53rd IEEE Conference on Decision and Control
December 15-17, 2014. Los Angeles, California, USA

Demand Response in Smart Grids: Participants, Challenges, and a Taxonomy

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***Abstract*— In recent decades, moves toward higher integration of Renewable Energy Resources have called for fundamental changes in both the planning and operation of the overall power grid. One such change is the incorporation of Demand Response (DR), the process by which consumers can adjust their demand in a flexible manner. This paper presents a survey of various aspects of DR including the different types of participants, as well as the underlying challenges and the overall potential of DR when it comes to large-scale implementations. Benefits of DR as reported in the literature for performance metrics such as frequency control and price control, as well as methods for ensuring privacy are discussed. A quantitative taxonomy of DR recently proposed in the literature based on the inherent magnitude, run-time, and integral constraints is discussed and its integration with economic dispatch is explored.**

I. Introduction

In recent decades, global warming and a growing concern for the environment has prompted massive investments in Renewable Energy Resources (RERs), such as wind turbines, hydropower plants and photovoltaic technology [1]. The integration of RERs introduces intermittency and volatility into the generation side of the electricity grid, creating the need for a new electricity grid architecture. Smart Grid, a cyber-enabled end-to-end transformation of the electric power system from fuel source to end use, that is currently of much attention and debate [2][3], seeks to carry out this integration by including among other things, two-way communication between the electric power generator companies all the way to the final consumers (residential, commercial or industrial) on the demand side and back. New and exciting opportunities are becoming available for balancing generation and demand, increasing energy efficiency and lowering electricity costs. One fundamental change is the involvement of consumers in power balancing and frequency regulation by intelligently adjusting demand, a concept referred to as Demand Response (DR).

The Federal Energy Regulatory Commission (FERC) defines DR as [4]

> *"changes in electric use by demand-side resource from their normal consumption patterns in response to changes in the price of electricity, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized."*

This definition clearly demonstrates the diversity of possible implementations within the DR paradigm. An equivalent definition by the European Network of Transmission System Operators for Electricity (ENTSO-E) is stated in [5]. In this paper, we provide a survey of recent publications on DR including an overview of the challenges, the proposed solutions and their potential for grid-wise implementations.

The remainder of this paper is organized as follows. In Section II the possible DR participants and their flexibility are examined. Section III discusses the challenges of implementing DR when it comes to large-scale implementations. In Section IV the potential of DR and its positive impacts are explored, and a taxonomy for classifying DR is presented. Finally, in Section V a summary is provided.

II. Participants

The demand side of the electricity grid is traditionally divided into residential, commercial and industrial consumer sectors. Comprehensive research is being conducted to clarify how each sector can and/or should participate to make DR an important player in the Smart Grid as well as its success in securing a new reliable, efficient and sustainable electricity grid. According to the U.S. Energy Information Administration (EIA), the distribution of electricity use in 2011 among these three sectors was 37%, 34% and 26%, respectively, with the remaining 3% in rail transportation and plug-in hybrid electric vehicles (PHEVs) [6]. Such an even sectoral distribution seems to indicate that all sectors should equally participate for the DR program to be optimal (see for example the FERC report [7]).

FERC distinguishes between two classes of DR participation [4]: time-based DR programs and incentive-based DR programs. In time-based (also refered to as price-based) DR programs, electricity consumers take voluntary actions to change their electricity consumption based on price signals, whereas changes are encouraged through incentives during system reliability threats or as market opportunities present themselves in incentive-based DR programs. The amount of reported potential peak reduction from time-based DR programs is increasing yearly, yet as of 2012, incentive-based DR programs remain dominant [4].

A. Commercial and Industrial Demand Response

Although commercial and industrial consumers collectively hold roughly half of the DR potential of the future Smart Grid [7], they amount to only about 10% of the

This work was supported in part by the NSF Grant No. ECCS-1135815 via the CPS initiative.

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978-1-4673-6088-3/14/$31.00 ©2014 IEEE

total number of electricity consumers [8]. Despite being low in numbers, the commercial and industrial consumers were responsible for 60% of the electricity usage in the United States (US) in 2011 [6], making them an important participant in an optimal DR program. Further, the commercial and industrial consumers are strongly motivated to participate in DR programs to increase the reliability of the electricity grid as they suffer greatly during outages. Based on publicly available data, [8] found the total annual economic cost of power interruptions to be $79 billion to US electricity consumers. More than 72% of the total outage cost is accounted for by the commercial sector alone, due to a high outage cost per consumer in this sector. Nearly 26% is accounted for by the industrial sector, and the residential sector represents less than a mere 2% of the total outage cost. The above numbers provide a compelling economic incentive for commercial and industrial consumers to participate in DR programs, besides the potential of heightened energy efficiency and lowered electricity cost.

