EVS29 Symposium
Montréal, Québec, Canada, June 19-22, 2016

Charge Management Optimization for Future TOU Rates

Jiucai Zhang and Tony Markel

National Renewable Energy Laboratory, Golden, Co 80007, {Jiucai.Zhang and Tony.Markel}@nrel.gov

Summary

The effectiveness of future time of use (TOU) rates to enable managed charging depends on the vehicle's flexibility and the benefits to owners. This paper adopts opportunity, delayed, and smart charging methods to quantify these impacts, flexibilities, and benefits. Simulation results show that delayed and smart charging methods can shift most charging events to lower TOU rate periods without compromising the charged energy and individual driver mobility needs.

Keywords: EV (electric vehicle), smart grid, charging, off-peak, renewable

1 Introduction

The growing penetration of renewable resources in the electricity grid results in higher levels of non-controllable variable generation resources [1]. The 2020 33% Studies [2] shows that by 2020, in times of low load and high renewable generation, as much as 60% of energy production could come from renewable generators. The high level of non-controllable variable generation resources will require far more flexibility of the green grid. The California Independent System Operator (CAISO) has created the "duck chart" [2, 3] to illustrate how net load varies with changing grid conditions. To maintain reliability, the Independent System Operator must direct controllable resources to match both variable demand and variable supply. The Independent System Operator uses pricing signals to influence these controllable resources to take advantage of low-cost electricity during over-generation of renewable energy but also encourages users to conserve energy during peak periods. Electric vehicles (EVs) present a demand that is flexible and potentially controllable [4, 5]. Managing a controllable EV load may benefit a utility by taking advantage of this to smooth the load by shaving peaks, filling valleys, and allowing more efficient use of excess energy produced by renewable energy resources. The effectiveness of price signals depends on the flexibility, availability, and benefits of EVs providing grid services. Therefore, there is a fundamental need to quantify the flexibility and benefits of EVs for providing the grid services and how the public charging affect the flexibility of EVs to provide the grid services.

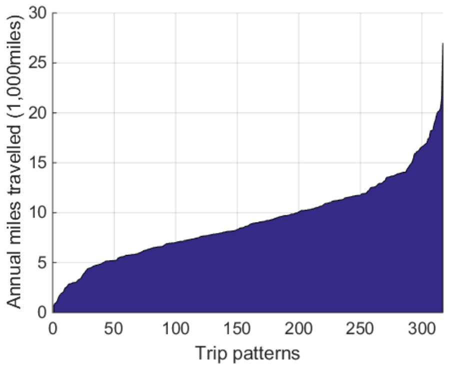
The existing research mainly focuses on the study of the impacts of vehicle charging on the grid side. The flexibility and benefits of smart charging to the EV owners are rarely studied. How public charging affects the flexibility and benefits of EVs has not been thoroughly studied. Wang et al. (2011) used a unit commitment model to study the interaction among plug-in hybrid EVs (PHEVs), wind power, and demand response [6]. The paper simulated four PHEV charging scenarios, including unconstrained charging, 3-hour delayed constrained charging, smart charging, and smart charging with demand response. Their simulation results showed that optimally dispatching the PHEV loads could significantly reduce the total system operating costs. Ahn et al. (2011) proposed a two-level optimal charging algorithm to achieve both load shifting and frequency regulation [7]. A decentralized charging algorithm is proposed for load shifting by emulating the charging pattern identified through linear programming optimization solutions. The simulation results showed that the proposed algorithm minimized electricity generation cost and emissions and reduced the usage of the conversional regulation power plants without compromising battery charging performance. Rotering and Ilic (2011) used a dynamic programming method to optimize the charging time and energy flows [8]. Their method offers a cost-competitive alternative to fast charging. The daily charging cost is reduced from $0.46 to $0.20. Cao et al. (2012) proposed an intelligent method to control EV charging load in response to time-of-use (TOU) price in a regulated market [9]. Their simulation results showed that the optimized charging pattern has great benefit in reducing cost and flatting the load curve if the peak and valley time periods are partitioned appropriately. Weiller (2011) concluded that non-home charging increases daily electric energy use of PHEVs from 24% to 29% (1.5–2 kWh/day) [10]. The delayed and average charging strategies can have the same fuel reduction as opportunity charging, but have different instances electricity consumption impacts [11]. Delayed charging at home-related locations can move PHEV charging from peak hours to off-peak and decrease the PHEV demand peak load by 50%.

