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Orchestration is necessary to maximise embedded PV-battery and network value

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Abstract

It has been suggested that the uptake of residential batteries, operated passively and in the sole benefit of their owners, will alleviate cost-drivers in LV networks, and even mitigate the technical and economic concerns of distribution network service providers. The purpose of this paper is to highlight some evidence to the contrary; that such passive or uncoordinated PV-battery operation often provide little benefit to distribution networks, and can in some settings exacerbate existing problems. We present the results of recent studies into both tariff-based responses of batteries (e.g. battery operation under time-of-use tariffs) and peer-to-peer trading schemes, demonstrating this finding. Against this background, we go on to argue for a *distribution service operator* (DSO), whose role is to coordinate or orchestrate the batteries and other *distributed energy resources* (DER) on distribution networks, in order to satisfy the goals of customers and network companies alike. The cases presented in this paper show that a DSO-coordinated PV-battery system can be used to mitigate the effects on distribution networks of high penetrations of DER and other technical problems. Thus, we effectively demonstrate that orchestration is necessary to maximise embedded PV-battery and network value.

1. Introduction

Embedded PV penetration on low voltage (LV) networks represents a large and growing energy supply resource in Australia. Specifically, projections by the Australian Energy Market Operator (AEMO) are for roof-top solar generation capacity to increase from 4.3GW in 2017 to 19GW in 2035 [1]. However, this increase in rooftop PV is producing technical problems on LV networks, including over-voltage, reverse power flows with congestion problems, and phase unbalance in LV networks [2]. These issues arise in addition to the conventional growth in loads that have driven much of the costly investment in distribution networks, much to the chagrin of customers, regulators and politicians alike. Specifically, the average household electricity price in OECD countries (using purchasing power parity) increased by over 33% between 2006 and 2017 (a rise from 13.16 to 17.52 US c/kWh), while according to the International Energy Agency figures, in Australia prices are currently about 20.4 US c/kWh, which is a dramatic increase from roughly 12.52 US c/kWh in 2006 [3]. Germany is another country to see similar price rises, and it is notable that these two are countries that have long had supportive renewable investment subsidies and generous FiT rates. Given these prices rises, it is not surprising that the PV-battery penetration levels in these two countries are also relatively high [1, 3]. This is expected to continue, and even accelerate, with a steady decline in the cost of batteries [4]. Moreover, the advent of innovations in information and communication technologies and consumer devices suggest a broader role for batteries and a range of other *distributed energy resources* (DER), such as hot water storage tanks, air-conditioning units and refrigerators, to play in managing customers' energy use. This places Australia at the forefront of developing technical approaches to managing LV networks using customers' behind-the-meter resources, and the many technical, regulatory and policy and challenges these developments present.

In response to these rapid mounting challenges, AEMO and the peak body representing power network companies in Australia, Energy Networks Australia (ENA) are investigating models of open energy networks [5]. Under an open energy networks architecture, technical network services are unbundled from the core service of access to power, so that contestable markets can be implemented and services procured at least cost from a range of suppliers, rather than most services being supplied by the network companies themselves. As part of this process, it has been suggested that the uptake of residential batteries and other DER, operated passively and in the sole benefit of their owners, will

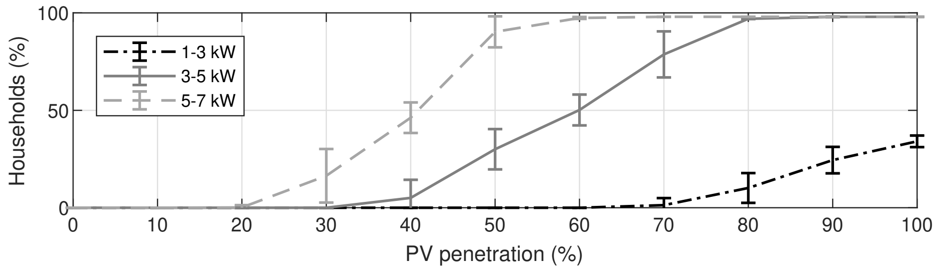

Figure 1: Effects of rooftop PV on LV networks: Percentage of households with overvoltage problems by PV penetration and PV system size

alleviate network cost-drivers and even improve LV network performance and efficiency [5]. Likewise, it is implicitly assumed that passive operation of DER will mitigate the technical and economic concerns of distribution network service providers [6]. The purpose of this paper is to highlight the mounting evidence to the contrary; that such passive or uncoordinated DER operation provides little benefit to distribution networks, and can in some settings exacerbate existing problems. Importantly, our evidence for this assertion comes from studies of both tariff-based responses of DER (e.g. battery operation under time-of-use tariffs) and in the context of peer-to-peer trading schemes.

In light of these findings, this paper highlights the shortcomings of uncoordinated DER, and in contradistinction, argues for an independent *distribution service operator* (DSO). The role of the DSO is to coordinate or orchestrate the DER on distribution networks as they move from passive to active participants in the electricity system. The cases presented in this paper focus on network services provided by DER, and show that coordinated DER can be used to mitigate the effects on distribution networks of high penetrations of DER and other technical problems. We provide simulation results as examples of how this could occur. The paper progresses as follows. The next section considers the value of passive and uncoordinated DER to power networks, highlighting the challenges and shortcomings, and emphasising the role that a DSO can play in overcoming them. After this, in Section 4 we show how coordinated, active DER can be used to effectively support distribution networks, while Section 5 shows how peer-to-peer trading overlayed with a DSO-administered bid permission structure can do the same. Section 6 concludes.

2. The effects of passive DER on distribution networks

When penetration levels of solar PV are small, the impact on the networks in negligible. For these settings, solely focusing on home energy management is warranted, and local, passive DER management approaches, such as appropriate tariff design, can be beneficial to customers and the power system. However, many countries have already reached levels where solar PV has a material impact on the performance of distribution networks, in particular at LV levels. In Australia, for example, state-wide PV penetration in Queensland and South Australia is already above 30%, with some feeders well above 50%.

As an illustration, consider a low-voltage distribution feeder with different penetration levels of rooftop PV. Fig. 1 shows the results of simulations of the effects of rooftop PV on LV networks, using a three-phase unbalanced LV network model and real customer data [7]. The figure illustrates the number of households with overvoltage problems as a function of PV penetration and the size of the PV system. As can be seen, problems start to emerge as early as at 20% PV penetration and can affect all users at 60% penetration for PV system sizes between 5-7 kW[1].

Different strategies have been proposed to mitigate the emerging LV network issues. While some methods leave the responsibility to the *distribution network service provider* (DNSP, a traditional network company responsible for investment in, e.g., grid reinforcement or active transformers with on-load-tap changers [8, 9]), other strategies consider a direct participation of end-users. For example, PV generation can be curtailed proportionally to avoid voltage problems using a *dynamic curtailment method* [10]. This method brings benefits to weak nodes which could be highly restricted due to their location in the network.

At the same time, the increasing uptake of residential batteries has led to suggestions that the prevalence of batteries on LV networks will serendipitously mitigate the technical problems induced by PV installations. However,

[1] In Australia, the average size of new installations in 2018 is around 5.5 kW.

