and consumers and flow constraints for lines and transformers are all included in the proposed analysis. The presented results evidenced that the combined operations of renewable energy systems and price responsive demands alleviate network constraints, while satisfying greater demand levels and reducing energy costs. A *Non-Linear Programming (NLP)* problem is formulated in [86] for the maximization of the power utility's profit, while considering other parameters, such as consumer's benefits and reactions to energy prices, minimum daily power consumption and constraints in the distribution network. The proposed scheme is based on a DA-RTP pricing method. The optimization problem is solved by using commercial software, while the *Benders decomposition method* is applied to make the model applicable to a large number of consumers.

The target of the optimization model presented in [175] is the maximization of the utility's profit, together with low costs to the consumers in a unidirectional V2G system. The same authors study the equivalent problem, but for a bidirectional V2G system in [176]. In both cases, the problem is formulated as a linear program. Furthermore, the profit maximization problem is also tackled in [70], where a real-time pricing scheme is considered in order to deal with the price uncertainty in V2G systems. The scheduling problem is formulated as a *Markov Decision Problem (MDC)*, where the decisions on the prices are made by considering the future profits. This problem is then solved by using a *Q-learning algorithm*, which is an iterative method that learns from experience and updates in each step. The main limitation of this algorithm is that the learning process is time consuming.

Heuristic approaches have been also proposed for the determination of the maximum social welfare. In [177], two models are developed for the minimization of the consumer's electricity cost and the minimization of the generating cost for the utility companies. The former problem is solved by a *greedy algorithm* that is applied to each time period for the optimal load scheduling, while the latter problem is solved by using a *filling method*. PSO has been used in an optimization model for V2G systems in [178] for the maximization of the utility's profit. Furthermore, variations of a *Coevolutionary PSO (CPSO)* are used in [179], in order to incorporate the

TABLE VI
CLASSIFICATION OF DR OPTIMIZATION METHODS BASED ON CONTROL MECHANISM, DECISION VARIABLE AND PRICING SCHEME.

	Task Scheduling	Energy-based scheduling
Centralized	[150] ⁹ , [152] ² , [153] ² , [155] ¹ , [157] ⁹ , [158] ⁹ , [160] ¹ , [161] ¹ , [171] ⁸ , [174] ^{1,4} , [86] ² , [177] ² , [181] ^{1,7} , [182] ⁹ , [185] ⁹ , [194] ⁹ , [201] ^{1,6} , [204] ⁶	[98] ³ , [153] ² , [155] ¹ , [171] ⁸ , [172] ² , [173] ² , [174] ^{1,4} , [181] ^{4,7} , [202] ⁵ , [203] ¹ , [204] ⁶ , [205] ⁴
Distributed	[8] ¹ , [144] ⁸ , [149] ⁹ , [162] ¹ , [180] ² , [111] ² , [183] ⁸ , [184] ² , [186] ² , [187] ² , [189] ² , [190] ² , [196] ² , [198] ⁸	[18] ¹ , [99] ¹ , [144] ⁸ , [149] ⁹ , [151] ¹ , [162] ¹ , [193] ⁸

1	RTP	6	TOU
2	DA-RTP	7	PLP
3	VCG		Price as a function of consumption
4	DLC	8	
5	DB	9	Not specified

coordination of distributed energy resources to the social welfare maximization.

C. Minimization of aggregated power consumption

The minimization of the power consumption is usually achieved by finding the optimal scheduling solution that consumers can use to schedule their loads to off-peak hours. Various optimization techniques have been applied for the determination of the optimal load scheduling. A MINLP is proposed in [180], that involves resource scheduling with different anticipation times: day-ahead, hour-ahead and 5 minutes ahead, while generators, storage units and intra-day market are considered by the hour-ahead management. Additionally, the proposed model considers the intensive penetration of distributed generation and the load curtailment opportunities that are enabled by the DR program. Commercial optimization software is used to solve the presented problem, while the obtained solutions are validated by using a power system simulation.

Optimal daily load scheduling is also achieved in [181] through an ILP technique, which is solved by using the *Branch and Bound* method. The resulting solution is used to derive the optimal power consumption, by taking into account loads that can shift their operation in succeeding time periods and loads that can adjust their power consumption in the current period. The proposed mechanism can be applied either in the residential environment, where a home energy management unit makes optimal scheduling decisions for all appliances, or in a local area, where scheduling decisions are made by a central control unit. Similarly, a linear programming model is also used in [182] for the optimization of the peak load reduction, through scheduling commercial, industrial and residential loads.

