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Bilevel Optimization Model for the Design of Distribution Use-of-System Tariffs

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ABSTRACT The design of distribution use-of-system tariffs has been traditionally driven by long-term cost recovery considerations. However, the emerging large-scale integration of distributed energy resources motivates the value of tariffs that are more adaptive to short-term conditions, in order to exploit the inherent flexibility of distributed energy resources and consequently increase the economic efficiency of distribution network operation. This paper addresses the problem of short-term distribution use-of-system tariffs design through a bilevel optimization model, capturing the interaction between a distribution system operator at the upper level and prosumers with distributed energy resources at the lower level. In contrast to previous relevant literature, this model considers a detailed representation of the power flow constraints, different levels of temporal and spatial granularity in the designed tariffs, as well as discrete tariff levels for preserving intelligibility. Furthermore, instead of relying on exogenous typical days, the developed model employs a clustering approach to design tariffs that adapt to the forecasted conditions of the upcoming day. The examined case studies demonstrate the impacts of different levels of tariff granularity on economic efficiency, and test the performance of the proposed clustering approach through out-of-sample simulations involving different scenarios regarding the selected number of clusters.

INDEX TERMS Bilevel optimization, clustering, distributed energy resources, distribution use-of-system tariffs, flexible demand.

NOMENCLATURE

Indices and Sets:

$i \in \mathcal{I}(\mathcal{I}^+)$	Nodes ($^+$ including the root).
$j_i \in \mathcal{I}$	Branch that ends at node i.
$a_i \in \mathcal{I}$	Parent node of node i.
$k \in \mathcal{K}_i$	Children nodes of node i.
$d \in \mathcal{D}$	Day-types.
$t \in \mathcal{T}$	Time periods in each day-type.
$n \in \mathcal{N}$	Tariff levels.

Parameters:

w_d	Number of days in each day-type d.
r_{j_i}, x_{j_i}	Resistance, reactance of branch j_i (Ω).
$\overline{F}_{j_i}$	Apparent power limit of branch j_i (MVA).
$\underline{u}_i, \overline{u}_i$	Lower, upper limit of the voltage at node i (V).
α_i	Demand shifting limit of prosumer at node i.
$d_{i,t,d}$	Baseline demand of prosumer at node i and period (t, d) (MWh).
$p_{i,t,d}$	PV output of prosumer at node i and period (t, d) (MWh).
π^e	Energy price (€/MWh).
π_n	Tariff level n (€/MWh).
π_i^D	Demand curtailment penalty factor at node i (€/MWh).
π_i^G	Generation curtailment penalty factor at node i (€/MWh).
ϕ_i	Power factor angle at node i.

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$\kappa^{\downarrow}_{i,t,d}$ Discomfort penalty of prosumer at node i associated with shifting demand away from period (t, d) (€/MWh).

$\kappa^{\uparrow}_{i,t,d}$ Discomfort penalty of prosumer at node i associated with shifting demand towards period (t, d) (€/MWh).

κ^{C} Profit margin of DSO.

Variables:

$d^{\downarrow}_{i,t,d}$ Demand shifted away from period (t, d) for prosumer at node i (MWh).

$d^{\uparrow}_{i,t,d}$ Demand shifted towards period (t, d) for prosumer at node i (MWh).

$c^{D}_{i,t,d}$ Demand curtailment at node i and period (t, d) (MWh).

$c^{G}_{i,t,d}$ Generation curtailment at node i and period (t, d) (MWh).

$\pi_{i,t,d}$ Distribution use of system (DUoS) tariff at node i and period (t, d) (€/MWh).

$u_{i,t,d,n}$ Binary variable of tariff level n at node i and period (t, d).

$P_{j,t,d}$ Active power flow on branch j and period (t, d) (MW).

$Q_{j,t,d}$ Reactive power flow on branch j and period (t, d) (MVar).

$v_{i,t,d}$ Square of the voltage at node i and period (t, d) (V^2).

I. INTRODUCTION

A. BACKGROUND AND MOTIVATION

The emerging large-scale integration of distributed energy resources (DERs), including various types of flexible demand, distributed generation, and energy storage [1] shifts the scope of distribution network pricing to a task with a shorter-term nature. In recent years, challenges and opportunities related to the active management of DERs are becoming increasingly relevant. Challenges relate to respecting distribution network constraints in the presence of non-dispatchable or variable DERs. On the other hand, many of these DERs exhibit significant flexibility potentials, thereby representing an opportunity for operating the grid more efficiently. Compared to long-term distribution use-of-system (DUoS) tariffs, new tariff schemes could reflect the possibility to manage DERs at a shorter time scale. Such a short-term management of DERs is becoming increasingly possible due to advancements in monitoring, communication and control technologies.

Traditionally, DUoS tariffs have been used as a means to recover previous (sunk) and future planned (prospective) investments in distribution assets, mainly based on long-term incremental cost principles [2], [3]. An important consideration has been to allocate these costs fairly among network users [4], [5]. According to Eurelectric [6], in addition to preserving revenue adequacy for the Distribution System Operator (DSO) and being fair, predictable and intelligible for the consumers, distribution network tariffs should also be aligned with the principles of cost-reflectiveness (reflecting the costs induced/saved by different users) and economic efficiency (yielding the lowest possible investment and operating costs). The same reference indicates that tariffs should reflect more closely the marginal network cost and thus mobilize price-based demand response. More recently, E.DSO [7] recommends similar priorities for new DUoS tariffs including: cost reflectivity, incentives for efficient network use, transparency and understandability, implementability, and limited complexity.

The theoretical efficiency benchmark in managing distributed energy resources is set by distribution locational marginal pricing (DLMP) [8], [9]. DLMP by design coordinates DERs optimally, so as to maximize operating efficiency [10], while ensuring that detailed distribution network attributes (including reactive flows, line losses and voltage constraints [11]) are properly accounted for. From an economic perspective, the centralized optimization of DERs through DLMPs is equivalent to a market equilibrium under perfect competition in a complete market that trades real and reactive power at a nodal level. Despite its theoretical appeal, the realization of DLMP stumbles upon a number of regulatory and implementation barriers in practice. Specifically, the organization of a complete market at the traditionally passively-operated distribution grid entails comprehensive restructuring of DSO practices and massive monitoring, communication and computation costs.

A possibly viable alternative, and the one that we focus on in this paper, is the mobilization of DER flexibility through DUoS tariffs that can vary in a shorter time scale than traditional tariffs (with the latter commonly varying on a year-ahead basis) but without requiring the organization of a distribution-level market. In this context, we consider the interaction between a DSO that directly sets DUoS tariffs with different levels of temporal and spatial variability, and the DERs that react to these tariffs. We formulate this interaction as a Stackelberg equilibrium problem which is recast as a bilevel optimization model.

B. LITERATURE REVIEW

Bi-level optimization constitutes a rigorous methodological framework for modelling non-cooperative interactions between different entities. It has been employed successfully in many power system applications, including strategic bidding in electricity markets [12], [13], electricity suppliers' / aggregators' pricing strategies [14], [15], and strategic generation investment planning [16], [17]. However, research efforts on the application of bilevel optimization to the problem of DUoS pricing for the effective management of DERs are still limited.

