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Assessing the value of electric vehicle managed charging: a review of methodologies and results

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Abstract

Driven by technological progress and growing global attention for sustainability, the adoption of electric vehicles (EVs) is on the rise. Large-scale EV adoption would both disrupt the transportation sector and lead to far-reaching consequences for energy and electricity systems, including new opportunities for significant load growth. Unmanaged EV charging can stress existing grid infrastructure, possibly leading to operational, reliability, and planning challenges both at the bulk and distribution levels. However, effective management of EV charging can resolve these challenges and provide additional value. The demand-side flexibility provided by managed EV charging offers significant potential benefits for the grid over multiple timescales and applications. Managed charging can support power system planning and operations during normal and extreme conditions, benefitting EV owners and other electricity consumers. However, the costs of enabling these services must be weighed against the benefits they provide. We summarize the benefits of managed EV charging, provide an overview of the landscape of existing implementations and costs of managed charging in the United States, critically review the state of the art of methodologies in analysis/modeling studies, and quantify the cost and benefits of managed charging as reported in the reviewed studies. Finally, we distill several key insights outlining the factors affecting the value of managed EV charging and identify critical gaps and remaining challenges to fully realize effective EV-grid integration.

Keywords

Electric vehicle, managed charging, smart charging, V1G, V2G, demand response, flexible loads, bulk power system, distribution system, power system modeling.

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1 Introduction

The adoption of electric vehicles (EVs) has increased rapidly over the last few years, thanks to major cost reductions and performance improvements in battery and electric drive technologies and a wide range of supportive measures including charging infrastructure buildout, incentives and other policies, and support or pledges from local communities and various stakeholders for reducing transportation emissions.[1,2] EVs offer demand growth opportunity for the electric industry (increase in retail electricity sales) after decades of stagnation in the United States and other regions.[3,4] Although the rapid rise in EV adoption can cause possible integration challenges, EV loads are highly flexible and offer unique opportunities for synergistic improvement of the efficiency and economics of electromobility and electric power systems as the two sectors become more integrated.

A vast body of literature has examined the possible impact of adding new EV loads to existing power systems, showing that if unmanaged or uncoordinated (assuming each EV charges as soon as it is plugged in without any consideration of electricity supply and grid conditions), EV charging may exacerbate net-load variability, impacting resource adequacy and attendant long-term planning, as well as contributing to bulk-level (generation and transmission) operational challenges.[4–8] However, based on historical growth rates, sufficient energy generation and generation capacity is expected to be available to support high EV market growth in the United States,[9] and the bulk power system is expected to be able to support widespread EV adoption. Because EV charging usually takes place at distribution systems (DSs), DS planners and operators could face challenges in effectively integrating EVs.[10–13] However, the impact of EVs on DSs is varied, given high heterogeneity in DS characteristics, and also dependent on the magnitude, timing, and location of charging events.[11,14–18] The impact of EVs on DSs might become more critical with high-power charging and concentration of EV loads, such as clusters of residential charging[10] and possibly depots for commercial vehicle charging. Proper planning and consideration of EV loads can likely resolve integration issues but might require expensive and time-consuming upgrades.[19]

Besides increasing loads, the demand-side flexibility provided by managed EV charging potentially offers significant benefits for the grid over multiple timescales and applications, supporting power system planning and operations during normal and extreme conditions and benefitting EV owners and other electricity consumers alike. Managed EV charging is a potential alternative to conventional power system solutions, such as peaking generators or stationary energy storage, and can broadly serve as a flexible resource.[20] In 1997, Kempton and Letendre[21] offered the first description of the concept of EVs providing grid services, either in the form of smart charging or bidirectional vehicle-to-grid (V2G) services. Since then, several studies have explored the value of managed EV charging as the prospect for EV adoption has increased and the transformation of the power system has highlighted the value of flexibility and demand-side resources. However, the value managed charging can provide will depend on the scale at which EVs are deployed, the grid policy and regulatory framework, and enablement costs, as well as how vehicles are used and charged (determining the flexibility in charging loads). Muratori *et al.*[1] summarize a range of future projections of EV adoption in the U.S. light-duty market (see Figure 1 in the cited article), showing multiple studies projecting rapid EV uptake and long-term opportunity for large-scale EV adoption. The potential for rapid growth in EV adoption and ultimately widespread success highlights the need for timely research on the value proposition for vehicle-grid integration and the growing potential benefits of managed charging, especially under scenarios with inadequate grid resources and high system stress.

EV-grid synergies are driven by two key factors: the value of demand-side flexibility in electricity systems and the ability of EVs to charge flexibly. Demand-side flexibility, including loads that can be shifted over time, are valuable for power system planning and operations since they reduce peak loads on the electricity supply side, reducing costs and increasing system efficiency and reliability. This is becoming more important as electric power systems are undergoing profound changes: Variable renewables are displacing conventional generation sources, distributed generation is disrupting utility business models, and the traditional system based on the premise that generation is dispatched to match an inelastic demand is evolving to create a system with greater participation in power system planning and operations from traditionally passive consumers.[22]

In addition, EV loads can be flexible and may be shifted in time and space without impacting the ability of EVs to accomplish their primary goal: providing mobility services. Most personal vehicles are driven for a small proportion of the day.[21,23] For example, an analysis of the 2017 National Household Travel Survey data[24] shows that personal light-duty vehicles in the United States are parked, on average, 95.8% of the time. Commercial vehicles are sometimes driven more, but several medium- and heavy-duty applications still offer ample charging flexibility.[19] If EVs are grid-connected for extensive periods (i.e., when a vehicle is not driven and a charging plug is available), they can provide demand-side flexibility in the form of managed charging or bidirectional power transfer to/from the grid and/or other loads.[25]

While managed EV charging can benefit the operation and planning of the power system across a broad range of spatiotemporal needs, it also requires targeted programs and compensating EV users for providing flexibility. Therefore, the costs of enabling managed EV charging must be weighed against the benefits provided. Cost-effectiveness assessments should adhere to basic principles, such as treating benefits and costs symmetrically, ensuring impacts are incremental to proper counterfactuals, and avoiding double counting.[26] As such, estimating managed EV charging costs and benefits is difficult, given the nascent markets for demand-side resources and different perspectives among stakeholders.

This paper provides a critical and comprehensive review of the value of EV managed charging, including context for the value of demand-side resources in rapidly evolving power systems; an overview of EV managed charging strategies, including current demand response programs focusing on managed EV charging in the United States, implementation options and mechanisms, and enablement costs; and a summary of methods, assumptions, and results in modeling and analysis studies and cost-benefit analyses. Finally, we identify critical gaps and remaining challenges, indicating research opportunities to properly assess the value of EV managed charging and fully realize the value of EV-grid integration.

2 Value of demand-side flexibility in the evolving power system

All power systems are designed and operated to match electricity supply and demand at all timescales and in all places, and utilities generally deploy a mix of generator types to minimize overall cost while maintaining adequate flexibility and reliability.[27] Operating the power system involves committing and dispatching generators to meet the variability of both supply and demand, while also maintaining adequate operating reserves for response to forecast uncertainty and contingencies.[28,29] However, with increasing deployment of variable generation (VG) (e.g., wind and solar photovoltaics [PV]) and associated increase in net load variability and uncertainty, power systems require greater system flexibility, including the need for greater ramping and operating reserves.[30–32] There is also a greater need to address the diurnal and sometimes seasonal mismatch between demand and VG supply to ensure sufficient capacity is available during net peak demand periods and avoid excessive generation during periods of low demand.[31,33–35]

While there has been a large focus on supply-side options for increasing grid flexibility, including energy storage, demand-side resources are another valuable and cost-effective source of power system flexibility that can support power system planning and operation.[36–43] It is sometimes more efficient to have demand match supply, as opposed to the more traditional approach of making supply match demand. There are numerous historical examples of demand response (DR) programs and market participation,[44,45] with DR applications starting in Europe as early as the 1950s.[46–48] Traditional DR provides load reductions at peak and other critical times, essentially providing a capacity service with additional infrequent but high-value energy benefits.[49]

There are numerous existing examples of DR programs in practice today that provide bulk power system services, including large commercial and industrial curtailable or interruptible load programs; peak shedding direct load control programs for air conditioners, water heaters, or pool pumps; critical peak pricing or critical peak rebates[44,49]; and energy shifting with time-of-use (TOU) pricing or direct load control programs.[50–53] More recently, DR has been used to provide operating reserves, especially in wholesale markets,[44] and to mitigate localized congestion, including at the transmission level.[54,55]

In addition to bulk system benefits, DR can support the distribution system, which delivers power to final users.[56] Alone or in combination with other resources, DR can alleviate localized congestion and defer other upgrades.[54,57] DR and other distributed energy resources (DERs) that interface the grid through power electronics (e.g., PV systems, battery energy storage, and EV chargers) can also provide voltage and frequency support[58–60] and supplement hardware-based techniques (e.g., voltage regulators, capacitors) that manage distribution system voltage and losses on an ongoing basis.[56]

Managed EV charging could provide a large and valuable source of system flexibility, with the potential to help address the challenges of balancing net load on both bulk power and distribution systems across multiple timescales (Fig. 1). Like traditional DR that addresses system peaks, managed EV charging can reduce systemwide or localized peak demand, thereby offsetting generation, transmission, or distribution capacity that might otherwise be needed at higher EV penetration levels. In particular, EV managed charging can provide a variety of services, including energy shifting, operating reserves, and voltage and frequency support, and offers opportunities to EV users to reduce charging costs while also lowering electricity costs for all.[61,62] Scheduling charging across timeframes of up to 1 week, sometimes providing power from EVs to the grid or other loads, or pairing EV managed charging with other DERs, would increase value over long timescales (but in turn limit charging flexibility) and potentially mitigate long outages associated with extreme events.

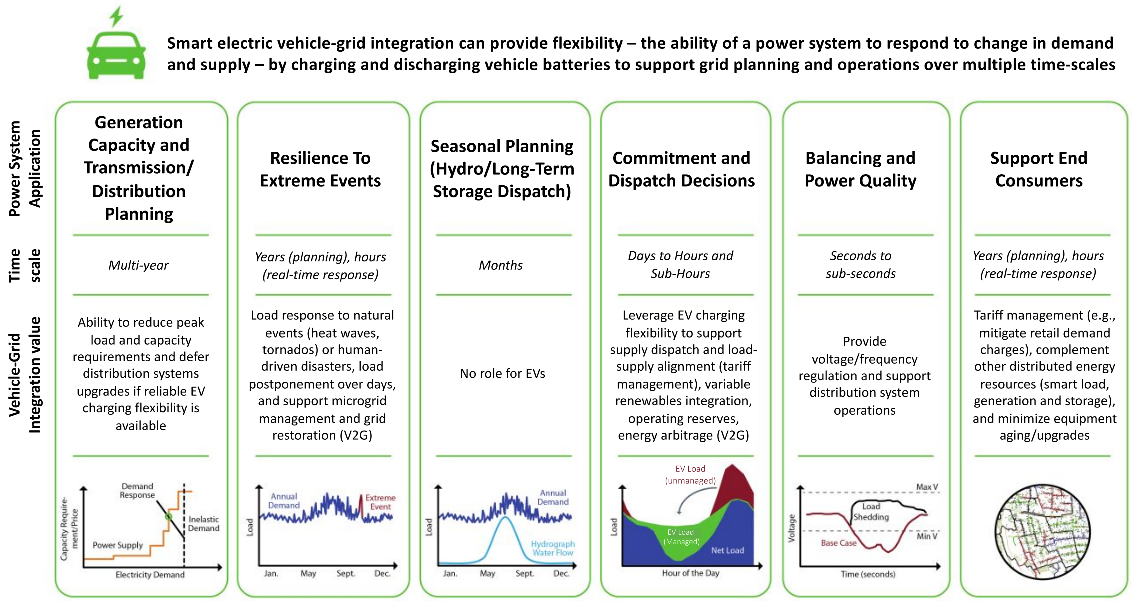


Fig. 1 Managed electric vehicle charging has the potential to support power system operations during normal and extreme conditions and benefit EV owners and non-owners alike.[1]

The value of demand-side flexibility depends on the value of the service provided, the cost of enabling DR, and the analogous costs for alternative resources, especially those of the most expensive unit, which sets price in least-cost planning and operational practices. The costs of enabling demand-side resources to provide grid services (e.g., new metering and control infrastructure costs; customer-side transaction costs, inconvenience, or foregone business; and utility program administration and marketing costs) have been catalogued and sometimes quantitatively estimated in various reports[63–65] (see Section 3.2 for EV-specific enablement costs). Capacity and energy services, which provide the megawatts and megawatt-hours to meet demand, are collectively the largest and most valuable electricity markets.[66,67] Enabling peak load reductions or energy shifting can be relatively low-cost, whereas enabling provision of ancillary services is often more costly due to higher communication and control requirements, and typically subject to stricter performance-based regulations (see Table 2 for a summary of ancillary or essential reliability services).[68] Because ancillary services represent a small percent of the total costs of operating the power system and the market opportunity is limited, this is a less promising but potentially complementary source of demand-side flexibility value.[66,67] On a practical level, the net costs of demand-side flexibility may be reduced by co-benefits.[68,69] On the other side of the ledger, grid service value may be reduced if the combined effects of retail tariffs (e.g., demand charges, time-of-use rates, or PV compensation policies) and DR programs are not aligned with bulk (e.g., capacity, energy, ancillary services) or more localized (e.g., distribution reinforcement deferral/avoidance, backup power, or local resiliency) grid needs.[66,70]

EV managed charging should be considered in the context of alternatives to provide equivalent services. For example, based on current DR deployment levels and recent studies,[45,68,71] some forms of DR are cost-effective alternatives to traditional peaking resources such as combustion turbines. In the future, lithium-ion batteries may define the competitive landscape for peaking resources if current trends continue.[72,73] If that is the case, managed charging can be competitive if charging infrastructure buildout, retail tariffs, and DR programs to compensate EV users (while satisfying users' mobility requirements) can be designed to provide grid services from managed charging at a lower cost than building and operating stand-alone stationary battery energy storage.

3 EV managed charging

EVs can be charged in a multitude of ways depending on vehicle characteristics, user preferences, trip requirements, infrastructure availability, and other factors. Unmanaged (or uncoordinated/uncontrolled) charging assumes each EV charges as soon as plugged in without any consideration of electricity supply (i.e., no charge management: park, plug in, and charge). Most studies postulate an "unmanaged" charging scenario where the grid is stressed by many EV drivers coming home from work and plugging in at roughly the same time, which happens to be coincident with daily peak load. With managed charging, EV charging is controlled considering electricity supply, within the constraints of the EV user's mobility needs. Managed charging, also referred to as "smart" or "coordinated" charging, most often occurs unidirectionally (V1G). This often involves shifting the EV charging times based on electricity pricing or other incentive signals. More advanced forms of managed or "smart" charging could include changes to charging locations on top of timing in response to dynamic grid signals or utilize inputs from the EV owner and the grid to develop optimal charging to meet mobility needs and support the grid. Managed charging can also occur bidirectionally between vehicles and the grid (V2G) or other loads (V2X) e.g., buildings turning EVs into temporary electricity suppliers to provide additional local benefits and improve resiliency (e.g., power appliances during power outages).

