Quantifying System-Level Benefits from Distributed Solar and Energy Storage

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Abstract

Microgeneration using solar photovoltaic (PV) systems is one of the fastest growing applications of solar energy in the United States. Its success has been partly fueled by the availability of net metering by electric utilities. However, with increasing solar PV penetration, the availability of net metering is likely to be capped. Households would then need to rely on distributed storage to capture the full benefits of their installed PV systems. Although studies of these storage systems to assess their benefits to the individual household have been examined in literature, the system-wide benefits have yet to be fully examined. In this study, the utility level benefits of distributed PV systems coupled with electricity storage are quantified. The goal is to provide an estimate of these benefits so that these savings can potentially be translated into incentives to drive more PV investment. An agent-based residential electricity demand model is combined with a stochastic programming unit commitment model to
determine these effects. A case study based on the California residential sector shows that at 10% penetration levels for households with a 4 kW solar PV panel with a 0.5 kWh battery, the daily systems cost savings per household could be over $5 a day in August.

**Keywords**: Energy Systems Modeling, Distributed Solar Photovoltaic, Distributed Storage, Stochastic Programming, Lithium Ion Batteries Second use

**Introduction**

There has been an increasing proliferation of small-scale electricity generation units, largely due to the growing availability of renewable electricity sources. Small-scale solar cells and micro-wind turbines are two examples of such units that are gaining acceptance in residential applications. These devices can help meet a portion of the household electricity demand and have the potential to reduce the reliance on electricity from the electrical grid. There are several obstacles that hinder the widespread usage of these microgeneration units. One challenge is the variability of power output from wind and solar resources. This can create problems when scheduling electricity production to meet the projected demand. The second problem is the mismatch between peak demand and energy availability from wind or solar. Solar irradiance is highest around mid-day and correspondingly that is when peak electricity generation from solar cells occurs. Unfortunately this creates a mismatch between supply and demand timing as the peak electricity demand for a residential household is generally in the evening when people typically finish their work activities and return home. Wind must be assumed to blow randomly and thus the matching of wind peak generation and demand peak is not practical. The problems of mismatch result in an inefficient usage of valuable energy resources (Bahaj and James 2007). The final problem with these renewable resources has to do with costs. Though it is expected that renewable energy resources in the future can be cost competitive to conventional energy sources, at current price levels, they still are not competitive. (Tidball et al. 2010).
There are several solutions to the problems stated above. One option is to allow these small generators to export excess electricity generated back to the grid when conditions are appropriate (Bahaj et al. 2007; Watson et al. 2008). This solution is commonly called net metering and could result in disincentives for utilities since it effectively reduces customers’ dependence on their own generation services (Watson 2004; Bettle et al. 2006). There is also the restriction of caps on the amount of net metering allowed in systems (Payne et al. 2000). A solution that is simpler from a regulatory perspective is the addition of distributed energy storage to the electrical grid. These storage resources allow for the microgeneration units to store excess electricity on site and to tap into these resources when needed. The value of these storage systems to the consumers comes from the reduction of electricity consumed from the grid. There are also benefits to the grid operators in the form of reduced intermittency of the renewable resources. System-wide savings also occur through the reduction in fuels in electricity generation.

In this study, the benefit of distributed solar generation is studied in conjunction with distributed storage. Most studies have focused on just distributed generation; however, distributed storage could play an important role when net metering is restricted in the face of increasing solar penetration. It is therefore important to be able to quantify potential system-wide savings when both distributed generation and storage are present. In this paper, the system-wide effects are obtained by means of a combined discrete event and agent-based demand model which is in conjunction with a stochastic programming unit commitment model. A key modeling component to achieve this is the representation of stochastic electricity demand. In this work we employ a novel simulation approach to generate electricity demand by combining discrete event and agent-based simulation, which can incorporate household’s behavior of electricity usage down to the appliance level. The simulated demand is then fed to a system-level stochastic unit commitment model. Based on the modeling approach, we show that there can be significant system-wide savings even at low penetrations of both distributed solar PV panels and distributed storage. In addition, batteries from electric vehicles can potentially serve as distributed storage from the cost-benefit point of view.
The organization of the paper is as follows. First, the background information and motivation of the study are provided. We then describe the demand side model followed by the formulation of the supply side stochastic programming model. An analysis of a case study using residential-sector data from California is presented. It is established that there are significant system-wide savings even at low penetrations of both distributed solar PV panels and distributed storage. Batteries from electric vehicles could potentially serve as one form of such distributed storage. The paper then ends with a concluding segment highlighting the major findings.

