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Two-stage optimization for energy management and power allocation in a Virtual Power Plant of residential microgrids

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Abstract. This paper proposes a dual-stage optimization process for a Virtual Power Plant that aggregates resources from various residential microgrids with photovoltaic generation, energy storage systems, and electric vehicles with bidirectional charging possibilities. The optimization objectives include cost reduction, peak shaving, and flexibility service provision. In the first stage, a genetic algorithm is employed to perform daily energy scheduling for the entire Virtual Power Plant, focusing on economic objectives, peak shaving and participation in flexibility markets. The second stage utilizes non-linear programming to optimize the 1-minute power allocation for each microgrid's resources, aiming to minimize the power exchange between each microgrid and the distribution grid. The proposed method demonstrates significant performance improvements, achieving a 29% reduction in electricity bill, peak shaving of up to 10 kW, and a reservation band of approximately 4 kW for flexibility service provision. The resources of the microgrids exhibit cooperative behavior, collectively achieving the optimization objectives.

Key words. Distributed energy resources; Energy management system; Microgrid; Flexibility market; Virtual power plant.

1. Introduction

Due to the energy transition policies, concerns about climate change, advancements in energy storage systems (ESS), renewable production technologies and electric vehicles (EV), there is a significant increase in the presence of distributed energy resources (DER) connected to distribution systems. This situation presents a new challenge for power systems: integrating as much renewable energy as possible without causing grid congestion and instability. The European Commission considers that incorporating flexibility into power systems (in generation, storage, and demand) will enhance the balance between generation and demand, thereby reducing dependence on fossil fuels and minimizing renewable energy curtailment [1]. The International Energy Agency defines power system flexibility as the ability to respond in a timely manner to variations in electricity supply and demand.

Residential prosumers are a primary source of distributed renewable energy production. However, the low power of both demand and generation restricts their business opportunities and their ability to contribute to distribution grid support. Aggregation is the solution to this constraint, forming the basis for Virtual Power Plants (VPP), which aggregate and centrally manage resources (renewable/non-renewable generation, controllable loads, ESS, and/or EV), that are not necessarily geographically close together, to increase their relative weight in electricity markets and ancillary services. By means of the joint management of DERs, the development of VPPs constitutes a means for better integrating and managing renewable energy systems as well as EV charging, with the help of ESS, valuing their economic and technical impact on power systems.

Conversely, distribution grid support must be provided locally to avoid congestion in specific sections of the grid. For this purpose, microgrids (MG), composed of neighboring resources that can be managed collectively, are recognized as an effective aggregation system for grid support. The aggregation and energy management of these resources are thoroughly analyzed in [3]. One advantage of the aggregation of DERs lies in the suitability of a higher-power joint resource to provide flexibility services. Transmission system operators count on multiple flexibility services, like the so-called ancillary services, to guarantee generation-demand balance. However, these kinds of services in distribution systems are still in development. Initiatives like the EPEX Spot Localflex trading [4] constitute a bidding flexibility market where DERs offer flexibility assets, like power reservation bands.

Other works have been published in scientific literature that address optimization of resources in VPPs and MGs. A summary of some relevant ones is included here for comparison. Authors in [5] propose Differential Evolution (DE) approach to solve the optimization problem in which the first scenario focuses on scheduling MG generation considering objective functions related to operating cost and pollutant emissions, without incorporating demand response systems. On the other hand, the second case scenario involves scheduling generation while incorporating demand response programs. Paper [6] presents the Building Virtual Power Plant (BVPP) concept, detailing its architecture, implementation, operational modes, and an optimized O-BVPP system that enhances demand response by analyzing and optimizing household energy usage. The O-BVPP uses SimHouse to analyze appliance usage in 500 households, clusters inefficient users via Fuzzy C-Means (FCM), and provides personalized energy-efficient usage plans, enabling demand response awareness and cost savings. A VPP application programming interface (API) architecture and data model for integrating DERs, enabling primary frequency reserves and energy forecasting in Northern Europe is presented in [7]. Paper [8] proposes a coordinated control method for a VPP integrating PV systems and controllable loads, optimizing power output via mixed-integer programming (MIP) to enhance frequency support and economic efficiency in an islanded MG. Authors in [9] include distributed frequency control for state of charge (SoC) balance, ESS aggregation using distributed state observers, and energy management for optimal power allocation. A digital twin model for incremental aggregation of multi-type load information in hybrid MGs, ensuring data integrity despite losses or inconsistencies, is proposed in [10]. Using the Leida criterion, cubic exponential smoothing, and an improved K-means algorithm. Article [11] proposes an optimal MG energy storage allocation method that considers the uncertainty of renewable energy generation using a multi-day scenario set by employing K-means clustering, Latin hypercube sampling, and a conditional generative adversarial network, the method constructs a double-layer optimization model. Paper [12] proposes a hybrid scheme combining the flower pollination algorithm (FPA) and phasor particle swarm optimization (PPSO) to improve generation planning in MGs. Authors in [13] propose a power allocation optimization strategy for distributed electricity-H_2 VPPs with aggregated flexible resources to enhance optimization scheduling in distribution networks using granular K-medoids clustering and improved zonotopic approximations. Although diverse optimization techniques have been used for VPP and MG optimization, none of the cited works includes the addition of EVs in the MGs. Also, none of the works includes the provision of flexibility services to the VPP or energy management system (EMS) to receive economic benefits. Only [6] includes the use of genetic algorithms (GA), as proposed in this paper, but it is only used for scheduling of the MG and not for the economic benefits.

