A Stochastic MPEC Approach for Grid Tariff Design with Demand Side Flexibility

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Abstract

As the end-users increasingly can provide flexibility to the power system, it is important to consider how this flexibility can be activated as a resource for the grid. Electricity network tariffs are one option that can be used to activate this flexibility. Therefore, by designing efficient grid tariffs, it might be possible to reduce the total costs in the power system by incentivizing a change in consumption patterns.

This paper provides a methodology for optimal grid tariff design under decentralized decision-making and uncertainty in demand, power prices, and renewable generation. A bilevel model is formulated to adequately describe the interaction between the end-users and a distribution system operator. In addition, a centralized decision-making model is provided for benchmarking purposes. The bilevel model is reformulated as a mixed-integer linear problem solvable by branch-and-cut techniques.

Results for a deterministic example and a stochastic case study are presented and discussed.

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***Index Terms*—Bilevel problem, grid tariffs, mathematical program with equilibrium constraints (MPEC), uncertainty**

NOMENCLATURE

Sets

c ∈ C	Consumers.
s ∈ S	Scenarios
h ∈ H	Hours.

Parameters

A	Time horizon considered (days)
$D_{c,s,h}$	Fixed load at consumer c in scenario s and time step h (kWh/h).
$D^{\Delta-}_{c,s}$	Flexible load at consumer c in scenario s (kWh).
D^{MAX}_{c}	Peak electricity load at consumer c (kWh/h).
F^{G}	Existing transmission capacity (kW).
fnt	Fixed cost part of network tariff (EUR).
$G_{c,s,h}$	Availability of PV at consumer c in scenario s and time step h (kWh/h/kW).
L^{G}	Transmission losses (%).
I^{G}	Annualized investment cost of grid capacity (EUR/kW-year).
NM	Net metering coefficient.
$P_{s,h}$	Power market price in scenario s and time step h (EUR/kWh).
T	Electricity tax (EUR/kWh).
$U^{\Delta+}_{c,s,h}$	Flexible load limit at consumer c in scenario s and time step h (kW).
U^{PV}_{c}	Installed capacity of PV at consumer c (kW).
VAT	Value-added tax (%).
VLL	Cost of load curtailment for DSO (EUR/kWh).
W_s	Weight for each scenario.

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Upper-level variables

c^{G}_{DSO}	Grid capacity investments made by DSO (kW).
cnt	Capacity-based network tariff (EUR/kW-day).
$e^{G}_{s,h}$	Total grid load in scenario s and time step h (kWh/h).
$ls_{s,h}$	Load curtailment in scenario s and time step h (kWh/h).
$op_{s,h}$	Off-peak variable determined by DSO in scenario s and time step h.
vnt	Volumetric network tariff (EUR/kWh).

Lower-level variables

$c^{G}_{c,s}$	Grid capacity allocation in scenario s (kW).
$d^{\Delta+}_{c,s,h}$	Flexible load in scenario s and time step h (kWh/h)
$e^{I}_{c,s,h}$	Energy imported from grid in scenario s and time step h (kWh/h).
$e^{E}_{c,s,h}$	Energy exported to grid in scenario s and time step h (kWh/h).
$g_{c,s,h}$	Electricity generation from PV in scenario s and time step h (kWh/h).

I. INTRODUCTION

A. Background

The transition from traditional, inelastic, electricity demand to more flexible consumers, means that the paradigm of demand as a passive load is no longer valid since demand can react to price signals. By introducing prosumers, who can both consume and produce electricity, the grid tariffs should provide efficient price signals to align the optimal end-user decisions with efficient utilization of the power system at a larger scale to avoid a sub-optimal outcome as demonstrated in [1].

Grid tariffs are mostly implemented as fixed amounts [EUR/period], volumetric charges [EUR/kWh], and possibly capacity-based [EUR/kW] charges. Although variations exist, electricity network tariffs can generally be reduced to these three fundamental structures [2]. A general issue regarding network tariffs is that there does not exist an ideal policy since it is necessary to balance efficiency with other aspects [3]. One principal problem of current tariff structures is that they primarily consist of fixed and volumetric charges. This is, as presented in [4], [5], [6], not a sufficient proxy for the overall network costs.

However, capacity-based tariffs may be a prospective solution since they more accurately reflect the upstream grid costs than volumetric tariffs as argued in [7], [8]. However, a flat capacity-based tariff scheme provides incentives to stay below the maximum usage in all hours, regardless of the congestion in the network. Furthermore, a flat capacity-based tariff neglects the fact that the grid load usually is well below the maximum capacity.

The overall research question we consider in this paper is: *How can we, by using network tariffs, incentivize flexible end-users to efficiently adapt their consumption patterns?* We address the problems concerning flat tariffs and present a novel approach by formulating the electricity network tariff design problem in the context of prosumers at the end-user level. Various network tariff structures are optimized subject to the prosumers best response in a game theoretical framework, which are benchmarked against a centralized system optimization.

