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Integrating Variable Distribution Use-of-System Tariffs and Local Flexibility Markets through a Bilevel Modelling Approach

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***Abstract*—Although the large-scale integration of distributed energy resources constitutes a fundamental pillar of low-carbon energy systems, it creates an increasing stress in distribution networks, requiring mobilisation of the flexibility of those resources to resolve network congestion. To this end, two alternative mechanisms that have recently gained attention are temporally- and spatially-differentiated distribution use-of-system tariffs and local flexibility markets. However, existing research has investigated these two mechanisms in silos, neglecting their potential synergies in mobilising distributed energy resources flexibility. This paper aims at addressing this research gap by proposing a bilevel optimisation model which captures the interactions between a distribution system operator designing variable distribution use-of-system tariffs and operating a local flexibility market based on capacity limitations, and aggregators of electric vehicles with smart charging capability reacting to the designed tariffs and procured capacity limitations. The model is tested on a real 47-node distribution network. The presented studies illustrate cases where the two mechanisms synergetically resolve congestion phenomena and demonstrate that their combination results in a significant reduction of total system costs.**

***Index Terms*—Aggregators, bilevel optimisation, capacity limits, congestion management, distribution networks, electric vehicles, local flexibility markets, network tariffs, use-of-system tariffs**

NOMENCLATURE

Indices and Sets

$i, j_i \in \mathcal{I}$	Nodes, branches ($^+$ when including the root)
$d \in \mathcal{D}$	Representative day-types
$t \in \mathcal{T}$	Time periods
$n \in \mathcal{N}$	Tariff levels

Parameters

w_d	Weight of each day-type d in days per year
r_{j_i}, x_{j_i}	Resistance, reactance at branch j_i (Ω)
$\overline{F}_{j_i}$	Apparent power limit at branch j_i (MVA)
$\underline{u}_i, \overline{u}_i$	Voltage bounds at node i (V)
$l_{i,t,d}$	Non-flexible demand at node i for period (t,d) (MWh)
$g_{i,t,d}$	Non-flexible generation at node i for period (t,d) (MWh)
ϕ_i	Power factor angle at node i
$\pi^e_{t,d}$	Wholesale energy price at period (t,d) (€/MWh)
π_n	Tariff level n (€/MWh)
$\underline{P}^{\text{cap}}_{i,d}, \overline{P}^{\text{cap}}_{i,d}$	Capacity limit bounds at node i for day-type d (MWh)
$\underline{e}_{i,t,d}, \overline{e}_{i,t,d}$	Charging bounds of aggregator at node i for period (t,d) (MWh)
$\underline{c}_{i,t,d}, \overline{c}_{i,t,d}$	Energy state bounds of aggregator at node i for period (t,d) (MWh)
$c^{\text{init}}_{i,d}, c^{\text{end}}_{i,d}$	Initial and final energy state of aggregator at node i and day-type d (MWh)
η	Charging efficiency
κ^D_i	Demand curtailment penalty factor at node i (€/MWh)
κ^G_i	Generation curtailment penalty factor at node i (€/MWh)
K^{fixed}	Fixed DSO costs (€)
κ^{C}	Profit margin of DSO

Variables

$\pi_{i,t,d}$	DUoS tariff at node i for period (t,d) (€/MWh)
$u_{i,t,d,n}$	Binary variable of tariff level n at node i for period (t,d)
$P^{\text{cap}}_{i,d}$	Capacity limit procured at node i for day-type d (MWh)
$P_{j_i,t,d}$	Active power flow at branch j_i for period (t,d) (MWh)
$Q_{j_i,t,d}$	Reactive power flow at branch j_i for period (t,d) (MVar)
$v_{i,t,d}$	Voltage squared at node i for period (t,d) (V^2)
$e_{i,t,d}$	Charging energy of aggregator at node i for period (t,d) (MWh)
$c_{i,t,d}$	Energy state of aggregator at node i for period (t,d) (MWh)
$c^D_{i,t,d}$	Demand curtailment at node i for period (t,d) (MWh)
$c^G_{i,t,d}$	Generation curtailment at node i for period (t,d) (MWh)

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I. INTRODUCTION

A. Background and motivation

The proliferation of distributed energy resources (DERs), including distributed generation, and flexible loads, constitutes one of the fundamental pillars of the emerging low-carbon future. Their integration into electricity systems brings both potential benefits associated with the operational flexibility of some DERs, but also significant challenges. One of the main challenges lies in the increasing stress for distribution networks (DNs) to which DERs are connected, both demand-driven (e.g., due to the increasing penetration of electic vehicles (EVs)), as well as generation-driven (e.g., due to the increasing penetration of photovoltaics (PVs)). Distribution system operators (DSOs) need to mobilise DER flexibility to address this challenge. Previous research suggests various mechanisms for flexibility mobilisation but few study their coexistence [1].

One mechanism lies in the employment of variable distribution use-of-system (DUoS) tariffs. In contrast to traditional fixed DUoS, whose only task has been the recovery of previous and prospective investment costs by the DSOs, variable DUoS vary with time and location, and can provide an economic incentive to DER owners to mobilise their flexibility for efficient network use [2]. Although some temporal variability in DUoS tariffs has already been deployed by DSOs, the benefits of extensive temporal and locational variability have also been recently demonstrated [3].

Another mechanism which has gained great interest during the last few years is local flexibility markets [4]–[6]. Although the regulatory framework around such markets is still under development, popular designs include DSO-operated markets with capacity limitation products offered by aggregators that provide guarantees to DSOs on maximum consumed power for a set period of time [7]. The motivation behind this paper is to model and analyse the synergy between variable DUoS tariffs and capacity limits, two popular flexibility motivation tools proposed for DSOs, and demonstrate how they can complement each other.

B. Relevant literature

The design of DUoS tariffs by modelling the interaction between the DSO and DER owners has been investigated in [3], [8]–[17]. Authors in [8] employ a game-theoretic model to design flat tariffs (i.e., tariffs without temporal or spatial variability), with the objective of recovering sunk network costs for the DSO. The research in [9] and [10] extends this model to a comprehensive bilevel optimisation model, which encapsulates the decision-making process of a regulatory authority designing the flat tariffs at the upper level, again with the goal of recovering network costs (sunk costs in [10] and prospective costs in [9]). In [9], the prospective network costs are modelled as a straightforward linear function of the network's overall peak demand. The research in [12] introduces a bilevel optimisation model for the design of volumetric and peak-power tariffs; while grid costs include load curtailment actions, their recovery is not discussed. The work in [11] and [13] focuses on the concept of local energy markets and their interaction with different DUoS tariff designs. The authors in [14] calculate network costs as a function of the maximum power flow on all branches and distribute them to each consumer according to their demand capacities. In [15] the authors use a bilevel scheme with flat tariffs to model the interaction between the DSO and consumers under network and distributed generation investment options. In [16] a similar scheme is applied in order to investigate and compare a voluntary and a mandatory demand-side connection agreement for consumers, and in [17] to assess the interaction between implicit and explicit demand-side flexibility.