Background

Microgeneration in the U.S has been rapidly gaining in popularity in recent years. More emphasis has been focused on micro solar generation than wind. This is not surprising in light of reports indicating that micro wind turbines are not as economical (Encraft 2009; Mithraratne 2009; James et al. 2010).

Residential based solar PV cells, especially in California, have been growing steadily over the past 5 years and it is reasonable to assume that these installations would continue to grow as acceptance grows (Go Solar California 2011).

As mentioned above, the continued acceptance of solar microgeneration relies heavily on the ability of owners to fully realize the benefits of solar generated electricity. Due to the problem of mismatch, there is heavy reliance on net metering to achieve those benefits (Payne et al. 2000). When the availability of net metering is limited, consumers would need to rely on other means to achieve these cost savings. It has been shown that it would be beneficial to consumers to install a localized electricity storage medium in the absence of net metering (Huang et al. 2010). Although there are many forms that electricity storage can take on, given current technology, there is no technology that has emerged as the clear choice. Electricity storage can take the form of fixed storage that is optimized for distributed storage needs. These storage technologies can be in the form of traditional lead-acid batteries (Jenkins et al. 2008) or even
hydrogen batteries (Kélouwani et al. 2005; Maclay et al. 2007). In this study, a generic electricity storage medium is assumed that is designed specifically for distributed storage purposes.

There is another category of batteries that can be available as distributed storage. These batteries may have been designed and optimized for other purposes and at the end of their useful lives, be repurposed and adapted to fixed distributed storage. One type can be advanced lithium ion batteries. Current costs of lithium ion batteries, the main type of batteries used in electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs), are very high. Estimates for the costs of these batteries can range from $650 / kWh to $1000 / kWh (Pesaran et al. 2007; Hidrue et al. 2011), which translates to a very significant proportion of a new vehicle cost. Industry standards for end-of-life battery capacities, according to the United States Advanced Battery Consortium (USABC), render these batteries unsuited for automotive purposes once battery capacity drops below 80% (USABC 2006). Proposed second use of these lithium batteries are gaining traction as viable alternative revenue streams for battery owners, allowing for these investors to recover some degree of investment capital (Neubauer et al. 2010; Williams and Lipman 2010). A possible scenario can be that a household owns an EV, leases the battery from the car company after its effective life and converts it into localized storage. However, an important aspect of these batteries is that the general capacities of the batteries are quite large. The battery of the Nissan Leaf is sized at 24 kWh. At 80% capacity, it is still 19 kWh, almost 70% of the average daily consumption of electricity for an American household. It is therefore important to determine the actual benefits of such an energy storage system.

There are quite a number of studies on the system-wide effects of distributed solar. These include several studies that have looked at the system reliability aspects of distributed solar generation (In-Su et al. 2004; Lu et al. 2007). There have also been estimates of environmental benefits through the implementation of distributed solar (Tsikalakis and Hatziargyriou 2007). Steps have also been taken to quantify potential benefits of these distributed systems (Daly and Morrison 2001; Chiradeja and Ramakumar 2004; Gil and Joos 2008). If networks were to expand to handle distributed generation, there would also be associated
costs (Cossent et al. 2009). Another recent study considered the solar penetration cap for a system without energy storage, limited mainly by resource mismatch. The maximum cost effective level of solar PV would be 20% of total electricity demand for the state (Myers et al. 2010). These studies, however have not considered the synergistic benefits of distributed storage with distributed generation. In this paper we would quantify system-wide cost savings of distributed solar PV generation coupled with distributed storage.

Methodology

A multi-paradigm simulation framework has been adopted in this study. A discrete event based residential model and an agent-based distributed solar and energy storage model are coupled with historical industrial and commercial demand data. The resulted aggregate demand is then fed into a stochastic programming unit commitment model. Error! Reference source not found. shows a simplified flow diagram of the overall approach. As our simulated demand depends on weather-related data, we choose a representative month of a year (August, in this case) to study. We seek to quantify the effect of these household level generation and storage technologies on the costs of electricity generation.

