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Exploring the Viability of Local Electricity Markets for Managing Congestion in Spanish Distribution Networks

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Abstract: This article presents the methodology and results developed as part of the Integration of Energy Resources through Local Electricity Markets (IREMEL) project, whose aim is to assess the capability of flexibility markets to manage eventual distribution network (DN) congestion produced by a high penetration of distributed energy resources (DERs), including photovoltaic (PV) panels, battery energy storage systems (BESSs), and electric vehicles (EVs). The distribution system simulator OpenDSS has been used to simulate three Spanish DNs under multiple DER penetration scenarios considering an urban and rural low-voltage network and an industrial medium-voltage DN. Likewise, the congestion events detected in the annual simulations have been used to measure the potential of flexibility markets under different DER penetrations and energy pricing. The results suggest that oversized distribution networks could prevent a profitable flexibility market implementation since the simulations developed in this article shows that networks with high congestion levels are prime candidates to solve this issue through a market mechanism. Likewise, the results suggest that a proper price for the energy managed through a local flexibility market (LFM) could have a bigger effect on market viability than DER penetration.

Keywords: local flexibility market; distribution system operator; congestion management; distribution networks; IREMEL project

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1. Introduction

1.1. Motivation

The stability and reliability of distribution networks (DNs) face significant challenges due to increasing penetration of distributed energy resources (DERs) such as photovoltaic (PV) systems, electric vehicles (EVs), and storage systems connected to the system [1], where inappropriate management of these technologies might increase the number of congestion events affecting the grid performance [2]. Recognizing this undesirable effect on distribution networks, in recent years, numerous studies have proposed different strategies and market frameworks for efficient integration and operation of the DERs to address line congestion issues through their participation in the electricity markets, offering different services to the system and customers [3].

Congestion on a DN could occur due to the violation of voltage limits [4] or when the demand for active power transfer exceeds the grid transfer capability [5,6], commonly referred to as overloading. In response to such congestion events, the literature identifies different methods for distribution system operators (DSOs) to address these congestion events, classifying them into direct and indirect methods [7,8]. Direct methods are related to network reconfiguration, reactive power control, and load management, while indirect mechanisms adopt market-based strategies, such that DSOs can harness the benefits of demand-side flexibility to face the challenges of the evolving electricity networks [9]. Proper DER use could handle congestion events in this context by providing flexibility services to DSOs under a market scheme when ancillary services are required [10]. Likewise, flexibility market implementation could significantly reduce investments in network reinforcement, as shown in [11]. As a result, the research community and countries worldwide are currently discussing the potential of market-oriented approaches in addressing congestion issues and optimizing distribution network performance.

1.2. Background

Jin et al., 2020 [12] define the LFM as an electricity trading platform to trade flexibility in geographically limited areas, such as communities, towns, and small cities. The work developed by Ramos et al. [13] understands the LFM as a place where different established parties exchange goods or services under rules previously defined. The Iberian Electricity Market Operator (OMIE) considers a local electricity market as a place where entities connected to the DN can control their consumption or generation following the distributor's requests. In this framework, energy could be traded under a free tariff based on customer requirements (prosumers, producers, aggregators, DSOs). Likewise, negotiations could be organized or monitored by the DSO and could occur in the day-ahead or intraday markets, or any other timeframe allowed by market guidelines.

Considering these definitions as a reference, several studies have proposed different strategies and market frameworks for handling congestion issues via flexibility markets. For example, a recent study by Iria et al. [14] compares the economic, network security performance, communication between actors, computational burden, and privacy requirements of the different strategies in the literature under an aggregator scheme. In the same vein, Shen et al., 2020 [15] formulate an optimal flexibility bidding model for aggregators, which models the energy payback condition and enables the aggregator to receive the maximum revenue with flexibility costs, protecting network privacy by the alternating direction method of multipliers (ADMM). Babagheibi et al. [10] also use the ADMM algorithm for modeling a request and response structure for flexibility service negotiation, addressing the price uncertainty using a robust optimization approach. A peer-to-peer (P2P) transaction mechanism that enables flexibility and energy transactions to support grid stability is introduced by [16] using the Stackelberg game approach for modeling the bidding process. Likewise, a hierarchical approach for local energy and flexibility trading among prosumers is presented by [17] to trade energy via P2P and transact flexibility in the local energy market to manage network constraints. The bilevel programming approach is used by [18] for modeling the flexibility services provided by multi-microgrid to the DN, such that the security constraint economic dispatch is managed at the upper level and the optimal bidding strategies at the lower level.

As a result of the potential use of DERs for handling congestion issues, markets located in EU countries or the USA currently offer the most significant incentives for a DSO to adopt new strategies to address today's energy challenges, including the creation of flexibility markets [19,20]. Within the EU, the development of these markets is guided mainly by Directive 2019/44 [21], part of the Clean Energy Package (CEP) [22], which established standard rules for the internal electricity market. In this document, the EU recognizes flexibility markets as one of the tools to optimize the use of the network, eliminate congestion, and defer investments in network elements. Thus, the CEP establishes that member states (MS) must provide the appropriate legal framework for DSOs to acquire flexibility services from suppliers of Distributed Generation (DG), demand response or energy storage through a market mechanism. It also indicates that DSOs, subject to the approval of the corresponding regulatory institutions, must define the specifications for the flexibility services to be obtained and, if applicable, the standardized products for this market. These specifications must guarantee all market participants' effective and non-discriminatory participation, including those that offer energy from renewable sources, demand response services, managers of energy storage facilities, and aggregators.

The previous context has motivated various initiatives to develop LFMs in the European environment [23], such as the CoordiNet Project [24]. However, most of these are in the early stages of development, such as the pilot in Denmark [11]. Radecke et al. [25] identify 11 projects with the specific objective of developing platform-based solutions to utilize local flexibility to alleviate congestion and broaden the scope of congestion management tools for distribution grid operators. This paper identifies Germany as the country with more incentives and projects in the pipeline, followed by the Netherlands and the UK [25]. In the study by Heinrich et al. [11], a summary of projects that seek to observe the technical feasibility of congestion management methods is presented, including Interflex [26], REnnovates [27], Reflexe [28], Empower and Invade [29], and iPower [30].