Specifically, previous works that apply this methodology to the examined problem include [18]–[23]. We summarize the main characteristics of this literature in Table 1. In [18], a game-theoretical model is employed for designing flat tariffs which aim at recovering sunk exogenous network costs. In [19], [20] the authors expand their analysis to a full bilevel model where the decision-making problem of a regulatory authority is expressed by the upper level and aims at recovering network costs (sunk costs in [20] and prospective costs in [19]). In [19], prospective network costs are expressed as a simple linear function of the overall peak power of the network. In [22], a bilevel model is presented for designing volumetric and peak-power tariffs. Grid costs entail load curtailment actions, nevertheless their recovery is not addressed. In [21], [23] the authors address the introduction of energy markets at the distribution level, and propose a model for designing flat, volumetric, peak-power and fixed tariffs. The authors consider prospective high and medium voltage transformer capacity upgrade costs in [23].

Regarding the modelling and computational methodology of the aforementioned literature, in [18], [20], [21], [23] tariffs are designed through an iterative process using incremental steps. This methodology can be applied in order to optimise a flat tariff, because a single decision variable is being optimized. This is in contrast to fully granular tariffs. The analyses in [18]–[23] consider tariffs that have no spatial or temporal granularity. Moreover, in these analyses the power flow constraints of the network are not modelled in detail. To summarize, [18]–[23] provide valuable insights into the problem of tariff design from the point of view of cost recovery and reducing network peaks.

Our analysis focuses on network tariffs that vary on a relatively shorter time frame. We thus envision a DSO that, in cooperation with the National Regulatory Authority (NRA), chooses the tariffs with respect to forward (e.g. day-ahead) predicted conditions. Authors in [24] discuss the applicability of ex-ante hourly pricing such as day-ahead pricing. It is argued that an ex-ante approach may stimulate greater participation in demand response initiatives than ex-post pricing schemes where the users need to predict price levels. The case study of the Georgia Power Company is also detailed in [24], where a day-ahead price scheme with hourly granularity is employed. According to [24], the pricing scheme induces a remarkable increase in the responsiveness of consumers to the price signal compared to real-time price incentives.

In addition to resorting to shorter-term pricing, we are interested in exploiting repeatable patterns in the behaviour of DERs, in order to improve tariff design. There are examples of pricing patterns based on seasonality such as methods employed in the past by EDF [25]. Previous literature on DUoS charges utilizes generic typical days, or typical days representing seasons for determining tariff levels, as indicated in Table 1. We expand on the topic by resorting to clustering methods [26] for characterising observable day-ahead conditions.

C. CONTRIBUTIONS

The present paper aims at addressing the following question: How can a DSO design simple variable DUoS tariffs in order to increase operating efficiency by exploiting the flexibility provided by DERs? We rely on the hypothesis that DERs exhibit recurrent patterns which can help design correspondingly simple tariffs. The contributions of this paper are the following:

TABLE 1. Summary of relevant literature. (F = Fixed, P = Peak-power/capacity, V = Volumetric).

Papers	Cost Recov.	Tariff type	Granu-larity	Network model	Day-types
[18]	Sunk	F,P,V	No	No	Typical
[19]	Prosp.	F,P,V	No	System Peak	Typical
[20]	Sunk	F,P,V	No	No	Typical
[21]	Sunk	F,P,V	No	No	Typical
[22]	No	P,V	No	HV/MV Trans.	Typical
[23]	Prosp.	P,V	No	HV/MV Trans.	Seasons
This paper	Prosp.	V	Spat. Temp.	LinDist Flow	Clust.

- We model the problem of designing DUoS tariffs as a bilevel interaction between the DSO (upper level) and prosumers with DERs (lower level). In contrast to [18]–[23], this bilevel problem considers a detailed representation of the distribution network power flow constraints (using the LinDistFlow model) in order to introduce temporal and spatial granularity in the derived tariffs, as well as discrete price levels for preserving intelligibility [6].
- In contrast to previous literature relying on exogenous typical days, we employ a clustering approach for identifying daily patterns that capture the variability of distribution network conditions across a whole year. This enables us to design tariffs that adapt to the conditions of the upcoming day. The performance of this approach is tested through out-of-sample simulations.
- We perform detailed case studies with two objectives. Firstly, we analyze the relationship between higher temporal / spatial granularity of the designed tariffs and operating efficiency, under different scenarios for the extent of prosumer flexibility. Secondly, we study the trade-off between a lower number of daily pricing patterns, which translates into higher intelligibility of the tariffs by end users, and a higher number, which translates into higher economic efficiency given the variability of distribution network conditions.

It is important to distinguish here that this work is focused on an arrangement where determining the energy retail price is decoupled from the problem of setting the DUoS tariffs, unlike [27]–[31]. In our work, DUoS tariffs aim at steering basic patterns in consumption and generation in distribution grids, while energy prices are assumed to be set exogenously by an independent retailer. Therefore, we focus our previous

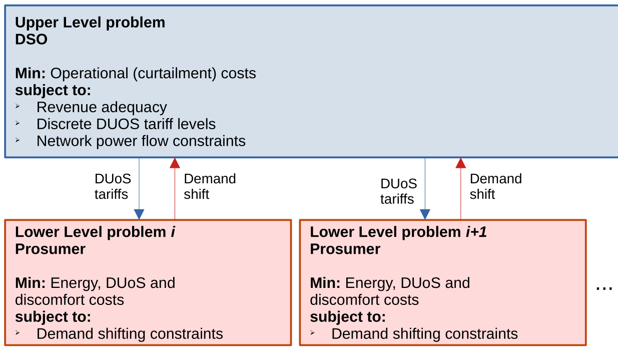

FIGURE 1. Structure of proposed bi-level optimization model.

literature review on works that target the design of DUoS tariffs.

II. PROBLEM FORMULATION

A. MODEL ASSUMPTIONS

The main assumptions of the proposed model are outlined below:

1) PROBLEM STRUCTURE

The examined DUoS tariff design problem is modelled as a Stackelberg game using bilevel optimization. The upper level expresses the decision-making problem of the DSO who designs tariffs in order to maximize the operating efficiency of the distribution network. The latter is measured by the total cost of demand curtailment and generation curtailment actions which the DSO needs to resort to in order to preserve the security of the network. Curtailment costs are used as an approximation of prospective investment costs induced by network congestion effects. The lower level expresses the decision-making problem of prosumers who optimize their demand response actions in response to the DUoS tariffs devised by the DSO as well as the energy tariffs offered by their supplier. Considering that the focus of this paper lies in the design of DUoS tariffs and for the sake of simplicity, we assume energy tariffs to be fixed and constant in time and location, though our modelling framework can accommodate more general assumptions.

Fig. 1 illustrates the coupling of the two problems. The DSO communicates the DUoS tariffs to the prosumers, whereas the prosumers react to those tariffs. Thus, the DSO observes their response (demand shift).