Managed charging of electric vehicles can be differentiated by (1) how charging is controlled (passive or active) and (2) the direction of electricity flow (unidirectional or bidirectional), as shown in Table 1. Managed charging relies upon signals between a utility and an EV user (or a third party, which in turn interacts with the EV user) to control charging events and can be used for measurement and verification (M&V) of the associated response. Under passive managed charging, the EV owner responds to prices or other signals to alter charging behavior, which could be accomplished automatically (e.g., EV owner could set a timer for charging) or manually (e.g., EV owner unplugs the vehicle). Passive managed charging has the added advantage that EV-specific M&V is typically not required and leverages other metering systems. Under active load control, the charger or vehicle responds directly to a signal from a utility or a third party (e.g., direct load control), or autonomously acts upon local conditions (e.g., under-frequency relay or power factor correction). However, EV owners still retain some level of control (e.g., an option to opt out of a managed charging event), blurring the distinction between active and passive controls. Active managed charging may or may not require dedicated M&V; even when required, M&V may be accomplished ex post rather than in real time. Technology requirements for managed charging vary depending on the implementation approach, which grid service is being provided or targeted, and availability of enabling technologies such as EV onboard communications and controls, smart metering, and elements of the smart grid.

Table 1 summarizes the different implementation strategies considered, comparing the potential for grid services; the requirements for communications and controls, measurement, verifications, and settlement; and additional key differentiators. For example, active load control may provide a wider range of grid services; however, it requires increasingly complex communication and control technology.

From a load flexibility perspective, there are trade-offs between different charging solutions. En-route charging, for example, involves a forced stop to charge an EV, usually at high power to minimize dwell time, limiting the opportunities for managed charging. The higher charging power requirements at en-route charging stations (usually DC fast charging) can, on the other hand, adversely impact the operation of power systems, including in terms of asset overloading, higher ramping requirements, and reduced power quality.[74] These challenges call for careful consideration of the techno-economic and infrastructure challenges attributed to placement and operation of high-powered fast charging stations, including coupled energy storage to decouple charging behavior from grid loads.[74,75] Opportunity charging,[76] on the other hand, leverages times during which a vehicle would be parked anyway (e.g., residential overnight charging) to provide Level 1 or Level 2 charging, and offers more flexibility. The higher the charging power (within opportunity charging), the faster and potentially more flexible the charging event can be in terms of time postponement, but higher peak loads are introduced. Vehicle charging can also occur dynamically while driving, via catenary or wireless charging, which allows for minimal flexibility. There are major technology and infrastructure barriers to implement dynamic charging, but it could eliminate most range limitations and require smaller batteries.[77–79] Charging flexibility also depends on the vehicle utilization; personal EVs, for example, may have higher flexibility due to longer parked periods compared to ride-hailing or other fleet vehicles that are driven more.

Table 1 Summary of managed charging strategies and considerations

Managed Charging Control	
Passive Static TOU and dynamic time-varying retail rates	**Active** Direct load control, under-frequency relay
Potential grid services • Limit generation, transmission, and distribution capacity expansion, energy arbitrage ***Communications and controls*** • Manual or automated controls • No dedicated communications required • Low complexity ***Measurement, verification, and settlement*** • EV-specific M&V typically not needed • Requires interval meter for settlement	***Potential grid services*** • All; however, smaller loads typically require aggregation (utility or third party) ***Communications and controls*** • Automated controls • Dedicated one-way or two-way communications required • Distribution system services require additional utility-side equipment • Low to high complexity depending on implementation ***Measurement, verification, and settlement*** • Real time, ex post, or statistical-/engineering-based M&V • May require direct telemetry or interval meter depending on implementation
Vehicle-Grid Power Flow Directionality	
Unidirectional (V1G) • Similar to demand response • No power injection to the grid	**Bidirectional (V2G)** • Similar to distributed storage • Power injection to the grid or support other loads providing additional benefits • Additional technical (e.g., battery degradation, distribution system protection equipment, onboard power converters) and nontechnical (e.g., vehicle warranties, lack of enabling regulations and standards, round-trip efficiency losses) barriers.

3.1 Implementation Strategies and Programs

There are a number of managed charging implementation strategies and programs at various levels of research, development, demonstration, and deployment (see Table 3 for a summary of exiting implementation programs in the United States). Passive load control through time-varying retail electricity rates (such as TOU electricity tariffs) is common, and there are many demonstration projects focused on developing real-time pricing, active managed charging through direct load control, and V2G. Managed charging to support distribution system services is limited to research and development and is discussed in Section 4.

The most basic implementation of managed charging is TOU electricity tariffs. With TOU, electricity prices are higher during peak electricity usage times and lower during off-peak times, incentivizing shifts in the timing of electricity use. Enrollment in TOU and other dynamic pricing programs has steadily increased over recent years, comprising 7% of residential, 11% of commercial, and 18% of industrial customers in 2019.[80] In 2017, 9% of all U.S. commercial tariffs applicable to DC fast-charging stations included TOU components.[81] Utilities also offer EV-specific TOU rates to encourage EV charging at off-peak times.[82–85] TOU rates have been successful in changing charging behavior in the United States. For example, a California Public Utilities Commission study concluded that charging load successfully shifted from peak evening hours to off-peak hours (overnight) by using TOU rates.[86] Similar results were shown for other locations.[87,88] A greater price variation between peak and off-peak rate has been shown to increase the shift in charging.[89,90] Among EV owners with access to TOU rates, a Smart Electric Power Alliance survey indicated that over 65% are enrolled in utility programs, and 87% of consumers charge off peak 95%–100% of the time.[84] Although TOU rates are well established and have been effective in modifying charging behavior, pricing signals may create a rebound peak. This may occur if many EVs consistently shift charging from the traditional peak period to a lower price period, thereby creating a new peak.[91–93] Additionally, ill-designed TOU rates can exacerbate both ramping concerns and the net load "duck curve" phenomenon if not aligned with renewable availability.[94,95] More intelligent and dynamic pricing mechanisms, supported with real-world testing and demonstration, can mitigate these issues.[91–93]

Beyond TOU rates, managed charging through unidirectional direct load control is a growing area of interest.[85] Some entities enable load control by subsidizing charging equipment for residential and commercial customers to ensure the equipment is compatible with direct load control requirements.[85,96–99] For utilities with existing DR programs, subsidization of the EV charger also requires enrollment and participation in DR programs.[85] Others offer incentive payments and/or bill credits for participating in DR events.[85,100–102] Customer satisfaction and participation in these programs in the United States have been high. For example, BMW reported 90%,[103] Avista 85%,[104] and Eversource 95%[105] of participation in call events. However, challenges have been reported for some implementations, including low resource availability (i.e., small fraction of vehicles plugged in at one time),[85,103,106] communication outages and latencies,[104] and high program costs.[104,107]

In order to provide other services, managed charging needs to participate in wholesale electricity markets. However, wholesale market participation may require aggregation to meet minimum size requirements: 100 kW under Federal Energy Regulatory Commission Order 2222.[108] Through aggregation, multiple EVs and chargers are pooled and collectively follow dispatch instructions. A number of managed charging demonstration projects utilize a non-utility third-party aggregator. For example, BMW piloted this capability in its ChargeForward project, leveraging their existing vehicle communications,[103,109] and Enel X's eMobility incorporates 35 MW of remotely controlled EV chargers in its DR.[110,111] Both projects bid into the California Independent System Operator (CAISO) energy market as proxy demand resources, but BMW implemented managed charging through the vehicles and Enel X used the charger—highlighting a range of potential approaches and enabling technologies.

To date, examples of managed charging with V2G in the United States are generally limited and focused on testing capabilities, such as provision of frequency regulation services by V2G-capable EVs.[105,112–115] Traditionally, regulations and market structures have not been established to handle bidirectional power flows. However, new partnerships and projects are being established.[116–118] Specifically, electric school buses have been targeted in multiple projects to provide V2G services given their large battery capacities and long scheduled idle time.[119–121] While bidirectional flow increases grid services from managed charging, uncertain battery impacts[122,123] and issues with vehicle warranties make implementation challenging. V2G also offers opportunities to power other loads, especially valuable during emergency events, and complement other DERs.[124]

Current direct load control of other loads may provide perspective on similar opportunities for managed charging. Particularly, the scale (power level) of the resource is an important factor in evaluating implementation strategies.[125] Power ratings of EV chargers vary from ~1 kW for Level 1 charging to several hundred kilowatts for DC extreme fast charging. Level 2 charging (~7 kW), common for residential homes, is higher power than typical residential central air-conditioning load but still relatively similar in scale. At this scale, common active DR strategies utilize one-way communications with direct load control (e.g., remote switches on pool pumps, air-conditioning units, and electric water heaters) and programable communicating thermostats. At the other end of the spectrum, DC fast chargers and fleet chargers have substantially larger loads (but might have more limited flexibility) and are similar in scale to commercial building equipment and industrial process loads. These larger loads are commonly controlled manually, but varying levels of supporting automation are also utilized.[68,126] Some facilities have under-frequency relays that shed load when power system frequency falls below some threshold value.[127] To date, DR providing frequency regulation is mostly limited to larger facilities, such as industrial electrolysis[128–130]; aggregations of industrial pumps; commercial heating, ventilating, and air-conditioning (HVAC) equipment; and commercial lighting.[131] Aggregations of smaller loads for frequency regulation have been proposed in the literature,[132] but due to the nascent nature of existing markets and technologies, have not been implemented.[133,134]

Across all sectors, fully automated DR with networked two-way communications between customer equipment or facilities and utilities, third-party aggregators, or power system operators remain limited. Still, there are many deployments in the field, and such implementations may grow in the near future.[66,135–138] Rather than real-time telemetry (that may be required for providing operating reserves[139]), ex post M&V is common and accomplished with interval metering (an interval meter measures and records data on either predetermined or remotely configurable time intervals). In the absence of interval meters, deemed values or statistical estimates from historical system data may suffice.[140]

There have been a handful of instances where DR has been proposed for distribution system services to defer capacity upgrades, as part of so-called non-wires alternatives[54]; however, on balance, successful DR implementations for the distribution system have been rare to date. Some projects have been successful in deploying DR.[141] Others, like the Brooklyn Queens Demand Management Program by Con Edison, have struggled: Although its DR auction procured significant load reductions, awardees have not been able to meet their obligations.[142] Utilizing geographically targeted DR for distribution system services faces a number of challenges,[143] and DR has been a minor contributor compared with other options such as energy efficiency, distributed generation, and conservation voltage reduction.[144]

3.2 Enablement Costs

Although managed charging can technically provide a wide range of grid services, there are potentially significant enablement costs. The costs of enabling managed charging are mostly associated with the incremental sensing, communication, and control costs. At the charger and vehicle levels, the incremental costs may depend upon factors such as the availability of interval metering, whether or not separate EV metering is required,[85] and whether or not there is a need for networked two-way communications[145] (e.g., to enable direct load control). Studies have reported incremental costs of \$679 and \$1,563–\$1,945 for a networked residential and commercial Level 2 charger, respectively.[65,104,146] For distribution system services, there are further costs depending on whether specific locations within the distribution system have the necessary equipment for monitoring and responding to network conditions.[143] Aside from the infrastructure costs, there may be additional costs such as customer acquisition, data charges, and network management and other backend services.[147] One study reports network support and communications costs of \$250/yr.[104]

Current estimates of costs may not be reflective of future costs, and many costs depend on allocation across multiple applications. For instance, widespread deployment of advanced metering infrastructure capable of distribution system state estimation and situational awareness or automated distribution system management could dramatically reduce the costs for managed EV charging to provide distribution system services.[148] Network access could also be widespread through EVs, avoiding upgrades to the charger and thereby embedding network access costs within the broader digital services provided to EV users.[145] Given the high costs of real-time telemetry, many load management strategies have sought to eliminate their need through statistical aggregation.[140,149] However, such approaches would tend to be applicable only to certain bulk power system services and may not be appropriate for distribution system services.[143] Managed charging costs scale differently among components. For instance, program administration and backend and network service costs decline on a per-user basis. However, other costs like real-time telemetry are fixed on a per-unit basis, supporting individually large managed charging enrollees.[150] How managed charging cost components scale may inform which implementation strategies are most important for different EV market segments.

4 Value of managed charging in analysis/modeling studies

As discussed in Section 2, EV managed charging can synergistically improve the efficiency and economics of electric power systems and electromobility. This section presents an overview of the electric vehicle load representation in analysis studies and a critical review of the modeling methodologies proposed in the literature for assessing the various managed charging (MC) value streams. The value of MC reported in the reviewed literature usually focuses on a future state and is based on specific modeling choices, assumptions, and test system configurations; therefore, we also discuss the key factors driving the differences in the value estimation of MC across studies. A summary of the number of studies categorized by their geographic scope, modeling perspective, model type, and methodology is presented in Fig. 2.

