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Coordination strategies in distribution network considering multiple aggregators and high penetration of electric vehicles

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Abstract

Given the current state of the society in which we live, in terms of energy pollution, several objectives have been set to try to reduce environmental problems. Some of these goals include an exponential increase in production through renewable energy, and Electric Vehicles (EVs) circulating on roads. Due to this high penetration of distributed energy resources in the electricity grid, several problems may exist: grid congestion, causing severe energy systems damage. Innovative coordination strategies must be developed to mitigate these situations. This paper proposes a methodology to minimize this problem in a smart grid with high penetration of Distributed Generation (DG) and EVs, taking into account multiple aggregators. Initially, the proposed model calculates each aggregator's profit through some business models and analyzes the network without any congestion strategy. This analysis is then done in the presence of Distribution Locational Marginal Pricing (DLMPs), which the aggregator receives from the Distributed System Operator (DSO). The DSO gets these prices after running the Optimal Power Flow (OPF), where these prices involve the market price, the cost of losses, and the cost of congestion at a given point in the network. Here the aggregators react according to these costs, such as trying to buy flexibility from their customers. In this study, the results prove that dynamic prices are more viable for the power grid by reducing congestion by analyzing each aggregator's profit.

Keywords: Aggregator; Congestion management; Distributed Locational Marginal Prices; Distribution network; Electric Vehicles

1. Introduction

Due to the objectives set to reduce the carbon footprint, increasing penetration of flexible demands such as electric vehicles (EVs) has been introduced. This high penetration of distributed energy resources (DER) brings to the distribution network (DN) several challenges that may impair its regular operation, given its uncertain nature. Concerning EV penetration, dumb charging by vehicle owners [1], especially at peak load times, can cause severe congestion problems, usually in medium and low voltage DNs [2]. Here the distribution system operator (DSO) will have to intervene since its objective is to guarantee the stability of the network it operates. So it will try to solve the congestion

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problems, through reinforcements of the system, that is, it will try to solve this problem in the long term, or it will try to implement market mechanisms [3].

In the context of the smart grid [4, 5], the optimization of energy resource management is becoming extremely important to avoid these congestion problems [6]. One of the strategies being implemented to reduce congestion is distribution locational marginal pricing (DLMP). This strategy becomes an extension of location marginal pricing (LMP), used for power transmission networks [7].

The DLMP includes the cost of energy in the market, the cost of losses, and congestion on a given network bus. This strategy forces consumers to change their consumption habits during periods of congestion so that the value they have to pay is lower, i.e., there will be a reduction in congestion.

There is a large amount of work in the literature developed with various strategies to reduce congestion in the DN. Reference [8] proposes a market mechanism based on the distribution congestion price (DCP) to relieve network congestion. To determine this parameter, the authors only remove the congestion cost from the DLMPs. Here the interaction of the DSO with two aggregators in the developed market is also studied. The results show that the load on the lines and the voltage profiles tend to improve with this mechanism. [9] analyzes the impact of high penetration of EVs in a 33 bus distribution network, taking into account users' random behavior. The authors calculate DLMPs through deterministic processes and chance-constrained programming. The latter presents better results in reducing congestion than deterministic methods. The paper in [10] like the previous paper analyses the impact of DER penetration, not only of EVs but also the penetration of heat pumps. The simulations are made for a 33 bus distribution network. The interaction between aggregators and DSO is illustrated in this work. The aggregators initially report to the DSO on their energy plans, and the DSO will then calculate the dynamic tariffs or DLMPs. Then the aggregators adjust these energy plans according to these tariffs. Here again, through the results obtained by the authors, there is a relief of congestion in the network.

This paper presents coordination strategies involving DLMPs in a DN of a smart city (SC) considering a high penetration of EVs and renewables. Multiple aggregators are deemed, and their interaction with the DSO is also presented. An analysis is made, taking into account three associated entities (aggregators, consumers, and the DN). The rest of the paper is organized as follows: Section 2 presents the proposed methodology for the developed mechanisms. The proposed case study is described in Section 3, where three different scenarios related to the market price are explained. The results of this work are discussed in Section 4 in the perspectives of the three entities. Finally, the conclusions are shown in Section 5.

