Smart Energy 3 (2021) 100034

Contents lists available at ScienceDirect

Smart Energy

journal homepage: www.journals.elsevier.com/smart-energy

# Activating the potential of decentralized flexibility and energy resources to increase the EV hosting capacity: A case study of a multi-stakeholder local electricity system in Norway

Magnus Askeland [a, b, *], Stian Backe [c], Sigurd Bjarghov [b], Karen Byskov Lindberg [b, d], 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, Norwegian University of Science and Technology, Trondheim, Norway
[d] Architectural Engineering, SINTEF Community, Oslo, Norway

ARTICLE INFO

*Article history:*
Received 18 January 2021
Received in revised form
9 June 2021
Accepted 9 June 2021
Available online 17 June 2021

*Keywords:*
Game-theoretic model
Bilevel game
Electrification
Grid tariffs
Trading mechanisms
EV integration

ABSTRACT

The increasing amount of flexible load in the energy system represents both a challenge and an opportunity. One primary source of load growth is the electrification of the transport sector and the subsequent charging of electric vehicles, which is a load type that can potentially adjust their load profiles. However, to activate the full potential of end-user flexibility, it is necessary to develop pricing mechanisms that can promote efficient load responses on a larger scale. In this paper, a trading mechanism is proposed and analysed within a capacity-based grid tariff scheme by formulating a game-theoretic framework that includes decentralized decision-making by self-interest pursuing end-users. The model is applied to a real-world case in Norway, and it is demonstrated how electrification of vehicles can be achieved with the existing infrastructure. It is found that capacity-based grid tariffs have a limited ability to reduce the coincident peak load in the system since they mainly incentivize individual peak load reductions. However, by including a capacity trading mechanism within the capacity-based tariff structure, we demonstrate that it is possible to increase the value of flexibility since the flexible end-users are incentivized to coordinate their flexibility dispatch with other stakeholders.



## 1. Introduction

At the distribution grid level, multiple stakeholders are sharing the same interconnection capacity. Due to the distribution grid's radial structure, the capacity needs to be sufficient to handle the coincident peak load for all the stakeholders sharing the same network connection point. Changing consumption patterns that increase grid load due to more power-intensive appliances, electrification of transport, and decentralized resources poses a challenge for the distribution grid. The peak load can increase rapidly compared to the need for energy (see, e.g., [1]). Since the need for grid capacity is driven by the coincident peak load, coordination across several stakeholders can increase the local utilization of energy resources and promote efficient dispatch of flexible load types.

For example, electric vehicle (EV) deployment is considered a challenge due to the added demand and an opportunity to increase grid utilization, given the inherent flexibility regarding when the charging occurs. Keeping everything else static, electrification of transport means that the need for electric energy increases. However, due to the flexibility potential in EV charging, the increase in energy need does not necessarily imply a significant impact on peak load [2,3].

Due to these trends at the end-user level, it becomes increasingly important to consider how efficient operation of flexible resources at the end-user level can be facilitated [4]. In a deregulated electricity market, the individual end-users are billed separately and can control their assets' operation according to their preferences. This means that it is necessary to create incentives that can facilitate an efficient operation of flexible resources to avoid unnecessary and costly coincident peak load increases. Hence, this paper's main objective is to investigate how the amount of EVs in a geographically confined area can be increased without significant grid upgrades by designing efficient pricing signals that fit into existing market structures.

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

https://doi.org/10.1016/j.segy.2021.100034
2666-9552/

After this introduction, the paper is structured as follows. First, section 2 presents the research context and the contributions of this paper. Next, in section 3 we formulate the modeling framework that has been developed to carry out the research before the case study setup is presented in section 4. After that, results and discussion of these are presented in section 5, including a discussion of practical implications. Finally, conclusions are drawn in section 6.

## 2. Related literature

### 2.1. Modeling of neighbourhood energy systems

Because of increased amounts of decentralized energy resources (DER) and flexible assets at the end-user level, it is relevant to model energy systems at the neighbourhood level to investigate how such systems should ideally be designed and operated. A fundamental principle that can be used to categorize such models is whether they assume centralized or decentralized control of end-user assets.

A rather large body of literature assumes centralized control of neighbourhood assets through the energy hub concept initially proposed in [5], which has been applied in several scientific studies [6,7,8,9,10,11]. The energy hub concept does not include grid tariffs at the end-user level since grid congestion is handled at the neighbourhood level instead. Since the energy hub concept requires centralized control of all assets at the neighbourhood level, it is not directly compatible with the current market structure, which is based on individual metering and end-users making their own decisions. Centralized control models can assess how the local system should ideally be designed and operated; however, they are not suited to evaluate the proper design of incentives within the neighbourhood.

Representation of decentralized decision-making in neighbourhoods requires game-theoretic modeling approaches. The literature on neighbourhood energy models with decentralized decision-making is rather scarce compared to the literature assuming centralized control. In [12,13,14], the authors formulates the tariff design problem in game-theoretic settings with cost-recovery conditions for the distribution grid operator (DSO). We have previously applied this approach [15,16], and found that there is a risk that grid tariffs can provide both suboptimal investment levels and suboptimal operation of the flexible assets. However, these papers are limited to a simple tariff design structure and predefined rules for setting the tariff levels.

Game-theoretic aspects concerning stakeholder interaction are also considered in the smart grid research community. In [17], the authors recognize the decentralized decision-making structure within a smart grid and propose an energy management scheme based on noncooperative game theory while [18] designs an auction-based scheme for sharing of energy storage. Using a similar approach, a method to discriminate price per energy unit within a smart grid is demonstrated in [19]. In the smart grid context, EV charging is increasingly relevant since it represents a highly flexible load that can be used to balance the system, and [20] propose a network model with self-interest pursuing EVs as a means of transporting energy between districts. Furthermore, a bi-objective method considering both the overall cost and user convenience for EV charging is formulated in [21]. These papers have a high level of abstraction (e.g., related to user preferences) since the focus is on the design of trading mechanisms within smart grids on a conceptual level without considering existing pricing structures such as electricity grid tariffs in the model framework. The present study takes a more practical approach to complement this literature by investigating pricing mechanisms that fit into existing market structures and applying them to an ongoing project challenged by EV integration issues.

Mathematical programs with equilibrium constraints (MPECs) can be used to formulate Stackelberg leader-follower games such as the tariff design problem in a mathematically consistent way (see, e.g., [22,23]). [24,25], utilize MPEC formulations to optimize a grid tariff design when considering the reaction from the end-users [25]. formulates the tariff design problem with regulatory constraints for the DSO. Furthermore, in our previous work [24], a tariff scheme with a time-dependent component was introduced to tune the capacity-based tariff. However, none of them consider a tariff component with interaction among the end-users as a tool to address the inherent flaws of imperfect network tariffs.

It can be argued that end-users with flexible assets will operate these resources to their own benefit rather than considering the neighbourhood's objective as a whole. Thus, the operation of assets is only aligned with the overall system's objective if the incentives are appropriately designed. This paper fits within the category of game-theoretic approaches, and we aim to investigate the proper design of grid tariffs and local trading mechanisms to facilitate efficient utilization of the grid capacity under decentralized decision-making.

### 2.2. Prospective grid tariff designs in Europe and Norway

Traditionally, domestic electricity loads have been regarded as inflexible, and the electricity grid tariff has served mainly as a mechanism to share the bill of providing electricity grids among the users of the grid. For practical reasons, the electricity grid tariffs for residential consumers have historically consisted of two parts: a fixed and a volumetric component.

As the amount of flexible loads and automatic control options increase, there is an ongoing debate in industry, regulatory, and academic circles regarding how to properly design grid tariffs to achieve more efficient utilization of the electricity grid through cost-reflective tariffs. A recent paper from the energy regulators in Europe [26] suggests that a power-based tariff component is needed to account for the capacity-based aspect of the grid connection. The conclusion that capacity-based tariffs are needed is in line with several scientific findings during recent years [27,28]. Despite the evidence that a capacity-based network component is needed, there is an ongoing debate regarding how it should be designed. In this context [13], highlights the problems regarding sunk cost recovery through capacity-based tariffs when end-users react to the tariff implemented. Also, in our previous works [15,16,29] we have demonstrated that an uncoordinated solution based on capacity-based tariffs may result in sub-optimal flexibility responses, which motivates the tariff design proposed in this paper.

In Norway, one of the capacity-based tariff structures that the regulator suggests is the subscribed capacity tariff originally formulated in [30]. With a subscribed capacity tariff, the end-user decides on the amount of contracted capacity and then needs to pay an overcharge fee for any excess load. Another variation of a capacity-based tariff structure is the measured peak tariff, where the end-user's maximum load over a given period is subject to a capacity-based fee.

A reduction of individual peak loads may not necessarily be effective at reducing the aggregate peak load, and a previous paper considering tariff designs found that it would be beneficial to design the network tariff based on several consumers' combined load rather than individual loads [29]. However, centralized control was assumed to achieve coordination among the end-users and do not consider how to properly remunerate the individual end-users if a combined tariff is implemented. In contrast, this paper seeks to address this gap by formulating a model that can determine the optimal grid tariff structure and handle the coordination aspects as an integrated part of the grid tariff structure rather than assuming centralized control.

### 2.3. Contributions

Assessment of how individual end-users should be remunerated when contributing to neighbourhood objectives requires consideration of the noncooperative aspects of neighbourhood stakeholders when tariff designs are to be assessed. In contrast to existing literature that assumes centralized control of flexible assets, our methodology captures the end-user's price incentives that may enable trading between the stakeholders. This paper, therefore, formulates a Stackelberg model to investigate individual responses to prospective grid tariff schemes as a tool to facilitate efficient utilization of existing grid capacity. Our approach endogenously determines the optimal grid tariffs and the design of optimal remuneration schemes for the individual end-user. This paper is based on issues that have been raised in our previous work [15,16,24,29,31,32], and the novel contributions are:

- Formulation of a model suitable for investigating different regulatory frameworks concerning grid tariff design in smart energy systems.
- Extension of established pricing structures with a mechanism for interaction between end-users to incentivize a practical and efficient allocation of capacity.
- Application of these concepts to a real-life project to analyse how the grid tariff design can increase the value of flexibility when integrating EVs in urban areas.

## 3. Method

This section presents the developed modeling framework to investigate grid tariff optimization with local capacity trading. First, the optimization problems of the DSO and the end-users are presented. After that, the solution procedure for coupling the two levels is described in section 3.4. A nomenclature is included in section 3.1, which provides an overview of mathematical symbols and describes how the parameters and variables relate to each level in the overall model. In the formulation of the model, the following core assumptions are made:

- The DSO does not consider the tariff income when making decisions since it is purely motivated by lowering the total system costs.
- Cost recovery for the DSO is not considered since the focus is on using capacity-based and volumetric tariffs to activate implicit flexibility at the end-user level.
- The possibility of load curtailment is a part of the DSOs planning problem since we do not consider grid investments to avoid curtailment.

