Economic Optimization of Distributed Energy Resources

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Abstract

This project analyzes the economic impacts of high penetrations of distributed energy resources (DERs) on a California distribution feeder. We determine the least-cost mix of DERs needed to meet electricity demand under both wholesale locational marginal price (LMP) and time-of-use (TOU) retail rates. This project creates a present-day baseline for future scenarios where falling solar PV and energy storage (ES) prices could result in high penetrations on distribution feeders, disrupting the current paradigm of one-way electricity flow from centralized generation to distribution feeders. It also provides insight on the impact of utility time-of-use rates on the deployment of DERs. This analysis could help inform policy-makers and utility stakeholders on how to facilitate the transition to a grid with high DER penetrations.

I. Introduction

A. Motivation and Background

Distributed energy resources are rapidly becoming more affordable and therefore more attractive to consumers. The increasing penetration of DERs on distribution grids impacts the utility's cost of providing energy, residential customers' costs of procuring energy services, and overall grid operations. These factors have implications for the amount and type of DER capacity that can be cost-effectively and reliably integrated into the distribution system.

Utilities, communities, and individual consumers are all impacted by energy choices made at the distribution level. In many jurisdictions, DER options are available to individual customers with some rules set by the utility; in other areas, communities are joining forces to maximize renewable penetration and minimize retail costs to the neighborhood, as seen in community solar cases.[1] California is leading the nation in solar PV deployment with about 4000 MW installed already [1]. A closer look at the economic impacts of deploying DERs from the utility, community and individual perspectives can provide insight on overall costs and benefits, and inform future policy work on electricity prices and renewable integration.

This project is unique because it makes use of data from an actual distribution feeder, whereas the literature mostly contains distribution-level analysis of hypothetical feeders. Also, the real feeder currently hosts a community scale PV system. The team obtained net demand, solar profiles, and micro-synchrophasor data from this feeder.

Our team brings previous experience with distribution feeder modeling, solar policy, and systems design to bear on this topic.

B. Relevant Literature

Zhao and Wu's 2013 paper [2] introduces the motivations for the optimization of operational costs while integrating grid constraints. It details their linear programming model, which combines the economic optimization of locational marginal prices (LMP) and physical network constraints associated with the integration of intermittent renewable sources of energy. Cohen and Callaway's 2015 paper [3] demonstrates how to choose representative feeders and solar resource data, and how to aggregate the physical and economic impacts across multiple feeders. This will provide a general framework for our analysis. Atwa *et al.*'s 2010 paper [4] sets up a methodology for optimizing the mix of DERs required to minimize energy loss on a feeder. Ultimately, we hope to extend this type of methodology to other physical constraints such as voltage limits. Papathanassiou *et al.*'s 2014 paper [5] on the hosting capacity of distribution feeders will inform our model's capacity constraints to determine how much DERs can be added to the optimal mix.

[1]Examples include the Pecan Street Project in Austin, TX and West Village at the University of California, Davis.

C. Focus of This Study

We performed an economic optimization that provides insight into how to meet electricity demand at lowest cost with a combination of solar photovoltaics (PV), energy storage (ES), and power from the centralized grid. We used optimization and modeling tools to conduct an economic optimization of deploying distributed energy technologies on a distribution feeder.

We performed this optimization from three perspectives:

1) The utility perspective, in which PV and ES compete with wholesale energy prices at the feeder level.
2) The community perspective, in which PV and ES compete with retail energy prices at the feeder level.
3) The individual perspective, in which PV and ES compete with retail energy prices at the home level.

This analysis creates a basis for future work. We intend to extend this project by (1) incorporating physical power flow constraints at the feeder level, (2) analyzing the impact of a variety of possible tariff structures on DER deployment, and (3) analyzing future load profiles with high electric vehicle deployment.

Table 1: Summary of Evaluated Perspectives.

Perspective	Utility	Community	Individual
Price Inputs	PV and ES costs, Wholesale Rates	PV and ES costs, Retail Rates (Time of Use)	
Scope of Optimization	Total electricity cost for all buildings on the feeder		Individual electricity cost for each building on the feeder
Load profiles	Aggregated building loads for the entire feeder		Individual building loads
Energy Generation	Distributed (rooftop) and centralized (community) solar		Distributed (rooftop) solar
Energy Storage	Household- and community-scale batteries deployed by community or utility		Household-scale batteries deployed by individual owners

The economic optimization model was built using MATLAB. For all cases, we optimize the cost of meeting electricity demand using (1) grid power, PV, and ES and (2) only grid power. For each scenario, we analyze the DER capacity mix on the feeder and the costs of supplying total demand.