The convex optimization model that is proposed in [111] is easily scalable to large number of users. This is due to the fact that the analysis is based on a task scheduling scheme with heterogeneity in delay tolerances. This fact allows the energy provider to estimate these delay tolerances based only on the aggregated data and not on the parameters of each

consumer. Similarly, another convex optimization problem is formulated in [183], that takes into account distributed power generators and electricity prices that are analogous to the total power consumption. This problem is solved by using a parallel distributed optimization approach, which significantly reduces the time complexity and communication costs. Moreover, a heuristic approach that is proposed in [184] can be applied to a large number of consumers. This methodology is called *Signaled PSO (SPSO)* and it is used in order to address the energy resources management problem. The comparison of the SPSO method with other methodologies revealed the superiority of the proposed scheme in terms of convergence, cost and time execution and absolute error. The consideration of a large number of thermostatic loads in [185] converts the optimization problem into a non-convex problem, with a significantly high complexity due to the on-off control of such devices. To this end, the authors of [185] propose a distribution structure for the optimal solution derivation, with a supervisor center (that broadcasts coordination signals) and local controllers for the consumer's appliances. Even though the distributed approach of the problem requires the communication between the thermostatic devices, the authors claim that the communication requirements of their proposed scheme are low.

Significant work has been conducted for the development of optimization models in microgrids [186]- [190]. One of the main challenges in these models is the incorporation of renewable energy sources and storage devices. A mixed integer programming model that targets on the determination of the optimal operation schedule of loads is presented in [186]. The impact of renewable generators and power storage devices on the optimal schedule of loads is studied and an estimation of the storage capacity according to the size of the microgrid is derived. The optimal scheduling of residential power consumption is also studied in [189], by introducing a mixed integer programming model. This model targets on the minimization of the total one day-ahead expense of the residential power consumption, which is achieved through the determination of an optimal scheduling for both the operation of the consumer's appliances and for the distributed energy generators. In the latter case, the derivation of the optimal scheduling is based on renewable energy output forecast (e.g. weather forecast is used for the case of wind generators).

The combination of DR and distributed generators is challenging, mainly due to the high computational complexity of centralized optimization. To overcome this problem, a 3-step optimization procedure is proposed in [190], for the minimization of the total power consumption of a distributed microgrid that services a residential community. The first step considers the dynamic DR based on day-ahead time-varying pricing, for the reduction of the energy consumption cost of the consumer, while the second step considers the reduction of the electricity cost in the entire microgrid. The third step involves the management of the storage of surplus wind energy and the discharge of this energy in high-demand hours. The electricity demands that are taken into account in this model are not only schedulable tasks, but also tasks that can be dropped by the agent to prevent system stress. The optimization problem for

the first two steps is solved with a PSO algorithm, which is considered as an advantageous method over other evolutionary algorithms, while the optimal solution for the third step is derived by applying a *Q-learning algorithm*.

D. Minimization of electricity cost and aggregated power consumption

In this section we target on both the minimization of the electricity cost and the total power consumption. Typically, optimization problems that consider multiple objective functions are solved either by considering decomposing algorithms, or utilizing Pareto-based optimization methods [191]. The main target of a decomposing algorithm is the disintegration of the power system into subsystems with reduced complexity; these subsystems are optimized separately by utilizing methods that are compatible with the optimum of the entire system. In Pareto-based methods, relations are created among solutions based on a Pareto-dominance concept and the set of optimal solutions is extracted based on these relationships. A third solution is the utilization of aggregated weight functions, where the objective functions are combined into a single function, while weights are considered to depict the importance of each original objective [192]. For example, the dual-objective problem of minimizing the cost in a microgrid and at the same time minimizing the amount of pollutants released into the air by thermal units (which are functions of the power generation) of [193] is solved by generating the non-dominated set of Pareto-optimal solutions.

The scheduling energy consumption problem is formulated as a linear programming problem in [194], for a deterministic approach of the scheduling problem. The proposed robust optimization model explicitly addresses the problem of correlated price data, while the principal component analysis and the minimum power decomposition methods are used for the solution of the robust problem. The model considers that correlation may exist among the uncertain electricity price data of successive time periods over which consumption is to be scheduled. For the evaluation of the proposed model, two case studies are presented that use prices from the Brazilian market. They tackle the determination of the appropriate consumption scheduling algorithms that could be used in the specific market and achieving the highest possible energy transfer from high- to low-demand periods.

