The Sharing Economy for Residential Solar Generation $^{\pi}$

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Abstract—This paper studies rooftop solar photovoltaic (PV) investment decisions of households. Two cases are considered: (a) the status quo of net-metering, and (b) a new sharing economy model. Under net-metering, households can sell back their excess generation to the utility at their retail tariff subject to the prevalent constraint that they cannot be net producers of electricity on an annual basis. In our sharing economy model, households can pool their excess PV generation and trade it in a spot market among themselves, but the collective cannot sell electricity back to the utility. Our objective in studying these two cases is that net-metering programs are under threat and being phased out, which places future residential PV investment at risk. In the event of this contingency, we argue that the sharing economy model offers a pathway to preserve and even accelerate residential PV investment.

We derive expressions for the optimal investment decisions in each case assuming that households are rational and wish to minimize their costs. We characterize the random clearing price in the spot market for excess PV generation under the sharing model. We show that the optimal investment decisions are determined by a simple threshold policy. Households whose PV productivity metric exceeds this threshold invest the maximum possible, while those that fall below the threshold do not invest. We offer a convergent algorithm to compute this threshold. We close with a small-scale simulation study that reveals the favorable properties of the sharing economy model for residential PV investments.

Index Terms—Sharing Economy, Photovoltaic Generation, Optimal Investment, Net-metering.

I. INTRODUCTION

Investment in photovoltaic (PV) systems has seen dramatic growth worldwide. For example, in the U.S. PV has experienced an average annual growth of 68% [1] over the last decade. In the five-year period between 2012 and 2017, U.S. solar industry related employment grew by 16% annually, adding 131,000 jobs. One in every 100 new jobs was a solar job [2]. Much of this dramatic growth has come from small-scale residential systems.

Three key factors drive growth in behind-the-meter PV systems. First, the integrated costs of PV have fallen by 50% over the last 6 years [3], and levelized electricity costs are now below \$0.16 per kWh for distributed rooftop systems in many regions [4]. Second, state and federal subsidies

improve the private economics of PV – for example the federal investment tax credit (equal to 30% of installation costs) [5]. Third, net-metering policies – in which utilities credit customers for hourly production in excess of their consumption – effectively mandate utilities to purchase excess distributed solar PV production at retail rates, which are much higher than utilities' avoided cost of purchasing energy from wholesale generators.

However, subsidies and tax credits are being phased out, and utilities strenuously oppose net-metering because it enables customers to avoid the true costs of infrastructure, reserves, and reliability. In some of the sunniest states (Arizona and Hawaii), net-metering programs are weakening or disappearing altogether [6].

Are there feasible and sensible strategies to sustain the future growth in behind-the-meter PV in the face of these challenges? We submit that the sharing economy business model offers a plausible pathway. Sharing has already transformed housing and transportation markets by allowing individuals to offer underutilized products like ridesharing (Uber, Lyft) and unoccupied real estate (Airbnb) on peer-to-peer platforms. In this paper we explore how connected communities of homes could share excess electricity generation. In our earlier work, we have explored a sharing economy business model in the context of firms sharing installed electricity storage to arbitrage against time-of-use tariffs [7].

There is an important precedent for solar sharing in the United States: at least 16 states have "virtual net-metering" programs that allow owners of one solar system to distribute net-metering credits to the bills of other customers [8], [9], [10]. In some states these programs are limited to individual properties (for example multi-tenant housing), but in other states all customers are eligible to pool credits with other customers. These programs extend net-metering to aggregations of buildings but continue to rely on the notion of reverse flow receiving the same credit as consumption. In addition, several pilot programs that allow peer-to-peer transactions among users are appearing [11]. Projects like the Brooklyn Microgrid in the US, expecting around 1000 users by the end of 2018 [12], or the NRGcoin project in Europe, are cases on which energy trade among users has been implemented using a blockchain-based framework. Here we investigate a model that could persist if the concept of net-metering is eliminated, in which groups of customers pool their hourly consumption and production, with pooled hourly net reverse flow receiving no utility credit. We analyze the PV investment decisions of individual homes under a sharing economy model, and

 $^{^{\}pi}$ This research is supported by the National Science Foundation under grants EAGER-1549945 and CPS-1646612, and by the National Research Foundation of Singapore under a grant to the Berkeley Alliance for Research in Singapore.

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compare them to decisions that would occur in the status quo net-metering case.