II. Technical Description

A. Data Collection

1) Feeder Data

The economic optimization was performed using real utility data from one distribution feeder located in California. The feeder has a maximum coincident load of approximately 12.5 MW which is comprised of a mix of residential, commercial, municipal, and apartment loads. One 7.5 MW PV system is connected near the substation. Peak electricity demand in real (kW) and reactive (kVAR) power is given by feeder section and customer type. Generic hourly load profiles for the represented customer types are provided as a percentage of the peak demand realized on a given type of day (peak day, weekday, and weekend) during each month of the year. Finally, 15-minute SCADA data at the substation provides information on reactive power and measured net load for the month of December 2015. This data indicates that the feeder experienced substantial periods of reverse power flow due to its PV system during that month.

2) Customer Loads

Aggregated real power demand for all three phases of the feeder was used as an input for the economic optimization. For all perspectives, we considered load profiles for residential all-electric households and residential households that also used natural gas. As expected, load profiles for all-electric households are higher on average than for residential gas households.

To perform the economic analysis for the community and utility perspectives, we assumed that residential and apartment customers paid residential TOU rates, while municipal and commercial customers paid commercial TOU rates. We applied hourly consumption data to the peak demand of each customer type to generate hourly load profiles for customers paying residential and commercial rates for the month of December 2015.

For the individual perspective, we chose a residential section of the feeder at random. We assumed that an individual residence would have a peak load of 1.5 kW and scaled the peak power demand for this section of the feeder proportionally. We then applied hourly consumption data for residential customers to generate hourly load profiles for an individual residential customer for the month of December 2015.

3) Retail Energy Tariffs

Retail customers can pay for their electricity consumption via several different pricing structures, such as flat rates or time-of-use (TOU) plans timed to coincide with increased electricity demand. Currently, California utilities use an increasing block pricing rate structure with four tiers. This rate structure is designed to encourage energy conservation: the more energy used, the higher the marginal rate rises. As required by the California Public Utilities Commission, electric rates will be consolidated from four tiers to two tiers by 2017, and the differences between the tiers will be reduced—ultimately to a 25% differential between two tiers [6]. The CPUC has proposed this consolidation to make rates more fair and equitable among all residential customers. By 2019, tiered rates will disappear and be replaced by TOU rates.

Time-of-use rate plans have the potential to better align the price of electricity with its cost at the time of production. Lower rates during partial-peak and off-peak hours offer an incentive for customers to shift their energy use away from more expensive peak hours, which can help reduce strain on the electric grid, save money for the customer, and help California meet its climate goals. A CPUC study of peak load reductions resulting from TOU rate implementation by other utilities found values as high as 45% (for EDF, a major European utility) [6]. All business customers will transition to TOU plans over the next several years in California, while residential customers are strongly encouraged to.

For this project, we assessed PV and storage penetration on distribution feeders in the context of PG&E TOU rates at current Tier 2 and Tier 3 levels. We assumed that Tier 2 and Tier 3 are the best estimates of consolidated tier pricing. PG&E is the only utility with easily-accessible tiered and TOU rates for both residential and business customers. For the sake of consistency, we decided to run our scenarios with PG&E costs. Table 2 summarizes current PG&E TOU rates for commercial and residential customers. Although the table shows TOU rates for both winter and summer, we only used winter rates in our report to match our December load and production data.

Some California time-of-use rate plans include demand charges to encourage businesses to spread their electricity use throughout the day. This demand charge is calculated by using the 15-minute interval during each billing month when a commercial customer's demand is highest. To offset this additional fee, volumetric electricity usage rates are approximately 25% lower than for a comparable rate plan without a demand charge. This gives commercial customers the opportunity to save on their bills if they can reduce their highest usage 15-minute interval. We did not incorporate demand charges into our project because we worked with hourly data, and the mismatch between 15-minute and hourly peak data could create distortions.

Table 2: Time-of-use rates for commercial and residential PG&E customers in California.

	Winter TOU Rates ($/kWh)			Summer TOU Rates ($/kWh)		
	Off-peak	Partial-peak	On-peak	Off-peak	Partial-peak	On-peak
Residential	(Weekends and 12am-5pm, 8pm-12am on weekdays)	(5pm-8pm on weekdays)	-	(12am-10am, 9pm-12am on weekdays, 12am-5pm, 8pm-12am on weekends, Holidays)	(10am-1pm, 7pm-9pm on weekdays, 5pm-8pm on weekends)	(1pm-7pm on weekdays)
Tier 2	**0.197**	**0.213**		**0.081**	**0.107**	**0.147**
Tier 3	**0.26**	**0.27**		**0.25**	**0.33**	**0.44**
Commercial	(12am-8h30am, 9h30pm-12am on weekdays)	(8h30am-9h30pm on weekdays)	-	(12am-8h30am, 9h30pm-12am on weekdays)	(8h30am-Noon, 6pm-9h30pm on weekdays)	(1pm-7pm on weekdays)
	0.087	**0.102**		**0.081**	**0.107**	**0.147**

4) Wholesale Power

Locational marginal prices (LMPs) are the prices at which the utility purchases power. Therefore, LMPs represent the utility's cost to supply electricity in a particular location. LMPs fluctuate throughout the day and throughout the year in response to variability of load patterns. To calculate the utility's cost of providing power, our model integrates the California ISO's LMPs set in the day-ahead market for the month of December 2015. The LMPs vary between locations and depend on the load and generation profiles, as well as the transmission system constraints.