The goal of this study is to quantify the flexibility and benefits of EVs due to delayed and smart charging with intelligent state-of-charge (SOC) management methods, the impact of the charging methods on the grid load, as well as needed communication. This paper firstly employs year-long sequences for 317 vehicles of trip and parking events to analyze the impact of EV charging on the green grid peak demand, and then studies the flexibility of EVs for providing grid services. This paper also quantifies the benefits to EV owners from delayed and smart charging.

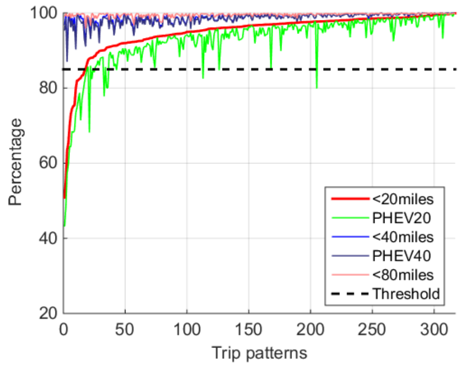
2 Methods

2.1 Trip Patterns

This simulation adopts 317 year-long sequences of trip and parking events as shown in Figure 1(a). These sequences of trip and park events were selected from 445 individual long-term trip history data from the Puget Sound Regional Council's Traffic Choices Study. Each sequence provides distance, duration, destination, and parking for each event.



(a) 317 year-long trip patterns



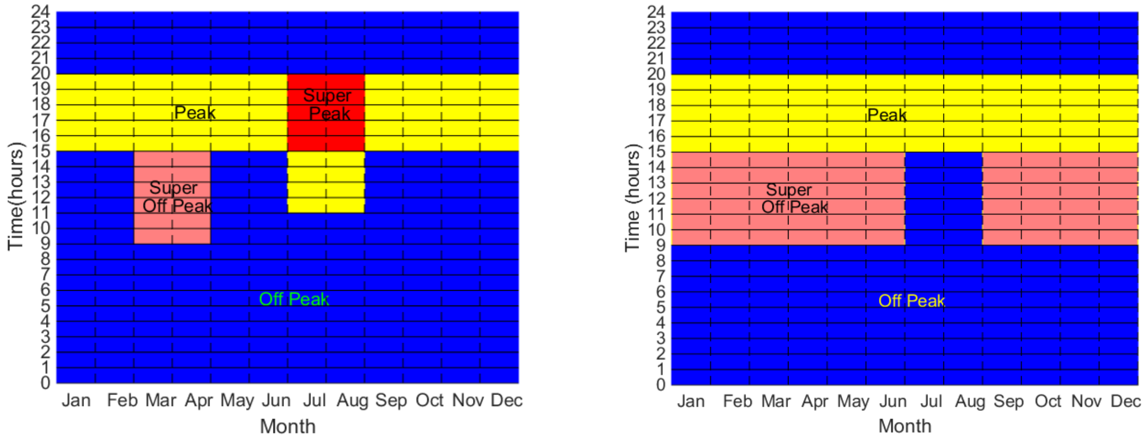
(b) Miles travelled distribution for 317 year-long trip patterns

Figure 1: The 317 year-long trip patterns and their miles travelled distribution, sorted based on annual miles travelled. The annual miles travelled range from less than 1,000 miles to more than 25,000 miles.

Figure 1(b) compares the distribution of miles travelled for the travel events and vehicle utility of 317 trip patterns. Vehicle utility is defined as the ratio of the miles traveled provided by the battery in the charge depleting mode to the total miles traveled per event. The trip pattern is sorted according to the percentage of travel events with fewer than 20 miles traveled per event. The percentage of travel events with fewer than 20 miles traveled is more than 85% for the last 299 trip patterns. The percentage of travel events with fewer than 40 miles traveled for all trip patterns is greater than 85%. If there are enough Level 2 chargers deployed, the utility of a PHEV with a range of 20 miles (PHEV-20) is very close to the percentage of travel events with fewer than 20 miles. The utility of a PHEV-40 is very close to the percentage of travel events with fewer than 40 miles. There are some spikes on the vehicle utility plots. These spikes are mainly caused by the limited time the vehicle is parked between neighboring travel events or the unavailability of charging stations. Charging events during these short parking time periods do not have much flexibility to delay charging or reduce the charging rate for providing grid services. If these charging events happen during demand hours, they increase the peak load of the utility.

