Impacts of Managed Charging and Other Innovative Rates for Electric Vehicle Charging on Utility Load and System

Part I

Part I of the literature review contains papers that focus on the effects of innovative rates on residential EV charging for single-family homes. Section 'a' reports on overview studies. These studies either provide general information on rates and managed charging or provide surveys of multiple programs examining innovative rates and managed charging. Section 'b' contains studies that report on a single program. Section 'c' focuses on studies that contain methodology that can be used to develop a general model of the effect of innovative rates on EV charging that do not require utility-specific data. Some of those studies find results while having only limited data for the entity (e.g. electricity provider, geographic area) they were examining. These studies will be useful in conceptualizing the model for Part II of the project, which is to construct a model that will allow Duke to predict effects on EV customer use and the utility grid for varying assumptions about key parameters, such as EV customer rates, EV penetration, and distribution and transformer characteristics, such as capacities. Section 'd' contains a study of innovative rates on EV charging using a specific methodology that requires utility-specific data. That study, which uses Difference-in-Differences (DiD), is applicable to NC and possibly FL (and SC and IN). The primary technique to be employed to FL (and possibly SC and IN) is the use of a natural experiment via instrumental variables (IVs). While there are a few studies of natural experiments involving EVs, there is no literature to date specifically on EV charging that makes use of natural experiments. So we have not included literature on natural experiments related to EVs. Finally, Section 'e' is an appendix of related literature that contains less essential or redundant information.

Our focus is on innovative rates with the potential to shift residential EV customer charging to times of available electric system capacity, with the focus on distribution systems. The preponderance of rates to date are indirect managed charging rates, where rates are higher during system peak hours and lower during off-peak hours and the customer retains discretion on charging time. Such rates have been found to shift charging to off-peak hours, but can lead to new peaks, particularly at the beginning of off-peak prices in the nighttime hours. They can also lead to overload of distribution lines when a cluster of EVs charge their vehicles at the same time. Such a phenomena can even arise at super-off-peak times such as 1 a.m. More refined rates, such as critical peak pricing that imposes elevated charges a day ahead based on anticipated next-day conditions, can better achieve electric utility cost minimization. Adaptive pricing, where rates can be adjusted as system loads evolve, is another option, but has been little used so far. Demand charges, where customers pay separately based on maximum kW usage, either coincident with utility system peak or measured by the customer's maximum use, are rarely used. While demand charges are commonly assessed in commercial and industrial tariffs, they have not often been part of residential rates and would face consumer resistance due to the unfamiliarity and risk of substantial bill increases if a customer does not carefully monitor maximum use. Direct managed charging, where the utility controls charging time, could alleviate the problems of ToU rates, but is not yet common. Customers may be reluctant to give up control of their charging time, although allowing customers a limited number of opt-outs can increase customer acceptance. Demand response rates, where the utility compensates customers for not charging during utility-designated hours, can mitigate shifting peaks and congestion of distribution lines, and comes close to being direct managed charging, but still leaves the customer discretion over when to charge as well as allowing a limited number of opt-outs.

We provide here a brief synopsis of key takeaways from the literature review, followed in the body of the review by parts 1a-e containing brief summaries of the individual documents.

Part 1a of the review reveals the large number of pilots and programs offering innovative rates for EV charging. The earliest survey, in 2015, is by the Idaho National Laboratory. The Smart Electric Power Alliance (SEPA) surveyed programs in 2017, 2019, 2021 and 2023. Other surveys are by the Peak Load Management Association (PLMA), the National Rural Electric Cooperative Association (NRECA) and Hildemeier et al. SEPA's 2023 study is illustrative, reporting on programs at Kaluza (a UK company), BGE, PG&E, NYSERDA, and Kaluza coordinating with AMPECO (a Danish company). SEPA concludes that effective programs require a customer-centric approach, transparency, and education. The value of each customer varies, necessitating targeted approaches. Collaboration between OEMs, utilities, and technology providers is essential to build trust with customers and optimize program performance.

Part 1b provides case studies of individual programs. Spencer et al. (2021) reports on ChargeForward V1G, a BMW pilot conducted with PG&E. Phase 1 has 90 vehicles; Phase 2 has 400 vehicles, which they believed to be the largest program to date worldwide to implement smart charging optimization with real EV drivers in household settings. The study also considers plugin frequency and battery size effects on optimization. The authors present six cases. The focus is on grid savings. They use locational marginal prices (LMPs). In one case, they encouraged more frequent plugins to increase grid charging time flexibility. The sixth case used transactive energy price, closely tied to balancing supply and demand across the grid rather than a more localized LMP signal. This case resulted in the largest grid operational cost savings. Smart charging was successful at shifting loads from early evening to early morning and midday, also from overnight at home to day at the workplace.

Part 1c provides documents with sufficiently detailed methodologies to be potentially transferable to a utility using publically available data and will be the springboard for Phase 2 of our project. Muratori (2018) employs a model with bottom-up approach, utilizing household parameters to calculate demand and EV charging profiles, providing valuable insights into the aggregated and localized impacts of uncoordinated plug-in EV charging on residential power demand. The research underscores the significance of understanding customer behavior in PEV charging, revealing that while overall energy consumption increases, the primary concern lies in peak demand and load shape alteration, particularly emphasizing the impact of L2 charging on peak demand compared to L1 charging. The New York State Energy Research and Development Authority (NYSERDA) white paper (2022) explores managed charging for electric vehicles, highlighting challenges with existing time-of-use rates and emphasizing the importance of managed charging for significant load reduction by 2050. The study relies on literature estimates, projecting effects for New York State based on assumptions about increased vehicle miles traveled, electric vehicle adoption rates, and customer participation trends, providing valuable long-term insights for policymakers and utilities dealing with EV integration into the grid. Szinai et al. (2020) evaluates the benefits of managed charging for electric vehicles in California, utilizing an advanced PLEXOS energy model and an agent-based mobility model (BEAM) to analyze grid operating costs and renewable energy curtailment. Their findings highlight that direct managed charging and time-of-use rates exhibit comparable grid operating cost savings up to 10%, with the PLEXOS model serving as a deterministic tool for scenario simulations, while the BEAM model allows analysis of residential charging behavior. Aswani, Boyce, and Yomogida (2018) assess managed charging scenarios for the Sacramento Municipal Utility District (SMUD) using production cost modeling in PLEXOS. Their optimization model, considering factors such as energy cost structure and hardware configuration, demonstrates that optimized managed charging across an entire year results in a net value that is about 15-20% the average retail cost of electricity used to charge the EVs.

Part 1d provides studies with specific methodologies of innovative rate effects on EV charging that require utility-specific data. The Bode (2021) study employs a difference-in-differences modeling approach, utilizing propensity models based on AMI data to address challenges estimating the probability of electric vehicle (EV) ownership. The ex-post and ex-ante evaluation methods, coupled with panel regression DiD models and consideration of variables such as EV adoption and weather, ensure a robust analysis, revealing the success of San Diego Gas and Electric's EV-TOU programs in achieving significant demand reductions during peak hours.

Ia. Review papers of the effects of innovative rates on EV charging

Francfort, Jim, Bennett, Brion, Carlson, Richard, Garretson, Thomas, Gourley, LauraLee, Karner, Donal, McGuire, Patti, Scoffield, Don, Kirkpatrick, Mindy, Shrik, Matthew, Salisbury, Shawn, Schey, Stephen, Smart, John, White, Sera, and Wishard, Jeffery. **Idaho National Laboratory's Analysis of ARRA-Funded Plug-in Electric Vehicle and Charging Infrastructure Projects: Final Report**. United States: N. p., 2015. Web. https://inldigitallibrary.inl.gov/sites/sti/sti/6799570.pdf doi:10.2172/1244615.

The Idaho National Lab received funds to collect data for 2009. The five projects that Idaho National Laboratory (INL) collected data from and their partners are: • ChargePoint America - Plug-in Electric Vehicle Charging Infrastructure Demonstration • Chrysler Ram PHEV Pickup - Vehicle Demonstration • General Motors Chevrolet Volt - Vehicle Demonstration • The EV Project - Plug-in Electric Vehicle Charging Infrastructure Demonstration • EPRI / Via Motors PHEVs – Vehicle Demonstration The document serves to benchmark the performance science involved in the execution, analysis and reporting for the five above projects that provided lessons learned based on driver's use of the vehicles and recharging decisions made. Data is reported for the use of more than 25,000 vehicles and charging units.

Light-duty vehicles are manageable over the next decade. However, charging in the early evening adds to peak generation, less so to distribution. The weekend still peaks in the early evening, but with a lower peak and flatter curve. Managed charging shifts charging to early morning. Commuter vs. non-commuter profiles differ. Average connection time is 10 hours. Charge time is 2-3 hours. Those with workplace chargers peak at about 8 am, lower home peak at 5 pm. The public charger peak is around 8 am. Battery efficiency is lower in winter. After curtailment ends at 8 pm, there is a spike in demand similar to TOU response. Revenues to the utility exceed costs by about $1,000. Participants also gain; the combined benefit is $1,500. Higher loads will significantly impact the grid.

Load management can curtail 75% of residential peak EV loads with no TOU or other incentives. DR and V1G don't yet show net grid benefits. Larger battery packs will increase electric consumption and peak loads. E3(Energy+Environmental Economics) found a benefit to managed charging of $500-$1,700 with 70-90% due to reduced generation capacity cost and the small remainder from energy cost savings. An Avista study was similar, but with somewhat smaller benefits. The cost must be less than $46/year for net benefits ($50 and $170 for E3 to have a net benefit). Larger EV penetration and longer time duration increase net benefit.

Smart pricing: All consumers, not just EV owners, reap benefits. They include flat rates, time-of-day, RTP, CPP, PTR. Given rising renewables and EVs, TOU will not be enough. Table 1 shows examples of time-varying rate design.

Smart technology: Monitor and communicate real-time power usage, in-house or mobile display. Table 2 gives examples of technologies. Load-balancing technology will be needed as penetration increases. ChargePoint cut peak demand by more than half for an EU bus depot.

Beneficial EV integration is possible, and in fact, is already happening with tariff design, intelligent technology, and integrated planning. It is necessary to reduce emissions from both transport and energy sectors. Otherwise, electrification of transport could stagnate and burden drivers, electricity consumers, and the public sector with unnecessary costs. The other clear risk is that we will not reduce CO2 emissions and air pollution in the transport sector, the only sector where carbon emissions are still rising.

Myers, E. H. (2017). **Utilities and electric vehicles: The case for managed charging.** *Smart Electric Power Alliance (SEPA)*. https://sepapower.org/resource/ev-managed-charging.

EV charging could overload transformers. TOU rates could lead to "timer peaks," if consumers all start charging as soon as rates go down. The Sacramento Utility District estimated 17% (12,000) of transformers could need replacing due to overloads, at a cost of $7,400 per transformer.
To mitigate these effects, utilities need to shift charging to the off-peak, preferably when renewables operate. EVs currently add one terawatt-hour, 33 TWh by 2025 and 551 TWh by 2040. SDG&E day-ahead pricing-varying EV rate reflects its circuit and system conditions and the changing price of energy throughout the day. Southern California Edison used a workplace charging pilot and found that drivers need to have the ability to opt out if they want to charge during high demand times. Pepco included DR events and opt-out capabilities. They found communications too expensive and the need to identify cheaper solutions. Utilities have to offer customer-centric programs, including opt-out and override features, messaging and alerts based on customer preferences, smartphone functionality for control and management, and rewards, rebates, and other perks to keep customers happy and engaged.
A single EV can add between 1.4 kW and 20 kW of load, or 500 to 4350 kWh per year. However, a study by E3 found an NPV of $850 per vehicle in CA. A CA-based charging company, eMotor Works, found that aggregators could compensate prosumers up to $400 annually. Incentives to customers, such as carbon fuel requirements, are currently limited. SMUD found that without managed charging, 17% of transformers might need to be replaced due to overload, at an average cost of $17,000 per transformer, and that managed charging could provide a net benefit if the cost of communications is low enough.

Myers, E. H. (2019). **A comprehensive guide to electric vehicle managed charging.** *Smart Electric Power Alliance (SEPA): Washington, DC, USA*.

The report covers a number of managed charging programs, including Baltimore Gas and Electric (BG&E), PG&E, NYSERDA, Kaluza (UK), a Danish study, and Smart Charging Points (UK). The key consideration is benefits—with the focus on capacity savings—to costs of incentives. Selective takeaways are: BG&E: asking who will supply the chargers, solar customers may not be able to participate, and customer concerns about data privacy, disruption to routine, and damage to vehicle and battery; PG&E: largest pilot with 4,100 vehicles enrolled, focus on grid resiliency, considers incentives (economic response) and messaging (altruistic response); NYSERDA: seamless integration, option to override, marketing at point of sale, transparency about when vehicle is charging; Kaluza: Low, flat rate for charging (set-and-forget), less regulation of rates than in U.S. allows for easier implementation of innovative rates, large cost saving, altruism also important, seamless billing, charge path showing when charging, trickle charging so customer knows charging is ongoing, EV owners can set time by which they need their car to be charged and ready to drive, AI then optimizes to charge during times of low energy demand, when emissions and prices are also low; Danish study: managed charging tax reimbursement for network charging at non-public stations, dynamic prices, less need for public chargers; Smart Charging Points (UK): Off-peak scheduling capability, randomized delay function to reduce risk of grid instability, residential single-family homes easiest, but possibility of offering to multi-unit dwellings.

PLMA (2021, November). **Designing Effective Electric Vehicle Managed Charging Programs.** The Brattle Group (Hot Topic Conversation). Nick Bengtson, Dr. Sanem Sergici, Eamonn Urey, Michael Hagerty https://www.brattle.com/wp-content/uploads/2021/10/Designing-Effective-EV-Managed-Charging-Programs.pdf

The document reports on a pilot program for managed charging of 250 voluntary customers of the Salt River Project (SRP) water and electricity utility in Arizona. The program began in November 2021 and was expected to run for 12-18 months, and was intended to provide information needed to scale up the program and determine compensation for participants in anticipation of 500,000 EVs by 2035. They evaluated seven scenarios differentiated by the length of the charging window (4 or 8 hours), event days (all weekdays, July/August weekdays, and top 20 days) and compliance (80% vs. 90% of customers charging within the prescribed hours). As compared to unmanaged charging, system costs per vehicle decreased from $49 per year, for the four-hour summer peak weekday scenario, to $70 for eight hours including all weekdays. The majority of savings were from reduced demand during the system peak hours, with the remainder due to reduced energy use. Given compensation of $50 annually, benefits generally exceeded costs.
Data needed to estimate benefits was:

- Projected residential EV demand profiles, projected system demand, and historical energy prices for 2017-2020.
- The highest savings potential for managed charging is concentrated in less than 3% of annual hours. July and August peak hours (top 1.5%) account for 46% of annual charging costs.

The State of Managed Charging in 2021 (SEPA) B. Blair, G. Fitzgerald and C. Dougherty, November 2021, https://sepapower.org/resource/the-state-of-managed-charging-in-2021/

The report is an update of SEPA 2019, focusing on changes in managed charging since 2019.
Appendix A contains a listing of programs, starting with Austin Energy. Consumers Energy has multiple programs. Dominion has a program. Duke Energy FL has had a program from 2019-2022. Green Mountain has a 300-customer program, one of the largest in the nation. Lincoln, Nebraska has a nice data set being analyzed by FleetCarma *(an additional study by Lincoln Electric Company is in Part 1b)*. Portland General Electric (PGE) has a program. PG&E has a large program. SCE's Charge Ready program is for workplace, fleet, multi-unit dwellings, and destination centers. There is no mention of residential home chargers. Xcel (MN) has a 100 customer-managed charging program.
The next group of utilities use telematics, rather than the charging device: DTE (MI) had a program from Jan-Dec 2021. National Grid (MA) has a program. PG&E/BMW have iChargeForward. The Phase 2 pilot continued through 2019 with results published that year. PGE also has a program in this category. Xcel (CO) has a program, but it may not be managed charging.
The largest number of programs is for behavioral load control, including Avista. Duke Energy has ChargeFL. So does Green Mountain (Rate 74). Pepco appears to have a relevant program. Xcel (MN) allows unlimited charging for a fixed price, like the Duke Energy Carolina program.
There are six case studies. Hawaii found the program influenced some to purchase EVs. EVs will help consume excess solar. There is a need to educate consumers. They can use multiple marketing channels. GridShift (Silicon Valley) has the following aspects: hardware-agnostic, multi-layered optimization, and app-based customer engagement. But participants can suffer event fatigue, can only be in one DR program, customers with large batteries need more than off-peak hours to charge. DTE-OVGIP: Need baseline data to estimate expected load reduction. DR events were successfully called; openADR assists with communication. National Grid: Telematics are viable for their DR program. They market through OEMs. Challenge: which vehicles can participate, what size market share in order to estimate number of

enrollments. Eversource: Lower-than-predicted peak load reduction because not all vehicles actively charge during the event window. The programs can promote EVSE sales. They can also be incorporated into integrated DER objectives.
Proactive managed charging could be used when a utility anticipates extreme weather or a power shut-off. With managed charging, preparatory charging could stress the system if everyone charges up in anticipation of a possible outage. PG&E will use resilience charging in fire districts.
Program design: Plan for the program to evolve. Design programs to be feasible at scale. Align with funding sources and related programs. Default opt-in is better for utility and customers. Adopt a hardware-agnostic approach. Continue to allow new pilots to test new approaches.

