Platone

PLATFORM FOR OPERATION OF DISTRIBUTION NETWORKS

Platone

PLATform for Operation of distribution NEtworks

D4.4 v1.0

Algorithm for optimal DER control

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Abstract

Deliverable 4.4: "Algorithm for optimal DER control" presents the framework methodology and the tool developed for the optimal control of Distributed Energy Resources (DER). The framework is based on the design of variable Distribution Use-of-System (DUoS) tariffs that can mobilize DER flexibility while retaining traditional traits such as cost recovery for Distribution System Operators (DSOs). The design of such 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. The methodology analysed in this deliverable presents a method to design DUoS tariffs through a bilevel optimization model, that captures the interaction between a (DSO) and prosumers with DER. Expanding on the state-of-the-art, the methodology 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. In addition, the developed methodology is not relying on exogenous typical days. Instead, it employs a clustering approach to design tariffs that adapt to the forecasted conditions of the upcoming day. Extensive 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. The results prove that variable DUoS tariffs can be deployed to mobilize most of the available DER flexibility in distribution networks.

Keyword list

Bilevel optimization, clustering, distributed energy resources, distribution use-of-system tariffs, flexibility

Executive Summary

*"*Innovation for the customers, innovation for the grid" is the vision of project Platone - Platform for Operation of distribution Networks. Within the H2020 programme "A single, smart European electricity grid", Platone addresses the topic "Flexibility and retail market options for the distribution grid". Modern power grids are moving away from centralised, infrastructure-heavy transmission system operators (TSOs) towards distribution system operators (DSOs) that are flexible and more capable of managing diverse renewable energy sources. DSOs require new ways of managing the increased number of producers, end users and more volatile power distribution systems of the future. Platone is using blockchain technology to build the Platone Open Framework to meet the needs of modern DSO power systems, including data management. The Platone Open Framework aims to create an open, flexible and secure system that enables distribution grid flexibility/congestion management mechanisms, through innovative energy market models involving all the possible actors at many levels (DSOs, TSOs, customers, aggregators). It is an open-source framework based on blockchain technology that enables a secure and shared data management system, allows standard and flexible integration of external solutions (e.g., legacy solutions), and is open to integration of external services through standardized open application program interfaces (APIs). It is built with existing regulations in mind and will allow small power producers to be easily certified so that they can sell excess energy back to the grid. The Platone Open Framework will also incorporate an open-market system to link with traditional TSOs. The Platone Open Framework will be tested in three European field trials and within the Canadian Distributed Energy Management Initiative (DEMI).*"*

Work Package 4 (WP4) includes the activities of the Greek demo at the Mesogia area of Attica. One of the key elements of the Greek demo is the development of algorithms for control of Distributed Energy Resources (DERs). 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-focused distribution use-of system (DUoS) tariffs, novel, more volatile, DUoS 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. To this end, this deliverable presents the methodology and corresponding tool that was developed in order design and test a new generation of DUoS tariffs that can mobilize DER flexibility while at the same time retaining traditional DUoS tariffs traits, such as DSO cost recovery through tariff revenue and simplicity/intelligibility for the end-user.

The proposed tool relies on a Stackelberg game formulation that forms a bilevel optimisation type mathematical model. There is a leader (upper level), in this case the DSO, and a follower (lower level), in this case the prosumers. The interaction of the two is two optimisation problems interacting with each other (hence bilevel optimisation). The upper level consists of the DSO objective, which is the minimisation of operational costs, and the constraints, which are the power flow constraints, tariff format constraints and revenue recovery of costs. The lower level consists of the prosumer objective, which is the minimisation of costs and discomfort, and the constraints include DER constraints from DERs that the prosumer operates. The model cannot be solved in its initial format; hence, it is transformed into its equivalent Mathematical Program with Equilibrium Constraints (MPEC) by making use of the Karush-Kuhn-Tucker (KKT) conditions of the lower level which are added as constraints to the upper level. The new model is then linearised in the case of non-linear and bilinear terms and it, finally, becomes a Mixed-Integer Quadratically constrained Program (MIQP) which can be solved reliably with commercial solvers. The tariffs that are created are not continuous variables but only a few distinct levels are used to retain intelligibility for the end-user.

The proposed tariff design model is not deployed each day of a year. This would contradict the principle of simplicity and would hinder the possibility for adoption by end-users. Instead, tariffs are designed once every year using historical data, where few tariff patterns are created in order to address such problems. The way tariffs are designed is by using clustering techniques on the historical data. Days are clustered into groups of similar samples based on the conditions in the network (line congestions, voltage issues, etc.) observed during each day. Then, each cluster is represented by one "representative" day (day-type) for which the corresponding tariff pattern is designed. The clustering

technique chosen in our tool is that of K-means with weighted averaging when calculating the representative day. The added weighting gives increased significance to the operationally worst days.

To test the methodology a design and validation framework is created. The different steps of the framework include analysis of the historical data and clustering, design of tariffs, testing on actual historical data over a period of a year and calculating efficiency improvement compared to a) the case where a DSO decides centrally the optimal allocation of DERs (theoretical optimal), and b) the Business-as-Usual case of Flat tariffs; a scheme that is used today from almost all DSOs.

A significant body of case studies was performed including: i) tariffs with different spatial and temporal granularity, ii) different levels of DER flexibility volume and, iii) different number of representative days (clusters) and different clustering approaches. A few of the most important conclusions were that as granularity increases (both temporal and spatial) so does efficiency. Moreover, the performance of the method is not affected by complexity or different flexibility volumes. The clustering approach outperforms non-learning-based techniques. As the number of clusters increases so does efficiency. The most significant result is that even with a very small number of tariff patterns (clusters / day-types), i.e., 4 day-types, efficiency of 77% is achieved. This means that a DSO can mobilize more than ¾ of the available DER flexibility with 4 tariff patterns which, according to the design framework we propose are broadcasted a year in advance, are simple (a few discrete tariff levels instead of continuous) while at the same time retaining revenue adequacy requirements for covering costs as traditional flat tariffs do. This result constitutes a policy worth considering by NRAs and DSOs.

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1 Introduction

The project “PLATform for Operation of distribution Networks – Platone” aims to develop an architecture for testing and implementing a data acquisition system based on a two-layer Blockchain approach: an “Access Layer” to connect customers to the Distribution System Operator (DSO) and a “Service Layer” to link customers and DSO to the Flexibility Market environment (Market Place, Aggregators, …). The two layers are linked by a Shared Customer Database, containing all the data certified by Blockchain and made available to all the relevant stakeholders of the two layers. This Platone Open Framework architecture allows a greater stakeholder involvement and enables an efficient and smart network management. The tools used for this purpose will be based on platforms able to receive data from different sources, such as weather forecasting systems or distributed smart devices spread all over the urban area. These platforms, by talking to each other and exchanging data, will allow collecting and elaborating information useful for DSOs, transmission system operators (TSOs), Market, customers and aggregators. In particular, the DSOs will invest in a standard, open, non-discriminatory, blockchain-based, economic dispute settlement infrastructure, to give to both the customers and to the aggregator the possibility to more easily become flexibility market players. This solution will allow the DSO to acquire a new role as a market enabler for end users and a smarter observer of the distribution network. By defining this innovative two-layer architecture, Platone strongly contributes to aims to removing technical and economic barriers to the achievement of a carbon-free society by 2050 [1], creating the ecosystem for new market mechanisms for a rapid roll out among DSOs and for a large involvement of customers in the active management of grids and in the flexibility markets. The Platone platform will be tested in three European trials (Greece, Germany and Italy) and within the Distributed Energy Management Initiative (DEMI) in Canada. The Platone consortium aims to go for a commercial exploitation of the results after the project is finished. Within the H2020 programme “A single, smart European electricity grid” Platone addresses the topic “Flexibility and retail market options for the distribution grid”.

1.1 Task 4.4

The aim of Task 4.4 is the development of the algorithm for optimal control of Distributed Energy Resources (DERs) with an emphasis on flexible loads, in order to alleviate line and voltage limit violation problems within the distribution network. Preferably, indirect control methods, such as dynamic tariffs should be employed.

1.2 Objectives of the Work Reported in this Deliverable

The objective of this Deliverable is to present the work developed in subtask 4.4.1. This includes the design, development and extensive validation of the Algorithm for DER control. The algorithm is based on the design of variable Distribution Use-of-System (DUoS) tariffs.

1.3 Outline of the Deliverable

Chapter 2 presents the required background. Chapter 3 describes the mathematical model and the clustering approach. Chapter 4 illustrates the design and validation modules, the input data and the development platform while Chapter 5 presents and analyses the results from the case studies. Finally, Chapter 6 provides the conclusion.

1.4 How to Read this Document

Some background on DER flexibility issues and different methodologies is beneficial for the understanding of the underlying motivation of DUoS tariffs vs locational marginal pricing. Relevant background to mathematical optimisation and bilevel models could be useful for comprehension of the model.

The report is, also, linked to D4.1 [2], which provides a detailed description of the Greek demo, its Use Cases and the related KPIs, and D1.2 [3], which elaborates on calculation methodology, data collection and baseline details for all Demos’ KPIs and defines Project KPIs.

2 Background

2.1 Network tariffs

During the last two decades, distribution systems have seen a continuously increasing presence of Distributed Energy Resources (DERs). These DERs include different types of flexible demand, renewable energy sources (wind and PV) and energy storage (batteries or EVs) [4]. Their presence inherently creates new conditions under which distribution network pricing is performed, namely, short term goals are introduced. At the same time, new problems, but also solutions, emerge for managing DERs located in distribution networks. Problems include the effort to keep distribution networks within operational limits in terms of voltage, line or transformer capacity limit violations. Solutions include the significant flexibility capabilities of most DERs. Therefore, in contrast to traditional Distribution Use-of-System (DUoS) tariff schemes that have a long-term outlook, new tariff schemes can exploit the possibility to incentivise more efficient DER operation with a short-term scope. Modern developments in ICT, monitoring infrastructure and controllability capabilities render such tariffs schemes viable from a practical point of view.

