Introducing price feedback of local flexibility markets into distribution network planning

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***Abstract*—Increasing penetration of distributed energy resources in distribution networks is expected to cause congestion in the near future. While grid reinforcement is the standard approach to resolve such issues, utilizing demand-side flexibility provides a viable and cost-efficient alternative.**

In this work, we propose a decision making tool for distribution system operators that allows them to integrate flexibility procurement from local flexibility markets in their planning process. The tool estimates the future cost of procuring flexibility services and compares them to alternative measures such as grid reinforcement. Long time horizons are considered, as the lead time of grid reinforcement projects can be several years. Price feedback from local flexibility markets is used to calibrate and improve the estimations. Results indicate that the proposed tool can be used to estimate flexibility service cost over several years, aiding distribution system operators in defining a cost-efficient long-term distribution network development strategy.

***Index Terms*—Congestion Management, Demand-side Flexibility, Distribution Networks, Distribution System Operators, Local Flexibility Markets**

I. Introduction

The penetration of flexible distributed energy resources (DERs), such as electric vehicles (EVs), heat pumps (HPs), or batteries, in distribution networks (DNs) is increasing as a result of the ongoing energy transition [1]. Typically, small DER operators do not individually participate in energy markets to offer services because of size requirements, high market complexity, or because it is not cost-efficient to do so. However, they can respond to variable electricity prices and thus perform implicit demand response. Aggregators pool groups of DERs to facilitate market participation and simplify control actions [2]. When using their flexibility potential, DERs can cause operational problems in DNs because an aggregator's coordinated response to prices may result in significantly higher load coincidence factors [3], [4]. EVs in particular have the potential to constitute a substantial flexible load as they can adapt their charging behaviour to electricity prices. If all EVs aim to minimize their cost, they would act on the same price signal, resulting in high peak loads [5]. In addition, the number of EVs is growing rapidly. The global share of electric car sales is projected to be 35% by 2030, compared to 14% in 2022 [6]. As a result, a growing level of capacity congestion in DNs is anticipated [7].

A. Literature Review

The conventional strategy of a distribution system operator (DSO) to deal with congestion is reinforcing the grid, which requires significant investments in infrastructure [8]. A promising alternative is using local supply- and demand-side flexibility to postpone, or even prevent, grid reinforcement, thus reducing the necessary investments [9]. For example, the flexibility potential of DERs can be used to improve network management [10]. Local flexibility markets (LFMs) are proposed to achieve this. A LFM constitutes a market that allows the trading of flexibility between system operators and flexibility providers, such as aggregators [11].

Several pilot projects of LFMs have been conducted to demonstrate how flexibility can be utilized. Most of these projects that are currently being developed by European transmission system operators (TSOs) and DSOs work on a day-ahead or intraday timescale and do not offer long-term horizons [1], [12]. Examples of such LFM platforms are Enera and Nodes, located in Germany and Norway, respectively [13]. They offer the possibility to trade flexibility on an intraday timescale with continuous auctions. This means that offers placed by aggregators on the platforms are continuously matched with flexibility demand orders submitted by DSOs [13]. However, such short-term offers are insufficient for risk-averse DSOs who want to include flexibility services in their long-term grid development plans, especially as liquidity in LFMs can be low, and thus a suitable offer far in the future that meets DSO demand is not guaranteed [14]. Long time horizons are needed as the lead time of grid reinforcement projects can be several years.

In contrast, there are examples of LFMs that work on timescales that span months or even years, e.g., Piclo Flex [1]. This particular market platform uses a baseline definition of flexibility services, i.e., flexibility is defined as a deviation from a previously defined reference, also known as baseline. The baseline definition can however be prone to manipulation

Submitted to the 23rd Power Systems Computation Conference (PSCC 2024). This research has been conducted within the SWEET PATHFNDR project funded by the Swiss Federal Office of Energy SFOE (grant Nr. SI/502259-01). C. Ziras is supported by the ELFORSK funded project e2flex - Enabling Flexibility ELF221-497388.

and/or not be necessarily transparent, as overestimated baselines would regularly overcompensate aggregators in case of load reductions [15]. Capacity limits (CLs) provide a definition of flexibility which does not suffer from these shortcomings. They impose a limit on the aggregator consumption during designated time periods. As there are no projects that consider both CLs and long time horizons, it remains unclear how a DSO should decide on a flexibility procurement strategy, meaning when and to what extent flexibility services should be procured.

