Collaborative Placement and Sharing of Storage Resources in the Smart Grid

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***Abstract*—The development of low-cost renewable energy generators transforms households into electricity prosumers. Given that generation from renewable sources is highly volatile and does not perfectly match the daily demand pattern of households, electricity storage has been proposed for balancing energy generation and demand. In this work, we suggest that, due to the high cost of Energy Storage Systems (ESS), prosumers should deploy and share ESSs in a collaborative fashion. This will allow them to leverage the temporal diversity in their energy generation and consumption patterns, so as to reduce the cost paid to the main grid and even to cover the deployment cost of ESSs.**

We address the question ”How much storage capacity should be placed and in which locations in the distribution network?”. In order to answer this question, we need also to consider how much each prosumer should charge and discharge each deployed ESS. The solution of this joint ESS placement-dimensioning and utilization problem depends on the energy distribution losses, expected electricity prices, and the diversity of prosumers' profiles. Accordingly, we employ the Nash bargaining framework to determine how this cost should be shared in a fair, and hence self-enforcing, fashion among prosumers. Based on realistic demand and generation traces, we show that collaborative prosumption of energy through properly placed ESS can lead to significant savings of up to 50% compared to a non-cooperating setting.

I. Introduction

Motivation. The decreasing cost of renewable Distributed Energy Resources (DER) motivates individuals to install small-scale units at their premises [1]. By deploying a solar panel or a wind turbine, a household can minimize its dependence on the main grid and eventually reduce its electricity bill. In this context, each household is both an energy consumer and an energy producer, i.e. a *prosumer*. However, more often than not, energy generation and demand are not perfectly matched in the time domain (Fig. 1). This results in temporal energy deficits and surpluses and hinders the energy savings that DERs can offer.

Selling the energy surplus to the main grid, and buying in case of deficit, addresses this issue only partially since it is not always an optimal or even a feasible solution. Namely, in many countries main grid operators buy electricity from prosumers (when they have surplus) at low wholesale prices and sell energy to them at higher retail prices[1]. Besides, houses located in isolated areas may not be connected with the main grid [2], hence making such transactions infeasible. To deal with this inefficiency, installation of energy storage systems

[1]In Australia for example [6], retail electricity price is 30 cents/kWh for residential users, while any surplus from DERs is being sold to the main grid at the wholesale price of 6 cents/kWh

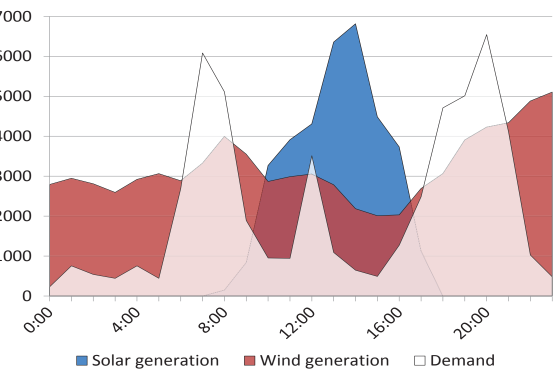


Fig. 1. Typical daily demand of a household and power generation patterns from a residential solar panel and a wind turbine. Households are characterized by diverse demand profiles resulting from the different daily schedules of their habitants [18]. Diversity is also observed in the generation side depending on the type of renewable installed [16],[17].

(ESS - hereinafter referred also as batteries) in close proximity with DERs has been proposed. An ESS accumulates energy surpluses, which can be then used to satisfy excess demand. Given though the current high monetary cost of ESSs, the option of installing one independently by each household is out of question [3].

Instead, we propose here a collaborative scheme where residential users form communities that share the costs and benefits of distributed energy generation and storage. We consider a small-scale community (within the microgrid) which can range from a large neighborhood to a small town. Households are characterized by diverse demand profiles given the different daily schedules of their inhabitants. Similarly, energy generation from a DER is intermittent within a day and its pattern is mainly determined by the type of the renewable and its location (Fig. 1). Prosumers can exploit temporal diversity of power generation and demand through appropriate placement of batteries that enables them to exchange any electricity surplus with each other and hence to achieve significant cost reduction.