2.2 Rate Structure

During certain times of the day, energy production can outpace demand. The CAISO duck chart shows that increased solar generation paired with conventional base load resources that cannot be turned off could cause excess generation in the afternoons during certain months beginning in 2018. Based on data from the California Public Utility Commission's 2024 long-term procurement planning process and 2021 wind and solar projections, as well as demand forecasts for 2021 and 2024 produced by the California Energy Commission[12, 13], CAISO created projections of future load time blocks of anticipated electricity needs, as shown in Figure 2. The load time blocks show that supply is expected to be constrained during the peak hours of 4 p.m. to 8 p.m. when the sun is setting and solar output is declining throughout the year. Increasing solar generation could cause excess generation during super off-peak hours from 10 a.m. to 4 p.m. from September to June when solar generation is at its highest. The low demand in March and April could result in super off-peak hours from 10 a.m. to 4 p.m. The high demand in July and August could also cause the peak hours to begin as early as noon and super peak hours to occur from 3 p.m. to 8 p.m. [2, 3, 8].



(a) Weekdays (b) Weekends and holidays

Figure 2: CAISO high-renewables TOU period [14]

To maximize the use of renewable resources and support greenhouse gas reduction, TOU price signals as listed in Table 1 could encourage customers to conserve energy consumption during peak and super-peak times [3], which could avoid the need to invest in additional generation and help keep electric costs down. Meanwhile, the TOU price could also provide incentives to consumers to take advantage of low-cost electricity during periods of excess generation, thereby reducing greenhouse gas.

Table 1: High-renewables TOU rates for Southern California Edison [14]

	Weekdays				Weekends and Holidays			
Month	Super Off Peak ($)	Off Peak ($)	Peak ($)	Super Peak ($)	Super Off Peak ($)	Off Peak ($)	Peak ($)	Super Peak ($)
1-2	-	0.14	0.17	-	0.075	0.14	0.17	-
3-4	0.075	0.13	0.33	-	0.075	0.13	0.33	-
5-6	-	0.14	0.31	-	0.075	0.14	0.31	-
7-8	-	0.15	0.41	0.6	-	0.15	0.41	-
9-12	-	0.14	0.17	-	0.075	0.14	0.17	-

Fixed Charge: $11.33 per month (in 2021)

2.3 Charging Methods

We adopted three charging methods: opportunity charging, delayed charging, and smart charging with SOC management to quantify benefits and impacts of the charging methods to EV owners. Opportunity charging charges vehicles immediately. Delayed charging selects the charging schedule based on TOU rates and driver's schedule, but charges the same energy per event as opportunity charging. Smart charging with SOC management not only delays vehicle charging based on TOU rates and the driver's schedule, but also manages charged energy per event based on the energy requirement for future trips.

2.3.1 Opportunity Charging

The opportunity charging method assumes that an EV is plugged in as soon as it arrives at a charge station. The vehicle is charged immediately after it is plugged in. The vehicle keeps charging until the battery pack is fully charged or unplugged. Opportunity charging ignores price signals and charges the vehicle as soon as possible. All price signals have the same priority when charging the vehicle.

2.3.2 Delayed Charging

The delayed charging method utilizes the relatively long parking period to selectively charge the vehicle at as low a TOU rate as much as possible at each charge event. It is known when the vehicle will leave and how much energy is required for the future trip. Delayed charging will charge the same energy for each event as opportunity charging. Delayed charging does not compromise future driving needs. Therefore, delayed charging will not affect the battery life and range anxiety. Delayed charging does not need the battery SOC information to control the charging process. This method employs simple energy and schedule information from the driver to maximize the benefits for EV owners and reduce grid peak demand.

We define each peak time period as a stage. For each charge event, the vehicle is charged to full or unplugged after the N^{th} stage. N is the total number of stages. The goal of delayed charging is to minimize charging cost under the constraint of the required charging energy throughput, which is formulated in Eq. 1.

$$C_{delayed} = min\sum_{i=1}^{N} r_i * p_i * \tau_i \tag{1}$$

$$\text{Subject to}: En_{delayed}(N) = En_{op}(N)$$

where p_i and r_i are the charging power and TOU rate at the i^{th} stage, respectively. $En_{delayed}(N)$ and $En_{op}(N)$ are charged energy for delayed and opportunity charging at the end of plugged in time, respectively. τ_i is the duration of the i^{th} stage.