Thermal storage potential in commercial buildings represents a highly untapped potential that can provide much needed services to the power grid. One of the major capacities in commercial buildings is the Heating, Ventilation, and Air Conditioning (HVAC) systems. HVAC systems are good candidates to participate in DR programs, supported by the fact that in 2002 HVAC systems accounted for 30% of the entire energy use in the commercial sector [9].

Another specific area within the commercial and industrial sectors which makes for good DR candidates is refrigeration. By 2005, over 111 million cubic meters of refrigerated space in the US required year-round conditioning. All in all, 16% of the food industry's total energy use stem from refrigeration [10]. Such large volumes and large percentages makes refrigeration systems very good candidates for DR. As pointed out in [11], some industrial refrigeration systems already have control systems installed, which can help facilitate the introduction of DR. In [12], a decentralized control method is proposed, which does not require a model of the supermarket refrigeration system.

The largest consumers of energy in the industrial sector is chemical factories, primary metal factories, and paper factories. Each one of them consumes more than 100 TWh making them ideal candidates for DR [13]. The DR potential of the chemical manufacturing industry has been investigated in [14] where it is shown how the type of participation depends on the hardware installed, as large manufacturing sites have the potential to participate in the reserve energy market with the correct investments. In [15], Alcoa Power Generating Inc. (APGI) show that they can provide fast regulative service for the power grid.

Commercial and industrial data centers have become a noticeable consumer of electricity within the recent decade. In fact, 1.3% of all the world's electricity usage was accounted for by data centers in 2010. In the US alone, it accounted for 2% of all electricity usage [16]. In [17], the participation of data centers as regulation service reserves is investigated while contractual Quality-of-Service (QoS) is met.

As final examples, [18] introduce a model for DR energy management systems in industrial facilities and [19] propose a load scheduling algorithm for industrial facilities.

B. *Residential Demand Response*

Large in numbers and representing 37% of the total electricity usage in 2011, research in residential DR participation is immensely active [6][8]. As outlined in [20], the smaller consumers of the residential sector hold useful properties compared to larger ones in the industrial and commercial sectors. Beginning at the level of modeling the load profiles of household appliances, such as washing machines, clothes dryers, air condition units, electric ovens and refrigerators, as done in [21], research in residential DR covers many areas.

In temperate climates, due to a significant thermal capacity in houses (through concrete floor heating, water heating or air conditioning in well insulated houses), individual houses can successfully participate in DR programs. In [22], the DR participation of a single-family house with an electric heat pump for floor heating is considered where the allowed change in indoor temperature is varied to analyse the potential. Thermostatically controlled loads (TLCs) in households are examined with the aim of providing regulation services in [23]. The DR participation of single-family houses is also investigated in [24], [25], [26].

Since the electricity usage of a single house inherently represents a negligible portion of the total electricity consumption, residential consumers are often considered in a collective manner, acting as one control entity under the term aggregator. In [27], an aggregator approach is used for DR participation of a collection of 1,000 thermostat-based residential consumption, whereas [28], [29], [30] investigate aggregation of residential consumers for participation in frequency balancing. Finally, [31], [32], [33], [34], [35] investigate various different aspects of aggregation of residential consumers with respect to DR participation. Particularly, the challenge of achieving useful aggregated consumption patterns while maintaining acceptable performance at each residential end-user is examined in [36].

III. Challenges

Traditional power grids are inflexible in design and lack communication between generation and demand side causing growing concern for reliability of the power grid, due to rising electricity demand and the occurring change from reliant and dispatchable power resources (such as nuclear and fossil-fired power plants) to RERs. While the introduction of DR relaxes this inflexibility, significant challenges and problems still remain when it comes to large grid scale implementations and is outlined in this section.