The main question that arises in this context is how much storage capacity should be installed and at which location within the microgrid so that collaborative sharing by prosumers is most beneficial and fair. In order to answer this question, we need to derive, at the same time, the charging - discharging decisions of prosumers for the deployed ESSs that are realized in a smaller time scale. In turn, these decisions are constrained by the actual needs of consumers and the energy generation of their DERs. Clearly, the actual values of these quantities are not known in advance, i.e., at the time of ESS placement and dimensioning decisions. Nevertheless, recent measurements [4]-[5] indicate that both demand and generation follow certain patterns. These findings have been exploited by industry, for designing commercial storage solutions [2],[6] and by academia for studying storage-related problems [7],[8]. We follow a similar approach here and propose a solution framework for the ESS placement and dimensioning, for any given user and DER generation pattern.

Optimal placement is affected by distribution losses. These typically amount to 7% of the transferred energy but may even reach 55% in extreme cases [9]. Placing ESS close to generation locations minimizes losses while charging, but it leads to increased losses when energy is transferred to remote locations. On the other hand, a centrally placed battery enables the aggregation of a larger number of prosumers with more temporally diverse energy generation and demand patterns. The community-wide objective is to minimize the total cost for all prosumers, which captures both the electricity cost paid to the main grid and the ESS deployment cost. A still unanswered question though is: *how should this cost be shared among users of the community in a fair fashion, so as to incentivize their participation in the collaborative energy prosumption scheme*?

Collaborative Prosumption of Energy. The proposed scheme is inspired by the concept of collaborative consumption (CoCo) that leverages trusted and networked communities to optimally exploit scarce and hence expensive resources. The term was coined in 1978 by Felson [10] and has been recently revisited [11]. CoCo is a cost-efficient and eco-friendly consumption model based on sharing, swapping, bartering, trading or renting resources, which stands in contrast to traditional ownership-based models. Today, an increasing number of companies is building on this idea. Prominent examples are peer-to-peer direct rental services such as *Airbnb*[2].

The advent of smart grid enables the design of similar models for energy demand and generation within a community of prosumers. Storage of energy and distribution automation enables residential users to exchange electricity with each other. The former smooths out imbalance of demand and supply, while the latter determines the flow of power within the distribution network. For small-scale energy distribution networks, the short spatial and social distance of the participants makes possible the design of CoCo models for electricity.

Related Work. The problem of optimal charging and discharging a single ESS under time-varying electricity prices has recently attracted significant research interest (see [12], [13] and references therein). In contrast, the problem of optimal dimensioning and placing of electricity storage systems within the distribution grid remains quite unexplored. In this direction, the work in [8] investigates the voltage regulation and peak-shaving performance benefits arising from battery placement under an annual monetary budget constraint, when energy transfer losses are negligible. In general though, optimal battery placement and dimensioning decisions are affected by the distribution losses, which are important in low-voltage distribution networks.

The problem of placing a fixed amount of storage capacity in the grid is studied in [7]. The objective is to minimize grid operating cost assuming however that there is no cost for storage devices. In a similar framework, a genetic algorithm named PLATOS is developed in [14] to derive the type, size and placement location of storage devices so as to optimize certain criteria such as improving voltage profiles or preventing overloads. In contrast to our work, PLATOS is a proprietary heuristic algorithm. Besides, both [7] and [14] do not consider how the investment cost should be shared among community members. The benefits arising from cooperation are studied in [15] but for the scenario of interconnected microgrids that directly exchange power with each other. However, neither the potential of energy storage nor the arising challenges are addressed.

Contributions. In this work, we introduce the concept of collaborative energy prosumption tailored for the smart grid. We formulate and solve the respective ESS deployment cost minimization problem. The size of the battery that will be placed in each facility, as well as the subset of the prosumers that will use it, depend on their energy generation and demand profiles, and on energy distribution losses. Ideally, one would like to match prosumers with diverse profiles located in close proximity.