Electricity Demand

Electricity demand consists of three parts: residential, commercial and industrial. The focus of this paper is the determination of the penetration effects of distributed generation and storage in the residential sector; hence, the commercial and industrial sectors are assumed to be unaffected and follow historical load patterns. Historical data for California are obtained from the California ISO’s (CAISO) database (CAISO 2011). An aggregated profile of both the commercial and industrial load is then formed by removing a generalized residential profile.

The residential electricity demand sector is broken down into its individual households in this study. Each household is then further assumed to be composed mainly of a set of electrical appliances. The appliances
form the basic units for electricity demand in the residential sector. To obtain a residential electricity demand profile for California, all individual appliances are first aggregated into a representative household and then the households are further aggregated to yield the residential electricity demand. The framework for a Californian household has been described in detail in (Huang et al. 2011) and hence will not be discussed in detail here. 100 representative households are simulated in combination with the aggregated industrial and commercial demand profile over a period of 120 days with parameters representative of the month of August.

**Weather Characteristics**

Solar irradiation patterns are crucial to the modeling of distributed solar panels. In this study, the weather characteristics are modeled in two portions. The first is the amount of cloud cover. Cloud cover can be assumed to be in three states: overcast, partial cloud cover and clear. Data for the number of clear and cloudy days per month per year are obtained from the Western Regional Climate Center (WRCC 2011). Such data are collected from four different Californian sites corresponding to the most populous urban centers in the state. These data points are then aggregated with a weighted average for population to obtain an average for the state of California. Consolidated data are presented in Table 5 below.

The second part of the model gives the solar radiation level for the household. Detailed solar radiation data for California have been obtained from the National Solar Radiation Database (NREL 2005). Hourly means and deviations for each month are available for different sites in the state. Once again, data are selected for the four most populous urban centers within the state and averaged according to population weight. The consolidated tables are included in the appendix as Table 6 and Table 7.

**Distributed Solar Panels and Battery Storage**

A generalized model for a solar panel is used in this study. It is assumed that solar panels are rated at standard conditions. The power generated from the panel is assumed to be a function of the solar irradiation it receives. At each time step, the solar panel has the option of feeding the electricity generated
to the residential household, to the electricity storage or to both. The routing decision is based on the state of electricity generation with respect to demand. For example, if there is excess electricity, the excess power is sent to the storage. The reference size of the solar PV array is assumed to be rated at 4kW. This array configuration is the most popular installation size in California (Go Solar California 2011).

The other part of the demand-side model is the energy storage agent. We consider two categories of storage mediums, a generic local storage designed specifically to be compatible with distributed storage and second-life advanced lithium ion batteries adapted for distributed use after their useful life in automotive applications. The first storage medium is assumed to be a generic battery capable of fulfilling the household storage needs. In this study, the battery efficiency is assumed to be 80% with an inverter efficiency of 95%. As stated above, the storage medium would only be charged when there is excess electricity generated from the solar panels. The second category would be advanced lithium ion batteries that have been designed for automotive purposes. These batteries have significantly large capacities that may not be optimal for distributed storage.

Practically, there can be two options for battery discharging if there is differentiation of electricity prices at different times of a day. Time Of Use (TOU) electricity pricing can potentially encourage selective discharging of battery power. This means that the battery would only discharge power to cover electricity usage when the price of electricity is the highest, i.e. during system-wide peak electricity consumption periods. The other scenario would allow for the battery to fulfill any electricity usage whenever solar production cannot cover the household electricity demand. In this study, it is assumed that the latter battery discharge logic is followed since selective discharge could potentially reduce the benefits of solar power (Huang et al. 2010).

**Supply Side Stochastic Programming Formulation**

The electricity system modeled in this paper is a Pool-based electricity market where the day-ahead resource scheduling and the real-time power dispatch are performed by independent system operators
(ISOs), and, the energy and the reserve markets are co-optimized. Details on this two-settlement mechanism are provided in (Xingwang et al. 2009). The uncertainty considered in the system is the variability of electricity demand. The uncertainty is due to the lack of perfect information on the weather conditions or general variability of household appliances usage. Stochastic programming has been frequently used to model problems that involve uncertainty (Birge et al. 1997). A two-stage stochastic programming model has been proposed to determine the spinning and non-spinning reserve requirements with a high penetration of wind power in (Morales et al. 2009; Xiao et al. 2011). The same methodology is applied in this paper to decide the on/off statuses, the power outputs, the spinning and non-spinning reserve levels of each generating unit in each hour by minimizing the expected system cost, subject to unit-level and system-wide constraints. However, our model differs from that of (Morales et al. 2009; Xiao et al. 2011) in two aspects. First, one binary variable is introduced for each generating unit to capture their (levelized) fixed operation and management (O&M) cost. By doing so we can capture both short-run and long-run benefits of distributed resources to a power system. Second, the minimum power production for each fast-start generator is assumed to be zero as their unit size is relatively small. Consequently, there is no need to create one additional second-stage binary variable for each unit, hour, and realization of uncertainty in order to model the fast-start generators, which would otherwise make large-size problems intractable to solve.