This paper is organized as follows: Section 1 introduces the problem and compares techniques proposed in literature for similar purposes; Section 2 presents the case study and summarizes the main contributions of the paper; Section 3 describes the optimization methods; Results are depicted and discussed in Section 4; Finally, Section 5 presents conclusions.

2. Case study and main contributions

This work proposes a two-stage optimization process to manage a VPP composed of MGs. This structure allows for the joint management of both electricity trading and grid support. Fig. 1 illustrates the proposed case study. Two MGs, which include residential consumption, photovoltaic (PV) generation, battery-based ESS, and EVs, are not connected to the same node of the distribution grid, but they are jointly managed by a VPP with which information is exchanged.

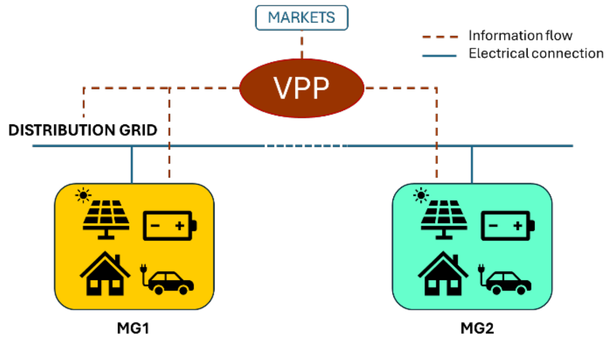


Fig.1. Case study: VPP composed of residential MGs.

Table I summarizes the energy resources and configuration data for both MGs. Each MG includes households with varying demand profiles (high, medium, and low demand), communal PV plants, battery-based ESS, and EV bidirectional chargers (refer to [14] for further details on resources). For both ESS and EVs, the sign criterion is defined as positive power during charging and negative power during discharging.

Table I. – Resources and configuration data in each MG

	MG1	MG2
Demand (number of houses)	5	3
PV generation power (kW)	10	5
ESS capacity (kWh)	16	8
ESS SoC range (%)	20-100	20-100
ESS charge/discharge power range (kW)	± 4	± 2
ESS charge/discharge efficiency (%)	95	95
ESS initial SoC (%)	55	40
Number of EV bidirectional chargers	2	2
EV charge/discharge power range per charger (kW)	± 7.36	± 7.36
EV charge/discharge efficiency (%)	75	75
EV battery capacity (kWh)	50	50
EV SoC range (%)	20-100	20-100
EV initial SoC (%)	90	80

Initial forecasted hourly generation and demand data (summed up for the entire VPP) are depicted in Fig. 2. EV are assumed to be available during the first 8 hours. EV charging is supposed to be performed at maximum power at the beginning of the day, as shown in Fig. 2.

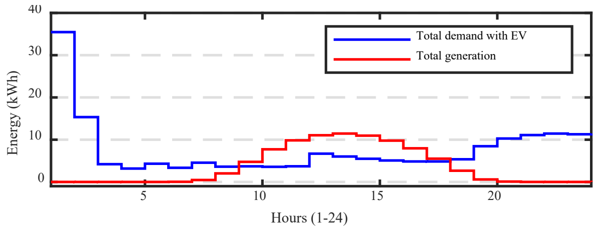


Fig.2. Initial generation and demand forecasted data for the entire VPP.