Once the optimal storage placement and utilization has been derived, prosumers must agree on how they will share the induced total energy and battery cost. Clearly, each prosumer should be motivated by paying less when she participates in the community compared to the respective cost if she independently deploys an ESS (or simply if she buys energy from the main grid). Moreover, prosumers expect to receive a fair share of the total cost reduction achieved by the community. Instead of equally sharing the costs among the participating users, we employ the Nash bargaining solution concept to find the fair, and hence self-enforcing, cost-sharing solution. The main contributions of this work are:

- We propose a model for collaborative *prosumption* of energy in a community that collectively deploys and uses energy storage systems.
- We formulate the problem of ESS placement and dimensioning, which should be jointly solved with charging - discharging decisions, based on prosumers' expected demands and energy generation. This is a numerically computable framework that is applicable to different prosumer profiles and microgrid architectures, based on consumption and production statistics [16], [17],[18].
- We employ Nash bargaining theory to find the fair share allocation of the benefits from the energy and battery cost reduction that is achieved by the community.
- Our trace-based simulations reveal that, for the current and projected future cost of batteries, the proposed model outperforms significantly the case where each prosumer acts independently. We also investigate how the community benefit is affected by factors such as energy distribution losses and the diversity of prosumer profiles.

The rest of the paper is organized as follows. In Section

[2]More info about these companies and similar business cases can be found in http://www.collaborativeconsumption.com/.

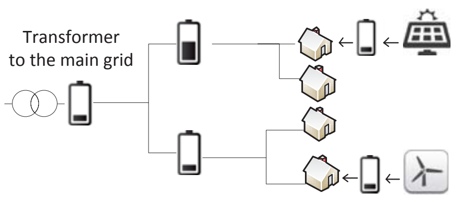


Fig. 2. Schematic diagram of a semi-urban neighbourhood consisting of users equipped with renewables. Batteries indicate possible locations for ESS deployment.

II we introduce the system model and present a motivating numerical example that highlights the various problem trade-offs. In Section III we formally introduce the collaborative energy prosumption problem and define the respective Nash bargaining solution concept that yields a notion of fair cost allocation. Finally, we present numerical results based on real traces in Section IV and conclude our study in Section V.

II. System Model

We consider the microgrid distribution network of Fig. 2 that comprises a set $\mathcal{I}$ of $I = |\mathcal{I}|$ energy *prosumers* and a set $\mathcal{N}$ of $N = |\mathcal{N}|$ predetermined locations, e.g. junction boxes, where an Energy Storage System (ESS) can be deployed. Each prosumer owns a renewable Distributed Energy Resource (DER), such as a wind-turbine or a solar panel, and has certain time-varying energy needs. We assume time-slotted operation and we study the system for a time period $\mathcal{T}$ consisting of T slots. Typical duration of a slot is 1-2 hours. Nevertheless, our framework is applicable to scenarios of any time granularity, which is determined by the input data.

Prosumer Model. Each prosumer $i \in \mathcal{I}$ in each time slot t may have an energy surplus or an energy deficit based on whether her DER produces more or less energy than her needs. We introduce the variables $s_i^t \geq 0$ and $d_i^t \geq 0$ to denote surplus and deficit respectively. We define also the vectors:

$$\boldsymbol{s}_i = (s_i^t : t = 1, 2 \ldots, T) \;\; \boldsymbol{d}_i = (d_i^t : t = 1, 2 \ldots, T),\, i \in \mathcal{I}$$

Clearly, for any given slot t, the surplus and deficit of each prosumer i cannot be both positive (i.e., $s_i^t d_i^t = 0$). Also, empirical and statistical data [19] indicate that typically individuals follow a specific routine, and hence the expected energy demand pattern of households can be to some extent characterized. This is true in particular for larger-scale prosumers e.g. industries. In addition, the expected energy generation pattern of each DER can be approximated by an average time sequence based on historical data [20]. The extraction of expected demand and generation patterns is performed through estimation techniques from historical data regarding the behavior of renewables/users, but this is beyond the scope of this work. Notice also that shared batteries serve as aggregation points that smooth out uncertainty by aggregating demand and generation of several closely-located prosumers.