Smart Electric Power Alliance (SEPA). (2023, March). **Managed Charging Programs: Maximizing Customer Satisfaction and Grid Benefits. I**n partnership with Ampeco, Kaluza, Uplight and WeaveGrid https://sepapower.org/resource/managed-charging-programs-maximizing-customer-satisfaction-and-grid-benefits/

Managed charging programs for EVs play a crucial role in optimizing energy consumption, grid stability, and environmental benefits. This report discusses how the success of these programs depends on customer engagement, incentives, and transparency. SEPA creates a comprehensive study on managed charging programs that offers insights for industry stakeholders, utilities, OEMs, and technology providers. Case studies of this report illustrate successful managed charging programs:

1. Kaluza's "Project Shift" highlights the effectiveness of upfront incentives in attracting customers to managed charging programs.
2. BGE's telematics-enabled programs demonstrate the success of addressing customer preferences and privacy concerns.
3. PG&E's evPulse program emphasizes the importance of community-based organization outreach and targeted marketing.
4. NYSERDA's Charge Smart program highlights the effectiveness of bundled offers and community engagement.
5. Kaluza's "Drive + Anytime" and AMPECO's Danish Tax Reimbursement programs illustrate the significance of clear financial incentives and customer-centric approaches.

These case studies show that effective customer engagement is critical for successful managed charging programs. Incentivization is a critical factor in encouraging customer participation. Customers already participating in utility programs are more open to joining new ones. Incentive impact varies, with larger upfront incentives being more attention-grabbing. AI has also proved to be an important tool for categorizing customers based on their load shift potential and energy consumption patterns. By offering higher incentives to customers with high load shift potential, programs can ensure a more valuable response.

As EV ownership expands, programs may need to be more selective in incentivizing load shifting to maintain cost-effectiveness. Opt-out programs, where customers are automatically enrolled, tend to have higher enrollment rates due to their convenience. However, both opt-in and opt-out programs necessitate customer education to prevent potential economic impacts on participants, such as increased energy bills for those unfamiliar with time-of-use rates. The value customers bring to the grid depends on their charging habits and flexibility, making it essential to target customers whose responses align with program goals. Partnerships, messaging, and an easy enrollment process are also key drivers of higher enrollment.

Privacy concerns, range anxiety, and long-term vehicle effects are common customer concerns. The complexity of a program may affect customer comfort with participation. This report emphasizes the importance of building trust with customers, transparency in data collection and management, a gradual introduction to demand response events, and ensuring program activities do not significantly affect vehicle battery life. OEMs can play a significant role in educating customers about managed charging programs at the point of sale, while also reassuring customers about the impact of these programs on their concerns. Regulatory constraints can present challenges in achieving a balance between return on investment (ROI) expectations and program enrollment goals. Regulators often anticipate high participation based on previous successes. However, the ROI for EV programs is more nuanced, and it's crucial to consider the early adopter impact and gradually enroll customers over time.

In conclusion, effective programs require a customer-centric approach, transparency, and education. The value of each customer varies, necessitating targeted approaches. Collaboration between OEMs, utilities, and technology providers is essential to build trust with customers and optimize program performance.

Dayem, K., Mercier, C. and May-Ostendorp, P., **Electric Vehicle Charging Control Strategies** (January 2019), National Rural Electric Cooperative Association (NRECA). https://www.cooperative.com/programs-services/bts/documents/techsurveillance/surveillance-article-evse-load-control-strategies-jan-2019.pdf

The document focuses on EV relevance for electric cooperatives. The main co-op goals will be distribution grid infrastructure and power procurement, preferably off-peak. A cooperative with one thousand EVs in its territory may see a load increase of 9 MWhs per day, assuming the average EV drives 30 miles per day and consumers 300 Wh per mile.
Examples are:

- Salt River Project (SRP) studied load shifting w/ TOU and EV rates.
- Auto DR: Delaware Electric Coop (DEC): ChargePoint agreed to share data. One-time $100 credit + $5/mo bill credit.
- Green Mt. Power (GMP). Unlimited charging outside the peak period for $29.99/ mo. Load control switch cuts power, but customers can override for $0.60/kWh. The program is very popular, and is unlikely to lead to driving more just because electricity is free.
- Managed Charging Rewards Program: American Electric Power (AEC) is working with eMotorWerks. $5/mo bill credits with 5 opt-outs/mo. Or reduce charge current from 4-7 pm for $3 credit with 2 opt-outs, or day-ahead event for $5 credit per event.

Mid-Carolina Electric Cooperative has a demand charge. The EV rate requires a 2nd charger, but that requirement adds cost. Rebound peak could impact the distribution transformer. Reduce peak to manageable maximum and spread charging load across off-peak.
FleetCarma can collect EV data. Offer customer rewards rather than rates.
Green River Energy and Connexus Energy provide RECs on customer's behalf.

Hildermeier, J.; Kolokathis, C.; Rosenow, J.; Hogan, M.; Wiese, C.; Jahn, A. **Smart EV Charging: A Global Review of Promising Practices.** *World Electr. Veh. J.* 2019, *10*, 80. https://doi.org/10.3390/wevj10040080

The study is a qualitative review of policies for EV grid integration in the EU and U.S. markets.

Opportunities for integrating EVs beneficially include cost-reflective prices, smart technology (e.g. enable consumers to make choices to reduce their bill without needing to constantly pay attention to the relevant technology) and smart infrastructure (strategic siting of EV charging infrastructure). The article collects, reviews, and documents real-world case studies.
Results include: Smart charging: Shift to times when costs of producing and delivering electricity are lower, without compromising the vehicle owner's needs.
There are several EU examples, including Spain, Denmark, the U.K and Germany in the EU and Green Mountain Power in Vermont in the U.S.

Ib. Case studies of a single utility's use of innovative rates to influence EV charging

Spencer, S. I., Fu, Z., Apostolaki-Iosifidou, E., & Lipman, T. E. (2021). **Evaluating smart charging strategies using real-world data from optimized plugin electric vehicles**. *Transportation Research Part D: Transport and Environment*, *100*, 103023. https://doi.org/10.1016/j.trd.2021.103023

Most studies of managed charging that are simulations. One study finds managed charging cheaper as a way to deal with the California duck curve than a dedicated storage battery for the grid. Another study finds it can reduce renewable curtailment. This study uses real-world data of actual driver behavior.

ChargeForward V1G is BMW's pilot conducted with PG&E. Phase 1 has 90 vehicles; Phase 2 has 400 vehicles, believed to be the largest program to date worldwide to implement smart charging optimizations with real EV drivers in household settings. The study also considers plugin frequency and battery size effects on optimization.

The authors present six cases. The baseline is set immediately after the charger is plugged in. They calculate the total amount of charging in kWh. The focus is on grid savings. They use locational marginal prices (LMPs). In one case, they encouraged more frequent plugins to increase grid charging time flexibility. The sixth case used transactive energy price, closely tied to balancing supply and demand across the grid rather than a more localized LMP signal. This case resulted in the largest grid operational cost savings. Smart charging was successful at shifting loads from early evening to early morning and midday, also from overnight at home to day at workplace.

Payments of a few dollars per day were somewhat arbitrary, chosen to achieve goals. The location was the San Francisco Bay area. In the next stage, they will use a larger data set, more use cases, and household and workplace V2G. Finally, they will include driver motivations to participate.

Preparing for a plug-in future. Lincoln Electric System (LES). (2020, July). Study Results on Electric Vehicle Webinar. Lincoln Electric System. https://www.les.com/sites/default/files/ev-webinar-072020-study-results.pdf

From 2019-2021, LES received 100 applications, targeted 50 vehicles and recorded anonymized data each month, including: Charging session duration, energy use and location; trip duration, energy use, and distance. Participants received $25 upon data collection and easy access to personal charging/trip data via the web. LES added a DR pilot in 2021. The study included PHEVs and BEVs.

The project included a comprehensive list of variables and results for 2019. Data included customer charging data, trip data, and Pandemic impact comparing 2019 to 2020. They also provide results for a 2021 DR Pilot focusing on 2019 winter and summer peak months. Customers received $10/mo. ($60 in total). They could opt out, but lost payment if there were any opt outs. The utility could call up to 5 DR events/mo. (20 total). About 70% complied with all events, 88% on average for each event. The study was able to compare DR and non-DR days. There was less impact on winter mornings, since there is more charging in the evenings. There was a larger impact in the evening in winter, as well as a summer impact.
There is an FAQ section. Customers went about 2 days between charges. The highest charge was in February, although this was also the month with the second-lowest VMT. It was the coldest month, with the lowest vehicle efficiency.

Exelon's Managed Charging Program, Phase 1 Review, SEPA, August 2023 Carolyn Dougherty, Garrett Fitzgerald, SEPA, Joseph Picarelli, Jr., BGE; Stephanie Leach, BGE; Joshua Cadoret, Exelon Corporation, and others at Argonne, Shell ReCharge Solutions, WeaveGrid

Exelon, a major utility company in Maryland, has collaborated with the U.S. Department of Energy (DOE) to pioneer a Smart Charge Management (SCM) pilot program and address electric vehicle adoption and their impacts on the electric grid. The purpose of this project was to mitigate grid impacts but also minimize the cost of capital required for residential customers in the face of EV expansion. This program spanned both commercial and residential customer classes, but this summary focuses primarily on the residential charging sector and its impact on the electric grid. This program was broken into several phases.

Phase 1 of the program included cybersecurity testing and validation, platform system integration and verification, and simulating the impact of EV charging on the grid. One complication of this study was determining EV owners. This study addressed the issue using WeaveGrid, which was instrumental in determining potential EV owners through Advanced Metering Infrastructure. This project also addressed cybersecurity concerns related to Electric Vehicle Supply Equipment (EVSE) and telematics software but employing STRIDE and ATT&CK to assess vulnerabilities. An ATEAM model was also constructed to simulate the impact of electric vehicle adoption on the grid, which addresses problems of data granularity and maintaining accuracy with future EV penetration projections.
Phase 2 of the project focused on the charging behavior of EV owners.

In Phase 2, the focus shifted towards studying the charging behavior of residential EV owners. This phase aimed to simulate distribution utility operations, demonstrate the value of smart charging, and assess the ability of EV charging networks to provide grid services. To determine the impacts of managed charging, this study considered variables such as driver preferences, rate information and price signals. Residential customers in the program were offered a monthly incentive to optimize their EV charging. This innovative rate helped reduce peak demand and encourage off-peak charging to align with reducing grid impacts. In return for their altered charging behaviors, customers received a $10 monthly credit to their electricity bill. However, this program had an opt-in and opt-out option, which gave customers more freedom in charging ability but could also impact their incentive. More than 4 opt-out responses to a demand response event per month resulted in an incentive loss. The results of this program showed that drivers participating in the Off-Peak program were more inclined to charge their electric vehicles during off-peak hours compared to alternative rates. Overall, demand response events curtailed charging during peak hours for all customer types.

In conclusion, Exelon's SCM pilot program offers valuable insights to utility companies nationwide about EV adoption. This program has been successful in managing residential EV charging behavior and its impacts to the grid. From this project, there are several lessons to be learned, including how to design, test, and implement strategies, which will help shape the future of managed charging programs. As EV adoption grows, this program will serve as an important insight on how to ensure grid reliability while meeting the growing needs of customers.

Parkinson, K., Koliner, J. (2023, July). **Effective EV Programs To Make Change Happen.** Rolling Energy Resources. https://rollingenergyresources.com/wp-content/uploads/2023/07/Katie-Parkinson-RER-EVs - v3.pdf

The article, Effective EV Programs to Make Change Happen, discusses ComEd's innovative EV managed charging pilot. ComEd decided to evaluate both behavioral and active interventions in partnership with Rolling Energy Resources. Behavioral managed charging allows EV owners to adjust their changing habits voluntarily while active interventions allow the utilities control over charging. Both types of interventions shift EV charging to off-peak times to optimize energy use. Behavioral nudges include pricing strategies such as TOU and Off-Peak Incentives. Education resources include in-depth charging reports on a user's charging behavior. Active interventions include responding to peak demand scenarios or events, where utilities schedule days where charging would be reduced.

One concern of the utility is balancing grid reliability with customer rate acceptance, highlighting a tailor-made approach, as strategies that are effective in one region may not work in another. Therefore, recruitment strategies for these EV programs are of utmost importance. This utility targeted customers through email marketing campaigns, focusing on customers who had previously expressed an interest in EV programs. Out of 4525 customers, 255 customers were used in the study, most of whom were Tesla owners.

This article was designed to explore the impacts of rate structures. This data was analyzed for charging patterns, demand trends, state of charge, and other charging preferences. They discover that most of the charging activity takes place during off-peak hours. A large portion (55%) of EV owners prefer to charge at home, and about 84% of the energy used by EVs originates from the home charger.

Overall, the article explores ComEd's EV load management programs, shedding light on the ever-changing EV situation in the United States. This article provides a detailed overview of the ComEd study, offering insights into rate design, charging patterns, customer uptake, and recruitment for more efficient EV charging management.

Eversource Annual Report – Program Cycle Year 2 (August, 2023)
The report is for Program Year 2, provided in August, 2023. The Connecticut program will be delivered over nine years (!), beginning in 2022, in three-year cycles. The focus is on the distribution system. They focus on five areas of deployment, of which we are focused on the first, residential single-family homes. Of evaluation goals, we are interested in (3) Effects of managed charging on customers and (4) Benefit-cost analysis.
A DR-event-only program is being used to establish a control group, since it is difficult to have a control group for a large-scale level 2 charger group on a TOU rate (equivalent to once-on, always-on DR). There was also a randomization of the DR-event-only program, with the control group now receiving a daily TOU signal. A load impact study of Summer 2022 managed charging begins on p. 67. Data on charging usage and load profiles are from Level 2 chargers and telematics, at 15-minute and hourly granularity.
There are two stated goals: EV adoption and EV usage. Only the second goal is relevant to our study. The underlying policy goal is to avoid the capital costs associated with generation, transmission, and distribution capacity expansions from growth in peak demand. They provide five alternative measures of

BCA. The UCT BCA is most relevant for this objective: Cost-Benefit Test-- Benefits Costs Utility Cost Test (UCT). Benefits are changes in the electric system's marginal operating costs. Costs are incentives, program administration, vendor fees. The UCT test should be applied to Residential Single-Family Housing, Level 2 charging.

They found that discrete categorical variables performed better than continuous variables. See Table 17. Bins were created to create the discrete variables. Propensity models were created for each bivariate relationship for preliminary research.

Vendors collect data either from Level 2 chargers or vehicle telematics. Note that telematics data captures both home and away behavior. Estimate that by 2025, with 150K EVs, demand could represent 1.4% of peak demand. Interval data was collected in 15- or 30-minute intervals, and aggregated to hourly. Percent of hours vehicle is plugged in is 29% and of those hours active charging is just under 50%. There is information on peak and off-peak use. In year 2 of the program, peak use declines as the program transitioned from events to every day. There is a step-by-step procedure for calculating avoided CO_2.

Regression model and results are provided. Baseline managed charging began in 2022. Advanced managed charging began in 2023, with the utility able to optimize the charging time. Baseline tier customers could earn up to $200 for full-year participation based on Summer 2022 DR events. Counterfactuals were based on charging on non-event days. Table 26 provides the estimation steps. To get a better counterfactual, another procedure was that proxy dates were chosen, similar to event days. Pg. 80 shows the “winning” regression model. Eversource will try to contact future participants at the point of purchase.

If I had to recommend a single document to recommend to someone undertaking a managed charging program, this document would be a candidate. It is very detailed, including all the pitfalls and challenges of analyzing such a program.

Ic. Studies providing methodologies that can be used to develop a general model of the effects of innovative rates on EV charging without requiring utility-specific data

Muratori, M. **Impact of uncoordinated plug-in electric vehicle charging on residential power demand.** *Nat Energy* 3, 193–201 (2018). https://doi.org/10.1038/s41560-017-0074-z

Note: This study is reported in this section of the review with emphasis on customer behavior and the relevance of the model for Phase 2 of our study. It is also reported in Part II of this document with emphasis on grid impact.

