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Comparing individual and coordinated demand response with dynamic and static power grid tariffs

Stian Backe [*], Güray Kara , Asgeir Tomasgard

Norwegian University of Science and Technology, Department of Industrial Economy and Technology Management, Norway

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A B S T R A C T

This paper investigates cost-optimal operation of flexible electricity assets with a capacity-based power grid tariff involving power subscription. The purpose of this research is to identify the characteristics of a subscribed capacity-based tariff that promotes efficient network development through demand response. Using historical load data, we compare two consumers with flexible assets being billed by their individual load versus their combined and coordinated loads in a two-stage stochastic program. The frequency of adjusting the subscribed capacity level (weekly versus annually) influences the effectiveness of the tariff in terms of reducing loads that dimension the grid. The results show that weekly subscription on average provides 5 − 6% cost savings, while annual subscription on average provides 3% cost savings. A combined annual peak load reduction of 15% occurs when the combined subscription level is adjusted weekly. We also find that when the subscription level is adjusted weekly, the load reduction is cost efficient even when capacity is not scarce, which ought to be avoided. Depending on where a bottleneck in the grid is located, the price signal should be based on the combined load of several consumers rather than individual loads if combined peak load shaving is to be cost-optimal.

1. Introduction

Successful mitigation of climate change will require decarbonization of the energy sector, increased production from variable renewable energy sources (RES), and electrification. Several of these measures are likely to be decentralized and require cross-sectoral thinking [1].

Flexibility in power systems relates to the ability to deal with variability in supply and demand. Demand-side flexibility through demand response has been proposed as being significant if assets can be coordinated and aggregated [2–6]. We will refer to consumers with demand-side flexibility as ‘prosumers’ because they both consume and produce energy services. Prosumers are seen as part of the solution to facilitate a large share of variable RES, making the demand-side more flexible through self-generation, market participation and active responses to price signals [7,8].

Several studies have been performed to analyze prosumer response to different grid tariffs [9–15]. However, to the authors' knowledge, no previous study compares dynamic intra-annual adjustment of tariff parameters with annually fixed parameters and simultaneously considers the difference between providing short-term price signals based on individual loads versus the combined load of several prosumers. To cover this gap, we propose a two-stage stochastic program where uncertainty is related to net load and spot prices with an hourly resolution for different prosumers. The novelty of this paper is using the two-stage stochastic programming framework to compare dynamically adjusting tariff parameters within a year versus statically fixing tariff parameters for a complete year. The paper also has the original contribution of comparing individual versus coordinated asset planning to analyze how effective different versions of a capacity-based grid tariff are in reducing load peaks in the grid. Based on our results, we address the implications for successful grid tariff design, i.e., a design that will trigger efficient utilization of the local flexible assets and reduce the highest loads.

The outline of the paper is as follows: Section 2 introduces the background regarding flexibility in energy systems and the purpose

Abbreviations: C1, Campus 1; C2, Campus 2; CA, Combined annual subscription scheme; CW, Combined weekly subscription scheme; DG, Distributed generation; DSO, Distribution system operator; IA, Individual annual subscription scheme; IW, Individual weekly subscription scheme; PV, Photovoltaic; RES, Renewable energy source.

* Corresponding author. Department of Industrial Economics and Technology Management, Norwegian University of Science and Technology, Høgskoleringen 1, 7491, Trondheim, Norway.

E-mail address: stian.backe@ntnu.no (S. Backe).

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of grid tariffs. Section 3 presents the model developed to analyze subscribed capacity-based grid tariff schemes and the assumptions and input for our case study. Section 4 states our model results, while Section 5 discusses the implications of these results. Finally, Section 6 concludes our paper and suggests further research.

2. Background and literature

This section elaborates on the literature and previous studies related to our paper. The first part (Sections 2.1-2.3) explains the context of our study linking flexibility in power systems to grid tariff design, while the last part (Section 2.4) presents the reasoning behind the use of the two-stage stochastic program in this paper.

2.1. Flexibility services in power systems

Flexibility is a term used to characterize a service or property that is part of tangible assets [16]. Flexibility can be characterized along three dimensions based on the *Nordic Balancing Concept*: time, location, and resource type. Properties of the *time* dimension include activation (response) time, ramp-up or down rate, and the duration of the service. The *location* dimension describes how the service from an asset can be provided in geographical locations, e.g. individual unit (building), neighborhood, country, and cross-border. For example, services based on reactive and active power have different geographical relevance. The *type of resource* dimension describes the type of asset in the following classes: supply-side, demand-side, grid-side, and storage [17].

In our analysis, we focus on time horizons with hourly resolution, demand-side flexibility assets, the neighborhood level, and assume that all flexibility assets provide a firm service (there is no uncertainty related to delivery). We assume that the scheduling of flexible assets is driven by the prosumers' wish to minimize the total cost of energy consumption, including net trades in the spot market and the grid tariff paid. In addition, we investigate the effect of prosumer coordination by investigating what happens when an aggregator controls all the flexibility assets to minimize total costs. We do not discuss how to share the benefits of this, e.g. in a flexibility market [18], only the total effect.

2.2. Allocation of ancillary service costs and flexibility

In a power system, distribution of electricity by preserving power quality and maintaining adequate assets in the low voltage grid are the main tasks of a distribution system operator (DSO). The DSO is commonly regulated as a natural monopoly which is challenged by the development of a smart grid [19,20]. Full and timely recovery of network costs is important for the DSO's financial sustainability [21]. A successful tariff design should increase network efficiency in the short-term and signal efficient network capital development in the long-term [22,23].

The tariff design normally includes up to three elements: a fixed element, a volumetric (energy) element, and a capacity element. Volumetric elements generally do not incentivize demand-side flexibility services [24] as opposed to capacity elements that partly charge consumers based on the power use over a measuring period [23]. Due to an increase in distributed generation (DG), especially solar photovoltaics (PV), power systems with net-metering tariff designs are faced with the threat of a *utility death spiral* [25]. The threat appears when DG behind the meter triggers not just energy cost savings, but also tariff savings. Unless the DG reduces the DSO's costs, it creates a marginally higher cost for consumers without DG, which is demonstrated in Ref. [26] where a capacity element in the grid tariff increases the electricity costs up to 10% for consumers with high power outtake in Norway. A redesign of network tariffs is needed to avoid the allocation of grid payments away from DG owners [27].

Most current grid tariff designs in Europe are *static*, i.e., dependent on a single element (commonly energy) without any temporal rate variation [28]. In contrast, a *dynamic* tariff design will depend on several elements and/or be subject to temporal variation. Static tariff designs are practical, predictable, and good at achieving a single long-term objective, e.g. increasing energy efficiency. In theory, dynamic tariffs reflect the DSO's costs better and could create signals to trigger flexibility services by prosumers [29]. However, dynamic tariffs are harder to implement [21] and could cause political challenges related to an 'unfair' change in network costs for certain consumer groups [30].

