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Helping end-users help each other: Coordinating development and operation of distributed resources through local power markets and grid tariffs

Magnus Askeland [a,b,*], Stian Backe [c], Sigurd Bjarghov [b], Magnus Korpås [b]

[a] Energy Systems, SINTEF Energy Research, Trondheim, Norway
[b] Department of Electric Power Engineering, Norwegian University of Science and Technology, Trondheim, Norway
[c] Department of Industrial Economics and Technology Management, Norwegian University of Science and Technology, Trondheim, Norway

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ABSTRACT

There is an ongoing transition in the power system towards an increasing amount of flexible resources and generation technologies at the distribution system level. An appealing alternative to facilitate efficient utilization of such decentralized energy resources is to coordinate the power at the neighbourhood level. This paper proposes a game-theoretic framework to analyze a local trading mechanism and its feedback effect on grid tariffs under cost recovery conditions for the distribution system operator. The novelty of the proposed framework is to consider both long-term and short-term aspects to evaluate the socio-economic value of establishing a local trading mechanism. Under our assumptions, the main finding is that the establishment of local electricity markets can decrease the total costs by facilitating coordination of resources and thus create higher socio-economic value than the uncoordinated solution. Furthermore, a sensitivity analysis on the tariff levels reveals that there are two equilibrium solutions, one where the grid costs are exactly balanced by tariff income and one where the neighbourhood decides to disconnect from the larger power system. These results indicate that although a local trading mechanism can reduce the need for grid capacity, it may not be cost optimal for neighbourhoods to become completely self-sufficient.

1. Introduction

One of the fundamental issues in power system economics is the potential of market failure due to a lack of demand-side elasticity (Stoft, 2002). At the distribution grid level, inelastic demand means that real-time control problems have traditionally been resolved at the grid infrastructure planning stage so that capacity is robustly adequate to cover the peak load (Strbac, 2008). However, there is an ongoing transition within power system development due to an increasing amount of flexible resources at the distribution grid level (Eid et al., 2016).

The price-responsiveness from end-users increase because of two fundamental drivers: (1) the information available to the end-users is increasing due to deployment of smart metering technologies, and (2) increased deployment of electricity as an energy carrier for potentially flexible demand types. Smart meters are currently being deployed throughout Europe, enabling hourly or sub-hourly billing of electricity consumption (Zhou and Brown, 2017). Such price variations can induce a change in consumption patterns if flexible energy resources such as smart management of heating systems and electric vehicle (EV) charging are available (Faruqui et al., 2010; Salpakari et al., 2017; Knezović et al., 2017).

An appealing alternative to facilitate efficient utilization of decentralized energy resources (DERs) is to balance the power at the neighbourhood level (Heinisch et al., 2019). However, as described in Askeland et al. (2019), the current regulatory framework in Norway and several other countries may not facilitate efficient decentralized decision-making when multiple stakeholders are involved.

This paper uses a game-theoretic framework to investigate a local trading mechanism, and its feedback effect on grid tariffs under cost recovering conditions for the distribution system operator (DSO) in a neighbourhood context. An equilibrium model comprising two levels is developed to study the efficiency of current and prospective pricing mechanisms. Also, a system optimization model serves as a benchmarking tool.

Abbreviations: **DER**, Distributed Energy Resources; **DSO**, Distribution System Operator; **ER**, 'Energy resources' agent group; **EV**, Electric Vehicle / 'Electric vehicle charging facility' agent group; **KKT**, Karush-Kuhn-Tucker; **LM**, 'Local market' case study; **MCP**, Mixed Complementarity Problem; **MPEC**, Mathematical Program with Equilibrium Constraints; **NOLM**, 'No local market' case study; **P2P**, Peer-to-peer; **RB**, 'Residential buildings' agent group; **SK**, 'Combined school and kindergarten' agent group; **SO**, 'System optimization' case study; **ZEN**, Zero Emission Neighbourhood.

* Corresponding author at: Energy Systems, SINTEF Energy Research, Trondheim, Norway.
E-mail address: Magnus.Askeland@sintef.no (M. Askeland).

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The remainder of this paper is organized as follows. In section 2 we provide a survey of related literature. The modeling framework is presented in section 3. The data used for a case study is presented in section 4. Section 5 presents results from the case study before conclusions are drawn in section 6.

2. Literature review

An adaptation of electricity grid pricing mechanisms is increasingly being addressed in the scientific literature. This paper is at the intersection between two related research topics, namely electricity grid tariff design and local electricity markets.

Electricity grids are natural monopolies due to economies of scale. Traditionally, the DSO is the sole owner of the electricity grid in a given area and passes the costs on to the end-user as fixed and volumetric grid tariffs (Eid et al., 2014). However, the current tariff structures can create distorted incentives for end-users to invest excessively in DERs (Eid et al., 2014; Pollitt, 2018). Capacity-based tariffs are being proposed as a prospective solution since it will be a better representation of the upstream grid costs and create an incentive to reduce the peak load (Simshauser, 2016). However, a reduction of individual peaks may not always be effective at reducing aggregate peak load (Backe et al., 2020), and several scholars suggest that the potential welfare gains from capacity-based tariffs can be limited (Passey et al., 2017; Brown and Sappington, 2018). In this context, we contribute to the literature by investigating how a combination of grid tariffs and local markets can provide incentives for efficient development and operation of the distribution grid.

There exists a rather large body of literature related to investigating the impact of various tariff schemes on specific end-user groups, see e.g. Kirkerud et al. (2016); Parra and Patel (2016); Bergaentzlé et al. (2019); Sandberg et al. (2019); Pinel et al. (2019); Backe et al. (2020). These studies investigate how the business case and decisions of different types of agents are affected by changes in the tariff structure. Our paper differs from this line of research because we consider the electricity grid tariffs as a modeling result in a bilevel approach rather than an input to a single level optimization problem.

Our work considers the interaction between the distribution network level and the end-users under cost recovery conditions for the DSO. In this regard, the approach of this paper is related to the research summarized in Table 1. However, some distinct differences can be pointed out since our research also include the interaction between agents at the local level through a local market mechanism. Besides, we consider grid investments and operation as a function of the aggregate neighbourhood load.

Interaction between agents at the local level can be achieved through ‘peer-to-peer’ (P2P) trading or other forms of local market mechanisms (Sousa et al., 2019). In Zhang et al. (2018) the authors analyze P2P trading for matching inflexible local generation with flexible demand in a microgrid, and they find that the trading triggers peak load reduction. Almenning et al. (2019) also analyzes P2P trading in a neighbourhood focusing on trading in response to a subscribed grid tariff, and they also find that P2P trading triggers a reduction of high loads. Lüth et al. (2018) focuses on the role of batteries in P2P trading, and their results highlight economic viability from an end-user perspective. None of these studies (Zhang et al., 2018; Almenning et al., 2019; Lüth et al., 2018) consider a reaction by the DSO (i.e., adjustment of the grid capacity) as a consequence of trading in a neighbourhood.

The properties of the problem addressed in this paper are consistent with non-cooperative Stackelberg-type games (Von Stackelberg, 2010), which are characterized by a leader who moves first and one or more followers acting optimally in response to the leader's decisions. Games with a Stackelberg structure can be formulated as mathematical programs with equilibrium constraints (MPECs) (Luo et al., 1996). This is the case for Zugno et al. (2013), Momber et al. (2016), Schittekatte and Meeus (2020), and Askeland et al. (2020) who formulate MPECs to investigate the effect of indirect load control. In this paper, we use an iterative procedure to solve the set of non-linear equations similar to Schittekatte et al. (2018), Hoarau and Perez (2019), Askeland and Korpås (2019), and Abada et al. (2020). The reason for choosing this procedure instead of an MPEC approach is that an iterative procedure has computational advantages over an MPEC formulation, which would severely impact our tractable problem size. Furthermore, there is no need for an MPEC formulation since the grid tariff structure we consider can effectively be handled by an iterative procedure based on cost recovery rules for the DSO. We formulate the neighbourhood equilibrium as a complementarity problem (Gabriel et al., 2012). A complementarity problem is the combination of the Karush-Kuhn-Tucker (KKT) conditions (Kuhn and Tucker, 1951) of all agents, which are being solved simultaneously to derive the equilibrium. Complementarity modeling is particularly useful for power market modeling since the introduction of dual variables in the model formulation allows for market interactions between agents to be formulated directly. More details on complementarity modeling for energy modeling purposes can be found in Gabriel et al. (2012). The complementarity formulation for the neighbourhood level allows for interaction between agents within the neighbourhood level and enables an investigation of local electricity markets without introducing the computational difficulties of an MPEC formulation.

To summarize, this paper brings together two related bodies of literature by considering both grid tariff design and a local market mechanism in a consistent modeling approach. Furthermore, the proposed approach allows for local markets to be coupled to existing market structures and allow consumers to choose which market to trade in. No prior works that consider local markets and its feedback effect on grid development and grid tariffs have been identified, and we aim to contribute to closing this gap in the literature.

3. Method

This section presents the game-theoretic setup that has been developed. First, the optimization problems of the agents in the neighbourhood and the DSO are presented. Thereafter, the solution procedure for coupling the two levels are described before the input data

Table 1
Related research on indirect load control.

Reference	Tariff calculation	Grid costs considered	Interaction between agents
Zugno et al. (2013)	MPEC	No	Retailer - consumer
Momber et al. (2016)	MPEC	No	Aggregator - EV consumer
Schittekatte et al. (2018)	Iterative procedure	Sunk	DSO - consumer
Hoarau and Perez (2019)	Iterative procedure	Sunk	DSO - consumer
Askeland and Korpås (2019)	Iterative procedure	Prospective	DSO - consumer
Abada et al. (2020)	Iterative procedure	Sunk	DSO - community
Schittekatte and Meeus (2020)	MPEC	Prospective	DSO - consumer
Askeland et al. (2020)	MPEC	Sunk	DSO - consumer
This paper	Iterative procedure	Prospective	DSO - consumer and between consumers

for the case study is presented. In the presented model, the following core assumptions are made:

- Grid charges only apply to electricity purchased from the wholesale power market and not on locally traded electricity. Since locally traded electricity is balanced locally at each time step, the local trade does not contribute to the capacity-based charge.
- We assume that there is sufficient grid capacity within the local system. Therefore, only the connection between the neighbourhood and the larger power system is constrained.
- We assume that the DSO can not choose to curtail load or generation. Hence, it is necessary to build sufficient capacity to cover the peak network usage. Although the economics concerning load or generation curtailment is outside the scope of this paper, this is an aspect that could be considered in further work.