A. *Grid Structure*

One of the major challenges when it comes to DR roll-out on a large scale is the change it necessitates to the existing grid structure. The current standard for electricity providers and system operators to communicate DR signals with each other and with their customers is the Open

Automated Demand Response (OpenADR) [37] which uses the existing IP-based communications network. In order for consumers to participate in DR programs in a broader scale, further advances are needed. Advanced Metering Infrastructure (AMI) is one such change set up by FERC in their national assessment of DR potential [7].

Also known as *Smart Meters*, AMI is currently being deployed all over the world with various adoption rates. European countries are projected to have an adoption rate of AMI from 80-100% by 2020 and Italy already implemented 100% penetration of AMI. China, Japan, and Australia are projected to have 100% penetration of AMI by 2020 and the US is projected to have 33% penetration of AMI by 2015 [38]. While AMI may not be central to DR in industrial and commercial sectors, they are more significant in the residential sector. One of the main reasons for AMI not being fully deployed is the relative high cost associated with production and installation. In the US, FERC has estimated the cost of AMI equipment and installation to be above $226 per unit and in Europe, Berg Insight estimates the cost to be between $130-$340 depending on location [39], [40].

Latencies are another challenge associated with AMI as they can affect both grid stability and performance [41], [42]. In [41], the effect of DR in the presence of delayed price responsiveness of consumers was investigated. It was shown that with a lag in response of 30 minutes, DR is still a viable and useful tool to reduce peak demand and mitigate the volatile behavior of the RERs, despite the fact that about 70% of the benefits of DR was lost due to the latency. In [42], delay in AMI communication and its effects on stability and robustness of the electricity grid was investigated.

B. *Privacy and Security*

With the introduction of increased communication in the electricity grid, there are growing concerns about privacy and security [4]. AMI introduces frequent communication between consumers and utility companies. This communication is highly private and sensitive and has been investigated in [21], [43]. In [21], it was shown how, from AMI data, one can distinguish major household appliances from each other and easily determine if they are turned on or off. In [43], the authors have studied the utility-privacy tradeoffs of AMI data and shed light on the impact of leaking data both from the utility and the consumer perspective. This demonstrates that the privacy of the consumers electricity and appliance usage can be highly compromised.

AMI can also be vulnerable to manipulation and alterations which constitute a big security risk. Manipulation of the signal between the consumer and utility company can have a negative effect on the price of electricity or even worse jeopardize the stability and reliability of the electricity grid. Intensive studies of security have been carried out in [44], [45], [46]. In [44], false data injection was investigated and it was proven that this is possible and can pass commonly used residual-based bad data detection tests. In [45], a secure routing protocol is demonstrated and the tradeoffs between efficiency, reliability and resilience in centralized and decentralized approaches for secure routing are investigated. In [46], the authors developed a formal model using intrusion detection methods to guarantee that no attack can violate the security policy without being detected.

C. *Time-based and Incentive-based Programs*

As mentioned in Section I, FERC divides DR into two different categories: time-based and incentive-based DR programs. Time-based DR programs include methods such as Critical Peak Pricing (CPP), Real-Time Pricing (RTP) [4], while incentive-based programs include methods such as Direct Load Control (DLC) and Spinning Reserves (SR) [4]. CPP is a rate and/or price structure designed to encourage reduced consumption during periods of high wholesale market prices or system contingencies by imposing a pre-specified high price on electricity for a limited time. RTP is a price structure in which the retail price of electricity typically fluctuates hourly or more often, to reflect changes in the wholesale price of electricity on a day-ahead basis. DLC is a DR activity in which the program operator remotely controls a customer's electrical equipment. SR programs are resources that are synchronized with the grid and ready to provide fast relieve for energy generation and demand imbalances within the first few minutes of an emergency event.

Both time-based and incentive-based DR face challenges if they are to be implemented in large scale. The challenges for incentive-based DR is to be competitive enough and provide enough incentive for the consumer to participate in the programs. Time-based programs may on the other hand, cause abrupt and unwarranted price increases due to discontinuous operation of generating units and transmission congestions [47] and in general introduce reliability issues [48]. In [34], the authors state that people are more comfortable with fixed prices and may be hesitant to enroll in DR programs with dynamic pricing due to complexity. Another potential challenge with time-based programs is that shifting too much power from expensive peak hours to non expensive off-peak hours may simply lead to new peaks of demand and potential congestion.