### 3.1. Model overview

An outline of the bilevel model is presented in Fig. 1. In this model, some decisions are made at the DSO level, while others occur at the neighbourhood level, and decision variables at one level are perceived as parameters for the other level. The DSO determines the tariff structure, and the tariff levels for the chosen structure are endogenous variables at the DSO level but exogenous parameters at the neighbourhood level. Also, the DSO can not directly control operational decisions at the end-user level but can incentivize a change in consumption patterns through the grid tariffs. The benefit of formally representing this bilevel structure is the ability to analyse the feedback effect between neighbourhood responses, indirect coordination of flexible assets, DSO strategy, and regulatory frameworks.

**Nomenclature**

| | |
|---|---|
| **Sets** | |
| $\omega \in [1, \ldots, \Omega]$ | Scenarios |
| $\psi \in [1, \ldots, \Psi]$ | Transmission segments |
| $c \in [1, \ldots, C]$ | End-users |
| $h \in [1, \ldots, H]$ | Hours |
| **Parameters** | |
| $C^G_\psi$ | Transmission segment capacity (kW) |
| $CF^{ch}_c$ | Energy storage capacity ratio for charging (kW/kWh) |
| $CF^{dis}_c$ | Energy storage capacity ratio for discharging (kW/kWh) |
| $D_{c,\omega,h}$ | Load profile (kWh/h) |
| $D^{\Delta-}_{c,\omega,h}$ | Outtake from storage (kWh/h) |
| $F$ | Capacity trading fee (€/kW/h) |
| $G_{c,\omega,h}$ | Energy resource availability (kW/kWp) |
| $L^G_\psi$ | Transmission losses (%) |
| $L^{ES}_c$ | Energy storage converter losses (%) |
| $M$ | Penalty factor (€/kWh) |
| $P_{\omega,h}$ | Power market price in hour h (€/kWh) |
| $R_c$ | Energy storage self-discharge (%/h) |
| $T$ | Excise tax (€/kWh) |
| $U^{ER}_c$ | Energy resource capacity (kW) |
| $U^{ES}_c$ | Energy storage capacity (kWh) |
| $VAT$ | Value added tax (%) |
| $VOLL$ | Value of lost load (€/kWh) |
| $W_\omega$ | Scenario weight (days) |
| **DSO-level variables** | |
| $a_M$, $a_S$ | Artificial variables for network tariff selection logic |
| $cnt^M_\omega$ | Measured peak network tariff (€/kW) |
| $cnt^S$ | Subscribed capacity network tariff (€/kW) |
| $d^{pen+}_{c,\omega,h}$, $d^{pen-}_{c,\omega,h}$ | Energy storage penalty terms (kWh/h) |
| $e^G_{\omega,h}$ | Neighbourhood load (kWh/h) |
| $ls_{\omega,h}$ | Load curtailment (kWh/h) |
| $lt_{\omega,h,\psi}$ | Transmission segment usage (%) |
| $n^{LIM}$ | Capacity trading limit (kWh/h) |
| $n^{pen+}_{\omega,h}$, $n^{pen-}_{\omega,h}$ | Capacity trading penalty terms (kWh/h) |
| $oc^S$ | Over-usage charge (kWh/h) |
| $vnt^E$ | Volumetric network tariff for exports (€/kWh) |
| $vnt^M$, $vnt^S$ | Volumetric network tariff for imports (€/kWh) |
| **Neighbourhood-level variables** | |
| $\lambda^N_{\omega,h}$ | Price for renting capacity (€/kWh/h) |
| $d^{\Delta+}_{c,\omega,h}$ | Energy storage charging (kWh/h) |
| $d^{\Delta-}_{c,\omega,h}$ | Energy storage discharge (kWh/h) |
| $_{c,\omega,h}$ | Energy exported to grid (kWh/h) |
| $g^{ER}_{c,\omega,h}$ | Energy generation (kWh/h) |
| $imp_{c,\omega,h}$ | Energy imported from grid (kWh/h) |
| $n^+_{c,\omega,h}$ | Renting of capacity (kWh/h) |
| $n^-_{c,\omega,h}$ | Provision of capacity (kWh/h) |
| $n^M_{c,\omega}$ | Measured peak capacity (kWh/h) |
| $n^S_c$ | Subscribed capacity (kWh/h) |
| $o_{c,\omega,h}$ | Energy usage above subscribed capacity (kWh/h) |
| $s_{c,\omega,h}$ | Energy storage charge level (kWh) |

### 3.2. DSO level

The DSO level describes the optimization problem of the DSO depicted in Fig. 1 in a regulatory context. In this problem, the neighbourhood level decisions regarding investments and operation are perceived as parameters outside the DSOs' direct control. However, the end-users decisions can be affected indirectly through the tariff design. Based on the neighbourhood-level responses, fixed load curtailment and tariff levels are optimized.

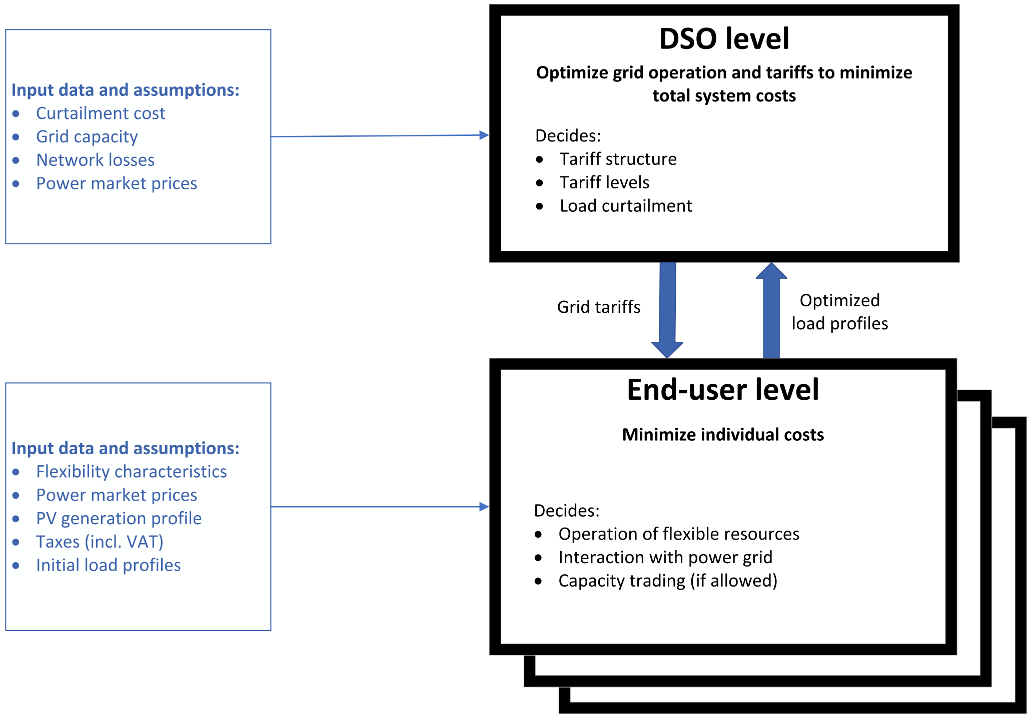



**Fig. 1.** Outline of the model structure.

### 3.3. Cost function of the DSO

The costs faced by the DSO for the considered operational period are depicted in (1). The first term in (1) quantifies costs related to losses through a piecewise linear loss function where the DSO needs to select segments ($lt_{\omega,h,\psi}$) with different losses ($L^G_\psi$). The intuition is that losses increase with the utilization of the capacity, which is further explained in section 3.2.3. The second term in (1) identifies load curtailment costs as a linear function of curtailed load ($ls_{\omega,h}$) and the value of lost load ($VOLL$). Potential sunk costs are not included in the cost function since these are not dependent on any of the decision variables in the optimization problem.

$$Cost_{DSO} = \sum_{\omega=1}^{\Omega}\sum_{h=1}^{H} W_\omega * \left(\sum_{\psi=1}^{\Psi} lt_{\omega,h,\psi} * L^G_\psi * P_{\omega,h} + ls_{\omega,h} * VOLL\right) \quad (1)$$

### 3.4. Electricity transmission

Given that some end-users might export to the power market while others import from it, the electricity flow to/from the neighbourhood is the absolute value of the aggregate net exchange with the power grid. To maintain the linear properties of the problem, the network flow is identified through (2a) and (2b). These constraints will correctly describe the aggregate load as long as power market prices are non-negative since excess electricity transmission is penalized when minimizing the cost function (1).

$$e^G_{\omega,h} \geq \sum_{c=1}^{C}(imp_{c,\omega,h} - exp_{c,\omega,h}) \quad \forall \omega, h \quad (2a)$$

$$e^G_{\omega,h} \geq \sum_{c=1}^{C}(exp_{c,\omega,h} - imp_{c,\omega,h}) \quad \forall \omega, h \quad (2b)$$

### 3.5. Losses and grid capacity

Network losses increase quadratic as the load increases, and (3a) - (3b) are formulated to represent piecewise linear losses. Losses incurred are a combination of losses in the different load segments $\psi$. Furthermore, according to (3a), the DSO needs to choose line segments with sufficient capacity, $C^G_\psi$, or incur curtailment ($ls_{\omega,h}$). Curtailment is a safety mechanism with higher costs than the cost of losses, and the DSO will usually exhaust all transmission segments before curtailing load. $lt_{\omega,h,\psi}$ is the fraction of usage for each transmission segment, and (3b) ensure that the sum of these fractions is equal to 1. Defining $lt_{\omega,h,\psi}$ as an SOS type 2 variable in the set $\Psi$, requires a combination of a maximum of two neighbouring capacity segments to be chosen.

$$\sum_{\psi=1}^{\Psi} lt_{\omega,h,\psi} * C^G_\psi + ls_{\omega,h} \geq e^G_{\omega,h} \quad \forall \omega, h \quad (3a)$$

$$\sum_{\psi=1}^{\Psi} lt_{\omega,h,\psi} = 1 \quad \forall \omega, h \quad (3b)$$

### 3.6. Grid tariff constraints

The DSO needs to choose between a measured peak and a subscribed capacity tariff structure and decide tariff levels for the implemented structure. The implementation of these tariffs at the end-user level is explained in section 3.3.1. The requirement that only one of the designs can be implemented is formulated according to (4a) - (4b). Artificial variables of SOS type 1, $a_M$, and $a_S$, couples the tariff designs and force the cost components of one design to be zero while the other can take any positive value. If the DSO wants to implement the measured peak tariff structure, it means that the variable $a_M$ takes a positive value. The SOS1 relation between $a_M$ and $a_S$ then requires that the subscribed capacity tariff's cost components need to be zero and vice versa.

$$cnt^M_\omega + vnt^M \le a_M \quad \forall\, \omega \tag{4a}$$

$$cnt^S + vnt^S + oc^S \le a_S \tag{4b}$$

All variables in the DSO problem, except the volumetric export tariff ($vnt^E$), are non-negative. The volumetric export tariff can be negative, meaning end-users save grid costs by exporting to the grid. The DSO will choose a negative export tariff if the export it incentivizes lowers the network losses, e.g., because local exports can go directly to other end-users. Constraint (5) is included to avoid situations where simultaneous import and export occur due to profit from energy looping.

$$vnt^M + vnt^S + vnt^E \ge 0 \tag{5}$$

### 3.7. Neighbourhood level

In this section, the problem of the individual end-user in the neighbourhood is described as an optimization problem. The end-user can be of different types: Inflexible load, flexible load, EV charging facility, owner of a power plant and storage, or a combination of these. The model formulation presented in this section allows all of these end-users to be represented through parameter specifications.