5) Solar Photovoltaics

Since 2009, installed solar PV prices have declined by approximately 13-18% per year for residential and non-residential systems. PV installation costs reflect economies of scale, with larger (i.e., non-residential) arrays typically priced lower per watt than smaller (i.e., residential) arrays. Prices differ substantially even within these categories: for example, median prices for 8-10 kW residential systems are 15% lower than for 2-4 kW systems. PV prices are also subject to significant regional variation. Several states, such as Delaware and Texas, see significantly lower prices than the national median, while prices in some relatively mature markets, including California, Massachusetts, and New York, are higher. High prices in California can be explained by several factors, including a large percentage of premium modules and relatively high siting rates at non-profit facilities, which tend to have higher installed costs than commercial sites [7]. For this study, we ran our optimization with installed median costs of PV in California in 2016 (Table 3). Median costs have declined by approximately 10% each year since 2009; we estimated 2016 costs under the assumption that this trend continues through 2016 [7]. To calculate annualized costs we assumed a 20-year technology lifetime and a 5% rate of interest.

Table 3: Installed median costs of solar PV [7]. Estimated 2016 costs of PV in California were used in this study.

Year	Location	Residential ($/W)	Non-Residential $\leq$ 500 kW ($/W)	Non-Residential >500 kW ($/W)
2014	United States	4.3	3.9	2.8
(Actual)	California	4.6	4.1	3.1
2016	United States	3.48	3.16	2.27
(Estimated)	California	3.73	3.32	2.51
	California (Annualized)	299.30 ($/kW)	266.41 ($/kW)	201.41 ($/kW)

6) Energy Storage

Energy storage addresses the issue of high intermittency associated with the integration of renewables, but also has the capacity to improve the implementation of distributed and aggregated solar PV on the grid. One advantage of energy storage from the customer's perspective as well as the utility's is the possibility of load shifting: storage provides an alternative source of electricity at times when high demand drives electricity prices up. Additionally, storage is beneficial from the utility's perspective as it has the ability to supply voltage regulation and frequency response, providing the utility with greater control of the power systems and more flexibility to supply electricity demand effectively [8]. When considering the type of energy storage deployed, many factors need to be considered: the various types of costs, the battery capacity, the efficiency, the number of cycles and the depth of discharge. However, capital costs and capacity are generally the main two criteria used when comparing batteries. The choice of battery capacity is inherently dependent on the required degree of grid autonomy, the capacity of the solar PV array installed, and the electricity load profiles.

Batteries have been shown to be a suitable technology to store solar PV electricity at the customer, community and utility scales. The market for lithium-ion batteries is growing exponentially and is expected to continue to do so. Technology costs have declined significantly over the past decade, making lithium-ion batteries an increasingly accessible option for smoothing PV output [9]. Vanadium flow batteries are characterized by a high cycle life, and are therefore especially appropriate for large-scale applications and deployment at the utility and community scale [10]. Aqueous hybrid ion is an emerging battery technology commercialized by Aquion Energy, which is a flow battery with a manganese oxide cathode and an activated carbon composite anode with a sodium sulfate aqueous electrolyte. This new technology is scalable, has applications at small and large scales, and provides a resistant alternative made of non-toxic materials with a high cycle life and efficiency [11].

Table 4 presents a review of available batteries deployed as energy storage in the context of grid integration of solar PV. It provides examples of the technologies introduced above and goes further in depth on the performance of such technologies. The numbers presented in Table 4 were used to make assumptions as to the inputs in our mathematical model in order to make the model as realistic as possible.

Table 4: Energy storage technologies coupled with solar PV. Made with data from [12] and [13]

Storage Type	Residential Scale			Community and Utility Scale		
	Tesla Powerwall Lithium-Ion	Iron Edison Lithium Ion	Aquion Energy S20P	Tesla PowerPack Lithium-Ion	Eos Aurora 1000—6000 Lithium-Ion	Imergy Vanadium Flow Battery
Capital Costs ($)	3,000	2,760	1,155	50,000	-	125,000
Operations & Maintenance Costs ($/kW-y)	12-30	12-30	-	12-30	12-30	24-65
Efficiency (%)	92	96	85	92	75	75
Usable Energy	7 kWh	4 kWh	2.66 kWh	100 kWh	6 MWh	250 kWh
Number of Cycles (Lifespan)	5,000	3,000	2,000	5,000 (15 yrs)	10,000 (30 yrs)	10,000 (30 yrs)

Table 5 contains the storage cost inputs used in the economic optimization model. The cost of batteries suitable for energy storage on all scales has drastically decreased in the last decade and is expected to continue dropping. The considered prices of energy storage are derived from information gathered on manufacturers' website and from scholarly sources. The cost of storage has been annualized over 10 years with a discount rate of 5%, to reflect the context of most purchases of solar energy storage by a household.