Nomenclature

$R_{(i,j)}$	revenue of the aggregator i in period j [€]
$C_{(i,j)}$	costs of the aggregator i in period j [€]
$C^{DLMP}_{(i,j)}$	costs of the aggregator i in period j considering DLMPs [€]
$PF_{(i,j)}$	profit of the aggregator i in period j [€]
$PF^{DLMP}_{(i,j)}$	profit of the aggregator i in period j considering DLMPs [€]
$Tariff$	flat tariff price of energy [€/MWh]
c^{net}	cost of access to the transmission and distribution networks [€/MWh]
c^{pol}	regulation costs [€/MWh]
$price^{MK}$	market price [€/MWh]
$DLMP_{(k,j)}$	DLMP cost associated to client k in period j [€/MWh]
$P_{(i,j)}$	total power of customers associated to aggregator i in period j [MW]
$P_{(k,j)}$	power consumption of client k in period j [MW]
n_i	number of clients associated with aggregator i

2. Proposed methodology

This section details the methodology applied in this work, where the business model proposed for the system in question is also presented.

The model performed is based on the methodology presented in [11], as shown in Fig. 1. This is an optimization model based on Benders decomposition because the problem of operation and reconfiguration of the distribution network is a mixed-integer non-linear program (MINLP). This problem is classified in this way due to the non-linear characteristics of an electrical grid, where non-linear functions are involved in power flow calculations. The Benders decomposition method is then applied to solve this complex optimization problem, since it is suitable for this type of problems [12, 13].

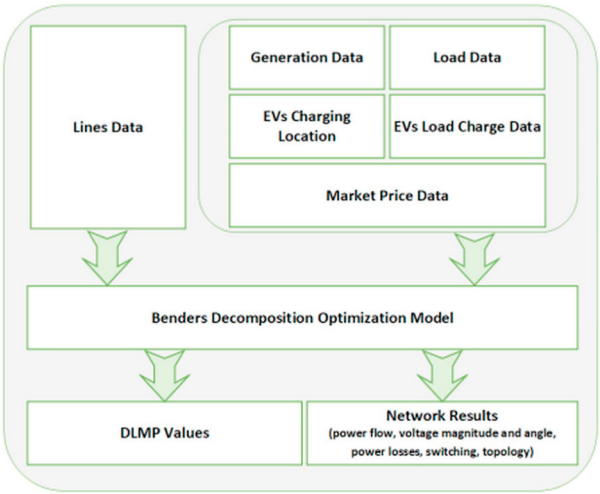

Fig. 1. Optimization model for the DN operation problem proposed in [11]

The DLMP values are then obtained through the optimal power flow (OPF) that the DSO performs based on network data, as shown in the figure.

This paper focuses on the perspective of aggregators. A business model for calculating the profit of this entity is presented. Initially, the calculation is made without the presence of DLMPs. Through the historical data that it has from its customers, the aggregator sees the amount of energy that it needs to buy and, in this case, goes only to the wholesale market to make its proposal. Each aggregator will calculate its profit through the difference between the revenue it has from selling energy to its customers and its costs in purchasing electricity. The mathematical model representing this situation is then:

$$R_{(i,j)} = Tariff \cdot P_{(i,j)} \cdot \Delta t \tag{1}$$

$$C_{(i,j)} = [price^{MK} + c^{net} + c^{pol}] \cdot P_{(i,j)} \cdot \Delta t \tag{2}$$

$$PF_{(i,j)} = R_{(i,j)} - C_{(i,j)} \tag{3}$$

The tariff in the (refequation1) is the same for all aggregators and has been taken from [14]. In (2), adding to the market prices at which the aggregator pays for energy, there are the costs of access to the transmission and distribution networks and the regulation costs implemented by the state. The reference [14] also allowed the calculation of these parameters. The formulation presented is not suitable for one of the aggregators, as this is an aggregator responsible for the DG. Here an incentive of 0.095 [€/kWh] that this aggregator pays to producers was considered. It was assumed that this incentive already includes network access costs and regulation costs.