The signal for flexibility need could be provided using market-based approaches, as proposed in e.g. Ref. [31–33]. An example of a market-based approach calling for flexibility can be found in Ref. [34] which proposes distribution locational marginal pricing. The idea of activating demand-side flexibility in both market-based solutions and through dynamic grid tariffs is to create price signals to trigger efficient flexibility responses. We analyze how market-based approaches could be similar to responding to a dynamic grid tariff. In Ref. [35], they analyzed different ways of creating incentives for prosumer flexibility, including tariff redesign and a direct payment to flexibility providers. They find that a redesign of network tariffs is up to 20% less costly than direct payment to flexibility providers. However [35], does not consider how the network tariffs should be redesigned.

2.3. Grid tariff design in Norway

Currently in Norway, grid tariffs for residential consumers have a fixed element and a volumetric element. The volumetric element is location dependent through a marginal loss factor, which reflects how far electricity generation is from a consumer [28]. The current Norwegian grid tariff design does not price high power outtakes for households [26], and it is shown that dynamic tariffs provide incentives for better utilization of the grid [36].

In this paper, we analyze the 'subscribed capacity' grid tariff scheme proposed by the Norwegian Regulator [37], where consumers subscribe to a capacity level. If their hourly load exceeds the subscribed level, a penalty is charged depending on the violation (see Fig. 1). As consumers pay both for the subscribed level and the penalty, they have incentives to subscribe to as low capacity as possible providing they can stay below it most of the time. We analyze four different versions of the subscribed capacity tariff scheme. In the first version, consumers have individual subscriptions that cannot be changed for a year (individual annual subscription). The second version is individual subscriptions where the consumers can adjust the subscription level on a weekly basis (individual weekly subscription). The third version is a combined capacity subscription on the total load of several consumers combined, and the subscription is fixed for one year (combined annual subscription). Finally, the fourth version is a combined subscription for several consumers that can be changed on a weekly basis (combined weekly subscription). By comparing these four versions of the subscribed capacity grid tariff, our contribution is to elaborate on the effect of providing inter-weekly rather than inter-annual tariff adjustment and coordinated rather than individual scheduling of flexibility assets. We study the effect on (1) the resulting cost savings and cost-optimized responses by prosumers minimizing their electricity bill and (2) the total peak load reduction for the grid. We assume the tariff rates are as presented in Ref. [37] (see Table 1). These rates are suggested by the Norwegian Regulator upon analyzing measured load data from 500 Norwegian consumers, and the rates are determined subject to the criteria that

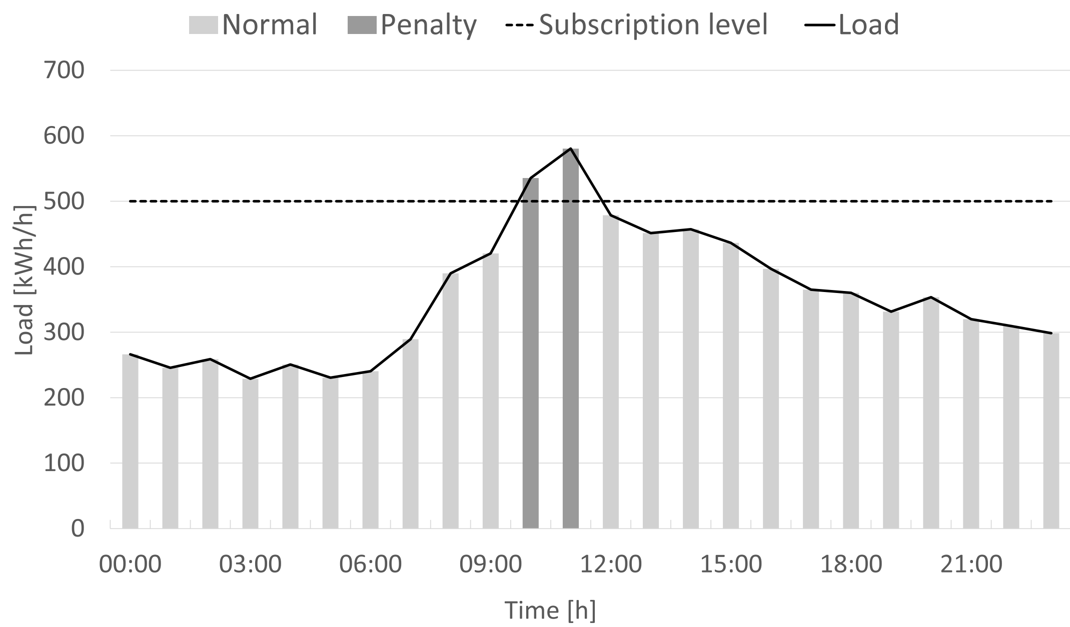


Fig. 1. Illustration of the 'subscribed capacity' grid tariff scheme. The illustration shows an example of measured hourly load over 24 h for the combined load of Campus 1 (C1) and Campus 2 (C2) and a combined subscription. The horizontal line represents the subscription level which causes a penalty charge for hours 11 and 12 (load exceeds subscribed level).

Table 1
Grid tariff rates provided as input in all our 52 instances. The rates are assumed to be as proposed by the Norwegian regulators [37] (see Section 2.3).

	c^{sub} [NOK/kW/year]	c^{norm} [NOK/kWh]	c^{pen}[NOK/kWh]
Rates	689	0.0500	1.00

the same annual income to the DSO is provided as with the current Norwegian gird tariff scheme.

2.4. Two-stage stochastic programming approach

Stochastic programming supports decision making under uncertainty [38]. In Ref. [39], a stochastic programming approach is used to analyze trading between prosumers under uncertainty; however, there are not multiple stages. Throughout different stages in stochastic programming, a decision maker ought to make decisions for short-term and long-term plans, where stages represent realization of uncertain outcomes. In our case, the short-term plans include operating flexible assets to minimize costs given a realization of prosumer load and day-ahead prices, and the long-term plan involves tuning the tariff parameters. We use two-stage stochastic programming to analyze the difference between long-term and short-term adjustment of the tariff parameters, where short-term adjustment of the tariff parameters is analyzed by solving deterministic versions of our two-stage stochastic program. Other examples of two-stage programming approaches for addressing uncertainty in energy management are [40–42].

3. The mathematical model

In this section, we present the model for the prosumer's cost-minimization problem. The model is a two-stage stochastic linear program [43] where the first-stage decisions include deciding the subscribed capacity level and the second-stage decisions include operating flexible assets. The complete nomenclature of the model can be found in Appendix A.

3.1. Time structure

The model considers one temporal scale with all operational time periods defined in the ordered set $\mathscr{T} = \{1, 2, \ldots, |\mathscr{T}|\}$. In every time step, decisions about how to operate a flexible asset is supported. Operational (second-stage) decisions can be different in all stochastic scenarios ω in the set of all scenarios Ω. Each stochastic scenario represents one realization of prosumer load and electricity spot prices for a time horizon. The flexible assets are located at different prosumers $p \in \mathscr{P}$, and the scenario independent first-stage decision is the subscribed capacity x_p^{I}.