The first stage of the optimization process involves daily planning of the energy management of ESS and the EV charging strategy of the entire VPP, based on forecasted hourly profiles of PV production and demand. The objective of this optimization is economic, aiming to achieve maximum profit/savings for the aggregated resources. This first stage of the optimization process was previously studied by the authors in [14], where GA were compared to other optimization techniques for this purpose, and they proved better performance. Although this optimization process has been extensively studied in the literature, this paper introduces a novel contribution: participation in a flexibility market by providing the distribution system with a reserve power band up and down. As a result of this first stage of the optimization process, an hourly energy profile is obtained for the VPP aggregated ESS and EV charging/discharging. Due to the wide range of possible solutions (24 hourly values for each resource are the variables to be obtained) and non-linear constraints, a metaheuristic GA is used for this first-stage optimization.

Prices are obtained from the Spanish Electricity Market (see Fig. 3). The reservation band of the ESS depends on the prices offered by the distribution system operator or cleared in a flexibility market. In this example, the price for power band reservation is assumed to be constant at 50 EUR/MW/h.

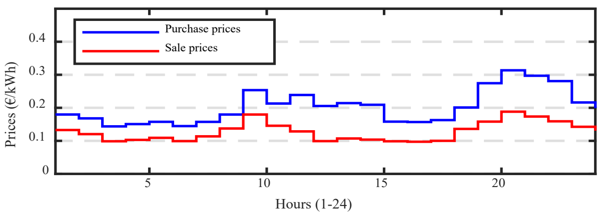


Fig.3. Energy price for prosumers according to regulated prices of the Spanish market on February 1st 2025 [15].

Based on the prices depicted in Fig. 3 and the demand and generation data shown in Fig. 2 (excluding the intervention of ESS and any revenues from the flexibility market), the cost of the electricity bill for the entire VPP amounts to 24.85 EUR/day.

The second stage of the optimization process aims to allocate the required power to the resources of each MG to implement the planned strategy of the entire VPP while also contributing to local distribution grid support. In this case, the optimization objective is to avoid grid congestion by minimizing the power interchange between each MG and the distribution grid. This second strategy does not result in a daily plan but approximates a real-time operation strategy, performed with a 1-minute resolution. In this case, only one value is obtained for each resource (power setpoint for the next minute), so a non-linear programming strategy is selected for the second stage optimization.

The main contributions of this paper can be summarized as follows:

- An innovative structure of VPP aggregation of residential MGs is proposed to jointly optimize the operation of distributed resources with dual economic and technical objectives.
- A two-stage optimization process is proposed to encompass daily economic planning and quasi-real-time operation of resources.
- Metaheuristic and non-linear programming are used for the two stages of the optimization process, due to their different requirements.
- A flexibility asset is included in the economic optimization process: a reserve band of power up and down to be provided to the distribution system and traded in a flexibility market.
- Both economic (optimal electricity bill) and technical (minimum grid congestion) objectives are targeted in the proposed strategy.

3. Optimization methods

A. Stage 1: VPP daily energy planning

The initial optimization process seeks to minimize the electricity bill, which is calculated as the sum of the cost of purchased energy minus the revenue from sold energy and the flexibility market, utilizing a GA. Starting from the energy balance of the entire VPP (1), the objective function is presented in equation (2).

$$E_{grid}(h) = E_{PV}(h) - E_{LD}(h) - E_{ESS}(h) - E_{EV}(h) \qquad (1)$$

$$f_1 = \sum_{h=1}^{24}\left[\left(I_{pur}(h)\cdot p_{pur}(h) - I_{sel}(h)\cdot p_{sel}(h)\right)\cdot \left|E_{grid}(h)\right|\right] - p_{flex}\cdot\left(\left|RP_{up}\right| + \left|RP_{down}\right|\right)\cdot 24 \qquad (2)$$

Here, $E_{grid}(h)$ represents the hourly energy interchanged with the grid at hour h, $E_{PV}(h)$, $E_{LD}(h)$, $E_{ESS}(h)$ and $E_{EV}(h)$ represent the PV generation hourly energy, load demand hourly energy, ESS hourly energy and EV hourly energy at hour h, respectively. All energy values are in kWh. $I_{pur}(h)$ and $I_{sel}(h)$ are binary indices, with a value of 1 or 0 when $E_{grid}(h) \leq 0$ and $E_{grid}(h) > 0$, respectively. $p_{pur}(h)$ defines the price for purchased energy at hour h in EUR/kWh and $p_{sel}(h)$ defines the price for sold energy at hour h in EUR/kWh.