2.3.3 Smart Charging with SOC Management (V1G)

The method of smart charging with SOC management not only charges a vehicle during low TOU rate periods as much as possible as in delayed charging, but also skips some charging periods at peak or super peak periods when the remaining SOC is high enough for the next trip. Smart charging uses the maximum of the predefined range to avoid charging at the peak periods as much as possible. Smart charging can still meet the range requirement for driving, but has the potential to increase driver's range anxiety and may impact battery life due to the increased SOC swing. This method represents a global optimized SOC management method. Smart charging manages SOC based on all future vehicle travel information, and no unexpected trips are taken.

The goal of smart charging (V1G) with SOC management is to minimize charging cost under the constraints of the SOC limits, as shown in Eq. 2.

$$C_{V1G} = min\sum_{i=1}^{K} r_i * p_i * \tau_i \tag{2}$$

$$\text{Subject to}: \begin{cases} SOC_i^- \geq SOC_{min} \\ SOC_i^+ \leq SOC_{max} \end{cases}$$

where K is total number of charge stages for the whole year. SOC_i^+ and SOC_i^- denote SOC before and after the i^{th} stage, respectively. The first constraint is to ensure that SOC after each driving event is above the minimum SOC limit. The second constraint is to avoid overcharging the EV battery.

Table 2 compares the three charging methods. The opportunity charging method is used as a baseline for this comparison. Delayed charging only adjusts the charging time according to the TOU rates to minimize the charging cost. There is no impact on the charging energy throughput, battery degradation, or range anxiety. Delayed charging needs a future trip schedule to select the charging time. No communication is needed to get the vehicle battery information. The V1G with SOC management schedules vehicle charging and optimizes the SOC according to the TOU rates and future trip information. The increased SOC swing speeds up the battery degradation. The V1G with SOC management also needs communication between vehicles and aggregators to get the battery status. The future travel schedule and trip information is also needed to manage charging.

Table 2: Impacts of three charging methods (per charge event)

Method	Energy	Degradation	Range Anxiety	Schedule	Future Trip	Communication
Opportunity	Base	Base	Base	No	No	No
Delayed	Base	Base	Base	Yes	No	No
Smart charging	Adjusted	Increased	Increased	Yes	Yes	Yes

2.3.4 Solution

In this section, we present a charge scheduling algorithm to find solutions for the optimization problem expressed in Eqs. (1) and (2). The objective of delayed charging and smart charging (V1G) is to selectively charge a vehicle at low TOU rates as much as possible to minimize the charge cost and maximize renewable energy utilization. The delayed charging algorithm selects the charge stages under the following three situations: (1) the charging time is equal to the time the vehicle is plugged in; (2) the plugged-in time is more than the charging time, and there is only one TOU rate stage while the vehicle is plugged in; (3) the plugged-in time is more than the charging time, and there is more than one stage while the vehicle is plugged in. For situation 1, there is no choice in terms of scheduling charging. The vehicle will be charged as long as it is plugged in. For situation 2, the vehicle has the flexibility to charge, but smart charging does not bring any benefits to the EV owners from the TOU rate. However, the vehicle may still be able to earn benefits from providing ancillary services, such as frequency regulation and spinning reserves. For situation 3, EV owners can utilize TOU rates to minimize the charging cost. According to Fig. 1(b), very few vehicles and charging events take place in situations 1 and 2. Therefore, the scheduling algorithms only focus on situation 3 in this paper.

The follow criteria are adopted to schedule vehicle charging: (1) charging time: the vehicle should be charged to the required energy as soon as possible. This criterion maximizes the availability of the vehicle for the future driving. (2) Charged energy per charge event: charged energy per charge event should be as close to the energy throughput for opportunity charging as possible. This criterion is to make the driver comfortable with managed charging. (3) Minimum SOC: the minimum SOC is defined as the minimum SOC that is required to cover future unexpected trips before the next charging event. This criterion tries to minimize the impact of smart charging on the EV's unavailability and is mainly used for SOC management of smart charging (V1G).

The objective of delayed charging is to charge the vehicle at each charging event at as low TOU rates as possible to minimize the charging cost. To achieve this goal, a priority-based scheduling algorithm is proposed. The priority of each stage is determined by the TOU rates. The lower the TOU rate, the higher the priority for charging, and vice versa. That is, the Super Off Peak period has the highest priority. The Super Peak period has the lowest priority for charging. The priorities of the different types of loads are listed in the Table 3, where a lower number represents a higher priority. The vehicle is charged at the highest priority stage to minimize charging cost. Equal-priority stages are scheduled in first-come first-serve order to charge vehicle as soon as possible. The vehicle stops charging until the charged energy per charge event reaches the energy throughput for opportunity charging.