The model includes flexible asset types $f \in \mathscr{F}$. If asset type f is located at prosumer p, it belongs to the set $\mathscr{F}_p \subseteq \mathscr{F}$. Any flexible asset type f is modelled as a conceptual storage. Depending on the asset type, it can be flexibly charged (prosumer demand can be increased, e.g. electric vehicle [44]); it can be flexibly discharged (prosumer demand can be decreased, e.g. curtailable loads [45]); or it can be both flexibly charged and discharged (e.g. battery [46]). Note that there is no resolving of uncertainty within a scenario as time passes, hence the storages are operated with perfect foresight within a scenario. For a static tariff where the subscribed capacity is decided for a year, each scenario may consist of all hours in a week with $\mathscr{T} = \{1, 2, \ldots, 168\}$. Scenarios can be sampled from historical data, and ideally, they represent seasonal variations over a year. If the scenarios represent all weeks of a year, we would have $\Omega = \{1, 2, \ldots, 52\}$. Note that each scenario is independent with no link or dependency between operations or storage levels in two subsequent scenarios.

3.2. Objective function

The objective function for an individual prosumer, z^{I}, minimizes the electricity bill by scheduling flexible assets subject to energy costs and a grid tariff:

$$\min z^{\mathrm{I}} = \sum_{p\in\mathscr{P}}\left(c^{\mathrm{sub}}x_p^{\mathrm{I}} + \sum_{\omega\in\Omega}\pi_\omega\sum_{t\in\mathscr{T}}\left(k_{p,t,\omega}^{\mathrm{I}} + c_{t,\omega}^{\mathrm{ret}}y_{p,t,\omega}^{\mathrm{load}}\right)\right), \tag{1}$$

where x_p^{I} are variables for the subscribed capacity level for prosumer p, the π_ω are scenario probabilities, and $k_{p,t,\omega}^{\mathrm{I}}$ are variables identifying the tariff cost depending on the prosumer's grid interaction in different scenarios. Resulting load profiles (import from the grid to the prosumer) are identified through the second-stage variables $y_{p,t,\omega}^{\mathrm{load}}$ and vary by scenario. The objective contains a time varying load dependent retail cost ($c_{t,\omega}^{\mathrm{ret}}$) and a fixed capacity dependent subscription cost (c^{sub}) for the capacity subscription.

For prosumer p, the tariff cost is identified through a two-step linear cost function depending on the subscribed capacity level x_p^{I} and the prosumer load $y_{p,t,\omega}^{\mathrm{load}}$:

$$c^{\mathrm{norm}}y_{p,t,\omega}^{\mathrm{load}} \le k_{p,t,\omega}^{\mathrm{I}}, p\in\mathscr{P}, t\in\mathscr{T}, \omega\in\Omega, \tag{2}$$

$$c^{\mathrm{pen}}\left(y_{p,t,\omega}^{\mathrm{load}} - x_p^{\mathrm{tariff}}\right) + c^{\mathrm{norm}}y_{p,t,\omega}^{\mathrm{load}} \le k_{p,t,\omega}^{\mathrm{I}}, p\in\mathscr{P}, t\in\mathscr{T}, \omega\in\Omega, \tag{3}$$

where c^{norm} and c^{pen} are load dependent prices for loads below and above the subscribed capacity, respectively. Constraints (2) make sure that the tariff has a lower bound of load multiplied by the cost below the subscribed capacity, whereas constraints (3) ensure that the tariff cost is increased when load exceeds the subscribed capacity to the penalty cost multiplied by the load.

3.3. Constraints

The original load before scheduling of the flexible assets (expected net demand) for electricity at prosumer p at time t in scenario ω is denoted $\xi_{p,t,\omega}^{\mathrm{load}}$. The total import from the grid to prosumers is identified in the following constraints:

$$\begin{aligned} y_{p,t,\omega}^{\mathrm{load}} = \xi_{p,t,\omega}^{\mathrm{load}} + \sum_{f\in\mathscr{F}_p}\left(w_{p,f,t,\omega}^{\mathrm{charge}} - \varepsilon_f^{\mathrm{discharge}}w_{p,f,t,\omega}^{\mathrm{discharge}}\right),\\ p\in\mathscr{P}, t\in\mathscr{T}, \omega\in\Omega, \end{aligned} \tag{4}$$

where $w_{p,f,t,\omega}^{\mathrm{charge}}$ is charging of flexible asset type f at prosumer p while $w_{p,f,t,\omega}^{\mathrm{discharge}}$ is discharging. Constraints (4) ensure that prosumer p at time t will have a resulting load equal to the original load plus the charged and discharged energy from all the flexible assets at the prosumer. Note that losses $\varepsilon_f^{\mathrm{discharge}}$ are only considered for discharged energy in (4).

In time period t, $w_{p,f,t,\omega}^{\mathrm{storage}}$ is the available energy in flexible asset type f at prosumer p. The balance of storage must be maintained in between operational time steps:

$$\begin{aligned} \kappa_{p,f}\eta_{p,f,1}^{\mathrm{storage}} + \varepsilon_f^{\mathrm{charge}}w_{p,f,1,\omega}^{\mathrm{charge}} - w_{p,f,1,\omega}^{\mathrm{discharge}} = w_{p,f,1,\omega}^{\mathrm{storage}}, p\in\mathscr{P}, f\in\mathscr{F}_p,\\ \omega\in\Omega. \end{aligned} \tag{5}$$

$$\begin{aligned} \varepsilon_f^{\mathrm{diff}}w_{p,f,t-1,\omega}^{\mathrm{storage}} + \varepsilon_f^{\mathrm{charge}}w_{p,f,t,\omega}^{\mathrm{charge}} - w_{p,f,t,\omega}^{\mathrm{discharge}} = w_{p,f,t,\omega}^{\mathrm{storage}}, p\in\mathscr{P}, f\in\mathscr{F}_p,\\ t\in\{2,\ldots,|\mathscr{T}|\},\\ \omega\in\Omega. \end{aligned} \tag{6}$$

Constraints (5) make sure that a flexible asset type f at prosumer p start the operational horizon ($t=1$) in scenario ω with an initial energy level equal to a percentage of installed capacity ($\kappa_{p,f}$) plus charging (subject to losses) minus discharging. Constraints (6) make sure that flexible asset type f at prosumer p has an energy level equal to the energy level from the previous period (subject to diffusion losses) plus charging in the current period (subject to losses) minus discharging for all operational time steps and scenarios. Losses are type dependent factors for flexible asset type f and they are considered for charging ($\varepsilon_f^{\mathrm{charge}}$), discharging ($\varepsilon_f^{\mathrm{discharge}}$) and diffusion of stored energy content ($\varepsilon_f^{\mathrm{diff}}$). Note that no losses are considered for discharging in (5) or (6) since it is accounted for in (4). The maximum energy content ($\eta_{p,f}^{\mathrm{storage}}$), charging ($\eta_{p,f}^{\mathrm{charge}}$) and discharging ($\eta_{p,f}^{\mathrm{discharge}}$) of flexible asset type f at prosumer p are defined as upper bounds for all time periods and scenarios.