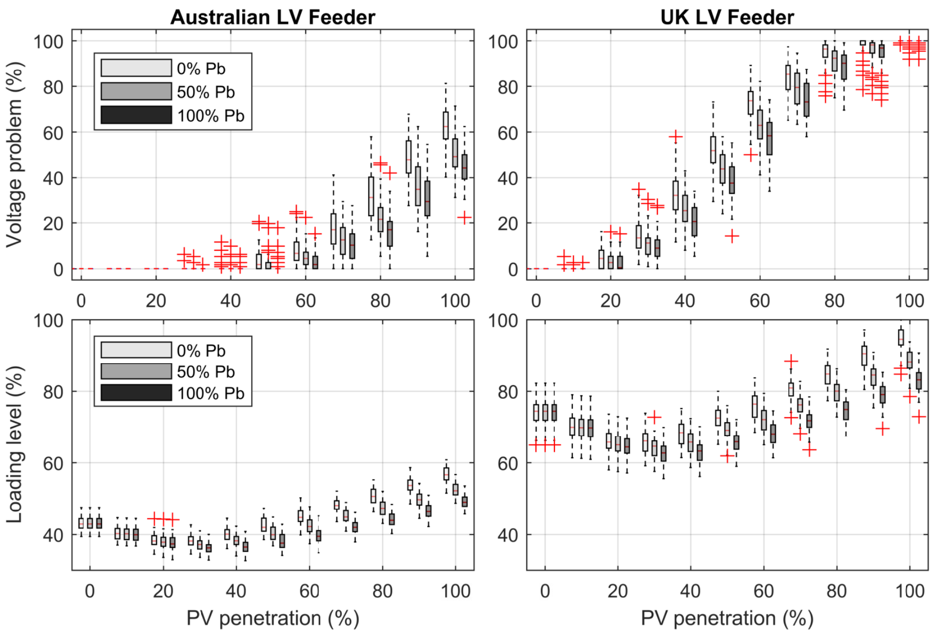

Figure 2: Percentage of customers with voltage problems (first row) and transformer loading level (second row) for three different battery penetration levels: 0%, 50% and 100%. Each bar from top to bottom shows the maximum value, 75 percentile, median value, 25 percentile and minimum values.

in general, the effects of PV-battery systems on LV networks have not been well studied. Therefore, we first look at the effect of uncoordinated penetration of DER on the performance of LV networks.

2.1. *Monte-Carlo Assessment of PV-Battery System Impacts on LV Distribution Networks*

To quantify the effects of uncoordinated DER use on LV networks we use the methodology proposed in [11]. In short, the methodology incorporates *home energy management* operational decisions within a *Monte Carlo* (MC) power flow analysis comprising three parts, described briefly below.

First, due to the unavailability of large number of load and PV traces required for MC analysis, we used a *maximum a-posteriori Dirichlet process* to generate statistically representative synthetic profiles [12]. Second, a *policy function approximation* (PFA) that emulates the outputs of the home energy management solver is implemented to provide battery scheduling policies for a pool of customers, making simulation of optimization-based home energy management feasible within MC studies [13]. The specific home energy management problem simulated is that of a customer operating their battery to minimise energy costs while facing a *time-of-use* tariff[2], and relatively low feed-in tariff, as is experienced in much of Australia. Third, the resulting net loads are used in a MC power flow time series study [11].

We show results for two representative suburban (~5 km long, ~250 customers) 0.4 kV LV feeders, an Australian one and a UK one. Typically, Australian LV networks are designed to have higher capacity than the UK ones, mainly due to much larger air-conditioning loads. In the analysis, the R/X of the UK feeder is three times higher than the Australian one, so we expect the UK feeder to be more prone to overvoltage problems at higher PV penetration levels. The results are summarized in Fig. 2, which shows the percentage of cases with overvoltage and overloading problems, respectively, for three different battery penetration levels: 0%, 50% and 100%.

The frequency of voltage problems with respect to the increasing PV and battery penetration on the LV feeders is shown in Fig. 2, row one. The percentage of customers with a voltage problem follows an increasing trend across both

[2]A time-of-use tariff, rather than a flat tariff, is chosen as a comparison as it is regularly proposed as sufficiently cost-reflective to mitigate network problems using passive DER.

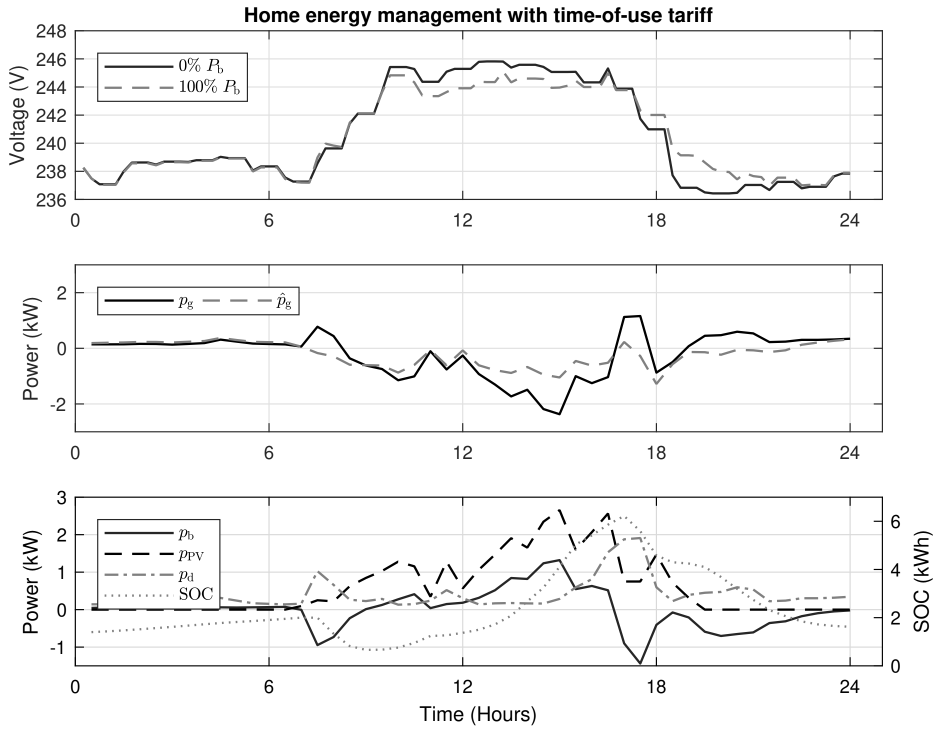

Figure 3: Voltage profiles (top), grid power (p_g and $\hat{p}_g$ denote grid power with and without battery, respectively) (middle), battery scheduling (p_b), PV (p_{PV}), demand (p_d), and the SOC (bottom) of a customer with 3 kW PV and 6.5 kWh battery installed on the Australian feeder on a particular summer day for home energy management with time-of-use tariff.

test feeders with respect to rising PV penetration, especially from 30 % to 100 %, while the UK feeder presents more voltage problems due to higher line impedances. Voltage problems can be reduced by 10-20 % across all test feeders using home energy management under time-of-use (ToU) tariff. This scheduling strategy encourages batteries to charge when electricity price is low, and discharge when the price is high (during peak hours). However, the timespan for high PV outputs can extend and even overlap with peak demand, especially in summer. This is illustrated for some specific case in Fig. 3, in which the peak demand occurs between 4pm and 6pm, causing the battery to discharge during high PV output. This reduces the grid power supply (p_g), when compared to the case without the battery ($\hat{p}_g$). As a result, p_g and $\hat{p}_g$ cross at around 4:30pm, where the voltages become the same. Furthermore, at 4:30pm, the rising demand causes the battery to decrease its charging power at high PV output, which keeps the voltage high. In these scenarios, home energy management under ToU is less effective at reducing over-voltage problems.

Although the HEM with ToU helps reduce voltage problems, it is far from the panacea for over-voltage problems. This goes to show that a different approach is needed to mitigate the adverse impact of DER penetration.