Since the optimization problems for the neighbourhood end-users are linear, their Karush-Kuhn-Tucker (KKT) conditions are sufficient for global optimality. Hence, to represent their best responses to changes in other end-users or DSO strategies, the problems for the end-users are represented through their KKT conditions, which are formulated as a mixed complementarity problem in A. We indicate dual variables associated with each of the constraints, which are used for the complementarity formulation of the problem.

### 3.8. Objective function of neighbourhood end-users

The objective of the neighbourhood end-users is to minimize their individual costs according to (6a). Details of the cost components are described in (6b) - (6e). These costs consist of energy purchase from the power market ($Cost^P_c$), electricity taxes and capacity trading fees ($Cost^T_c$), grid tariff costs ($Cost^G_c$), and capacity trading cost or income ($Cost^N_c$).

$$Cost_c = Cost^P_c + Cost^T_c + Cost^G_c + Cost^N_c \tag{6a}$$

$$Cost^P_c = \sum_{\omega=1}^{\Omega}\sum_{h=1}^{H} W_\omega * \Big((1+VAT)*imp_{c,\omega,h} - exp_{c,\omega,h}\Big)*P_{\omega,h} \tag{6b}$$

$$Cost^T_c = \sum_{\omega=1}^{\Omega}\sum_{h=1}^{H} W_\omega * \Big((1+VAT)*imp_{c,\omega,h}*T + n^+_{c,\omega,h}*F\Big) \tag{6c}$$

$$\begin{aligned} Cost^G_c = n^S_c*cnt^S + \sum_{\omega=1}^{\Omega} W_\omega*\Bigg(n^M_{c,\omega}*cnt^M_\omega + \sum_{h=1}^{H}\Big(imp_{c,\omega,h}*\Big(vnt^M \\ + vnt^S\Big) + exp_{c,\omega,h}*vnt^E + o_{c,\omega,h}*oc^S\Big)\Bigg) \end{aligned} \tag{6d}$$

$$Cost^N_c = \sum_{\omega=1}^{\Omega}\sum_{h=1}^{H} W_\omega*\lambda^N_{\omega,h}*\Big(n^+_{c,\omega,h} - n^-_{c,\omega,h}\Big) \tag{6e}$$

The grid costs in (6d) requires some elaboration. There is a regulatory decision to employ either the measured peak tariff or the subscribed capacity tariff structures at the DSO level. Note that it is not feasible to employ a combination of both tariff schemes. First, if a measured peak tariff is employed, the tariff components with superscript $S$ will be zero in (6d). Likewise, if a subscribed capacity tariff is employed, the tariff components with superscript $M$ will be zero in (6d). Hence, the grid tariff costs are reduced to the resulting tariff structure. The tariff consists of two components in the case of a measured peak tariff or three components in the case of a subscribed capacity tariff:

1. A volumetric fee per kWh ($vnt^M$ or $vnt^S$) for electricity consumption.
2. A capacity-based fee per kW ($cnt^M_\omega$ or $cnt^S$) for the contracted capacity.
3. An overcharge fee per kWh above the subscribed capacity ($oc^S$) in the case of a subscribed capacity tariff structure.

The model includes a trading mechanism between the end-users. Constraints (6e) describe the income or cost due to capacity trading. The term is calculated for all end-users based on the amount of capacity bought ($n^+_{c,\omega,h}$), sold ($n^-_{c,\omega,h}$), and the time-dependent price of capacity originating from the dual variable of the neighbourhood capacity market formulated in section 3.3.6 ($\lambda^N_{\omega,h}$).

### 3.9. Energy balance

The energy balance of the end-users is described by (7) and states that energy imports subtracted exports must be equal to initial demand modified by storage operation subtracted generation from PV at each end-user for every hour and scenario.

$$\begin{aligned} D_{c,\omega,h} + d^{\Delta+}_{c,\omega,h} - d^{\Delta-}_{c,\omega,h} - g^{ER}_{c,\omega,h} = imp_{c,\omega,h} \\ - exp_{c,\omega,h} \quad \forall\, c,\omega,h \quad \Big(\lambda^{EB}_{c,\omega,h}\Big) \end{aligned} \tag{7}$$

### 3.10. Energy storage

Energy storage makes it possible to shift energy load or generation temporally. This temporal load shifting is represented in (8a), which describes how the charge level depends on the storage level in the previous time step and the operation. Converter losses are imposed linearly through the parameter $L_c$, while self-discharge from one time-step to the next is imposed through the parameter $R_c$. Inventory constraints are computationally challenging since these link all time-steps together, and therefore the formulation includes slack terms ($d^{pen+}_{c,\omega,h}, d^{pen-}_{c,\omega,h}$) that are considered as parameters at the end-user level. These terms are zero in the obtained solution due to the penalty incurred in the objective function (13) but speed up the progress of the solver since they allow for the discovery of solutions that are close to satisfying the inventory constraints.

$$s_{c,\omega,h} = s_{c,\omega,h-1} * (1 - R_c) - D^{\Delta-}_{c,\omega,h} + d^{\Delta+}_{c,\omega,h} * \left(1 - L^{ES}_c\right) - d^{\Delta-}_{c,\omega,h} * \left(1 + L^{ES}_c\right) + d^{pen+}_{c,\omega,h} - d^{pen-}_{c,\omega,h} \quad \forall c, \omega, h > 1 \quad \left(\lambda^{ES1}_{c,\omega,h}\right) \tag{8a}$$

The formulation allows for representing various kinds of storage, including a bidirectional battery, unidirectional EV charging, and DHW heating. Outtake from the storage, for example related to EV driving or DHW usage, is represented by the parameter $D^{\Delta-}_{c,\omega,h}$. We specify boundary conditions for the storage charge level, as described in (8b). The boundary conditions mean that the charge level in the last time-step is round coupled to the first time step in each scenario. Thereby, we do not need to specify the initial charge level since the optimization model calculates it.

$$s_{c,\omega,1} = s_{c,\omega,H} * (1 - R_c) - D^{\Delta-}_{c,\omega,1} + d^{\Delta+}_{c,\omega,1} * \left(1 - L^{ES}_c\right) - d^{\Delta-}_{c,\omega,1} * \left(1 + L^{ES}_c\right) + d^{pen+}_{c,\omega,1} - d^{pen-}_{c,\omega,1} \quad \forall c, \omega \quad \left(\lambda^{ES1}_{c,\omega,1}\right) \tag{8b}$$

Furthermore, the amount of energy that can be stored, charged, and discharged by each end-user during each hour and scenario are limited according to the maximum capacity (9a) - (9c). In the case of unidirectional EV charging or DHW heating, the discharging factor is set to zero.

$$s_{c,\omega,h} \le U^{ES}_c \quad \forall c, \omega, h \quad (\mu^{ES2}_{c,\omega,h}) \tag{9a}$$

$$d^{\Delta+}_{c,\omega,h} \le U^{ES}_c * CF^{ch}_c \quad \forall c, \omega, h \quad (\mu^{ES3}_{c,\omega,h}) \tag{9b}$$

$$d^{\Delta-}_{c,\omega,h} \le U^{ES}_c * CF^{dis}_c \quad \forall c, \omega, h \quad (\mu^{ES4}_{c,\omega,h}) \tag{9c}$$

### 3.11. Energy resources

Energy output from distributed energy resources, $g^{ER}_{c,h}$, is described by (10) and has the option of generation curtailment by generating less than the hourly resource availability. The maximum output is the resource availability in each time-step multiplied with the installed capacity, where the resource availability is specified according to, e.g., wind or solar conditions.

$$g^{ER}_{c,\omega,h} \le U^{ER}_c * G_{c,\omega,h} \quad \forall c, \omega, h \quad (\mu^{ER}_{c,\omega,h}) \tag{10}$$

### 3.12. Tariff-related constraints

The model allows for one of two different tariff designs, namely measured peak power and subscribed capacity, billable depending on different cost components.

Measured peak power at each end-user is equal to the maximum power withdrawn from the wholesale power market and is identified through constraint (11a) where at least 1 h will be binding for each end-user and scenario in the optimal solution.

$$imp_{c,\omega,h} \le n^M_{c,\omega} + n^+_{c,\omega,h} - n^-_{c,\omega,h} \quad \forall c, \omega, h \quad \left(\mu^M_{c,\omega,h}\right) \tag{11a}$$

With a subscribed tariff, every end-user's optimal subscribed capacity level needs to be determined, and consumption beyond this limit in any hour or scenario will be billed at a higher volumetric tariff rate than consumption below the subscription. This is ensured by constraint (11b) where the grid import cannot exceed the end-user's subscription level and over-usage.

$$imp_{c,\omega,h} \le n^S_c + o_{c,\omega,h} + n^+_{c,\omega,h} - n^-_{c,\omega,h} \quad \forall c, \omega, h \quad \left(\mu^S_{c,\omega,h}\right) \tag{11b}$$

The model allows for trading of grid capacity among the end-users through presence of the variables $n^+_{c,\omega,h}$ and $n^-_{c,\omega,h}$ in (11a) and (11b). Trading removes or adds capacity to the limit and therefore provides an additional mechanism to contract capacity. However, the rented capacity needs to origin from other end-users as described in section 3.3.6. The trading can be limited through the upper-level variable $n^{LIM}$ according to (11c). When trading of capacity is not allowed, $n^{LIM}$ is set to zero.

$$n^+_{c,\omega,h} + n^-_{c,\omega,h} \le n^{LIM} \quad \forall c, \omega, h \quad (\mu^N_{c,\omega,h}) \tag{11c}$$

Depending on the tariff design, either constraint (11a) or (11b) will be binding for at least 1 h for all end-users and scenarios and thus incur end-user grid costs through the tariff components in the objective function. This is because the tariff design that is not implemented will have zero costs in all end-users objective functions according to (4a) - (4b) in the DSO level. For example, if a subscribed capacity-based tariff is chosen, $cnt^M_\omega$ will be zero in (6d), and thus $n^M_{c,\omega}$ can take any feasible value in the optimal solution because it does not affect the objective function of the end-user. Hence, due to zero costs for the tariff that is not implemented, only one of constraints (11a) or (11b) will have a positive dual value for at least 1 h per end-user and scenario. The decision-making related to the tariff design is further elaborated in the DSO problem formulation in Section 3.2.