Constraints (7) ensure that the energy level of flexible asset type f at prosumer p is at least the required level $\gamma_{p,f,t}^{\mathrm{req}}$ in period t for all scenarios:

$$\gamma_{p,f,t}^{\mathrm{req}} \le w_{p,f,t,\omega}^{\mathrm{storage}}, p\in\mathscr{P}, f\in\mathscr{F}_p, t\in\mathscr{T}, \omega\in\Omega. \tag{7}$$

The individual objective z^{I} in (1) is combined with constraints (2)–(7) to find the subscribed capacity level that minimize the combined energy and tariff cost.

3.4. Coordinated scheduling of flexible assets

The individual prosumer model can be extended to a model where an aggregator coordinates all flexible assets by changing the objective. The combined objective function minimizes the electricity bill for all consumers with flexible assets where the billing of the grid tariff is based on the combined load profile in the following way:

$$\min z^{\mathrm{C}} = c^{\mathrm{sub}}x^{\mathrm{C}} + \sum_{\omega\in\Omega}\pi_\omega\sum_{t\in\mathscr{T}}\left(k_{t,\omega}^{\mathrm{C}} + \left(\sum_{p\in\mathscr{P}}c_{t,\omega}^{\mathrm{ret}}y_{p,t,\omega}^{\mathrm{load}}\right)\right), \tag{8}$$

where x^{C} is a decision variable for the combined subscription level for all prosumers, and $k_{t,\omega}^{\mathrm{C}}$ are variables identifying the combined tariff cost depending on the sum of imports from the grid to all prosumers.

The total electricity load of all prosumers will determine the combined tariff cost through a two-step linear function:

$$c^{\mathrm{norm}}\sum_{p\in\mathscr{P}}y_{p,t,\omega}^{\mathrm{load}} \le k_{t,\omega}^{\mathrm{C}},\ t\in\mathscr{T}, \omega\in\Omega, \tag{9}$$

$$c^{\mathrm{pen}}\left(\sum_{p\in\mathscr{P}}y_{p,t,\omega}^{\mathrm{load}} - x^{\mathrm{C}}\right) + c^{\mathrm{norm}}\sum_{p\in\mathscr{P}}y_{p,t,\omega}^{\mathrm{load}} \le k_{t,\omega}^{\mathrm{C}},\ t\in\mathscr{T}, \omega\in\Omega. \tag{10}$$

Similar to constraints (2) and (3), constraints (9) make sure that the tariff has a lower bound of *the combined* load multiplied by the cost below the subscribed capacity, whereas constraints (10) ensure that the tariff cost is increased when *combined* load exceeds the subscribed capacity to the penalty cost multiplied by the load, respectively.

The combined objective z^{C} in (8) along with constraints (4)–(7) and (9)–(10) form a problem that cannot be decomposed per

Table 2
Assumed operational characteristics of the flexible asset types available for demand-side management at each of the two prosumers (Campus 1 (C1) and Campus 2 (C2)). The parameters identify available capacity for charging, discharging and storage.

Flexible asset	η^{charge}[kWh/h]	$\eta^{discharge}$[kWh/h]	$\eta^{storage}$ [kWh]
Electric battery	100	100	200
Vehicle charging	50.0	0.00	500
Curtailable loads	0.00	50.0	200

prosumer due to constraints (9)–(10) that make the tariff cost $k^{C}_{t,\omega}$ dependent on the load of all prosumers.

4. Case study for capacity-based grid tariff in Norway

In this section, the models presented in Section 3 are used to analyze the scheduling of flexible assets reacting to both an hourly retail price and a subscribed capacity-based grid tariff. We present the input data and assumptions (Section 4.1) before the results (Section 4.2). All input data, the implemented model, and output data is available in Refs. [47] for the reproduction of this case study.

4.1. Input data and problem instances

We build four classes of problem instances:

1. Individual Annual (IA): Subscribed capacity tariff based on the individual objective (1) under annual decisions on subscribed capacity level,
2. Individual Weekly (IW): Subscribed capacity tariff based on the individual objective (1) under weekly decisions on subscribed capacity level,
3. Combined Annual (CA): Subscribed capacity tariff based on the combined objective (8) under annual decisions on subscribed capacity level,
4. Combined Weekly (CW): Subscribed capacity tariff based on the combined objective (8) under weekly decisions on subscribed capacity level.

For IA and CA, we use stochastic models with sampled weeks representing the scenarios. Each week is a scenario with 168 h. For IW and CW, we optimize the subscribed capacity level weekly (only one scenario). This resembles a dynamic subscribed capacity tariff. As the model is solved under perfect foresight, it is overestimating the ability to estimate exactly the optimal subscribed capacity for the week.

The tariff rates used are as proposed by the Norwegian Regulator in Ref. [37] (see Table 1). We sample historical hourly load profiles from a rural Norwegian university campus, Campus Evenstad, from 50 weeks during 2016. We assume that two university campuses exist in the same part of the distribution grid, 'Campus 1' (C1) and 'Campus 2' (C2). Odd weeks are sampled from Campus Evenstad to create weekly load profiles with hourly resolution for C1 and even weeks for C2. Here, the samples are made so that two consecutive weeks from Campus Evenstad occur in parallel for C1 and C2 making up a total of 25 weeks for the study.

Three flexible asset types exist in the model at both prosumers: electric battery, electric vehicle charging and curtailable loads (e.g. fuel switching from electric to bio-based heating). Their assumed operational characteristics are presented in Table 2. Losses are assumed to be 1% for charging and discharging of all flexible assets. Diffusion losses are only defined for the electric battery at 0.1% per time step.

For vehicle charging, an annual demand of $14,000$ km per vehicle is chosen based on the average use of battery electric vehicles in 2018 in the county of Campus Evenstad (Hedmark) [48]. Further, we assume one electric car needs 0.2 kWh per km,[1] so one car needs (on average) $\frac{14,000}{52}(0.2) = 54$ kWh/week. Then, a weekly demand of 500 kWh covers nine to ten vehicles (see Table 2). Some of the weekly demand must be met every 24 h, meaning daily demands sum up to the total weekly demand (see Fig. 2). The vehicle charging demand is essentially a lower bound for the energy level in the flexible asset f at prosumer p and time t implemented through the variables $\gamma^{req}_{p,f,t}$and constraints (7).

C1 and C2 face hourly retail prices that are dependent on the historical market data from price zone NO1 in Nord Pool in 2016. Retail prices follow the Nord Pool day ahead spot price plus Norwegian electricity charges and 25% VAT, and we sample hourly prices from odd weeks in 2016.

The two deterministic classes (IW and CW) for the two prosumers represent in total 50 instances for the 25 weeks, while the two stochastic classes (IA and CA) represent in total two instances for the 25 weeks. The model is implemented in the open-source optimization modeling language Pyomo [49] through Python version 2.7.8 and solved using Gurobi version 8.0.1. The optimization was run on a computer with an Intel(R) Core(TM) i7-7500U processor with CPU at 2.70 GHz and 16.0 GB installed memory (RAM). The total run time for all instances (50 deterministic + 2 stochastic) including reading, building, solving and printing results is around 60 s.