In order to compare flexibility services with network reinforcement, a DSO needs to estimate the cost and benefit associated with employing flexibility services and thus the value they provide. This value does not necessarily correspond to the cost of the services obtained in the LFMs. There are several approaches in literature to quantify this value, which are mostly based on the cost of congestion in terms of load shedding, transformer overload, and the resulting reduction in asset lifetime [4]. However, given the usual overdimensioning of DN components, frequent overloadings that may affect transformer lifetime would occur only in future scenarios with high shares of DERs. Thus, the benefit of procuring services in the DN cannot be quantified on the basis of current load shedding or reduction of component (e.g., transformer) lifetime due to overloading. This is because DSOs do not tolerate such extreme load cases and reinforce the grid before they occur. Typically, DSOs do not allow transformers to be overloaded by more than 30% except for infrequent short-time peaks [16]. As the penetration of DERs increases and electricity demand rises, these peaks will become more frequent, increasing the need for expensive grid reinforcements [9]. The availability of alternatives such as LFMs could change this paradigm. DSOs would be able to reduce load peaks through the procurement of flexibility services and maintain safe operational margins, reducing the need for new grid infrastructure. Therefore, the benefit of flexibility services lies in postponing or even preventing grid reinforcement.

B. Contribution and Organization

The question arises as to how can DSOs integrate flexibility services in their long-term grid planning strategy without prior knowledge of their cost and value, which would allow a comparison with alternative congestion management methods. The main contribution of this paper is the development of a DSO decision making tool for long-term grid planning strategy to prevent congestion by integrating flexibility services. The tool uses feedback from actual prices obtained from LFMs to estimate the DSO's cost for flexibility services over multiple years and compare it to the cost of alternative measures, such as grid reinforcement. More specifically, an LFM is first simulated to procure flexibility for congestion management based on future estimations of load and electricity prices. This allows to determine an envelope for the cost of flexibility services in which it is beneficial for aggregators to offer them and for DSOs to procure them, rather than evaluating their exact value for DSOs. After a designated timeframe, real prices for flexibility services serve as feedback and are compared to the estimated ones to evaluate the quality of the price estimation and ultimately improving it. This enables DSOs to take strategic decisions on the most efficient measure to prevent congestion. A case study on a test system consisting of 200 residential households, EVs, and a transformer is conducted to illustrate applications of the proposed DSO tool.

The remainder of this paper is structured as follows. The DSO decision making tool is presented in Section II. Section II-A describes the LFM framework the tool is operating in and Section II-B provides a step-by-step description of the workflow. A case study with two use cases shows how the DSO tool can be utilized in Section III. Key findings are summarized and the paper is concluded in Section IV.

II. DSO Decision Making Tool

The goal of the DSO decision making tool is to continuously estimate the future costs of flexibility services. By comparing them to the cost of alternative measures, it can assist the DSO in defining cost-optimal strategies for congestion management in its grid area. Figure 1 shows how the proposed tool can be included in the DSO decision-making process. The DSO uses forecasts of electricity prices and load in the DN. Such forecasts can then be used as input to the tool, which will provide the DSO with an economic assessment to determine the optimal measure for congestion management, i.e., flexibility procurement or grid reinforcement.

This is a continuous process as external factors change over time and impact the state of the DN, requiring periodically updated forecasts. Additionally, the state of the DN is affected by network development measures as well as DER uptake and consumer behavior. The outcome of the tool is not only influenced by updated forecasts, but also by the prices of flexibility services which are procured on the LFM. Actual prices for flexibility can be used as feedback for comparison to the estimated prices. This enables DSOs to evaluate the quality of their forecasts and the cost estimation, to make adjustments as needed, update the forecasts if the actual cost of services significantly differs from the estimated one, and ultimately improve the performance of the tool. This emphasizes the need to use the tool at regular intervals.

A. Local Flexibility Market Platform

The proposed tool relies on an LFM that enables DSOs to procure flexibility from aggregators. In this work, the two main requirements for implementing such an LFM are that flexibility can be procured with a lead time of at least one year and that flexibility is traded in the form of CLs, as argued in Section I-A.

When providing a CL service, an aggregator agrees to keep the aggregated load of its entire portfolio within a grid area below a defined limit CL_m during a specified period m [4]. The CLs are traded in blocks over a period m and can be defined long before going into delivery. This ensures a predictable service provision to the DSO and allows the aggregator to hedge against price volatility while still being

