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A ready-to-use framework for harvesting flexibility using state estimation and use-of-system tariffs: Insights from the H2020 Platone Project

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***Abstract*—Flexibility from distributed energy resources is a key component in the transformation of modern power systems. Most frameworks, that propose solutions for utilising this flexibility, rely on infrastructure maturity that is not available to most system operators, such as smart metering systems. In this paper, we present a framework for harvesting distribution flexibility which relies solely on data and procedures that system operators can obtain relatively easily, without large infrastructure upgrades. The framework utilises state estimation and implicit flexibility motivation via distribution use-of-system tariffs. A validation setup is designed to measure the efficacy of the proposed framework under realistic conditions using field data. Results show that using the suggested methodology a system operator can harvest 64% of the available flexibility.**

***Index Terms*—Aggregator, bilevel optimisation, DERs, DUoS tariffs, network tariffs, flexibility, prosumer, state estimation**

I. INTRODUCTION

A. Motivation and Background

The increasing presence of distributed energy resources (DERs) is creating new challenges in managing distribution networks (DNs). DER flexibility is a common practice for addressing some of these challenges, such as network congestions. There are a number of suggested frameworks for utilising this flexibility such as centralised control [1], decentralised control [2], tariffs [3] and markets [4]. However, most frameworks assume preconditions that are impeded by either technical, infrastructural, policy or practical obstacles, or combinations of them.

B. Relevant literature

Distribution use-of-system (DUoS) tariffs, a traditional distribution system operator (DSO) responsibility, have recently being re-imagined as a more dynamic process serving more than one goals, including enhancing DER flexibility [5]. The main research strand on the topic models a tariff design task which considers DER response [4], [6], [7] and DSO cost recovery. In [3], the authors presented a framework for DUoS tariff design that utilises machine learning and bilevel optimisation to produce few, simple tariff partners, capable of temporal and spatial granularity, which motivate flexibility, achieving more than 75% of the theoretical optimal cost reduction. The only requirement of the model in [3] is the knowledge of load and generation at each node of the DN.

In parallel to the development of DER flexibility literature, the ongoing investments on ICT and metering infrastructure leads to rapid advances in the field of distribution state estimation (DSE), which is a fundamental process for monitoring purposes [8]. The inadequate instrumentation in traditional DNs, which has been a serious impediment to the development of DSE, is being reinforced in order to meet the envisioned smart grid capabilities, thus, facilitating the deployment of viable DSE functionalities [9]. State estimation (SE) is essentially capable of assigning values to unknown (missing) electrical quantities of the network (e.g., voltage magnitude/ angle) based on the available measurements [10]. Hence, DSE provides real-time estimates of the grid state, mostly defined by the nodal voltage phasors. Also, it performs data cleansing, thus, estimating the true values of all measurements, which are subject to errors either they are actual (e.g., from telemetry) or not (e.g., pseudomeasurements) [11]. Until now, few works such as [12], [13] have attempted to explore the benefits reaped from DSE in real-life distribution management tasks to which the DUoS tariff design problem also belongs.

C. Contributions and Organisation

The first contribution of this paper is to introduce the practical application of DSE on the DUoS tariffs design problem. It sets the work of [3] in a more solid foundation by combining well-established SE techniques with the DUoS tariff design problem. The result is a ready-to-use flexibility incentivisation framework for DSOs that relies solely on data that they already have or can easily obtain and on mechanisms and regulations that already exist, such as non-flat DUoS tariffs. The second contribution is the validation of the efficacy of the proposed framework against the theoretical optimal, which consists of the DSO having perfect knowledge and controllability over flexible assets. The results of the case studies can contribute to the decision making of DSOs with respect to the value of

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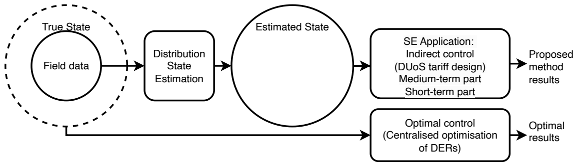

Fig. 1: Overview of the methodology.

SE and implicit flexibility schemes, such as flexible DUoS tariffs.

The structure of this paper is as follows: In Section I, the scope and motivation is introduced. Next, in Section II, the proposed methodology and its application framework are presented. In Section III, the case studies are described and the corresponding results are analysed. Finally, in Section IV, conclusions are drawn and future work is discussed.

