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Intelligent Electrification as an enabler of Clean Energy and Decarbonization

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Abstract Purpose: Electrification efforts will change electric demand patterns, but must be made beneficial to the deployment of renewable generation. To ensure this, we need intelligent coordination of millions of resulting distributed energy resources (DERs). We provide an overview of challenges and opportunities associated with *intelligent electrification* as a means to enable decarbonization and clean energy. **Summary**: Intelligent electrification can bring value to the grid and consumers, but depends on its implementation and cyber-physical coordination architecture to manage consumer quality of service (QoS), grid services, and grid reliability. We also review and discuss challenges with getting intelligent electrification efforts to scale. **Findings**: We find that many methods already exist for coordinating DERs to deliver valuable grid services, but that practical implementation barriers exist regarding feedback control, integrating grid-data, and deploying intelligent electrification at scale. In addition, accurately characterizing and maximizing the available flexibility of a fleet of DERs is an open technical problem.

Keywords Distributed energy resources · Renewable generation · Electrification · Distributed control · Virtual batteries · Virtual power plants

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1 Introduction

Climate change mitigation requires increasingly significant decarbonization efforts across the globe. In the U.S. alone, decarbonization policies will require terawatts (TWs) of new renewable generation capacity (mostly solar PV and wind) [39]. At this scale and due to the inherent variability of renewable generation, grid operators across the country will have to re-think century-old operating paradigms and planning methodologies. This undertaking represents a major technical challenge and raises concerns around resilience and reliability in future, low-carbon energy systems [16].

Fortunately, decarbonization will benefit from extensive electrification efforts that redirect energy consumption in transportation, heating, and cooling towards clean electric demand [19]. With increased electric demand, we must think beyond the static nature of today's efficiency programs and enable intelligent shaping (and re-shaping) of flexible demand based on various market, grid, and environmental signals [34],[36]. This will unlock portfolios of millions of connected, responsive, and distributed grid assets, such as batteries, electric vehicles, and HVAC systems[47]. Some of these assets will be front-of-the-meter (e.g., in a substation) and directly observable to and controlled by grid operators. However, many others will be highly distributed and reside behind the meter (BTM) in homes and businesses and under the direct authority of consumers and/or technology providers (e.g., 3rd party aggregators).

Thus, to realize a vision of flexible demand that underpins intelligent electrification, we need scalable control and optimization approaches for distributed energy resource (DER[1]) coordination and effective cyber-physical architectures and cyber-secure information management systems that tame the complexity of the highly distributed, responsive, and networked DERs. Figure 1 illustrates the technical challenges with DER coordination when it comes to different spatio-temporal scales.

Some of the first approaches to behind-the-meter DER coordination were presented in the 1980s at technical conferences [74],[60]. One utility even instituted novel demand subscription services (DSS) programs to actively manage demand [69]. However, the coordination schemes back then either relied heavily on human involvement (i.e., humans actively managing loads at home based on a subscribed limit) or an assumption of readily available, low-cost computing and connectivity (i.e., sensor required at each controllable load cost \$1000s [74]). Today, however, the cost of sensor technologies has dropped precipitously, which enables ubiquitous connectivity, responsive DERs, and, with that, intelligent electrification efforts [56].

[1] Herein, we use the FERC Order No. 2222 definition of a DER [89], which is broad and includes BTM loads: "*DERs are small-scale power generation or storage technologies (typically from 1 kW to 10,000 kW) that can provide an alternative to or an enhancement of the traditional electric power system. These can be located on an electric utility's distribution system, a subsystem of the utility's distribution system or behind a customer meter. They may include electric storage, intermittent generation, distributed generation, demand response, energy efficiency, thermal storage or electric vehicles and their charging equipment.*"

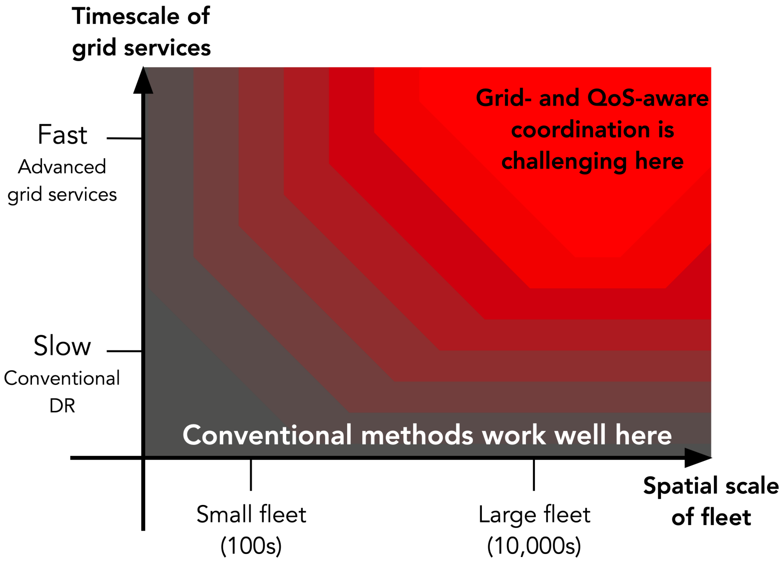

Fig. 1 Compare spatio-temporal elements of coordination. Coordinating a few items on a fast time-scale and millions of devices on a slow timescale does not represent a challenge. However, as we push temporal and spatial scales of coordination, the ability to effectively account for device-level (QoS-aware) constraints and grid-level constraints (grid-aware) represent a technical challenge.

Thus, intelligent electrification represents a complex interaction between deploying and activating DERs at scale, leveraging ubiquitous communications for coordination, turning streaming energy data into actionable information, enabling responsiveness with distributed control and optimization, and interfacing DERs with traditional and upcoming market, grid, and decarbonization services. Since the ability to deliver these services depends on the fleet's composition and DER parameters, operating point, and coordination methodology, there is significant interest in low-order, compact battery-like aggregate models (i.e., virtual battery or VB, and virtual power plant or VPP products on market today). These VBs or VPPs seek to characterize and predict the available flexibility in terms of the maximum deviation from the current operating point (power or MW), the ability to sustain said deviation (duration or MWh), and ramping ability (rate of change or MW/min).

Next, we motivate and make the case for intelligent electrification by considering favorable trends and policies (Section 2). Then we discuss the value proposition of intelligent electrification (Section 3) and the different classes of DER coordination schemes that underpin intelligent electrification (Section 4). Lastly, we outline challenges with scaling intelligent electrification (Section 5).

2 Making the case for intelligent electrification

Flexibility in power systems has historically come from thermal power plants whose supply follows (or tracks) demand. This is achieved with primary and secondary frequency control (via governor droop and automatic generation control, or AGC, feedback loops). With thermal power plants retiring (from old age or economics) and being replaced by cleaner, but less dispatchable supply (due to the inherent variability of renewable generation), new sources of flexibility will be needed to regulate any future grid supply-demand balancing. In addition, as renewable generation scales up, the marginal energy cost will be driven towards zero but with increased price volatility, which will place an even greater dependability on the grid's responsiveness and ability to flex demand and supply (or *net-demand*). To meet the need for flexibility, wholesale markets have developed transparent pay-for-performance grid services to incentivize responsive grid assets to deliver important balancing services (e.g., PJM's Performance Scores for its Reg-D ancillary service market product) [67]. With transparent metrics and clear incentives, responsive assets can generate significant value for their owners/investors. Thus, it is no surprise to see industry deploying responsive grid assets across transmission and distribution systems. Specifically, industry has focused on two major deployment strategies for grid balancing services: (1) centrally dispatched utility-scale energy storage and (2) thousands of coordinated and distributed kW-scale assets, including thermostatically controlled electric loads (TCLs; e.g., water heaters, HVAC, and heat-pumps), batteries, and EV chargers.

Strategy one (1) largely represents a modern power system version of status quo with centrally dispatched large/utility-scale energy storage assets (e.g., 100 MW-scale batteries) delivering valuable grid services, as if they were (more responsive) thermal power plants [2]. This is unfolding in many places, including in Australia, where 26GW of battery storage projects have been proposed to complement 260MW of battery capacity in 2021 [4], and the U.S., where a total battery storage capacity of 7.8GW are operating as of October, 2022, and 30GW of capacity are expected by late 2025 [83]. While utility-scale batteries are being deployed at record rates, can deliver highly responsive grid services [17], and out-compete natural gas peaker plants economically, they are still capital-expensive investments with system costs of $850-1500 per kW capacity [18].