B. Literature review

Overall, the existing related literature can be assigned to two different groups. One major group focuses on the impact of various tariff structures for specific consumer types and technologies [9], [10], [11], [12]. In general, this line of research is able to assess the impact of various tariff schemes on these stakeholders. The approach in this research area differs from our research because they treat the grid tariffs as exogenous parameters and do not attempt to design the tariffs optimally by considering the consumers and the grid as an integrated system.

The second line of research is more closely related to our work, approaches the subject of electricity grid tariffs by determining an equilibrium between end-users and a grid entity (e.g., DSO). This means that it is necessary to consider a bilevel problem. Using an equilibrium approach, [13], [14] formulate the problem by defining the lower level as a system of optimization problems and iteratively calculating the tariffs until network costs equal the charges. The aforementioned approaches are limited to selecting the level of flat tariffs, and do not allow for consideration of different scenarios and determining off-peak periods.

Equilibrium models are widely applied to power market research because of the ability to represent various market structures and interactions between market participants. The properties of the tariff design problem addressed in this paper are consistent with Stackelberg-type games [15], which are characterized by a leader who moves first and one or more followers acting optimally in response to the leader's decisions. Games with a Stackelberg structure can be formulated as mathematical problems with equilibrium constraints (MPECs) [16]. MPEC models are widely applied to power systems for analyzing, e.g., strategic investment decisions [17], [18], [19] and strategic bidding in electricity markets [20], [21]. Although the MPEC formulation is increasingly being used for power system applications and is suitable for grid tariff optimization, we have not found any prior papers formulating an MPEC approach for electricity network tariff computation under flexible demand.

C. Contributions

In this work, we address the gap in the literature concerning tariff optimization and analyze how tariff schemes can be used to activate consumer flexibility and efficiently reduce grid load by developing an MPEC. This paper provides a novel method of determining grid tariffs that can provide more efficient grid pricing and reduce total system costs. The primary contributions of this paper are as follows:

- Development of a stochastic MPEC model for optimizing electricity network tariffs subject to active end-users. The model formulates end-users responding to the tariffs determined by the system operator. Uncertainty is represented by stochastic demand, market prices, and PV output.
- Formulation of an electricity network tariff structure capable of incentivizing flexible end-users to use electricity when the grid load is low.
- Two case studies to highlight the model features and to assess how demand flexibility can be efficiently activated by grid tariffs in a setting with limited grid capacity and decentralized decision-making. The case studies are benchmarked against a system optimal solution with centralized decision-making.

D. Structure of paper

The rest of this paper is structured as follows. Section II describes the leader and follower optimization problems and how these are coupled in an overall system. A description of both a system optimization model used for benchmarking and a MPEC formulation is provided. Furthermore, section III describes reformulations and the computational setup used. Section IV presents a deterministic illustrative example and a stochastic case study. Finally, conclusions are provided in section V.

II. Model formulation

In this section, we formulate the lower-level and upper-level problems considered as part of the MPEC. Then, the resulting MPEC where the DSO decides the tariffs applied to the consumers as depicted in Fig. 1 is formulated.

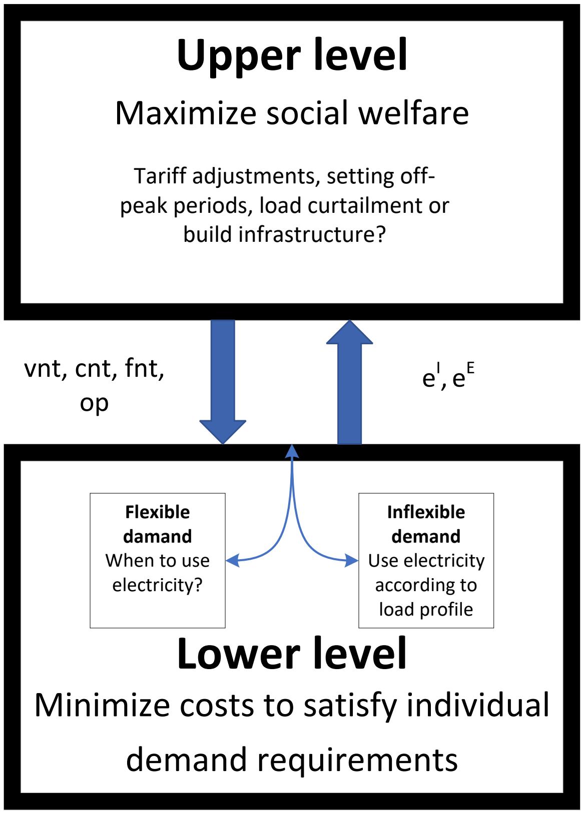


Fig. 1: Structure of the modeled bilevel tariff optimization problem.