II. METHODOLOGY

A. Overview

The proposed methodology assumes a DSO which collects data from the field and, reasonably, does not have the true state of the DN due to their related errors, possible insufficient amount etc., see Fig. 1. Using a DSE algorithm, the DSO obtains an estimated state, on which tariff design (medium-term part) and tariff application (short-term part) are performed. Results are compared with an unobtainable ideal situation where the DSO has perfect knowledge of the state and can directly control and optimise all resources.

B. Fundamentals of distribution state estimation

The developed DSE algorithm employs the well-established weighted least squares (WLS) method [14], which has been found to be a suitable solver for DSE [15]. It processes the currently available network model (parameters and configuration) and measurements, which are treated as a snapshot capturing the steady state of the network, in order to estimate its optimal status according to the WLS criterion.

Let us consider a power system of n_b nodes. The SE problem is founded on the measurement model below:

$$\boldsymbol{z} = \boldsymbol{h}(\boldsymbol{x}^{true}) + \boldsymbol{e}_z \tag{1}$$

where $\boldsymbol{h}$ is the function vector mapping the vector of $2n_b - 1$ (or $2n_b$ in case synchronised measurements are available) true system states $\boldsymbol{x}^{true}$ to the measurement vector $\boldsymbol{z}$, and $\boldsymbol{e}_z$ denotes the vector of the associated measurement errors which are assumed to be independent with $E[e_i] = 0, i = 1, ..., m$.

Modelling the ith measurement z_i as a Normal random variable with $E[z_i] = h_i(\boldsymbol{x})$ and variance $\sigma_i^2 = E[e_i^2]$, the maximum likelihood estimate of $\boldsymbol{x}^{true}$, $\hat{\boldsymbol{x}}$ is obtained via the following WLS optimisation formula:

$$\min_{\boldsymbol{x}} J(\boldsymbol{x}) = \big(\boldsymbol{z} - \boldsymbol{h}(\boldsymbol{x})\big)^{\top} \mathbf{R}_z^{-1} \big(\boldsymbol{z} - \boldsymbol{h}(\boldsymbol{x})\big) = \sum_{i=1}^{m} \Big(\frac{z_i - h_i(\boldsymbol{x})}{\sigma_i}\Big)^2 \tag{2}$$

where J is the objective function, $r_i = \big(z_i - h_i(\boldsymbol{x})\big)/\sigma_i, i = 1, ..., m$ are the weighted measurement residuals and the inverse of the error covariance matrix $\mathbf{R}_z = \mathrm{diag}(\sigma_1^2, ..., \sigma_m^2)$ is used a weighting matrix so that the weights assigned to measurements increase with their accuracy.

In the general case, the measurement model is nonlinear, thus, the WLS problem is iteratively solved via the Gauss-Newton method as follows:

$$\boldsymbol{x}_{k+1} = \boldsymbol{x}_k + \mathbf{G}^{-1}(\boldsymbol{x}_k)\mathbf{H}^{\top}(\boldsymbol{x}_k)\mathbf{R}^{-1}\big(\boldsymbol{z} - \boldsymbol{h}(\boldsymbol{x}_k)\big) \tag{3}$$

where the vector $\boldsymbol{x}_k$ ($\boldsymbol{x}_{k+1}$) is calculated at the end of iteration k ($k+1$), $\mathbf{H}(\boldsymbol{x}) = \partial\boldsymbol{h}/\partial\boldsymbol{x}$ is the Jacobian matrix and $\mathbf{G}(\boldsymbol{x}) = \mathbf{H}^{\top}(\boldsymbol{x})\mathbf{R}^{-1}\mathbf{H}(\boldsymbol{x})$ is the gain matrix of the problem, both evaluated at $\boldsymbol{x} = \boldsymbol{x}_k$. The problem is solvable and, thus, the power system under study is said to be observable on condition that the system of equations in (1) is overdetermined, i.e., the m_l linearly independent measurements outnumber the states or, symbolically, $(m =>) m_l > n$. Hence, $\mathbf{H}(\boldsymbol{x})$ is full rank, that is, $\mathrm{rank}\mathbf{H}(\boldsymbol{x}) = n$, and, subsequently, $\mathbf{G}(\boldsymbol{x})$ is non-singular. $\mathbf{G}(\boldsymbol{x})$ is related to the accuracy of the WLS procedure, since its inverse matrix coincides with the state error covariance matrix evaluated at the estimated state $\hat{\boldsymbol{x}}$:

$$\mathrm{Cov}(\hat{\boldsymbol{x}}) = \mathbf{G}^{-1}(\hat{\boldsymbol{x}}) \tag{4}$$