Based on the large queues of battery projects around the globe, the wholesale market value proposition for flexibility far outweighs the utility-scale battery costs. Yet, a lower-cost alternative exists and is given by option two (2): coordinated DERs [12],[11],[35]. Unlike, centrally dispatched and "deterministic" MW-scale energy storage, which have known power and energy bounds,

[2] It would be prudent to mention that utility-scale energy storage can generally deliver a wider variety of grid services than thermal peaker plants to support frequency and voltage stability, energy arbitrage, and black start capabilities. However, this manuscript will mainly focus on grid services related to active power and frequency control capabilities as their incentives are well-defined.

direct measurements, and fits well into existing whole-sale market templates, cobbling a fleet of thousands or millions of kW-scale DERs together across large geographical areas necessarily requires a sophisticated system of distributed control, estimation (as there is no single sensor), and communication. Forty years ago, that would be technically infeasible and economically nonviable [74]. But with the costs of sensing and (edge) computing dropping precipitously over the past 15 years [56] and connectivity becoming ubiquitous, sophisticated coordination of DERs is not only possible, but a viable technical alternative to centralized grid assets [2],[76],[80],[35].

To enable economic viability of aggregated and coordinated DERs, recent government policies have promoted the inclusion of DERs in whole-sale energy markets, such as FERC orders No. 745 (2011, that demand response is equivalent in value to generation [25]), No. 841 (2018, that energy storage should have access to whole sale markets [26]) and No. 2222 (2020, that all DERs should have access to whole sale markets, including aggregated resources [27]). These rulings enable the potential of aggregated fleets (or portfolios) of DERs to access and actively participate in whole-sale energy markets on equal footing with (traditional) grid-scale assets. A key provision of FERC Order No. 2222 is that the minimum capacity of a DER aggregation be no larger than 100kW, which means that DER coordination can be technically and economically viable as long as there are enough DERs to connect to and aggregate [89]. However, that is exactly why public policies, e.g., Inflation Reduction Act of 2022, that accelerate and enhance electrification efforts are so critical. Specifically, vast electrification efforts around the country are expected to produce millions of connected and controllable loads, e.g., EV chargers, heat pumps, thermostats, and water heaters, to provide about 60GW of flexibility by 2030 and up to 200GW by 2050 [36],[35]. Another 8GW of distributed, behind-the-meter batteries will be coming online by 2025 [18]. Combined, aggregated DERs will reduce peaks by more than 30% [47] and can reduce bills by up to 40% [22]. All these new DERs will need coordination schemes that allow seamless onboarding and whose performance scales with the size of the fleet. In fact, DER coordination is not just needed, but will be required for electrification efforts to successfully transition electric power systems to a clean energy future.

Consider for example the absence of (intelligent) coordination: if uncoordinated, EV charging will require costly grid upgrades, as electrification of transportation takes off, to avoid impacting grid reliability. The adverse impact of uncoordinated integration of DERs on grid reliability could range from congestion in transmission lines to voltage violations and/or thermal overloading of transformers in distribution systems. However, utilities are unlikely to just be able to build their way out with expensive T&D upgrades, since a) the time to complete infrastructure upgrades is significant (e.g., a utility may not be able to upgrade more than 0.5% of lines per year but require 50% of lines to be upgraded) and b) cost of upgrades can no longer be offset by year-on-year (volumetric) load growth assumptions, as was the case 20-50 years ago [50]. For example, consider an electric vehicle with average driving pattern (13,500 mi/yr) and efficiency (3.5mi/kWh), which results in an average annual average consumption of 0.44kW (i.e., annual energy use of 3860kWh/yr). This is similar to the demand of an electric resistive water heater. With about 205 million EVs expected by 2050 [57], the additional demand from electrifying personal transportation will be ca. 90GW (i.e., 791TWh/yr), which represents less than an 8% increase from today's U.S. generation capacity of 1140GW and less than 1% year-on-year volumetric growth (i.e., 18% total growth by 2050) [84]. While these increases are not trivial, they are in line with U.S. national trends from the past decade and do not represent significant demand growth [52].

Today, such *en masse* grid upgrades would result in large rate increases, which would further incentivize consumers to pursue increasingly cheap solar PV and other DER alternatives. These competing investments on both sides of the meter are undesired by regulators [22]. Instead, utilities and regulators should incentivize consumers to own DERs, embrace intelligent electrification, re-think rate structures to include capacity, and defer and carefully manage T&D upgrades over the next two decades to keep energy affordable. For example, a recent U.S. Department of Energy study on grid impact of electric vehicles (EVs) found that, with smartly managed EV charging strategies (via a price-minimization scheme), the EV resource adequacy could be more than doubled - increasing the adequacy number for light-duty EVs from a projected 30 million to 65 million across the U.S. [42]. Besides EVs, it took just 57 recently installed 3-kW heat-pumps in Denmark to overload a 10/0.4kV transformer, which left 335 customers in the dark on a cold Christmas Eve [82]. It happened again three days later before the distribution network operator realized that the problem was caused by the unbalanced addition of the heat-pumps on the same phase. That is, the grid cannot be built big enough to handle uncoordinated ("dumb") electrification.

Furthermore, as we seek to coordinate DERs, we need to be careful about price signals and rolling out time-of-use (TOU) rates, which can actively synchronize "smart" connected appliances (e.g., HVAC thermostats) and EV chargers around myopic (local economic) objectives [50]. The price signals can indirectly synchronize DERs, coincidentally increase demand, and cause extreme demand peaks, e.g., when transitioning from long periods of high prices to new low prices [32], or perhaps triggered by small oscillations in price-signals (or, price-based control commands)[44],[64]. It is, therefore, not sufficient to just coordinate, but to *coordinate intelligently.*

Thus, as we electrify demand and deploy DERs at scale to integrate the necessary terawatts (TWs) of renewable generation, we must seamlessly enroll them and intelligently coordinate their actions to deliver high-performance grid services.

3 Value proposition of intelligent electrification

Unlike traditional thermal generators, coordinated DERs are generally energy-constrained in aggregate. This means that if you increase demand for too long, you lose capacity (i.e., the fleet's capacity at time t depends on its past actions). That is, DER fleets have memory! Thus, the duration of participation and the capacity to respond are coupled. This internal coupling poses a technical challenge to deliver grid services. Today, the traditional (whole-sale energy market) grid services that can provide the most value to coordinated DERs are capacity, energy, and ancillary markets, which are described next. After discussing the value proposition [3] of wholesale grid services, we re-direct attention to more local value propositions that specifically leverage the distributed nature of (kW-scale) DERs.

3.1 Wholesale Grid Services

- **Avoided generation and T&D capacity** (i.e., peak demand reduction) operates over hourly windows and values flexibility at approximately \$120/kW-yr, which is significant and derived from avoiding costs associated with generation capacity and T&D investments, such as expensive new power plants and substation upgrades. This value is attained by maximally reducing total demand during critical peak hours each month and is generally the largest source of revenue for flexibility (about 25-75% of total flexibility value stack today) and motivates most utility load management and energy storage programs. The capacity mechanism itself is rather unsophisticated and only requires an ability to minimize demand for 2-6 peak hours 10-20 times per year, which is why the classic demand response "hammer" has worked so well with fleets of thermostatically controlled loads. The duration of the peak period generally depends on the quality of peak load forecasts. This peak period is often referred to as a singular "peak event." The key challenges associated with coordinating DERs during peak events are two-fold: i) the more aggressively the fleet reduces demand, the shorter the available duration, because ii) reducing demand during peak events can curtail loads to the point where consumers' quality of service (QoS) is directly impacted (e.g., they get uncomfortably hot or cold or their EV is not getting the charge they require). If QoS is not managed carefully, then DER owners will opt-out of the coordination scheme altogether which can threaten long-term viability of load management programs. With increased renewable generation, the number of peak events will also increase significantly over time, which will require far more emphasis on QoS than has been in the past (i.e., there will be less room for "hammers" and a need for many "scalpels" to manage with existing grid capacity).
- **Energy arbitrage** (i.e., avoided energy costs) operates on 5-30 minute timescales and values flexibility at roughly \$50/kW-yr, where the value is derived from actively shaping net-demand to reduce/increase demand when prices are high/low (i.e., energy arbitrage on real-time market prices or via local time-of-use rates or a mix of the two). This represents a non-trivial

[3] Note that the \$/kW-yr values provided for wholesale grid services are representative of price-taking, marginal values from [22],[7],[36],[35] within a 2030 and 2040 time-frame.

value proposition today of about 25-50% of total flexibility value stack. The key technical challenge associated with energy arbitrage is to map real-time prices (or high/medium/low classification) to DER fleet power deviations. This can be accomplished with receding horizon, open-loop fleet optimization, which requires predictive models of the fleet's capabilities along with forecasted prices to engender a "glide path" for the DER coordinator to track in aggregate.

