Energy Research and Development Division

FINAL PROJECT REPORT

Maximizing Solar Forecast-Based Distributed Energy Resources

California Energy Commission

Edmund G. Brown Jr., Governor

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PREFACE

The California Energy Commission's Energy Research and Development Division supports energy research and development programs to spur innovation in energy efficiency, renewable energy and advanced clean generation, energy-related environmental protection, energy transmission and distribution and transportation.

In 2012, the Electric Program Investment Charge (EPIC) was established by the California Public Utilities Commission to fund public investments in research to create and advance new energy solution, foster regional innovation and bring ideas from the lab to the marketplace. The California Energy Commission and the state's three largest investor-owned utilities – Pacific Gas and Electric Company, San Diego Gas & Electric Company, and Southern California Edison Company – were selected to administer the EPIC funds and advance novel technologies, tools, and strategies that provide benefits to their electric ratepayers.

The Energy Commission is committed to ensuring public participation in its research and development programs, which promote greater reliability, lower costs and increase safety for the California electric ratepayer and include:

- Providing societal benefits.
- Reducing greenhouse gas emission in the electricity sector at the lowest possible cost.
- Supporting California's loading order to meet energy needs first with energy efficiency and demand response, next with renewable energy (distributed generation and utility scale), and finally with clean conventional electricity supply.
- Supporting low-emission vehicles and transportation.
- Providing economic development.
- Using ratepayer funds efficiently.

Maximizing Solar Forecast-Based Distributed Energy Resources is the final report for the project Solar Forecast-Based Optimization of Distributed Energy Resources (EPC-14-005), conducted by University of California, San Diego. The information from this project contributes to Energy Research and Development Division's EPIC Program.

For more information about the Energy Research and Development Division, please visit the Energy Commission's website at www.energy.ca.gov/research/ or contact the Energy Commission at 916-327-1551.

ABSTRACT

Solar photovoltaic (PV) variability and uncertainty limit solar penetration into the electric power system. Solar forecasting helps reduce the uncertainty of solar PV. The University of California, San Diego research team developed potential “use cases" for distributed energy resource technologies that include solar PV, solar forecasting, and controllable loads. The distributed energy resources can provide benefits to the electric grid and the distributed energy resource-owning utility customer.

The research team used nine sky imaging cameras in the Greater Los Angeles area with a specific focus on warehouse rooftop areas. More accurate forecasts due to real-time updates from these cameras enabled smarter charging of a fleet of electric vehicles at the workplace. Electric vehicle fleets range in number and vehicle sizes, up to a school bus. PV forecasts are leveraged to shape a combined electric vehicle load profile that consumes excess PV generation. The smart charging algorithm was successful in flattening the net load. This study also considered the economics of selected use cases. Forecasting-aware scheduling benefits the customer the most by reducing demand charges. Conversely, wholesale market sales of PV energy directly to the California Independent System Operator (California ISO) day-ahead market are economically unattractive. The ratepayer benefit of reducing loads during high grid stress are small due to high reliability of the California ISO system. Recommendations are provided to increase the availability of daytime electric vehicle charging to support the concepts developed in this contract.

Keywords: Electric vehicles, smart charging, solar forecast.

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EXECUTIVE SUMMARY

Introduction

Solar photovoltaic (PV) power sources and electric vehicles pose unique challenges to the electric grid. PV production is inherently variable because of weather, resulting in uncertain power output and potentially underserving or overserving load demand. Electric vehicles, on the other hand, increase demand. The increase in electric vehicle demand can be especially harmful if it occurs during peak time in the evening after commuters return home. Solar forecasting helps reduce the uncertainty of solar PV, and optimized scheduling of electric vehicle charging at the workplace can better absorb excess PV generation.

Project Purpose

The University of California, San Diego (UCSD) research team explored how warehouse rooftops in the Greater Los Angeles area can host substantial zero-emission solar generation and how "smart charging" of electric vehicles using solar forecasts can reduce the variability in solar power production. The project also demonstrated how electric vehicles can work in harmony with solar PV to accelerate adopting clean energy in California.

Project Process

The UCSD team developed the potential "use cases" for a suite of distributed energy resource technologies that include solar PV, solar forecasting, and controllable loads. The distributed energy resources can provide benefits systemwide to the electric grid, as well as the distributed energy resource-owning utility customer.

Nine sky imaging cameras used in the Greater Los Angeles area generated solar forecasts. This unique network of cameras provided real-time wide-area coverage with a specific focus on warehouse rooftops improving forecast accuracy. More accurate forecasts allowed smarter charging of workplace electric vehicles. These electric vehicles had long layover periods when they were connected to the grid. Electric vehicles ranged from regular cars up to medium-duty vehicles, such as school buses. Solar PV forecasts shaped a combined, electric vehicle load profile that consumes excess PV generation. Real-time control updates acted upon the present and forecast net load, as well as the connected electric vehicles and the associated departure times.

The project team demonstrated solutions to reduce solar unevenness by considering the operation of a "virtual power plant" with a large PV system and 49 daily electric vehicle arrivals. The charging schedule of each electric vehicle was optimized each day by considering five business cases:

- Noncoincidental demand charges specifically demand charges applied to demand at any time of day.
- Peak demand charges specifically demand charges applied only to demand during peak times.

- Volumetric retail energy costs with a real-time price tariff.
- Sale of PV generation to the wholesale market.
- Reduce ratepayer costs by avoiding charging during periods of high grid stress.

These first four business cases reduce customer utility bills. The project investigated the cost of maximizing PV for each business case individually, considering all business cases together and operating without any optimization. Virtual power plant operation with and without the optimized schedule was simulated for a full year from April 1, 2016-April 1, 2017.

Project Results

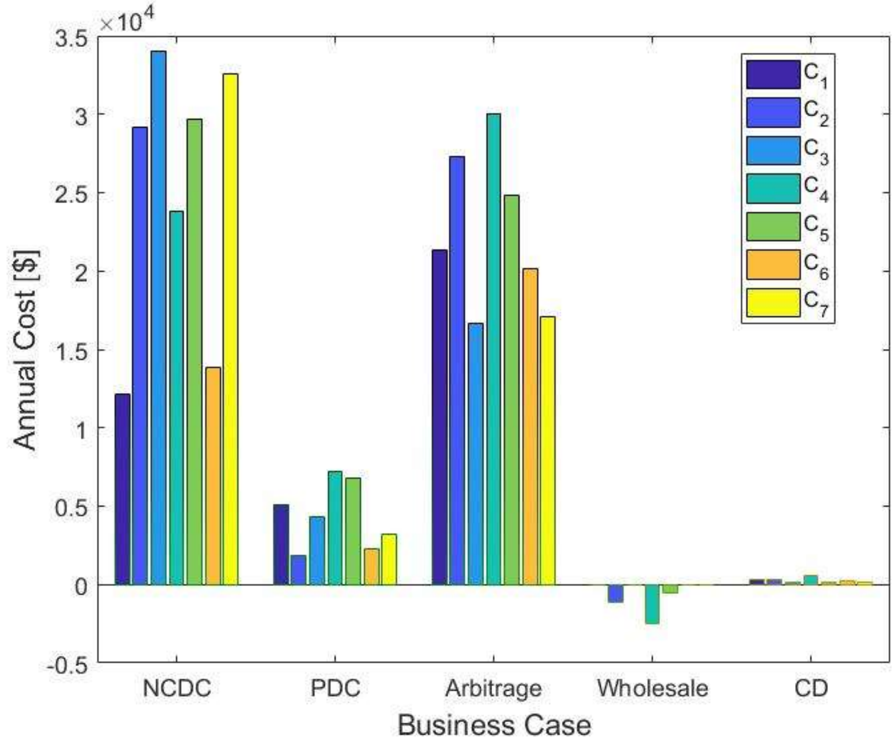
Figure ES-1 shows annual operating costs for each optimization scheme with costs separated by type. The noncoincident demand charge was the largest cost for the majority of scenarios, and optimization reduces this cost the most. The energy purchases were the second largest cost but actually tended to increase as a result of the optimization (a side effect of reducing demand charges). The wholesale market sales generated little profit in any scenario. This is from a combination of generally low spot prices (case C_4) and the tradeoff against reducing demand charges.

This study revealed that using aggregated electric vehicle load large enough to absorb the solar output on the studied circuit is many years away. For the studied circuit, roughly 9,000 electric vehicles must be connected during the solar output period to create an adequately sized energy sink to absorb the full amount of this oversupply. This is beyond the reach of today's electric vehicle adoption rates and those for years to come.

Medium- and heavy-duty commercial vehicles can play an important role in solar integration, but not all will be available for "long-dwell" layovers during solar energy output hours necessary for smart charging. School buses are uniquely suited to take advantage of excess solar energy during daytime, while most other commercial vehicles, such as forklifts, are typically in use during the day and must be charged as soon as possible.

The UCSD team made presentations at technical conferences, such as DistribuTech, Institute of electrical and electronic Engineers (IEEE) PV Specialists Conference and the Joint Center for Energy Storage Research Symposium. UCSD also conducts at least one tour each week of the microgrid to build an effective information base of the technology to stimulate market growth for microgrids and PV.

Figure ES-1: Distribution of Annual Costs When Optimizing for Different Business Cases



C_1- Non coincident demand charge only; C_2- Peak demand charge only; C_3- Energy arbitrage only; C_4- Wholesale market sales only; C_5- Capacity deferment only; C_6 – All objectives; C_7 – non-optimized charging. The costs for each business case are split by category (x-axis) into Non coincidental demand charge (NCDC); Peak demand charge (PDC); Energy arbitrage; Wholesale market sales; Capacity deferment (CD).

Source: Center for Energy Research, University of California San Diego, 2018

The solar forecasting and electric vehicle smart charging tool developed will be commercially used and tested in a new project with the Nuuve Corporation. Nuueve Corporation will test a vehicle-grid integration technology with one direction and two directional power flow using light fleet vehicles.

Moreover, controllable loads available during peak solar energy output periods could be accelerated through the following new policies and incentives:

- Encourage some electric vehicle owners to plug in at work whether they need to or not, for example, by providing lower electricity rates than for evening home charging or remunerate electric vehicle owners for allowing flexible charging or both.
- Encourage employers to add more electric vehicle charging stations than they might otherwise.
- Emphasize the load-augmentation advantages of smart fast Level 2 charging stations as they double the charging capacity compared to Level 1 and are able to communicate with the user, site host, and utility grid.
- Offer incentives for using more medium and heavy-duty commercial vehicles with “long dwell” charging patterns during the day, such as school buses.

Benefits to California

The project showed that utility customers who use solar forecasting and smart electric vehicle charging could achieve a 67 percent reduction in energy costs over the year. Monthly peak demand was reduced by 63 percent on average.

Ratepayer savings for the capacity deferment business case were orders of magnitudes smaller than other costs for all cases. However, optimizing for real-time prices also increased the ratepayer savings. This reduction was due to the overlap between peak pricing period and the times when the loss of load expected was greatest (likely by design).

CHAPTER 1: Introduction

Solar photovoltaic (PV) is an increasingly significant energy resource in California, providing near-zero emissions power to the electric grid. In 2015, solar surpassed wind to become the leading source of renewable energy for California utilities.[1] However, in contrast to other traditional resources, solar PV resources are limited by output which is variable and uncertain and depends on the amount of solar irradiance in each location. Solar forecasting helps reduce the uncertainty of solar PV by estimating the amount of solar generation that can be expected in the near future. Distributed energy resources (DERs) can further reduce the uncertainty of solar PV energy production, e.g. by storing energy generated from solar PV and dispatching it later.

In this project, the research team considers the potential business cases or “use cases" for a suite of DER technologies that include solar PV, solar forecasting, and controllable loads (including energy storage and electric vehicles). In principle, the DERs can provide benefits to both the electric grid as well as the DER-owning utility customer. The research team focuses on the role that solar forecasting can play in enhancing these benefits.

The term “use case” is defined as the intended purpose or business case for deploying and operating the suite of DER technologies. This project seeks to identify use cases for DERs that will potentially yield benefits to utility customers or the utility system as a whole, using solar forecasting techniques paired with rooftop PV and controllable load technologies. Here electric vehicles (EV) are controllable loads.

In Chapter 2, the authors provide an overview of the main controllable loads use cases that have been identified through team and stakeholder discussions. Chapter 3 describes the deployment of solar forecasting instrumentation in the Greater Los Angeles Area and forecast accuracy results. Results for using workplace EV charging to smooth net load fluctuations introduced by solar PV are presented in Chapter 4. The value proposition of doing so is presented in Chapter 5. Chapters 6 and 7 provide conclusions and recommendations, respectively.