Table 3: Priority of the different peak loads

Load Type	Super Off Peak	Off Peak	Peak	Super Peak
Priority	0	1	2	3

The objective of smart charging (V1G) is to charge the vehicle at lower TOU rates as much as possible to minimize the charging cost. Smart charging provides a global optimization method to schedule vehicle charging to minimize the total charging cost. To find the solution, we use the Lagrange multiplier method to relax two constraints in Eq. (2). The relaxed problem can then be solved using dynamic programming. Specifically, we first define the set of admissible decision vectors $U=[u_1,u_2,\ldots,u_k]$, where u_i is charged energy at the i^{th} stage. Then, we define a Lagrangian cost function in Eq. 3.

$$J_{\lambda_1,\lambda_2}(U) = \sum_{i=1}^{K} r_i * p_i * \tau_i + \lambda_1 SOC_i^- + \lambda_2 SOC_i^+ \tag{3}$$

where λ_1 and λ_2 are the Lagrange multipliers. It can easily be derived from [15] that, if there exists a pair λ_1^* and λ_2^* such that $\alpha^*=arg[minJ_{\lambda 1*,\lambda 2*}(U)]$, which leads to $SOC_i^- \geq SOC_{min}$ and $SOC_i^+ \leq SOC_{max}$, then U is also an optimal solution to Eq. (2). Therefore, the task of solving Eq. (2) is converted into an easier one, which is to find the optimal solution to the unconstrained problem in Eq. (3). The problems can be easily solved by the dynamic programming algorithm.

3 Simulation Results

3.1 Experiment Setup

3.1.1 Charger Power and Availability

Two different power levels are considered for chargers within this study, as listed in Table 4. Each driver assigns his or her own home charge station in his or her place of residence. This is assumed to be a dedicated charger that is available per the elected charger timing scenario. Implementation of the workplace class is performed identically, with the exception that the charger is located at the driver's place of business. The public class assumes chargers are available per the elected charger timing scenario at every location that is not the driver's place of residence or work. Note that we do not discriminate between commercial and residential locations nor do we consider the possibility that such chargers are unavailable due to use by other drivers. As such, this represents an idealized, best-case scenario with respect to providing drivers access to charging infrastructure. Charge timing scenarios are set to maximize the periods that EVs are connected to the grid, such that use of the EVs would improve the charging flexibility. The charge timing scenarios also enable active thermal management to improve battery life.

Table 4. Charge station parameters

Scenario	AC Circuit	Efficiency [16]	DC Power
Level 1(L1)	120V,16A	86%	1.6kW
Level 2(L2)	240V,32A	86%	6.6kW

3.1.2 Charge Station Selection

Each driver will select the power level of his or her power station at home. We assume that the driver will select the same power level as the charge station at his or her workplace. The public charging station provides Level 2 power to speed up the charging process. To quantify the impact of the power level on the flexibility of EV charging and the impacts on the grid, six groups of charging stations have been selected to represent driver preferences. Groups I, II, V, and VI assign charging power levels according to their battery sizes, which represents the typical way to select the charge station. Groups III and IV assign Level 2 charge stations to charge PHEV-20s at residential and work places. Both groups represent the preferences of drivers who prefer to charge their vehicle at a high power rate. Groups I, III, and V denote the EV owners who do not like public charging. Groups II, IV, and VI denote the EV owners who like public charging. All of these groups are used to study the impact of public stations and charging rates on battery life.

3.2 Simulation Results

3.2.1 The Effectiveness of the Delayed and Smart Charging Methods on the Peak Shaving

Figure 3 compares the time percentages of the six groups of charging stations with the three charging methods. The opportunity charging method mostly charges vehicles at Off Peak and Peak time blocks and uses 5% and 10% of charging time to charge vehicle at Super Off Peak and Super Peak, respectively. The opportunity charging method does not fully utilize the renewable energy and TOU rates. The delayed charging method significantly shifts the charging time from high TOU rates to low TOU rates, which improves the renewable energy utilization and reduces the charging cost. Compared with the delayed charging method, the smart charging method only shifts the charging time from high TOU rates to low TOU rates with public charge stations. The high power levels of charging stations, large battery sizes, and public charging improve the effectiveness and flexibility of the delayed and smart charging methods on peak shaving.