1.3. Research Gap and Contribution

The previous section has shown that significant advances have been made in studying LFM modeling, market frameworks and bidding strategies and the current discussion about policy incentives to adopt new market strategies to face energy challenges. However, despite various advances being made toward developing such markets in Spain, there are currently no local electricity markets in operation. At the moment of the IREMEL project release, simulation studies in real Spanish DNs have not been conducted to assess the profitability of these new market schemes. Thus, under this national context, the Institute for Energy Diversification and Saving (IDAE) and OMIE have promoted initiatives studying renewable resource integration through local markets aligning with Directives 2018/2001 [31] and 2019/44 [21], including the IREMEL project [32]. The methods and results in this paper are derived from work done as part of the IREMEL project and focus on performing a technical and economic analysis of a potential LFM to manage network congestion from increased electricity demand and DER penetration for 2030 in Spain. This is done through simulation of network operation in urban, rural, and industrial Spanish networks. The main contributions of this work are as follows:

- A congestion assessment is developed in real-world low- and medium-voltage Spanish DNs characterized by urban, rural, and industrial settings via simulation considering the expected penetration of DERs in Spain by 2030;
- A methodological framework based on Python and OpenDSS programming is implemented to identify the manageable energy required to reduce congestion on different Spanish DNs under several DER penetration scenarios;
- A comprehensive economic assessment is developed to estimate the potential revenues that the participants could receive from an eventual Spanish LFM to address congestion in a DN, considering the manageable energy and reserve market price projections for 2030.

The rest of the paper is structured as follows. Section 2 presents the methodological framework to detect congestion events in Spanish distribution networks by simulating the yearly operation of DERs for different scenario penetration. Section 3, describes the parameters used to model the DNs, load profiles, and DERs. Section 4 shows the simulation results highlighting the congestion patterns for each DN. The revenue sizing for the participants of a potential LFM and the market analysis is addressed in Section 5. Finally, the project conclusions are discussed in Section 6.

2. Methodology

A standardized methodology following the IREMEL project requirements has been developed to create and identify the congestion generated by DER integration into different DNs. These requirements included real-world DNs, which means thousands of lines–buses and managing hundreds of DERs in a one-year time horizon with one-hour time steps. In this context, optimization techniques were not considered because optimization models based on AC-optimal power flow constraints involve a high computational burden [14], and hence, they cannot address the project requirements even using algorithms based on decomposition methods. Thus, OpenDSS [33] was chosen to simulate the yearly operation of the different balanced Spanish DNs while a Python code managed the data related to the scenarios, load, and random allocation. Figure 1 provides a general process overview and highlights the tool used in every step.

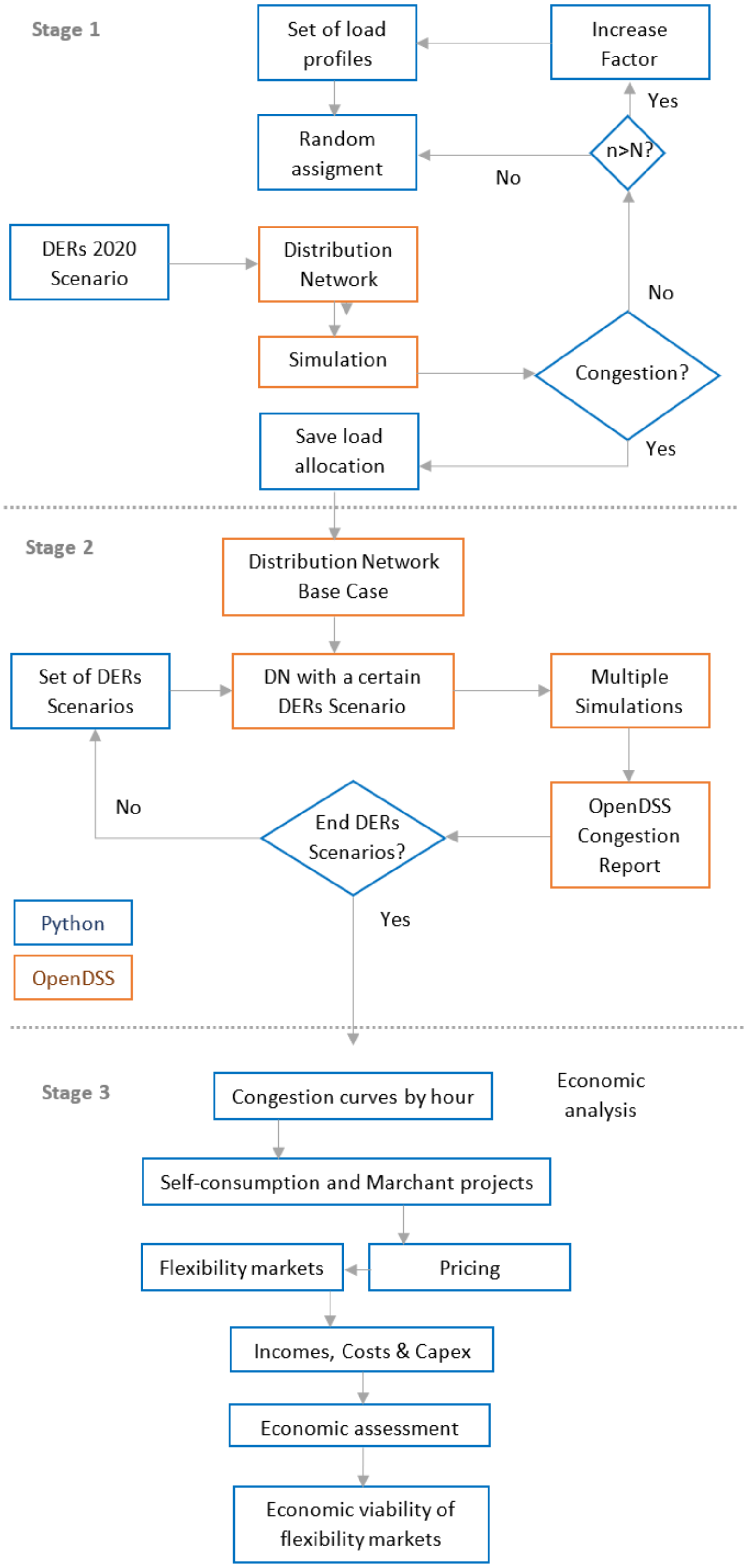

Figure 1. Methodology.

