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Impact of local electricity markets and peer-to-peer trading on low-voltage grid operations

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ABSTRACT

Local electricity markets based on peer-to-peer (P2P) trading schemes have emerged as an innovative mechanism to sell electricity from prosumer to consumer, to utilise efficiently and value local flexibility, and to support grid management. In this paper, we analyse a local market applied to a real-life neighbourhood of 52 households in Norway. As prosumers and consumers trade within this community, we analyse the value of P2P trading compared to cases where no local markets are available, along with the impact of PV, batteries and EVs deployment. As these technologies and local trading interactions might create challenges to the physical operations of the grid, we analyse the effect on power flows, voltage variations and system losses. The main findings indicate that there are no significant impacts on the grid operation of the P2P market when only PVs are installed in the system. With decentralised batteries available, the P2P trade induced more voltage fluctuations and 14 % more losses within the neighbourhood than the case with no local market. However, the local market brings overall savings for the end-user and sets the frame to design pricing schemes (e.g. manage losses) that are tailored to support DSO operations.

1. Introduction

The ongoing deployment of distributed renewable energy sources is transforming the way we consume and produce electricity. Solar PV production in homes and buildings are expected to account for 530 GW by 2024 globally [1]. This is mainly due to the investment costs in solar PVs and batteries have been declining exponentially over the recent years [2,3]. This trend shows that small-scale energy technologies are becoming affordable for regular households, creating the transition from consumerism to prosumerism. This development is complemented with the advancement of ICT technologies, enrolment of smart metres, and potentials from distributed ledger technologies (e.g. blockchains). Digitalisation and automatisation will enable a closer interaction between end-users, DSOs, and other system agents (e.g. aggregators), and introduces the possibility of a more consumer-centric power system [4].

Energy communities and Peer-to-Peer (P2P) trading in local electricity markets provide a new framework to manage renewables in low-voltage grids. In the last years, there has been a growth in real-life pilot projects demonstrating their viability and challenges [5–7]. The decentralised management and collaborative principles characterising these structures allow for the prosumers' preferences to be taken in consideration in the creation of a local market [8]. Studies suggest that P2P trading reduces total electricity costs, improve self-consumption, and promote more effective utilisation of local distributed energy resources (DER) [9–11]. However, the exchange of electricity is different from other goods' trade, as the agents are connected to a complex power system. This raises the question, how this emerging local market structures will concur with the hard technical constraints of the grid? That is, if local electricity markets based on P2P schemes take place within a distribution network will they induce more grid losses, voltage variations, grid congestion, or other physical constraints to DSO operations? For example, P2P trading might be driven by prosumer-to-consumer overall welfare benefits and leave behind any downturns or challenges to grid operators. In this regard, while existing literature note some initial insights on the coordination between local markets and distribution grid operations [12,13], the research in this area is still limited (see recent review on the topic [14]).

To understand the impact of P2P trading in grid operations, this paper analyses both the market clearing decisions and the power quality features of the low-voltage grid. In short, the objective is to understand:

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- What is the impact of local markets on voltage variations, grid dependency, and losses? (comparing the value of P2P trading compared to cases of no local trading)
- How does the local market behaviour vary with different assets available, and how do the following decisions affect the grid operations?

In order to address these research questions, we developed a two-step modelling framework: a P2P market optimisation and an AC power flow. Based on this approach, we analyse the economic effects of the trading and the technical impacts on the grid separately. Different cases based on PV and storage deployment, are analysed and the operational impacts of having a P2P market or not are compared for each. Additional cases are evaluated to perform sensitivity analyses of the obtained results. Moreover, a novel framework proposition to manage losses is incorporated into the P2P market model. All these cases are applied to a real-life distribution grid in Norway compromised of 52 customers. Fig. 1 illustrates the overall idea on linking a P2P market decisions to the grid operations.

The paper is organised as follows. The following section presents related literature and summarises the contribution of the paper. Section 3 describes the models and methods. Section 4 summarises the neighbourhood grid, houses, and overall data scope, while the results and analysis are given in Section 5. Then, Section 6 summarises conclusions and perspectives for future work.

2. Related literature

In the early stage of studying local energy systems, the concept of flexibility was introduced as a potential key asset for system operators. Demand response would support the DSO with voltage control and congestion management, and balancing power and frequency control for the TSO [15,16]. Significant effort has been devoted to this literature stream [17–19]. As the idea of P2P trading has emerged, the focus has shifted towards the market and end-user perspective rather than the implications for the grid operators (Refer to Tushar et al. [20] for comprehensive review on the research of these markets).

Over the recent years, several real-life pilot projects for P2P markets has been deployed. Well-know examples include the Brooklyn Microgrid [6,21] and the sonnenCommunity in Germany [22]. Both projects are constituted to help out the DSO by completely decoupling or controlling the electricity supply in case of natural emergencies and use mechanisms to balance supply and demand. However, it seems to be an overall larger focus on the development of the trading platforms rather than investigating the daily operational impacts the projects have on the distribution grid.

Recent academic studies have emerged considering the technical constraints associated with trading within a low-voltage power system. Guerrero et al. [13] propose a method based on sensitivity analysis to evaluate the technical impacts caused by the P2P transactions in a low voltage network and to ensure that no network constraints are violated. They utilise sensitivity coefficients for voltage change, system losses, and power distribution factors to predict the network state caused by each transaction made in the P2P market dispatch. The study provides an analysis of the network state after the grid constraints have been implemented.

Zizzo et al. [23] evaluate power loss allocation due to energy exchanges using blockchain technology in a medium voltage network. Tushar et al. [12] proposes a game theoretical approach, facilitating an interaction between prosumers and the DSO to minimise consumption peaks. Incentives for peak demand shaving are also discussed by Wang et al. [24]. Others, like Munsing et al. [25] and Baroche et al. [26] have utilised different versions of decentralised optimal power flow and grid utilisation costs strategies. Almasalma et al. [27] propose a grid voltage control scheme, based on PV inverter control, integrated into the P2P trading model. None of these methods, however, explore the actual impacts on the grid, as they mainly focus on the market solutions obtained with the grid constraints integrated into the market optimisation.

Azim et al. [28] analyse the power losses caused by P2P trading by comparing the results with that of a non-P2P technique. The differences were found to be insignificant, but increasing with the amount of storage available to the prosumers. Nikolaidis et al. [29] introduce a graph-based approach to allocate the losses occurring in the grid when introducing transactive energy trading in radial distribution grids. Di Silvestre et al. [30] uses indexing for the same purpose, emphasising the challenge of allocating losses caused by local transactions due to the mismatch between the virtual and physical power flows.

Hayes et al. [31] provides a similar co-simulation approach of the P2P trading and power flow analysis, but only simulate over a 24 h period. Orlandini et al. [32] performs a full AC power flow to analyse the grid impacts of P2P trading. An iterative methodology is proposed, which utilises product differentiation and artificial congestion tariffs to motivate market participants to avoid grid congestion. The study focuses on line congestion and how it changes under the proposed tariff scheme.

Differing from most of the aforementioned work, this study will focus on the technical impacts of a non-interfered P2P market dispatch. An approach similar to Orlandini et al. [32] is applied, but with a different market structure and a broader focus on voltage levels, losses, and peak demand values. This paper analyses various cases with different system configuration that considers: Solar PV, Batteries, EVs, and fix-tariffs vs dynamic tariffs. The diversity of these cases allows to understand the effects of P2P trading into voltage and system losses under different settings. As we use a real-life case study, the study provides new perspectives on the impacts of implementing a P2P market.

Table 1 summarises key studies focused on the grid impacts of P2P trading. There we have modelling approaches that include network constraints in the market clearing model, e.g. optimal power flow. In some cases, the branch flow equations are derived based on the radial grid structure while others utilise sensitivity coefficients like voltage sensitivity or power transfer distribution factors to estimate potential problems in the physical layer. Others accommodate a separate market and grid evaluation, but do not consider different market or system configurations. The separated structure of the proposed method splits the market and the grid layers so that it is attainable to calculate the impact of P2P trading on the grid precisely. A wide range of scenarios organised in different cases is selected to investigate the impact of P2P energy trading in combination with different assets on a realistic grid. Based on this Table overview, the contribution of this paper provides:

- Analysis of the grid impacts (voltage and losses) caused by P2P trading based on a real-life case study.
- Analysis and comparison of these impacts with different market and system configurations (level of distributed energy sources, e.g. EVs, solar PV and home batteries).
- Proposition of mechanism to empirically estimate and include losses to the P2P market clearing.
- Provide further insights on the implications of P2P for regular consumers, and DSO integration of distributed energy sources based on P2P (e.g., the importance of tariff design on these).