IV. Potential

Governments around the world are pushing for increases in penetration levels of RERs (meaning percentage of peak energy generation stemming from RERs) as a response to global climate changes. In China, about 8% of the energy comes from RERs as of 2013, with a goal of reaching 15% RER penetration by 2020 [49]. In Europe, all member countries of the European Union have committed to national renewable energy action plans setting goals for RER penetration levels by 2020. Examples are listed in Table I.

In the US, President Bush stressed the need for greater energy efficiency and a diverse energy portfolio in 2006 which in turn has led to a 2030 plan of covering 20% of the US electricity needs by wind energy. The costs, challenges and impacts have been extensively examined by National Renewable Energy Laboratory (NREL) and U.S. Department

TABLE I
RER PENETRATION LEVELS AND GOALS FOR SELECT EU MEMBER COUNTRIES.

Country		RER penetration Actual in 2005	Goal by 2020
United Kingdom	[52]	1.3%	15%
Italy	[53]	4.92%	17%
Germany	[54]	5.8%	18%
Spain	[55]	8.7%	20%
France	[56]	9.6%	23%
Denmark	[57]	17%	30%
Austria	[58]	24.4%	34%
Sweden	[59]	39.8%	49%

of Energy (DOE) [1]. A sample remark from [1] is worth noting:

> *"The 20% Wind Scenario would require end users to be able (via price signals and technology) to respond to system needs by shifting or curtailing consumption. Time-shifting of demand would help reduce today's large difference between peak and off-peak loads and encourage more flexible loads (such as plug-in hybrid cars, hydrogen production, and smart appliances) that take energy from the grid during low-load periods. These practices would smooth electricity demand and open a larger market for off-peak wind energy."*

This is a direct statement of the need for DR (as defined by FERC [4]) and possibly energy storage to accommodate that level of wind penetration. In a report prepared by GE Energy in 2010, looking only at the price aspect, additional energy storage is found unjustifiable at levels of 10-20% of wind penetration scenarios, leaving the task to DR programs [50]. This thesis is also confirmed in [51], where results show no need for increase in reserve requirements at 13% wind generation penetration if a 15% DR penetration is present.

Higher levels of RER penetration however mandate new solutions, and in particular, the ability to curtail demand i.e., reduce peak consumption. In [4], FERC reports an estimated US DR capability of 72 GW, about 9.2% of peak demand. FERC estimates the peak reduction potential of DR to be 14% in an achievable DR participation level scenario by 2019 [7]. In [60], reductions in peak demand and electricity cost for the consumer are shown to be achievable with DR and distributed storage in microgrids. Using 50% Time-of-Use (ToU) tariffs adoption, peak demand is shown to be reducible and an increase in Social Welfare (SW) is achieved in [61]. SW is a performance metric that includes consumer and generator surpluses that is widely used as the parameter to maximize in analyses of DR programs. Peak-to-average ratio (PAR) is another parameter often used to measure the ability of DR programs to curtail and/or shift demand. (PAR reductions have many different names in present literature e.g., demand shaping, valley filling.) In [25], the PAR is reduced by almost 20% and the average electricity cost is reduced by more than 15% with a residential DR program. Shifting the demand to off-peak periods is shown to lower electricity cost in [62] and in [63], increase in SW and reductions in electricity cost are presented with a DR program which combines shifting demand to off-peak periods and curtailing demand in response to price signals.

HVAC systems has great potential to be beneficial in fast regulation services. In [64] authors show, in numerical examples, that 15% of the fan power capacity in commercial buildings, HVAC systems can be deployed for regulation purposes, without having significant influence on the temperature in the building. They further show that existing commercial buildings in the US can provide in the vicinity of 70% of the current national required regulation reserve. In [65], it is shown that HVAC fan power control can be used to absorb a great deal of the intermittency in energy generated by solar photovoltaic (PV), during cloudy days, with very little cost compared to existing methods. In [66], a model is developed reducing the number of states in a commercial HVAC system. The developed model can then be applied to a vast majority of buildings requiring only little adjustment, which greatly enhance the possibility of participating in DR programs. In [67], authors present a new method for analysing 15 minute interval electrical load data of commercial buildings reducing energy consumption from sectors such as HVAC systems.

Financial benefits are a huge motivator in the adoption of DR programs. In [68], annual savings of €360 are shown possible in a representation of a single-family electrically heated Danish house acting as thermal storage. In another approach, [22] demonstrates 7% savings for a single-family electrical heat pump heated house. Looking at residential and small business consumers, [34] proposes a DR program capable of lowering the total energy cost by more than 12%. In the industrial sector, [17] shows data centers able to save 30% on monetary costs by participation in the regulation services without significant loss in QoS. Further, [12] shows reduced power consumption of industrial refrigeration systems and [14] presents examples indicating as much as a 30% increase in operating profits for a chemical manufacturing site.