In case of surplus, the excess energy of the prosumer can be used to charge the installed batteries. We denote with x_{in}^t the amount of energy transferred from prosumer i to battery n in slot t and we define the respective *charging matrices*:

$$\boldsymbol{x}_i = (x_{in}^t \geq 0 : n \in \mathcal{N}, t = 1, \ldots, T),\, \forall\, i \in \mathcal{I}$$

Similarly, when $d_i^t > 0$, the prosumer can use energy from the installed batteries to satisfy her additional energy needs. We denote with z_{ni}^t the energy retrieved from battery n by prosumer i during slot t, and we introduce the respective *discharging matrices*:

$$\boldsymbol{z}_i = (z_{ni}^t \geq 0 : n \in \mathcal{N}, t = 1, \ldots, T),\, \forall\, i \in \mathcal{I}$$

The amount of energy transferred from prosumer $i \in \mathcal{I}$ to battery $n \in \mathcal{N}$ experiences losses which depend on their distance and the amount of transferred energy [21]. The energy loss function $\theta_{in}(x)$ denotes the actual amount of energy that reaches (i.e., excluding the losses) battery $n \in \mathcal{N}$, when x units of energy are transferred from prosumer $i \in \mathcal{I}$. A typical such function is [15], [21]:

$$\theta_{in}(x) = x - \ell_{in}(x) = x - \beta x - \frac{R_{in}}{V^2} x^2, \tag{1}$$

where the losses $\ell_{in}(\cdot)$ are determined by the resistance $R_{in} > 0$ of the distribution line connecting prosumer i and ESS n, the corresponding voltage V, and parameter $\beta > 0$ capturing (voltage) transformation losses. For the distribution grids $R = 0.2$ Ohms per km, $V = 22$kV and $\beta = 0.02$ are typical values [21].

Depending on the microgrid scale, prosumers and batteries may be close enough so that no transformation from low to medium/high voltage is involved, i.e., $\beta = 0$. On the other hand, low-voltage (thus high-current) power transfer incurs comparatively high transfer losses per unit of distance. In other scenarios, e.g., for rural settings, transformation losses may be non-negligible. Clearly, different microgrid architectures are characterized by different energy transfer loss functions. Hereinafter, we formulate and discuss the problem using a generic concave loss function $\theta_{in}(x)$.

ESS Model. Each facility $n \in \mathcal{N}$ is a candidate location for deploying an Energy Storage System. The decision to be made is whether an ESS will be placed in a certain facility and, if so, what should be its capacity. We denote with $y_n \geq 0$ the capacity of the ESS deployed in facility $n \in \mathcal{N}$, and define the respective *ESS deployment vector* $\boldsymbol{y} = (y_n \geq 0 : n \in \mathcal{N})$.

Notice that battery deployment is a one-shot decision (an ESS is either deployed in a certain location for the entire time horizon $\mathcal{T}$ or not), while the charging - discharging decisions are taken on a slot-by-slot basis. The deployment is realized once at a cost of $w \geq 0$ per unit of storage capacity, which can be interpreted as the normalized (i.e. projected on the time horizon $\mathcal{T}$) monetary cost of purchase and maintenance of the battery [22].

Each ESS $n \in \mathcal{N}$ has accumulated at slot t a certain amount of energy q_n^t which depends on the charging and discharging decisions of prosumers in the previous time slots. We can calculate this amount using the recursive formula:

$$q_n^{t+1} = \min\{y_n, \max\{q_n^t + \sum_{i \in \mathcal{I}} \theta_{in}(x_{in}^t) - \sum_{i \in \mathcal{I}} z_{ni}^t, 0\}\} \tag{2}$$

Clearly, the accumulated energy can neither exceed the capacity y_n of the battery, nor can it be negative.