3.1. Model overview

An outline of the model is presented in Fig. 1. The structure is a bilevel model where some decisions are made on the DSO level while others occur on the neighbourhood level. We consider the DSO as the leader in the Stackelberg game since it sets the grid tariff rates while the end-user agents responds to the tariff determined by the DSO. Decision variables at one level are perceived as parameters for the other level. One example is the level of grid tariffs, which is determined based on cost recovery criteria on the DSO level but perceived as parameters by the agents at the neighbourhood level. The benefit of this bilevel structure in our modeling framework is the ability to analyze the feedback effect between neighbourhood response, coordination, DSO strategy, and regulatory framework. Appendix A provides an overview of mathematical symbols and describes how the parameters and variables relates to each level in the overall model.

3.2. Neighbourhood level

In this section, the problem of the individual agent in the neighbourhood is described as an optimization problem. The agents can be of different types: customer with inflexible load, prosumer, EV charging facility, owner of a power plant and grid storage, or a combination of these. The model formulation presented in this section allows for all of these types of agents to be represented through different parameter settings.

Since the optimization problems for the agents in the neighbourhood are linear, their KKT conditions are both necessary and sufficient for global optimality (Kuhn and Tucker, 1951). Hence, to allow for the modeling of a local market mechanism, the optimization problems for the agents in the neighbourhood are represented through their KKT conditions, which are formulated as a mixed complementarity problem (MCP) in Appendix B. We indicate dual variables associated with each of the constraints. These dual variables are used in the MCP formulation of the problem.

3.2.1. Objective function of neighbourhood agents

The objective of the neighbourhood agents is to minimize their individual costs according to (1a). Details of the cost components are described in (1b) - (1f). These costs consist of investments in storage and energy resources ($Cost_c^N$), energy from the power market ($Cost_c^P$), energy from the local market ($Cost_c^L$), electricity taxes ($Cost_c^T$), and grid charges ($Cost_c^G$). The grid charges apply to energy purchased from the

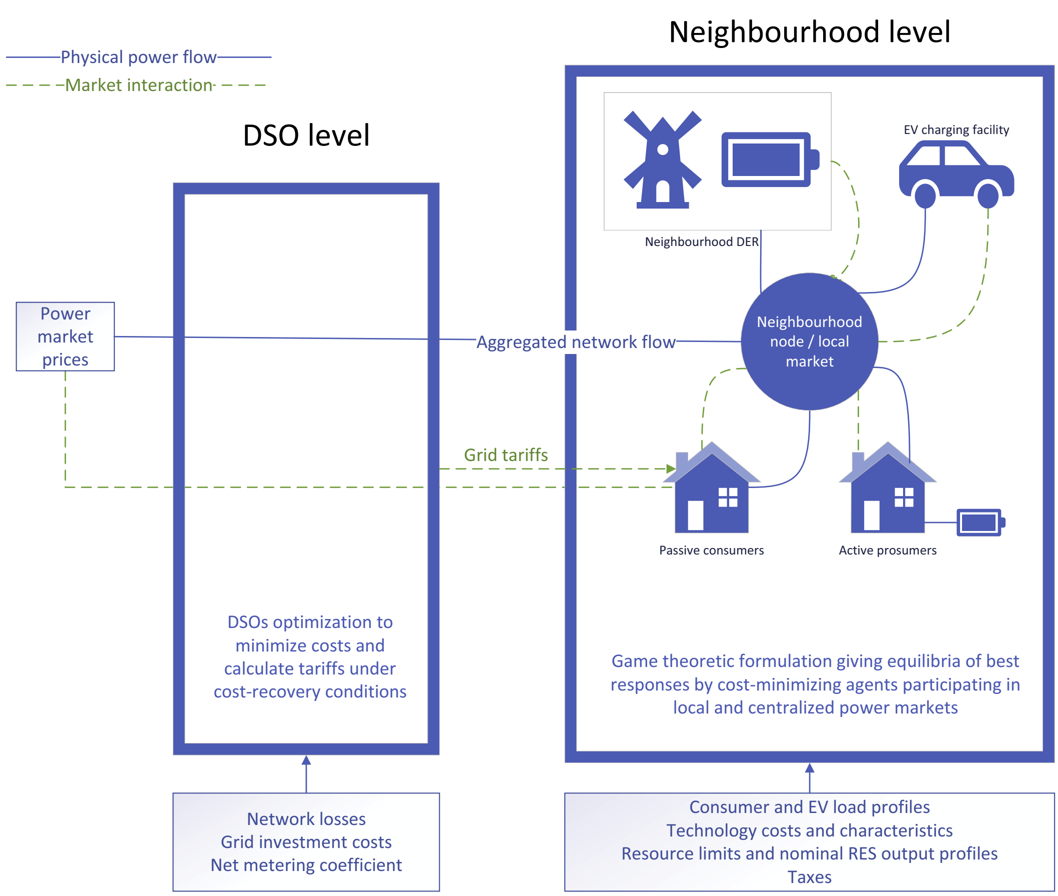


Fig. 1. Outline of the model structure.

power market, but not to locally traded energy. The actual grid costs are not considered directly at the building level since these costs are imposed indirectly through the grid tariffs (*vnt* and *cnt*).

$$Min : Cost_c = Cost_c^N + Cost_c^P + Cost_c^L + Cost_c^T + Cost_c^G \tag{1a}$$

$$Cost_c^N = I_c^S * c_c^S + I_c^E * c_c^E \tag{1b}$$

$$Cost_c^P = \sum_{h=1}^{H} W_h * \left(imp_{c,h}^P - exp_{c,h}^P\right) * \lambda_h^P \tag{1c}$$

$$Cost_c^L = \sum_{h=1}^{H} W_h * \left(imp_{c,h}^L - exp_{c,h}^L\right) * \lambda_h^L \tag{1d}$$

$$Cost_c^T = \sum_{h=1}^{H} W_h * \left(imp_{c,h}^P + imp_{c,h}^L\right) * T \tag{1e}$$

$$Cost_c^G = \sum_{h=1}^{H} W_h * \left(imp_{c,h}^P - NM * exp_{c,h}^P\right) * vnt + c_c^G * cnt \tag{1f}$$

In these equations, W_h denotes the scaling factor to provide operational costs on an annual basis. To represent annual costs the scaling factor takes the value $W_h = \frac{8760}{H}$ for hourly time-steps.

3.2.2. Energy balance

The energy balance of the agents is described by (2) and states that energy imports subtracted exports must be equal to fixed and flexible demand subtracted generation from PV at each agent.

$$\begin{aligned} &D_{c,h} + d_{c,h}^{\Delta+} - d_{c,h}^{\Delta-} - g_{c,h}^E \\ &= imp_{c,h}^P - exp_{c,h}^P + imp_{c,h}^L - exp_{c,h}^L \; \forall c, h \quad \left(\lambda_{c,h}^{EB}\right) \end{aligned} \tag{2}$$

The agents can trade both with the local and centralized electricity markets to satisfy their energy balance.

3.2.3. Battery charge level

A battery makes it possible to shift energy load temporally. This temporal load shifting is represented in (3), which describes how the charge level depends on the charge level in the previous time step and on the battery operation. Converter losses are imposed through the parameter L_c, while self-discharge of the battery from one time-step to the next is imposed through the parameter R_c.

$$\begin{aligned} &s_{c,h} = s_{c,h-1} * (1 - R_c) \\ &+ d_{c,h}^{\Delta+} * (1 - L_c^S) - d_{c,h}^{\Delta-} * (1 + L_c^S) - D_{c,h}^{\Delta-} \; \forall c, h > 1 \; (\lambda_{c,h}^{S1}) \end{aligned} \tag{3}$$

The battery formulation allows for the representation of both a bidirectional battery which can store electricity for later use and unidirectional EV charging. In the case of EV charging, the parameter $D_{c,h}^{\Delta-}$ represents the energy used for EV driving needs.

We specify boundary conditions for the battery charge level as described in (4). This means that the charge level in the last time-step is linked to the first time step. Thereby, we do not need to specify the initial charge level since the optimization model calculates it.

$$\begin{aligned} &s_{c,1} = s_{c,H} * (1 - R_c) \\ &+ d_{c,1}^{\Delta+} * \left(1 - L_c^S\right) - d_{c,1}^{\Delta-} * \left(1 + L_c^S\right) - D_{c,1}^{\Delta-} \; \forall c \quad \left(\lambda_{c,1}^{S1}\right) \end{aligned} \tag{4}$$

Potentially, this formulation can result in simultaneous charge and discharge during the same time step. However, positive converter losses and energy costs will prevent this from occurring due to the associated costs.

3.2.4. Storage capacity

The agent decides the storage capacity to be installed, so the case that the economic benefit of having an additional unit of storage exceeds the investment costs will trigger additional investments. However, a maximum limit on battery storage capacity can be imposed according to (5). In order to represent agents without investment options, the maximum capacity limit can be set to zero.

$$c_c^S \le U_c^S \; \forall c \quad \left(\mu_c^{S2}\right) \tag{5}$$

Furthermore, the amount of energy that can be stored and the installed storage capacity limits the converter capacities according to (6)–(8). In the case of unidirectional EV charging, the discharging power factor (P_c^{dis}) can be set to zero. Note that the model is also capable of handling vehicle-to-grid directly, but this is out of the scope of this paper.

$$s_{c,h} \le c_c^S \; \forall \; c, h \quad \left(\mu_{c,h}^{S3}\right) \tag{6}$$

$$d_{c,h}^{\Delta+} \le c_c^S * P_c^{ch} \; \forall \; c, h \quad \left(\mu_{c,h}^{S4}\right) \tag{7}$$

$$d_{c,h}^{\Delta-} \le c_c^S * P_c^{dis} \; \forall \; c, h \quad \left(\mu_{c,h}^{S5}\right) \tag{8}$$

3.2.5. Measured peak power

Measured peak power at each end-user is equal to the maximum power injected to or withdrawn from the wholesale power market according to (9). Although the maximum load usually occurs as a result of an import situation, we also account for situations where the peak power is defined by exports to the grid. This means that we assume a grid tariff scheme where the agents have to pay a capacity-based grid tariff for their measured peak power for the whole period considered.

$$imp_{c,h}^P + exp_{c,h}^P \le c_c^G \; \forall \; c, h \quad \left(\mu_{c,h}^G\right) \tag{9}$$

Note that electricity traded in the local market do not influence the agent's peak power since any electricity sold locally also has to be consumed by the other agents at the local level.