The system demand in hour $h$, denoted by $\omega_h$ (MW), is sampled from a truncated normal distribution:

$$\omega_h \sim N\left(\mu_h, \sigma_h\right), \omega_h \in \left(\mu_h - 3\sigma_h, \mu_h + 3\sigma_h\right),$$

which is obtained from the aggregated results of the agent-based simulation. A $K$-point discrete distribution $\left(d^k_h, p^k_h\right)$ is used to approximate the hourly demand $\omega_h$, where $d^k_h$ represents the value of realization $k$, and $p^k_h$ the corresponding probability to take on this value.

The set of decisions consist of two groups: first-stage and second-stage decision variables. In the first stage, the generation resources are assigned to meet the anticipated demand in each hour of the following
day. Let \( n, n = 1, \ldots, N \) be the indices for the slow-start generators, which are responsible for generating electricity and providing spinning reserve; and \( m, m = 1, \ldots, M \) be the indices for the fast-start generators, which are eligible for providing non-spinning reserves. The first-stage decision variables include:

1) \( y_n (y_m) \) 0-1 variable that equals 1 when unit \( n(m) \) is committed day-ahead to operate in the following day.

2) \( z_{h,n} (z_{h,m}) \) 0-1 variable that equals 1 when unit \( n(m) \) is scheduled day-ahead to provide power and/or reserve generation in hour \( h \) of the following day. \( y_n (y_m) = 0 \) implies that \( z_{h,n} (z_{h,m}) = 0, \forall h \).

3) \( x_{h,n} \) The power generation scheduled day-ahead for unit \( n \) to generate in hour \( h \) of the next day (MW).

4) \( s_{h,n} \) The spinning reserve scheduled day-ahead for unit \( n \) to provide in hour \( h \) of the next day (MW).

5) \( r_{h,m} \) The non-spinning reserve scheduled day-ahead for unit \( m \) to provide in hour \( h \) of the next day (MW).

In the second stage, the uncertainty is realized and the outputs of the available generating units selected in the first stage are dispatched to meet the real-time system demand. For each realization of uncertainty, there is a set of second-stage decision variables associated with it. Hence there is a superscript \( k \) for each second-stage variables, which are listed in the following.

1) \( \psi^k_h \) The unsatisfied demand in hour \( h \) (MW)

2) \( s^k_{h,n} \) The actual deployment of the spinning reserve for unit \( n \) in hour \( h \) (MW)

3) \( r^k_{h,m} \) The actual deployment of the non-spinning reserve for unit \( m \) in hour \( h \) (MW)
Let $\beta^F_n$ ($\beta^V_m$) denote the fixed O&M cost for unit $n$ ($/\text{MW/day}$), $\beta^V_n$ ($\beta^V_m$) the fuel cost and variable O&M cost for unit $n$ ($/\text{MWh}$), $\beta^\text{SR}_n$ ($\beta^\text{NR}_m$) the cost for providing the spinning (non-spinning) reserve services from unit $n$ ($/\text{MWh}$), $\beta^{UL}$ the value of unsatisfied demand (i.e., lost load) ($/\text{MWh}$). The stochastic programming problem can be converted to a deterministic mixed integer linear programming (MILP) problem by writing out explicitly the constraints corresponding to each realization of uncertainty. The objective function of the programming problem is to minimize the expected total system cost (denoted as $EC$).

$$EC = \sum_{h=1}^{H} \left[ \sum_{n=1}^{N} (\beta^F_n y_n + \beta^V_n x_{h,n} + \beta^\text{SR}_n s_{h,n}) + \sum_{m=1}^{M} (\beta^F_m y_m + \beta^\text{NR}_m r_{h,m}) \right] +$$

$$\sum_{h=1}^{H} \sum_{k=1}^{K} p^k_h \left[ \beta^{UL} y^k_h + \sum_{n=1}^{N} \beta^V_n s^k_{h,n} + \sum_{m=1}^{M} \beta^V_m r^k_{h,m} \right]$$