3. Modelling local markets and low-voltage grid operations

The overall methodology is illustrated in Fig. 1. We analyse the local market dynamics based on an optimisation model. Then, we implement the market decision into a power flow framework. Lastly, we partially combine both modelling frameworks.

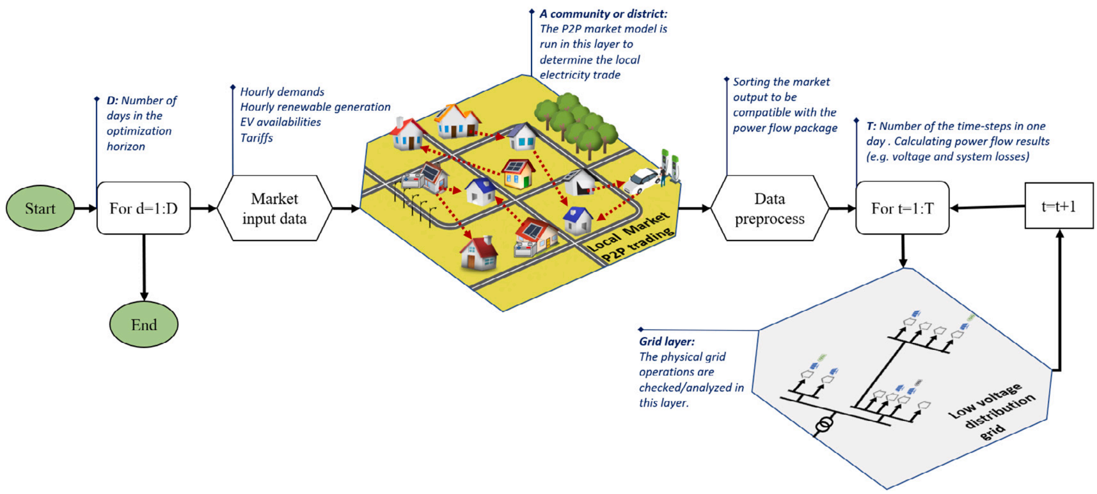

Fig. 1. Features on representing a local P2P market together with low-voltage grid impacts. The flowchart illustrate the models implementation and interplay.

Table 1
Related papers considering grid impacts of local electricity markets.

Paper	Modelling framework	Includes power losses costs	Considers various cases/assets
Guerrero et al. [13]	According to the Voltage Sensitivity Coefficients, one determines that the P2P transaction causes a voltage problem or not. Also, Power Transfer Distribution Factors are employed to determine the utilisation rate of the lines and line congestion.	The grid losses caused by each transaction is approximated by Loss Sensitivity Factors. Agents involved in that transaction are penalised.	The case of P2P trading with two scenarios (1. the proposed market model and grid limitation in the paper, and 2. curtailing the energy injections leading to overvoltage or capacity problems)
Azim et al. [33]	Assumes that the inverters regulate the voltage at the point of common coupling by curtailing the excess energy.	Comparing the power flow with and without the P2P transactions	Economic Benefits - over voltage - Transaction Losses/PV
Li et al. [34]	It includes the branch flow model of the radial distribution network in the formulation, as an optimal power flow. Nash Bargaining game is applied.	No	Two case studies(IEEE 37-Bus and IEEE 123-Bus Distribution Systems)/PV
Wang et al. [35]	Minimises the cost of the electricity generation and thermal losses as an optimal power flow.	Adding a term (thermal losses) to the objective function	cases with and without considering the P2P trading /Fully controllable DERs by the operator in day-ahead schedules-DERs
AlSkaif et al. [36]	Optimal power flow coordinates the interactions of the DERs using the branch flow equations in a single-phase distribution grid.	No	One scenario (Convergence of the proposed algorithm)/EV
Van Leeuwen et al. [37]	Optimal power flow and market model combined in one model.	No	8 scenarios; baseline, trade only, grid only and grid + trade, all for summer and winter/PV+Battery+EV.
Lilla et al. [38]	Distributed market clearing using ADMM, considering approximated losses. Losses are then calculated and allocated to each transaction.	Losses are first estimated then recalculated and allocated to each transaction.	2 (4) scenarios/PV+Battery.
Paudel et al. [39]	Power distribution factors estimate network fees that are provided before the market clearing.	Network fees considers approximated losses.	4 scenarios, all p2p with or without losses and network fees/Unspecified.
Zhong et al. [40]	Cooperative market model considering branch flows.	Cost coefficient for power losses used to calculate network tariff	Compared to different benchmark models; No Volt-Var, No DN and No price constraints. All p2p cases/Unspecified.

3.1. P2P model

The P2P model is a multi-period linear programming model that assumes perfect competition, and it does not consider network constraints nor physical features (for a similar model see Lüth et al. [9]). The model is open-sourced, as elaborated in Appendix A. With a community-based P2P market structure, the objective function comprises the total electricity costs for the whole neighbourhood, subject to supply, demand, trade and storage constraints. Similar to the day-ahead market in the wholesale electricity market, the model finds an optimal solution for the next 24 h based on predefined demand and supply quantities. That is, we assume that the consumers face wholesale market prices and this stimulates local market trading. This is the same approach as used in [9,41].

The objective function that is represented in Eq. (1) aims to minimise the total costs related to the community's electricity consumption.

$$min \quad \sum_{h} \left(\sum_{t} (c_{spot}^{(t)} + c_{en}) \cdot G^{(t,h)} - \sum_{t} c_{spot}^{(t)} \cdot \psi \cdot E^{(t,h)} \right) \tag{1}$$

Table 2
Nomenclature of P2P model.

Sets		
$t \in T$	Hours t in time horizon T	hours
$h, p \in H$	Houses h and peers p in community H	–
$d \in D$	Days d in time horizon D	days
Scalars		
ψ	System loss factor	%
$\bar{s}/\underline{s}$	Upper/lower bounds of storage levels in battery	kWh
α/β	Maximum charge/discharge rate of battery	kW
η^C/η^D	Battery charging/discharging efficiency	%
c_{en}	Energy term of grid tariff	øre/kWh
Parameters		
$dem^{(t,h)}$	Demand of house h in time step t	kW
$res\_pv^{(t,h)}$	Electricity production from PV of house h in time step t	kW
$c_{spot}^{(t,h)}$	Wholesale spot price for electricity from the grid in time step t	øre/kWh
$S_0^{(d,h)}$	Energy storage level at beginning of optimisation period d	kWh
Variables		
$C^{(t,h)}$	Charge of battery at house h in time step t	kW
$D^{(t,h)}$	Discharge of battery at house h in time step t	kW
$S^{(t,h)}$	Energy storage level in battery of house h in time step t	kW
$G^{(t,h)}$	Grid consumption of house h in time step t	kW
$E^{(t,h)}$	Export to grid from house h in time step t	kW
$I_{p,p2p}^{(t,h\leftarrow p)}$	P2P electricity purchase of house h from peer p in time step t	kW
$X_{p,p2p}^{(t,h\rightarrow p)}$	P2P electricity sold by house h to peer p in time step t	kW
$I_{p2p}^{(t,h)}$	P2P electricity purchase of house h in time step t	kW
$X_{p2p}^{(t,h)}$	P2P electricity sold by house h in time step t	kW

As the P2P trade is happening within the community, and thus the price someone pays cancel out what someone earns, these transaction costs are not included in the objective function. Compared to the objective function in the model of Lüth et al. grid tariff consideration and the possibility to sell electricity to the grid has been added. Since each house in the community is subject to the fixed-term of the grid tariff regardless of the market strategy, this is excluded from total costs. The energy term is, however, added to the costs of importing electricity from the grid. The Feed-in-Tariff (FiT) is calculated based on the method currently used by Norwegian DSOs [42], where the spot-price is multiplied with a marginal loss factor ψ. This factor is determined by the local DSO. Table 2 denotes the nomenclature of the P2P optimisation model.