3.2.6. Energy resource capacity and generation

Similar to energy storage, the agent can invest in energy resources such as rooftop PV. A limit, for example due to limited rooftop area, can be imposed according to (10). This value can also be set to zero if the agent cannot invest in energy resources due to factors outside the modeling framework.

$$c_c^E \le U_c^E \; \forall \; c \quad \left(\mu_c^{E1}\right) \tag{10}$$

Electricity generation, $g_{c,h}^E$, is described by (11) and has the option of generation curtailment, by generating below the limit given by the resource availability. The maximum output is the nominal generation each time-step multiplied with the installed capacity. Hence, the nominal generation is specified according to e.g., wind or solar conditions.

$$g_{c,h}^E \le c_c^E * G_{c,h}^E \; \forall \; c, h \quad \left(\mu_{c,h}^{E2}\right) \tag{11}$$

3.2.7. Local energy market

The local exports must equal the local imports according to (12). We assume that there are no grid constraints at the local level, making trading with the neighbours an alternative to purchasing energy from the grid.

$$\sum_{c=1}^{C}\left(imp^{L}_{c,h}-exp^{L}_{c,h}\right)=0\ \forall\ h \quad \left(\lambda^{L}_{h}\right) \tag{12}$$

Note that this is the equilibrium condition in the neighbourhood. The dual value of this constraint becomes the market price in the local energy market. The local market price is the value of energy at the local level, considering both short-term operation and long-term investments.

3.3. DSO level

The DSO level describes the optimization problem of the DSO in a regulatory context. In this problem, the decisions at the neighbourhood level regarding investments, operation, and trading in the local and wholesale markets are perceived as parameters outside the DSOs control. Based on the aggregate neighbourhood-level decisions, grid capacity investments and tariff levels are optimized.

3.3.1. Objective function of the DSO

The objective of the DSO is to minimize the grid costs, as formulated in (13a). With the DSO as a perfectly regulated leader, the DSOs goal would be welfare maximization by reducing the combined costs of the DSO and all the end-user agents. However, in our modeling framework the DSO considers the end-user agent decisions as parameters and therefore only the DSOs costs are considered by the DSO. This has a close resemblence to how DSOs are currently regulated in Norway[1] since the regulator defines a maximum income and the self-interest pursuing DSO is incentivized to reduce costs in order to increase profits. The costs faced by the DSO consist of investment costs and variable costs. Potential sunk costs are assumed to be collected through a fixed annual fee independent of this optimization problem. Since the DSO has no decisions related to the sunk costs, these are not included in the objective function.

$$Min:\ Cost_{DSO}=Cost^{N}_{DSO}+Cost^{V}_{DSO} \tag{13a}$$

$Cost^{N}_{DSO}$ is the investment cost for additional grid capacity and consists of the amount of capacity multiplied with annualized investment costs as described in (13b). The DSOs variable costs, $Cost^{V}_{DSO}$, consist of linear network losses, according to (13c).

$$Cost^{N}_{DSO}=I^{G}_{DSO}*c^{G}_{DSO} \tag{13b}$$

$$Cost^{V}_{DSO}=\sum_{h=1}^{H}W_{h}*e^{G}_{h}*L^{G}*\lambda^{P}_{h} \tag{13c}$$

3.3.2. Neighbourhood load

Given that some neighbourhood agents might export to the power market while others import from it, these individual flows are aggregated for each time step to calculate the total net electricity flow in to or out from the neighbourhood. Therefore, the electricity flow to/from the neighbourhood is the absolute value of the aggregate trading with the power market. To maintain the linear properties of the problem, the network imports are represented by (14) while exports are represented by (15). Only one of these terms will have a nonzero value at each time step and the total electricity transmission is calculated in (16). This formulation is valid as long as power market prices are non-negative since the transmission of electricity is penalized in the objective function due to the associated losses.

[1] https://www.nve.no/norwegian-energy-regulatory-authority/economic-regulation/

$$e^{GI}_{h}\geq\sum_{c=1}^{C}\left(imp^{P}_{c,h}-exp^{P}_{c,h}\right)\ \forall h \tag{14}$$

$$e^{GE}_{h}\geq\sum_{c=1}^{C}\left(exp^{P}_{c,h}-imp^{P}_{c,h}\right)\ \forall h \tag{15}$$

$$e^{G}_{h}=e^{GI}_{h}+e^{GE}_{h}\ \forall h \tag{16}$$

Note that the electricity trade within the local market is not a part of the DSOs consideration since the supply and demand remain within the neighbourhood level.

3.3.3. Grid capacity

The DSO needs to ensure enough capacity for the transmission of electricity, as described in (17). The network capacity consists of already built infrastructure given exogenously, and investments in infrastructure. We assume that the DSO do not have the option of curtailment as an alternative to building grid capacity.

$$C^{G}_{DSO}+c^{N}_{DSO}\geq e^{G}_{h}\ \forall h \tag{17}$$

3.3.4. Grid tariff calculation

Based on the optimization, the DSO also calculates the resulting grid tariffs according to (18) for the volumetric tariff $\left(\frac{EUR}{kWh}\right)$ and (19) for the capacity-based tariff $\left(\frac{EUR}{kW}\right)$. Here, it is assumed that the DSO will recover the variable costs through the volumetric tariff and investment costs through the capacity-based tariff. For simplicity, and since the aim is to investigate the economic feasibility of substituting grid capacity with local flexibility, we do not include sunk cost recovery. Sunk cost recovery is a topic that has been extensively considered in Schittekatte et al. (2018) and Hoarau and Perez (2019).

$$vnt=\frac{Cost^{V}_{DSO}}{\sum_{c=1}^{C}\sum_{h=1}^{H}W_{h}*\left(imp^{P}_{c,h}-NM*exp^{P}_{c,h}\right)} \tag{18}$$

$$cnt=\frac{Cost^{N}_{DSO}}{\sum_{c=1}^{C}c^{G}_{c}} \tag{19}$$

Note that with this formulation, all the DSOs costs are recovered through the tariff income from the neighbourhood agents. Cost recovery at the DSO level means that cost differences in the resulting cases are due to the effect of regulations on system costs and not because of grid tariff avoidance. Therefore, this setup, with all the DSOs costs recovered by the tariff income, enables a holistic investigation of tariff design in combination with local energy markets.

3.4. Solution approaches

Even though the physical properties of the system are the same, the different decision-making assumptions require different solution approaches. Both a centralized optimization and a game-theoretic equilibrium is computed to assess the efficiency of various pricing mechanisms. The main difference between these approaches lies in the decision-making assumptions. For the system optimization, it is assumed that all investment and operational decisions on both the DSO and the neighbourhood agent level are made by one entity. Such a system optimal solution provide the theoretically best outcome in terms of total costs, but the assumption that agent decisions (such as DER investments and operation) can be controlled centrally is not valid in a market context since such choices are up to the individual agents. Contrary to system optimization, the game-theoretic equilibrium approach allows for decentralized decision-making by the individual agents and the DSO. Decentralized decision-making requires modeling of the pricing mechanism between the agents such as grid tariffs and local market prices.

3.4.1. Centralized optimization

For the centralized optimization, all the direct costs on both the DSO and neighbourhood agent levels are combined in one objective function, as described in (20).

$$Min: \ Cost_{DSO} + \sum_{c=1}^{C} \left(Cost_c^N + Cost_c^P + Cost_c^T \right) \tag{20}$$

Furthermore, we include the technical constraints for the neighbourhood agents in (2)–(12) and for the DSO in (14)–(17). Note that we include the local market balance since it taxes energy transfer from one agent to another in the same way as the equilibrium. Furthermore, the grid tariff cost component is not included since the DSOs costs are considered directly instead.

The centralized optimization forms a single linear programming problem which is solved directly in GAMS with the CPLEX solver.

3.4.2. Decentralized decision-making

In the case of decentralized decision-making, we assume non-cooperative behaviour for all the agents in the model. Therefore, each agent optimizes their individual objective function and interact with the other agents through pricing mechanisms. Decentralized decisions require a game-theoretic equilibrium approach with two levels: (1) The DSO level, and (2) The neighbourhood agent level. The DSO level is solved by treating the variables of the neighbourhood agents as parameters and solving the optimization problem in section 3.3. The neighbourhood agent equilibrium requires a complementarity formulation due to the interaction between the agents in the local market. Therefore, the neighbourhood agent problem described in section 3.2 is represented by its KKT conditions formulated as MCP conditions in Appendix B.

Modeling of two levels requires a solution algorithm to iterate until convergence is reached. The convergence criterion is that the cost

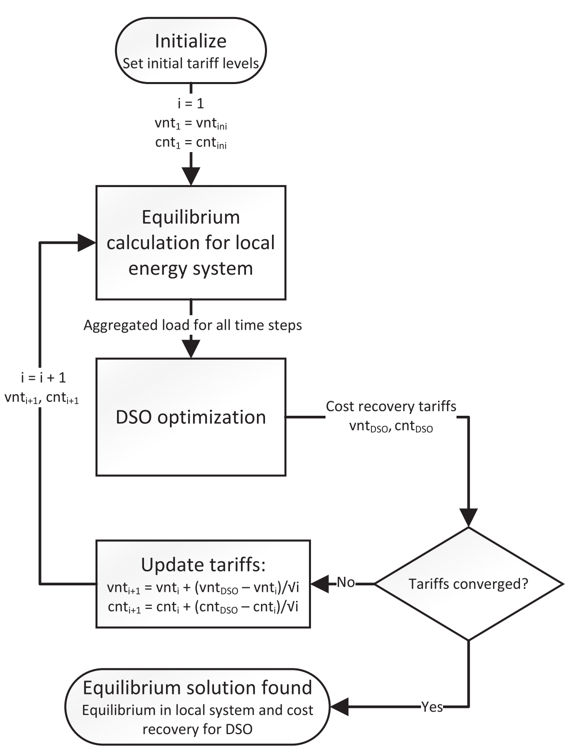


Fig. 2. Outline of equilibrium solution algorithm.

recovering grid tariffs do not change from one iteration to the next. The iterative solution algorithm presented in Fig. 2 is inspired by the procedure employed in Schittekatte et al. (2018) and can be described as follows:

1. Initialize the algorithm with starting tariff values (e.g., zero).
2. For the given tariffs, calculate the equilibrium of the neighbourhood level by solving the complementarity problem presented in Appendix B.
3. For the resulting grid transmission, solve the DSOs optimization problem presented in section 3.3.
4. For the given set of cost recovery tariffs, compare to previous tariffs and determine if change is lower than convergence tolerance.
5. If tariff convergence not reached: Update tariffs with decreasing step size and go to step 2.
6. If tariff convergence is reached: Equilibrium solution with DSO cost recovery found.