A. Lower-level formulation

The lower level comprises the end-users of electricity, which can be either consumers or prosumers. The problem of the individual end-user is described as an optimization problem that is similar for both consumers and prosumers. However, for regular consumers, many of the variables will be zero as there are no generation resources and flexible load. A fully passive consumer will simply exhibit the specified demand on the grid without any decentralized decision-making involved. We indicate the dual variables associated with each of the constraints (5) - (9).

1) Objective function: We assume the objective of the end-users is to minimize their costs according to (1). Three scenario-dependent cost components are included: Cost of purchasing power from the power market, $Cost^P_{c,s}$, taxes, $Cost^T_{c,s}$, and grid costs, $Cost^G_{c,s}$. The cost components are described by (2) - (4). Note that the actual network costs are not considered at the end-user level since these costs are imposed indirectly through the network tariffs.

$$Min : Cost_{c,s} = Cost^P_{c,s} + Cost^T_{c,s} + Cost^G_{c,s} \quad (1)$$

$$Cost^P_{c,s} = \sum_{h=1}^{H} (e^I_{c,s,h} * (1 + VAT) - e^E_{c,s,h}) * P_{s,h} \quad (2)$$

$$Cost^T_{c,s} = (1 + VAT) * T * \sum_{h=1}^{H} e^I_{c,s,h} \quad (3)$$

$$Cost^G_{c,s} = (1 + VAT)(\sum_{h=1}^{H} (e^I_{c,s,h} - NM * e^E_{c,s,h}) * vnt + c^G_{c,s} * cnt + fnt) \quad (4)$$

Note here the NM parameter that quantifies to which extent the electricity exports are subject to net metering:

- $NM = 1$: The end-user only pays volumetric charge for net imports.
- $NM = 0$: The end-user pays volumetric charge for all imports.
- $NM = -1$: The end-user pays volumetric charge for both imports and exports.

2) Energy balance: The energy balance of the prosumer is described by (5) and states that energy imports subtracted exports must be equal to fixed and flexible demand subtracted generation from PV.

$$\forall c, \forall s, \forall h : D_{c,s,h} + d^{\Delta+}_{c,s,h} - g_{c,s,h} = e^I_{c,s,h} - e^E_{c,s,h} \quad (\lambda^{EB}_{c,s,h}) \quad (5)$$

3) Flexible load: Inspired by EV charging requiring an amount of electricity for each day, (6) describes the total flexible load for each scenario. This means that a flexible consumer can choose when to consume the flexible load, as long as the total load across all hours in a scenario is equal to the specified amount.

$$\forall c, \forall s : D^{\Delta-}_{c,s} = \sum_{h=1}^{H} d^{\Delta+}_{c,s,h} \quad (\lambda^{FL}_{c,s}) \quad (6)$$

4) Flexibility capacity: The maximum flexible load during each time step is limited by (7). This is analogous to EV charging capacity.

$$\forall c, \forall s, \forall h : d^{\Delta+}_{c,s,h} \leq U^{\Delta+}_{c,s,h} \quad (\mu^{FC}_{c,s,h}) \quad (7)$$

5) Grid capacity allocation: The end-user has to subscribe to the maximum power injected to or withdrawn from the grid according to (8). However, during the off-peak hours set by the DSO (if $op_{s,h} = 1$), the constraint is relaxed to allow for increased grid utilization.

$$\forall c, \forall s, \forall h : e^I_{c,s,h} + e^E_{c,s,h} \leq c^G_{c,s} + D^{MAX}_c * op_{s,h} \quad (\mu^G_{c,s,h}) \quad (8)$$

6) PV generation: PV generation is described by (9) and has the option of curtailing in the case of situations with an over-production.

$$\forall c, \forall s, \forall h : g_{c,s,h} \leq U^{PV}_c * G_{c,s,h} \quad (\mu^{PV}_{c,s,h}) \quad (9)$$

B. Upper-level formulation

1) DSO costs: The DSO is responsible for building and maintaining the electricity grid. The costs related to the DSO are network losses, load curtailment costs and infrastructure costs. These costs related to the DSO's activities are described by (10) and (11). $Cost^P_{DSO,s}$ denotes operational costs, while $Cost^C_{DSO}$ denotes investment costs.

$$Cost_{DSO,s}^{P} = \sum_{h=1}^{H}(e_{s,h}^{G} * L^{G} * P_{s,h} + ls_{s,h} * VLL) \quad (10)$$

$$Cost_{DSO}^{C} = I^{G} * c_{DSO}^{G} \quad (11)$$

2) Transmission of electricity: Furthermore, the DSO needs to transfer electricity at each time step according to the total imports or exports generated by the end-users described by (12).

$$\forall s, \forall h : e_{s,h}^{G} = |\sum_{c=1}^{C}(e_{c,s,h}^{I} - e_{c,s,h}^{E})| \quad (12)$$

It should be noted that (12) includes an absolute function, which we handle as described in section III-A1.