1 http://ww2.kqed.org/news/2016/01/11/solar-power-california-top-source-of-renewable-energy.

CHAPTER 2: Use Cases

2.1 Use Case Overview

This chapter describes the four use cases for DER systems with forecasting technology that were examined as part of the overall project. The project team initially identified 10 potential use cases (Table 1) in two basic categories: those that benefit primarily the end-use electricity customer, and those that benefit all utility customers through avoided utility system costs.

Table 1: Summary of All Use Cases

Use Case	Brief Description
Use Cases for Participating Customers	
Demand Charge Management	*Controllable load is dispatched to minimize demand charges*
TOU Arbitrage	*Energy storage is used to arbitrage between peak and off-peak TOU rates.*
Wholesale Market Sales	*After optimizing for retail value, excess DER capacity participates in California ISO markets for energy and ancillary services.*
Enhanced Power Quality	DER helps reduce unwanted fluctuations in voltage that could damage equipment
Enhanced Reliability	DER helps provide backup power in the event of an outage
Green EV Charging	Charging electric vehicles using the power directly from the sun
Use Cases for Utility System (All Ratepayers)	
Generation Capacity Savings	*DER contributes to deferred or avoided investment in new generation capacity.*
Generation Energy Savings	DER reduces overall generation costs by reducing cost of fuel consumption and ancillary services (e.g. operating reserves needed for ramping).
Transmission and Distribution Fixed Cost Savings	DER avoids or defers investment in additional transmission and distribution equipment due to high demand or over-generation.
Distribution O&M Cost Savings	DER reduces cost of operation and maintenance due to operation of voltage control equipment.

Source: Center for Energy Research, University of California San Diego, 2018

2.2 Demand Charge Management

In this use case, the DER system minimizes demand charges for the participating utility customer, taking into account the customer's load profile and demand charge rate structure. End-use customers would purchase or lease the DER technologies (here solar power and electric vehicles) for their own benefit. Solar forecasting could help anticipate when solar PV production helps offset high levels of demand, and when and how much controllable load and energy storage would need to be dispatched to optimize savings.

Operation of the DER system would reduce the demand charge portion of the customer's monthly bill relative to business as usual (BAU). This benefit would accrue over the life of the DER asset and depends upon current and future utility rate structures.

2.3 Time-of-Use Energy Arbitrage

In this use case, the DER system minimizes volumetric energy charges for a participating utility customer by using the DER system to arbitrage between different time-of-use (TOU) rates. DER systems that include energy storage allow customers to charge during periods with lower TOU rates and dispatch the storage to offset consumption during periods with higher TOU rates. End-use customers would purchase or lease the integrated DER technologies for their own benefit. Solar forecasting helps anticipate how much energy will be available in a storage device to be discharged as on-peak energy during the following period.

Operation of the DER system would reduce the energy portion of a customer's monthly bill relative to BAU. This benefit would accrue over the life of the DER asset and depends upon current and future utility rate structures.

2.4 Wholesale Market Sales

In this use case, DERs would generate revenue for the participating customer through participation in California's wholesale energy markets, which are operated by the California Independent System Operator (California ISO). In principle, a system with controllable load equipment or an energy storage device can participate by providing market products, including energy and ancillary services. California ISO has specific rules governing how nongenerator resources (such as storage) and controllable loads can participate in these markets.[2] For this investigation, the primary focus will be the ancillary services markets, where participating customers can be remunerated for the provision and consumption of power on short notice. To participate in ancillary services markets, information from the DER system (e.g. capacity, bid price, etc.) would need to be provided to California ISO. California ISO would then provide instructions to dispatch (or not dispatch) the DER resource. Wholesale market participants whose bids

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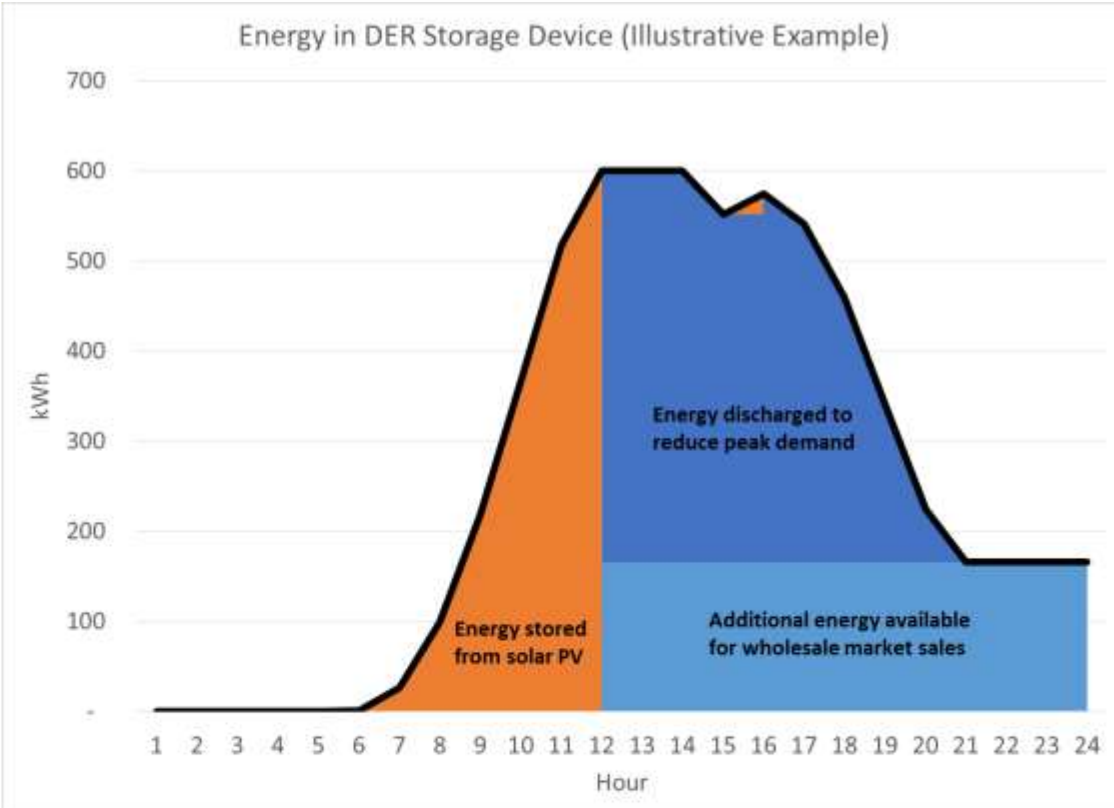
2 See https://www.caiso.com/participate/Pages/Storage/Default.aspx or https://www.caiso.com/participate/Pages/Load/Default.aspx#PL.

successfully clear are awarded a payment based on the market clearing price, including any participating DER resources. Thus, DER owners stand to benefit financially if they are able to successfully deliver wholesale market products that clear the market.

Figure 1: Energy Storage Component Use for Retail Bill Benefits and Wholesale Revenues



How the energy storage component of a DER system could be used to provide retail bill benefits and wholesale revenues
Source: Center for Energy Research, University of California San Diego, 2018

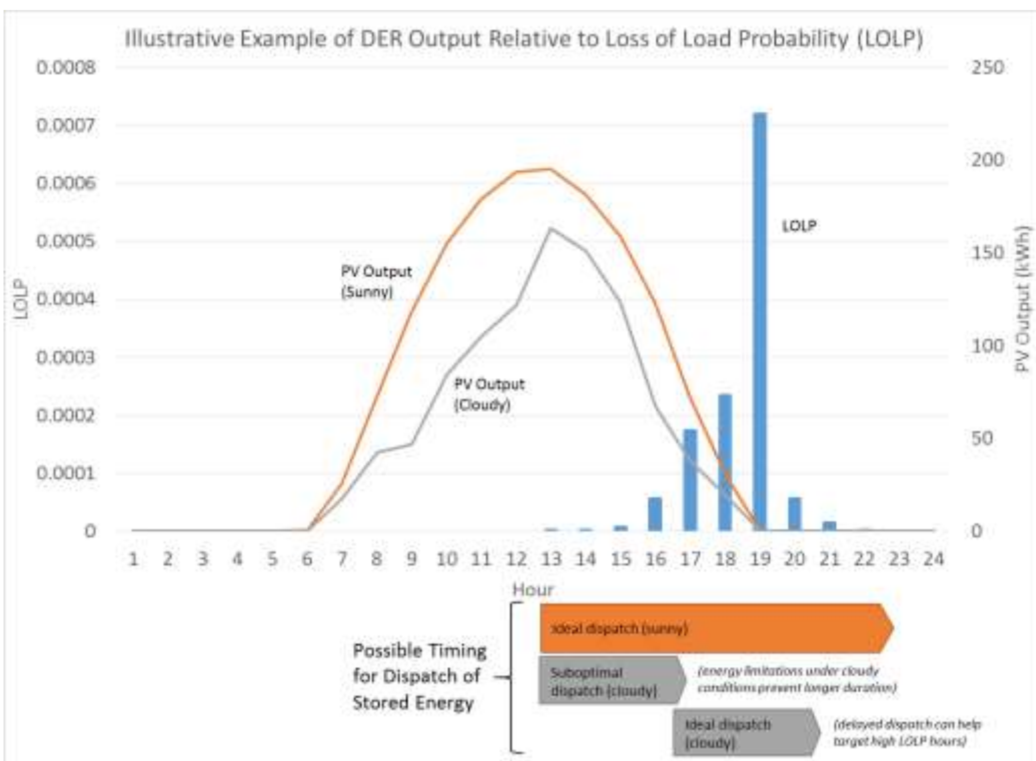
2.5 Generation Capacity Savings

The electric system must be planned to maintain resource adequacy (RA), ensuring sufficient generation is installed to meet system peak demand. The traditional planning approach was to install new supply-side generation resources as demand grows over time. New plant costs would ultimately be borne by all utility customers through increased rates. Today, demand-side resources, such as DERs, leverage customer investments to help reduce demand and, therefore, avoid or delay installation of costly new power plants that would otherwise be needed for system peak.

Increasingly, system planners are also seeking resources to meet constraints beyond peak capacity. In particular, flexible resources are necessary to address increased ramping needs due to higher penetrations of solar PV. Ramping capability has traditionally been provided by conventional resources like gas-fired combustion turbines. However, DERs that can quickly charge and discharge to follow rapidly changing load conditions offer another potential solution. Flexible DER resources will become increasingly valuable as ramping needs increase over time.

This use case considers the benefits to all utility customers that can be realized by avoiding investment in new supply-side generation capacity by installing DERs. Energy generated by solar PV or a reduction in load through a load-controlling device can all contribute to a reduction in overall customer demand and, therefore, provide capacity value to the grid Figure 2. Solar forecasting does not inherently increase or decrease energy demand on its own, so the contribution of solar forecasting to avoid capacity is less direct. However, in some circumstances, greater certainty about solar output may reduce the need for system operators to carry operating reserves for unexpected solar ramping events. To the extent that utilities would invest in additional new supply-side generation to provide these operating reserves, solar forecasting may also provide capacity value through DER. In all cases, the capacity benefit from DER is likely to be more pronounced in transmission-constrained areas with local capacity needs (such as the Greater Los Angeles Area). In this use case, the DER system could be either directly owned by the utility or subsidized by the utility on behalf of its customers to capture the value of the avoided generation capacity costs.