2.2. Uncoordinated peer-to-peer trading

Local, peer-to-peer (P2P) energy trading between consumers and prosumers (producer-consumers) is one of the new scenarios of growing importance in the domain of distribution networks. Local P2P distribution markets have been proposed as means of efficiently managing the uptake of DERs [14, 15]. This involves the creation of new roles and market platforms that allow the active participation of end-users and the direct interaction between them. This scenario brings potential benefits for the grid and users, by facilitating: (i) the efficient use of demand-side resources, (ii) the local balance of supply and demand, as well as (iii) opportunities for users to receive economic benefits through sharing and using clean and local energy.

However, most of the proposed P2P market designs are network-oblivious, in that they do not take into account network effects or constraints. For example, let us assume that a group of end-users in a typical UK LV network [16] participates in P2P energy trading without considering the network constraints in their trading mechanism, and the

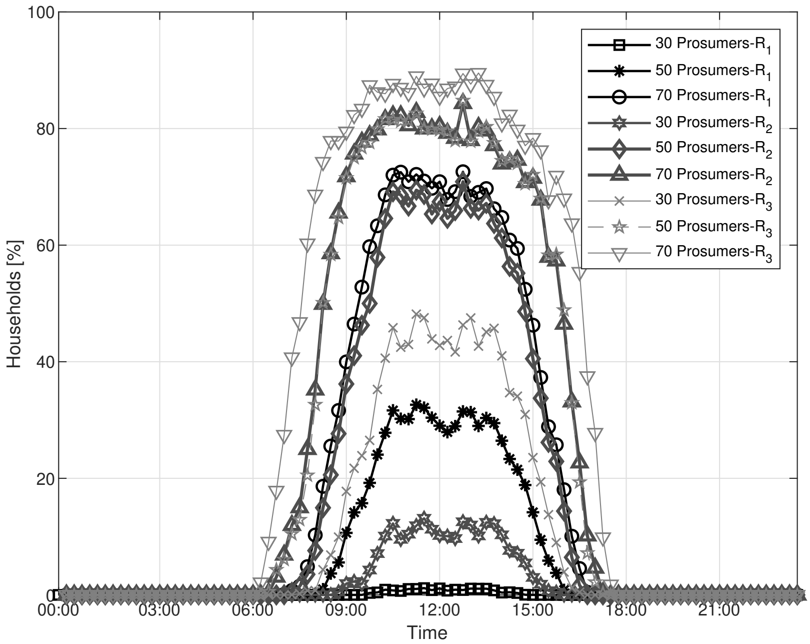

Figure 4: Percentage of households with voltage problems, with conductor resistances $R_1 < R_2 < R_3$ [7].

energy traded is supplied by non-dispatchable generation such as PV systems [7]. Based on the probabilistic impact assessment methodology proposed in [17], we evaluated the voltage issues at different levels of PV penetrations, and for different conductor resistances $R_1 < R_2 < R_3$.

Fig. 4 illustrates the impact of PV penetration using different types of conductors in the network, showing the voltage issues may be worst for networks with greater resistance values. Throughout the day (Fig. 4), the most critical situation happens around midday (peak of PV generation). Similarly, the situation is worst when there are more prosumers in the network. As in the case of passively-operated batteries, it is clear that P2P trading on its own does not resolve the network issues arising from increased PV and DER penertrations. Specifically, since the P2P scheme is only a financial trading mechanism, with the non-dispatchable PV and no knowledge of the network, the results are the same whether P2P is used or not.

3. DSO-orchestrated operation of DER in distribution networks

In contrast, orchestrated responses by DERs to LV network conditions have demonstrated excellent prospects for improving embedded PV-battery and network value [18]. In particular, current network access and operation arrangements (and those of almost all electricity industries around the world) do not provide economically efficient means for consumers to actively participate in distribution network management to reduce costs, be that their own private energy costs or electricity system-wide costs. More generally, the role that a wide range of DER — such as local generation, storage and flexible loads — might play in delivering network services, while understood in theory, is only just being realised in practise. Given the continued evolution of technological developments in this space, it comes as little surprise that designs for the institutions and market arrangements that enable and facilitate the delivery of these services, and their integration into existing energy market and frameworks, are not settled.

In our view, the requirement for effective and active coordination of DER, at distribution network level and at power system level, is absolutely critical. Lack of coordination of DER will in future result in, at best, sub-optimal outcomes which result in inefficient use of resources and ultimately a relatively higher cost of delivery of energy and services, to inefficient investment in assets by customers and/or network service providers, to, at worst, significant problems within local networks and at whole of system level which may result in loss of service for customers. Some of these outcomes are demonstrated above. We suggest, therefore, that active orchestration, enabling optimal use of resources (DER and centralised resources) is an important objective when designing a new distribution network operational framework.

Currently, the primary objective of a DNSP is to provide their customers with safe and reliable access to electricity, and to do this within a limited operating budget. With customer adoption of DER, this objective is shifted towards not just providing customers with access to electricity supply, but also with the opportunity to provide energy and power services back to the network and system. Putting faults to one side, the key physical constraints that limit a DNSP's ability to achieve these outcomes in a high DER future are

(i) the current carrying capacity of equipment (e.g., conductors and transformers) and

(ii) their rated voltage limits.

In addition, regulated limits on voltage at the point of customer supply must also be considered.

However, several additional challenges should be incorporated into a DSO design from the outset. Nonetheless, a good starting point for an DSO architecture for day-to-day operations of a distribution network is a model of the physical network itself, which would likely be provided by the DNSP (which, for the intents of this paper we assume is a separate entity, whether through ring-fencing arrangements or completely independent ownership). This model may be used by the DSO to simulate the voltages and currents on the network, incorporating line limits and voltage constraints. This simulation then can be used to define operating envelopes for DER and other active participants on the distribution network.

Beyond this, the DSO may operate DER in a way that optimises some objective, taking into consideration any variable operating costs. These costs may be those known to the DSO, such as the operating costs of a diesel generator or the degradation cost on a substation transformer, or they may be those negotiated with assets owned by other parties, such as customer-owned batteries. Such a model of interaction requires detailed consideration of the supporting market design, in addition to technical models of networks and DER. On the other had, the DSO may play a less active role in operating distribution networks, and instead act only as a gate-keeper to trades over the network. Here, the design of the market can be less tightly coupled to the network model, and the DSO's role less prescriptive with respect to the participating DER.

Two such DSO-administered approaches to active DER management in distribution networks are covered in this paper. First, in Section 4, the effects of operating a dispatch-based DSO are assessed in [19], where a fleet of distributed battery energy storage systems successfully moderated losses, voltage variations and phase unbalance on LV networks. In practice, this can be scaled to 1000s of customers using advanced techniques such those in [20] or [21]. Indeed, the CONSORT project demonstrates the potential of this type of orchestrating technology [18], which could sit behind a future DSO, as flagged by [5]. Moreover, by embedding this type of dispatch engine into an appropriate auction format, whole-of-feeder dispatchable energy and service markets, potentially arranged hierarchically into wholesale energy and services markets, become a technical possibility.

Second, Section 5 explores an alternative approach involving overlaying a permission structure on peer-to-peer energy markets, which allows only trades that do not violate network technical constraints. This represents a less active role for the DSO, and relies on a greater degree of active participation by prosumers (or their agents), but nonetheless our results demonstrate that it is sufficient to keep the LV network operating within its technical limits as PV penetrations increase, while also improving outcomes for PV and battery owners and regular customers alike.