We note that there is a substantial amount of research on optimal sizing and siting of distributed generation. This work focuses on engineering impacts, cost minimization or utility profit maximization; for example [13], [14], [15], [16], [17], [18]. In addition, game theoretical approaches, e.g. [19], [20], [21], study different peer-to-peer energy trading schemes among producers and consumers. However, research in this space takes the perspective of individual customers or of distribution system operators. We are unaware of efforts to evaluate how optimal decisions change when customers are able to share, or aggregate, their hourly production. While the core idea of aggregating variable energy production has been applied in other contexts, e.g. [22], [23], [24], [25], [26], researchers have yet to leverage aggregation as an alternative to net energy metering for individual customers.

Contributions: In this paper we formulate solar investment decisions under various pricing and sharing schemes as optimization problems that explicitly model uncertainty arising from behind-the-meter energy consumption and solar production. We show that investment decisions in the shared solar case can be cast as a game that admits a unique, social welfare supporting Nash equilibrium. We also derive a simple optimal investment threshold policy for individual customers participating in the shared setting. We then use numerical experiments to show that investment outcomes differ strongly between the standalone and sharing economy cases, with total investment levels in the shared case exceeding those in the standalone case. We also show that some standalone customers will over-invest and others will under-invest, relative to the social-welfare maximizing decisions of the shared solar case.

NOTATION

We write x^+ to mean $\max\{x,0\}$, and $\mathbb{E}[X]$ for the expectation of the random variable X. For random sequences $X(t), Y(t), \ t=1,\cdots,T$, we write the average expectations as

$$\begin{split} & \overline{\mathbb{E}}\left[X\right] &= & \frac{1}{T}\sum_{t}\mathbb{E}\left[X(t)\right] \\ & \overline{\mathbb{E}}\left[X|Y\right] &= & \frac{1}{T}\sum_{t}\mathbb{E}\left[X(t)\mid Y(t)\right]. \end{split}$$

khousehold or firm index ttime index number of households nTnumber of time slots panel area investment decision for home k a_k max area available to install PV panels for home k m_{k} $w_k(t)$ effective irradiance at firm k in time slot tload of firm k in time slot t $\ell_k(t)$ π^{s} amortized capital cost of PV per m² per time slot π^{g} retail electricity tariff net-metering price

II. PROBLEM SET-UP

Imagine we have a connected community of n households or firms indexed by k. These homes are considering installation of rooftop solar PV. The investment decision for home k is the panel area a_k for its PV system. We consider a multiyear investment horizon broken into small time intervals (e.g., 5 min, 15 min, or 1 hr), and time slots are indexed by t. We use a simple linear model of investment costs: the price of PV panels amortized over their lifetime is π^s \$/m² per time slot. This can be derived by combining commonly used \$/watt PV levelized cost figures with production models (see Section V).

Home k receives irradiance $w_k(t)$ in slot t. If it invests in a_k of panel area, this home generates $a_k w_k(t)$ kWh of electricity in slot t. Thus, $w_k(t)$ captures the *effective* irradiance including factors such as panel efficiency, inverter efficiency and relative declination of incident sunlight. It varies with time of day and technology choice. The electricity demand for home k in slot t is $\ell_k(t)$. We treat ℓ_k and w_k as non-stationary random sequences. The household demand $\ell(t)$ is first served by its own local PV production. The deficit or net-load $(\ell(t) - aw(t))^+$ is bought from the utility at the retail tariff π^g . In some situations, any surplus may be sold back to the utility through its net-metering program at the net-metering price π^{nm} . For the likely future scenario where net-metering programs are phased out, we can set $\pi^{nm} = 0$. The situation we consider is shown in Figure 1.

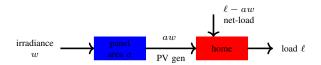


Fig. 1: Set-up: irradiance, PV generation, and net-load for a home.

III. STANDALONE INVESTMENT DECISIONS

In this section, we analyze the PV investment decisions of a household under the *status quo*. The situation we consider is shown in Figure 2.

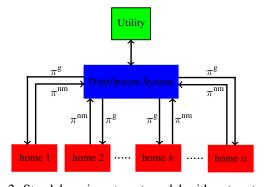


Fig. 2: Standalone investment model with net-metering

Households act independently and do not trade excess generation with each other. They participate in conventional net-metering programs under which excess PV generation is sold back to the utility at a fixed price $\pi^{\rm nm}$. This is often the retail electricity price $\pi^{\rm g}$. Most importantly, there is an annual cap that limits PV investments: households cannot be net energy producers over the course of a year.