Table 5: Energy storage parameters used in the economic optimization model.

Scale	Residential	Community and Utility
Cost ($/kWh)	470	400
Annualized Cost with ITC ($/kWh)	42.61	36.26
Efficiency (%)	90	85

The cost of energy storage is affected by the investment tax credit for renewable energy, which was recently renewed for five more years. The investment tax credit (ITC) provides a 30% credit on the cost of the energy storage installed. However, this tax credit is only available if the power stored in the battery is coming from solar energy. This cost reduction and constraint pertaining to the power stored in the battery are included in the economic optimization model.

B. Economic Optimization Framework

The economic optimization uses the following algorithm:

$$\min_{S_{PV}, S_{ES}, P_{ES}(k)} S_{PV}c_{PV} + S_{ES}c_{ES} + \sum_{k=0}^{N} c_{grid}(k)[P_{load}(k) - S_{PV}P_{PV}(k) + P_{ES,in}(k) - P_{ES,out}(k)] \quad (1)$$

Where:
S_{PV}: PV system size [kW]
S_{ES}: energy storage capacity [kWh]
c_{PV}: levelized annual cost per kW of PV [$/kW]
c_{ES}: levelized annual cost per kWh of ES [$/kWh]
$c_{grid}(k)$: vector of cost per kWh of grid power [$/kWh]
$P_{load}(k)$: household load in each timestep k [kWh]
$P_{PV}(k)$: PV energy output per kW installed [kWh/kW]
$P_{ES,in}(k)$: energy stored during timestep k [kWh]
$P_{ES,out}(k)$: energy discharged per timestep [kWh]
η_c: charging efficiency of the battery and inverter
η_d: discharging efficiency of the battery and inverter
$E(k)$: state of charge (SOC) of the battery [kWh]
P_{ES}^{max}: maximum ES power rating. [kWh/timestep]
$E(N)^{min}$ and $E(N)^{max}$: limits on the final ES SOC

Subject to:

$$E(k+1) = E(k) + \eta_c P_{ES,in}(k) - (1/\eta_d)P_{ES,out}(k) \quad (2)$$
$$0 \le P_{ES,in}(k) \le P_{ES}^{max} \quad (3)$$
$$0 \le P_{ES,out}(k) \le P_{ES}^{max} \quad (4)$$
$$0 \le E(k) \le S_{ES} \quad (5)$$
$$E(0) = 0 \quad (6)$$
$$E(N)^{min} \le E(N) \le E(N)^{max} \quad (7)$$
$$S_{PV}P_{PV}(k) + P_{ES,out}(k) - P_{load}(k) - P_{ES,in}(k) \le 0 \quad (8)$$
$$\sum_{k=0}^{N} S_{PV}P_{PV}(k) - P_{load}(k) \le 0 \quad (9)$$
$$P_{ES,in}(k) \le S_{PV}P_{PV}(k) \quad (10)$$
$$S_{PV} \ge 0 \quad (11)$$
$$S_{ES} \ge 0 \quad (12)$$

The objective function, Equation (1), aims to minimize the total customer cost of energy over the set time horizon. This cost is equal to the levelized cost of PV (per kW) and ES (per kWh) multiplied by their size-scaling factors, plus the cost of grid electricity multiplied by the net energy consumption in each timestep. This net demand profile is equal to load and ES charging, minus PV production and ES discharging.

The first equality constraint, Equation (2), describes the evolution of the energy stored in the battery. The energy level in timestep (k+1) is equal to the current level, increased or decreased by the energy added or discharged in that timestep. An efficiency factor accounts for losses during this process.

Equations (3) and (4) ensure that the battery does not charge or discharge faster than the power capacity rating of the battery (or battery inverter) allows. Equation (5) keeps the energy level from falling below zero or above the rated energy capacity of the battery.

Equation (6) initializes the ES's energy level at 0 kWh, and Equation (7) gives a range for the final energy level.

Equation (8) states that the net load must be greater than zero. This can be thought of as a no-export restriction (as seen in Hawaii's new "self-supply" tariff option), or as an anti-reverse-power-flow constraint when optimizing at the feeder scale. This constraint was not imposed for any of the individual residential or commercial cases (California has no equivalent "self-supply" option), and the community-scale optimizations were run both with and without this constraint.

Equation (9) provides an upper bound on the size of PV array that can be built—the total energy produced by the array cannot exceed total load over the time horizon. This is a common sizing heuristic in the solar industry, and accounts for the fact that utilities typically do not compensate PV owners for production beyond their own consumption under net metering. The volumetric portion of the monthly energy bill cannot go below zero, and any additional kWh generated do not roll over to the following year.