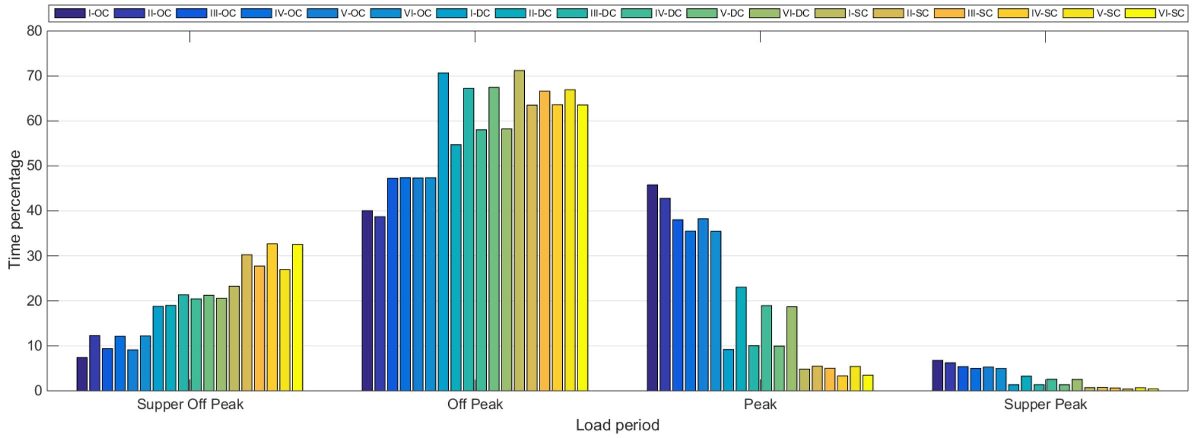


Figure 3: The charging time percentages of six groups of charging stations with three charging methods, where OC, DC, and SC denote opportunity, delayed, and smart charging methods, respectively.

5.2.2 Charged Energy Throughput and Benefits Analysis

Figure 4 compares the annual electricity cost of the six groups of charging stations in Table 5 with the three charging methods. Delayed charging reduces the annual electricity cost to 70% of the annual cost of opportunity charging. The cost reduction mainly comes from shifting the charging time to lower TOU rates, especially from Peak and Super Peak times to Off Peak times. The smart charging method further reduces the annual electricity cost. Considering battery degradation, range anxiety, and additional overhead for the communication devices and components for SOC management, the reduced electricity cost may not cover the additional overhead to enable SOC management and battery degradation. Public and/or Level 2 charge stations provide more opportunities and energy to charge vehicles, which increases charging flexibility and reduces the electricity price for delayed and smart charging. A large battery provides more flexibility for shifting the charging time from peak and super peak periods to Off Peak and Super Off Peak periods. An increased battery size provides more energy for driving, but it also needs to charge at peak periods to provide enough energy. Because a larger battery provides more charge-depleting miles for driving, an increased battery size does not help to reduce the annual electricity cost.

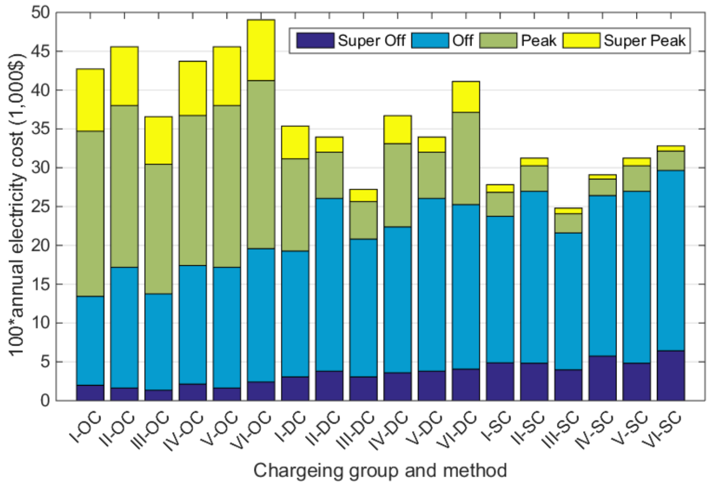


Figure 4: Annual electricity costs of six groups of charging stations with three charging methods,where OC, DC, and SC denote opportunity, delayed, and smart charging methods, respectively.