With the presence of DLMPs, the aggregators will have to react according to the cost of energy present in the various buses. If there is high congestion on a given bus, the aggregator's fee will be high, since the DLMP comprises the market price of energy, congestion cost, and losses cost. From its perspective, this is not ideal, i.e., the aggregator will seek to reduce congestion on that bus through incentives to its customers to ensure flexibility. This flexibility causes the consumer to delay or advance their standard consumption period for periods where energy price is not as significant, for periods where demand is lower. For the proposed business model, the aggregator, after knowing the value of the DLMPs, calculates its profit as follows:

$$C_{(i,j)}^{DLMP} = [\sum_{k=1}^{n_i} P_{(k,j)} \cdot DLMP_{(k,j)} + 0.5 \cdot c^{net} \cdot P_{(i,j)} + c^{pol} \cdot P_{(i,j)}] \cdot \Delta t \tag{4}$$

$$PF_{(i,j)}^{DLMP} = R_{(i,j)} - C_{(i,j)}^{DLMP} \tag{5}$$

Again the methodology adopted for the production aggregator was different from that presented. In this case, the cost associated with this aggregator will be the incentive it pays to the producers as it was the case without the presence of DLMPs. Here its revenue is different from the others. It is considered that this aggregator sells energy at the cost of the DLMP. Only half of the cost of access to the transmission and distribution networks is also assumed in the proposed business model, as it is in (4). This situation is since the DLMP is already composed of multiple costs, as previously mentioned.

3. Case Study

The proposed methodology is applied to a medium voltage (MV) distribution network of an SC located at the BISITE laboratory [11]. High penetration of EVs and renewables (wind and PV) are considered in this case study. The distribution network that feeds the SC has one 30MVA substation and 25 load points. A total of 15 DG units (i.e., 2 wind farms and 13 PV parks), four capacitor banks of 1 Mvar, and are included in the network, as can be seen in Fig. 2. Moreover, the SC has seven charging stations or parking lots for EV charging, four (two in bus 7 and two in bus 11) slow charging stations (7.2 kW for each connection point) and three (two in bus 2 and one in bus 5) fast-charging stations (50 kW for each connection point). Each slow charging station has 250 spaces for EVs, and the fast-charging stations have 80 slots.

Five types of loads compose the DN: 1) Residential buildings (1375 homes); 2) Office buildings (7 buildings); 3) Hospital; 4) Fire Station; 5) Shopping mall.

In this case study, five independent aggregators are considered. One of the five aggregators was exclusively responsible for the DG. The division of the five aggregators and the customers affected by them is done as follows: Agreggator 1: Hospital, fire station and shopping mall; Agreggator 2: Residential buildings; Agreggator 3: Office building; Agreggator 4: DG (wind and PV); Agreggator 5: Charging Stations.

The tariff at which each aggregator sells energy corresponds to a flat tariff, i.e., the tariff remains constant throughout the day. Each tariff associated with each aggregator was taken from [14], as mentioned in Section 2. The simulations performed considered a population of 5000 EVs with the characteristics present in Table 1. It was considered 96 periods, a day with 15 minutes intervals to validate what was developed.

In the present work, the case study is divided into three different scenarios. The change made from scenario to scenario is related to the change in market prices so that an analysis can then be made in terms of results. The market prices used for this work were obtained from [15].

In the first scenario, an average of all market prices for the year 2019 is performed. This average is made for one week, that is, a sum of the amounts of each day of the week is made, and then divided by the total number of corresponding days. The second scenario considers not the entire year of 2019, but only the winter period where three months were considered (January, February, and December). Likewise, in the third scenario, the summer period is considered for the simulations, where the average is made for June, July, and August. Fig. 3 shows the variation of the averages calculated for the market prices used in the simulations for each scenario.

As mentioned in Section 2, the calculation of each aggregator's costs is the sum of several components. Fig. 4 shows the variation over time of these various components for scenario one, with and without DLMPs. These values,

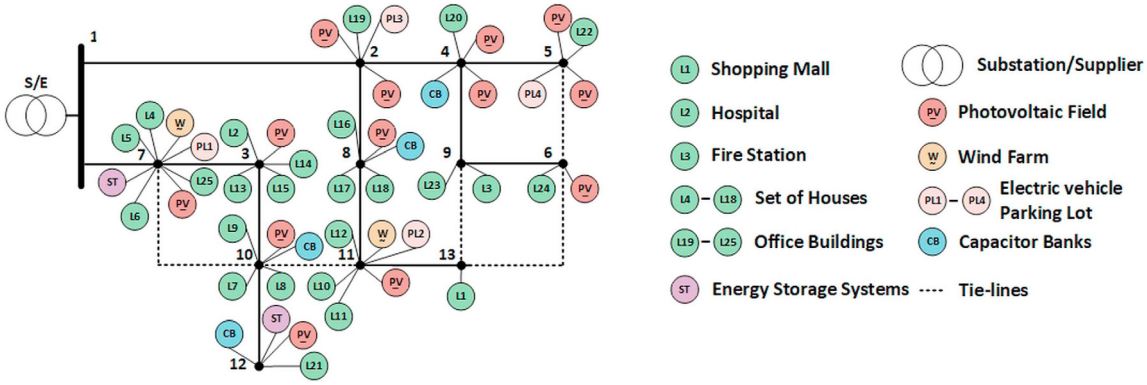

Fig. 2. Diagram of the distribution network [11]

Table 1. EV characteristics.