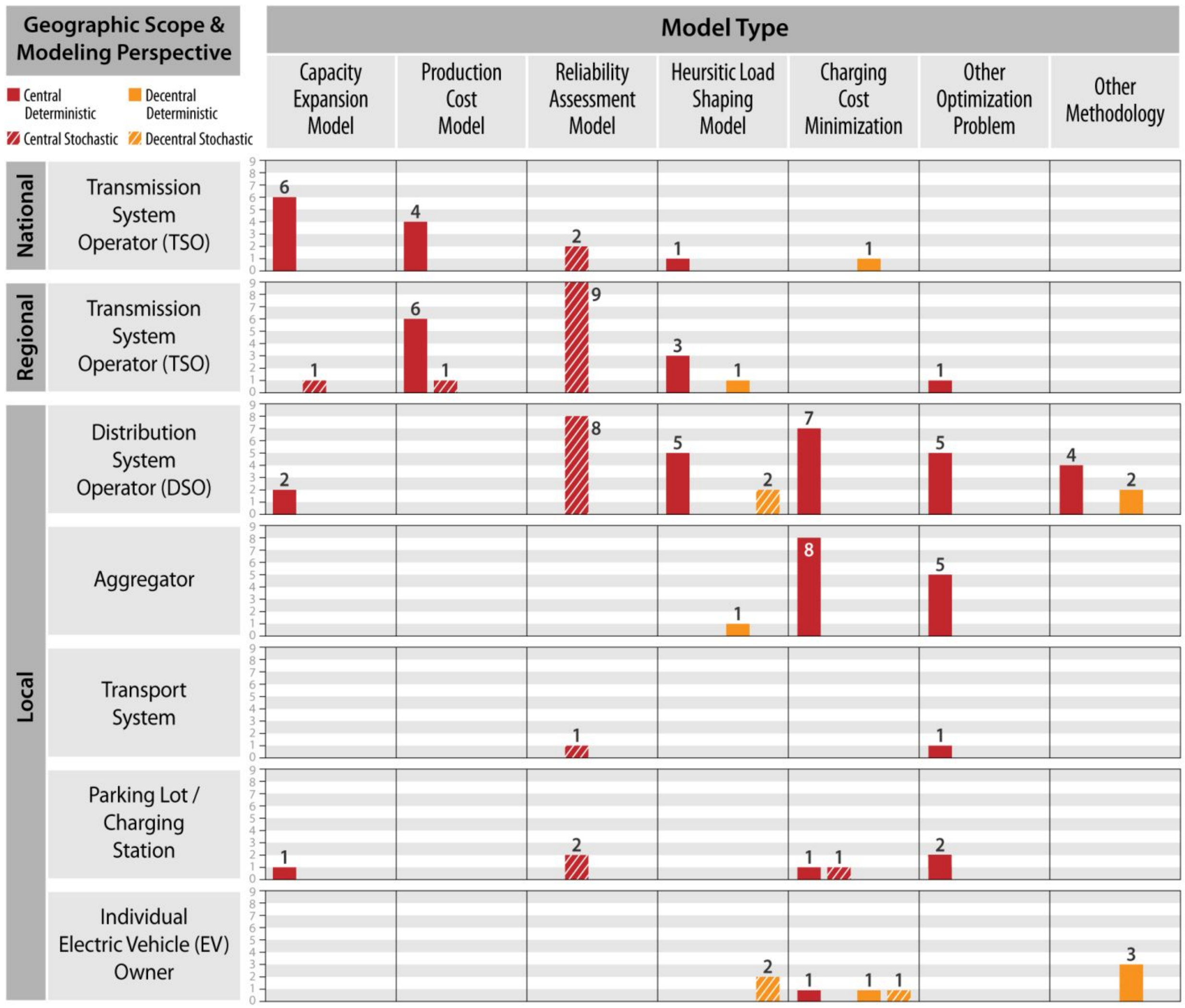


Fig. 2 Summary of the reviewed modeling/analysis studies by their geographic scope, modeling perspective, model type and methodology. Capacity Expansion Models and Production Cost Models are typically used for optimizing bulk power system planning and operation, respectively. Reliability Assessment Models predominantly utilize Monte Carlo Simulation, both at the TSO and DSO levels. Heuristic Load Shaping models usually follow some pre-defined set of rules for modifying EV charging load shapes. On the other hand, Charging Cost Minimization problems optimize the EV charging behavior based on external price signals. There can be other optimization objectives for managing EV charging (e.g., distribution losses minimization, peak load minimization, etc.), which are categorized under Other Optimization Problems. Other Methodologies include other, not very commonly used, methodologies (e.g., Droop-based Control, asset loss-of-life probability assessment, etc,).

At the national and regional levels (bulk power system), studies are typically performed from the perspective of the transmission system operator (TSO) and implement standard model types. For instance, analyses focusing on bulk system planning, operation, and reliability predominantly use capacity expansion models (CEMs), production cost models (PCMs), and Monte Carlo simulations, respectively. On the other hand, studies at the local level have focused on multiple perspectives including that of the distribution system operator (DSO), aggregator, transport system, parking lot/charging station, and/or individual EV users. To capture several topics of interest and objectives, studies exploring the value of managed charging at local scales leverage a wide variety of model types/formulations, with charging cost minimization typically based on optimal power flow formulations, heuristic load-shaping models, and other optimization problems being the most common. It is also evident that models even looking at local scales are primarily formulated in a centralized framework assuming that a central entity such as the DSO, aggregator or parking lot owner can directly manage/control the charging pattern of the entire EV fleet. The computational complexities associated with decentralized methodologies limits them typically to smaller-scale local studies primarily focusing on individual EV owners. Additionally, Fig. 2 reveals that a majority of model types are formulated as deterministic problems, with the exception of reliability assessment. A more detailed summary of the reviewed studies, including other details such as study goals, EV population/penetration assumptions, and implementation schemes, is presented in Table 4 in the Appendix.

4.1 Electric vehicle charging loads

To determine the value of managed charging, studies must first develop profiles for electric vehicle charging and their flexibility based on EV adoption, traveling demand, charging opportunities, and MC implementation. All these elements are uncertain given nascent EV markets, and different studies have made widely differing assumptions.

The simplest approach for modeling EV loads is based on annual travel statistics, such as vehicle miles traveled (VMT) and typical usage times, which have often been used to determined average daily charging loads.[151–153] Such annual methodologies based on vehicle miles traveled might be appropriate for aggregate impact studies (e.g., greenhouse gas emissions benefits), but they lack the temporal granularity required for most power sector analyses. Several MC analyses use more granular data from travel surveys to model EV loads.[154–158] Historical trip data and/or GPS measurements have also been used to model EV use and charging needs and opportunities,[159–161] providing spatiotemporally resolved information about vehicle use, including arrival and departure times and locations. The travel pattern statistics or empirical distributions obtained from travel surveys, GPS measurements, or historical data can be used to generate deterministic or stochastic vehicle use and charging profiles. Travel data can also be combined with demographical data to derive more insights on charging.[162] In the absence of survey or other information, some studies have also used exogenous assumptions about travel demand probability distributions for determining EV load profiles.[163–165] Finally, agent-based models have also been used to project EV loads,[166,167] but their application requires complex calibration and these models are usually intractable for regions bigger than a city or metropolitan area.

Besides using varied methodologies to project EV charging loads, different studies focus on different levels of aggregation. Typically, studies focusing on bulk power system require aggregate loads for reducing computational burden, and therefore consider aggregate charging profiles for the whole EV population or large clusters of vehicles rather than tracking the behaviors of individual vehicles, thereby missing heterogenous behaviors. The aggregate EV charging constraints are often based on a range of charging scenarios and usually assume that EV charging flexibility resembles a grid-connected battery with effective parameters, such as power and energy limits.[156,160,166,168] On the other hand, studies focusing on localized phenomena, such as impacts on distribution networks or single facilities, usually track charging profiles of individual vehicles such that travel patterns are enforced explicitly.[158,159,169,170]

Finally, widely differing assumptions are made on charging behavior, managed charging strategies and flexibility constraints, and consumer participation in DR programs. Studies often rely on collective rule-based approaches (e.g., nighttime charging only,[171,172] full vehicle availability and participation[173–175]), exogenous time-varying electricity tariffs,[166,176] or scheduled EV charging based on optimization models considering EV charging constraints at different levels of resolution.[166,170,177]

4.2 Bulk power system operation

EV managed charging can provide various operational benefits for bulk power systems (BPSs), including reducing system operation costs, greenhouse gas emissions, and peak loads, and curtailing variable renewable generation. These potential benefits of MC in improving BPS operation are usually analyzed using PCMs, such as unit commitment (UC) or economic dispatch, which typically model a single future year and focus on macro regions with fixed generation portfolios. These models co-optimize the scheduling of electricity generators and EV charging, typically at an hourly resolution, by minimizing system operation costs subject to operational constraints (e.g., power balance, reserve requirements, transmission network constraints), generation units' constraints (e.g., minimum and maximum generation, ramping capabilities, minimum up and down times), and aggregate EV demand constraints.[178–180] Although there is not a standard set of aggregate EV constraints, PCMs generally include such constraints as daily energy demand constraints, charging/discharging power limits, and battery state-of-charge limits.[178,181,182]

BPS operation studies often use commercially available tools. For example, Zhang et al.[173] use the PLEXOS model[183] to assess the value of MC in California's 2030 power system under high renewable scenarios with varying degrees of grid flexibility. Szinai et al.[166] also use PLEXOS for the 2030 California system; however, in contrast to Zhang et al., which considers a simplified representation of EV load (using the same daily aggregate EV demand profile for the whole year and assuming that charging can be temporally shifted without any constraints), Szinai et al. use a transportation agent-based model that explicitly considers constraints on mobility and charging infrastructure. PLEXOS has also been used to study the value of MC for the 2025 Irish power system,[152] 2030 Barbados power system,[184] and a hypothetical system with large-scale variable renewable energy (VRE) generation.[168] While PLEXOS allows customization of the UC objective function and constraints, the UC model in these PLEXOS-based studies typically minimizes total system operation costs subject to typical PCM and aggregate EV constraints, as discussed. Among the PLEXOS-based studies, both Taibi, del Valle, and Howells[184] and the International Renewable Energy Agency[168] consider V2G in addition to V1G, but only the former considers the associated battery degradation costs. These studies report a noticeable reduction in system operation costs due to V2G (as compared to V1G), as well as reduced participation of EVs in load shifting when battery degradation costs are considered.

Other PCMs besides PLEXOS have also been used. For instance, the value of V2G services (considering battery degradation costs) in the ERCOT system is studied using a deterministic UC tool in several studies.[155,185,186] Whereas Sioshansi and Denholm's 2009 article[185] focuses on emissions reduction benefits, their 2010 article[186] examines the system cost savings and V2G value for plug-in hybrid electric vehicle (PHEV) owners, and Sioshansi's 2012 article[155] compares the performance of optimal charging profiles estimated by the UC model with those obtained based on time-varying tariffs. The value of V1G with large-scale VRE integration in the German and Beijing systems is studied using bespoke deterministic UC models in Schill and Gerbaulet[187] and Chen et al.,[188] respectively. Vaya and Andersson[189] compare a centralized optimal power flow model (without discrete UC variables) against a decentralized TOU-based EV charging methodology in which optimal nodal TOU tariffs are determined accounting for the feedback impact of TOU tariffs on nodal charging profiles. The authors report that although centralized charging control leads to the least-cost solution, the results of the decentralized nodal TOU-based scheme were comparable, both in terms of costs and shape of the system load.

In contrast to the aforementioned deterministic PCMs, Liu et al.[157] present a stochastic UC model to assess the value of MC in the Illinois BPS under wind uncertainty, whereas Saber and Venayagamoorthy[190] consider both EV load and generation (wind and solar) uncertainty in a stochastic UC model. Similarly, a stochastic UC tool is used in Khodayar, Wu, and Shahidehpour[191] to assess the value of V2G in mitigating the impacts of wind power uncertainty. These studies report that stochastic models are computationally more expensive than their deterministic counterparts, and they report a slight increase in the value of MC (in terms of reducing system operation costs) under uncertainty.

In addition to PCMs, other methodologies have also been used to capture specific BPS operation benefits. For instance, Denholm and Short[151] and Fitzgerald, Nelder, and Newcomb[90] evaluate the peak load and power plant cycling reduction potential of MC by dispatching EV load to lowest-demand periods (referred to as valley-filling). However, such rule-based MC approaches cannot properly capture spatial, infrastructural, and demand-satisfaction constraints of EV loads and other system-level operational constraints. In contrast, Coignard et al.[154] use centralized quadratic optimization for minimizing either peak load or net load ramping, subject to constraints on EV SOC limits and charge point availability, for assessing the benefits of V1G and V2G in reducing ramping and VRE curtailment in the 2025 California BPS. Similarly, centralized quadratic optimization for flattening the demand at BPS and DS levels in Great Britain is presented in Crozier, Morstyn, and McCulloch.[192] Instead of the commonly used centralized methodologies, a decentralized Lagrangian decomposition-based approach is proposed in Ma, Callaway, and Hiskens[169] to control a large population of PHEVs in the Midwest ISO region. The authors show that the proposed decentralized control methodology can provide similar outcomes as centralized control, and therefore could be particularly useful in applications where fully centralized control is not possible, Finally, the operational benefits of MC have also been reported in studies using BPS planning models,[177,160] which aim to capture the impacts of MC on both system operational and investment costs, as discussed in Section 4.5.

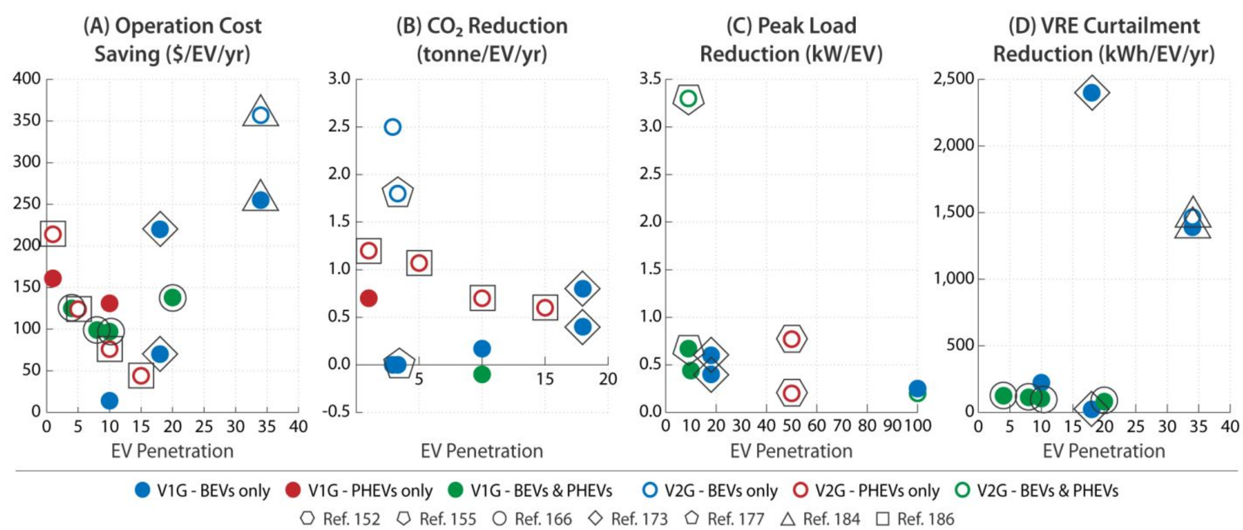


Fig. 3 Benefits of EV managed charging (compared to unmanaged charging) in improving bulk power system operation in terms of (A) system operation cost, (B) CO_2 emissions, (C) system peak load, and (D) curtailment of VRE. Each colored dot represents a data point from 14 studies. Multiple values from the same reference are enclosed within the same shape (defined in the legends) for more direct comparison. The impacts vary significantly across studies, based on EV penetration assumptions, vehicle type (BEV or PHEV), charging direction (V1G or V2G), system characteristics, and charging strategies.

Fig. 3 summarizes the BPS operational value of MC estimated in the studies reviewed. It is important to note here that the benefits of MC in improving bulk power system operation apply for a given generation portfolio. Therefore, they do not consider how the power system generation portfolio could optimally evolve with increasing EV adoption. Such analyses can be performed using BPS planning models, such as CEMs, which are discussed in detail in Section 4.5. The BPS operation benefits of MC vary significantly across studies: cost savings between \$15–\$360/EV/year, CO_2 emissions of −0.1 to 2.5 tons CO_2/EV/year, peak load reductions of 0.2–3.3 kW/EV, and VRE curtailment reduction of 23–2,400 kWh/EV/year. Studies consistently find that system cost reduction per EV decreases with increasing EV penetration.[166,186] The only exception to this declining trend is the sudden increase in cost savings potential at around 20% EV penetration in Szinai et al.,[166] because unmanaged charging in this case causes loss of load (resulting in very high costs), which can be avoided by MC. The declining marginal value of MC with increasing EV penetration is also observed in the CO_2[186] and VRE curtailment reduction potentials.[166] These trends indicate the presence of shallow value streams that could become saturated at certain EV penetration levels.