4.2. Results

This section describes the results from analyzing the four capacity subscriptions (IW, CW, IA, and CA) presented in Section 4. Recall that the modified load profile is a result of the model responding to the different schemes by (a) finding the cost minimizing subscribed capacity level and (b) operating the flexible assets to minimize the total electricity bill including variable energy costs and grid costs.

Table 3 presents the total electricity bill costs before and after the flexibility responses are optimized for the four different schemes. The cost ex-ante optimization is calculated by optimizing the subscription level without any flexibility available and includes constant charging to meet weekly vehicle charging demand of 500 kWh at each campus site. On average, the flexibility responses contribute to 5–6% savings for the weekly subscriptions (IW and CW), while 3% savings are achieved on average for the annual subscriptions (IA and CA).

The top part of Table 3 shows the results from the most expensive scenario (week 24), where costs avoided from responding to the grid tariff scheme ('Grid' in Table 3) are the dominant part of the savings as compared to the saved energy cost ('Energy' in Table 3). The results of all weeks for the weekly subscriptions (IW and CW) show that the grid savings are the dominant part of the savings for 23 weeks, i.e., there are more savings related to the grid tariff than hourly retail prices for the weekly subscriptions. For the annual subscriptions, the grid savings only dominate the savings for eight weeks for the IA scheme and six weeks for the CA scheme, indicating that responding to retail prices is more valuable than responding to the grid tariff for the annual subscriptions (the opposite to the weekly subscriptions). The bottom part of Table 3 lists the results from the scenario with the highest savings (week 2). Here, the energy costs avoided from responding to retail price variations are the dominant part of the

[1] https://pushevs.com/electric-car-range-efficiency-epa/accessed: April 15, 2020.

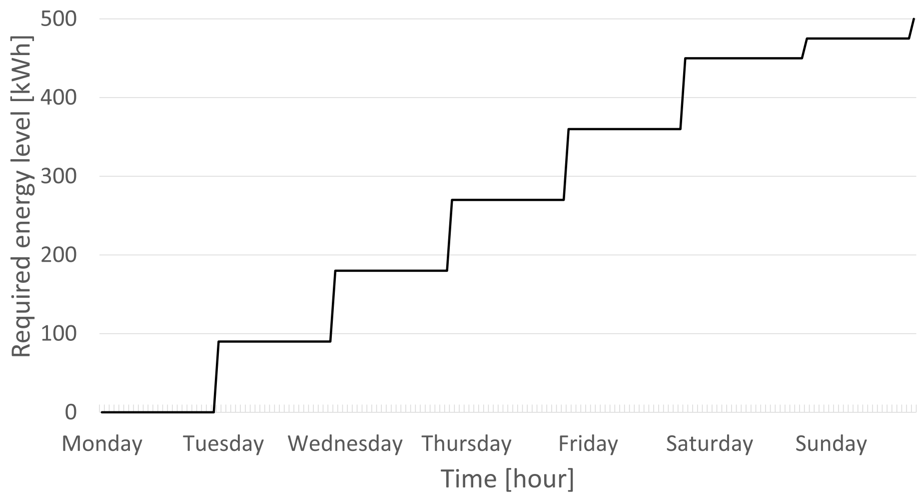


Fig. 2. The lower bound for energy that must be charged by time $t \in \mathcal{T}$ to battery electric vehicles. This offers flexible charging in every time-step with some constraints (daily demands).

Table 3
Cost results summed for both prosumers in NOK ex-ante (before flexibility responses) and ex-post (after flexibility responses) for the individual weekly (IW), combined weekly (CW), individual annual (IA), and combined annual (CA) schemes. The table displays results for the most expensive scenario (week 24, top) and the scenario with highest cost savings from flexible operation (week 2, bottom). The two last columns show cost savings from responding to a variation in day-ahead spot price ('Energy') and responding to the subscribed capacity scheme ('Grid').

Scheme	Total cost,	Total cost,	Cost decrease	
	ex-ante	ex-post	Energy	Grid
Week 24				
IW	59,300 NOK	57,600 NOK (−3%)	468 NOK	1220 NOK
CW	58,900 NOK	57,100 NOK (−3%)	494 NOK	1230 NOK
IA	69,100 NOK	67,900 NOK (−2%)	475 NOK	716 NOK
CA	68,100 NOK	66,800 NOK (−2%)	448 NOK	825 NOK
Week 2				
IW	48,200 NOK	43,300 NOK (−10%)	4170 NOK	676 NOK
CW	46,900 NOK	42,300 NOK (−10%)	3990 NOK	615 NOK
IA	48,700 NOK	44,100 NOK (−9%)	4110 NOK	401 NOK
CA	46,900 NOK	42,400 NOK (−10%)	4000 NOK	526 NOK

savings for all schemes, which is linked to the average weekly spot price being highest for week 2 (0.72 NOK/kWh). This indicates that the load reduction in response to a grid tariff could be challenged by high and variable retail prices if the two price signals are not correlated.

Table 4 presents the weekly subscription level for C1 and C2. The last two columns in Table 4 are the sum of subscription levels for C1 and C2 from the individual metering schemes. Note that for the annual subscriptions (IA and CA), the subscription level is the same for all weeks. The average of the weekly subscription levels for all 25 weeks is consistently less than the annual subscription levels (see the bottom row in Table 4), which strengthens the need for the two-stage stochastic programming approach. The highest weekly combined subscription level is chosen in week 24 (591 kWh/h, see the CW column in Table 4). The sum of the weekly individual subscription levels for week 24 exceeds the combined subscription level (246 + 374 = 620 kWh/h, see the last two columns in Table 4), which is also the case for 92% of the weeks (all weeks except weeks 4 and 23, see Table 4). This is an indication that rationing several prosumers combined is less conservative than rationing them individually.

Table 4
Resulting cost-optimal subscription levels in kWh/h in all 25 weeks. The columns represent the subscription levels for the individual weekly (IW), combined weekly (CW), individual annual (IA), and combined annual (CA) schemes for Campus 1 (C1), Campus 2 (C2), and combined. The last column shows the sum of individual subscription levels (C1+C2) for comparison with the combined subscription level.