4. DSO-operated storage

A first alternative for active DSO management of LV networks is for the DSO to invest in and operate their own utility battery systems. These battery systems can be used as non-network solutions, as alternatives to conventional network augmentation or reconfigurations, thereby adding value by avoiding or deferring large capital investment in place of a smaller capital and operating cost, thereby improving the efficiency with which electricity is delivered to customers [22]. Specifically, battery systems can be used to ensure voltage and thermal constraints are satisfied, while also moderating power losses, improving rooftop PV hosting capacity and rectifying network unbalance. In particular, they can mitigate over voltages by absorbing excessive renewable generation in LV networks, and release the stored energy whenever it is needed [23]. Considering these benefits, the value of battery systems to network companies has risen significantly, especially in Australia, where PV penetration is significantly higher than the rest of the world [24].

However, there is still considerable debate as to whether one community battery system or several distributed battery systems is more valuable to networks, and currently few studies have compared their benefits and drawbacks.

This section describes a method for managing such DSO-operated utility battery systems in unbalanced LV networks. A *mixed integer quadratic programming* (MIQP) model is used to minimize annual energy losses and determine the sizing and placement of battery systems, while satisfying voltage constraints. A real unbalanced LV UK grid is adopted to examine the effects of battery systems under two scenarios: the installation of one community battery system (CBS) and several distributed battery systems (DBS), and the impacts of battery systems in power losses and the hosting capacity in LV networks are investigated.

Specifically, two scenarios are examined: (i) the installation of a single CBS, and (ii) the installation of multiple DBS with the same aggregated size. In this section, order to determine the optimal location and the associated capacity of the battery systems in both scenarios, a linearised approximation of AC *optimal power flow* (OPF) is applied. The optimization model aims to minimize annual energy losses while satisfying voltage constraints. Given the results of simulations, we assess, quantify and compare the effectiveness of these two battery storage configurations.

The study that follows uses an unbalanced AC OPF model formulation to determining the optimal location and the associated battery system capacity. Our results show that the DBS configuration has an edge over the CBS configuration in accomplishing the tasks described above, although both of them are highly effective. The description begins with the battery system model, before considering the optimal location and sizing problem formulation, and then discussing simulation results.

4.1. Battery system model

Key to this problem is modeling the performance and inter-temporal couplings of the battery systems. To begin, a battery system's *state of charge*, at time t, is a function of the state of charge at time $t-1$ and its charging and discharge rates during this time interval. The charging and discharging rates stated are for one phase only, so they must be multiplied by 3, giving the following state-of-charge transitions for a battery placed at bus i:

$$e_{t,i} = e_{t-1,i} + 3(\eta^{+} p^{+}_{t,i} - \frac{1}{\eta^{-}} p^{-}_{t,i})\Delta t. \tag{1}$$

For convenience, the initial state of charge after each cycle (typically one day) is fixed, and given by:

$$e_{\Omega} = e_0. \tag{2}$$

To ensure that the above constraint can be satisfied, the total charged and discharged power for one cycle must be the same:

$$\sum_{t\in\mathcal{T}} \left(\eta^{+} p^{+}_{t,i} - \frac{1}{\eta^{-}} p^{-}_{t,i}\right) = 0. \tag{3}$$

In addition, the state of charge cannot exceed the minimum and maximum states of charge at all times, and similarly, charging and discharging rates at each time interval Δt are constrained by the battery systems characteristics:

$$0 \le 3p^{+}_{t,i} \le \overline{p}^{+} \tag{4}$$
$$0 \le 3p^{-}_{t,i} \le \overline{p}^{-} \tag{5}$$
$$\underline{e} \le e_{t,i} \le \overline{e}. \tag{6}$$

Last, we note that in this study, the charging and discharging efficiencies in the model are neglected.

4.2. Optimization problem formulation

The optimization model aims to place and size a CBS (or multiple DBS) in an unbalanced LV network in order to minimize annual system losses. Let $\mathcal{B}$ be the set of buses, $\mathcal{L}$ be the set of total network lines, indexed lm where l and m are elements of $\mathcal{B}$. Denote the single-phase resistance and impedance $R_{f,lm}$ and $X_{f,lm}$, respectively, for phase $f \in \mathcal{F}$.

The CBS objective is to minimize system losses, is formally stated as:

$$\underset{p_l^{+,t},p_l^{-,t},B_l^{\mathrm{loc}},e^{\mathrm{com}}}{\text{minimize}} \sum_{d\in D}\sum_{t\in\mathcal{T}}\sum_{lm\in\mathcal{L}} p_{lm}^{\mathrm{loss},t}, \tag{7}$$

where $\mathcal{D}$ are the days in a year, $\mathcal{T}$ are the hours in a day, and $p_{lm}^{\mathrm{loss},t}$ is given by:

$$p_{lm}^{\mathrm{loss},t} = \sum_{f\in\mathcal{F}} R_{f,lm}\frac{\left(p_{f,lm}^{t}\right)^2+\left(q_{f,lm}^{t}\right)^2}{v_{sub}^2} \quad \forall\, f\in\mathcal{F}. \tag{8}$$

This objective function indicates that the overall model is a *quadratic* problem.

For the DBS case, the single variable e^{com} in (7) is replace with N variables e^{dist_n}. Similarly, the battery storage location constraint, corresponding to the binary variables B_l^{loc} and given by:

$$\sum_{l\in\mathcal{E}} B_l^{\mathrm{loc}} = N. \tag{9}$$

is adjusted by varying N from 1 (for the CBS case) to the largest number of distributed battery storage installations under consideration, where $\mathcal{E}\subseteq\mathcal{B}$ are the set of buses suited to a battery installation.

The study reported below compares the impacts between a CBS and multiple DBS. Therefore, the battery location model above is used to determine the optimal locations and capacities for multiple DBS, assuming they have the same aggregated capacity as the CBS. In this scenario, N in equation (9) must be considered as a variable instead of a problem parameter. At the same time, a constraint equating the aggregated capacity of the DBS to the size of the CBS is added to the optimization model:

$$\sum_{j\in\mathcal{E}} e_j^{\mathrm{dist}} = e^{\mathrm{com}}. \tag{10}$$

4.3. Network and voltage constraints

In addition to the battery characteristics and battery system location variables and constraints described above, the model is also subject to branch flow constraints and voltage constraints. Load flows in LV networks with numerous branches can be difficult to solve, especially when the network is unbalanced and each phase must be taken care of individually. Here, we use a simplified and linearised version of the *branch flow* model introduced in [25] and [26], which has been shown to be accurate in modelling power flows in radial distributed networks [27, 28]. The equations in this model show that power flows on each phase from bus l to bus m, can be formulated as a function of power flows and power losses entering bus m, and the generation and consumption at bus m. The modified power flow equations with battery storage placed on bus m, phase $f\in\mathcal{F}$ are presented below (dropping the time index t as there are no inter-temporal couplings in the network constraints):

$$p_{f,lm} \approx \sum_{mn\in\mathcal{L}} p_{f,mn} + p_m^{\mathrm{load}} - p_m^{\mathrm{pv}} + \sum_{j\in\mathcal{E}}(p_m^{+}-p_m^{-}) \quad \forall\, f\in\mathcal{F}. \tag{11}$$

$$q_{f,lm} \approx \sum_{m,n\in\mathcal{L}} q_{f,mn} + q_m^{\mathrm{load}} - q_m^{\mathrm{pv}} \quad \forall\, f\in\mathcal{F}. \tag{12}$$

$$v_{f,m} \approx v_{f,l} - \frac{p_{f,lm}R_{f,lm}+q_{f,lm}X_{f,lm}}{v_{\mathrm{sub}}} \quad \forall\, f\in\mathcal{F}. \tag{13}$$