Traditionally, DUoS tariffs have been designed aiming at recovering previous (called ***sunk***) and future planned (called ***prospective***) investments in distribution network infrastructure, mainly on long-term incremental cost principles [5], [6]. Additional consideration has been given to fair allocation of costs among the various network users [7], [8]. Eurelectric's report [9] highlighted the need for DUoS tariffs to ensure ***revenue adequacy*** for the Distribution System Operators (DSOs), fairness, predictability, intelligibility for the consumers. Apart from that, tariffs should have the attributes of cost-reflectiveness (i.e., reflecting the costs induced or saved by different users) and economic efficiency (i.e., yielding the lowest possible investment and operating costs) and should reflect more accurately the marginal network costs and thus mobilize price-based demand response. Adding on Eurelectric's arguments, the E.DSO recently published its own guidelines [10]. In this report, E.DSO confirms these attributes including, cost reflectivity, incentives for efficient network use, transparency/understandability, implementability and limited complexity.

Ideally, DERs located at all voltage levels in a power system should be managed by the principles of marginal locational pricing. This means that the true value of energy should be represented accurately at all nodes of the network. In distribution systems, approaches that follow this principle are named distribution locational marginal pricing (DLMP) [11], [12]. DLMP by its definition coordinates resources optimally and thus, maximises operating efficiency [13], while ensuring that distribution network requirements are respected (such minimum reactive flows or power losses and safe operation in terms of voltage and line constraints [14]). From an economic perspective, optimisation of DERs via DLMP, whether centralised, decentralised or distributed, is equivalent to a market equilibrium under perfect competition in a market that trades real active and reactive power at each node. Despite it being theoretically the optimal strategy, DLMP is difficult to realise due to implementational and regulatory obstacles. The realisation of a complete market in current distribution networks requires a substantial restructuring of DSO practices and massive monitoring, ICT infrastructure and computation costs.

Considering the above arguments, this report discusses a different methodological approach. This approach involves the utilisation of DUoS tariffs in order to increase DER flexibility by considering tariffs that vary in a shorter time scale than traditional tariffs of currently passive distribution networks. The proposed methodology is independent of whether a distribution level energy market exists. The overall framework requires a DSO that directly designs DUoS tariffs, having the choice of introducing different levels of temporal and spatial variability, and DERs that react to said tariffs.

2.2 What is innovative in Platone?

The interaction between DSO and DERs described in the previous section is a typical Stackelberg game which is recast as a bilevel optimisation problem in order to facilitate its modelling. Such models are very useful in the context of non-cooperative interactions, as the one described here. Moreover, they have been successfully deployed in power system applications several times in the past. In [15] [16] bilevel optimisation is used for strategic bidding in wholesale electricity markets, in [17] [18] for electricity suppliers' / aggregators pricing strategies, and in [19] [20] for strategic generation investment planning. However, past works on the application of bilevel optimisation on DUoS tariff design for effective management of DERs are limited. Specifically, previous works that apply this methodology to the examined problem include [21] [22] [23] [24] [25] [26]. We summarize the main characteristics of this literature in Table 1.

Table 1: Summary of relevant literature.

Paper	Cost Recovery	Tariff type	Granularity	Network model	Day-types
[21]	Sunk	Fixed, Peak-power/Capacity, Volumetric	No	No	Typical
[22]	Prospective	Fixed, Peak-power/Capacity, Volumetric	No	System peak	Typical
[23]	Sunk	Fixed, Peak-power/Capacity, Volumetric	No	No	Typical
[24]	Sunk	Fixed, Peak-power/Capacity, Volumetric	No	No	Typical
[25]	No	Peak-power/Capacity, Volumetric	No	HV/MV transformer	Typical
[26]	Prospective	Peak-power, Volumetric	No	HV/MV transformer	Seasons
Platone	Prospective	Volumetric	Spatial Temporal	LinDist Flow	Clustering

In [21], a game-theoretical model is employed for designing flat tariffs which aim at recovering sunk exogenous network costs. In [22] [23] 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 [23] and prospective costs in [22]).In [22], prospective network costs are expressed as a simple linear function of the overall peak power of the network. In [25], 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 [24] [26] 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 [26].

Regarding the modelling and computational methodology of the aforementioned literature, in [21], [23], [24], [26] 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 [21], [22], [23], [24], [25], [26] 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, [21], [22], [23], [24], [25], [26] provide valuable insights into the problem of tariff design from the point of view of cost recovery and reducing network peaks.

The analysis presented in this report focuses on network tariffs that vary on a relatively shorter time frame. The authors 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 [27] 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 [27], where a day-ahead price scheme with hourly granularity is employed. According to [27], 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, the approach described in this report is 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 [28]. 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 [29] for characterising observable day-ahead conditions.

The overarching question that the methodology for DUoS tariffs used in the Greek demo is trying to answer is the following. **How simple DUoS can be designed with the purpose of exploiting DER flexibility in order to increase economic efficiency in distribution networks?** A positive answer to this question relies on the simple hypothesis that both energy sources and consumption put together present underlying patterns that can be learned and exploited in order to use simple tariffs to capture a large percentage of that variation and direct it to a more efficient operation.

The first tangible advantage of the described methodology is that it describes the DUoS tariffs by formulating the interaction as a Stackelberg leader-follower game described by a bilevel optimisation model. The tariffs have spatial and temporal characteristics due to the consideration of multiperiod optimisation and the network model. Their variation is limited to discrete levels to enhance their adoption potential by users.

The second advantage of the method is that the design of the tariffs is more realistic than previous approaches as it employs actual clustering analysis on historical data. Prices are designed for **day-types** derived from said analysis and not demonstrated in arbitrary typical profiles that are lacking any practical connection to one of the core components of DUoS tariffs, the revenue adequacy requirement. Moreover, the tariffs are adjusted to the day ahead conditions each day by assigning each day to one of the predefined day-types. The performance of a few day-types in capturing much of the available efficiency is tested via out-of-sample simulations.

3 Problem formulation

3.1 Model Assumptions

Before discussing the mathematical formulation, it is important to discuss the main assumptions. These assumptions are not simplifications but describe key aspects of the proposed methodology that are also reflected in the formulation. These assumptions are with regards to the problem structure, the tariff types, the way DERs are represented by prosumers and the network model used.

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 which 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. Figure 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).

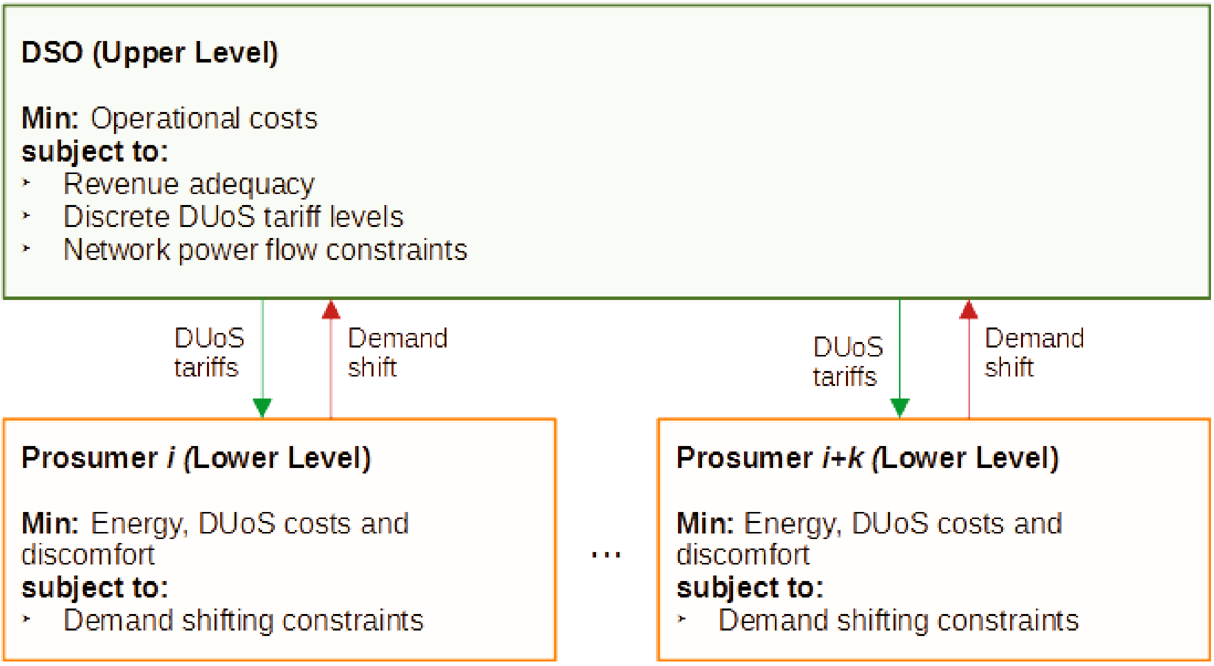

Figure 1: Leader-follower model (bilevel optimisation) of the proposed methodology.

Tariff type: In general, tariffs in energy can be categorised as volumetric (€/MWh), peak-power or capacity (€/MW) (although peak-power and capacity tariffs can be fundamentally different), and fixed (€). The methodology suggested in the Greek demo focuses on volumetric tariffs that can vary both temporally and spatially. To enhance intelligibility and adoptability by the public, we introduce discrete price levels instead of continuous. Moreover, all DUoS tariffs should include revenue recovery for DSOs. The volumetric tariffs used in the proposed methodology are associated with operational costs.

Prosumer models: In this basic context of the Greek demo, prosumers are assumed to own and operate PV generation. In addition, some of their demand is flexible, meaning that certain assets can move their demand to different hours of the same day. We use generic model to capture the demand flexibility of prosumers. Specific constraints enforce that overall consumption within a day remains the same, regardless of the shifting that takes place (i.e., demand shifting is energy neutral). However, demand shifting does entail a quantifiable discomfort cost.

Network model: The power flow constraints of the distribution network are represented through the LinDistFlow model [30], [31]. We employ Figure 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.

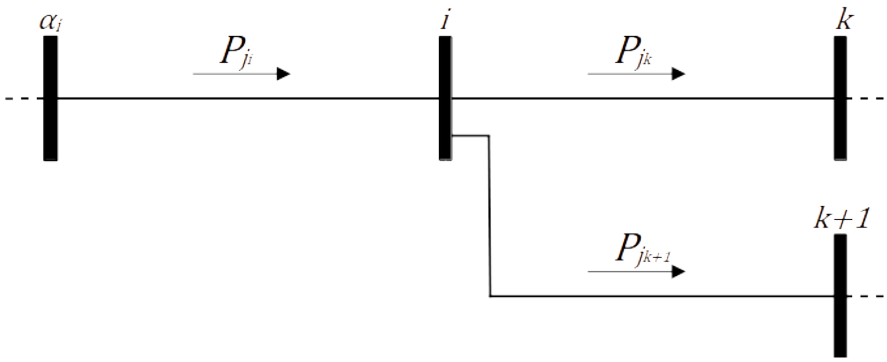

Figure 2: Illustration of part of the distribution network.