Main Grid. The microgrid is connected to the main grid, hence prosumers can buy energy whenever their deficit cannot be satisfied by an ESS. Specifically, we denote with b_i^t the amount of energy that prosumer i retrieves from the main grid

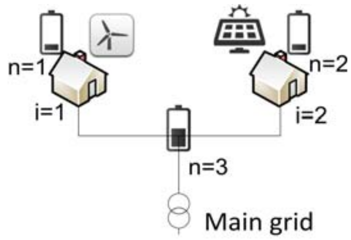


Fig. 3. A migrogrid with 2 prosumers and 3 battery facilities. The surplus and deficit vectors are $\boldsymbol{s}_1 = (2, 0, 2, 0, 4, 0, 3, 0)$, $\boldsymbol{s}_2 = (0, 2, 0, 5, 0, 3, 0, 2)$ and $\boldsymbol{d}_1 = (0, 5, 0, 6, 0, 5, 0, 1)$, $\boldsymbol{d}_2 = (5, 0, 1, 0, 2, 0, 6, 0)$. The distribution loss functions are $\theta_{i3}(x) = 0.9x$, $\theta_{11}(x) = x$, $\theta_{12}(x) = 0$, $\theta_{21}(x) = 0$, $\theta_{22}(x) = x$. The energy and battery costs for cases A, B and C are ($J_1^A = 17p_0$, $J_2^A = 14p_0$), ($J_1^B = 8p_0 + 4w$, $J_2^B = 5p_0 + 7w$) and ($J_{12}^C = 11.8p_0 + 1.8w$) respectively.

during slot t. We define also the respective vector $\boldsymbol{b}_i = (b_i^t \geq 0 : t = 1, 2 \ldots, T)$, $\forall\, i \in \mathcal{I}$.

We assume that energy needs of prosumers are inelastic and hence the following constraint should be satisfied:

$$b_i^t + \sum_{n \in \mathcal{N}} \theta_{in}(z_{ni}^t) = d_i^t,\ t \in \mathcal{T},\, i \in \mathcal{I}$$

The main grid is assumed to charge a fixed price $p_0 > 0$ per unit of energy at all times, leading to a total cost of $\sum_{t\in\mathcal{T}} p_0 b_i^t$ for prosumer $i \in \mathcal{I}$. Under such a fixed pricing model, prosumers buy from the main grid only to satisfy their current needs (i.e., ESSs are not charged by the main grid).

Motivating Numerical Example. Next, we provide a numerical example that highlights the various aspects and tradeoffs of the problem. Consider the toy microgrid consisting of $\mathcal{I} = \{1, 2\}$ prosumers and $\mathcal{N} = \{1, 2, 3\}$ battery facilities depicted in Fig. 3. We study the system for a single day, divided in, say, $T = 8$ slots. In this setting, there are three possible scenarios for the operation of the microgrid.

- *Case* A : The users have no batteries and buy (independently) energy from the main grid when they have energy deficits. Let J_i^A be the cost paid by i to the main grid.
- *Case* B : Each user deploys her own battery which is charged whenever she has surplus and discharged whenever she has an energy deficit. Let J_i^B be the total cost paid for the energy from the main grid and battery deployment.
- *Case* C : Users collaborate and deploy in a central point a battery which they share and jointly charge and discharge according to their energy surpluses and deficits. The total cost in that case, J_{12}^C depends also on the losses.

The cost values for each case and the basic system parameters are depicted in Fig. 3. In this setting, we observe that, (i) the total cost in Case C is always smaller than that in Case B, i.e. $J_{12}^C < J_1^B + J_2^B$ for any p_0, w. (ii) depending on the values of p_0 and w, prosumers may either benefit ($J_i^B < J_i^A$) or not ($J_i^B > J_i^A$) from using batteries. For example, when p_0 is much smaller than w a prosumer may prefer to cover her deficit directly from the main grid. (iii), for larger distribution losses and/or when the energy generation and consumption patterns of the prosumers are less diverse, it may be beneficial for each user to deploy her own battery.

Therefore, the critical questions for this problem are the following: (i) What is the battery placement-dimensioning policy $\boldsymbol{y}$, and the charging-discharging policy $(\boldsymbol{x}_i,\, \boldsymbol{z}_i)_{i\in\mathcal{I}}$ that minimize the total cost for energy use and battery deployment for a community of prosumers? (ii) How should this reduced cost be shared in a fair, and hence self-enforcing fashion among prosumers? To answer the first question we formulate and solve an optimization problem. For the second question, we model the *collaborative prosumption game* as a multi-person Nash bargaining game.