3) Interconnection capacity: Existing and new interconnection capacity needs to cover the electricity transferred less load curtailment according to (13).

$$\forall s, \forall h : F^{G} + c_{DSO}^{G} \geq e_{s,h}^{G} - ls_{s,h} \quad (13)$$

4) Total system costs: In the modeled system, costs occur both at the end-user and DSO levels. The total costs in the system are described by (14). The tariff costs are not included since these would be added to consumer costs and subtracted from the DOS's costs, resulting in zero net contribution towards total costs. Therefore, neglecting cost recovery for the DSO, the grid tariffs are purely tools to incentivize end-user behavior in this model.

$$TC = \sum_{s=1}^{S} A * W_s * (Cost_{DSO,s}^{C} + \sum_{c=1}^{C}(Cost_{c,s}^{P} + Cost_{c,s}^{T})) + Cost_{DSO}^{C} \quad (14)$$

C. System optimization model

The benchmark case is a system optimization where all decisions are made centrally. This would for example be the case if the DSO could directly control EV charging at the consumer level. The system optimization means that the bilevel problem is replaced by a linear problem which considers all costs and technical restrictions both at the DSO and end-user level directly. The system optimization is formulated below:

$$\text{Min } TC \quad (15)$$

Subject to constraints (5) - (9) and (12) - (13).

D. Bilevel model

Similar to the system optimization, we consider that the upper level tries to maximize social welfare by minimizing total costs as depicted in (16).

$$\text{Min } TC \quad (16)$$

In addition, we include the upper-level constraints (12) - (13).

The optimization problems of the end-users are linear and with convex constraints. Due to these properties, the individual optimization problems can be replaced by their Karush-Kuhn-Tucker (KKT) optimality conditions formulated in (17) - (26) below.

$$\forall c, \forall s, \forall h : (P_{s,h} + T + vnt) * (1 + VAT) - \lambda_{c,s,h}^{EB} + \mu_{c,s,h}^{G} \geq 0 \perp e_{c,s,h}^{I} \geq 0 \quad (17)$$

$$\forall c, \forall s, \forall h : -P_{s,h} - NM * vnt * (1 + VAT) + \lambda_{c,s,h}^{EB} + \mu_{c,s,h}^{G} \geq 0 \perp e_{c,s,h}^{E} \geq 0 \quad (18)$$

$$\forall c, \forall s : (1 + VAT) * cnt - \sum_{h=1}^{H} \mu_{c,s,h}^{G} \geq 0 \perp c_{c,s}^{G} \geq 0 \quad (19)$$

$$\forall c, \forall s, \forall h : \lambda_{c,s,h}^{EB} - \lambda_{c,s}^{FL} + \mu_{c,s,h}^{FC} \geq 0 \perp d_{c,s,h}^{\Delta+} \geq 0 \quad (20)$$

$$\forall c, \forall s, \forall h : -\lambda_{c,s,h}^{EB} + \mu_{c,s,h}^{PV} \geq 0 \perp g_{c,s,h}^{PV} \geq 0 \quad (21)$$

$$\forall c, \forall s, \forall h : e_{c,s,h}^{I} - e_{c,s,h}^{E} - D_{c,s,h} - d_{c,s,h}^{\Delta+} + g_{c,s,h} = 0 \perp \lambda_{c,s,h}^{EB} \quad (22)$$

$$\forall c, \forall s, \forall h : c_{c,s}^{G} + D_{c}^{MAX} * op_{s,h} - e_{c,s,h}^{I} - e_{c,s,h}^{E} \geq 0 \perp \mu_{c,s,h}^{G} \geq 0 \quad (23)$$

$$\forall c, \forall s, \forall h : U_{c}^{PV} * G_{c,s,h} - g_{c,s,h}^{PV} \geq 0 \perp \mu_{c,s,h}^{PV} \geq 0 \quad (24)$$

$$\forall c, \forall s : \sum_{h=1}^{H} d_{c,s,h}^{\Delta+} - D_{c,j}^{\Delta-} = 0 \perp \lambda_{c,j}^{FL} \quad (25)$$

$$\forall c, \forall s, \forall h : U_{c,s,h}^{\Delta+} - d_{c,s,h}^{\Delta+} \geq 0 \perp \mu_{c,s,h}^{FC} \geq 0 \quad (26)$$

III. SOLUTION APPROACH

A. Linearization methods

The model formulated in section II-D contain two sources of nonlinearities:

- Absolute value term in the upper-level constraint (12).
- Complementarity conditions (17) - (26) in the MPEC formulation (shown as $\perp$).