The dual minimization problem of both the operational cost and the load power are solved by using a MILP model in [195], for the proposed home energy management system with distributed energy resources. The presented case study refers only to a single household, which cannot be an indicator for the complexity level of the model. On the other hand, the case study for the home energy management system proposed in [196] considers a scenario with 60 residential users with three controllable loads in each residence. The proposed analysis targets on the minimization of the real-time market cost and the total energy consumption. Customers are encouraged to participate in the program by using the motivation that they will not pay additional money compared to the cost they optimized by participating in the program. The optimization problem is formulated as an approximate *certainty*

TABLE VII
CLASSIFICATION OF DR OPTIMIZATION METHODS BASED ON VARIOUS PERFORMANCE METRICS.

Reference	Uncertainty included	Scalability	Responsiveness	Communication requirements	Multiple load-types support
[8]	×	low	medium	high	✓
[18]	×	low	medium	high	×
[23]	×	high	high	high	×
[70]	✓	low	high	high	×
[86]	×	high	high	low	×
[98]	×	low	medium	low	×
[99]	×	low	medium	medium	×
[111]	×	high	low	medium	✓
[144]	×	low	medium	medium	✓
[150]	×	high	medium	low	✓
[151]	×	high	medium	low	×
[152]	✓	medium	medium	high	✓
[153]	×	low	low	high	✓
[155]	✓	medium	low	high	✓
[157]	✓	low	medium	low	×
[158]	×	high	high	low	✓
[160]	×	high	high	low	✓
[161]	✓	high	high	low	✓
[162]	×	high	medium	high	✓
[163]	×	medium	medium	medium	×
[167]	✓	high	high	high	✓
[168]	×	high	high	high	✓
[169]	×	high	high	high	×
[171]	×	low	low	low	×
[172]	✓	low	medium	medium	×
[173]	✓	low	medium	low	×
[174]	✓	high	high	medium	×
[175]	×	high	high	low	×
[176]	×	high	high	low	×
[177]	×	low	medium	medium	×
[178]	×	high	high	medium	×
[179]	✓	medium	high	low	×
[180]	✓	medium	medium	medium	×
[181]	×	medium	low	medium	✓
[182]	×	low	medium	low	×
[183]	✓	high	high	low	×
[184]	×	high	medium	medium	×
[185]	×	medium	low	low	✓
[186]	✓	low	low	medium	×
[187]	×	low	medium	medium	✓
[189]	×	low	medium	medium	✓
[190]	×	low	medium	medium	×
[193]	✓	medium	high	medium	×
[194]	✓	medium	high	low	×
[195]	×	low	low	low	✓
[196]	×	medium	medium	high	✓
[198]	×	low	medium	medium	✓
[201]	✓	low	low	medium	×
[202]	×	high	high	low	×
[203]	✓	high	medium	medium	×
[204]	×	low	low	low	×
[205]	×	low	medium	low	✓

equivalent control dynamic programming problem, while its computational complexity is highly affected by the number of residential users and the number of controllable appliances. To increase the model scalability to higher numbers of users and appliances, a decentralized algorithm recomposes the problem to parallel subproblems, where each residence computes its scheduling solution locally. However, due to multiple iterations required by the decentralized algorithm, the model requires real-time exchange messages between the users, thus causing possible overheads in the communication network.

E. Maximization of social welfare and minimization of aggregated power consumption

The dual optimization problem of social welfare maximization and optimal power consumption can be solved by using various optimization schemes. Convex optimization models have been used in [99], [144]. In the latter case, the dual problem can be solved under a cooperative multi-residence scheduling approach, which assumes that each consumer has two classes of adjustable loads. Loads that belong to the first class must consume a specified total amount of energy over the scheduling horizon, but the consumption can be adjusted across different time periods. Loads that belong to the second type have adjustable power consumption patterns, without a total energy requirement, but the load operation at reduced power results in discomfort at the end-user side. The resulting convex optimization problem is solved through a *distributed subgradient algorithm*. Similar communication requirements, as the ones in [99], are needed in the analysis presented in [144], but in the latter case a single type of adjustable load is assumed. The proposed energy and welfare optimization models are based on a real-time pricing scheme. This problem can also be solved by using a convex programming technique, such as the *centrally-fashioned interior-point method*.