The P2P trading set up within the community allows for direct trade of electricity among all peers, regardless of an actual physical connection. Therefore, the import of prosumer h from p equals to the export of p to h for each time step.

$$I_p^{(t,h\leftarrow p)} = X_p^{(t,p\rightarrow h)} \qquad \forall\, p \neq h, \tag{2}$$

The total amount of sold electricity through P2P trade $X_{p2p}^{(t,h)}$ from each house $h \in H$ for each time step $t \in T$ is defined by Eq. (3).

$$X_{p2p}^{(t,h)} = \sum_{p\neq h} X_{p,p2p}^{(t,h\rightarrow p)} \qquad \forall t \in T, \forall h \in H \tag{3}$$

The total amount of purchased electricity through P2P trade $I_{p2p}^{(t,h)}$ is defined similarly by Eq. (4).

$$I_{p2p}^{(t,h)} = \sum_{p\neq h} I_{p,p2p}^{(t,h\leftarrow p)} \qquad \forall t \in T, \forall h \in H \tag{4}$$

It is assumed that the P2P trade is limited to stay within the community, with the variable $E^{(t,h)}$ defining the potential surplus leaving the community. A constraint to ensure that the sum of sales made by P2P trade equals the sum of purchases is thus defined by Eq. (5). Compared to other P2P models in the literature [9,43], there is no system loss coefficient included in this constraint. As the actual losses for each trade are found by performing a power flow analysis in this model, it was considered superfluous to have it in the market model as well.

$$\sum_h X_{p2p}^{(t,h)} = \sum_h I_{p2p}^{(t,h)} \qquad \forall t \in T \tag{5}$$

A central constraint in the model is the power balance equation, represented in Eq. (6). This constraint ensure that the supply equals the demand at each house h at each time step t.

$$\begin{aligned} &G^{(t,h)} + I_{p2p}^{(t,h)} + D^{(t,h)} + res\_pv^{(t,h)} \\ &\quad \geq dem^{(t,h)} + X_{p2p}^{(t,h)} + C^{(t,h)} + E^{(t,h)} \qquad \forall t \in T, \forall h \in H \end{aligned} \tag{6}$$

For the cases involving batteries, some additional constraints have to be added to the market model to control their behaviour. For each battery, there is an upper and lower bound in both SOC and charging and discharging rate, represented by Eqs. (7) and (8).

$$\underline{s} < S^{(t,h)} < \bar{s} \qquad \forall t \in T, \forall h \in H \tag{7}$$

$$0 < D^{(t,h)} < \beta \quad ; 0 < C^{(t,h)} < \alpha \qquad \forall t \in T, \forall h \in H \tag{8}$$

The SOC for each battery in each time step is also a function of the SOC of the previous time step and the charge and discharge of this time step. This is one of the main motivations of performing a multi-period optimisation as the decisions of time step t will depend on the decisions made in time step $(t-1)$.

$$S^{(t,h)} = S_0^{(d,h)} + \eta^C \cdot C^{(t,h)} - \frac{1}{\eta^D} \cdot D^{(t,h)} \qquad \forall t \in T, \forall h \in H, \forall d \in D \tag{9}$$

Eq. (9) represents the SOC calculation for the first time step (t = 1) for each period d. Here, d represents the day in the overall time horizon D which are being optimised. At the first day, S_0 is set to be zero for all batteries, while S_0 for all consecutive days are set to be equal to $S^{(t,h)}$ at the last time step t of $(d-1)$. As the market model only finds the optimal solution for each time step d, this battery behaviour creates a more realistic dependency between the periods. Note that the peers are allowed to perform arbitrage operations and charge their batteries with electricity procured from the wholesale market.

3.2. Power flow model

After the P2P model has determined the optimal solution for the day d, the next step is to perform a power flow analysis. Due to the distribution grid's distinct topology [44], we use the forward/backward sweep method with power summation [45].

One of the main ideas behind the proposed method is to combine the market and technical models. The P2P model finds a global optimal solution for the hours t within period d. The power flow is then executed for each hour of the market solution. As an output from the P2P model, we get the seven first matrices described under 'Variables' in Table 2. These must be adapted to fit the input requirements of the power flow, which is the net active and reactive demand at each node. The net active power demand is assumed to be the sum of the capacity imported to the node minus the capacity exported from the node. Hence, for each house h the active power demand for each time step t is calculated by Eq. (10). The battery charging and discharging is assumed to happen behind the connection point at each node and is thus not included in the net power injection calculation.

$$P_d^{(t,h)} = G^{(t,h)} + I_{p2p}^{(t,h)} - E^{(t,h)} - X_{p2p}^{(t,h)} \qquad \forall t \in T, \forall h \in H \tag{10}$$

The P2P model only treats the exchange of active power and neglects the changes in reactive power caused by this exchange. However, the reactive power net injection at each node would likely be influenced by the trade as well. The net reactive power demand for each node must thus be calculated for each time step t. For simplicity, it was decided to find an average power factor for each of the nodes, and keep that constant for all time steps. From the given load data, it was obtained that all buses maintained a constant power factor of 0.98. The reactive power demand for each house h for each time step t was thus calculated with Eq. (11).

$$Q_d^{(t,h)} = \sqrt{\frac{P_d^{(t,h)^2}}{\cos\phi^2} - P_d^{(t,h)^2}} = \sqrt{\frac{P_d^{(t,h)^2}}{0.98^2} - P_d^{(t,h)^2}} \qquad \forall t \in T, \forall h \in H \quad (11)$$

After calculating the net active and reactive power injections of various houses in day d based on Eqs. (10) and (11), the main model proceeds to the power flow analysis part. This part of the model is based on the open-source analysis tool MATPOWER [46]. The tool accommodates a forward/backward sweep algorithm, called upon with the option struct 'PQSUM'.

The load flow problem is then solved by the algorithm described in the following steps.

1. Set all voltages to 1 p.u.
2. The apparent branch power flow at the receiving end (s_t^k) is set to be equal to the total demand at receiving end (s_d^k) and the power drawn by the shunt admittance (y_d^k) connected to bus k. n_b represents the total number of buses in the system.

$$s_t^k = s_d^k + \frac{(y_d^k)^*}{v_k^2}, \qquad k = 1, 2, \dots, n_b \tag{12}$$

3. *Backward sweep*: The sending end branch flows are calculated as the sum of the receiving end branch flows and branch losses by Eq. (13). Power summation is performed starting from the branch with the biggest index and heading towards the branch connected to the slack node. Eq. (14) adds the receiving power at bus k to the sending power of the corresponding branch.

$$s_f^k = s_t^k + z_s \cdot \left|\frac{s_t^k}{v_k}\right|^2 \qquad k = n_l, n_l - 1, \dots, 2 \tag{13}$$

$$s_{t,new}^i = s_t^i + s_f^k \qquad k = n_l, n_l - 1, \dots, 2 \tag{14}$$

4. *Forward sweep*: The receiving end bus voltages are calculated with known sending power, voltage and series impedance.

$$v_k = v_i - z_s^k \cdot \left(\frac{s_f^k}{v_i}\right)^* \qquad k = 2, 3, \dots, n_l \tag{15}$$

5. Compare voltages derived in iteration ν with the voltages from iteration $\tau - 1$ using Eq. (16).

$$\max_{i=1,\dots,n_b} = \left\{ \left| v_i^{\tau} - v_i^{\tau-1} \right| \right\} < \varepsilon \tag{16}$$

If the difference between the voltage magnitudes is greater than the specified error limit ε, more iterations are needed and the process goes back to step 2. In MATPOWER, the default tolerance is set to be 10^{-8}.

After the *runpf* function is executed, the discrepancy between the flows in each direction is used to determine the power losses in the system, by Eq. (17). Here, i and k represents the nodes at each end of the branch.

$$P_{loss} = P^{(i\to k,t)} + P^{(k\to i,t)} \qquad \forall i, k \in N \quad \forall t \in T \tag{17}$$

Fig. 1 illustrates the interactions between the market and power flow model. In short, observe that the market model finds an optimal solution for day d, while the load flow is executed for each hour t within d. It also includes the extension further described in Section 3.3, marked with a red square.