Fig. 3 also shows that V2G can further reduce operation costs, CO_2 emissions, and peak load (compared to V1G) by displacing inefficient peaking generators.[154,177,184] The benefits of V2G, however, are not clear in terms of reducing VRE curtailment.[184] Different BPS characteristics also affect the value of MC. For instance, the operation cost savings due to MC would likely be significantly lower in systems that have other flexibility competitors (e.g., pumped storage, stationary batteries, other sources of DR).[173] Additionally, VRE curtailment reduction can also vary considerably, with curtailment reduction due to MC noticeably larger in systems with high VRE penetrations and limited flexibility.[173] CO_2 emission reduction benefits of MC would be highly sensitive to the generation mix. Although large-scale VRE integration and limited grid flexibility can result in significant emission reduction benefits,[173,177] MC might have marginally positive to even adverse impacts on emissions (e.g., −0.1 tons CO_2/EV/year) if off-peak generation units have greater emission rates than on-peak units and if the charging algorithm doesn't account for the impacts/costs of emissions.[105,187,193]

It is also interesting to note the underlying relationships between the value streams shown in Fig. 3. For instance, reductions in CO_2 emissions due to managed charging are typically accompanied by operation cost savings as well, as demonstrated in Zhang et al.[173] and Sioshansi and Denholm.[186] This is primarily because CO_2 emissions have associated costs (e.g., fuel costs of CO_2-emitting plants, carbon taxes), and therefore reducing emissions inherently reduces operation costs. Similarly, reductions in peak loads reduce peak capacity needs, and therefore also operation costs (e.g., as shown in Zhang et al.[173]), because of the reduced need for running expensive peaking generators. Moreover, reduced VRE curtailment due to managed charging also tends to correlate with operation cost savings,[166,173,184] as VRE generation resources such as wind and solar have almost zero marginal costs. Finally, results in Zhang et al.[173] indicate that reduction in CO_2 emissions would also be aligned with reduced VRE curtailment, as higher VRE utilization inherently reduces the CO_2 content of the generation mix.

Different charging strategies can also lead to different MC value propositions. For instance, Sioshansi[155] reports that randomized EV charging start times outperformed TOU-based and real-time pricing (RTP)-based MC in reducing operation costs and emissions. The authors demonstrate that RTPs (determined using marginal prices from UC) performed the worst among different time-varying prices because RTPs cannot capture power plant operational non-convexities (e.g., binary on/off decisions, minimum up/down time constraints), causing significantly more startups (and associated costs). Similarly, Szinai et al.[166] show that if TOU tariffs are not aligned with periods of VRE generation availability, MC based on TOU tariffs can shift EV loads to periods of low VRE generation, thereby resulting in greater VRE curtailment than unmanaged charging.

MC can also improve other aspects of BPS operation, such as increasing the load factors of base-load and mid-merit generators and reducing their daily cycling.[186] Additionally, MC can reduce net load ramping, which might be particularly beneficial in systems with high VRE penetration.[154] Finally, MC can reduce other harmful emissions such as NO_x and SO_2, but the magnitude of these reductions would also be system-dependent.[185]

4.3 Distribution system operation

At the DS level, MC can alleviate the negative impacts of unmanaged charging, such as reducing the overloading of DS components/assets, improving voltage quality, and reducing energy losses. These benefits not only facilitate safe and reliable operation of the DS but can also increase the feasible EV penetration (also called the maximum hosting capacity) without violating network operational constraints.[194] However, the vast variability of DS design and conditions, lack of detailed models of actual DSs, and the uncertainty associated with electricity loads and their flexibility make it particularly challenging to simulate the real-world value of MC and generalize results from single simulations. Furthermore, the significant differences in modeling detail and methodologies also make comparison of the value of MC across different studies rather difficult. The following discussion describes the various methodologies reported in the literature, highlighting their relative strengths and limitations.

The operational value of MC in DSs has been assessed for various charging strategies using power flow analysis/simulations, which determine the DS's operating state (e.g., voltages, line flows, energy losses) for given loads (including EV charging profiles) and generation conditions.[171,172,175,195–197] Leemput et al.[172] use a valley-filling approach for determining EV-managed charging profiles, whereas Voumvoulakis et al.[196] compare valley-filling with "peak-curtailment" charging, whereby EVs can charge only when the total DS load is below a predefined value. It is shown that while peak curtailment charging results in higher energy losses compared to the valley-filling approach, it leads to lower peak DS loads, and therefore higher feasible EV penetrations.[196] Kamruzzaman, Bhusal, and Benidris[175] assume a "fully controlled" MC profile, such that EV charging can be completely shifted as long as the maximum capacities at selected nodes are not violated. Compared to these demand-based approaches, EV managed charging profiles in Hu, Li, and Bu[171] are modeled based on cost minimization under TOU tariffs, and the authors also explore a V2G strategy, whereby EVs are allowed to discharge to the grid during the evening peak. Mehta et al.[197] compare charging cost minimization and demand peak-to-average ratio (PAR) minimization strategies while considering battery degradation costs due to V2G services. They demonstrate that MC profiles based on PAR minimization result in significantly lower DS peak loads and higher feasible EV penetrations as compared to the charging cost minimization approach.

Although power flow-based studies are helpful in comparing charging profiles, they can lead to suboptimal results because the MC profiles are not co-optimized with DS operation. This suboptimality can be reduced by including some critical DS constraints when determining "optimal" EV charging profiles under MC. For instance, maximum power limits specified by the DSO are included in the cost minimization problems of EV aggregators in Hu et al.[161] and Wang et al.[164] Compared to Hu et al.,[161] where only active power limits are considered, Wang et al.[164] also include reactive power limits. Alternatively, Sundstrom and Binding[159] propose an iterative coordination methodology that considers the interactions of a charging service provider (CSP) with the DSO and a retailer. The retailer issues a reference power profile to the charging service provider, who tries to minimize the deviation from this profile. The output is sent to the DSO to check operational feasibility. If infeasible, constraints are generated and sent to the charging service provider for re-optimization until the charging profile is feasible for the DS.

EV charging can be further optimized for DS operation through endogenous representation of power flow constraints (in addition to EV demand constraints) in MC optimization problems, which comes at the cost of additional computational burden. Such optimization problems with power flow constraints are referred to as optimal power flow (OPF) problems. Steen et al.[162] compare loss-optimal (minimizing DS energy losses) and cost-optimal OPFs for MC in residential and commercial DSs. Similarly, De Hoog et al.[170] compare OPFs for maximization of stored energy in EVs and minimization of charging costs. However, in contrast to Steen et al.,[162] which models nonlinear AC power flow constraints, De Hoog et al.[170] implement linearized approximations for improving computational tractability. A hierarchical corrective disconnection control methodology is proposed in Quirós-Tortós et al.,[198] which is shown to provide similar results as AC-OPF while using significantly limited information. An OPF for maximizing EV penetration is presented in Lopes et al.,[199] whereas a multi-objective OPF minimizing EV charging costs, PAR, and voltage deviation is proposed in Mazumder and Debbarma.[200] Liu et al.[201] present a distribution locational marginal pricing scheme (based on a linear DC-OPF) for reducing DS congestion.[2] The distribution locational marginal prices are included in EV aggregators' cost minimization problem, rendering EV charging more expensive during periods of high DS loading. The strategic interactions between a parking lot owner and DSO are modeled using bilevel optimization in Sadati et al.,[163] where the DSO maximizes its profits subject to network constraints in the upper level, while the parking lot owner maximizes its profits (considering battery degradation costs) in the lower level. The results demonstrate that the DSO makes greater profits and incurs lower energy losses in the bilevel model as compared to centralized optimization. In contrast to the aforementioned studies where only the power system aspects are considered, the methodology in Geng et al.[202] coordinates the operation of transportation and power distribution systems for reducing peak load and traffic congestion while incorporating EV demand elasticity.

Decentralized methodologies have also been used for providing DS services through MC.[158,203–206] For instance, Le Floch, Belletti, and Moura[159] and Le Floch et al.[206] use a dual-splitting technique for distributed coordination of EVs to minimize load variance while considering battery degradation costs. Similarly, a decentralized algorithm for reducing PAR is proposed in Rassaei, Soh, and Chua,[204] in which aggregated demand profiles are broadcasted to EV owners who sequentially solve their individual optimization problems. In contrast to optimization-based decentralized schemes, the methodology in Knezović and Marinelli[205] involves droop-based EV reactive power control as a function of active power consumption and phase-to-neutral voltage. Similarly, Martinenas, Knezović, and Marinelli[206] propose and experimentally validate a droop-based methodology for controlling EV charging current as a function of phase-to-neutral voltage.

Fig. 4 summarizes the DS operational value of MC reported in several studies. Since different DSs can handle different numbers of EVs, it is hard to normalize results and these data are difficult to compare. As shown in Fig. 4A, MC can noticeably reduce DS peak loads and congestion, with total peak load reduction potential increasing with increasing number of EVs in the DS.[199] However, the marginal peak load reduction (for each additional EV) might decrease with increasing EV penetration in cases where rising diversification effects of a larger number of EVs lead to reduction in simultaneity. Additionally, V2G can achieve higher reductions in peak load as compared to V1G,[204] but the magnitude of these benefits can be substantially different. For instance, Wang et al.[164] report that V2G can reduce peak loads by 67%, but only 10% peak load reduction is observed in Sadati et al.[163] These variations can be attributed to different DS characteristics

[2] Locational marginal prices represent the incremental cost of additional energy at a specific location. This concept is used in all wholesale markets in the United States but has not been applied at the distribution system level, which requires much finer resolution.

and different charging schemes. While Wang et al.[164] optimize EV charging subject to DS active and reactive power limits, Sadati et al.[163] consider time-varying prices, which can increase charging simultaneity, thereby reducing the peak reduction potential. Indeed, charging EVs based on wholesale market prices (without considering DS constraints) can even result in higher congestion and peak loads than unmanaged charging.[163,207]

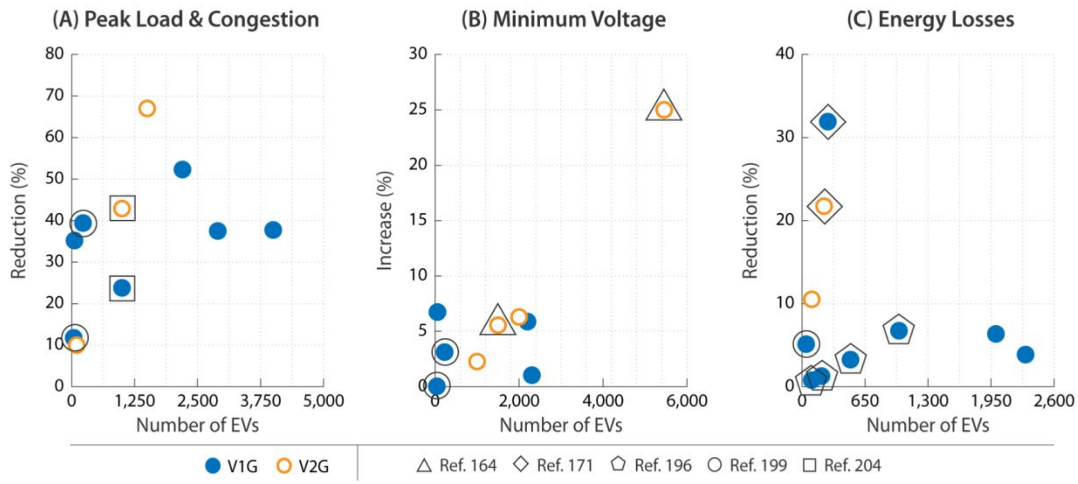


Fig. 4 Benefits of EV managed charging (compared to unmanaged charging) in improving distribution system operation in terms of (A) peak load and congestion, (B) minimum voltage, and (C) energy losses. Each colored dot represents a data point from 13 studies. Blue circles represent V1G and orange triangles V2G. Multiple values from the same reference are enclosed within the same shape (defined in the legends) for more direct comparison. The impacts vary significantly across studies, based on different EV penetration levels, charging direction (V1G or V2G), DS characteristics, and charging strategies.

MC can also reduce voltage drops caused by uncontrolled EV charging, as shown in Fig. 4B. However, the magnitude of voltage quality improvement can also vary considerably. MC can avoid potentially larger magnitudes of voltage drops at higher EV penetrations.[164,199] DS characteristics also play a major role, and the voltage support value of MC is higher in DSs with longer electrical distances between the substation and the loads.[192,196] Voltage improvements also depend on the charging strategies considered. For instance, optimal EV charging under voltage constraints is more likely to reduce voltage drops compared to charging based only on cost minimization.[162] Finally, provision of reactive power from EVs also leads to greater improvements in DS voltage.[164,200,205]

Fig. 4C shows that the total reduction in energy losses due to MC usually increases as more EVs are connected to a DS.[196,199] Interestingly in Hu, Li, and Bu,[171] V1G leads to a greater reduction in network losses compared to V2G. This is primarily because the V2G case in this study does not shift the EV load, but only allows discharging energy to the grid during peak load hours. Indeed, other studies have also shown that the impacts of charging strategies on DS losses can be fairly substantial. For instance, charging cost minimization under wholesale prices can, in some cases, even lead to higher losses than unmanaged charging.[162,207] Finally, the highest loss reductions due to MC are typically observed in networks with significantly overloaded assets and/or voltage unbalance issues.[196,205,208]

The value of MC for DS operation is also revealed by the increase in maximum feasible EV penetration (also called EV "hosting capacity") without violating DS constraints or implementing network upgrades, as shown in Fig. 5. Feasible EV penetration in a specific DS significantly depends on the system characteristics and the EV loads. For example, the three studies grouped at the top of Fig. 5 suggest that in DSs with higher levels of redundant capacity,[162] lower load density,[172] and underutilized transformers,[198] full (100%) EV adoption can be accommodated without DS upgrades with MC. In other cases, much lower

EV adoption can be supported by DS without upgrades if EV charging is unmanaged. While the literature reports that MC can noticeably increase the maximum feasible EV penetration for such DSs, additional network upgrades/reinforcements are projected in these cases to accommodate full EV adoption (or EV charging for applications not considered in these studies, such as commercial vehicles). In addition to the DS characteristics, EV load modeling/assumptions also play a major role in these results. For instance, the value of MC is higher in scenarios with higher-rated (faster) charging (as unmanaged fast charging can overload DS components even at low EV penetrations)[172,197] and when consideringV2G capability.[200] Finally, charging strategies and MC objectives also play a critical role in determining the EV hosting capacity in a specific system. EV charging based on peak curtailment resulted in higher feasible EV penetration, without requiring network upgrades, compared to valley-filling charging in Voumvoulakis et al.[196] Additionally, charging based on cost minimization under wholesale prices was not only significantly outperformed by PAR minimization in Mehta et al.,[197] but it even led to lower feasible EV penetration than uncontrolled charging in Steen et al.[162]

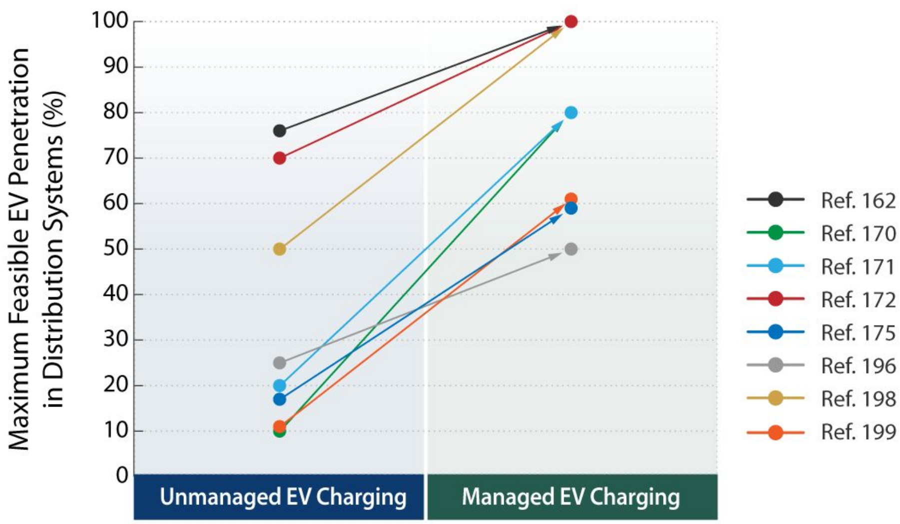


Fig. 5 Results from eight studies highlighting the potential of EV managed charging to increase the maximum feasible penetration of EVs in distribution systems without implementing additional network upgrades or violating operational constraints. The increase in the maximum feasible EV penetration due to MC would depend on the redundant capacity in the DS, load density, charging direction (V2G vs. V1G), charging speeds (faster unmanaged charging can overload DSs even at low penetrations), and charging strategies.