Regarding the flexibility asset, p_{flex} is the price for power band reservation, in EUR/kW/h, and RP_{up} and RP_{down} are values for the reservation band, in kW, that are kept available from the ESS to either increase or decrease the power, respectively. They are defined as a demand increase/decrease because positive values of ESS power correspond to charging power values. As an ESS converter is a fully controllable bidirectional device, the power range at each hour can be used to address uncertainties in generation or demand forecasting and to provide other ancillary services to the distribution grid. For example, the distribution system operator might send a power setpoint to the VPP to avoid network congestion in high-demand hours or to smooth power, aiming to better exploit grid capacity and manage grid losses. This reservation band is intended to be maintained throughout the 24 hours, at a constant price.

The variables of the problem are the hourly charging/discharging energy of the ESS (E_{ESS}) and the EVs (E_{EV}, assuming a Vehicle-to-Grid strategy) for the next 24 hours, and the optimal power-up/power-down bands (RP_{up} and RP_{down}) to be reserved for the flexibility market. A constant power value is assumed throughout each hour; therefore, at this optimization stage, an hourly energy value in kWh is equivalent to a power value in kW. The constraints of the problem are as follows (cumulative values for the entire VPP):

- Maximum/minimum values for ESS power.
- Maximum/minimum values for ESS SoC.
- Maximum difference between ESS SoC at the beginning and the end of the day to ensure availability for the next day (absolute difference between initial and final SoC must be 10% at most).
- Availability of EVs at the charging point (from 0 to 8 hours).
- Maximum/minimum values for EV power.
- Maximum/minimum values for EV SoC.
- EV battery SoC must be 100% at the end of the availability time slot (after the first 8 hours) to ensure sufficient autonomy for mobility purposes.
- Potential increase/decrease of ESS power must be higher than the reserved band. This potential increase/decrease is constrained by the charging/discharging power and the distance to the extreme values of the SoC.
- Maximum energy exchanged with the grid each hour is limited to 10 kWh.

The SoC of both ESS and EV at the end of the hour h is calculated using (3):

$$SoC(h) = SoC_{in} + \sum_{i=1}^{h} \left(I_{ch}(i) \cdot E(i) \cdot \eta_{ch} + I_{di}(i) \cdot \frac{E(i)}{\eta_{di}} \right) \quad (3)$$

In equation (3), SoC_{in} is the initial value of SoC, E denotes the hourly energy (positive when charging) I_{ch} and I_{di} are binary indices for charging and discharging, respectively, and η_{ch} and η_{di} are charging and discharging efficiency rates.

The result obtained from the first stage, using a GA, implemented in Matlab®, is a set of 24 hourly energy values for the cumulative ESS and EV of the entire VPP, along with the optimal values for the power-up and power-down reserve bands for the flexibility market.

B. Stage 2: Power allocation for each MG's resources

Building on the daily scheduling for the entire VPP, the next stage involves allocating power setpoints for each MG's DERs with a higher time resolution (1 minute). This allocation must align with the scheduled total energy values of the VPP and also aim to minimize the power interchanged by each MG with the distribution grid to locally reduce grid congestion. This second-stage optimization process is performed using a non-linear programming tool with four variables: next-minute power for ESS and EV in MG1, and next-minute power for ESS and EV in MG2.

The objective function to be minimized is the net power interchange between each MG and the distribution grid (4):

$$f_2 = P_{grid\_MG1}^2 + P_{grid\_MG2}^2 \quad (4)$$

Where P_{grid_MG} is the power interchanged by each MG with the grid, obtained from the power of each DER, by means of a calculation equivalent to equation (1).