Equation (10) states that ES charging in each timestep cannot exceed PV production in that timestep, ensuring that the PV self-supply criteria for the ITC is met. If this constraint were not imposed, the energy storage system would charge at night, when TOU prices are low, and sell at mid-day. The imposition of this constraint significantly reduces the economic case for storage under current tariff structure. Shifting peak TOU times away from peak PV generation (as is expected to happen in forthcoming rate plans) or eliminating net metering would serve as two key drivers for future residential ES adoption in California.

Equations (11) and (12) impose non-negativity constraints on the PV and ES sizing.

This optimization model makes the following assumptions:

- Full net metering: compensation for exported electricity equals the cost of consuming electricity.
- The sizes of the PV and ES are treated as continuous quantities, as opposed to integer quantities of specific commercially-available products.
- Storage capacity refers to effective storage capacity, after accounting for depth of discharge. Most residential lithium-ion ES uses a depth of discharge of roughly 90%.

C. Proof of concept

Running the optimization in MATLAB posed a handful of computational challenges. At first, the constraint array A was too large for the computer's memory. This issue was resolved by using the sparse matrix format. However, the optimization problem remained too large to solve when using a time horizon of one year. Therefore, the optimization was augmented to use any arbitrary time horizon, with a maximum value of roughly 100 days. Below is a three-day snapshot of an individual household optimization using the grid, PV and battery storage. For now, the optimization is choosing 0 kW/0kWh capacity for PV and storage due to the current cost figures and rate structure. In order to bypass this issue, the values of the PV and ES were fixed at 5 kW and 7 kWh respectively. The figures show that the model's ITC self-consumption constraint is active at midday, causing the storage system to charge. This does not completely eliminate export to the grid, but significantly reduces it.

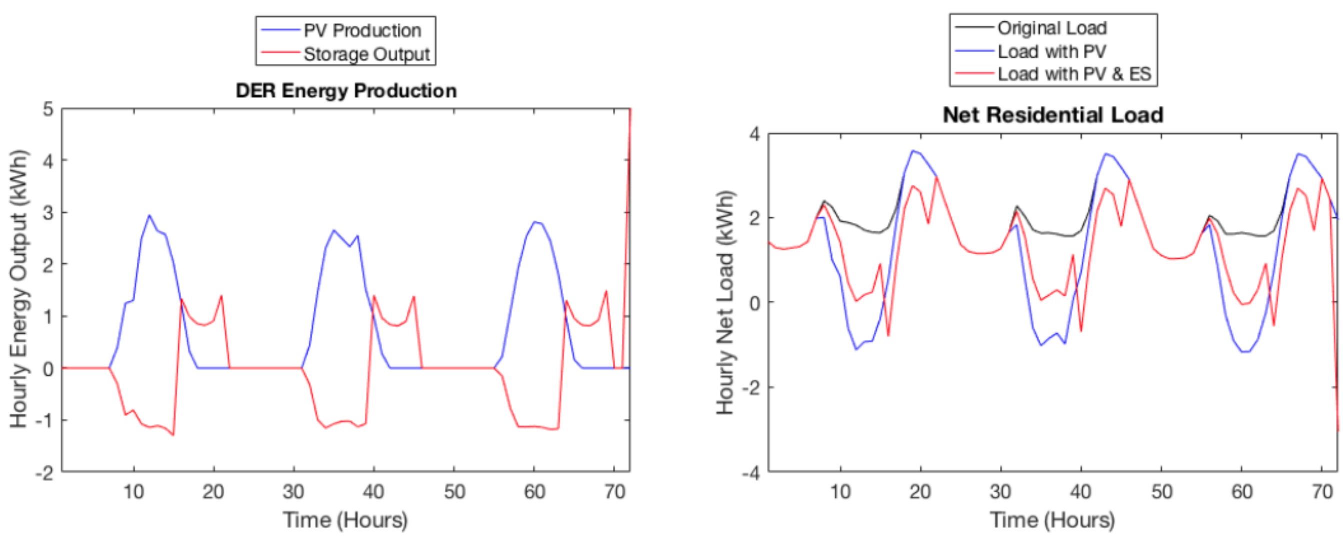


Figure 1: Sample Dispatch of Residential DERs.

D. Scenario Analysis

For all optimizations, PV size was limited to no more than the maximum energy consumption of the individual household or feeder. Exports of electricity to the grid were allowed in all cases. The costs of supplying power under the optimized distributed generation scenarios were compared to the baseline scenarios, i.e., getting energy only from the grid.

1) Individual Perspective

The economic optimization model was applied to individual load and PV generation profiles at two types of households: all-electric households and households using electricity and gas. For each type of household, the optimization was run twice to evaluate PV and ES adoption under Tier 2 and Tier 3 rate structures, as discussed earlier in Section II-A3. For all cases evaluated at the individual household level, the model included residential solar PV prices and the residential market price point for home energy storage.

2) Community and Utility Perspectives

The community and utility optimizations were divided into two parts to account for rate structure and load profile differences between residential and commercial customers. We computed the aggregated residential load and the aggregated commercial load on the distribution feeder. The aggregated residential loads were computed for two scenarios: all-electric households and all houses on the feeder using both electricity and gas.