3.2 Mathematical formulation

In this section, the mathematical model is discussed. First, we present the upper (DSO) and lower (prosumers) level models and then we transform the bilevel formulation into a Mathematical Problem with Equilibrium Constraints (MPEC) in order to be able to solve effectively. First, we define each period of the model which is denoted by (t, d), where t denotes a particular hour and d a particular day.

3.2.1 Upper level (DSO)

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

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

where,

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

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

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

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

$$P^2_{j_i,t,d} + Q^2_{j_i,t,d} \le \overline{F}^2_{j_i} \tag{1d}$$

$$v_{i,t,d} = v_{a_i,t,d} - 2\left(r_{j_i}P_{j_i,t,d} + x_{j_i}Q_{j_i,t,d}\right) \tag{1e}$$

$$\underline{v}^2_{i,t,d} \le v_{i,t,d} \le \overline{v}^2_{i,t,d} \tag{1f}$$

$$0 \le c^{G}_{i,t,d} \le p_{i,t,d} \tag{1g}$$

$$0 \le c^{D}_{i,t,d} \le d_{i,t,d} - d^{\downarrow}_{i,t,d} + d^{\uparrow}_{i,t,d} \tag{1h}$$

$$\pi_{i,t,d} = \sum_{n\in\mathcal{N}} u_{i,t,d,n}\pi_n \tag{1i}$$

$$\sum_{n\in\mathcal{N}} u_{i,t,d,n} = 1 \tag{1j}$$

$$\sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}}\sum_{i\in\mathcal{I}} w_d\, \pi_{i,t,d}\left(d_{i,t,d} - d^{\downarrow}_{i,t,d} + d^{\uparrow}_{i,t,d} - p_{i,t,d} - c^{D}_{i,t,d} + c^{G}_{i,t,d}\right) = (1+\kappa^{C})\mathcal{J}^{u} \tag{1k}$$

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. Constraint (1e) represents the relationship between nodal voltage magnitudes and adjacent power flows, while constraints (1f) enforce voltage limits for each node. Constraints (1g) and (1h) 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.

3.2.2 Lower level (Prosumer)

The lower level expresses the decision-making problem of the prosumers. It is described by the following model:

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

where,

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

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

$$\left(\underline{\zeta}_{i,t,d}, \overline{\zeta}_{i,t,d}\right): \quad 0 \le d^{\downarrow}_{i,t,d} \le \alpha_i d_{i,t,d} \tag{2b}$$

$$\left(\underline{\eta}_{i,t,d}, \overline{\eta}_{i,t,d}\right): \quad 0 \le d^{\uparrow}_{i,t,d} \le \alpha_i d_{i,t,d} \tag{2c}$$

$$\left(\gamma_{i,d}\right): \quad \sum_{t \in \mathcal{T}} \left(-d^{\downarrow}_{i,t,d} + d^{\uparrow}_{i,t,d}\right) = 0, \ \forall i \in \mathcal{I}, d \in \mathcal{D} \tag{2d}$$

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 $d^{\downarrow}_{i,t,d}$ and $d^{\uparrow}_{i,t,d}$ 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 [18], 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.

3.2.3 Formulation of the Mathematical Program with Equilibrium Constraints (MPEC)

As described in Figure 1, the two problems (upper and lower) are coupled. This means that the optimal solution of the one affects the optimal solution of the other and vice versa. More specifically, the optimal DUoS tariffs of the upper level affect the optimal demand shifting of the lower level, whereas said demand shifting affects the constraints of the upper level. As it is typical with such bilevel optimisation problems, one can replace the lower level problem with its Karush-Kuhn-Tucker (KKT) conditions [32]. The KKT conditions of the lower lever $\forall i \in \mathcal{I}, t \in \mathcal{T}, d \in \mathcal{D}$ are:

- **Primal constraints:**

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

- **Dual constraints**

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

- **Complementary slackness:**

$$\underline{\zeta}_{i,t,d}\left(-d^{\downarrow}_{i,t,d}\right) = 0 \tag{3c}$$

$$\overline{\zeta}_{i,t,d}\left(d^{\downarrow}_{i,t,d} - \alpha_i d_{i,t,d}\right) = 0 \tag{3d}$$

$$\underline{\eta}_{i,t,d}\left(-d^{\uparrow}_{i,t,d}\right) = 0 \tag{3e}$$

$$\overline{\eta}_{i,t,d}\left(d^{\uparrow}_{i,t,d} - \alpha_i d_{i,t,d}\right) \tag{3f}$$

- **Gradient of the Lagrangian:**

$$(d^{\downarrow}_{i,t,d}): \quad w_d\left(\left(\pi^e + \pi_{i,t,d}\right) + \kappa^{\downarrow}_{i,t,d}\right) - \underline{\zeta}_{i,t,d} + \overline{\zeta}_{i,t,d} - \gamma_{i,d} = 0 \tag{3g}$$

$$(d^{\uparrow}_{i,t,d}): \quad w_d\left(\left(\pi^e + \pi_{i,t,d}\right) + \kappa^{\uparrow}_{i,t,d}\right) - \underline{\eta}_{i,t,d} + \overline{\eta}_{i,t,d} + \gamma_{i,d} = 0 \tag{3h}$$

If one adds the KKT conditions of the lower level as additional constraints to the upper level, one forms a single level problem that is, by definition, equivalent to the bilevel optimisation problem. The new formulation is a Mathematical Program with Equilibrium Constraints (MPEC). The new optimisation problem becomes:

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

where,

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

subject to:

$$\text{(1b)-(1k), (3)} \tag{4b}$$

3.2.4 Linearisation of the 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 [33] replaces each of these conditions with the following set of mixed-integer linear conditions: $\delta \geq 0$, $p \geq 0$, $p \leq z\,M$, $\delta \leq (1-z)M$. Here, z is an auxiliary variable and M is a sufficiently large positive constant. Illustrating an example from the current formulation, Equation (3c) can be linearized as follows $\forall i \in \mathcal{I}, t \in \mathcal{T}, d \in \mathcal{D}$:

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

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

3.2.5 Linearisation of the revenue adequacy constraint

The revenue adequacy constraint (1k) involves four bi-linear terms. Namely: $\pi_{i,t,d} d^{\downarrow}_{i,t,d}$, $\pi_{i,t,d} d^{\uparrow}_{i,t,d}$, $\pi_{i,t,d} c^{D}_{i,t,d}$ 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. Thus, one by exploiting Equations (2d), (3c), (3d), (3e), (3f), (3g) and (3h) obtains the following linear equation:

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

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:

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

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

$$u_{i,t,d,n} c_{i,t,d}^{D} = z_{i,t,d,n}^{D} \tag{7b}$$

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

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

Thus, we obtain:

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

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.

3.3 Clustering

As discussed in Chapter 2, 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 the same chapter, 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 $d_{i,t,d}^{\downarrow}$ and $d_{i,t,d}^{\uparrow}$) and demand / generation curtailment when such actions are allowed.

Next, we use the **k-means** algorithm [34] to cluster the days into *k* clusters. Each representative day-type is comprised 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.

4 Testing Setup

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

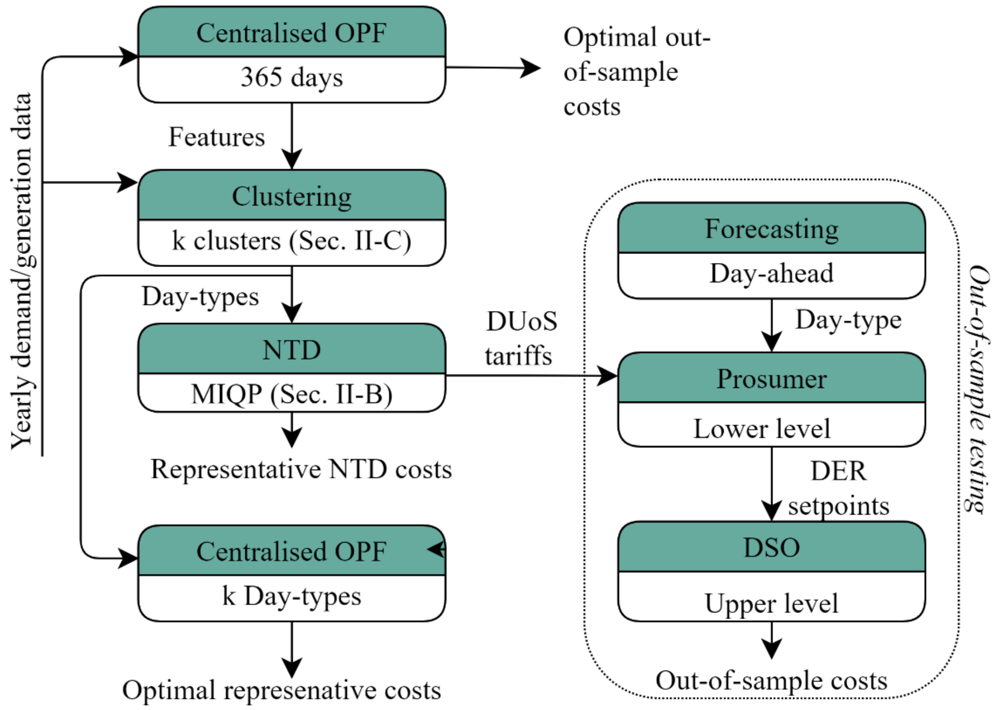

Figure 3: Illustration of modules.

4.1 Design and Validation Modules

4.1.1 Centralised OPF module

This model represents a DSO that has complete controllability over all decision variables (of the upper and lower levels). A centralised OPF single level equivalent of the bilevel formulation is solved instead. Such a setup is not realistic, of course, in practice. The module is used for validation purposes. First of all, OPF studies are used to derive some of the features used in the clustering approach, described in the corresponding chapter. Secondly, the centralised OPF is used for benchmarking the proposed methodology. It is called alternatively *Optimal mode* and it represents the theoretical optimal flexibility allocation that can be achieved. Having the theoretical optimal and the Business-as-usual (BaU) results, one can find the level of *efficiency* achieved under a proposed method and scheme, see Figure 4.

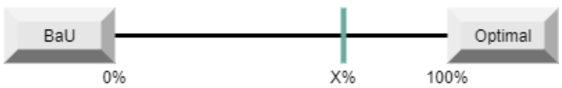

Figure 4: Illustration of how efficiency is calculated.