The following constraints are considered:

- The sum of power of ESS and EVs of both MGs must match the planned hourly energy values previously obtained by the entire VPP with sufficient accuracy.
- The sum of power of ESS of both MGs must guarantee the reservation band for the entire VPP.
- Maximum/minimum values for power charge/discharge of each ESS and each EV.
- Maximum/minimum values for SoC of each ESS and each EV.
- Availability of EVs (EV power must be zero outside the availability time slot of 0-8 hours).
- To avoid recirculating power among EVs (and reduce losses due to lower efficiency than ESS), both must be charging or discharging simultaneously (both values must be positive or negative at the same time).

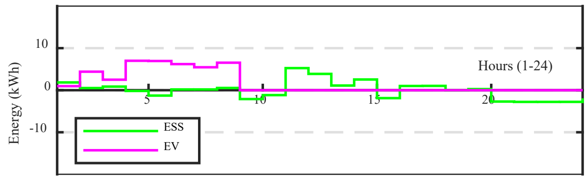
The result of the second-stage optimization is next-minute value for ESS and EV power of each MG, obtained using the non-linear programming tool *fmincon* in Matlab®.

4. Results and discussion

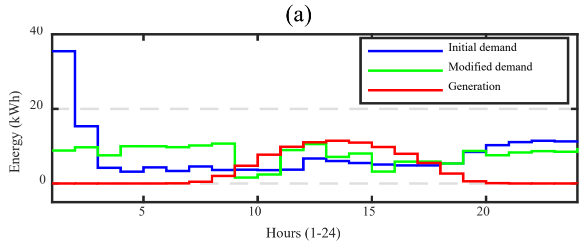
A. Results of stage 1: VPP daily energy planning

The general scheduling for ESS and EV of the entire VPP obtained after the first optimization stage using GA is depicted in Fig. 4a, while the modification of demand is shown in Fig. 4b versus the PV generation. The modified demand results from the addition of the initial demand and the net charge of ESS and EV.

It can be observed in Fig. 4a that the EVs of the entire VPP are consistently charging after optimization, following a smooth profile during the availability time slot (first 8 hours). Conversely, ESS charge or discharge at different hours according to economic optimization. Fig. 4b demonstrates that the energy generated in the VPP during the central hours of the day is utilized to charge ESS, thereby reducing energy demand during the peak-price hours in the evening.



(a)



(b)

Fig.4. Optimization results for the entire VPP: (a) Hourly energy obtained for the ESS and EVs of the entire VPP, and (b) Modified demand versus generation.

Due to this resource optimization and the provision of flexibility services through the power reservation bands, the electricity bill for the entire VPP has been reduced by 29% amounting to 17.68 EUR/day.

Additionally, the peak shaving constraint (as seen in the power interchange with the grid in Fig. 5) may reduce the contracted power and, consequently, the grid tariff, by up to 10 kW. This tariff reduction has not been factored into the electricity bill in this paper.

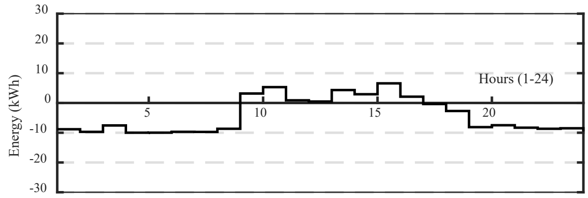
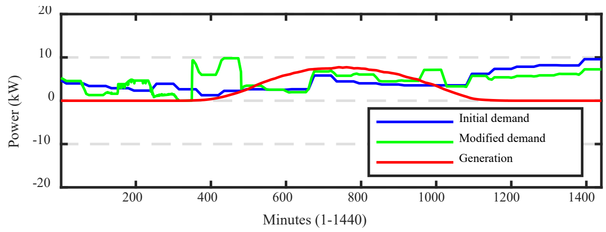


Fig.5. Energy interchange of the entire VPP with the distribution grid.

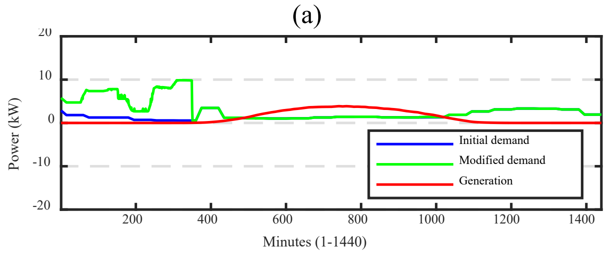
Finally, the obtained reserved band is 0.75 kW up and 3.22 kW down throughout the day (with "up" considered an increase in demand). Clearly, both the width of the reservation band and the cost savings are highly dependent on the flexibility service price. In this case example, the width of the band (approximately 4 kW) is of medium size compared to the ± 6 kW of charge/discharge power range of the ESS for the entire VPP.