2.1. Stage 1: Setting the Base Case

The first stage seeks to define the DN base case considering 2020 DER penetration levels and allocate load profiles to generate low congestion levels. For each particular grid (in this article: urban, rural, or industrial DN), a set of load profiles is randomly assigned to every bus, considering the technical node requirements. Likewise, every DN possesses specific DER penetration levels for 2020, based on the trends established in [34]. Thus, when the load profiles and the DERs are assigned, an OpenDSS simulation is run for one year with an hourly time step. If the DN does not present congestion at any level, then the load profiles are randomly reassigned N times; when the iterations are greater than N, the load profiles are increased by a specific factor, and the process starts again until some congestion level is found. When the DN presents any congestion level, the load profile allocations are saved as the DN base case. In practice, the N iteration tries depended on the DN but never exceeded 30 tries.

2.2. Stage 2: Creating Expected 2030 Scenarios

In the second stage, using the DN base case obtained in the previous step, the load profiles and the DER penetration are increased, depending on the expected 2030 values set according to the trends reported in [34]. Thus, for each scenario, 15 simulations are run in OpenDSS such that every simulation considers a random allocation of DERs. That is, for a particular scenario, each simulation assigns the DERs randomly to available buses, considering the loads and bus requirements established in the first stage, generating multiples subscenarios, always respecting the DER penetration levels defined by the principal scenario. In addition, each simulation generates a congestion report developed by OpenDSS, which indicates, among other things, the voltage levels at every hour and the energy not supplied due to technical network violations. All of these reports are saved and aggregated in a consolidated report used as input for the market analysis.

2.3. Stage 3: Economic Assessment

Finally, the hourly congestion levels obtained from the simulations carried out for every DN and scenario are used in the market analysis (stage 3) to assess the economic viability of the local flexibility markets considering different assumptions for key parameters such as operational and investment costs, access to financial support, future energy pricing, and LFM operational framework.

The DER technologies include PV systems, EVs, and BESSs, while HPs are considered to measure part of the thermal electrification. The customers considered in the article are residential, commercial, and industrial, and six scenarios are defined to study the congestion in the urban, rural, and industrial networks: 2020, 2030, 2030-HP, 2030-PV, 2030-BESS, and 2030-EV. The first scenario considers DER penetration in Spain in 2020 and the second, the expected DER penetration in 2030. The remaining scenarios use the 2030 scenario and increase the penetration of one particular technology.

A subprocess is defined to properly include the random allocation of a DER with its respective rated power into the DN as shown in Figure 2, which summarizes the assignment process applied to the scenarios belonging to the rural and urban DNs. Firstly, every bus is classified to accept EV charging, residential, or commercial loads, according to the technical limits of the nodes. Secondly, for each residential and commercial category, five new labels associated with five load ranges are created to differentiate between different building consumption levels typical to residential and commercial uses. Then, the set of load profiles, classified into residential and commercial, with their respective power-rated label, are randomly allocated based on the bus classification and category.

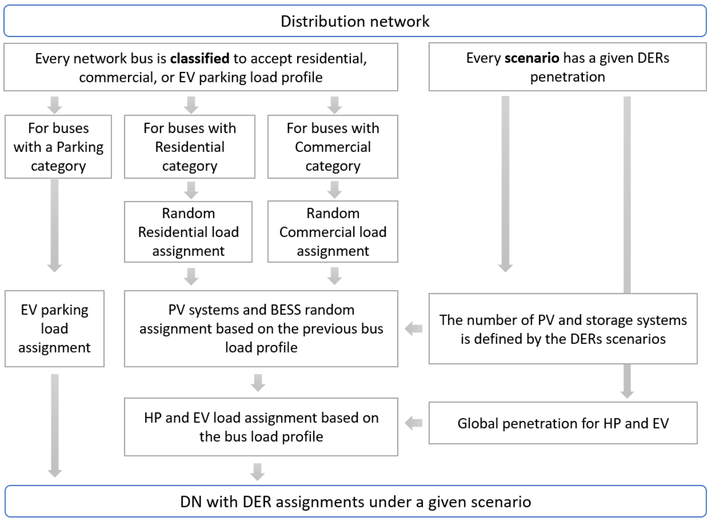

Figure 2. Random assignment process.

In parallel, the number of PV systems and BESSs required to fulfil a given DER scenario is estimated based on the load profiles categories and the typical sizes reported by the Spanish self-consumption report [35]. e.g., the residential category RC1 accepts load profiles with a power rating between 1.5 and 4 kW, therefore, the PV system assigned to this category is 3 kW. A similar process is followed to add the HP and the EV load to the residential and commercial load profiles previously assigned. The load profiles used in every case are adequately addressed in the next section. Thus, different load profiles are randomly allocated into the DN with their respective distributed resources, based on a global DER penetration.

The process is more straightforward for the industrial DN because the load profiles are individually assigned based on the industrial park configuration that serve to built the network model. Thus, the DERs are allocated following the load rated power of every individual customer without considering EVs and HPs.

3. DER Modeling, Scenarios, and Networks Parameters

The following subsections describe in detail the process for modeling DERs in OpenDSS, the different scenarios, and the DN technical parameters.

3.1. PV Systems Modeling

The main parameters required to model PV systems into DNs through OpenDSS are the nominal power of every PV system installed, the bus where the system is installed, the temperature, and the irradiance [36]. Other parameters like nominal voltage, efficiency, power factor, number of phases, inverter nominal power, and the relation between power and temperature are constants, and depend on the main parameters or are defined by default. The hourly temperature and the irradiance were obtained from [37], corresponding to the city of Barcelona, which has a Mediterranean climate. As explained previously, the allocation is assigned randomly in each simulation, and the rated power is classified into five categories, as shown in Table 1.

For residential PV self-consumption, it is assumed that the average size in Spain for PV systems is 3.5 kW for homes and 1 kW per floor in multi-family buildings based on experience from IDAE [38]. For commercial PV systems, a minimum power of 20 kW and a maximum of 100 kW were assumed, considering the topology of commercial buildings included in the model. For industrial consumers, a minimum value of 50 kW and a maximum of 1000 kW have been considered for self-consumption systems. In addition, a PV system with a power of 1.8 MW is considered in the industrial network as an extra scenario.

Table 1. PV and BESS capacity installed by category and by network.