2) TARIFF TYPE

As illustrated in Table 1, DUoS tariffs can be classified into volumetric (€/MWh), peak-power/capacity (€/MW) and fixed (€) tariffs. In this paper, we focus on volumetric tariffs that can generally vary per hour and node (although we examine various scenarios of different temporal and locational granularity in the case studies). Furthermore, we assume that these tariffs involve a set of discrete price levels. This assumption is in tune with tariff intelligibility for both the DSO

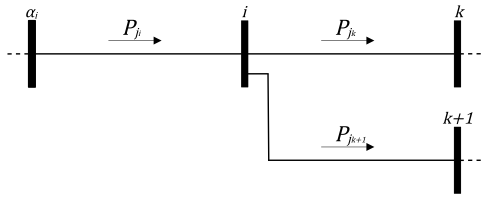

FIGURE 2. Illustration of part of the distribution network.

and the end users [6], [25], [32], [33]. Finally, considering the principle of revenue adequacy [6], we impose that the designed tariffs recover the total operating costs of the DSO.

3) PROSUMER MODELS

The prosumers, represented by the lower level of our model, own and operate PV generation and flexible demand assets. Demand flexibility is represented through a generic, technology-agnostic model. The model captures the ability of prosumers to shift the operation of their loads in time. We assume that such shifts are energy neutral within the examined daily horizon and that they entail a quantifiable cost of discomfort [15].

4) NETWORK MODEL

The power flow constraints of the distribution network are represented through the LinDistFlow model [34], [35]. We employ Fig. 2 in order to describe notation. The set of distribution nodes is denoted by $\mathcal{I}^+$, while the subset $\mathcal{I}$ does not include the root node. Since we are assuming a radial network, we can also denote the set of branches as $\mathcal{I}$. We denote by j_i the branch ending at node i. Finally we denote by a_i the parent node of node i and by K_i the set of children nodes of node i.

B. MATHEMATICAL FORMULATION

Each *period* of the model is denoted by (t, d) and corresponds to a particular hour t and day d.

1) UPPER LEVEL

The upper level expresses the decision-making problem of the DSO. It is formulated as follows:

$$\min_{\mathcal{V}_{UL}} \mathcal{J}^u = \min_{\mathcal{V}_{UL}} \sum_{d\in\mathcal{D}} w_d \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}} \left(\pi^D_{i,t,d} c^D_{i,t,d} + \pi^G_{i,t,d} c^G_{i,t,d}\right) \tag{1a}$$

where,

$$\mathcal{V}_{UL} = \{\pi_{i,t,d}, u_{i,t,d,n}, c^D_{i,t,d}, c^G_{i,t,d}, P_{j_i,t,d}, Q_{j_i,t,d}, v_{i,t,d}\}$$

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

$$P_{j_i,t,d} = d_{i,t,d} - d^{\downarrow}_{i,t,d} + d^{\uparrow}_{i,t,d} - p_{i,t,d} - c^D_{i,t,d} + c^G_{i,t,d} + \sum_{k\in\mathcal{K}_i} P_{j_k,t,d} \tag{1b}$$

$$Q_{j_i,t,d} = (d_{i,t,d} - d^{\downarrow}_{i,t,d} + d^{\uparrow}_{i,t,d} - p_{i,t,d} - c^D_{i,t,d} + c^G_{i,t,d}) \tan\phi_i + \sum_{k\in\mathcal{K}_i} Q_{j_k,t,d} \tag{1c}$$

$$P_{j_i,t,d}^2 + Q_{j_i,t,d}^2 \leq \overline{F}_{j_i}^2 \tag{1d}$$
$$v_{i,t,d} = v_{a_i,t,d} - 2(r_{j_i} P_{j_i,t,d} + x_{j_i} Q_{j_i,t,d}) \tag{1e}$$
$$\underline{v}_{i,t,d}^2 \leq v_{i,t,d} \leq \overline{v}_{i,t,d}^2 \tag{1f}$$
$$0 \leq c_{i,t,d}^G \leq p_{i,t,d}, \tag{1g}$$
$$0 \leq c_{i,t,d}^D \leq d_{i,t,d} - d_{i,t,d}^{\downarrow} + d_{i,t,d}^{\uparrow} \tag{1h}$$
$$\pi_{i,t,d} = \sum_{n \in \mathcal{N}} u_{i,t,d,n} \pi_n \tag{1i}$$
$$\sum_{n \in \mathcal{N}} u_{i,t,d,n} = 1, \text{ and} \tag{1j}$$
$$\sum_{d \in \mathcal{D}} \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{I}} w_d \pi_{i,t,d} (d_{i,t,d} - d_{i,t,d}^{\downarrow} + d_{i,t,d}^{\uparrow} - p_{i,t,d} - c_{i,t,d}^D + c_{i,t,d}^G) = (1 + \kappa^C) \mathcal{J}^u \tag{1k}$$

The objective function (1a) minimizes the total operating cost of the DSO over the analyzed yearly horizon. This cost is expressed as the sum of demand curtailment costs (first term) and generation curtailment costs (second term). Constraints (1b) and (1c) express the nodal active and reactive power balance constraints, respectively. Constraints (1d) enforce the apparent power limits of each branch. Constraints (1e) represent the relationship between nodal voltage magnitudes and adjacent power flows, while constraints(1f) enforce voltage limits for each node. Constraints (1h) and (1g) express the curtailment limits of generation and demand at each node. Constraints (1i)-(1j) capture our assumption that the tariff levels are discrete. Finally, constraint (1k) imposes the recovery of the total operating cost of the DSO (augmented by a profit margin) from the collected network charges. The profit margin of the DSO is chosen as a margin above costs that creates a reasonable return which can be employed as an incentive to improve DSO performance on tasks not related to operational cost, e.g. customer services. Our formulation allows for the NRA to set any profit margin, including no margin at all.

2) LOWER LEVEL

The lower level expresses the decision-making problem of the prosumers. It is formulated as follows:

$$\min_{\mathcal{V}_{LL}} \mathcal{J}^l = \min_{\mathcal{V}_{LL}} \sum_{d \in \mathcal{D}} w_d \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{I}} \big[(\pi^e + \pi_{i,t,d}) \big(d_{i,t,d} - d_{i,t,d}^{\downarrow} + d_{i,t,d}^{\uparrow} - p_{i,t,d} \big) + \kappa_{i,t,d}^{\downarrow} d_{i,t,d}^{\downarrow} + \kappa_{i,t,d}^{\uparrow} d_{i,t,d}^{\uparrow} \big] \tag{2a}$$

where,

$$\mathcal{V}_{LL} = \{ d_{i,t,d}^{\downarrow}, d_{i,t,d}^{\uparrow} \}$$

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

$$(\underline{\zeta}_{i,t,d}, \overline{\zeta}_{i,t,d}) : \ 0 \leq d_{i,t,d}^{\downarrow} \leq \alpha_i d_{i,t,d} \tag{2b}$$
$$(\underline{\eta}_{i,t,d}, \overline{\eta}_{i,t,d}) : \ 0 \leq d_{i,t,d}^{\uparrow} \leq \alpha_i d_{i,t,d}, \text{ and} \tag{2c}$$
$$(\gamma_{i,d}) : \sum_{t \in \mathcal{T}} (-d_{i,t,d}^{\downarrow} + d_{i,t,d}^{\uparrow}) = 0, \quad \forall i \in \mathcal{I}, \ d \in \mathcal{D} \tag{2d}$$