### 3.13. Capacity trading mechanism

Since we assume that grid congestion occurs on the neighbourhood level rather than at each individual end-user, (12) specifies the capacity trading between the neighbourhood end-users. The capacity market is cleared for every time step, and the dual variable of the local capacity market becomes the short-term marginal cost of capacity considered by the end-users.

$$\sum_{c=1}^{C} \left(n^+_{c,\omega,h} - n^-_{c,\omega,h}\right) + n^{pen+}_{\omega,h} - n^{pen-}_{\omega,h} = 0 \quad \forall \omega, h \quad \left(\lambda^N_{\omega,h}\right) \tag{12}$$

Note that this is the equilibrium condition in the neighbourhood, ensuring that demand and supply for the capacity match for each time step. The dual value of this constraint becomes the hourly uniform price for renting or providing capacity in the end-user objective function. The capacity trading couples all end-user problems together and makes the overall problem difficult to solve since all end-user KKT conditions need to be solved simultaneously. Therefore, slack terms ($n^{pen+}_{\omega,h}, n^{pen-}_{\omega,h}$) are included. The slack terms are zero in the final solution due to the penalization in the objective. Similar to the storage level slack terms, these improve the computational performance by allowing intermediate solutions that are close to satisfying the equilibrium condition.

### 3.14. Solution approaches

The overall optimization occurs at the DSO level, and we assume that the DSO is interested in minimizing total system costs. As depicted in Table 1, two main formulations are used: (1) system optimization and (2) bilevel model.

The objective function for the system is formulated in (13). This objective includes costs at the DSO and end-user level in addition to penalty terms for violating the energy storage and market balances. The penalty terms are included since this was found to enable a more efficient search for candidate solutions in the MILP tree. Thus, the penalty factor ($M$) needs to be sufficiently high to ensure solutions without positive penalty terms. For the analyses in this paper, a penalty term of $M = 10$ was found to be sufficient.

$$\begin{aligned} Cost = Cost_{DSO} + \sum_{c=1}^{C}\left(Cost_c^P + Cost_c^T\right) + M^* \sum_{\omega=1}^{\Omega}\sum_{h=1}^{H} \\ W_\omega{}^*\left(\sum_{c=1}^{C}\left(d_{c,\omega,h}^{pen+} + d_{c,\omega,h}^{pen-}\right) + n_{\omega,h}^{pen+} + n_{\omega,h}^{pen-}\right) \end{aligned} \tag{13}$$

The system optimization assumes centralized and direct control of all resources at the end-user level and serves as a benchmark. In this formulation, we relax the requirement of noncooperative behaviour and optimize the system as a whole. Therefore, all technical constraints are included, but the end-user optimality conditions are excluded from the problem. Since we include the DSOs costs directly, there is no interaction through grid tariffs in the system optimization model. The optimization considers all costs at both the DSO and end-user level and finds the optimal operation of all assets; thus, grid tariffs are not used. In contrast to system optimization, the bilevel model captures the aspect of decentralized control of flexible assets and seeks to design the optimal incentives. Hence, the optimality conditions are included since the DSO needs to consider the best response by the end-users when designing the policy instead of only respecting technical constraints. End-user responses are implemented by linearizing the KKT-conditions using SOS1 variables according to the methodology proposed by [33].

## 4. Case study setup and input data

### 4.1. The Røverkollen housing cooperative

In 2017, the Oslo municipality decided to reduce its greenhouse gas (GHG) emissions by 95% within 2030 compared to the 2009-level. Currently, about 50% of Oslo's GHG emissions are caused by transportation, and hence modular changes of personal transport (from car to bus, bike, or walking), as well as electrification, are seen as one of the main strategies to reach the city's climate target [1]. In Oslo, about 70% of inhabitants live in apartments with limited access to charging points at home. Studies have shown that limited charging possibilities are a significant barrier for individuals to shift from fossil to electric cars (see, e.g., Ref. [34]. Therefore, the Oslo municipality grants investment support for charging points connected to housing cooperatives. This paper has chosen the Røverkollen housing cooperative as a case study, which is the main pilot in the EU-project GreenCharge. Røverkollen has 246 apartments and is situated north-east of Oslo. Each apartment has access to their personal parking space in a 4-story garage. Currently, 26 charging points are actively in use, but the garage grid connection should handle the complete electrification of all 230 vehicles.

The case study is a neighbourhood of six apartment blocks and a garage with EVs and a PV system. The blocks have a shared supply of DHW heated by air-sourced heat pumps (ASHP) coupled with electric boilers. The apartments at Røverkollen are heated by electric radiators, creating a prominent peak of the neighbourhood's aggregate electricity load during winter. The garage has four floors, and each floor has an entrance with electric heating cables in the ground to prevent icing for safety reasons.

### 4.2. System setup

In our case study, we have defined three end-user types (described in section 4.4) and one DSO (described in section 4.3) as depicted in Fig. 2. In addition to the stakeholders involved, the figure also shows the two different decision-making assumptions that are investigated: a) the centralized optimization treating all stakeholders as one joint agent acting to the best for the total system, and b) the bilevel game with four stakeholders, one upper and three lower, optimized individually based on their self-interest. Note that the bilevel model in Fig. 2b has additional system boundaries compared to the centralized optimization in Fig. 2a since each stakeholder optimizes individually.

The input data is gathered from the Røverkollen housing cooperative (see section 4.1) and the local DSO, Elvia. In the following, the properties of the input data will be described. Based on the properties of the available data, we employ an hourly time-step ($H = 24$).

### 4.3. DSO and overall system

Table 2 presents the parameters related to prices, taxes, and existing infrastructure. The power market price is assumed to be constant because we want to isolate the temporal variations to the end-users load profiles.

The DSO faces costs related to network losses and load curtailment costs. Based on the load profiles, we specify a maximum capacity of 1300 kW, sufficient to cover the historical peak load but not enough for large amounts of uncoordinated EV charging coinciding with the peak load. The specification of the maximum capacity is a critical assumption for this paper since we aim to investigate how we can create incentives that allow for EV charging without significantly increasing the peak load. We represent the electric losses as a quadratic function of load, and we assume that an average loss of 6%[2] occurs when the load is at half the capacity. The losses are represented by a piecewise linear formulation as described in section 3 by using four segments, each with a capacity of 325 kW, as presented in Fig. 3.

### 4.4. End-users

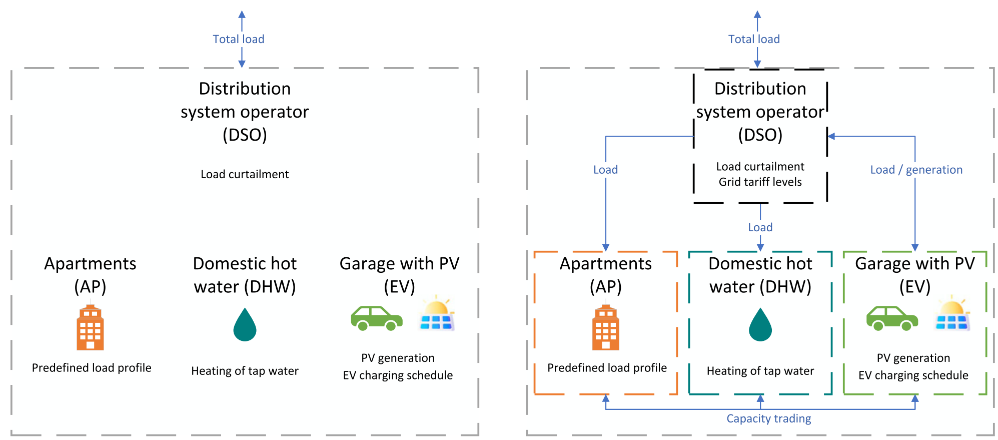
Table 3 presents the technology parameters for each stakeholder in the considered system. In addition, there are three sources of temporally variable data:

[1] www.oslo.kommune.no/politics-and-administration/green-oslo/best-practices/oslo-s-climate-strategy-and-climate-budget/[Accessed: 2020-12-04].

[2] data.worldbank.org/indicator/EG.ELC.LOSS.ZS?locations = NO[Accessed: 2020-12-10].

**Table 1**
Solution approaches.

| | System optimization | Bilevel model |
|---|---|---|
| Problem type | MILP | MPEC reformulated as MILP |
| Solver | CPLEX | CPLEX |
| DSO cost representation | Directly | Grid tariffs |
| Decision-making structure | Centralized | Decentralized |
| Objective | Minimize (13) | Minimize (13) |
| Constraints at the DSO level | (2a) - (3b) | (2a) - (5) |
| Constraints at the end-user level | (7)–(10) | (A.1) - (A.23) |




(a) Centralized optimization. All operational decisions are controlled directly by the DSO.

(b) Bilevel game where decisions are made based on the stakeholders own self-interests.

**Fig. 2.** System boundaries for the different modeling approaches.

1. Load profiles
2. Outtake from storage
3. PV generation

The load profiles are gathered from the central electricity metering data hub in Norway, Elhub[3]. The following subsections describe how the properties of each end-user have been specified.

## 4.5. *Apartments (AP)*

The load of the apartments consists of electricity use for lighting, electric appliances, and space heating demand. Hot tap water is provided through a shared system and is not included in the apartments' load profile. Although space heating, in theory, could be controlled flexibly, suitable equipment for flexible load activation is currently not present. It can be argued that the apartments may have implicit flexibility due to a potential behaviour change, but such effects are outside the scope of this paper. Therefore, the only decisions relevant for this end-user is renting/provision of grid capacity. Hence, the apartments are represented as an inflexible load based on aggregated load data provided by the DSO.