Reliability and stability are important properties of the Smart Grid which DR programs must support. In [28], [29], DR programs are demonstrated to be able to provide frequency regulation using residential consumer appliances and the high heat capacity of thermal loads, respectively. A hierarchical transactive controller, handling power imbalances and frequency drops due to wind generation loss, presented in [69], is shown to increase SW by proposing a hierarchical architecture of dynamic market transactions at the top level and active frequency control at the lower area and unit levels with faster time scales. Running from early 2006 through March 2007, the Grid Friendly Appliance Project managed by the Pacific Northwest National Laboratory (PNNL) demonstrated a DLC DR program able to provide underfrequency protection [70]. Autonomous, grid-responsive controllers, called Grid Friendly^{TM} appliance (GFA) controllers, were installed in 150 residential clothes dryers and 50 residential water heaters making the appliances able to react when the grid frequency dropped below 59.95 Hz and shed the load. Despite lacking the scale to significantly affect and control grid frequency, the project concluded that they

> *"succeeded in demonstrating the reliability of and opportunity for grid-responsive underfrequency protection controllers like the GFA controller."*

The GFA Project was one part of the two field-demonstration project by PNNL called the Pacific Northwest GridWise$^{\text{TM(b)}}$ Testbed Demonstration. The second, referred to as the Olympic Peninsula Project, tested whether automated two-way communication could improve electrical and economic efficiencies. With five water pumps, two distributed diesel generators, and residential DR for electric water and space heating in 112 households, the project demonstrated shift of thermostatically-controlled loads, peak load reduction, and improved system efficiency [71]. Another example of a large scale implementation of DR is in [72], showing peak reduction in the vicinity of 7% in 2006.

Finally, the role of the aggregator is of high interest in the context of high penetration of DR. In [31], they conclude that an aggregator should coalesce 10% of the residential users in a grid area to achieve a useful power reduction. With an aggregation of supermarket refrigeration and a chiller with ice storage, [73] shows a heterogeneous aggregation portfolio superior to a homogeneous one using the ability of utilizing the flexibility in a clever manner.

A. A Quantitative Taxonomy of DR

As demonstrated throughout this paper, current research in DR examines many different cases covering the immense possibilities in various areas of a Smart Grid. Consequently, the topic is accompanied by an abundant amount of abbreviations, technical terms and quantities, and classifications of participation. One method by which these various methods of participation can be organized is based on the inherent magnitude, run-time, and integral constraints that may be present in any demand. One such taxonomy proposed in [74] includes three classes of DR denoted as *Buckets*, *Batteries* and *Bakeries*, and is discussed in some detail below.

Definitions of the three DR classes are given below and are illustrated on Figs. 1, 2 and 3. In these definitions, T_s denotes the time step size, $P_{D_i}(k)$ denotes consumed power, $\underline{P_D}_i$ and $\overline{P_D}_i$ denote consumption rate limits, $E_{D_i}(k)$ denotes stored energy, $\underline{E_D}_i$ and $\overline{E_D}_i$ denote energy storage limits and $u_i(k)$ is the binary on/off state of *Bakery* i at time k.

Definition 1 (Bucket): The demand $P_{D_i}(k)$ is defined to be a *Bucket* if $P_{D_i}(k)$ and the stored energy $E_{D_i}(k)$ satisfy the following constraints:

$$E_{D_i}(k+1) = E_{D_i}(k) + T_s P_{D_i}(k) \qquad k = 0, 1, \ldots, \infty \quad \text{(1a)}$$

$$\underline{P_D}_i \leq P_{D_i}(k) \leq \overline{P_D}_i \qquad k = 0, 1, \ldots, \infty \quad \text{(1b)}$$

$$\underline{E_D}_i \leq E_{D_i}(k) \leq \overline{E_D}_i, \qquad k = 0, 1, \ldots, \infty \quad \text{(1c)}$$

where $\underline{P_D}_i \leq 0 \leq \overline{P_D}_i$. The set of all demands in a *Bucket* is denoted as $\mathcal{C}_n$.