Model	Battery (kWh)	Slow Charge Power (kW)	Fast Charge Power (kW)	Consumption (kWh/km)
Nissan Leaf	40.00	6.60	50.00	0.1553
Tesla Model S 70D	75.00	7.40	50.00	0.2100
BMW i3	33.20	7.40	50.00	0.1584
Renault Zoe	41.00	7.40	-	0.1460
Renault Kangoo	33.00	7.40	-	0.1926
VW e-Golf	24.20	7.20	40.00	0.1584
Ford Focus	33.50	6.60	50.00	0.1926
Hyundai IONIQ	30.50	6.60	50.00	0.1429

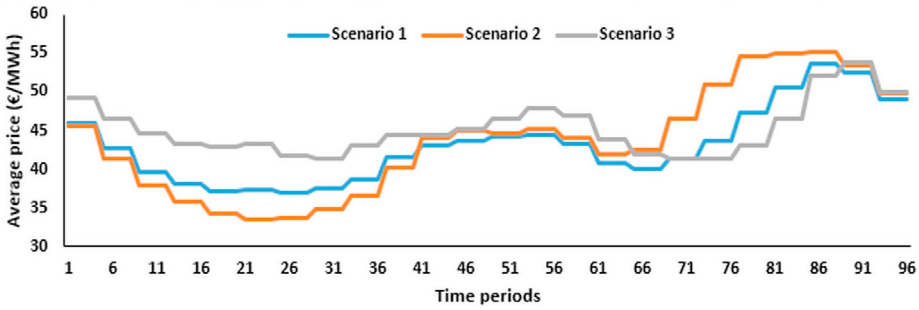

Fig. 3. Market prices

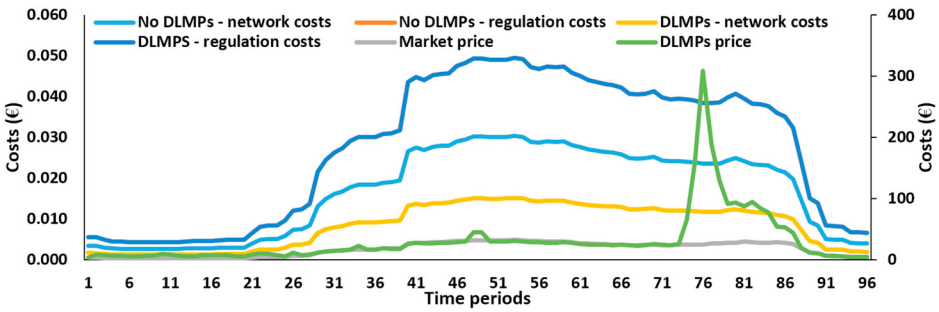

Fig. 4. Variation of cost components with and without DLMPs for scenario 1, aggregator 1

presented in euros, are associated with aggregator one, and as can be seen in the figure, the market price and DLMP values show a different scale from the other costs. On the main axis of the graph are then the regulation costs and the costs associated with the transmission and distribution networks, and on the secondary axis are the values of DLMPs and market prices. It should be noted that in both cases, the policy cost curves overlap as there is no change in this parameter.

This work has been developed on a computer with one Ryzen R5 3600 processor and 16 GB of RAM running Windows 10 Home. In addition to R language (for EV user behavior simulator for the charging station consumption), the MATLAB R2018a and TOMLAB 8.1 64 bits with CPLEX and SNOPT solvers were used for the optimization problems.

4. Results and discussion

The methodology presented in Section 2 was applied to the three scenarios introduced in Section 3. In this section, the results are presented, taking into account the profit obtained by multiple aggregators in the various situations.