DN	System	Cat 1 [kW]	Cat 2 [kW]	Cat 3 [kW]	Cat 4 [kW]	Cat 5 [kW]
Industrial	PV-Ind	50	100	200	500	1000
	PV	1800	3000	0	0	0
	BESS	25	50	90	170	250
Rural	PV-R	4	6	8	10	20
	PV-C	4	6	8	10	20
	BESS-R	4	4.6	6	7.2	8
	BESS-C	8	16	26	32	40
Urban	PV-R	4.5	8	10	15	20
	PV-C	20	40	65	80	100
	BESS-R	4	4.6	6	7.2	8
	BESS-C	8	16	26	32	40

3.2. BESS Modeling

OpenDSS allows the modeling the storage devices through a curve representing the hourly demand/prices and two charges/discharges parameters, called ChargeTrigger and DischargeTrigger, respectively, [33]. Thus, when the curve is below the ChargeTrigger value, the battery starts charging, and when the curve is above the DischargeTrigger value, the battery discharges. In this way, the batteries associated with a PV system follow the respective load consumption curve (BESS-D), and the batteries without a self-generation system follow the market price curve (BESS-P). Note that the BESSs are modeled using the trigger mechanism available in OpenDSS, and they do not solve an optimization problem.

3.3. Heat Pumps

The HP loads curves (HP-R, HP-C and HP-I) have been modeled separately from the load consumption to manage different HP scenarios. The average power values estimated by IDAE in [39] for residential and commercial Spanish consumers are 12 kW per single-family home, 5 kW per floor, and 0.075 kW/m^2 in commercial buildings. Industrial HP curves have not been considered because the HP consumption depends on the business activities performed by the user, which does not allow for an average treatment like those of residential and commercial users.

It is assumed that the HP total installed power is sized based on the hour with the highest thermal difference reported in the year. In hours when the internal and external temperatures are within less extreme operational ranges, the HP power used is adjusted proportionally keeping the comfort indoor temperatures at 26 °C in summer and 21 °C in winter. The coefficient of performance (COP) for the 2020 scenario is based on [39], and for the 2030 scenario, the HPs considered include only COPs greater than or equal to 3.5, as shown in Table 2. The 2020 annual HP loads have been contrasted with [40], which simulated the heating and cooling need for single-family homes and flats in Seville and Madrid, obtaining similar results.

Table 2. Percentage of heat pumps considered by sector according to their COP.

	Residential		Commercial	
COP	**2020**	**2030**	**2020**	**2030**
1.5	-	-	0.3%	-
2.5	15.4%	-	17.2%	-
3.5	55.6%	15.4%	60.2%	17.5%
4.5	26.3%	55.6%	21.2%	60.2%
5.5	2.7%	26.3%	0.6%	21.2%
6.5	-	2.7%	0.5%	1.4%

3.4. Electric Vehicles

EV charging curves for public parking, commercial, and residential profiles are developed from information reported by [41] regarding daily charging station usage, connection frequency per hour and EV type, and average electricity consumption per charging event. Ten profiles are created for each category considering the trends presented in [41]. For public parking spots, 10 extra profiles are built considering a higher usage frequency, as it is assumed that in the scenarios with higher EV usage, public charging points will be used more frequently. In this way, four EV profile categories are established: public EV parking with high demand (P-EV-H), public EV parking with regular demand (P-EV-R), charging point for commercial EV (EV-C), and charing point for residential EV (EV-R). The profiles have an average consumption of 3.25 MWh/year, 2.5 MWh/year, 2.7 MWh/year, and 2.55 MWh/year, and a occupancy factor of 22%, 15%, 20%, and 18%, respectively.

3.5. Distribution Networks and Load Profiles

Table 3 presents the main parameters of the three balanced Spanish DNs used to run the simulations. The urban grid [42] is the biggest, with 10,290 lines and 8087 loads. It includes 30 transformers, which divide the DN into 30 electrical zones that allow us to study congestion events separately as well as defining zones with different profiles: residential, commercial, or mixed zones. The rural network is a smaller grid with 1908 lines and 562 load points, and 19 transformers that do not divide the network into zones. The industrial network includes only industrial load profiles, 160 load points, 1050 lines, and 2 transformers. Figure 3 shows the urban and rural topologies where the red points indicate the transformers and the blue crosses the load points. The details of the network characteristics have been provided by Energias de Portugal (EDP) and the Cuerva Group for the simulation of the rural and industrial networks, respectively. However, for reasons of confidentiality agreements in place in the IREMEL project, the details of the network characteristics are not reported in this article. Likewise, the electricity consumption profiles of these two networks have also been protected for confidentiality reasons but correspond to real metering data for rural and industrial Spanish networks. For the urban network case, the load profiles have been obtained from [43] and normalized to adjust them to the peak load reported in the original urban network in [42].

Table 3. Distribution networks parameters.

	Urban	Rural	Industrial
Type of DN	LV	LV	MV
Rated Voltage [kV]	22–0.42	22–0.42	66–20
Frequency [Hz]	50	50	50
Nº Transformers	30	19	2
Nº Lines	10,139	3531	1038
Nº Breakers	36	26	0
Nº Buses	10,290	1908	1050
Nº Loads	8087	562	160

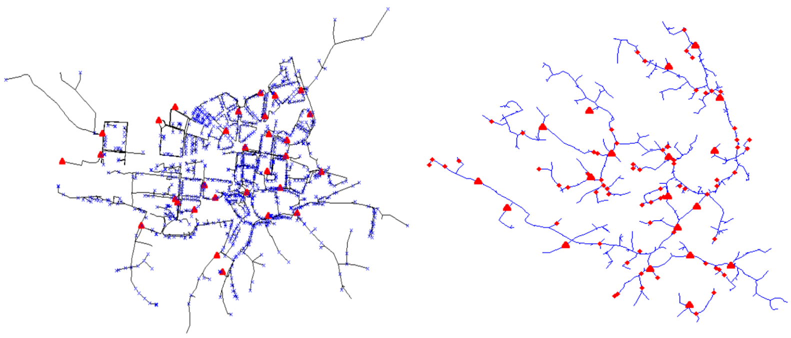

Figure 3. Urban (**left**) and rural (**right**) distribution networks modeled in this study.