The objective function (2a) minimizes the total operating cost of the prosumers. This cost is expressed as the sum of the total electricity payments (first term, including both energy costs and network charges) and the discomfort cost associated with demand shifting (second and third terms). The demand shifting flexibility of the prosumers is expressed by constraints (2b)-(2d). The non-negative variables $d_{i,t,d}^{\downarrow}$ and $d_{i,t,d}^{\uparrow}$ represent the shifting of demand away from and towards period (t, d) for prosumer i, relative to its respective baseline level $d_{i,t,d}$. Following [15], the upper limits of such demand shifting actions correspond to a ratio α_i of the baseline level. This is expressed by constraints (2b)-(2c). Finally, constraints (2d) ensure that demand shifting is energy neutral within a daily horizon.

3) FORMULATION OF THE MATHEMATICAL PROGRAM WITH EQUILIBRIUM CONSTRAINTS (MPEC)

The upper level and lower level problems are coupled. The DUoS tariffs determined by the upper level problem affect the objective function (2a) of the lower level problem. Moreover, the demand shifting actions determined by the lower level problem affect constraints (1b)-(1c) and (1h)-(1k) of the upper level problem. In order to solve this bilevel optimization problem, the lower level problem is replaced by its Karush-Kuhn-Tucker (KKT) conditions [36], which can be expressed as follows $\forall i \in \mathcal{I}, t \in \mathcal{T}, d \in \mathcal{D}$: Primal constraints:

$$\text{(2b), (2c), (2d)} \tag{3a}$$

Dual constraints:

$$\underline{\zeta}_{i,t,d}, \ \overline{\zeta}_{i,t,d}, \ \underline{\eta}_{i,t,d}, \ \overline{\eta}_{i,t,d} \geq 0 \tag{3b}$$

Complementary slackness:

$$\underline{\zeta}_{i,t,d}(-d_{i,t,d}^{\downarrow}) = 0 \tag{3c}$$
$$\overline{\zeta}_{i,t,d}(d_{i,t,d}^{\downarrow} - \alpha d_{i,t,d}) = 0 \tag{3d}$$
$$\underline{\eta}_{i,t,d}(-d_{i,t,d}^{\uparrow}) = 0 \tag{3e}$$
$$\overline{\eta}_{i,t,d}(d_{i,t,d}^{\uparrow} - \alpha d_{i,t,d}) = 0 \tag{3f}$$

Gradient of the Lagrangian:

$$(d_{i,t,d}^{\downarrow}) : \ w_d \big((\pi^e + \pi_{i,t,d}) + \kappa_{i,t,d}^{\downarrow} \big) - \underline{\zeta}_{i,t,d} + \overline{\zeta}_{i,t,d} - \gamma_{i,d} = 0 \tag{3g}$$
$$(d_{i,t,d}^{\uparrow}) : \ w_d \big(\pi^e + \pi_{i,t,d}) + \kappa_{i,t,d}^{\uparrow} \big) - \underline{\eta}_{i,t,d} + \overline{\eta}_{i,t,d} + \gamma_{i,d} = 0 \tag{3h}$$

The KKT conditions are inserted as constraints to the upper level problem. We thus convert the original bilevel optimization problem to a single-level equivalent MPEC, which is formulated as follows:

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

where,

$$\mathcal{V}_{MPEC} = \mathcal{V}_{UL} \cup \mathcal{V}_{UL} \cup \{ \underline{\zeta}_{i,t,d}, \overline{\zeta}_{i,t,d}, \underline{\eta}_{i,t,d}, \overline{\eta}_{i,t,d}, \gamma_{i,d} \}$$

subject to: (1b)-(1k), (3) (4b)

4) LINEARIZATION OF COMPLEMENTARITY CONDITIONS

The complementary slackness conditions (3c)-(3f) involve bi-linear terms which can be expressed in the generic form $\delta p = 0$, with δ and p representing dual and primal terms, respectively. The Fortuny-Amat linearization approach [37] replaces each of these conditions with the following set of mixed-integer linear conditions: $\delta \geq 0$, $p \geq 0$, $p \leq zM$, $\delta \leq (1-z)M$. Here, z is an auxiliary binary variable and M is a sufficiently large positive constant. For example, (3c) can be linearized as follows $\forall i \in \mathcal{I}, t \in \mathcal{T}, d \in \mathcal{D}$:

$$d^{\downarrow}_{i,t,d} \leq z^{\zeta}_{i,t,d} M \tag{5a}$$

$$\underline{\zeta}_{i,t,d} \leq (1 - z^{\zeta}_{i,t,d}) M \tag{5b}$$

5) LINEARIZATION OF REVENUE ADEQUACY CONSTRAINT

The revenue adequacy constraint (1k) involves four bi-linear terms $\pi_{i,t,d} d^{\downarrow}_{i,t,d}$, $\pi_{i,t,d} d^{\uparrow}_{i,t,d}$, $\pi_{i,t,d} c^{D}_{i,t,d}$, and $\pi_{i,t,d} c^{G}_{i,t,d}$. The first two are linearized by using a subset of the KKT conditions of the lower level problem. Concretely, by exploiting Eqs. (2d), (3c), (3d), (3e), (3f), (3g) and (3h), the sum of these two terms is replaced by the following linear equation:

$$\begin{aligned}\sum_{d\in\mathcal{D}} w_d \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}} \pi_{i,t,d}(-d^{\downarrow}_{i,t,d} + d^{\uparrow}_{i,t,d}) \\ = -\sum_{d\in\mathcal{D}} \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}} \big[w_d \big(\pi^{e}(-d^{\downarrow}_{i,t,d} + d^{\uparrow}_{i,t,d}) + \kappa^{\downarrow}_{i,t,d} d^{\downarrow}_{i,t,d} \\ + \kappa^{\uparrow}_{i,t,d} d^{\uparrow}_{i,t,d}\big) + \overline{\zeta}_{i,t,d} a_i d_{i,t,d} + \overline{\eta}_{i,t,d} a_i d_{i,t,d} \big]\end{aligned} \tag{6}$$

The last two bi-linear terms are linearized through binary expansion. For example, for $\pi_{i,t,d} c^{D}_{i,t,d}$, one can write:

$$\pi_{i,t,d} c^{D}_{i,t,d} = \sum_{n\in\mathcal{N}} u_{i,t,d,n} \pi_n c^{D}_{i,t,d} \tag{7a}$$

This expansion results in the multiplication of the binary variable $u_{i,t,d,n}$ with the continuous variable $c^{D}_{i,t,d}$. We therefore introduce the auxiliary variable $z^{D}_{i,t,d,n}$, where

$$u_{i,t,d,n} c^{D}_{i,t,d} = z^{D}_{i,t,d,n} \tag{7b}$$

$$0 \leq c^{D}_{i,t,d} - z_{i,t,d,n} \leq M_1(1 - u_{i,t,d,n}) \tag{7c}$$

$$0 \leq z_{i,t,d,n} \leq M_1 u_{i,t,d,n} \tag{7d}$$

Thus, we obtain:

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

After the linearization of the complementarity conditions and the revenue adequacy constraints, the MPEC is transformed to a Mixed-Integer Quadratic Program (MIQP) which can be tackled by commercial solvers.