Definition 2 (Battery): The demand $P_{D_i}(k)$ is defined to be a *Battery* if $P_{D_i}(k)$ and the stored energy $E_{D_i}(k)$ satisfy the following constraints:

$$E_{D_i}(k+1) = E_{D_i}(k) + T_s P_{D_i}(k) \qquad k = 0, 1, \ldots, \infty \quad \text{(2a)}$$

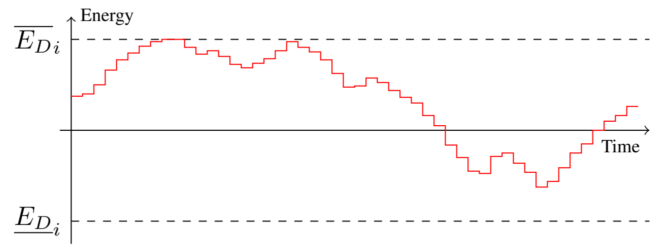

Fig. 1. Illustration of the power and energy properties of a *Bucket*.

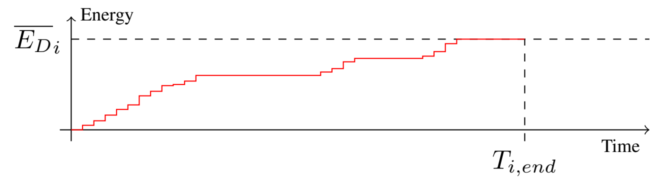

Fig. 2. Illustration of the power and energy properties of a *Battery*.

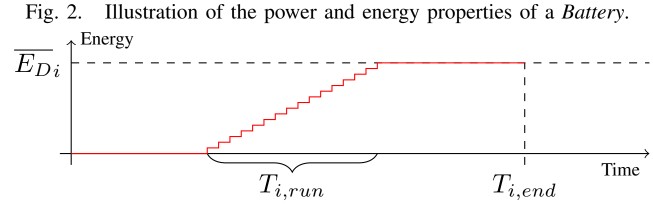

Fig. 3. Illustration of the power and energy properties of a *Bakery*.

$$0 \leq P_{D_i}(k) \leq \overline{P_D}_i \qquad k = 0, 1, \ldots, \infty \quad \text{(2b)}$$

$$0 \leq E_{D_i}(k) \leq \overline{E_D}_i \qquad k = 0, 1, \ldots, \infty \quad \text{(2c)}$$

$$E_{D_i}(T_{i,end}) = \overline{E_D}_i, \quad \text{(2d)}$$

where $T_{i,end} \in \mathbb{N}^+$. The set of all demands in a *Battery* is denoted as $\mathcal{T}_n$.

Definition 3 (Bakery): The demand $P_{D_i}(k)$ is defined to be a *Bakery* if $P_{D_i}(k)$ and the stored energy $E_{D_i}(k)$ satisfy the following constraints:

$$E_{D_i}(k+1) = E_{D_i}(k) + T_s P_{D_i}(k) \qquad k = 0, 1, \ldots, \infty \quad \text{(3a)}$$

$$P_{D_i}(k) = \overline{P_D}_i u_i(k) \qquad k = 0, 1, \ldots, \infty \quad \text{(3b)}$$

$$0 \leq E_{D_i}(k) \leq \overline{E_D}_i \qquad k = 0, 1, \ldots, \infty \quad \text{(3c)}$$

$$E_{D_i}(T_{i,end}) = \overline{E_D}_i \quad \text{(3d)}$$

$$0 \leq \sum_{l=k}^{k+T_{i,run}-1} u_i(l) - T_{i,run}\Big(u_i(k) - u_i(k-1)\Big), \quad \text{(3e)}$$

where $\overline{P_D}_i \geq 0$, $\overline{E_D}_i = \overline{P_D}_i T_{i,run}$, $T_{i,end} \in \mathbb{N}^+$, $T_{i,run} \in \mathbb{N}^+$ and $T_{i,end} \geq T_{i,run}$. The set of all demands in a *Bakery* is denoted as $\mathcal{K}_n$.

The *Bucket* is a power and energy constrained integrator, and could be an example of a simplified model for thermal energy storage, air conditioner units, and refrigeration systems. The *Battery* is similar to a Bucket, but has an additional constraint of a specific deadline for reaching a fully charged state. Examples of a *Battery* could be PHEVs and swimming pool circulations and filtering systems. Lastly, the *Bakery* is an extension of the *Battery*, as it has one more constraint requiring that the charging must happen in one continuous period with a constant consumption. Any batch process with a predetermined production cycle such as large industrial production facilities, could exemplify *Bakeries*.