Fig. 5a shows the variation over the day of the profit of the various aggregators for the case without DLMPs. The DG aggregator presents higher profit peaks in comparison with the other aggregators, in line with what was previously mentioned. This situation is because there is a high PV production during the periods when the profit peak occurs; that is, this aggregator has more significant energy to sell. This situation is similar for scenarios 2 and 3, as shown in Fig. 6a and Fig. 7a. In Fig. 6a it appears that the aggregators for the first 30 periods present a higher profit compared to the other two scenarios. This scene is since the market prices in scenario 2 for these periods are lower than in the other scenarios.

Fig. 5b presents the variation during the simulated day of the various aggregators' profit for the case with DLMPs. It can be seen from the figure that the aggregator 5 has a very negative peak in gain compared to the other aggregators. This situation is because when this peak occurs, there is a high number of EVs being charged on the charging stations (CSs) buses, which causes high network congestion in that period. This makes the DLMP high, hence the profit of this aggregator being highly negative. This situation is similar to scenarios 2 and 3, as shown in Fig. 6b and Fig. 7b.

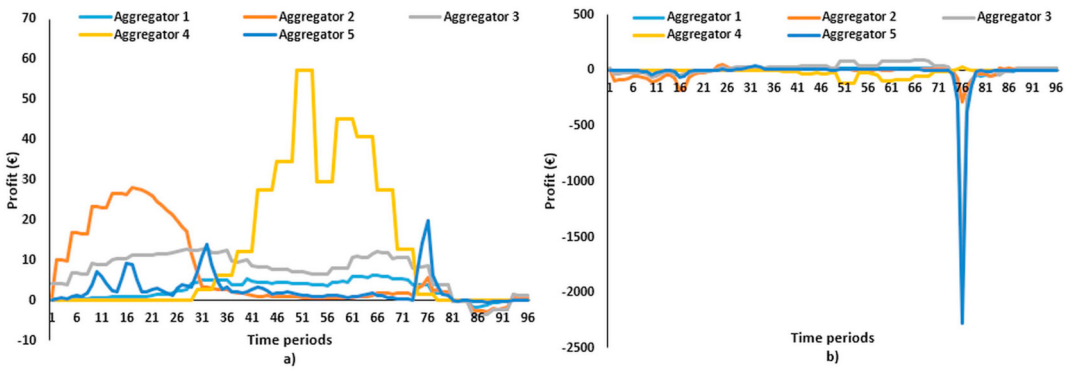

Fig. 5. Variation of the profit o each aggregator in a simulated day or scenario 1. a) Considering no DLMPs. b) Considering DLMPs

For each scenario, using the values presented in Table 2, for the case without the existence of the DLMP strategy, the highest profit was presented by aggregator 4, which is the DG aggregator. After implementing the DLMP strategy, it can be seen from the table that the values are quite negative, especially for aggregator 5, which presents the worst profit.

From the results presented, the price variations did not change significantly from scenario to scenario. This situation means that changing the market prices does not improve the proposed models, given that prices have not changed considerably with the averages.

The DLMPs are an excellent strategy for network management. As far as the aggregators are concerned, these without the presence of DLMPs always show high profits for the simulated day, especially the aggregator 4, with the business model implemented. With DLMPs, the situation is already opposite since aggregators 4 and 5 are the ones with the most negative profits. Aggregator 4 is due to the model implemented for this aggregator, where it sells energy

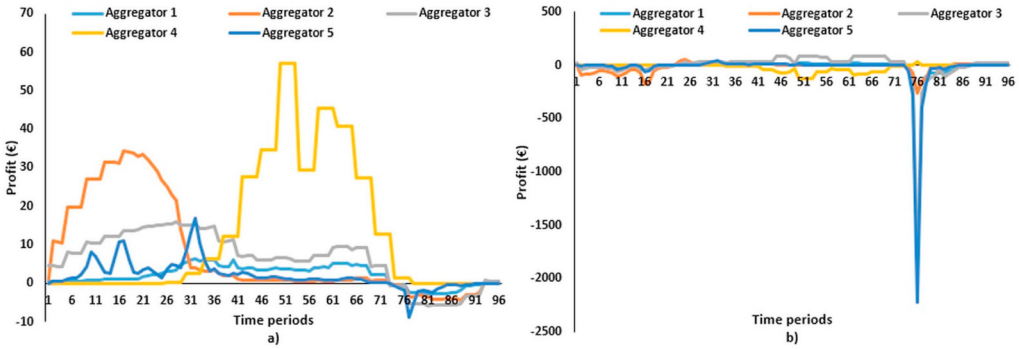

Fig. 6. Variation of the profit o each aggregator in a simulated day or scenario 2. a) Considering no LMPs. b) Considering LMPs