In this standalone scenario, the PV investment decisions of households are *decoupled*. Home k decides how much PV panel area a_k to install based on the joint statistics of its own load and irradiance, together with panel costs and electricity prices. The cost function for firm k is

$$J_k(a_k) = \underbrace{\pi^{\mathrm{s}} a_k}_{\text{capital cost}} + \underbrace{\pi^{\mathrm{g}} \overline{\mathbb{E}} [(\ell_k(t) - a_k w_k(t))^+]}_{\text{cost of buying deficit}} - \underbrace{\pi^{\mathrm{nm}} \overline{\mathbb{E}} [(a_k w_k(t) - \ell_k(t))^+]}_{\text{revenue from selling surplus}}$$

It is simple to verify that this cost function is convex in the scalar decision variable a_k .

We now explore constraints on a_k . The maximum panel area supported at household k is m_k . Net-metering riders constrain households to be net consumers of electricity on an annual basis. Let $\overline{\mathbb{E}}_{Yi}[\cdot]$ denote the average expectation conducted over year i. This constraint reduces to

$$\overline{\mathbb{E}}_{Yi}[\ell_k(t) - a_k w_k(t)] \ge 0$$
, for $i = 1, 2, \cdots$

Equivalently, we obtain

$$a_k \le \frac{\overline{\mathbb{E}}_{Yi}[\ell_k(t)]}{\overline{\mathbb{E}}_{Yi}[w_k(t)]} \text{ for } i = 1, 2, \cdots$$
 (1)

Using representative historical load and production data, we can compute these annual cap constraints. Other distribution system constraints (ex: reverse power flow, transformer sizing) also impose limits on a_k . All these constraints can be combined into a single upper bound $a_k \leq a_k^{\max}$. We shall see in Section V, that most often it is the annual cap constraints (1) and not the physical panel area constraints that are binding.

The optimal investment a_k^* of home k is determined by solving

$$a_k^* = \arg\min J_k(a_k)$$
 subject to $0 \le a_k \le a_k^{\max}$

Theorem 1: Assume $\pi^{nm} = \pi^g$. Then, the optimal PV investment decisions of household k under the standalone model are given by the threshold policy:

$$a_k^* = \begin{cases} a_k^{\text{max}} & \text{if} & \overline{\mathbb{E}}[w_k] > \pi^{\text{s}}/\pi^{\text{g}} \\ 0 & \text{else} \end{cases}$$
 (2)

Proof: If the net-metering price is pegged to the retail electricity price, i.e. $\pi^{nm} = \pi^g$, the cost function simplifies to

$$J_k(a_k) = \pi^{\mathrm{s}} a_k + \pi^{\mathrm{g}} \overline{\mathbb{E}} [(\ell_k(t) - a_k w_k(t))]$$

Observing that this is linear in a_k with slope $(\pi^s - \pi^g \overline{\mathbb{E}}[w_k])$, yields the result.

In the general case of discounted net-metering prices $\pi^{\rm nm} < \pi^{\rm g}$, we can show that the cost function (while not linear) is convex. We can derive a closed form for the optimal investment decisions. In any event, these optimal PV investment decisions a_k^* for each household can be easily computed using historical data to form empirical expectations.

IV. INVESTMENT DECISIONS UNDER SHARING

In this section, we analyze the PV investment decisions of a household under a *sharing economy model*. The situation we consider is shown in Figure 3.

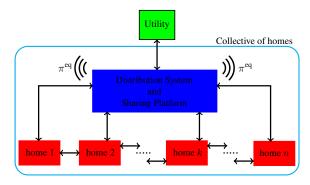


Fig. 3: Sharing economy investment model with no netmetering

A home may have a deficit of net-load $(\ell_k - a_k w_k)^+$ in some time slots. This can be purchased from homes who have a surplus, or from the utility at the fixed price π^g \$/kWh. The utility is the supplier of last resort. Homes may also have an excess net generation $(a_k w_k - \ell_k)^+$ in some time slots. This can be sold to other homes, or returned to the utility under net-metering. To simplify our exposition, from this point forward we shall consider the sharing economy investment model with *no net-metering*, i.e. we set

$$\pi^{\text{nm}} = 0 \tag{3}$$

Indeed, our objective is to argue that the sharing economy model can supplant net-metering in some (likely) future scenario when utilities withdraw these programs. We will argue that under the sharing economy model, investment in residential PV will continue to thrive.