3.3. Pricing for loss reduction

To pass on the insights of the power flow analysis to the P2P market optimisation model, this case incorporated a marked-based price that reduces system losses and hence affect the P2P decisions. The idea was to trigger "grid friendly" P2P trading decisions that: (i) still minimises grid imports for the whole community based on P2P trading and (ii) considers the effect of losses by penalising an empirical estimate of these. To implement this, a linear regression can be determined based on the loss time series obtained from the previous cases (with the power flow model and analysis described previously, see red square in Fig. 1). With this novel approach, a new constraint was included in the market model. Accordingly, the losses are computed empirically within the market model in a linear regression. These losses are a function of the dynamics of demand, grid imports (variable in the optimisation model) and PV generation. Hence, they will have the coefficients ρ, μ and γ, respectively which is determined by the regression. Eq. (18) represents this new constraint applied to the local market model. All parameters have the unit of kW.

$$Losses^{(t)} = \rho \cdot \sum_h dem^{(t,h)} + \mu \cdot \sum_h G^{(t,h)} + \gamma \cdot \sum_h res\_pv^{(t,h)} \qquad \forall t \in T \tag{18}$$

The overall market model aims to minimise the total community costs. In order to minimise the system losses, they are thus included in the objective function, with allocated costs. It is assumed that the costs should reflect the costs of additional power needed to be imported from the wholesale market in order to cover the losses. Accordingly, the same costs are allocated to the losses as for the grid import. The updated objective function is as follows:

$$min \quad \sum_h \left(\sum_t (c_{spot}^{(t)} + c_{en}) \cdot (G^{(t,h)} + Losses^{(t)}) - \sum_t c_{spot}^{(t)} \cdot \psi \cdot E^{(t,h)} \right) \tag{19}$$

4. Implementation on a real low-voltage network

The low-voltage distribution grid case is based on data from a real grid located at the municipality of Steinkjer in Mid-Norway. The town and the local grid was subject to a large smart grid project. This has create rich grid and consumption data which was used in several studies [47–49]. The overall system part of the demo project comprised 856 customers, 32 distribution transformers and a small-scale hydropower plant [49]. In this study, the low-voltage distribution grid connected to one of these transformers was chosen. The system is connected to the main grid through a 315 kVA distribution transformer. The voltage magnitude of the external grid, which is considered as the slack bus was fixed to 1 p.u. equal to 230 V.

Fifty-two end users are connected to the distribution grid, through 16 feeder lines. All these nodes, as well as the bus bars connecting the feeder lines with the end-user branches, were modelled as PQ buses. In total, there are 70 nodes in the system, see Fig. 2 for a full overview of the case study.

4.1. Input data

Demand Profiles: Data sets for the entire area were provided by Zaferanlouei et al. [49], including both demand for each house and technical grid specifications. These are consumption data from real consumers connected to the distribution grid, with a 15 min granularity. The demand for each node was aggregated to fit a one hour time step to match the availability of solar data. It is expected that the most significant differences will occur during summer, because of more local trading due to high PV generation. Hence, a 21 days in the summer of 2012 were used. In this period, the average peak demand per customer was around 2.7 KW.

PV Production Time Series: As the distribution grid is located in Mid-Norway, historical PV production time series for this area were obtained from the site renewables.ninja [50]. The site gets, in turn, its data set from the NASA MERRA-2 database which contains meteorological data for the area from 2019 [51]. As the years of the demand data and the PV data did not match, it was chosen to use arbitrary days from June and July in the PV data, to capture the effects of different degrees of irradiation. As recommended for the geographical area, a panel tilt of 45° was used.

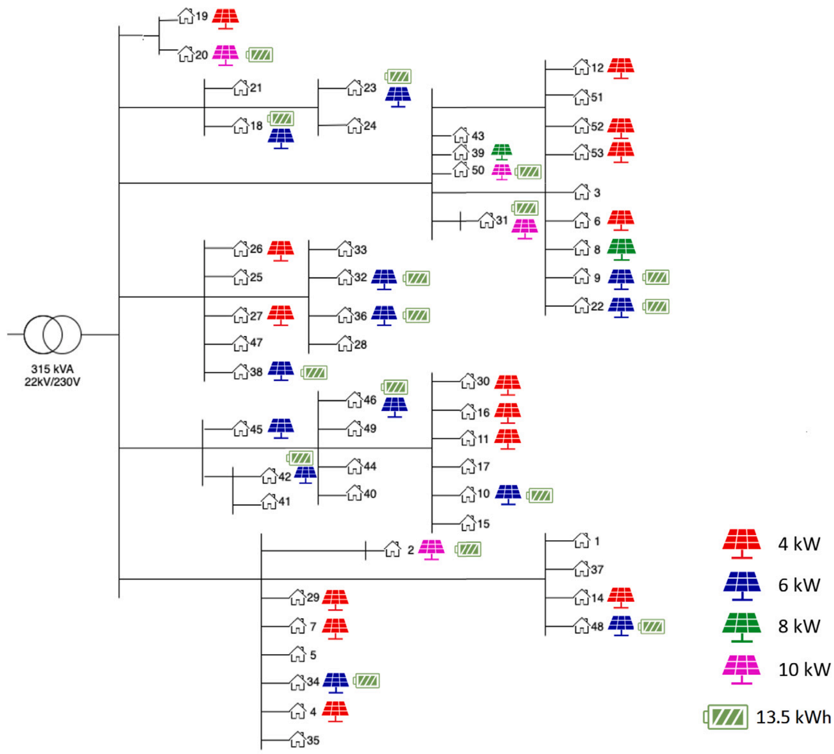

Fig. 2. Single-line diagram of distribution system used in the case studies.

Battery Specifications: We assume that the houses with battery presence have installed a Tesla Powerwall 2AC, with an upper state-of-charge level of 13.5 kWh. Both charging and discharging are constrained by an inverter of 5 kW nominal power (α/β), yielding full charge/discharge within 2.7 h. The charging and discharging efficiency, η^C and η^D, are both 95%, yielding a round-trip efficiency of 90%. As the focus of this paper is to analyse the technical impacts of P2P trading to grid operations, a more detail representation of the batteries physical characteristics is not strictly necessary and will not affect the main results. That is, no degradation processes are considered, and all efficiencies are assumed to be constant (not affected by the battery state-of-charge level).

Electricity Prices: The market decisions of the P2P model are sensitive on the electricity price. This can be a retail fixed tariff or the wholesale spot prices. For a fixed retail tariff we use a 0.8 NOK/kWh based on [52]. As for assuming a wholesale price,[1] these prices are retrieved for the NordPool pricing area NO5, Trondheim (Norway). Historical time series are openly available at NordPool's website, and three weeks corresponding to the demand data, but from 2019, were used. The grid tariff is determined by the local DSO, which in this case is Tensio AS. As of 2020, the energy term for households is set to 52.6 øre/kWh [53]. The loss factor ψ used to calculate the FiT is set to reflect the marginal loss rate of 5% (ψ = 95%), used by the same local DSO during summer [42].

4.2. Case descriptions

To this real-case in Steinkjer, we apply five main cases. Table 3 summarises the cases and here some with the following additional information:

- *Reference Case:* Reflects the business as usual setting. Here, there are no PV panels or batteries installed. Consumers buy their electricity from the wholesale market or at fixed retail tariff. This reflects the current situation in most Norwegian low-voltage distribution grids.
- *PV case:* This case assumes that most of the houses in the neighbourhood have PV panels installed. The PV size varies as it is illustrated in Fig. 2. Considering this system setup, two variations of no local market and P2P market are studied. With no local market present, each house can cover their demand by generation from their own PVs or buy from the grid. Each prosumer can also sell their excess electricity back to the grid, but not directly to any of its neighbours. While, in the other version related to the PV case, the neighbourhood peers establish a local P2P market. The prosumers can sell their additional surplus to the grid.
- *Battery Case:* Some prosumers with PVs in the previous case have now a home battery. This mainly applies to houses with high demand. All the homes assume to have a Tesla Powerwall battery. Arbitrage operation is allowed. Similar to the PV case, both a model with no local trading and a P2P market model are studied for this configuration. The setup will be referred to as the PV + Battery case.
- *Loss Management Case:* As introduced in Section 3.3, based on the results of the PV case simulations (without and with P2P market), a regression can be estimated to empirically calculate the losses as a function of grid imports, total system demand, and solar power production. The regression provides a function to calculate the losses within the market model and hence create a penalty or pricing (cost) of losses in the objective function. To be able to derive a statistically significant linear regression, various regression models were tested and analysed. The regression model with losses as the dependent variable is as follows: $Losses = \rho \cdot DEMAND + \mu \cdot GRID_{Import} + \gamma \cdot PV_{Gen}$.

[1] Smart metring is almost ubiquitous in Norway. All consumers have access to hourly and daily information on their consumption patterns. Smart metring allows prosumers in Norway to have information on the established feed-in tariff that follows the wholesale market price (this is a real setup in Norway).

The reported R^2[2] is quite high and has no significant deviation from the adjusted R^2. Statistically speaking, this provides high confidence in the regression accuracy. The R^2 value could perhaps be improved even further by considering non-linear components in the model or introduce discrete variables (e.g. peak time). However, this would make the optimisation model non-linear or integer. Therefore, it was preferred to have a linear regression model. All the regression coefficients report being statistically significant with a P-value lower than 0.001. This confirms that the regression model will provide an almost accurate calculation of losses. The regression results estimates the following coefficients: −0.00658 for $\rho \cdot DEMAND$, 0.0218 for $\mu \cdot GRID_{Import}$, and 0.00537 for $\gamma \cdot PV_{Gen}$.