Here, only the active power flow of battery storage is considered. It has been clearly illustrated by the literature that the nonlinear terms in the branch flow equations representing power losses can be neglected, as the impacts of these terms on the objective function are limited [27], validating equations (11) and (12). Similarly, based on [28] and [27], voltage expressions can be linearised by assuming voltage variations at an arbitrary bus m are close to 0 at all times,

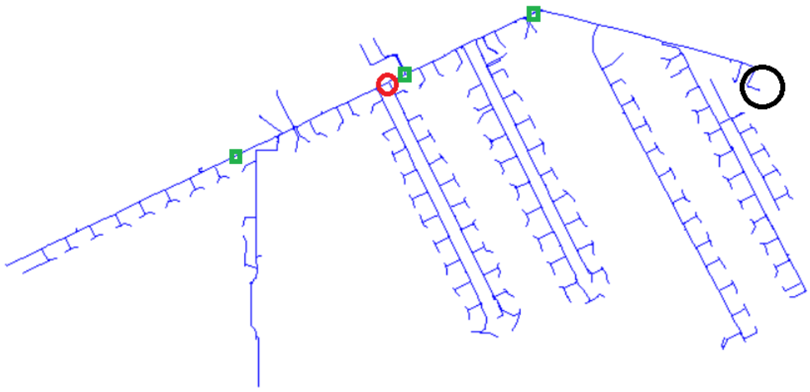

Figure 5: The unbalanced LV network, the black and red circles denote the substation transformer and CESS, while the three green squares represent DESSs [16].

e.g. $v_{f,m} - v_{\text{sub}} \approx 0$; the accuracy of equation (13) has been justified by the authors in [26]. A complete derivation of these expressions is provided in [19].

In addition, the model should satisfy the voltage limits for all three phases in presence of loads and PV generation:

$$\underline{v} \le v_{f,l} \le \overline{v} \quad \forall f \in \mathcal{F}. \tag{14}$$

The battery system formulations from (1) to (6) and the branch flow equations (11), (12), (13), and (14), along with voltage and battery storage constraints (9) and (10), formulate a mixed integer quadratic programming model for determining the optimal location and the associated capacity for the CBS and the DBS. We now report on a comparison of the effects using the two different installation patterns.

4.4. Test case

The test LV feeder is from the UK, which consists of 175 single phase consumers with a total length of 4.3 km. This is an unbalanced network with 61, 60 and 54 consumers sitting on phase A, B and C, respectively. Each load, which follows a specific load profile, adopts a single phase PV system. This feeder covers a large area and it is reasonably loaded, presenting great potential for over-voltages. The network diagram is shown in Fig. 5.

Load and PV profiles for one year are generated using the CREST model, which allows one to generate high resolution PV and load profiles [29]. For this study, each individual load and PV system are assigned with unique daily load and PV profiles with 1 hour resolution, respectively. When performing simulations, the base voltage is 0.4 kV (1 pu) and the phase votlage of transformer secondary winding is fixed at 0.23 kV.

The two performance indices are power losses and the hosting capacity, which are explained next. First, the primary task of the optimization model is to reduce annual network energy losses. For the base scenario, without any battery storage, simulations are performed for a year. The total network losses in summer, autumn, winter and spring are approximately 2530 kWh, 2820 kWh, 4660 kWh and 2190 kWh, respectively. It can be seen that the total energy loss in winter is significantly higher than other seasons due to the employment of heating facilities. The annual network loss is 12 200 kWh, which is expected to be decreased by implementing the two battery storage configurations.

Second, in order to determine the hosting capacity, the rated power generation of PV systems on the entire feeder is gradually increased until the voltage threshold is met. This is most likely to occur at loads towards the end of the feeder. Specifically, the installed PV capacity is 175 kVA in the case that all PV system is rated at 1 kW. Iterative power flow simulation is performed, which automatically increases PV generation until the voltage limit is exceeded. A typical summer day is tested using the algorithm since summer usually presents less network loading and reasonably high PV generation. The outcomes indicate that the upper limit is exceeded at bus 2266 at 1pm when each rated PV generation is raised to 2.1 kW. This means the 100 % penetration of this network without battery storage is 368 kW.

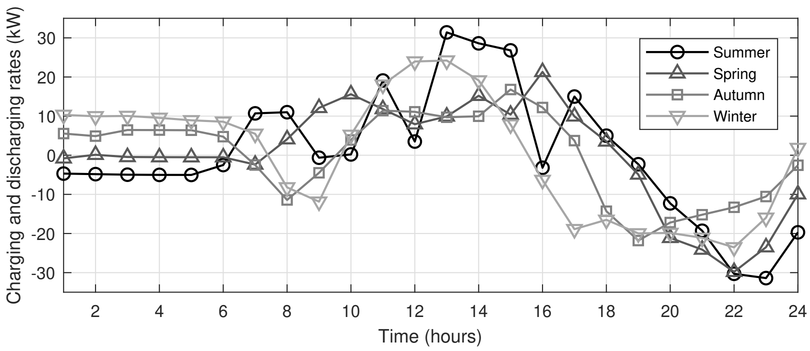

Figure 6: Charging and discharging rates on a typical day in each season.

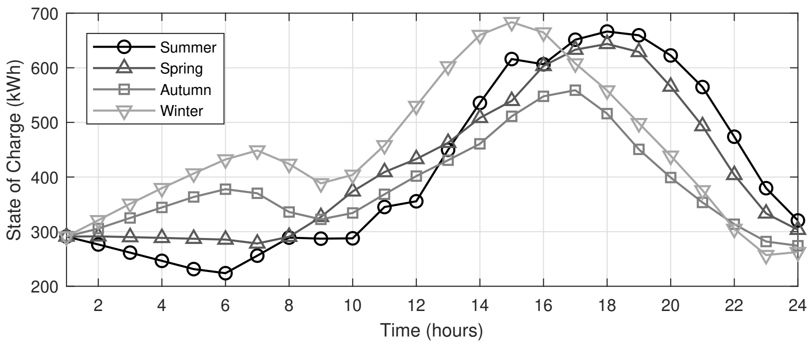

Figure 7: State of Charge on a typical day in each season.

4.5. *Community Battery Storage*

The results of installing a CBS in the LV network are shown and analyzed in this section. Optimization-based simulations are performed for one year, and the outcomes suggest an installation at bus 702 with the capacity being 942 kWh. The initial state of charge for each cycle is 282 kWh. The annual network energy loss in this case drops to 9410 kWh which shows a 22.9% reduction compared with the base scenario. The detailed charging and discharging patterns of a sample day for each season are observed and presented in Fig. 6. It can be seen that summer presents the highest charging rates around mid-day due to high PV penetration. Meanwhile, the discharging period comes at around 4pm in winter as night falls faster, while this time is delayed in summer as expected. Due to the long discharging period in winter, the battery storage must charge in early mornings to maintain the state of charge on the pre-defined level at the beginning of each cycle. The corresponding state of charge is illustrated by Fig. 7, from which we observe that the winter curve reaches its peak at 850 kWh at around 5pm, earliest and highest among all, then drops rapidly due to the high energy consumption.

The battery system with the same charging and discharging patterns is implemented in OpenDSS to quantify the hosting capacity in this scenario. Applying the same method as in the base scenario, an over voltage is discovered at bus 2266 on a typical summer day at 1pm with PV systems at all loads being rated at 2.71 kW. This shows that the CBS is capable of increasing the hosting capacity of the network by 27.8 %.