1) Line flow constraint: The amount of transferred electricity is described by an absolute value function (12) since it is the maximum of either imports or exports. However, since losses have nonnegative costs with nonnegative power market prices, a cost minimizing DSO will select the lowest amount of grid transfer possible. Therefore, equality (12) can be replaced by inequalities (27) - (28), which does not include absolute value terms, as long as power market prices are nonnegative.

$$\forall s, \forall h : e^G_{s,h} \geq \sum_{c=1}^{C} (e^I_{c,s,h} - e^E_{c,s,h}) \tag{27}$$

$$\forall s, \forall h : e^G_{s,h} \geq \sum_{c=1}^{C} (e^E_{c,s,h} - e^I_{c,s,h}) \tag{28}$$

2) Complementarity conditions: The complementarity conditions on the form:

$$f(x) \geq 0 \perp x \geq 0 \tag{29}$$

Can be replaced by:

$$f(x) \geq 0, x \geq 0, f(x) \leq \alpha * M, x \leq (1 - \alpha) * M \tag{30}$$

Where α is a binary variable and M is a large enough constant. However, choosing an appropriate value for M is important for numerical stability, but can be a challenging task in itself [22]. To overcome the issues concerning a "big-M" formulation, the complementarity conditions can also be transformed by using SOS type 1 variables as presented in [23]. Hence, (29) can be reformulated into the following:

$$f(x) \geq 0, x \geq 0 \tag{31}$$

$$u = \frac{x + f(x)}{2} \tag{32}$$

$$v^+ - v^- = \frac{x - f(x)}{2} \tag{33}$$

$$u - (v^+ + v^-) = 0 \tag{34}$$

Where v^+, v^- are SOS type 1 variables.

The SOS type 1 based approach provides a global optimal solution in a computationally efficient way. In addition, we avoid having to specify an appropriate value for M to ensure that the complementarity conditions are not violated. Therefore, complementarity conditions (17) - (26) are linearized using the SOS type 1 approach, forming a MILP.

B. Computational set-up

The models are implemented in GAMS v27.3.0 and solved as LP for the benchmark case and MILP for the MPEC cases by CPLEX v12.9.0.0 on a personal computer with an Intel(R) Core(TM) i7-8850H 6-core CPU and 32GB of RAM.

1) System optimization: The system optimization is formulated as a linear problem which with the linearized line flow constraint can be solved directly by off the shelf optimization software.

2) MPEC: After the linearizations described in sections III-A1 and III-A2, the MPEC is reformulated into a MILP with SOS1 variables to handle the complementarity conditions. The resulting formulation can be directly solved with commercial MILP solvers. A relative gap tolerance of 1% was used in all cases.

IV. Case studies

In this section, we present results for the following cases:

- SO: System optimal solution
- MPEC-F: MPEC with flat capacity based tariff ($op_{s,h}$ fixed at zero).
- MPEC-P: MPEC with capacity-based tariff and scenario dependent off-peak period selection ($op_{s,h}$ binary and decided by DSO).
- MPEC-PN: MPEC with capacity-based tariff and off-peak period constrained by nonanticipativity ($op_{s,h} = op_h$ binary and decided by DSO).

A. Illustrative example

For simplicity, we first consider a deterministic example of one scenario with a fixed and a flexible load and limited grid capacity. The scenario comprises one day with two segments which are denoted segment 1 and 2, respectively. Segment 1 comprises the first 12 hours of the day, while segment 2 comprises the second 12 hours. The fixed load is high in the first segment, and low in the second segment. Furthermore, the electricity price is low in the first segment and high in the second segment. This means that we have a situation where fixed demand is high when electricity prices are low and opposite. Therefore, with limited grid capacity, it is beneficial for the grid if most of the flexible load occur in the high-price period to avoid load curtailment. We assume that it is not possible to invest in additional grid capacity, meaning that c^G_{DSO} is fixed at zero. An overview of the input data for the illustrative example is provided in Table I.

TABLE I: Input parameters for illustrative example

Parameter	Symbol	Value
Time horizon	A	365 days
Fixed load in segment 1	$D_{1,s,h}$	9 kWh/h
Fixed load in segment 2	$D_{1,s,h}$	4 kWh/h
Flexible load	$D^{\Delta-}_{1,s}, D^{\Delta-}_{2,s}$	0 kWh/day, 70 kWh/day
Transmission capacity	F^G	10 kW
PV generation	$G_{c,s,h}$	0
Transmission losses	L^G	6%
Net metering coefficient	NM	0
Market price in segment 1	$P_{s,h}$	0.05 EUR/kWh
Market price in segment 2	$P_{s,h}$	0.10 EUR/kWh
Electricity tax	T	0.016 EUR/kWh
Flexible load limit	$U^{\Delta+}_{c,s,h}$	5 kW
PV capacity	U^{PV}_c	0 kW
Value-added tax	VAT	25%
Load curtailment cost	VLL	3 EUR/kWh
Scenario weight	W_s	1

Since we only consider one scenario, case MPEC-PN is not included in the illustrative example. All cases were solved in less than 1 minute. Results are provided in Table II and Fig. 2.