- *Sensitivity analysis cases:* These are additional cases that test the sensitivity of the results by introducing the following: (i) test a retail tariff that removes batteries arbitrage decisions which changes the P2P trade strategy and hence its grid effect, and (ii) include EVs patterns instead of batteries to see the effect on the load curve.

5. Results

The presentation of the results are divided in three main parts. The first part details the results of the market model. Then, this is followed with the grid impact results as the second part. Lastly, the third part showcases the loss management case and the sensitivity cases.

5.1. Market results

5.1.1. Local trading

Fig. 3 presents the total capacity traded through the P2P market scheme for the two cases of DER integration for each day of the simulation period. It is clear that with the presence of batteries, the amount traded within the community is almost twice as much in some days than without storage opportunities. For both cases, day six yields the most local trade and is thus chosen as exemplary for the following comparisons of results. One can also observe from Fig. 3(a) that there are some days with no local trade in the PV case. This happens in situations with little solar irradiation where self-sufficiency will be a priority for the peers, and there is subsequently no local trading. With batteries available, however, electricity is traded within the community every day, as can be seen in Fig. 3(b). The batteries allow for price arbitrage and extend the trading period, thus allowing more peers to trade locally. It is important to note that by not considering the battery degradation, these results can be considered optimistic, as degradation limits the value of storage.

5.1.2. Operational decisions

For the sake of showcasing the different operational decisions of the nodes, one arbitrary node from each peer category is chosen. Node 2 represents peers with both solar and storage, node 48 represents peers with PV only, and node 24 represents the pure consumer peers. With no local market in operation, the only option for pure consumers like the house located at node 24 is to import from the main grid, as shown in Fig. 4(a). Considering the P2P trading opportunity provided by the local market, this house is able to exploit the lower P2P prices to cover its demand by P2P purchases when possible. With no storage available in the system (PV case), as can be seen in Fig. 4(b), local trade is only possible when the PVs are generating electricity. The consumer has no choice but to import from the grid during night-time. However, in the PV + Battery case, as Fig. 4(c) illustrates, even with no generation or flexibility of its own, the consumer located in node 24 participates actively in the local market when given the opportunity. The peer goes from being a passive price-taker relying solely on wholesale grid import, to being able to take more active decisions of the origin of its electricity consumption in order to minimise its electricity bill.

The operation of node 48 with only PVs installed, for both market schemes and both cases, are illustrated in Fig. 5. For this house, all surplus from PV generation is exported regardless of market structure. Comparing the presented schemes, one can observe that the same capacity is exported from the node, only differing in purpose. When a local market is present, the peer prioritises to sell its excess power within the community. Fig. 5(b) illustrates that some export to the grid between noon and 2 pm, probably due to a saturated local market when there is no storage in the system. However, integrating storage to the grid leads to a change in the behaviour of the participants. The following observations can be figured out about the house connected to node 48, comparing Fig. 5(a), (b), and (c):

- All surplus is exported in all cases. However, P2P trade is prioritised over grid feed-in in Fig. 5(c).
- The peer relies on purchasing electricity from other peers with charged batteries during the evening and morning when the P2P market is available, as can be seen in Fig. 5(c).

From Fig. 6, comparing no market and local market structures for node 2, the following insights emerge about houses with both PV & storage:

- For both cases, the peer is self-sufficient in times of PV generation and mostly self-sufficient by battery discharge in the evening and morning. During the night, the demand is covered by grid import.
- For both cases, surplus electricity is being exported and no PV generation is curtailed.
- In both cases, the battery is charged by surplus PV generation during the day.
- When the peer has the opportunity to trade electricity locally, it prioritises this over grid feed-in.
- For both cases, the peer imports electricity to charge the battery. With the P2P market, one can observe that the peer prioritises discharging its battery in order to sell locally, instead of using it for self-consumption.
- In the case of P2P, in Fig. 6(b), the peer chooses to import from the grid despite having an excessive PV generation. One can observe that this is due to an arbitrage operation, where the imported capacity is used to charge the battery for then to be sold to other peers at more favourable prices during peak time.
- For both cases, there is a maximum charging of 5 kW to the battery for a couple of time steps during the night. This indicates that it is profitable for the peers (community) to procure extra from the grid during the low price time-slots and save it for later self-consumption or local trade, even with a 10% loss in the round-trip charge/discharge of the battery.

5.1.3. Community costs

As the optimisation model aims to minimise the electricity related costs for the whole community, a lower objective function value indicates a more effective usage of local flexibility assets and P2P trade. In Table 4 the total community costs for the 21 day simulation period are presented for each case, and compared with the reference case. The share of expense and revenue from grid import/export is also given.

As can be noted from the results in Table 4, all cases with integrated DERs lower the total costs with around a third compared to the reference case. This is a consequence of the community relying less on centrally generated electricity, due to local production. The savings of establishing a P2P market is, however, of less eminence. It is also clear that both cases with P2P market yields a lower dependency on grid import, as the community is able to utilise the locally generated

[2] **Regression Statistics:** Multiple R: 0.9647, R^2: 0.9306, Adjusted R^2: 0.9283, Standard Error: 0.4760, Observations: 504.

Table 3
Summary of the main cases analysed.

Case	Assets	Local market	Description
Reference	No PV No battery	No market	All consumers procure electricity from the retailer or the grid. It is a business as usual case.
PV	PV (%33 of demand) No battery	No market	PV supplies individual homes. PV surplus or deficit is traded (feed-in) directly to the grid.
		P2P	Along with the options available in No market, each house can trade with the other peers.
PV + Battery	PV (%33 of demand) Battery (%51 of PV owners)	No market	PV supplies the demand. Surplus or deficit is traded with the upper grid.
		P2P	Along with the options available in No market, each peer can trade with the others.
Loss management	PV (%33 of demand) Battery (%51 of PV owners)	P2P	The P2P model includes the empirically estimated grid losses function to create a penalty or pricing for losses in the objective function. All options from PV + Battery case are available.
Sensitivity analyses	PV Case + EVs PV + Battery under a fixed local tariff	P2P	Here we introduce various sub-cases that include sensitivity analysis by including: (i) Electrical vehicles and (ii) a local fixed tariff that creates a different P2P trade strategy.

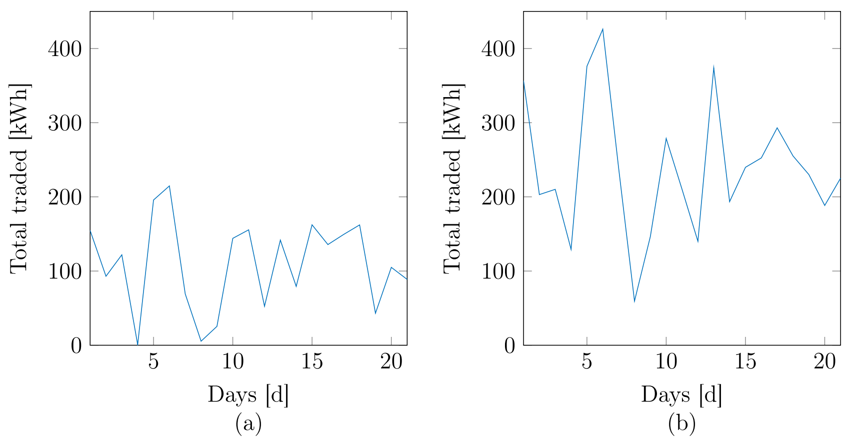

Fig. 3. Total amount traded by P2P for (a) PV case (b) PV + Battery case.

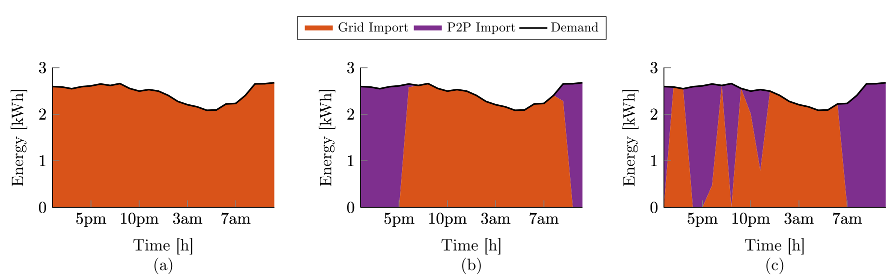

Fig. 4. Operation of node 24 day 6 for (a) No local market (b) PV case, P2P (c) PV + Battery case, P2P.