- **Ancillary services** (e.g., frequency regulation or spinning/ramping reserves) operates on 1-300 second timescales and values flexibility at circa $30-160/kW-yr, which generally represents a relatively small slice of 0-25% of the total flexibility value stack (depending on specific regions and the type of ancillary services provided). Interestingly, since there are so few market participants for ancillary services, it still represent the lucrative grid service for responsive grid assets, which explains why so many batteries have flooded frequency regulation markets in Australia, Europe, and the US. From the perspective of a DER coordinator, this grid service is among the most technically challenging to deliver. This is mainly due to the aggressive timescales (i.e., 2-30 seconds) within which MW-scale power deviations are needed from a highly distributed fleet of DERs [10]. Thus, any DER coordination scheme that seeks to deliver this grid service with high performance must be highly responsive, which prohibits centralized, fleet-wide DER optimization-based dispatch schemes. Instead, advanced methods from distributed optimization and control are needed and must balance a number of cyber-physical trade-offs to be technically and economically viable [9].
- **Decarbonization services** complement the other grid services with additional value derived from avoided CO2 emissions (e.g., limiting peaker plant operating hours and avoiding renewable curtailment reduces overall CO2 pollution from the power sector). This new "service" represents a climate benefit to intelligent electrification [11]. The exact carbon calculus to quantify the value of these decarbonization services is still an open question, but requires the use of either short- or long-run marginal or average emissions rates ($/kWh) along with a socialized cost of carbon, which today has a broad range of $50-200/metric ton [35],[23]. From [35], 60GW of flexibility provided $20B in societal benefit over a 10-year period, which roughly represents an average annual value of flexible capacity of $33/kW-year through 2030. Another study highlighted savings of 44-59 million tons of CO2 in 2050 from 200GW of flexible demand, which carries a societal value ranging from $11/kW-year to $59/kW-year depending on the cost of carbon [11] Across the two studies, the decarbonization revenue from socialized value of flexible demand represents a value proposition similar in scope to energy arbitrage and ancillary services.

Combining these four types of market-facing grid services, the total value of price-taking flexibility ranges from about $211/kW-yr to $389/kW-yr in whole-sale market, where the kW represents *flexible kW* (which is less than the rated DER capacity for electric loads). Thus, an electric water heater (e.g., about 0.25-0.33kW average flexibility), A/C (e.g., about 1kW average flexibility in three summer months), and a BTM battery (e.g., 5kW up/down flexibility) would generate annual revenues of \$53-\$128/yr, \$53-\$97/yr, and \$1060-\$1950/yr, respectively. Of course, these revenues do not all go to the DER owner or consumer or coordinators, but are split between DER program owners (e.g., utility enrolling customers), DER hardware manufacturers (e.g., providing API access to hardware), DER coordination platform provider (e.g., 3rd party aggregator), and DER owner/consumer (e.g., incentive payments for enrolling). Unfortunately, connecting to DERs often requires API access fees from the manufacturers, which can run anywhere from \$5-\$30/device-year. The remaining revenue can then be split between the DER program owners, platform providers, and device owner.

Remark 1 : The marginal values (\$/kW-yr) of flexibility presented above are representative of the next 10 years or so (e.g., 2030), when the grid can effectively host and benefits from additional flexibility (e.g., “first kW-year”). This expected need for flexibility is due to a mix of the following: *i*) retirements of fossil-fuel power plants, *ii*) aging T&D infrastructure needing deferred upgrades, *iii*) electrification efforts causing variable demand, and *iv*) renewable generation driving up a variable, uncontrolled supply [88]. However, as more and more flexibility is added to the grid, the marginal value of new flexibility is expected to decrease [3]. This means that, in 2050 and beyond, *new* flexible capacity will likely be worth less. Nonetheless, as flexible capacity ages, it needs to be replaced/upgraded in a distributed manner, which will continue to drive demand for DER technologies.

Beyond wholesale markets, local DER services also beget value for consumers and distribution utility operators.

3.2 Local DER services

Value streams exist locally to: (*i*) reduce the DER device owner’s energy costs (e.g., minimize export of solar PV due to net-metering rules or reducing one’s load to reduce demand-charges); and (*ii*) enhance the device owner’s energy resilience (i.e., backup generation from energy storage).

In particular, demand charges (i.e., \$/kW-month charges from a customer tariff) represent a customer’s personal peak minimization problem, which requires additional coordination among all DERs behind-the-meter (e.g., to make sure that a refrigerator, EV charger, heat-pump, and water heater do not run coincidentally). This greatly increases complexity of any DER coordination schemes by significantly constraining the fleet and reducing the flexibility available. The effects of the myopic nature of demand charges on total fleet flexibility is also recognized in broader criticisms of demand charges as: (1) an insufficient proxy for shared generation and T&D capacity costs; and (2) a minimizer of coincident peaks across customers [48].

The resilience component of DERs is generally reserved for BTM energy storage and, possibly, Vehicle-to-Home (V2H) and Vehicle-to-Grid (V2G) systems. However, just as community solar PV allowed customers to band together, DER coordination could enable a "community battery," where neighbors band together for a larger battery and leverage DER coordination to maximize resilience during potential outages. The exact value placed by consumers on backup generation is hard to measure. However, from recent utility filings in Vermont, one utility has been able to rate-based its resilience service offering to customers. The offer consists of consumers leasing two BTM Tesla PowerWall batteries (with combined rating of 26kWh/10kW) for just $55 per month for 10 years (i.e., total payment of $6,600, which compares well with the average installed costs of about $20,000) [30]. Of course, this offer requires that the customer allows the utility to operate the batteries during 5-10 critical peak reduction events per year when they are not needed for personal resilience. Similar programs exist in California where Tesla, as of February 2022, has actively enrolled almost 6,200 homes with backup batteries in the Tesla *Virtual Power Plant* DER coordination service, which has a total rated capacity exceeding 50MW in California and discharges up to 25MW for up to 1.5 or 2 hours in PG&E's territory alone [21]. Other technology companies are in the process of building up their own DER coordination services from a variety of DERs to gain access to the flexibility value stack.

Clearly, there are economic incentives for coordinating DERs. On top of that, electrification efforts are creating waves of new, connected, and responsive DERs that will become available for (intelligent) coordination. At the same time, public policies are working to give DERs greater access to whole-sale energy markets. However, performance of DER coordination schemes depends on a number of critical factors, including the cyber-physical (control and communication) architecture and the composition of DER fleets. These topics are described next.

4 General Methods of Coordination DERs

When designing and developing methods for coordinating DERs, one must account for at least some of the following:

- expected size of fleet: large fleets beget computational bottlenecks more easily than smaller fleets.
- desired composition of fleet: diversity of DERs can improve performance but increase complexity.
- desired responsiveness of the fleet: grid services have different timescales.
- available sensing and communications: control architectures enable different feedback mechanisms.
- local comfort and convenience requirements: quality of service (QoS) constrains device behavior and fleet performance.

Conversely, any coordination method (or more accurately, its control architectures) makes implicit assumptions about available devices, data, commu-

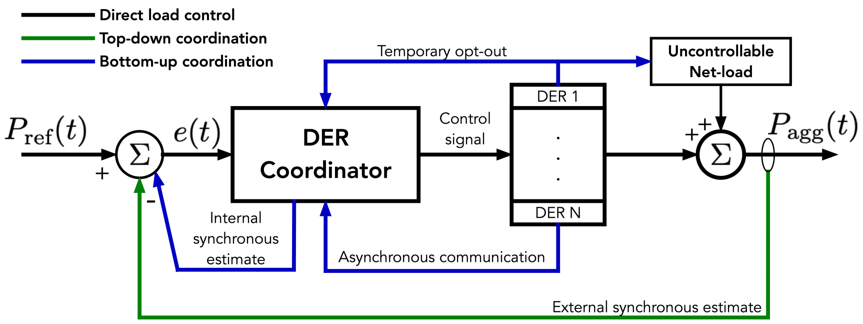

Fig. 2 DER Coordination architectures depends on the role of feedback and communication protocols. Direct load control is illustrated via black lines and is effectively an open-loop synchronous dispatch based on a desired reference or a pre-determined control signal (e.g., all DERs off). Broadcast-based methods (in green) augment DLC with feedback ($P_{\mathrm{ref}}(t)$ from an external synchronous estimate), synchronous control signal to DERs, which have local computing/sensing capabilities. The bottom-up scheme (blue) leverages asynchronous, bidirectional DER communications, where by DERs communicate requests to the coordinator and the coordinator make simple decisions based on $e(t)$. In addition, the bottom-up coordinator can construct a synchronous internal estimate of the aggregate demand, P_{agg}, which is employed with feedback.

nication, and timescales [77],[43, 78]. While it is beyond the scope of this manuscript to discuss every method, there are generally three broad classes of coordination schemes: direct load control (DLC, of which one implementation represents conventional DR), broadcast-based/top-down coordination, and device-driven/bottom-up coordination. Figure 2 illustrates the key differences between the methods.