We now classify all references on DR into one or more of the three classes defined above, as shown in Table II. Such a classification of DR is unique, to the best of our knowledge, in its span, applicability, and analytical tractability.

It should be noted that no such distinct analytical classification as above currently exists in the literature with the exception of [63]. In [63], DR is classified as adjustable and shiftable where adjustable demand comes from participants that have the ability to curtail their consumption, whereas shiftable demand participants must consume a given amount within a certain time horizon but are flexible during that period. Similarly to *Buckets*, *Batteries* and *Bakeries*, both adjustable and shiftable DR can be under a time-based or an incentive-based DR program. The *Buckets*, *Batteries* and *Bakeries* classification as above is more comprehensive and a significant improvement over [63].

B. Economic Dispatch with Integration of DR

The benefit of the above taxonomy of various DR devices is that it has the potential to enable a direct integration of DR into economic dispatch (ED). We describe one possible strategy below which is based on a security-constrained unit commitment (SCUC) approach [75].

The underlying problem is one of constrained optimization, posed as

$$\min \sum_{i=1}^{N_P} \sum_{k=0}^{N_T} \Big[C_i\big(P_{G_i}(k)\big) + C_i^{\text{on}}(k) w_i^{\text{on}}(k) + C_i^{\text{off}}(k) w_i^{\text{off}}(k) \Big] \tag{4}$$

subject to

$$\sum_{i\in\Theta_n} P_{G_i}(k) - \sum_{i\in\mathcal{C}_n} P_{D_i}(k) - \sum_{i\in\mathcal{T}_n} P_{D_i}(k) - \sum_{i\in\mathcal{K}_n} P_{D_i}(k) - \sum_{m\in\Omega_n} P_{nm}(k) = 0 \quad \forall n \in \Omega, \forall k \in T \tag{5a}$$

$$-\underline{R_G}_i v_i(k) - \underline{P_G}_i w_i^{\text{off}}(k) \le P_{G_i}(k) - P_{G_i}(k-1) \quad \forall i \in \Theta, \forall k \in T \tag{5b}$$

$$P_{G_i}(k) - P_{G_i}(k-1) \le \overline{R_G}_i \big[1 - w_i^{\text{on}}(k)\big] + \underline{P_G}_i w_i^{\text{on}}(k) \quad \forall i \in \Theta, \forall k \in T \tag{5c}$$

$$\underline{P_G}_i v_i(k) \le P_{G_i}(k) \le \overline{P_G}_i v_i(k) \quad \forall i \in \Theta, \forall k \in T \tag{5d}$$

$$0 \le \big[T_i^{\text{on}}(k-1) - \underline{T}_i^{\text{on}}\big]\big[v_i(k-1) - v_i(k)\big] \quad \forall i \in \Theta, \forall k \in T \tag{5e}$$

$$0 \le \big[T_i^{\text{off}}(k-1) - \underline{T}_i^{\text{off}}\big]\big[v_i(k) - v_i(k-1)\big] \quad \forall i \in \Theta, \forall k \in T \tag{5f}$$

$$-\overline{P}_{nm} \le P_{nm}(k) \le \overline{P}_{nm} \quad \forall n \in \Omega, \forall m \in \Omega_n, \forall k \in T \tag{5g}$$

All variables in (4) and (5) are defined in Table III, and the demand $P_{D_i}(k)$ in (5a) includes *Buckets*, *Batteries* and *Bakeries* and satisfy the constraints in (1), (2) and (3), respectively. Non-responsive demand is also included with *Buckets*, *Batteries* and *Bakeries* by application specific specification of power consumption, energy storage, and run-time limits. Generation constraints include nodal power balance in (5a), generator ramping constraints in (5b) and (5c), operating constraints in (5d), on- and off-time constraints in (5e) and (5f) and transmission line constraints in (5g). In general, the inclusion of bakeries is expected to be more challenging as it introduces nonconvexities. The final point to note is that the SCUC problem formulation in (4)-(5) should be viewed as a *generalized* unit commitment problem, where the units include both the conventionally included generation ones but also DR-compatible units such as *Buckets*, *Batteries*, and *Bakeries*.