4.1.2 Clustering module

This module implements the proposed clustering approach for devising representative day-types (outlined in the previous chapter).

4.1.3 Network tariff design (NTD) model module

This module is the core model of the methodology. It is the formulation described in Chapter 3, starting from the bilevel model with its final form being the single level MPEC model. This model is implemented on the representative days of each cluster (called day-types) and its output are the DUoS tariffs, see also Figure 5.

4.1.4 Forecasting module

The day-ahead forecasting module determines the day-type to which the following day is assigned. The forecasting approaches employed in the methodology are as follows. Two alternative cases for the forecasting approach are employed:

- 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.

4.1.5 Prosumer model module

This module simulates the decision-making problem of the prosumers and corresponds to the lower level problem of Chapter 3. 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, see also Figure 3 and Figure 5.

4.1.6 DSO model module

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

4.2 Out-of-sample Validation Setup

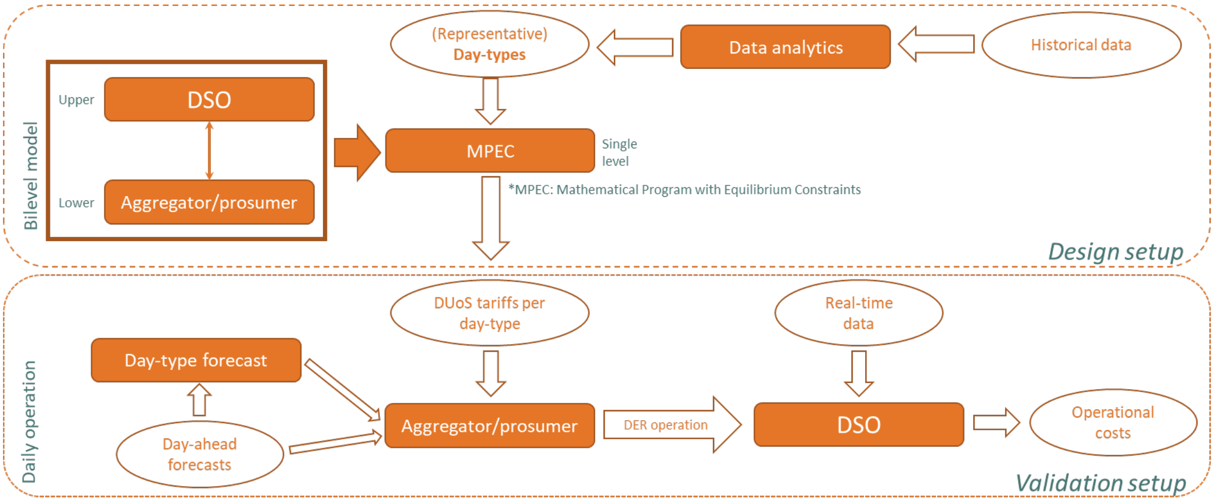

Figure 5: Overall design and validation setups as presented in the Platone workshop.

The combination of modules 4.1.4 to 4.1.6 constitutes the out-of-sample testing procedure, see also Figure 3. 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 also Figure 3 and Figure 5:

a) Identify the day-type to which the day belongs. This is performed using the Forecasting module.
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.

4.3 Assumptions and Input Data

4.3.1 Tariff types

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.

4.3.1.1 Flat tariffs

Flat tariffs constitute 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 MPEC model of Chapter 3:

$$\pi_{i,t,d} = \pi_{i',t',d}, \qquad \forall \boldsymbol{i}, \boldsymbol{i'} \in \boldsymbol{\mathcal{I}}, \boldsymbol{t}, \boldsymbol{t'} \in \boldsymbol{\mathcal{T}}, \boldsymbol{d} \in \boldsymbol{\mathcal{D}} \qquad (8)$$

4.3.1.2 Hourly tariffs

Hourly 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 MPEC model of Chapter 3.

$$\pi_{i,t,d} = \pi_{i',t,d}, \qquad \forall \boldsymbol{i}, \boldsymbol{i}' \in \boldsymbol{\mathcal{I}}, \boldsymbol{t}, \boldsymbol{t}' \in \boldsymbol{\mathcal{T}}, \boldsymbol{d} \in \boldsymbol{\mathcal{D}} \qquad (8)$$

4.3.1.3 Hourly-loc tariffs

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 MPEC model of Chapter 3 without any modifications. Hourly-loc is short for hourly-locational and refers to the spatial granularity.

4.3.2 Network data

The case studies are carried out on a model of a rural medium voltage distribution feeder in Greece, see Figure 6, with 12 prosumers. Table 2 summarises basic input data.

Table 2: Summary of basic input data

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%

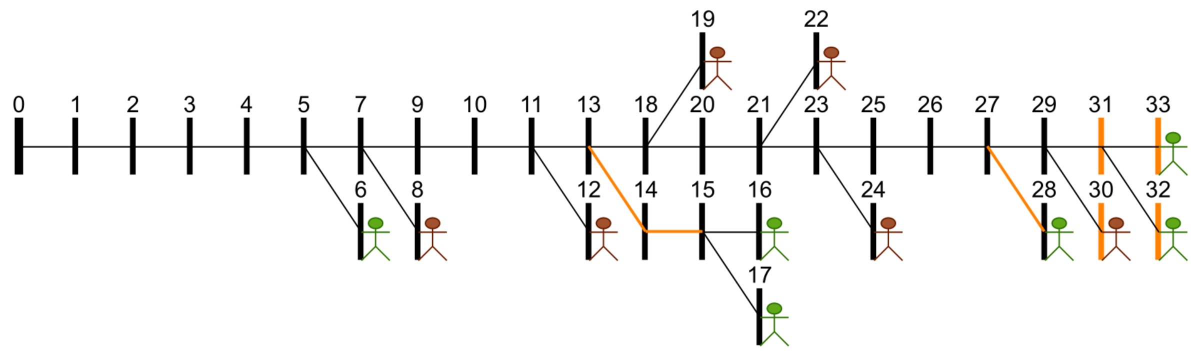

Figure 6: Illustration of rural medium voltage feeder employed in the case studies.

In Figure 6, Passive and active prosumers are indicated by brown and green colour, respectively. Orange colour indicates network branches and nodes with regular congestion

We first analyse 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 Figure 6).

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.

4.3.3 Testing equipment characteristics

The proposed model has been implemented in Julia [35] using the package JuMP [36] and solved using the optimisation software Gurobi [37] on a computer with a 4-core 2.6 GHz Intel(R) XCore(TM) i7-4720HQ processor and 16 GB of RAM.

5 Case studies

5.1 Design of tariffs with different levels of granularity

As explained in Chapter 3, the number of day-types for which DUoS tariffs are designed is a hyper-parameter chosen by the user (i.e., the DSO). In this section we will show in detail results for 4 representative day-types. This means that the historical days were clustered in 4 clusters and we deployed the NTD model on each of the representative day-types. This means that 4 distinct tariff patterns were produced, one for each day-type. The NTD model was deployed 3 times, one for each tariff scheme (flat, hourly, hourly-loc). Figure 7, Figure 8, and Figure 9 present the optimal curtailment actions of the DSO for each of the representative day-types under the three tariff schemes. The demand shifting limit, α_i, of flexible prosumers is assumed to be equal to 20%. Figure 10, Figure 11 and Figure 12 present the optimal network tariffs under the flat, hourly and hourly-loc schemes, respectively.

Table 3 presents the total curtailment costs of the DSO for each of these three schemes. The total costs under the 3 schemes are compared to the theoretical optimal curtailment costs that would occur if the DSO had full control of all decisions in both the upper and lower level. For the optimal costs the centralised OPF is used. The efficiency calculation is illustrated in Figure 4. 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.

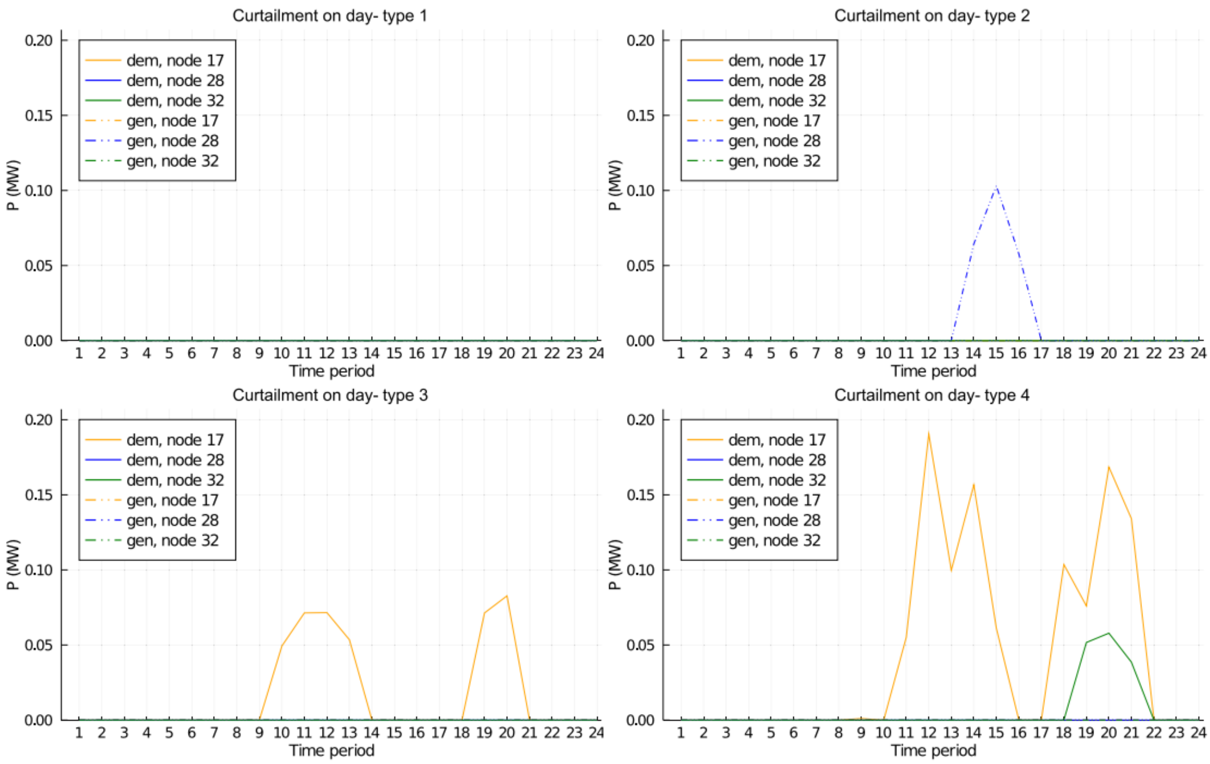

Figure 7: Demand (dem.) and generation (gen.) curtailment under the Flat tariff case and a demand shifting limit of 20%.