Table 5: Charge station selection

Group	I	II	III	IV	V	VI
EV Model	PHEV-20	PHEV-20	PHEV-20	PHEV-20	PHEV-40	PHEV-40
Public	-	L2	-	L2	-	L2
Work	L1	L1	L2	L2	L2	L2
Home	L1	L1	L2	L2	L2	L2

Table 6 lists the annual cost, annual charged energy, average electricity prices, and relative prices for the six groups of charging station options with three charging methods. A relative price is defined as the ratio of an actual electricity price to an average electricity price. According to the future TOU rates in Table 1, the annual average electricity price is $0.167/kWh. Using a public charging station, a higher power EVSE, and a large battery in the vehicle provide more opportunities and flexibility to charge vehicles but at an increased annual cost and charged energy throughput. The lowest electricity price for opportunity charging is $0.186/kWh, which is 11% higher than the annual average electricity price. Opportunity charging discourages EV owners from participating in the future TOU rate plan. The prices of both delayed charging and smart charging are lower than the annual average electricity prices. Because public charge stations often charge vehicles at peak or super peak periods with limited plugged-in time, delayed charging has little flexibility to optimize TOU rates for public charging. The lowest electricity price for delayed charging using public charging is $0.156/kWh, for which the relative price is 93%. Due to charging flexibility at a workplace and at home, delayed charging reduces the relative price to around 85%. Smart charging enhances charge flexibility by scheduling both the charged energy and time and can avoid most of the charge events at peak and super peak periods, especially for charge station optiions with public charging. The lowest electricity price for smart charging is $0.125/kWh, and its relative price is 74%. Smart charging provides the lowest electricity cost for charging.

Table 6: Comparison of six groups of charging station options

EVSE	Parameters	Average Price	I	II	III	IV	V	VI
Annual Charged Energy (MWh)		-	490,258	680,475	605,385	742,019	756,489	834,203
Relative Charged Energy (%)		-	100	139	123	151	154	170
Opportunity	Annual Cost ($)	-	99,968	135,430	115,951	138,575	144,461	155,494
	Price ($/kwh)	0.167	0.204	0.199	0.192	0.187	0.191	0.186
	Relative Price (%)	100	122	119	115	112	114	111
Delayed	Annual Cost ($)	-	69,475	112,088	86,272	116,359	107,617	130,328
	Price ($/kwh)	0.167	0.142	0.164	0.143	0.157	0.142	0.156
	Relative Price (%)	100	85	98	86	94	85	93
Smart Charging	Annual Cost ($)	-	64,532	88,181	78,615	99,214	99,042	103,998
	Price ($/kwh)	0.167	0.132	0.130	0.130	0.124	0.131	0.125
	Relative Price (%)	100	79	78	78	74	78	75

4 Conclusion

This paper has analyzed the flexibility and benefits of EV charging for six groups of charging stations, two types of PHEVs, and three charging methods. Delayed and smart charging methods can shift most charging events to lower TOU rate periods without compromising the charged energy and individual driver mobility needs. Using a public charging station, a higher power EVSE, and a large battery provide more opportunities and flexibility to charge the vehicle, but at an increased annual charged energy and cost. The electricity price for opportunity charging is at least 11% higher than the annual average electricity price. Opportunity charging discourages EV owners from participating in the TOU rate plan. Delayed charging effectively reduces the relative electricity price to 93% of the annual average electricty price with public charging and 85% without public charging. Smart charging enhances charging flexibility by scheduling both charged energy and time and can avoid most of the charge events at peak and super peak periods. Smart charging reduces the electricity price to 75% of the annual average electricity price. Compared with delayed charging, smart charging significantly reduces the electricity prices for scenarios using a public charging station, but slightly reduces the electricity price for the scenarios without public charging. Smart charging provides the lowest electricity cost for charging.

Acknowledgments

This work was supported by the U.S. Department of Energy under Contract No. DE-AC36-08GO28308 with the National Renewable Energy Laboratory. Funding was provided by the U.S. DOE Office of Energy Efficiency and Renewable Energy Vehicle Technologies Office. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a

References

[1]. J. Kim and J. Lee, *A model of stability*, IEEE Power and Energy Magazine, 9(2011), 75-81.

[2]. CAISO, *What the duck curve tells us about managing a green grid*, California Independent System Operator (CAISO), Folsom, CA, Tech. Rep. 1-4, 2013. [Online]. Available: https://www.caiso.com/Documents/ FlexibleResourcesHelpRenewables FastFacts.pdf.

[3]. CAISO, *Dealing with the duck: how utilities are using pricing to address projected solar impacts*, California Independent System Operator, Folsom, CA, Tech. Rep. 1-15, 2013. [Online]. Available: http://www.clean-coalition.org/site/wp-content/uploads/2013/06/Renewables-Integration Power-08 ssw-17-May-2013.pdf.