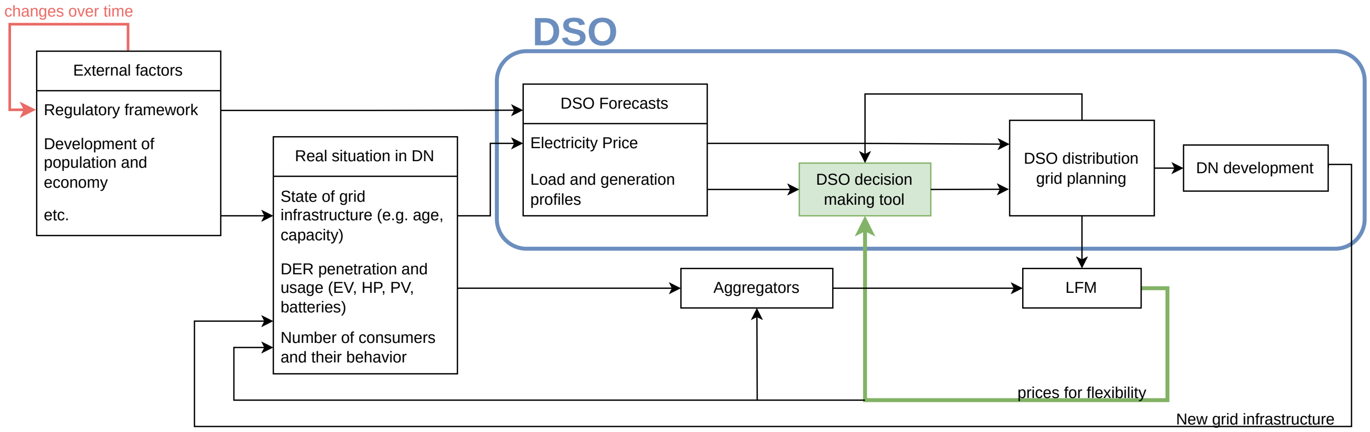

Fig. 1. Overview of how the proposed tool can be included in the DSO decision-making process. The green arrow indicates the flexibility price feedback.

able to optimize its portfolio freely under a CL_m restriction. As it is difficult for DSOs to predict the precise need for CLs for a defined time horizon, m can span from minutes to years.

B. Step-by-Step Description

Figure 2 shows the detailed structure of the proposed DSO tool. Based on load and price forecasts and the optimization process shown in Section II-B2, the tool outputs a price range for the flexibility service within which benefits for both the DSO and the aggregator are ensured, as the upper bound is lower than the DSO's grid reinforcement cost and the lower bound is larger than the aggregator's opportunity cost. The envelope is then used as input for the DSO grid planning process to determine a congestion management strategy: reinforcing the grid or procuring CL services. The strategy depends not only on the cost envelope, but also on the evolution of the envelope over time and the risk management guidelines of the DSO. More generally, the envelope also indicates the prices to expect for procuring flexibility in the future.

1) Input: The proposed DSO decision-making tool relies on forecasts of flexible/ non-flexible load and electricity prices to estimate the future cost of flexibility services. While flexible loads, such as EVs, batteries, or HPs, can be controlled by the aggregator and shifted in time, non-flexible loads, such as standard household consumption, are assumed to be uncontrollable. This work does not aim to develop sophisticated forecasting methods as they are beyond the scope of the proposed tool and can vary among different DSOs.

2) Optimization Problem: The input is subsequently used in an optimization problem which aims to determine a flexible load profile that minimizes the aggregators cost function. The problem is solved twice, once without CLs constraints and once enforcing them. By comparing the resulting costs, the opportunity cost an aggregator faces when providing the CL service can be calculated. More precisely, CL_m for the time period m is determined by comparing the maximum value of