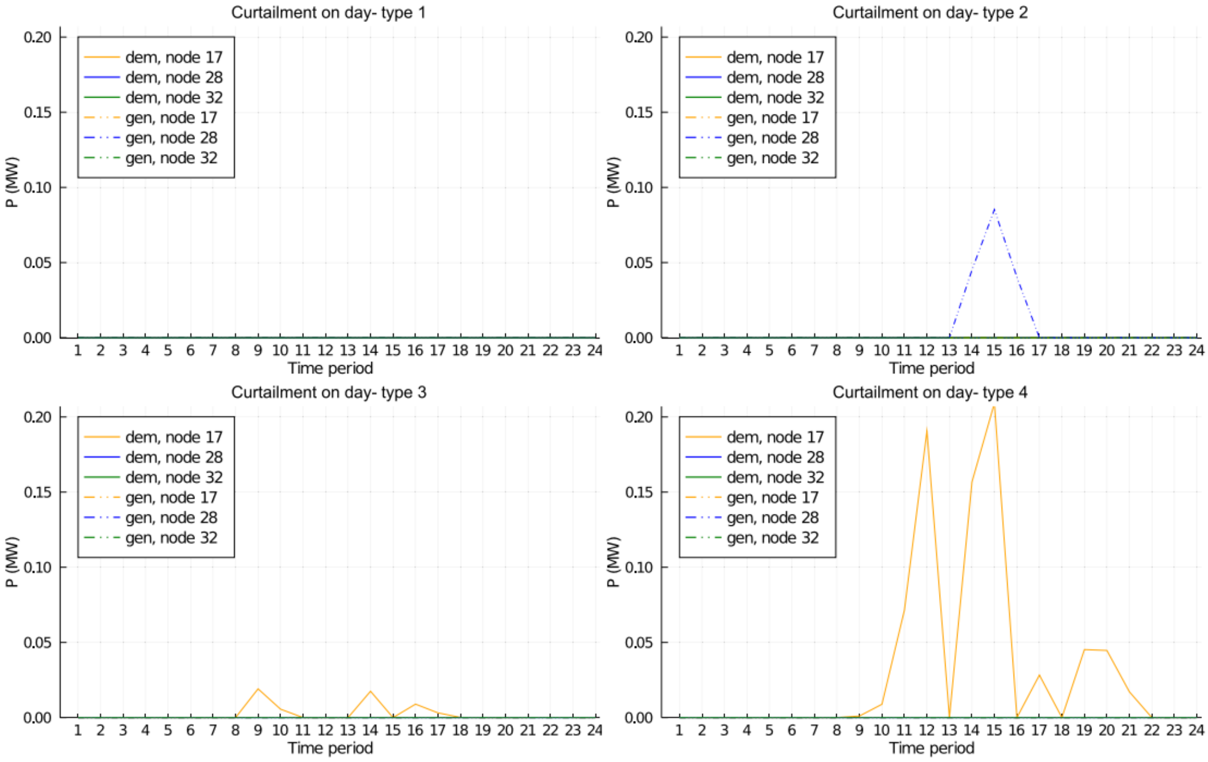

Figure 8: Demand (dem.) and generation (gen.) curtailment under the Hourly tariff case and a demand shifting limit of 20%.

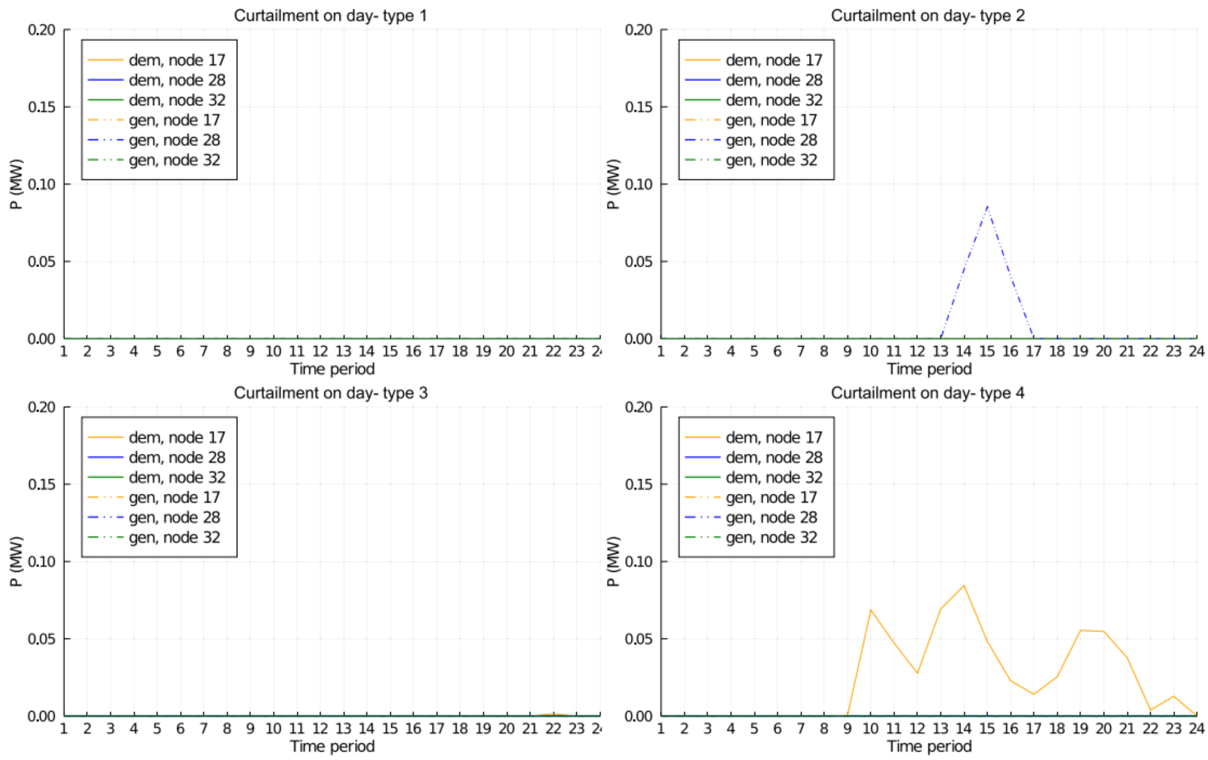

Figure 9: Demand (dem.) and generation (gen.) curtailment under the Hourly-loc tariff case and a demand shifting limit of 20%.

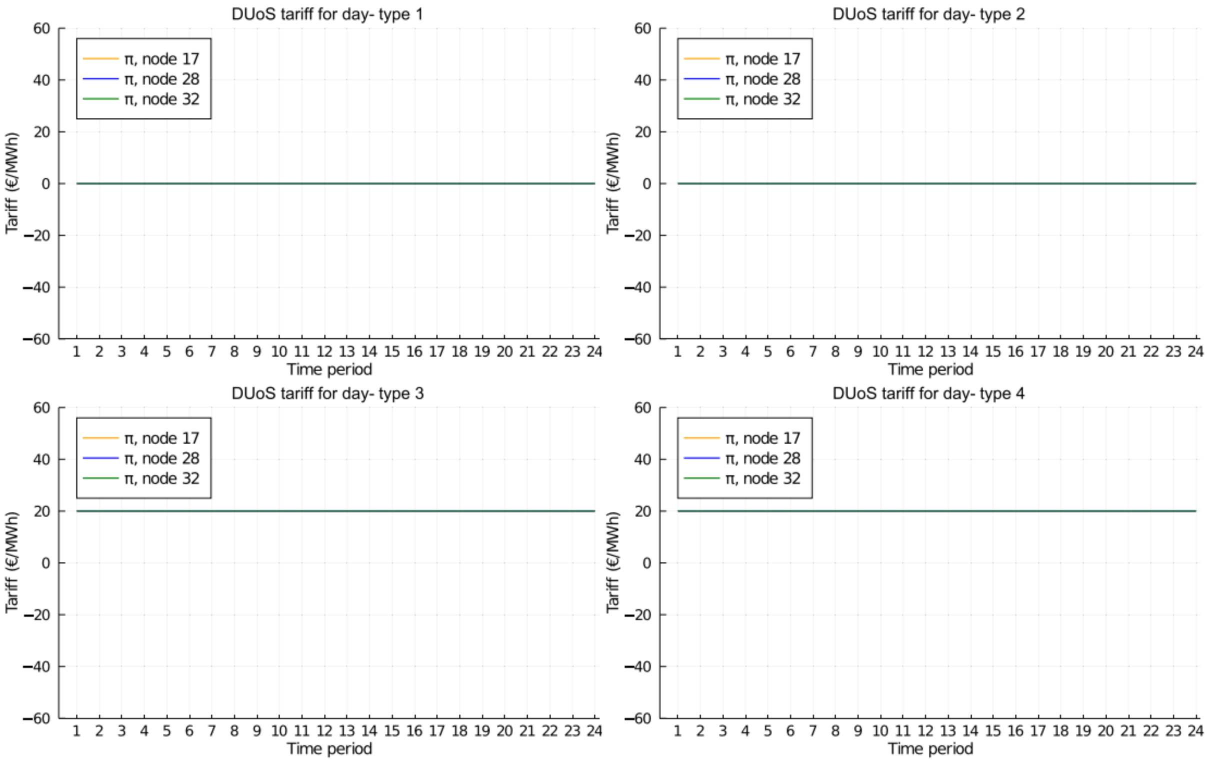

Figure 10: Flat network tariffs under a demand shifting limit of 20%.