4. Simulation Results

A total of 15 simulations have been executed for each of the five scenarios corresponding to the three DNs, resulting in 225 simulations using the weather conditions of Barcelona, Spain. Table 4 presents a summary of the results obtained in the 2030 scenario, including the number of residential, commercial, and industrial buildings considered in every simulation, as well as the total energy consumption and energy not supplied (ENS) produced by congestion events. The results are averaged for each of the 15 simulations and five scenarios. Note that OpenDSS simulations compute the ENS as the total energy at risk of not being supplied due to potential failures in the DN due to exceeding normal voltage limits. Thus, the ENS is divided into normal and emergency congestion corresponding to voltage level violations. Normal voltage violations are between 0.95 and 1.05 pu and emergency conditions are between 0.9 and 1.08 pu. Thus, the results show that the rural grid possesses a lower number of violations than the urban and industrial networks. Only 0.08% of the total energy demand is not supplied in the rural network, in contrast with 1.94% in the industrial grid.

Table 4. Global results. SC: Self-consumption.

Parameter	Urban	Rural	Industrial
Nº Residential properties	2035	495	-
Nº Commercial properties	360	1	-
Nº Mixed properties	-	30	-
Nº Industrial properties	-	-	160
Nº Parking for EVs	50	10	16
Nº PV systems not to SC	-	-	2
Avg. Annual demand [MWh/year]	97,034	3758	356,417
Aggregated peak demand [MW]	25.54	0.98	71.74
Avg. Energy not supplied [MWh]	780.15	3.06	6924.05
Avg. Energy not supplied [%]	0.80%	0.08%	1.94%
Avg. Normal Congestion [MWh]	772.35	2.96	6923.83
Avg. Emergency Congestion [MWh]	0.07	0.096	0.22

The industrial grid does not include the HP scenario but instead includes a new scenario in which an extra PV system is considered, which is not related to any customer. Despite being much smaller than the other networks, the consumption in the industrial DN is significantly higher than in the urban and rural grids due to the customers' consumption profiles. Specifically, the average consumption is 231 kW for the industrial grid, 4.5 kW for the urban network, and 0.8 kW for the rural case.

Congestion Patterns

The graphs in Figure 4 include two vertical axes to analyze patterns related to the occurrence and intensity of congestion based on the ENS delivered by OpenDSS simulations. The left axis represents the probability of congestion, while the right axis indicates the magnitude of the congestion as a percentage of the total electricity load. In general, congestion levels in urban and rural networks represent a maximum of 5% of the total demand during critical hours, with varying timeframes for congestion occurrences. For instance, in the rural network (see Rural 2030), there is a 30% probability of network congestion between 19:00–20:00 h, but the energy involved represents only 2% of the total demand. Conversely, in the morning, the probability of congestion is close to 10%, but the power involved reaches 4% of the total demand. In other words, in the morning hours, we observe more congestion volume with a small occurrence probability than in the afternoon, when the probability of congestion is greater, but the level of congestion is lower. This pattern persists in the rural network even with a high penetration of PV systems; however, congestion issues intensify during the middle of the day, when the solar panels are active.

Similarly, in rural scenarios where heat pumps are widely adopted (see Rural 2030 BC), the probability and energy involved in congestion events increase during nighttime hours.

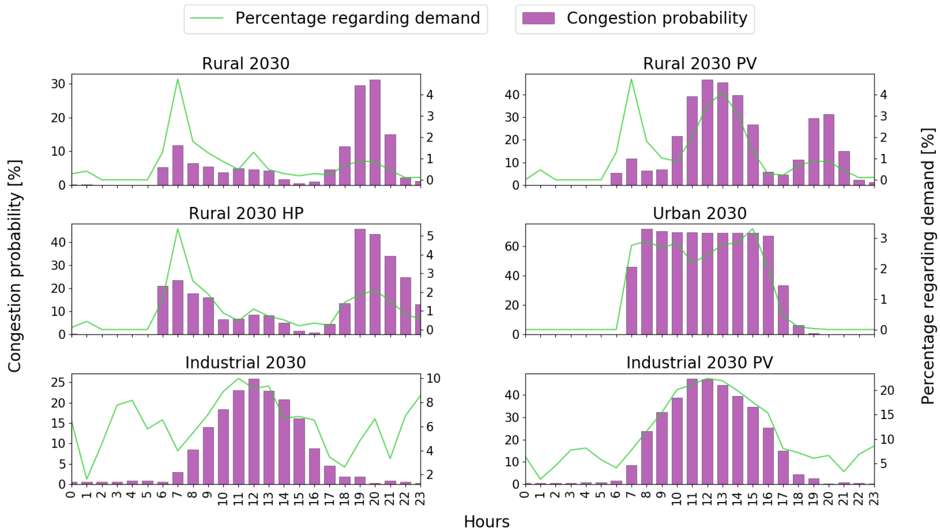

Figure 4. Congestion patterns detected for the different distribution networks.

No significant changes in congestion patterns were identified in the urban network compared to the base scenario. In this regard, the Urban 2030 case in Figure 4 reveals a high probability (around 60%) of congestion occurring at 7 a.m. and 5 p.m., explained mainly by under-voltage issues. However, these congestion events would only account for 3% of the total demand. Conversely, in the industrial case, congestion is observed during the early morning, solar panel operation, and nighttime. Nevertheless, the probability of these events occurring is generally low (less than 5%), except for congestion related to PV panels, which has a probability of approximately 25% in the base scenario and increases to 40% in the scenario with a higher penetration of solar panels. Finally, in the industrial case, congestion magnitudes when PV panels are not operational remain below 2%, while during panel operation hours, they can range from 10% to 20% of the total demand. Note that from the 15 scenarios tested, only 6 show a congestion pattern, and among them, congestion levels surpassed 5% of the demand only in 2 cases. Thus, these simulation results support the idea that the oversized Spanish distribution networks could have low volumes of manageable energy in 2030, so a flexible market to manage these events may not be required unless external mechanisms promote its operation.

5. DER Economic Viability Assessment

This section uses the congestion levels detected in the simulations to quantify and assess under what pricing and market assumptions DERs are an economically viable mechanism to manage congestion events. Thus, the day-ahead and intraday markets are the energy markets modeled in this analysis, considering the NPV, payback, and IRR as the main criteria for assessing the viability of different case studies.