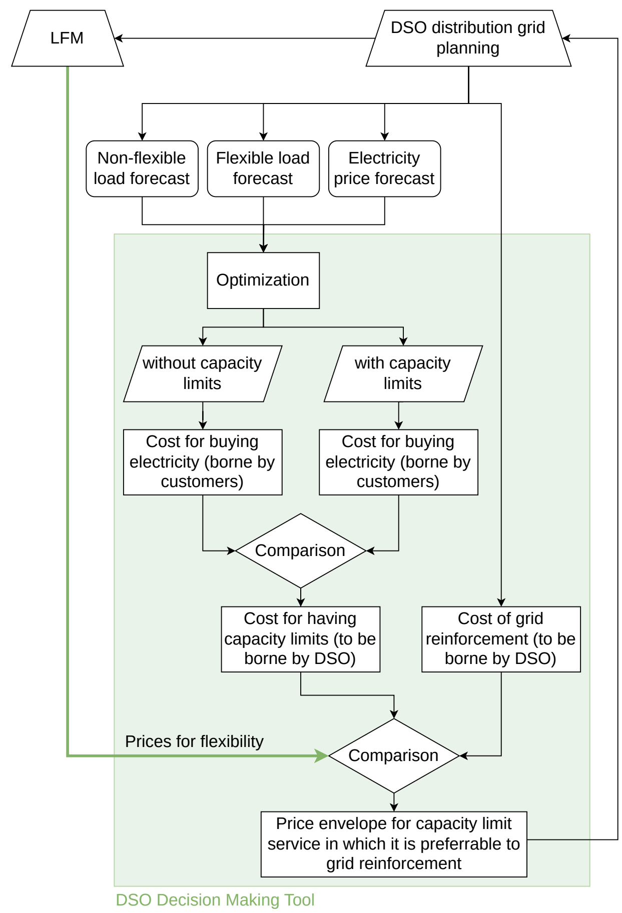

Fig. 2. Detailed structure of the DSO decision making tool.

the forecasted total non-flexible load $\bar{l}_m^{\mathrm{NF}}$ in period m to the designed grid capacity C_{Grid}:

$$CL_m = C_{Grid} - \bar{l}_m^{\mathrm{NF}}. \tag{1}$$

The generic formulation of the optimization problem used in the CL service cost calculation is described in Equation (2).

The objective is to minimize the aggregator's cost function $f_{\text{cost}}(\boldsymbol{p})$ which depends on the aggregator's flexible load $\boldsymbol{p}$.

$$\min_{\boldsymbol{p}} f_{\text{cost}}(\boldsymbol{p}) \tag{2a}$$

$$g(\boldsymbol{p}) = 0, \quad h(\boldsymbol{p}) \leq 0 \tag{2b}$$

$$q(\boldsymbol{p}) \leq CL_m \tag{2c}$$

Equation (2b) expresses the problem's constraints. The capacity limits are enforced by constraint (2c).

3) Service Cost Estimation: The dominant pricing method used on existing LFM platforms is pay-as-bid [1]. In this mechanism aggregators place offers that may not represent their true cost, resulting in a gap between the aggregators true cost and the price DSOs pay for flexibility services. In this work, the cost of the CLs service is defined as the opportunity cost faced by aggregators when offering such services, providing a lower bound of the market price [3]. The proposed tool calculates opportunity cost by comparing the aggregator's cost with and without service provision [17]:

(i) The flexible load is optimized without considering CLs, resulting in the aggregator's cost for electricity procurement c_{noCL}.
(ii) The flexible load is optimized while enforcing CLs through constraint (2c), resulting in the aggregator's cost for electricity procurement with CLs c_{withCL}
(iii) The aggregator's opportunity cost for providing the CL service is calculated as follows:

$$c_{\text{opp}} = c_{\text{withCL}} - c_{\text{noCL}} \tag{3}$$

4) Cost Envelope: The resulting estimation of future CL service cost is the lower bound of the cost envelope. It represents the aggregator's opportunity cost, i.e., the cost below which an aggregator would sell the CL service at a loss and the minimum cost at which a DSO can procure flexibility. The available real prices from LFMs can be compared to past price estimations to evaluate if the forecasts used in the CL service cost estimation result in accurate estimation. If not, the forecasts have to be adjusted accordingly and the tool needs to be updated.

The upper bound indicates a threshold above which other measures to prevent congestion are more cost-efficient. The cost of grid reinforcement is case specific and depends on various parameters, such as: age and size of the installed infrastructure, cost and availability of new grid components, cost and availability of labour, or the current interest rate environment. Thus it needs to be defined by each DSO individually for each case. Assuming accurate forecasts, the resulting envelope can be used by the DSO to:

(i) Define grid planning strategies over a timeframe of years. E.g., if the lower bound is much smaller than the upper bound, it means that procuring CLs is more cost-effective than reinforcing the grid. However, if the lower bound is higher than the upper bound, it means that that reinforcing the grid is more economically efficient.
(ii) Evaluate offers from aggregators. E.g., if the aggregator's offer for the CL service is close to the lower bound, it means that the premium to be paid for the aggregator's services and risk management is low. Conversely, if the offer is above the upper bound, upgrading the grid's capacity is more cost-effective than procuring CL services.

5) Dealing with Forecast Uncertainty: As described in Equation (2), the tool estimates the CL service costs using the forecasted electricity prices as exogenous input. To deal with forecasting uncertainty a set of N different electricity price inputs λ_n, each associated with a probability ρ_n, can be provided as input to the DSO tool. This results in N different opportunity costs $c_{\text{opp},n}$ which can be used to build a probabilistic service cost estimation. The resulting probability density function (PDF) can be used to provide boundaries within which the value of c_{opp} will fall with a certain level of probability that has to be defined by a DSO's risk management strategy. The expected value of the CL service cost can be calculated by using

$$\mathbb{E}[X] = \int_{-\infty}^{+\infty} x f(x)\, dx \tag{4}$$

where the random variable X is c_{opp}, x are the values of X and $f(x)$ is the resulting PDF. It indicates the value of c_{opp} which is most likely to occur. The same principle can be applied to the other forecasted input data, i.e., flexible and non-flexible load profiles.