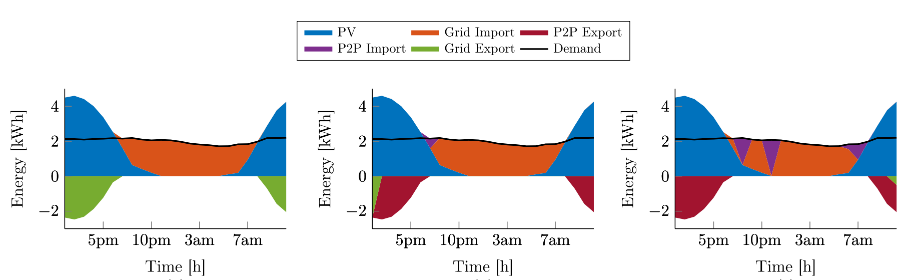

Fig. 5. Operation of node 48 day 6 for (a) No local market (b) PV case, P2P and (c) PV + Battery case, P2P.

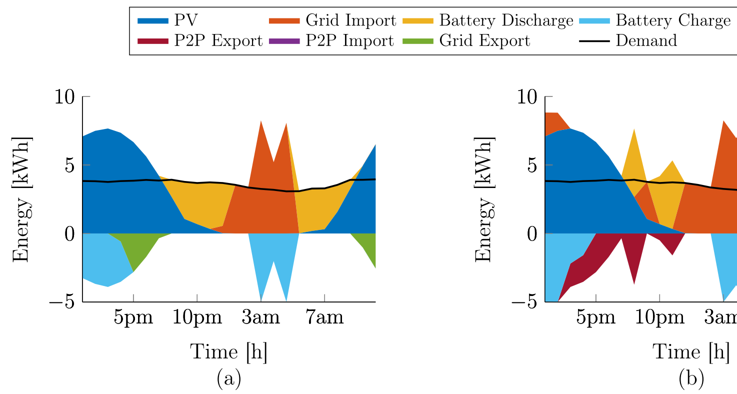

Fig. 6. Operation of node 2 day 6 for (a) No local market (b) PV + Battery case, P2P.

Table 4
Comparison of total community costs for each case, given in NOK.

	Reference	PV		PV + Battery	
		No market	P2P	No market	P2P
Total costs	**51,971**	**36,007** (−30.7%)	**34,766** (−33.1%)	**35,219** (−32.2%)	**34,293** (−34.1%)
Costs no market vs. P2P	–	–	−3.5%	–	−2.6%
Costs of grid import	51,971	36,695	34,847	35,644	34,303
Revenue of grid export	–	687	82	425	10
Total grid import [kWh]	65,236	46,361	44,061	45,442	43,875
Total grid export [kWh]	–	2657	356	1622	41
Total P2P trade [kWh]	–	–	2300	–	5026
Demand by grid	100%	71.1%	67.5%	69.6%	67.2%
Demand by local DERs	0%	28.9%	32.5%	30.4%	32.8%

electricity in a more efficient manner. As the peers prioritise local trade over grid export, as seen in the previous section, the amount exported to the grid in both these cases are significantly lower than their corresponding cases with no local market.

As the market model does not include the P2P transaction costs, an exact measure of the economic benefits for each individual peer is impossible to provide. However, with the assumption that the local market price always will be between the grid consumption and the grid feed-in price, some estimations can be made. By using the feed-in tariff as a lower bound for the P2P price, the consumer located at house 24 saves approximately 8% and 15% by participating in a P2P market with PVs or PV + Battery, respectively. It should be noted that this is an optimistic estimation, using the lowest possible P2P price.

5.2. Grid impact results

5.2.1. Voltage profiles without local market

Four nodes have been chosen to illustrate the different impacts on voltage levels of the case simulations. All four nodes are placed at the end of its radials.

Fig. 7 shows the voltage levels at the representative nodes for the sixth day of the simulation with no local market present. Fig. 7(a) shows the voltage levels for the reference case. Since the nodes are placed at the end of their respective radials, the voltages are always lower than 1 p.u. The voltage levels at each of the nodes are relatively stable for all time steps, with a slight increase at night when the load is lower. The voltage levels at the representative nodes when PV panels are installed are presented in Fig. 7(b). As can be expected, the voltages rise correspondingly with the PV production at the nodes, reaching a level above 1 p.u. at the peak generation hours. With the PV + Battery case the load at the corresponding node increases at the time of charging, since the batteries are allowed to be charged from power imported from the grid. With the wholesale spot prices being lower at night, this is a logical choice of charging time for battery owners. The effects can be seen in Fig. 7(c) with quite significant voltage drops between 3 and 5 a.m. All charging power is imported from the grid due to no PV generation at this time.

5.2.2. Voltage profiles with local market

Since all PV surplus is injected to the grid, regardless of the market structure, the voltage levels in the PV case remains unchanged. But, in the PV + Battery case, battery charging and discharging along with opportunity to trade within the community changes the voltage levels. This can be seen in Fig. 8. It shows some of the same tendencies as the profile in Fig. 7(c), with significant drops between 3 and 5 a.m. However, the voltage at each node tends to fluctuate more in the case of P2P trading. This is especially evident between 6 and 10 p.m., when the demand is high and PV generation is low.

5.2.3. Peak grid import

As the distribution network must be dimensioned for peak capacity, this value is of great interest for the local DSO. In Table 5, peak demand and total grid import is presented for all cases. The values stated for peak demand represents the neighbourhood's maximum total demand for import from the external grid in one time step, via the transformer. It is clear from the table that the installation of roof-top PVs reduces the peak demand for both market strategies. The peak value does, however, increase significantly with the integration of batteries regardless of market structure. In this model, the battery owners are allowed to charge their batteries with procured electricity from the grid, not just their own solar panels. Consequently, at times with low spot prices, and little PV generation, situations can occur where households consume power both for their regular demand and for battery charging.

In the reference case, the peak consumption hour happens at 2 pm at the second day of the simulation period. In Fig. 9, one can observe how the integration of DERs and storage has shifted the grid import profile this day. Here, one can clearly see the differences stated in Table 5. The grid import of the PV case is never higher than the reference case and matches the reference level during the night. The peak grid import of the PV + Battery case is, however, shifted to the early morning hours and is much higher than the reference case. A similar profile is obtained for all the other days of simulation.

Fig. 10 shows the duration curve for grid import for all five simulations. In line with the values in Table 5, the peak consumption for

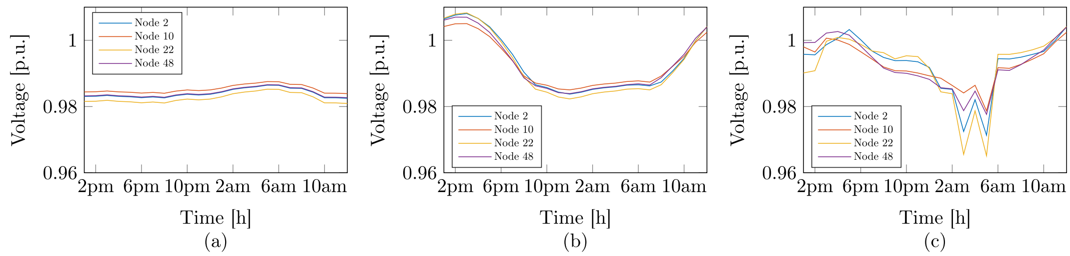

Fig. 7. Voltage levels at representative nodes for Day 6 of simulation period with no market situation (a) reference case (b) PV case and (c) PV + Battery case.

Table 5
Comparison of peak consumption for each case.

	Reference	PV		PV + Battery	
		No market	P2P	No market	P2P
Peak grid consumption [kWp]	185.95	160.42	160.42	221.64	221.64
Compared to reference	–	−13.7%	−13.7%	+19.2%	+19.2%
Total grid consumption [kWh]	65,236	46,361	44,061	45,442	43,875
Compared to reference	–	−28.9%	−32.5%	−30.3%	−32.7%
Demand by grid	100%	71.1%	67.5%	69.6%	67.2%
Demand by local DERs	0%	28.9%	32.5%	30.4%	32.8%

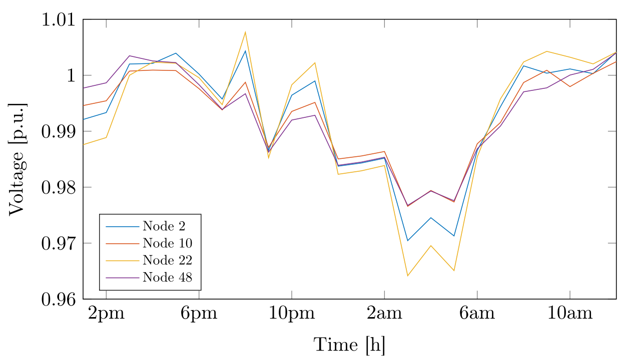

Fig. 8. Voltage levels at representative nodes for the PV + Battery case with P2P market. Day 6 of simulation period.