Figure 2: DER With Solar Forecasting Could Help Target Energy Output to Hours of the Day



When resource adequacy value is highest. This condition can help increase effective load-carrying capacity and in turn the capacity-deferral value of the resource.
Source: Center for Energy Research, University of California San Diego, 2018

CHAPTER 3: Sky Camera Deployments

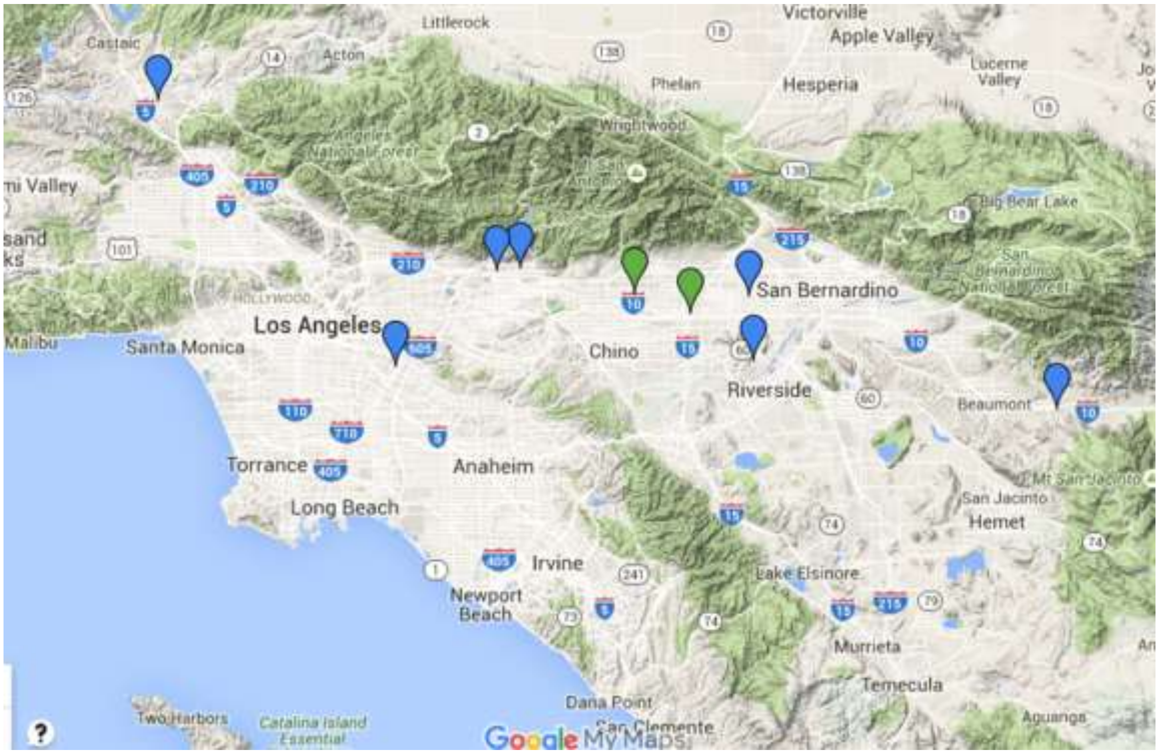
3.1 Hardware

The UC San Diego team has developed a high-quality sky camera system (UCSD Sky Imager or USI) to provide observational data for solar forecasting. The USI captures images using an upward-facing, charge-coupled device (CCD) image sensor that senses red-green-blue (RGB) channels at 12 bit precision and 1,748 x 1,748 pixel resolution. Using composite high dynamic range (HDR) imaging, the USI outputs fish-eye images at 16 bit with a dynamic range of 84 decibels (dB). When used with UCSD's advanced computer vision and image processing methods, the USI can identify, geolocate, and track clouds accurately with high spatial, temporal, and radiometric resolution. At a cost of $30,000, the USI is not always economical for solar forecasting. Therefore, the majority of the Greater Los Angeles Area camera network was equipped with lower-cost sky cameras. The Vivotek FE8171V is a fisheye fixed dome network camera featuring a 3.1 MP-resolution sensor.

3.2 Deployment Sites

The South Coast Air Quality Management District (SCAQMD) agreed to host sky imaging systems at air pollution monitoring sites. Figure 3 show the sites where sky imagers were used. Figure 4 shows photographs of each sky imaging system as used and a sample sky image.

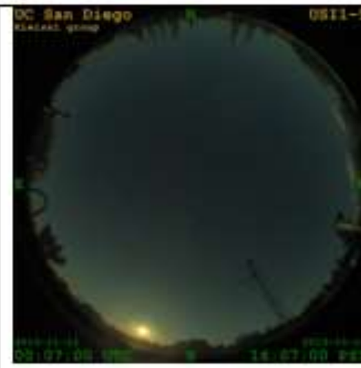
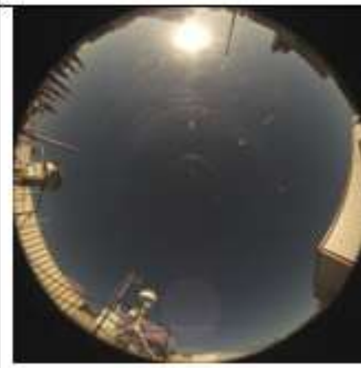
Figure 3: Map of Sky Imager Site Locations

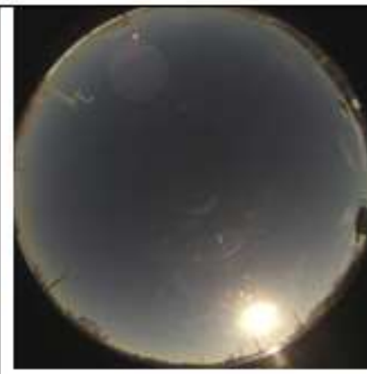


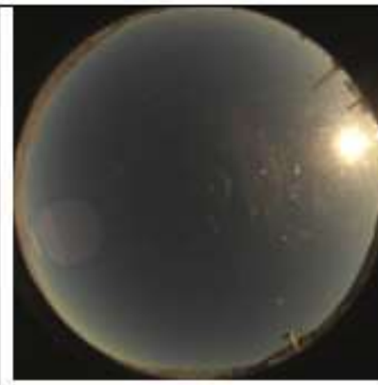
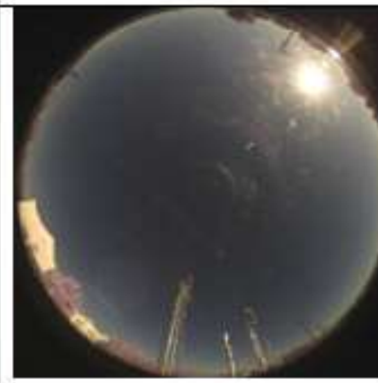
Source: Center for Energy Research, University of California San Diego, 2018

Figure 4: Photographs of Each Sky Imaging System as Installed and a Sample Sky Image

Location	Photo of sky imager as deployed	Sample Sky Image
Ontario Etiwanda-Near Road (UCSD Sky Imager)		 Date: 11/10/2015 Time: 4:07PM PST

Upland (UCSD Sky Imager)		 Date: 11/10/2015 Time: 4:07PM PST
Fontana (Vivotek)		 Date: 12/8/2015 Time: 3:27PM PST
Glendora (Vivotek)		 Date: 12/8/20153 Time: 3:07PM PST

Azusa (Vivotek)		 Date: 12/8/2015 Time: 3:07 PM PST
Santa Clarita (Vivotek)		 Date: 12/14/2015 Time: 3:01 PM PST
Pico Rivera (Vivotek)		 Date: 12/14/2015 Time: 3:18PM PST

Banning Airport (Vivotek)		 Date: 12/8/2015 Time: 3:27PM PST
Rubidoux (Vivotek)		 Date: 12/8/2015 Time: 3:10PM PST

Source: Center for Energy Research, University of California San Diego, 2018

3.3 Solar Forecast Method

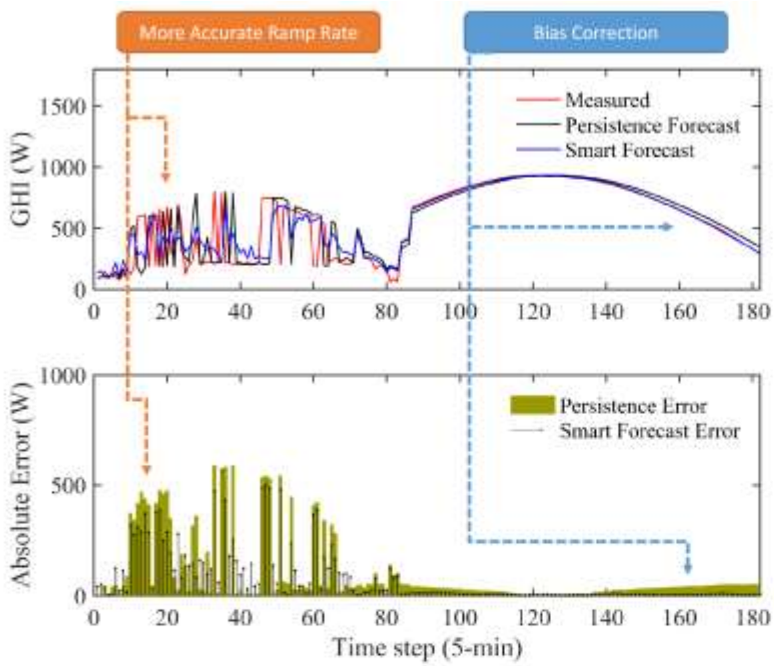
The solar forecasting model in this work is developed based on Artificial Neural Network (ANN), a popular stochastic learning tool for pattern recognition, data classification and regression, and is useful for non-linear input/output mapping. Therefore, ANN is commonly employed in solar forecast applications. The ANN model generates predictions using inputs of endogenous lagged Global Horizontal Irradiance (GHI) values and three exogenous numerical image features extracted from sky images based on the Normalized Red Blue Ratio (NRBR). The weights and bias of ANN are estimated using the training dataset by a supervised learning process. The calculations of error metrics are limited to instances during daytime. The persistence model is the baseline model to benchmark the ANN forecasting models.

3.4 Solar Forecast Accuracy

3.4.1 By Site

The ANN forecast model and the reference persistence model are evaluated on the testing dataset. Sample time series of 10 minutes ahead GHI forecasts and absolute errors against measures GHI are plotted in Figure 5. The forecasts show excellent performance during clear periods. The forecasts are capable of predicting the presence of solar ramps under different weather conditions. The ability to predict solar ramps is considered a success of solar forecasts for most solar energy applications. In addition, some of the improvements achieved by the smart forecast are annotated in the figure: more accurate predictions of ramp rates during cloudy period, and the forecast bias is minimized during clear period. Therefore, the proposed model achieved the highest overall forecast skills.

Figure 5: Sample Time Series of 10-Minutes-Ahead GHI Forecasts



Includes Absolute Errors Against GHI at Banning Airport
Source: Center for Energy Research, University of California San Diego, 2018

Table 2 quantifies for all models and all locations how the relative root mean square error (rRMSE) increases with the forecast horizon, because cloud conditions constantly change and these changes are more difficult to detect farther in the future. For example, the persistence rRMSE at the Azusa increases from 0.175 to 0.226 when the forecast horizon increases from 5 minutes to 15 minutes.

For all locations, the ANN forecast models achieve error metrics that are lower than the reference persistence model, particularly for longer horizon forecasts. The ANN model outperforms the persistence model every time step, achieving averaged forecast skills between 6-14 percent.

Table 2: GHI Forecasting Results for 5-, 10-, and 15-Minute Horizons

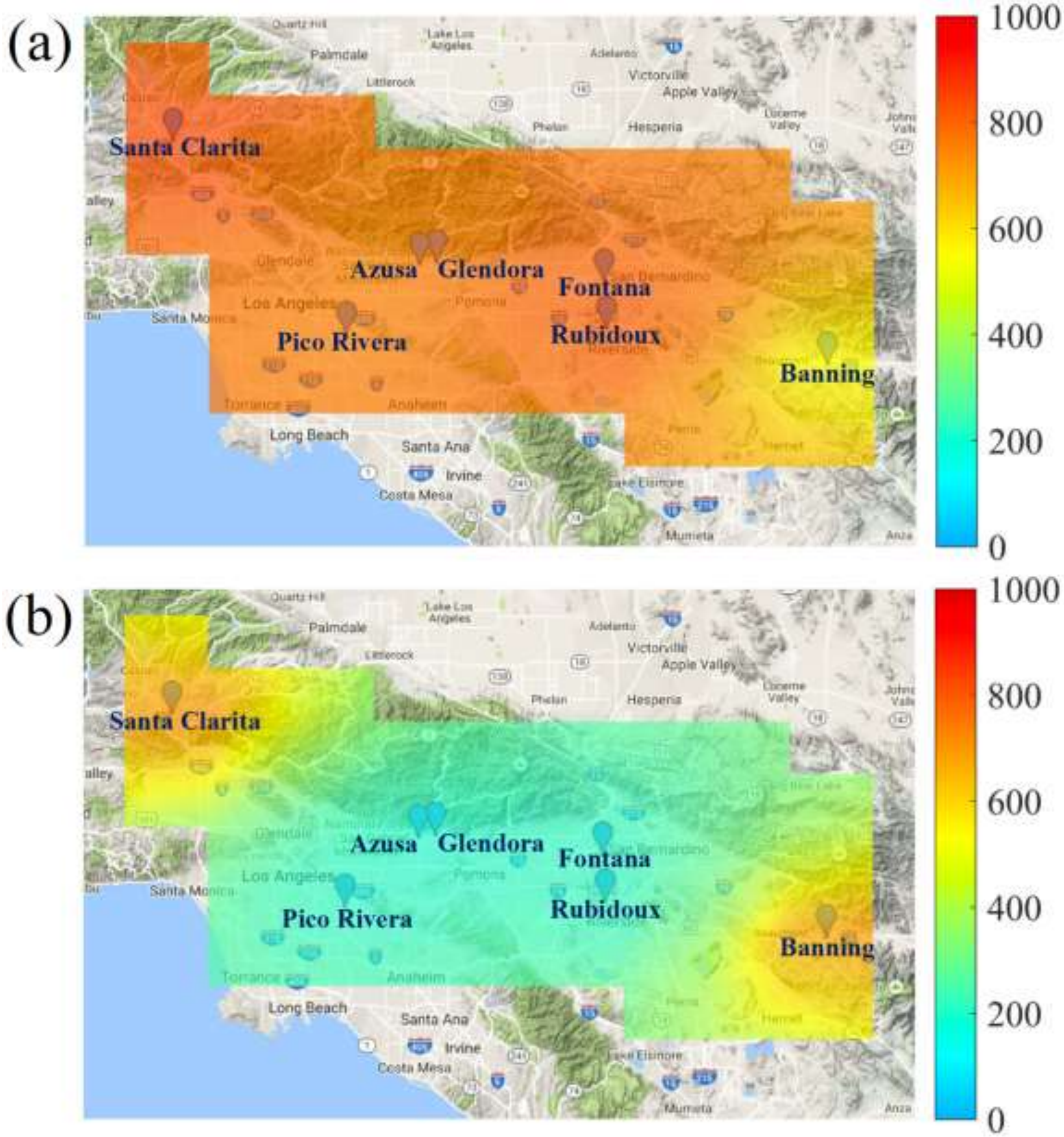
		Persistence Forecast		ANN Forecast		Spatial Forecast	
		5 min	**15 min**	**5 min**	**15 min**	**5 min**	**15 min**
Azusa	rRMSE [-]	0.175	0.226	0.158	0.195	0.264	0.273
	s [-]			0.095	0.138		
Banning	rRMSE [-]	0.146	0.193	0.134	0.172	0.249	0.254
	s [-]			0.080	0.110		
Fontana	rRMSE [-]	0.224	0.285	0.212	0.259	0.260	0.262
	s [-]			0.054	0.091		
Glendora	rRMSE [-]	0.191	0.243	0.175	0.216	0.323	0.328
	s [-]			0.080	0.109		
Pico Rivera	rRMSE [-]	0.175	0.232	0.162	0.205	0.225	0.232
	s [-]			0.077	0.117		
Rubidoux	rRMSE [-]	0.202	0.252	0.185	0.226	0.270	0.284
	s [-]			0.086	0.102		
Santa Clarita	rRMSE [-]	0.179	0.229	0.163	0.199	0.255	0.258
	s [-]			0.090	0.131		