C. CLUSTERING

As we discuss in Section I-B, we rely on representative day-types in order to reduce the number of tariff options presented to prosumers. Concretely, tariffs are designed for each day-type, instead of every single day of the year. Each day can then be assigned to a day-type that is closest to it in similarity, based on observable day-ahead conditions. The corresponding day-ahead network tariffs are then communicated to prosumers.

However, as explained in Section I-C, and in contrast to previous literature that relies on exogenous typical days, we employ a clustering approach for determining the representative day-types based on historical data. Each day in our dataset corresponds to one data point, characterized by a number of dimensions (features). In this paper, we employ derivative features for clustering. Specifically, the chosen features are based on centralized optimal power flow (OPF) calculations on the *historical data* that quantify: a) the extent of thermal and voltage limit violations (i.e. the extent of violating constraints (1d) and (1f)), when demand curtailment, generation curtailment, and demand shifting are not allowed, and b) the extent of optimal demand shifting (i.e. the optimal values of the decision variables $d^{\downarrow}_{i,t,d}$ and $d^{\uparrow}_{i,t,d}$) and demand / generation curtailment when such actions are allowed.

Next, we use the **k-means** algorithm [38] in order to cluster the days into k clusters. Each representative day-type is comprized of 80% of the average active and reactive power of loads and PV generation for each cluster and 20% of the respective average values of the 5% worst days of the cluster. The latter is measured in terms of curtailment costs as produced by the centralized OPF calculations. In other words, we enhance the significance of the worst days in the clusters.

D. TESTING SETUP

The overall testing setup employed in our paper is illustrated in Fig. 3. It includes the following modules:

1) CENTRALIZED OPF

In this model, the DSO optimizes the demand shifting actions of the prosumers directly. This module is used for a) extracting the derivative features of our clustering approach (Section II-C), and b) for benchmarking our overall proposed approach relative to the theoretically optimal cost of the DSO.

2) CLUSTERING

This module implements our proposed clustering approach for devising representative day-types (Section II-C).

3) NETWORK TARIFF DESIGN (NTD) MODEL

This module involves the MIQP that is formulated in Section II-B for designing network tariffs by modelling the interaction of the DSO and prosumers. The model is solved for each of the representative day-types, as determined by the proposed clustering approach.

4) FORECASTING

The day-ahead forecasting module determines the day-type to which the following day is assigned. The forecasting

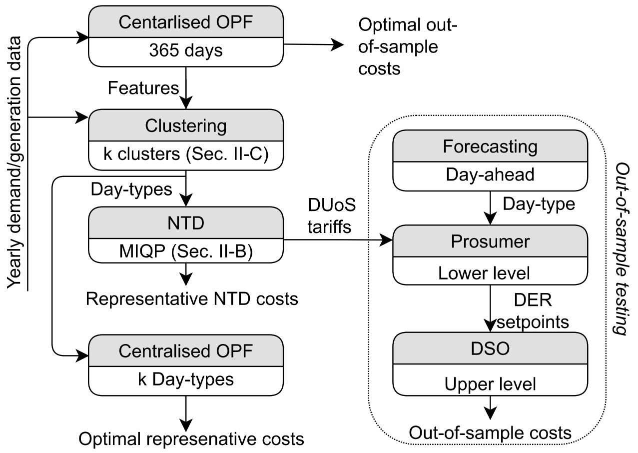

FIGURE 3. Illustration of testing setup.

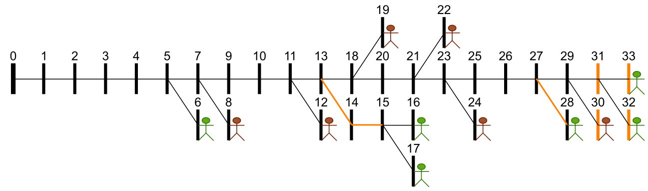

FIGURE 4. Illustration of rural medium voltage feeder employed in the case studies. Passive and active prosumers are indicated by brown and green color, respectively. Orange color indicates network branches and nodes with regular congestion.

approaches employed in our paper are described in Section III-A.

5) PROSUMER MODEL

This module simulates the decision-making problem of the prosumers and corresponds to the lower level problem of Section II-B. The inputs to the model are the network tariffs that are assigned to each day. The outputs are the optimal demand shifting actions of the prosumers.

6) DSO MODEL

This module simulates the decision-making problem of the DSO and corresponds to the upper level problem of Section II-B. Its inputs are the demand shifting actions of the prosumers. The outputs are the optimal curtailment actions and operating costs of the DSO.

The combination of modules 4-6 constitutes an out-of-sample testing procedure. We simulate daily operations as follows. Given the network tariffs for each day-type, we perform the following steps for each day of the year (see Fig. 3):

a) Identify the day-type to which the day belongs. This is performed using forecasting, as described in Section III-A.

b) Use the Prosumer model in order to obtain the optimal demand shifting actions. This model considers the energy prices and the DUoS tariffs that have been broadcast to prosumers.

c) Use the DSO model in order to quantify the optimal curtailment actions of the DSO. These curtailment actions are influenced by the demand shifting actions of prosumers. The model is used for computing the out-of-sample operating costs of the DSO.

III. CASE STUDIES

A. DESCRIPTION AND INPUT DATA

The case studies aim at applying the proposed model in order to demonstrate the impacts of different levels of temporal/spatial granularity in the designed tariffs on cost efficiency. In this context, we have implemented and compared three cases for the designed tariffs:

- *Flat:* This constitutes the simplest, business-as-usual case, where the network tariffs are fixed for every hour of the day and every network node. This case is implemented by introducing the following additional constraint (8) in the MIQP model of Section II-B:

$$\pi_{i,t,d} = \pi_{i',t',d}, \quad \forall i, i' \in \mathcal{I}, \ t, \ t' \in \mathcal{T}, \ d \in \mathcal{D} \tag{8}$$

- *Hourly:* In this case the tariffs can vary by hour but are fixed for every node in the network. This case is implemented by introducing the following additional constraint (9) in the MIQP model of Section II-B.

$$\pi_{i,t,d} = \pi_{i',t,d}, \quad \forall i, i' \in \mathcal{I}, \ t \in \mathcal{T}, \ d \in \mathcal{D} \tag{9}$$

- *Hourly-Loc:* This constitutes the case with the highest spatial-temporal granularity. In this case, the tariffs can vary by both hour and network node. This case is implemented through the MIQP model of Section II-B without any modifications.