A decreasing step size is employed to ensure stable progress towards the equilibrium point. As we change the tariffs, the neighbourhood has a unique equilibrium for each set of grid tariffs since the KKT conditions are necessary and sufficient for optimality. An increase in grid tariffs gives the following effects:

- **DSO income effect 1:** A change in tariff levels will give a positive change on the tariff income per unit of capacity and electricity consumption.
- **DSO income effect 2:** A change in tariff levels will have a zero or negative effect on the contracted capacity and electricity consumption since grid usage might be substituted by something else.
- **DSO cost effect:** A change in tariff levels will give a zero or negative change in DSO costs since the grid usage will stay constant or be decreased when the cost of using grid capacity is increased.

Hence, because a change in tariff levels work in different directions, a change in tariff levels can give both a positive and negative change in DSO profits. Therefore, the model can potentially have several equilibrium solutions that satisfy the DSO cost recovery constraint. We do a tariff sensitivity analysis in section 5.4 that demonstrates the existence of two equilibrium points for the case considered in this paper. However, it should be noted that the existence of two equilibrium point in our analysis is not a general result since the DSO profit is a nonmonotone function of the grid tariffs. More details regarding the equilibrium tariffs and convergence of the model can be found in section 5.4.

The decentralized model is also implemented in GAMS and solved as a linear program with the CPLEX solver for the DSO level. The neighbourhood equilibrium is calculated by solving the complementarity formulation in Appendix B using the PATH solver. These models are solved iteratively until convergence is reached (see Fig. 2).

4. Case study

This section describes the input data used for the case study. The system we model is inspired by the Zero Emission Neighbourhood (ZEN[2]) pilot project called Ydalir.[3] Investment costs are represented through their annual payment costs with an interest rate of 5% and technology-specific lifetimes.

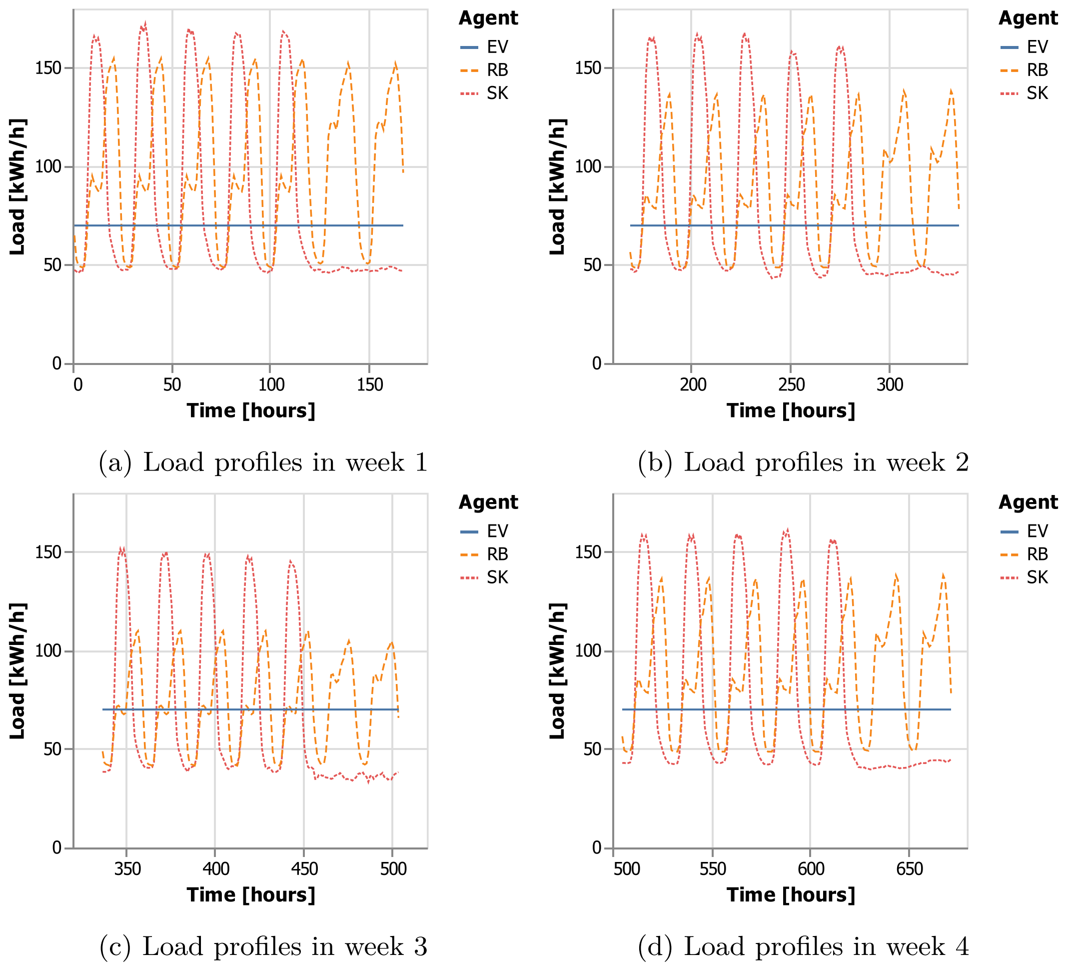
4.1. Agents and load profiles

Since the focus of this paper is on the interaction between agents with different characteristics under various regulatory frameworks, agents are categorized by five agent groups: Combined school and kindergarten (SK), residential buildings (RB), large scale energy resources

[2] https://fmezen.no/
[3] https://www.ydalirbydel.no/ydalir/

Table 2
Agents represented in the model.

Agent group	Load profile	Investment options	Flexible resources
Combined school and kindergarten (SK)	3000 m^2 kindergarten +7000 m^2 school	N/A	N/A
Residential buildings (RB)	20,000 m^2	Batteries and PV available	Battery operation and PV curtailment
Large scale energy resources (ER)	N/A	Batteries and PV available at lower cost	Battery operation and PV curtailment
EV charging facility (EV)	Charging of 200 EVs per day	N/A	Charging of EVs
Distribution system owner (DSO)	Aggregate load of neighbourhood agents	Grid capacity	N/A



(a) Load profiles in week 1
(b) Load profiles in week 2
(c) Load profiles in week 3
(d) Load profiles in week 4

Fig. 3. Load profiles for the neighbourhood agents.

(ER), EV charging facility (EV), and distribution system operator (DSO). An overview of the characteristics of each group can be found in Table 2.

Electricity load profiles for agents SK and RB have been generated based on the floor area according to the methodology presented in Lindberg et al. (2019). We generate four representative weeks for a year, one for each season. Regarding the demand for EV charging, a yearly driving distance of 14,000 km per vehicle is assumed.[4] Further, one electric car needs 0.2 kWh per km (Sørensen et al., 2018), so one car needs about $\frac{14,000}{365}*0.2 = 8$ kWh/day. For 200 EVs, we get a daily charging need of about 1,600 kWh/day. Based on these assumptions, a charging need of 70 kWh for each hour is specified for the EV agent. The load profiles for the neighbourhood agents are presented in Fig. 3.

The energy resource agent (ER) does not have any load profile specified but can invest in batteries and PV capacity to trade electricity with other neighbourhood agents or the power market. Lastly, the DSOs load profile is the aggregate load of all the other neighbourhood agent groups.

4.2. Technology costs and characteristics

In the modeled system, some of the agents can invest in technologies such as grid capacity, PV systems, and batteries. Also, the EV agent has inherent flexibility regarding when to charge the EVs.

The DSO is responsible for the grid capacity connecting the neighbourhood to the transmission network. For the regional grid in Norway, the transmission fee is approximately 50 €/kW of peak power measured at the point of the TSOs grid.[5] Furthermore, it is assumed that the DSOs costs are approximately equal to the transmission

[4] SSB, Road traffic volumes 2005–2018, https://www.ssb.no/en/statbank/table/12576/

[5] https://www.statnett.no/en/for-stakeholders-in-the-power-industry/tariffs/this-years-tariff. Accessed: 2020-10-07]

system cost per unit of capacity. This gives an assumed total cost of 100 €/kW of grid capacity, which is used for the case study. In general, grid costs are lumpy and vary depending on site-specific properties. However, since our interest is mainly regarding game-theoretic aspects of pricing mechanisms, this simplification is appropriate for investigating such fundamental pricing aspects. In our case study, all network capacity needs to be built. In addition to the investments, network losses are specified to 6%.

The Danish energy agency publish characteristics for a range of technologies including PV and batteries.[6] The technology costs for the ER agent is based on the general technology cost in 2020 where the utility-scale PV systems cost is 0.42 M€/MWp. Note that this cost level is very low in the context of neighbourhood-scale systems, but we use it to illustrate a situation where it is cost optimal for end-users to invest in PV systems. It can also be argued that this cost is realistic as a consequence of investment subsidies.[7] Using an interest rate of 5% and a lifetime of 20 years, this translates to an annual cost of 34 €/kWp for the ER agent. Large scale lithium-ion battery costs are currently around 150 €/kWh. Assuming a lifetime of 10 years for batteries and an interest rate of 5% gives an annual cost of 19 €/kWh for battery capacity.

It is assumed that because of economies of scale, small scale systems cost more than large scale ones per unit of capacity. A premium of 20% is therefore assumed for smaller systems, which in this example applies to the RB agent. Therefore, the annual PV cost is 40.8€/kWp, while annual battery costs are 22.8 €/kWh for the RB agent.

Converter losses are assumed to be 5% for batteries in both directions. Furthermore, the power/energy for batteries is assumed to be fixed at 0.5 kW/kWh. The self-discharge of batteries is assumed to be 0.1% per hour.