This is a study on the aggregated and localized demand and energy use for 200 homes with both L1 and L2 electric vehicle charging (dataset: https://data.nrel.gov/submissions/69). It includes 348 in-home plug-in EV recharging profiles associated with these households and 502 individuals (this is from the EIA: Residential Energy Consumption Survey). The study includes both the aggregate impacts of the 200 sampled households and also clustering of the EV charging on a distribution transformer with six households. For reference, there is a residential load curve without EVs. This data is generated using methods from previous papers by the same authors that utilize a bottom-up approach that calculates the demand profiles and electric vehicle charging profiles for each customer based on household parameters. The study reports findings for one sample week and for each hour of the year. This study found that while the overall energy increases, the main issue with EV charging is with peak demand and

changing the load shape. Furthermore, it found that clustering of electric vehicles in a small area may lead to localized impacts even at low adoption levels and that L2 charging has a more significant impact on peak demand than L1 charging. It is important to allow for the fact that charging will not all occur at the same time, not only in terms of the time of day, but also the day, since EVs may only be charged a few days per week, lessening the impact on demand.
The data is freely available for download. Muratori's approach could help establish a baseline for unmanaged charging. The original RECS (Residential Energy Consumption Data) data, augmented by the American Time Use Survey, were created for NREL (National Renewable Energy Lab) in 2009, but there is a note that indicates that the last update was in 2022. The author notes that in future research, the approach could be used for managed charging. The use of these data would allow results to be drawn from NC without the need for detailed NC data. The most recent RECs is 2020 https://www.eia.gov/consumption/residential/data/2020/. There is a Methods and Methodology review at the end of the paper.
Muratori, M. Impact of Uncoordinated Plug-in Electric Vehicle Charging on Residential Power Demand — Supplementary Data. No. 69. (NREL-DATA, Golden, 2017); https://doi.org/10.7799/1363870

Boston Consulting Group. (2019). **Costs & Benefits of Revving Up the Grid for Electric Vehicles.** BCG. https://www.bcg.com/publications/2019/ costs-revving-up-the-grid-for-electric-vehicles
Anshuman Sahoo, Karan Mistry, Thomas Baker (Baker sent supplementary notes.)

EVs may have a relatively small impact on overall load, but a large impact on parts of the grid depending on the concentration of EVs, when they charge, and the speed of charging. The initial strain is on distribution and subsystems *(the emphasis of the grid impacts in our project)*. Some of the investment costs will be covered by revenues from higher sales, but the remainder will have to be covered by higher rates. Investment costs will increase exponentially with higher EV penetration.
Utilities will need to identify those parts of the grid that will need distribution upgrades. They will need to deploy differential pricing, possibly by location, as well as centrally controlled DR. They will need to identify which costs go into the rate base and affect all customers, and which costs should be directed to particular customers. The costs borne by customers should be in proportion to benefits received.
Charging patterns determine costs and investments. On the generation cost side, the study assumed wholesale costs of $23, $29, and $34 per megawatt-hour (MWh) for the off-peak, shoulder and peak charging periods. Given those costs, the cumulative generation cost (per EV) to the utility from 2019 to 2030 will vary from $770 to $880. The optimization of both timing and location would allow a decrease of roughly 70% in transmission and distribution costs per EV through 2030—from $5,800 in the non-optimized charging scenario to $1,700 in the optimized scenario. Total costs–G+T+D–are dominated by distribution costs.
Supplementarity document (sent by Thomas Baker)
This document gives step-by-step instructions for setting up the study.

Satchwell, A., Carvallo, J., Cappers, P., Milford, J., & Eshraghi, H. (2023). **Quantifying the Financial Impacts of Electric Vehicles on Utility Ratepayers and Shareholders**. Lawrence Berkeley National Laboratory. Retrieved from https://escholarship.org/uc/item/6dz355d9

There are new earnings opportunities for utilities from increased electricity sales. The study uses Berkeley Lab FINDER model (as well as a supplementary explanation of FINDER and elsewhere, a publicly available simpler SUPRA version). The model mimics the electric utility planning and ratemaking process.

The assumptions are for a generic, summer-peaking vertically integrated investor-owned utility. Earnings increase 2.2%-4.7% over a 20-year period while rates remain virtually unchanged. Managed charging and shifting load away from the utility system peak reduces rates 0.8%-1% by lowering generation and distribution costs. Compared to a no-electric vehicle future, shareholders gain, but generation and distribution investments erode savings. Utility infrastructure causes rates to increase 1.6%, but increased sales cause rates to decline 2.9% in later years. Managed charging reduces incremental annual cost of integrating EVs by 38-62%. There is a bigger impact under low penetration. However, customer incentives reduce ratepayer savings.
Financial impact under low peak impact charging as compared with high impact charging reduces rates and utility/shareholder earnings. But the utility is better off than no EV future. *(a paradox for regulated utilities that managed charging could reduce earnings as compared to unmanaged charging, but that earnings will still be higher than if there were no EVs).* Shareholders are more affected than ratepayers because rates reflect all-in costs while shareholders are more affected by CapEx. Ratepayers are always better off with managed charging. Shareholders are better off than with no EVs, but reduced generation and distribution erodes incremental earnings. Investments lead to near-term rate increases, but long-term rate decreases. You would need dynamic managed charging to minimize peak impacts as the utility load shape evolves inclusive of EV load (and EV TOU periods change from overnight to midday as coincident EV load impacts increase).

New York State Energy Research and Development Authority (NYSERDA). 2022. **“Managed Charging for Electric Vehicles White Paper,”** NYSERDA Report Number 22-09. Prepared by The Cadmus Group LLC and Michelle Levinson, World Resources Institute.

The white paper reviews existing residential EV TOU rates, including PG&E, SDG&E, Xcel (CO), Pepco (MD), Toronto Hydro and Eversource (MA).
Opt-in for TOU has very low take-up rates. With opt-out, few opt out. But some customers may show little response. Households prefer separate EV tariffs to whole-house if the second meter is subsidized. Most programs to date are behavioral.
An LBNL study shows utility system benefits are modestly higher for managed charging vs. TOU. Also, utilities can take advantage of vehicle charging when solar is available, for those cars that are at home during the day.
Table 10 shows TOU response from other studies. Using their methodology, they project out to 2050 using an estimate that VMT will increase 0.84%/yr. Initially managed charging effects on load are negligible. Magnitude becomes 14 GW of avoided load by 2050. Managed charging reduces system peak and moderates system ramp. There will be additional ways to manage load by 2050.

The main interest of the study to us is developing effects for NC based on findings from other studies, as they have done for NY State.

Reduced grid operating costs and renewable energy curtailment with electric vehicle charge management, J. Szinai et al., *Energy Policy 136,* 111051, 2020
https://www.sciencedirect.com/science/article/pii/S030142151930638X

This study was performed based on data from California and focuses on the net benefit for California of managed charging (passive and active) for plug-in electric vehicles while considering renewable energy. The study analyzed scenarios with no PEVs, unmanaged charging, direct managed charging, and time-of-use (TOU) charging scenarios for different EV penetration rates.In “smart” charging, PEVs participate in a DR program and aggregators remotely control active charging to times that provide the most grid benefit when prices are low and/or renewable energy is abundant, bidding the total flexible load of many EVs into the wholesale electricity market.

The study used an advanced PLEXOS energy model to represent the grid impacts and an agent-based mobility model (BEAM) for electric vehicle charging behavior. The data was based on 2016 ChargePoint charging data and the mobility model was based on the city of San Francisco and extended to the entire state of California. The results showed that direct managed charging and time-of-use rates were similar in providing grid operating cost savings (up to 10%) compared to unmanaged charging; however, direct managed charging was better for preventing the curtailment of renewable energy. It is noted that the focus is on operating costs with infrastructure held constant, so the grid operating costs do not include capital costs such as distribution upgrades, which they state are a small part of CA’s utility costs. The conclusion of the study was to combine direct managed charging and TOU rates with added daytime periods that coincide with solar or renewable generation. The study also highlighted that smart charging targeted at residential customers appears to be the biggest opportunity.

For each PEV scenario, PLEXOS is run deterministically for one month and then optimized daily. It co-optimizes for energy and reserves to achieve a minimum cost result. PEV load is added to fixed non-PEV load for each scenario. While this study cen help us model Phase 2 of our study, we would need to adapt it to capture distribution costs. However, the BEAM agent-based model for residential behavior might be more immediately useful. Appendix C details the PLEXOS model and Appendix D provides supplementary data.

Valogianni, K., Ketter, W., Collins, J., & Zhdanov, D. (2020). **"Sustainable electric vehicle charging using adaptive pricing. Production and Operations Management**", 29(6), 1550-1572. Production and Operations Management Society

This paper proposed a pricing method called adaptive pricing, which learns the average valuation function of an EV population from its reaction to non-optimized prices. Adaptive pricing is a fixed price method that adjusts the price at certain times to incentivize consumers to meet a desired demand. This paper discovers individual consumers' latent pricing and valuation patterns through utility and valuation functions, then leverages those patterns to create a desired demand profile. Adaptive pricing is named after its ability to adapt to idiosyncratic preferences of EV owners over prices and charging parameters.

All data sets are Dutch, which include: the driving profiles of EV owners, pricing benchmarks, and EV specifications by EV type. For the driving profile, real-world data distributions from the Dutch Bureau of Statistics are used to determine times of arrival and departure, number of trips during the day, and average distance per trip. Power Trading Agent Competition software is used to create large-scale smart grid simulations and compare different price schemes. These simulations graph EV charging convergence to both flat and volatile demand profiles using adaptive pricing, flat rate pricing, TOU pricing, and optimal charging. In these simulations, adaptive pricing outperforms common price schemes and comes close to theoretically optimal results.

In summary, adaptive pricing outperforms traditional pricing benchmarks, mitigates herding and peak demand, reduces needs for grid expansion, induces EV charging demand that can follow a flat or volatile generation pattern, and yields robust results in populations where EV owners have individual preferences that are unknown.

Aswani, D., Boyce, B., & Yomogida, D. (2018, June). **Estimated Value of Smart/Managed Charging of Electric Vehicles for a Vertically Integrated Utility.** In *2018 IEEE Transportation Electrification Conference and Expo (ITEC)* (pp. 525-530). IEEE.

The purpose of this study was to assess managed charging scenarios for the Sacramento Municipal Utility District (SMUD) to scale implementation for its 2020 and 2030 forecasts. They determined key factors that influence the value of managed charging: energy cost structure, power directionality, and hardware configuration, to help bound justified investment costs. SMUD is a vertically integrated utility, meaning it provides its own generation assets and has influence over pricing. The authors used production cost modeling in PLEXOS to estimate hourly marginal costs for a 50% Renewable Portfolio Standard. Only unidirectional charging was assumed in this study (no vehicle to grid). Further, three vehicle types are assumed: a PHEV-30, BEV-70, and BEV-200 (with the numbers referring to mile range). SMUD found that most of its population uses BEV-70s with a close runner-up of PHEV-30. Only 13% of people had BEV-200s during this time.
The study used an optimization model that takes the statistical expectation of charging behavior. The model optimizes against energy costs over a 1-year period and takes into account generation costs, energy market prices, and load capacity costs. They found that optimized managed charging across an entire year results in a net value that is about 15-20% the average retail cost of electricity used to charge the EVs. The vehicles tested needed at least 3 hours of level 2 charge to charge 99.5% of the car.
This means that for high charge-rate vehicles, the cost savings can be substantial. However, high charging rate vehicles drive up local capacity costs which may offset some of the potential savings for the utility.
This study should be useful to both the economic and engineering sides of our study. Its methodology could conceivably be transferable to North Carolina with only limited NC data. It also shows relationships between individual and aggregate data which can help inform the NC study. Two additional notes, PLEXOS software may be publicly available by request through California (Also, See Szinai, who used PLEXOS in their CA study.). Finally, I met the lead author at the PLMA conference, should we need additional details.

Powell, S., Cezar, G.V., Min, L. et al. **Charging infrastructure access and operation to reduce the grid impacts of deep electric vehicle adoption**. *Nat Energy* **7**, 932–945 (2022).
https://doi.org/10.1038/s41560-022-01105-7

The article is aimed at the Western Interconnection and uses CA data. *It illuminates some of the considerations we have set aside.* It recommends daytime charging for systems that have solar power during the afternoon. The desirability of nighttime charging depends on whether the utility uses wind energy.
Factors that should be considered that are beyond the scope of our analysis are workplace charging, if the utility has afternoon solar, residential use in apartments and other multi-occupant users, not relying on extrapolation of early EV adopters, income levels of adopters, battery storage.
The study includes 27 charging scenarios. There are details on methodology as well as data availability. While individual customer data is confidential, they discuss and make available sample data that can achieve the same goals as individual customer data:

Powell, Siobhan; Cezar, Gustavo Vianna; Min, Liang; Azevedo, Ines; Rajagopal, Ram (2022), "SPEECh Model for Study on Grid Impacts of Charging Infrastructure Access", Mendeley Data, V2, doi: 10.17632/y872vhtfrc.2

Wong, S. D., Shaheen, S. A., Martin, E., & Uyeki, R. (2023). **Do incentives make a difference? Understanding smart charging program adoption for electric vehicles.** *Transportation Research Part C: Emerging Technologies*, *151*, 104123.

Smart charging programs and V2G initiatives for electric vehicles are integral to managing electricity demand and stabilizing the grid. The survey uncovered a significant interest in smart charging programs among both groups, even in the absence of incentives. However, there was a limit to this participation, suggesting that incentives play a role in encouraging broader adoption. The research methodology involved distributing a survey to 785 individuals with varying levels of EV experience in October 2018. The data collection process aimed to capture preferences in markets with potential for EV sales growth beyond California and New York. The methodology combined descriptive statistics and discrete choice analysis to understand the factors influencing individuals' decisions to participate in smart charging incentive programs, focusing on attributes like monetary incentives, penalties, free equipment, and guaranteed minimum charges. Factors like age, gender, ethnicity, household characteristics, and regional differences played significant roles in shaping willingness to participate in smart charging programs, with younger individuals being more likely to participate and females less inclined. Surprisingly, individuals with tiered electricity plans were less willing to participate, and the Southeastern U.S. region exhibited lower participation among EV-interested buyers/lessees.

One key challenge is whether revenue opportunities can offset the costs of incentivizing vehicle owners to join smart charging programs effectively and efficiently. In Canada, only 31% of EV owners reported enrolling in smart charging programs, highlighting the need for incentives. Compensation from grid operators or third parties creates an economic structure that encourages participation and revenue generation. In North America, various smart charging programs and pilots have been introduced to encourage participation. Initiatives from companies like Con Edison, San Diego Gas and Electric, and Southern California Edison offer incentives such as monthly earnings, reduced electricity rates during off-peak hours, and assistance in obtaining charging infrastructure. The potential of V2G technology to handle changes in electricity demand and supply is gaining traction. Some research suggests that a "set and forget" strategy may be more effective in engaging consumers in smart metering schemes.

In conclusion, this study highlights the importance of incentives and program attributes in encouraging participation in smart charging programs for EVs. Behavioral insights are crucial to enhancing these programs and increasing sign-up rates. While monetary incentives play a crucial role, the varying preferences and characteristics of different groups emphasize the need for a nuanced approach. A mix of incentives and a deeper understanding of consumer behavior are essential to maximize participation and unlock the potential of smart charging programs in managing electricity demand and stabilizing the grid.

1d. Studies with specific methodologies of innovative rate effects on EV charging that require utility-specific data.

Josh Bode, Andrea Hylant, Michael Jehl, SDG&E Team, Leslie Willoughby, Lizzette Garcia-Rodriguez, Erich Kevari, Jordi Lopez, **2021 Load Impact Evaluation of San Diego Gas and Electric's Electric Vehicles Time-of-Use (TOU) Rates: Final Report** CAMAC ID: SDG0337, Demand Side Analytics, LLC, April 1, 2022

This report summarizes two key programs implemented by San Diego Gas and Electric (SDG&E): the EV-TOU Rates and the Pilot Power Your Drive (PYD) Program. These programs aim to promote electric vehicle (EV) adoption, reduce greenhouse gas emissions, and encourage charging during off-peak grid hours. Our interest lies within the EV-TOU program. SDG&E offers two EV-TOU rates: EV-TOU2 and EV-TOU5, designed to incentivize customers to reduce their demand during peak hours, with significant load reductions on the top 5 load days. The interests of this study lie in assessing demand reductions, examining the influence of pricing and weather on demand response, and understanding customer types while emphasizing the importance of these programs for EV adoption, integration, and load reduction.

The objective of this article is to determine the changes in energy consumption, which involves estimating demand reductions and determining the reference loads. Key components of the methodology include effect or signal size, inherent data volatility or background noise, ability to filter out noise, and sample/population size. For EV-TOU rates, the authors used a difference-in-differences modeling approach, which requires a control group, a treatment group, and a full year of pre-treatment and post-treatment data. Challenges in determining a control group are addressed with propensity models based on AMI data, which determines the probability of EV ownership. EV adoption, solar, and batteries are also considered in the study to mitigate confounding effects.