Furthermore, we consider two alternative cases for the forecasting approach employed in our out-of-sample testing (Fig. 2):

-Persistence (S): According to persistence forecasting, we assume that the type of the next day is identical to the type of the current day. This case is meant to represent the simplest forecasting approach that can be adopted by DSOs and thus provides a lower bound for out-of-sample cost efficiency.

-Perfect (F): This idealized benchmark assumes perfect forecasting. In other words, we assume that we can perfectly anticipate the day type to which the following day belongs. This case is meant to represent the most advanced forecasting approach that can be adopted by DSOs and thus provides a higher bound for out-of-sample cost efficiency.

The case studies are carried out on a model of a rural medium voltage distribution feeder in Greece (Fig. 4) with 12 prosumers. Table 2 summarises basic input data, while the full dataset, including the technical characteristics of the network (resistances, reactances, apparent power limits) as well as profiles of baseline demand and PV output of the 12 prosumers, are included in a supplementary document [39].

Table 3 presents the maximum demand and PV generation values of all prosumers. The demand curtailment penalty of active and passive prosumers is differentiated in the case study. Nevertheless, assuming an equal curtailment penalty does not affect the emerging trends in the results.

TABLE 2. Basic input data for the case studies.

Parameter	Value
Voltage limits	[0.9,1.1] p.u.
Power factor	0.95
Energy price	75 €/MWh
Network tariff levels	[-60, -40, -20, 0, 20, 40, 60] €/MWh
Generation curtailment penalty factor	115 €/MWh
Demand curtailment penalty factor (active prosumers)	200 €/MWh
Demand curtailment penalty factor(passive prosumers)	400€/MWh
Profit Margin of the DSO	20%

TABLE 3. Maximum demand and PV generation of all prosumers.

	Active prosumers					
Max.	6	16	17	28	32	33
Dem. (MW)	0.38	0.35	0.48	0.46	0.30	0.31
Gen. (MW)	0.08	0.1	0.0	0.82	0.06	0.1
	Passive prosumers					
Max.	8	12	19	22	24	30
Dem. (MW)	0.13	0.12	0.11	0.15	0.14	0.11
Gen. (MW)	0.0	0.0	0.0	0.0	0.0	0.0

We first analyze the network using the available historical demand and PV output data. We find that the following network congestion effects emerge regularly: a) the thermal limits of the branches between nodes 13-15 are breached during midday and evening hours due to high demand, b) the thermal limit of the branch between nodes 27 and 28 is breached during midday hours due to high PV output, c) the lower voltage limits of nodes 30, 31, 32 and 33 are breached during evening hours due to high demand (see also Fig. 4).

We assume that prosumers at nodes 8, 12, 19, 22, 24, and 30 are passive. This implies that they do not exhibit demand shifting flexibility. The demand shifting limit of the remaining (active) prosumers is assumed to be identical and varies between 0% and 30% in the scenarios that we examine below. The discomfort penalty associated with shifting demand towards a particular period (t, d) is assumed to be proportional to the baseline demand at (t, d). This implies that prosumers feel less comfortable about shifting demand towards periods during which they already operate many of their loads. On the other hand, the discomfort penalty associated with shifting demand away from a particular period (t, d) is assumed to be inversely proportional to the baseline demand at (t, d). This implies that prosumers feel less comfortable about shifting demand away from periods during which they operate few of their loads. The profiles of these penalties for each prosumer with demand shifting flexibility are included in the supplementary document [39].

The proposed model has been implemented in Julia [40] using the package JuMP [41] and solved using the optimisation software Gurobi [42] on a computer with a 4-core 2.6 GHz Intel(R) XCore(TM) i7-4720HQ processor and 16 GB of RAM.

B. DESIGN OF TARIFFS WITH DIFFERENT LEVELS OF GRANULARITY

In this section, we consider 4 representative day-types in our clustering approach ($k = 4$). We present the results of the NTD module (Fig. 3) for each of the 3 variations of DUoS tariffs. Figs. 5-7 present the optimal curtailment actions of the DSO for each of the representative day-types, under the Flat (Fig. 5), Hourly (Fig. 6) and Hourly-loc (Fig. 7) schemes. The demand shifting limit, α_i, of flexible prosumers is assumed to be equal to 20%. For the same case, Figs. 8-10 present the optimal network tariffs, under the Flat (Fig. 8), Hourly (Fig. 9) and Hourly-loc (Fig. 10) cases, respectively. Finally, Table 4 presents the total curtailment costs of the DSO for each of these 3 schemes. The table further reports the theoretically optimal curtailment costs, as determined by the centralised OPF. The results in the table consider 4 different demand shifting limits (0%, 10%, 20%, and 30%) for active prosumers. We discuss 3 prosumers in our analysis as indicative of the overall patterns in our case study, and because of their proximity to the key congested locations.

The calculated tariffs under the Flat tariff case are illustrated in Fig. 8. By design, flat tariffs fail to provide an economic motivation to prosumers for mobilising their flexibility in shifting demand. This results in congestion. Consequently, the total curtailment costs are equal to their value under a scenario without demand flexibility ($\alpha_i = 0\%$), irrespectively of the actual demand shifting limit of the active prosumers (as indicated in Table 4). No curtailment is required for the first day-type, as indicated in Fig. 5. Note that the first day-type corresponds to the largest cluster, and consists of 154 days. The second day-type, which consists of 148 days, involves mostly summer days with high PV output leading to congestion of the branch between nodes 27 and 28. This, in turn, necessitates the curtailment of PV output at node 28. The third and fourth day-types involve significantly fewer days, i.e. 37 and 26 days, respectively. These day-types are characterised by high demand and low PV output. This leads to both thermal and voltage congestion effects. Consequently, it is necessary to curtail demand at nodes 17 and 32.

Under the Hourly scheme, tariffs with temporal variation are determined by the NTD module for the three representative day-types characterised by congestion effects. The need for generation / demand curtailment in these day-types is indicated Fig. 6. The hourly tariffs mobilise demand shifting and thereby reduce curtailment, as indicated in Fig. 6. The associated costs are also reduced, as indicated in Table 4. Concretely, in the second representative day-type, higher prices apply in the high-demand periods 21-22 and lower prices apply in periods 14-16 when the system experiences

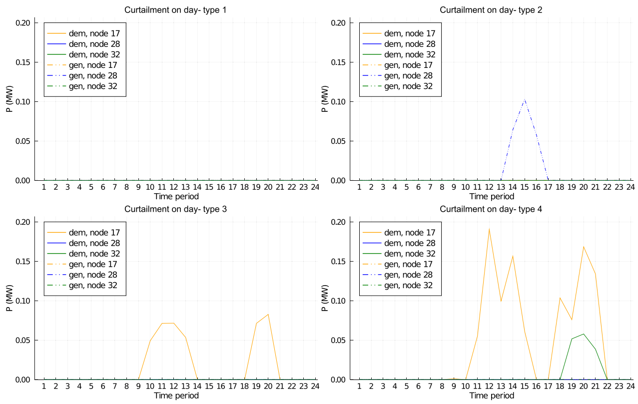

FIGURE 5. Demand (dem.) and generation (gen.) curtailment under the Flat tariff case and a demand shifting limit of 20%.