The results presented in this section highlight that DS characteristics and MC strategies would play a critical role in shaping the value of MC for DSs. It is also evident that MC profiles determined based on wholesale market signals could be detrimental for DS operation, which points to the need for developing holistic strategies that consider the value proposition and trade-offs across the whole power system. Finally, considering the limited benefits of MC in some DSs, it would be critical to assess the benefits of MC on a given system in comparison to the costs of MC implementation.

4.4 Power system reliability

The reliability of a power system is defined as its ability to provide an adequate supply of electricity to customers with a reasonable assurance of continuity and quality.[209,210] To be reliable, the power system must have adequate power generation and balancing resources to keep pace with changing consumer demands, retiring plants, and addition of new resources and technologies.[211]

At the BPS level, system contingencies (e.g., plant outages) can lead to loss of load, and in extreme cases set off cascading failures causing large-scale blackouts.[212] Reliability of a BPS can therefore be measured by the adequacy of its generation capacity to meet total system load. The most commonly used BPS generation adequacy indices are Loss of Load Probability (LOLP), Loss of Load Expectation (LOLE), and Expected Energy Not Served (EENS) (also called Loss of Energy Expectation [LOEE]), which reflect the probability, expected frequency, and magnitude of lost load over a certain time period, respectively.[213]

Unmanaged charging of large EV loads has been projected to increase both frequency and magnitude of lost load.[174,176,214–217] However, these studies also report that by shifting the EV load and injecting energy into the grid during capacity shortfalls, MC can improve BPS reliability relative to unmanaged charging. Evaluation of reliability benefits of MC is usually done using Monte Carlo simulation, which involve simulating a large number of realizations of uncertain system attributes, such as generator outages, variations in load and VRE output, and EV charging parameters. Considering the inter-temporal dependence of EV battery SOC levels, EV-based reliability studies typically use sequential Monte Carlo simulation (c) as it allows capturing these chronological aspects. Bremermann et al.[214] compare the value of valley-filling and centrally optimized smart charging through SMCS, considering generator outages (using Markov models) and system load and wind uncertainty (based on normally distributed error forecasts). The results demonstrate that the centralized smart charging strategy can significantly improve BPS reliability compared to valley-filling.[214] Similarly, Božič and Pantoš[218] demonstrate the benefits of MC based on system reliability maximization (compared to charging cost minimization). Colonetti et al.[215] compare the reliability impacts of rule-based MC strategies (including valley-filling, charging postponement, and V2G during scarcity events), whereas Liu et al.[216] compare the reliability benefits of V2G against V1G. In addition to the typical reliability indices, Liu et al.[216] also propose new load-oriented indices that measure the expected frequency and magnitude of energy compensation by EVs for providing reliability services. The impacts of using different probability distributions (for modeling the EV load) on generation adequacy are analyzed in Bremermann et al.[174] The authors demonstrate that utilization of non-homogenous Poisson distribution can better represent end-user mobility and the EV opportunity to provide spinning reserves compared to the standard Poisson distribution.[174] The effectiveness of changing PHEV charging start times on improving system reliability are studied in Wang and Karki,[219] whereas a framework for comparing EV charging responses under TOU tariffs and dynamic scarcity pricing is proposed in Almutairi and Salama.[176] Compared to the static transmission network topology assumed in the aforementioned studies, Li et al.[220] allow optimal network reconfiguration, in addition to MC, for improving BPS reliability. Finally, in contrast to other BPS reliability studies, Hou et al.[221] capture the impacts of the interaction between the transportation and power systems and propose new indices for capturing the extra time spent by EV drivers in finding charging stations or calling for help during insufficient EV charging situations.

BPS reliability benefits of MC can also be evaluated using analytical approaches. Compared to running a multitude of simulations, analytical techniques use direct mathematical formulations for evaluating the reliability indices.[222] da Rosa et al.[217] present a convolution-based analytical approach for estimating the reliability value of centrally controlled smart charging, whereas Hajebrahimi and Kamwa[223] propose a Combined Outage Probability Table-based approach for assessing the impacts of advanced metering infrastructure failure. Although these analytical approaches might not capture complex interactions of stochastic variables, they significantly reduce the computational burden associated with SMCS.

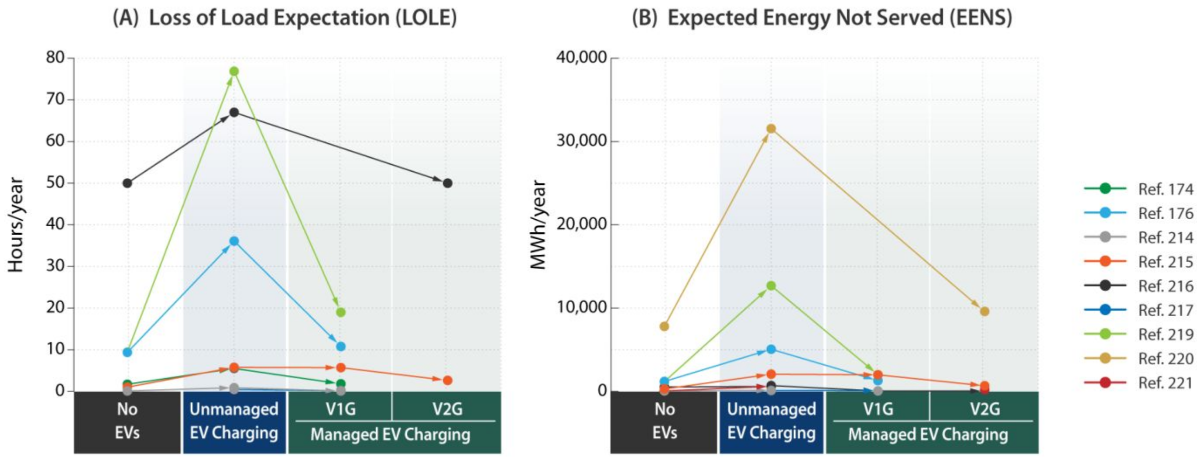


Fig. 6 Impacts of unmanaged and managed EV charging (with V1G and V2G capability) on bulk power system reliability indices (LOLE and EENS) from 9 studies (direct comparison of absolute results across studies is complex, but trends are consistent and informative). Unmanaged EV charging invariably worsens BPS reliability, while MC can bring the reliability indices down to values close to the case without EVs. The improvement in reliability indices due to MC depends on BPS characteristics, EV adoption assumptions, charging direction (V1G vs. V2G) and charging strategies.

Fig. 6 summarizes the value of MC in improving BPS reliability. Although unmanaged charging is usually projected to cause more frequent (higher LOLE) and severe (higher EENS) loss of load events (mostly as a result of EV loads being added to a system without considering any network upgrades; similar results could be expected when analyzing the addition of other electricity loads in isolation), MC (both V1G and V2G) can bring the indices down to values close to the case without EVs, allowing for a similar reliability of the baseline system but serving a larger demand. The extent of reliability improvement depends not only on power system characteristics (e.g., generation mix, VRE penetration,[221] network topology,[220] and weather conditions[214]), but also on EV load modeling/assumptions. Wang and Karki[219] show that increasing EV penetration increases the reliability benefits of MC; however, a saturation effect was observed in Hou et al.,[221] where the reliability improvement kept increasing until 20% EV penetration, beyond which the marginal improvements started to decline. V2G capability also increases the reliability benefits of MC.[215,216] Finally, different MC schemes lead to different reliability outcomes. Optimally controlled EV charging outperformed valley-filling charging in Bremermann et al.,[214] whereas dynamic DR signals significantly improved BPS reliability compared to TOU tariffs in Almutairi and Salama.[176] Conversely, strategies based on minimizing EV owners' charging cost under static tariffs and worst-case scenarios like synchronizing EV charging start times to peak periods could lead to reduced system reliability compared to uncontrolled charging.[218,219]

Reliable operation of DSs is also very important, as component failures in DSs are the most frequent cause of customer interruptions.[211,224] Compared to systemwide indices used for BPS reliability, DS reliability indices are usually customer-oriented. The most commonly used DS reliability indices are System Average Interruption Frequency Index (SAIFI), System Average Interruption Duration Index (SAIDI), and Customer Average Interruption Duration Index (CAIDI).[225] Whereas SAIFI reflects the frequency of customer interruptions, SAIDI and CAIDI capture the interruption durations normalized by total number of DS customers and number of interrupted customers, respectively. In combination with these indices, magnitude-based indices such as EENS are also used for assessing DS reliability.

Whereas unmanaged charging of EVs can reduce DS reliability compared to the no-EV case,[226,227] studies have shown that MC can improve the reliability indices (compared to unmanaged charging), particularly by injecting electricity to the grid (V2G) and/or into customers' homes (V2H). Therefore, bidirectional charging/discharging is a topic of significant interest in DS reliability studies. SMCS is the preferred approach (implemented in all studies discussed below) for assessing the DS reliability value of MC. The impacts of EV penetration with fast and slow charging and V2G capability on the reliability of urban and rural DSs are analyzed in Galiveeti, Goswami, and Choudhury.[228] In addition to DS reliability indices, the authors also propose indices for capturing the impacts of DS outages on EVs' expected energy not charged.[228] Similarly, indices for average frequency, duration, and magnitude of EV charging interruption are proposed in Guanglin et al.[227] Compared to Galiveeti, Goswami, and Choudhury,[228] where the methodology decides whether all EVs need to provide V2G during network failure (considering the energy needed for load restoration), the methodology in Guanglin et al.[227] allows all EVs to provide V2G as soon as an islanding situation is detected. The methodologies in Xu and Chung[232] and Al-Muhaini[233] consider the value of EVs directly injecting energy into customers' homes (V2H), in addition to V2G services. The DS reliability value of EV parking lots providing V2G services during typical office hours is explored in Guner and Ozdemir[234] and Zeng, Gao, and Zhu.[235] Unlike the aforementioned studies, the methodology in Tan and Wang[233] uses a condition-dependent outage model that explicitly considers the impact of EV charging strategies on DS component failure rates. Finally, the model in Zhang et al.[234] incorporates the impacts of traffic congestion on DS reliability by integrating a quasi-dynamic traffic flow model with a reliability assessment tool.

Fig. 7 shows the value of MC in improving DS reliability. By allowing EVs to provide grid support during network outages, MC with bidirectional capability (V2G and V2H) can reduce EENS not only compared to unmanaged charging, but also relative to the case without EVs. Similarly, MC with bidirectional capability can also reduce interruption duration (lower SAIDI) through load restoration. Conversely, most of the studies (except Al-Muhaini[233] and Tan and Wang[236]) report very limited to no improvement in the frequency of customer interruption (SAIFI) due to MC. This is because these studies (except Tan and Wang[233]) do not capture the dependence of network outages on EV charging, and unlike SAIDI (where partial load restoration would improve the metric), SAIFI can only be improved if MC can fully restore the network load.

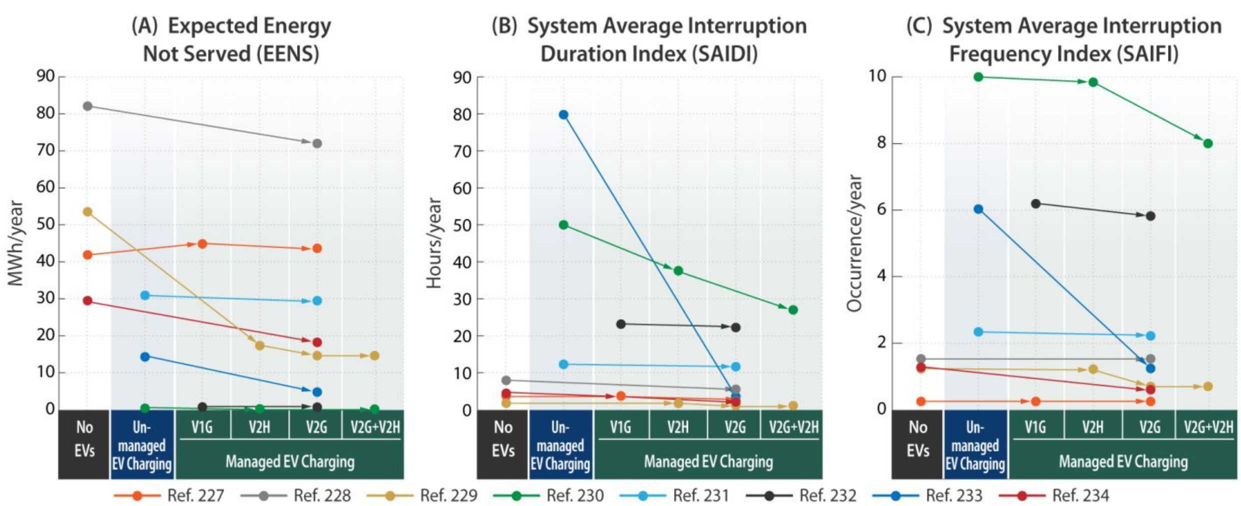


Fig. 7 Impacts of unmanaged and managed EV charging (with V1G and V2G capability) on distribution system reliability indices ((A) EENS, (B) SAIDI, and (C) SAIFI) from eight studies. Unmanaged EV charging worsens DS reliability, wheras MC—particularly by injecting electricity to the grid (V2G) and/or into customers' homes (V2X)—can result in greater DS reliability, even compared to the case without EVs. The improvement in reliability indices due to MC depends on DS characteristics, EV adoption assumptions, charging direction (V1G vs. V2G), charging speed, and charging strategies.