Remark 1: We stress that traditional net-metering is not sharing. True resource sharing would pool excess PV generation and trade this over a spot market. We next analyze a stylized model of this spot market.

A. Spot Market for Sharing Excess PV Generation

We explore a simple spot market model for sharing excess PV generation from households. The collective supply S and demand D of shared electricity are

$$S = \sum_{k} (a_k w_k - \ell_k)^+, \ D = \sum_{k} (\ell_k - a_k w_k)^+.$$

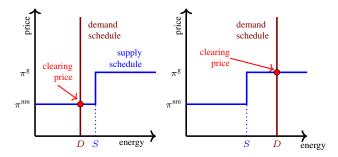


Fig. 4: Clearing price for shared electricity: (a) left panel S > D, (b) right panel S < D.

Consider time slot t. If the collective supply S(t) in this time slot exceeds the collective demand D(t), homes with excess PV generation will compete against each other. As a result, this shared electricity will trade at the floor price offered by the utility under net-metering $\pi^{\rm nm}$ (which we have set to 0). If the collective demand D(t) exceeds the collective supply S(t), homes with a net deficit of electricity will compete against each other. As a result, this shared electricity will trade at the ceiling price imposed by the utility $\pi^{\rm g}$. These effects are illustrated in Figure 4.

In summary, the spot market price for shared electricity is:

$$\pi^{\text{eq}} = \begin{cases} \pi^{\text{nm}} = 0 & \text{if} & S > D \\ \pi^{\text{g}} & \text{else} \end{cases}$$
 (4)

This clearing price is random - it depends on market conditions in each time slot.

For $t = 1, \dots, T$, define the random sequences

$$L(t) = \sum_{k} \ell_k(t), \quad G(t) = \sum_{k} a_k w_k(t)$$

$$X(t) = L(t) - G(t)$$
(5)

Note that L(t) is the collective load, G(t) is the collective generation, and X(t) is the collective net-load in time slot t. Observe that

$$S - D = \sum_{k} (a_k w_k - \ell_k)^+ - \sum_{k} (\ell_k - a_k w_k)^+$$
$$= \sum_{k} a_k w_k - \ell_k = G - L$$

As a result, the spot market price for shared electricity (4) can be re-written as

$$\pi^{\text{eq}} = \begin{cases} 0 & \text{if} \quad X < 0 \\ \pi^{\text{g}} & \text{else} \end{cases}$$
 (6)

B. Optimal Investment Decisions

The expected cost faced by household k (per time slot) has three components:

$$J_{k}(a_{k} \mid a_{-k}) = \underbrace{\underline{\pi^{s}} a_{k}}_{\text{capital cost}} + \underbrace{\overline{\mathbb{E}} \left[\pi^{eq} (\ell_{k} - a_{k} w_{k})^{+} \right]}_{\text{cost of buying deficit}} - \underbrace{\overline{\mathbb{E}} \left[\pi^{eq} (w_{k} - a_{k} \ell_{k})^{+} \right]}_{\text{revenue from sharing surplus}}$$
(7)

Note that the objective function for household k depends on the investment decisions a_{-k} of other households. This induces a *PV investment game*. The social cost is

$$J(a_1, \cdots a_n) = \sum_k J_k$$

We first consider the academic case of common irradiance with no bound on maximum panel area supported at each household. We can show the following:

Theorem 2: Assume all households receive common irradiance, i.e. $w_k = w$ for all k. Then,

- (a) the PV investment game admits a unique Nash equilibrium
- (b) the optimal total investment A is the unique solution of

$$0 = \pi^{\mathrm{s}} - \pi^{\mathrm{g}} \cdot \frac{1}{T} \sum_{t} \mathbb{E}\left[p(t)w(t) \mid L(t) > Aw(t)\right]$$

where $p(t) = \text{Prob}\{L(t) > Aw(t)\}$

(c) at this Nash equilibrium, the optimal investment of household k is

$$\frac{a_k^*}{A} = \frac{\overline{\mathbb{E}}\left[\ell_k \mid L = Aw\right]}{\overline{\mathbb{E}}\left[L \mid L = Aw\right]}$$

(d) this Nash equilibrium supports the social welfare

Proof: Omitted because of space considerations.