5.1. Case Studies

A total of 10 different case studies grouped in two sets, namely Self-consumption and Merchant projects, have been considered to assess the viability of DERs to manage congestion events. The Self-consumption group includes four individual cases considering the most common archetypes in the networks and assumes they have additional economic aid from the market price to operate in a flexible market. Thus, the first case corresponds to a rural single-family house (Case IA), the second to a user belonging to the service sector (Hotel) in an urban context (Case IB), the third to a food-producing factory in an industrial estate (Case IC), and the fourth to a collective self-consumption case, which considers a building with 20 families in an urban context (Case ID). Table 5 shows the parameters used for each case, considering cases with and without a BESS to measure the effect of a BESS on case viability. Conversely, the second group corresponds to the Merchant projects, including two case studies: a PV system not associated with any user (Case III) and a battery dedicated to energy arbitrage (Case IV). In both cases, it is assumed that they do not have additional economic incentives, so their viability depends entirely on the income obtained from the sale of energy in the markets. However, the economic incentives are replaced by three different pricing scenarios—Optimistic, Trend, and Pessimistic—based on the expected evolution of technologies in 2030.

Table 5. Parameters for the self-consumption cases. SC: Self-consumption.

Indicator	Case IA	Case IB	Case IC	Case ID
Power PV installed [kW]	4	70	50	11.2
BESS capacity [kWh]	4.6	35	25	5.6
Energy from PV system [MWh/year]	6.4	111.4	79.6	17.8
Energy demanded [MWh/year]	14.5	346.5	79.1	41.4
Self consumed energy without BESS [%]	58.5%	91.7%	50.0%	60.5%
Demand covered by SC without BESS [%]	25.7%	29.5%	49.7%	26.1%

In this analysis, it has been assumed that the local market would work through an auction scheme at the distributor's request after the forecast of congestion in some areas under its jurisdiction. Such congestion forecasts will be obtained with the previous methodology for the different scenarios proposed in the industrial, rural, and urban network models. Thus, for each hour where there is a voltage imbalance, above or below normal limits, it is considered that there is a need to activate the local flexibility market to acquire local products. In this regard, this study assumed that the market has appropriate policy regulation and the economic incentives to manage congestion issues using the DER's flexibility via an LFM. The reason for this strong assumption relies on the study's aim, which is to quantify the operational margin of a flexibility market and estimate an upper limit for its economic viability. Hourly prices from the continuous intraday market in 2019 and the price projection for the daily market proposed by OMIE around 2030 were used. Similarly, the day-ahead market prices are projected to 2030 based on the the day-ahead market prices from OMIE. These prices represent the E0 price scenario. Three additional scenarios were created to add sensitivity to day-ahead market prices considering the average price per Megawatt-hour for the year to be 10%, 35%, and 45% higher than in scenario E0, corresponding to the scenarios E1, E2, and E3, respectively.

5.2. CAPEX and OPEX

Table 6 presents the investment (CAPEX) and operation and maintenance (OPEX) costs used for each case evaluated in this study. All values have been taken from projections to 2030 made by the Joint Research Center (JRC) [44]. The costs used for the IC Case correspond to those projected for a large-scale system with fixed tilt solar. In the cases evaluated for domestic users (Case IA and Case ID), the projected cost for residential systems is used, while for Case IB—in a commercial building—the projected costs for commercial-scale photovoltaic systems are considered. In addition to the OPEX values, an additional cost has been considered—introduced in the model in year 15—for replacing the inverter, whose useful life is shorter than those of the other components. According to the projections by the Fraunhofer Institute for Photovoltaic Solar Systems [45] for the year 2030, it is assumed that the cost of this component is equivalent to 7% of the initial CAPEX. In terms of the operational degradation of the system, an annual reduction in efficiency of 0.5% is considered, which gives an aggregated annual factor with a mean of 18.17% under the meteorological conditions of the base case (Mediterranean-North climate).

The costs of lithium-ion batteries correspond to those projected to 2030 under the moderate learning curve in a study by Tarvydas [46] that evaluates possible cost scenarios for batteries in mobile and stationary applications. For BESS-A, which is associated with residential systems (PV-R), the cost of a residential lithium-ion battery system was used. The OPEX of storage systems for residential users is assumed to be zero, as in [47], while for the other applications, it is assumed to be equal to 2% of the CAPEX [48]. Additionally, for all BESS systems analyzed, an annual battery degradation of 0.5% is assumed [49], and a maximum depth of discharge of 90%.

Table 6. CAPEX and OPEX estimation for Self-consumption and Merchant projects.

		PV System			BESS		
Case Study	**Scenario**	**CAPEX [€/kW]**	**Annual OPEX [% CAPEX]**	**Lifetime**	**CAPEX [€/kWh]**	**Annual OPEX [% CAPEX]**	**Lifetime**
Case IA	Residential–Rural	995.03	2%	25	427	0%	25
Case IB	Commercial	839.56	2.50%	25	489.7	2%	25
Case IC	Industrial	746.27	1.70%	25	489.7	2%	25
Case ID	Residential–Urban	995.03	2%	25	427	0%	25
Case III	Optimistic	404.23	1.70%	25	-	-	-
Case III	Trend	746.27	1.70%	25	-	-	-
Case III	Pessimistic	901.75	1.70%	25	-	-	-
Case IV	Optimistic	-	-	-	227.03	2%	25
Case IV	Trend	-	-	-	289.14	2%	25
Case IV	Pessimistic	-	-	-	332.91	2%	25

For Merchant projects, the PV system costs are presented in Table 6 and correspond to those projected for large-scale systems [44]. The other assumptions are the same as those considered for Self-consumption PV systems. Likewise, for Case IV—which considers a BESS for energy arbitrage—the costs projected for 2030 by JRC [46] for stationary lithium-ion battery systems designed for energy applications were used, assuming an OPEX equal to 2% of CAPEX [48]. As in Case III, three scenarios were considered: the expected scenario that corresponds to projected prices under a moderate technological learning rate, the optimistic scenario that considers a fast learning rate, and the pessimistic scenario with a slow learning rate.

5.3. Other Considerations

Within the cases of self-consumption, the surplus energy generated and not consumed by the user is discharged into the network for sale in the available global and local energy markets. A tax on the Value of the Production of Electric Energy (IVPEE) is assumed for incomes generated by selling energy, corresponding to 7%. Likewise, it was assumed that the user pays 2% of the income generated to the trading company—or aggregator—that manages the sale of energy in the corresponding electricity markets.