III. Case Study

Two use cases are presented to demonstrate possible applications of the proposed DSO tool. The first use case shows how a DSO can use the tool to estimate flexibility costs until 2040, while the second one calculates a service cost envelope and shows how a DSO can use it to define its DN development strategy for an upcoming year.

A. General Setting

The general settings are similar for both use cases. A neighbourhood with 200 households connected radially to the medium voltage (MV) grid by a $250\,\text{kVA}$ transformer is considered. Thus, only DERs connected downstream specific grid nodes can be used to prevent congestion at those nodes. As DNs are usually either radial or weakly meshed, radial topology can be fairly assumed [18]. By neglecting reactive power, the transformer imposes a limit of $250\,\text{kW}$ on the aggregated load. To simplify the interpretation of the results, photovoltaic (PV), batteries, and HPs are neglected and EVs are the only flexible load considered. Furthermore, a single aggregator controlling all EVs is assumed.

For the non-flexible load forecast input publicly available residential smart meter data from 2021 provided by a Swiss DSO [19] is used, from which 200 households are randomly selected. The dataset provides smart meter readings in 15 minute time resolution. These load profiles were used to create synthetic load profiles of subsequent years, with adjustments to match weekly patterns and the end-of-year holidays. The trend of the non-flexible load is not increased over the years as it is assumed that energy efficiency improvements will counteract the load increase due to non-flexible electrification. This allows to better investigate the impact of growing flexible load on CLs, as CL service price differences do not stem from non-flexible load changes, but only from changes in the flexible load and electricity prices. For the flexible load forecast input, EV charging session data from public chargers in residential areas is used [20]. The dataset includes arrival/departure time and amount of charged energy for each session. The level of EV penetration for each year is taken from the Swiss government's Energy Perspective 2050+ basis scenario expectations [21].

A technology-specific example of the optimization problem in Equation (2) is provided in Equation (5) for EVs. It assumes that the aggregator minimizes cost for electricity procurement. Only uni-directional EV charging is considered as flexible load. EV charging- and standby losses are not considered because the relevant information is missing in the used dataset; besides, given the exploratory nature of the case study their impact on the obtained results is not substantial. Equation (5) provides the aggregator's flexible load profile for an ideal case with perfect controllability of EVs and perfect foresight.

$$\min_{\boldsymbol{p}} \sum_{t\in\mathcal{T}} \lambda_t^{\text{el}} \sum_{j\in\mathcal{J}} p_{j,t}\Delta t \tag{5a}$$

$$0 \le p_{j,t} \le P_j, \forall t \in \mathcal{T}^j, \forall j \in \mathcal{J} \tag{5b}$$

$$\sum_{t\in\mathcal{T}_k^j} p_{j,t}\Delta t = E_{k,j}, \forall k \in \mathcal{K}^j, \forall j \in \mathcal{J} \tag{5c}$$

$$\sum_{j\in\mathcal{J}} p_{j,t} \le CL_m, \forall t \in \mathcal{T} \tag{5d}$$

t denotes the time interval in the optimization, j denotes the EV index, and k the charging session. The normalized duration of t is Δt, while the average charging power of EV j in t is represented by $p_{j,t}$. $\mathcal{T}$ is the set of all time intervals of the optimization, the set $\mathcal{T}^j$ contains all time intervals in which EV j is connected to a charging station, and $\mathcal{J}$ is the set of all EVs. Additionally, λ_t^{el} denotes the price the customer pays for electricity during t. P_j represents the charging power capacity of EV j, while $E_{k,j}$ is the total charged energy during charging session k of EV j. $\mathcal{K}^j$ is the set of all charging sessions of EV j and $\mathcal{T}_k^j$ consists of all time intervals of charging session k of EV j. Equation (5a) minimizes the aggregator's cost for electricity procurement. Equation (5b) enforces uni-directional charging of the EV and limits the charging power to the charging power capacity of each EV during charging sessions. Everywhere else, $p_{j,t} = 0, \forall t \notin \mathcal{T}^j, \forall j \in \mathcal{J}$ applies. Equation (5c) ensures that for each charging session, the amount of energy defined by the customer is charged. The capacity limits are enforced by constraint (5d), which ensures that the total flexible load stays below the defined CL_m. Constraint (5d) being in place differentiates c_{withCL} from c_{noCL}.