4.6. *Distributed Battery Storage*

In this section, the results of installing multiple DBSs, which have the same aggregated size as the CBS, in the network are detailed and compared with the performance indices and the first scenario. Table 1 and Fig. 8 illustrate the improvements in annual energy losses and the hosting capacity with respect to different numbers of DBS. A large decrease in energy losses is shown as the CBS is implemented. However, as we consider DBS and continue to raise the number of battery storage, the reduction flattens out. When three batteries are installed (Fig. 5 shows the optimal locations of three DBS, indicated by green squares), energy loss is decreased only by 190 kWh to 9220 kWh from the

Table 1: Improvement in energy losses and the hosting capacity with respect to different numbers of batteries.

No of batteries	Locations	Sizes (kWh)	Power loss reduction	Increase in hosting capacity
1	702	942	22.9%	27.8%
2	234, 1704	527, 414	23.6%	29.1%
3	153, 676, 1786	322, 451, 169	24.5%	29.2%
4	170, 652, 996, 1786	322, 427, 114, 78	24.6%	31.1%
5	153, 429, 728, 996, 1786	179, 269, 312, 63, 117	24.7%	29.2%
6	234, 652, 820, 1484, 1851, 2191	320, 346, 114, 57, 49, 54	24.8%	31.4%
7	153, 429, 728, 996, 1484, 1786, 1924	179, 269, 312, 39, 34, 17,89	24.8%	30.6%

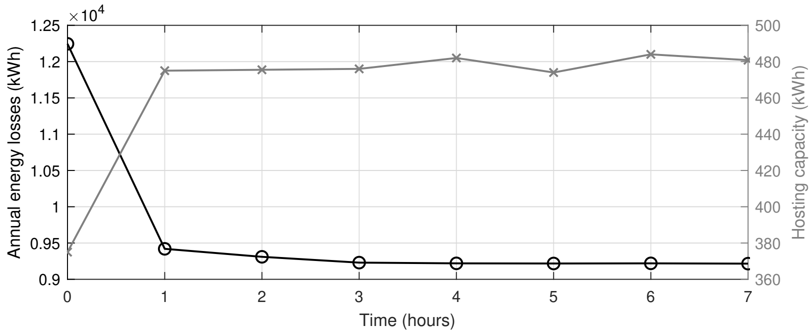

Figure 8: Annual energy losses (left) and hosting capacity (right) wrt number of batteries.

previous scenario. After this, the reduction becomes insignificant. This is because the aggregated size is fixed, which limits the performance of the DBS, while the marginal benefits of supporting the network by spreading the storage devices across more locations rapidly decrease.

The results presented in Table 1 and Fig. 8 show that there is an obvious increase, 27.8 %, in the hosting capacity after the CBS is installed. However, this rate of improvement does not continue when the large battery storage is divided into DBSs. Specifically, after two installations, the curve experiences minor fluctuations and the increase becomes subtle. The utilities must consider this with the trade-off between the battery storage costs and performance introduced previously for deciding the most beneficial number of installations.

4.7. Comparisons of community and distributed battery storage

Overall, both CBS and DBS can accomplish the tasks described in this study. Minor improvement can be made when attempting to decrease the VUF by replacing the CBS with multiple DBS, while this improvement is larger regarding power losses and the hosting capacity. It is important to realize that the performance can be improved significantly when increasing the aggregated capacity of distributed battery storage. However, this is not the case for the CBS, for whom a further increase in size will result in more energy losses. Therefore, in general, DBS can be more effective than CBS if the correct number of DBS is placed at optimal locations with reasonable sizes, and consequently, they can make distribution upgrade deferral and increased PV generation a reality.

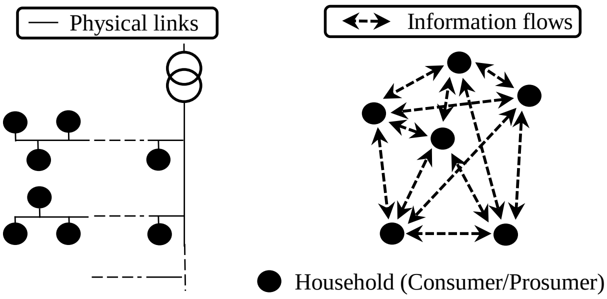

Figure 9: Model of information flows and physical links between households under a P2P scheme [7].

5. DSO-administered peer-to-peer energy trading

Decentralized peer-to-peer (P2P) architectures have been proposed to implement local energy trading. Unlike to the traditional scheme, under a P2P scheme, prosumers can trade their energy surplus with neighboring users. Decentralised market platforms are now technically possible due to recent advances in information and communication technology, such as *blockchain* and other *distributed ledger technologies* (DLTs), which support transparent and decentralised transactions. Many studies have already considered DLTs as the base of their P2P energy trading platforms [30, 31]. For example, [32] proposed a P2P energy trading model for electrical vehicles, showing the potential of blockchain to enhance cybersecurity on the P2P transactions. Similarly, the work in [33] demonstrates the benefits of a blockchain-based microgrid energy market using smart contracts. Additionally, commercial P2P trading pilot projects have also been implemented recently. Most of these create a cryptocurrency that is used to trade energy between users, for example, PowerLedger (https://powerledger.io), Enosi (https://enosi.io) and LO3 Energy (https://lo3energy.com).

However, electricity exchange is different from any other exchange of goods. Residential users are part of an electricity network, which imposes hard technical constraints on the energy exchange. Completely decentralized energy trading, without any coordination, compromises the operation of the network within its technical limits. Therefore, physical network constraints must be included in energy trading models.

5.1. P2P model

We consider a smart grid system for a P2P energy trading in a low-voltage (LV) network under a decentralized scheme proposed in [7], where residential users interact through an online platform. The P2P scheme is illustrated in Fig. 9. The information flows between peers in a decentralized manner. As such, every peer can interact through financial flows with the others. Users can sell and buy energy to/from their neighbors or a retailer. We consider this a realistic assumption since currently there are pilot projects based on this concept, and it does not interfere with existing institutional arrangements (retail)[3]. A general P2P scheme is a method by which households interact directly with other households. Users are self-interested and have complete control of their energy used (different to centralized direct load control structures, in which some entity may have control of some appliances).

Let $\mathcal{H} = \{1, 2, \ldots, H\}$ be the set of all *households* in the local grid. The time is divided into time slots $t \in \mathcal{T}$, where $\mathcal{T} = \{1, 2, \ldots, T\}$ and T is the total number of time slots. The set of all households $\mathcal{H}$ is composed of the union of two sets: consumers $\mathcal{P}$ and prosumers $\mathcal{C}$ (*i.e.*, $\mathcal{H} = \mathcal{P} \cup \mathcal{C}$). We assume that all households are capable of predicting their levels of demand and generation for electrical energy for a particular time slot t. Specifically, we assume consumers bid in the market based on their demand profiles. As such, a demand profile is not divided into tasks or device utilization patterns, so that the demand levels represent the total energy consumption over time. Prosumers are classified into two types. Type 1 prosumers include those which have only PV systems; Type 2 includes prosumers which have PV systems, battery storage and home energy management systems. Prosumers have two options to sell

[3]Examples of pilot projects include Decentralized Energy Exchange (deX) Project, available at https://arena.gov.au/projects/decentralised-energy-exchange-dex/; and White Gum Valley energy sharing trial, available at https://westernpower.com.au/energy-solutions/projects-and-trials/white-gum-valley-energy-sharing-trial/.

their energy surplus: (i) they can sell to the retailer and receive a payment for the amount of energy (e.g. feed-in tariff), or (ii) they can sell on the local market to consumers who participate in the P2P energy trading process.