[4]. Z. Fan, *A distributed demand response algorithm and its application to PHEV charging in smart grids*, IEEE Transactions on Smart Grid, 3(2012), 1280-1290.

[5]. M. Alam, K. Muttaqi, and D. Sutanto, *A controllable local peak-shaving strategy for effective utilization of PEV battery capacity for distribution network support*, IEEE Transactions on Industry Applications, 51(2015), 2030-2037.

[6]. J. Wang, C. Liu, D. Ton, Y. Zhou, J. Kim, and A. Vyas, *Impact of plug-in hybrid electric vehicles on power systems with demand response and wind power*, Energy Policy, 39(2011), 4016-4021, Special Section: Renewable energy policy and development. [Online]. Available: http://www. sciencedirect.com/ science/article/pii/S0301421511000528.

[7]. C. Ahn, C. Li, and H. Peng, *Optimal decentralized charging control algorithm for electrified vehicles connected to smart grid*, Journal of Power Sources, 196(2011), 10 369-10 379.

[8]. N. Rotering and M. Ilic, *Optimal charge control of plug-in hybrid electric vehicles in deregulated electricity markets*, IEEE Transactions on Power Systems, 26(2011), 1021-1029.

[9]. Y. Cao, S. Tang, C. Li, P. Zhang, Y. Tan, Z. Zhang, and J. Li, *An optimized EV charging model considering TOU price and SOC curve*, IEEE Transactions on Smart Grid, 3(2012), 388-393.

[10]. C. Weiller, *Plug-in hybrid electric vehicle impacts on hourly electricity demand in the United States*, Energy Policy, 39(2011), 3766-3778.

[11]. L. Zhang, T. Brown, and G. Samuelsen, *Fuel reduction and electricity consumption impact of different charging scenarios for plug-in hybrid electric vehicles*, Journal of Power Sources, 196(2011), 6559-6566.

[12]. California Public Utilities Commission, *Long Term Procurement Planning: 2014 - 2024*, [Online]. Available: http://www.ora.ca.gov/ltpp.aspx

[13]. B. Alcorn, M. Ciminelli, N. Fugate, A. Gautam, C. Kavalec, K. Sullivan, and M. Weng-Gutierrez, *California energy demand 2014–2024 final forecast*, California Energy Commission, Tech. Rep. CEC-200-2013-004-V1-CMF, 2013, [Online]. Available: http://www.energy.ca.gov/2013publications/CEC-200-2013-004/CEC-200-2013-004-V1-CMF.pdf

[14]. CAISO, *Matching time-of-use rate periods with grid conditions maximizes use of renewable resources*, California Independent System Operator, Folsom, CA, Tech. Rep. 1-2, 2015.

[15]. H. Everett, *Generalized LaGrange multiplier method for solving problems of optimum allocation of resources*, Operations Research, 11(1963), 399-417.

[16]. E. Forward, K. Glitman, and D. Roberts, *An assessment of level 1 and level 2 electric vehicle charging efficiency*, Vermont Energy Investment Corporation, Tech. Rep., 2013. [Online]. Available: https://www. veic.org/docs/Transportation/20130320-EVT-NRA-Final-Report.pdf.

Authors

Jiucai Zhang is a research engineer at National Renewable Energy Laboratory in Golden, Colorado. He got his Ph.D. in computer engineering from the University of Nebraska-Lincoln in 2011. His research focuses on electric vehicle grid integration and battery life analysis. Prior to joining NREL, he designed and developed algorithms and software for battery management systems as well as control systems for utility-scale grid energy storage systems, telecommunications cell tower backup power systems, and electric vehicles at General Electric and A123 Systems, Inc.

Tony Markel is a Senior Engineer and has worked on systems analysis of advanced vehicles for the past 19 years at the National Renewable Energy Laboratory in Golden, Colorado. Tony is currently focused on electric vehicle grid integration technology development. He earned a B.S. in Mechanical Engineering from Oakland University in 1995 and an M.S. in Mechanical Engineering from the University of Colorado. Tony's expertise spans advanced vehicle technologies, including hybrid electric, fuel cell, plug-in hybrid, and electric vehicles and was instrumental in the development of the ADVISOR software tool for vehicle systems simulation. He leads a team researching grid integration challenges facing plug-in vehicles with a mission to highlight opportunities for electrified transportation to reduce our nation's petroleum consumption and enable a smart, renewable, future electricity grid.