Since the algorithm exploits the measurement redundancy to filter out their errors, it also delivers estimates of the true values of the measured quantities, computed in $\hat{\boldsymbol{z}} = \boldsymbol{h}(\hat{\boldsymbol{x}})$. In most DNs, the implementation of DSE requires the use of pseudo-measurements, i.e., manufactured data based on load forecasts or DER schedules, for supplementing the incomplete measurement sets since the limited actual data do not suffice to achieve observability [9], [16]. Pseudo-measurements are prone to low precision to the detriment of the DSE accuracy and, thus, are assigned very small weights, which, when combined with the very large weights of zero injection measurements raise ill-conditioning issues, leading to a nearly singular $\mathbf{G}(\boldsymbol{x})$ [17]. Poor conditioned matrices are also caused by the structural particularities of DNs which often result in adjacent branches with disparate impedance values [17]. Besides, the high R/X ratios and their unbalanced operation contribute to the complexity in problem formulation [9]. All the issues above need to be carefully considered during the design of a DSE procedure.

C. DUoS tariff design model

The DUoS tariff design process is based on the method presented in [3] where the problem is modelled as a Stackelberg game using bilevel optimization, depicted in Fig. 2. The upper level expresses the decision-making problem of the DSO who designs tariffs in order to maximise the operating efficiency of the DN. The latter is measured by the total cost of demand and generation curtailment actions which the DSO needs to resort to in order to preserve the security of the network. The lower level expresses the decision-making problem of prosumers who optimise their demand response actions in response to the DUoS tariffs devised by the DSO as well as the energy tariffs offered by their supplier. The two problems are coupled and in order to solve the model they are replaced by the single level equivalent problem which consists of the upper level and the

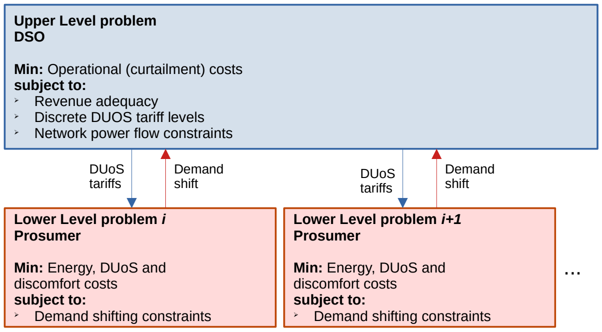

Fig. 2: Structure of the tariff design model.

Karush-Kuhn-Tucker (KKT) conditions of the lower level. The resulting Mathematical Program with Equilibrium Constraints (MPEC) is linearised and solved efficiently using commercial solvers. The full model can be accessed in [3].

Important characteristics of the proposed tariff design model are the following. First, it is not a market clearing process. In the line of research of [3], the DSO models and anticipates the prosumers' reaction to tariffs (modelled here as simple demand shifting) using raw historical data. Hence, the DSO is the leader and prosumers cannot be strategic as they do not actively participate in the game. Secondly, the DSO is responsible for keeping network conditions within limits. This contrasts with literature focusing on bilevel models for market clearing and energy price, where the clearing lies on the lower level and DUoS tariffs, if present, are not granular, e.g., [18]. Hence, the network conditions are modelled in the upper level.

The tariff design method includes a preliminary step where few representative **day-types** are created and on which the model is applied. The day-types are created using weighted k-means clustering on historical data. As expected, [3] proves that there is a trade-off between the simplicity of fewer patterns and the cost efficiency achieved by the tariffs.

D. *Proposed framework*

One of the most important prepositions confirmed in [3], is that few well-designed representative day-types can serve as the basis for the designing equally few DUoS tariff patterns which harvest a significant percentage of the available cost reduction due to DER flexibility. The method in [3] assumes perfect knowledge of the network state which is unachievable for a DSO in realistic conditions. In this paper, this assumption is omitted and the tariff design model relies on SE data.