Of the existing literature, only in our previous work [3] the tariff design model allows for both spatial and temporal granularity, while retaining important DUoS tariff attributes such as cost recovery and simplicity. However, in [3] costs incurred by DSOs were modelled solely using curtailment actions, and a generic load shifting model to represent flexibility was used.

Indeed, load curtailment is an undesirable last-resort measure, and since DUoS tariffs cannot provide DN operational guarantees, DSOs would need to have market-based alternatives [18] at their disposal to mitigate congestion. Local flexibility markets are advocated by EU legislators as a market-driven approach that allows DSO access to flexibility while fostering competition [19], [20]. The products which are traded in such markets take the following two forms: baseline-based and capacity-based (capacity limitations). Baselines introduce uncertainties to both DSOs and flexibility providers [21], while they have been shown to be prone to manipulation and difficulty in establishing commonly agreed methodologies for the involved parties [22]. Transparency has been shown to be a property of particular importance in establishing efficient local flexibility markets [23]. Capacity limitations impose temporary capacity limitations in the total power imports/exports of aggregations of DERs. They have been shown to exhibit more favourable properties in terms of service transparency and verification [7], while effective market clearing mechanisms have been proposed to trade such services between DSOs and aggregators [24].

C. Contributions

Although previous work has demonstrated that both variable DUoS tariffs and local flexibility markets can effectively mobilise DER flexibility to resolve congestion in distribution networks, these two mechanisms have been investigated in silos, neglecting their potential synergies. This paper aims at addressing this research gap by proposing a novel integrated optimisation model of both mechanisms. Specifically, the proposed model is a bilevel optimisation model which captures the interactions between a) a DSO (at the upper level) optimally designing temporally- and spatially-differentiated DUoS tariffs and operating a local flexibility market based on capacity limitations, with the overall aim to resolve network congestion with the minimum total system costs, and b) aggregators of EVs with smart charging capability (at the lower level) who react to the designed DUoS tariffs and procured capacity limitations, with the overall objective to minimise their own total costs. The proposed model considers PV generation since it constitutes the most dominant type of distributed generation across the world and EVs because a) they constitute a significant concern for DSOs since their increasing penetration combined with a potential inflexible mode of charging is likely to create demand-driven congestion phenomena, and b) on the other hand, recent technological advancements have enabled flexible modes of charging with the most prominent one being smart charging. However, it is worth noting that the proposed model can be extended to capture any type of flexible DER. Furthermore, the model considers DSO cost recovery constraints as well as discrete tariff levels to ensure their intelligibility by the aggregators.

In other words, the novel contribution of our paper is that, to the best of our knowledge, it constitutes the very first work that investigates the implications of variable DUoS tariffs and local flexibility products for DSOs in combination rather than in silos. Case studies carried out on a real 47-node distribution network in Greece verify the validity of the method and examine different scenarios concerning the temporal and spatial variation of the designed DUoS tariffs. The results demonstrate that in certain cases network congestion phenomena cannot be resolved independently by either variable DUoS tariffs or local flexibility markets, but rather through their synergetic effects.

Compared to [1], in this paper: a) the introduction and literature review have been expanded and updated, b) model formulation has been described in greater detail and new attributes have been added (e.g., curtailment as a last resort measure), c) a larger case study has been employed that consists of a real 47 node MV network provided by the Greek DSO and real demand and generation data from the same area. Moreover, the case study includes analysis of more tariff schemes with higher granularity.

II. Proposed Methodology

A. Overview

We suggest a framework where the DSO designs yearly ex-ante DUoS tariff patterns using historical data and representative day-types, see also Fig. 1. Aggregators submit flexibility offer curves for each day-type and the DSO decides on few, simple tariff patterns and flexibility procurement using the tariff design method. The tariff design method models the interaction between DSO, in the upper level, and aggregators, at the lower level, as a Stackelberg game using bilevel optimisation, see Fig. 2. The objective of the DSO is to minimise flexibility procurement, curtailment, and aggregator costs, collectively called system costs, while constrained by the network's physical limits. The designed tariffs are volumetric (€/MWh), and can vary temporally and spatially. We use discrete tariff levels to augment intelligibility and usability and we impose cost recovery via tariff revenue for the DSO [25], [26]. The Aggregator manages EV chargers with smart charging capability (vehicle to grid is not considered), and minimises total charging (energy and DUoS) costs constrained by EV energy needs and flexibility agreements with the DSO.

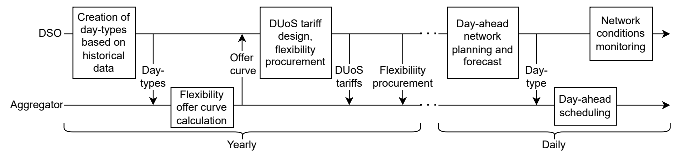

Fig. 1: Illustration of the proposed methodology.

B. Mathematical formulation

1) Network model: We employ the LinDistFlow model [27] to represent power flow constraints. A more detailed description can be found in [3]. The distribution nodes are denoted by set $\mathcal{I}$, using $\mathcal{I}^+$ when including the root node. Set $\mathcal{I}$ applies, also, to branches as we assume a radial distribution network, with j_i denoting the branch ending at node i. a_i and K_i denote the parent node and set of children of i, respectively. $t \in \mathcal{T}$ denotes the time period and $d \in \mathcal{D}$ the representative day-type, with w_d the weight of each day-type.

2) Upper level: Total injection to each node is $p_{i,t,d}$, ϕ_i its power angle, and $\pi^{\mathrm{e}}_{t,d}$ denotes the wholesale energy price. DUoS tariffs $\pi_{i,t,d}$ are expressed in discrete levels with $u_{i,t,d,n}$ the binary decision on each tariff level π_n (see also [3]). κ^{C} is the regulated profit margin of the DSO added to the flexibility procurement costs and K^{fixed} are costs exogenous to the network conditions.