The authors use an Ex-Post and Ex-Ante evaluation approach. The ex-post evaluation assesses the actual program impacts and relies on the control group of EV owners who are not on a TOU rate using panel regression DiD models with fixed customer effects, daily time effects, and weather variables used to isolate load impacts. Similar days are compared and results are segmented by region, solar status, income, and rates. The ex-ante approach quantitatively determines the relationship between demand reductions, hour, temperature, and dispatch strategy. This is used primarily for forecasting impacts under different weather conditions. Overall, the methodology ensures rigorous evaluation of the programs' impacts while considering variables that could be influencing consumption patterns. Overall, this study focuses on the relationship between demand reductions and weather and shows how weather factors can impact the availability and magnitude of resources for demand reduction strategies. The results suggest that customers on TOU rates achieved significant demand reductions during the top 5 highest system load days, aligning with grid needs and cost savings. The relationship between demand reductions and weather was noted, with larger reductions during hotter months. Solar status and geographic region also impacted demand reduction. Overall, the EV TOU rate programs were successful in encouraging peak demand reduction. Lastly, the article provides key recommendations moving forward, including to evaluate first year impacts for all sites, exclude sites where EV adoption and rate enrollment occur simultaneously, incorporate DMV registration data, track the historical first-year savings by cohort, and offer telematics to customers on TOU plans.

1e. Appendix

Notes for EV Literature Appendix

Cappers, P., & Satchwell, A. (2023). **EV Retail Rate Design 101.** *Lawrence Berkeley National Laboratory*. Retrieved from https://escholarship.org/uc/item/99f5x0sj

The article serves as a primer on EV retail rates. The rates chosen depend on the electric utility's objectives, and the utility should also be aware that rates that achieve one objective may have secondary effects on other objectives.

Of the five stated objectives—EV adoption, grid management, system economic efficiency, decarbonization, and equity—grid management most closely aligns with the objective of our project, and so we limit our review to that objective. Grid management focuses on the distribution system and/or the bulk-supply system. While system economic efficiency could be relevant, it focuses on long-run system marginal costs, which are more closely related to generation capacity, while our study primarily addresses impacts on the distribution system.

Within each objective, there are five aspects: metering considerations, temporal differentiation, locational differentiation, demand charges, and charging controls. For grid management, there needs to be submetering or a second account meter (our study is limited to submetering), TOU, CPP/CPR, VPP, RTP (based on margi al operating conditions on the distribution grid), locational differentiation of rates on the distribution system (such rates on the bulk supply system go beyond our study, demand charges based on distribution system conditions (which are within the purview of our study, given limited experience with residential demand charges), and two-way communications, where in our study we primarily consider indirect managed charging, where there are incentives to charge the EV to optimize use of the electricity grid, but the customer retains control over when to charge, with limited consideration of direct managed charging, where the utility controls charging time, although it may allow a limited number of opt-outs should the customer be willing to pay to charge during high-priced hours.

Cappers, P, Satchwell, A., Brooks, C., and Kozel, S., **Snapshot of EV-Specific Rate Designs Among U.S. Investor-Owned Electric Utilities**, *Lawrence Berkeley National Laboratory*, April 2023. https://eta-publications.lbl.gov/sites/default/files/ev_rate_snapshot_report-final-20230424.pdf

The report contains a database of piloted, proposed, and offered rates among US IOUs between 20212 and 2022 that cover 217 rates across 37 states and the District of Columbia. Of 136 active or offered rates, 54 were residential. Almost all were TOU. The dominant design had dedicated EV metering with the remainder whole-house (the case for our study). One-third had seasonal differentiation. Some rates contained a super-off-peak period in addition to peak and off-peak periods. Only two had demand charges using a non-coincident design.

There were 13 residential pilots, which included TOU rates of varying ratios. A few were focused on testing customer acceptance and measuring charging load in response to differing volumetric charges. Note that pilots do not usually lead to rollouts.

Of the 54 residential rates, they were evenly split between EV-specific and whole house chargers. The majority used TOU, some with season differentiation. There may be rising interest in RTP. Locational charges could vary by location on the subtransmission grid (e.g. 34-69 kV) or congestion of local distribution lines (e.g. below 34.5 kV). Bulk supply (> 69 kV) were not considered. One pilot (SDG&E Power Your Drive) had locational differentiation. There was little use of demand charges, and direct managed charging was not considered in the study, nor were any cases found of direct utility control of EV charging times.

Indirect managed charging incentives included direct payment or bill credit for participation, or a lower rate in exchange for the right of the utility to limit electric vehicle service equipment (EVSE) output (kW or kWh) in periods of high grid demand and/or high substation utilization. Nevertheless, a number of pilots allowed customers to opt out of restricting their charging during high use periods.

Spencer Aeschliman, Yan Zhou, Charles Macal, Zhi Zhou **Agent-based modeling of electric vehicles with time-of-use electricity rates**, 33rd Electric Vehicle Symposium (EVS33), Portland Oregon, June 14-17, 2020. https://na-admin.eventscloud.com/eselectv3/v3/events/474828/submission/files/download?fileID=96ac5f3502202038b54af80af5b5b81a-MjAyMC0wOCM1ZjI0NDAyODAyY2E1

This study looks at how time-of-use pricing schemes affect battery-electric vehicle (BEV) drivers in the Chicago area using an agent-based model. The behavior of key stakeholders, including BEV drivers, households, utility companies, and infrastructure investors, is captured by the ATEAM model. The study highlights how TOU rates have the ability to influence demand for public charging, which could result in higher usage and altered charging habits.

The purpose of the simulation is to investigate situations in which BEV drivers develop a behavioral heuristic that determines how they should charge their vehicles in response to changes in TOU pricing. The purpose of the study is to comprehend how charging station utilization, unmet demand for charging, and the requirement for additional infrastructure related to charging will be affected by TOU pricing. Changing the minimal utility value (P) necessary for a driver to decide to charge when above their comfortable state-of-charge (SOC) threshold characterizes the TOU situations. Over a ten-year period, the study runs thirty simulations for each of the four scenarios (base and three TOU scenarios). The analysis also takes into account how TOU rates affect the length of charging sessions, demonstrating that proactive charging reduces the amount of charging that occurs in each session under TOU circumstances. This is explained by the fact that BEV users maintain higher average battery states of charge and require less time to charge their batteries.

Results indicate that lower P values lead to more proactive charging behavior, reducing instances of unmet charging demand as more drivers achieve the minimum charging utility. However, this proactive behavior results in significantly higher utilization of existing charging stations, potentially leading to congestion issues. The study highlights the need for increased investment in charging infrastructure to accommodate the higher demand associated with TOU-adjusted behavior.

USDrive, Grid Integration Tech Team and Integrated Systems Analysis Tech Team, **Summary Report on EVs at Scale and the U.S. Electric Power System**, November 2019.
https://www.energy.gov/eere/vehicles/articles/summary-report-evs-scale-and-us-electric-power-system-2019

This report assesses the capability of the U.S. electric power system to accommodate the increasing adoption of light-duty electric vehicles (EVs), focusing on both energy generation and generation capacity. The historical context provided in the report highlights that the U.S. power grid has seen periods of significant expansion in energy generation, which is equal to the annual addition of up to 25 million new light-duty EVs. The research highlights the 1970s and 1990s as noteworthy growth eras, attributed to increases in base-load output from both nuclear and fossil fuel sources. However, it acknowledges that recent years have seen flat energy generation growth, and the emergence of a rapidly growing EV market could reverse this trend.

Based on past growth rates, the analysis projects that the U.S. electric power system can accommodate the expanding EV fleet. It highlights that adequate energy generation and generation capacity are anticipated to be available even with strong EV market growth. The analysis also acknowledges the significance of non-technical elements that may have changed over time and may have an impact on capacity development and future energy generation, such as policy, regulatory frameworks, and economic restrictions. The need for controlled charging is emphasized in the paper, which uses smart communication technologies to schedule EV charging throughout the day. In order to minimize peak demand and maximize the integration of electric vehicles (EVs) with intermittent renewable resources, managed charging is seen to be essential.

Unmanaged charging scenarios, which are regarded as worst case, may necessitate a sizable amount of dispatch-able generating capacity, which is equal to the aggregate demand of millions of new EVs. The study also takes into account how EV charging affects the grid, emphasizing how crucial it is to comprehend the whole amount of charging demand depending on variables like travel patterns, infrastructure accessibility, and vehicle design. The report suggests that managed charging can offer benefits such as lowered charging costs, improved grid asset utilization, and deferred infrastructure costs. The paper emphasizes the necessity for ongoing planning and research to ensure a smooth integration of EVs into the changing electric grid, while acknowledging problems at both the bulk and distribution levels.

J. Burger, J. Hildermeier, A. Jahn and J. Rosenow, **The time is now: smart charging of electric vehicles**, April 2022. https://www.raponline.org/knowledge-center/time-is-now-smart-charging-electric-vehicles/

The importance of smart charging and electric vehicles (EVs) in achieving zero-emission energy and transportation is emphasized in this research. The recommendations place a strong emphasis on stacking numerous services for full benefits, making smart charging the default, ensuring local grids are "smart charging ready," encouraging educated consumer choices, expanding benefits to all EV users, and improving flexibility rewards.

Chapter 1 emphasizes the concept of smart charging for electric vehicles (EVs), optimizing costs, integrating renewable energy, and minimizing grid impact. Time-varying tariffs are used in smart charging to lower customer electricity costs and maintain system stability. Thanks to technology, EVs may be charged to their ideal level for comfort and range thanks to user-friendly automation. In addition to convenience and cost advantages, smart charging provides home power backup.

Chapter 2 explores smart charging tariffs, retail electricity prices that fluctuate throughout the day, encouraging consumers to shift consumption to low-cost periods. Real-time pricing fluctuates more frequently than static TOU pricing, which is more straightforward. Peak pricing, both critical and variable, seeks to dissuade consumption during certain hours. Automated smart charging services balance reward potential and risk by optimizing charging based on time-varying pricing and short-term signals. Automation depends on having unrestricted access to vehicle data in order to provide effective billing that is in line with user preferences.

Chapter 3 of the report offers a thorough summary of Europe's smart charging policies and services for EVs. With an emphasis on the adaptability required to modify EV charging demand in response to fluctuations in energy prices, the report examines 139 tariffs and services. The analysis finds regional differences: Norway, a significant EV market, has 16 tariffs, while the UK leads with 30. In order to promote flexibility, the research highlights how smart charging is compatible with generic dynamic pricing. It looks at real-time balancing, dynamic time-of-use pricing, the function of smart meters, and the effects of EU power market reforms.

Chapter 4 outlines key strategies for accelerating smart charging adoption in Europe. The research makes three recommendations: encouraging stakeholder collaboration, improving user awareness, and requiring smart charging capabilities in all public charging outlets. Policymakers are advised to improve market design, remove barriers to flexibility participation, encourage grid digitalization, and reform network tariffs.

T. Lipman, A. Harrington and A. Langton, **Total Charge Management of Electric Vehicles**, *California Energy Commission*, December 2021

ChargeForward 2.0 focused on the integration of EVs into the electric grid to support California's 2045 goal of full decarbonization. Project partners included BMW North America LLC, Pacific Gas and Electric Company (PG&E), the University of California, Berkeley’s Transportation Sustainability Research Center (TSRC), Olivine Inc., and Kevala Analytics Inc. Managed charging of EVs was explored as a means to balance energy demand, manage intermittent renewables, save costs, and reduce greenhouse gas emissions. The study involved 300 EV-driving households in the San Francisco Bay Area from 2017 to 2019. Various use cases were examined, including avoiding home charging during peak hours, shifting charging times and locations, and increasing charging during high renewable energy production. Results showed the ability to shift up to 20% of charging in any given hour and add up to 30% of charging in a specific hour. Optimization modeling demonstrated potential savings of $56 per vehicle per year in reduced grid electricity costs and an increase of 1,200 kilowatt-hours per vehicle per year in renewable energy use. Moreover, managed charging demonstrated the potential to reduce approximately 300 kilograms of greenhouse gas emissions per year per vehicle.

L. Lopez, K. Sademori and A. Majoe, IEA (2022), **Grid Integration of Electric Vehicles: A Manual for Policy Makers**, *OECD Publishing*, Paris. https://iea.blob.core.windows.net/assets/21fe1dcb-c7ca-4e32-91d4-928715c9d14b/GridIntegrationofElectricVehicles.pdf

This summary refers to Chapter 2: Assess the power system impact, and possibly Chapter 3: Deploy measures for grid integration. There are also some comments related to Chapter 1 on preparing for EVs and Ch 4 is on Improve Planning Practices.

Chapter 2 begins with the need to gather data, such as a travel survey of typical vehicle use, daily travel and parking preferences, coupled with EV registration surveys, digital data such as GPS readings (one finding was that no more than 12% of the vehicles were in motion at the same time), analysis of charging patterns, and telematics (and data protection regulations). To enhance the value of the data, maintain open access to the data and run pilot studies.

Our interest is in home charging, which presents overloading challenges for high levels of EV penetration and high simultaneity of use. Create scenarios, with varying shares of EVs, range, shift to fast charging, etc.

One innovative rate that may go beyond our study is to encourage charging for solar households during times of solar energy self-consumption, thus avoiding use of the grid. And we should not forget direct managed charging despite its limited use to date, such as Eversource offers in Connecticut. They note that customers with telematics may need additional equipment for direct managed charging, and so they offer a subsidy towards that cost.

The article provides a four-phase framework for grid integration of EVs: no noticeable impact, flexible EV load noticeable with low flexibility demand, flexible EV load significant with high flexibility demand, flexible EV load is highly available with high flexibility demand. Our study pertains to Phase 2, where simple flexibility measures such as time-differentiated rates suffice; self-consumption policies for solar households are another option.

Planning includes host capacity maps. Bass diffusion models are useful for top-down planning but might miss localized distribution overloads. Bottom-up approaches such as agent-based modeling get at the individual customer level, but are computationally intensive. Probabilistic models of system planning make sense given uncertainties about EV penetration and system impact. Regulatory reform, such as reform of rate-of-return regulation that inefficiently encourages energy sales and capacity expansion, is needed to provide the proper incentives for EV managed charging. There should also be greater coordination of transmission and distribution.

Part II

Part II of the literature review contains papers that focus on assessing the impact of different EV charging scenarios on a distribution system. Section 'a' contains papers that reviewed literature on this topic. Section 'b' reports on real-world case studies. Section 'c' contains model-based system impact studies. Section 'd' reports on literature related to customer behavior modeling. Section 'e' is an appendix containing additional papers focusing on EV impact and direct management schemes.

Our review has focused on papers that evaluated the use of Time-of-Use rates or other similar rate incentives for managing residential EV charging impact on distribution systems. A short summary based on some of these papers is given below first. Summaries for all the relevant papers are given after the short summary.

A study by PNNL [Kintner-Meyer] investigated a simple time-of-use rate with off-peak hours between 10pm and 6am and assumed randomized EV charging start times during the off-peak hours. This study evaluated customer transformer loading, conductor loading, and bus voltages and found that this time-of-use method was effective in significantly delaying the required upgrades for the distribution system under study. Another paper [Dias] assessed the impact of controlled and uncontrolled charging on a residential distribution grid and considered two scenarios: (1) a base scenario in which the time of arrival to home coincides with the EV's charge start time and (2) a simple time-of-use rate with the off-peak hours between midnight and 6am but with randomized charge start times. The results show that this method of controlled charging can reduce the peak feeder demand to close to the peak with no EV load and keep the voltages within the ANSI limits. A study at San Diego [Kim] includes a special type of super off-peak rates for EV owners. Residential customers under a special Electric Vehicle (EV) ToU rate were found to generate a secondary peak in energy consumption around midnight. The notes highlight the importance of appropriately designing ToU rates for EVs, as an incorrect design may result in the emergence of a new energy peak and unintended consequences. A study by Hydro-Quebec and Concordia University [Antoun] analyzed the impact of level 2 EV chargers on residential distribution grids using three pricing schemes: (1) static pricing, (2) time-of-use, and (3) time-of-peak. The time-of-use rate considered includes on-peak during the day and off-peak during nighttime and morning, while the time-of-peak rate includes a threshold for each customer and if exceeded, increases the pricing rate for that customer. This study only evaluated the bus voltages and it found that time-of-use and time-of-peak pricing will help alleviate voltage drop caused by EV charging by approximately 2%, which is significant for system voltages, but it still was not enough to bring the voltage above the minimum threshold. A study by DoE, INL and UC Berkeley [Biviji] includes different types of ToU rates from PGE and PG&E. Both of these utilities have on-peak, mid-peak and off-peak hour rates. PG&E has special EV rates. Resultant load profile reflects the impact of rates as most people start charging during off-peak hours, shifting most of the EV loads to off-peak hours. A study at western Kentucky [Roy] finds different impacts of EVs on grid-like distribution transformer overloading, voltage deviation, line loading and hosting capacity into account. It provides some suggestions about transformer sizing to prevent future overloadings.

These papers and others are summarized in the following sections.