(1)

Let $\bar{G}_n$ ($\bar{G}_m$) denote the maximal power output of unit $n$ ($/\text{MWh}$), $G_n$ the minimal power output of slow-start unit $n$. The minimum power production from the fast-start units are assumed to be zero since their unit size is relatively small. The first-stage constraints include:

**Day-ahead power balance**

$$\sum_{n=1}^{N} x_{h,n} = \mu_h, \quad \forall \ h$$

(2)

**Day-ahead operation limits**
The model can be extended to consider the inter-temporal constraints such as ramp rates and minimum up/down times in the day-ahead planning market. Detailed formulations and descriptions can be found in (Carrion and Arroyo 2006; Morales et al. 2009).

The second-stage constraints include:

*Real-time power balance*

\[
y^k_n \leq z^k_{h,n}, \quad \forall \ h, n
\]

\[
y^k_m \geq z^k_{h,m}, \quad \forall \ h, m
\]

\[
x^k_{h,n} + s^k_{h,n} \leq \bar{G}^k_{h,n}, \quad \forall \ h, n
\]

\[
x^k_{h,m} \leq \bar{G}^k_{h,m}, \quad \forall \ h, m
\]

\[
x^k_{h,n}, s^k_{h,n}, r^k_{h,m} \geq 0, \quad \forall \ h, n, m
\]

\[
y^k_n, y^k_m, z^k_{h,n}, z^k_{h,m} \in \{0, 1\}, \quad \forall \ h, n, m
\]
incorporated into the two-stage model, following the similar approaches in Morales et al., 2009 and Carrión and Arroyo, 2006. However, including the engineering and network details would add significant modeling and computation complexity, and yet, without adding notable insights to the results shown in this paper. As a result, we defer the effort of integrating a full-fledged unit commitment model with the demand side simulation to our future work.

Supply Characteristics

The generation system consists of 320 nuclear, hydropower, and natural gas generators, and the total electricity generation capacity considered is 58,762 MW. Table 1 shows the distribution of the generation capacity by energy sources. The hydropower and natural gas generators with the unit capacity smaller than 10 MW are aggregated so that the smallest unit in the system has the capacity of 10 MW. The minimum power production of each slow-start unit is assumed to be equal to 25% of its maximum production level. The fixed O&M, variable O&M, and fuel costs characteristics for these three electricity generating technologies (see Table 2) are extracted from (Tidball et al. 2010) and (EIA 2010). The offer cost for spinning reserve is assumed to be equal to 25% of the a slow-start unit’s marginal cost; and, the fast-start generators can offer the non-spinning reserve at a rate equal to 20% of its marginal cost. The minimum-up and down times are assumed to be 24 hours for the slow-start units, and one hour for the fast-start units. Further it is assumed that the cost of the unsatisfied demand is $4,000 per MWh.

The resulting MILP problem includes approximately 8,000 binary variables, 127,000 continuous variables, and 135,000 constraints when the number of second-stage demand realizations for each hour is equal to 15, i.e. \( K = 15 \). Note that in this model the demand in each period is independent of the demand in the previous period, and consequently, the computation of the second-stage objective value can be separated among 24 time periods and there is no need to generate the scenario tree. In addition, due to the presence of the unsatisfied demand variables, the second-stage problem is always feasible regardless of the realization of demand uncertainty. All problems were successfully solved by the CPLEX solver (called from GAMS) within several minutes, given that the relative termination tolerance is less than
0.1%; this means that the returned objective function value is not more than 0.1% from the value based on the ‘estimated best’ possible solution or the solution of the relaxed problem depending on which solver is used.

**Results and Discussion**

**Effects of Electricity Storage on Households**

In order to capture the full benefits of solar panels in residential households in the absence of net metering, some form of energy storage is needed to capture the excess electricity generated during the solar peak at noon. For a fixed solar cell capacity, it is interesting to gauge the benefits of increasing electricity storage sizes on the household. In essence, the maximum benefits that can be reaped from the installation of solar panels by households would occur when the household has access to infinite energy storage. This approximates the state that households face when they can redirect excess electricity generated back to the grid. In this study, the household is assumed to have a 4 kW rated solar panel installed with varying capacities of electricity storage.