$$\min_{\mathcal{V}_{\mathrm{UL}}} \mathcal{J}^{\mathrm{u}} = \min_{\mathcal{V}_{\mathrm{UL}}} \mathcal{J}^{\mathrm{DSO}} + \sum_{d\in\mathcal{D}} w_d \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}} \pi^{\mathrm{e}}_{t,d} e_{i,t,d} =$$
$$\min_{\mathcal{V}_{\mathrm{UL}}} \sum_{d\in\mathcal{D}} w_d \sum_{i\in\mathcal{I}} \mathcal{F}_{i,d}(P^{\mathrm{cap}}_{i,d})$$
$$+ \sum_{d\in\mathcal{D}} w_d \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}} (\kappa^{\mathrm{D}}_i c^{\mathrm{D}}_{i,t,d} + \kappa^{\mathrm{G}}_i c^{\mathrm{G}}_{i,t,d})$$
$$+ \sum_{d\in\mathcal{D}} w_d \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}} \pi^{\mathrm{e}}_{t,d} e_{i,t,d} \tag{1a}$$

where, $\mathcal{V}_{\mathrm{UL}} = \{\pi_{i,t,d}, u_{i,t,d,n}, P^{\mathrm{cap}}_{i,d}, c^{\mathrm{D}}_{i,t,d}, c^{\mathrm{G}}_{i,t,d}, P_{j_i,t,d}, Q_{j_i,t,d}, v_{i,t,d}\}$

subject $\forall i \in \mathcal{I}, t \in \mathcal{T}, d \in \mathcal{D}$ to:

$$p_{i,t,d} = l_{i,t,d} - g_{i,d,t} + e_{i,t,d} \tag{1b}$$
$$P_{j_i,t,d} = p_{i,t,d} + \sum_{k\in\mathcal{K}_i} P_{j_k,t,d} \tag{1c}$$
$$Q_{j_i,t,d} = p_{i,t,d} \tan\phi_i + \sum_{k\in\mathcal{K}_i} Q_{j_k,t,d} \tag{1d}$$
$$P^2_{j_i,t,d} + Q^2_{j_i,t,d} \le \overline{F}^2_{j_i} \tag{1e}$$
$$v_{i,t,d} = v_{a_i,t,d} - 2(r_{j_i} P_{j_i,t,d} + x_{j_i} Q_{j_i,t,d}) \tag{1f}$$
$$\underline{v}^2_{i,t,d} \le v_{i,t,d} \le \overline{v}^2_{i,t,d} \tag{1g}$$
$$0 \le c^D_{i,d,t} \le l_{i,t,d} \tag{1h}$$
$$0 \le c^G_{i,d,t} \le g_{i,t,d} \tag{1i}$$
$$\underline{P}^{\mathrm{cap}}_{i,d} \le P^{\mathrm{cap}}_{i,d} \le \overline{P}^{\mathrm{cap}}_{i,d} \tag{1j}$$
$$\pi_{i,t,d} = \sum_{n\in\mathcal{N}} u_{i,t,d,n} \pi_n \tag{1k}$$
$$\sum_{n\in\mathcal{N}} u_{i,t,d,n} = 1 \tag{1l}$$
$$\sum_{d\in\mathcal{D}} \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}} w_d \pi_{i,t,d} p_{i,t,d} = (1+\kappa^{\mathrm{C}})(\mathcal{J}^{\mathrm{DSO}} + K^{\mathrm{fixed}}) \tag{1m}$$

Objective function (1a) minimises the DSO costs and the aggregator energy (excluding DUoS) costs over the analysed yearly horizon. The first term expresses the flexibility

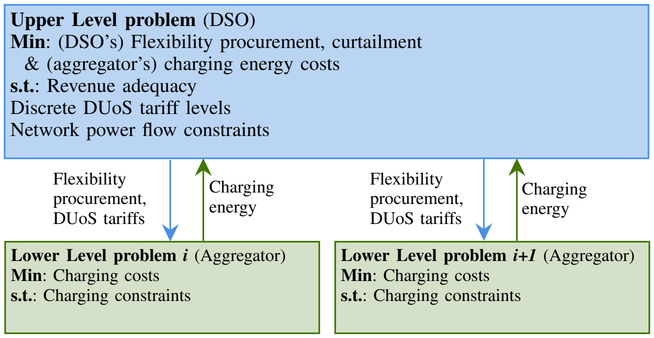

Fig. 2: Structure of the proposed bilevel optimisation model.

procurement cost, which is a function $\mathcal{F}_{i,d}$ of the relevant capacity limit $P^{\text{cap}}_{i,d}$. The second term is the cost of any emergency curtailment actions taken by the DSO. The third term is solely the aggregator's charging energy costs, i.e., excluding the DUoS tariff costs. We include this term in the upper level objective to express the economic implications of DSO actions on the aggregator's utility. Constraints (1c) and (1d) enforce the power balance at each node, while (1e) the apparent power limit along the branches. Constraint (1f) defines voltage squared magnitude at each node, while constraints (1g) the corresponding bounds. (1h) and (1i) set the limits for curtailment of demand and generation at each node. Constraint (1j) bounds the capacity limit set by the DSO and constraints (1k)-(1l) enforce tariff discreteness. Finally, constraint (1m) enforces that the income from network tariffs recovers flexibility procurement and curtailment costs, with consideration for a profit margin.

3) Lower level: Considering that at most one aggregator is connected to each node i, the LL problem of the respective aggregator is formulated as:

$$\min_{\mathcal{V}_{LL}} \mathcal{J}^{\text{l}} = \min_{\mathcal{V}_{LL}} \mathcal{J}^{\text{Agg}} =$$
$$\min_{\mathcal{V}_{LL}} \sum_{d\in\mathcal{D}} w_d \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}} (\pi^e_{t,d} + \pi_{i,t,d}) e_{i,t,d} \tag{2a}$$
$$\text{where, } \mathcal{V}_{LL} = \{e_{i,t,d}, c_{i,t,d}\}$$
$$\text{subject } \forall i \in \mathcal{I}, t \in \mathcal{T}, d \in \mathcal{D} \text{ to:}$$

$$(\underline{\kappa}_{i,t,d}, \overline{\kappa}_{i,t,d}): \quad \underline{c}_{i,t,d} \le c_{i,t,d} \le \overline{c}_{i,t,d} \tag{2b}$$
$$(\underline{\lambda}_{i,t,d}, \overline{\lambda}_{i,t,d}): \quad \underline{e}_{i,t,d} \le e_{i,t,d} \le \overline{e}_{i,t,d} \tag{2c}$$
$$(\mu_{i,t,d}): \quad c_{i,t,d} = c^{\text{init}}_{i,d} + \eta \cdot e_{i,t,d}, \quad \text{for } t = 1$$
$$c_{i,t,d} = c_{i,t-1,d} + \eta \cdot e_{i,t,d}, \quad \forall t > 1 \tag{2d}$$
$$(\mu^{\text{end}}_{i,d}): \quad c_{i,t,d} = c^{\text{end}}_{i,d}, \quad \text{for } t = T \tag{2e}$$
$$(\nu_{i,t,d}): \quad e_{i,t,d} \le P^{\text{cap}}_{i,d} \tag{2f}$$

Objective function (2a) minimises the aggregator total costs, consisting of its energy and DUoS costs. Constraints (2b) and (2c) express the battery model power/energy limits, and (2d), (2e) describes the energy state evolution, including its initial and end conditions. Constraint (2f) limits consumption to the contracted capacity $P^{\text{cap}}_{i,d}$ of the flexibility market.