Acronyms: Mean absolute percentage error (MAPE), relative root mean square error (RMSE), forecast skill(s).
Source: Center for Energy Research, University of California San Diego, 2018

3.4.2 Spatial Forecasts

The sky imager network can also be leveraged to provide continuous spatial forecasts. Sample 10-minute irradiance forecast fields are presented in **Error! Reference source not found.** for two time instances on a mostly clear day and a mostly cloudy day, respectively. Overall statistics are presented in Table 2. The interpolated forecasts for all locations have larger errors than single locations forecasts discussed in the previous section. These results suggest that the distribution density of monitoring stations is overly sparse for the vast Greater Los Angeles Area. A distance of less than 10 kilometers (km) between two sensors would be recommended to optimize the forecast accuracy when deploying a sensor network. The existing station distances range from 5 km (Azusa to Glendora) to 158 km (Banning to Santa Clarita). The L.A. metropolitan area with an area of 12,561 square kilometers (km^2) would require at least 126 sites.

Figure 6: Sample GHI Field of 10-Minute-Ahead Spatial Forecasts



For (a) a Mostly Clear Day and (b) a Mostly Cloudy Day The color scale is in W/m^2. The blue drop markers represent the locations of SkyCam stations.
Source: Center for Energy Research, University of California San Diego, 2018

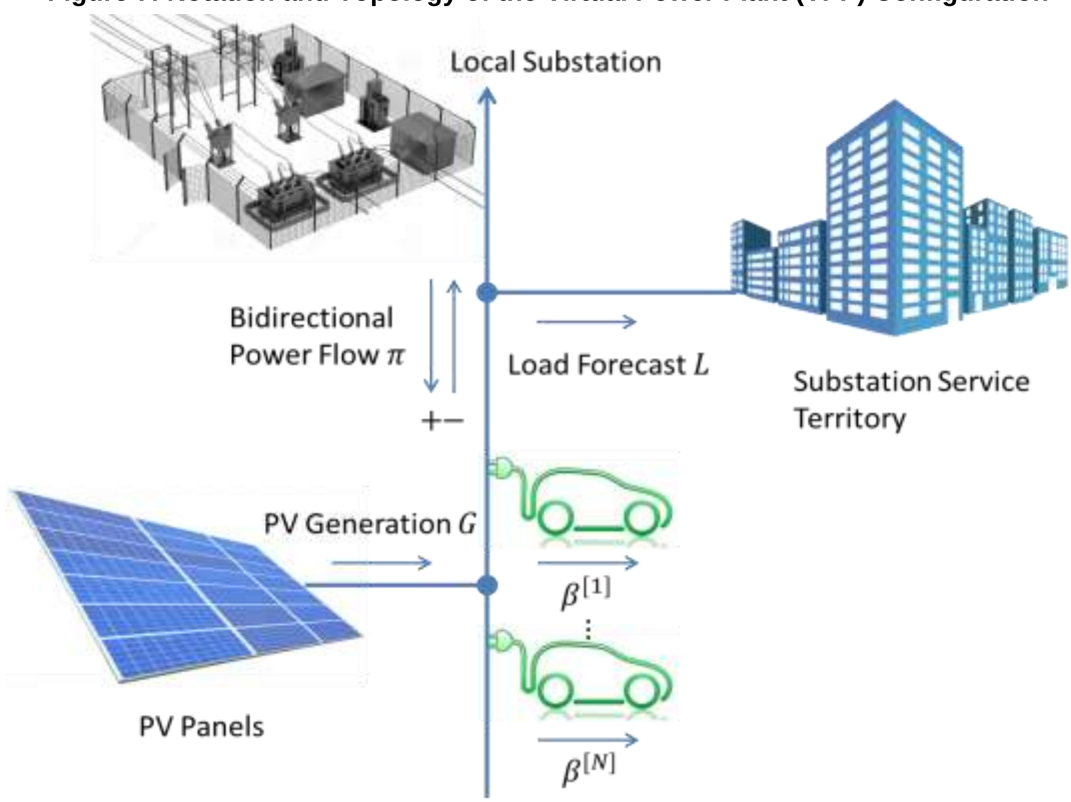
CHAPTER 4: Scheduling EV Charging to Reduce PV Variability Impacts

4.1 Scheduling Overview

Distribution feeder circuits are designed to tolerate considerable variability. However, sharp variations in energy inputs at different locations on a given circuit can undermine power quality for utility customers and create economic challenges for the distribution and transmission system operators. Providing a technical pathway to address these variations in real time and smooth them with controllable loads holds tremendous value. Such a construct of jointly operated PV and controllable (here EV) loads is called a *virtual power plant* (VPP) and illustrated in Figure 7. For example, the EV loads on high PV penetration circuits can be leveraged to:

- Maintain the net load on a given distribution circuit within a "tolerance band."
- Achieve better voltage control at different locations on the circuit.
- Avoid energy flowing from customers towards the substation during peak PV output periods.

Figure 7: Notation and Topology of the Virtual Power Plant (VPP) Configuration



Source: Center for Energy Research, University of California San Diego, 2018

Real-time solar PV forecasting technology can help distribution systems reduce solar energy variability and associated power quality and economic challenges. In particular, the authors demonstrate how a controllable load consisting of workplace plug-in electric vehicle (PEV) loads (with long layover periods during which they are connected to the grid) can be controlled in a way that:

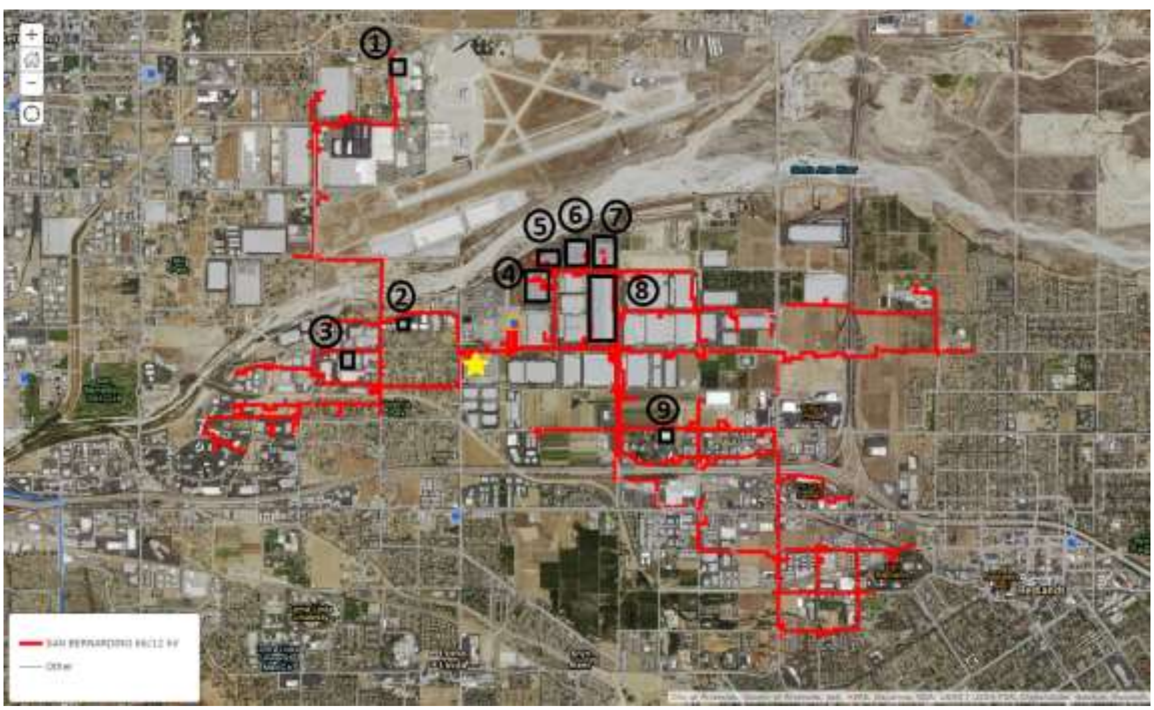
- Leverages real-time solar energy output forecasts for PV arrays.
- Respects the energy needs and planned departure time of the PEV owner.
- Is seamless and simple for the consumer.
- Aligns with the location-specific control signals.
- Addresses power quality challenges using controllable PEV loads.

4.2 Load Curve, PV Output, EV Fleet, and Communications

The project team modeled (Figure 8):

- A load curve on a Southern California Edison distribution feeder circuit in San Bernardino.
- The output forecast of large warehouse-scale solar PV arrays on commercial buildings connected to the San Bernardino feeder.

Figure 8: Rooftop PV Systems and USI in Substation Service Territory



Rooftop PV systems in black, USI in yellow, and Substation Service Territory in red
Source: Center for Energy Research, University of California San Diego, 2018

Load and solar generation were then combined to create a net-load curve for the circuit. Subsequently, the project team simulated how an intelligent load control system connected to local clusters of PEV charging stations can use PEV loads to reduce variability challenges on the distribution circuit. Light- and medium-to-heavy-duty PEVs with varying battery sizes, onboard charger capacities, arrival and planned departure times were simulated.