For the EV agent, we assume the flexibility associated with the charging of EVs is 8 hours by specifying an EV storage capacity of $70 * 8 = 560$ kWh. In addition, the charging capacity factor is set to 0.5 to allow for a charging capacity of up to 280 kW. No discharge to the grid is allowed by setting the discharging capacity factor to zero. EV charging losses are equal to the bi-directional batteries at 5%.

The nominal PV generation data is obtained from PVGIS[8] for the location of the Ydalir project. After PV-system losses, the annual PV generation is 779 kWh/kWp of installed capacity. Nominal PV generation for the four representative weeks is presented in Fig. 4.

4.3. Market price and regulatory assumptions

End-users can have different contracts ranging from spot price based contracts varying each time step to fixed price contracts. For simplicity, and in order to focus on the variability of load profiles and decentralized generation, the wholesale energy price is set to 0.05€/kWh for all time steps. For systems with large shares of energy communities, there might be an effect on the wholesale price, but this aspect is out of the scope of this work. This means that the time-varying input data is limited to the load profiles and PV generation.

Electricity consumption is usually subjected to taxes. In this paper, it is assumed that such a tax applies to power imports from both the wholesale power market and the local market and is specified to 1.6¢/kWh according to the current taxes on electric power in Norway.[9]

The grid tariffs are endogenous to the model, but it is necessary to specify the net metering coefficient exogenously. In this case study, the net metering coefficient has been set to zero, which means that only electricity imports are subject to the volumetric grid tariffs. This is in line with current practice in several countries, including Norway.

4.4. Regulatory frameworks

The analyses are based on three different cases:

1. **Case LM:** Assumes decentralized decision-making where the agents in the neighbourhood optimize their individual objective, but can trade with each other. The neighbourhood agents can also trade with the wholesale power market, and the DSO agent sets the grid tariffs for such trades based on cost-recovery conditions.
2. **Case NOLM:** Similiar to case LM, but local trades are not allowed. This situation is similar to current regulations in many countries.
3. **Case SO:** System optimization model used for benchmarking. All decisions are assumed to be made centrally to minimize the total system cost for the neighbourhood and the DSO as a whole. The system cost incorporates the grid costs directly in addition to costs for all neighbourhood agents. Grid costs are distributed evenly by dividing the total grid costs by the number of agents in the neighbourhood.

5. Results and discussion

5.1. Total system costs and resource allocation

First, we focus on the system as a whole under different regulatory frameworks. Fig. 5 provide information on total system costs and how these costs are distributed among the neighbourhood agents. The DSO is not represented explicitly as an agent in these figures since the grid costs are imposed on the neighbourhood agents through the grid fees. Since the grid costs are forwarded to the neighbourhood agents through the grid tariffs, the net costs for the DSO are zero. Furthermore, Table 3 provides more detailed information regarding costs, tariffs, and investments.

The total costs are lowest in the SO case, which provides a benchmark for the cases with decentralized decision-making. We use the SO case as a benchmark since it provides the optimal solution for the system as a whole when the aim is to minimize total costs. Hence, from an efficiency point of view, policies should aim to achieve a solution close to the SO solution under decentralized decision-making. Compared to the SO solution, we observe a cost increase of 1.2% for the LM case where local trading is allowed and 4.1% for the NOLM case where no trading occurs within the neighbourhood. In addition to the total cost decrease, the LM solution pareto-dominates the NOLM solution since no agent is worse off and some are better off when the local market is included. The grid capacity is the same for the LM and the SO cases, while it is significantly higher in the NOLM case. The fact that the LM case provides a system with the same grid capacity as in the SO case indicates that the combination of decentralized trading and a rather simple grid tariff scheme can impose the grid costs on end-users in a cost-reflective way.

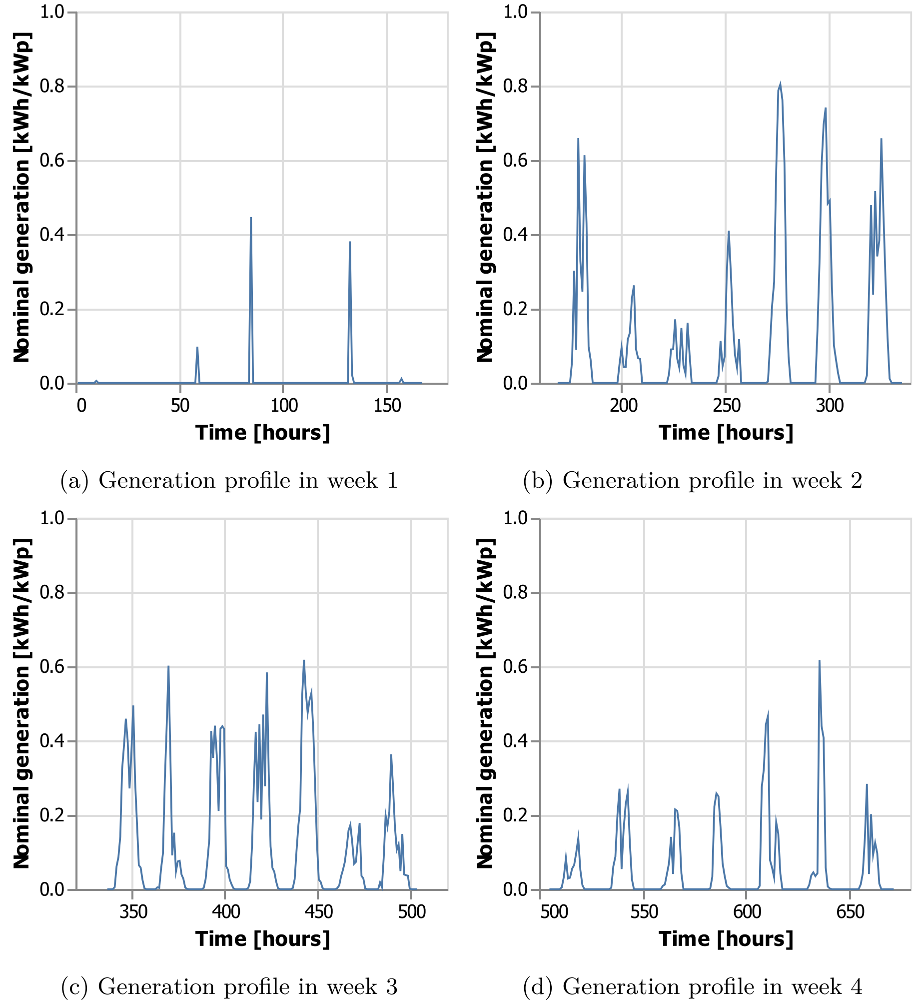
In general, the LM solution can not achieve lower total costs than the SO solution since it is not technically possible to achieve lower costs than the centralized optimization. Also, if we keep the tariff rates fixed, the LM solution will never have higher total costs than the NOLM solution since the neighbourhood agents can always choose to not trade and achieve the NOLM outcome. Hence, if tariff rates does not change, the LM solution will always be equal to or between the system optimal solution and the NOLM solution. However, since the tariff rates are designed as a response to the neighbourhood equilibrium, some agents might be negatively affected by the introduction of such a market. The composition of the neighbourhood agents will be important for the benefits provided by the local market. The market has the highest value when there are some inflexible and some flexible agents since such a situation means that we need a mechanism to incentivize the flexible agents to flatten the coincident peak for the neighbourhood rather than their individual peak.

[6] https://ens.dk/en/our-services/projections-and-models/technology-data [Accessed: 2020-02-04]

[7] https://www.enova.no/privat/alle-energitiltak/solenergi/el-produksjon-/

[8] https://ec.europa.eu/jrc/en/pvgis

[9] https://www.skatteetaten.no/en/business-and-organisation/vat-and-duties/excise-duties/about-the-excise-duties/electrical-power-tax/ [Accessed: 2020-10-07.]



(a) Generation profile in week 1

(b) Generation profile in week 2

(c) Generation profile in week 3

(d) Generation profile in week 4

Fig. 4. Nominal PV generation in the neighbourhood.

Comparing the LM and the NOLM cases, it can be observed that a local market can efficiently allocate the resources in the neighbourhood since the solution is close to the SO case. In the following, we will dig deeper into these findings to explain how local market mechanisms can benefit both the DSO and other neighbourhood agents.

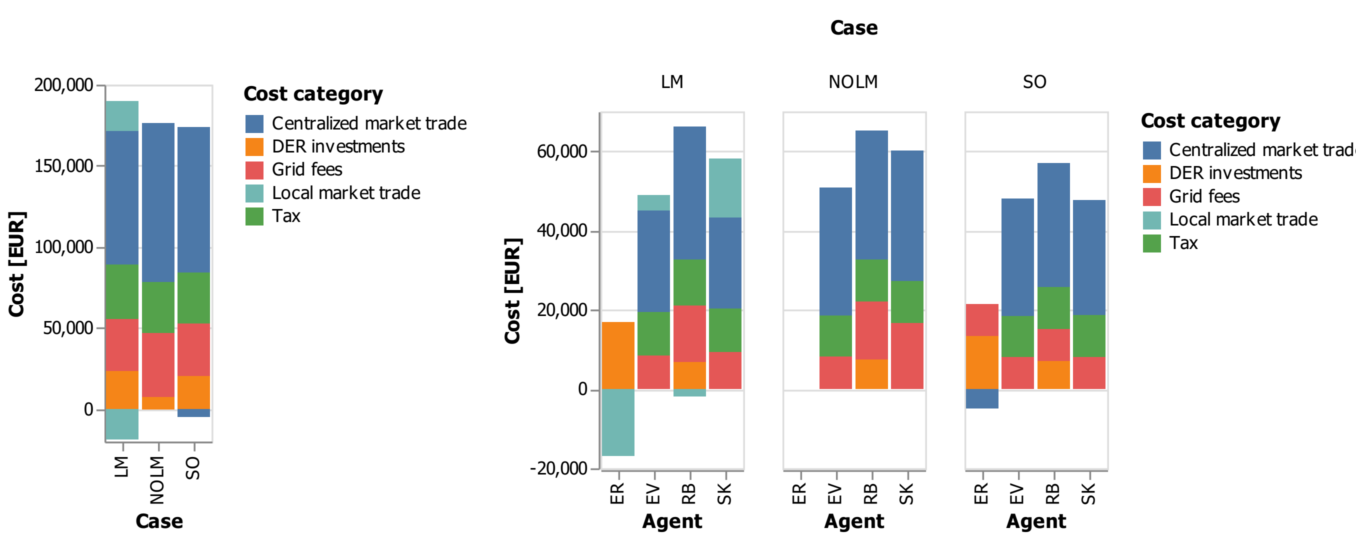


Fig. 5. Total system costs (left) and cost allocation per agent (right) for three cases: Decentralized decision-making with local market (LM), decentralized decision-making without local market (NOLM) and centralized decision-making (SO).