The proposed framework has a medium-term (**design**) and a short-term (**implementation**) part. The medium-term part is executed for every design horizon. Its length is decided by the responsible DSO. We assume a horizon of one year in this paper. The medium-term part consists of three processes that are executed consecutively, see Fig. 3. Field data for a given historical span, obtained from supervisory control and data acquisition (SCADA) systems, phasor measurement units (PMUs), smart meters etc., are gathered and passed to the DSE step, which produces an estimation of the power injection (load and generation) at each node for every time period of that span. This output is passed to the data analytics step which reduces it to k representative day-types using optimal power flow (OPF) analysis, feature derivation, and, finally, clustering. The tariff design is performed on the representative load and generation data producing k number of tariff patterns that would be used throughout the year, instead of 365 patterns.

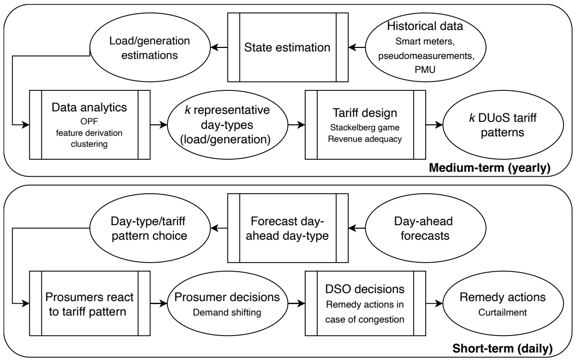

Fig. 3: Illustration of the two parts of the proposed framework.

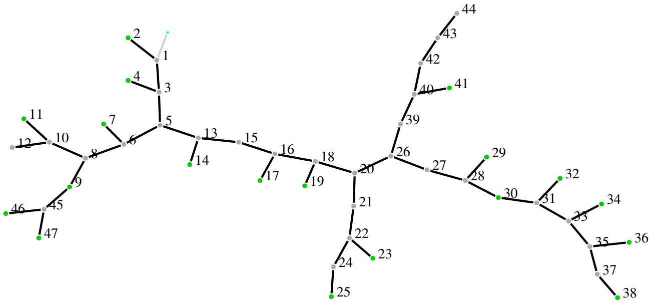

Fig. 4: Test network: active prosumers at 2, 23, 25 and PV at 29, 32, 34, 36, 38.

The short-term part is taking place daily, in day-ahead and close to real-time context. The DSO forecasts to which day-type the coming day belongs and prosumers are informed accordingly, hence they know which tariff pattern applies. Then, they decide on how to manage their flexibility, considering the DUoS tariffs. In real-time, the DSO gathers field data, estimates the network conditions and, when necessary, performs remedy actions, such as load or generation curtailment.

III. RESULTS

A. *Description and Input Data*

For the case studies, we use part of a radial MV feeder located in a semi-rural area in Attica Province, Greece, see Fig. 4. Both network and field data are provided by the Greek DSO. The network has 47 nodes, including the slack, of which, 19 nodes can serve any type of load, and 46 branches. In order to properly test the efficacy of the proposed method, we need to know the real state of the network for all hours of the testing period. In order to create realistic case studies for which we know the actual operating conditions, we use the available measurement data as well as typical load profiles, since, currently, this part of the feeder is not fully monitored,

TABLE I: Basic information and input data of the case studies.

Parameter	Value
Voltage limits	[0.95,1.05] p.u.
Congested sections	Nodes 1 to 2, nodes 5 to 20
Power factor	0.95
Energy price	75 €/MWh
Network tariff levels	[-60,-40,-20,0,20,40,60]€/MWh
Generation curtailment penalty	115 €/MWh
Demand curtailment penalty (active, passive prosumers)	200,400 €/MWh
Active prosumers	[2,23,25]
Demand shifting limit of active prosumers	20%

Initially, there are actual injection data from the 4 PV plants along the section between nodes 26 and 38 which, notably, often lead to reverse power flows all the way to the HV/MV substation. Pre-analyses show that there line congestions at two sections and both under- and overvoltage problems. As for the nodes hosting MV prosumers, namely, nodes 2, 9, 17, 23, and 25, we use measurement data from other nodes in the area, which have similar characteristics (transformer capacity, power factor etc.). All of them have significant consumption levels, and we assume that 3 of them are flexible, namely 2, 23, and 25. Moreover, standard load profiles from LV consumers are properly processed and randomly assigned to the rest 10 nodes according to the nominal capacity of their MV/LV transformer. Finally, the voltage profile of the slack bus is also based on actual data. The dataset we constructed corresponds to 327 out of 365 days of a year and has hourly resolution. Table I lists important information and parameters used in the case studies.