4.1 Direct Load Control (DLC) / Demand Response (DR)

This category is generally considered the “hammer” of flexibility and usually implemented in open-loop fashion with a control signal broadcast to the entire population. Often the control signals are pre-programmed like sprinkler schedules to turn off/on during certain periods. For larger DER fleets under DLC, less sensing and communications are assumed available, and, thus, DLC reverts to the conventional DR methodology, where consumer QoS is often ignored and DERs are curtailed for hours at a time to deliver avoided capacity services (e.g., HVAC thermostat and water heater DR programs). Poor QoS management can lead DR programs to lose a large number of enrolled devices each summer, because customers do not like coming home to or working in a hot home. That is, feedback mechanisms are generally not present in these conventional DR schemes. For small fleets (e.g., up to 100s of DERs), some feedback can be implemented to extract updated state measurements from each DER. In addition, at smaller scales, full observability and controllability of DERs in the fleet can be reasonably achieved, which permits computationally-tractable (stochastic) optimization-based dispatch schemes that can explicitly incorporate QoS constraints during DER coordination (e.g., a microgrid setting with DERs minimizing energy costs or peak demand over a day).

4.2 Top-down / Broadcast-based coordination

DER coordination schemes based on top-down principles make up a large proportion of literature and implementations. As the name implies, the coordinator (on top) broadcasts out its control signal to all devices. However, unlike DLC, the DERs in top-down schemes can be outfitted with local sensing and computing capabilities that allows them to effectively filter the broadcast control signals and differentiate (or prioritize) their expected responses across the fleet and over time [54],[55],[81]. For example, if the coordinator wants to ramp up power from the fleet, the broadcast signal could be created to increase the likelihood that the ACs with higher measured room temperatures switch from off to on first. The concept of filtering the DER responses to the broadcast control signal can also be used to group different DER device types.

Broadcasting of control signals is easily scalable (i.e., see radio signals), can preserve QoS when combined with local DER sensing, and the signal can be updated at a rate that matches the desired responsiveness of the fleet, which allows participation in most grid services. However, broadcast control is similar to a mega-phone: *you are heard by all, but cannot hear anyone.* That is, top-down implementations have a major drawback in that they cannot directly gauge which devices respond to the signal and by how much and which devices do not respond. This means that top-down methods lack the inherent ability to feed back the aggregate (net) demand of the fleet to the coordinator in real-time and, instead, have to rely on some (open-loop) estimate of the total (net) fleet demand or an overriding assumption that most/all (net) demand at any given time is from to the fleet's DERs, which then permits a simple measurement of the aggregate (net) demand from SCADA (e.g., distribution substation). Nonetheless, these are strong assumptions for any practical DER coordination scheme today.

Furthermore, since a DER's location is unobservable in top-down methods and since the same broadcast signal is sent to all DERs, there is no simple mechanism to design the DERs' responses based on local constraints imposed by the grid (e.g.,transformer or voltage limits) and devices (e.g., cycling). This lack of network awareness has implications on the ability of the DER coordinator to resolve or alleviate bottlenecks in distribution networks.

4.3 Bottom-up / Device-driven coordination

In bottom-up (or device-driven) coordination schemes, the coordinator's megaphone is replaced by a microphone that, instead of "yelling" commands to DERs, listens for and acts on incoming (asynchronous) DER communications.

Specifically, DERs in device-driven schemes are outfitted with the same sensing and computing capabilities as in the top-down coordination schemes. However, instead of filtering an *incoming* broadcast signal, DERs in device-driven coordination schemes produce an asynchronous **outgoing** communication or request to the coordinator [28],[29],[86]. A DER's outgoing signal can include a request to turn on/off/charge/discharge for NkW over T seconds and include additional device information, such as address, rated capacity, and cycling constraints in any request, which can be used to directly gauge the DER's availability or "fitness" to respond, if its request is accepted. Separately, the DER could compute its own fitness value and just communicate that to the coordinator. In addition, the rate at which each DER communicates represents a local control policy that can be designed to correlate with the device's QoS (e.g., the hotter the room, the more frequently a request is made to turn on) [24],[2].

The asynchronous nature of the DER updates is exactly enabled by the bottom-up concept and allows each DER to operate with its own clock. Thus, over any small time interval Δt only a small fraction of the fleet's DERs will communicate, which reduces communication overhead and coordinator complexity. For example, the DER coordinator could process requests in real-time as they arrive (i.e., like a relay controller that accepts a request only if $e(t) > 0$) [2] and/or queue up multiple devices' requests for later processing [86],[63],[8].

Furthermore, since the coordinator receives the DERs' communicated requests and determines which are accepted and denied, it can accurately infer the changes in (net) power from a sequence of control signals. Thus, the coordinator can accurately reconstruct the aggregate fleet power, in real-time, from just the incoming requests (and any potential opt-out actions, which are also communicated to coordinator). That is, the bottom-up scheme engenders a practical, closed-loop implementation that is responsive to real-time grid services.

5 Challenges with scaling intelligent electrification

Despite the promising value proposition and advanced DER coordination schemes being developed there are still numerous major technical and practical challenges to intelligent electrification and coordination. Some practical challenges have previously been highlighted in other works, e.g., lack of DER communication standards, missing incentives in rate design, and cyber security [2],[50],[68]. Below, we discuss the need for and challenges related to grid-aware coordination, accurately characterizing flexibility, and speeding up deployment of intelligent electrification.

5.1 Grid-aware Coordination

As intelligent electrification efforts scale up and dispatchable DERs grow in numbers, distribution substations, MV and LV feeders, and transformers may be driven to their voltage, current, power, and temperature limits by DER coordination schemes [73],[79],[8]. This will impact future grid reliability and resilience [59]. This means that grid operators will need to (a) better understand their own grid's capacity for DER coordination across different timescales; and/or (b) share grid data with DER coordinators; and/or (c) receive data from DER Coordinators as illustrated in Fig. 3.

In one extreme case, grid operators (e.g., utilities) could embody the DER coordinators' roles and, thus, maintain full observability of (FTM) grid and (BTM) DER data and control stacks to engender a so-called "utility-centric" Grid-Aware Coordination scheme, which would represent all of Fig. 3. This extreme was studied for a large NY utility in [1], where a large penetration of solar PV, smart inverters, and intelligent water and ACs were controlled in a hierarchical top-down coordination scheme to provide various grid services. In fact, almost all grid-optimization-based (or optimal-power-flow-based) DER coordination schemes embody a utility-centric scheme (since it needs both Grid and DER data). Recently, utility-centric schemes are becoming more common as exemplified by numerous utilities working very closely with and dispatching DERs via 3rd party platform providers [6]. While these utilities do not directly control BTM DERs, they are still controlling the fleet directly via software and customer-owned broadband internet (e.g., WiFi). Having the utility access data and control BTM DERs is relatively new and should raise concerns from a privacy perspective and from 3rd party aggregators, who depend on utilities to scale their services (rather than providing valuable DER services directly to consumers).

Another extreme scheme is when real-time grid data is made openly available to all DER Coordinators, who can then design Grid-Aware Coordination schemes given some reliability criteria/requirements [41]. The Grid Operator could publish the data as a traffic-light dashboard to obfuscate grid conditions or the DER Coordinator could have numerous sensors distributed throughout the grid (e.g., via battery or PV inverters). However, this extreme case is unlikely to unfold given the critical nature of distribution system infrastructure data and the desire of utilities to remain "in control."

In between these extremes are two alternative grid-aware classes. The first class of schemes has the Grid Operator actively filter/truncate the broadcast control signals from the DER coordinator to avoid potential grid overloads. In this case, the utility investigates the impact of a range of feasible control signals on grid conditions (e.g., via simulation or sensitivities) and determines constraints (e.g., filter) that that DER coordinator must apply to its control signal to ensure grid reliability [72],[38]. While it affords the DER coordinator more freedom in pursuing grid services and generating revenue, it puts the Grid Operator in a dominant position to effectively regulate the aggregator's performance based on (potentially overly conservative, worst-case) assump-