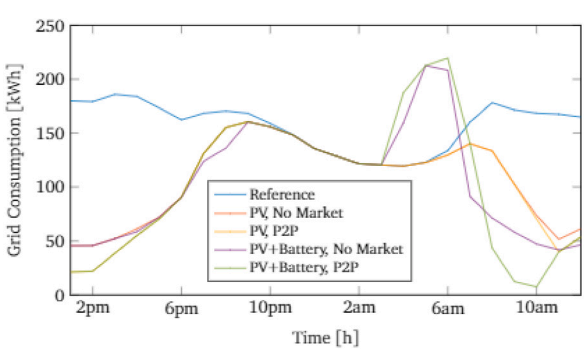

Fig. 9. Illustration of grid import for all five cases for day 2 of simulation period.

the PV + Battery case are the highest. There is, however, not many hours of the simulation period that requires this high capacity, and both curves descend quite steeply. Now, one can also observe a difference between the trading schemes with the PV case, as the P2P curve is slightly steeper. For both cases of P2P trading, several hours in the period requires no import from the external grid. This implies that the community can utilise the local assets more efficiently with a local market in place, and is an important finding of this study. This is also confirmed by the results in Table 5, with the demand covered by DERs in percentage.

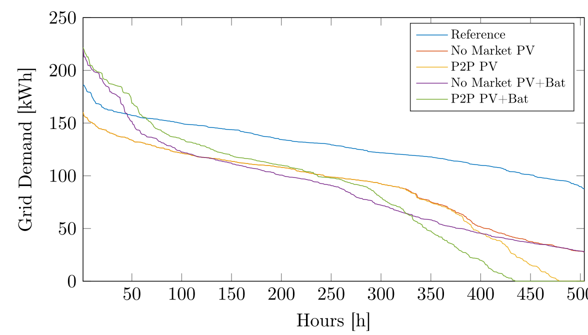

Fig. 10. Duration curve for all five cases.

5.2.4. System losses

An essential motivation for integrating DERs in the distribution network is the prospect of reducing the total system losses. A focus in this project was thus to investigate if establishing a P2P market would further enhance or diminish these positive effects of DERs. Note that the system losses analysed in the following sections refer to the losses within the low-voltage distribution network.

The total losses for day 6 for the reference case are depicted in Fig. 11(a), to illustrate how both integration of DERs and local electricity trading affect the system losses. One can observe that the amount of losses is higher during the day and lower during the night. This correlates with the grid usage, as there is higher total demand during the day and lower at night-time. All other days within the simulation period show the same tendency.

As the neighbourhood invests in PV panels, the system behaviour in terms of system losses changes significantly. The total system losses for the sixth simulation day is presented in Fig. 11(b). Compared to the reference case, the shape of the curve has an almost opposite tendency, with high system losses during the night and low during the day. This correlates with the PV production profile and confirms that self-consumption from private DERs during production hours is prioritised among the peers in the absence of storage alternatives. With a higher degree of self-sufficiency, there is less need for transfer capacity in the distribution grid and hence fewer losses. One can also observe that there are no differences between the two market strategies. This is true for the whole simulation period. Without the opportunity to store any excess electricity, the only other option than curtailing is to export. The identical system losses behaviour is a consequence of the power flows in the system being the same regardless of the trading scheme. The net load for each house at each time step is the same for both cases, whether the power flow is due to local or wholesale trading.

When batteries are installed in the neighbourhood, the effect of the chosen market strategy becomes more evident. As can be observed from Fig. 11(c), the curve shares some of the same tendencies as with the PV cases, with a high amount of losses during the night and low during the day. However, compared to Fig. 11(b), the period with higher losses in Fig. 11(c) is shorter and the quantity is bigger. As price arbitrage with the batteries is allowed regardless of market structure,

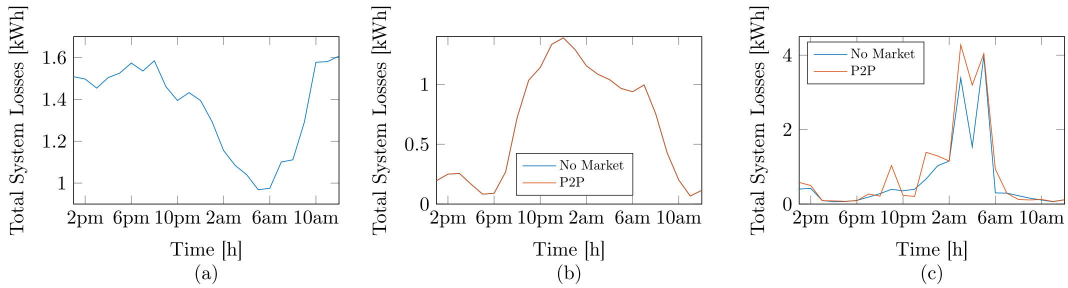

Fig. 11. Total system losses, day 6 of simulation period for (a) reference case, (b) PV, and (c) PV + Battery.

Table 6
Comparison of total system and battery losses for each case.

	Reference	PV		PV + Battery	
		No market	P2P	No market	P2P
Total system losses [kWh]	937.15	517.96	517.96	566.36	644.47
Compared to reference	–	−44.7%	−44.7%	−39.6%	−31.2%
No market vs. P2P	–	–	0%	–	+13.8%
Battery losses [kWh]	–	–	–	581.69	650.70

the increased grid usage causes in both cases higher losses than the PV cases. Now there is also a distinct difference between the case of P2P trade and the case with no local market. Due to different operation of the batteries, the distribution line usage also varies between the cases. As mentioned before, a peer with batteries will often sell stored energy locally rather than using it for self-sufficiency, and the grid is thus used more. Accordingly, this leads to more losses compared to the case with no local market.

In Table 6, a comparison of the total system losses of all five cases are presented. These numbers represent the total losses over the entire simulation period of 21 days. With the high degree of self-sufficiency in all cases involving DERs, it is clear that the losses decrease significantly compared to the reference case. Still, for the versions of PV + Battery case, a P2P market structure leads to 13.8% more losses than with no local trading. Note that with a 90% round-trip efficiency of the batteries, the losses induced by charging/discharging is of quite a significance. These are additional to the total system losses.

5.3. Loss pricing case

In this case, the additional constraint and updated objective function presented in Sections 3.3 and 4.1 is applied to the model. The case simulated with this model is the PV + Battery case with P2P trading. As can be noted from Table 7, the actual losses calculated with the power flow model output is reduced with 4.7% compared to its corresponding case without the price signal. The total losses are still more than in the corresponding case of no market, but the difference between the losses yielded with a P2P market and no market is reduced by 38.5%.

The total consumption of electricity procured from the grid is almost the same for both P2P cases, as seen in Table 7. The total community costs of the pricing case represents the objective function value subtracted the costs of losses, and are almost identical to the original P2P case costs. By percentage, the total costs of losses are small to the total community costs. There is also a significant decrease in the total amount traded locally, along with a decrease in losses induced by the batteries. These results indicate that the community values self-consumption among the peers over P2P trade with this pricing scheme, as well as less price arbitrage with the batteries. There is also a slight increase in grid export, possibly to compensate for the additional costs induced by the losses.

As the total system losses are included as a variable in this version of the model, the losses calculated by the regression constraint can also be analysed. As can be seen in Table 7, this value is a about 5% higher than the losses calculated by the power flow model. The value is about the same as the power flow losses from the P2P case without the pricing scheme.

Fig. 12 depicts the changes in voltage levels caused by the pricing scheme. As one can observe, some of the most considerable fluctuations that occurred in the original P2P case are slightly dampened. The drop during night-time is, however, unchanged. This is a consequence of less local trading and an almost unaffected charging behaviour. The peak demand value remains unchanged, at 221.64 kWp.