The model of section II-C and Fig. 2 allows for the modelling of different tariff granularity levels, both temporal and spatial. In this paper we have 3 tariff schemes.

- The **Flat** scheme which is the simplest and Business-as-Usual (BaU) case. In this scheme, the tariffs are fixed for every time period and every network node.
- The **Hourly** scheme in which the tariffs can vary by hour but not by node, i.e. all nodes share the same tariff.
- The **Hourly-loc** scheme which constitutes the case with the highest spatial-temporal granularity. In this case, the tariffs can vary by both hour and network node.

In addition, we use the **Optimal** scheme in the case studies. This is the case where the DSO has full controllability over all resources and when applicable, has knowledge of the real state of the network, instead of the estimated state.

B. Validation setup

As we mentioned in section II-A, the proposed method is tested against an ideal situation where the DSO has perfect knowledge and controlability and the BaU which is the flat tariffs the Greek DSO uses today.

The proposed validation setup includes two distinct phases, see Fig. 5. The first phase is the design phase, where we deploy the 3 steps of the proposed framework on historical data to produce the DUoS tariff patterns for the next year. In order to reproduce real-life network conditions, we start from full knowledge of the network state and reduce data inputs in order to simulate the level of network data that DSOs usually have access to. The second phase it the validation phase where three distinct cases are tested during daily operation on actual network conditions. The first case is the BaU case of Flat tariffs which, as expected, do not motivate flexibility. This case serve as the baseline result. The second case is the application of the proposed framework where the DUoS tariffs, designed in the previous phase (hence ex-ante tariffs). The third case is the theoretical optimal where the DSO directly controls all available flexibility and has perfect knowledge.

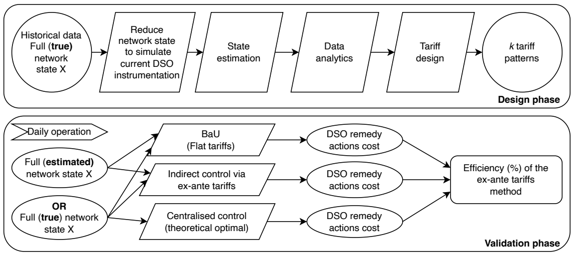

Fig. 5: Illustration of the validation setup.

The case studies will investigate how the proposed framework can reduce DSO remedy actions cost (such as curtailment) compared to the BaU case of Flat tariffs. Furthermore, the effectiveness of the framework is compared to the BaU on one side, and the theoretical optimal on the other side, aiming to determine the achieved efficiency percentage. The MATLAB based toolbox for power system simulation MATPOWER [19] was used as a basis for the development of the DSE algorithm and its simulated operation. For the tariff design model and the validation setup, the Julia programming language was used [20].

C. State estimation setup and results

To initiate the simulations on DSE, we used a power flow solution based on the data outlined in section III.A, in order to produce the actual network state. In the sequel, all measured values were obtained by perturbing the corresponding quantities from the power flow with Gaussian noise. The available measurements (and the associated maximum errors) were: the voltage magnitude at the slack bus (1.5%) and the power injections gathered from the PV plants (5%) as well as from the MV prosumers (10%). The use of pseudo-measurements with maximum error of 35% was assumed for the rest of the load buses, whereas no error is presumed for the zero injection measurements. The measurement variances were calculated as in [15]. The SE solution includes the estimates of the state vector (nodal complex voltages) and of the true values of the measurements, as stated in section II.B. Importantly, the estimated nodal power injections are the main data inputs to the tariff design model.

The numerical studies on the dataset showed that, with the exception of a single hourly interval, the DSE algorithm successfully converged to a reliable solution for the $327\text{x}24 = 7848$ intervals. To examine its accuracy, we calculated the

TABLE II: Max and min values of SE accuracy indices.