The DS reliability value of MC also depends on EVs' mode of operation during outages. Fig. 7 shows that V2H provides limited improvement in DS reliability indices, primarily because the reduction in energy not supplied is capped by the consumption of each household.[230] Also, V2H would not be able to restore the loads of households without EVs and would not be useful if the household is not affected by the outage. On the other hand, V2G can significantly reduce the duration and magnitude of customer interruptions.[229,230] Additionally, the number of EVs allowed to discharge during network outages also noticeably affects the reliability benefits of MC.[228] Finally, the total value of MC in improving DS reliability is reported to increase with increasing EV penetration.[229,233]

The results presented in this section highlight, not surprisingly, that in simulation studies introducing EV load without any system upgrades, unmanaged charging typically worsens system reliability, at both the BPS and DS levels. However, managed EV charging, particularly through bidirectional charging, can significantly improve reliability indices for a given system. Still, the extent of the benefits would significantly depend on whether the EVs provide support only to selected homes/buildings or also to the grid, as well as whether the improved reliability comes at the expense of EV users' mobility. In particular, the reliability value of MC, particularly of V2G/V2H, would reasonably diminish under scenarios with high, inflexible mobility requirements and prolonged system outages where users might be unwilling to forego the transportation utility of EVs. Consequently, further experimental validation needs to be performed to assess the realistic potential of bidirectional charging to increase system reliability considering mobility requirements, user preferences (especially during extreme events), and the complexity of equipment/controller installation.

4.5 Bulk system planning

Simultaneous uncontrolled charging of large EV populations can increase system peak loads, which could necessitate expansion of generation capacity, all else equal.[90,168] By reducing energy consumption during peak hours, MC can potentially reduce the need for additional generation capacity, thereby reducing BPS planning/investment costs and improving system efficiency. MC can also complement greater investments in VRE generation and could thus have significant implications for long-term planning and support decarbonization policies.

The systemwide planning benefits of MC are usually evaluated using centralized CEMs. These models typically minimize total system costs (including investment and operation costs) comparing the value of competing technologies subject to some policy constraints and/or reliability targets.[235] Manríquez et al.[236] use a CEM that optimizes investments in both generation and transmission capacity to assess the value of MC under various EV penetration levels for the 2030 Chilean power system. Kiviluoma and Meibom[237] use a linear CEM (Balmorel) coupled with a stochastic UC tool (WILMAR) to evaluate the potential of V1G and V2G in reducing generation investment and operation costs for the Finnish system. A similar sequential approach is used in Taljegard et al.,[160] where the BPS planning outputs from a CEM (ELIN) are used in a PCM (EPOD) to evaluate MC benefits in future Scandinavian-German power systems. BPS planning benefits of V1G and V2G for Central West Europe, Nordic and Baltic countries, and the United Kingdom are studied in Gunkel et al.[156] using the Balmorel model with battery degradation costs and transmission investments. In contrast to other CEMs, the model in Ramírez, Papadaskalopoulos and Strbac[238] co-optimizes generation investments and the percentage of flexible EVs by explicitly modeling EV flexibility enabling costs (including metering, control and communication, and battery degradation costs). Carrión, Domínguez, and Zárate-Miñano[239] introduce a stochastic CEM for capturing the impacts of long- and short-term uncertainties on the value of MC. In comparison to the aforementioned models, a whole-system assessment methodology is used in Aunedi and Strbac[177] that quantifies the planning and operational benefits of V1G and V2G not only on BPS generation and transmission, but also on DS reinforcement costs, which are modeled using calibrated functions of net peak load in each DS. Instead of using a CEM, Donadee et al.[240] maximize the utility's avoided costs under exogenous prices of different value streams (e.g., energy and ancillary service prices, generation capacity prices, DS capacity values). Although the model does not capture the evolution of installed generation and transmission capacities, it provides a computationally tractable framework for estimating the business case of MC infrastructure investments.

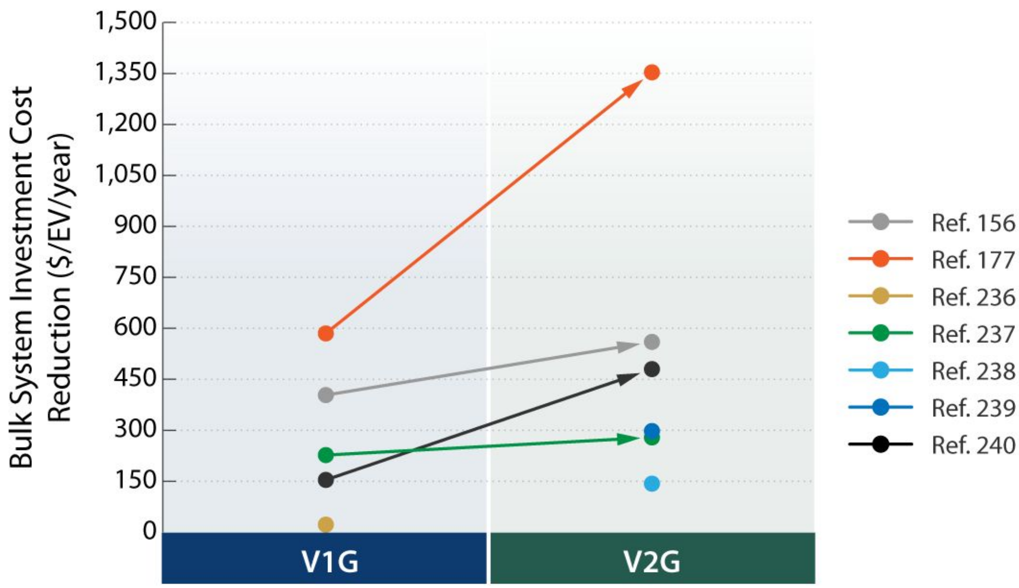


Fig. 8 Comparison of managed EV charging (V1G and V2G) in terms of reducing bulk system investment costs relative to unmanaged charging reported in seven studies. Managed charging is shown to consistently provide hundreds of dollars in investment cost savings per EV each year. V2G capability tend to enable greater investment cost reductions compared to V1G; however, the extent of these benefits depends on BPS characteristics, EV adoption assumptions and EV flexibility modeling, and enablement costs (usually not explicitly considered in these studies).

Fig. 8**Error! Reference source not found.** summarizes the marginal BPS investment cost reduction benefits of MC, which highlights the significantly greater potential of V2G (over V1G). Several other factors are also important in determining BPS planning benefits of MC. In addition to cases with bidirectional capability, the marginal benefits are higher under lower EV penetrations.[236,238] Although the presence of other sources of flexibility (e.g., energy storage) can reduce the planning benefits of MC,[177,237] MC can also outcompete other flexible resources.[156,239] Moreover, investment cost reduction due to MC noticeably increases if transmission expansion is also considered.[156] Conversely, the cost reduction potential of MC reduces if battery degradation costs are considered[240] and could completely disappear beyond certain values of flexibility enabling costs.[238]

In addition to investment cost reduction, MC can also increase installed VRE capacities.[156,160,168,236] However, the type of resource facilitated by MC depends on the indigenous resource quality. For instance, higher solar availability factors in the regions modeled by the International Renewable Energy Agency[169] and Manríquez et al.[239] lead to greater installation of PV units (compared to wind generation) due to MC. Conversely, European studies[156,160] show that MC benefits wind development and might even reduce PV capacities compared to unmanaged charging. This is primarily because in Northern Europe, solar PV mainly produces during peak price hours, and therefore the load shifting capability of EV reduces the revenues for solar PV, resulting in reduced investments in PV capacities.

The results presented in this section highlight that by reducing system peak loads, MC can noticeably reduce the need for investments in new generation capacity, particularly in cases with V2G capability. However, the value benefits of MC could be limited in systems with other flexibility competitors and under assumptions of high battery degradation and enablement costs.

4.6 Distribution system planning

DS planning involves determining the reinforcements/upgrades required to distribution systems to ensure reliable power supply to all customers. Considering that the challenges attributed to uncontrolled charging would likely manifest at the DS level first (due to "clustered" EV adoption), long before affecting BPSs,[90,241] MC would be of utmost importance for avoiding/deferring DS upgrades.

The typical approach for assessing DS planning benefits of MC is running power flow analysis/simulations, whereby asset/component loading and voltages are assessed under different EV charging profiles. Subsequently, reinforcement requirements are estimated for avoiding the potential overloading/voltage issues. The reduction in number of DSs requiring upgrades based on MC profiles determined using peak demand minimization and load flattening is evaluated in Coignard et al.[195] and Crozier, Morstyn, and McCulloch,[192] respectively. However, these studies do not evaluate investment cost savings due to MC. To this end, Verzijlbergh et al.[208] use power flow analysis to determine the reduction in percentage of overloaded transformers and cables by shifting the EV load to night hours, and subsequently use marginal component costs for determining the total investment cost reduction. Similarly, the impacts of MC profiles under dynamic pricing on the reduction of DS reinforcement costs in German DSs are analyzed in Kühnbach et al.[167] The authors then estimate the reduction in household electricity bills due to reduced reinforcement costs. Veldman and Verzijlbergh[207] compare the impacts of different charging strategies (unmanaged, peak load minimization, and charging cost minimization) on component loading, replacement costs, and energy losses in 48 Dutch DSs with high EV penetration. In contrast to studies that only consider the impacts of transport electrification, Pudjianto et al.[242] analyze the value of managing the power consumption of heat pumps, in addition to EVs, in residential DSs under different future electrification scenarios in the United Kingdom.

Although power flow-based methodologies are useful, they do not optimize the MC profiles for reducing DS reinforcement costs, which might lead to suboptimal results. This limitation can be avoided by using integrated optimization problems, similar to CEMs, for minimizing DS investment and operation costs. For instance, the model presented in Fernandez et al.[243] minimizes DS investment and operation costs, subject to constraints on EV energy requirements, voltage limits, and transformer/line capacities. Similarly, Lin et al.[244] minimize annual investment, maintenance, depreciation, and operation cost considering V2G services provided by an EV charging station.

In contrast to methodologies assessing the replacement/upgrade requirements of multiple DS assets, the methodology in Soleimani and Kezunovic[245] implements a detailed thermal model to determine the value of MC in reducing the loss-of-life probability and failure hazard of a single transformer.

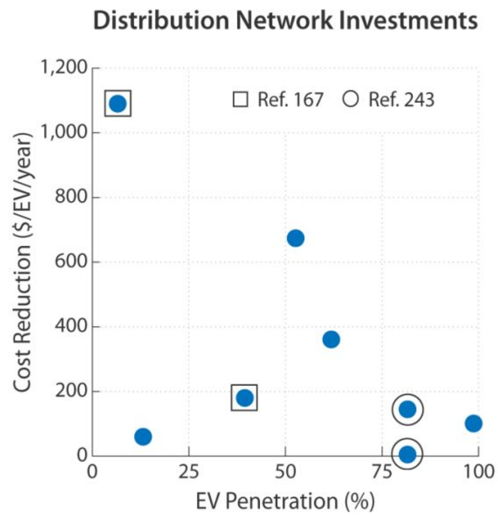


Fig. 9 Reduction in distribution system investment costs due to managed EV charging. Each colored dot represents a data point from six studies. Multiple values from the same reference are enclosed within the same shape for more direct comparison. The DS planning benefits of MC have been shown to be higher under lower EV penetrations and in DSs with high load density.

Studies have shown a wide range of DS investment cost reduction values of MC, ranging from $5–$1,090/EV/year, as shown in Fig. 9. These substantial variations can be attributed to several factors. The marginal investment cost reduction benefits of EVs may diminish with increasing EV penetration.[167] Also, the value of MC in reducing DS investments is shown to be higher ($145/EV/year) in an urban area with high load density and underground cables, but fairly limited ($5/EV/year) in a rural area with highly dispersed loads.[243] Studies have also reported that DS reinforcement deferral values of MC would be higher under scenarios with widespread fast charging.[167,208] Finally, charging management schemes also affect the outcomes. For instance, charging based on EV owners' cost minimization led to almost 70% higher reinforcement costs compared to uncontrolled charging, and ~260% higher costs compared to charging based on peak load minimization.[207] Also, Crozier, Morstyn, and McCulloch[192] report that while 28% of the DSs in the United Kingdom would require updates if EV charging is not managed, managing EV charging to flatten the load at the BPS level reduced this percentage to 19%, which can be further reduced to 9% if EV charging is managed to flatten the load at the DS level. This also points to the fact that MC based on improving BPS operation might not be optimal in terms of DS performance. Therefore, MC strategies need to be carefully designed considering the trade-offs at the BPS and DS levels.

4.7 Charging costs and revenue from grid services

Many of the benefits of MC described above can provide revenue to charging station operators and aggregators, and offset some of the costs of charging to the EV owner. A number of studies have analyzed these benefits from the perspective of these entities. This analysis evaluates how different MC approaches might impact revenue opportunities

As an example, Donadee and Ilić[246] present an approximate stochastic dynamic programming problem for maximizing the expected profits from price arbitrage (charging during lowest price periods) and providing frequency regulation (FR) for an EV owner under market price uncertainty. Similarly, an optimal control problem is implemented in Rotering and Ilic[153] to maximize an EV owners' price arbitrage and FR profits while considering the impacts on battery degradation. Sioshansi and Denholm[186] use marginal prices of energy and reserve and optimal EV participation values from a PCM to assess the value of V2G for EV owners. In contrast to optimization-based methodologies, a droop-based scheme for provision of FR using

EVs is presented in Calearo and Marinelli.[247] The droop-based charging/discharging power of EVs is then used to calculate the associated revenues (based on FR prices) and battery degradation costs (using semi-empirical functions). Wu and Sioshansi[248] maximize the profits from price arbitrage and FR for an EV charging station using stochastic optimization, whereas the impacts of a charging station's strategy (cost minimization vs. PAR minimization) on charging costs and DS operation are compared in Mehta et al.[197] Similarly, the impacts of different pricing schemes not only on the profitability of a parking lot owner and DSO, but also on DS operation, are evaluated using bilevel optimization in Sadati et al.[163]

The potential of MC in minimizing an EV aggregator's (EVA's) charging costs is analyzed in Le Floch, Di Meglio, and Moura[249] using an optimization problem based on partial differential equations subject to individual EVs' charging requirements and constraints on provision of contracted FR services. Similarly, Hu et al.[162] and Wang et al.[165] analyze the impacts of considering power consumption limits set by the system operator on EVA's charging costs, whereas Clairand, Rodríguez-García, and Álvarez-Bel[165] incorporate penalties associated to the violation of such power consumption limits in the objective function of an EVA. Instead of constraint violation penalties, distribution locational marginal prices are included in the EVA's cost minimization problem presented in Liu et al.[201] Compared to including power consumption constraints and/or costs associated to the grid services provided by the EVA, Steen et al.[163] and De Hoog et al.[171] include DS power flow constraints within the EVAs' optimization problems, transforming them into OPFs.