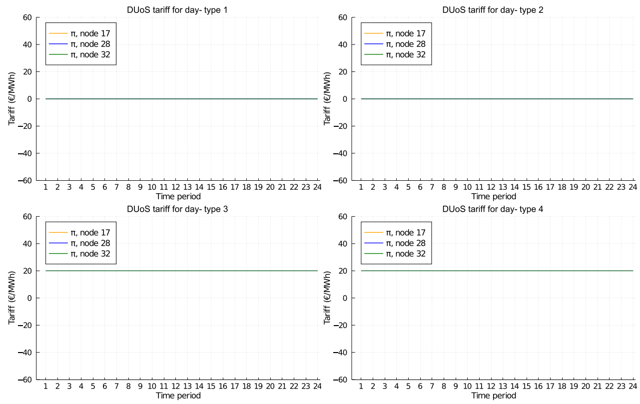

FIGURE 8. Flat network tariffs under a demand shifting limit of 20%.

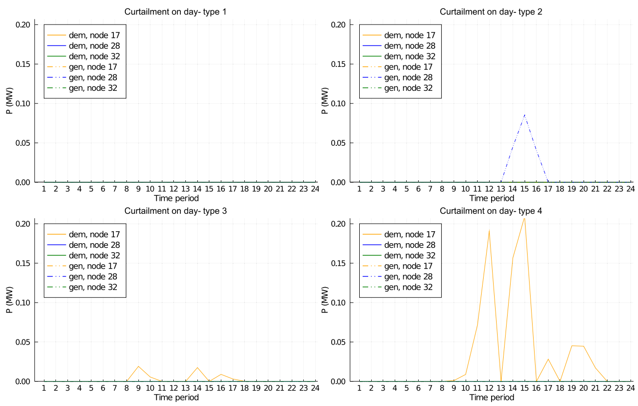

FIGURE 6. Demand (dem.) and generation (gen.) curtailment under the Hourly tariff case and a demand shifting limit of 20%.

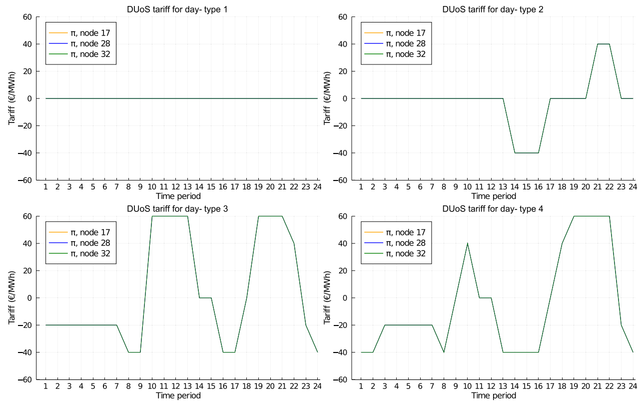

FIGURE 9. Hourly network tariffs under a demand shifting limit of 20%.

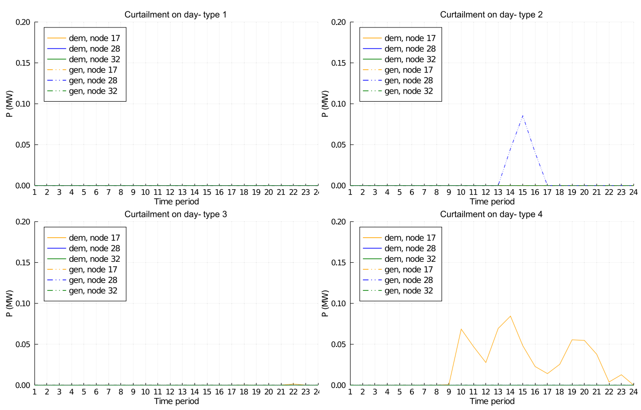

FIGURE 7. Demand (dem.) and generation (gen.) curtailment under the Hourly-loc tariff case and a demand shifting limit of 20%.

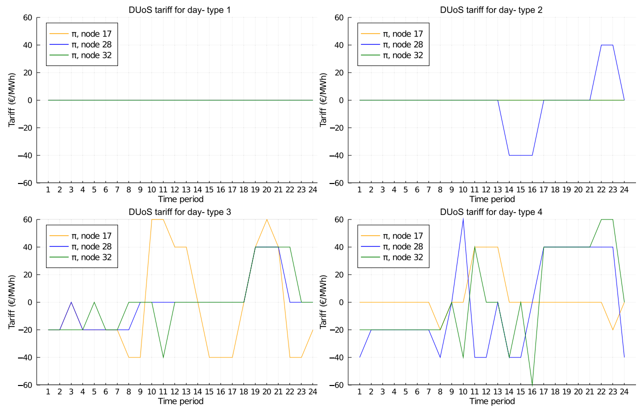

FIGURE 10. Hourly-loc network tariffs under a demand shifting limit of 20%.

high PV output. This is indicated in Fig. 9. Consequently, the tariff induces demand shifting towards the latter periods. This results in lower PV curtailment, as indicated in Fig. 6. The only exception to this beneficial effect of the Hourly case, relative to the Flat case, is observed during hours 14-15 of the fourth representative day-type. During these hours, the required demand curtailment for the prosumer at node 17 is increased. The reason behind this effect lies in the absence of locational granularity in the designed tariffs. Consequently, it becomes impossible to balance network congestion effects associated with prosumers at different nodes. In this particular example, a lower tariff is introduced during hours 14 and 15 in order to mobilise demand shifting towards these hours by prosumers at nodes 32 and 33. This aims

TABLE 4. Total curtailment costs (in €) for $k = 4$ clusters.

	Total curt. costs			
Scheme	$\alpha = 0\%$	$\alpha = 10\%$	$\alpha = 20\%$	$\alpha = 30\%$
Flat	24745.8	24745.8	24745.8	24745.8
Hourly	24745.8	15090.1	12612.0	10473.3
Hourly-loc	24745.8	14657.9	10935.0	8481.5
Optimal	24745.8	14656.5	10906.0	8481.5

TABLE 5. Total use-of-system costs of all prosumers (in €) for $k = 4$ clusters.

	Total prosumer use-of-system costs			
Scheme	$\alpha = 0\%$	$\alpha = 10\%$	$\alpha = 20\%$	$\alpha = 30\%$
Flat	30974.4	30974.4	30974.4	30974.4
Hourly	30974.4	19320.2	16371.7	13768.3
Hourly-loc	30974.4	18920.5	14319.7	11438.7

TABLE 6. Execution times for each scheme.

	Execution time (hours)			
Scheme	$\alpha = 0\%$	$\alpha = 10\%$	$\alpha = 20\%$	$\alpha = 30\%$
Flat	0.1	1.5	1.5	1.5
Hourly	0.2	10	18	24
Hourly-loc	0.05	0.3	1.5	2
Optimal	0.05	0.05	0.05	0.05

to address voltage congestion effects occurring later in the day. However, this lower tariff also induces demand shifting towards the same hours by prosumers at nodes 16 and 17. This, in turn, aggravates the thermal congestion effects on the branches between nodes 13-15. Thus, such a short-term local aggravation might occur as often as days of day-type 4 emerge (26 per year).