B. Results of stage 2: Power allocation for each MG's resources

Building on the results of the first optimization stage for the entire VPP over the 24 hours of the day, the second stage yields power values for each DER for the next minute. This process is repeated multiple times to complete a daily simulation and verify the adherence to the daily scheduling. Fig. 6 illustrates the obtained power balance throughout the day for both MGs. As before, the modified demand results from the addition of the initial demand and the net charge of ESS and EV.



(a)



(b)

Fig.6. Power balance in MG1 (a) and MG2 (b) after power allocation.

In both cases, the net power interchange with the distribution grid is constrained to below 10 kW.

Fig. 7 demonstrates that the reserve power band committed by the entire VPP is maintained after the power allocation among MGs (as indicated by red dashed lines in Fig. 7).

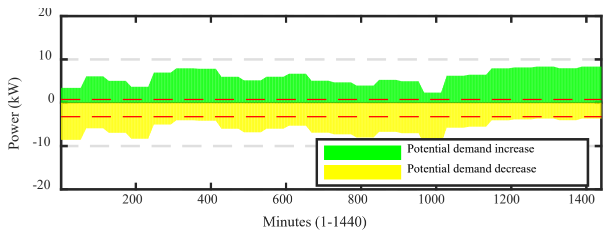


Fig.7. Potential increase/decrease in demand of both MGs after power allocation.

Additionally, the EVs of both MGs can be considered fully charged at the end of their availability time slot (8 hours, see Fig. 8).

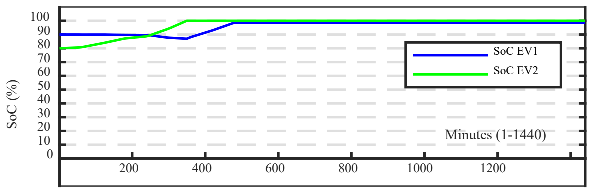


Fig.8. SoC of the EVs of both MG throughout the day.

It is shown that the EVs in MG1 (with a lower initial SoC) charge at the beginning until they are fully charged, whereas the EVs in MG2 charge later, closer to the end of the available time slot.

Fig. 9 illustrates the evolution of the ESS SoC throughout the day.

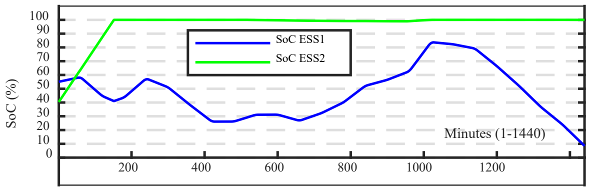


Fig.9. SoC of the ESSs of both MG throughout the day.

It is interesting to observe that the ESS of MG2 is fully charged during the early hours of the day and remains full throughout the day. In contrast, the ESS in MG1 adjusts to follow the scheduling of the entire VPP. According to these results, the ESS of MG2 is primarily dedicated to providing part of the potential demand decrease if required as a flexibility service, given its lower maximum power discharge and capacity compared to the ESS in MG1.

5. Conclusions

A two-stage optimization process has been designed and tested for the energy management and power allocation of DERs within a VPP composed of residential MGs. Both economic optimization and the provision of flexibility services are considered. The results demonstrate the appropriate behavior of the DERs, the fulfillment of constraints, and significant economic savings.

Following the power allocation of resources in both MGs, a cooperative behavior is observed between them. EVs alternate in charging to meet the VPP scheduling. Meanwhile, the ESS in MG2 is fully charged at the beginning of the day to be available for power reservation, while the ESS in MG1 follows the overall VPP scheduling. This collaboration results in economic benefits (due to both shared energy trading and flexibility service provision) that would not have been possible individually.

Currently, the participation of low-power resources in flexibility markets is not a viable option. However, the aggregation of resources in energy communities or VPPs represents a trend towards improving the energy and economic efficiency of such resources and increasing the pool of flexibility services providers at the distribution level. This paper demonstrated the effectiveness of a method to manage distributed resources for this purpose.

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