TABLE II: Illustrative example: Key results

	SO	MPEC-F	MPEC-P
Total costs [EUR]	9587	34222	9587
Cost change	0%	+257%	0%
Curtailment [kWh]	0	8395	0
cnt [EUR/kW]	NA	0.6	0.6
vnt [EUR/kWh]	NA	0	0
Optimality gap	Optimal	0.052%	Optimal
CPU time	$<$ 1 min	$<$ 1 min	$<$ 1 min

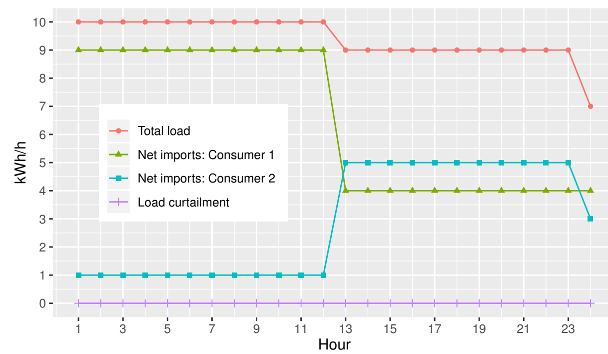
The benchmark case is SO, which takes a central planning approach. The MPEC cases can be compared to the SO case to assess the performance of the different tariff schemes. Regarding total costs, MPEC-P is equal to SO, while MPEC-F has higher total costs due to load curtailment occurring in segment 1. The load curtailment can be explained by the flat tariff scheme in MPEC-F, which means that the prosumer has incentives to keep the maximum load as low as possible in any hour. Hence, the lowest peak load is obtained by dividing the total load of 70kWh by 24 hours, resulting in a flat load of 2.92kWh/h for the entire day. This operational pattern can be observed in Fig. 2b. Therefore, since the DSO is unable to provide any time-dependent incentives, case MPEC-F results in load curtailment during the first segment of the day even though the load could be served in segment 2.

In contrast to MPEC-F, load curtailment is completely avoided in case MPEC-P since segment 2 is set as off-peak by the DSO. Hence, because of the off-peak period, the prosumer has incentives to shift most of the load towards segment 2, even though the power prices are higher in this segment.

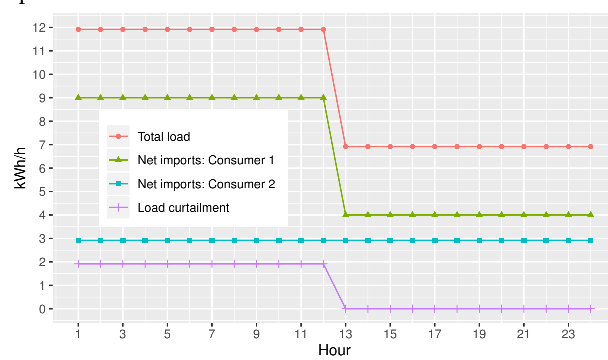
B. Stochastic case

Next, we consider the case of a residential area coupled with a PV generation and an EV charging facility. We assume consumer 1 is an inflexible residential demand for 1000 square meters of apartments. Furthermore, consumer 1 also has a PV system with an installed capacity of 50kW. Consumer 2 is an EV charging facility who shares the grid connection with consumer 1. Since the grid connection is shared between the consumers, coordinated EV-charging can potentially be important for the DSO, because it impacts the total load.

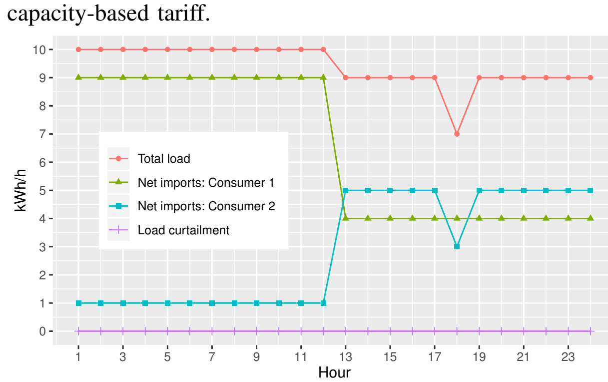
1) Input data: Input data for the case study is provided in Table III. Demand data representing 1000 square meters of apartments is generated according to the methodology presented in [24]. We cluster the data into two representative days, or scenarios by applying a hierarchical clustering algorithm, to keep the problem size tractable. The algorithm minimizes the distance between two days using PV generation, demand, and electricity price for each hour of the day as observations. The scenario-dependent information, presented in Fig. 3, is: (1) load profile for fixed demand, (2) PV generation, and (3) power market prices. Furthermore, we assume that a current interconnection capacity of 25 kW exists, and that is is not possible to increase the interconnection capacity. Scenario 1 has an overall higher load than scenario 2 for consumer 1. Also, there is a significant variation of the fixed demand within the day. Therefore, to avoid load curtailment, it is preferable for the DSO if consumer 2 perform the EV charging when consumer 1 has a low load.