5.2. *Household agent model*

A household $h \in \mathcal{H}$ uses d_t^h units of electrical energy in slot t. Likewise, a household $h \in \mathcal{H}$ has w_t^h units of energy surplus in slot t. The total quantity of electrical energy purchased in a slot t is given by x_t^+, and its price is denoted by s_t^+. The total energy consumption x_t^+ includes the amount of electrical energy purchased from the grid and from the local market. Similarly, the quantity of electrical energy sold in a slot t is given by x_t^-, and its price is denoted by s_t^-. While the energy surplus of Type 1 prosumers in $\mathcal{P}$ comes entirely from the PV system, each prosumer Type 2 in $\mathcal{P}$ uses its home energy management system to optimize its self-consumption, considering their demand and energy surplus by solving the following mixed-integer linear programming (MILP) problem [34]:

$$\begin{aligned} \underset{x \in \mathcal{X}}{\text{minimize}} \quad & \sum_{t \in \mathcal{T}} (s_t^+ x_t^+ - s_t^- x_t^-) \qquad (15) \\ \text{s.t.} \quad & \text{device operation constraints,} \\ & \text{energy balance constraints, } \forall t \in \mathcal{T}, \end{aligned}$$

where $\mathcal{X}$ is the set of decision variables $\{x_t^+, x_t^-\}$. State variables in the model are s_k^+ and s_t^-. The former is associated with the price of energy in time slot t, and the latter with the incentive received for the contribution to the grid. In other words, s_t^+ and s_t^- are related to import tariffs (e.g. flat, time-of-use) or export tariffs (e.g. feed-in-tariff). Device operation and energy balance constraints closely resemble those in Equations (1-6), but changed according to residential battery specifics.

The outcome of this process provides *net load profiles* for users with a home energy management system. After their self-optimization, prosumers can export their energy surplus to the grid, or trade it with other energy customers. The market mechanism for a P2P energy trading consists of three components [7, 35]: (i) a *continuous double auction* (CDA), (ii) the agents' bidding strategies, and (iii) the network permission structure, as described below.

5.3. *Continuous double auction*

A CDA matches buyers and sellers in order to allocate a commodity. It is widely used, including in major stock markets like the NYSE. A CDA is a simple market format that matches parties interested in trading, rather than holding any of the traded commodity itself. This makes it very well suited for P2P exchanges. Bids into a CDA indicate the prices that participants are willing to accept a trade, and reflect their desire to improve their welfare. As such, the CDA tends towards a highly efficient allocation of commodities [36]. In more detail, a CDA comprises:

- A set of *buyers* $\mathcal{B}$, where each $b \in \mathcal{B}$ defines its trading price π_b and the amount of energy to purchase σ_b.
- A set of *sellers* $\mathcal{S}$, where each $s \in \mathcal{S}$ defines its trading price π_s and the amount of energy to sell σ_s.
- An *order book*, with bids $o_b(b, \pi_b, \sigma_b, t)$, made by buyers $\mathcal{B}$, and asks $o_s(s, \pi_s, \sigma_s, t)$, made by sellers $\mathcal{S}$.

A breif outline of the CDA is given below, and full details of the mechanism can be found in [7] or [35]. A CDA is run for each time slot separately. Any intertemporal couplings that arise on a customer's side from using batteries or loads with long minimum operating times are not passed up to the market clearing entity. Once the market is open, arriving orders are queued in the *order book* for trades during a fixed interval t_d (Lines 2-8), which is limited by the start time t_d^{st} and the trading end time t_d^{end} (*i.e.*, $t_d^{\text{end}} = t_d^{st} + t_d$). During the trading period, orders are submitted for buying or selling units of electrical energy in time-slot t. At the end of the trading period, the market closes, thereby no more offers are received. We assume the orders arrive according to a Poisson process with mean arrival rate λ. The current best bid (ask) is the earliest bid (ask) with the highest (lowest) price. A bid and an ask are matched when the price of a new bid (ask) is higher than or equal to the price of the best ask $o_s^*(s^*, \pi_s^*, \sigma_s^*, t^*)$ (the best bid $o_b^*(b^*, \pi_b^*, \sigma_b^*, t^*)$) in the order book (Line 9). However, if a new bid (ask) is not matched, then it is added to the order book, recording its arrival time and price. Note that after matching, an order may be only partially covered. If this is the case, it will remain at the top of the order book waiting for a new order. This process is executed continually during the trading period as new asks and bids arrive.

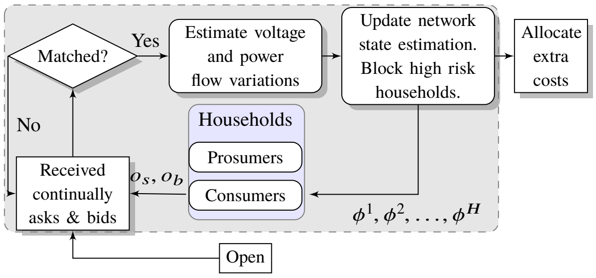

Figure 10: Schematic of the P2P trading under network constraints.

5.4. *Bidding Strategies*

Conventionally, market participants (buyers and sellers) define their asks and bids based on their preferences and the associated costs. The home energy management systems act as agents for the customers, and are continually responding to new stochastic information. As such, they appear very unpredictable from the outside. Moreover, because the market is thin, this can produce large swings in available energy and prices. In this context, constructing an optimal bidding strategy is futile, but simple bidding heuristics are still valuable. In particular, in our study the agents are *zero intelligence plus* (ZIP) traders [7, 35, 37]. ZIP traders use an adaptive mechanism which can give performance very similar to that of human traders in stock markets. Agents have a profit margin which determines the difference between their limit prices and their asks or bids. Under this strategy, traders adapt and update their margins based on the matching of previous orders. Indeed, the participation of ZIP traders in a CDA allows us to assess the economic benefits of the market separate from that of a particular bidding strategy. Specifically, ZIP traders are subject to a budget constraint ($L_{\max}$ and $L_{\min}$ are the maximum and minimum price respectively) which forbids the trader to buy or sell at a loss. Then, buyers and sellers select their bids or asks uniformly at random between these limits.

5.5. *Network permission structure*

The outline of the mechanism is presented in Fig. 10. A DSO validates the transactions using a network permission structure based on the network's features and sensitivity coefficients. Specifically, we incorporate the following sensitivities in the market mechanism (for full details see [7]):

- *Voltage sensitivity coefficients* (VSCs): Through VSCs, we can estimate the variation in the voltages as a function of the power injections in the network;
- *Power transfer distribution factors* (PTDFs): These reflect the changes in active power line flows due to an exchange of active power between two nodes;
- *Loss sensitivity factors* (LSFs): These reflect the portion of system losses due to power injections in the network.

Every time one ask and one bid are matched, voltage variation and line congestion are evaluated. All households receive a signal (ϕ^h) which informs them if they can still participate in the market without causing problems in the network. For instance, one prosumer could be blocked from injecting power into the grid at a certain time due to the high risk of causing voltage problems in the network. This is achieved using the VSCs and PTDFs. If the transaction is approved, the extra cost associated with the network constraints are allocated to the users involved in the matched transaction.

Importantly, power curtailment is implicitly incorporated in the trading. Thus, this method may bring extra benefits in comparison to others curtailment methods. For example, users at the worst node location still have the opportunity to participate if their order can be matched and if the mechanism allows the trade. This improves the efficiency by allowing greater participation of consumers and a better reflect of network conditions.