Authors in [197] argue that the social welfare maximization and the optimal resource allocation introduce communication network externalities, caused by the uncertainty in message signaling due to transmission network constraints. Therefore, the proposed framework jointly optimizes the data network component of the smart grid, so that the uncertainty on the communication (e.g. delay) is reduced. The optimal scheduling procedure is derived by a distributed algorithm that considers the fact that a consumer may be affected by the action of other consumers.

The aforementioned optimization models consider a group of consumers that are served by a single load-serving entity or that each consumer has only two classes of appliances. The key assumption of the analysis presented in [198] is that each residence is equipped with different appliances of diverse power demands. In addition, a consumer is also equipped with a battery that provides further flexibility for optimization of the residence's power consumption across time. The optimal power scheduling and maximization of social welfare problems are solved by a distributed algorithm, which considers that the power utility and the consumers jointly compute an equilibrium based on a gradient algorithm. In the latter algorithm, the power utility sets the prices to be the marginal costs of electricity and each consumer solves its own net benefit maximization problem in response.

F. Application of Game Theory to DR Programs

Game theory can be considered as a collection of analytical tools that provides the understanding of phenomena that are observed when decision-makers interact [199]. Consequently, game theory is suitable to address demand response management, where the players are the consumers, the actions are the strategies that players follow to optimize a utility function, while the solution (the outcome of the game) is

the optimal utility function [200]. Based on the target of the solution, game-theoretic methods can be classified by using the categorization of the optimization procedures that are presented in the previous subsections.

Game theory has been used for the formulation of the appropriate energy consumption procedure that results in minimum electricity cost. The scheduling game that is proposed in [8] considers consumers as the players and the daily load schedules as their strategies. The target of this approach is to minimize the electricity cost, which is achieved at the Nash equilibrium, and also to minimize the Peak-to-Average Ratio (PAR). Users interact with each other via message exchange, in order to coordinate their electricity usage, so that reduction of the PAR is achieved. The resulting problems are solved by using the *interior point* method.

A game theoretical method can also be used to capture the conflicting economic interests of the retailer and their consumers. Authors in [201] propose optimization models for the maximization of the expected market profits for the retailer and the minimization of the electricity cost for the consumer. The proposed approach considers real-time prices for must-run loads. Solutions to these two separated problems are provided through the formulation of one bilevel problem as an MILP model. The MILP solution is provided by using commercial optimization software. However, the computational complexity of the proposed approach is significant and the authors provide an example with only three consumers. In addition, *auctioning games* have been used in [202] to allocate load demands among customers, while maximizing the social welfare. These repeated *Vickrey auctions* use the optimal demand scheduling problem, which is solved by applied a *water filling* heuristic method. Furthermore, the utility cost minimization problem is formulated as a convex optimization, with a solution that is derived under the generation capacity constraint. The solutions of the two problems are used to maximize customers' social welfare.

A problem that can significantly affect the performance of a DR program is the unwillingness of consumers to reveal their real power demands. This problem is the subject of the study in [203], where a cheat-proof game theoretic DR method is proposed. The participation in the program is motivated by a simple RTP scheme, where consumers calculate their own optimal demand and report it to the utility. A similar problem motivated the game-theoretic approach in [204], where the utility uses a TOU pricing scheme that is announced ahead of time. In this way, consumers are not obliged to respond to the complex procedure of a time-varying pricing process. The designed utility function (profit minus the cost of the users) is optimized with linear constraints and solved for Nash equilibrium.

Game theoretical models have been also employed for the optimal solution to the dual minimization problem of the electricity cost and the aggregated power consumption. In [205], a two-level optimization framework is presented, with a game-theoretic framework at the upper level and a static convex optimization problem at the lower level. On the upper level, a nonzero-sum differential game is used to capture the interaction among different players, who seek to find an

optimal demand policy to maximize their long term payoff. At the lower level, a static convex optimization problem leads to an optimum solution, which is found for the scheduling of each consumer, while considering different appliances per household. Similarly, a Stackelberg game model is used in [104] for the optimal scheduling of loads. In this game, the utility plays the leader level game by setting the real-time price and the consumer plays the follower level game and schedules the appliances' operation. An RTP-based pricing scheme is used, where prices are determined by the utility according to the current load level, while optimal power consumption occurs by shifting power consumption in forwarding time periods. Furthermore, a non-cooperative game theoretical framework is applied, to model the DR problem in a distributed smart grid environment, which is equipped with energy storage devices, connected in a decentralized fashion. Based on the game theoretical approach, the distributed algorithm is determined and minimization of both the aggregated power consumption and the total energy cost is achieved.