(a) Illustrative case SO: Operational pattern in the system optimal solution.



(b) Illustrative case MPEC-F: Operational pattern with flat capacity-based tariff.



(c) Illustrative case MPEC-P: Operational pattern with capacity-based tariff and off-peak period selection.

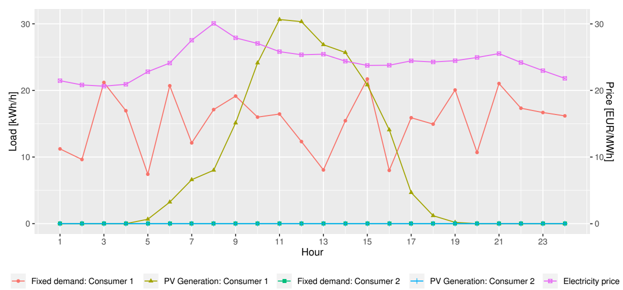
Fig. 2: Illustrative example: Operational decisions for centralized optimization and two different tariff structures with decentralized decision-making.

2) Results: Computationally, the main difference compared to the illustrative example is that more than one scenario is considered. When increasing the number of scenarios, the computational burden increases because some decisions at the upper level are nonanticipative. Hence, even though the lower-level problems are completely scenario dependent, the overall bilevel problem can not be directly decomposed by the individual scenarios.

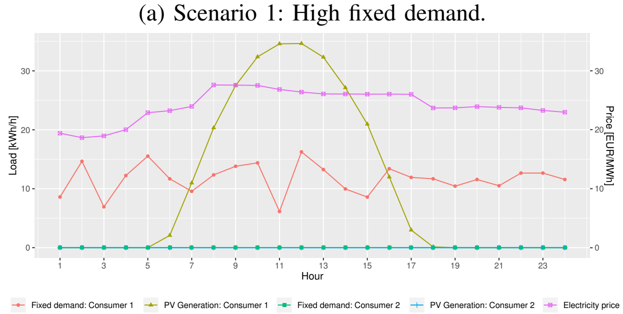
Case MPEC-F, with a flat capacity-based tariff, gives a similar result as for the deterministic case since the flexible demand of consumer 2 is simply divided by the number of hours in the day to give the minimum charging capacity during

TABLE III: Input parameters for case study

Parameter	Symbol	Value
Time horizon	A	365 days
Fixed load	$D_{c,s,h}$	See Fig. 3
Flexible load	$D^{\Delta-}_{1,s}, D^{\Delta-}_{2,s}$	0 kWh/day, 200 kWh/day
Transmission capacity	F^G	25 kW
PV generation	$G_{c,s,h}$	See Fig. 3
Transmission losses	L^G	6%
Net metering coefficient	NM	0
Electricity price	$P_{s,h}$	See Fig 3
Electricity tax	T	0.016 EUR/kWh
Flexible load limit	$U^{\Delta+}_{c,s,h}$	20 kW
PV capacity	U^{PV}_1, U^{PV}_1	50 kW, 0 kW
Value-added tax	VAT	25%
Load curtailment cost	VLL	3 EUR/kWh
Scenario weight	W_1, W_2	0.493, 0.507



(a) Scenario 1: High fixed demand.

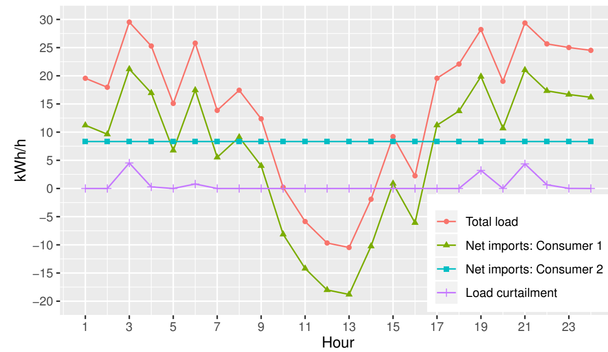


(b) Scenario 2: Low fixed demand.