	C1		C2		Combined		C1+C2	
Week	IW	IA	IW	IA	CW	CA	IW	IA
1	151	197	181	216	315	387	332	413
2	251	197	196	216	398	387	447	413
3	138	197	134	216	271	387	272	413
4	143	197	137	216	282	387	280	413
5	137	197	280	216	405	387	417	413
6	197	197	86	216	283	387	283	413
7	108	197	118	216	223	387	226	413
8	111	197	171	216	273	387	282	413
9	186	197	184	216	337	387	370	413
10	122	197	138	216	247	387	260	413
11	142	197	120	216	258	387	262	413
12	112	197	101	216	208	387	213	413
13	79	197	79	216	157	387	158	413
14	76	197	78	216	154	387	154	413
15	39	197	40	216	78	387	79	413
16	50	197	123	216	159	387	173	413
17	98	197	115	216	211	387	213	413
18	136	197	135	216	262	387	271	413
19	156	197	122	216	263	387	278	413
20	96	197	159	216	212	387	255	413
21	148	197	216	216	340	387	364	413
22	268	197	193	216	416	387	461	413
23	254	197	215	216	478	387	469	413
24	246	197	374	216	591	387	620	413
25	164	197	253	216	374	387	417	413
Average	144	197	158	216	288	387	302	413

Table 5
Annual original and resulting peak load in kWh/h for Campus 1 (C1), Campus 2 (C2) and combined for the individual weekly (IW), combined weekly (CW), individual annual (IA), and combined annual (CA) schemes. Note that the 'original' column represents the annual peak load ex-ante flexibility responses. The bold font marks the scheme triggering the lowest annual peak for C1, C2, and combined. The numbers in parentheses identify the week in which the annual peak load occurs.

Prosumer	Original	IW	CW	IA	CA
C1	413 (2)	**322** (2)	365 (2)	413 (2)	410 (2)
C2	479 (5)	**426** (24)	441 (24)	444 (24)	444 (24)
Combined	696 (24)	672 (24)	**591** (24)	696 (24)	696 (24)

Table 5 presents the results for the annual peak load at the individual prosumers (C1 and C2) and combined for both prosumers. Weekly individual (IW) subscription triggers the largest individual annual peak shaving, while weekly combined (CW) subscription best achieves combined annual peak shaving. The CW scheme reduces the original annual combined peak by 105 kWh/h (−15%), which is more than four times the annual combined peak shaving triggered by the IW scheme (24 kWh/h, −3%) (see Table 5). Annual subscriptions (IA and CA) trigger little or no annual peak load reduction of individual or combined load profiles (see Original, IA, and CA columns in Table 5).

Fig. 3 shows how the different schemes perform in reducing the weekly peak loads. For weekly subscriptions (IW and CW), some peak shaving is cost-optimal in all weeks, including weeks where the original weekly combined peak load is small (see e.g. the blue and orange bars in week 15 in Fig. 3). For annual subscriptions (IA and CA), the weekly combined peak load generally increases in low demand weeks and decreases in high demand weeks (see the yellow and gray bars in Fig. 3). However, the highest weekly combined peak load is unaffected for the annual subscriptions (see the yellow and gray bars in week 24 in Fig. 3).

Fig. 4 presents the hourly load profiles in week 24 with the highest annual combined load originally. The plot also shows the hourly retail price linked to the hourly day-ahead wholesale price. For all pricing schemes, flexible assets are operated to generally increase the load in low retail price hours, and decrease the load in high retail price hours: low loads occur in all pricing schemes when the retail price (green dotted line) is peaking in Fig. 4. For the weekly subscriptions (see Fig. 4a and b), load profile modifications are similar; however, combined peak shaving is significantly larger for the CW scheme compared to the IW scheme (see bottom row in Table 5).

Fig. 5 presents the relationship between grid costs (grid price multiplied by the load) and the combined load from C1 and C2 for the different pricing schemes. The CA scheme (yellow in Fig. 5) offers the highest cost (344 NOK/kWh) during the annual peak load in week 24 because it is the highest combined load and it exceeds the combined subscription level (387 kWh/h, see Table 4). Note that (a) paying this high penalty is cost-optimal in the CA scheme considering total cost over the whole year and (b) there is no combined peak load shaving in week 24 as a consequence of the high penalty (see the bottom row in Table 5 and the yellow bar in week 24 in Fig. 3). Fig. 5 also shows that the IA scheme has many penalty hours below the sum of the subscribed levels (413 kWh/h, see Table 4) because the individual loads exceed the individual subscription levels without causing a high combined load. This is a shortcoming of the individual subscribed capacity tariff in terms of signaling efficient grid utilization, as it often penalizes situations where the total flow into C1 and C2 is lower than the joint subscribed capacity (recall that the sum of the individual subscription levels is higher than the combined subscription level in 92% of the weeks, see Table 4). For the weekly subscriptions (IW and CW), there are significantly less penalty hours than for the annual subscriptions since the subscription can be adjusted for each week (see yellow and gray dots compared to orange and blue dots in Fig. 5). The CW scheme has the least amount of penalty hours after flexibility responses (see orange dots in Fig. 5), and it is the scheme that most successfully reduces the annual combined peak load (see Table 5).

5. Discussion

Our case study has been performed assuming perfect foresight on hourly load and retail prices for 25 weeks and no disutility (costs) of operating flexible assets except energy losses (see constraints (4)–(3.3) in Section 3.3). This means our results represent an upper bound to how much cost reduction prosumers can obtain for the different pricing schemes. Note that the stochastic structure of the problem in our case study is related to price and load variation between weeks, i.e., there is no uncertainty within a week. Note also that because we consider energy losses from flexibility responses, total energy consumption increases slightly after demand response even though total costs decrease.

The CW scheme is better at decreasing the weekly combined peak load than the IW scheme. This is a central feature as it is the combined load that dimension the grid connecting C1 and C2 to the rest of the system. However, three weeks show a higher combined peak load for the CW scheme compared to the IW scheme (see

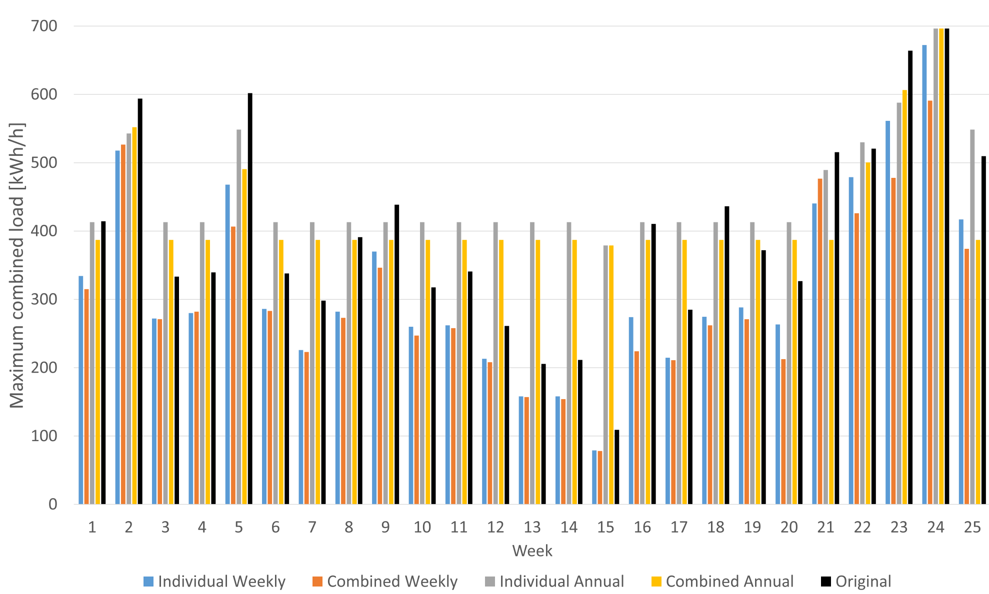
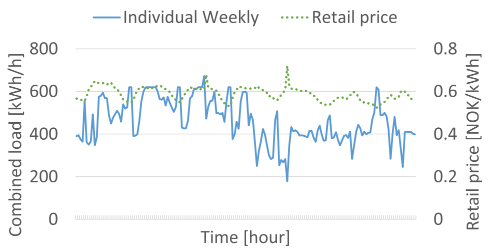
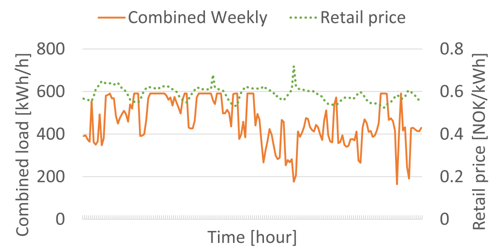