Table 3
Overview of key results for three cases: Decentralized decision-making with local market (LM), decentralized decision-making without local market (NOLM) and centralized decision-making (SO). Cost data are for one year based on the four weeks condidered in the analyses.

	LM	NOLM	SO
Total costs [€]	171,148	176,089	169,174
Net costs ER agent [€]	0	0	16,637
Net costs EV agent [€]	48,853	50,834	47,967
Net costs RB agent [€]	64,256	65,119	56,936
Net costs SK agent [€]	58,039	60,136	47,634
Volumetric tariff [¢/kWh]	0.301	0.299	N/A
Capacity-based tariff [€/kW]	100	85.5	N/A
Grid capacity [kW]	271	337	271
Total PV [kW]	663	175	568
ER agent PV [kW]	495	0	395
RB agent PV [kW]	168	175	173
Total battery [kWh]	0	14	0
ER agent battery [kWh]	0	0	0
RB agent battery [kWh]	0	14	0

5.2. Business case for stakeholders and assets

Now, we focus on the difference between the LM and the NOLM cases. The NOLM case is most representative of current regulatory frameworks in Europe.

The ER agent has no load profile but can invest in energy resources if this turns out to be profitable. Therefore, the ER agent can obtain zero costs if no investments are made. This happens in the NOLM case, where all electricity needs to be traded with the wholesale electricity market. Since the available neighbourhood-scale plants cannot recover the investment costs by participating in the wholesale market, no investments are made by the ER agent when there is no local market. Instead, despite higher unit costs, neighbourhood investments are exclusively made by the RB agent, which invests in a PV system with batteries to decrease the agents' individual costs through behind the meter optimization.

Fig. 5 also reveal that the investments in a PV system become profitable for the ER agent when the local market is introduced. Furthermore, Table 3 shows that the ER agent has zero costs also in the LM case since it invests until the point that the income from the local market exactly balances the investment costs.[10]

Investments made by the ER agent are exclusively in a PV system in the LM case, and there are no investments in batteries for the neighbourhood for neither the LM case nor the SO case (see Table 3). Consequently, batteries are not able to reduce the total system costs since no battery investments occur in the SO case. Despite the lack of bidirectional batteries in the LM and the SO cases, the neighbourhood has a significant flexibility resource through the EV agent since neighbourhood load balancing can efficiently be performed by appropriate charging of the EVs within certain limits. Additional investments in batteries are only profitable in the NOLM case for the RB agent (see Table 3). The battery investments occur in the NOLM case because each agent optimizes behind their own meter and, therefore, can benefit from investing in resources that limit their interaction with the grid. However, such individualistic behaviour produces higher total system costs because the regulatory framework triggers sub-optimal investments. Sub-optimal investments also induce sub-optimal operations, which we elaborate on next.

5.3. Pricing mechanisms and operational decisions

One key finding from the previous sections is that the local market can reduce the required grid capacity to the neighbourhood (see Table 3). This is feasible because the aggregate neighbourhood peak load is reduced in the LM and the SO cases compared to the NOLM case. Fig. 6 shows the aggregate load for the week with the highest load (week 1) along with the local market price. Note that the price can be very high and such price spikes might be hard to monitor in practice. Price spikes can also give the impression of market power, although such effects are outside the scope of this paper since we model the neighbourhood agents as price-takers. The introduction of a local market leads to better coordination of the flexible resources in the neighbourhood, and the aggregate peak load is 20% lower in the LM and SO cases compared to the NOLM case. When the market is not available, we see load spikes even though the agents are faced with a grid tariff penalizing high loads. The lacking aggregate neighbourhood peak load reduction in the NOLM case happens because the agents with flexible resources are incentivized to reduce their individual peak load rather than contributing to reducing the aggregate neighbourhood peak load.

Fig. 7 highlights the importance of coordination within the neighbourhood. The plot represents 24 h during the winter season when the original aggregate neighbourhood peak load is the highest (time steps 25–48), and we will refer to this time period as 'the critical winter day'. It is evident that during 'the critical winter day', the neighbourhood agents all employ a flat trading profile seen from the wholesale power market in the LM case compared to the NOLM case. Constant power purchase from the centralized power market would not be possible for the SK agent in particular without the local market since the SK agent has no flexible resources, and its demand varies over the day.

Since trading with the centralized power market is rather constant during this day, we can extract some information from how the agents interact with the local market, as depicted in Fig. 8. For example, the EV agent buys more than 100 kWh/h during the first 5 h through the SK and RB agents in the local power market, and the EVs are charged while the SK and RB agents have unused capacity. Note that the local trading happens even though the SK and RB agents do not produce energy, but are forwarding power bought from the centralized power market. The roles are switched during daytime when the EV and RB agents sell power to the SK agent during the second half of the day.

Note that the EV sales are not due to discharging (vehicle-to-grid) from the EVs; it is electricity purchased from the centralized power market by the EV agent that is sold in the local market instead of being used for EV charging. The forwarding of power from the centralized market via neighbourhood agents occurs because of the tariff scheme in place, where the agents pay for their individual peak load. When agents have unused capacity (low load), they choose to use this capacity to buy more power than needed for their own consumption and sell it to other neighbourhood agents that need it. Forwarding power to a neighbouring agent is an illustration of how local markets can facilitate coordination among different stakeholders by creating appropriate incentives for coordination. The incentives are created because the grid capacity is free of charge for end-users that are not close to their peak power while it is expensive for end-users that are close to their peak power. Hence, since different agents value the same resource differently, the business case for a local market is created. Consequently, situations where the aggregate neighbourhood load is high will be signalled to the end-users through high prices in the local market when all the end-users are close to their peak load.

These findings highlight that with the local market framework, agent EV charges the EVs during the first part of the day in order to balance the electricity consumption for the neighbourhood as a whole. Without the local market, the rational choice for the EV agent is to spread the EV charging evenly throughout the day to minimize the agents individual peak load, regardless of the overall load situation (see Fig. 9). Such individualistic incentives are consistent with the situation without a local market (NOLM) and result in a higher aggregate neighbourhood peak load, as depicted in Fig. 6.

[10] The ER agent does not turn a profit due to the price-taker assumption inherent in the equilibrium conditions in the model.

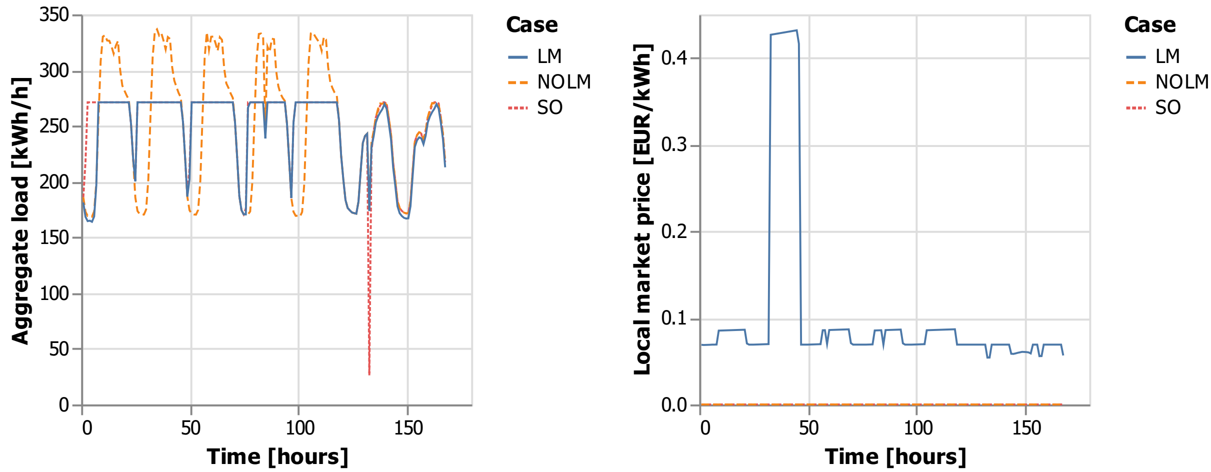


Fig. 6. Aggregate load for three different regulatory frameworks (left) and corresponding local market price for the LM case (right) during the winter week.

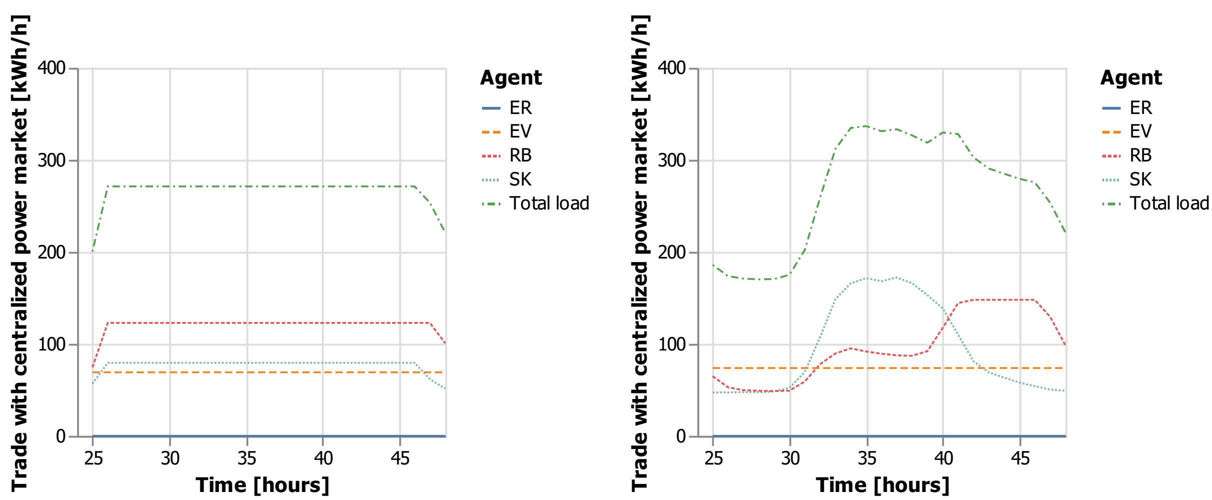


Fig. 7. Trading with the centralized power market during 'the critical winter day' when the local market is available (left) and without the local market (right).