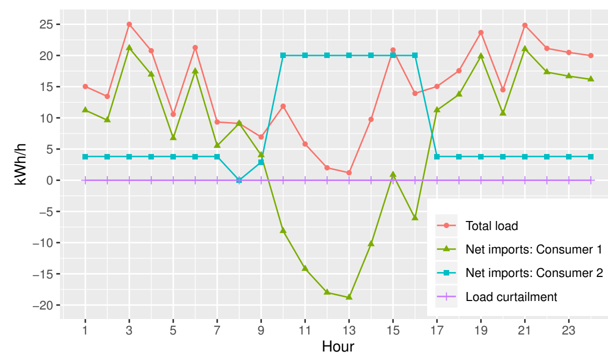
Fig. 3: Input-data for the two scenarios considered in the case study

each time step. This operational pattern can be observed in Fig. 4a, where the total load exceeds the interconnection capacity during some time steps. Therefore, with 200 kWh of charging during the day, the flexible load is 8.33 kWh for each hour. This results in load curtailment when the fixed demand is above 16.67 kWh per time step. This occurs in scenario 1, but not in scenario 2 as the fixed load of consumer 1 is low enough to allow for 8.33 kWh of charging during all time steps. Another observation is that during the middle of the day, the PV system at consumer 1 produces significant amounts of electricity by PV, which could be directly used for EV charging at consumer 2. However, due to the flat tariff structure, consumer 2 does not have any incentives to try to shift charging to these hours.

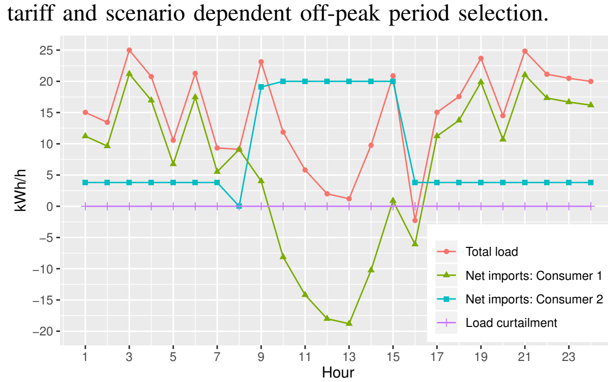
Key results are provided in Table IV. It can be observed that total costs for cases MPEC-P and MPEC-PN comes close to the theoretically optimal result in case SO. The difference between MPEC-P and MPEC-PN is that in MPEC-P, the



(a) Case MPEC-F: Operational pattern with flat capacity-based tariff.



(b) Case MPEC-P: Operational pattern with capacity-based tariff and scenario dependent off-peak period selection.



(c) Case MPEC-PN: Operational pattern with capacity-based tariff and scenario independent off-peak period selection.

Fig. 4: Case study: Operational decisions in scenario 1 for three tariff structures.

DSO can select off-peak hours for each scenario individually, whereas for MPEC-PN, the off-peak hours have to be equal for all scenarios.

Operational patterns for case MPEC-P in scenario 1 is provided in Fig. 4b. We see that in contrast to case MPEC-F, the load for consumer 2 changes over time as a response to the off-peak periods set by the DSO. As a result, load curtailment is completely avoided since consumer 2 is incentivized to consume as much as possible when consumer 1 produce significant amounts of electricity from the PV system.

Having off-peak hours depend on the scenario might be unrealistic due to the added complexity of the tariff scheme and need for communicating the off-peak hours on a daily

TABLE IV: Case study: Key results

	SO	MPEC-F	MPEC-P	MPEC-PN
Total costs [EUR]	5850	10875	5949	5969
Cost change	0%	+85.9%	+1.7%	+2.0%
Curtailment [kWh]	0	1594	0	0
cnt [EUR/kW-day]	NA	0.13699	0.06743	0.07154
vnt [EUR/kWh]	NA	0	0	0
Optimality gap	Optimal	0.05%	1%	1%
CPU time	<1 min	<1 min	11.3 h	13.6 h

basis. Therefore, Case MPEC-PN ensures that off-peak hours need to be equal for all scenarios by adding nonanticipativity constraints to the off-peak period selection. The nonanticipativity constraint alters the operational patterns slightly as shown in Fig. 4c, but the overall benefit of including off-peak periods is intact.

V. Conclusions

In this paper, a methodology for optimal grid tariff design under decentralized decision-making is presented. The presented bilevel model include a realistic formulation of the interaction between the end-user and distribution system operator. Uncertainty is included in the form of scenarios for fixed demand, PV generation, and electricity market prices. In addition, a centralized decision-making model is provided for benchmarking purposes.

An illustrative example to highlight the model features in a deterministic setting and a stochastic case study is presented. Case studies describes how flexible consumers can be incentivized to change their consumption patterns to reduce overall power system costs. By including off-peak period selection, the flexible consumer can be effectively incentivized to shift the charging to off-peak hours and hours with significant PV generation available at the local level. In contrast, a flat capacity-based tariff structure is not able to provide efficient incentives for load shifting.

Therefore, it can be concluded that in light of flexible end-users the electricity network tariff scheme should include a time-dependent capacity-based component such as the one presented to provide efficient incentives for load shifting.

The presented model is tractable, but computationally expensive. Further work is needed to speed up the calculations when increasing the amount of scenarios. In this context, decomposition techniques can be applied to increase the tractable problem size.

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