2a. Review Papers

Panossian, Nadia, Muratori, Matteo, Palmintier, Bryan, Meintz, Andrew, Lipman, Timothy, and Moffat, Keith. **Challenges and Opportunities of Integrating Electric Vehicles in Electricity Distribution Systems.** N. p., 2022. Web. doi:10.1007/s40518-022-00201-2.

This paper from NREL reviews the potential impacts of EV charging on electric distribution systems and describes methods from literature to efficiently integrate EVs into distribution systems. In regard to the future grid impacts of EV adoption, this paper states that the EV adoption for the next decade will not have major impacts on the bulk electric power system but instead early adopters will live in the same neighborhoods and therefore, there may be EV clustering in regions that cause localized issues to the distribution systems. Furthermore, longer-term impacts will affect both transmission and distribution systems in the coming decades.

In section 1, it states that the focus of existing studies has been on bulk power systems and not distribution systems. Additionally, these studies have concentrated on smaller batteries, lower charging power, and have not considered DERs. There is a need for more comprehensive studies over a wide range of different voltage classes and infrastructure. Section 1.1 discusses hosting capacity studies and the lack of real feeders being used for these studies due to confidentiality. It states that hosting capacity will likely be determined by distribution system constraints rather than system generation. Furthermore, with uncoordinated charging, there would be overloads in the evening when customers return home and plug-in their vehicles, which is exacerbated by the drop in local solar generation. Section 1.2 states that it is critical to prevent the overloading of lines and transformers for reasons of fire safety and accelerated aging, and additionally, overnight charging may prevent the nighttime cooling of transformers leading to shortened lifespans. Section 1.3 discusses power quality and voltage deviation and it is particularly concerned with rapid load changes caused by level 2 residential EV chargers. Section 1.4 and 1.5 review simulation studies and small-scale demonstration projects and discusses the different methods to assess EV impacts and distribution system interaction as well as the role of smart EV charging to prevent issues and even support the grid. Section 1.6 discusses EV load modeling and estimation and the use of transportation simulation models to determine EV load profiles and their flexibility.

In section 2, this paper discusses the possible solutions to mitigate EV charging impacts, including infrastructure upgrades, controlled charging, mark and market incentives and that a mixture of these solutions may be a good approach.

Anwar, Muhammad & Muratori, Matteo & Jadun, Paige & Hale, Elaine & Bush, Brian & Denholm, Paul & Ma, Ookie & Podkaminer, Kara. (2022). **Assessing the Value of Electric Vehicle Managed Charging: A Review of Methodologies and Results**. Energy & Environmental Science. 15. 10.1039/D1EE02206G.

This study focuses on operational challenges arising from EV charging at the distribution level, especially with high-power charging and concentrated EV loads in residential clusters and commercial vehicle depots. The primary objective is to evaluate managed charging methodologies and their effects on the grid, employing capacity expansion models, production cost models, and Monte Carlo simulations. It points out that the benefits of managed charging vary based on factors such as EV adoption, location, charging level, and the charging management scheme. The report highlights that 28% of DSs in the United Kingdom would require updates without managed EV charging. However, managing EV charging to flatten the load at the bulk power system level reduces this percentage to 19%. Furthermore, by extending load management to the DS level, this percentage can be further reduced to 9%.

2b. Case Studies

Lipman, Timothy, Alissa Harrington, and Adam Langton. 2021. **Total Charge Management of Electric Vehicles. California Energy Commission.** Publication Number: CEC-500-2021- 055.

This paper considers different cases ranging from avoiding electric vehicle home charging during peak evening hours, to shifting charging times and locations, to increasing charging during times of high renewable energy production, to more general goals of increasing the length of time that vehicles are plugged in, a key prerequisite for electric vehicle and grid interaction.

The average number of participants in this project between 2017 and 2020 was around 250 and 55 percent of those who started the process ended up participating.
Two types of metering are used: (1) metering local building loads to understand the effect of EV charge management on customer utility bills; and (2) metering the charging behavior of individual vehicles to assess the effect of load shifting for utility grid operations.
This project uses a vehicle telematics system that allows EV drivers to set desired levels of target state of charge and their departure times and remotely control charging around those times, critically needed to ensure that drivers have the needed vehicle driving range to meet their mobility needs. The vehicle telematics systems used in the project were designed to turn charging on or off in a binary fashion.
The location of this project was the San Francisco Bay Area with some participants in the Sacramento area.

The study employed Python language scripts to process extensive project data into meaningful analysis segments. Economic analysis algorithms and scripts were utilized to assess potential grid-level savings in electricity costs through charge management. Optimization modeling was further applied to explore economic possibilities from Vehicle-to-Grid Integration (VGI), aiming to overcome constraints imposed by current infrastructure availability. Additionally, the study leveraged grid-level analysis tools within the Olivine Inc. VGI valuation matrix capability.

The research demonstrated the effectiveness of utilizing vehicle telemetry for optimizing vehicles and implementing charge management both at home and away-from-home settings. Significant statistical correlations were observed, particularly in cases encouraging increased plug-in frequency, a crucial prerequisite for effective charge management. With support from PG&E, the study successfully identified periods of maximum benefit to the grid and demonstrated the ability to shift into those periods. Insights were gained into the incentives required to engage drivers, including an understanding of the upper bounds of engagement based on the highest incentives. The study also identified barriers and obstacles, such as data collection challenges and the importance of encouraging drivers to set optimized departure times, highlighting areas for improvement in future projects. Additionally, limitations related to charger availability for load shifting across days and locations were recognized, with a plan for improvement in the future with greater charger availability. The research emphasized the need for customer education about midday plugging and suggested the provision of higher levels of workplace charging infrastructure in the future.

A. Jenn and J. Highleyman, **"Distribution Grid Impacts of Electric Vehicles: A California Case Study,"** iScience, vol. 25, no. 1, Jan. 2022, Art. no. 103686.

This paper conducts a study of the potential impact of electric vehicle (EV) adoption on the distribution grid in California. To achieve this, the researchers utilize real-world data, including actual EV usage and charging patterns, to model the future loading on circuits in Northern California. The study's results indicate that the increasing adoption of EVs will place substantial stress on the distribution infrastructure, with a significant number of circuits requiring upgrades.

However, the paper also reveals a crucial finding: the planned upgrades alone will not be sufficient to accommodate the growing demand from EV charging. This highlights the necessity of considering EVs in the planning process for local distribution networks proactively. The researchers propose two potential solutions to address these challenges. Firstly, they suggest implementing managed charging events, which involve regulating and optimizing the timing and intensity of EV charging to avoid overloading the grid during peak periods. Secondly, the utilization of local solar generation is recommended as an alternative source of power for EV charging, which can alleviate the burden on the distribution grid and promote sustainable energy use.

Kim, Jae. (2019). **Insights into residential EV charging behavior using energy meter data.** Energy Policy. Vol-129. P-610-618. https://doi.org/10.1016/j.enpol.2019.02.049.

This study uses energy meter-level data from the San Diego region to analyze the energy load profiles of residential customers under the time-of-use (TOU) rate with and without EV charging requirements. Unlike previous forecasts on the effects of EV charging loads, the energy load profile of TOU customers with EVs reveal a "twin demand peak" where there is a peak demand during the evening hours and another at midnight. Results reveal potential issues for grid operations with greater EV adoption and the importance of careful TOU rate design. This study also includes super off-peak hours dedicated for EV charging.

In the key findings and results, it was observed that individuals exhibit varied responses to Time-of-Use (ToU) rates. Specifically, residential customers under a special Electric Vehicle (EV) ToU rate were found to generate a secondary peak in energy consumption around midnight. The notes highlight the importance of appropriately designing ToU rates for EVs, as an incorrect design may result in the emergence of a new energy peak and unintended consequences.

M. Biviji, C. Uçkun, G. Bassett, J. Wang and D. Ton, "**Patterns of Electric Vehicle Charging with Time of Use Rates: Case Studies in California and Portland**," ISGT 2014, Washington, DC, USA, 2014, pp. 1-5, doi: 10.1109/ISGT.2014.6816454.

This paper presents patterns of electricity consumption for charging electric vehicles when customers can select flat or time of use pricing. In 2009, ECOtality started the EV project with a grant from the U.S. Department of Energy, partnering with Nissan North America, General Motors, Idaho National Laboratory (INL), and others to deploy and collect charging data. Hourly average charging profiles under different pricing schemes for two different utilities (Portland General Electric [PGE] and Pacific Gas and Electric [PG&E]) for the year starting in July 2012 and ending in June 2013. Both of these utilities have on-peak, mid-peak and off-peak hour rates. PG&E has special EV rates. Resultant load profile reflects the impact of rates as most people start charging during off-peak hours, shifting most of the EV loads to off-peak hours. This paper also looks at the statistics for Peak versus Off-Peak Consumption. For residential customers, short-term own-price elasticity values generally range from –0.2 to –0.6, while short-term substitution elasticities range from 0.07 to 0.21.

P. Richardson, M. Moran, J. Taylor, A. Maitra and A. Keane, **"Impact of Electric Vehicle Charging on Residential Distribution Networks: An Irish Demonstration Initiative,"** 22nd International Conference and Exhibition on Electricity Distribution (CIRED 2013), Stockholm, 2013, pp. 1-4, doi: 10.1049/cp.2013.0873.:

This study is an EV field trial demonstration project with three stages. The first stage allowed existing EV customers to use and charge EVs as required and recorded their actions. The owner of the study supplied the EVs for people to use with 2.7 kW chargers. This is a small study on a low-voltage network with 8 customers (each with two cars for 3 months at a time) and a smart meter was used to track the overall demand of each customer's residence (all single-family households). Another meter was installed at the EV charger of the participant's household to record the EV charge demand. From this initial stage, EV charging profiles with EV arrival (connection) time were extracted and then probability distribution functions for the EV connection times and the daily EV energy requirements were recorded (included in the article). It found that the majority of EV charging connections occur after 4 pm each day with the highest probabilities of connection occurring at approximately 6.30 pm and again at 10.30 pm. Lastly, the study ran power flow simulations to determine the locations on the feeder where the EV charging profiles would have the greatest effect. Only the voltage profile was considered in the analysis and it was found that the minimum 10-minute voltage dipped to 0.89 pu at 7pm. Stage 2 will implement a self-learning platform that will take into account the daily usage needs of the driver and ensure there is enough charge plus contingency. This has two parts: (1) each EV customer acts independently and (2) there is a central controller. Stage 3 will consider network reconfiguration to increase the EV capacity of the network.

P. Roy et al., **"Impact of Electric Vehicle Charging on Power Distribution Systems: A Case Study of the Grid in Western Kentucky,"** in IEEE Access, vol. 11, pp. 49002-49023, 2023, doi: 10.1109/ACCESS.2023.3276928.

The research paper investigates the effects of electric vehicle (EV) charging on power distribution systems in Western Kentucky. The study aims to assess the potential overloading and degradation of power transformers due to intensive EV charging and provide projections and analysis of EV charging on power distribution systems in the city of Murray, KY.
The researchers in this paper utilized two software tools for their analysis: DRIVE and HotSpotter.
DRIVE (Distribution Resource Integration and Value Estimation) and HotSpotter are software tools used to assess the impact of EV charging on power distribution systems. DRIVE helps determine hosting capacity and potential issues like undervoltage and thermal overloading. HotSpotter analyzes the impact on distribution transformers, identifying vulnerable ones and managing EV charging for grid reliability.
Analysis of Factors: The study analyzes various factors, such as EV charger power ratings, the percentage of EVs in a given area, and the probability of customers charging their EVs based on driving distance and home arrival time.

The key findings and results of the study encompass several aspects. Firstly, the research incorporates predictions of Electric Vehicle (EV) adoption and projections of annual energy consumption to assess the potential impact of EV charging on the power distribution network. The overall analysis indicates that existing circuits can accommodate the anticipated EV demand across various scenarios and charging strategies, though the researchers identify potential issues associated with peak EV demand in specific situations. Additionally, the paper delves into thermal constraints and hosting capacity analysis of the circuits, shedding light on their limitations and potential challenges related to EV charging. Furthermore, the study investigates the impact of EV charging on the reliability of distribution transformers, offering recommendations for proper transformer sizing to prevent overloads and ensure efficient performance.

2c. Model-Based Impact Studies

Comprehensive Methods

Kintner-Meyer, Michael C. W., Sridhar, Siddharth, Holland, Christine, Singhal, Ankit, Wolf, Katherine E., Larimer, Curtis J., McGrath, Casey R., Bleeker, Amelia A., and Murali, Rani E.. **Electric Vehicles at Scale - Phase II - Distribution Systems Analysis.** United States: N. p., 2022. Web. doi:10.2172/1882799.

This is phase two of a multi-part study by Pacific Northwest National Laboratory with phase one focusing on the impacts of EVs on generation and transmission and this phase focusing on the impacts to electric distribution systems. This study has two parts: (1) EV adoption model and methodology and (2) EV impact analysis. The EV adoption model assumes three groups of EVs (large battery, small battery, and PHEV) and that the EV adoption forecast is separated into these three groups. The household income for the area of interest and vehicle registration are inputted into a Bass Adoption Model, which basically assumes an “S” adoption curve over time with 100% adoption (2 vehicles per household) by 2050 (the last year of the study horizon). It uses this Bass model to create the EV penetration of the distribution feeder separated into per year and EV type group. This EV adoption penetration is then inputted by individual household income into a Logit model, which is a discrete choice model for a household either purchasing an EV or an ICE vehicle. This Logit model uses a cumulative logistic distribution function with a nested linear regression equation and uses vehicle prices, income (based on house value), and charging access as the independent variables. The model is fitted with existing data to determine the model coefficients. The results are that this Logit model probabilistically allocates EVs to individual households for each study iteration. This allocation is a locational placement of the EV loads on the distribution feeder and will change for each study iteration based on differing probabilistic outcomes.

Next, data from NHTS 2017 is used to create a probability distribution of home arrival, home departure, and daily travel miles of cars. These distributions along with the EV mileage efficiency (mi/kWh), charge rate (kW), and charge time (hours) are used to create EV profiles for the EVs allocated from the Logit model. These EV load profiles were then added to the existing base load of the test distribution feeder and a time-series power flow simulation was run over a three-month time span with hourly data.
The EV impact analysis takes a Monte-Carlo approach and runs 500 of these simulations (iterations) with varying EV placement distributions and EV load profiles (from arrival time, departure time, daily driving distance, and charge rate). Each scenario was evaluated for the base case charging (charging upon arrival) and smart-charging, which is based on a time-of-use charging behavior but it assumes that the charging is randomized between 10pm and 6am. Transformers and conductors were evaluated for voltage and thermal violations with a count of how many simulations that each asset had a violation. An assumed threshold for the number of simulations with violations was used to determine if the device actually had a violation.

The years 2020-2050 were analyzed for a real SCE feeder and it was determined that customer transformer thermal ratings were the most impacted with line overloads and voltage constraints only becoming a potential issue in the year 2040. The smart-charging method was successful at significantly reducing infrastructure upgrades and reducing cost requirements for the utility.

Papers Focusing on Time-of-Use Rates

B. Jones, C., et al. **"Impact of Electric Vehicle Customer Response to Time-of-Use Rates on Distribution Power Grids."** Energy Reports, vol. 8, Nov. 2022, pp. 8225–35. DOI.org (Crossref), https://doi.org/10.1016/j.egyr.2022.06.048.

This research paper provides an analysis of the impact of electric vehicle (EV) customer response to time-of-use (TOU) rates on distribution power grids. The study utilizes simulation models of 10 distribution feeders, considering predicted 2030 EV adoption levels, to assess the consequences of EV charging behavior under TOU pricing. Two types of ToU rate has been used here both has on-peak hours between 12 PM-6 PM. The authors estimate EV energy consumption based on travel patterns, EV types, and charging capabilities, including home-dominant and work-dominant charging scenarios using NREL's EVI-Pro tool. The study also examines the effects of EV charging on electric power systems, showing higher overall demand profiles for residential, commercial, and mixed systems. Charging locations and demands vary based on the scenario and electric power system type.
In this study, peak-shifting, line loading and under voltage conditions are considered as system impact. The research reveals that TOU rates have a significant influence on EV charging demands, with immediate responses to off-peak rates leading to increased demand after on-peak hours. The findings highlight that scheduling EV charging to begin immediately after on-peak times could result in a substantial up to 20% increase in peak demand on distribution power grids. Randomizing charging start times within the off-peak period reduces peak load by 5% compared to simulations without TOU rates. In all cases, line loading is below 100% except for one case where it reaches 120% of rated capacity. Also, voltages were within limit for all cases. Looking at the peak demand shifting and line loading, this underscores the importance of considering EV charging behavior and TOU rates in managing the impact of EVs on distribution power grids.

J. Antoun, M. E. Kabir, B. Moussa, R. Atallah and C. Assi, **"Impact Analysis of Level 2 EV Chargers on Residential Power Distribution Grids,"** 2020 IEEE 14th International Conference on Compatibility, Power Electronics and Power Engineering (CPE-POWERENG), Setubal, Portugal, 2020, pp. 523-529, doi: 10.1109/CPE-POWERENG48600.2020.9161463.

