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Community energy storage: A smart choice for the smart grid?

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HIGHLIGHTS

- We compare batteries deployed in 4500 individual households with 200 communities.
- Using real demand, PV data and locations we form community microgrids.
- We find that community batteries are more effective for distributed PV integration.
- Internal rates of return depend on the number of PV households.

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ABSTRACT

Energy storage can help integrate local renewable generation, however the best deployment level for storage remains an open question. Using a data-driven approach, this paper simulates 15-min electricity consumption for households and groups them into local communities of neighbors using real locations and the road network in Cambridge, MA. We then simulate PV for these households and use this framework to study battery economics in a high PV adoption, high electricity cost scenario, in order to demonstrate significant storage adoption. We compare the results of storage adoption at the level of individual households to storage adoption on the community level using the aggregated community demands. Under the simulated conditions, we find that the optimum storage at the community level was 65% of that at the level of individual households and each kWh of community battery installed was 64–94% more effective at reducing exports from the community to the wider network. Therefore, given the current increasing rates of residential battery deployment, our research highlights the need for energy policy to develop market mechanisms which facilitate the deployment of community storage.

1. Introduction

It is well known that the generation from roof-top PV systems is not generally aligned with peak electricity loads and this can lead to limits on the proportion of solar generation that can be integrated in traditional systems [1]. Until recently this has not caused significant concern for grid operators as PV adoption rates have been low, however several factors mean this is now changing, including continual declines in the price of solar panels [2], continually increasing residential electricity prices, favorable public opinion towards solar [3] and strong government support mechanisms [4]. As a result, evermore households are installing roof-top PV systems. This has led to significant concerns regarding the over-prevalence of PV generated electricity in electricity networks [5,6].

Concurrent with increasing residential electricity prices, the rewards for exported solar electricity are falling. Therefore, local PV self-consumption is gaining attention in several countries [7,8]. Energy storage is one effective way of allowing a larger fraction of demand to be met by PV-generation [9] and recent work has demonstrated that batteries can be used to increase the amount of PV that can be reliably integrated into the distribution network [10]. Other methods of increasing PV penetration include novel curtailment methods [11] and better PV and demand forecasting [12]. However, motivated by progress in battery development and public attention, recent studies have examined the techno-economic impacts of PV-coupled batteries in individual dwellings, examining the required conditions for economic profitability in terms of capital expenditure as well as retail tariffs and export prices [13–15]. Together with storage for frequency control, PV-coupled batteries have become a key business area for energy storage developers, with regions such as Germany and California leading the

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Nomenclature

Acronyms

CES	Community Energy Storage
EAC	Equivalent Annual Cost
EAV	Equivalent Annual Value
EFC	Equivalent Full Cycles
IRR	Internal Rate of Return
NPV	Net Present Value

Subscripts

i	for the *i-th* consumer
j	for the *j-th* cluster
y	for the *y-th* year

Parameters and variables

ϵ	uniformly distributed random variable in the range [−1,1]
η^{chg}/η^{dis}	battery charging/discharging efficiency (%)
π^{grid}/π^{ex}	electricity price for the grid, for exported solar ($/kWh)
C_i	cost of electricity for consumer i ($)
C_i^{PV}	cost of electricity with PV only ($)
CF_y	cash flow in year y ($)
J	within cluster sum of squares
K	number of clusters
Li	battery lifetime (years)
OM	operation & maintenance cost ($)
P^B	battery power (kW)
$P^{R,chg}$,$P^{R,dis}$	battery rated charge/discharge (kW)
S^M	monthly saving ($)
SOC	battery state of charge (kWh)
SOC^{min}/SOC^{max}	min/max battery state of charge (kWh)
ΔSOC	change in battery state of charge (kWh)
c_j	centroid location of the j^{th} cluster
$capCost$	total capital costs ($)
d_i	demand of consumer i (kW)
d_i^0	initial demand of consumer i (kW)
l_i	location of consumer i
r^d	discount rate (%)
s_i	PV generation of consumer i (kW)
t	time period (15-min timestep)
Δt	duration of time period t

way [16].