Accuracy index	Max	Min
$Macc_V$(pu)	0.19	0.06
$MAPE(\%)$	11.83	2.75

Euclidean norm of the error between the vectors of true and estimated complex voltages, $\boldsymbol{V}^{true}$ and $\hat{\boldsymbol{V}}$, respectively, per hourly interval:

$$Macc_V = \|\boldsymbol{V}^{true} - \hat{\boldsymbol{V}}\|_2 = \sqrt{\sum_{i=1}^{n_b} \left| V_i^{true} - \hat{V}_i \right|^2} \tag{5}$$

and the mean absolute percentage error between the true and estimated values of the nonzero active power injection at node k, z_k^{true} and $\hat{z}_k$, respectively, for all hourly intervals:

$$MAPE_k = \frac{1}{7847} \sum_{j=1}^{7847} \left| \frac{z_{kj}^{true} - \hat{z}_{kj}}{z_{kj}^{true}} \right| 100\% \tag{6}$$

The obtained results are summarised in Table II. For reasons of convenience, we cite only the maximum and minimum values of the indices. The highest $MAPE$ value refers to node 29, whereas the lowest one to node 32. As observed, both indices are kept relatively low, so, we conclude that the DSE algorithm delivered quality estimates.

D. *Tariff design results*

First, we show the results from the tariff design phase. We choose $k = 4$ day-types, i.e., 4 tariff patterns, which are a good compromise between simplicity and effectiveness in cost reduction, as proved in [3]. The clustering module gives that each day-type has a weight of 60, 19, 98 and 150, respectively. Indicatively, Fig. 6 illustrates the curtailment decisions of the model under the BaU case of the Flat tariff. One can notice that, the most problematic day-type is day-type 2, which corresponds to 14 days only. The most common day-type is number 4 for which no issues are observed. Day-types 1 and 3 correspond to solely demand and generation related problems, respectively.

Fig. 7 to 8 show the designed tariff patterns for the hourly and hourly-loc scheme. The Flat scheme is 20€/MWh for all nodes, hours and day-types which is currently the DUoS tariff scheme in Greece and is not shown in a separate figure for simplicity. This scheme cannot induce demand shifting from the prosumers and results to the maximum possible curtailment costs, as show in Fig. 6. Next, is the Hourly scheme which has only temporal granularity. One can verify that the most complex day is day-type 2, while some hours in day-types 3 and 4 have a tariff of 0€/MWh. Finally, the Hourly-loc scheme allows for full temporal and spatial granularity and the corresponding patterns attempt to motivate the optimal demand shifting from the prosumers independently. See, how day-type 2 is still the most complex and how the tariff at node 2 is 0€/MWh for day-types 3 and 4, which translates to a total 248 out of 327 days. This means that the prosumer at node 2 has only to worry about the tariff a few days per year.

TABLE III: Projected curtailment costs (€).

	Curtailment costs		
Scheme	Demand	Generation	Total
Flat	23,885.5	1,766.6	25,652.0
Hourly	141.2	1,449.3	1,590.4
Hourly-loc	141.1	1,414.9	1,556.0
Optimal	141.1	1,414.9	1,556.0

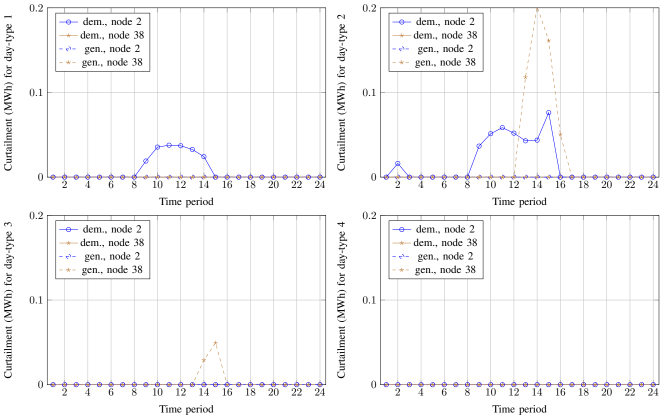

Fig. 6: Demand (dem.) and generation (gen.) curtailment under the Flat tariff case.

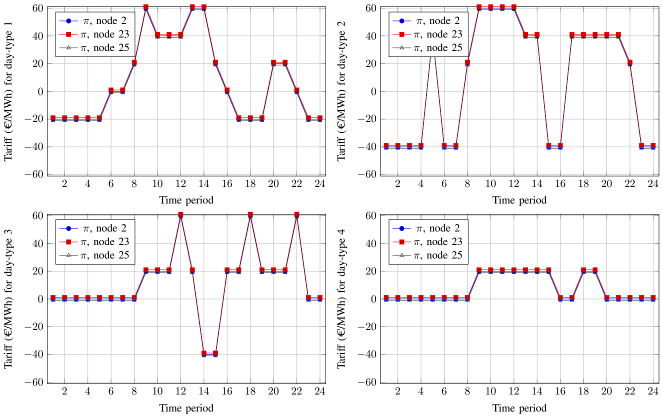

Fig. 7: Hourly network tariffs at active prosumer nodes.