Under the much more realistic condition of diverse irradiance, we can again show that there is a unique Nash equilibrium for the PV investment game. We cannot offer a closed form expression for this Nash equilibrium. Also, this Nash equilibrium *does not* support the social welfare (i.e. a social planner would have ordered households to make alternate investment choices). The PV investment game models Cournot competition as it accounts for the statistical influence households have on the price $\pi^{\rm eq}$ of shared electricity.

Let us assume that home k can invest at most m_k m² of panel area due to physical limitations at the site. Also, we assume that a large number n of households participate in PV sharing. With this realistic assumption, we will have asymptotically (in n) perfect competition. The perfect competition equilibrium concept is much easier to analyze principally because no single firm can influence the statistics of the clearing price π^{eq} .

We have our main result:

Theorem 3: In the sharing economy model, under the perfect competition model and no net-metering the optimal PV investment decisions of household k are given by the threshold policy:

$$a_k^* = \left\{ \begin{array}{ll} m_k & \text{if} & \pi^{\mathrm{g}} \sum_t \mathbb{E}[p(t) w_k(t) \mid X(t) > 0] > \pi^{\mathrm{s}} T \\ 0 & \text{else} \end{array} \right.$$

where X(t) is the net-load random sequence, $p(t)=\operatorname{Prob}\{X(t)>0\},$ and T is the number of time slots.

Proof: With the simplifying assumption of no net-metering (3), the cost function (7) can be written as

$$J_k(a_k) = \pi^{\mathrm{s}} a_k + \overline{\mathbb{E}} [\pi^{\mathrm{eq}} (\ell - a_k w_k)^+]$$

= $\pi^{\mathrm{s}} a_k + \frac{\pi^{\mathrm{g}}}{T} \sum_t p(t) \mathbb{E} [\ell_k(t) - a_k w_k(t) \mid X(t) > 0]$

Note that because of the perfect competition model, the cost function for household k depends only on its own investment decision a_k . This cost function is linear in the decision variable a_k with slope

$$\phi = \pi^{\mathrm{s}} - \frac{\pi^{\mathrm{g}}}{T} \sum_{t} p(t) \mathbb{E}[w_k(t) \mid X(t) > 0]$$

As a result, the optimal investment is $a_k^* = 0$ if this slope $\phi > 0$, and $a_k^* = m_k$ otherwise. This can be rearranged to yield the threshold policy of Theorem 3.

Remark 2: If we assume the load ℓ_k and irradiance w_k are stationary random sequences, p(t) = p is independent of t. In this case, the threshold policy of Theorem 3 becomes

$$a_k^* = \begin{cases} m_k & \text{if} & \mu_k = \mathbb{E}[w_k \mid L > G] > \theta \\ 0 & \text{else} \end{cases}$$
 (8)

where the threshold θ is the unique solution of

$$\theta = \frac{\pi^{\rm s}}{\pi^{\rm g} p} \tag{9}$$

The quantity $\mu_k = \mathbb{E}[w_k \mid L > G]$ captures the value of PV for home k. This home will invest the maximum possible if $\mu > \theta$, and not invest otherwise.

C. Computing the Threshold θ

Computation of the threshold θ in (9) is not trivial: θ determines the PV investments of households, which influences the statistics of the collective load L and generation G, and this, in turn, affects θ . We now offer an algorithm to compute θ . We treat the case where the load ℓ_k and irradiance w_k are stationary random sequences, but our procedure readily generalizes to the realistic case where these sequences are non-stationary.

Define the index sets of households

$$\mathbb{S}$$
 = homes that elect to invest in PV = $\{k : a_k = m_k\}$
 \mathbb{T} = homes that elect not to invest in PV = $\{k : a_k = 0\}$

Our algorithm iteratively updates S and T in order to determine the threshold θ . Convergence is guaranteed. The algorithm initializes the set S, by adding the best firms without considering the collective deficit, and initializes the set \mathbb{T} using the other ones. With this, an iterative process starts, in which the threshold θ is updated and the worst firm $k \in \mathbb{S}$ (firm with the minimum merit $\mu_k < \theta$) is removed from the set S and added to the set T. On the other hand, the best firm $k \in \mathbb{T}$ (firm with the maximum merit $\mu_k > \theta$) is removed from \mathbb{T} and added to \mathbb{S} . This process is repeated until no changes of firms occur or the same changes are occurring after two iterations.