Several studies show that MC can reduce EV charging costs for the EV owners and aggregators by about 10%–60% depending on intra-day price variability, charging schemes,[162,170] V2G capability,[186,200] participation in FR,[246,249] and participation in unmonetized DS services. Results also show that if EV charging is controlled to provide unmonetized DS services, the charging costs can increase by ~5%–90% (compared to cost minimization without considering DS operation). This is primarily because EV charging based on lowest wholesale prices might cause DS congestion, voltage quality issues, and/or energy losses.[162,163,207] Therefore, charging EVs while avoiding these impacts tends to be more expensive. These results highlight that it would be imperative to holistically consider the trade-offs between BPS and DS benefits of MC, and to adequately monetize DS services to incentivize the participation of EVs in improving network operation.

4.8 Benefit-cost analyses

While Sections 4.2–4.7 highlighted the numerous benefits of MC across various aspects of the power system, the value of managed charging is a function of benefits and costs (see Section 3.2 for MC enablement costs) and how they are allocated to different entities, including EV users, electric utilities, general ratepayers, and others. Numerous benefit-cost analyses have been performed by utilities to assess the impacts of increased EV adoption in a region. These are often used to inform investment decisions, rate designs, and other regulatory processes, and to better understand consumer and societal benefits (e.g., value of emissions reductions, consumer fuel cost savings). Some of these analyses also considered the value of MC, even though limited to passive implementations, mostly involving TOU tariffs. Under baseline charging assumptions, these studies have reported utility benefits exceeding costs by hundreds of dollars per EV.[250] MC has been estimated to roughly double those net benefits, with annual value of MC ranging from \$34/EV to \$166/EV.[251–256] This large variability in the value of MC for utilities is driven by a number of factors, ranging from analysis scope, approaches, EV adoption projections, and assumed flexibility and heterogeneous characteristics of different power systems. A single case even projected declining value for the utility with implementation of MC.[251] The same study, however, reports EV users' net benefits of participating in a managed charging program (lower cost of off-peak TOU charging) ranging from \$148/vehicle to \$571/vehicle, not including the one exception discussed previously.

Across benefit-cost analyses, a number of common themes emerge. When examining the long-term utility perspective, avoided generation capacity is typically the largest benefit of managed charging, followed by either avoided distribution infrastructure costs or avoided generation energy costs.[251–256] The utility financial impacts of managed charging, however, may vary due to the characteristics of the retail and wholesale electricity markets in which utilities operate. Most utilities can take advantage of MC to reduce peak demand and capacity-related costs. However, there may be instances where distribution-only and retail choice utilities cannot directly realize the benefits of MC due to how they procure electricity supply on behalf of their retail customers. Ultimately, the incentive to invest in managed charging programs will be based upon the value proposition or regulation.

Overall, a critical review of these benefit-cost analyses highlights limitations and major uncertainties, mostly driven by limited information on MC cost given nascent EV markets (most benefit-cost analyses assume zero enablement cost since they focus on TOUs), simplifications needed to capture the complex managed charging approaches and implications, and a lack of holistic consideration and detailed modeling of benefits of MC across various elements on the power system. Moreover, benefits and costs will likely evolve as technologies develop, EV adoption increases, and power systems and other loads evolve, making analysis more complex. Synergies between EVs and renewable integration, for example, might enhance the value of MC in high-VRE systems.[58,168,184,191] As such, developing a broader assessment of managed charging value continues to be an active area of research.

5 Conclusions, key insights, and research gaps

Increasing EV adoption is a great opportunity for utilities, and it is often projected to be the main driver of future electricity demand growth in the United States.[4,55] While EVs can pose operational challenges for existing electric power systems when charging is unmanaged, management of EV charging offers unique opportunities to support power system operation and planning. The increased load (and retail sales) from EV deployment may require investments to upgrade various parts of the power system, but several studies have shown that widespread EV adoption coupled with managed charging can reduce average retail electricity rates for all consumers. [54,55,157,245] Managed charging is particularly valuable in systems with high levels of variable renewables to provide flexibility to match supply and demand. The value of managed charging, however, must consider both the benefits that MC can provide as well as the costs of implementation. Benefits have been estimated in many studies, but not in a holistic framework that consistently considers all the values that managed charging can provide and their trade-offs. Individual estimates might therefore be underestimating the full value of managed charging. On the other hand, combining individual benefits reported in different studies can lead to overestimation of benefits, primarily due to the lack of consideration of trade-offs between multiple value streams. Enablement and implementation costs remain highly uncertain due to limited market implementations. Overall, a complete benefit-cost assessment, even at a regional level, is still missing that considers the entire extent of values, enablement costs, and the perspectives of all stakeholders, including utilities, EV owners, charging station operators, and rate payers.

This paper reviews numerous studies that quantify the value of managed charging across the power system. Here, we synthesize several insights from these studies:

Benefits of Managed Charging:

- Compared to unmanaged EV charging, managed charging can provide significant benefits, reducing operation costs for bulk and distribution systems, improving reliability and voltage quality, supporting renewable integration and reducing curtailment, and potentially reducing the need for additional generation, transmission, and distribution capacity, thereby reducing planning/investment costs and times.
- Modeling studies show that EV managed charging can provide various operational benefits for bulk power systems, including reduction of system operation costs (\$15–\$360/EV/year), greenhouse gas emissions (−0.1 to 2.5 tons CO_2/EV/year), peak loads (0.2–3.3 kW/EV), and curtailment of variable renewable generation (23–2,400 kWh/EV/year).
- Managed EV charging can support and complement the expected large-scale VRE deployment, with significant implications for long-term planning and to support decarbonization policies.
- While the increased load from EV deployment may require investments to upgrade various parts of the power system, which could in principle increase electricity costs, several studies have shown that widespread EV adoption coupled with managed charging improves overall system efficiency and can reduce average retail electricity rates for all consumers.
- The benefits of EV managed charging vary significantly across studies due to different approaches, assumptions, and heterogeneity in power systems, EV adoption, use, and charging flexibility scenarios, making direct comparison difficult.
- Studies consistently find that the marginal operation and planning benefits of managed charging diminish with increasing EV penetration, owing to the presence of shallow value streams and competition with other technologies or approaches that provide flexibility cost-competitively.
- Differences in charging management schemes and time-varying tariffs lead to substantial differences in the benefits managed charging can provide. Without careful consideration, managed

charging can lead to unintended operational problems. Particularly, EV charging solely based on cost minimization (under wholesale market prices) can be worse than uncontrolled charging for the distribution system.

- Different power system characteristics also affect the value of managed charging. For instance, the managed charging operation cost savings could be significantly lower in systems that have other cost-completive sources of flexibility (e.g., energy storage). Also, the value of managed charging is computed with respect to a baseline. As strategies and other flexibility options are employed, the incremental value of increasingly complex managed charging implementations may decline as the baseline evolves in step.
- The value of managed charging will likely change over time as power systems evolve, more EVs are deployed for different applications, and charging approaches and consumer behavior evolve.
- V2G can potentially further reduce operation costs, CO_2 emissions, and peak load (compared to V1G) by displacing inefficient peaking generators.
- Unmanaged charging of large EV loads can increase both frequency and magnitude of lost load. Managed charging can support grid reliability by reducing loss of load and energy not served, particularly by injecting electricity to the grid (V2G) and/or to customers' homes or buildings (V2X). While managed charging can reduce both the severity and frequency of loss-of-load events at the BPS level, the reduction in frequency of outages at the distribution level are only evident if condition-dependent component outage models are used, and/or if managed charging can completely restore the local network load. Challenges due to unmanaged EV charging could manifest at the distribution system level first. However, the monetary value of managed charging at the bulk power system may exceed those of the distribution system in the long run.
- The range of benefits for distribution systems is particularly wide—where issues are location- and system-specific. Managed charging can noticeably reduce distribution system peak loads and congestion, and consistently increase the maximum feasible EV penetration for existing systems, even though "hosting capacity" is location-specific and also impacted by EV use, consumer participation, and managed charging programs. Generalization of the insights from modeling and analysis studies require simulating the impacts of managed charging in more diverse and realistic distribution systems under varying assumptions.

Managed Charging Implementations:

- While V1G is similar to demand response for other loads, there are significant differences in the EV market that suggest experiences may diverge.
- Benefits of more complex implementations (e.g., active V2G) are greater but more costly to implement. Full benefit-cost analyses to date, which rely on simplified approaches, are limited to passive V1G.
- The V2G benefits reported in the reviewed literature represent an upper bound achievable under ideal situations. In realistic applications, the V2G capability of EVs may be significantly restricted by the mobility requirements, particularly for long-duration value streams, such as reliability and capacity value.

These insights suggest a number of **gaps as well as research and development/demonstration needs:**

- Characterizing the needs of different EVs used for different applications is the first step to study managed charging. Most managed charging literature has focused on personal light-duty vehicles using average statistics, with earlier studies focusing on PHEVs. It is important to capture differences in vehicle use and charging opportunities. Also, with growing interest for battery electric vehicles in ride-hailing fleets and medium- and heavy-duty applications that might charge at higher power levels, it is important to consider these emerging trends. Additional data, modeling, and analysis studies are needed to better estimate charging needs, customer participation, and constraints for various vehicle types and applications that will ultimately determine charging loads and ability to provide demand-side flexibility

- Since the value of managed charging is impacted by the characteristics of both the bulk power and distribution systems (as well as other flexible loads and energy storage technologies) and looking at these systems independently may result in discrepancies and suboptimal solutions, a comprehensive analysis across the entire power system is needed to better understand the total benefit managed charging can provide. Conflicting charging solutions might maximize different value streams, suggesting the existence of trade-offs and an overall optimal solution for assessing the systemwide benefits of EVs when simultaneously providing multiple grid services. This would, however, require development of methodologies for improving the computational tractability of modeling such complex system holistically.
- Capturing these system benefits (not always explicitly monetized in today's markets) will require ways to demonstrate and market mechanisms to pass on these savings to participants and compensate EV users for providing flexibility while ensuring other stakeholders are also benefitting from managed charging.
- The role of charging infrastructure in enabling and supporting managed charging remains an open research question, with limited insights informing cost-benefit trade-offs and guiding investment decisions (e.g., what are the trade-offs between residential and workplace/public charging considering infrastructure costs as well as cost and benefits for the power system).
- While the impacts of managed EV charging on power system reliability have been analyzed in several studies, there is a dearth of literature on the benefits in improving grid resilience under high-impact, low-probability events such as natural disasters, as well as the value of local resilience (e.g., residential building backup power during such events).
- Estimation of the value of managed EV charging under different regulatory requirements, particularly for evaluating the potential of V2G in improving power system reliability, remains an unexplored area to inform evolving regulations and the design of future power markets.
- Realizing the central role of EV owners' behaviors and preferences in shaping the flexibility of managed charging, a multidisciplinary assessment approach is required to evaluate managed charging in the context of the social sciences and humanities.
- As the EV market rapidly evolves, it is important to consider new technologies and charging solutions in assessing integration challenges and managed charging opportunities. Future work should consider more EV applications and emerging mobility trends, such as ride-hailing, autonomous vehicles, and e-commerce, and their impact on EV charging needs and flexibility.

Appendix

Summary of Ancillary or Essential Reliability Services

Table 2 Summary of ancillary or essential reliability services

Operating Reserves	
Frequency-Responsive Reserves	Services that act to slow and arrest the change in frequency via rapid and automatic responses that increase or decrease output from generators providing these services. These services include inertial response and primary frequency response (PFR). An emerging product is "fast frequency response," which may replace some fraction of traditional inertia/PFR.
Regulating Reserves	Also known as frequency regulation. Rapid response by generators used to help restore system frequency. These reserves may be deployed after an event and are also used to address normal random short-term fluctuations in load that can create imbalances in supply and demand.
Contingency Reserves	Reserves used to address power plant or transmission line failures by increasing output from generators. These include spinning reserves, which respond quickly and are then supplemented or replaced with slower-responding (and less costly) non-spinning/replacement reserves.
Ramping Reserves	An emerging and evolving reserve product (also known as load-following or flexibility reserves) that is used to address "slower" variations in net load and is increasingly considered to manage variability in net load from VRE.
Other Services	
Black-Start	Capacity that can be started without either external power or a reference grid frequency, and then provide power to start other generators.
Voltage Support	Used to maintain voltage within tolerance levels and provided by local resources.

Summary Table of Existing Implementations of Managed Charging

Table 3 summarizes existing implementations of managed charging, as discussed in Section 3. The following summary is not intended to be exhaustive or comprehensive, but rather provides an overview of programs and projects across differing MC strategies. Examples range from established utility-scale pricing schemes to exploratory, small-scale demonstration projects for emerging technologies (e.g., V2G). Examples for the following table were primarily identified from more comprehensive summaries presented in other references.[85,90,105,115]

Table 3 Summary of existing implementations of managed charging

Direct/ Indirect	Charging Direction	Mechanism	Sector(s)	Project/Program and Timeframe	Goal(s)	Size	Participation	Compensation	Value
Direct	V1G	Demand response signal	Residential light-duty vehicle (LDV)	BMW/PG&E ChargeForward Pilot, 2015–2020[103,109]	Potential for grid services to reduce EV costs, support renewable energy integration	Phase 1: 96 drivers, Phase 2: >400 drivers	90% success in call events	$1,000 upfront, ongoing incentive for each day with no opt-out	$325/vehicle per year in grid savings 1,200 kWh of renewable energy/vehicle per year
			Residential LDV, commercial LDV	Avista EVSE Pilot, 2016–2019[104]	Understand LDV EV load profiles, grid impacts, costs, and benefits; support EV adoption	439 charging ports	85% opt-in rate	Installation and operation of EVSE	75% curtailment of peak EV load
Indirect	V1G	EV TOU	Residential LDV	NV Energy, Active[258]	Not specified	Not specified	Not specified	TOU rate, credit for difference from flat rate for first 12 months	Not specified
			Residential LDV	SDG&E PEV TOU, 2014[87]	Understand impact of EV charging and mitigate negative impacts	Not specified	86%–94% off-peak or super off-peak charging	TOU rate	Not specified
		EV day-ahead pricing	Residential LDV, workplace LDV	SDG&E Power Your Drive, Active[99]	Not specified	Not specified	Not specified	Day-ahead time-varying rates	Not specified
		Charging rebates	Residential LDV, Commercial light-, medium-, and heavy-duty vehicle	ConEdison SmartCharge New York, Active[85]	Incentivize off-peak charging, understand customer response	Not specified	Not specified	Monthly and per-kWh rebates for off-peak charging	Not specified
Direct	V2G	Frequency regulation market	Commercial LDV, medium-duty vehicle	Los Angeles Air Force Base Vehicle to Grid Demonstration, 2016–2017[113]	Explore cost savings potential of plug-in electric vehicles via V2G	29 vehicles	Not applicable	CAISO regulation market tariffs	$2,200 per season for fleet (29 vehicles)—likely not economical

Meta-Analysis Table of Managed Charging Modeling/Analysis Studies

Table 4 summarizes the modeling/analysis studies reviewed in this paper. In particular, it presents the geographic scope, modeling perspective, study goal(s), methodological details (including model type, formulation framework, and treatment of uncertainty), value streams, number/penetration of EVs, implementation mechanisms, and charging direction(s) (V1G and/or V2G) considered in these studies. The table is primarily organized by the type of analysis (indicated by different row colors), starting with bulk system operation, followed by distribution system operation, bulk system reliability, distribution system reliability, bulk system planning, distribution system planning, and charging costs and revenues. Within each analysis type, the studies are arranged according to geographic scope, starting with national scope and followed by regional, local, and individual scopes. Studies with the same geographic scope are subsequently ordered according to the modeling perspective(s) starting at the TSO level, going down to individual EV owners' perspective. Finally, studies with the same analysis type, geographic scope, and modeling perspective(s) are arranged in the order in which they appear in the manuscript.