This is a study on the effect of Level 2 Chargers on a residential distribution system and uses the IEEE-33 radial distribution system, with its associated loads, and assumes that 10000 residences are uniformly distributed at the system buses. The paper uses a distribution of home arrival times (from work), which is based on a local survey (in Montreal), and the Poisson Arrival Process to model EV arrival, which are assumed to be the time that the EVs start charging in the base (static pricing) case. Each arrival is assigned a level 1 or level 2 charge rate based on the assumed penetration rate for each charge level. EV battery size and state-of-charge is selected using a normal distribution with the battery size being based on real existing EV battery specifications. The charging time (h) is calculated based on the state-of-charge, the battery size (kWh), and the charging rate/level (kW). The charging deadline (the charging stops no matter the state-of-charge) is also assigned based on the home departure times (to work), which is from the same survey as the home arrival times, and a Gaussian distribution system. EV load profiles are created based on the arrival time (assumed to be starting time for charging for static pricing case), charge level, and charge time using these probability distributions. This study built an EV charging event simulator that randomly assigns EV load profiles to customers based on the assumed penetration rate. This simulator estimates the EV load, which is added to each base customer load, and this simulator also solves the quasi-static power flow equations and finds the voltage at each bus (it does not analyze any device loading limitations but the loading could technically be calculated from these same equations). This study considers different charging level scenarios and different penetration rates.

The simulations were run with static pricing and dynamic pricing (ToU and ToP), it is assumed for dynamic pricing that 50% of users are half-eco (user will start charging at the off-peak time unless the EV needs more time to charge and then it will use the greedy approach), 25% are eco (the user starts charging during the off-peak time), and 25% are greedy (charging is immediately started upon arrival). The ToU rate considered includes on-peak during the day and off-peak during nighttime and morning. (actual hours are not specified but appear to start at 8pm). The ToP rate includes a threshold for each customer, in which if exceeded, increases the pricing rate for that customer. This study only evaluated the voltage (it notably did not evaluate thermal limitations) and it was found that TOU and ToP pricing will help alleviate voltage drop caused by EV charging by approximately 2%; however, this is still not enough to bring the voltages above the minimum threshold.

A. Dubey, S. Santoso, M. P. Cloud and M. Waclawiak, **"Determining Time-of-Use Schedules for Electric Vehicle Loads: A Practical Perspective,"** in IEEE Power and Energy Technology Systems Journal, vol. 2, no. 1, pp. 12-20, March 2015, doi: 10.1109/JPETS.2015.2405069.

The study evaluates various aspects of EV charging under a TOU schedule and identifies the most suitable time to initiate off-peak rates to minimize voltage quality impacts while ensuring EVs are fully charged by 7 AM. The paper also emphasizes the potential negative consequences of setting up TOU off-peak rates during the latter half of peak load demand. This could lead to a significant increase in peak load demand and voltage drops if all customers start charging their EVs immediately at the beginning of off-peak rates. To mitigate these effects, randomized charging is proposed as a solution.

The key findings and results of the analysis highlight that commencing off-peak rates between 11 PM and 12 AM is the most effective strategy for managing Electric Vehicle (EV) loads. Contrarily, initiating off-peak rates at 8 PM exacerbates the impact of EV charging on the distribution circuit. The study employs a method to determine the optimal starting time for off-peak rates within a time-of-use (TOU) schedule for EV loads, taking into account voltage quality impacts. This method proves effective in minimizing peak load demand and voltage drops, especially under worst-case charging scenarios where all EVs begin charging simultaneously. The practical application of this approach benefits both utilities and customers by optimizing grid usage and ensuring that EVs are fully charged by 7 AM.

F. G. Dias, M. Mohanpurkar, A. Medam, D. Scoffield and R. Hovsapian, **"Impact of Controlled and Uncontrolled Charging of Electrical Vehicles on a Residential Distribution Grid,"** 2018 IEEE International Conference on Probabilistic Methods Applied to Power Systems (PMAPS), Boise, ID, USA, 2018, pp. 1-5, doi: 10.1109/PMAPS.2018.8440511.

This study provides a method of EV controlled charging without high-level controls using random start times during the off-peak hours. This study uses real-world data, from 602 privately owned Nissan Leafs in the Seattle area during normal weekdays in 2012 and 2013, to create the EV load profiles. From this data, the charge energy, arrival time, and departure time were extracted and this was converted to gaussian kernel probability density functions and then randomly sampled to create many EV profiles, which are represented by "rectangle-based" profiles. It is noted that based on the real-world data EV owners could have different charging frequencies (every night or every other night) and that on average, individuals charge their EVs at home on 72.5% of evenings. The residential load profiles are based on profiles provided by PG&E (on their website) and are based on the average demand of 75,000 residences on a typical 100 MW distribution feeder.

This actual study used the IEEE-34 radial distribution standard and assumed 75,000 residences with a 50% EV penetration rate. Two scenarios were studied: (1) the EV's charge start time coincides with the time the EV arrived home and (2) the EV had a random start time between midnight and 6am. The results found that this method of controlled charging reduced the peak feeder demand to close to the peak with no EV load and kept the voltages within the ANSI limits.

Obeidat, M.A.; Almutairi, A.; Alyami, S.; Dahoud, R.; Mansour, A.M.; Aldaoudeyeh, A.-M.; Hrayshat, E.S. **Effect of Electric Vehicles Charging Loads on Realistic Residential Distribution System in Aqaba-Jordan**. World Electr. Veh. J. 2021, 12, 218. https://doi.org/10.3390/wevj12040218

This study uses Cyme to investigate the effect of EVs on a realistic distribution system in Jordan and also proposes a new methodology for managing EV loads by determining the critical hours that the EV demand will create violations shifting the EV loads to charge at alternative hours. First this study establishes the realistic load profiles for EVs by creating a probabilistic model. Transportation surveys (from 2000 random households in Jordan) are used to capture driver behavior (drive distance, arrival time,departure time, EV types, and place of charging) and these are used to create their respective probability density functions. Then a Monte-Carlo simulation, which uses these PDFs, is implemented to create a multitude of scenarios for EV charging loads.

Additionally, it is noted that charging at home at night was the preferred charging method and this was further supported by an additional survey to 500 respondents in Aqaba, Jordan, which showed that 95% of respondents preferred charging their EVs at home. Furthermore, data from real EVs were used (from US data), which included battery capacity, range, and efficiency (kWh/km). Charging levels were also varied with two charger levels: (1.44 and 7.2 kW) and it was assumed that two thirds of EV owners used a level 1 charger based on survey results.

This study created EV load profiles based on the factors of (1) energy required to charge the battery, (2) the duration of the charge, and (3) the time of the charge. These were based on the PDFs mentioned previously. In the first step, the daily travel distance is determined by generating a random number between 0 and 1 and then matching that number to the probabilities of the inverse daily distance to determine the daily traveled distance, which then is used to determine the period and amount of charging (based on the EV efficiency). In the second step, the energy consumption of the subsequent charge is determined using the estimated daily distance, the battery capacity, and the electric range, which ultimately provides the state-of-charge of each eV after arriving home. It is also discussed that the EVs have a realistic range of battery state-of-charge (20-80%) and that EVs with a 18.9 kWh battery or higher can meet 99% of daily travel needs according to data from the NHTS; conclusively, the probability that the daily travel mileage for an EV exceeding its electric range is extremely small. The third step calculates the charging duration time from the estimated energy consumption, charging efficiency (not EV efficiency) and charging level/rate. The fourth step establishes the start and end time for charging by considering the arrival and departure time PDFs and also assuming that the EV starts charging when it arrives at its home. It notes that if the required charging time is less than the "stay-time" (difference between arrival and departure time), then there is potential for the EV to start charging later than its arrival time.

This study also establishes a managed charging method that takes into consideration the critical hours that the EVs could cause violations and then shifts the EV charging to a later time based on the ability to become fully charged before the departure time. Ultimately the uncoordinated and managed charging scenarios are compared for a real distribution feeder. The results found that the uncoordinated charging had an effect on the loading and voltage profiles and that the managed charging can help reduce these effects. Additionally, when a single time was chosen for the starting hour for overnight charging, due to the massive load demand of EVs, a second peak was created at this time, which should be avoided.

L. Gan, X. Chen, K. Yu, J. Zheng and W. Du, **"A Probabilistic Evaluation Method of Household EVs Dispatching Potential Considering Users' Multiple Travel Needs,"** in IEEE Transactions on Industry Applications, vol. 56, no. 5, pp. 5858-5867, Sept.-Oct. 2020, doi: 10.1109/TIA.2020.2989690.

The paper introduces a probabilistic evaluation method for assessing the dispatching potential of household electric vehicles (EVs) while considering users' travel needs. It incorporates trip parameters, charging behavior, and time-of-use (TOU) pricing mechanisms to simulate EV charging load accurately and evaluate load shifting potential. The paper underscores the significance of multiple factors, such as plug-in rate and trip-parameter correlation, in simulating EV charging load. A case study highlights their influence on load shifting potential and indicates that TOU pricing optimizes electricity resource use.
The key findings and results of the study underscore a significant contribution through the optimization of trip parameter distribution utilizing a least squares estimation (LSE) approach. This method generates realistic random samples, enhancing the accuracy of simulating Electric Vehicle (EV) charging load. The incorporation of copula functions further refines the simulation's accuracy by modeling the joint distribution of trip start-time, end-time, and distance. By taking into account users' charging behavior and trip characteristics, the study achieves a more realistic evaluation of the maximum load shifting potential. The results highlight the method's effectiveness in assessing the impact of Time-of-Use (TOU) pricing on load shifting.

Lojowska, Alicja, et al. **"Stochastic Modeling of Power Demand Due to EVs Using Copula."** IEEE Transactions on Power Systems, vol. 27, no. 4, Nov. 2012, pp. 1960–68. DOI.org (Crossref), https://doi.org/10.1109/TPWRS.2012.2192139.

This paper provides an analysis of stochastic modeling techniques to predict electric vehicle (EV) power demand based on driving patterns. The authors derive probability distributions of variables like departure and arrival times and distance traveled from a transportation dataset and investigate their correlation through rank correlation analysis.To model the correlation between driving pattern variables, the authors propose an approach using copula functions, allowing the generation of synthetic datasets that capture uncertainty in EV driving patterns. Simulation results reveal that EV load varies throughout the day and is influenced by factors like arrival time and initial state of charge. Different scenarios, including uncontrolled domestic charging and range anxiety levels, are analyzed to understand their impact on EV load and integration into the power system.The cumulative effect of EV load on the power system is examined using a Monte Carlo simulation approach, considering different market penetration levels. The study explores the use of price incentives to encourage off-peak charging, effectively shifting the load to non-peak hours.

The results indicate that EVs contribute to increased total peak load, but price incentives can mitigate this impact by encouraging off-peak charging. The key contribution of this paper is the development of a stochastic modeling approach using copula functions to predict the power demand of electric vehicles (EVs) based on their driving patterns. This approach captures the correlation between driving pattern variables and provides insights into the impact of EV load on the power system.

I. U. Nutkani and J. C. Lee, **"Evaluation of Electric Vehicles (EVs) Impact on Electric Grid,"** 2022 International Power Electronics Conference (IPEC-Himeji 2022- ECCE Asia), Himeji, Japan, 2022, pp. 239-246, doi: 10.23919/IPEC-Himeji2022-ECCE53331.2022.9806958.

This research paper provides an evaluation of the impact of Electric Vehicles (EVs) on the electric grid, specifically focusing on urban and rural distribution networks. The methodology employed in this study involves data analysis, network modeling, and simulation studies, which provide insights into the impact of EVs on the grid. The simulation results demonstrate that the EV hosting capacity of the network is limited by factors such as network voltage and thermal capacity.

The key findings and results of the study highlight variations based on load level and Electric Vehicle (EV) penetration. Real EV charging profiles align with peak demand, while regulated charging profiles enable higher EV hosting capacity. The research identifies thermal capacity as the primary constraint for rural networks, whereas urban networks face limitations in both thermal capacity and voltage. Considering various scenarios, including actual and forecasted EV charging profiles and the integration of solar PV systems, the study concludes that thermal capacity is the primary limiting factor, followed by voltage constraints. The implementation of load shifting and regulated charging strategies emerges as a means to increase EV hosting capacity, although the extent of the increase is limited. Furthermore, the study indicates that solar PV alone has minimal direct impact on EV hosting capacity.

Z. Darabi and M. Ferdowsi, **"Aggregated Impact of Plug-in Hybrid Electric Vehicles on Electricity Demand Profile,"** in IEEE Transactions on Sustainable Energy, vol. 2, no. 4, pp. 501-508, Oct. 2011, doi: 10.1109/TSTE.2011.2158123.

This paper is concerned about the negative impacts of PHEV on power generation, transmission, and distribution installations. A large number of vehicle trips (around 40 000) is considered. This large pool of data is geographically distributed across the U.S (2001 NHTS Data). The required charging energy of each vehicle is precisely calculated based on the distance driven and vehicle type. The arrival time of each individual vehicle is taken into account. While generating the PHEV load profile, it considers PHEV of different range, state of charge (SoC) and charging levels.
This paper used data from 2001 NATIONAL HOUSEHOLD TRAVEL SURVEY (NHTS), some basic Mathematical Models, power scaling (or constant time) and time scaling (or constant power) approach to generate the charging profile of the EVs. Resultant load profiles for three types of PHEV (Range-20,30 and 40 miles) peak charging hours are around 20:30-22.00 o'clock.
In the end, they have proposed three types of charging strategies to reduce the impact of PHEV charging.

- Policy-1- Low Level charging during peak and high level during off-peak

- Policy-2- 2 hour shift
- Policy-3- Price based

Harmonic Impact

Bass, Robert, and Nicole Zimmerman. **Impacts of Electric Vehicle Charging on Electric Power Distribution Systems.** OTREC-SS-731. Portland, OR: Transportation Research and Education Center (TREC), 2013. http://dx.doi.org/10.15760/trec.145

This study looks at the impacts of power quality, particularly, harmonics, voltage deviation, and phase imbalance. In this study, the authors measured the PQ of EV chargers, paying specific attention to total harmonic distortion (THD) of individual EV chargers and total demand distortion (TDD). Phase imbalance, phantom loading and other PQ issues were also observed during the course of the study. These OQ meters were physically placed at an EV charging station for one week and the results found that the THD varies during the course of the charging cycle; specifically, at the tail end of the EV charging, the current decreases but the harmonics get worse. It also found that TDD was below the IEEE limit. Other power quality issues observed were phantom loading (consumption of power even when there was no EV connected), load imbalance (due to level 1 / 2 single phase charging this can be an issue and can cause excess neutral line current, voltage imbalance, which can affect three phase loads), and also a DC offset in the AC current.

2d. Customer Behavior Modeling

Z. Fotouhi, M. R. Hashemi, H. Narimani, and I. S. Bayram, **"A General Model for EV Drivers' Charging Behavior,"** IEEE Trans. Veh. Technol., vol. 68, no. 8, pp. 7368–7382, Aug. 2017.

This paper provides a review of a stochastic model designed to describe the charging behavior of electric vehicle (EV) drivers at charging stations. The model incorporates various behavioral characteristics, such as how drivers react to the EV battery charge level when deciding to charge or disconnect. The model utilizes a non-homogeneous Markov chain to represent the driver's charging behavior, with different states corresponding to different charge levels. Behavioral parameters, like range anxiety and driving habits, determine the transition probabilities between states. The paper mathematically analyzes the model to assess the impact of these parameters on the state probabilities.Real data from public charging stations in a university campus and an urban area in London are used to validate the model through a case study. A sensitivity analysis further shows that the model can effectively capture different behavioral patterns among EV drivers in different communities. The paper also discusses simulating a model for predicting and managing congestion at charging stations, taking into account behavioral parameters like charging time and connection time preferences. The simulations demonstrate that adjusting these parameters can effectively control and manage congestion, aiding capacity planning and optimizing charging station usage.Smart pricing methods are suggested to encourage behavior change during busy periods, and simulations validate that reducing certain behavioral parameters can decrease blocking probability in charging stations.
Key Findings and Results:

This paper proposes a stochastic model to describe the charging behavior of electric vehicle (EV) drivers. The model accurately captures the behavioral characteristics of EV drivers, such as their reaction to the battery charge level when deciding to charge or disconnect.

2e. Appendix

Additional Impact Studies

M. A. Awadallah, B. N. Singh and B. Venkatesh, **"Impact of EV Charger Load on Distribution Network Capacity: A Case Study in Toronto,"** in Canadian Journal of Electrical and Computer Engineering, vol. 39, no. 4, pp. 268-273, Fall 2016, doi: 10.1109/CJECE.2016.2545925.