For the community perspective, the optimization for the aggregated residential loads was performed at Tier 2 and Tier 3 rates. For the optimization of the commercial customers, median commercial time-of-use rates were used. We ran each optimization first with large-scale PV and battery storage prices. For scenarios where the optimized PV size was over 500 kW, we re-ran the simulation with a lower cost for solar PV due to economies of scale, as mentioned in Section II-A5.

For the utility perspective, DER adoption for aggregated residential and commercial customers was optimized in the context of LMP prices to simulate the utility's cost of providing electricity to the feeder.

III. Results and Discussion

Table 6 presents the optimization results obtained for each scenario described previously.

Table 6: Economic optimization results.

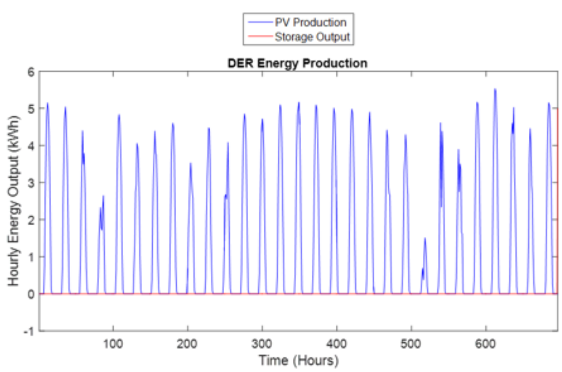
<table>
<tr><th rowspan="2">Perspective</th><th rowspan="2">Customer</th><th rowspan="2">Load Type</th><th rowspan="2">Dec. Load (kWh)</th><th rowspan="2">Rate Structure</th><th colspan="2">Optimal Size</th><th colspan="2">Costs of Supplying Power ($/kWh)</th></tr>
<tr><th>PV (kW)</th><th>ES (kWh)</th><th>Option for PV & ES</th><th>Utility Power Only</th></tr>
<tr><td rowspan="4">Individual</td><td rowspan="4">Residential</td><td rowspan="2">All-Electric</td><td rowspan="2">783</td><td>Tier 2</td><td>0</td><td>0</td><td>0.197</td><td>0.197</td></tr>
<tr><td>Tier 3</td><td>7</td><td>0</td><td>0.222</td><td>0.257</td></tr>
<tr><td rowspan="2">Gas</td><td rowspan="2">654</td><td>Tier 2</td><td>0</td><td>0</td><td>0.197</td><td>0.197</td></tr>
<tr><td>Tier 3</td><td>6</td><td>0</td><td>0.222</td><td>0.256</td></tr>
<tr><td rowspan="5">Community</td><td rowspan="4">Residential</td><td rowspan="2">All-Electric</td><td rowspan="2">3,384,514</td><td>Tier 2</td><td>31,658</td><td>0</td><td>0.151</td><td>0.198</td></tr>
<tr><td>Tier 3</td><td>31,658</td><td>0</td><td>0.151</td><td>0.258</td></tr>
<tr><td rowspan="2">Gas</td><td rowspan="2">2,885,180</td><td>Tier 2</td><td>26,987</td><td>0</td><td>0.151</td><td>0.198</td></tr>
<tr><td>Tier 3</td><td>26,987</td><td>0</td><td>0.151</td><td>0.258</td></tr>
<tr><td>Commercial</td><td>-</td><td>3,024,710</td><td>Median TOU</td><td>0</td><td>0</td><td>0.095</td><td>0.095</td></tr>
<tr><td rowspan="3">Utility</td><td rowspan="2">Residential</td><td>All-Electric</td><td>3,384,514</td><td rowspan="2">LMPs</td><td>0</td><td>0</td><td>0.027</td><td>0.027</td></tr>
<tr><td>Gas</td><td>2,885,180</td><td>0</td><td>0</td><td>0.028</td><td>0.028</td></tr>
<tr><td>Commercial</td><td>-</td><td>3,024,710</td><td>LMPs</td><td>0</td><td>0</td><td>0.028</td><td>0.028</td></tr>
</table>

A. Residential Scale

The retail prices of electricity for Tier 2 are approximately 30% lower than the prices of Tier 3. From an individual household perspective with an energy consumption corresponding to Tier 2 pricing, the optimization model recommends no PV and no storage. This is explained by the fact that the solar PV electricity production does not offer significant returns when compared to its capital costs at Tier 2 retail rates. However, the Tier 3 rates appear to make PV advantageous due to the ability to sell the produced electricity to the grid at high retail rates. The cost of having PV can be more easily offset for households subjected to Tier 3 pricing and with larger electricity bills. The comparison of these two cases shows that there is a value of the time-of-use retail rates at which solar PV becomes economically favorable.