Table 4 Summary of managed charging modeling/analysis studies

Legend:

Geographic Scope: National Regional Local Individual

Modeling Perspective: TSO DSO Aggregator Transport System Parking Lot/ Charging Station Individual EV Owner

Value Stream:
R: Reliability IC: Investment Costs MP: Maximum EV Penetration OC: Operation Costs PL: Peak Load E: Emissions
RC: RE Curtailment AO: Asset Overloading EL: Energy Losses FS: Frequency Support VQ: Voltage Quality CC: Charging Cost

Methodology:

Uncertainty:
Deterministic Model: D- Stochastic Model: S-

Model Type:
Capacity Expansion Model: CEM
Droop-based Control: DBC
Charging Cost Minimization: CCM
Load Shaping Model: LSM
Production Cost Model: PCM
Monte Carlo Simulation: MCS
Other Optimization Problem: OOP
Other Methodology: OM

Framework:
Centralized: Blue Decentralized: Red N/A: Black

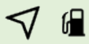
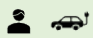
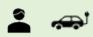
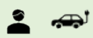
Ref.	Geographic Scope & Modeling Perspective(s)	Study Goal(s)	Methodology	Value Streams	No. of EVs/ Penetration	Implementation Mechanism	Charging Direction(s)
152		Evaluating the impacts of managed charging on overall system operation based on minimization on operation costs	D-PCM	OC, E	260,000 (10%)	Not Specified	V1G
160		Evaluating the impacts of V2G on long- and short-term system performance based on minimization of investment and operation costs	D-CEM	IC, OC, E, RC	76 million	Not Specified	V2G
177		Evaluating the impacts of V1G and V2G on long- and short-term system performance based on minimization of investment and operation costs	D-CEM	IC, OC, E	1 million	Not Specified	V1G, V2G

184		Evaluating the impacts of V1G and V2G on overall system operation based on minimization of operation costs	D-PCM	OC, RC	27,000	Not Specified	V1G, V2G
187		Evaluating the impacts of managed charging on overall system operation based on minimization of operation costs	D-PCM	PL, E, RC	4.8 million	Not Specified	V1G
189		Comparing the impacts of centralized and decentralized EV charging on overall system operation	D-PCM, D-CCM	OC, PL	1 million (25%)	Optimal Control compared to TOU tariffs	V1G
192		Evaluating the potential of smart charging in flattening transmission and distribution network load	D-LSM	PL, EL, VQ, AO	100%	Not Specified	V1G
151		Evaluating the benefits of V2G in terms of peak load reduction and improving power plant operation	D-LSM	PL	Up to 50%	Not Specified	V2G
154		Evaluating the benefits of V1G and V2G in terms of reducing net load ramping and VRE curtailment	D-LSM	PL, RC	1.5 million	Not Specified	V1G, V2G
155		Comparing optimal EV charging profiles with those obtained using time varying rates	D-PCM	OC, E	1%	Time-varying prices	V1G
157		Evaluating the impacts of managed charging on overall system operation based on minimization on expected operation costs under uncertainty	S-PCM	OC	735,000 (10%)	Not Specified	V1G
166		Evaluating the impacts of MC on overall system operation based on minimization on operation costs. Also, comparing optimal EV charging with TOU-based charging	D-PCM	OC, RC	0.95–5 million (4% to 20%)	Dynamic pricing compared against TOU tariffs	V1G
168		Evaluate the impacts of V1G and V2G on overall system operation based on minimization on operation costs	D-PCM	PC, PL, RC, E	50%	Not Specified	V1G, V2G
169		Evaluating the effectiveness of a decentralized charging strategy for valley filling	D-LSM	PL	10 million	Coordination Pricing	V1G
173		Evaluating the impacts of managed charging on overall system operation based on minimization of operation costs	D-PCM	OC, PL, E, RC	3 million	Not Specified	V1G
185		Evaluating the impacts of V2G on emissions based on minimization on operation costs	D-PCM	E	0.075–1.14 million (1% to 15%)	Not Specified	V2G
186		Assessing impacts of V2G on system operation cost savings and value for EV owners	D-PCM	OC	0.075–1.14 million (1% to 15%)	Not Specified	V2G
90		Evaluating the peak load reduction potential of managed charging	D-LSM	PL	23%	Not Specified	V1G
171		Evaluating the impacts of different charging schemes on DS operation and maximum EV penetration	D-CCM	MP, PL, VQ	80%	TOU-tariffs	V1G, V2G
172		Assessing impacts of EV charging rates on maximum feasible EV penetration	D-LSM	MP, AO, PL, VQ	100%	TOU-tariffs	V1G
175		Evaluating the potential of managed charging in increasing the maximum feasible EV penetration	D-OM	MP	1,510	Not Specified	V1G
195		Evaluate the benefits of managed charging for reducing DS upgrades	D-LSM	PL, AO, VQ	4,000–8,000 (100%)	Not Specified	V1G

196		Evaluating the impacts of different charging schemes on DS operation and maximum EV penetration	D-LSM	MP, PL, EL	1,000–2,000	Not Specified	V1G
198		Demonstrating the effectiveness of the proposed control algorithm for simultaneous thermal and voltage management	D-OM	MP, AO, VQ	86	Direct Load Control	V1G
199		Evaluating the benefits of managed charging for improving DS operation	D-OOP	AO, EL, E	227 (67%)	Direct Load Control	V1G
202		Coordinate the operation of DS and transport network to reduce charging costs, peak loads, and traffic delays	D-OOP	PL, VQ, CC	Not specified	Dynamic Coordination Pricing	V1G
159		Operation of a charging service provider in coordination with a retailer and DSO	D-OOP	PL, AO, VQ	2,200	Direct Load Control	V1G
161		Coordinating the operation of DS operator, fleet operator and EV owners using a distribution grid capacity market scheme	D-CCM	CC, PL	36 (60%)	Direct load control	V1G
162		Assessing impacts of EV charging strategy (uncontrolled, price optimal or loss optimal) and demographic data on DS operation	D-OOP, D-CCM	MP, PL, VQ, EL, CC	254 in Area A, 2,306 in Are B	Price Optimal: Dynamic spot prices; Loss Optimal: Direct load control	V1G
164		Optimally coordinate the active and reactive power dispatch of EVs for minimizing charging costs improving DS operation	D-CCM	CC, VQ, PL	1,500	Not Specified	V2G
201		Assessing the effectiveness of distribution LMPs for reducing DS congestion	D-CCM	CC, AO	100%	Direct load control	V1G
163		Assessing the value of bilevel optimization as compared to centralized optimization for maximizing the profits for the distribution company and PL owner	D-OOP	CC, EL	100	Critical Peak Pricing	V2G
158		Comparing the effectiveness of a decentralized methodology TOU and external marginal cost pricing for reducing peak loads and load variance	S-LSM	PL	500	Coordination Pricing	V1G, V2G
203		Evaluating the effectiveness of a decentralized methodology for reducing peak loads and load variance	S-LSM	PL	315	Coordination Pricing	V1G, V2G
205		Evaluate effectiveness of a droop control methodology for improving DS voltage quality	D-DBC	VQ	100%	Droop Control	V2G
206		Experimental validation of a droop control methodology for improving DS voltage quality	D-DBC	VQ	3	Droop Control	V1G
170		Comparing impacts of charging cost minimization and maximization of total stored energy in EVs on DS operation	D-OOP, D-CCM	MP, PL, AO, VQ, CC	57 (50%)	Not Specified	V1G
200		Comparing impacts of charging mechanism (V1G or V2G) and charging rate (fast or slow) on maximum feasible EV penetration	D-OOP	MP, AO, PL, VQ, CC	1,000	Not Specified	V1G

204		Evaluating the effectiveness of decentralized algorithms for reducing energy consumption and peak loads	D-LSM	PL	1,000	Demand shaping signal	V1G, V2G
197		Comparing impacts of charging cost minimization and PAR minimization on maximum feasible EV penetration	D-CCM, D-OOP	MP, AO, PL, CC	1,000	Direct Load Control	V1G
214		Evaluating the adequacy of BPS with electric vehicles and high wind penetration	S-MCS	R	2%	Direct Load Control	V1G
217		Comparing the proposed analytical methodology with SMCS for evaluating the reliability benefits of managed charging	S-OM	R	10%	Not Specified	V1G
174		Evaluating the effectiveness of the proposed stochastic EV charging model in capturing the reliability impacts of EV charging	S-MCS	R	5.5%–11%	Not Specified	V1G
176		Evaluating the effectiveness of the proposed framework is assessing the reliability impacts of EV charging	S-MCS	R	0%–50%	TOU tariffs and Critical Events Call	V1G
215		Evaluating the impacts of V1G and V2G on BPS reliability	S-MCS	R	100%	Not Specified	V1G, V2G
216		Evaluating the benefits of V2G on BPS reliability	S-MCS	R	15,000	Direct Load Control	V2G
218		Evaluating the impacts of EV charging objective on BS reliability	S-MCS	R	69,000	Direct Load Control	V2G
219		Evaluating the impacts of managed charging on BPS reliability	S-MCS	R	50%	Not Specified	V1G
220		Evaluating the impacts of different charging strategies and transmission network operation strategies on BPS reliability	S-MCS	R	480,000 (25%)	Not Specified	V2G
221		Evaluating the impacts of VRE and EV penetration on BPS and EV charging reliability	S-MCS	R	10%	Not Specified	V2G
223		Evaluating the impact of Advanced Metering Infrastructure (AMI) failure on BPS reliability assessment.	S-OM	R	21,000	Scarcity Pricing	V1G
227		Evaluating the impacts of EV penetration and charging rate on DS reliability	S-MCS	R	30%, 50%	Not specified	V1G, V2G
228		Evaluating the impacts of EV penetration and charging scheme on DS reliability	S-MCS	R	Up to 62%	Direct Load Control	V2G
229		Evaluating the impacts of EV mode of operation on DS reliability	S-MCS	R	100%	Direct Load Control	V2H, V2G
230		Evaluating the impacts of EV mode of operation on DS reliability	S-MCS	R	31%	Direct Load Control	V2H, V2G

233		Evaluating the benefits of V2G on DS reliability considering a condition-dependent outage mode	S-MCS	R	10%–100%	Real time pricing, Reliability incentives	V2G
234		Evaluating the impacts of EV penetration on DS reliability while considering traffic congestion	S-MCS	R	0% to 100%	Not specified	V2G
231		Evaluating the benefits of PL V2G charging on DS reliability	S-MCS	R	1 Parking Lot	Direct Load Control	V2G
232		Evaluating the benefits of PL managed charging on DS reliability considering behavioral aspects	S-MCS	R	1 Parking Lot	Direct Load Control	V1G, V2G
156		Evaluating the impacts of V1G and V2G on generation and transmission system investments	D-CEM	IC, OC, E	36 million	Not Specified	V1G, V2G
236		Evaluating the impacts of EV charging schemes on generation and transmission system investments	D-CEM	IC, OC, PL	0.18–0.56 million	Not Specified	V1G
238		Evaluating the impacts of co-optimization of BPS investments and proportion of flexible EV demand	D-CEM	IC, OC	0%–100%	Direct load control	V2G
237		Evaluating the benefits of managed charging in reducing long-term investment and operation costs	D-CEM	IC, OC, E	1 million	Dynamic Marginal Pricing	V1G, V2G
239		Evaluating the impacts of EV charging controllability on generation and storage expansion	S-CEM	IC, OC	30,000 (30%)	Direct load control	V2G
240		Quantifying the potential investment and operation cost reduction benefits of V1G and V2G	D-OOP	IC, OC	5	Not Specified	V1G, V2G
208		Evaluating the impacts of managed charging on DS investments and energy losses.	D-LSM	IC, AO, EL	720,000 (75%)	Not Specified	V1G
242		Evaluating the benefits of different DR technologies for improving DS operation and asset management	D-LSM	IC, PL	3.42 million (10%)	Not Specified	V1G
243		Evaluating the impacts of EV penetration on DS investments and energy losses.	D-CEM	IC, EL	Area A: 2,335, Area B: 17,748	TOU or RTP	V1G
245		Evaluating the impacts of EV charging on distribution transformers	D-OM	IC, AO	10 (40%)	Direct Load Control	V1G
244		Evaluating the benefits of V2G in reducing DS investments	D-CEM	IC, OC	3,000	Direct Load Control	V2G
167		Evaluating the impacts of charging power and management on DS investments end electricity procurement costs	D-CCM	IC	2–12 million (5%–30%)	Dynamic Pricing	V1G
207		Assessing the financial impact of various EV charging strategies on distribution grids.	D-CCM, D-OOP	IC, AO, EL	430,000 (47%)	Not Specified	V1G
165		Minimizing aggregator's charging cost	D-CCM	CC	Up to 1,000	Direct Load Control	V1G
249		Minimizing the cost of charging plug-in EVs, subject to supplying sufficient energy to the grid and sufficiently charged EVs to the drivers	D-CCM	CC, FS	2,225	Direct Load Control	V1G

248		Maximizing the profits from energy arbitrage and frequency regulation services	S-CCM	CC, FS	1 Parking Lot	Direct Load Control	V1G
153		Maximizing profits from energy arbitrage and frequency regulation services	D-CCM	CC, FS	1	Dynamic Energy and Reserve Pricing	V1G
246		Maximizing expected profits from energy arbitrage and frequency regulation services considering price uncertainty.	S-CCM	CC, FS	1	Dynamic Energy and Reserve Pricing	V1G
247		Maximizing profits from frequency regulation while considering battery degradation	D-DBC	CC, FS	1	Droop Control	V2G

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