C. Formulating the MPEC

The two levels are coupled via the DUoS tariffs and flexibility procurement in the form of capacity limits (upper level variables) and the charging energy (lower level variables), see Fig. 2. The solution to this bilevel optimisation problem is the derivation of a single level equivalent mathematical program with equilibrium constraints (MPEC). The Karush-Kuhn-Tucker (KKT) conditions of the lower level are added as constraints to the upper level [28], [29]. The KKT conditions are as follows $\forall i \in \mathcal{I}, t \in \mathcal{T}, d \in \mathcal{D}$:
Primal and complementarity constraints:

$$0 \le \underline{\kappa}_{i,t,d} \perp (c_{i,t,d} - \underline{c}_{i,t,d}) \ge 0 \tag{3a}$$
$$0 \le \overline{\kappa}_{i,t,d} \perp (\overline{c}_{i,t,d} - c_{i,t,d}) \ge 0 \tag{3b}$$
$$0 \le \underline{\lambda}_{i,t,d} \perp (e_{i,t,d} - \underline{e}_{i,t,d}) \ge 0 \tag{3c}$$
$$0 \le \overline{\lambda}_{i,t,d} \perp (\overline{e}_{i,t,d} - e_{i,t,d}) \ge 0 \tag{3d}$$
$$0 \le \nu_{i,t,d} \perp (P^{\text{cap}}_{i,d} - e_{i,t,d}) \ge 0 \tag{3e}$$

Gradient of the Lagrangian:

$$(c_{i,t<T,d}): \; -\underline{\kappa}_{i,t,d} + \overline{\kappa}_{i,t,d} + \mu_{i,t,d} - \mu_{i,t+1,d} = 0 \tag{3f}$$
$$(c_{i,t=T,d}): \; -\underline{\kappa}_{i,t,d} + \overline{\kappa}_{i,t,d} + \mu_{i,t,d} + \mu^{\text{end}}_{i,d} = 0 \tag{3g}$$
$$(e_{i,t,d}): \quad w_d\big(\pi^e_{t,d} + \pi_{i,t,d}\big) - \underline{\lambda}_{i,t,d} + \overline{\lambda}_{i,t,d} - \mu_{i,t,d}\eta + \nu_{i,t,d} = 0 \tag{3h}$$

The original bilevel optimisation problem is formulated into a single level equivalent MPEC as follows:

$$\min_{\mathcal{V}_{MPEC}} \mathcal{J}^u \tag{4a}$$

$$\text{where, } \mathcal{V}_{MPEC} = \mathcal{V}_{\text{UL}} \cup \mathcal{V}_{\text{UL}} \cup \{\underline{\kappa}_{i,t,d}, \overline{\kappa}_{i,t,d}, \underline{\lambda}_{i,t,d}, \overline{\lambda}_{i,t,d}, \mu_{i,t,d}, \nu_{i,t,d}\}$$
subject to: (1b)-(1m), (3)

D. Linearisation of the MPEC

Complementarity conditions: Conditions (3a)-(3e) include bilinear terms which can be linearised using the Fortuny-Amat method [30]. Assume a general bilinear term of the form $\delta p = 0$, where δ and p represent dual and primal terms, respectively. This term can be replaced by the following constraints: $\delta \ge 0$, $p \ge 0$, $p \le zM$, $\delta \le (1-z)M$, where M is a sufficiently large positive constant and z is an auxiliary binary variable. Using (3a) as an example of the linearisation, it follows $\forall i \in \mathcal{I}, t \in \mathcal{T}, d \in \mathcal{D}$:

$$(c_{i,t,d} - \underline{c}_{i,t,d}) \le z^{\underline{\kappa}}_{i,t,d} M \tag{5a}$$
$$\underline{\kappa}_{i,t,d} \le (1 - z^{\underline{\kappa}}_{i,t,d}) M \tag{5b}$$

Revenue adequacy constraint: Constraint (1m) includes a bilinear term, too, namely $\pi_{i,t,d} p_{i,t,d} \rightarrow \pi_{i,t,d} e_{i,t,d} \rightarrow u_{i,t,d,n} e_{i,t,d}$, which is linearised with binary expansion. An additional variable $z^e_{i,t,d,n}$ is introduced along with M_1, another sufficiently large number:

$$u_{i,t,d,n}e_{i,t,d} = z^e_{i,t,d,m} \tag{6a}$$
$$0 \leq e_{i,t,d} - z^e_{i,t,d,n} \leq M_1(1 - u_{i,t,d,n}) \tag{6b}$$
$$0 \leq z^e_{i,t,d,n} \leq M_1 u_{i,t,d,n} \tag{6c}$$

It follows that:

$$\pi_{i,t,d}e_{i,t,d} = \sum_{n\in\mathcal{N}} \pi_n z^e_{i,t,d,n} \tag{7}$$

Using (7) one obtains:

$$\sum_{d\in\mathcal{D}} w_d \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}} \pi_{i,t,d}e_{i,t,d} = \sum_{d\in\mathcal{D}} w_d \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}} \Big(\sum_{n\in\mathcal{N}} \pi_n z^e_{i,t,d,n}\Big) \tag{8}$$

Thus, (1m) becomes:

$$\mathcal{J}^{\text{rev}} = (1+\kappa^C)(\mathcal{J}^{\text{DSO}} + K^{\text{fixed}}) \tag{9}$$

Where:

$$\mathcal{J}^{\text{rev}} = \sum_{d\in\mathcal{D}} \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}} w_d \pi_{i,t,d}(l_{i,t,d} - g_{i,t,d}) + \sum_{d\in\mathcal{D}} \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}} w_d \Big(\sum_{n\in\mathcal{N}} \pi_n z^e_{i,t,d,n}\Big) \tag{10}$$

E. Relaxing the revenue adequacy constraint:

Constraint (1m), or equivalently (9), is an equality with binary decision variable in both sides that potentially can increase the computational burden. We suggest a relaxation of this constraint by reformulating it as an inequality and replacing the minimisation of DSO costs $\mathcal{J}^{\text{DSO}}$ with that of the DSO revenue $\mathcal{J}^{\text{rev}}$. In the results we verify that this relaxation is tight for our model. Thus:

$$\mathcal{J}^{\text{rev}} \geq (1+\kappa^C)(\mathcal{J}^{\text{DSO}} + K^{\text{fixed}}) \tag{11}$$

The **final optimisation model** is constructed as:

$$\min_{\mathcal{V}_{\text{final}}} \mathcal{J}^{\text{rev}} + \sum_{d\in\mathcal{D}} w_d \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}} \pi^{\text{e}}_{t,d} e_{i,t,d} \tag{12a}$$

where, $\mathcal{V}_{\text{final}} = \mathcal{V}_{\text{UL}} \cup \mathcal{V}_{\text{UL}} \cup \{\underline{\kappa}_{i,t,d}, \overline{\kappa}_{i,t,d}, \underline{\lambda}_{i,t,d}, \overline{\lambda}_{i,t,d}, \mu_{i,t,d}, \nu_{i,t,d}, z^e_{i,t,d,m}\}$

subject to: (1b)-(1j), (11), (6), (3) and (5) (12b)

F. Auxiliary modules

1) Unconstrained aggregator charging: All aggregator charging energy costs are presented as the increase from a lower bound. This bound is established by solving model (2) in the absence of DUoS tariffs and excluding (2f), i.e., unconstrained charging, see also Fig. 6.