Two use cases are investigated:

1) Use Case 1: The goal is to show that a DSO can use the proposed tool to estimate the cost of using CLs as an alternative to upgrading the transformer. In this way the DSO is able to *wait and see* how other developments in the grid, such as increased solar and battery penetration, influence the level of congestion and possibly render grid reinforcement unnecessary [9].

For the electricity price forecast input, grid tariffs $\lambda_t^{\text{tariff}}$ from a Swiss DSO [22] and a projection of future electricity prices from [23] are considered. Electricity spot price data was taken from the reference scenario and interpolated to generate a continuous price profile λ_t^{spot}. An offset $\lambda_t^{\textbf{offset}}$ represents taxes and transmission grid tariffs. The three components were combined to model the price λ_t^{el} a private customer would pay for electricity:

$$\lambda_t^{\text{el}} = \lambda_t^{\text{spot}} + \lambda_t^{\text{tariff}} + \lambda_t^{\text{offset}}. \tag{6}$$

The average p_{el} for 2023 is 0.32 CHF/kWh, matching small consumer electricity prices in 2023 [24].

2) Use Case 2: The goal is to show how a DSO can use the described tool to estimate CL service cost in upcoming years while dealing with electricity price forecast uncertainty. To reduce the simulation time, the time horizon is limited to one year, instead of the several years that a DSO would typically cover.

To deal with uncertainty in the electricity price forecast input, 48 different yearly price profiles are used as inputs. They are all based on the day-ahead electricity prices for Switzerland from 2015 to 2022 [25]. Random noise and/ or offsets were added to the original yearly profiles. This method resulted in 48 different, but still realistic price profiles, that due to the exceptionally high electricity prices in 2022 also contain extreme cases that can be considered as worst case realizations. A constant set of 97 EVs is chosen to match the one expected in 2040 by [21] to simulate a congested DN. To focus on the effect of different price realizations, uncertainties in the non-flexible load and EV charging behaviour are neglected. However, they can be handled similarly.

B. Use Case 1

The application of the DSO tool results in total costs of 2648 CHF over the 17 years from 2023 until 2040. As shown in Figure 3, the annual cost of the CL service starts to take non-zero values after 2032. This is the first year the transformer load would exceed its capacity without the use of flexibility services. This means that flexibility services are not needed until 36 EVs are added - (5d) is thus non-binding and the true cost of the service equal to zero.

If EV adoption continues to increase above the threshold at which congestion occurs, flexibility service costs increase rapidly. However, the rate of this increase is not constant. From 2036 to 2037 the cost of the service increases by 325 CHF, but from 2037 to 2038 the cost increases only by 223 CHF even though in both years the same number of EVs (8) was added to the neighbourhood. This can be attributed to the differences in charging behaviour for each individual vehicle and the level of congestion already present. From 2038 to 2039, when also 8 new EVs are added to the neighbourhood, the cost increase for the service is again different at 295 CHF. Figure 4 shows that with the CL activated (orange line), the transformer load can

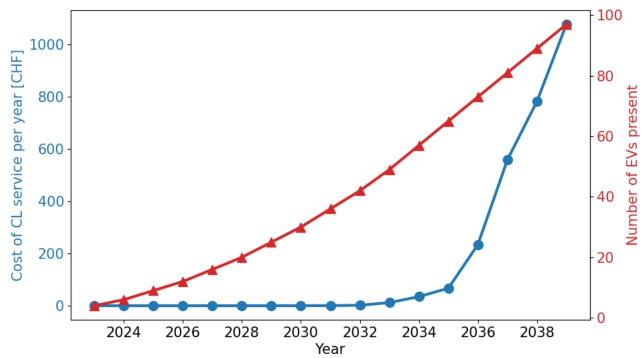

Fig. 3. Estimated true cost of CL service per year and number of EVs per year in use case 1. As the non-flexible load is forecasted to stay the same for each year, the differences in CL service prices stem primarily from increasing flexible load and changes in the electricity price, modeled according to Equation (6).