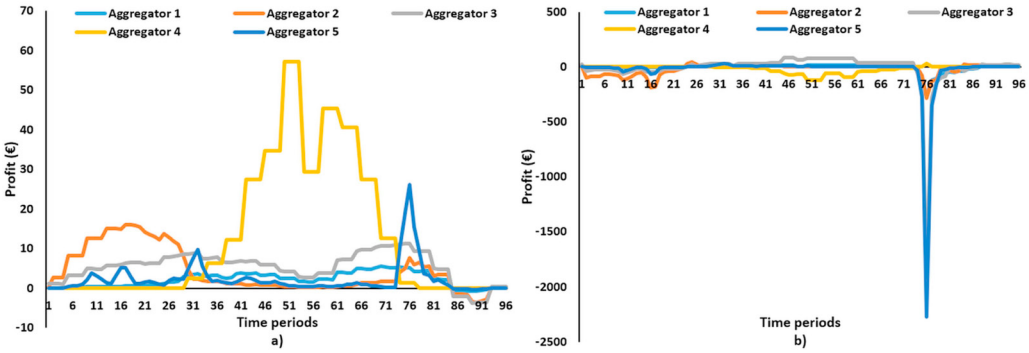

Fig. 7. Variation of the profit o each aggregator in a simulated day or scenario 3. a) Considering no LMPs. b) Considering LMPs

Table 2. Total profit of each aggregator for the simulated day in each scenario (in €).

Aggregators	Scenario 1		Scenario 2		Scenario 3	
	No DLMPs	DLMPs	No DLMPs	DLMPs	No DLMPs	DLMPs
1	256.97	-295.49	192.43	-445.05	207.39	-376.26
2	666.02	-1762.55	722.79	-1588.55	410.79	-1972.26
3	713.74	-724.53	622.54	-905.18	522.20	-1091.80
4	1190.26	-1864.51	1190.26	-1955.95	1190.26	-1841.12
5	247.09	-3119.75	184.98	-3182.61	214.32	-3204.42

at the price of the DLMP and still pays the incentive to producers. Aggregator 5, on the other hand, is because there is a high penetration of EVs in the network, which causes high congestion on the lines where the CSs are located.

This strategy concludes that the tariff at which aggregators sell their energy is not sufficient to pay the surrounding costs. Several strategies can resolve this situation, the simplest being for aggregators to increase their sales tariff or pass on the value of DLMP to their customers. Both from a customer perspective would not be advantageous.

DLMPs are an excellent strategy for the network, as mentioned, but not for the various aggregators or customers. Therefore, it can be assumed that this strategy should be implemented in situations where there are mechanisms to reduce the risk of congestion, for example, resource management systems for customers.

5. Conclusions

This paper presented some business models for calculating the profit of multiple aggregators, taking into account three scenarios. What varied from scenario to scenario was the value of market prices. These prices were obtained through several averages, one annual and the other two for the winter and summer season.

It was possible to understand the applicability of the models presented, and of course, some assumptions were made that came from some experience already obtained when working with these cases. These assumptions form the work are less realistic, but it was possible to draw several conclusions about the results obtained. If there is congestion in some lines, the amount to be paid at the points where these lines are inserted will be significant, as was found in the aggregators' profit, mainly in aggregator 5, which was the aggregator of the CSs. Because there was a high penetration of EVs, congestion was higher on lines supplying power to CSs due to vehicles' high demand. In other words, DLMP is a good strategy from the network's point of view, as the aggregator will try to pay incentives to the customer to alleviate this congestion to avoid the situation of a loss of profit. If it is not possible as a last resort, the DLMP will be deducted by the customer itself, which both entities' interests. Here customer management systems can be implemented by the client to alleviate their demand.

As future works, the presented business model can be simulated with new tariffs. Moreover, another business model can be present where the aggregator passes the cost of DLMPs to its customers, as explained in Section 4. Other strategies could be implemented in this case study as demand response strategies, where there could be a demand response aggregator. An exciting work would be to implement local market mechanisms in the DN with the various entities involved.

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