The model does not recommend the implementation of storage. This occurs because the savings that an individual household can achieve by load shifting using storage do not offset the cost per kWh to acquire storage. The difference between the retail prices of electricity between off-peak and partial peak periods in the winter is only 2 cents, which limits the potential savings any arbitrage could achieve. The expected behavior of storage coupled with PV is to charge at night and discharge power to the grid during the day. However, the investment tax credit (ITC) restriction states that storage should charge with energy produced by the PV system (see Section II-A6), which does not allow this charge/discharge pattern and therefore serves to limit the economic case for storage.

For the household perspective, the optimized system for households relying only on electricity outputs a PV size of 7 kW, which is slightly higher than the optimized PV capacity for households using electricity and gas. This appears to be due to the higher total December load for all-electric households.



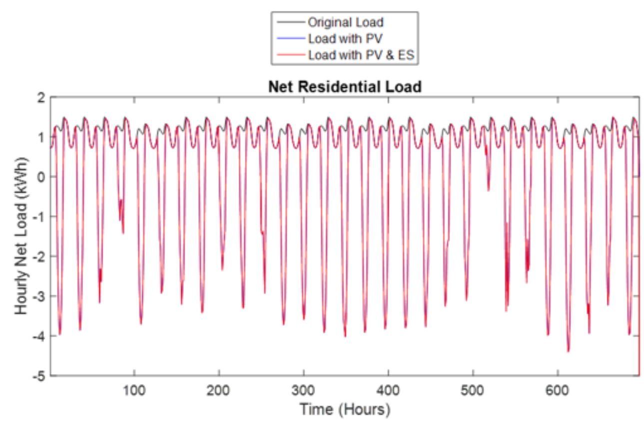


Figure 2: Residential Electric Profile, Tier 3. For this scenario, 7 kW of PV with no battery storage was deployed. This occurs because the arbitrage between the Time Of Use electricity prices was not large enough to justify the cost of storage. Comparing this scenario to an all-electric household subject to Tier 2 prices demonstrated that Tier 2 prices are too low to justify PV deployment.

B. Community Scale

The optimization model dispatched the maximum capacity of solar PV allowed for both tier pricing scenarios. This maximum capacity is defined in the model by the total load for each scenario. The total amount of dispatched PV is lower for the case with residential households relying on both electricity and gas, which is consistent with the fact that these households have lower electric loads.

For Tier 2, the optimized deployment of solar PV achieves a reduction in price of almost 5 cents per kWh, representing 25% savings on electricity costs. For Tier 3, the savings from the implementation of solar PV are even more obvious, with the potential of a decrease in 10 cents per kWh, which represents a 40% reduction in electricity costs when compared to power supplied only by the utility.

Because the optimal solar PV capacity is over 500 kW at the community scale, the final results for the cost of supplying electricity take into account the lower solar prices. When comparing community-scale and individual-residential results, it appears that there is a breakeven point for levelized solar PV price at which it becomes economically beneficial to completely offset load with solar PV.

The optimization for the commercial users at the community scale does not output any solar PV or storage due to the low commercial TOU rates, similarly to the residential-scale Tier 2 scenario. However, in this case, the solar prices associated with large-scale solar PV systems are applied but do not counterbalance the economic effect of the low TOU rates in this case. Similarly to the residential case, the optimization does not recommend the implementation of storage, for the reasons stated in the previous section.

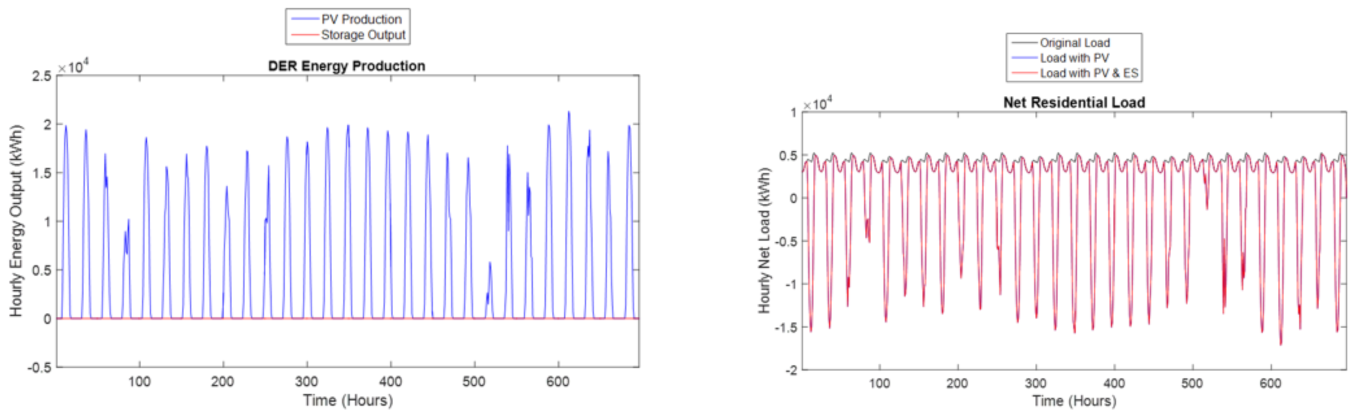


Figure 3: Community Gas and Electric Profile, Tier 3. For this scenario, 27 MW of PV with no battery storage was deployed. This occurs because the arbitrage between the Time Of Use electricity prices was not large enough to justify the cost of storage. PV deployment under both Tier 2 and Tier 3 prices at the community scale demonstrated that the lower cost of larger PV systems relative to small rooftop systems makes community-scale PV economical.