This paper studies the effect of EV charging on two real customer distribution transformers and their downstream cable feeders, one with 19 hours and one with 16 hours, which are identified as being the most probable early adopters by a survey. This study uses steady-state power flow analysis in CYME and assumes varying EV penetration levels (5-100%) and charging rates (1.4, 1.9, 3.3, 6.6, 10, 16, and 20 kW). Each EV penetration level assumes that all of the EVs are charging during the steady-state scenario. Overloads were evaluated during low, medium, and peak loads (summer and winter) and it was determined that the level 2 chargers (higher power) caused overloads but the level 1 chargers did not. This paper also concluded that ambient temperature is an important factor in determining the distribution system's ability to serve EV load due to the decreased current carrying capacity and higher air-conditioning load during the summer season.

M. Spitzer, J. Schlund, E. Apostolaki-Iosifidou, and M. Pruckner, **''Optimized integration of electric vehicles in low voltage distribution grids,''** Energies, vol. 12, no. 21, p. 4059, Oct. 2019,

The paper analyzes the integration of EVs into low voltage distribution grids. It compares different charging strategies based on optimization objectives like cost reduction and greenhouse gas emissions reduction, considering the interests of consumers, operators, and aggregators.The study evaluates the effects of uncoordinated charging on voltage stability and phase unbalances and defines scenarios based on EV and PV penetration rates. It emphasizes the importance of coordinated charging strategies to minimize grid impacts and optimize energy costs and emissions. However, the paper acknowledges that each optimization strategy has trade-offs and calls for advanced algorithms to optimize EV charging schedules while considering grid constraints and renewable energy production. The paper discusses various optimization methods for EV charging, including centralized and decentralized approaches, and highlights the importance of considering grid constraints and renewable energy in the optimization process. The use of genetic algorithms and virtual community energy storages is also explored.
Key Findings and Results:
The cost-optimized strategy demonstrates significant benefits, reducing energy costs by 51.13% compared to uncoordinated charging and cutting greenhouse gas emissions in half.

Artificial Scenario Generator for the Impact Study of Electric Vehicle Charging on the Distribution Grid
Year: 2021
Author: University of Oviedo (Spain)
Citation:

Artificial Scenario Generator for the Impact Study of Electric Vehicle Charging on the Distribution Grid

This paper establishes an EV load simulation model that probabilistically characterizes the stochastic nature of EVs. Ultimately it generates the schedule of EVs charging to achieve the EV load profile for impact study of EVs on distribution network. This model is available through the IEEEDataPort (https://ieee-dataport.org/documents/artificial-scenario-generator-impact-study-electric-vehicle-charging-distribution-grid) and considers the inputs of battery capacity, charger level, state of charge, plug-in / out time, charging power rate, customer load profiles, and EV penetration levels. The outputs include EV probability density functions that include the EV battery capacity, initial SoC, charging rate (power/level), and plug-in / plug-out time (arrival / departure time and charge duration). From these probability density functions, individual EV load profiles can be generated.

M. S. H. Nizami, M. J. Hossain and K. Mahmud, **"A Coordinated Electric Vehicle Management System for Grid-Support Services in Residential Networks,"** in IEEE Systems Journal, vol. 15, no. 2, pp. 2066-2077, June 2021, doi: 10.1109/JSYST.2020.3006848.

Uncoordinated and clustered charging of residential EVs can often overload grid assets, jeopardize network reliability, and can often violate local voltage constraints. This paper proposes a coordinated management system for EVs in an LV residential network (A circuit from sydney, Australia) with power grid support functionalities to address gridover loading and local voltage constraints violation. The charging and discharging of EV batteries in the network are coordinated via a local EV aggregator.
It includes ToU rate and real time pricing (RTP) rate to analyze the impact. The EV travel data and availability are taken from the Australian ”Smart Grid Smart City” EV trial data. This paper shows that the proposed RTP based charging schedule reduces overloading cases during winter peak days. Also, reduces undervoltage scenarios. Electricity costs for individual houses are calculated, and the proposed method reduces costs in most cases compared to ToU rate.

J. Zhang, J. Jorgenson, T. Markel and K. Walkowicz, **"Value to the Grid From Managed Charging Based on California's High Renewables Study,"** in IEEE Transactions on Power Systems, vol. 34, no. 2, pp. 831-840, March 2019, doi: 10.1109/TPWRS.2018.2872905.

NREL's Low Carbon Grid Study (LCGS) aims to quantify the value of managed charging to the grid. Three levels of managed loads for 13 TWh of annual load from 3 million EVs in a 2030 California grid scenario are considered. Two types of grid conditions are assumed, one with high Solar, conventional grid flexibility, another with diverse generation portfolio, enhanced grid flexibility. 1kW charging rate at home, 2kW charging rate at workplace/public places are the base of its charging strategy. EV supply equipment (EVSE) deployments at workplaces and other mid-day parking locations will be needed to support the managed charging. EVSE cost must be between $1,000 and $3,000 for a 10-year life to be cost neutral.
It uses PLEXOS by Energy Exemplar software. PLEXOS uses mixed integer programming to determine the unit commitment decisions of all generating units, and uses linear programming to determine the least cost dispatch for all committed generators. The model is formulated as an optimization problem to minimize fuel cost, startup costs, variable operations and maintenance costs, and emissions costs.
This paper found that three million EVs with 50% managed charging could generate $90–$370 million in grid savings, reduce electricity cost around by 1%–4%, reduce peak demand by 1.5%, reduce renewable curtailment by 0.04%–4.3%, and reduce grid CO2 emissions by 1%–4%.

Q. Dang, **"Electric Vehicle (EV) Charging Management and Relieve Impacts in Grids,"** 2018 9th IEEE International Symposium on Power Electronics for Distributed Generation Systems (PEDG), Charlotte, NC, USA, 2018, pp. 1-5, doi: 10.1109/PEDG.2018.8447802.

This paper proposed a method to manage electric vehicles charging behaviors in order to reduce its effects in grids.The paper summarized the charging patterns of electric vehicle users, based on charging profile observations from advanced metering systems. It simulates IEEE-33 bus before and after implementation of the proposed method. It uses EV data of Muller community of Austin, Texas, residential load profile of Independent Electricity System Operator (IESO) in Ontario. MATPOWER is used to simulate the system. The method follows a flow chart consisting of EV charging history check, determining charge start time, computing charging pattern, price signal checking, Bus voltage check along with potential of installing/switching of SVC. It shows that for unmanaged conditions, bus voltage where a charging station is introduced falls under 0.96pu, whereas, it can be kept above 0.96 pu for managed cases.

Z. Wan, H. Li, H. He, and D. Prokhorov, **"Model-Free Real-Time EV Charging Scheduling Based on Deep Reinforcement Learning,"** IEEE Trans. Smart Grid, vol. 10, no. 5, pp. 5246–5257, Sep. 2019

The paper presents a novel model-free approach for real-time electric vehicle (EV) charging scheduling based on deep reinforcement learning. The proposed approach does not rely on any system model information and instead utilizes real system data to learn the state transition and evaluate the quality of charging/discharging schedules using a reward function. The authors employ a deep neural network (DNN) to approximate the action-value function, enabling the determination of optimal schedules through a greedy strategy. The performance of the approach is assessed in terms of cumulative rewards and charging costs. The results indicate that the proposed approach successfully learns an optimal scheduling policy, leading to significant cost reduction compared to benchmark solutions.One notable aspect of the proposed approach is its ability to reduce charging costs and meet the user's driving demand without the need for a forecasting model. The paper also addresses the trade-off between cost-saving and range anxiety reduction objectives, as well as the impact of battery cost on charging/discharging schedules. The proposed method also aims to maximize the utilization of renewable energy sources while minimizing the cost of electricity consumption. The evaluation using real-world data demonstrates that the proposed method outperforms existing methods in terms of cost reduction and renewable energy utilization.

Uncoordinated EV Charging Impacts

Muratori, M. **Impact of Uncoordinated Plug-in Electric Vehicle Charging on Residential Power Demand.** *Nat Energy* 3, 193–201 (2018). https://doi.org/10.1038/s41560-017-0074-z

This is a study which assesses the impact of uncoordinated residential EV charging both on an aggregated feeder and also at the transformer level without considering EV charging optimization control or coordination strategies. This study takes a bottom-up approach to calculating residential customer demand over time (10-minute resolution) with EV loads based on a detailed low-level model for the individual household (HVAC, appliances, etc.) and a detailed EV charging model based on vehicle use data (both residential and EV charging profiles are available for download). The methodologies for these profiles are provided in separate papers. This study assumes that 60% of the EVs will be pure EVs with a range of 200 miles and 40% will be PHEVs with a range of 40 miles. It also assumes that level 1 charging will operate at 1.92 kW and level 2 charging will operate at 6.6 kW. Household member's behaviors (to produce the residential power demand and EV charging profiles) are simulated using a Markov process with time-use data from the US Bureau of Labor Statistics. The aggregated feeder scenario studied 200 residential households (502 people and 348 passenger vehicles) in the Midwest region of the US with data from the Residential Energy Consumption Survey (EIA) and is validated with metered data from the region (provided by the utility). This is used as a proxy for the aggregated residential power demand. The local transformer level scenario studied 6 households on a single transformer (30 kW with .98 peak load factor and .32 average load factor) with varying EV penetration rates (19 residents and 11 total passenger vehicles).

Overall, this study used temporal residential load profiles and EV charging profiles to determine impacts without modeling an actual feeder. The results found that the increase in energy (kWh) might be minimal (compared to the existing energy consumption), but that uncoordinated EV charging could drastically change the shape of the aggregate residential demand and impact distribution grid infrastructure. Furthermore, at the distribution transformer level, there is potential for EV customers to cluster and cause thermal violations, particularly with level 2 charging as opposed to level 1 charging.

R. T. Goolsby, **"Electric Vehicle Charging and Rural Distribution Systems,"** 2021 IEEE Rural Electric Power Conference (REPC), Savannah, GA, USA, 2021, pp. 1-5, doi: 10.1109/REPC48665.2021.00007.

This is a study on the effect of EV Charging on rural electric distribution systems, which have longer feeders with more dispersed customers and thus are limited by voltage drop more than thermal limitations. This study uses the 2017 NHTS survey to obtain the daily miles driven per vehicle in Ohio and then assumes an EV efficiency of 115 MPGe (or roughly 3.5 miles per kWh). It also considers the efficiency losses in EV charging and it assumes this to be 85%. The analysis was performed using steady-state peak load and to model the EV charging, it was assumed that every third residential customer (33%) has an EV and charges during peak load. Therefore, 7 kW (level 2 charge rate) was added to each. They did a systemwide study with 57 feeders and analyzed and it was found that the main impact was on distribution transformers and that the number of distribution transformers that exceeded their capacity and voltage limitations increased by ten times. The other impacted components were protective devices (mainly fuses), which had their capacity increased by six times. This study also evaluated the effect of EV charging on their contingency switching scenarios and the results found that voltage drop or capacity constraints prevented the load transfer on 23 out of 57 feeders. It also discusses that if the same energy is delivered during off-peak, the load factor will improve and the utility will have a lower average cost per delivered kWh. It concludes that a time-of-use rate would incentivize customers to charge on-peak or pay higher on-peak rates, which could in turn be used to fund distribution system improvements.

J. Waddell, M. Rylander, A. Maitra and J. A. Taylor, **"Impact of Plug in Electric Vehicles on Manitoba Hydro's Distribution System,"** 2011 IEEE Electrical Power and Energy Conference, Winnipeg, MB, Canada, 2011, pp. 409-414, doi: 10.1109/EPEC.2011.6070235.

This is a study on the impact of EV charging on a suburban 12.47kV feeder supplying mainly detached residential homes. This paper uses the NHTS travel data; specifically, the summary of travel day data by home type, purpose, end time of the last trip, and miles per vehicle. They used this data to create a probability distribution of customer home arrival times and driving distances, which they then used to create the likelihood that an EV owner would charge based on the available SoC of the EV battery. It is assumed that the EV customer will charge their vehicle upon arriving home. A real distribution feeder was evaluated for capacity and voltage constraints using stochastic analysis. This analysis varied the penetration levels as well as charger type, EV SoC, temporal diversity based on home arrival time, and spatial diversity of EV locations. The results found that the individual distribution transformer overloads were the most impacted. It is also noted that EV clustering would likely randomly occur throughout the system based on the system configuration and customer adoption; however, these will likely be limited.

Studies on Direct Charging Methods

Crozier, Constance & Morstyn, Thomas & Mcculloch, Malcolm. (2020). **The Opportunity for Smart Charging to Mitigate the Impact of Electric Vehicles on Transmission and Distribution Systems.** Applied Energy. 268. 10.1016/j.apenergy.2020.114973.

The paper analyzes the impact of a large penetration of electric vehicles on the power network in Great Britain and the potential of smart charging to mitigate the impact. This is a study on the impacts of both the bulk power system (Transmission and Generation) and the localized distribution system and also the interaction / conflict between the two for the entire Great Britain utility system. This study discusses that the effect of charging on losses, loading, and voltage will be specific to a particular network topology and for the distribution system analysis, three residential distribution systems were considered that are intended to represent the urban, suburban, and rural network topologies, respectively. The base load was created using 1 minute resolution household loads from a UK trial for the distribution system analysis and the historical national demand was available at 5 minute resolution for the transmission and generation portion of this study.

This study considers the scenarios of no EV charging, uncontrolled EV charging, distribution controlled EV charging, and transmission/generation controlled EV charging. The uncontrolled EV charging was represented using a stochastic model that uses real-world EV charging trial data mapped to vehicle usage from survey data (this is to decrease bias with only using trial data). This methodology allows the use of the survey data to more accurately capture the EV profiles for different regions. Furthermore, the distance that the vehicle travels is converted into energy expenditure (kWh/mile). The controlled EV charging used a constrained optimization model that minimizes the electricity demand and charging power of EVs.

For the transmission and generation simulations, a single worst case data is modeled in which the aggregate peak demand of the system is the highest. The transmission system was simplified into “supply points” and vehicle loads were assigned to those points based on travel survey data to account for the geospatial variations.

For the distribution simulations, separate simulations were constructed for each local utility authority and for each location, the relevant test feeder was selected (urban, suburban, and rural). For this analysis, scaled household demand (according to the area’s electricity demand) and scaled EV charging profiles (according to the local vehicle usage recorded in the travel survey) were used for a Monte-Carlo simulation. At each iteration, the four EV charging scenarios were evaluated (no EVs, uncontrolled, controlled by Transmission/Generation, controlled by Distribution).

This study concluded that smart charging can eliminate the need for additional generation infrastructure required with 100% EV adoption and reduce the percentage of distribution networks that would require reinforcement from 28% to 9%. It is noted that there is a conflict between the constraints of the transmission and distribution systems when it comes to flattening the load for both residential distribution circuits and the larger grid simultaneously.

X. Zhu, P. Mishra, B. Mather, M. Zhang and A. Meintz, **"Grid Impact Analysis and Mitigation of En-Route Charging Stations for Heavy-Duty Electric Vehicles,"** in IEEE Open Access Journal of Power and Energy, vol. 10, pp. 141-150, 2023, doi: 10.1109/OAJPE.2022.3233804.

This research paper conducts a comprehensive analysis of the grid impact resulting from heavy-duty electric vehicle (EV) charging stations. The authors propose a mitigation strategy that employs smart charger functionality, on-site photovoltaic generation, and on-site energy storage to address voltage-related grid impacts. The study aims to determine the grid hosting capacity for different charging station sizes and locations while minimizing capital costs. Real-world vehicle telemetry data and EV system modeling are used to establish charging schedules. The authors define vehicle and station agents with specific parameters and conduct simulations for various scenarios. These scenarios include different charging station locations, number of charging ports, charging load patterns, and system load patterns. Additionally, the authors propose a PV-ES-charger solution and sizing strategy to mitigate grid impacts, considering system voltage limits and total capital cost.
Key Findings and Results:
The analysis shows that the proposed PV-ES-charger solution effectively mitigates voltage impacts on the grid with minimal capital cost. Incorporating smart charger functionality, on-site photovoltaic generation, and on-site energy storage provides valuable insights into the grid hosting capacity for different charging station sizes and locations.

P. H. Hoang et al., **"A Dual Distributed Optimal Energy Management Method for Distribution Grids With Electric Vehicles,"** in IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 8, pp. 13666-13677, Aug. 2022, doi: 10.1109/TITS.2021.3126543

The paper proposed a method for efficiently managing power generation and delivery in distribution grids with the integration of electric vehicles (EVs). The primary goals of this method are to maintain power quality, reduce operating costs, and enhance resiliency.The proposed method involves two steps. Firstly, the optimization task is relaxed by temporarily neglecting voltage and reactive power constraints, enabling the optimal allocation of active power for dispatchable sources to improve global optimality searching. In the second step, constraints are reconfigured based on the results from the first step, ensuring all constraints are considered while finding the optimal solution.To solve the optimization problem in a distributed energy management system, the paper presents a distributed algorithm based on the singular perturbation method. This algorithm creates a two-time-scale dynamical system with fast and slow dynamic layers. The fast dynamic layer estimates average power injections, while the slow dynamic layer optimizes bus voltages. The paper also explores the use of the ADMM algorithm for optimization. It introduces a dual distributed optimal energy management method for distribution grids with electric vehicles (EVs), optimizing power generation and delivery for improved power quality, cost reduction, and enhanced resiliency.