One way to quantify the benefits of a battery is to determine the electricity demand savings of a household per kWh of battery installed. It can be seen from Error! Reference source not found. that the incremental household savings per kWh drops when the battery capacity increases. To visualize this, we calculate a ratio of reduction in electricity consumption to battery capacity. A ratio of 1 signifies electricity savings of the full capacity of the battery per day; that is a 4 kWh battery reduces electricity usage by 4 kWh. The value of this ratio is represented by the solid line in Error! Reference source not found.. A 0.5 kWh battery would have a ratio of 1.59, while a 2 kWh hour battery would have a ratio of 1.23. This means that the capacity of a battery is not as effectively utilized as the installed capacity increases. These diminishing returns occur due to the fact that the solar PV capacity fixed. With this fixed capacity, the amount of excess electricity generated at any point in time would decrease in relation to
increasing battery capacity, reducing battery capacity utilization. This reduction in returns could also indicate that in terms of investment, a 0.5 kWh battery gives a better return per kWh purchased than a 2 kWh battery. With battery prices potentially being high, these returns on investments would be a major concern for potential energy storage installations.

For a 4 kW solar PV panel in California, the ratio approaches 1 as battery capacity increases beyond 7 kWh. For a ratio below a value of 1, the battery is underutilized, indicating excess battery capacity for a residential household. The battery of the Chevrolet Volt is sized to have an effective battery capacity of 8.8 kWh. At the end of its useful life for the car, the battery could be expected to have a capacity of 7 kWh. Hence, a potential second use for this battery can be as distributed storage in California. Bigger batteries in other EVs like the Nissan Leaf and Think City are expected to have much larger capacities at the end of their effective life. Although capacities much larger than 10 kWh would be able to capture all of the excess electricity generated, the diminishing returns of additional battery capacity make them not as cost effective as the batteries of smaller capacities when combined with a 4 kW solar panel. If the EV/PHEV battery packs could be effectively redistributed in smaller capacities, they can then serve as distributed storage economically.

Another effect of distributed storage would be the shaving of residential peaks. Since the onset of solar peak does not correspond to residential peak, residential electricity demand peak is not reduced by solar microgeneration. However, with the presence of electricity storage, the residential peak can potentially be reduced. This can have significant implications for utility capacity planning for transformer loads. Error! Reference source not found. shows the electricity demand profile for an average residential household in California for the month of August. The base profile is a load of the household without any distributed generation or storage. A 4 kW solar panel is installed and indicated by the double red line. Subsequently, different capacities for batteries are examined. It can be seen that the increase in battery capacity reduces the residential peak very significantly. With a 10kWh battery, the average residential peak is reduced by almost 50%.
Effects of Distributed Solar on the Electricity Grid

The presence of distributed generation in the residential sector translates to an overall reduction in electricity demand from the electricity grid. This reduction in electricity demand in turn translates to a reduction in costs associated with the production of electricity. The quantification of these cost savings would allow for a possible discussion on the allocation of these benefits to relevant parties, allowing for possible incentives for the use of distributed solar. Error! Reference source not found. shows the reduction in overall system costs with respect to the installation of 4 kW solar PV panels. The main driver for the decrease in costs is the reduction in fixed operating and maintenance costs. At a 10% penetration of solar PV panels in the system, the reduction in overall costs is 9.12%. This is a very significant decrease in cost in light of the fact that essentially this is a 10% household penetration in a sector that accounts for only about 30% of the total electricity consumption of California. At 100% penetration, the overall savings reach a maximum of 17.84%. This signifies that the incremental system cost savings are greatest at 10% among the scenarios examined. The cost savings per solar PV installed would equal about $5 a day in August or $155 for a single month. Over the effective life of a solar panel, this adds to a substantial amount of savings. If a portion of this savings could be translated to incentives for solar PV panels, it could make solar PV more attractive to residential home owners.