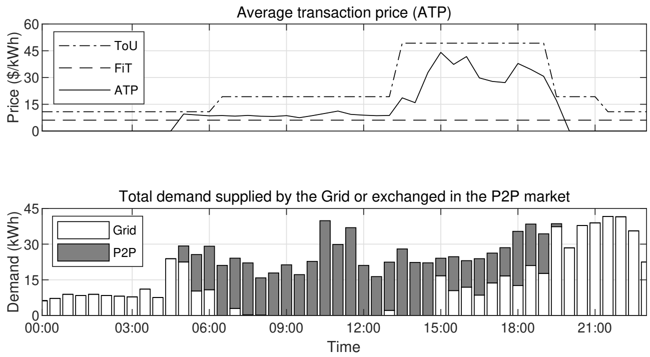

Figure 11: Average transaction prices (top), demand and generation levels (bottom).

5.6. P2P trading case study

As an illustration, we consider a smart grid system for energy trading at a local level. The methodology is applied to the UK LV network shown [16], comprising one feeder and 100 single phase households. The simulations are carried out with $T = 24$ hours, $\Delta\tau = 15$ minutes and up to 100 agents. There are 50 consumers and 50 prosumers, 40 for Type 1 (PV) and 10 for Type 2 (PV, battery and a home energy management system). Each household has a stochastic load consumption profile, with load profiles using the tool presented in [38]. Similarly, PV profiles are generated considering sun irradiance data, capturing the sunniest days in order to evaluate the method on the most challenging yet realistic scenarios. We assume that all prosumers have a PV system with installed capacity of 5.0 kWp. Each Type 2 households has a battery of 3 kW and 10 kWh.

Additionally, there is one *community electricity storage* (CES) of 25 kW and 50 kWh operated by the retailer. In particular, the operation objective of the CES is to apply peak shaving during peak load hours. The CES' strategy is to buy only the energy to charge in the P2P market to other prosumers around midday (when there are low rates and a high number of prosumers with energy surplus) and resell the energy during peak demand hours to the consumers. Like the prosumers behavior, the CES is modeled as a ZIP trader. We define the price constraints $L_{\max}$ and $L_{\min}$ based on the values of import and export electricity tariffs through the day. $L_{\max}$ depends on the time-of-use tariff (ToU) and $L_{\min}$ on the feed-in-tariff (FiT). These definitions are consistent in the sense that no buyer would pay more than the tariff of a retailer (ToU), and no seller would sell their units cheaper than the export tariff (FiT).

Fig. 11 shows the average transaction price (ATP) and the amount of energy purchased from the grid or in the P2P market during one day. The transaction prices remain in the range of ToU and FiT rates because of the ZIP limits $L_{\max}$ and $L_{\min}$. Hence, both prosumers and consumers obtain monetary benefits by participating in P2P trading. Most of the energy is traded during 8:00 and 14:00. During that time, there is an excess of energy due to PV generation. Notably, there is a peak of energy sold in the market around 11 am because of the charging strategy of the CES. There is some energy traded after 18:00 due to the CES and the prosumers who kept some energy in the battery. Once the peak time ends (20:00), the ZIP maximum limit ($L_{\max}$) is low. As a consequence, no prosumers submit any new asks to trade in the market. Moreover, in this case, when the total energy surplus from prosumers is greater than the total demand of consumers (e.g. around midday), some prosumers (those who do not match their asks with consumers' bids) have to curtail their power generation.

Fig. 12 presents a histogram of voltages at all users' nodes during one day of simulation. There are no cases of overvoltage. The voltages varied between 0.945 pu and 1.022 pu. Around 55% of the voltages are between 0.99 pu and 1 pu. As such, all exchanges respect the network constraints, and the external costs were attributed among the households involved in each transaction.

As demonstrated in Fig. 13, P2P with network permission consistently outperforms alternative power curtailment methods used to manage adverse impacts of DER penetration, including capacity reduction (Red. Cap), tripping and droop-based active curtailment (APC-OLP). The results show that in the P2P case there is more energy traded, and the prosumers' revenue is bigger in comparison with the other methods. In particular, the drawback of the power curtailment methods is that they do not consider the impact on the end-users' revenue. In contrast, the P2P scheme offers greater economic benefits to all users.

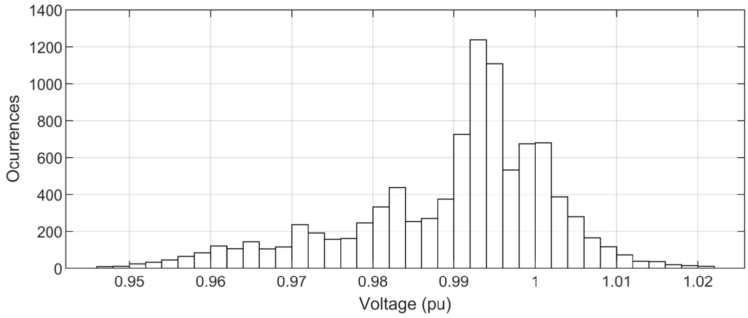

Figure 12: Histogram of voltages at users' nodes - number of occurrences in one day period at a certain voltage [pu].

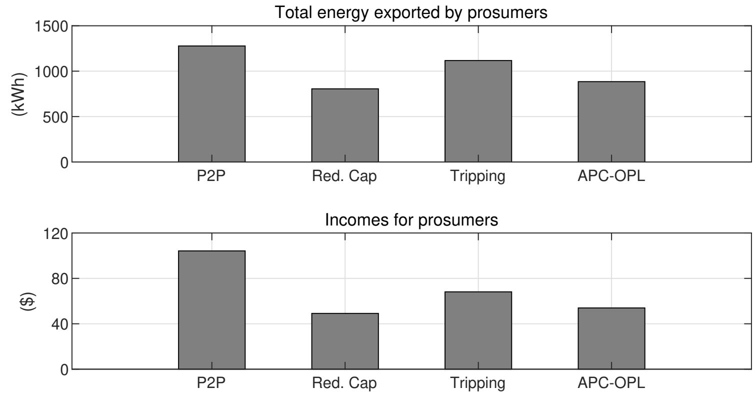

Figure 13: P2P vs alternative solutions: prosumers' total energy supplied and income received.

6. Conclusions and Further Work

A combination of government support and dropping technology cost has resulted in a rapid uptake of behind-the meter distributed energy resources. For a while, the networks were free-ride beneficiaries of that wave, mainly because of reduced peak demands. That era, however, is close to over. In many countries (e.g. Germany and Australia) the uptake has reached a point where high and uncoordinated penetration of behind-the meter distributed energy resources is beginning to cause localised network issues, so alternative solutions for the operation of LV networks need to be found. In this paper, we have shown that not all is doom and gloom. On the contrary, DERs can offer network services while minimizing cost for the owners and DNSP. However, we have shown that passive efforts to heard DER in the direction of behaviour that reduces operating and long-run marginal costs of providing distribution network services can be ineffective once DER penetration levels exceed moderate levels. In contrast, we demonstrate two approaches to orchestrated DER, indicating what is technically possible when DER is actively managed, and useful for situations where moderate-to-high DER penetration is causing, rather than solving, network problems. We have not directly addressed the question who should own or manage the DSO, whether it be a third-party entity or part of the DNSP, or how its actions can be integrated into the existing market framework, all of which are subjects for future work. In summary, given these observations, this paper argues that there is an essential role for orchestration of DER on distribution networks, in order to maximise distributed generation and distribution network value.

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