Algorithm 1: Collective of firms investing in PV

- 1: Initialization:
- Compute maximum generation for each firm $\bar{q}_k := \overline{\mathbb{E}}[m_k w_k]$.
- Sort the firms by \bar{g}_k on descending order.
- Start with $\mathbb{S}=\mathbb{T}=\varnothing$ and add the upper half of the sorted firms to the set \mathbb{S} , while the bottom half to the set \mathbb{T} .
- for iteration $i = 1, \dots$ do
 - Compute the collective generation $G(t) = \sum_{k \in \mathbb{S}} m_k w_k(t)$.
- Compute the probability of deficit $p = \Pr\{\overline{L} > G\}$. 7:
- 8: Update threshold $\theta = \pi^{s}/(\pi^{g}p)$.
- 9: **for** firms k on \mathbb{S} **do**
- Compute merit of site k as $\mu_k = \overline{\mathbb{E}}[w_k|L>G]$ If $\exists k: \mu_k < \theta$, pick firm k^{L} with the minimum μ_k and 11: remove it from the set S.
- 12: end for

10:

13:

15:

- for firms k on \mathbb{T} do
- 14:
- Compute merit of site k as $\mu_k:=\overline{\mathbb{E}}[w_k|L>G]$ If $\exists k:\mu_k>\theta$, pick firm k^{H} with the maximum μ_k and remove it from the set \mathbb{T} .
- 16: end for
- Add firm k^{L} to the set \mathbb{T} and firm k^{H} to set \mathbb{S} . 17:
- Halt if no firms are moving or the same moves are being done after two iterations.
- 19: end for
- 20: Solve the standalone case for indecisive firms, that are the last firms on changing between sets.

V. SIMULATION STUDY

If net-metering programs end, could shared solar maintain current investment levels in photovoltaics? In this section we use a variety of simulation experiments to explore how solar adoption differs in a status quo net-metering policy landscape versus a shared solar model. As we shall show, if sharing is available as a policy tool, total solar investment could be equal to or greater than what currently occurs with netmetering. However the distribution of customers who invest could change significantly, which could raise fairness and equity concerns.

A. Data

Prices. Based on [3], we use a levelized cost of 2.80 W_{DC} for solar PV. A typical residential panel of 165 \times 99 cm (1.64 m^2) has a rated power of 300 W_{DC} [27] (corresponding to 18.3% efficiency at 1000 W/m² irradiance). With that, an investment cost of 512.2 \$/m² is required per household. Considering a discount rate r of 5% and a time horizon of 10 years, we obtain an annuity of 66.36 \$/m², that yields a price of $\pi^{\rm s}=0.0076~{\rm s/m^2}$ per hour. We use a retail price $\pi^{\rm g}=0.17$ \$/kWh and net-metering price $\pi^{\rm nm}=\gamma\pi^{\rm g}$ for the standalone model, with $\gamma \in [0,1]$ depending on the study case. In the sharing economy model we set $\pi^{nm} = 0$ (no net-metering), but no annual cap on production from individual customers.

Load and Irradiance. In this initial simulation study we use synthetic solar production and load data. In all cases we simulate load for 1000 homes. These data are generated with heterogeneity across homes in load patterns, solar resource availability and available roof area. We will ultimately show simulation results from different scenarios on available roof area, which is a key unknown parameter. However because the data are synthetic, our results should only be interpreted as suggestive of what is possible, and this investigation should be followed by detailed simulations using real customer demand and solar data.

To create load data, we begin with the 2016 aggregated hourly profile for the San Francisco Bay Area load zone define this time series at $\mathcal{L}(t)$. We then set the average hourly consumption across all homes to be $\bar{\ell}(t) = \alpha \mathcal{L}(t)/(\sum_t \mathcal{L}(t))$, where $\alpha = 10766$ kWh is the average annual consumption for an American home [28]. To generate a time series for each simulated home we add a unique white noise time series $\varepsilon_k(t)$ to the scaled profile such that each home's simulated load is $\ell_k(t) = \bar{\ell}(t) + \varepsilon_k(t)$.

We derive PV profiles from the average hourly solar irradiance (in kW/m²) in the San Francisco Bay Area in 2016. Those irradiances are converted to a generic PV production profile by scaling the irradiance by 18.3% panel efficiency as defined above, and a balance of system efficiency of 93%. For each user, we generate synthetic PV power per m² of roof area, $w_k(t)$, by scaling the generic PV profile by a random number drawn from a uniform distribution $\sim \mathcal{U}([0.6, 1.1])$. This scaling represents heterogeneity across customers due from roof orientation, shading and local climate effects.