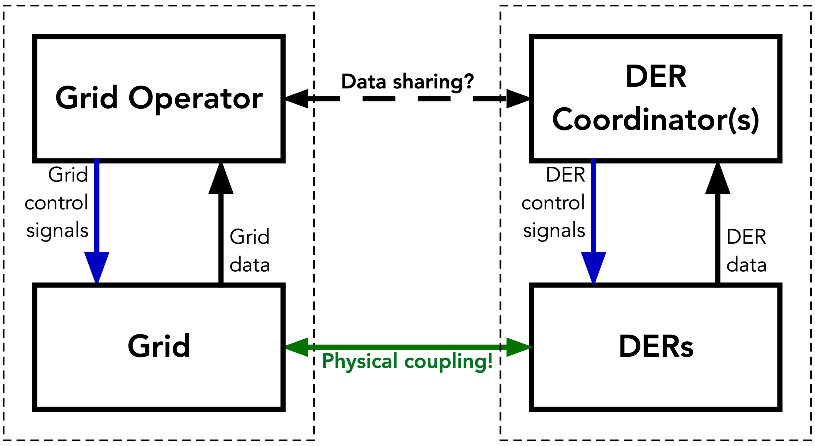

Fig. 3 With intelligent electrification, the physical Grid-DER coupling (green) between grid operators and DER coordinators will necessitate some form of information sharing between the two to guarantee reliability of the grid. The information shared could be a mix of data (black) and control signals (blue). However, the minimum information sharing necessary to ensure reliability is an open question today, i.e., is it necessary to share DER control signals with the grid operator or just DER data and can grid operators share grid data with DER coordinators?

tions. In addition, the approach needs to carefully consider multi-aggregator settings and giving aggregators equitable access to the grid. The second class of grid-aware schemes leverages existing hosting capacity framework to construct a data sharing mechanism between Grid Operator and DER Coordinators. Specifically, the Grid Operator computes an operating envelope (or dynamic hosting capacity) [61],[49],[66], which represents a timeseries sequence of bounds on the network injections (at each node in the grid at each time). The Grid Operator then offers these bounds to available aggregators, who through an allocation mechanism (e.g., bidding process [62]) can secure their “slice” of the grid’s capacity. Once the capacity has been allocated (e.g., for the hour), the aggregators are free to operate as they please within these bounds. Of course, the scheme’s operating envelope depends on forecasted demand at fast timescales (which introduces uncertainty) and assumes that DER Coordinators always stay within their allocated bounds. Robust methods are, therefore, needed to guarantee that the bounds are valid under realistic operating conditions.

Thus, numerous schemes for grid-aware DER coordination exist today and (partly) tackle the asymmetry of information between Grid Operators (who have grid data, but not DER controls) and DER Coordinators (who have DER controls, but no grid data). However, in practice and at scale, the relationship between Grid Operators and DER Coordinators is still an open challenge that neither policy nor technology tools can solve today.

5.2 Characterizing available flexibility

Accurate characterization of the flexibility of DERs can help enable efficient DER coordination schemes and play a critical role in the operations and planning of the grid. These characterization typically contain useful information about the DERs ability and willingness to respond to DER coordination commands and/or incentives, including 1) its speed of response (or, flexibility ramp rates), 2) its ability to deviate from typical or baseline power consumption without sacrificing end-user QoS (or, flexible power capacity), and 3) its ability to sustain the aforementioned deviation over a period (or, flexible energy limit). Often the cost of a DER providing grid services and/or responding to DER coordination signals, measured either in financial terms or via its impact on the end-user QoS, is also considered as a key feature of flexibility characterization [71]. The cost component becomes useful in constructing the bids for various grid services in a multi-market participation by the DERs (via an aggregator). Characterization of DER flexibility, therefore, is often a techno-economic problem which requires identifying different technical (ramp rate, power capacity, and energy limit) and economic (cost) features of DER flexibility.

Traditionally, the flexibility of generating resources are characterized by two-dimensional regions of feasible operating points defined by the active (P) and reactive (Q) power generation, typically referred to as the P-Q capability curves. Unlike these traditional resources, flexible loads are constrained by the duration over which they can sustain the demand flexibility (driven by QoS), much like an energy storage. This has led to the concept of representing the flexible DERs in the form of virtual batteries (VB), virtual power plants (VPP), or virtual energy storage (VES). However, this representation remains an approximation (or, a simplification), and typically there is no unique virtual battery representation for a group of DERs, but rather a family of virtual batteries [33]. The selection of the virtual battery model largely depends on the nature of the DER coordination strategies or the grid operational/planning problem that is going to use those DER flexibility models. For example, while some use-cases might require a conservative estimate of the DER flexibility (a *sufficient* virtual battery), akin to a minimal flexibility characterization; other applications might want to work with the best-case scenario by characterizing the maximal DER flexibility (a *necessary* virtual battery). Regardless, virtual battery-based flexibility modeling offers a couple of key advantages, as illustrated in Fig. 4. Firstly, it allows a generalized form of flexibility characterization, masking the heterogeneity of the collection of DERs, thereby simplifying its integration in DER coordination schemes and/or grid operational/planning problems. Secondly, via the use of a dynamic model of the (virtual) state-of-charge, the virtual batteries allow temporal coupling between the different grid services. For example, while a short-duration primary frequency response may deplete the flexible power capacity momentarily, a slow ramping event over a longer period may deplete the available flexible energy limits. It is this versatility of the virtual battery models in characterizing inter-temporal flexibility

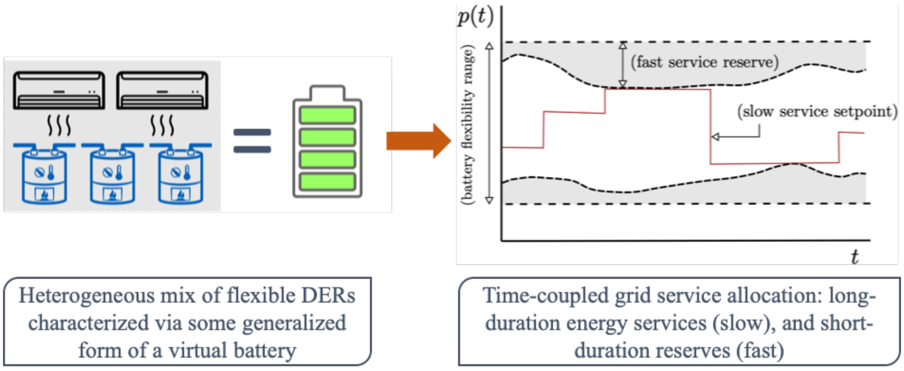

Fig. 4 When coordinated intelligently, flexible DERs can be characterized as a single dispatchable resource called a "virtual battery" or VB (left). The VB has time-varying energy and power bounds and can be dispatched to deliver time-coupled grid services, such as fast and slow reserves.

constraints, that makes these models useful in multi-timescales DER coordination and resource allocation problems. This allows provisioning of concurrent grid services, e.g., primary frequency response, frequency regulation, and ramping services [5].

While the information regarding the availability and the power, and energy ratings of a physical battery may be easily accessible and reliable, those often have to be estimated and updated online for a virtual battery. For a collection of relatively simpler, and homogeneous, mix of DERs – e.g., a group of similarly rated residential air-conditioning units – the identification process often simplifies to algebraic calculations based on available boilerplate information on the individual DERs [33]. However, in most realistic scenarios, such information are often unreliable or unavailable due to lack of sensors, privacy concerns, etc. In such cases, virtual battery-based flexibility characterization must rely on available limited measurements data, with the use advanced algorithmic methods and data analytics, from mathematical optimization [37], to statistical estimation methods [24], to deep neural networks [13],[53]. One advantage these data-driven methods is their applicability and generalizability to a wider and complex pool of DERs. For example, the study in [37] successfully demonstrated the data-driven virtual battery characterization algorithms on a large (5900 sq. m.) commercial building – an airport terminal – with a peak load of 600 kW in late summer.

Flexibility characterization methods typically adopt one of the two following approaches. One approach looks at the collection of DERs in aggregate, and directly characterizes the flexibility of the aggregated DERs as one entity. This approach is highlighted by some of the aforementioned works, such as [37],[13],[24]. The other approach takes a more bottom-up route to flexibility characterization. In this approach, each DER (or a sub-group of DERs) report their individual flexibility characterization to the DER aggregator/coordinator in some pre-specified form, who then constructs the aggregated flexibility model by suitably summing up (e.g., via Minkowski sum) the individual flexibility models. While such summation usually scales poorly, there exist useful approximation and algorithmic methods to perform these summations in an efficient manner, across different types of DERs [87],[46],[45],[65]. The advantages of the bottom-up approach stem from its adherence to end-user privacy (no need to share DER details and/or consumption data), and affinity towards modularity and plug-and-play (easy to update aggregated flexibility after removal/inclusion of DERs).