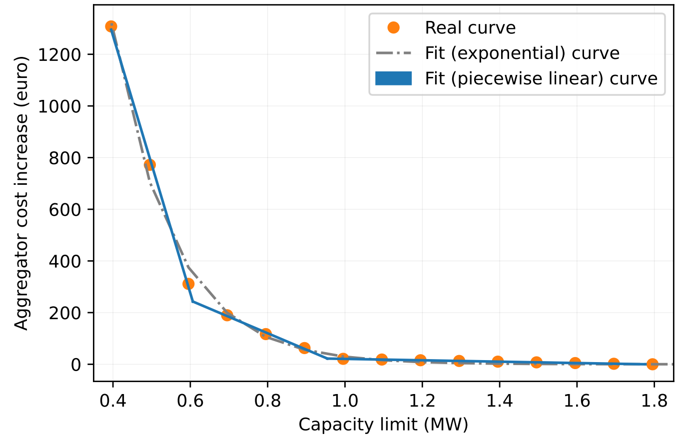

Fig. 3: Indicative aggregator capacity limit cost curve for day-type 1 at node 2, together with the fitted exponential and piecewise linear curves.

2) Theoretical optimal: In order to have a better understanding of the efficacy of the proposed method, we make use of a theoretical optimal model of the proposed problem. This is in practice a centralised optimisation problem in which the DSO has direct control of all flexibility procurement, curtailment and EV charging decisions. Under this scheme, there is no need for tariffs to motivate flexibility, hence, they are not modelled. The centralised optimal power flow (OPF) model is presented in the Appendix.

G. Capacity limit cost function

The capacity limit cost function is obtained using the approach of [31]. A range of capacity limits, from max to min (step= 0.1MW) is imposed on the problem of each aggregator and the corresponding increase in energy costs is calculated, see Fig. 3. The maximum value of the limit is such that larger values have zero effect on costs (i.e., capacity limitation constraints are non-binding). The minimum value is chosen as the minimum value that does not render the Aggregator's problem infeasible. Similar to [7], an exponential fit provides a good approximation of the cost function. However, as a non-linear function it cannot be used with a variety of available solvers. Therefore, a piecewise linear function is preferred, as in [32]. Results with the latter option show execution times in the order of seconds for a problem of this scale.

III. CASE STUDIES

A. Test data and examined cases

In the case studies we apply the proposed model in order to investigate the synergies between tariffs, flexibility procurement and related costs. Three separate tariff schemes have been examined:

Flat: This is the Business-as-Usual (BaU) scheme, where the network tariffs do not have temporal or spatial variation. It is implemented by adding (13) to model (12):

$$\pi_{i,t,d} = \pi_{i',t',d}, \;\; \forall i,i' \in \mathcal{I}, t,t' \in \mathcal{T}, d \in \mathcal{D} \tag{13}$$

TABLE I: Case studies' parameters.

Parameter	Value
PV power capacity	3.7 MW
EV charging power capacity	7.4 MW
Apparent power flow limits	1 MVA
Voltage limits	[0.9,1.1] p.u.
Power factor	0.95
Network tariff levels	[0, 60], step=10 €/MWh
DSO Profit Margin	20%
Fixed costs (K^{fixed})	10,000€
Curtailment penalty ($\kappa^{\text{D}}, \kappa^{\text{G}}$)	1,415 €/MWh
Number of representative day-types	2 (Winter, Summer)

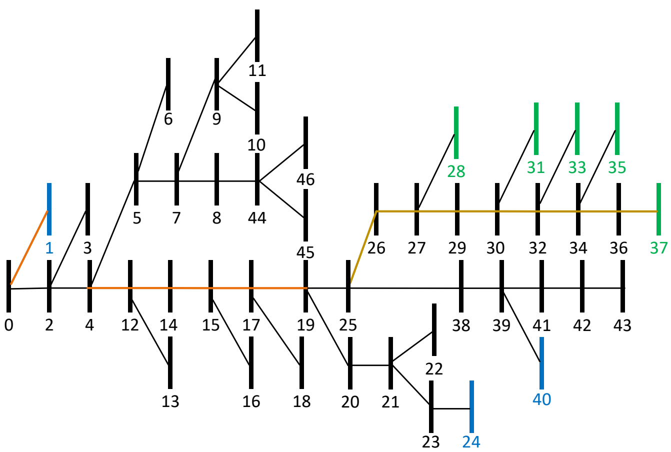

Fig. 4: Test network with 47 nodes [33]. CP aggregators and PV plants are denoted with blue and green colour, respectively. Sections with line congestions are denoted with orange and with overvoltage at their end with brown colour.

Hourly: The tariffs have hourly temporal but no spatial variation. It is implemented by adding (14) to model (12):

$$\pi_{i,t,d} = \pi_{i',t,d}, \;\; \forall i, i' \in \mathcal{I}, t \in \mathcal{T}, d \in \mathcal{D} \tag{14}$$

Hourly-loc: The tariffs have hourly temporal and nodal spatial variation as presented in model (12).

The test system is a part of a Greek semi-urban MV distribution feeder (Fig. 4) with 47 nodes [33]. Table I summarises the basic input data. There are 11 MV/LV feeders, 5 passive MV consumers, and 3 charging points (CPs) aggregators. MV/LV feeder and MV consumer data are provided by the Greek DSO. Power flow congestion issues are likely to occur along the branch [0-1] as well as section [4-19]. In addition, overvoltages due to PV generation can occur at the end of section [25-37]. The EV CP data used are those of [34] from which we extract charging and energy state limits for the CPs. The energy prices we use are from the Danish spot market corresponding to the same years as the EV data. Representative day-types are created from typical seasonal (winter, summer) profiles.

B. Results

There are mainly two types of figures we employ for the illustration of the obtained results. The first type, including Fig. 6-10 and 13, illustrates the EV charging energy, $e_{i,t,d}$, at node i, period t and day-type d, as well as the energy state, $c_{i,t,d}$, which is the accumulated charging energy so far

TABLE II: Resulting cost and revenue components in the examined case studies under the the Flat, Hourly and Hourly-loc tariff schemes, as well as the theoretical optimal.