## 4.6. *Garage (EV)*

The garage's load consists of electricity use for lighting, heating cables, and charging of EVs. We assume the EV charging to be flexible and the rest of the load as inflexible.

To identify the fixed load related to lights and snow melting, this data was obtained from the period before the PV system and EV charging in the garage was introduced. Also, the garage has a flexible load related to EV charging, but there were no temporal load profile data of EVs being charged inside the garage available at the time of this work. Therefore the aggregate EV load from 4 semi-fast EV chargers situated outside the garage was used as a proxy. Furthermore, this EV load profile was scaled to reflect the current 26 EVs currently being charged inside the garage, assuming a driving distance of 14000 km per year. Based on information of the actual cars, the average storage capacity of the EVs' batteries is assumed to be 30 kWh per car, and for simplicity, we assume that 25% of the capacity is available for smart charging at any time.

**Table 2**
Input data related to the overall system.

| Parameter | Symbol | **Value** |
|---|---|---|
| Maximum network capacity | $C^G_\Psi$ | 1300 kW |
| Network segment capacities | $C^G_\psi$ | See Fig. 3 |
| Network segment losses | $L^G_\psi$ | See Fig. 3 |
| Consumption excise tax | $T$ | 1.713 ¢/kWh |
| Local capacity trading fee | $F$ | 1 ¢/kW/h |
| Power market price | $P_{\omega,h}$ | 5 ¢/kWh |
| Value of lost load | $VOLL$ | 2 €/kWh |
| Value-added tax | $VAT$ | 25% |

The garage also has a PV system of 70 kW. Since the PV system did not yet have metering data available at the time of this work, PV data was simulated using renewables.ninja[4] [35] for the location of the Røverkollen housing cooperative using properties of the existing system with 50% east/50% west orientation and 10° tilt.

[3] https://elhub.no/.

[4] https://www.renewables.ninja/.

**Table 3**
Input data related to each stakeholder in the local system.

| Parameter | Symbol | AP | EV | DHW |
|---|---|---|---|---|
| Charging converter losses [%] | $L_c^{ES}$ | – | 5 | 0 |
| Charging ratio [kW/kWh] | $CF_c^{ch}$ | – | 0.467 | 0.50 |
| Discharging ratio [kW/kWh] | $CF_c^{dis}$ | – | 0 | 0 |
| Energy storage self-discharge [%/h] | $R_c$ | – | 0.1 | 1 |
| Energy resource capacity [kW] | $U_c^{ER}$ | 0 | 70 | 0 |
| Energy storage capacity [kWh] | $U_c^{ES}$ | 0 | 195 | 406 |

### 4.7. Domestic hot water (DHW)

The DHW load reflects electricity use for heating of domestic hot water in a shared facility that provides hot tap water from a central unit to each apartment. Also, some electricity is used to light the staircases inside the apartment blocks and electric heating cables to avoid ice on the walkways between the blocks. The DHW end-user does not have any generation resources.

Parts of the load related to tap water heating have been characterized as flexible since the hot water tanks allow for some temperature deviation without negatively affecting the users. Based on an assumed $\Delta T$ of 30 °C, the total volume of the tanks, and the heat capacity of water, the tanks' energy storage capacity is estimated to 406 kWh. The charging ratio was calculated by assuming the charging capacity to be equal to the peak load and dividing this by the storage capacity.

### 4.8. Identifying the critical day

We identify the critical day as the day containing the highest total load in the system based on an entire year. In general, the peak load for residential buildings in Norway occurs during the winter due to significant heating needs covered through electricity. In our dataset, the critical day was found to be on the 31st of January. In the following, the critical day load profiles are used as a basis for the analyses in this paper and are provided in Fig. 4.

### 4.9. Cases

Based on the presented input data, five different cases are analysed:

1. **Case FIX:** No activation of flexibility, decisions are fixed to the underlying input data.
2. **Case SO:** All decisions are controlled directly by the DSO to minimize the system's total costs.
3. **Case MP:** Neighbourhood-level decisions are decentralized while the DSO decides a measured peak tariff for indirect load control.
4. **Case SC:** Neighbourhood-level decisions are decentralized while the DSO decides a subscribed capacity tariff for indirect load control.
5. **Case MPT:** Like case MP, but also includes a capacity trading mechanism between the end-users.

Here, SO is calculated using the system optimization setup outlined in Fig. 2a, while MP, SC, and MPT are calculated using the bilevel approach outlined in Fig. 2b. FIX yields the same result regardless of the setup since all operational decisions are fixed.

In the MP and SC cases, the only information exchange between the stakeholders is the grid tariffs imposed on the end-users by the DSO. In case MPT, there is also an interaction between the end-users since a capacity market with a uniform price is established

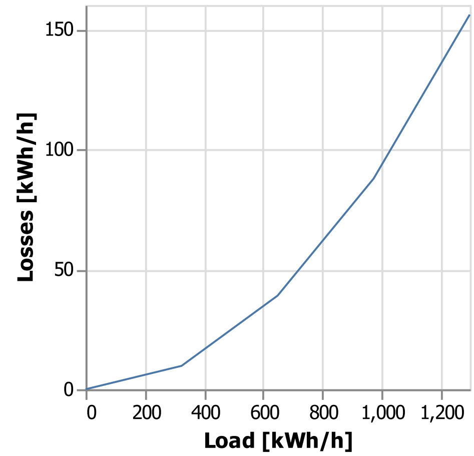



**Fig. 3.** Network losses ($L_\Psi^G$) as a function of the aggregate load ($C_\Psi^G$).

where each end-user decides how much capacity it wants to procure from or sell to the market at each time step. This implementation differs from a peer-to-peer market since each end-user interacts with the local pool rather than directly with other end-users, but it is similar at a conceptual level. The information required to clear this market is bids with capacity and prices from the participants for each time step. Since it is not realistic that end-users will engage directly in such a market, this trading process can be handled by optimization software on behalf of the end-users or through an aggregator.

## 5. Results and discussion

### 5.1. Current situation

We start by solving the model based on the historical data for the critical day as described in section 4, with the load profiles as described in Fig. 4a where the amount of EV charging is relatively modest (26 vehicles). In these initial analyses, the total costs do not vary between different tariff structures because the peak load is always lower than the grid's capacity and the DSO is unable to shift load from peak load periods to when the total load is lower.

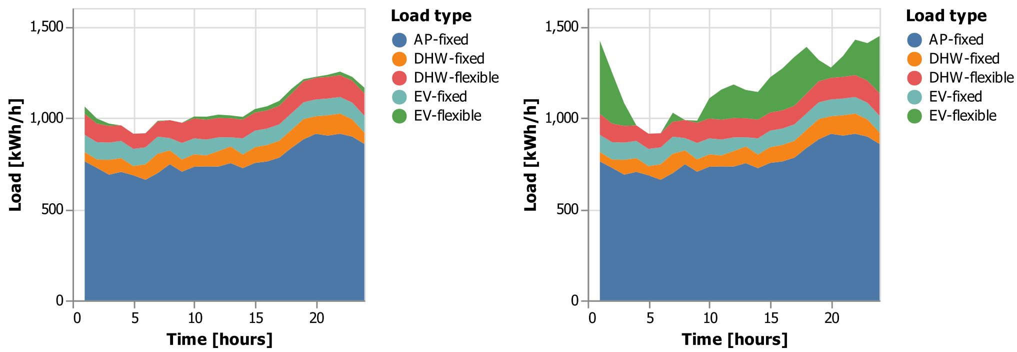
When tariffs are implemented instead of the direct control of decentralized assets, the DSO prefers to either employ zero tariffs in the case of the measured peak tariffs or a very low capacity-based tariff in the case of a subscribed capacity tariff.[5] This DSO choice indicates that, when there is no risk of curtailment, the DSO cannot improve the system operation by employing a measured peak tariff and only marginally improves the system's operation when a subscribed capacity tariff is employed.

Compared to the overall costs, the losses only contribute to a small amount, and therefore the difference is small when the total load is not close to the capacity of the grid connection ($C_\Psi^G$). However, this paper's primary motivation is to assess how various tariff schemes can handle increased EV load in the system, which we explore next.

### 5.2. Electrification of vehicles

In Norway, it is expected that within 2030 most cars will be

[5] We investigate the outcome for each of the tariff designs by exogenously specifying $a_S = 0$ to study a measured peak tariff or $a_M = 0$ to study a subscribed capacity tariff.




(a) Current load profiles of the housing cooperative, with electrification of 26 EVs.

(b) Load profiles with full electrification of vehicles, EV charging is scaled up by a factor of 10.

**Fig. 4.** Load profiles for the critical day. The end-users DHW and EV are separated in two load types to represent fixed and flexible load.

electrified. To assess this situation for the Røverkollen housing cooperative, the EV load is scaled up by a factor of 10, representing complete electrification of all vehicles in the garage as presented in Fig. 4b.

### 5.3. Cost distribution and value of flexibility

Key results on costs, load curtailment, and tariff levels are reported in Table 4. Net costs are calculated according to (6a) for the end-users, and (1) for the DSO. The cases FIX and SO represent a worst and best case, respectively, since FIX represents the case without flexibility activation while SO represents the case with optimal activation of flexible assets from a system optimization perspective. Therefore, the value of flexibility is calculated based on the cost difference to the case without any activation of flexibility (FIX). Regardless of the decision-making structure, we see that flexibility is useful for reducing the total costs and that the obtained value of flexibility is dependent on the tariff structure. The SO solution provides an upper bound for the value of flexibility since all flexible resources are controlled directly to minimize the total system costs. Without centralized control, we see from Table 4 that it is beneficial to introduce a local trading mechanism (MPT) as this gives a significantly higher value of flexibility than the pure individual tariffs (SC and MP).

The SO case demonstrates that load curtailment is avoidable under centralized control. The main reason for the higher cost in MP and SC is that although load curtailment is reduced compared to FIX, the incentive structures fail to avoid it altogether. Case MPT demonstrates that it is possible to completely avoid the load curtailment and achieve total costs close to the system optimal solution also under decentralized control. In the next section, we explain further how load profiles are affected by the various decision-making assumptions and regulatory frameworks.