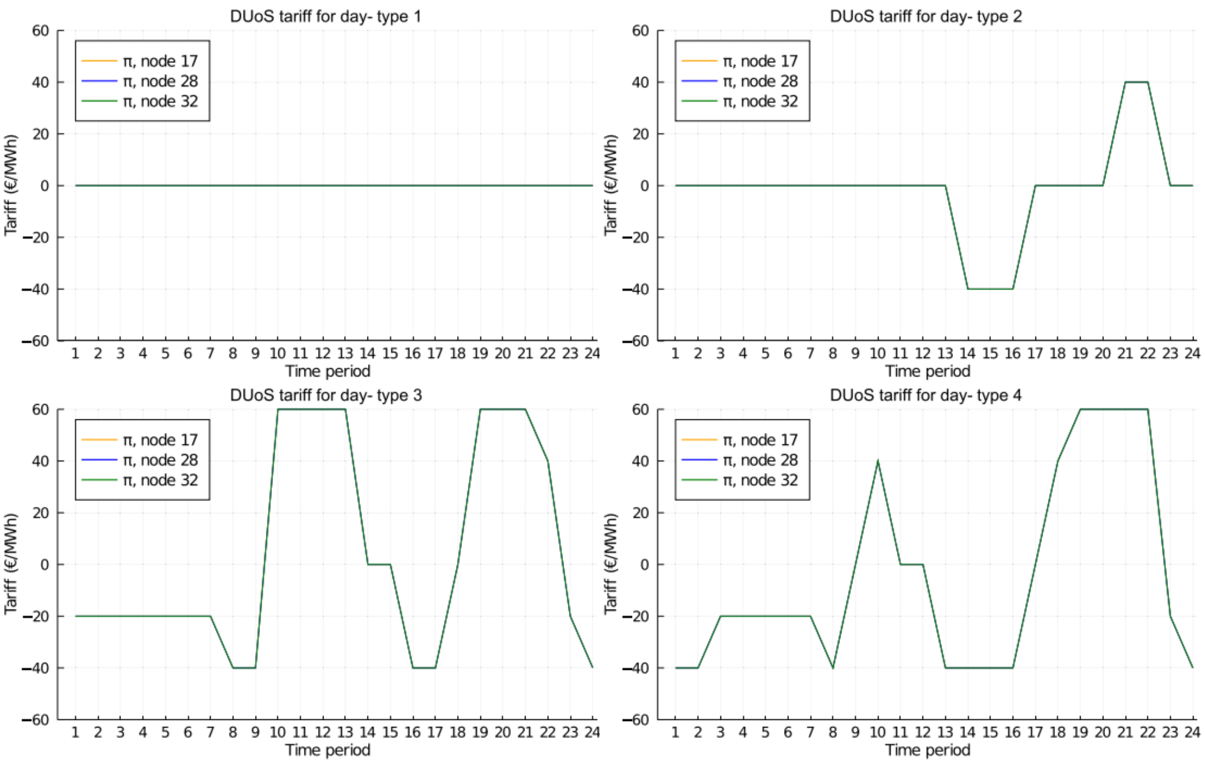

Figure 11: Hourly network tariffs under a demand shifting limit of 20%.

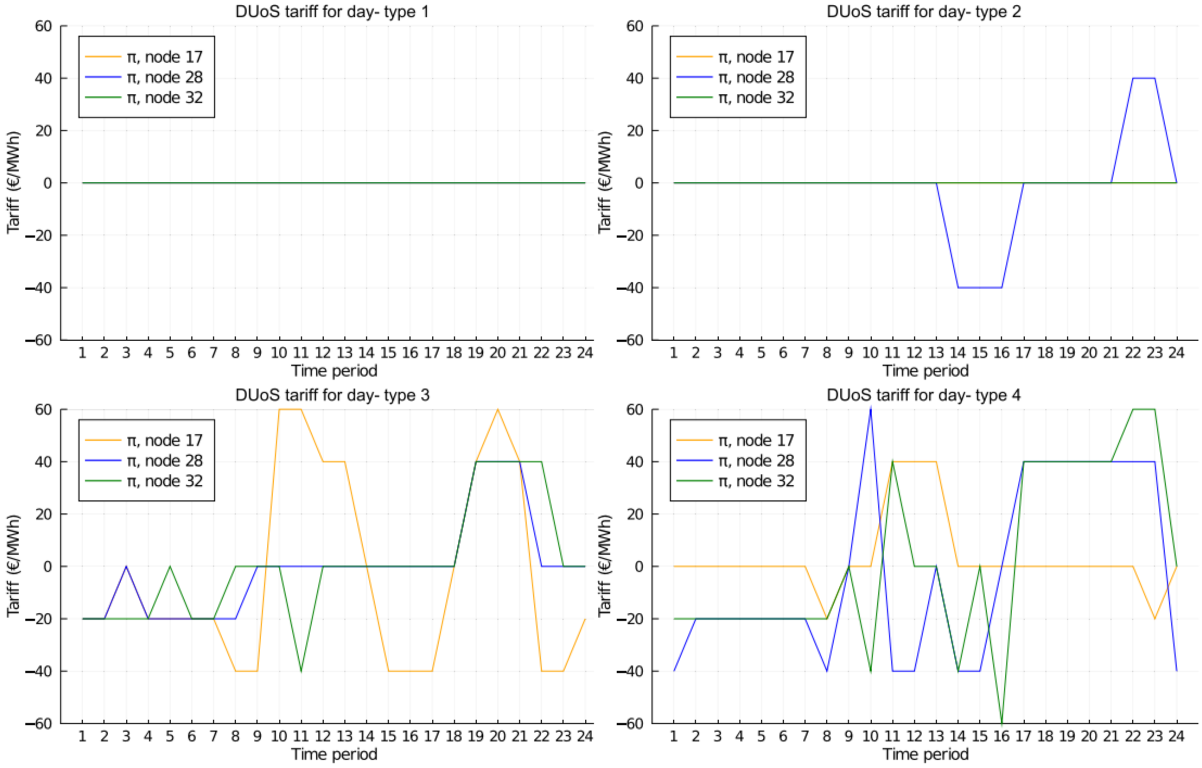

Figure 12: Hourly-loc network tariffs under a demand shifting limit of 20%.

Table 3: Total curtailment costs (in €) for $k = 4$ clusters.

Scheme	Total curtailment costs			
	$\alpha = 0\%$	$\alpha = 10\%$	$\alpha = 20\%$	$\alpha = 30\%$
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	14565.5	10906.0	8481.5

The calculated tariffs under the Flat tariff case are illustrated in Figure 10. 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 3). No curtailment is required for the first day-type, as indicated in Figure 7. 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 3 out of 4 representative day-types, characterised by congestion effects. The need for generation/demand curtailment in these day-types is suggested by Figure 8. The hourly tariffs mobilise demand shifting and thereby reduce curtailment, as indicated in Figure 8. The associated costs are also reduced, as indicated in Table 3. 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 high PV output. This is indicated in Figure 11. Consequently, the tariff induces demand shifting towards the latter periods. This results in lower PV curtailment, as indicated in Figure 8. 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 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 Figure 12. These tariffs induce locationally differentiated demand shifting actions. As a result, this further reduces curtailment, as demonstrated in Figure 9, and the associated costs, as demonstrated in Table 3. 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 3. 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 4: Total use-of-system costs of all prosumers (in €) for $k = 4$ clusters.

Scheme	Total prosumer use-of-system costs			
	$\alpha = 0\%$	$\alpha = 10\%$	$\alpha = 20\%$	$\alpha = 30\%$
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 4 presents the total use-of-system costs of all prosumers under each of the examined tariff schemes and demand shifting scenarios. The emerging patterns show similar trends with the total curtailment costs of Table 3. In other words, the prosumers' use-of-system costs are reduced as the granularity of the employed tariff scheme and the demand shifting flexibility are increased.

Another important aspect of the proposed methodology is the execution time. Indeed, for some cases execution time has been an obstacle that delayed significant the development process and the extraction of the results. It is apparent that dedicated resources for the DUoS tariff design task should be committed in case of real-life deployment of the methodology. Apart from that, the increased computational burden caused delays to the overall development schedule of WP4. Table 5 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, despite the heavy computational burden, 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.

Table 5: Execution times for each scheme.

Scheme	Execution time (hours)			
	$\alpha = 0\%$	$\alpha = 10\%$	$\alpha = 20\%$	$\alpha = 30\%$
Flat	0.10	1.50	1.50	1.50
Hourly	0.20	10.0	18.0	24.0
Hourly-loc	0.05	0.30	1.50	2.00
Optimal	0.05	0.05	0.05	0.05

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%.

5.2 Out-of-sample validation

The results of the out-of-sample validation are a direct product of the process described in Chapter 4.2. The represent "*what would happen in real life"* if all our models were an accurate representation of reality. Although, these not 100% true, the models used are proven to be a good representation of overall behaviour, hence the trends that emerge are of use to the system operators. Picking up where we left off from the case with four clusters, Table 6 presents the out-of-sample curtailment costs of the DSO. As before, the demand shifting limit of active prosumers is 20%. We report results for each of the three tariffs, and each of the two examined forecasting approaches to show what the simplest and optimal forecasts can achieve. The table, also, presents the benchmark results of perfect coordination that are determined by the centralized OPF (theoretical optimal). 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. As explained in subsection 4.1.1, we define the cost efficiency of a tariff as the percentage (%) of the optimal cost reduction achieved by the tariff in the validation runs, see also Figure 4.

Table 6: Out-of-sample total curtailment costs (in €) and efficiency (%) for $k = 4$ and a demand shifting limit of 20%.

Scheme	Total curtailment 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%

The out-of-sample results exhibit the same trends as the results produced by the NTD module, illustrated in section 5.1. This means that we observe a reduction in curtailment costs, and thus an increase in the efficiency (in %), 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, where demand shifting flexibility is not mobilized. As a result, the forecasting approach does not affect the results.

Table 7: 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		59.2%		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%

In the previous and current sections so far, we focused on four clusters. The reason behind this decision is twofold. Firstly, it is easier to explain the emerging trends when focusing on one case and follow this case through the different attributes of the method. Secondly, four clusters mean four different tariff patterns for the consumers/end-users. If four tariffs types can achieve a significant efficiency (which they do, as we saw) then we expect improvement if the number of clusters is improved. To prove this point, 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 7. Under a perfect (F) forecasting approach, as the number of clusters increases, the efficiency of both Hourly and Hourly-loc tariffs is increased two. This is because 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.

To completely perform a rational check in our method, we consider a case where the representative day-types are based solely on seasons, as in [26]. Seasonal tariffs have been considered before in practice, see for example [28]. 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 same k-means clustering methodology that is explained in Chapter 3.3. Therefore, the first two rows of Table 7 correspond to 4 clusters and they demonstrate that the more advanced clustering approach proposed in this methodology achieves significant benefits with respect to the simpler seasonal approach under perfect forecasting.