Tariff/ scheme	DSO's flexibility procurement costs	Aggregator's energy costs increase	Curtailment costs	Total system costs
Flat	7,729.4€	2,468.6€	24,824.2€	35,022.2€
Hourly	6,718.9€	3,638.1€	0.0€	10,357.0€
Hourly-loc	2,044.2€	3,199.5€	0.0€	5,243.8€
Optimal	0.0€	3,078.0€	0.0€	3,078.0€

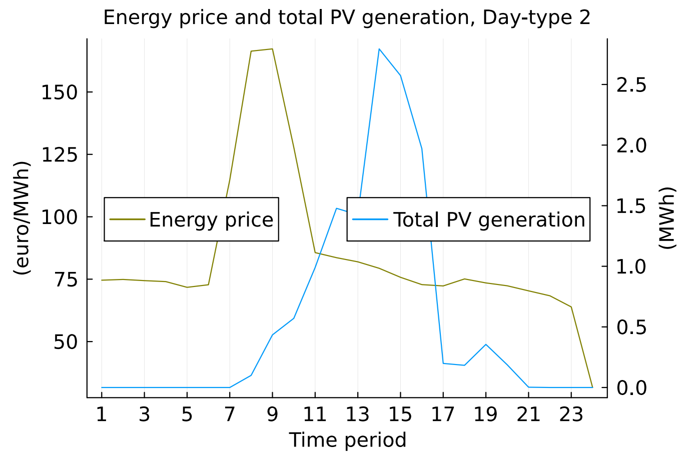

Fig. 5: Wholesale energy price and total PV generation (sum of all PV nodes) for day-type 2.

in the day. The opaque red area around $c_{i,t,d}$ represents its lower and upper limits $\underline{c}_{i,t,d}$ and $\overline{c}_{i,t,d}$, respectively, which depend on the number of EVs parked at each time period of the day. The second type, including Fig. 11 and 12, illustrates the designed DUoS tariffs at three critical (with respect to network congestion phenomena) nodes of the network. Furthermore, Fig. 5 illustrates the temporal variation of the wholesale energy price and the total PV generation, which are two important parameters affecting the decisions of the model.

1) Unconstrained charging: First, we execute model (2) in the absence of tariffs and capacity limits to quantify overall aggregator charging energy costs. Fig. 6 illustrates the charging pattern of the aggregator at node 40 for day-type 2 (summer). There is a charging spike at hour 17. Although the price at hour 17 is not the lowest price of the day, it is the lowest price during hours with a significant number of EVs parked in the CP, a fact shown by the energy state range available during those hours. See how even a marginally lower energy price triggers the charging spike. Shifting charging an hour before or after would result in a minimal increase in charging energy costs for the aggregator but could incur significant benefits to the DSO. It is apparent that flexibility motivation can be useful in reducing peaks, often without large discomfort to aggregators.

Table II presents all cost values and DSO revenue where applicable for the different tariffs schemes and the theoretical optimal model. Due to congestion issues there are incurred costs, different for each scheme. Next, we analyse and compare the schemes one by one.

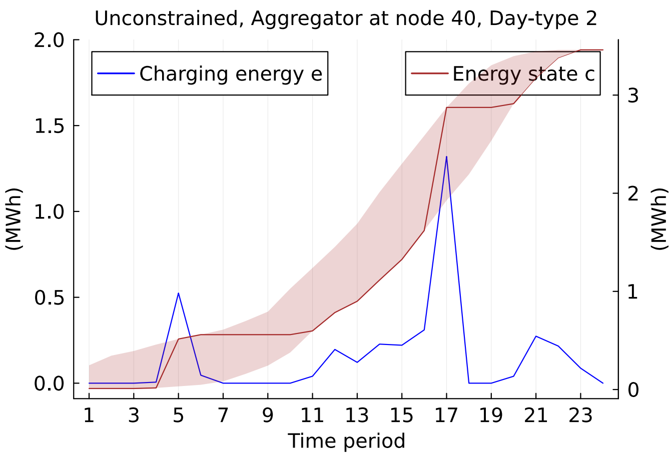

Fig. 6: Charging energy $e_{i,t,d}$ and energy state $c_{i,t,d}$, with its available range $\underline{c}_{i,t,d}, \overline{c}_{i,t,d}$, when the aggregator's problem is unconstrained (model (2)) for the CP at **node 40** and day-type 2.

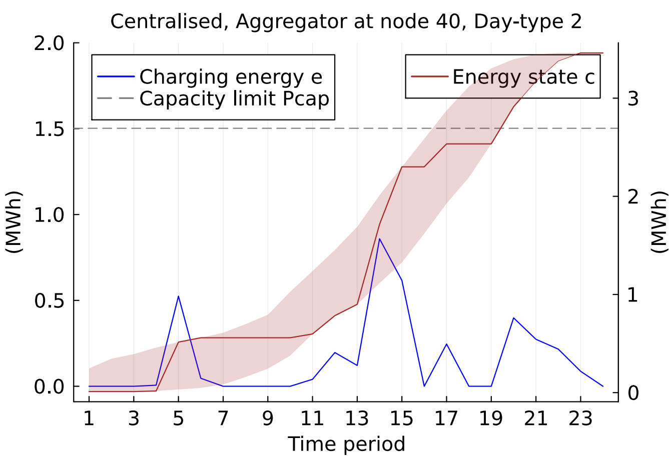

Fig. 7: Charging energy $e_{i,t,d}$ and energy state $c_{i,t,d}$, with its available range $\underline{c}_{i,t,d}, \overline{c}_{i,t,d}$, under the centralised **theoretical optimal solution** for the CP at **node 40** and day-type 2.

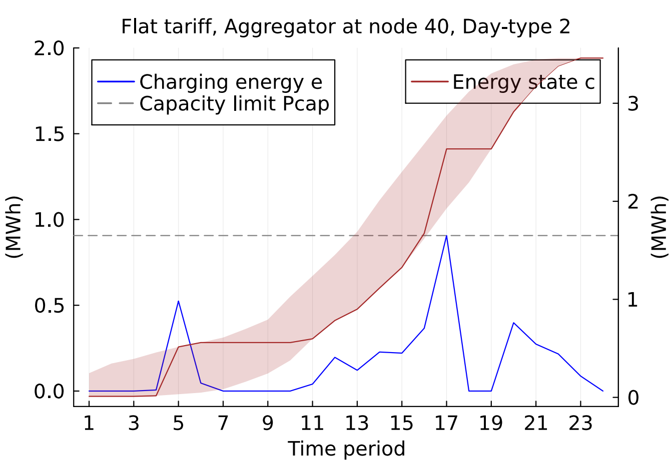

Fig. 8: Charging energy $e_{i,t,d}$ and energy state $c_{i,t,d}$, with its available range $\underline{c}_{i,t,d}, \overline{c}_{i,t,d}$, under the **Flat** tariff scheme for the CP at **node 40** and day-type 2.