For self-consumption in the industrial-type network (Case IC), three types of incentives are considered following the provisions of incentive programs 1 and 2 of Royal Decree 477/2021 [50], aimed at self-consumption facilities with renewable energy sources in the service sector. The incentives vary according to the size of the company requesting the incentive and are applicable to the total cost of the asset. Thus, for Large Companies (LC), the applicable percentage is 15%, while for Medium Companies (MC), it is 25%, and for Small Companies (SC), 35%. Similarly, industrial-type users have access to three levels of support for BESS installation: 45% for LCs, 55% for MCs, and 65% for SCs.

The profitability of the projects is analyzed using the potential variable income that each of these could obtain under the different DER scenarios and price conditions considered. Additionally, the impact of using different discount rates—low, medium, and high—is evaluated (5%, 7%, 9%). Thus, to be considered viable, the project should have a positive VAN, a Payback Period shorter than the asset's useful life, and a TIR higher than the discount rate set for each user based on their typology and risk level. However, the cost of operating the flexibility market was not included in the VNP analysis, so the NPV could be slightly overestimated.

5.4. Projects Feasibility

Table 7 summarizes the economic assessment developed for every case study considering different pricing and scenarios. Specifically, for Case IA, although economic incentives are not necessary to achieve economic viability, their use increases the IRR by an average of 14%, which would help the cases maintain their profitability even using credit financing. However, the discount rate and chosen price impact each case's NPV and payback. The economic model for Case IB finds that installing a PV system is viable in all the cases evaluated, even considering the low price scenario and the highest discount rate. The payback without incentives varies between 8 years for the most favorable case (price scenario E3 and a discount rate of 5%) to 15 years for the most unfavorable case (price scenario E0 and discount rate of 9%), and the IRR is between 35% (E0) and 47% (E3). All the financial parameters improve when considering incentives, reaching a payback lower than five years.

Incorporating BESSs in the model does not improve the financial results; however, the projects maintain their viability in most cases. In fact, when including incentives, all price scenarios offer a profitable case, even at discount rates of 9%. When considering the total cost of the asset, without economic incentives, the project is no longer profitable for the price scenarios E0 and E1 under a discount rate of 9%. Likewise, considering economic incentives increase the IRR values between 18% and 23%. Conversely, even with incentives, the payback for cases including BESSs decreased to less than five years for all the analyzed scenarios.

The economic model results for Case IC without storage show that all the cases analyzed are viable when considering the discount rate of 5%, which is low for this type of user. However, with higher rates, the project's viability depends on the price scenario and the level of incentives. When not considering any incentives, the project is unfeasible for price scenarios E0 and E1, with discount rates of 7% and 9%. It should be remembered that 7% is the average rate applicable to this type of user [35], so the results obtained for this value are especially relevant. Likewise, when considering the discount rate for LC, the E0 scenario is not viable for these values, but profitability levels are reached under the E1 scenario and the 7% discount rate. When considering incentives for MC—which covers the results shown in Table 7—all cases are viable except for scenario E0 with a discount rate of 9%. Likewise, adding BESSs does not improve the economic results, and the effect on the DER scenario is minimal, especially when only the PV system is considered. By incorporating the batteries, the variation between the IRR values obtained for each DER scenario is greater, but the differences do not exceed 1% and only occur in some scenarios (2030 PV, 2030 PV2, 2030 VE). Conversely, considering incentives has a greater impact, especially from zero economic incentives to incorporating the discount applicable to LC, where the IRR increases by 2%. Likewise, considering more favorable price scenarios also impacts the IRR values, especially when comparing the results of scenarios E2 and E3 (which present similar metrics to each other) against those obtained for scenarios E0 or E1.

The Merchant project, Case III, is viable only considering optimistic costs for the price scenarios E1, E2, and E3. In this regard, profitability is only achieved with a discount rate of 5%, considered low for this type of project but still within reasonable investment values. For price scenarios E2 and E3, the optimistic case is profitable under all defined discount rates, including the high level (9%). The IRR values obtained for the optimistic cost scenario are: 2% for the price scenario E0, 6% for prices E1, and 11% for prices E2 and E3. Likewise, the payback period for the viable cases found within this project varies between 11 years under the most favorable conditions (prices E3 and a discount rate of 5%) and 19 years in the case of scenario E1 (which is only viable considering a discount rate of 5%).

Table 7. Economic assessment results developed for every case study considering different pricing and scenarios. Dr: Discount rate; O: Optimistic scenario; T: Trend scenario; P: Pessimistic scenario. ✓: Positive NPV, ×: Negative NPV.

		Price E0			Price E1			Price E2			Price E3		
Case	**Scenario**	**Dr [5%]**	**Dr [7%]**	**Dr [9%]**	**Dr [5%]**	**Dr [7%]**	**Dr [9%]**	**Dr [5%]**	**Dr [7%]**	**Dr [9%]**	**Dr [5%]**	**Dr [7%]**	**Dr [9%]**
IA,IB	2030	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	HP	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	PV	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	BESS	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	EV	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
IC,ID	2030	✓	✓	×	✓	✓	✓	✓	✓	✓	✓	✓	✓
	PV	✓	✓	×	✓	✓	✓	✓	✓	✓	✓	✓	✓
	PV2	✓	✓	×	✓	✓	✓	✓	✓	✓	✓	✓	✓
	BESS	✓	✓	×	✓	✓	✓	✓	✓	✓	✓	✓	✓
	EV	✓	✓	×	✓	✓	✓	✓	✓	✓	✓	✓	✓
III O	2030	×	×	×	✓	×	×	✓	✓	✓	✓	✓	✓
	PV	×	×	×	✓	×	×	✓	✓	✓	✓	✓	✓
	BESS	×	×	×	✓	×	×	✓	✓	✓	✓	✓	✓
	EV	×	×	×	✓	×	×	✓	✓	✓	✓	✓	✓
III T	2030	×	×	×	×	×	×	×	×	×	×	×	×
	PV	×	×	×	×	×	×	×	×	×	×	×	×
	BESS	×	×	×	×	×	×	×	×	×	×	×	×
	EV	×	×	×	×	×	×	×	×	×	×	×	×
III P	2030	×	×	×	×	×	×	×	×	×	×	×	×
	PV	×	×	×	×	×	×	×	×	×	×	×	×
	BESS	×	×	×	×	×	×	×	×	×	×	×	×
	EV	×	×	×	×	×	×	×	×	×	×	×	×
IV O	2030	×	×	×	✓	×	×	✓	×	×	✓	✓	×
	PV	×	×	×	✓	×	×	✓	×	×	✓	✓	×
	BESS	×	×	×	✓	×	×	✓	×	×	✓	✓	×
	EV	×	×	×	✓	×	×	✓	×	×	✓	✓	×
IV T	2030	×	×	×	×	×	×	×	×	×	✓	×	×
	PV	×	×	×	×	×	×	×	×	×	✓	×	×
	BESS	×	×	×	×	×	×	×	×	×	✓	×	×
	EV	×	×	×	×	×	×	×	×	×	✓	×	×
IV P	2030	×	×	×	×	×	×	×	×	×	×	×	×
	PV	×	×	×	×	×	×	×	×	×	×	×	×
	BESS	×	×	×	×	×	×	×	×	×	×	×	×
	EV	×	×	×	×	×	×	×	×	×	×	×	×