To capture heterogeneity in available roof area, we also draw panel area limits from a uniform distribution $m_k \sim \mathcal{U}([\alpha, \beta])$ where α and β vary in different scenarios. For the standalone case we also include a constraint that installed area cannot exceed

$$a_k^{\mathrm{cap}} = rac{ar{\mathbb{E}}[\ell_k(t)]}{ar{\mathbb{E}}[w_k(t)]}$$

to ensure that individuals in the standalone case are not net producers over a year.

B. Results and Discussion

1. Small available panel area m_k . We first consider investment decisions under both market structures for a case with low maximum available roof area $m_k \sim \mathcal{U}([2,6])$ m². This area distribution is small for single family homes, whith floor space averaging roughly 220 m² in the U.S.; if only 10 percent of an average two-story home's roof area were available, about 11 m² of area would be available for solar.

Under this scenario, for different values of $\pi^{nm} = \gamma \pi^g$ in the standalone case, both market structures yield nearly identical results. This equivalence results from the fact that if m_k is small enough, $\ell_k(t) - m_k w_k(t) > 0$ for all time steps. For standalone customers in that situation, the net-metering price is irrelevant; they simply install as much solar as possible $(a_k = m_k)$ if the retail price compares favorably to the cost of solar. Therefore in this case all standalone customers with sufficiently high $\overline{\mathbb{E}}[w(t)]$ install their maximum and all other customers install none. Furthermore, if $\ell_k(t) - m_k w_k(t) > 0$

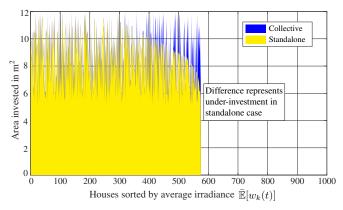


Fig. 5: Comparison of investment decision with $\gamma=0.8$ for the mid-range maximum available panel area case. A low rank on the horizontal axis corresponds to relatively high irradiance.

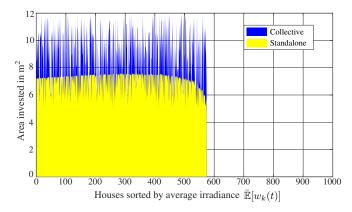


Fig. 6: Comparison of investment decision with $\gamma=0$ for the mid-range maximum available panel area case.

for most hours and customers, then L(t)-G(t)>0 for at least as many hours, meaning virtually the same customers install solar in the collective case as well.

2. Mid-range available area distribution: $m_k \sim \mathcal{U}([5,12])$ m². We view this distribution as a conservative, though not overly so, estimate of the available roof area for typical single family homes in the U.S. With this allowable area, customers have the option to install enough capacity that their net-load would be negative in some hours, meaning they are exposed to the net-metering price in those hours.

Figure 5 depicts results with a standalone net-metering price similar to the retail price ($\gamma=0.8$). Here we begin to see results differ in important ways. Standalone customers install roughly 3% less capacity because their net-load is negative in hours when the collective net-load is not; though $\pi^{\rm nm}$ is close to π^g , the economics of reverse flow are slightly worse and customers invest slightly less. Note, however, that the set customers that choose to install solar is the same in both the collective and standalone cases. This is because the available roof area remains low enough that if all customers with favorable solar availability invest to their maximum,

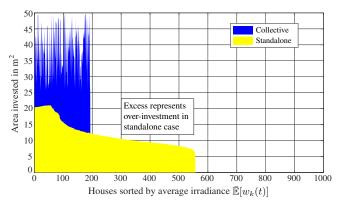


Fig. 7: Comparison of investment decision with $\gamma = 0.8$ for the large maximum available panel area case.

the collective net-load L(t)-G(t) remains positive and the collective equilibrium price is always the retail price. We will see this condition change in the high available area case.

Figure 6 depicts a second case in which net-metering is unavailable for standalone customers (i.e. $\gamma=0$). Now the impact of sharing is significant; though the same subset of customers invest as before, all standalone customers invest less because their economics have degraded.

3. Large maximum available panel area: $m_k \sim \mathcal{U}([25,50]) \text{ m}^2$. We chose this area to correspond to what might be available from large single story single family homes' roofs, or if customers choose to install ground mounted solar on their property. Under this case, all homes could produce more than their annual consumption if they installed their maximum area available m_k ; therefore in the standalone case a_k^{cap} is the binding area constraint.