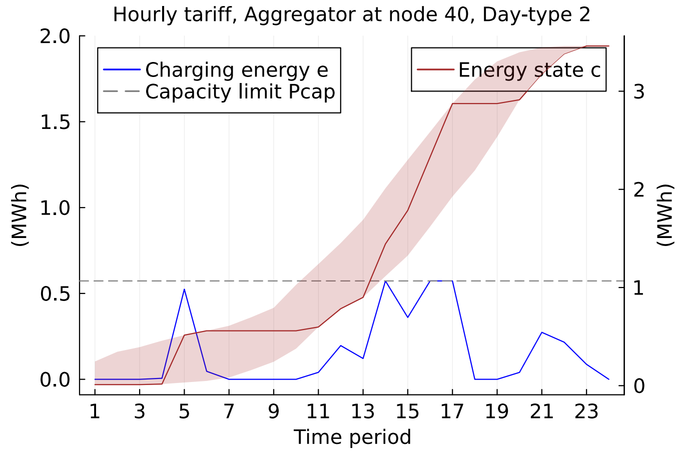

Fig. 9: Charging energy $e_{i,t,d}$ and energy state $c_{i,t,d}$, with its available range $\underline{c}_{i,t,d}, \overline{c}_{i,t,d}$, under the **Hourly** tariff scheme for the CP at **node 40** and day-type 2.

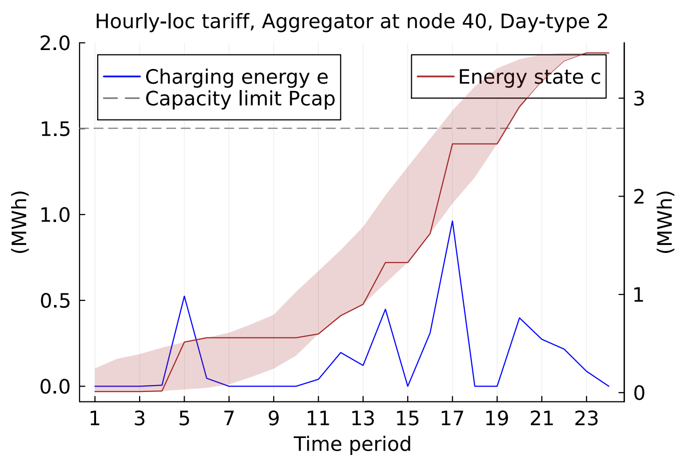

Fig. 10: Charging energy $e_{i,t,d}$ and energy state $c_{i,t,d}$, with its available range $\underline{c}_{i,t,d}, \overline{c}_{i,t,d}$, under the **Hourly-loc** tariff scheme for the CP at **node 40** and day-type 2.

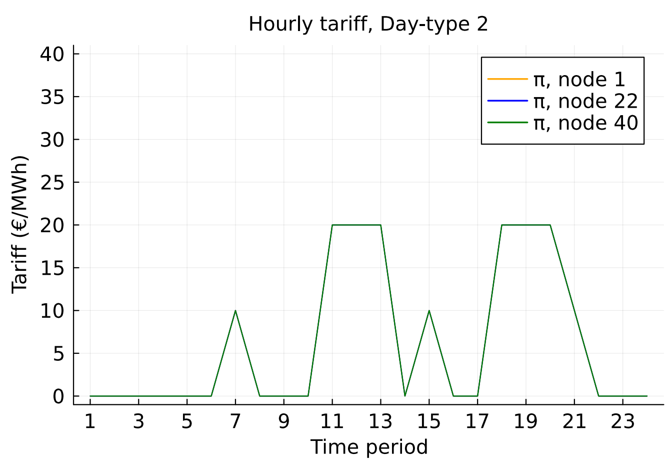

Fig. 11: Hourly tariff pattern for day-type 2 at the three aggregator CP nodes.

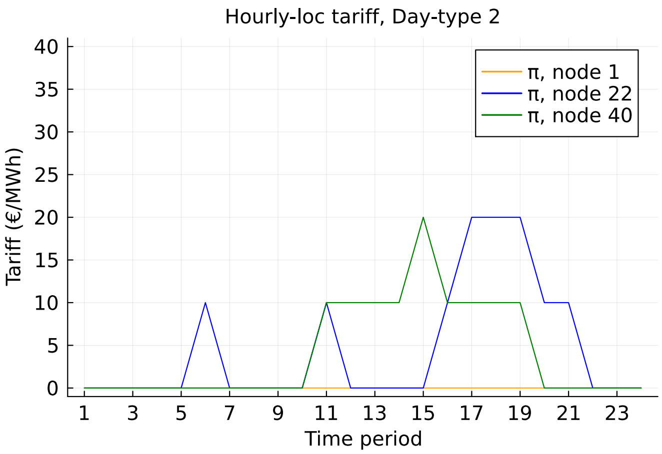

Fig. 12: Hourly-loc DUoS tariff pattern for day-type 2 at the three aggregator CP nodes.

2) Theoretical optimal: In Table II it can be observed that for the centralised theoretical optimal solution flexibility procurement costs are zero. As a centralised solution this scheme can dictate all charging decisions directly. There is some charging energy cost increase for aggregators which is the only incurred cost under this scheme. The need to shift charging due to network constraints induces an increase in energy costs which is unavoidable as, by definition, the least expensive pattern (from the aggregators' point of view) is the unconstrained one.

Fig. 7 depicts the charging pattern of the same aggregator and day-type under the theoretical optimal scheme. Comparing with Fig. 6 one observes that, as expected, direct control of the charging energy decisions of the aggregator by a centralised solution reduces peaks. Moreover, we see that a significant volume of charging energy is shifted towards hours 14 and 15. This is due to the presence of excess PV generation during those hours, that can be used for EV charging. As we will discuss below, without this shifting the DSO will have to curtail generation. Furthermore, the capacity limit is equal to its upper limit $\overline{P}_{i,d}^{\text{cap}}$ which means that it is not used.

3) Flat tariff scheme: Under the Flat tariff scheme the calculated tariff is 10€/MWh every time period of every day-type. By definition, flat tariffs do not motivate aggregators to mobilise flexibility. The result is congestion that is solved by the DSO through capacity limit procurement and curtailment (which is very expensive). Table II shows the resulting flexibility, curtailment and aggregator energy increase costs. The total system costs are $31,944.2$€ higher than the theoretical optimal, namely, $35,022.2$€compared to only $3,078.0$€. The increase in charging energy costs is the lowest of all schemes and is induced solely by capacity limit procurement as tariffs are flat.

Moreover, it is worth noting that there are only generation curtailment actions (i.e. the PVs at nodes 32, 34, 36, 38) which are avoided in all other schemes. This fact illustrates the additional benefit from non-flat tariffs which complement capacity based flexibility.

Fig. 8 presents the charging pattern of the aggregator at node 40 and day-type 2 under the Flat tariff scheme. The capacity limit does not allow for spikes to occur and the charging energy volume of hour 17 is spread to neighbouring hours, mostly 16 and 20. However, excess PV generation occurs during hours 14 and 15, hence, the induced flexibility is not effective in reducing generation curtailment costs.

4) Hourly tariff: The Hourly tariff scheme produces a significant reduction in total costs compared to the Flat tariff scheme, see Table II. In fact, the Hourly tariff costs are only 7279.4€ higher than the theoretical optimal which, compared to the $31,944.2$€ of the Flat tariff scheme, is a 77.2% reduction. Capacity limit procurement is also increased, compared to the Flat tariff, but aggregators charging energy costs increased. This is due to tariffs inducing shifting in charging decisions.