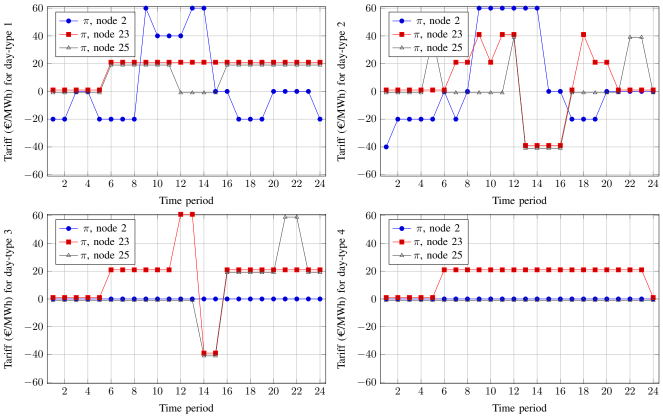

Fig. 8: Hourly-loc network tariffs at active prosumer nodes.

The projected curtailment costs of the model of Fig. 2 are shown in Table III. We see that the projected costs of the

TABLE IV: Out-of-sample total curtailment costs (€) and efficiency (%) for $k = 4$ using the true and estimated state.

	Estimated state		True state	
Scheme	Curt. costs	Efficiency	Curt. costs	Efficiency
Flat	5,402.8	0%	-	
Hourly	3,779.6	55.9%	3,415.6	68.4%
Hourly-loc	3,493.5	65.8%	3,124.5	78.5%
Optimal	-		2,499.3	100%

design model are 10 times higher under the Flat tariff scheme compared to the Optimal. The Hourly scheme is very close whereas the Hourly-loc achieves the exact same results as the optimal. The projected costs of the design phase are useful in the calibration of the model but are not the main critetion for the success of the method. In the next section, we test how the tariff patterns perform in an daily operation context.

E. Out-of-sample validation

In this section, we show the results from the validation of the tariff efficiency under realistic conditions for a full sample of one year. The results are given in Table IV. The true results of the method are in the right half of the table as these are the curtailment costs and the corresponding efficiency when the estimated state is used in all steps. On the left half, we show the same results under the case where the true state of the network was known in all steps. This allows us to quantify how much of the efficiency is lost due to the DSE. We see 12.5% and 12.7% for the Hourly and Hourly-loc schemes, respectively.

Furthermore, efficiency percentages when using the true state are consistent with those of [3] where only the true state was used. Table IV cannot tell us how much efficiency from using the estimated state is lost during the design and how much during the validation phase. In other words, does the SE make the clustering or the curtailment decisions during daily operation less accurate? Or both? If we assume the DSO has magically knowledge of the true state solely during daily operation, then the efficiency of the two granular schemes deviates only by few decimal percentage points, e.g. $< 0.5\%$ for the Hourly-loc scheme. This tells us that most of the efficiency is lost during daily operation decisions. This result is expected because the tariff design employs clustering and day-types which are an average of many samples, hence, the randomness of the SE error is eliminated.

IV. CONCLUSIONS

This paper presented a ready-to-use framework for implicit flexibility motivation that DSOs can employ with minimal or no upgrades on their infrastructure. It is based on the cooperation between DSE and flexible DUoS tariffs. The former provides an estimated state of the DN for any time period of a dataset on which the latter is designed. A validation setup was created to test its the efficacy under realistic conditions and varying tariff granularity.

Results demonstrate that the DSE algorithm performs well and, overall, the proposed framework can yield 64% of the available cost reduction via flexibility motivation when leveraging the most effective tariff scheme. The loss of efficacy due to the usage of state estimates by the DSE, compared to the true states, is around 10%. This loss can be attributed mostly on the accuracy of the daily congestion mitigation decisions of the DSO. In other words, the tariff design model is mostly indifferent to whether true or estimated state is used.

The framework can be further improved by deploying an equality constrained WLS formulation which is more immune to ill-conditioning compared to the conventional one. Moreover, the analysis can be expanded to more tariff schemes and clustering techniques which can potentially improve cost efficiency further.

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