A wide range of possible approaches can be used to solve this problem including dynamic market mechanisms (e.g., [63], [78]). This in turn will directly enable a quantitative assessment of the distribution of DR devices, *Buckets*, *Batteries* and *Bakeries* and perhaps leads to an integration of a

TABLE II

OVERVIEW OF MODELED FLEXIBILITY IN REFERENCED LITERATURE.

DR Program Behavior	References
Bucket	[68], [30], [76], [77], [60], [73], [27], [11], [12], [14], [17], [22], [24], [28], [29], [35], [41], [42], [61], [71]
Battery	[51], [70]
Bakery	[25], [19]
Bucket and *Battery*	[63], [47], [32], [33]
Battery and *Bakery*	[31], [62], [18]
Bucket, *Battery* and *Bakery*	[21], [34]

TABLE III

NOMENCLATURE.

Symbol	Description
$C_i(\cdot)$	Production cost function of unit i
$C_i^{\text{on}}(k)$	Startup cost‡
$C_i^{\text{off}}(k)$	Shutdown cost‡
$\mathcal{C}_n$	⋆ *Bucket* demands at bus n
$\mathcal{K}_n$	⋆ *Bakery* demands at bus n
N_P	Number of generating units
N_T	Maximum time of interest
$P_{G_i}(k)$	Power generation‡
$\overline{P_G}_i$	Maximum power generation†
$\underline{P_G}_i$	Minimum power generation†
$P_{nm}(k)$	Power flow from bus n to m at time k
$\overline{P}_{nm}$	Maximum power capacity of line n to m
$\overline{R_G}_i$	Generation ramp-up limit†
$\underline{R_G}_i$	Generation ramp-down limit†
T	⋆ time period of interest
$T_i^{\text{on}}(k)$	On-time‡
$\underline{T}_i^{\text{on}}$	Minimum on-time†
$T_i^{\text{off}}(k)$	Off-time‡
$\underline{T}_i^{\text{off}}$	Minimum off-time†
$\mathcal{T}_n$	⋆ *Battery* demands at bus n
$v_i(k)$	Binary on/off state‡
$w_i^{\text{on}}(k)$	Binary startup state‡
$w_i^{\text{off}}(k)$	Binary shutdown state‡
Ω	⋆ buses
Ω_n	⋆ buses connected to bus n
Θ	⋆ generating units
Θ_n	⋆ generating units at bus n

† of unit i, ‡ of unit i at time k, ⋆ Set of indices of

high percentage of RERs.

V. Summary

Moves toward higher integration of RERs in the recent decade have called for transformative changes in the planning and operation of the electricity grid. An ideal example of such a change is the incorporation of DR. In this paper, a comprehensive survey of DR including participants of DR programs, challenges, and potential associated with DR for large-scale implementations was presented.

Various participating parties in the electricity market are traditionally divided into residential, commercial and industrial sectors. At present, commercial and industrial sectors are participating more in DR programs than the residential sector but the latter has great potential of participating in future DR programs. All sectors however have interest in participating in DR program due to potentially lower electricity prices, higher energy efficiency, and minimization of expensive outages in the electricity grid.

AMI is being rolled out all over the world to accommodate the need for two-way communication between the utilities and consumers in a Smart Grid. Challenges regarding implementation of AMI are the costs associated with it and the delays they can introduce which, if not handled, can cause reliability and stability issues in the electricity grid. Some of the data communicated from AMI can be highly sensitive and private, making privacy a growing concern. Security is also an issue since AMI data can be subject to manipulation which can be hard to detect and handle.

All countries in the European Union have individual goals for RER penetration by 2020, as do many other countries e.g., China, and US setting 2030 as the target. All of these goals emphasize the need for demand side solutions and to fully explore the potential of DR to help cope with the volatile nature of RERs.

Several questions still remain to be answered regarding large-scale implementation of DR. One such question is about the percentage of DR which can be realistically achieved in the residential sector that can lead to a meaningful reduction in peak demand. A related question is if aggregation of residential DR can help in mitigating the intermittent and volatile behavior of RERs. The quantitative framework proposed in this paper as well as ongoing investigations in this topic are preliminary steps in answering these questions to realize large scale implementations of DR in a Smart Grid.

VI. Acknowledgments

The authors would like to extend special thanks to Tariq Samad and He Hao for several useful comments and suggestions.

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