Fig. 9 illustrates the charging pattern of aggregator at node 40 for day-type 2. The capacity limit is used significantly by the DSO, i.e., a very low capacity limit is procured. See, also the Hourly tariff pattern for the nodes of the three CPs aggregators and day-type 2 in Fig. 11. Obviously, the main goal behind this pattern is shifting demand towards hours 14, 15 and 16. Going again to Fig. 9 we see that, in combination with the use of the capacity limit, this goal is achieved and there are no spikes. As a result, the Hourly tariff scheme succeeds in avoiding expensive curtailment actions completely as shown in Table II.

5) Hourly-loc tariff: Under the Hourly-loc tariff scheme total system costs are $2,165.8$€ higher than the theoretical optimal, see also Table II. Compared to the Flat tariff scheme, where costs where $31,944.2$€ higher than the theoretical optimal, there is a 93.2% reduction. The use of capacity limitation is reduced more than threefold, charging energy costs are 12% less compared to the Hourly scheme and curtailment is completely avoided.

Fig. 10 shows the charging pattern of Aggregator at node 40 and Fig. 12 the Hourly-loc tariff patterns for day-type 2. In Fig. 10 one can observe how the tariffs, with consideration of the available charging energy range and the energy price, shift charging away from hour 17 and towards hours 20 and 14. The tariff makes charging more expensive during hour 15 instead of 14, and as a result hour 14 is preferred. Moreover, since hours 11 to 19 are now more expensive, due to the DUoS tariff, hour 20 is used more for charging. For this specific aggregator and day-type, there is no procurement of capacity limitation.

However, at node 1 capacity limitation is employed, see Fig. 13. In that area of the network there are no PVs and the congestion problem is rather straightforward. Namely, there is a peak in charging energy during hour 17 due to the slightly lower energy prices and the large number of EVs parked. Capacity limitation is the preferred choice in cases where simple peaks cause congestion, whereas, non-flat DUoS tariffs are of value in more complex cases where the interaction with distributed generation is important. Therefore, there are benefits from deploying both variable DUoS and capacity limitations at the same time, to deal with congestion phenomena in different locations.

Finally, we verify that thermal and voltage constraints are enforced by the proposed model. In the case of unconstrained

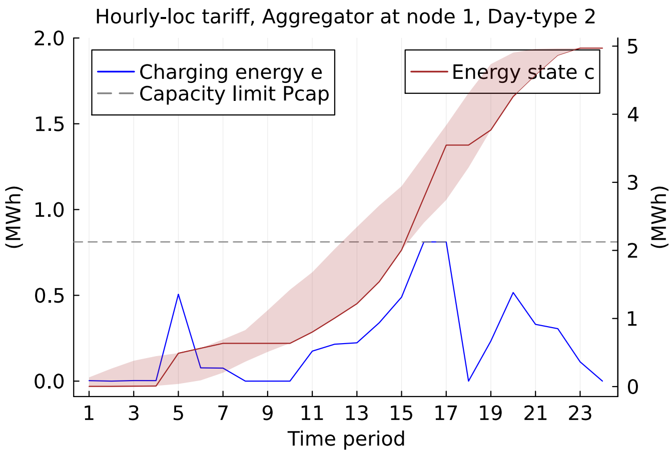

Fig. 13: Charging energy $e_{i,t,d}$ and energy state $c_{i,t,d}$, with its available range $\underline{c}_{i,t,d}, \overline{c}_{i,t,d}$, under the **Hourly-loc** tariff scheme for the CP at **node 40** and day-type 2.

EV charging, and assuming thermal and voltage constraints are not enforced, the maximum observed voltage is 1.07 p.u. and the lowest observed voltage is 0.89 p.u. (i.e., the lower voltage limit is violated). In contrast, under the proposed model, the maximum observed voltage is 1.063 p.u. and the lowest observed voltage is 0.948 p.u., both observed under the Hourly-loc scheme.

IV. Conclusion

This paper contributes to the area of DER flexibility mobilisation for resolving congestion phenomena in the electricity distribution network by proposing a novel model which can capture in an integrated fashion two mechanisms, namely temporally- and spatially-differentiated DUoS tariffs, and local flexibility markets based on capacity limitations. This advances the state-of-the-art in this area since previous research has only investigated these two mechanisms independently, neglecting their potential synergies.

The proposed model employs a bilevel optimisation approach to capture the interactions between the DSO designing variable DUoS tariffs and operating a local flexibility market, and aggregators of DERs (namely EVs with smart charging capability, although the model can be extended to any type of flexible DERs) reacting to the designed DUoS tariffs and procured capacity limitations. Furthermore, the model considers the cost recovery constraints of the DSO as well as discrete tariff levels to ensure their intelligibility by the aggregators.

Case studies on a real 47-node distribution network demonstrate that in certain cases network congestion phenomena are not resolved independently by the two mechanisms, but rather through their synergetic effects. Specifically, these include cases where demand-driven and generation-driven congestion coexist in the network. Furthermore, their combination is shown to yield a significant reduction of total system costs.

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Appendix

The centralised equivalent (theoretical optimal) is:

$$\begin{aligned}
\min_{\mathcal{V}_{\text{UL}}} \mathcal{J}^{\text{u}} = \min_{\mathcal{V}_{\text{UL}}} \mathcal{J}^{\text{DSO}} + \sum_{d\in\mathcal{D}} w_d \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}} \pi^{\text{e}}_{t,d} e_{i,t,d} \\
= \min_{\mathcal{V}_{\text{UL}}} \sum_{d\in\mathcal{D}} w_d \sum_{i\in\mathcal{I}} \mathcal{F}_{i,d}(P^{\text{cap}}_{i,d}) \\
+ \sum_{d\in\mathcal{D}} w_d \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}} (\kappa^{\text{D}}_i c^{\text{D}}_{i,t,d} + \kappa^{\text{G}}_i c^{\text{G}}_{i,t,d}) \\
+ \sum_{d\in\mathcal{D}} w_d \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}} \pi^{\text{e}}_{t,d} e_{i,t,d} \qquad \text{(15a)}
\end{aligned}$$

where, $\mathcal{V}_{centr} = \{P^{\text{cap}}_{i,d},, c^{\text{D}}_{i,t,d}, c^{\text{D}}_{i,t,d},\ P_{j_i,t,d}, Q_{j_i,t,d} v_{i,t,d}\} \cup \mathcal{V}_{LL}$

subject to: $\forall i \in \mathcal{I}, t \in \mathcal{T}, d \in \mathcal{D}$ to:(1b)-(1j), (2b)-(2f) (15b)

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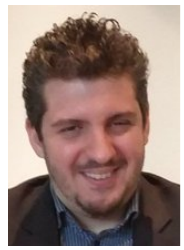

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