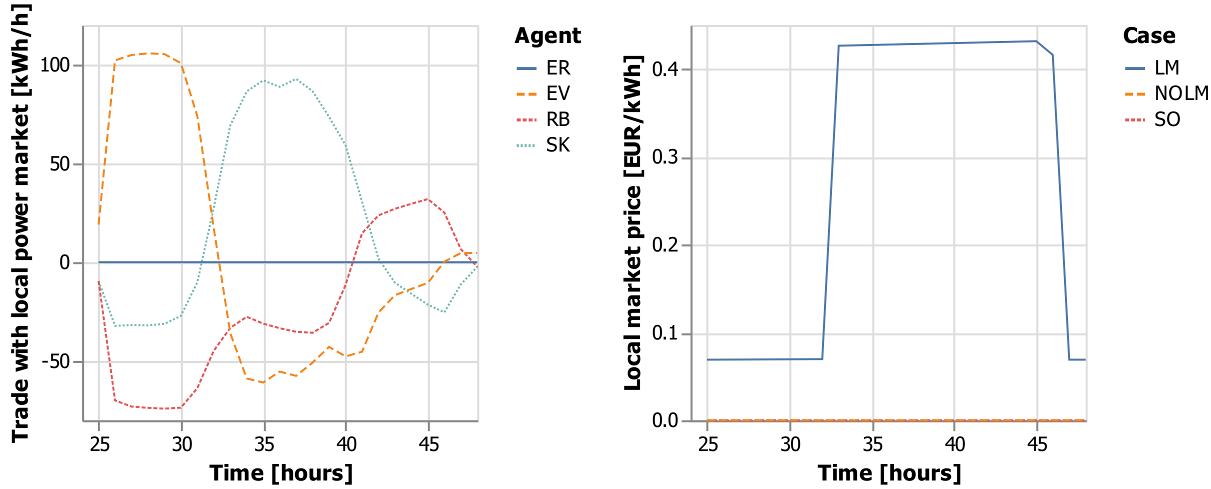


Fig. 8. Trading in local market (left) and corresponding local market price (right) during the critical winter day (hours 25–48).

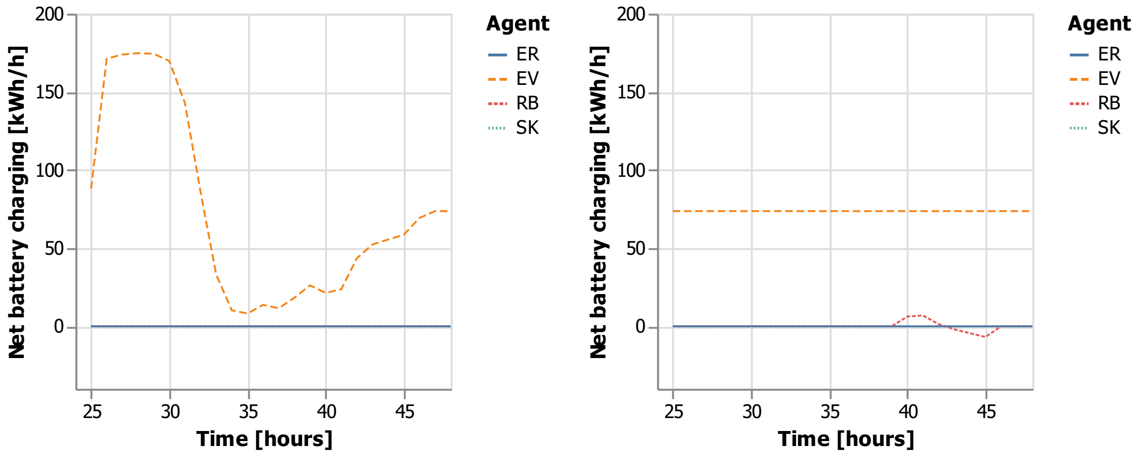


Fig. 9. EV charging and battery operation during 'the critical winter day' when the local market is available (left) and without the local market (right).

5.4. Equilibrium tariffs and DSO cost recovery

For completeness, we explore what happens when the tariffs deviate from the equilibrium state for the LM case. Fig. 10 presents how the DSOs profit, and the grid capacity changes when we vary the tariffs from zero and upwards. The base tariffs, representing a 0% deviation, are equivalent to case LM. We run analyses using the MCP model starting from a tariff deviation of −100% and increase the tariffs in 10% intervals. Agent ER and RB invest in increasing amounts of PV and batteries as the tariffs increase since interaction with the wholesale market becomes increasingly expensive.

Fig. 10 shows that we have two equilibria that satisfy the DSO cost recovery criterion of zero profits. The first equilibrium occurs at a tariff deviation of 0%, which is the LM solution where the DSOs expenses are exactly balanced by tariff income. The second equilibrium occurs when the tariffs are increased by more than 42 times (+4,210%) from the first equilibrium level. The second equilibrium occurs when the tariffs becomes so high that the neighbourhood agents decide to be completely self-sufficient, and the DSO has no investments and no income. These results indicate that it can be costly to replace the grid entirely with decentralized resources.

5.5. Impact of tax rate on the results

So far, we have included an electricity tax on imports from both the wholesale power market and the local market. However, such a tax inherently promotes behind the meter optimization in the local market and therefore we expect the tax rate to limit the trading in the local market. To investigate the effect of the electricity tax rate on the results, we compare the results for different tax rates in the LM case.

Table 4 reports the results for three different electricity tax rates: 1) zero taxes, 2) tax as before, 3) double tax rate. The total costs are almost equal to the SO case when we remove the electricity tax and the LM solution becomes more expensive than the SO solution as the electricity tax is incresed. The reason for the deviation from the system optimal solution is mainly that the tax limits the trading in the local market since the agents need to pay a premium on electricity imports from the other agents in the local market.

The tax rate makes imports from both the wholesale and local markets more expensive. An increase in the tax rate mainly affects the PV capacity in the local system. When there is no tax on electricity, all the PV capacity is installed at the ER agent since it has the lowest investment costs. As the tax increases, the PV capacity shifts to the RB agent

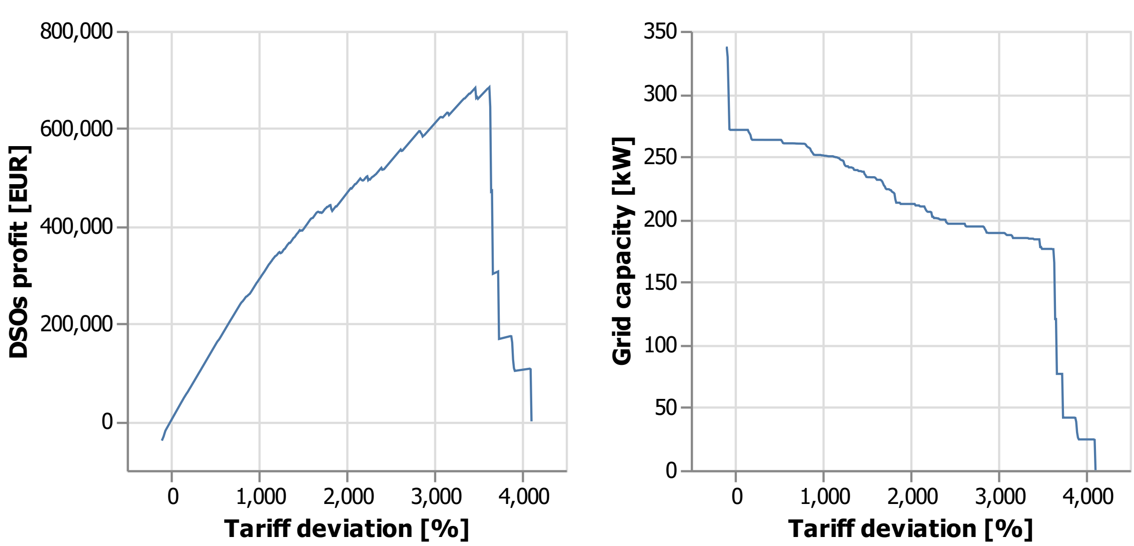


Fig. 10. Response by neighbourhood to increasing grid tariffs. Figure shows DSOs profit (left) and the grid capacity (right). The figures start at a − 100% deviation from the tariffs in the LM case.

Table 4
Sensitivity to tax change for the LM case.

	Tax = 0	Tax = 1.6	Tax = 3.2
Cost change from SO [%]	+0.01	+1.17	+1.97
Volumetric tariff [¢/kWh]	0.300	0.301	0.301
Capacity-based tariff [€/kW]	100	100	100
Grid capacity [kW]	271	271	271
Total PV [kW]	610	663	769
ER agent PV [kW]	610	495	460
RB agent PV [kW]	0	168	309
Total Battery [kWh]	0	0	0

as the cost reduction from self-consumption of energy dominates the investment cost increase at the RB agent. The ER agent, however, decreases investments because it becomes less competitive in the local market when its product is taxed. In total, the PV capacity increases with a higher tax rate since the increase at the RB agent is higher than the decrease at the ER agent.

6. Conclusion and policy implications

In this paper, we propose a game-theoretic framework to analyze a local trading mechanism and its feedback effect on grid tariffs under cost recovering conditions for the DSO. In this game-theoretic model, we construct a case study which is inspired by regulatory issues that have been identified in an ongoing pilot project in Norway. Our results are based on calculations using representative data from four weeks, where each week represents one season of the year.

Within our assumptions, our main finding is that the establishment of a local electricity market in a neighbourhood pareto-dominates the situation without a local market and could decrease the total costs by facilitating local coordination of resources and thus create socio-economic value. The novelty of our analysis is to show how local market activity does not just save costs for neighbourhood stakeholders, but in fact, impacts the regulated tariff rates as the local market activity defer some of the DSO costs. When we compare the establishment of a local market with a regulatory framework without any local market, we observe a reduction in total costs including the need for grid capacity for the system as a whole.