One of the main challenges in DER flexibility characterization stems from uncertainty and unpredictability. A key driving factor behind unpredictability in DER flexibility characterization is the end-user behavior. While DER flexibility characterization often involves (direct or indirect) learning of the impact of end-usage behavior on flexibility, the human factors involved in the process continue to inject uncertainties. Broadly, there are two ways of accounting for uncertainties in DER flexibility models. One that provides a conservative (robust) estimate of the flexibility considering the worst-case uncertainty scenarios [20]; the other that extends the flexibility model into a stochastic one by accounting for the probability distributions of the uncertainty scenarios [14], including decision-dependent uncertainties introduced from the (unknown) response of consumers to simultaneous discomfort (driving down flexibility) and incentives (driving up flexibility) [70]. The worst-case considerations could lead to overly conservative, and hence impractical, flexibility estimates. The stochastic flexibility models, on the other hand, are typically more computationally intensive to identify, and may not be easily integrable into grid operations that are largely deterministic. Another challenge in DER flexibility characterization is in capturing the network constraints. Much like the need for grid-aware coordination, there is also a need for accounting for grid constraints in the aggregate DER flexibility characterization, especially when performed over a wider section of a distribution feeder. This is especially useful when an aggregated DER flexibility model might need to be developed at the substation level, as in [20], but could also be developed at the nodal level [66] for better coordination strategies.

Finally, with the emergence of advanced sensing, communication, and realtime controls for DERs, there is an increasing cyber-vulnerability driven by an ever-expanding cyber-attack surface [68]. As such, any flexibility characterization methods – especially those relying on DER operations data from residential broadband connections – would have to be designed to be robust against malicious data manipulations, including at the utility's point of connection, where both utility and DER assets may be controlled by the same tools. Of course, no cyber-physical methods can guarantee cyber-security as long as a human operator has need-to-know access. However, there are industry practices that DER coordinators should follow to minimize risks, including multi-factor authentication for employees with cloud or device privileges, transport layer security (e.g., TLS 1.2) protocols for encrypted device-to-cloud communications, and device-level hardware/software encryption. In addition, new industry-developed standard, Matter [40], seeks to standardize the security of communications and privacy of data exchanges across connected home device manufacturers. Enabling a cyber-secure power grid under high penetration of DERs would require not only securing the information technology (IT) network but also the operational technologies (OT) via integrated IT/OT monitoring and detection [15],[75]. For additional information on cyber-security and DERs, please refer to the Smart Grid Interoperability Standards by NIST [31] and the recent report by U.S. DOE Office of Cybersecurity, Energy Security, and Emergency Response (CESER) [68].

As the techno-economic value propositions of DERs continue to increase – 20% of the residential TCLs in California, US, are expected to generate almost the same revenue as a physical battery of 500MW/1000MWh [85] – advanced flexibility characterization methods need to be developed, that better handle uncertainties in end-usage, efficiently account for network constraints, and are robust against adversarial data manipulations.

5.3 Slow pace of deployment

Clearly, coordinating kW-scale DERs requires the availability of an existing fleet or the deployment of new electrical assets, such as water heaters, heat-pumps, thermostats, EV chargers, or battery systems. Since the aggregate flexibility of a fleet depends on the total number of available DERs, there is a huge incentive to deploy fast and at scale to enroll as many DERs as possible. However, physically deploying thousands of kW-scale DERs in any particular location is an arduous process due to the following practical challenges: (*i*) development of marketing program(s) and contract(s) with utilities or public service institutions to manage incentives (e.g., bill credits); (*ii*) waiting on voluntary customer enrollment; and (*iii*) availability of trade-persons to complete DER installations. In particular, the lack of trade-persons is a fundamental barrier to DER deployment over the next decade, which will slow deployment of intelligent electrification. Some technologies are being developed and being tested in pilot studies to more efficiently tie together the electrification process: from initial consumer interest, to incentives, sales, installation, and enrollment [51]. Other efforts are more focused on increasing the number of tradepersons through new academic initiatives to turn high school and community college students into well-paid intelligent electrification deployment warriors with a two-year education [58].

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Annotated References

1. C.Han, D.Witthaut, L.R.Gorjao,and P.C. Bötcher,“Collective effects and synchronization of demand in real-time demand response,” Journal of Physics:

Complexity, vol. 3, no. 2, p. 025 002, Jun. 2022. Annotations: This paper examines the role pricing strategies in bringing about instability in a fleet od DERs. It takes an interesting (statistical) physics angle to illustrate stability and dynamics complexities.

2. J. Taft and J. Ogle, "Grid Architecture Guidance Specification for FAST-DERMS," en, PNNL, Tech. Rep. PNNL-31172, Apr. 2021. Annotations: The PNNL report provides an updated and modern view on DER control architectures, including coordination, communication, and intelligence. Furthermore, it encompasses various transmission and distribution and aggregator interface considerations.
3. S. Riaz and P. Mancarella, "Modelling and characterisation of flexibility from distributed energy resources," IEEE transactions on power systems, vol. 37, no. 1, pp. 38–50, 2021. Annotations: The paper takes an interesting systematic view of flexibility (power, duration, and responsiveness) from DERs and considers both flexibility at one time (static) and over a time horizon (dynamic). In addition, the paper considers a costs of (achieving) flexibility as much as flexibility itself, which represent an interesting coupling between available flexibility and any potential incentives to perform.

References

1. Almassalkhi M, Brahma S, Nazir N, Ossareh H, Racherla P, Kundu S, Nandanoori SP, Ramachandran T, Singhal A, Gayme D, Ji C, Mallada E, Shen Y, You P, Anand D (2020) Hierarchical, Grid-Aware, and Economically Optimal Coordination of Distributed Energy Resources in Realistic Distribution Systems. Energies 13(23):6399, DOI 10.3390/en13236399, URL https://www.mdpi.com/1996-1073/13/23/6399
2. Almassalkhi M, Frolik J, Hines P (2022) Packetizing the power grid: The rules of the internet can also balance electricity supply and demand. IEEE Spectrum 59(2):42–47, DOI 10.1109/MSPEC.2022.9706403
3. Alstone P, et al (2017) 2025 California Demand Response Potential Study – Charting California's Demand Response Future. Tech. Rep. LBNL-2001113, LBNL
4. Australian Energy Market Operator (2021) Batteries Explainer: Big Batteries. URL https://aemo.com.au/en/learn/energy-explained/energy-101/energy-explained-big-batteries
5. Bhattacharya A, Hansen J, Kalsi K, Lian J, Nandanoori SP, Reeve H, Adetola V, Lin F, Leichtman T, Gourisetti SN, et al. (2019) Incentive-based control and coordination of distributed energy resources. Tech. Rep. DOE-PNNL-28724, Pacific Northwest National Lab.(PNNL), Richland, WA (United States)
6. Blair B, Fitzgerald G, Dougherty C (2021) The State of Managed Charging in 2021. Tech. rep., Smart Electric Power Alliance, Washington, D.C.
7. Bolun Xu, Dvorkin Y, Kirschen DS, Silva-Monroy CA, Watson JP (2016) A comparison of policies on the participation of storage in U.S. frequency

regulation markets. In: 2016 IEEE Power and Energy Society General Meeting (PESGM), IEEE, Boston, MA, USA, pp 1–5, DOI 10.1109/PESGM.2016.7741531, URL http://ieeexplore.ieee.org/document/7741531/
8. Botkin-Levy M, Engelmann A, Mühlpfordt T, Faulwasser T, Almassalkhi MR (2022) Distributed control of charging for electric vehicle fleets under dynamic transformer ratings. IEEE Transactions on Control Systems Technology 30(4):1578–1594, DOI 10.1109/TCST.2021.3120494
9. Brahma S, A Khurram, Ossareh H, Almassalkhi M (2022) Optimal Frequency Regulation using Packetized Energy Management. IEEE Transactions on Power Systems
10. Brahma S, Ossareh H, Almassalkhi MR (2022) Statistical Modeling and Forecasting of Automatic Generation Control Signals. In: IREP Symposium - Bulk Power System Dynamics and Control
11. Brehm K, Dyson M, McEvoy A, Usry C (2023) Virtual Power Plants, Real Benefits. Tech. rep., RMI, URL https://rmi.org/insight/virtual-power-plants-real-benefits/
12. Cammardella N, Mathias J, Kiener M, Busic A, Meyn S (2018) Balancing California's Grid Without Batteries. In: IEEE Conference on Decision and Control, pp 7314–7321, publisher: IEEE
13. Chakraborty I, Nandanoori SP, Kundu S (2018) Virtual battery parameter identification using transfer learning based stacked autoencoder. In: 2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA), IEEE, pp 1269–1274
14. Chakraborty I, Nandanoori SP, Kundu S, Kalsi K (2020) Stochastic virtual battery modeling of uncertain electrical loads using variational autoencoder. In: 2020 American Control Conference (ACC), IEEE, pp 1305–1310
15. Chan K, Kim Y, Jo JY (2022) Der communication networks and their security issues. In: 2022 IEEE 12th Annual Computing and Communication Workshop and Conference (CCWC), IEEE, pp 0785–0790
16. Clarke L, Wei YM, Navarro ADLV, Garg A, Hahmann A, Khennas S, Azevedo I, Löschel A, Singh A, Steg L, Strbac G, Wada K (2022) Energy systems. In: Shukla P, Skea J, Slade R, Khourdajie AA, van Diemen R, McCollum D, Pathak M, Some S, Vyas P, Fradera R, Belkacemi M, Hasija A, Lisboa G, Luz S, Malley J (eds) Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, UK and New York, NY, USA, book section 6, DOI 10.1017/9781009157926.008, URL https://www.ipcc.ch/report/ar6/wg3/downloads/report/IPCC_AR6_WGIII_Chapter06.pdf
17. Clean Energy Council (2021) Battery storage: The new clean peaker. Tech. rep., CEC, Australia, URL https://assets.cleanenergycouncil.org.au/documents/resources/reports/battery-storage-the-new-clean-peaker.pdf
18. Cole W, Frazier AW, Augustine C (2021) Cost Projections for Utility-Scale Battery Storage: 2021 Update. Renewable Energy