III. The Collaborative Prosumption Game

The Minimum Cost Problem. The objective of the prosumers is to minimize the cost for the energy they buy from the main grid and the cost for battery deployment. Specifically, the optimal policies can be derived from the solution of the following Collaborative Prosumption (CPro) optimization problem:

$$\min_{(\boldsymbol{x}_i, \boldsymbol{y}_i, \boldsymbol{z}_i, \boldsymbol{b}_i)_{i\in\mathcal{I}}} \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}} p_0 b_i^t + w \sum_{n\in\mathcal{N}} y_n$$

s.t.

$$q_n^{t+1} = q_n^t + \sum_{i\in\mathcal{I}} \theta_{in}(x_{in}^t) - \sum_{i\in\mathcal{I}} z_{ni}^t,\ \ n \in \mathcal{N}, t \in \mathcal{T} \quad (3)$$

$$0 \leq q_n^t \leq y_n,\ \ n \in \mathcal{N},\, t \in \mathcal{T} \quad (4)$$

$$b_i^t + \sum_{n\in\mathcal{N}} \theta_{in}(z_{ni}^t) = d_i^t,\ i \in \mathcal{I},\, t \in \mathcal{T} \quad (5)$$

$$\sum_{n\in\mathcal{N}} x_{in}^t \leq s_i^t,\ i \in \mathcal{I},\, t \in \mathcal{T} \quad (6)$$

$$\sum_{i\in\mathcal{I}} z_{ni}^t \leq q_n^t,\ n \in \mathcal{N},\, t \in \mathcal{T} \quad (7)$$

$$x_{in}^t \geq 0,\, z_{ni}^t \geq 0,\, b_i^t \geq 0,\, y_n \geq 0\, n \in \mathcal{N},\, i \in \mathcal{I}, t \in \mathcal{T} \quad (8)$$

where p_0 and w are the main grid energy price and the projected battery cost respectively[3]. Constraints (3)-(4) are the decomposed version of (2), equation (5) captures the fact that demands are inelastic and constraint (6) says that the total charging performed by a prosumer within a slot is bounded by her respective surplus. Finally, constraint (7) dictates that the retrieved energy from each battery is upper-bounded by the accumulated energy in each time slot.

CPro is a problem with a linear objective function and a convex and compact constraint set. The obtained solution $(\boldsymbol{x}_i^*, \boldsymbol{y}_i^*, \boldsymbol{z}_i^*, \boldsymbol{b}_i^*)_{i\in\mathcal{I}}$ yields a total cost:

$$J_{cc} = \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}} p_0 b_i^{t\,*} + w \sum_{n\in\mathcal{N}} y_n^* \quad (9)$$

The value of J_{cc} decreases as the diversity of energy consumption and generation patterns of prosumers increases. For example, if the generation and consumption patterns of two prosumers are symmetric, then they can fully satisfy each other's needs in each slot. Moreover, the total amount of deployed storage depends on the relative values of battery and energy cost. Finally, the battery placement depends on distribution losses (for low losses, central locations are preferable).

The Bargaining Game. In order to study how the total battery deployment and energy cost should be distributed

[3]The model can be directly extended to include battery installation costs. This would transform the problem into an NP-hard facility location problem [23], which can be solved by an exhaustive search method using, for example, CPLEX. Notice that the ESS deployment and dimensioning problem is solved offline.

among prosumers, we employ the Nash bargaining theory [24]. The so-called Nash bargaining solution (NBS) determines the portion of jointly produced welfare each player should receive so as to agree to cooperate with the other players. The NBS is fair, self-enforcing and also Pareto optimal.