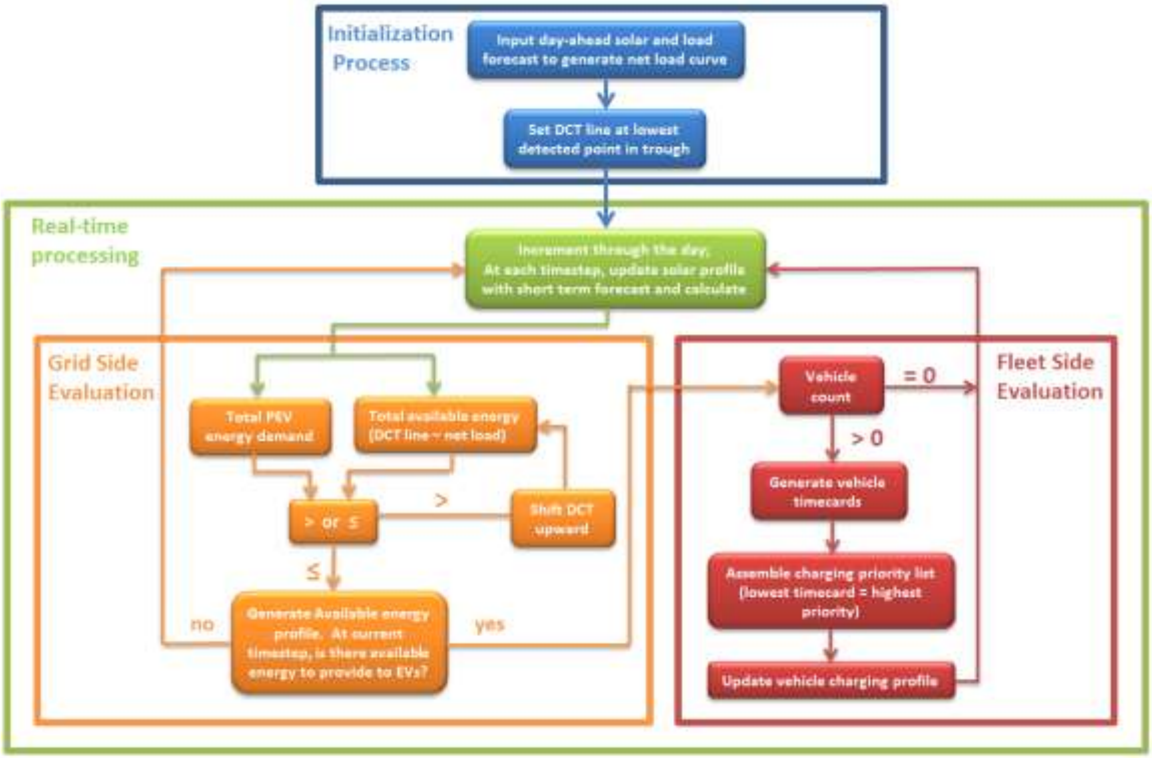
The technology to implement such smart charging already exists for example in the standard for bidirectional communications between PEVs and charging stations known as ISO/IEC 15118: vehicle-to-grid communication interface. This global interoperability standard provides electric system operators with a scalable control system that translates real-time grid conditions into a common, unique language that PEVs can understand and react to in real time.

A sample demand clearing house logic sequence (DCHLS) to govern PEV charging is illustrated in Figure 9. The PEV energy management success metric is a PEV load profile that flattens a load curve that experiences a deep valley during midday due to PV generation. At the beginning of each day (midnight), the DCHLS reads an input 24-hour-ahead solar and (non-EV) load forecast to produce a net load profile. A valley in the net load profile is expected during midday hours as result of high PV penetration. Throughout the day, the DCHLS conducts evaluation on the grid side and the fleet side in 15-minute intervals. On the grid side evaluation, the total available energy for PEV charging is computed at each time step. The minimum in net load (valley) is increased (filled) until the resulting charging energy equals the energy required by the PEVs. As a result, the daily net load profile including PEV charging will exhibit less variability, which reduces grid impacts such as tap operations and voltage variations, and promotes grid wide energy balancing.

From a PEV user perspective, energy management is successful if all vehicles are charged at departure time. From a grid perspective, the energy management is optimal if the DCT is constant throughout the daytime charging period. Then the PEV charging energy is distributed across the daytime to flatten the net load.

Charging power is controlled through the use of a demand control threshold (DCT). If grid net load is above the DCT, EV charging is interrupted. If grid net load falls below the DCT, charging resume. In a real-time environment where EVs connect at different times or disconnect prematurely, the DCT level is adjusted at every time step, depending on updates to the net load forecast, current number of vehicles connected, and total fleet energy demand. As vehicles plug in, the DCT level will rise (filling the valley from the bottom up) until total available energy equals the total energy demand for the remainder of the day.

Figure 9: Demand Clearing House Logic Sequence Flow Diagram

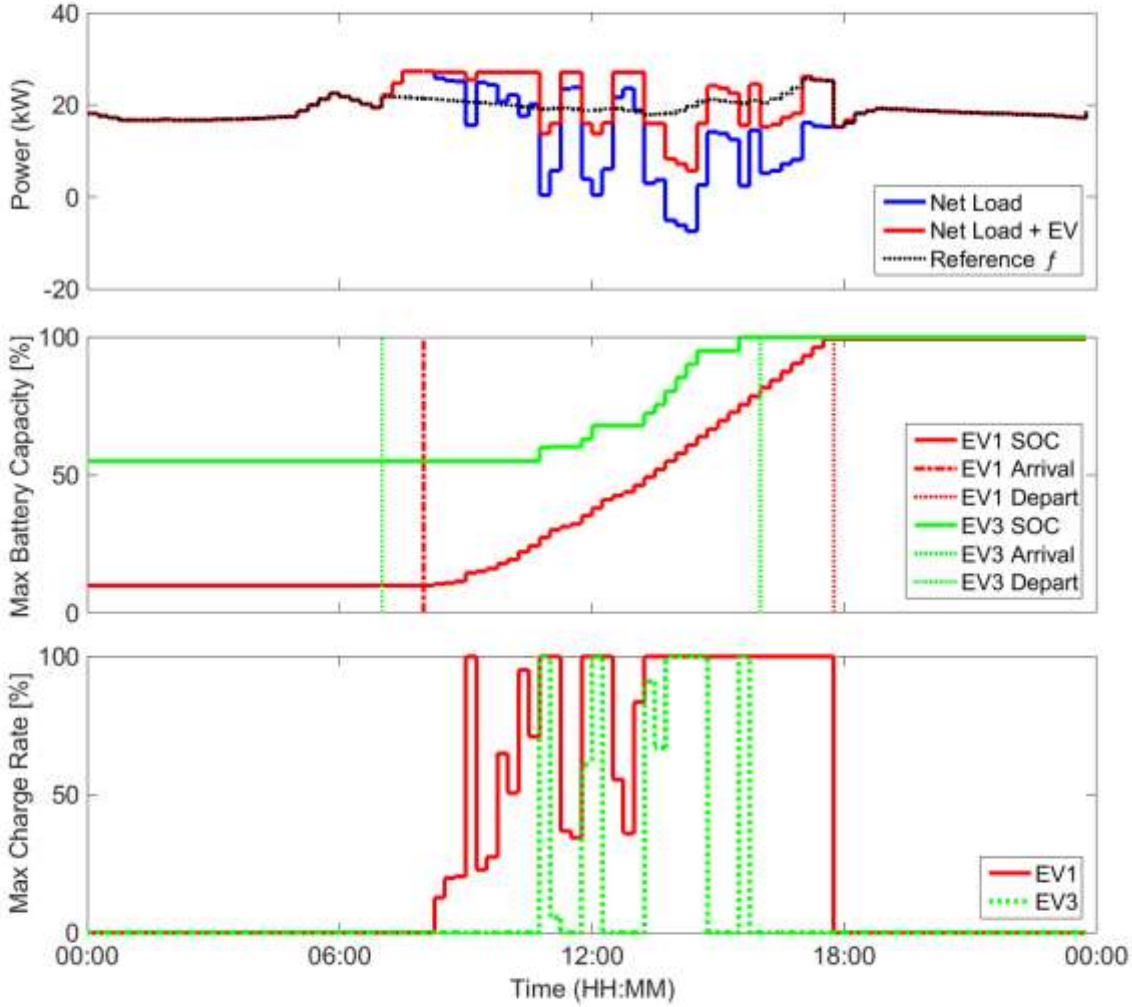


Source: Center for Energy Research, University of California San Diego, 2018

4.3 One-Day Case Study

The optimization is illustrated on a single day to produce an EV charging schedule given perfectly forecasted load and solar generation. A day with broken cumulus clouds was chosen, producing high PV output variability. Figure 10 shows the valley-filling/optimization results for two EVs. The actual grid net load profile (blue) is computed by subtracting PV power from the feeder load. The area between blue and red indicates the share of the energy valley that is absorbed by EV charging. EVs with initial state of charge (SOC) of 10% and 55% are fully charged (100%) by the scheduled departure time (middle plot).

Figure 10: Sample Optimized Electric Vehicle (EV) Charging Schedule for Valley Filling with Two EVs



Top: Original grid net load profile (load demand minus PV power, blue) showing an energy valley during midday interrupted by episodes of cloud cover. Optimized net load (red, including EVs) is obtained by filling the valley towards a reference power (f, black). Middle: EV state of charge (SOC) in %. Colors distinguish EV with their arrival time (dashed) and departure time (dotted). Bottom: EV charge power divided by its maximum charge capacity.

Source: Center for Energy Research, University of California San Diego, 2018

The algorithm dynamically shifts the charge schedule to periods with an energy valley while obeying all constraints. For example, EV 1 has a large energy demand of 76.5 kWh, but the layover period of 9 hours, 40 minutes is comparably short, because EV 1 requires 7 hours, 39 minutes of charging at the highest charging rate to reach full charge. Thus, the algorithm has limited flexibility (two hours) to shift the battery charge schedule or reduce the charging rate or both. EV 1 connects to charge at 08:00 PST, and charging occurs from 08:15 PST when PV generation starts to depress the net load profile. The two-hour flexibility is used to charge at a rate that is below the maximum capacity from 08:15 to 13:30 PST. By lowering the charge rate, the algorithm shifts EV charging from times of relatively large net load to times with a larger energy valley later in the day. The algorithm increases charge power of EV 1 to maximum capacity after

13:30 PST so that the EV can be fully charged exactly at its departure time. because the algorithm is not able to completely shift the EV charging to periods with larger energy valleys due to limited EV flexibility, it schedules charging during off-peak solar generation (08:00 – 10:45 PST).

On the other hand, EV 3 has more charging flexibility with a smaller energy demand (7.7 kWh or 2 hours, 20 minutes of charging at maximum capacity), which is spread over about the same layover period (nine hours). Thus, the algorithm can schedule charging to occur only during the four major energy valleys (clear periods during midday) while limiting charging in cloudy conditions and at the beginning and end of the day. EV 3 is also fully charged at its departure time.

4.4 Pilot Testing and Simulation Results

4.4.1 Solar Forecasts

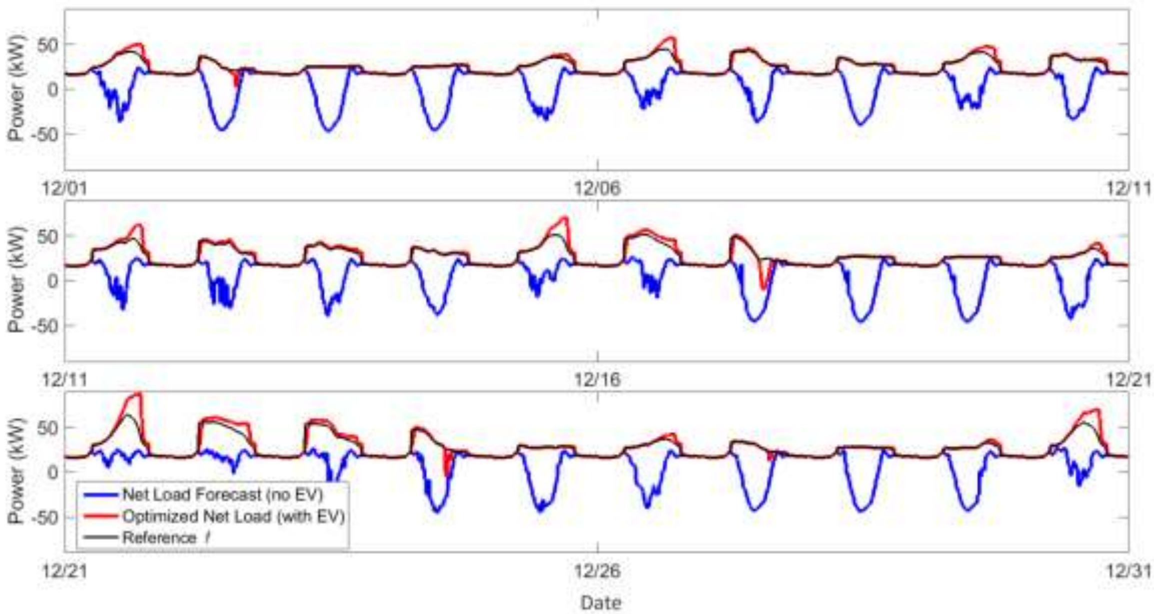
To evaluate how the VPP performs with actual solar forecasts compares to benchmark solar forecasts, a suite of solar forecasts is input.