The local market creates value because it is able to coordinate the flexible assets on the neighbourhood level rather than at the individual end-user level. The presence of a capacity-based tariff in combination with a local market mechanism is crucial for these findings since it creates the appropriate price signal to lower the aggregate peak load for the neighbourhood. The peak load is reduced because the local market price reflects the scarcity of capacity in the overall neighbourhood.

Two equilibrium solutions satisfy the DSO cost-recovery criterion: (1) The DSOs costs are exactly balanced by tariff income and a significant interaction between the neighbourhood and the larger power system and (2) at very high tariffs the neighbourhood decides to completely disconnect from the larger power system. In the second equilibrium, the DSO has zero costs and income. These results indicate that although a local trading mechanism can reduce the need for grid capacity, it can be costly to disconnect from the system completely.

Local electricity markets are currently prohibited in most parts of the world. Although the establishment of a local electricity market shows promising potential according to our results, there are several considerations to be made upon evaluating the allowance of local electricity trading. Firstly, the cost of establishing and administrating a local electricity market cannot exceed its net saving potential. With automation and smart metering infrastructure, this countervailing cost is hopefully small enough. Secondly, the saving potential identified in our analysis is dependent on rational and reliable reactions by distributed market participants to reduce peak neighbourhood load rather than increasing the grid capacity. Thirdly, the highest value of establishing a local market is likely to be related to deferring grid development, i.e., defer upgrading grid capacity in an area where power outtake is increasing.

Whether a DSO is willing to depend on the rational reactions by market participants rather than relying on robust development and dimensioning of grid infrastructure is worth considering. An underlying assumption in this paper is that the agents are risk-neutral and, therefore, purely motivated by reducing their expected costs. However, since different regulatory frameworks might fundamentally affect the cost distribution for the involved stakeholders, further research could go in the direction of including risk preferences in the modeling framework.

Acknowledgement

This paper has been written within the Research Centre on Zero Emission Neighbourhoods in Smart Cities (FME ZEN). The authors gratefully acknowledge the support from the ZEN partners and the Research Council of Norway.

Appendix A Mathematical symbols

Nomenclature

Sets	
$c \in [1,\ldots,C]$	Neighbourhood agents
$h \in [1,\ldots,H]$	Hours
Parameters	
λ_h^P	Power market price in hour h (€/kWh)
C^G	Existing transmission capacity (kW)
$D_{c,\,h}$	Electricity demand in hour h (kWh/h)
$D_{c,\,h}^{\Delta-}$	EV demand in hour h (kWh/h)
$G_{c,\,h}^E$	Energy resource availability at agent c in hour h (kW/kWp)
I_c^E, I_c^S	Annualized investment costs at agent c (€/kW/year)
I^G	Annualized investment cost for grid capacity (€/kW/year)
L^G	Transmission losses (%)
L_c^S	Energy storage converter losses at agent c (%)
NM	Net-metering coefficient
P_c^{ch}	Energy storage capacity ratio for charging at agent c (kW/kWh)
P_c^{dis}	Energy storage capacity ratio for discharging at agent c (kW/kWh)
R_c	Energy storage self-discharge at agent c (%/h)
T	Excise tax (€/kWh)
U_c^E, U_c^S	Resource limits at agent c (kW)
W_h	Weight of hour h (h/h)
Upper-level variables	
c_{DSO}^G	Investment in interconnection capacity (kW)
cnt	Capacity-based network tariff (€/kW)
e_h^{GE}	Neighbourhood exports in hour h (kWh/h)
e_h^G	Neighbourhood load in hour h (kWh/h)
e_h^{GI}	Neighbourhood imports in hour h (kWh/h)
vnt	Volumetric network tariff (€/kWh)
Lower-level variables	
$exp_{c,\,h}^P$	Energy exported to grid at agent c in hour h (kWh/h)
λ_h^L	Market price in the local market in hour h (€/kWh)
c_c^E	Energy resource capacity at agent c (kW)
c_c^G	Measured peak load at agent c (kW)
c_c^S	Storage capacity at agent c (kWh)
$d_{c,\,h}^{\Delta+}, d_{c,\,h}^{\Delta-}$	Battery charge/discharge at agent c in hour h (kWh/h)
$exp_{c,\,h}^L$	Energy exported to local market at agent c in hour h (kWh/h)
$g_{c,\,h}^E$	Energy generation at agent c in hour h (kWh/h)
$imp_{c,\,h}^P$	Energy imported from grid at agent c in hour h (kWh/h)
$imp_{c,\,h}^L$	Energy imported from local market at agent c in hour h (kWh/h)
$s_{c,\,h}$	Battery state of charge at agent c in hour h (kWh)

Appendix B MCP formulation of local energy system

We derive the KKT conditions of the neighbourhood level based on the optimization problem described in section 3.2. Since our original problem is linear and has a convex feasible area, the KKT conditions are necessary and sufficient.

$$I_c^S + \mu_c^{S2} - \sum_{h=1}^{H}\left(\mu_{c,h}^{S3} + P_c^{ch} * \mu_{c,h}^{S4} + P_c^{dis} * \mu_{c,h}^{S5}\right) \geq 0 \perp c_c^S \geq 0 \ \forall c \tag{B.1}$$

$$I_c^E + \mu_c^{E1} - \sum_{h=1}^{H} \mu_{c,h}^{E2} * G_{c,h}^E \geq 0 \perp c_c^E \geq 0 \ \forall c \tag{B.2}$$

$$W_h * \left(\lambda_h^P + T + vnt\right) - \lambda_{c,h}^{EB} + \mu_{c,h}^G \geq 0 \perp imp_{c,h}^P \geq 0 \ \forall c,h \tag{B.3}$$

$$-W_h * \left(\lambda_h^P + NM*vnt\right) + \lambda_{c,h}^{EB} + \mu_{c,h}^G \geq 0 \perp \ exp_{c,h}^P \geq 0 \ \forall c,h \tag{B.4}$$

$$W_h * \left(\lambda_h^L + T\right) - \lambda_{c,h}^{EB} \geq 0 \perp imp_{c,h}^L \geq 0 \ \forall c,h \tag{B.5}$$

$$-W_h * \lambda_h^L + \lambda_{c,h}^{EB} \geq 0 \perp \ exp_{c,h}^L \geq 0 \ \forall c,h \tag{B.6}$$

$$cnt - \sum_{h=1}^{H} \mu_{c,h}^G \geq 0 \perp c_c^G \geq 0 \ \forall c \tag{B.7}$$

$$\lambda_{c,h}^{EB} - \left(1 - L_c^S\right) * \lambda_{c,h}^{S1} + \mu_{c,h}^{S4} \geq 0 \perp d_{c,h}^{\Delta+} \geq 0 \ \forall c,h \tag{B.8}$$

$$\left(1 + L_c^S\right) * \lambda_{c,h}^{S1} - \lambda_{c,h}^{EB} + \mu_{c,h}^{S5} \geq 0 \perp d_{c,h}^{\Delta-} \geq 0 \ \forall c,h \tag{B.9}$$

$$-\lambda_{c,h}^{EB} + \mu_{c,h}^{E2} \geq 0 \perp g_{c,h}^E \geq 0 \ \forall c,h \tag{B.10}$$

$$\lambda_{c,h}^{S1} - (1 - R_c) * \lambda_{c,h+1}^{S1} + \mu_{c,h}^{S3} \geq 0 \perp s_{c,h} \geq 0 \ \forall c, h < H \tag{B.11}$$

$$\lambda_{c,H}^{S1} - (1 - R_c) * \lambda_{c,1}^{S1} + \mu_{c,H}^{S3} \geq 0 \perp s_{c,H} \geq 0 \ \forall c \tag{B.12}$$

$$imp_{c,h}^P - exp_{c,h}^P + imp_{c,h}^L - exp_{c,h}^L - D_{c,h} - d_{c,h}^{\Delta+} + d_{c,h}^{\Delta-} + g_{c,h}^E = 0 \perp \lambda_{c,h}^{EB} \ \forall c,h \tag{B.13}$$

$$(1 - R_c) * s_{c,h-1} + (1 - L_c) * d_{c,h}^{\Delta+} - (1 + L_c) * d_{c,h}^{\Delta-} - D_{c,h}^{\Delta-} - s_{c,h} = 0 \perp \lambda_{c,h}^{S1} \ \forall c, h > 1 \tag{B.14}$$

$$(1 - R_c) * s_{c,H} + (1 - L_c) * d_{c,1}^{\Delta+} - (1 + L_c) * d_{c,1}^{\Delta-} - D_{c,h}^{\Delta-} - s_{c,1} = 0 \perp \lambda_{c,1}^{S1} \ \forall c \tag{B.15}$$

$$U_c^S - c_c^S \geq 0 \perp \mu_c^{S2} \geq 0 \ \forall c \tag{B.16}$$

$$c_c^S - s_{c,h} \geq 0 \perp \mu_{c,h}^{S3} \geq 0 \ \forall c,h \tag{B.17}$$

$$c_c^S * P_c^S - d_{c,h}^{\Delta+} \geq 0 \perp \mu_{c,h}^{S4} \geq 0 \ \forall c,h \tag{B.18}$$

$$c_c^S * P_c^S - d_{c,h}^{\Delta-} \geq 0 \perp \mu_{c,h}^{S5} \geq 0 \ \forall c,h \tag{B.19}$$

$$c_c^G - imp_{c,h}^P - exp_{c,h}^P \geq 0 \perp \mu_{c,h}^G \geq 0 \ \forall c,h \tag{B.20}$$

$$U_c^E - c_c^E \geq 0 \perp \mu_c^{E1} \geq 0 \ \forall c \tag{B.21}$$

$$c_c^E * G_{c,h}^E - g_{c,h}^E \geq 0 \perp \mu_{c,h}^{E2} \geq 0 \ \forall c,h \tag{B.22}$$

$$\sum_{c=1}^{C}\left(exp_{c,h}^L - imp_{c,h}^L\right) = 0 \perp \lambda_h^L \ \forall h \tag{B.23}$$

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Helping end-users help each other: Coordinating development and operation of distributed resources through local power markets and grid tariffs.

Magnus Askeland: Conceptualization, Methodology, Software, Validation, Investigation, Writing - Original Draft, Writing - Review & Editing, Visualization.

Stian Backe: Conceptualization, Methodology, Writing - Review & Editing.

Sigurd Bjarghov: Conceptualization, Writing - Review & Editing.

Magnus Korpås: Conceptualization, Methodology, Writing - Review & Editing, Funding acquisition, Supervision.

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