In contrast to storage in individual dwellings, energy storage can also be introduced for communities, *i.e.* Community Energy Storage (CES) [17]. The CES is then shared between members of the smart energy community, who are typically (although not exclusively) located in close proximity. Already many countries have experienced increases in “renewable energy communities”, groups of neighbors motivated to reduce their energy costs and promote the development of renewable energy [18]. In general, the CES then acts as an energy management system for the community. Related to the local energy communities concept are microgrids, localised electrical systems that can operate independently from the larger grid [19]. The topic of optimizing microgrids for renewable integration has gained much attention in the last decade [20], as well as their interactions with electricity markets [21] and ability to provide demand response [22] with electric vehicles and stationary energy storage devices [23]. Recent research has also studied the optimal power flows between clusters of microgrids [24] and optimized over multiple criteria, including costs and robustness related factors [25]. While microgrids imply independent control from the wider electrical network and clear electrical boundaries, smart energy communities can form in localised sections of the main electricity system without significant autonomy.

Similar to the advantages for community renewable energy, potential advantages of CES acknowledged in the previous literature are economies of scale for batteries and benefits related to the lower likelihood of short duration consumption peaks [26]. However, a systematic comparison of batteries for individual dwellings and communities in terms of size, location, electricity flows and economic attractiveness is so far lacking and this study aims at providing insights into the optimum aggregation level of storage deployment next to the consumption centres. One particular problem in the study of smart energy communities is the lack of location data associated with openly available electricity meter data, due to privacy concerns. Therefore, in this work we simulate community formation by connecting together neighboring households along the road network and matching real monthly consumption values to data sources where 15-min consumption is available [27]. We also simulate realistic PV generation profiles based on real PV generation data. We then use the household demand profiles or the aggregate community demand profiles to estimate an economically optimum level of storage for each household and community respectively, with the main contribution of our work being a comparison between the two storage scales.

We utilize monthly electric bills obtained from a local electric utility in Cambridge and smart meter data from the Pecan Street project, based in Austin Texas. This provides a source of 15-min resolution electricity data for in excess of 1000 households, as well as solar generation with the same temporal resolution for those households with rooftop PV installed [28]. Fig. 1a shows the daily load and generation data for an example home on a typical April day. We define misalignment as the proportion of a consumer’s solar generation that they do not consume, as shown in Eq. (1).

$$\text{misalignment} = \frac{\text{PV exported}}{\text{Total generation}} \tag{1}$$

Fig. 1b shows the distribution of total misalignments for consumers in the Pecan Street data with PV installations for the month of April. It can be seen that the misalignment between the generation and consumption is significant and it is observed that the average misalignment for all homes over the month of April is 57%, therefore only 43% of electricity they produce matches their demand. We also compare the misalignment estimated at two temporal resolutions and see that higher temporal resolutions are important for accuracy [7].

The rest of this paper is structured as follows. Section 2 describes the creation of the local smart energy communities, the simulation of the 15-min electricity consumption and PV generation, and the battery model. Section 3 gives the simulation results, including the effects of

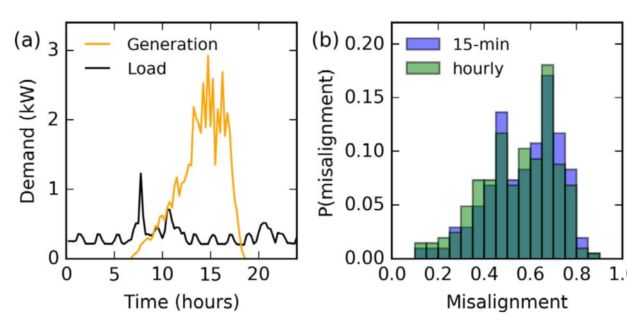

Fig. 1. (a) A daily load and generation profile in April. (b) Monthly misalignment values between generation and demand for all homes.