1. Base Forecast: A 24-hour persistence forecast (denoted as "p") is defined as solar power data at the same time of the previous day. The method is also conventionally adopted in modeling load forecast in power system.
2. Perfect Forecast: Perfect solar forecast (real PV generation data, denoted as "perfect") brackets the net load flattening that is achievable.
3. Operational Forecasts (denoted as "p+SkyCam"): Since SkyCam forecasts are limited to a 15-minute horizon, only the first time step of the persistence (base) forecast is corrected by replacing the 24-hour persistence forecast output, while the output in the remaining 24-hour time horizon is left unchanged.
4. Benchmark forecast (denoted as "p+perfect") is similar to the operational forecast, but now the first 15 minutes of the 24-hour persistence forecast are replaced with real PV generation data. This forecast elucidates whether improvements in the short-term solar forecast accuracy would result in better flattening of the net load.

4.4.2 Light-Duty EV Charging

A full month of optimized net load ($NL_{p+SkyCam}$) with 31 light-duty EVs is analyzed in detail and illustrated in Figure 11 along with reference f (preferred grid net load profile determined from the expected net load and the cumulative EV energy demand) and net load based on perfect and operational forecast without EV. On most days, valleys are completely filled, and $NL_{p+SkyCam}$ is closely aligned with the reference f, indicating that the method works as designed. On clear days, for example December 3–4, 2016, the energy valley is large and smooth, which provides a sufficient amount of energy to charge all EVs. On cloudy days (for example December 10 and December 13, 2016), solar variability is large and less energy is available in the valley, resulting in increased $NL_{p+SkyCam}$ level and variability.

Figure 11: Results for 30 Days of EV Scheduling Using 31 EVs

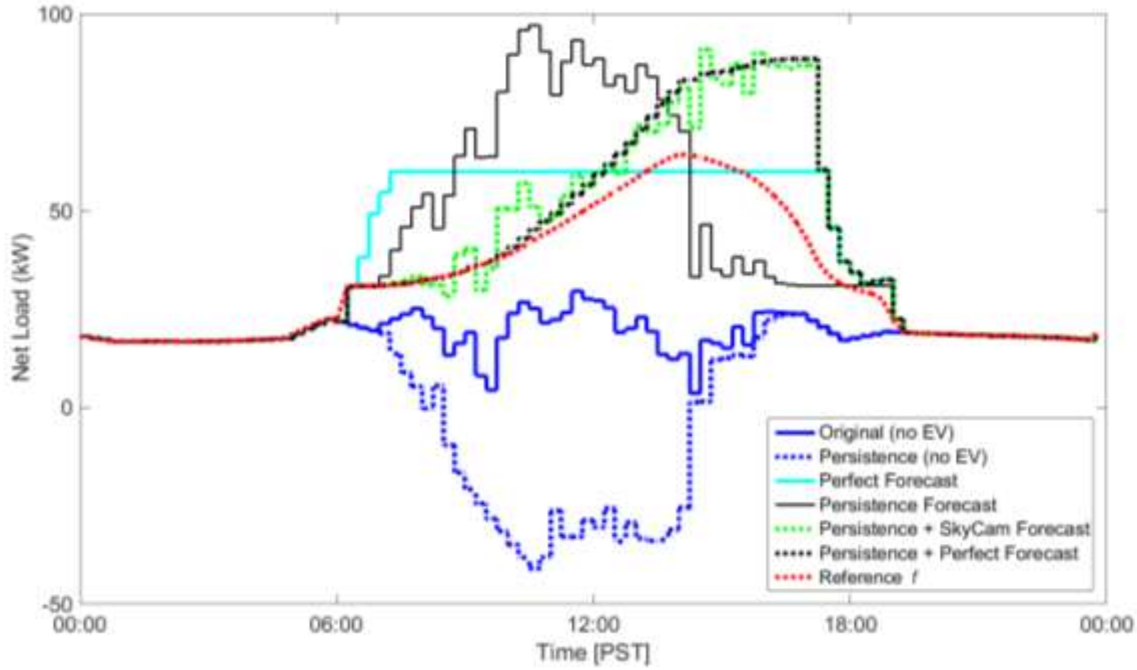


On each day, the grid net load (blue) is created based on a perfect load forecast and operational solar forecast. Smart EV charging reduces net load variability (red) in reference to a preferred net load profile (black). The analyzed days were from 2016.
Source: Center for Energy Research, University of California San Diego, 2018

Exceptions are observed on December 6, 11, 15, 17, 21 and 30, with a large peak in the $NL_{p+SkyCam}$. For example, on December 21, an overcast day was preceded by a clear day. Figure 12 shows that the persistence solar forecasts source of NL_p (black) predicts a large valley (dotted blue) indicating a clear day while the day is actually overcast (solid blue). In this scenario, the algorithm introduces one major peak on the optimized net load (10:00 – 14:00 PST).

While short-term forecast improvements modify the charging pattern, $NL_{p+SkyCam}$ (dotted green) and $NL_{p+perfect}$ (dotted black) actually do not noticeably improve net load variability and peak demand. This is because the algorithm optimizes EV charging for the entire day, while the short-term forecast corrects only the first 15-minute interval. Operating under the assumption of persistence forecast for less than 15-minute horizons, the algorithm expects a large energy valley later in the day and delays most of the noncritical EV charging. When the persistence forecast is replaced with the SkyCam or a perfect forecast for the next 15 minutes, the forecast net load increases. Thus, the optimization preferentially schedules EV charging for less than a 15-minute time horizon. At the next time step, the situation is similar, and EV charging is again rescheduled for later. Noncritical EV charging is therefore delayed until 13:00 PST, when early departure EVs start to approach the associated charge time limit. To reach full charge by the EV departure time, early departure EVs have to start charging at the maximum charge capacity immediately. Since solar energy production is still depressed, net load rises steeply between 11:00 to 14:00 PST. Net load remains elevated until 17:00 PST, when most EVs have departed, causing a steep net load down ramp.

Figure 12: Optimized Net Load Comparison Using Different Solar Forecasts Sources on Dec. 21, 2016



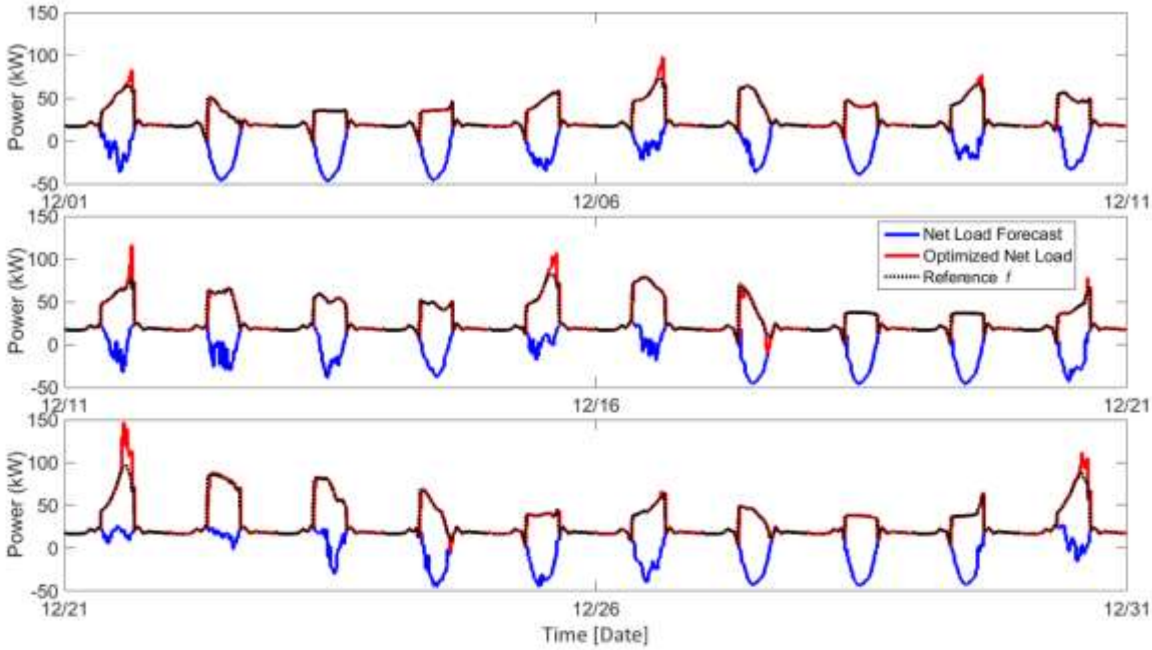
The $NL_{perfect}$ (load minus actual PV generation, blue) yields the ideal optimized net load (cyan). When PV forecasts with errors are used, EV charging profiles yield the black line for NL_p, dotted green for $NL_{p+SkyCam}$, and dotted black for $NL_{p+perfect}$. The red line indicates the targeted power f on this day. For reference, the net load of the previous day (equaling load minus PV persistence forecast) is provided in dotted blue.
Source: Center for Energy Research, University of California San Diego, 2018

This illustrates that optimization results are most deficient when sky conditions change dramatically between two consecutive days. Similar peaks are found to occur for similar day-to-day changes in sky conditions. If the present day is cloudier than the previous day, the persistence forecast will cause the algorithm to push the EV charging peak forward (December 15 and December 21). Conversely, if the present day has fewer clouds than the previous day, the persistence forecast will push the peak backward (December 17 and December 24).

4.4.3 Medium- to Heavy-Duty EV Charging

A full month of optimized net load with electric school bus charging is presented in Figure 13. The daily energy demand aggregated over all buses is chosen to be identical to the light-duty EV fleet in Section 4.4.2. Overall, the performance of valley filling is similar to light-duty EVs. However, unlike for light-duty EVs the net load profile before 8:00 PST and after 16:00 PST exhibits a power ramp. In addition, the power level of the flattened net load is noticeably higher than in Figure 12. This is a result of the limited school bus layovers; all school buses arrive in the parking lot after 8:00 PST, and by 16:00 PST all buses are on route for pickup. Thus, the layover duration is shorter than the solar day. Since the modeled school bus energy demand is equivalent to that of a light-duty EV, a shorter charging window results in a higher charging demand. The shorter charging window also unavoidably causes an up ramp in net load as the first bus connects and a down ramp as the last bus departs.

Figure 13: Same as Figure 12, but Using Electric School Buses



Source: Center for Energy Research, University of California San Diego, 2018

A better valley filling result would be expected if the school bus fleet was pooled with light-duty EV (for example early-riser residential EVs) that return from work at about the time when the school buses depart.

CHAPTER 5: Value Proposition Analysis

5.1 Motivation and Methods

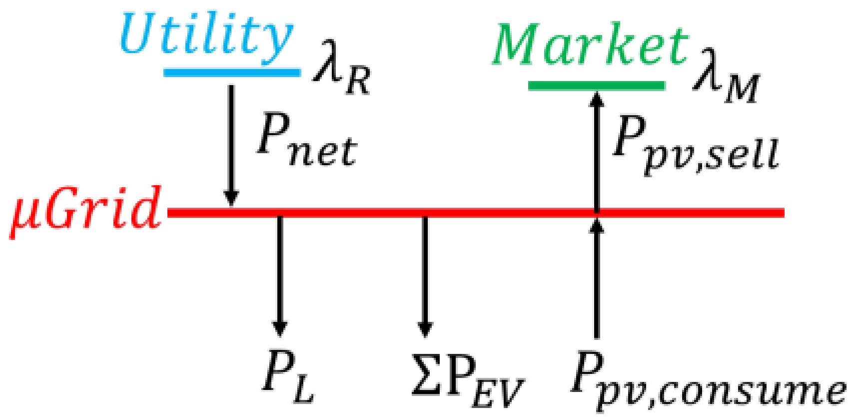
This report shifts focus to the economics or value proposition of smart EV charging for the VPP shown in Figure 14. Light-duty EV charging is optimized at a large warehouse in the Greater Los Angeles Area to create value for all ratepayers. Unlike in the optimization in Section 4, the optimum result may not necessarily be a flat net load curve. The authors aim to quantify the reduction in operating costs of the commercial customer under different charging scenarios and considering several business cases. Furthermore, they investigate additional ratepayer benefits through capacity deferment savings.

The charging schedule of each EV is optimized daily considering five business cases:

- Noncoincidental demand charges specifically demand charges applied to demand at any time of day.
- Peak demand charges specifically demand charges applied only to demand during peak times.
- Volumetric retail energy costs with a real-time price tariff.
- Sale of PV generation to the wholesale market.
- Reduce ratepayer costs by avoiding charging during periods of high grid stress (loss of load probability, LOLP).

The first four business cases reduce customer utility bills. The authors investigated the cost of optimizing around each business case individually $C_1 - C_5$, a multiobjective optimization composed of all business cases C_6, and the operation without any optimization C_7. Microgrid operation with and without the optimized schedule was simulated for a full year from April 1, 2016 – April 1, 2017.