Fig. 3. Weekly combined maximum load after cost-optimal response to the individual weekly (IW) scheme (blue), combined weekly (CW) scheme (orange), individual annual (IA) scheme (gray), and combined annual (CA) scheme (yellow). The original maximum loads in the different weeks are displayed in black. The highest combined load occurs in week 24 where the combined weekly (CW) scheme triggers most peak load shaving. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

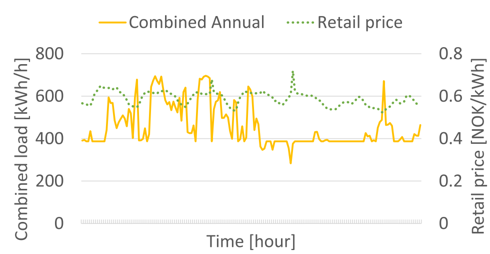


(a) Resulting cost-optimal load (blue) with the individual weekly (IW) scheme.



(b) Resulting cost-optimal load (orange) with the combined weekly (CW) scheme.

(c) Resulting cost-optimal load (gray) with the individual annual (IA) scheme.



(d) Resulting cost-optimal load (yellow) with the combined annual (CA) scheme.

Fig. 4. Resulting combined hourly load profile for 168 h for the individual weekly (IW) scheme (Fig. 4a), combined weekly (CW) scheme (Fig. 4b), individual annual (IA) scheme (Fig. 4c), and combined annual (CA) scheme (Figure d) in week 24 when the original maximum combined load is occurring. The left axis shows hourly load in kWh/h (solid lines) and the right axis shows hourly retail price in NOK/kWh (green dotted lines). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

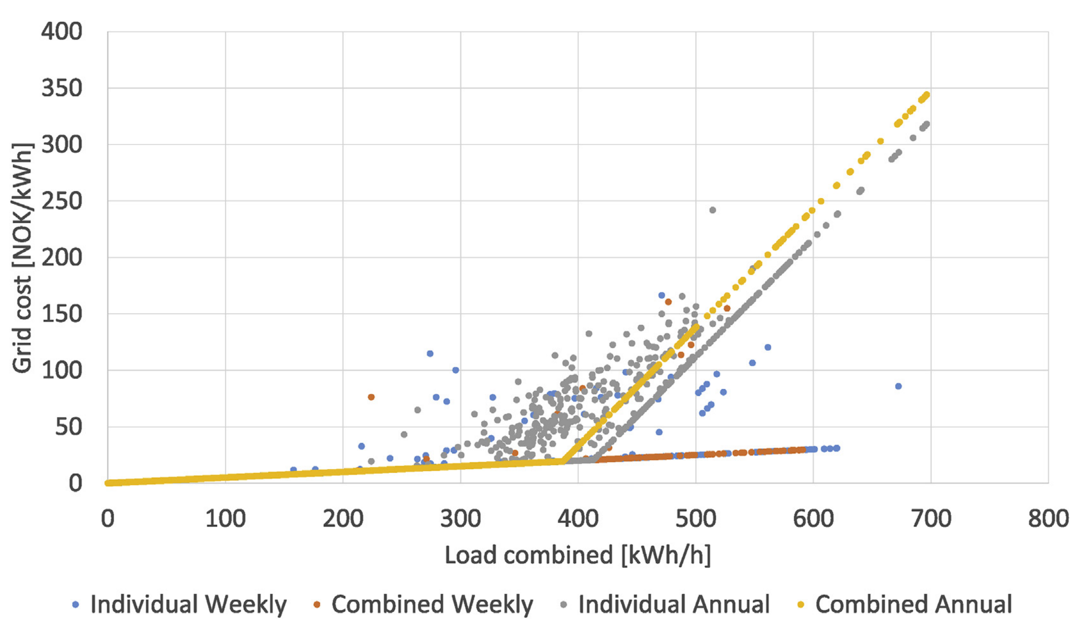


Fig. 5. Resulting hourly load dependent grid tariff costs, i.e., load dependent price multiplied by the load, in NOK/kWh plotted against the combined load of Campus 1 (C1) and Campus 2 (C2) for the individual weekly (IW) scheme (blue), combined weekly (CW) scheme (orange), individual annual (IA) scheme (gray), and combined annual (CA) scheme (yellow). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

weeks 2, 4, and 21 in Fig. 3). This occurs due to three different (but related) reasons that are worth noticing:

- For week 2, the opportunity to respond to retail prices is more valuable than responding to the grid tariff scheme (see Table 3). The two opportunities for cost saving could be conflicting.
- For week 4, the sum of the individual subscription levels is slightly lower than the combined subscription level (see Table 4), so the individual subscriptions are more ‘conservative’ than the combined subscription.
- For week 21, low subscription cost and high penalty loads in the CW scheme are compensated by high subscription cost and low penalty loads in the IW scheme, so peak shaving is not always the cost-optimal response with the subscribed capacity scheme.

Two main factors should be considered depending on the goal of introducing a capacity-based grid tariff scheme: (1) The dynamics of the grid tariff, i.e., the adjustment frequency of tariff rates and subscription levels, and (2) the load signal that the grid tariff will depend on.

The first factor, the grid tariff dynamics, will impact the achievement of peak shaving through flexibility (see Fig. 3). For an annual decision on the grid subscription level, the cost-optimal strategy is to consider a full year of costs when finding the best subscription level. This consideration means the subscription level is too low for critical hours because costs are minimized for the whole year. Annual subscriptions also lead to more penalty hours than weekly subscriptions, i.e., annual subscriptions make it cost-optimal for prosumers to exceed their subscription level. However, weekly subscriptions trigger load reduction in weeks when grid capacity is not scarce, which results in a potential loss of consumer welfare by penalizing utilization of idle grid capacity. A lower bound on the subscription level combined with dynamic subscription rates can be introduced to avoid rationing of capacity during non-critical hours.