As with Case III, the viability of Case IV depends mainly on the price and cost scenario chosen and the discount rate. Likewise, no profitable scenarios are identified when considering the E0 prices, while for E1, all the DER scenarios are profitable with optimistic costs and a 5% discount rate. Unlike the previous case, for E2 prices, only the desired financial metrics are obtained when the discount rate of 5% and the optimistic cost scenarios are considered. Conversely, using E3 prices, profitable cases are obtained under the 5% discount rate since the E3 scenario has the highest average prices during peak hours, which benefits energy arbitrage projects. Considering the high discount rate (9%), no scenario is feasible, not even under E3 prices. The IRR values obtained are 5% for scenarios E0 and E1, 6% for scenario E2, and 7% for scenario E3. The payback of viable cases is between 15 years for the most favorable (5% discount rate, optimistic costs, E3 prices) and 22 years for the least favorable (5% discount rate, trend costs, E3 prices).

Therefore, some Merchant projects would need supplementary income sources to be profitable in low-price scenarios. Conversely, most Self-consumption projects demonstrated viability, especially when the solar systems were sized according to the users' needs. Finally, we observed that adopting an energy arbitrage scheme could result in significant income within a flexible market context.

5.5. Costs for Managing Congestion Issues

Two alternative schemes were considered to calculate the cost associated with the acquisition of the manageable energy necessary to solve congestion at the distributor level. The first proposal, called the current model, is based on the current scheme for balance markets where the distributor would act as the counterparty of the DERs (Balance Responsible Party, BRP). The second proposal—called the alternative model—consists of a scheme where the participants go to the local market to solve the congestion issue, making an offer that is matched against those of other agents that operate in markets managed by the global market operator (for example, the continuous intraday market).

In the current model, the system operator settles with the distributor the deviation produced by acquiring the requirements activated in the local markets. For each hour where it was considered necessary to activate the local market, a mechanism based on the sign and direction of the deviation within the system was used to estimate the potential income or extra cost that the transaction would represent for the distributor. Energy prices for the current model were constructed using an open database in the I90 files published by REE (Red Eléctrica España) for the year 2019. In the alternative market, the participants make an offer in the intraday market as a counterpart to the offer made in the local market to meet the requested requirement under the pricing framework described previously corresponding to E0, E1, E2, and E3, and applied for both schemes.

In the industrial network, the alternative model has a lower cost to the distributor than the current model, considering the base price scenario E0, which increases in scenarios with higher PV penetration. However, the gap between the two models decreases as market prices increase. Conversely, in the rural network, both models show similar costs (the alternative model is slightly less expensive by 2% compared to the current model), with the difference becoming more noticeable in scenarios with increased solar panel penetration. Finally, continuing the trends in other networks, in the urban network, the alternative model represents a lower cost to the distributor (around 5%) across the different penetration and price scenarios. In conclusion, based on the assumptions considered, the model where market participants manage congestion events through a local flexibility market controlled by a global market operator is, in terms of cost, preferable to the distributor acting as a counterparty.

6. IREMEL Project Conclusions

This article evaluated the formation of congestion in three networks, industrial (MV), urban (LV), and rural (LV), at different levels of DER use, in order to measure the capability of the electricity flexibility market to address congestion. Thus, the valuable information obtained from the previous analyses is summarized below to better understand the impact of using local flexibility markets to manage congestion within DNs.

- The oversizing of DNs will probably be reflected in low volumes of manageable energy to be traded in the local markets. The industrial and urban networks were oversized concerning the demand and distributed generation existing in the network, so initially, it was not possible to observe congestion even under the scenarios with a greater use of DERs. By adjusting the capacity through a proportionality factor, it was possible to identify congestion in both networks to carry out the analyses required in this study. However, this may be the case in many distribution areas, given that Spanish DNs tend to be oversized. Under these conditions, there may be no congestion events, so a flexible market to manage these events would not be required;

- The results suggest that considering different DER scenarios has little effect on project profitability and the benefits of using market mechanisms for congestion management at the distribution level, except for drastically off-trend scenarios. One example is the 2030 PV scenario of the industrial network. In this regard, economic conditions—especially projected market prices—strongly impact the results of the analyses carried out in this study;
- Networks with a significant number of hours with predicted congestion events but relatively low power levels of congestion have an opportunity to benefit more from the implementation of a local flexibility markets than networks with very high levels of congestion for limited hours. In this context, using a market instrument is more attractive if the additional cost that this represents for the distributor is considered. However, for DER participants, it offers a less attractive scenario, especially for Merchant projects. However, it is expected that Self-consumption projects sized according to the user's demand or associated users will maintain their profitability and participate in the local market as an additional activity to self-consumption;
- Self-consumption projects are viable for most of the conditions evaluated, especially when the DERs are dimensioned according to the users' needs. Likewise, incorporating batteries in Self-consumption solar projects was not seen to be financially viable given the assumptions of this study. Similarly, some Merchant projects will require income in addition to that obtained through the markets to be profitable in low price scenarios. Finally, it was observed that an energy arbitrage scheme could generate significant income in a flexible market context.

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