Figure 14: The Topology of the Microgrid in Terms of Incoming/Outgoing Power Sources



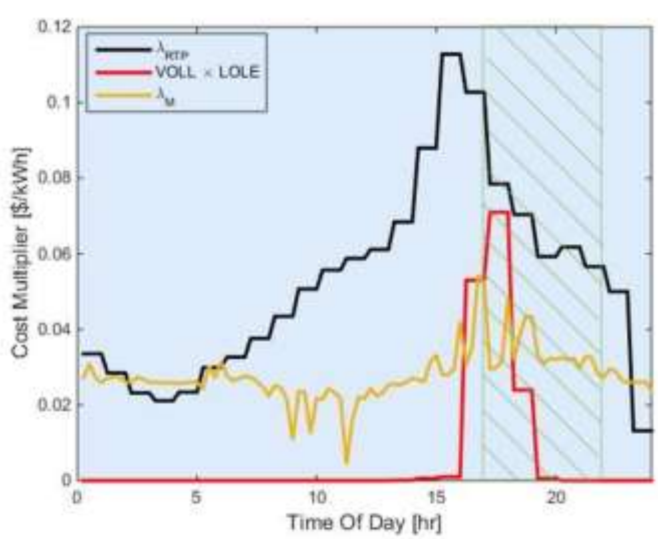
The net load at the substitution (P_{net}) is composed of the aggregate building load (P_L), aggregate EV load (P_{EV}), and less the portion of the PV power which is used to meet load locally ($P_{pv,consume}$), and purchases from the utility at the retail price (λ_R). The microgrid is also connected to the market, so that it has the option to sell a portion of its PV power that is not consumed locally ($P_{pv,sell}$) at market price (λ_M).

Source: Center for Energy Research, University of California San Diego, 2018

5.2 Case Study

To show the effects of optimized charging on the microgrid, the results for a day September 8, 2016 are introduced and discussed in the following section. This day is chosen as i) LOLP is nonzero; ii) EVs are present during peak hours; and iii) the moderate previous day temperature was 81^o F (specifically not extreme time-of-use pricing). The electric rates and generation capacity savings are shown in Figure 15.

Figure 15: Price Scheme for September 5, 2016

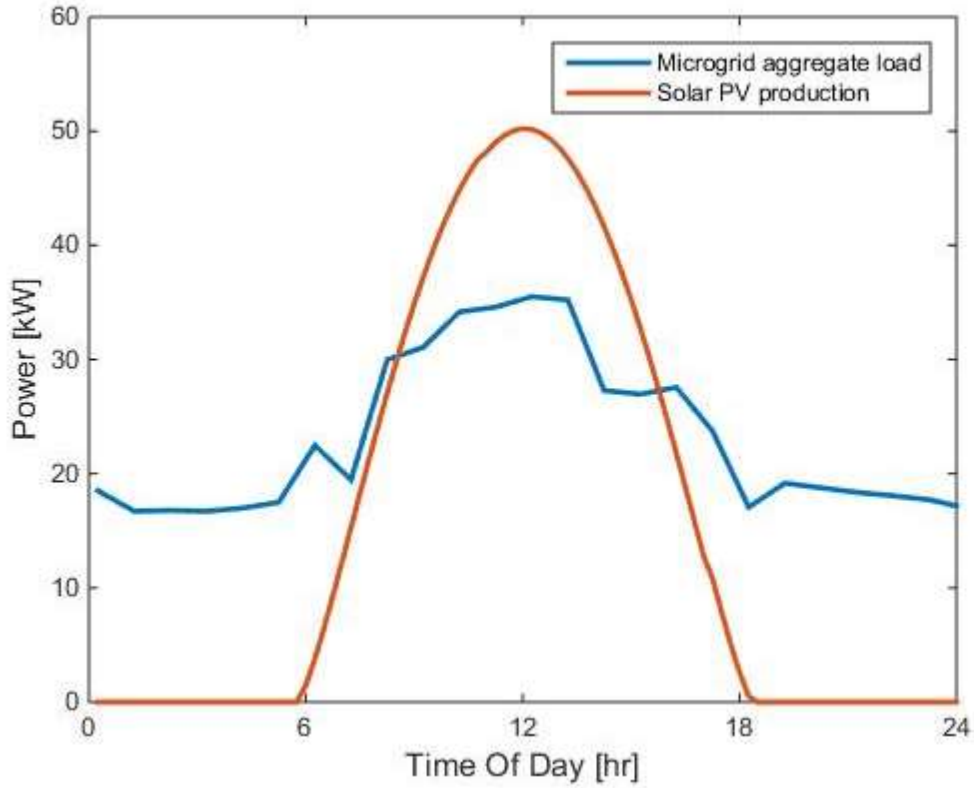


The black and red curves represent the energy cost multipliers for real-time pricing (RTP) and value of lost load (VOLL), respectively. The blue shaded area represents the period in which the noncoincidental demand charge applies (all day). The green checkered area represents the period in which the peak demand charge applies.

Source: Center for Energy Research, University of California San Diego, 2018

The solar production is plotted with the microgrid aggregate load in Figure 16. Both profiles peak around noon. The solar production resembles a clear day and exceeds the microgrid aggregate load during peak hours.

Figure 16: Aggregate Substation Load Demand and Solar Generation for 9/5/2016



Source: Center for Energy Research, University of California San Diego, 2018

The net load profile (building load + EV load – solar production) for each use case is given in Figure 17. Several key characteristics of each optimization objective can be observed in the figure. Each case C_x represents a different set of optimization objectives that are discussed:

$\boldsymbol{C_1}$ – *Noncoincidental Demand Charge Only:* For the objective of minimizing demand charge during the noncoincidental period, the profile is flat nearly across the entire day and has the lowest peak demand.

$\boldsymbol{C_2}$ – *Peak Demand Charge Only*: The objective focuses on minimizing the demand during the peak hours from 17:00 - 22:00 pm. The demand is the lowest during the peak period. Although, other objectives temporarily show lower demand during the peak period, the lower demand is countered with higher demand at other times in the period. Objective J_2 also possesses the largest demand peak of all cases at 16:45 PST as a result of shifting load away from the peak period by precharging EVs.

$\boldsymbol{C_3}$ – *Energy Arbitrage Only*: The objective is concerned with shifting energy purchases from periods of high price to low price. Indeed, the peak of purchases occurs at a period of very low price. Conversely, no energy purchases occur during 12:30 to 15:00 PST when the energy price peaks. Zero-net load during high pricing can be achieved due to the availability of solar and the ability to shift the EV load to earlier or later in the day.

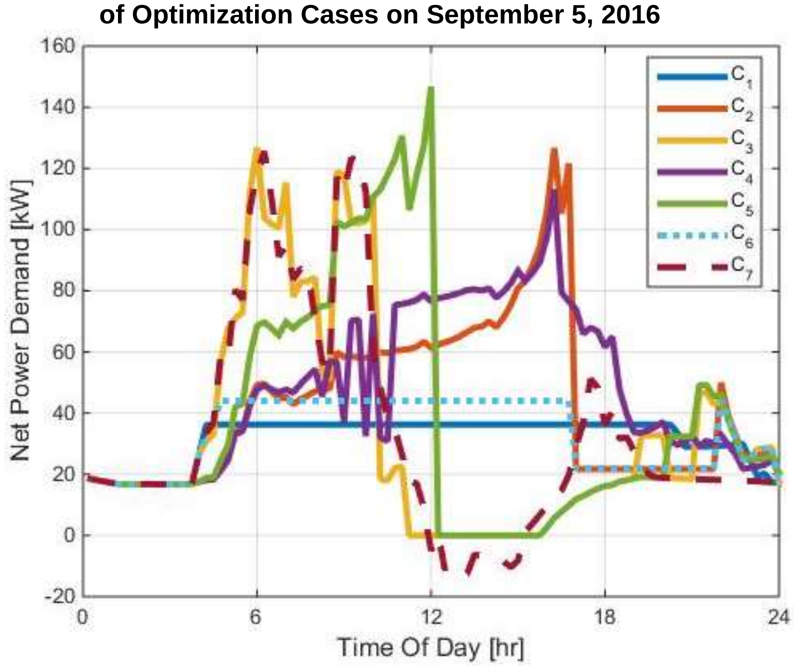
$\boldsymbol{C_4}$ – *Wholesale Market Sales Only*: The objective maximizes the sales of generated PV power. As a result, the charging appears random as it does not influence the objective function. Large demand is observed near the peak hours.

$\boldsymbol{C_5}$ – *Capacity Deferment Only*: The objective minimizes the demand during periods of high LOLP. Similar to C_3 the net demand goes to zero during high LOLP, and EV charging is scheduled before and after the high LOLP period instead. $\boldsymbol{C_5}$ incurs the largest demand peak of all cases.

$\boldsymbol{C_6}$ – *All Objectives Considered*: The optimization considers all objectives. A blend of the objectives discussed above are observed. The demand charge terms appear to exert the greatest influence on $\boldsymbol{C_6}$ as the net load profile is mostly flat with two levels of net demand during peak (higher) and non-peak (lower) periods.

$\boldsymbol{C_7}$– *Non-Optimized Charging*: No optimization is considered. The vehicles simply charge as soon as they arrive at full charging power until they are completely charged. All solar power is consumed until the net demand is zero; excess power is sold back to the utility. As a result, the charging profile shows several demand peaks of varying magnitude throughout the day. Negative demand is observed in the middle of the day, resulting in reverse power flow back to the utility at a time when the energy price is low. The most alarming characteristic however is the spike in demand during the peak hours.

Figure 17: Net Load Demand at the Substation for Each Set of Optimization Cases on September 5, 2016



C_1- Noncoincidental demand charge only; C_2- Peak demand charge only; C_3- Energy arbitrage only; C_4- Wholesale market sales only; C_5- Capacity deferment only; C_6 – All objectives; C_7 – Non-optimized charging

Source: Center for Energy Research, University of California San Diego, 2018

The net load performance statistics for September 5, 2016, are provided in Table 3. The total cost is determined as the sum of all business cases. The table agrees with the behavior observed in the net load profiles. Case 1 (C_1) has the lowest peak demand over the day followed by the optimization with all objectives (composite optimization, C_6). Considering all objectives results in a higher peak demand as it increases demand during off-peak hours to avoid peak demand charges during the peak period. Cases $C_1, C_3,$ and C_6 use the available solar energy completely (100% self-consumption) and, thus, have the fewest energy purchases.

With respect to minimizing consumption during periods of high LOLP, both C_5 (capacity deferment, by definition) and C_3 (energy arbitrage) have the same effect. This is because the highest costs for both objectives occur during the same time, and thus both work to minimize EV charging during this period. As expected, considering all objectives (C_6) results in the lowest cost over the day, while objective C_5 incurs the greatest cost. The large cost is because LOLP is very low and thus incurs minimal costs in comparison to the demand charges and energy charge, which are increased in an effort to reduce consumption during large LOLP.

Table 3: Energy and Cost Statistics for the Operation on September 5, 2016

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Peak Power Demand [kW]	37.8	126.7	126.9	113.1	146.7	44.0	125.6
Energy Purchase [kWh]	805	1019	805	1139	917	805	832
PV Self Consumption [%]	100	44	100	12.1	70	100	92.7
Ratepayer Costs [$]	5.68	2.58	0.73	2.53	0.73	4.23	4.88
Total Cost [$]	879	2169	2300	2304	2632	871	2313

The most desirable value in each row is highlighted in blue, and the least desirable is highlighted in red. The optimization cases are as follows: C_1- Noncoincidental demand charge only; C_2- Peak demand charge only; C_3- Energy arbitrage only; C_4- Wholesale market sales only; C_5- Capacity deferment only; C_6 – All objectives; C_7 – non-optimized charging

Source: Center for Energy Research, University of California San Diego, 2018

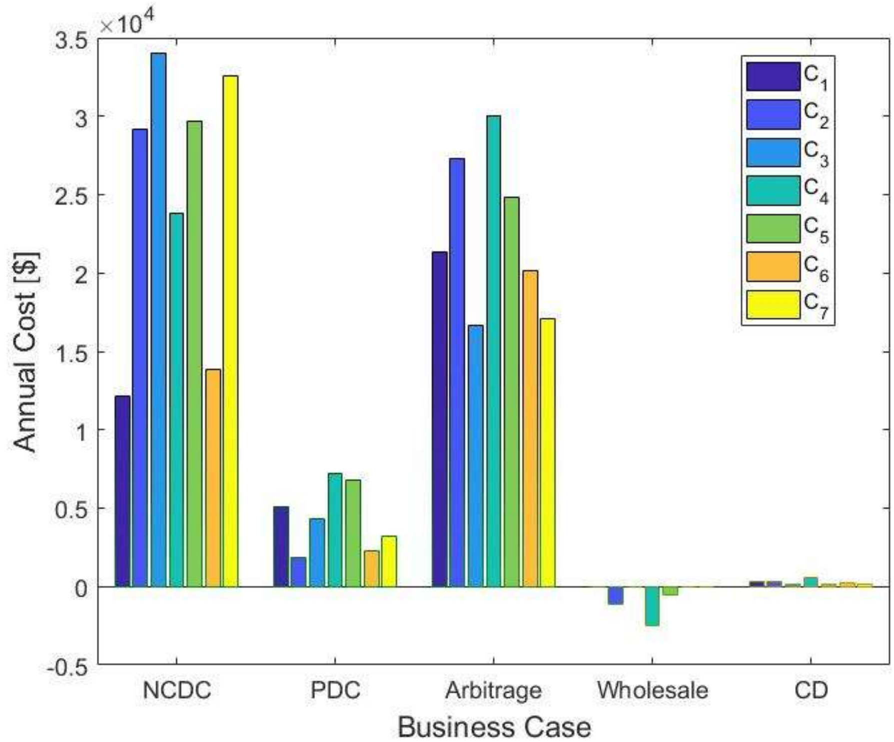
5.3 Annual Operation

The cost for considering each optimization case for the year is displayed in terms of the cost associated with each business case in Figure 18As expected, the optimization objective that considers all business cases (C_6) possesses the least cost (greatest profit) in that category.