In detail, a bargaining problem among a set $\mathcal{I}$ of $I = |\mathcal{I}|$ players is defined by the set of all feasible allocations (possible outcomes) $\mathcal{J} \subset \mathbb{R}^I$, and the disagreement points $\mathcal{D} \subset \mathbb{R}^I$ for each player. For the CPro problem, the latter are the costs incurred to the prosumers when they do not collaborate with each other. For each prosumer i we can find the disagreement cost J_i^d by solving CPro for $\mathcal{I} = \{i\}$ and $\mathcal{N} = \{i\}$. Formally, we define the bargaining problem $G_P = (\mathcal{I}, \mathcal{J}, \mathcal{D})$ where the set of possible outcomes is:

$$\mathcal{J} = \{(J_1, J_2, \ldots, J_I) : \sum_{i \in \mathcal{I}} J_i = J_{cc},\ J_i \geq 0,\ \forall\, i \in \mathcal{I}\}$$

and $\mathcal{D} = \{J_1^d, J_2^d, \ldots, J_I^d\}$. The NBS is the vector $\boldsymbol{J}_N^* = (J_i^*)_{i \in \mathcal{I}}$ derived by the solution of the following Nash bargaining problem (NBP):

$$\max_{\boldsymbol{J}_N \in \mathcal{J}} \Pi_{i \in \mathcal{I}} \big(J_i^d - J_i\big) \tag{10}$$

$$\text{s.t.} \qquad J_i \leq J_i^d,\ \forall\, i \in \mathcal{I} \tag{11}$$

The NBP has certain desirable properties as it stated by the following lemma.

Lemma 1: NBP admits always a unique optimal solution.

Proof: Objective function (10) is strictly concave since it is a composition of (strictly) concave functions. Additionally, the constraint set is compact, convex and non-empty. Notice that constraint (11) can always be strictly satisfied by some solution point. This holds because the collaborative solution contains the independent (standalone) solution where each prosumer acts on his own (placement and usage of battery per prosumer), as a special case solution. The latter is achieved if one sets the respective charging and discharging decisions of the prosumer to zero for the other batteries. ■

Notice that here we have implicitly assumed that users are risk-neutral and hence they have linear utility functions for cost [24]. In general though, one can consider users with different sensitivity in cost variations, e.g. being risk-averse. In this case, the objective of the NBP will change by substituting J_i with the respective utility functions, i.e., $U_i(J_i)$. The solution methodology however is the same.

IV. Numerical results

In this section, we use real demand and generation traces in order to quantify the benefits of collaborative energy prosumption. We consider a neighborhood of 10 houses, each equipped with either a solar panel or a wind turbine. For the wind-turbine plants we use the wind-generation data of [16], while for the photovoltaics we use data from [17]. Demand data for each house are generated according to the synthetic electricity consumption traces of [18]. We assume a fixed electricity price $p_0 = 0.3$ \$/kWh, and that distribution losses are linear in the amount of transferred energy and in distance.

Initially, we investigate the cases when collaborative placement of energy storage within the distribution network is preferable. In Fig. 4 we depict the impact of distribution losses on the actual cost improvement $\sum_{i \in \mathcal{I}} J_i^d - J_{cc}$ due to collaboration over the independent deployment at house premises. Initially, we focus on the current market scenario by using the typical battery price of 500 \$/kWh (Fig. 4(a)). Given that the lifetime of a battery is 5 years, we calculate the corresponding normalized cost w. In order to investigate the impact of temporal diversity of users' demand-generation profiles on cost improvement, we consider three scenarios: a low-diversity, a medium-diversity and a high-diversity one. We observe that diversity does increase the benefits of collaboration. In addition, low losses favour the collaborative deployment of batteries, while placing batteries at the user side is meaningful only for distant enough prosumers, as indicated by the almost zero benefit when losses are high. *In the current status where battery deployment cost is significant, cooperation is generally the dominant strategy.*