### 5.4. Load profiles and flexibility potential

The total load and load profiles for the different stakeholders are presented in Fig. 5. The aggregate load is plotted in Fig. 5a, which reveals that although all cases have the same underlying load profiles, the optimized load profiles are different for the different cases. The only stakeholder with a constant load pattern is the apartment load in Fig. 5b, which is unchanged because it does not have any flexibility. Hence, it cannot adapt the load pattern to changing regulatory frameworks. Fig. 5c and d plots the optimized load profiles for the garage and the water heating, and since these stakeholders have flexible assets, the optimized load profiles changes depending on the regulatory framework. A key observation is that the MP and SC tariff structures mainly reduces individual peak loads, while the coincident peak load is reduced by lowering the garage load when the apartment load is high for the MPT tariff structure, which is more in line with the optimal operation represented by the SO case.

The maximum capacity of the connection is 1300 kW, which is exceeded when there is no flexibility activation with 679 kWh of curtailment in case FIX. Furthermore, the tariff structures in cases MP and SC reduce the curtailment to 130 kWh (−81%) by incentivizing a flattening of the flexible end-users' load profiles. It is technically possible to avoid curtailment entirely as, presented in SO, where centralized control is assumed. Furthermore, when the assumption of centralized control is removed, and capacity trading among end-users is allowed in the MPT case, curtailment is avoided also under decentralized control. The coordination between stakeholders in case MPT highlights the fundamental impact of introducing capacity trading: Rather than incentivizing all end-users to flatten their load, it is more efficient to create an incentive that induces those with the flexibility to support a flattening of the aggregate load.

### 5.5. Capacity trade and flexibility operation

The effect of a capacity trading scheme can be observed in Fig. 6, which presents the capacity trading between the end-users and compares the storage operation for the measured peak tariff with and without capacity trading for the MPT and MP cases, respectively. Fig. 6a illustrates that there is no capacity trading for most of the hours since the potential benefit does not justify paying the trading fee. However, during the evening, there is a scarcity situation that induces the AP end-user to procure capacity, mainly from the EV end-user. Thus, it can be observed that when the overall grid capacity is scarce, the trading mechanism can allocate the available capacity to where it is needed by providing an incentive for the flexible stakeholders to adapt their storage operation.

Even though capacity trading only occurs when there is a scarcity situation, the trading mechanism between the end-users induces a change in the operational patterns for the entire day. Fig. 6b compares the EV and DHW end-users storage operation for the MP and MPT cases, and it is evident that the capacity market has a significant impact on the filling of the storage. For the EV end-user, we see that the storage filling is higher in the MPT case until the AP end-user procures capacity, which is done to prepare the storage in anticipation of the load reduction needed in the evening.

The DHW storage operation also changes when the capacity trading is available, but not to relieve grid stress. In fact, the DHW load increases during the evening peak of the aggregate load, and this occurs because the EV end-user has enough flexibility to even out the total grid load. Furthermore, since the self-discharge is high

**Table 4**
Overview of key results.

| Case | FIX | SO | MP | SC | MPT |
|---|---|---|---|---|---|
| Decision-making structure | – | Fig. 2a | Fig. 2b | Fig. 2b | Fig. 2b |
| Total costs [€] | 3957 | 2609 | 2871 | 2871 | 2613 |
| Net costs AP [€] | 1554 | 1554 | 1784 | 1765 | 1625 |
| Net costs EV [€] | 479 | 480 | 541 | 541 | 499 |
| Net costs DHW [€] | 374 | 374 | 424 | 424 | 390 |
| Net costs DSO1 [€] | 1550 | 201 | 122 | 141 | 98 |
| Value of flexibility [€] | 0 | 1348 | 1086 | 1086 | 1344 |
| Load curtailment [kWh] | 679 | 0 | 130 | 130 | 0 |
| Volumetric tariff [¢/kWh] | – | – | 0 | 0 | 0 |
| Capacity-based tariff [€/kW] | – | – | 0.2522 | 0.2522 | 0.0794 |
| Over-usage charge [¢/kW] | – | – | – | 2.1822 | – |
| Export tariff [¢/kW] | – | – | 0 | 0 | 0 |

[1] Positive net DSO costs are not covered through the capacity-based and volumetric tariffs. These costs can be collected through e.g., a fixed tariff component, but this consideration is outside the scope of this paper.

at the DHW end-user relative to the EV end-user, DHW tries to avoid preheating more water than necessary. These observations show that flexibility dispatch, in this case by EV, has effects beyond reducing peak load; it also allows DHW to reduce its operational costs.

### 5.6. Practical implications

The game-theoretic aspects considered represent a significant computational complexity. Therefore, it was necessary to limit the temporal horizon and focus the analyses on one day to demonstrate how tariffs can relieve grid congestion and provide a more efficient allocation of resources. Also, the flexibility potential is characterized by using a simplified formulation due to a lack of more detailed data and the need to limit the computational complexity. Our results might overestimate the value of flexibility since more details in the modeling of flexibility might introduce additional operational constraints not captured by our model. However, we have tried to limit the flexibility potential by assuming that only 25% of the EVs are controllable at any time, and it is possible that we underestimate the share of controllable EVs and that our results underestimate the flexibility potential. Despite this limitation, our model provides a general formulation of flexibility that can be used to assess the efficiency of different pricing mechanisms in a comparative way.

Our analyses conceptually demonstrate the efficiency of a capacity-based tariff in relieving grid congestion when trading of capacity is allowed between the end-users. In practical applications, the peak measurement period may be longer than one day, e.g., one month. Nevertheless, if the end-users are interested in lowering their measured peak for a period different than one day, the incentive structure remains the same. The capacity trading can both reduce the occurrence of unnecessary load shifting and lower the peak load for the aggregate system depending on the situation in the grid:

- Low-load periods: If the network capacity is not challenged, end-users will have an unused capacity that can be rented out without any inconvenience. Thus, this capacity can be rented at low or zero costs and removes unnecessary behaviour changes if some end-users prefer high usage of capacity during such periods.
- High-load periods: If the network capacity is challenged, most or all end-users will fully utilize their capacity either due to their underlying load or due to renting out to other end-users. Hence, rental of capacity will be costly, and the capacity will be allocated to those with the highest willingness to pay.

Based on this, a capacity-based tariff with trading of capacity among end-users provides efficient incentives for flexibility operation regardless of the measuring period for the tariff. The challenges facing the Røverkollen housing cooperative are representative of a general trend, and to avoid sub-optimal solutions on the neighbourhood scale, a mechanism to incentivize resource coordination is needed in a multi-stakeholder system. In principle, a similar outcome can be achieved by centralized control and an allocation scheme for the obtained savings, but such a setup is not compatible with the current market structure in Norway.

The case-specific properties that drive our results are network capacity, underlying load profiles, and the technologies present in the system. However, our implemented tariff designs are generic fees per unit of energy usage (kWh) and per unit of capacity (kW) and could therefore be tested on different cases. In this work, we assumed the tariff components to be fully adjustable, but some countries may have regulations regarding the level of tariff components.

Introducing capacity trading in addition to a capacity-based grid tariff is beneficial for both grid companies and end-users. First, grid companies can reduce their costs by introducing capacity trading since the coincident peak load is reduced, and the daily operation becomes more efficient. The peak load reduction is the most crucial aspect in this regard since grid infrastructure upgrades can be reduced or postponed. Secondly, the end-users will also save costs since they ultimately need to bear the grid costs. On the end-user level, the capacity trading mechanism can be beneficial for inflexible end-users since they can reduce their costs by procuring capacity from flexible end-users, while flexible end-users can create an income stream by adapting their load patterns.

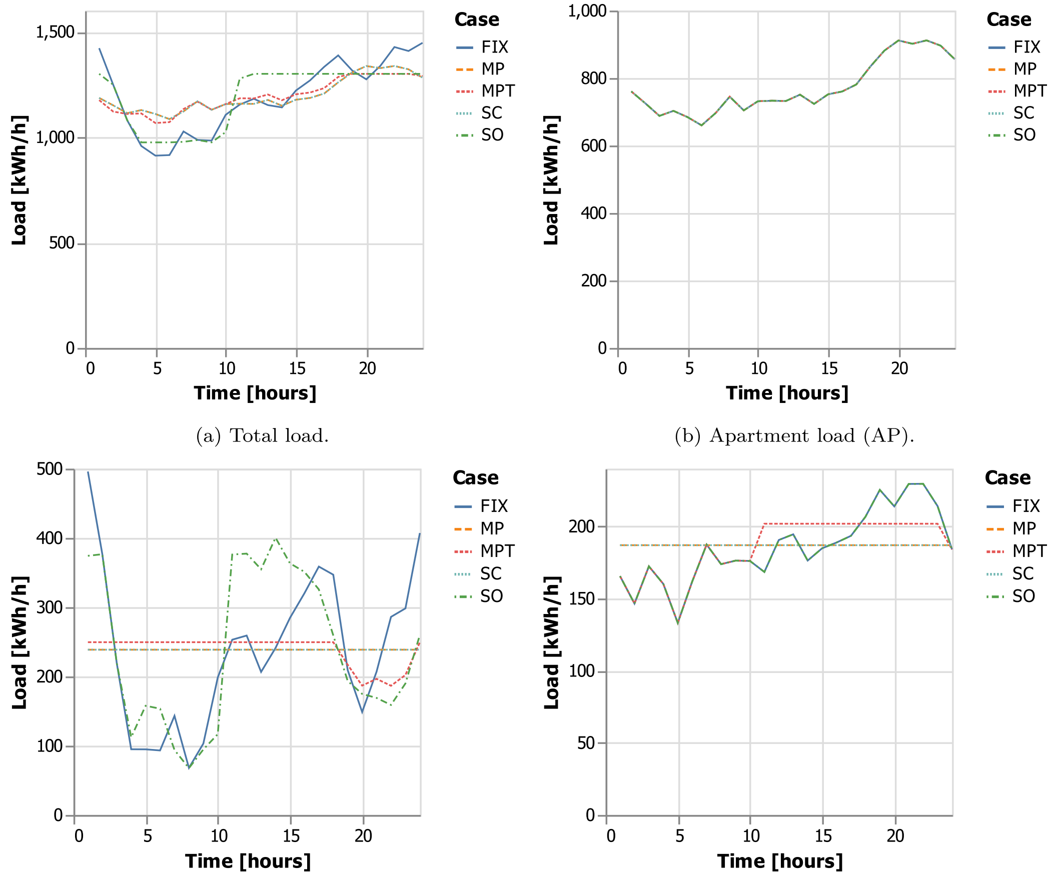
## 6. Conclusion

This paper investigates prospective tariff schemes, including capacity trading between end-users in a game-theoretical modeling framework. The model is applied to a real-life project with different stakeholders involved to investigate how we can design a regulatory framework that facilitates an increasing amount of EV charging in the system by efficiently exploiting the flexibility potential. Different regulatory frameworks are compared to extract information regarding how tariff schemes can enable a favorable outcome for the system compatible with the individual stakeholders' self-interest.