Figure 7 shows a standalone case with $\gamma = 0.8$ in comparison with a sharing economy model without netmetering. As with medium available area, total investment is greater in the collective case; these customers invest in roughly 8% more total PV area and produce roughly 15% more energy. And roughly the same standalone customers invest in both the medium and high available area cases. But in stark contrast to conditions with medium available area, in the collective case the distribution of customers who invest is much smaller. Only the customers with the most favorable PV economics invest in the collective case, and these customers become "suppliers" for the remaining customers in the collective. In other words, the threshold θ becomes more challenging to meet as available area increases. In Figure 8 the collective conditions are unchanged but net-metering is no longer available to standalone customers ($\gamma = 0$). In this case the distribution of customers who invest is roughly the same, but because their economics have degraded, standalone customers invest even less.

Summary. Differences between investment in the standalone and shared solar cases are strongly influenced by the area each customer has available for solar. When this

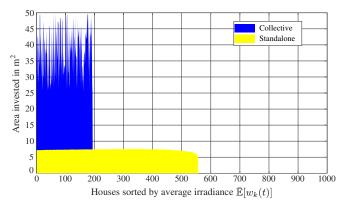


Fig. 8: Comparison of investment decision with $\gamma=0$ for the large maximum available panel area case.

area is low, customers whose standalone PV economics are favorable to install their maximum in both the standalone and shared cases. At intermediate areas, the set of customers installing PV is the same for both cases, however customers under-invest in the standalone case because their net-load is negative in more hours than the collective. When available area is high, the pattern we see in the standalone cases is that a fraction of customers under-invests while others over-invest relative to social-welfare maximizing decisions. Standalone under-investors exist due to their annual production cap (when net-metering is available) or a lack of remuneration (when net-metering is unavailable). Standalone over-investors exist because, although their merit is worse than others in the community, for their private economics solar remains cheaper than retail electricity.

VI. CONCLUSIONS

In this paper, we considered residential PV investment decisions problems for households under two models: (a) the standalone or status quo of net-metering with an annual production cap, and (b) a sharing economy model where households can trade their surplus generation in a spot market. In the standalone model, the households make independent investment decisions. Under the sharing economy model, investment decisions of households are coupled as they collectively influence the clearing price for electricity in the spot market. In this situation, for a large number of households we have asymptotically perfect competition. We have shown that the optimal investment decisions are determined by a simple threshold policy. Households whose PV productivity metric exceeds this threshold invest the maximum possible, while those that fall below the threshold do not invest. We offer a convergent algorithm to compute this threshold.

We compare standalone and sharing economy models in a small-scale simulation study. This study suggests that in the likely future scenario where net-metering programs disappear, the sharing economy could sustain or even increase total behind-the-meter PV investment. Under the sharing economy model, customers collectively make larger investments in PV and all customers see a modest reduction in their expected average electricity costs as the spot market price is zero in some hours. In this sense the sharing economy model can be said to benefit all participating customers. However, it is important to consider that, when available area is high, some customers who would have invested in solar in the standalone case will choose not to in the shared case. Though these customers will see a modest reduction in energy costs in the sharing case relative to a case without any solar, some would receive greater private benefits in the standalone case. These distributional implications need to be thought through carefully.

To fully understand the merits of a sharing economy model for solar, comprehensive simulation studies are needed. These must be based on larger, and more realistic production and load data. The maximum physical panel area can be deduced from GIS databases. Detailed irradiance data is available from meteorological databases. This future study should consider (a) more detailed PV panel cost model broken into fixed and variable components, (b) distribution system constraints such as transformer capacity and reverse power flow, (c) a fair payment to utilities for use of their distribution infrastructure, and (d) more complex and widely used retail pricing including time-of-use and volumetric tariffs.

Many research questions remain open. These include (a) developing the power-electronics technology necessary to enable sharing of excess PV generation, (b) the market infrastructure to support the sharing economy spot market, (c) strategic behaviour from users when perfect competition conditions are not satisfied, and (d) incentives to encourage households to join sharing communities. Detailed studies are necessary to understand the nature of connected communities for whom sharing is economically beneficial, while addressing fairness and equity issues. These will be in terms of community size, and statistical diversity of PV generation and load between their participants. In long-term evolution, we can even imagine communities participating directly in wholesale markets where they collectively sell their generation surplus and purchase their consumption deficits.

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