Under the Hourly-loc scheme, this challenge is addressed by introducing locational, in addition to temporal, granularity in the designed tariffs. The resulting tariffs are presented in Fig. 10. These tariffs induce locationally differentiated demand shifting actions. As a result, this further reduces curtailment, as demonstrated in Fig. 7, and the associated costs, as demonstrated in Table 4. For the example of the fourth representative day-type, which we discuss above, the tariff offered to the prosumer at node 17 does not include a lower value at hours 14 and 15 anymore. It is worth noting that the total curtailment costs under this tariff are almost identical to the benchmark value of perfect coordination, as we can observe in Table 4. Finally, although the tariff pattern includes frequent changes, this is not expected to drive communication speed and reliability concerns, since the tariffs are computed and communicated annually, while the specific tariff for the following day is chosen in the day ahead horizon.

Table 5 presents the total use-of-system costs of all prosumers under each of the examined tariff schemes and demand shifting scenarios. The emerging trends follow the trends of the total curtailment costs (Table 4): the prosumers' use-of-system costs are reduced as the granularity of the employed tariff scheme is enhanced and the demand shifting flexibility is increased.

TABLE 7. Out-of-sample total curtailment costs (in €) and efficiency (%) for k = 4 and a demand shifting limit of 20%.

Scheme	Total curt. costs	Efficiency
Flat(S)	26304.6	0 %
Flat(F)	26304.6	0 %
Hourly(S)	19221.3	48.8 %
Hourly(F)	17228.5	62.6 %
Hourly-loc(S)	17406.8	61.3 %
Hourly-loc(F)	15128.0	77.0 %
Optimal	11795.6	100 %

We conclude this analysis with Table 6, which presents the required execution time for each of the examined scenarios. The results demonstrate that the Hourly tariff scheme exhibits higher execution times than the Hourly-loc tariff scheme, because the model attempts to balance conflicting network congestion effects at different locations through a locationally uniform tariff (i.e., through fewer degrees of freedom). It should be also noted that the reported execution times (in the scale of hours) are deemed acceptable since the DUoS tariff design task is performed once every year in our examined framework.

Finally, we have performed a meta-analysis to investigate the error introduced by the employment of the LinDistFlow model, with respect to a complete, non-linear AC power flow model for the net injections induced by the calculated tariffs. The results have indicated that the LinDistFlow model does not introduce a significant loss of accuracy; for example, the loss of accuracy in voltage for the last node (33) during the most congested day-type 4 is 0.5%.

C. OUT-OF-SAMPLE VALIDATION

This section presents the results of the out-of-sample testing approach that is described in Section II-D. Starting from the case with $k = 4$ clusters, Table 7 presents the out-of-sample curtailment costs of the DSO. We assume a demand shifting limit of 20% for active prosumers. We report results for each of the 3 tariffs, and each of the 2 examined forecasting approaches. The table also presents the benchmark results of perfect coordination that are determined by the centralized OPF. We define the cost reduction of each scheme as the savings in yearly curtailment costs relative to the flat tariff. The *optimal* cost reduction is that achieved by the centralized OPF, performed daily. We define the cost efficiency of a tariff as the percentage (%) of the optimal cost reduction achieved by the tariff in the validation runs.

The out-of-sample results exhibit the same trends as the results produced by the NTD module in Section III-B. Concretely, we observe a reduction in curtailment costs, and thus an increase in the % efficiency, as we move towards more granular tariff designs. Furthermore, as expected, the curtailment costs are reduced when we assume a perfect forecasting approach compared to a simple persistence forecasting approach, since the latter is naturally characterized by forecasting errors. The only exemption lies in the Flat case,

TABLE 8. Cost efficiency (%) using the proposed methodology for different numbers of clusters and a demand shifting limit of 20%.

Representative day-types	Hourly		Hourly-loc	
	(S)	(F)	(S)	(F)
Season	59.1%	59.2%	60.9%	61.2%
$k=4$	48.8%	62.6%	61.3%	77.0%
$k=8$	56.3%	69.1%	63.3%	80.3%
$k=16$	57.2%	72.9%	61.9%	81.8%
$k=32$	58.0%	75.7%	61.3%	84.0%
$k=64$	57.6%	78.8%	61.0%	86.1%
$k=365$	59.2%	90.3%	57.6%	99.8%

where demand shifting flexibility is not mobilized. Consequently, the forecasting approach does not affect the results.

In addition, we perform a sensitivity analysis on the number of representative day-types (k) that are employed in our clustering approach. The results are presented in Table 8. Under a perfect (F) forecasting approach, as the number of clusters increases, the efficiency of both Hourly and Hourly-loc tariffs is enhanced. This is due to the fact that additional clusters allow for a more complete representation of the varying operating conditions in the designed tariffs. Note, however, that the incremental gain is reduced as k increases. Under a simple persistence forecasting approach (S), such a gain is not always emerging, since a higher number of clusters aggravates forecasting errors.

Finally, we consider a case where the representative day-types are based solely on seasons [23]. Seasonal tariffs have been considered before in practice, see for example [25]. In the seasonal case, days are simply grouped according to the season of the year to which they belong, without using any learning techniques. Representative day-types for each season are constructed using the k-means clustering methodology that is explained in the last paragraph of Section II-C. Therefore, the first two rows of Table 8 correspond to 4 clusters and they demonstrate that the more advanced clustering approach proposed in Section II-C achieves significant benefits with respect to the simpler seasonal approach under perfect forecasting.

IV. CONCLUSION

Considering the emerging large-scale integration of DERs and relevant opportunities around exploiting their flexibility to increase the economic efficiency of distribution network operation, this paper has focused on the problem of designing DUoS tariffs that are more adaptive to short-term operating conditions. We have addressed this problem through a bilevel optimization model, capturing the interaction between a DSO designing the DUoS tariffs at the upper level and prosumers with PV generation and flexible demand DERs who react to the tariffs at the lower level. In contrast to previous works, this model considers a detailed representation of the distribution network power flow constraints, different levels of temporal and spatial granularity in the designed tariffs, as well as discrete tariff levels for preserving intelligibility. Furthermore, instead of relying on exogenous typical days, the developed model employs a clustering approach to design tariffs that adapt to the forecasted conditions of the upcoming day.

The results of the examined case studies have demonstrated that tariffs with higher degrees of temporal and spatial granularity can effectively mitigate the implications of network congestion effects and enhance the economic efficiency of distribution network operation, thus constituting a policy worth considering by NRAs and DSOs. Furthermore, the proposed clustering approach is validated through out-of-sample simulations, demonstrating that a higher number of clusters enhances the economic efficiency of tariff schemes with temporal and spatial granularity, provided that an effective forecasting approach is adopted.

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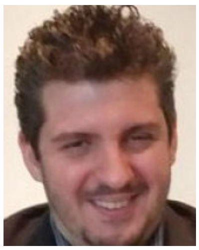

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