Integration of EVs in multi-stakeholder electricity systems necessitates a smarter design of the pricing mechanisms because the need for grid capacity is based on the coincident peak load rather than individual peak loads. Based on this study, we conclude that a combination of capacity-based grid tariffs and a capacity trading mechanism within the tariff structure is a feasible solution to increase the EV hosting capacity. The main advantage of adding a capacity-trading mechanism between end-users is the ability to efficiently incentivize temporal load shifts to allocate the capacity to where it is most needed.

It is vital to consider the applicability of pricing mechanisms, and in this regard, capacity trading can be implemented as a part of capacity-based grid tariffs. The mechanisms proposed in this paper are compatible with the current market structures in many countries if the regulatory framework is adapted according to the following two steps:

- **Step 1:** A grid tariff structure where the peak load significantly affects the cost of using the grid.
- **Step 2:** Possibilities for trading flexibility across different end-users as a tool to adjust the individual peak load.



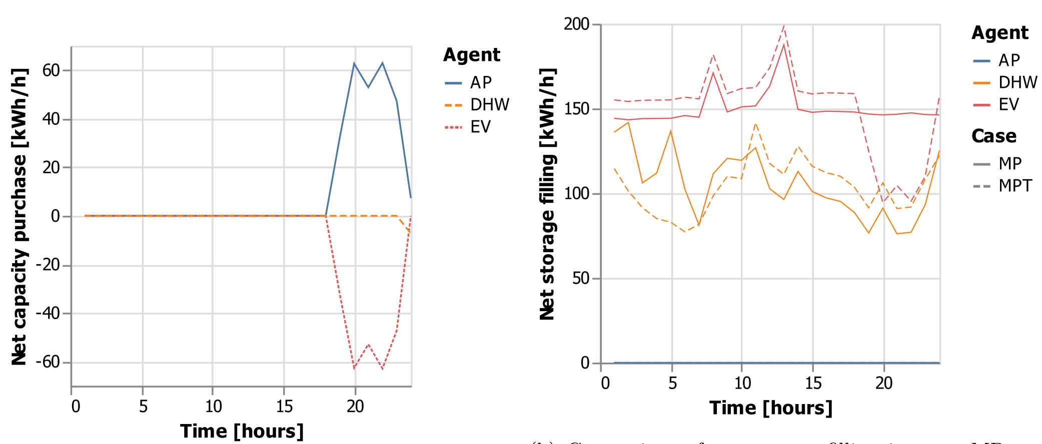

(a) Total load.

(b) Apartment load (AP).

(c) Garage load (EV).

(d) Domestic hot water load (DHW).

**Fig. 5.** Load profiles for the different cases when EV load is increased. Note that some of the plots are coinciding.




(a) Net capacity purchase positions for the MPT case.

(b) Comparison of net storage filling in cases MP and MPT.

**Fig. 6.** Capacity interaction between end-users and storage filling operation.

Although the regulators in many countries currently adapt the regulations according to step 1, we conclude that step 2 is also required to reap the full potential of end-user flexibility. Trading of flexibility can take many forms, and an important area for further research is how trading schemes can be implemented in practice to benefit both grid companies and end-users. In this context, the end-users motivation and behaviour are vital aspects to consider in future research, and the concepts presented in this paper can be tested in neighbourhood-scale systems. Also, future research could go in the direction of investigating the end-user willingness to participate in trading schemes and the possibility of flexible stakeholders exercising market power in local electricity systems.

## 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.

## Acknowledgement

This paper has been written within the Research Centre on Zero Emission Neighbourhoods in Smart Cities (FME ZEN) and in collaboration with the project GreenCharge. The authors gratefully acknowledge the support from the ZEN partners and the Research Council of Norway. Furthermore, the authors of this paper, on behalf of the GreenCharge consortium, acknowledge the European Union and the Horizon 2020 Research and Innovation Framework Programme for funding the project (grant agreement no 769016). The authors would like to thank the project partners Røverkollen Housing Cooperative, Elvia, and eSmart systems.

## Appendix A

*MCP formulation of local energy system*

We derive the KKT conditions of the neighbourhood level based on the optimization problem described in section 3.3. Since our original problem is linear and has a convex feasible area, the KKT conditions are necessary and sufficient for optimality.

$$W_\omega * (1+VAT) * (P_{\omega,h}+T) + W_\omega * \left(vnt^M + vnt^S\right) - \lambda^{EB}_{c,\omega,h} + \mu^M_{c,\omega,h} + \mu^S_{c,\omega,h} \geq 0 \perp imp_{c,\omega,h} \geq 0 \quad \forall c,\omega,h \tag{A.1}$$

$$W_\omega * \left(-P_{\omega,h} + vnt^E\right) + \lambda^{EB}_{c,\omega,h} \geq 0 \perp exp_{c,\omega,h} \geq 0 \quad \forall c,\omega,h \tag{A.2}$$

$$W_\omega * \left(F + \lambda^N_{\omega,h}\right) - \mu^M_{c,\omega,h} - \mu^S_{c,\omega,h} + \mu^N_{c,\omega,h} \geq 0 \perp n^+_{c,\omega,h} \geq 0 \quad \forall c,\omega,h \tag{A.3}$$

$$W_\omega * \left(-\lambda^N_{\omega,h}\right) + \mu^M_{c,\omega,h} + \mu^S_{c,\omega,h} + \mu^N_{c,\omega,h} \geq 0 \perp n^-_{c,\omega,h} \geq 0 \quad \forall c,\omega,h \tag{A.4}$$

$$W_\omega * oc^S - \mu^S_{c,\omega,h} \geq 0 \perp o_{c,\omega,h} \geq 0 \quad \forall c,\omega,h \tag{A.5}$$

$$W_\omega * cnt^M_\omega - \sum_{h=1}^{H} \mu^M_{c,\omega,h} \geq 0 \perp n^M_{c,\omega} \geq 0 \quad \forall c,\omega \tag{A.6}$$

$$cnt^S - \sum_{\omega=1}^{\Omega} \sum_{h=1}^{H} \mu^S_{c,\omega,h} \geq 0 \perp n^S_c \geq 0 \quad \forall c \tag{A.7}$$

$$\lambda^{EB}_{c,\omega,h} - \left(1 - L^{ES}_c\right) * \lambda^{ES1}_{c,\omega,h} + \mu^{ES3}_{c,\omega,h} \geq 0 \perp d^{\Delta+}_{c,\omega,h} \geq 0 \quad \forall c,\omega,h \tag{A.8}$$

$$-\lambda^{EB}_{c,\omega,h} + \left(1 + L^{ES}_c\right) * \lambda^{ES1}_{c,\omega,h} + \mu^{ES4}_{c,\omega,h} \geq 0 \perp d^{\Delta-}_{c,\omega,h} \geq 0 \quad \forall c,\omega,h \tag{A.9}$$

$$\lambda^{ES1}_{c,\omega,h} - (1 - R_c) * \lambda^{ES1}_{c,\omega,h+1} + \mu^{ES2}_{c,\omega,h} \geq 0 \perp s_{c,\omega,h} \geq 0 \quad \forall c,\omega,h < H \tag{A.10}$$

$$\lambda^{ES1}_{c,\omega,H} - (1 - R_c) * \lambda^{ES1}_{c,\omega,1} + \mu^{ES2}_{c,\omega,H} \geq 0 \perp s_{c,\omega,H} \geq 0 \quad \forall c,\omega,h = H \tag{A.11}$$

$$-\lambda^{EB}_{c,\omega,h} + \mu^{ER}_{c,\omega,h} \geq 0 \perp g^{ER}_{c,\omega,h} \geq 0 \quad \forall c,\omega,h \tag{A.12}$$

$$imp_{c,\omega,h} - exp_{c,\omega,h} - D_{c,\omega,h} - d^{\Delta+}_{c,\omega,h} + d^{\Delta-}_{c,\omega,h} + g^{ER}_{c,\omega,h} = 0 \perp \lambda^{EB}_{c,\omega,h} \quad \forall c,\omega,h \tag{A.13}$$

$$s_{c,\omega,h-1} * (1 - R_c) + d^{\Delta+}_{c,\omega,h} * \left(1 - L^{ES}_c\right) - d^{\Delta-}_{c,\omega,h} * \left(1 + L^{ES}_c\right) - D^{\Delta-}_{c,\omega,h} - s_{c,\omega,h} + d^{pen+}_{c,\omega,h} - d^{pen-}_{c,\omega,h} = 0 \perp \lambda^{ES1}_{c,\omega,h} \quad \forall c,\omega,h > 1 \tag{A.14}$$

$$s_{c,\omega,H} * (1 - R_c) + d^{\Delta+}_{c,\omega,1} * \left(1 - L^{ES}_c\right) - d^{\Delta-}_{c,\omega,1} * \left(1 + L^{ES}_c\right) - D^{\Delta-}_{c,\omega,1} - s_{c,\omega,1} + d^{pen+}_{c,\omega,h} - d^{pen-}_{c,\omega,h} = 0 \perp \lambda^{ES1}_{c,\omega,1} \quad \forall c,\omega,h = 1 \tag{A.15}$$

$$U^{ES}_c - s_{c,\omega,h} \geq 0 \perp \mu^{ES2}_{c,\omega,h} \geq 0 \quad \forall c,\omega,h \tag{A.16}$$

$$U^{ES}_c * CF^{ch}_c - d^{\Delta+}_{c,\omega,h} \geq 0 \perp \mu^{ES3}_{c,\omega,h} \geq 0 \quad \forall c,\omega,h \tag{A.17}$$

$$U^{ES}_c * CF^{dis}_c - d^{\Delta-}_{c,\omega,h} \geq 0 \perp \mu^{ES4}_{c,\omega,h} \geq 0 \quad \forall c,\omega,h \tag{A.18}$$

$$U^{ER}_c * G_{c,\omega,h} - g^{ER}_{c,\omega,h} \geq 0 \perp \mu^{ER}_{c,\omega,h} \geq 0 \quad \forall c,\omega,h \tag{A.19}$$

$$n^M_{c,\omega} + n^+_{c,\omega,h} - n^-_{c,\omega,h} - imp_{c,\omega,h} \geq 0 \perp \mu^M_{c,\omega,h} \geq 0 \quad \forall c,\omega,h \tag{A.20}$$

$$n^S_c + o_{c,\omega,h} + n^+_{c,\omega,h} - n^-_{c,\omega,h} - imp_{c,\omega,h} \geq 0 \perp \mu^S_{c,\omega,h} \geq 0 \quad \forall c,\omega,h \tag{A.21}$$

$$n^{LIM} - n^+_{c,\omega,h} - n^-_{c,\omega,h} \geq 0 \perp \mu^N_{c,\omega,h} \geq 0 \quad \forall c,\omega,h \tag{A.22}$$

$$\sum_{c=1}^{C} \left(n^+_{c,\omega,h} - n^-_{c,\omega,h} + n^{pen+}_{c,\omega,h} - n^{pen-}_{c,\omega,h}\right) = 0 \perp \lambda^N_{\omega,h} \quad \forall \omega,h \tag{A.23}$$

## References

[1] Newcomb James, Lacy Virginia, Hansen Lena, Bell Mathias. Distributed energy resources: policy implications of decentralization. ISSN 10406190 Electr J 2013;26(8):65–87. https://doi.org/10.1016/j.tej.2013.09.003. 10.1016/j.tej.2013.09.003.