Game theory may also be applied for power scheduling and control, especially for the case of distributed microgrids. The interested reader may refer to [200] for an overview of game theoretic models in distributed microgrids. Furthermore, game theory has also been applied for the interaction of PHEVs and the retailer, where players are the PHEVs who are involved in a non-cooperative game, while their actions are the load demand values. The solution of the game is obtained for the maximum profit from the retailer's perspective, and the optimal tradeoff between the benefit from battery charging and the associated cost, from the PHEV's perspective. This target is achieved by the generalized Stackelberg game presented in [206], where PHEVs select their strategies in order to optimize their benefit, while the retailer consider these strategies to maximize its profit. Apart from the optimal profit of either the retailer or the PHEV owners, other characteristics of the PHEV-retailer system can be optimized. The authors in [207] present a four-stage nested game, where players are not only the PHEV owners, but also residential users. The objective of the retailer is to maximize its profit, but also to perform frequency regulation through matching the power supply and demand. The optimal performance of frequency regulation in a real-time pricing scenario is also the objective of the game-theoretic model presented in [208]. However, this model does not incorporate the dynamics of the regulation signals, the energy restrictions of the EVs' batteries and the battery degradation due to frequent charging/discharging. These characteristics of the PHEV-aggregator system are considered in [209], where a stochastic optimization problem is proposed, based on the Lyapunov optimization technique. It should be noted that the constraints in the aforementioned models refer to the aggregated demand of the PHEVs and to the charging/discharging procedures (e.g. charging and discharging cannot be performed simultaneously).

V. CONCLUSION: LESSONS LEARNED AND FUTURE DIRECTIONS

In this paper we presented the background and key characteristics of DR programs that have been proposed for the

efficient operation of the smart grid. We provided an extensive review on DR methods and we classified them into categories based on the control mechanism of the DR program, on the motivations offered to customers to reduce or shift their power demands, and on the DR decision variable. We also reviewed a wide range of optimization algorithms that have been proposed for the optimal operation of the smart grid, with special attention given to V2G systems and microgrids.

From the study of the various DR schemes and programs a number of useful lessons can be derived. Firstly, the successful implementation of a DR program relies on the participation of the consumers that contribute to reduce of the overall power consumption in peak-demand hours. This involvement does not imply that consumers have to pull the plug on major appliances, or to compromise their lifestyle and intimidate their comfort. It is up to them to decide the amount of their participation in a DR program. The study of 70 tests performed on dynamic pricing-based DR pilots carried out in Europe, North America and Australia showed that in general, consumers marginally respond to these programs, while others do not respond at all [211]. Furthermore, the result of a DR program may not be beneficial for all customers. For example, the implementation of DR programs in Victoria, Australia [212] and in Illinois, U.S.A. [63], resulted in higher electricity bills for the low income earners, since they usually do not use much energy and so, the amount of demand reduction is limited. Based on these facts, a DR program should also offer information tools to the consumers, regarding the participation benefits and the optimal use of their appliances, in order to increase the consumer participation rate. In addition, financial incentives should be offered to retail customers to invest on smart metering infrastructure that enables the switch from a fixed retail rate to a more dynamic pricing [213].

Secondly, the majority of DR programs are based on customer baselines that are used to determine the demand reduction, while they also define the price formation. The setting of the customer baselines is a complex procedure, since it is based on varying load patterns. Therefore, the challenge for the DR provider is to establish an efficient baseline that avoids producing significant problems in the price formation in wholesale markets, while also urges the consumers to realize the potentials and advantaged of demand control [214]. However, a successful DR program is not only founded on the proper definition of customer baselines; other uncertainties may have a penetrating influence on the success of a DR program. Government policies, fuel prices, technology breakthroughs, demand fluctuations and capital costs for the infrastructure renovations are highly related to the price formation and are expected to play a significant role in the elaboration of efficient DR programs [215]. A powerful process that enables the uncertainty resolution is the implementation of pilot programs; in this way, valuable information and credible results may improve the effectiveness of a DR program [216].