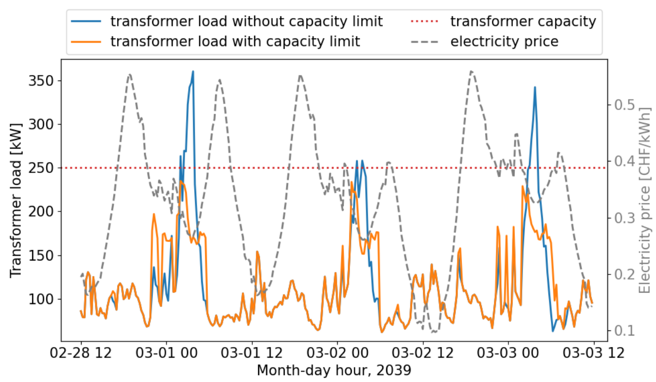

Fig. 4. Transformer load profile without (blue) and with (orange) capacity limits. The designed capacity is shown in red dotted line. Electricity price is shown in grey.

be kept below its designed capacity of $250\,\mathrm{kW}$ (red dotted line). It can also be seen that when there is no flexibility service (blue line), load peaks are very high when electricity prices (grey dashed line) are low, since most of the connected EVs synchronize their charging.

The lower bound for the expected cost of CL services over a long horizon can now be compared to grid reinforcement cost estimated by the DSO to decide on a cost-effective strategy for congestion management. Such lower bounds reflect the estimated aggregator's opportunity cost but neglect other factors such as market behaviour and profit margins. As more EVs are being adopted in the neighborhood, the service incurs higher costs if the same transformer limit is to be imposed. In the absence of capacity limits, large peaks occur when electricity is the cheapest due to synchronized charging. Those peaks are distributed to the next-cheapest hours if CLs are imposed. The price difference between the cheapest hour and the next-cheapest hours determines the aggregator's opportunity cost, along with the energy needs of the vehicles, which are proportional to their number.

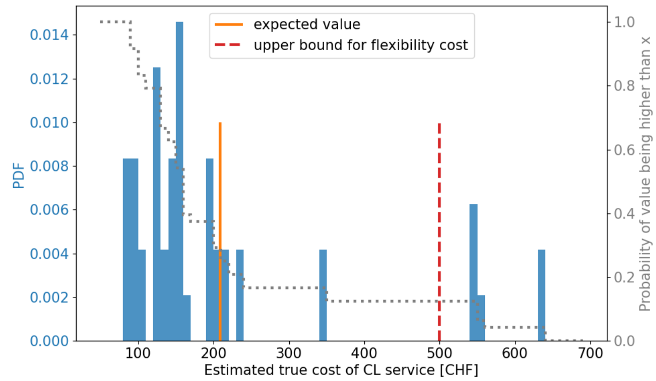

Fig. 5. PDF of CL service cost in use case 2 for 48 different electricity prices. The expected value is indicated in orange and the upper bound for flexibility service cost in red. The grey line shows the probability of the estimated true CL cost being larger than the x-axis value.

C. Use Case 2

The transformer in question was installed 10 years ago for a cost of $20\,000\,\mathrm{CHF}$. Assuming a constant write-off over a lifetime of 40 years, the transformer has a residual value of $10\,000\,\mathrm{CHF}$ in the upcoming year. Assuming further a Weighted Average Cost of Capital (WACC) of 5% determined by the regulator, the DSO gets a return of $500\,\mathrm{CHF}$ from its investment in the upcoming year [26]. Thus, by postponing the transformer's replacement by a year, the DSO saves $500\,\mathrm{CHF}$, making this the maximum price it is willing to pay for CL services. This provides the upper bound for flexibility procurement costs.

To estimate the annual cost of CL services, the DSO can use multiple electricity price scenarios to tackle price uncertainty, as described in Section II-B5. 48 price signals are used to simulate the impact of different electricity prices on the cost of the services. This leads to an annual CL service cost for the considered network between $80.67\,\mathrm{CHF}$ and $635.90\,\mathrm{CHF}$. The distribution of possible cost realizations can be seen in Figure 5. There is a 12.5% probability that the annual CL service cost will be above the upper bound of $500\,\mathrm{CHF}$. By using (4) and assuming equi-probable price scenarios, the expected value of the CL service cost for the upcoming year is $209.04\,\mathrm{CHF}$. By comparing the probabilistic service cost estimation shown in Figure 5 to the upper bound of $500\,\mathrm{CHF}$, the DSO can now prepare a strategy to deal with congestion in the upcoming year. Depending on its choice of confidence interval and value at risk, the DSO can decide to accept the risk of CL service cost being higher than grid reinforcement cost and procure flexibility services. In case the DSO decides on a risk-averse grid development strategy, the grid should be reinforced. When deciding on a DN development strategy for the upcoming year, the situation on the LFM needs to be taken into account as well. For example, in case the aggregators' offering prices exceed the upper bound of €500, the DSO could decide to either reject the service and reinforce the network or simply tolerate this higher cost until it is possible to implement the necessary upgrades. However, when deciding whether to conduct larger reinforcement such as MV lines or transformers, a DSO should not rely on estimations for such short timescales. Given the relatively long lead and execution times of large reinforcement projects, and the high electricity price volatility, it would be preferable for a DSO to take decisions only based on longer timescales. Indeed, service procurement costs may be exceptionally high during a year of unprecedented prices volatility, such as 2021-22, but could significantly reduce once market conditions stabilize, rendering CL services more cost-efficient in the long run than grid reinforcement. Therefore, using a longer term in the decision process, as shown in use case 1, may be preferable when deciding on a long-term strategy. The DSO could combine the processes showcased in both use cases and produce probabilistic estimates of service costs over multiple years and evaluate service procurement costs over longer horizons, as a more sound DN expansion planning strategy.