C. *Utility Scale*

The model does not recommend implementing any solar PV or storage from the utility's perspective. The results show that it costs the utility approximately 3 cents per kWh to supply electricity in a Winter month like December. Solar PV and storage cannot compete economically with the low LMPs at which PG&E can buy electricity in winter months.

IV. Summary

The goal of this project is to optimize the amount of solar PV and energy storage that can be cost-effectively integrated on a typical feeder, considering economic constraints from three different perspectives and the need to balance energy supply and demand. By modeling and optimizing the costs associated with the integration of solar PV and storage from the perspectives of utilities, households, and communities, we aimed to provide a deeper understanding of each party's incentives to embrace or resist the growth of DERs. The results of our economic optimization demonstrate that TOU rates and prices of solar and storage can be prime drivers or barriers to the deployment of these technologies.

The analysis of the different scenarios reveals the critical impact of the TOU rates on the optimal economic size of PV at the household and community levels. We observe that there is a single breakeven point at which sufficiently high TOU rates, here represented by PG&E Tier 3 prices, cause the optimization algorithm to recommend deploying the maximum allowable PV size for residential customers. TOU rate structures are planned to change in the future, and will have a key role to play in the future deployment of PV, with the potential to accelerate the implementation of solar PV systems.

Our analysis also identifies the drastic impacts of changing solar PV prices. Community-scale PV, with a lower cost per kilowatt of installed capacity than residential-scale PV, is more likely to be deployed to offset residential customers' loads. The cost of implementing solar PV is most likely going to continue its decline in the coming years, which will further encourage the deployment of solar at the household and community levels.

The implementation of storage has a lot of potential at the three perspectives considered. However, our economic optimization did not ultimately deploy any storage in the context of December load profiles. We believe that the full potential of storage coupled with solar PV is not fully captured in this study due to the fact that the analysis pertains to a winter month. However, the cost of batteries has significantly decreased and is predicted to continue to do so, likely leading to more storage deployment that will be beneficial in all seasons.

From the results, we observed that there are conflicting interests when considering the implementation of PV and storage. Depending on the TOU rates and capital costs involved, solar PV and storage can be economically favorable from the household and community perspectives. The implementation of storage by the utility at the feeder level will likely expand in the future, due to the many ancillary services it can provide to the grid.

V. Future Work

Analyzing the differences between the residential, community, and utility perspectives on deploying solar and storage perspectives can provide insight into the current viewpoints and actions of stakeholders in the California electric power system. These results will also inform further qualitative analysis on the potential for demand side management.

The initial scope of the study was reduced in order to accommodate a larger number of possible relevant scenarios. As initially planned, distribution grid modeling will be performed in OpenDSS using the economic optimization results obtained here, in order to validate the feasibility of these scenarios, and to assess if they violate any power constraints on the feeder, such as voltage and thermal limits. Our goal is to incorporate the results of this economic optimization into a power flow simulation to provide insight on the physical feasibility of the results of the economic model. We will assign economic costs from literature to physical impacts and re-run our economic model to account for grid dynamics.

We also hope to extend this study by applying the model over one year to get insight on the impact of seasonal variability of load profiles, solar PV electricity production, and electricity prices. Additionally, we would like to perform a sensitivity analysis on the TOU rates and the prices of solar PV and storage to get further insight on how our results are impacted by these factors. Another important component of electricity prices are demand charges for commercial customers, which were not included in this model due to challenges associated with the resolution of the data.

Another potential extension of this work is to distinguish between the impact of residential and community-scale solar arrays by using PV power output variability as a proxy. Since PV power production depends strongly on solar irradiance, shading and cloud cover can lead to vastly different power outputs at different moments in time from nearby arrays. Properly characterizing the variability of PV resources can help improve the design of a system (e.g. by adding properly sized storage capabilities). The power output of nearby PV arrays is highly correlated: they experience ramps at the same time and vary in sync, so the fleet exhibits nearly the same relative variability as the individual systems. In contrast, the variability of a fleet of identical PV plants with uncorrelated power outputs is reduced with distance by $\sqrt{N}$, where N is the number of plants. This information can enable a qualitative estimate of the impact of spatial spread of distributed (residential- or community-scale) PV within a community and yield more precise results about the most favorable type of PV deployment.

Finally, we expect that California will see increasing adoption of electric vehicles in the near future. It would be interesting to use this model to run a scenario considering high EV integration to evaluate how EVs could affect the optimized PV and storage sizing for the three different perspectives considered.

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