H. Wang, Y. Jia, M. Shi, P. Xie, C. S. Lai and K. Li, **"A Hybrid Incentive Program for Managing Electric Vehicle Charging Flexibility,"** in IEEE Transactions on Smart Grid, vol. 14, no. 1, pp. 476-488, Jan. 2023, doi: 10.1109/TSG.2022.3197422.

The paper proposed a hybrid incentive program designed to effectively manage EV charging flexibility. By combining static and dynamic incentives, the program offers simplicity, consistency, and controllability. The authors develop an optimal incentive price selection model to determine prices for EV charging

flexibility, leading to cost reduction for EV owners and decreased energy market bills.To efficiently solve the optimization problem, the proposed solution methodology employs an adaptive ADMM algorithm. This algorithm linearizes and decomposes the model into a distributed form, ensuring convergence through the update of scaled dual variables.
This paper shows that the proposed hybrid program outperforms existing TOU and transactive control approaches in case studies. It also lowers energy procurement costs, increases charging station profitability, and significantly reduces charging fees for EV owners.
A hybrid incentive program for managing EV charging flexibility, combining static and dynamic incentives for simplicity and control. It presents an optimal price selection model and an efficient ADMM algorithm. Case studies show its superiority, reducing costs for EV owners and energy bills while increasing charging flexibility utilization.

J. Bollerslev et al., **"Coincidence Factors for Domestic EV Charging From Driving and Plug-In Behavior,"** in IEEE Transactions on Transportation Electrification, vol. 8, no. 1, pp. 808-819, March 2022, doi: 10.1109/TTE.2021.3088275.

The paper provides an analysis of the coincidence factor (CF) of electric vehicle (EV) charging and its impact on the electrical grid. They emphasize the importance of considering factors such as the number of EVs, charging power, battery size, driving behavior, and plug-in behavior when defining the CF. The authors employ a Monte Carlo approach, combining data sources from travel surveys and recorded EV charging data. They model travel and plug-in behaviors to generate single-EV charging time series and derive the CF from statistical analysis of multiple runs. The study examines the influence of EV battery size, rated charging power, and plug-in behavior on the CF.
The CF decreases to less than 25% when considering more than 50 EVs with a charging level of 11 kW, with the CF strongly dependent on the number of EVs considered. Driving behavior and battery size have a minor influence on the CF. Increasing the charging power reduces the coincident peak demand on the electrical grid, although the effect is less pronounced for larger battery sizes. The study also finds that different plug-in curves have minimal impact on the coincident peak demand.
The paper's key contribution lies in modeling and analyzing the coincidence factor (CF) of EV charging behavior and its impact on the electrical grid. It reveals the CF's sensitivity to factors like EV battery size and charging power, with a significant influence of the number of EVs and charging power on the CF. The study also examines the impact of EV charging behavior on the coincident peak demand, finding that increasing charging power reduces peak demand, but less so for larger battery sizes.

S. Rafique, M. S. H. Nizami, U. B. Irshad, M. J. Hossain and S. C. Mukhopadhyay, "**EV Scheduling Framework for Peak Demand Management in LV Residential Networks,"** in IEEE Systems Journal, vol. 16, no. 1, pp. 1520-1528, March 2022, doi: 10.1109/JSYST.2021.3068004.

This paper proposes a scheduling framework to manage peak demand in low-voltage residential networks with electric vehicles (EVs). It uses a mixed-integer programming approach to optimize EV charge-discharge schedules, minimizing energy costs, and complying with grid constraints. A stochastic model accounts for uncertainties in day-ahead scheduling. The strategy considers uncertainties in load demand, PV generation, and EV availability. It models EV travel patterns and range efficiencies based on historical data. The optimization model minimizes aggregated energy costs, considering transaction costs and battery degradation. Simulation studies show that this strategy effectively reduces electricity costs for EV owners, manages peak demand for grid operators, and outperforms existing EV scheduling methods. It emphasizes incentivizing EV owners to support grid services to address capacity issues.

Key Findings and Results:
The paper introduces a coordinated system for EV charge-discharge scheduling in residential networks, utilizing stochastic modeling and optimization to minimize energy costs while adhering to grid constraints.

Z. Liu, Q. Wu, S. Huang, L. Wang, M. Shahidehpour and Y. Xue, **"Optimal Day-Ahead Charging Scheduling of Electric Vehicles Through an Aggregative Game Model,"** in IEEE Transactions on Smart Grid, vol. 9, no. 5, pp. 5173-5184, Sept. 2018, doi: 10.1109/TSG.2017.2682340.

The paper presents a study on the optimal day-ahead charging scheduling for electric vehicles (EVs) using an aggregative game model. The authors address the issue of the interaction between EV charging demand and electricity spot prices, and propose a game theory-based approach to minimize charging costs while considering the energy plans of other EVs. The proposed model is tested using real-world driving data .By analyzing the impacts of EV driving patterns and price forecasts on EV demand, the authors demonstrate the effectiveness of their model in reducing peak demand and energy costs
The robustness of the proposed method to randomness in EV driving patterns and price forecast errors. This paper proposes an optimal day-ahead charging scheduling model for EVs using an aggregative game model. It minimizes charging costs considering EV charging demand and electricity spot prices, proven to have a unique Nash equilibrium. Real-world data validates its effectiveness in reducing peak demand and energy costs.

M. S. H. Nizami, M. J. Hossain and K. Mahmud, **"A Coordinated Electric Vehicle Management System for Grid-Support Services in Residential Networks,"** in IEEE Systems Journal, vol. 15, no. 2, pp. 2066-2077, June 2021, doi: 10.1109/JSYST.2020.3006848.

This paper presents a coordinated management system for electric vehicles (EVs) in residential networks, offering an effective solution to tackle grid overloading and voltage constraint violations. The authors propose a multiagent system architecture that employs a mixed-integer programming-based optimization model to coordinate EV battery charging and discharging through a local EV aggregator. The main objective is to minimize electricity costs for EV owners while ensuring compliance with grid constraints. To validate their approach, the authors conducted simulation studies on an LV residential feeder in Sydney, Australia, involving 42 detached residential buildings, 15 of which had EVs equipped with vehicle-to-grid (V2G) capabilities. Using actual meter readings and EV travel data, the simulation accurately represented load demand and EV charging patterns for a typical winter weekday, with a 15-minute dispatch interval. The EV aggregator successfully managed these EVs using the proposed methodology, providing grid-support services while meeting user preferences for EV charging.
The coordinated EV management system optimizes charging schedules, shifting them to off-peak hours, resulting in cost savings and preventing grid overloading and undervoltage in residential networks. The proposed method surpassed other strategies in handling grid overloading, maintaining voltage profiles, and offering cost savings for EV owners. This system is highly scalable and can handle increased numbers of EVs effectively.
In short, this paper presents a coordinated management system for EVs in residential networks, addressing grid overloading, minimizing costs for EV owners, and emphasizing scalability and incentives for their participation in grid support services.

J. Antoun, M. E. Kabir, R. Atallah, B. Moussa, M. Ghafouri and C. Assi, "**Assisting Residential Distribution Grids in Overcoming Large-Scale EV Preconditioning Load,"** in IEEE Systems Journal, vol. 16, no. 3, pp. 4345-4355, Sept. 2022, doi: 10.1109/JSYST.2021.3104185.

This research paper presents an analysis of the effects of large-scale electric vehicle (EV) preconditioning on residential distribution grids. The authors propose a hybrid solution, combining V2G technology and network reconfiguration, to tackle the challenges of increased EV preconditioning demand.The main objective of the hybrid approach is to minimize power losses in the distribution network while ensuring that voltage levels remain above the operational threshold. Network reconfiguration helps to choose a new radial topology for the system, reducing power loss, while V2G technology enables EVs to discharge energy to offset the preconditioning load.
Key Findings and Results:
The paper suggests a hybrid solution, merging V2G technology and network reconfiguration, to minimize the impact of EV preconditioning on residential grids. It achieves a 50% reduction in power losses and maintains voltage levels above the operational threshold.

S. Deilami, A. S. Masoum, P. S. Moses, and M. A. S. Masoum, **‘‘Real-time coordination of plug-in electric vehicle charging in smart grids to minimize power losses and improve voltage profile,’’** IEEE Trans. Smart Grid, vol. 2, no. 3, pp. 456–467, Sep. 2011.

This paper presents a real-time load management solution, called RT-SLM, for coordinating the charging of plug-in electric vehicles (PEVs) in smart grid systems. The objective is to minimize power losses and improve the voltage profile by considering time-varying market energy prices and PEV owner preferences. The proposed algorithm, based on maximum sensitivities selection (MSS) optimization approach, aims to reduce system overloads, power peaks, and premature transformer failures. The RT-SLM algorithm demonstrates its capability to optimize the charging schedule of PEVs in real-time, considering system constraints, cost minimization, and PEV owner preferences. Coordinated charging using RT-SLM outperforms random uncoordinated charging in terms of reducing power demand, voltage deviations, and power losses.
The algorithm optimizes the charging schedule of PEVs based on real-time cost minimization and voltage regulation, leading to improved system performance and reduced operational costs. Coordinated charging using RT-SLM effectively reduces power demand and voltage deviations, ensuring a stable and reliable smart grid system. This algorithm incorporates PEV owner preferred charging time zones based on priority selection, enhancing user satisfaction and convenience.
The extensive simulations provide empirical evidence of the algorithm's effectiveness in improving the efficiency and economy of smart grids, reducing system overloads, power peaks, and the risk of premature transformer failures. However, while the simulations demonstrate the algorithm's performance, there is a need for real-world implementation and validation to assess its practical feasibility and scalability. The paper briefly mentions the consideration of time-varying market energy prices but does not delve into the specific mechanisms or implications of this factor in the algorithm.

J. de Hoog, T. Alpcan, M. Brazil, D. A. Thomas, and I. Mareels, **‘‘Optimal charging of electric vehicles taking distribution network constraints into account,’’** IEEE Trans. Power Syst., vol. 30, no. 1, pp. 365–375, Jan. 2015.

This paper provides a review of optimal charging strategies for electric vehicles (EVs) in distribution networks, considering various constraints and factors. The authors propose a linear optimization approach that frames EV charging as a receding horizon optimization problem, accounting for transformer and line limitations, phase unbalance, and voltage stability within the network.By formulating the problem as an optimization challenge with linear constraints, the authors introduce two objective functions: greedy charging and greedy charging with pricing. These objectives aim to maximize total charging of all vehicles and minimize the cost of charging, respectively. The results reveal that the optimal charging method successfully avoids breaching network constraints and significantly enhances network performance compared to uncontrolled charging.

The authors investigate the impact of optimal load control and price-based optimal charging on network sustainability and cost savings. They discover that optimal load control can support high levels of EV adoption without requiring infrastructure upgrades, leading to more efficient utilization of existing assets. Additionally, price-based optimal charging effectively schedules charging during periods of low electricity prices, resulting in cost savings for consumers.

The paper also emphasizes the significance of considering spatial distribution when evaluating the effect of EVs on voltage stability in distribution networks. It discusses various techniques and approaches, such as cost-benefit analysis and model predictive control, for coordinating EV charging to ensure the efficient operation of distribution networks.

J. Wang, G. R. Bharati, S. Paudyal, O. Ceylan, B. P. Bhattarai, and K. S. Myers, **"Coordinated electric vehicle charging with reactive power support to distribution grids,"** IEEE Trans. Ind. Informat., vol. 15, no. 1, pp. 54–63, Jan. 2019

This paper introduces hierarchical coordination frameworks for optimizing the active and reactive power dispatch of electric vehicles (EVs) within distribution grids. It presents two optimization models—one for the distribution grid and one for the EV load. The distribution grid model's objective is to maximize the integration of flexible loads, including EVs, while the EV load model aims to minimize the cost of charging EVs. Through coordinated charging with reactive power support, the authors demonstrate that this approach can lead to reduced charging costs and alleviation of grid constraints.The paper focuses on mathematically modeling the distribution grid and EVs, emphasizing the inclusion of reactive power support from EVs. It explores how coordination with load shifting and curtailment can accommodate more EVs on constrained grids, leading to improved EV penetration and optimized grid and EV operation.
The key findings and results of the study are highlighted by the introduction of reactive power in the optimal Electric Vehicle (EV) charge scheduling formulation, a novel extension of prior work and the first to consider both active and reactive power in this context. The research involves modeling a comprehensive distribution optimal power flow, encompassing flexible reactive power support from EVs, load shifting, and curtailment as demand response options. The study demonstrates the benefits derived from dispatching reactive power from EVs to the grid, resulting in reduced charging costs within dynamic energy pricing schemes. Additionally, the coordination of reactive power injection from EVs with load shifting and curtailment proves effective in accommodating an increased number of EVs on constrained grids.

S. Martinenas, K. Knezović, and M. Marinelli, **''Management of power quality issues in low voltage networks using electric vehicles: Experimental validation,''** IEEE Trans. Power Del., vol. 32, no. 2, pp. 971–979, Apr. 2017, doi: 10.1109/TPWRD.2016.2614582.

The paper explores the potential of electric vehicles (EVs) in mitigating power quality issues in low-voltage networks. The study presents an experimental analysis of a local smart charging algorithm based on a droop controller in EVs to assess its effectiveness. EVs equipped with local smart charging controllers were connected to the end of the feeder, and their charging power was adjusted based on voltage measurements. The results demonstrate that intelligent EV charging effectively improves power quality in a highly unbalanced grid by mitigating voltage drops and imbalances.

O. Sundstrom and C. Binding, ‘‘**Flexible charging optimization for electric vehicles considering distribution grid constraints,’’** IEEE Trans. Smart Grid, vol. 3, no. 1, pp. 26–37, Mar. 2012.

The paper introduces the role of the Charging Service Provider (CSP), which encompasses various operational functions such as data collection, trip forecasting, and charging optimization. The CSP utilizes historical trip data and customer information to predict future trips and compute charging schedules for each EV. The optimization process considers factors like maximizing EV utilization, minimizing charging costs, and preventing grid congestion. Additionally, the CSP can collaborate with a retailer to outsource charging flexibility and communicate the preferred aggregated load curve. The Distribution System Operator (DSO) manages the distribution grid and can interact with the CSP to influence charging schedules in case of grid overloading.The feasibility of loads and generation in each time slot is validated using two methods: the flow network method and the load flow method. The flow network method involves constructing a flow network based on grid connectivity and loading rate limitations, solving a maximum flow problem to determine feasibility, and creating power limitations for EVs in congested network areas if necessary. The load flow method employs traditional load flow analysis to determine power limitations based on maximum loading rates or voltage drop limitations. The results demonstrate that coordinating charging schedules can effectively reduce grid congestion and voltage problems. The algorithm for handling grid constraints is shown to converge in a reasonable number of iterations.
Key Findings and Results:
This paper proposes a method for optimizing electric vehicle (EV) charging while considering distribution grid constraints. The authors introduce the concept of a Charging Service Provider (CSP) that predicts future trips and computes charging schedules for each EV. The method aims to prevent grid congestion by coordinating charging schedules and considering power and voltage limitations

W. Infante and J. Ma, **"Coordinated Management and Ratio Assessment of Electric Vehicle Charging Facilities,"** in IEEE Transactions on Industry Applications, vol. 56, no. 5, pp. 5955-5962, Sept.-Oct. 2020, doi: 10.1109/TIA.2020.2987773.

The power and transportation sectors are two separate sectors. But with the increment of EVs, coordination is required. Change in electricity demand profile is very likely with the adoption of EVs. The cost of adequate facilities is a great concern. Different research has already been conducted on the charge station model and costs but not aggregated one with Home Charging Station (HCS). Also, Lack of research that includes all stakeholders like DisCO, charging station owners and EV drivers This paper aims to Coordinate the scheduling of power transfers and address the complexity of EV charging facility decisions to satisfy the optimizations of the main stakeholders: EV drivers, multiple station owners, and DisCo operators. Also it assesses charging facility ratios of Battery charging stations (BCSs), Battery swapping stations (BSSs), and HCSs for different renewable energy penetration levels.
It uses Australian New South Wales data and mathematical optimization models (Lagrangian Relaxation & Subgradient Methods) to generate EV load profiles.
Preliminary level coordination proposed by this paper is like DR which depends on communication of price signals and power transfers between EV owners and station owners. A comprehensive level coordination encourages people to charge at battery charging stations or battery swapping stations at lower prices compared to house charging.

In the last part, they tried to find the ratios of different charging stations (BCS, BSS and HCS). For different renewable integration and retail prices, HCS will be the most dominant as a charging place followed by BSS and BCS.