6 Conclusion

The current report presents the design and development of the framework and the corresponding tool for optimal DER control that will be deployed in the Greek demo. In the core of the tool lies a novel design for variable DUoS tariffs that aims at mobilizing DER flexibility while at the same time retains all traditional DUoS tariff properties such as cost recovery for DSOs and simplicity for the end-user. Considering the emerging large-scale integration of DERs and relevant opportunities to exploit their flexibility to increase the economic efficiency of distribution network operation, the proposed tool has focused on the problem of designing DUoS tariffs that are more adaptive to short-term operating conditions.

The design is based on 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 past efforts on the subject, 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 or indicative data samples that do not really represent yearly conditions on a distribution network, the proposed tool employs a clustering approach to design tariffs that adapt to the forecasted conditions of the upcoming day. The clustering is performed on actual historical data. The clustering technique is based on the K-means algorithm, augmented with a weighted average provision to account for the special complexities of the specific problem, where the effect of worst days of the results is significantly higher.

To properly test the proposed methodology a full design and validation setup was created where, the efficacy of the proposed tool was tested on real historical data. The full validation setup ensures that the designed tariffs mobilize the required flexibility but also test the efficiency of the clustering approach. 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. As one might have expected, tariffs with locational granularity outperform tariffs with simple temporal variation. Compared to the theoretical optimal in the case of an “all-powerful” DSO that performs the optimal DER control daily for the entire yearly sample, the designed tariffs capture nearly 80% of the possible efficiency even with only 4 tariff patterns for the entire year. Furthermore, a higher number of clusters enhances even further the economic efficiency of tariff schemes with temporal and spatial granularity, provided that an effective forecasting approach is adopted. However, a clear trade-off between tariff complexity and resource allocation efficiency exists in this case.

The main conclusion of the case studies that a few tariff patterns can capture most of the efficiency improvement due to DER flexibility is an important result of the analysis and the main thesis of this work. Its confirmation constitutes a policy worth considering by NRAs and DSOs.

7 List of Tables

8 List of Figures

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[1] European Commission, “2050 long-term strategy”,” [Online]. Available: https://ec.europa.eu/clima/policies/strategies/2050_en.

[2] Platone, *D4.1: Report on the definitions of KPIs and UCs,* EU Commision , 2020.

[3] Platone, *D1.2: Project KPIs definition and measurement methods,* EU Commission, 2020.

[4] A. O'Connell, J. Taylor, J. Smith and L. Rogers, “Distributed Energy Resources Takes Center Stage: A Renewed Spotlight on the Distribution Planning Process,” *IEEE Power and Energy Magazine,* vol. 16, pp. 42-51, 2018.

[5] C. Gu, F. Li and Y. He, “Enhanced Long-Run Incremental Cost Pricing Considering the Impact of Network Contingencies,” *IEEE Transactions on Power Systems,* vol. 27, no. 1, pp. 344-352, 2012.

[6] W. Zhange, X. Wang, X. Wu, F. Li and C. Cao, “Enhanced long-run incremental cost charging considering the impact of demand response,” *IET Generation, Transmission & Distribution,* vol. 12, no. 22, pp. 6011-6020(9), 2018.

[7] L. Qiao, L. Zhang and H. Gao, “Distribution Network Cost Allocation Based on Nodal Price,” in *2018 IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia)*, 2018.

[8] T. Soares, M. Cruz and M. Matos, “Cost allocation of distribution networks,” in *2019 International Conference on Smart Energy Systems and Technologies (SEST)*, Porto, Portugal, 2019.

[9] Distrib. Regulation Policy, Working Group, “Network tariff structure for a smart energy system,” Eurelectric, 2013.

[10] European Distribution System Operators for Smart Grids, “Future Distribution Network Tariff Structures - Guidance,” E.DSO, Brussels, Belgium, 2021.

[11] F. C. Schweppe, M. C. T. R. D. Caramanis and R. E. Bohn, Spot Pricing of Electricity, Boston, MA, USA: Springer, 1988.

[12] M. Caramanis, E. Ntakou, W. W. Hogan, A. Chakrabortty and J. Schoene, “Co-Optimization of Power and Reserves in Dynamic T amp;D Power Markets With Nondispatchable Renewable Generation and Distributed Energy Resources,” *Proceedings of the IEEE,* vol. 104, no. 4, pp. 807 - 836, 2016.

[13] A. Papavasiliou, “Analysis of Distribution Locational Marginal Prices,” *IEEE Transactions on Smart Grid,* vol. 9, no. 5, pp. 4872-4882, 2018.

[14] P. Pediaditis, C. Ziras, J. Hu, S. You and N. Hatziargyriou, “Decentralized DLMPs with synergetic resource optimization and convergence acceleration,” *Electric Power Systems Research,* vol. 187, p. 106467, 2020.

[15] B. Hobbs, C. Metzler and J.-S. Pang, “Strategic gaming analysis for electric power systems: an MPEC approach,” *IEEE Transactions on Power Systems,* vol. 15, no. 2, pp. 638-645, 2000.

[16] Y. Ye, D. Papadaskalopoulos and G. Strbac, “Investigating the Ability of Demand Shifting to Mitigate Electricity Producers’ Market Power,” *IEEE Transactions on Power Systems,* vol. 33, no. 4, pp. 3800-3811, 2018.

[17] J. Yang, J. Zhao, F. Wen and Z. Y. Dong, “A Framework of Customizing Electricity Retail Prices,” *IEEE Transactions on Power Systems,* vol. 33, no. 3, pp. 2415-2428, 2018.

[18] D. Qiu, D. Papadaskalopoulos, Y. Ye and G. Strbac, “Investigating the Effects of Demand Flexibility on Electricity Retailers’ Business through a Tri-Level Optimization Model,” *IET Generation, Transmission, Distribution,* vol. 14, 2020.

[19] S. J. Kazempour, A. J. Conejo and C. Ruiz, “Strategic Generation Investment Using a Complementarity Approach,” *IEEE Transactions on Power Systems,* vol. 26, no. 2, pp. 940-948, 2011.

[20] T. Oderinwale, D. Papadaskalopoulos, Y. Ye and G. Strbac, “Bi-level optimization, Electricity markets, Flexible demand, Generation investment planning,” *International Journal of Electrical Power & Energy Systems,* vol. 119, p. 105881, 2020.

[21] T. Schittekatte, I. Momber and L. Meeus, “Future-proof tariff design: Recovering sunk grid costs in a world where consumers are pushing back,” *Energy Economics,* vol. 70, pp. 484-498, 2018.

[22] T. Schittekatte and L. Meeus, “Least-Cost Distribution Network Tariff Design in Theory and Practice,” *The Energy Journal,* vol. 41, 2020.

[23] Q. Hoarau and Y. Perez, “Network tariff design with prosumers and electromobility: Who wins, who loses?,” *Energy Economics,* vol. 83, pp. 26 - 39, 2019.

[24] I. Abada, A. Ehrenmann and X. Lambin, “Unintended consequences: The snowball effect of energy communities,” *Energy Policy,* vol. 143, p. 111597, 2020.

[25] M. Askeland, T. Burandt and S. A. Gabriel, “A stochastic MPEC approach for grid tariff design with demand-side flexibility,” *Energy Systems,* 2020.

[26] M. Askeland, S. Backe, S. Bjarghov and M. Korpås, “Helping end-users help each other: Coordinating development and operation of distributed resources through local power markets and grid tariffs,” *Energy Economics,* p. 105065, 2020.

[27] S. Borenstein, M. Jaske and A. Rosenfeld, “Dynamic Pricing, Advanced Metering, and Demand Response in Electricity Markets,” UC Berkeley: Center for the Study of Energy Markets, Berkeley, CA, USA, 2002.

[28] R. Wilson, “Short course on non-linear pricing,” Stanford Business School, Stanford, CA, USA, 1999.

[29] M. Farhoumandi, Q. Zhou and M. Shahidehpour, “A review of machine learning applications in IoT-integrated modern power systems,” *The Electricity Journal, Special Issue: Machine Learning Applications To Power System Planning And Operation,* vol. 34, no. 1, p. 106879, 2021.

[30] E. M. Baran and F. F. Wu, “Network Reconfiguration in distribution systems for loss reduction and load balancing,” *IEEE Transactions on Power Delivery,* vol. 4, no. 99, pp. 1401--1407, 1989.

[31] P. Šulc, S. Backhaus and M. Chertkov, "Optimal Distributed Control of Reactive Power Via the Alternating Direction Method of Multipliers," *IEEE Transactions on Energy Conversion,* vol. 29, no. 4, pp. 968-977, 2014.

[32] S. Boyd and L. Vandenberghe, Convex Optimization, Cambridge, U.K.: Cambridge Univ. Press, 2004.

[33] J. Fortuny-Amat and B. A. McCarl, "Representation and Economic Interpretation of a Two-Level Programming Problem," *J Oper Res Soc,* vol. 32, p. 783–792, 1981.

[34] X. Jin and J. Han, "K-Means Clustering," in *Encyclopedia of Machine Learning*, Boston, MA, Springer US, 2010, pp. 563--564.

[35] J. Bezanson, A. Edelman, S. Karpinski and V. B. Shah, "Julia: A fresh approach to numerical computing," *SIAM Review,* vol. 59, no. 1, pp. 65--98, 2017.

[36] I. Dunning, J. Huchette and M. Lubin, "JuMP: A Modeling Language for Mathematical Optimization," *SIAM Review,* vol. 59, no. 2, pp. 295-320, 2017.

[37] Gurobi Optimization, LLC, *Gurobi Optimizer Reference Manual,* 2021.