5.4. Sensitivity analysis

As the results obtained in this study are likely highly dependent on both the physical system and the market scheme, some additional analyses have been conducted. The most significant impacts to the grid found in the PV + Battery cases are believed to be caused by the arbitrage operation of the batteries. To eliminate this effect, the varying price of the electricity purchased from the wholesale power market was replaced by a flat tariff. This tariff includes the volumetric grid tariff of 0.3 NOK/kWh obtained by Askeland et al. [52] and a constant power market price of 0.5 NOK/kWh. As [52] also considers a local market in a Norwegian context, with both PVs and batteries integrated in the system, these tariffs were considered to be adaptable to the case of this study as well. The results are presented in Table 8, compared to the results obtained for the same system with dynamic pricing.

As can be observed, by removing the incentives for arbitrage behaviour, the grid losses are reduced by 20.7%. As the batteries are only used for increasing self-consumption in this case, almost all results are adjusted to the same level as the PV cases without batteries. Combined with the significant decline in battery losses, around 93%, this indicates a limited use of the batteries. It is important to note the arbitrage behaviour may be limited when considering battery degradation and thus decrease the difference between these two results.

As a final case study, it was found interesting to investigate the impact of EV integration. Accordingly, we replaced all batteries with EVs with a nominal storage capacity of 50 kWh each and a round trip efficiency of 96% [41]. The EVs are assumed to get charged at the owners' houses and are estimated to be available (connected to the charger) between 18:00 and 08:00 the next day. Also, to take the impact of the EVs' uncertain behaviour into account, it is assumed that their arrival and departure times follow the behaviour presented in [54] and [55]. Finally, we assume that EVs arrive home with a state of charge between 40 to 60%, and they should have stored energy at least by 70 % of their capacity before they depart [41].

The additional burden enforced on the grid by the EVs leads to an 8.7% higher grid import compared to the original P2P PV + Battery case. The amount exported to the grid is increased by four times and 70% higher P2P trading among the consumers. These results are caused by the increased capacity of the energy storage through the sizes of the EV batteries. Also, in comparison to the original cases with batteries, this storage is not available at all time steps, limiting the window of opportunity for price optimising behaviour. The resulting peak grid consumption is thus doubled compared to the PV + Battery case.

Table 7
Comparison of results for cases of PV+Battery, with and without loss pricing.

	PV + Battery without pricing		PV + Battery with pricing
	No market	P2P	P2P
Power flow model losses [kWh]	566.36	644.47	614.39
Compared to no market case	–	+13.8%	+8.5%
Compared to P2P case	–	–	−4.7%
Market model losses [kWh]	–	–	646.12
Battery losses [kWh]	581.69	650.70	615.88
Total grid consumption [kWh]	45,442	43,875	43,890
Total grid export [kWh]	1622	41	63
Total P2P trade [kWh]	–	5026	3794
Total costs [NOK]	35,219	34,293	34,327
Total costs of grid import [NOK]	35,644	34,303	34,343
Costs of losses [NOK]	–	–	502

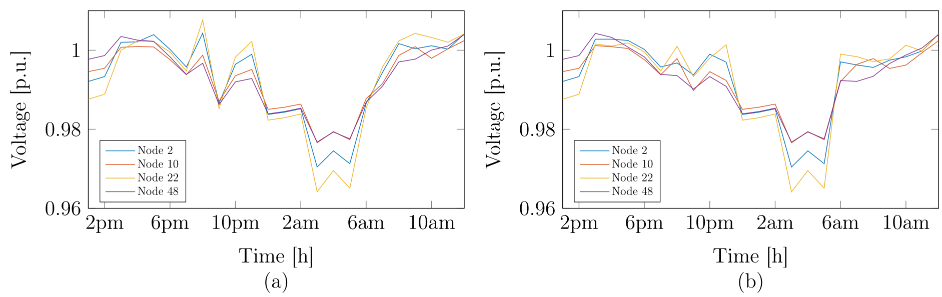

Fig. 12. Comparison of voltage levels for (a) P2P without loss pricing and (b) P2P with pricing, day 6.

Table 8
Comparison of flat vs. dynamic grid import price.

	PV (dynamic) P2P	PV + Battery (dynamic) P2P	PV + Battery (flat) P2P
Total system losses [kWh]	517.96	644.47	511.27
Battery losses [kWh]	–	650.70	45.38
Peak grid consumption	160.42	221.64	160.42
Total grid consumption [kWh]	44,061	43,875	43,812
Total grid export [kWh]	356	41	63
Total P2P trade [kWh]	2300	5026	2129
Demand by grid	67.5%	67.2%	67.1%
Demand by local DERs	32.5%	32.8%	32.9%

6. Conclusions

The overall results showed that the integration of PVs within the distribution grid helped to mitigate both peak grid import and total system losses, with a decrease of respectively 13.7% and 44.7%. The establishment of a P2P market showed no differences in these results, due to the physical nature of the system power flows. The total amount of electricity procured from the wholesale market did, however, decrease with almost 5% with the P2P market. In this case, the neighbourhood was even wholly independent from the external grid for 26 h in total over the 21 day period. This implicates a more efficient use of local resources and higher resilience of the community.

Accordingly, the same trend was observed when introducing P2P trade to the PV + Battery case, with 70 h of grid-independent operation. An uncontrolled charging of the private batteries led to voltage drops and an increased peak consumption of 19.2% compared to the reference case. At the same time, the discrepancies in the results caused by the market design also became more apparent. The window of possible local trading was extended beyond the PV generation period, thus inducing more voltage fluctuations and a 13.8% increase of system losses compared to the case of no local market. Replacing the batteries with EVs led to further increased losses and voltage fluctuations, as well as higher peak consumption. These results are mainly caused by the arbitrage operation of the batteries and EVs, proven by testing the same case without this opportunity. Economically, the P2P cases yielded the lowest aggregated community costs in total.

A novel approach was introduced to include aggregated system losses in the market model. A regression was conducted based on the loss data obtained from the PV case with P2P trading. This resulted in a constraint and an updated objective function, attempting to minimise the system losses as a function of total grid import, demand and PV generation. The overall intention was to reduce the total grid import. The results confirmed that the approach could affect the peers' behaviour according to the grid conditions, and showed a $\sim 5\%$ decrease of system losses. However, the operational decisions mainly affected the local trade instead of grid consumption.

The results in this study are likely highly system dependent, as observed through the sensitivity analyses, both in terms of market design and system setup. With the market model featuring a centralised approach, the community's assets and trade capacity are operated according to the optimal solution for the entire neighbourhood. This market structure is reliant on transparency and willingness to share data, which for many, is a significant barrier for joining the market. The coordination between the market agents and the DSO, however, may easier be facilitated with such a market structure with a local market operator serving as an interface.

P2P market models have gained popularity in academic research and real-life projects over the recent years, and this paper contributes to an important aspect of the implementation. As the market is connected to a complex power system, it is essential to thoroughly analyse the effects such behaviour will have on the physical operation of the grid. Any realistic assessment has to take into consideration the specifications of the relevant grid and location and characteristics of the DERs or storage assets installed. As such, the study does not provide a definite conclusion to the grid impacts of a local market, but creates new insights and a novel framework for further analyses on the topic.

To complement and extend the results presented in this paper, further research should investigate the grid-impacts of other local market models,[3] as well as the more rapid effects such as output transients caused by, e.g. variations in solar irradiation. Battery degradation caused by the extensive arbitrage operation should also be examined. Further, an interesting further step is to develop a closed-loop model, where new constraints are added to the market optimisation model if any technical violations are discovered in the load flow analysis.

CRediT authorship contribution statement

Marthe Fogstad Dynge: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Pedro Crespo del Granado:** Conceptualization, Methodology, Formal analysis, Investigation, Resources, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Naser Hashemipour:** Formal analysis, Resources, Writing – original draft, Writing – review & editing. **Magnus Korpås:** Conceptualization, Methodology, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

We provide the Market P2P model and code as open science. That is, the full model is open for download and use. This is publicly available on GitHub: https://github.com/LocalEnergyMarkets/PCDGModel-LocalCommunities

There, we provide an illustrative small test case and data for a community of 25 houses based on open available data (see [56] for full example and details). This contains the option to download the Matlab code of the community-based P2P trading under the MIT license.

It is worth noting that the day-ahead transactions of fifty-two end users connected to the low-voltage distribution grid located in Steinkjer were calculated in 12.79 s on a MacBook Pro Intel Core i7 Dual-core, 3.3 GHz. The problem was solved by employing the Matlab linprog function with the Dual-simplex solver.

[3] For example, it would be interesting to look at two districts with different levels of PV and BESS proliferation and served by different substations, how would the flow and purchasing/sharing will bring benefits? (intra local market case).

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