19. Creutzig F, Roy J, Devine-Wright P, Díaz-José J, Geels F, Grubler A, Maizi N, Masanet E, Mulugetta Y, Onyige C, Perkins P, Sanches-Pereira A, Weber E (2022) Demand, services and social aspects of mitigation. In: Shukla P, Skea J, Slade R, Khourdajie AA, van Diemen R, McCollum D, Pathak M, Some S, Vyas P, Fradera R, Belkacemi M, Hasija A, Lisboa G, Luz S, Malley J (eds) Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, UK and New York, NY, USA, book section 5, DOI 10.1017/9781009157926.007, URL https://www.ipcc.ch/report/ar6/wg3/downloads/report/IPCC_AR6_WGIII_Chapter05.pdf
20. Cui B, Zamzam A, Bernstein A (2021) Network-cognizant time-coupled aggregate flexibility of distribution systems under uncertainties. In: 2021 American Control Conference (ACC), IEEE, pp 4178–4183
21. Davis R (2023) What is Tesla's Virtual Power Plant? URL https://www.lastbulb.com/virtual-power-plant
22. Dyson M, Mandel J, et a (2015) The Economics of Demand Flexibility. Tech. rep., RMI, URL http://www.rmi.org/electricity_demand_flexibility
23. EnergyHub (2023) A better way to evaluate the carbon impact of virtual power plants. URL https://www.energyhub.com/blog/a-better-way-to-evaluate-the-carbon-impact-of-virtual-power-plants/?utm_content=245975845&utm_medium=social&utm_source=linkedin&hss_channel=lcp-595749
24. Espinosa LAD, Almassalkhi M (2020) A Packetized Energy Management Macromodel With Quality of Service Guarantees for Demand-Side Resources. IEEE Trans Power Syst 35(5):3660–3670, DOI 10.1109/TPWRS.2020.2981436, URL https://ieeexplore.ieee.org/document/9039692/
25. FERC (2011) Demand Response Compensation in Organized Wholesale Energy Markets
26. FERC (2018) Electric storage participation in markets operated by regional transmission organizations and independent system operators
27. FERC (2020) Participation of Distributed Energy Resource Aggregations in Markets Operated by Regional Transmission Organizations and Independent System Operators
28. Frolik J (2004) Qos control for random access wireless sensor networks. In: Proc. 2004 Wireless Communications and Networking Conference (WCNC04), Greenville, SC
29. Frolik J, Hines P (2012) Random access, electric vehicle charge management. In: 1st IEEE International Electric Vehicle Conference. (IEVC), Greenville
30. GMP (2020) GREEN MOUNTAIN POWER CORPORATION ENERGY STORAGE SYSTEM SERVICE. URL https://greenmountainpower.com/wp-content/uploads/2020/06/GMP-Powerwall-Program-Tariff-and-Lease-2020.pdf

31. Gopstein A, Nguyen C, O'Fallon C, Hastings N, Wollman D (2021) NIST Framework and Roadmap for Smart Grid Interoperability Standards, Release 4.0. Tech. rep., National Institute of Standards and Technology, URL https://nvlpubs.nist.gov/nistpubs/SpecialPublications/NIST.SP.1108r4.pdf
32. Han C, Witthaut D, Gorjão LR, Böttcher PC (2022) Collective effects and synchronization of demand in real-time demand response. Journal of Physics: Complexity 3(2):025002, DOI 10.1088/2632-072X/ac6477, URL https://iopscience.iop.org/article/10.1088/2632-072X/ac6477
33. Hao H, Sanandaji BM, Poolla K, Vincent TL (2015) Aggregate Flexibility of Thermostatically Controlled Loads. IEEE Transactions on Power Systems 30(1):189–198, DOI 10.1109/TPWRS.2014.2328865
34. Hledik R (2016) The Hidden Battery. Tech. rep., Brattle Group
35. Hledik R, Peters K (2023) Real Reliability: the Value of Virtual Power. Tech. rep., Brattle Group
36. Hledik R, Faruqui A, Lee T, Hingham J (2019) The National Potential for Load Flexibility. Tech. rep., Brattle Group
37. Hughes JT, Domínguez-García AD, Poolla K (2016) Identification of virtual battery models for flexible loads. IEEE Transactions on Power Systems 31(6):4660–4669, DOI 10.1109/TPWRS.2015.2505645
38. Jang S, Ozay N, Mathieu JL (2022) Data-driven estimation of probabilistic constraints for network-safe distributed energy resource control. In: 2022 58th Annual Allerton Conference on Communication, Control, and Computing (Allerton), IEEE, Monticello, IL, USA, pp 1–8, DOI 10.1109/Allerton49937.2022.9929351, URL https://ieeexplore.ieee.org/document/9929351/
39. Jenkins JD, Luke M, Thernstrom S (2018) Getting to Zero Carbon Emissions in the Electric Power Sector. Joule 2(12):2498–2510, DOI 10.1016/j.joule.2018.11.013, URL https://linkinghub.elsevier.com/retrieve/pii/S2542435118305622
40. Jennifer Pattison Tuohy (2023) What Matters about Matter, the new smart home standard. URL https://www.theverge.com/22832127/matter-smart-home-products-thread-wifi-explainer
41. Khan A, Paudyal S, Almassalkhi M (2022) Performance Evaluation of Network-Admissible Demand Dispatch in Multi-Phase Distribution Grids. In: IREP Symposium - Bulk Power System Dynamics and Control
42. Kintner-Meyer M, Davis S, Sridhar S, Bhatnagar D, Mahserejian S, Ghosal M (2020) Electric vehicles at scale–phase I analysis: High EV adoption impacts on the western US power grid. Tech. Rep. PNNL-29894, Pacific Northwest National Laboratory (PNNL)
43. Kristov L, De Martini P, Taft JD (2016) A tale of two visions: Designing a decentralized transactive electric system. IEEE Power and Energy Magazine 14(3):63–69
44. Kundu S, Hiskens IA (2014) Nonlinear dynamics of hysteresis-based load controls. IFAC Proceedings Volumes 47(3):5419–5425

45. Kundu S, Chandan V, Kalsi K (2018) Scalable Computation of 2D-Minkowski Sum of Arbitrary Non-Convex Domains: Modeling Flexibility in Energy Resources. In: Hawaii International Conference on System Sciences, URL http://arxiv.org/abs/1809.04265, arXiv: 1809.04265
46. Kundu S, Kalsi K, Backhaus S (2018) Approximating Flexibility in Distributed Energy Resources: A Geometric Approach. In: Power Systems Computations Conference, Dublin, Ireland, URL http://arxiv.org/abs/1803.06921, arXiv: 1803.06921
47. Langevin J, Harris CB, Satre-Meloy A, Chandra-Putra H, Speake A, Present E, Adhikari R, Wilson EJ, Satchwell AJ (2021) US building energy efficiency and flexibility as an electric grid resource. Joule 5(8):2102–2128, DOI 10.1016/j.joule.2021.06.002, URL https://linkinghub.elsevier.com/retrieve/pii/S2542435121002907
48. LeBel M, Weston F, Sandoval R (2020) Demand Charges: What Are They Good For? Tech. rep., REGULATORY ASSISTANCE PROJECT (RAP), URL https://www.raponline.org/wp-content/uploads/2020/11/rap-lebel-weston-sandoval-demand-charges-what-are-they-good-for-2020-november.pdf
49. Liu MZ, Ochoa LN, Riaz S, Mancarella P, Ting T, San J, Theunissen J (2021) Grid and market services from the edge: Using operating envelopes to unlock network-aware bottom-up flexibility. IEEE Power and Energy Magazine 19(4):52–62, DOI 10.1109/MPE.2021.3072819
50. Lo H, Blumsack S, Hines P, Meyn S (2019) Electricity rates for the zero marginal cost grid. The Electricity Journal 32(3):39–43, DOI 10.1016/j.tej.2019.02.010, URL https://doi.org/10.1016/j.tej.2019.02.010, publisher: Elsevier
51. Lomas N (2023) Lun is in a mad rush to help heat-pump installers decarbonize homes. TechCrunch URL https://techcrunch.com/2023/03/22/lun-seed/
52. Lorenczik S, Zavala PB, Fraser P (2022) Electricity market report. Tech. rep., International Energy Agency, URL https://www.iea.org/reports/electricity-market-report-december-2020
53. Matar M, Mavalizadeh H, Brahma S, Almassalkhi MR, Wshah S (2023) Learning the state-of-charge of heterogeneous fleets of distributed energy resources with temporal residual networks. Journal of Energy Storage 70:107979, DOI https://doi.org/10.1016/j.est.2023.107979, URL https://www.sciencedirect.com/science/article/pii/S2352152X23013762
54. Mathieu JL, Koch S, Callaway DS (2013) State estimation and control of electric loads to manage real-time energy imbalance. IEEE Transactions on Power Systems 28(1):430–440, DOI 10.1109/TPWRS.2012.2204074, URL http://ieeexplore.ieee.org/document/6246658/
55. Meyn SP, Barooah P, Busic A, Chen Y, Ehren J (2015) Ancillary Service to the Grid Using Intelligent Deferrable Loads. IEEE Transactions on Automatic Control 60(11):2847–2862, DOI 10.1109/TAC.2015.2414772, URL http://ieeexplore.ieee.org/document/7063922/