The second factor, the load signal, will impact at which connection point peak shaving is triggered (see Table 5). Under the condition that prosumers have significantly different hourly load profiles,[2] shaving peaks based on individual metering does not maximize the annual peak shaving of the combined load profile. There is more variety in load profiles of buildings for various purposes (e.g. households, shops, offices, etc.) [50], and the flexibility potential will likely vary for the different buildings [51]. The objective of reducing individual loads could be in competition with reducing the combined load, i.e., the individual load could increase and the combined load decrease within a measuring period (and vice versa). If the goal of a capacity-based grid tariff scheme is to trigger combined peak load shaving for a collection of prosumers, price signals based on individual metering are likely to be sub-optimal (see Table 5) and could compromise consumer welfare when considering the disutility of offering flexibility. If the price signal is based on the combined load at a bottleneck connection of the grid, it is more likely to trigger combined peak load shaving.

In Norway, all grid-connected consumers are obliged to have individual metering, and this requirement is not challenged by introducing combined price signals. One could identify combined loads through: (a) summing individually metered data, or (b) combined metering at a potential bottleneck. This also points to other alternatives for local coordination in the grid, for example through flexibility markets. The efficiency of flexibility markets for resource allocation, either as an alternative or supplement to dynamic capacity-based grid tariffs, is an interesting area of future research.

[2] A quality check has been performed with our model confirming there is no difference between individual (IW and IA) and combined (CW and CA) metering schemes when two prosumers have identical load profiles.

6. Conclusion

This paper analyzes four different capacity-based grid tariff subscriptions by using a two-stage stochastic programming model in a case study of a Norwegian campus site with flexible assets. The novelty of our analysis includes: (1) comparing long-term annual tariff adjustment with short-term weekly tariff adjustment and (2) comparing the combined and coordinated demand response of several prosumers with the individual responses of single prosumers. The results show that cost-optimal operation of the flexible assets varies depending on the design of the grid tariff scheme. We find that a weekly adjustment of the subscribed grid tariff triggers a reduction in the maximum weekly load more efficiently than an annual subscription in 92% of the simulated weeks, while the combined subscription triggers combined load reduction more efficiently than individual subscriptions in 88% of the simulated weeks. According to our results, the capacity-based grid tariff subscription scheme is likely to be successful in promoting efficient grid development if: (1) the tariff parameters (subscription level) can be adjusted more frequently than annually and (2) the price signals for scarcity in the grid depend on the combined load of several consumers rather than the individual loads. The analysis also indicates that the tariff rates should be adjusted within a year to account for annual load variability and avoid rationing when grid capacity is not scarce. Depending on where a bottleneck in the grid is located, the price signal from a capacity-based tariff should be based on the combined load of several consumers behind this bottleneck (rather than individual load profiles) given different individual load profiles.

Further research should expand the stylized case study to see the impact in a larger collection of different prosumers and consumers. Also, the case study does not address remuneration to flexibility providers, for example in a flexibility market as a supplement or alternative to capacity-based grid tariffs. Combined metering schemes call for some remuneration from all who benefit from flexibility to those who provide flexibility. Further research should compare the difference and substitution between flexibility market designs and capacity-based grid tariff schemes.

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.

CRediT authorship contribution statement

Stian Backe: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Visualization, Data curation, Writing - original draft. **Güray Kara:** Conceptualization, Writing - original draft. **Asgeir Tomasgard:** Conceptualization, Supervision, Writing - review & editing.

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Appendix A. Nomenclature

List of model components	
Sets	
$\mathscr{F}$	Set of flexible asset types
$\mathscr{F}_p$	Set of flexible asset types at $p \in \mathscr{P}$
$\mathscr{P}$	Set of prosumers
$\mathscr{T}$	Set of market clearing time steps
Ω	Set of stochastic scenarios
Input Data	
$\varepsilon_f^{\text{charge}}$	Charging losses of $f \in \mathscr{F}$
$\varepsilon_f^{\text{diff}}$	Diffusion losses (self-discharge) of $f \in \mathscr{F}$
$\varepsilon_f^{\text{discharge}}$	Discharging losses of $f \in \mathscr{F}$
$\eta_{p,f}^{\text{charge}}$	Charging capacity of $f \in \mathscr{F}_p$ at $p \in \mathscr{P}$
$\eta_{p,f}^{\text{discharge}}$	Discharging capacity of $f \in \mathscr{F}_p$ at $p \in \mathscr{P}$
$\eta_{p,f}^{\text{storage}}$	Energy storage capacity of $f \in \mathscr{F}_p$ at $p \in \mathscr{P}$
$\gamma_{p,f,t}^{\text{req}}$	Minimum required energy content of $f \in \mathscr{F}_p$ at $p \in \mathscr{P}$ at time $t \in \mathscr{T}$
$\kappa_{p,f}$	Share of energy storage capacity initially available in $f \in \mathscr{F}_p$ at $p \in \mathscr{P}$
π_ω	Probability of scenario $\omega \in \Omega$
$\xi_{p,t,\omega}^{\text{load}}$	Net demand for electricity at $p \in \mathscr{P}$ in time $t \in \mathscr{T}$ and scenario $\omega \in \Omega$
c^{norm}	Energy dependent grid cost below subscription level (per kWh)
c^{pen}	Energy dependent penalty cost for exceeding grid subscription level (per kWh)
$c_{t,\omega}^{\text{ret}}$	Retail cost of electricity import (incl. taxes) at time $t \in \mathscr{T}$ and scenario $\omega \in \Omega$ (per kWh)
c^{sub}	Grid subscription cost per power level (per kWh/h)
Variables	
$k_{t,\omega}^{\text{C}}$	The (combined) tariff cost on import from the grid in time $t \in \mathscr{T}$ and scenario $\omega \in \Omega$
$k_{p,t,\omega}^{\text{I}}$	The (individual) tariff cost on import from the grid to $p \in \mathscr{P}$ in time $t \in \mathscr{T}$ and scenario $\omega \in \Omega$
$w_{p,f,t,\omega}^{\text{charge}}$	Charging of $f \in \mathscr{F}_p$ at $p \in \mathscr{P}$at time $t \in \mathscr{T}$and scenario $\omega \in \Omega$
$w_{p,f,t,\omega}^{\text{discharge}}$	Discharging of $f \in \mathscr{F}_p$ at $p \in \mathscr{P}$at time $t \in \mathscr{T}$and scenario $\omega \in \Omega$
$w_{p,f,t,\omega}^{\text{storage}}$	Available energy in flexible asset type $f \in \mathscr{F}_p$ at prosumer $p \in \mathscr{P}$ at time $t \in \mathscr{T}$ and scenario $\omega \in \Omega$
x^{C}	The (combined) subscribed capacity level
x_p^{I}	The (individual) subscribed capacity level at prosumer $p \in \mathscr{P}$
$y_{p,t,\omega}^{\text{load}}$	Resulting grid import at $p \in \mathscr{P}$ in time $t \in \mathscr{T}$ and scenario $\omega \in \Omega$

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