The largest overall cost for all cases is due to the noncoincidental demand charges and energy purchases, while all other business cases produce costs that are an order of magnitude less. Energy sales produce little profit in all cases due to the low wholesale market prices. In the cases where the noncoincidental demand charge is considered (C_1 , C_6), the market sales are non-existent. This result is because to sell power to the market, the generation would not be available to offset local demand, requiring more energy purchases and increasing the peak demand. The large discrepancy between the demand charge and the volumetric price of electricity makes it undesirable to raise the demand to sell electricity. A similar logic can be applied to describe the lack of wholesale market sales when considering only energy arbitrage (C_3).

The cost of capacity deferment is also negligible in all cases, relative to the other business cases. The discrepancy is because 1) LOLP is negligible for most of the year and small when nonnegligible; and 2) VOLL is a relatively small value. Larger VOLL in specific microgrid applications that require high reliability would yield a higher importance and cost.

Figure 18: Distribution of Annual Costs Among the Terms of the Objective Function/Business Cases for All Seven Cases



C_1- Noncoincidental demand charge only; C_2- Peak demand charge only; C_3- Energy arbitrage only; C_4- Wholesale market sales only; C_5- Capacity deferment only; C_6 – All objectives; C_7 – non-optimized charging. The costs for each business case are split by category (x-axis) into Non coincidental demand charge (NCDC); Peak demand charge (PDC); Energy arbitrage; Wholesale market sales; Capacity deferment (CD).

Source: Center for Energy Research, University of California San Diego, 2018

CHAPTER 6: Conclusions

6.1 Value of Solar Forecasting and EV Charging to the Microgrid Customer

In Chapters 2 through 4, the authors demonstrated how a regional solar forecasting network can improve solar forecast accuracy. Further, improved solar forecast accuracy was shown to improve the ability of EV charging schedules to flatten net load. Chapter 5 represents the culmination of the work where all techniques were applied to analyze the value of solar forecasting and flexible EV charging to microgrid customers and ratepayers.

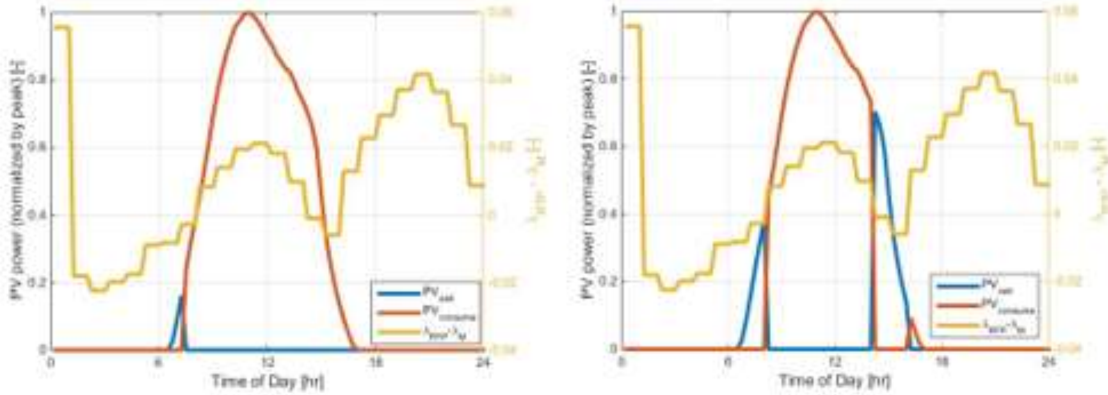
The microgrid customer costs and behaviors are dominated by demand charges. Simply scheduling around the demand charges will have the largest impact on costs for the customer, similar in magnitude to optimizing for all costs (C_6). In most cases, optimizing for any other singular optimization objective (C_2-C_5) actually increases microgrid costs over the non-optimized (C_7), as demand charges increase.

Optimizing around market sales only was shown to generate the highest costs. The high costs are due to the fact that PV is not used to meet load. This has the effect of requiring higher energy purchases and increasing daily demand charges because scheduling occurs sporadically. The market spot prices are typically much lower than the utility energy tariffs.

For similar reasons, considering market sales in the full optimization has little effect. Specifically, when balancing energy purchases with market sales, it is economically viable to sell power only when the market price exceeds the real-time price, which occurs only 6.1% of all time steps. For fixed cost and time-of-use schemes even fewer periods of favorable wholesale prices exist. This is expected since it indicates periods when the utility sells energy at a loss.

However, even during periods when the price is favorable for wholesale market sales, all power cannot be sold, as shown in Figure 19. The market price exceeds the retail price from 01:15 - 08:00 PST and 14:15 - 16:00 PST. In the morning, all available generation is sold during the price surplus. However, in the afternoon, no power is sold. As observed the power is sold in the afternoon only when the demand charges are not considered in the optimization. to sell PV generation (as opposed to using it to offset local demand), energy must be purchased from the utility, thus raising the demand level for the day. The profit from energy sales is not enough to overcome the increase in demand charge.

Figure 19: PV Generation Use on June 26, 2016



Considering the Optimization of (left) All Objectives (C_6) and (right) Objectives With the Demand Charges Removed (C_4)The left y-axis describes the relative PV power that is sold or consumed. The right y-axis plots the price difference between market price and retail price.
Source: Center for Energy Research, University of California San Diego, 2018

The authors expect that, since the microgrid costs are governed mostly by demand charges, allowing the EVs to discharge will have little effect on the net load curve (specifically flat net load profile across the majority of day). Allowing EVs to charge and discharge may make the wholesale market sales more viable, as more power can be sold when wholesale rates exceed retail rates, thus increasing the overall profit observed from this use case.

6.2 Ratepayer Costs for Capacity Deferment

Overall, the ratepayer costs for capacity deferment are a small fraction of the total costs. This is because the LOLP and the value of unserved load are too small for the California ISO system. LOLP is nonnegligible for only 3% of the year. The low-capacity deferment costs actually cause the full optimization scheme to increase ratepayer costs by 22% compared to the non-optimized operation.

However, 26% and 20% reductions in ratepayer costs for capacity deferment are observed by optimizing for either ratepayer costs (C_5) or energy arbitrage (C_3), respectively. The RTP peak costs typically coincide with high LOLP; thus, RTP serves as an effective proxy for reducing ratepayer costs while actually targeting microgrid costs. In fact, RTP energy arbitrage is superior at reducing load during periods of peak demand as arbitrage opportunities exist every day of the year, as opposed to just periods of high LOLP.

CHAPTER 7: Recommendations

This study reveals that using aggregated vehicle load large enough to absorb the solar output on the studied circuit is years in the future. The studied circuit showed that connected PV output created an energy valley of 64.5 MWh. Using a typical commuter PEV that requiring an average of 7 kWh means that roughly 9,200 vehicles must be connected during the solar output period to create an adequately sized energy sink to absorb the full amount of this oversupply. The feeder serves about 220 office, retail, and restaurant buildings that could potentially host EV charging stations however, charging 9,200/220 = 42 EVs on average per building seems unrealistic. For reference, as of January 2018, www.plugshare.com listed 12 locations with 20 stations within the feeder territory. Assuming 8 hours of charging at 9,200 stations, the load increase for the feeder would be 8 MW over the workday, which would likely trigger costly upgrades to lines and secondary transformers. The goal of absorbing all of this energy is beyond the reach of today's PEV adoption rates and indeed those rates for years to come. On the other hand, Executive Order B-48-18 calls all state entities work with the private sector and all appropriate levels of government to put at least 5 million zero-emission vehicles on California roads by 2030 and to spur the construction and installation of 200 hydrogen fueling stations and 250,000 zero-emission vehicle chargers, including 10,000 direct current fast chargers, by 2025. The executive order will improve the perspectives for EV charging and grid net load balancing in California. But at 929,000 commercial buildings in California, Oregon, and Washington (Commercial Building Energy Consumption Survey, 2015), even 250,000 chargers will fall short of the amounts required in this example.

Considering the scope and scale of the energy valley, accelerated adoption of EVs is required to provide adequate valley filling and further assist the system operator in mitigating grid variability during peak solar production.

- **Business Model Weakness in Public Infrastructure:**
  Currently, workplace charge hosts find that providing this amenity for employees is a break-even proposition at best. Panel upgrades, trenching, and other installation costs can be as high as $5,000 per outlet. An average electric vehicle charging station will likely deliver 8 kWh/day on average. Assuming a markup of $0.10/kWh, the undiscounted payback period for equipment and installation can be more than 10 years, longer than the life span of the equipment.

- **Commercial Medium and Heavy-Duty Vehicles Help**
  Medium- and heavy-duty commercial vehicles can play an important role in solar integration, but not all will be available for "long-dwell" layovers during solar

energy output hours needed for smart charging. School buses are uniquely suited to take advantage of excess solar energy during daytime, while most other commercial vehicles (forklifts, etc.) typically are in use during the day and need to be charged as soon as possible when plugged in.

- **Mismatch Between Vehicles Necessary and Vehicles That Charge at Work:**
    - EVs with the largest batteries and onboard chargers are capable of providing the biggest grid-support benefits.
    - Conversely, these EVs need workplace charging (or any public AC Level 2 charging) the least of any EVs on the road.
    - Plug-in hybrid electric vehicles are more likely to use workplace charging than EVs due to the average commuting distance for most people falling well within the range of the average EV.

What Can This Mean for Policy Makers?

- **New thinking on incentives may be necessary:** To make these controllable loads available during peak solar energy output periods when they can provide important reliability benefits, new policies, and incentives must be devised that:
    - Encourage some BEV owners to plug in at work whether they need to or not, for example, by providing lower electricity rates than for evening home charging or remunerate EV owners for allowing flexible charging or both.
    - Encourage employers to add more EV charging stations than they might otherwise
    - Emphasize the workplace load-augmentation advantages of smart Level 2 over Level 1 EV charging stations.[3] Smart EVSE are offered in Levels 1, 2, and 3 commercial duty qualities and are generally more expensive than basic chargers. They offer differing levels of communication with the user, site host, utility grid, and the Internet, depending on model and manufacturer.
    - Offer incentives for using more medium and heavy-duty commercial vehicles with "long-dwell" charging patterns during the day, such as school buses.

3 Level 2 charging EV is generally twice as fast as Level 1 and provides 10 to 20 miles of range per hour of charging. It requires 240 V service, which is readily available in many buildings and homes.

ACRONYMS AND ABBREVIATIONS

Acronym	Definition
AAN	Artificial Neural Network
AC	
BAU	Business as usual
BEV	Battery Electric Vehicle
California ISO	California Independent System Operator
CCD	Charge-coupled Device
DCHLS	Demand cleaning house logic sequence
DCT	Demand control threshold
DER	Distributed Energy Resource
EV	Electric Vehicle
EVSE	Electric Vehicle Supply Equipment
GHI	Global Horizontal Irradiance
HDR	High Dynamic Range
LOLP	Loss of Load Probability
MAPE	Mean Absolute Percentage Error
NL	Net Load
NRBR	Normalized Red Blue Ratio
PEV	Plug-in Electric Vehicle
PV	Photovoltaic
RA	Resource adequacy
RGB	Red green blue
RMSE	Root Mean Square Error
RTP	Real time pricing
SCAQMD	South Coast Air Quality Management District
SOC	State of charge
TOU	Time of use
USI	UCSD Sky Imager
VOLL	Value of lost load
VPP	Virtual Power Plant)