Combined Effects of Distributed Generation and Distributed Storage on the Electricity Grid

The cost reductions associated with different battery sizes are examined next. Battery sizes are varied at a 100% penetration of 4 kW distributed solar PV panels. Cost savings are summarized in Error! Reference source not found.. Once again, the addition of the smallest battery capacity examined triggers the greatest marginal cost reduction. The addition of a 0.5 kWh battery produces a cost savings of 2.68%. A large 10 kWh capacity battery allows for system-wide costs savings of 30%. This leads to a large statewide reduction in fuel requirements for electricity production.
As noted above, the addition of a relatively small battery to a solar PV panel allows for a rather significant reduction in electricity consumption at the household level. In order to quantify the benefits of distributed storage at the system level, a 0.5 kWh battery is assumed to be paired with a 4 kW solar PV panel. The incremental savings from adding a 0.5 kWh battery to a 4 kW solar PV panel is summarized in Table 4. The table represents the difference in cost at various penetration levels of a household with and without a 0.5 kWh battery. The average cost savings that can be attributed to the battery is around $0.27 a day or $8.37 for the month. Once again, if a proportion of these savings could be transformed into incentives for batteries, it would make the adoption of these technologies much more attractive. It must be noted that the cost savings do not increase uniformly with increasing penetration of batteries. This can be attributed to the fact that the electricity generating resources being displaced by these savings are not homogeneous. They differ in capacities and costs. Hence it would be expected that the savings would not increase in a linear manner.

**Distributed Storage and Net Metering**

The effects of distributed storage could be expected to be markedly different from net metering effects. In net metering, the excess electricity is absorbed by the grid and is theoretically utilized immediately. It would be interesting to visualize how these two profiles would differ. We address this issue by comparing two scenarios. In one scenario, a 4 kW solar PV panel is installed in a residential household with access to net metering. In the other scenario, a 10 kWh capacity battery is assumed to be installed with every solar panel. This allows for an approximation of complete utilization of electricity generated by the solar panel. Error! Reference source not found. gives the profiles of these two scenarios at both 100% and 50% penetration of solar panels.

At 50% penetration of distributed solar, the excess electricity generated actually helps to decrease the system peak of California, effectively shifting the peak electricity demand to the later part of the day. However, as the penetration of distributed solar reaches 100%, it produces a valley during midday when solar peak occurs. Although the absolute peak of the system is reduced, the appearance of a valley
actually increases the absolute difference in the daily peak and minimum electricity demand of the system. On the other hand, the integration of distributed storage into the system gradually smoothes out the system load profile. This difference in demand profiles is especially pronounced when the daily system costs of electricity generation are compared. Table 6 indicates that at 100% penetration of solar, a large battery offers better system-wide cost savings than net metering. This can be attributed mainly to the higher O&M costs, both fixed and variable, associated with net metering. Although the system-wide absolute amount of electricity used may be similar, the big gap between peak and low demand requires a larger generation capacity with lower utilization factors.

**Conclusion**

In this work, a multi-paradigm modeling approach is used to analyze the effects of both distributed solar electricity generation and storage. California’s residential sector is used as a case study. For a 4 kW solar panel, a 7kWh battery could provide excellent utilization of excess electricity generated by the solar panel. This corresponds nicely with the expected end-of-life capacity of the battery pack of a Chevrolet Volt, thus, providing a viable second use for PHEV batteries. It is observed that a low penetration of distributed solar PV generation capacity provides a good degree of system-level cost savings. At 10% distributed generation penetration levels, a 4 kW solar PV panel could generate $5 in cost savings a day in the month of August. Similarly, a small battery connected to a solar panel can provide excellent cost savings. Based on the simulation results, a 0.5 kWh battery yields a system level cost reduction of about $0.27 per day. A percentage of these system-wide savings could potentially be provided as incentives for consumers to accelerate adoption of these technologies. The allocation and structure of these incentives shall be discussed in future research.
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Table 1: California energy sources

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<tr>
<th>Energy sources</th>
<th>Nuclear</th>
<th>Hydropower</th>
<th>Slow-start Natural Gas</th>
<th>Fast-start Natural Gas</th>
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<tbody>
<tr>
<td>No. of Units</td>
<td>2</td>
<td>126</td>
<td>52</td>
<td>140</td>
<td>320</td>
</tr>
<tr>
<td>Capacity (MW)</td>
<td>4,577</td>
<td>13,337</td>
<td>32,179</td>
<td>8,669</td>
<td>58,762</td>
</tr>
</tbody>
</table>
Table 2: Characteristics of electricity generating technologies