Thirdly, useful information can be derived from the results of already implemented pilots. A survey on various case studies of several dynamic pricing programs is presented in [217]. The general conclusion from these case studies is that

the greatest motivation for participation of the consumers is the bill reduction. However, only a few consumers responded to critical peak events, either by reducing or shifting their loads, unless significant incentives are offered. For example, Pepco's customers in Washington, DC, that utilize a CPP program, reduced their peak summer usage by an additional 20%, compared to those who do not participate in the program. Similar results are obtained from the case studies presented in [218]. What is interesting is that in the case of the Hydro One's pilot in Ontario, Canada, an average 6.5% of power consumption reduction is achieved without offering any price incentives, but by simply providing the customer with real-time feedback, through the use of in-home displays. The general conclusion of these studies, as well as of other case studies in Europe and China (e.g. [219]-[221]), is that the successfulness of a DR program is not only based on the offered incentives; DR providers should also consider the provision of information tools for the efficient participation, as well as the supply of complimentary smart equipment to the consumers.

Based on the above survey, we can focus on the challenges, advantages and also limitations that arise from the implementation of these DR methods, which should be addressed in order to make more efficient and cost effective decisions for the implementation of the future smart grid. The key factor that aims at changing the demand in order to follow the available supply is the efficient and reliable utilization and control of various energy sources. This effort will be even more challenging in the future, mainly due to the high penetration of renewable energy sources. The stochastic nature of these sources and the large variations of the renewable energy are triggering the need for efficient, real-time power-generation, and demand forecasting methods. Power predictions can be used by the power utility to adjust its forthcoming operation and properly schedule the consumers' demands. A number of efforts have been made in order to design an accurate forecasting model [8], [204], [222]-[224]. These efforts include algorithms that are based on fuzzy logic [222], neural networks [223], [224] and game theory [8], [204]. Also, attention has been given on using machine learning for forecast decisions in smart grid environments [225]-[227]. Nevertheless, the research in the field of demand forecasting is still at its infancy and there are many fundamental issues that still need to be addressed, in order to jointly consider the random distribution of the various smart grid components and the stochastic behavior of the renewable energy sources. This can be realized by applying the aforementioned artificial intelligence techniques, or other techniques, such as sum of products, regression fusion and meta-classification, that can provide practical in advance results on the definition of the margins for reliable operation of the smart grid system. Finally, it is highly desirable to generate simpler dynamic pricing schemes, based on the application of these forecasting techniques, and more efficient automated procedures for the DR implementation.

APPENDIX A LIST OF ABBREVIATIONS

AEP	American Electric Power
ASM	Ancillary Services Market
BPSO	Binary Particle Swarm Optimization
CMP	Capacity Market Programs
CPSO	Coevolutionary Particle Swarm Optimization
CLPU	Cold Load PickUp
CPP	Critical Peak Pricing
DA-RTP	Day-Ahead Real-Time Pricing
DB	Demand Bidding
DR	Demand Response
DSM	Demand Side Management
DLC	Direct Load Control
DMS	Distribution Management System
DSO	Distribution System Operator
ERCOT	Electric Reliability Council of Texas
EDRP	Emergency Demand Response Programs
EMC	Energy Management Controller
FERC	Federal Energy Regulatory Commission
HVAC	Heating, Ventilation and Air-Conditioning
ISO	Independent System Operator
I/C	Interruptible/Curtailable
ILP	Integer Linear Programming
MDC	Markov Decision Problem
MILP	Mixed Integer Linear Programming
MINLP	Mixed-Integer Non-Linear Programming
MIP	Mixed Integer Programming
NLP	Non-Linear Programming
PSO	Particle Swarm Optimization
PDR	Peak Day Rebates
PLP	Peak Load Pricing
PAR	Peak-to-Average Ratio
PHEVs	Plug-in Hybrid Electric Vehicles
QoE	Quality of Experience
RTP	Real-Time Pricing
RTO	Regional Transmission Operator
SPSO	Signaled Particle Swarm Optimization
TCA's	Thermostatically Controlled Appliances
TOU	Time-Of-Use
VCG	Vickrey-Clarke-Groves
V2G	Vehicle-to-Grid

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