D. Discussion

The case study shows that the proposed tool aids DSOs in determining a suitable congestion management strategy. It offers a comparison between grid reinforcement and the use of flexibility services based on an estimation of future service cost in the face of forecast uncertainty. Based on this comparison, a DSO can decide on an appropriate grid development strategy. Results further indicate that the main drivers for flexibility service cost are the level of DER penetration and the difference in electricity prices between the originally intended consumption time and the time when consumption must occur to remain within the CL. Those drivers might lead to a service cost in the future for which grid reinforcement is a more cost-effective method for congestion management. This suggests that flexibility services may not prevent the need for grid reinforcement, but rather delay it and reduce its scope.

The proposed tool and performed analysis still have a few limitations that need to be considered. The case study employed basic forecasting methods to create inputs for the proposed DSO tool. More advanced methods can be used to improve forecast accuracy. Additionally, it was assumed that the end-customer received a flexible electricity price signal. While in the European Union all electricity customers are entitled to such dynamic electricity tariffs [27], customers have no perfect foresight of future tariffs to optimize DER consumption, but know prices for the following 11-35 hours. Furthermore, perfect foresight was assumed for all future EV charging sessions. In reality the availability of EVs depends on user behaviour, causing uncertainty in the flexible load forecast and their optimization. A method for dealing with that uncertainty was proposed in Section II-B5 and showcased in Section III-C for uncertainty in electricity price forecasts. To reduce the complexity of the case study and improve the interpretability of the results other DERs such as batteries, HPs, and PV were neglected. This is justified as EVs are projected to be the main driver for transformer reinforcement in DNs until 2035 [9]. However, the proposed framework allows for the accommodation of the effects of integrating other DERs. Additional flexible loads can be included in the optimization problem and flexible load forecasts, but this will require further input to be forecasted by the DSO. Finally, it is noteworthy that EV flexibility is mainly used to reduce the self-inflicted load peaks due to spot-price synchronization. In the following years EVs may be controlled to offer multiple services (revenue stacking) and their behaviour may be less predictable than it is today, when they only react to electricity tariffs. This reinforces the need for frequent periodic updates in the tool, for example to better and more realistically model EV charging behaviour based on real observations (EV and smart meter data).

IV. Conclusion

In this paper we propose a DSO tool to estimate the cost of flexibility services for congestion management and identify the most cost-effective strategy when comparing with alternatives. The key novelty is that by using this tool price feedback of LFMs can be introduced to the DN planning process. This would constitute big step forward in decarbonisation as it helps DSOs to operate and develop their grids in a more efficient manner, reducing costs and increasing the speed at which DERs can be introduced to DNs. Results confirm that increasing the number of flexible loads will cause congestion in DNs. While congestion can be avoided by using CLs, the proposed DSO tool shows that the cost for CL services grows rapidly as the number of flexible loads increases. There exists a threshold above which grid reinforcement will be more favorable than procuring flexibility services. One of the goals of this tool is to predict when reinforcement starts becoming more effective, but at the same time utilize flexibility when it is a much more efficient and economical congestion management strategy. In addition, results indicate that the proposed tool allows DSOs to take uncertainty-aware decisions.

Future work will focus on including additional DERs, such as PV, batteries and HP in the optimization to determine how their adoption influences congestion in DNs and how this affects the cost of CL services over time. It would be interesting to investigate whether the use of PV and batteries could even bring down congestion to a level at which CL services are constantly more cost-effective than grid reinforcement. In addition, strategic market behaviour of aggregators, revenue stacking from offering flexibility on multiple markets, and market clearing mechanisms on LFMs need to be studied in more detail. This would allow a more realistic estimation of the CL service cost. In future work the long-term LFM platform can be combined with a short-term one, allowing the DSO to continuously refine its CL procurement and adapt it to changing forecasts, leading to a more efficient use of the DN. Lastly, an in-depth analysis of how uncertainties in load and electricity price forecasts influence CL service prices can provide better estimations of future costs.

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