56. Microsoft Research (2019) Manufacturing trends report. Tech. rep., Microsoft, URL https://info.microsoft.com/rs/157-GQE-382/images/EN-US-CNTNT-Report-2019-Manufacturing-Trends.pdf
57. Milovanoff A, Posen ID, MacLean HL (2020) Electrification of light-duty vehicle fleet alone will not meet mitigation targets. Nature Climate Change 10(12):1102–1107, DOI 10.1038/s41558-020-00921-7, URL https://www.nature.com/articles/s41558-020-00921-7
58. Mohan N, Robbins B, Raju S, Maiden Mueller D, Airineni MR, Guggilam S, Venkatraman D (2023) Electric Power Engineering – A National Imperative! A Report on NSF-NAE Workshop. Tech. rep., University of Minnesota
59. Molzahn D, Roald LA (2019) Grid-aware versus grid-agnostic distribution system control: A method for certifying engineering constraint satisfaction. In: Hawaii International Conference on System Sciences
60. Morgan MG, Talukdar SN (1979) Electric Power Load Management: Some Technical, Economic, Regulatory and Social Issues. Proceedings of the IEEE 67(2):241–312
61. N Nazir, Almassalkhi M (2019) Convex inner approximation of the feeder hosting capacity limits on dispatchable demand. In: IEEE Conference on Decision and Control, Nice, France
62. N Nazir, Almassalkhi M (2022) Market mechanism to enable grid-aware dispatch of Aggregators in radial distribution networks. In: IREP Symposium - Bulk Power System Dynamics and Control
63. Nandanoori SP, Kundu S, Vrabie D, Kalsi K, Lian J (2018) Prioritized threshold allocation for distributed frequency response. In: 2018 IEEE Conference on Control Technology and Applications (CCTA), IEEE, pp 237–244
64. Nazir MS, Hiskens I (2021) Analysis of synchronization in load ensembles. Electric Power Systems Research 190:106779
65. Nazir MS, Hiskens IA, Bernstein A, Dall'Anese E (2018) Inner approximation of minkowski sums: A union-based approach and applications to aggregated energy resources. In: 2018 IEEE Conference on Decision and Control (CDC), IEEE, pp 5708–5715
66. Nazir N, Almassalkhi M (2022) Grid-Aware Aggregation and Realtime Disaggregation of Distributed Energy Resources in Radial Networks. IEEE Transactions on Power Systems 37(3):1706–1717, DOI 10.1109/TPWRS.2021.3121215
67. Nethercutt EJ (2023) Demand Flexibility within a Performance- Based Regulatory Framework. Tech. rep., National Association of Regulatory Utility Commissioners, Washington, D.C.
68. Office of Cybersecurity, Energy Security, and Emergency Response (2022) Cybersecurity Considerations for Distributed Energy Resources on the U.S. Electric Grid. Tech. rep., U.S. Department of Energy
69. Oren SS (2013) A Historical Perspective and Business Model for Load Response Aggregation Based on Priority Service. In: 46th Hawaii International Conference on System Sciences, IEEE, pp 2206–2214, DOI

10.1109/HICSS.2013.39, URL http://ieeexplore.ieee.org/document/6480109/
70. Qi N, Pinson P, Almassalkhi MR, Cheng L, Zhuang Y (2023) Chance-constrained generic energy storage operations under decision-dependent uncertainty. IEEE Transactions on Sustainable Energy pp 1–14, DOI 10.1109/TSTE.2023.3262135
71. Riaz S, Mancarella P (2021) Modelling and characterisation of flexibility from distributed energy resources. IEEE transactions on power systems 37(1):38–50
72. Ross SC, Ozay N, Mathieu JL (2019) Coordination between an Aggregator and Distribution Operator to Achieve Network-Aware Load Control. In: 2019 IEEE Milan PowerTech, IEEE, Milan, Italy, pp 1–6, DOI 10.1109/PTC.2019.8810635, URL https://ieeexplore.ieee.org/document/8810635/
73. Ross SC, Vuylsteke G, Mathieu JL (2019) Effects of Load-Based Frequency Regulation on Distribution Network Operation. IEEE Transactions on Power Systems 34(2):1569–1578, DOI 10.1109/TPWRS.2018.2879464, URL https://ieeexplore.ieee.org/document/8520738/
74. Schweppe FC, Tabors RD, Kirtley JL, Outhred HR, Pickel FH, Cox AJ (1980) Homeostatic utility control. IEEE Transactions on Power Apparatus and Systems PAS-99(3):1151–1163
75. Singh R, Hines PD, Howerter SE, Reilly JT (2022) Beyond derms: Demonstration of automated grid services, mode transition, and resilience. Tech. rep., Argonne National Lab.(ANL), Argonne, IL (United States)
76. St John J (2023) Inside the software running Sunrun's home solar-battery fleets. Canary Media URL https://www.canarymedia.com/articles/grid-edge/inside-the-software-running-sunruns-home-solar-battery-fleets
77. Taft J (2016) Grid architecture 2. Tech. Rep. PNL-24044 2, PNNL
78. Taft J, Ogle J (2021) Grid Architecture Guidance Specification for FAST-DERMS. Tech. Rep. PNNL-31172, PNNL
79. Taheri S, Jalali M, Kekatos V, Tong L (2021) Fast probabilistic hosting capacity analysis for active distribution systems. IEEE Transactions on Smart Grid 12(3):2000–2012, DOI 10.1109/TSG.2020.3038651
80. Tesla (2023) Join Tesla& PG&E to Create a Virtual Power Plant. URL https://www.tesla.com/support/energy/powerwall/own/tesla-pge-virtual-power-plant-pilot
81. Tindemans SH, Trovato V, Strbac G (2015) Decentralized control of thermostatic loads for flexible demand response. IEEE Transactions on Control Systems Technology 23(5):1685–1700
82. TORNBJERG J (2022) Jule-blackout varsler hårdere belastning af elnettet. Intelligent Energi URL https://ienergi.dk/nyheder/jule-blackout-varsler-haardere-belastning-elnettet
83. US Energy Information Administration (2022) U.S. battery storage capacity will increase significantly by 2025. URL https://www.eia.gov/todayinenergy/detail.php?id=54939#

84. US Energy Information Administration (2023) Batteries Explainer: Big Batteries. URL `https://www.eia.gov/electricity/`
85. Wu D, Hao H, Fu T, Kalsi K (2018) Regional assessment of virtual battery potential from building loads. In: 2018 IEEE/PES Transmission and Distribution Conference and Exposition (T&D), IEEE, pp 1–5
86. Zhang B, Baillieul J (2016) Control and Communication Protocols Based on Packetized Direct Load Control in Smart Building Microgrids. Proceedings of the IEEE 104(4):837–857
87. Zhao L, Zhang W, Hao H, Kalsi K (2017) A geometric approach to aggregate flexibility modeling of thermostatically controlled loads. IEEE Transactions on Power Systems 32(6):4721–4731
88. Zhou E, Mai T (2021) Electrification Futures Study: Operational Analysis of U.S. Power Systems with Increased Electrification and Demand-Side Flexibility. Tech. Rep. NREL/TP-6A20-79094, NREL, DOI https://doi.org/10.2172/1785329
89. Zhou E, Hurlbut D, Xu K (2021) A Primer on FERC Order No. 2222: Insights for International Power Systems. Tech. Rep. NREL-TP-5C00-80166, 1823766, MainId:42369, NREL, DOI 10.2172/1823766, URL `https://www.osti.gov/servlets/purl/1823766/`