10 List of Abbreviations

Abbreviation	Term
API	Application Program Interface
DER	Distributed Energy Resources
DLMP	Distribution Locational Marginal Price/Pricing
DSO	Distribution System Operator
DUoS	Distribution Use-of-System
EV	Electric Vehicle
ICT	Information and Communication Technology
KKT	Karush-Kuhn-Tucker
KPI	Key Performance Indicator
LinDist	Linear Distribution Power Flow
MIQP	Mixed-Integer Quadratically constrained Program
MPEC	Mathematical Program with Equilibrium Constraints
NRA	National Regulatory Authority
NTD	Network Tariff Design
PV	Photovoltaic
OPF	Optimal Power Flow
TSO	Transmission System Operator

Annex A Indicative data used in the analysis

A.1 Demand sample

Table 8: Demand per hour (MW) indicative sample

Hour | Prosumer	1	2	3	4	5	6	7	8	9	10	11	12
1	0.102	0.081	0.071	0.071	0.070	0.074	0.097	0.131	0.168	0.224	0.245	0.283
2	0.074	0.063	0.058	0.057	0.051	0.052	0.055	0.063	0.061	0.056	0.060	0.061
3	0.054	0.052	0.048	0.049	0.045	0.048	0.052	0.053	0.067	0.076	0.089	0.092
4	0.083	0.069	0.062	0.062	0.059	0.062	0.075	0.095	0.116	0.145	0.160	0.180
5	0.067	0.057	0.052	0.052	0.048	0.049	0.056	0.065	0.074	0.082	0.091	0.098
6	0.062	0.054	0.050	0.050	0.046	0.048	0.055	0.063	0.075	0.087	0.098	0.105
7	0.023	0.021	0.019	0.019	0.018	0.018	0.020	0.021	0.024	0.026	0.030	0.031
8	0.025	0.021	0.018	0.018	0.017	0.018	0.022	0.028	0.034	0.042	0.046	0.052
9	0.027	0.022	0.020	0.020	0.018	0.019	0.021	0.026	0.028	0.032	0.034	0.037
10	0.023	0.019	0.017	0.017	0.017	0.018	0.022	0.027	0.035	0.044	0.049	0.056
11	0.025	0.022	0.021	0.020	0.018	0.019	0.020	0.022	0.024	0.024	0.026	0.027
12	0.022	0.019	0.018	0.018	0.017	0.018	0.021	0.024	0.030	0.036	0.041	0.045
Hour | Prosumer	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
1	0.266	0.258	0.234	0.187	0.182	0.209	0.224	0.212	0.222	0.218	0.222	0.196
2	0.072	0.072	0.072	0.067	0.072	0.081	0.096	0.107	0.098	0.109	0.108	0.082
3	0.093	0.094	0.096	0.080	0.083	0.077	0.083	0.083	0.078	0.070	0.074	0.065
4	0.174	0.170	0.159	0.131	0.130	0.144	0.157	0.154	0.155	0.154	0.156	0.135
5	0.101	0.100	0.097	0.083	0.085	0.093	0.104	0.107	0.103	0.106	0.107	0.088
6	0.106	0.105	0.103	0.086	0.088	0.091	0.100	0.102	0.098	0.096	0.099	0.084
7	0.032	0.033	0.033	0.029	0.030	0.029	0.033	0.034	0.032	0.031	0.032	0.027
8	0.051	0.049	0.046	0.038	0.037	0.043	0.047	0.046	0.047	0.048	0.048	0.041
9	0.039	0.038	0.036	0.031	0.032	0.037	0.042	0.043	0.042	0.044	0.044	0.036
10	0.053	0.052	0.049	0.039	0.039	0.042	0.045	0.044	0.044	0.043	0.044	0.039
11	0.030	0.030	0.030	0.027	0.028	0.030	0.034	0.037	0.034	0.036	0.036	0.029
12	0.044	0.044	0.042	0.035	0.035	0.035	0.038	0.037	0.037	0.034	0.036	0.032

A.2 PV production sample

Table 9: PV production per hour (MW) indicative sample

Hour | Prosumer	1	2	3	4	5	6	7	8	9	10	11	12
1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.009	0.053	0.186	0.344	0.391
3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.005	0.014	0.025	0.042
4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.015	0.024	0.037
5	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.005	0.046	0.078	0.075	0.085
6	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.027	0.042	0.069	0.081
7	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
10	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
11	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hour | Prosumer	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	0.339	0.313	0.324	0.254	0.246	0.305	0.388	0.000	0.000	0.000	0.000	0.000
3	0.050	0.054	0.043	0.041	0.052	0.043	0.034	0.000	0.000	0.000	0.000	0.000
4	0.038	0.019	0.017	0.043	0.048	0.038	0.027	0.000	0.000	0.000	0.000	0.000
5	0.073	0.046	0.067	0.085	0.085	0.085	0.082	0.000	0.000	0.000	0.000	0.000
6	0.087	0.085	0.085	0.085	0.084	0.082	0.079	0.000	0.000	0.000	0.000	0.000
7	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
10	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
11	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

A.3 Demand shifting downwards penalty sample

Table 10: Daily demand downwards shifting penalty per hour (€/MW) sample

Hour | Prosumer	1	2	3	4	5	6	7	8	9	10	11	12
1	46.45	49.04	50.28	50.29	50.35	49.93	47.06	42.86	38.34	31.46	28.87	24.16
2	49.43	50.86	51.48	51.68	52.40	52.33	51.91	50.94	51.11	51.75	51.26	51.13
3	48.45	48.94	49.57	49.54	50.21	49.67	48.85	48.70	46.00	44.24	41.65	41.21
4	46.12	48.28	49.37	49.43	49.82	49.43	47.33	44.37	41.04	36.54	34.25	31.16
5	47.86	49.45	50.25	50.37	50.99	50.75	49.69	48.14	46.71	45.28	43.86	42.68
6	47.24	48.64	49.48	49.54	50.15	49.76	48.51	47.06	44.70	42.41	40.33	38.92
7	48.19	49.14	49.81	49.88	50.62	50.26	49.57	49.03	47.47	46.69	44.89	44.56
8	46.36	48.71	49.80	49.90	50.29	49.99	47.96	44.82	42.02	37.95	36.07	33.01
9	48.02	49.85	50.67	50.83	51.43	51.26	50.17	48.29	47.24	45.94	44.87	43.53
10	46.69	48.64	49.72	49.71	49.99	49.50	47.25	44.30	40.25	34.90	32.22	28.82
11	48.72	49.98	50.63	50.78	51.52	51.33	50.78	49.98	49.41	49.45	48.39	48.17
12	47.23	48.48	49.35	49.33	49.83	49.29	47.72	46.16	42.70	39.07	36.35	34.40
Hour | Prosumer	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
1	26.29	27.31	30.24	35.96	36.62	33.30	31.52	32.94	31.77	32.17	31.72	34.96
2	49.72	49.73	49.71	50.35	49.74	48.52	46.58	45.28	46.39	44.96	45.11	48.45
3	41.01	40.72	40.33	43.35	42.81	44.10	42.96	42.77	43.84	45.45	44.64	46.28
4	32.03	32.62	34.38	38.78	38.90	36.71	34.77	35.24	35.05	35.19	34.79	38.16
5	42.17	42.34	42.86	45.14	44.77	43.55	41.67	41.09	41.78	41.29	41.12	44.32
6	38.81	38.93	39.44	42.54	42.21	41.59	39.88	39.65	40.30	40.66	40.21	43.03
7	43.79	43.62	43.38	45.51	44.90	45.12	43.54	42.83	43.99	44.31	43.89	46.42
8	33.67	34.33	36.18	40.14	40.26	37.56	35.48	35.75	35.54	35.11	34.90	38.57
9	42.95	43.23	43.98	46.00	45.68	43.83	41.81	41.14	41.72	40.68	40.68	44.21
10	30.21	30.82	32.70	37.69	37.95	36.12	34.50	35.41	34.98	35.81	35.22	38.02
11	47.01	46.95	46.83	48.12	47.50	46.87	45.05	43.98	45.13	44.43	44.33	47.39
12	35.00	35.15	35.90	40.01	39.85	39.61	38.19	38.55	38.90	40.17	39.44	41.72

A.4 Demand shifting upwards penalty sample

Table 11: Daily demand shifting upwards penalty per hour (€/MW) sample

Hour | Prosumer	1	2	3	4	5	6	7	8	9	10	11	12
1	12.55	9.96	8.72	8.71	8.65	9.07	11.94	16.14	20.66	27.54	30.13	34.84
2	9.57	8.14	7.52	7.32	6.60	6.67	7.09	8.06	7.89	7.25	7.74	7.87
3	10.55	10.06	9.43	9.46	8.79	9.33	10.15	10.30	13.00	14.76	17.35	17.79
4	12.88	10.72	9.63	9.57	9.18	9.57	11.67	14.63	17.96	22.46	24.75	27.84
5	11.14	9.55	8.75	8.63	8.01	8.25	9.31	10.86	12.29	13.72	15.14	16.32
6	11.76	10.36	9.52	9.46	8.85	9.24	10.49	11.94	14.30	16.59	18.67	20.08
7	10.81	9.86	9.19	9.12	8.38	8.74	9.43	9.97	11.53	12.31	14.11	14.44
8	12.64	10.29	9.20	9.10	8.71	9.01	11.04	14.18	16.98	21.05	22.93	25.99
9	10.98	9.15	8.33	8.17	7.57	7.74	8.83	10.71	11.76	13.06	14.13	15.47
10	12.31	10.36	9.28	9.29	9.01	9.50	11.75	14.70	18.75	24.10	26.78	30.18
11	10.28	9.02	8.37	8.22	7.48	7.67	8.22	9.02	9.59	9.55	10.61	10.83
12	11.77	10.52	9.65	9.67	9.17	9.71	11.28	12.84	16.30	19.93	22.65	24.60
Hour | Prosumer	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
1	32.71	31.69	28.76	23.04	22.38	25.70	27.48	26.06	27.23	26.83	27.28	24.04
2	9.28	9.27	9.29	8.65	9.26	10.48	12.42	13.72	12.61	14.04	13.89	10.55
3	17.99	18.28	18.67	15.65	16.19	14.90	16.04	16.23	15.16	13.55	14.36	12.72
4	26.97	26.38	24.62	20.22	20.10	22.29	24.23	23.76	23.95	23.81	24.21	20.84
5	16.83	16.66	16.14	13.86	14.23	15.45	17.33	17.91	17.22	17.71	17.88	14.68
6	20.19	20.07	19.56	16.46	16.79	17.41	19.12	19.35	18.70	18.34	18.79	15.97
7	15.21	15.38	15.62	13.49	14.10	13.88	15.46	16.17	15.01	14.69	15.11	12.58
8	25.33	24.67	22.82	18.86	18.74	21.44	23.52	23.25	23.46	23.89	24.10	20.43
9	16.05	15.77	15.02	13.00	13.32	15.17	17.19	17.86	17.28	18.32	18.32	14.79
10	28.79	28.18	26.30	21.31	21.05	22.88	24.50	23.59	24.02	23.19	23.78	20.98
11	11.99	12.05	12.17	10.88	11.50	12.13	13.95	15.02	13.87	14.57	14.67	11.61
12	24.00	23.85	23.10	18.99	19.15	19.39	20.81	20.45	20.10	18.83	19.56	17.28