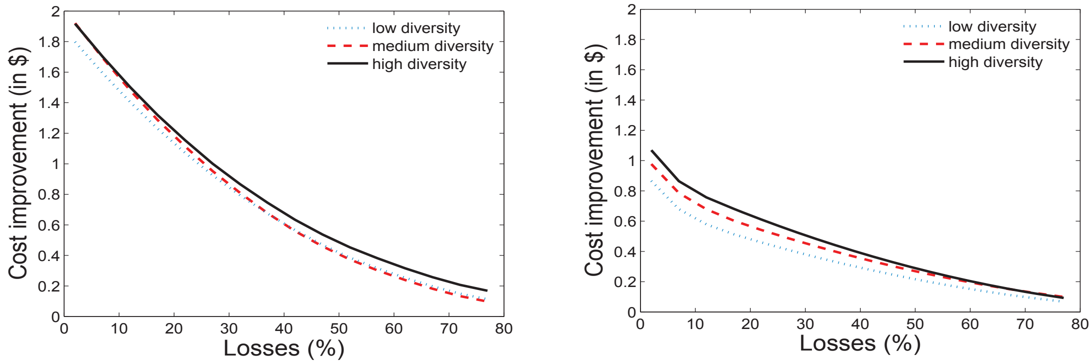
Next, we depict in Fig. 4(b) a scenario based on the projected battery prices so as to investigate the future behaviour of the collaborative prosumption approach. Given that battery prices drop by a rate of 5% per year the depicted scenario of a battery price of 100 \$/kWh is not expected to happen until 2030. In this case, due to lower battery cost, the benefits of collaboration are less evident, and deploying batteries at the user side is also a valid option. However, given that distribution losses are generally low (significantly lower than 20% in developed countries), the collaborative prosumption approach will be the road ahead for at least the next 20 years.

Finally, we consider the impact of battery cost w on the total battery capacity installed, and the total cost that has to be paid by the community. We consider a typical scenario where losses to the most distant battery location are 7%. In Fig. 5 we compare the total battery capacity and energy cost achieved by the collaborative prosumption approach and the non-cooperative reference strategy. As expected, high battery prices lead to less electricity storage being deployed and higher cost.

In both cases, battery placement reduces electricity cost by covering energy deficits from stored energy, previously generated by renewables. Collaborative prosumption though, can further amplify the resulting financial benefits by enabling users to exchange energy and by exploiting diversity of demand and generation of different households. Thus, *the collaborative approach achieves a lower cost with less storage capacity*. In particular, in this scenario of low distribution losses, collaboration leads to daily savings of 4\$ (i.e. > 1200 \$ annually), which is more than double the savings of the reference strategy. Interestingly, the amount of battery installed is generally a piece-wise constant function of battery cost, indicating *the robustness of battery placement in system parameter deviations*. In a plateau, the cost reduction arises from the smaller investment that is required for the same amount of electricity storage.

V. Conclusions

This work provides a first understanding of the reasons that hinder large-scale penetration of renewables and electricity storage in the residential sector. We identified collaboration of households as the missing piece that could eventually bring



(a) The current setting of battery price w=500 \$/kWh (b) The future setting of projected battery price w=100 \$/kWh

Fig. 4. Daily cost improvement due to user collaboration as a function of losses for scenarios of different demand - generation diversity across users.

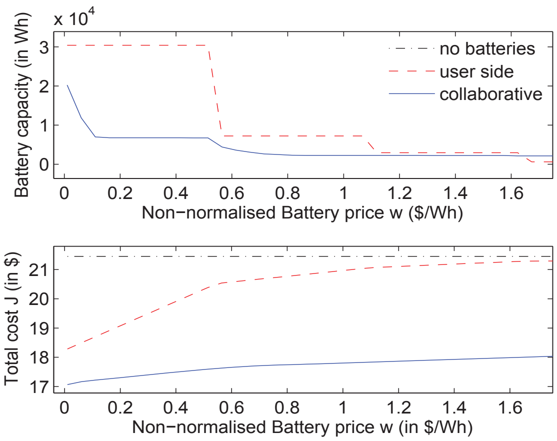


Fig. 5. Total capacity of installed batteries and the corresponding daily cost for a scenario of low distribution losses.

electricity storage into the distribution network and unleash the potential of renewable energy resources. We proposed a collaborative prosumption scheme that exploits diversity of demand and generation through batteries so as to minimize the electricity cost of a community. Based on realistic generation and demand data, we showed that collaborative battery deployment is meaningful even for the current high cost of batteries and without any subsidy, while additional benefits may arise from ancillary services enabled by collaborative storage. We believe that our work paves the way for small-scale user-centric collaborative energy prosumption architectures that will exploit upcoming storage availability [3].

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