<table>
<thead>
<tr>
<th></th>
<th>Nuclear</th>
<th>Hydropower</th>
<th>Natural Gas</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Standard Deviation</td>
<td>Mean</td>
</tr>
<tr>
<td>Fixed O&amp;M ($/MW/yr)</td>
<td>85,968</td>
<td>10,751</td>
<td>13,930</td>
</tr>
<tr>
<td>Variable O&amp;M ($/MWh)</td>
<td>0.868</td>
<td>0.735</td>
<td>2.490</td>
</tr>
<tr>
<td>Fuel Cost ($/MWh)</td>
<td>9.848</td>
<td>0.130</td>
<td>0</td>
</tr>
</tbody>
</table>
## Table 4: Cost savings for distributed storage

<table>
<thead>
<tr>
<th>PV Penetration</th>
<th>10%</th>
<th>30%</th>
<th>50%</th>
<th>70%</th>
<th>100%</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost Difference ($)</td>
<td>519,000</td>
<td>1,805,000</td>
<td>731,000</td>
<td>2,075,000</td>
<td>1,960,000</td>
<td>-</td>
</tr>
<tr>
<td>Savings per Battery / Day ($)</td>
<td>0.40</td>
<td>0.46</td>
<td>0.11</td>
<td>0.23</td>
<td>0.15</td>
<td>0.27</td>
</tr>
<tr>
<td>Savings per Battery / Month ($)</td>
<td>12.38</td>
<td>14.35</td>
<td>3.49</td>
<td>7.07</td>
<td>4.67</td>
<td>8.37</td>
</tr>
</tbody>
</table>
Table 6: Average daily system costs for August with approximated full utilization of distributed solar energy

<table>
<thead>
<tr>
<th></th>
<th>100% PV Penetration</th>
<th>50% PV Penetration</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Net Metering</td>
<td>10 kWh Bat</td>
</tr>
<tr>
<td>Total Cost ($)</td>
<td>53,052,000</td>
<td>49,437,000</td>
</tr>
<tr>
<td>Fixed O&amp;M Cost ($)</td>
<td>30,261,000</td>
<td>25,605,000</td>
</tr>
<tr>
<td>Variable O&amp;M and Fuel Costs (Generation) ($)</td>
<td>21,165,000</td>
<td>22,368,000</td>
</tr>
<tr>
<td>Contract Cost for Reserve ($)</td>
<td>739,820</td>
<td>629,580</td>
</tr>
<tr>
<td>Variable O&amp;M and Fuel Costs (Reserve) ($)</td>
<td>535,330</td>
<td>499,090</td>
</tr>
<tr>
<td>Unsatisfied Demand Cost ($)</td>
<td>351,080</td>
<td>335,500</td>
</tr>
</tbody>
</table>
## Appendix

Table 5: Proportion of clear skies, cloudy and partial cloud cover per month

<table>
<thead>
<tr>
<th>Month</th>
<th>Clear Skies</th>
<th>Cloudy</th>
<th>Partial</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>0.38</td>
<td>0.37</td>
<td>0.25</td>
</tr>
<tr>
<td>February</td>
<td>0.38</td>
<td>0.36</td>
<td>0.26</td>
</tr>
<tr>
<td>March</td>
<td>0.38</td>
<td>0.33</td>
<td>0.28</td>
</tr>
<tr>
<td>April</td>
<td>0.39</td>
<td>0.29</td>
<td>0.32</td>
</tr>
<tr>
<td>May</td>
<td>0.38</td>
<td>0.26</td>
<td>0.36</td>
</tr>
<tr>
<td>June</td>
<td>0.48</td>
<td>0.20</td>
<td>0.32</td>
</tr>
<tr>
<td>July</td>
<td>0.66</td>
<td>0.06</td>
<td>0.28</td>
</tr>
<tr>
<td>August</td>
<td>0.67</td>
<td>0.06</td>
<td>0.27</td>
</tr>
<tr>
<td>September</td>
<td>0.61</td>
<td>0.12</td>
<td>0.27</td>
</tr>
<tr>
<td>October</td>
<td>0.52</td>
<td>0.21</td>
<td>0.27</td>
</tr>
<tr>
<td>November</td>
<td>0.48</td>
<td>0.25</td>
<td>0.26</td>
</tr>
<tr>
<td>December</td>
<td>0.42</td>
<td>0.34</td>
<td>0.24</td>
</tr>
</tbody>
</table>