[2] Finn P, Fitzpatrick C, Connolly D. Demand side management of electric car charging: benefits for consumer and grid. ISSN 03605442 Energy 2012;42(1):358–63. https://doi.org/10.1016/j.energy.2012.03.042. 10.1016/j.energy.2012.03.042.

[3] Pudjianto Danny, Djapic Predrag, Aunedi Marko, Gan Chin Kim, Goran Strbac, Huang Sikai, Infield David. Smart control for minimizing distribution network reinforcement cost due to electrification. ISSN 03014215 Energy Pol 2013;52:76–84. https://doi.org/10.1016/j.enpol.2012.05.021. 10.1016/j.enpol.2012.05.021.

[4] Bell Keith, Gill Simon. Delivering a highly distributed electricity system: technical, regulatory and policy challenges. ISSN 03014215 Energy Pol 2018;113(October 2017):765–77. https://doi.org/10.1016/j.enpol.2017.11.039. 10.1016/j.enpol.2017.11.039.

[5] Geidl Martin, Andersson Goran. Operational and structural optimization of multi-carrier energy systems. Eur Trans Electr Power 2006;16(5):463–77. https://doi.org/10.1002/etep.112. ISSN 1430144X.
[6] Haupt Leon, Schöpf Michael, Wederhake Lars, Weibelzahl Martin. The influence of electric vehicle charging strategies on the sizing of electrical energy storage systems in charging hub microgrids. ISSN 03062619 Appl Energy 2020;273(May):115231. https://doi.org/10.1016/j.apenergy.2020.115231. 10.1016/j.apenergy.2020.115231.
[7] Maroufmashat Azadeh, Taha Taqvi Syed, Miragha Amir, Fowler Michael, Ali Elkamel. Modeling and optimization of energy hubs: a comprehensive review. Inventions 2019;4(50).
[8] Orehounig Kristina, Mavromatidis Georgios, Evins Ralph, Dorer Viktor, Jan Carmeliet. Towards an energy sustainable community: an energy system analysis for a village in Switzerland. ISSN 03787788 Energy Build 2014;84: 277–86. https://doi.org/10.1016/j.enbuild.2014.08.012. 10.1016/j.enbuild.2014.08.012.
[9] Orehounig Kristina, Evins Ralph, Dorer Viktor. Integration of decentralized energy systems in neighbourhoods using the energy hub approach. ISSN 03062619 Appl Energy 2015;154:277–89. https://doi.org/10.1016/j.apenergy.2015.04.114. 10.1016/j.apenergy.2015.04.114.
[10] Pinel Dimitri, Bjarghov Sigurd, Korp Magnus. Impact of grid tariffs design on the zero emission neighborhoods energy system investments, vols. 1–6. 2019 IEEE Milan PowerTech; 2019.
[11] Sadeghi Hadi, Rashidinejad Masoud, Moeini-Aghtaie Moein, Abdollahi Amir. The energy hub: an extensive survey on the state-of-the-art. Appl Therm Eng 2019;161(December 2017):114071. https://doi.org/10.1016/j.applthermaleng.2019.114071. ISSN 13594311.
[12] Hoarau Quentin, Perez Yannick. Network tariff design with prosumers and electromobility: who wins, who loses?. 01409883 Energy Econ 2019;83: 26–39. https://doi.org/10.1016/j.eneco.2019.05.009. 10.1016/j.eneco.2019.05.009.
[13] Schittekatte Tim, Momber Ilan, Meeus Leonardo. Future-proof tariff design: recovering sunk grid costs in a world where consumers are pushing back. ISSN 01409883 Energy Econ 2018;70:484–98. https://doi.org/10.1016/j.eneco.2018.01.028. 10.1016/j.eneco.2018.01.028.
[14] Vespermann Niklas, Huber Matthias, Paulus Simon, Metzger Michael, Hamacher Thomas. The impact of network tariffs on PV investment decisions by consumers. 2018-June(3). In: International conference on the European energy market. EEM; 2018. p. 1–5. https://doi.org/10.1109/EEM.2018.8469944. ISSN 21654093.
[15] Askeland Magnus, Korpås Magnus. Interaction of DSO and local energy systems through network tariffs. In: International conference on the European energy market. EEM; 2019. 9781728112572.
[16] Askeland Magnus, Backe Stian, Bjarghov Sigurd, Korpås Magnus. Helping end-users help each other: coordinating development and operation of distributed resources through local power markets and grid tariffs. ISSN 01409883 Energy Econ 2021;94:105065. https://doi.org/10.1016/j.eneco.2020.105065. 10.1016/j.eneco.2020.105065.
[17] Tushar Wayes, Chai Bo, Yuen Chau, Smith David B, Wood Kristin L, Yang Zaiyue, Vincent Poor H. Three-party energy management with distributed energy resources in smart grid. IEEE Trans Ind Electron 2015;62(4): 2487–98. https://doi.org/10.1109/TIE.2014.2341556. ISSN 02780046.
[18] Tushar Wayes, Chai Bo, Yuen Chau, Huang Shisheng, David B, Smith H. Vincent poor, and zaiyue yang. Energy storage sharing in smart grid: a modified auction-based approach. IEEE Transactions on Smart Grid 2016;7(3): 1462–75. https://doi.org/10.1109/TSG.2015.2512267. ISSN 19493053.
[19] Tushar Wayes, Yuen Chau, Smith David B, Vincent Poor H. Price discrimination for energy trading in smart grid: a game theoretic approach. IEEE Transactions on Smart Grid 2017;8(4):1790–801. https://doi.org/10.1109/TSG.2015.2508443. ISSN 19493053.
[20] Rong Yu, Zhong Weifeng, Xie Shengli, Yuen Chau, Stein Gjessing, Zhang Yan. Balancing power demand through EV mobility in vehicle-to-grid mobile energy networks. IEEE Transactions on Industrial Informatics 2016;12(1):79–90. https://doi.org/10.1109/TII.2015.2494884. ISSN 15513203.
[21] Chung Hwei Ming, Wen Tai Li, Yuen Chau, Wen Chao Kai, Crespi Noël. Electric vehicle charge scheduling mechanism to maximize cost efficiency and user convenience. IEEE Transactions on Smart Grid 2019;10(3):3020–30. ISSN 23318422.
[22] Gabriel Steven A, Conejo Antonio J, David Fuller J, Hobbs Benjamin F, Ruiz Carlos. Complementarity modeling in energy markets, vol. 180. Springer Science & Business Media; 2012. https://doi.org/10.1007/978-1-4419-6123-5. ISBN 978-1-4419-6123-5 (eBook).
[23] Luo Zhi-Quan, Pang Jong-Shi, Ralph Daniel. Mathematical programs with equilibrium constraints. Cambridge University Press; 1996.
[24] Askeland Magnus, Burandt Thorsten, Gabriel Steven A. A stochastic MPEC approach for grid tariff design with demand side flexibility. ISSN 1868-3975 Energy Systems 2020. https://doi.org/10.1007/s12667-020-00407-7. 10.1007/s12667-020-00407-7.
[25] Schittekatte Tim, Meeus Leonardo. Least-cost distribution network tariff design in theory and practice. Energy J 2020;41(1):119–56. https://doi.org/10.5547/01956574.41.5.tsch. ISSN 01956574.
[26] Ceer. CEER paper on electricity distribution tariffs supporting the energy transition. 2020.
[27] Ryan Hledik, Greenstein Gus. The distributional impacts of residential demand charges. ISSN 10406190 Electr J 2016;29(6):33–41. https://doi.org/10.1016/j.tej.2016.07.002. 10.1016/j.tej.2016.07.002.
[28] Paul Simshauser. Distribution network prices and solar PV: resolving rate instability and wealth transfers through demand tariffs. ISSN 01409883 Energy Econ 2016;54:108–22. https://doi.org/10.1016/j.eneco.2015.11.011. 10.1016/j.eneco.2015.11.011.
[29] Backe Stian, Kara Güray, Tomasgard Asgeir. Comparing individual and coordinated demand response with dynamic and static power grid tariffs. ISSN 03605442 Energy 2020;201:117619. https://doi.org/10.1016/j.energy.2020.117619. 10.1016/j.energy.2020.117619.
[30] Doorman Gerard L. Capacity subscription: solving the peak demand challenge in electricity markets. IEEE Trans Power Syst 2005;20(1):239–45. https://doi.org/10.1109/TPWRS.2004.841230. ISSN 08858950.
[31] Askeland Magnus, Backe Stian, Lindberg Karen Byskov. Zero energy at the neighbourhood scale: regulatory challenges regarding billing practices in Norway. IOP Conf Ser Earth Environ Sci 2019;352(1). https://doi.org/10.1088/1755-1315/352/1/012006. ISSN 17551315.
[32] Bjarghov S, Askeland M, Backe S. Peer-to-peer trading under subscribed capacity tariffs - an equilibrium approach. In: 17th international conference on the European energy market. EEM); 2020. https://doi.org/10.1109/EEM49802.2020.9221966. 9781728169194.
[33] Siddiqui Sauleh, Steven A. Gabriel. An SOS1-based approach for solving MPECs with a natural gas market application. Network Spatial Econ 2013;13(2): 205–27. https://doi.org/10.1007/s11067-012-9178-y. ISSN 1566113X.
[34] Vassileva Iana, Campillo Javier. Adoption barriers for electric vehicles: experiences from early adopters in Sweden. ISSN 03605442 Energy 2017;120: 632–41. https://doi.org/10.1016/j.energy.2016.11.119. 10.1016/j.energy.2016.11.119.
[35] Pfenninger Stefan, Staffell Iain. Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data. ISSN 03605442 Energy 2016;114:1251–65. https://doi.org/10.1016/j.energy.2016.08.060. 10.1016/j.energy.2016.08.060.